



UNIVERSITÀ DEGLI STUDI DI NAPOLI
FEDERICO II

Doctoral Dissertation
Doctoral Program in Industrial Engineering (37th Cycle)

Integration and optimisation of urban-scale energy systems: From end-user to building to urban energy districts

GIUSEPPE RUSSO

Supervisor:

Prof. Annamaria Buonomano

Co-Supervisor:

Dr. Cesare Forzano

Doctoral Examination Committee:

Prof. Jian Song	University of Birmingham
Prof. Constantinos Vassiliades	Neapolis University Pafos
Prof. Alfonso Capozzoli	Politecnico di Torino
Prof. Francesco Guarino	Università degli Studi di Palermo
Prof. Maria Vicidomini	Università degli Studi di Napoli Federico II

Università degli Studi di Napoli Federico II
2024



Declaration

I hereby declare that the contents and organization of this dissertation constitute my own original work and does not compromise in any way the rights of third parties, including those relating to the security of personal data.

Giuseppe Russo

12/11/2024

Abstract

The increasing urbanisation of modern societies necessitates advanced approaches to urban energy systems that support the transition to sustainable and low-carbon cities. This dissertation introduces a structured framework for urban-scale energy system modelling, designed to address complex and interdependent energy demands across three key scales: end-user, building systems, and district systems. By capturing the distinct needs and interactions at each scale, this research provides a holistic approach to optimising energy use, reducing emissions, and enhancing resilience within urban areas.

The study explores occupant behaviour at the end-user level to inform demand management strategies that align energy use with real comfort requirements. Building systems modelling is then developed to integrate renewable energy sources, storage, and control mechanisms that enhance efficiency while addressing dynamic building demands. Finally, at the district level, the research introduces models for coordinated energy management across district heating and cooling systems and energy communities, enabling high self-sufficiency, balanced energy flows, and emissions reduction on a broader urban scale.

Employing both physics-based and data-driven modelling approaches, this work provides essential insights and optimised strategies tailored to urban contexts. These models contribute valuable tools for urban planners, engineers, and policymakers, enabling informed decision-making for sustainable, energy-efficient cities. Overall, the dissertation underscores the critical role of urban energy system modelling in supporting the energy transition and in achieving adaptable, resilient, and occupant-centred urban environments.

Table of contents

Abstract.....	1—2
List of Figures	1—9
List of Tables.....	1—1
Chapter 1 Introduction.....	2
1.1 The role of urbanisation in energy transition	3
1.2 Urban-scales energy system modelling.....	5
1.2.1 End-user	5
1.2.2 Building systems	7
1.2.3 District systems.....	9
1.2.4 Modelling multi-scales interaction	11
1.3 Problem statement and research objectives	12
1.3.1 Research objectives.....	13
1.4 Methodology and contributions	15
1.4.1 Contributions.....	19
1.5 Dissertation outline.....	25
Chapter 2 A physics-based human model for assessing the energy impact of comfort needs.....	28
Summary	28
Keywords	28
Nomenclature.....	29
2.1 Introduction	30
2.1.1 Thermal sensation and comfort assessment.....	30
2.1.2 Thermoregulation mechanism of human body	31
2.1.3 Thermo-hygrometric smart control for indoor spaces.....	31
2.1.4 Aim and contributions	32
2.2 Methodology.....	33

2.2.1	Physiological thermal model	35
2.2.2	Heat transfer within the human body tissues	36
2.2.3	Indoor air temperature and relative humidity control strategies	40
2.3	Case study	42
2.4	Main findings	44
2.4.1	Physiological adaptation of the human body	44
2.4.2	Building energy simulation and comfort analysis	48
2.4.3	Further remarks	51
2.5	Conclusions	55

Chapter 3 Occupant-centric control for enhancing building energy efficiency 56

Summary	56
Keywords	56
Nomenclature	57
3.1 Introduction	58
3.1.1 Managing Occupant-Centric Control through physiological information	58
3.1.2 Building energy performance tools implementing personal comfort models	59
3.2 Objectives and contributions	62
3.3 Methodology	63
3.3.1 Building energy model	65
3.3.2 MLNLP optimisation for indoor setpoint evaluation	66
3.3.3 MPC for HVAC operation	68
3.3.4 MPC optimisation problem	69
3.4 Experimental setup	71
3.4.1 NEXT.ROOM: targeting human-centric and multi-domain investigation	71
3.4.2 A study approach for assessing human physiological information	72

3.5	Proof of concept	74
3.6	Results	76
3.6.1	Accuracy of the physiological thermal model	76
3.6.2	Proposed HVAC control strategies	79
3.6.3	Results comparison	86
3.7	Conclusions.....	90
Chapter 4	Predictive control of solar-assisted energy hubs in district heating systems	91
	Summary	91
	Keywords	91
	Nomenclature.....	92
4.1	Introduction	93
4.1.1	Literature gap	95
4.1.2	Aim and contributions	96
4.2	Methodology.....	97
4.2.1	Solar field mathematical model	99
4.3	Control strategies	102
4.3.1	Rule-Based control strategy.....	103
4.3.2	MPC control strategy	104
4.3.3	Optimisation problem	105
4.4	Proof of concept analysis	106
4.5	Experimental validation	110
4.6	Results proposed scenarios	112
4.6.1	Proposed scenario 1 (PS1).....	113
4.6.2	Proposed scenario 2 (PS2).....	115
4.6.3	Proposed scenario 3 (PS3).....	117
4.6.4	Results comparison	118
4.6.5	Yearly energy analysis.....	119
4.7	Conclusions.....	122

Chapter 5	Optimisation of temperature management in 5th generation district heating and cooling systems	124
Summary		124
Keywords		124
Nomenclature.....		125
5.1	Introduction	126
5.1.1	5G district heating network modelling	126
5.1.2	Optimisation and control strategies to improve efficiency 128	
5.1.3	Work contributions	130
5.2	Methodology.....	131
5.2.1	Heat pumps substations modelling	133
5.2.2	Central thermal station modelling.....	134
5.2.3	Pipes thermal network	134
5.2.4	Optimisation problem	136
5.3	5GDHC model validation.....	136
5.4	Proof of concept	139
5.5	Results	143
5.5.1	5GDHC network daily optimal temperature.....	143
5.5.2	Comparison of proposed scenarios	144
5.5.3	Energy performance analysis.....	147
5.6	Conclusions.....	152
Chapter 6	Designing aggregation methods for peer-to-peer energy communities	153
Summary		153
Keywords		153
Nomenclature.....		154
6.1	Introduction	155
6.1.1	Literature review	156
6.1.2	Contributions.....	159

6.2	Methodology.....	160
6.2.1	Building archetypes for EC users' energy modelling	162
6.2.2	Electrical load estimation: equipment and lights	163
6.2.3	Sequential HNN model for heating / cooling demands.	164
6.2.4	Peer-to-Peer model for users' energy sharing	166
6.2.5	Pricing strategy	168
6.2.6	EC design methodology	169
6.2.7	Aggregation criteria	171
6.2.8	Optimisation of P2P cluster archetypes	172
6.2.9	P2P cluster archetypes aggregation	173
6.3	Proof of concept	174
6.4	Results	176
6.4.1	HNN model prediction accuracy.....	177
6.4.2	EC design	180
6.4.3	Users' energy management.....	184
6.4.4	Cost analysis: prosumers and consumers	188
6.4.5	Energy performance of EC.....	190
6.5	Conclusions.....	191
	Appendix A	192
	Appendix B	194
Chapter 7	Predictive strategies for energy communities in grid flexibility and balancing.....	196
	Summary	196
	Keywords	196
	Nomenclature.....	197
7.1	Introduction	198
7.1.1	Sharing mechanisms in energy communities.....	198
7.1.2	Electric vehicles as sharing technology	199
7.1.3	Models for energy dispatching mechanisms	200
7.1.4	Objective functions and optimisation procedures.....	201

7.1.5	Aim and contributions	202
7.2	Methodology.....	202
7.2.1	User level energy dispatch.....	203
7.2.2	Strategies for community sharing.....	203
7.2.3	Energy community for electricity grid balancing	208
7.2.4	Optimisation problem	210
7.3	Proof of concept	211
7.4	Results	216
7.4.1	Energy sharing optimisation analysis.....	216
7.4.2	P2P energy sharing	217
7.4.3	Vehicles-to-Clusters / Clusters-to-Vehicles.....	218
7.4.4	Energy community for grid balancing	219
7.4.5	Community load flattening for grid stability	219
7.4.6	Power grid regulation services	220
7.4.7	Comparison between optimisation strategies.....	221
7.5	Conclusions.....	225
Chapter 8	Discussions and main findings	226
	Discussions.....	227
	Main findings.....	236
References		242

List of Figures

Figure 1. Modelling the complexity of multi-scale energy systems in urban contexts: Interaction between end-users, building systems, and district energy systems, with integrated control and optimisation strategies to enhance energy efficiency.....	14
Figure 2. Modelling tools and techniques for each urban scale – end-user, building systems, and district systems – along with optimisation routines for energy system design and operational control.....	16
Figure 3. Overview of the dissertation’s key contributions: Classification of chapters by their focus on modelling individual urban scales, interactions between scales, and the optimisation of interconnected system design and control strategies.....	23
Figure 4. Discretisation procedure for human body simulation.	35
Figure 5. Resistive-capacitive thermal network of human body.	37
Figure 6. Synoptic block diagram of the developed control strategies.	40
Figure 7. Synoptic block diagram of the optimisation procedure.	41
Figure 8. Thermohygrometric parameters resulting from the dynamic control strategies.....	45
Figure 9. Physiological response due to thermoregulatory process: a) reference case, b) 1st strategy, c) 2nd strategy, d) 3rd strategy.	47
Figure 10. Dynamic trend of thermal loads and energy consumption for the 1st week of January.	48
Figure 11. Dynamic trend of thermal loads, energy consumption, and indoor air temperature for the 1st week of July.	49
Figure 12. Comfort analysis in the 1st week of January.....	50
Figure 13. Comfort analysis in the 1st week of July.	51
Figure 14. Monthly energy consumption for heating and cooling needs. .	52
Figure 15. Scatter plot of recurring temperature and relative humidity over the year.	53
Figure 16. Cumulation of temperature values that occur throughout the year.	54
Figure 17. Research framework.	64
Figure 18. Optimisation procedure of MLNLP problem.	67

Figure 19. Sensors' representation inside the NEXT.ROOM facility: (a) plan view with sensors and subject disposition in the test room, (b) 3D view.....	72
Figure 20. First experimental path.....	73
Figure 21. Second experimental path.	73
Figure 22. Room air temperature and velocity near the workstations of the two subjects.	76
Figure 23. T_{skin} comparison between measured and simulated for (left) subject 1 and (right) subject 2.	77
Figure 24. Temperature of the human body tissues vs. radius and time for (left) subject 1 and (right) subject 2.	77
Figure 25. T_{skin} temperature –simulated versus measured for test subject 1 (a) and test subject 2 (b); boxplot for assessment of distribution of percentage relative error (c).	78
Figure 26. (left) CO ₂ and IAQ for test 2 and (right) CO ₂ emissions during test 2.	79
Figure 27. Optimisation procedure to determine optimal indoor setpoints for test 1: (top) PMV* constraint space; (middle) PIAQ constraint space; (bottom) solution space of Q_{HVAC}	80
Figure 28. MPC strategy for test 1: (top) manipulated variables prediction; (bottom) prediction of reference variable $h_{\text{air,ref}}$ of the system and cost function optimisation.	82
Figure 29. Energy analysis for test 1: (top) optimised setpoints and cooling thermal needs; (bottom) optimised supply air thermal power and HVAC electricity needs.	83
Figure 30. Energy analysis for test 2: (top) optimised setpoints and heating thermal needs; (bottom) optimised supply air thermal power and HVAC electricity needs.	84
Figure 31. Comfort analysis for test 1: (top) thermal comfort; (bottom) perceived indoor air quality.	85
Figure 32. Comfort analysis for test 2: (top) thermal comfort; (bottom) perceived indoor air quality.	86
Figure 33. Comfort analysis comparison: reference versus proposed test #1 (top) and test #2 (bottom).....	87

Figure 34. Energy analysis comparison: reference vs proposed test #1 (top) and test #2 (bottom).....	89
Figure 35. Scheme of a generic poly-generative district heating network.....	98
Figure 36. Schematic diagram showing the developed tool inputs and outputs.	99
Figure 37. Iterative process to assess thermal solar production.	102
Figure 38. Scheme of rule-based control strategy.....	103
Figure 39. Scheme of MPC control strategy.	104
Figure 40. Existing Geneva solar field.....	107
Figure 41. Innovative TVP solar MT Power collector efficiency curve vs. standard technologies.	108
Figure 42. Schematic layout of the investigated solar field.	109
Figure 43. Validation results time histories and relative errors of $T_{sf,out}$ (from 13 th to 15 th of June).....	111
Figure 44. Validation results time histories and relative errors of m_{sf} (from 13 th to 15 th of June).	111
Figure 45. PS1: rule-based control strategy of m_{sf} (from the 13 th to the 15 th of June).	113
Figure 46. PS1: thermal power supplied to load (from the 13 th to the 15 th of June).	114
Figure 47. PS1: pressure drops and pump power (from the 13 th to the 15 th of June).	114
Figure 48. PS2: a) actual and foreseen weather data, b) optimised and foreseen economic results, c) optimised and foreseen mass flowrate, d) optimised and foreseen solar field output temperature - (13 th and 14 th June).	116
Figure 49. PS3: a) optimised and foreseen mass flowrate, b) optimised and foreseen solar field output temperature, c) optimised and foreseen tilt angle - (13 th and 14 th June).	118
Figure 50. RS vs. PSs: a) flow rate, b) thermal power, c) mechanical power (13 th February – left, and 13 th June - right).	119
Figure 51. RS vs. PSs monthly and annual thermal energy supplied to the users.	120

Figure 52. Annual mechanical energy of pump for reference and proposed scenarios.....	120
Figure 53. Primary energy savings and avoided CO ₂ emissions for all the proposed solutions.	121
Figure 54. Overview of the developed tool for modelling and optimisation of 5GDHC systems.	132
Figure 55. Heat pump layout schematisation and representation of T-s diagram.	133
Figure 56. 5GDHC prototype developed at the ENEA research centre (left) and related system layout (right).	137
Figure 57. Temperature comparison among simulated and measured values: a) station evaporator; b) substation evaporator; c) condenser, dry-cooler, recuperator.	138
Figure 58. Percentage relative error of temperatures comparison among simulated and measured values.....	139
Figure 59. Comparison among simulated and measured EER of HP substation.....	139
Figure 60. Scheme of 5GDHC network configuration.	140
Figure 61. Buildings thermal loads: a) residential; b) office; c) data center.	141
Figure 62. Optimisation procedure to assess the optimal daily temperature of the DHC network.....	144
Figure 63. PS1 vs. PS2: time histories of a) inlet, and outlet water temperature, and network thermal gain; and b) primary energy and energy efficiency ratio of energy hub.	146
Figure 64. PS1 vs. PS2: HPs performance and electrical power for three sample days in case of a) data centre; b) residential building; c) office.	147
Figure 65. PS1 vs. PS2: users' heat pumps COP probability density: a) residential; b) office; c) datacentre.	148
Figure 66. PS1 vs. PS2 primary energy consumption on yearly and monthly basis: a) residential building; b) office; c) data centre.....	150
Figure 67. PS1 vs. PS2: energy hub primary energy consumption on yearly and monthly basis.....	151

Figure 68. PS1 vs. PS2: overall 5GDHC system primary energy consumption on yearly and monthly basis.	151
Figure 69. Overview of the developed methodology for designing and optimising the management of energy communities.	161
Figure 70. Schematisation of sequential Hybrid Neural Network model.	165
Figure 71. Algorithm used to model the P2P energy exchange mechanism.	168
Figure 72. Synoptic diagram related to the aggregation criteria for EC design.	170
Figure 73. Comparison between the real and predicted electrical cooling demand for building archetype 1: a) comparison from July 29 th to August 4 th ; b) from October 7 th to October 12 th	178
Figure 74. Relative percentage deviation between simulated and real data: a) time series comparison of electrical load P_{HVAC} ; b) monthly comparison of electrical cooling energy needs E_{cool}	179
Figure 75. Results of the first optimisation level referred to cluster archetype #52: top) self-sufficiency of all investigated solutions; bottom) choice of the optimal configuration within the feasibility range.	181
Figure 76. Selection of the optimal energy community configuration maximising the global self-consumption.	183
Figure 77. Dynamic trend of single user energy management from 10 th to 13 th of June: top) PV production dispatching of prosumer #5 of cluster #19; bottom) electrical load of consumer #6 of cluster #52.	185
Figure 78. Annual PV production management for each prosumer type of the EC's cluster archetypes.	186
Figure 79. Rates of energy exchanged with the different types of consumers: top) 1st DL; bottom) 2nd DL.	187
Figure 80. Annual analysis of coverage of electricity needs and self-sufficiency by type of EC user.	187
Figure 81. Energy pricing strategy, balancing of demand and supply curves.	188
Figure 82. Economic analysis: top) prosumers' revenues; bottom) users saving.	189

Figure 83. Results of the first optimisation level referred to cluster archetype #52: top) self-sufficiency of all investigated solutions; bottom) choice of the optimal configuration within the feasibility range.	190
Figure 84. Equipment and lights electrical load: a) power rating; b) occupancy profile pattern of the 6 buildings archetypes of investigated EC; c) usage probability factor of equipment and lights during weekdays; d) usage probability factor of equipment and lights during week-end days.	193
Figure 85. EC's users electrical load: a) dynamic profile of total electricity consumption from July 8th to July 11th; b) annual electricity consumption for different users' types.	194
Figure 86. PV systems production for each prosumer type: a) dynamic profile of electricity production from July 8th to July 11th; b) cumulative annual electricity production for different prosumer's types.	195
Figure 87. Energy balances for consumers, prosumers, and EVs in P2P sharing.	205
Figure 88. Schematisation of priority-based dispatching strategy.	206
Figure 89. Work-flow schematisation of proposed strategy with community acting as grid regulator.	209
Figure 90. Consumers' electrical loads: a) weekly dynamic trend; b) annual needs.	212
Figure 91. Prosumers energy management: a) weekly dynamic trend; b) annual needs.	213
Figure 92. Global charging and discharging profile of EVs and cumulative kilometres travelled individually.	214
Figure 93. EVs load: a), b) charging discharging profiles of EV5 and EV7; c) individual annual needs.	215
Figure 94. Optimisation procedure of priority dispatching strategy.	216
Figure 95. Energy management of PV production of prosumer #5.	217
Figure 96. Energy balance of electrical load of consumer #6, a) 14-16 January; b) 20-22 May.	218
Figure 97. Charging/discharging profile of EV #5 for V2C/C2V strategy.	219
Figure 98. Grid balancing optimisation: a) energy management of community's flattened demand profile; b) energy management of PV production of prosumer #5.	220

Figure 99. Power grid regulation from energy community: a) foreseen and real load of entire electricity grid; b) Power grid regulation required from community; c) Optimised energy management of community for grid regulation.	221
Figure 100. Comparison between 1st proposed strategy on the left and 2nd one: a) energy balance of consumers; b) energy management of prosumers; c) EVs energy management.	223
Figure 101. Energy performance comparison between reference case 1st, and 2nd proposals.....	224
Figure 102. Framework for modelling interactions and influences between urban scales, enabling optimised solutions across subsystems.....	230
Figure 103. Comparative diagram of key findings, modelling connections between urban scales, and outcomes across the dissertation chapters.	237

List of Tables

Table 1. Human body thermal properties.	36
Table 2. Geometrical and thermal properties of test room.	43
Table 3. Annual energy analysis for each strategy.....	52
Table 4. Annual discomfort analysis for reference case strategy.	52
Table 5. NEXT.ROOM lighting and HVAC systems characteristics.	74
Table 6. Body data and clothes – subject 1 and 2.....	74
Table 7. Characteristics of investigated scenarios.	75
Table 8. Comparison of energy and comfort analysis for proposed scenarios vs reference.	89
Table 9. Solar field parameters.	107
Table 10. TVP solar MT Power vacuum collector characteristic.	108
Table 11. Validation indices of all the investigated parameters for all the sample days.	112
Table 12. 5GDHC network modelling approaches.	127
Table 13. 5GDHC network optimisation procedure.	129
Table 14. 5GDHC network prototype characteristics.	137
Table 15. Cluster buildings characteristics.	140
Table 16. Substations HPs characteristics.	142
Table 17. Taxonomy of literature review.	159
Table 18. Users building archetypes properties.	175
Table 19. PV systems characteristics, type and count of prosumers.	176
Table 20. Optimal configuration of cluster archetypes.	182
Table 21. Optimal configuration of Energy Community.	184
Table 22. Pay-back time of prosumers investments.....	189
Table 23. Characteristics of energy community users.....	211
Table 24. Characteristics of community power systems.	212
Table 25. Characteristics of EVs.	214
Table 26. Comparison of the results obtained by the optimisation strategies.....	224

Chapter 1

Introduction

Greenhouse gas emissions are the primary drivers of environmental degradation and public health issues, significantly contributing to climate change and global warming [1]. Recent data indicates that the Earth was approximately 1.36°C warmer in 2023 than the preindustrial average (1850-1900), marking the fastest warming period in recorded history [2].

In December 2023, the UAE Consensus at the COP28 climate change conference in Dubai culminated in a historic agreement that heralded the "beginning of the end" of the fossil fuel era. Governments committed to doubling the annual rate of energy efficiency improvements and tripling the global deployment of renewable energy capacity by 2030 [3].

The European Union targeting climate neutrality by 2050 as a key aim of the European Green Deal [4]. The roadmap to this goal includes ambitious milestones [5]: a projected 860% increase in photovoltaic installations in households, a 500% increase in solar thermal and geothermal systems, and a 203% rise in the renewable share of power generation. Furthermore, energy efficiency initiatives aim to boost the rate of zero-carbon buildings from 1% to 85%, reduce heating and cooling energy demand in buildings by 80%, and lower energy consumption due to appliances by 40%. Electrification strategies are set to increase heat pump installations by 1000% and elevate the share of electric vehicles from 1% to 86%. Behavioural changes also play a critical role, focusing on reducing hot water consumption, optimising indoor temperatures, enhancing plastic collection rates in industry, and increasing the use of public transportation.

These multifaceted efforts reflect the urgent need to mitigate greenhouse gas emissions and transition towards sustainable urban energy systems.

1.1 The role of urbanisation in energy transition

Cities and urban areas are responsible for approximately 75% of global energy consumption and 70% of greenhouse gas emissions [6]. With urbanisation set to rise from 55% of the global population in 2023 to an estimated 68% by 2050, the environmental impact of urban growth continues to intensify [7]. Nearly 10% of the increase in global emissions since 2015 can be attributed to urbanisation, which now accounts for a record high of nearly 29 billion tonnes of CO₂ annually [8]. This makes cities pivotal actors in the effort to face climate change and reduce global emissions. As a result, sustainable urban energy system design will be crucial in transitioning towards a climate-neutral energy system.

Several strategies offer pathways to sustainable and energy-efficient urban environments. These include: 1) Integration of renewable energy sources, such as solar photovoltaics, wind turbines, biofuel cogenerators, and geothermal plants, to decarbonise urban energy systems [9]. 2) Reduction of energy consumption in buildings, which play a crucial role in urban emissions, by retrofitting for higher efficiency and implementing zero-carbon building designs [10]. 3) Electrification of heating and cooling demands, enabling buildings to rely on renewable energy-powered heat pumps rather than fossil fuel-based systems [11]. 4) Electrification of transportation systems, replacing traditional vehicles with electric options, leading to reduced emissions and less air pollution [12]. 5) Energy sharing mechanisms, such as energy communities and low temperature district heating and cooling systems, where local generation and consumption can be coordinated to improve self-sufficiency of the urban environment [9]. 6) Integration of energy storage systems to enhance the flexibility and reliability of renewable energy use, thereby maximising self-consumption and reducing dependence on external power grids [13].

These possibilities represent the potential for cities to lead the energy transition by improving energy efficiency and reducing environmental impacts. However, the complexity of urban energy systems, which involve diverse energy technologies, consumption patterns, and operational requirements, calls for advanced modelling and simulation tools [14]. These tools are essential for assessing, optimising, and managing the interactions among various urban scales.

In this context, recent research has focused on Urban Building Energy Modelling (UBEM), which is primarily used to estimate energy demand at the urban scale [15]. UBEM refers to physics-based models that simulate the performance of groups of buildings, considering dynamic interactions and interconnections between them [16]. While UBEM serves as a valuable tool for estimating building energy demand and assessing energy efficiency, it has limitations [17]. UBEM can struggle to capture the complexity of the single sub-system interactions that characterise the urban environments [18].

Urban areas consist of multiple interdependent subsystems, each with unique characteristics and complexities that influence the overall energy performance [19].

This dissertation identifies three main subsystems that constitute the complex urban energy domain, each of these subsystems involves a variety of components, technologies, and interactions. These subsystems are represented by:

- 1) **End-users**, whose behaviours significantly impact building energy consumption [20].
- 2) **Building systems**, which comprise HVAC systems, renewable energy generation, and electric vehicles [21].
- 3) **District systems**, including both thermal and electrical network infrastructures, as well as building clusters that interact through these networks [22].

The complex relationships between them cannot be overlooked when seeking to manage energy efficiently within urban environments. This insight has shifted attention towards Urban Scale Energy System Modelling (USEM) tools. USEM tools are specifically designed to simulate the multiple scales within urban areas, addressing the unique characteristics of each subsystem and their interactions [23]. This forms the basis for the objectives of this dissertation.

The key challenge for USEM tools is developing an integrated modelling platform that captures the interactions among these subsystems [24]. These tools can be used as the basis for optimising the design and management of energy systems for urban sustainable transition.

In the next section, a detailed exploration of the multi-scale components that shape the urban energy system will be presented.

1.2 Urban-scales energy system modelling

As previously reported, the urban energy system can be understood as a set of three interrelated scales: **end-users**, **building systems**, and **district systems**. This section aims to describe these scales and highlight the key characteristics that influence the design, energy performance, and management of urban energy systems. Examining energy systems across these three scales provides a comprehensive understanding of urban energy dynamics and can lead to the development of strategies to enhance sustainability, resilience, and overall system performance. Furthermore, a detailed literature review of each of these scales can be found in the introduction sections of the following chapters of this dissertation.

1.2.1 End-user

The role of end-users is central to the performance of urban energy systems, as they drive energy demand through their activities and behaviours [25]. Therefore, enhancing modelling techniques to incorporate end-user behaviour is crucial for accurately assessing the complexities and fluctuations of urban energy demand. This, in turn, assists decision-makers in implementing more efficient measures to manage urban building systems [26, 27]. End-users can be categorised into three primary roles: as building occupants, consumers, or prosumers within the district system.

When acting as **occupants**, end-users influence the energy consumption and power demand profiles of building systems through their choices, which are principally driven by comfort needs. Energy consumption associated with these comfort needs encompasses multiple domains, including thermal comfort, indoor air quality, and visual comfort [28, 29]. Individual activities, such as watching television, cooking, or using electronic devices, further impact the consumption of building equipment [30, 31]. These needs are closely tied to individual factors such as psychology, social habits, and personal preferences [32, 33]. As a result, occupants are responsible for the energy loads associated with HVAC systems and electrical appliances. The modelling challenges in this area centre on accurately capturing occupant features that influence their perception of comfort, including thermoregulatory responses, individual singularities, and cultural and social factors, as well as the habits that dictate equipment usage and, consequently, power load fluctuations [26, 34].

End-users also play a significant role in energy network systems, encompassing both district heating and cooling systems and electricity grids. This role has gained prominence in recent years due to the proliferation and integration of renewable-based distributed energy resources (DERs). The management of DERs by end-users, combined with the unpredictability of renewable generation and fluctuations in energy demand (both thermal

and electrical), presents a critical influence on the behaviour of energy network systems [35, 36]. In this context, end-users can fulfil various roles:

- **Consumers:** End-users who interface with the energy network as simple consumers, purchasing energy to meet their needs.
- **Prosumers:** End-users who both consume and produce energy. They act as consumers when their energy production falls short of their needs and sell excess energy back to the system when their production exceeds their requirements. Prosumers are vital for increasing the share of renewable energy within the centralised network. They also play a crucial role in energy communities [37], peer-to-peer energy sharing [36], and fifth-generation district heating and cooling systems [38], all of which aim to maximise self-consumption of renewable energy through energy-sharing mechanisms.
- **Flexumers:** Consumers and prosumers willing to adjust their power demand profiles flexibly to benefit the energy network. Flexumers can receive financial incentives for adapting their behaviour to support the network, helping to mitigate voltage and frequency imbalances [39]. A flexumer may also be a prosumer, managing their energy injections into the network to counteract the unpredictability of renewable energy sources (RES). To achieve this, prosumers often utilise storage systems (e.g., thermal energy storage and batteries [40]) to enhance their flexibility [41]. Consequently, modelling challenges in this field involve simulating and capturing the uncertainties in end-user behaviours that can impact the energy performance of district heating and cooling systems and power grids.

Additionally, an important role not captured in previous classifications is that of the end-user as a **driver**. The rise of electric vehicles (EVs) presents opportunities for developing urban management strategies that optimise EV operation while realising energy savings in urban systems. The vehicle-to-grid (V2G) and grid-to-vehicle (G2V) mechanisms enable EVs to connect to the power grid via bidirectional charging stations. In this framework, EV batteries can store excess grid energy for balancing or sell energy back to the grid during periods of low generation availability [42]. Similarly, the vehicle-to-building (V2B) and building-to-vehicle (B2V) mechanisms allow EVs to supply stored energy to meet building loads [43]. This approach enhances the utilisation of renewable energy or energy purchased at lower tariffs and supports the development of management strategies aimed at improving building energy efficiency [44]. Thus, modelling in this area is increasingly focused on defining typical user behaviours and driving routes, which represent significant inputs for investigating the potential of these frameworks.

Various modelling techniques have been adopted to simulate end-user behaviour. Physics-based models are employed to simulate the physiological responses of occupants' driving comfort needs [45] while capturing the unpredictability and fluctuations of power load profiles remains a key challenge in the literature. Recently, research has shifted towards

data-driven [46] and stochastic techniques [47], which are well-suited for simulating the energy patterns and behaviours associated with different types of end-users. Modelling end-user behaviour is essential in urban energy systems, as they are the primary drivers of energy demand, and their behaviours significantly influence energy systems management. Consequently, the design and optimisation of urban environments must be grounded in an end-user-centric perspective.

1.2.2 Building systems

The building domain within the urban energy system encompasses a variety of interdependent systems, which extend beyond the **building** itself. These systems include **electrical equipment** specific to the building's intended use, **HVAC systems** designed to meet heating and cooling requirements, **renewable-based DERs technologies**, **storage systems**, and **EVs**, whose energy needs are integrated into the building's overall consumption profile [10]. The efficiency and performance of these systems are fundamental in determining the building's energy demand and, consequently, its impact on the broader urban energy system [48].

Buildings host electrical equipment and HVAC systems, such as heating/cooling coils and heat pumps, which are integral to maintaining thermal comfort. These systems significantly influence energy consumption patterns by converting energy to meet the thermal and electrical demands of the building. The power conversion efficiency of these systems is a critical factor in reducing overall energy consumption [49].

EVs are increasingly recognised as part of the building's energy domain, given their need for charging infrastructure [50]. Their energy consumption can be managed to align with the building's load, adding both complexity and flexibility to the energy system.

Rooftop photovoltaic (PV) panels, solar thermal systems, and other renewable sources are commonly installed at the building level [51]. The performance of these systems is often constrained by factors such as roof space, orientation, and weather conditions, which impact their efficiency and electricity generation capacity [52].

Both thermal and electrical storage systems are essential for enhancing the flexibility and autonomy of buildings [53]. They help balance supply and demand, reduce dependency on the grid, and increase the utilisation of on-site renewable energy generation [54].

Building systems do not operate in isolation; their performance and efficiency directly affect the broader energy network at the urban scale. For instance, HVAC systems contribute to peak energy demand, while the integration of DERs and storage systems can help reduce grid dependency and manage energy loads more effectively [55]. However, the variability in system performance due to factors like climatic conditions, occupant behaviour, and equipment efficiency introduces significant modelling challenges.

Modelling the energy performance of building systems is essential for optimising their operation and integrating them into urban energy strategies. Various modelling approaches are used, ranging from detailed physics-based models to data-driven techniques, each with specific advantages and limitations:

- **Physics-based Models:** These models simulate the physical behaviour of building systems. For example, software such as EnergyPlus and TRNSYS are widely used to simulate the thermal characteristics of building envelopes and the performance of HVAC systems [56]. These tools rely on detailed physical equations to predict energy flows and temperature dynamics. Physics-based models are especially effective for evaluating the thermodynamic performance of heat pumps and HVAC systems [57], allowing for the optimisation of component design and system efficiency [58].
- **Resistive-Capacitive (RC) Models:** RC models are a common approach for simulating the thermal response of buildings. These models represent the building envelope as a network of thermal resistances and capacitances, simulating temperature evolution in different building zones [59]. Reduced-order RC models simplify this approach by using fewer thermal nodes, making them computationally efficient while still providing reasonable accuracy [60].
- **Grey-box and Black-box Models:** Grey-box models combine physics-based principles with data-driven techniques, where the values of thermal resistances and capacitances are derived from empirical data [61]. Black-box models, on the other hand, rely purely on data-driven methods to predict building energy consumption without requiring detailed knowledge of the underlying physical processes [62]. These models are particularly useful for capturing the variability in energy consumption due to occupant behaviour and external weather conditions.
- **Optimisation and Control Strategies:** The optimisation of building systems, particularly HVAC and heat pump systems, is crucial for improving energy efficiency [63]. Advanced control strategies, such as Model Predictive Control (MPC), are increasingly being used to minimise energy costs while maintaining occupant comfort [64]. These strategies allow for dynamic adjustment of system operation based on real-time data, helping to reduce peak loads and enhance the overall energy performance of the building.

Despite the progress in building energy performance simulation (BEPS) tools such as EnergyPlus and TRNSYS, significant challenges remain in integrating all the components of building systems into a cohesive optimisation framework [65]. One key limitation of these tools is their inability to manage the interactions between different subsystems – such as HVAC, renewable energy generation, and storage systems – in a holistic manner [21]. To fully capture the complexity of building systems and their interactions with the urban energy network, there is a need for more integrated and flexible modelling tools. These tools must

be capable of optimising energy management strategies across multiple systems, considering both energy supply (renewables) and demand (occupants and equipment) in real-time.

Additionally, the unpredictability of renewable energy generation and the mismatch between energy supply and demand remain significant challenges. Coupling renewable systems with storage and implementing effective control strategies can mitigate these issues [66]. However, accurately predicting the performance of these integrated systems requires advanced modelling techniques that can account for factors like weather variability, system degradation, and occupant behaviour.

1.2.3 District systems

The district system scale encompasses groups or clusters of buildings, energy hubs, and network infrastructures that interconnect end-users and building systems [10]. This domain plays a critical role in the performance of urban energy systems, heavily influenced by both the behaviours of end-users and the characteristics of building systems at the smaller scale.

District systems represent an aggregation of energy demands and supplies, where **clusters of buildings** contribute significantly to the overall urban energy consumption. These clusters consist of diverse buildings with different thermophysical properties, intended uses, occupant types, energy-use behaviours, energy equipment, and DERs systems [67]. Due to this complexity, conducting an accurate energy analysis of building clusters requires a detailed classification of buildings and their end-users. Recent research has advanced the use of archetypes for urban energy modelling, but many of these approaches focus primarily on geometric and thermophysical characteristics. Such an oversimplification can lead to inaccurate energy demand estimations, as it overlooks critical factors like occupant behaviour and usage patterns [17]. Thus, more comprehensive criteria for the classification of urban users within building clusters are required, integrating behavioural and technological factors alongside physical properties.

Energy hubs are a pivotal component of district systems, playing a crucial role in facilitating the energy transition of urban areas. These hubs enable the integration of renewable energy sources, supporting the decarbonisation of the built environment [68]. Modelling energy hubs presents several challenges, particularly in accurately predicting their performance under varying weather conditions and fluctuating energy demands. The complexity of these hubs arises from the integration of multiple energy sources – solar, wind, hydro, or biomass cogeneration – along with thermal, electrical, and hydraulic systems. The literature presents detailed models to simulate the behaviour of these hubs, accounting for physical characteristics and the interactions between different energy sources and technologies [69]. However, optimising energy hubs within urban environments requires models that not only capture these dynamics but also account for the climatic zone features

and energy demands specific to the area. These models must support the design of efficient energy management strategies, such as MPC techniques, which optimises both the design and operation of energy hubs in response to real-time conditions [70].

Networks, both electrical and thermal, are fundamental to district systems, as they enable interactions between urban users and enhance the flexibility of the overall energy system [71]. By allowing energy sharing mechanisms, district networks can increase the self-consumption of renewable energy, reduce dependence on central grids, and enable cost savings for end-users [72]. Thermal networks, particularly district heating and cooling (DHC) systems, have evolved significantly over the years. The shift towards lower operating temperatures and higher integration of renewable energy sources is embodied by 5th generation DHC (5GDHC) systems [73]. Operating at temperatures between 20-30°C, these systems enable bidirectional thermal energy flows between users, who can act as consumers or prosumers depending on their ability to supply heat or cooling back to the network [74]. Heat pumps, integrated between users and the network, play a crucial role in coupling buildings with different thermal requirements, supporting the electrification of heating and cooling demands. Moreover, 5GDHC systems facilitate the use of renewable energy sources, industrial waste heat, and natural thermal sources such as rivers or seas, alongside thermal storage solutions that enhance energy-saving potential [75].

The modelling challenges for 5GDHC systems are multifaceted. Effective models must capture the interaction between buildings' thermal properties, heat pumps, and the district network's hydraulic and thermal characteristics, including thermal balancing stations, renewable energy systems, and storage technologies. Furthermore, these models must support the optimisation of energy management strategies that aim to reduce primary energy consumption and increase system flexibility.

On the electrical side, energy sharing mechanisms, such as energy communities [76], peer-to-peer (P2P) energy trading [77], and collective self-consumption schemes, are emerging as key solutions for addressing the unpredictability of renewable energy generation and electrical load fluctuations [78]. These mechanisms help preserve grid stability while maximising the use of locally generated renewable energy. The challenge here lies in developing innovative management strategies that optimise energy sharing among users, leveraging storage systems and EVs as energy dispatchers. Modelling approaches in this field range from game theory [79] and numerical methods [13] to advanced optimisation techniques, all designed to enhance the energy savings and efficiency of district systems.

The complexity of district systems, particularly in terms of their interactions with end-users and building systems, presents significant modelling challenges. However, with the

development of advanced tools and strategies, district systems have the potential to drive significant progress in achieving energy-efficient and low-carbon urban environments.

1.2.4 Modelling multi-scales interaction

To conclude the section on urban-scale energy system modelling (USEM), it is essential to underscore the importance of modelling the interactions between end-users, building systems, and district systems. These three scales are deeply interconnected, and addressing their combined effects is critical for developing energy-efficient and sustainable urban environments.

To effectively model these interactions, different approaches can be adopted, including **sequential**, **co-simulation**, and fully **integrated models** [18]. Sequential models offer a straightforward method where data is passed from one sub-model to another in a step-by-step process [80]. This approach works well when the coupling between subsystems is weak, but it can fail to capture dynamic feedback effects that occur in more interconnected systems. Co-simulation, on the other hand, allows for real-time data exchange between sub-models, enabling more dynamic and complex interactions to be modelled. Depending on the level of coupling – whether weak or strong – co-simulation can account for intricate dependencies between scales, such as the interaction between building thermal loads and district heating network performance [81]. However, it may still face challenges with integration and data synchronisation.

Fully integrated models, *object of this dissertation*, represent the most sophisticated approach, combining all relevant subsystems into a single cohesive framework. This method allows for the simulation of interactions between end-users, buildings, and districts in real time, considering both energy flows and control strategies. Integrated models are particularly advantageous when analysing systems that require high levels of coordination, such as energy communities or district heating networks operating under MPC schemes. By simulating these subsystems together, fully integrated models can provide a more accurate representation of how energy is consumed, transferred, and shared within urban areas [23].

The need for these advanced modelling techniques stems from the growing complexity of urban energy systems. Modern cities must balance multiple objectives: reducing greenhouse gas emissions, increasing the use of renewable energy, ensuring energy security, and maintaining affordability. Modelling tools that account for interactions between different urban scales are essential to meet these goals. For example, optimising energy management at the district level requires an understanding of user behaviour and building system performance, as these factors directly affect the load profile of the district [9]. Conversely, decisions made at the district level – such as energy-sharing mechanisms, network design, or energy hub configurations – will influence building operations and end-user experiences.

Therefore, effective urban-scale energy system modelling must take a holistic approach, integrating detailed sub-models of each scale to capture these dynamic interactions. By doing so, it becomes possible to design more resilient, flexible, and sustainable urban energy systems. Whether through sequential, co-simulation, or fully integrated methods, the key to achieving this lies in ensuring accurate data exchange, strong system coupling, and the capacity to simulate real-world complexities [82]. Ultimately, these models provide the foundation for optimised energy management strategies that reduce overall energy consumption, enhance renewable integration [83], and support the transition to low-carbon cities [84].

1.3 Problem statement and research objectives

As discussed in previous sections, the energy systems within today's urban areas are increasingly complex, presenting significant challenges in modelling and optimisation. This complexity arises from several factors, including decentralised systems, fluctuating energy markets, the unpredictable nature of renewable energy sources, energy mismatches between demand and generation, and the need for flexibility through demand-side management and storage technologies. Moreover, the uncertainties introduced by climate change further complicate scenario analysis [85]. To address these challenges and support the urban energy transition, it is essential to develop robust simulation tools capable of capturing these intricate dynamics.

Urban areas can be understood as an infrastructure of interacting sub-systems, which in this dissertation are conceptualised as urban energy scales: **end-users**, **building systems**, and **district energy systems**. These scales are highly interconnected, with each influencing the others. Modelling these interactions is an emerging challenge in the field of urban energy research. By incorporating these interactions into the models, it can be achieved a deeper understanding of energy performance, leading to more effective design, control optimisation, and savings in energy and costs.

While substantial research has been dedicated to modelling each of these sub-systems individually, gaps remain in understanding their interactions. For instance, research on end-users frequently focuses on human behaviour, social influences, and occupants' physiological responses [23]. These studies aim to assess the real thermal comfort needs of occupants and the influence of their behaviour on energy-use patterns [86]. However, most fail to consider how these behaviours impact broader energy systems, such as the effect of occupant behaviour on HVAC units, building heating/cooling loads, or district energy interactions. Similarly, widely used Building Energy Models (BEMs) often neglect the dynamic impacts of occupant behaviour on building energy performance [17]. In the context of district systems, recent research has explored energy clusters, energy hubs, and district heating and cooling (DHC) systems, which play critical roles in reducing emissions and fossil

fuel consumption by integrating renewable energy sources [9]. However, many of these studies do not account for the interactions between different users and systems (e.g., buildings, heat pumps, electricity grids, electric vehicles) or the bidirectional energy flows necessary for a fully integrated energy community.

Urban Building Energy Modelling (UBEM) tools have traditionally been employed to model urban energy demand, either through top-down or bottom-up approaches [87]. While these tools provide valuable insights into energy demand patterns across building clusters, they fall short when it comes to capturing the complexity of multi-scale interactions. Specifically, they do not adequately account for the dynamic effects of occupant behaviour on building systems or for the integration of distributed energy resources (DERs) and district energy systems. To bridge these gaps, there is a growing consensus in the recent literature to shift towards **Urban-Scale Energy systems Modelling (USEM)**, which can better account for the multi-dimensional challenges of urban energy optimisation [18].

1.3.1 Research objectives

In light of these gaps, this dissertation aims to contribute to the development of advanced modelling tools and algorithms that assess the complexities of multi-scale urban energy systems. The primary objective is to promote energy efficiency and reduce reliance on fossil fuels through better system design and control strategies. As illustrated in Figure 1, this work will focus on several specific objectives:

- **End-Users Scale:** Model occupants' thermal comfort needs based on thermoregulatory responses and define user archetypes informed by social aspects and energy-use behaviours.
- **Building Systems Scale:** Conduct building energy modelling through both physics-based and data-driven methods; estimate renewable-based distributed energy resource (DER) power generation while considering climate influences, conversion efficiencies, energy losses, and technology features; develop management strategies for optimising storage technologies to enhance system flexibility and increase the self-consumption of renewable energy; model thermal and electrical performance of building equipment (e.g., HVAC systems) while accounting for interactions with heat pumps and heating/cooling coils; and assess electric vehicle routes and battery charging/discharging in relation to DER power generation systems and building energy needs.
- **District Systems Scale:** Classify and characterise buildings for energy cluster modelling; develop thermal and electrical energy hub models considering system layouts, climate impacts, and transient operations; model district heating and cooling systems, incorporating pipe networks, thermal substations, and balancing thermal

stations; and design frameworks for energy sharing within energy communities and smart grids.

- **Interaction Among Scales:** Implement thermal comfort models based on physiological responses within building energy modelling and HVAC control strategies; incorporate social aspects and usage patterns to classify building clusters into archetypes; model bidirectional interactions between building and district networks to evaluate their mutual impacts on performance, particularly regarding heat pumps; and integrate building power generation systems and storage technologies within energy communities and smart grids to enhance flexibility, reduce dependence on the central grid, and optimise renewable energy self-consumption, ultimately maximising revenues and savings for consumers and prosumers.
- **Control and System Optimisation:** Develop algorithms for the optimisation of system design and control, aimed at maximising energy efficiency, achieving primary energy savings, minimising energy costs, and ensuring reasonable pay-back periods.

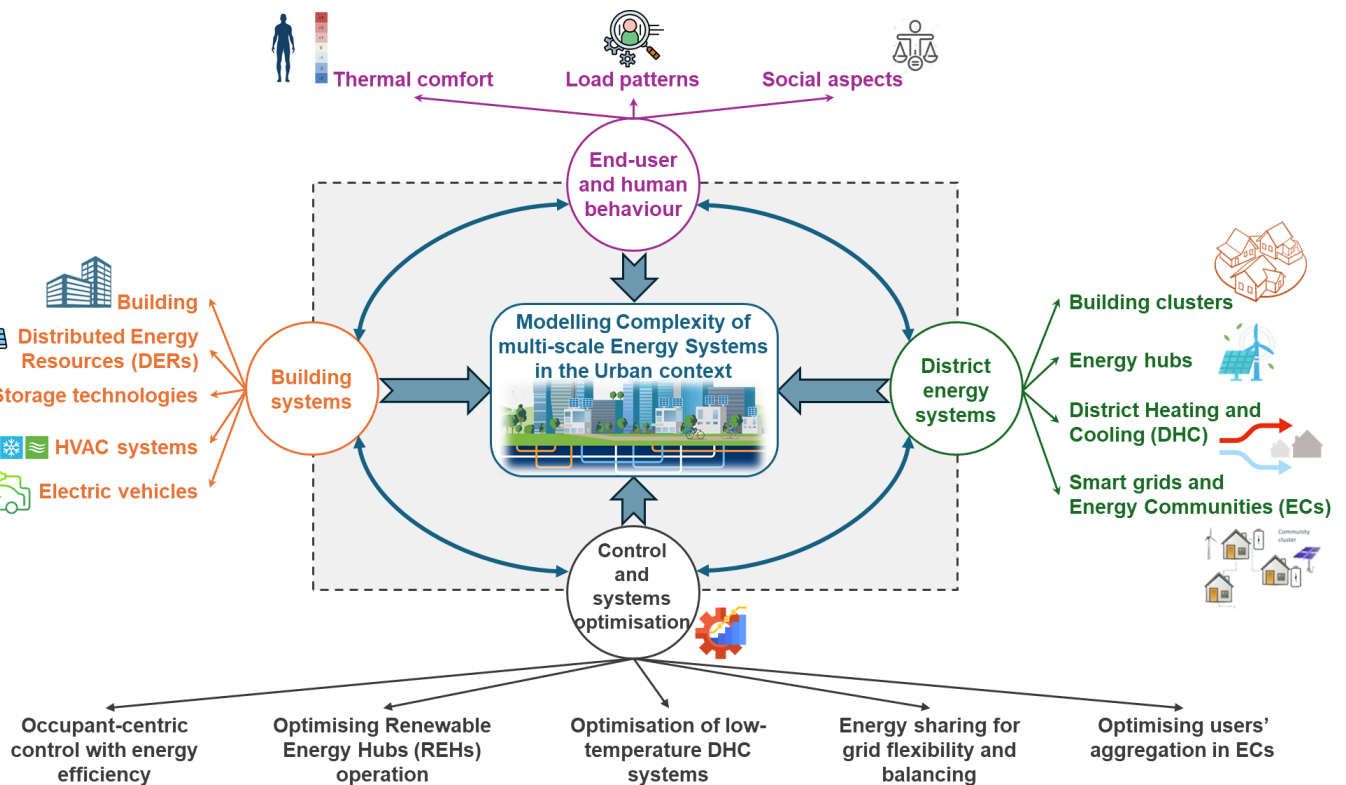


Figure 1. Modelling the complexity of multi-scale energy systems in urban contexts: Interaction between end-users, building systems, and district energy systems, with integrated control and optimisation strategies to enhance energy efficiency.

1.4 Methodology and contributions

This section describes the adopted methodology, modelling techniques, and the main contributions of the dissertation, which will be presented in the subsequent chapters.

This dissertation focuses on the modelling of urban energy systems across three primary scales: **end-users**, **building systems**, and **district systems**, each contributing to a holistic understanding of energy consumption and efficiency in urban settings.

At the **end-user scale**, the focus is on individual occupants and their behaviours, which significantly impact energy consumption patterns. By modelling occupant characteristics and classifying users into archetypes, the research aims to optimise energy usage and enhance self-consumption within energy communities.

The **building scale** examines components contributing to energy performance, including building energy modelling, photovoltaic (PV) systems, energy storage batteries, electric vehicles (EVs), heat pumps, and HVAC systems. Advanced thermal comfort models are integrated within simulation tools to assess the interactions between occupant needs and energy systems, ultimately improving energy efficiency and comfort.

The **district scale** encompasses the collective energy infrastructure serving multiple buildings and users within a defined geographical area. This scale includes energy hubs for district heating applications, low-temperature district heating and cooling systems, and energy communities that facilitate energy sharing among users. The integration of renewable energy sources and storage systems is explored to enhance system resilience and reduce reliance on fossil fuels. By simulating the interactions between buildings, users, and district systems, the research identifies strategies for optimising energy flows and maximising the utilisation of renewable resources.

The developed modelling tools for each urban scale are illustrated in Figure 2 and will be described in detail.

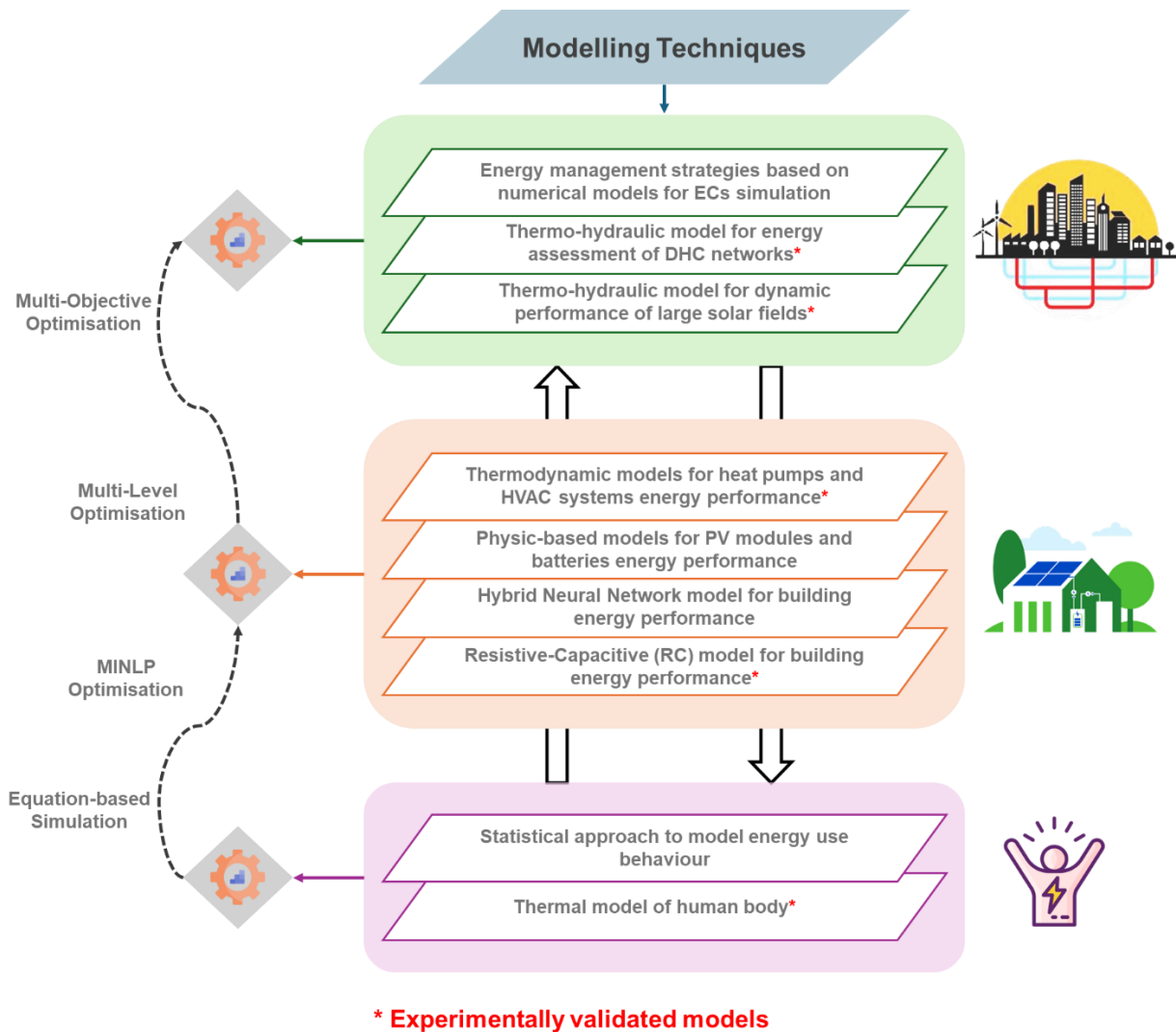


Figure 2. Modelling tools and techniques for each urban scale – end-user, building systems, and district systems – along with optimisation routines for energy system design and operational control.

The **end-user domain** is divided into two main sub-systems based on the role of the end-user: one when acting as an occupant of an indoor space and the other when their behaviours and social habits influence the energy use of building equipment.

The end-user as an occupant is modelled using a thermal model of the human body to assess thermoregulatory responses and body temperature variations. This approach characterises their influence on thermal comfort sensation and indoor air quality perception. Notably, this model has been experimentally validated by comparing simulated body temperatures with measurements from various occupants with different physiological characteristics. The experimental tests were conducted in test cell rooms, where the thermo-hygrometric setpoint was varied to observe the body thermoregulatory response. In contrast,

a statistical approach is adopted to simulate energy-use behaviour, classifying end-users based on social habits, age, and the types of equipment utilised.

Subsequently, as schematised in Figure 2, the modelling techniques adopted for the sub-systems within the **building domain** will be analysed.

Building energy performance, particularly the assessment of thermal and electrical loads, has been conducted using an in-house multi-resistive-capacitive (RC) model. This model captures the temperature evolution of the building envelope and simulates multi-zone thermal energy interactions. It has been validated in a previous work [88] and is employed in this dissertation for energy performance estimation and the implementation of control strategies for HVAC and heat pump systems. Additionally, a grey-box model has been developed to enhance the reliability and accuracy of assessing thermal and electrical loads in buildings. This model accounts for the intermittency of end-user behaviour, which significantly influences building energy performance. The grey-box model integrates the characteristics of physics-based models, which describe thermal phenomena, with the predictive capabilities of artificial neural networks (ANN). It operates as a sequential model, linking the outputs of the physics-based model to the inputs of the ANN model.

For modelling renewable-based power generation systems, storage systems, and electric vehicle batteries, a physics-based approach is employed. PV systems installed at the building level are modelled by considering various factors such as PV technology power conversion efficiency, weather influences (solar irradiance, ambient temperature, and wind velocity), tilt angles, system layout, and thermal losses due to cell overheating and heat dissipation through conduction, convection, and irradiation. Additional considerations include shading losses and balancing of plant losses. Batteries used in residential applications and electric vehicles are modelled through transient energy balance equations to evaluate charging and discharging processes as well as stored energy. This approach incorporates power losses due to degradation and constraints related to the maximum current and voltage of battery cells. Energy management strategies are also included to optimise these processes. In the case of electric vehicles, battery discharges are evaluated based on vehicle route patterns and energy-sharing events with buildings and the central power grid.

Heat pump systems, designed to meet space heating and cooling requirements, are modelled using a thermodynamic approach that employs energy balance equations in a transient regime. This simulation reflects the operation of source and load side heat exchangers, with compressor control adapted to external boundary conditions and variations in thermal loads. The model for assessing heat pump system performance has been validated by comparing simulated results for temperature and electrical power consumption with experimental measurements obtained from a laboratory at the national research centre in Portici (ENEA).

The main components of the HVAC system have been modelled using energy balance equations and fan efficiency curves to determine electrical consumption required for diverting airflow rates. Control strategies are integrated to optimise system operation. Furthermore, a simplified approach based on performance maps is employed to describe system efficiencies under varying boundary conditions, particularly in contexts where the primary aim is optimising control system operation.

The **district systems domain** comprises sub-elements including energy hubs for district heating applications, district heating and cooling (DHC) networks, and energy communities (EC). The investigated energy hub focuses on a solar field composed of thermal collectors for district heating applications. The modelling approach employed is physics-based, utilising energy balance equations and numerical solutions to evaluate the thermal performance and determine the temperature evolution of the solar field. This model integrates hydraulic behaviour assessment, accommodating the large size of the solar field and the connections among various hydraulic components, such as ball valves, three-way valves, and section reductions. Validation of this model was achieved by comparing simulated thermal performance and electrical consumption of pump systems used for flow diversion in the field with measurements from an existing solar field in Geneva, featuring high-evacuated flat plate collectors developed by TVP Solar.

The DHC network is modelled by considering thermal dissipation through the ground due to conduction and convection, which is related to water flow circulation, alongside hydraulic behaviour for calculating pressure drops along network sections. Additionally, the network model is capable of accounting for bidirectional thermal exchanges with users, particularly in fifth-generation DHC systems. The model has been validated by comparing simulated results for temperature and pressure drop with experimental measurements obtained from a DHC prototype system at the national research centre in Portici (ENEA).

The model for energy communities within building clusters is based on a mathematical algorithm that employs a matrix approach rooted in graph theory. In this model, each node of the matrix represents a user within the energy community (either a consumer or prosumer). For each node, information pertaining to the required electrical load, electrical surplus (in cases of prosumers with power generation systems), and storage capacity of users employing storage batteries is dynamically assessed at each time step throughout the analysed time horizon. Furthermore, the weights of the Laplacian matrix in the edge-weighted graph determine the amount of shared energy among users.

Another significant contribution of the works presented in this dissertation relates to the **optimisation and control strategies** implemented to minimise costs, energy expenditure, and payback time while maximising self-consumed renewable energy and self-sufficiency. This optimisation process involves the sizing, technology selection, control strategies, and

design of systems. Specifically, as illustrated in Figure 2, Mixed Integer Non-Linear Programming (MINLP) techniques have been adopted to optimise control with Model Predictive Control (MPC) strategies, accounting for constraints and minimising costs. Multi-objective optimisation has been employed to identify the best layout configurations and systems in accordance with the investigated objective functions, while multi-level optimisation techniques have been applied when prioritised optimisation is required.

1.4.1 Contributions

The contributions of this dissertation are illustrated in Figure 3. Each chapter provides a detailed analysis of individual scales – **end-users**, **building systems**, and **district systems** – along with an assessment of the **interactions** among the elements within each **urban scale** or domain. Furthermore, control and optimisation strategies based on these interactions are proposed to enhance the overall energy and economic performance of the investigated systems. The main contributions of each chapter are summarised as follows.

Chapter 2: This chapter focuses on the development of a thermal comfort model specifically tailored to the physiological responses of occupants. A novel aspect of this model is its incorporation of human body singularity and the impact of thermoregulatory adaptation, particularly through heart rate, thereby increasing the robustness and accuracy of thermal comfort assessments. The model has subsequently been integrated into a building energy performance simulation tool to evaluate the interaction between end-users and the building. Notably, a control strategy for dynamic regulation of indoor thermo-hygrometric setpoints, aligned with the thermal comfort needs of occupants during their presence, has been proposed. This approach demonstrates the necessity of revising the guidelines suggested by existing thermal comfort standards. The interaction assessment further aims to quantify the energy implications for space heating and cooling needs, highlighting discrepancies with standard-derived outcomes and their influence on the sizing and design of HVAC systems and control operations.

Chapter 3: This chapter continues to address the comfort needs of occupants in indoor spaces by enhancing the thermal comfort model to include the effects of physiological responses on perceived air quality, thereby creating a multi-domain comfort model. Validation of this model was achieved through comparisons with experimental tests conducted in test cell rooms. The integration of models pertaining to end-users, buildings, and HVAC systems formed the foundation of a Model Predictive Control (MPC) strategy designed to manipulate control variables of the HVAC system, such as the fresh air flow rate, recirculated flow rate, and enthalpy properties of the supply flow rate. This strategy aims to minimise the operational costs of the HVAC system while adhering to the thermal comfort and air quality needs of occupants. The findings suggest innovative possibilities for controlling HVAC systems that ensure the minimisation of energy consumption alongside

maximisation of the actual comfort and wellness requirements of occupants in indoor environments.

Chapter 4: The contribution of this chapter lies in the optimisation of energy performance for a solar thermal collector field utilised in a large district heating system in the city of Geneva. This case study features an innovative solar field characterised by high-evacuated flat plate collectors developed by TVP Solar, enabling validation of the thermo-hydraulic model designed to simulate the system performance of the solar field. The primary objective was to optimise energy output to enhance the self-sufficiency of the district heating system and reduce dependence on fossil fuels. This goal was achieved through the implementation of a predictive control logic with a one-day prediction horizon, regulating the flow rate circulating within the solar field to minimise the time required to reach the desired outlet temperature, thereby increasing the thermal energy supplied to district heating users.

Chapter 5: This chapter focuses on the design and optimisation of network temperature control for fifth-generation DHC applications, characterised by low-temperature operation, simultaneous heating and cooling demands from users, bidirectional thermal fluxes, and integration of renewable and waste heat sources. The advantages of this DHC generation include the aggregation of consumers and prosumers, which facilitates thermal self-balance within the network by managing opposite thermal fluxes (heating and cooling) supplied to the network, ultimately reducing energy consumption required for regulating water loop temperature. The chapter integrates the modelling of buildings, heat pumps, and the DHC thermal network, with validation achieved through a comparison of simulation results with the performance of a prototype fifth-generation DHC system. The building was simulated using an RC model that estimates temperature evolution in occupied spaces, accounting for external disturbances from weather conditions and thermal/cooling energy supplied by the water-to-water heat pump. Each component of the heat pump system was modelled using a physics-based approach.

A Proportional-Integral-Derivative (PID) control strategy was implemented to regulate the refrigerant flow rate and the opening of the expansion valve in response to dynamic thermal conditions at both the load side (represented by the building's thermal demands and capacities that affect the heat pump's response time) and the source side (represented by the heat exchanger interfacing with water circulating in the DHC network). The thermal network model estimated thermal dissipations through the ground and hydraulic pressure drops while also accounting for thermal interactions with each heat pump user within the DHC system. The temperature adjustments resulting from these mechanisms were managed via a balancing thermal station comprising chillers and heaters to achieve the desired set point.

This integrated model facilitated the assessment of energy efficiency and primary/electrical energy requirements for the overall system. Additionally, it contributed to investigating the impact of a predictive strategy for regulating network temperature one day ahead of the prediction horizon, aimed at optimising the operation of users' heat pumps. An optimiser was subsequently implemented to maximise energy savings across the systems by determining a trade-off temperature for the network, thereby enhancing the efficiency for consumers (requiring heating) and prosumers (requiring cooling). The significant potential for energy savings realised through this approach underscores the role of low-temperature DHC systems in reducing emissions associated with the thermal demands of buildings, thereby promoting electrification and flexibility in building clusters.

Chapter 6: The energy community (EC) framework represents a promising solution for accelerating the energy transition in urban areas. The complexity of ECs is influenced by various factors, including the unpredictability of distributed renewable power systems, the behaviours of end-users, fluctuations in users' electrical demands, mismatches between production and consumption, the integration of electrified systems (e.g., electric vehicles), energy sharing among users, flexibility through demand-response strategies, and the management of electrical storage systems. Additionally, these factors impact the imbalances within the central power grid. Modelling this complexity is essential for assessing the potential impact of ECs on energy efficiency, flexibility, and economic benefits for individual users and entire urban areas.

This chapter emphasises the significance of a key variable often overlooked in existing literature: the optimisation of user aggregation, taking into account their energy behaviours and types of prosumers. This optimisation aims to enhance self-consumption, self-sufficiency, and the economic potential of ECs. The developed model integrates the unique characteristics of each system and accounts for their interactions. In particular, the fluctuations in building users have been estimated by classifying them into archetypes that characterise their energy-use behaviours, considering the social influences and activities of family members. The distributed power systems (such as PV installations) of prosumers have been modelled using the previously described techniques, while also considering space constraints inherent to the buildings of the prosumers. A peer-to-peer (P2P) energy-sharing mechanism among users has been designed using a matrix approach, where user connections are manipulated through a centralised strategy that maximises energy interactions among users while limiting surplus energy injections into the grid. The proposed methodology outlines guidelines for designing ECs in urban areas, prioritising the aggregation of consumers and prosumers based on the identified archetypes and the available surplus energy from prosumers. It is demonstrated that optimising the aggregation of consumers and prosumers leads to significant improvements in self-consumption and self-sufficiency, resulting in cost savings on energy and increased revenues for prosumers.

Chapter 7: This chapter explores the role of energy communities (ECs) in grid balancing and their potential to provide ancillary services. The proposed methodology outlines an optimisation strategy for controlling the energy systems within an EC, aimed at safeguarding the central grid from the unpredictability associated with renewable-based power systems and the fluctuations in users' electrical demands. The methodology encompasses P2P energy-sharing strategies among consumers and prosumers, as well as Vehicle-to-Community (V2C) and Community-to-Vehicle (C2V) systems, facilitating the sharing of surplus electricity stored in the batteries of prosumers. Additionally, load-shifting strategies and the provision of ancillary services are included to maximise the cost-benefit for each EC user while enhancing self-consumption and self-sufficiency.

To optimise the role of ECs in stabilising the operation of the central grid, a novel index, termed the Grid Balancing Factor (GBF), has been introduced. This index serves as the objective function within the optimisation procedure governing the management strategy of EC systems. The model accounts for the integration of each EC system, considering the energy demands of consumers and prosumers based on user behaviours, the performance of PV systems, and the battery storage capacities of prosumers, alongside EV routes informed by user behaviours, employing a graph-based approach.

The management strategy adopted is predictive, involving centralised control to determine, one day in advance, the optimal utilisation of energy systems to enhance self-consumption, self-sufficiency, and the GBF. Results from this control optimisation procedure yield a stable and flat demand profile for the EC, mitigating the effects of load fluctuations on the central grid. It also highlights the utilisation of PV power production to supply ancillary services for upward frequency regulation, while the capacities of batteries and EVs are leveraged for downward frequency regulation. The model further details the energy shared among users through P2P exchanges, Batteries-to-Peers / Peer-to-Batteries, V2C, and C2V.

The findings underscore the significant role that ECs can play, when managed through a centralised control strategy, in achieving the objectives of power grid flexibility and balancing.

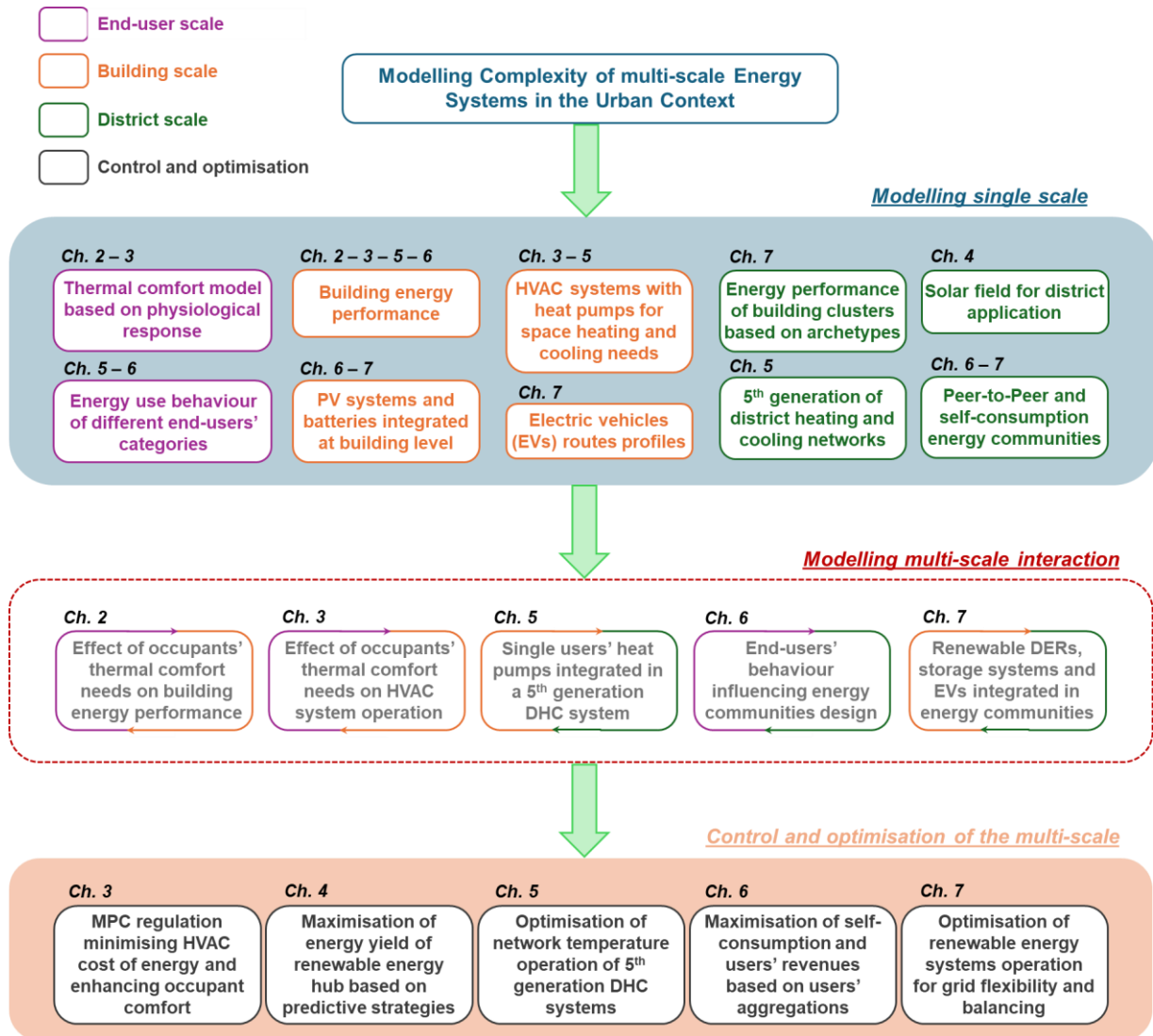


Figure 3. Overview of the dissertation's key contributions: Classification of chapters by their focus on modelling individual urban scales, interactions between scales, and the optimisation of interconnected system design and control strategies.

The closing chapter of this dissertation (**Chapter 8**) serves as a comprehensive discussion of the key findings derived from the research conducted throughout the dissertation. This chapter aims to synthesise the insights gained from the various studies.

The first significant finding highlights the necessity of developing **new modelling methods** that account for **system interactions across** different **urban scales**. By designing integrated models within a unified framework, this dissertation presents an innovative approach that enhances the understanding of multi-scale interactions in urban energy systems. Such models are essential for capturing the complexities of urban

environments and their interdependencies, ultimately leading to more effective energy management solutions.

Secondly, the chapter underscores the **pivotal role of occupant-centric approaches** in controlling building energy systems. By focusing on real comfort needs rather than solely on energy cost savings, the research illustrates the importance of developing control strategies that are practically applicable in real-world scenarios. This occupant-centric perspective not only enhances thermal comfort but also ensures that energy systems meet the genuine needs of users, promoting sustainable energy use.

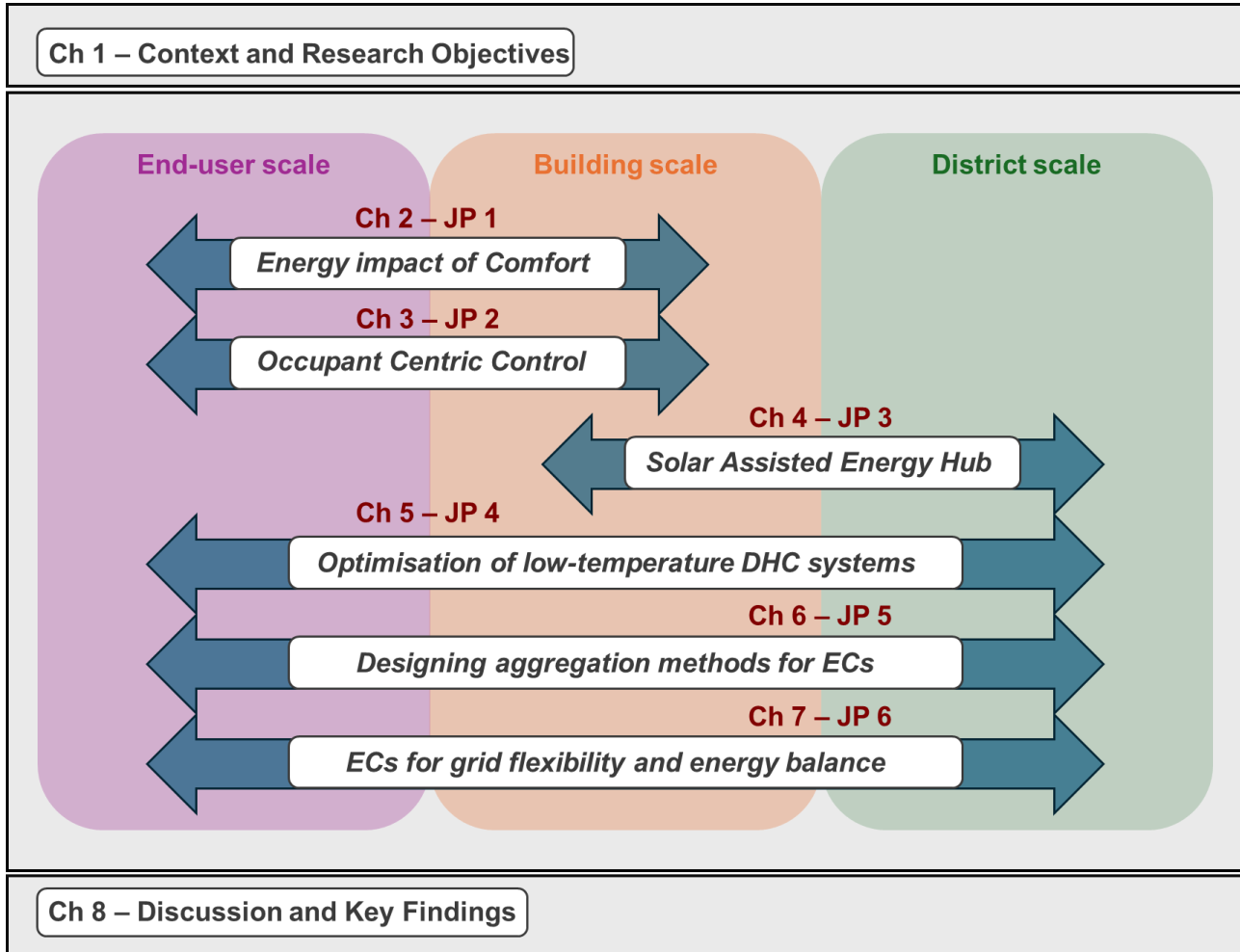
Moreover, the **guidelines for designing energy communities** in real-context scenarios are discussed. The findings reveal the critical importance of optimising the aggregation of users – both consumers and prosumers – to enhance energy efficiency and cost potential. By considering the diverse behaviours of end-users and the performance of installed power generation systems, the research contributes valuable insights for practitioners and policymakers in the design and implementation of energy communities.

The chapter also addresses the urgent need for **electrification** within **district heating and cooling systems**, advocating for the adoption of 5th-generation DHC systems. These advanced systems enable bidirectionality in thermal fluxes, facilitate self-balancing capabilities within thermal networks, and allow the utilisation of renewable and low-temperature waste heat sources. The potential of these systems to increase flexibility and reduce emissions is crucial for the sustainable energy transition.

In addition, the **optimisation algorithms** developed throughout this dissertation form the basis for implementing effective control strategies. This chapter discusses the importance of adaptive control mechanisms that can respond dynamically to real-time data, enabling energy systems to adjust to fluctuations in demand and supply efficiently.

Finally, this chapter encourages the application of these guidelines to inform urban policymaking, fostering a proactive approach to energy transition. By advocating for the integration of these insights into policy frameworks, the dissertation aims to contribute to the broader **movement towards sustainable urban energy systems**.

1.5 Dissertation outline



This graphical outline illustrates the structure of the dissertation, which builds upon journal publications produced during the doctoral programme. Each chapter addresses specific challenges within the field of urban energy transition, focusing on the development of modelling tools to optimise urban energy systems. The aim of these works is to enhance urban system design and control strategies, achieving reduced primary energy consumption due to fossil fuels, increased renewable energy self-consumption, improved grid flexibility, and economic benefits for the subsystems composing the urban domain.

The dissertation, as mentioned in the previous section, progresses through the interactions of the three primary urban scales – end-user, building, and district. Chapter 2, corresponding to Journal Publication 1 (JP 1), investigates the energy impact of comfort at the end-user scale, assessing how comfort-driven behaviour influences energy consumption in the building subsystem. Chapter 3 (JP 2) explores occupant-centric control strategies, proposing methods to align energy usage with actual comfort needs through model

predictive control approaches. Chapter 4 (JP 3) examines the concept of a solar-assisted energy hub, presenting a modelling tool for optimally integrating solar energy into district heating systems, thereby enhancing renewable energy utilisation within urban infrastructure. The focus then shifts to district-scale solutions developing modelling tools that account for the interaction among end-users, building systems, and district systems. Chapter 5 (JP 4) investigates the optimisation of low-temperature district heating and cooling (DHC) systems. This chapter addresses the design and management of low-temperature networks, aiming to boost energy efficiency and system flexibility. Chapter 6 (JP 5) introduces aggregation methods for energy communities (ECs), proposing strategies to group prosumers and consumers in a way that maximises self-sufficiency and economic returns within energy communities. Finally, Chapter 7 (JP 6) explores the role of energy communities for grid flexibility and energy balance, where the developed modelling tool is applied to balance electricity demand and supply, ensuring grid stability. This chapter examines the potential of energy communities to contribute to grid frequency regulation and demand flattening by effectively managing distributed energy resources.

The findings of these chapters are collectively discussed in Chapter 8, which synthesises the key insights and contributions towards urban energy transition goals.

Publications that compose the dissertation

Journal Paper 1

Barone G., Buonomano A., Forzano C., Giuzio G.F., Palombo A., Russo G. (2023). A new thermal comfort model based on physiological parameters for the smart design and control of energy-efficient HVAC systems. *Renewable and Sustainable Energy Reviews*, 173, 113015.

Journal Paper 2

Buonomano A., Forzano C., Gnecco V.M., Pigliautile I., Pisello A.L., Russo G. (2024). Enhancing energy efficiency and comfort with a multi-domain approach: Development of a novel human thermoregulatory model for occupant-centric control. *Energy and Buildings*, 303, 113771.

Journal Paper 3

Buonomano A., Forzano C., Palombo A., Russo G. (2023). Solar-assisted district heating networks: Development and experimental validation of a novel simulation tool for the energy optimization. *Energy Conversion and Management*, 288, 117133.

Journal Paper 4

A. Buonomano, C. Forzano, L. Mongibello, A. Palombo, G. Russo. (2024). Optimising low-temperature district heating networks: A simulation-based approach with experimental verification. *Energy*, 304, 131954.

Journal Paper 5

G. Barone, A. Buonomano, G. Cipolla, C. Forzano, G.F. Giuzio, G. Russo. (2024). Designing aggregation criteria for end-users integration in energy communities: Energy and economic optimisation based on hybrid neural networks models. *Applied Energy*, 371, 123543.

Journal Paper 6

G. Barone, A. Buonomano, C. Forzano, A. Palombo, G. Russo. (2023). The role of energy communities in electricity grid balancing: A flexible tool for smart grid power distribution optimization. *Renewable and Sustainable Energy Reviews*, 187, 113742.

Chapter 2

A physics-based human model for assessing the energy impact of comfort needs

This chapter was previously published as:

Barone G., Buonomano A., Forzano C., Giuzio G.F., Palombo A., Russo G. (2023). A new thermal comfort model based on physiological parameters for the smart design and control of energy-efficient HVAC systems. *Renewable and Sustainable Energy Reviews*, 173, 113015.

Summary

Indoor thermal comfort is a critical factor in building design, yet reference standards often neglect the human body's thermal adaptability. HVAC control strategies typically rely on steady-state assumptions, leading to inaccurate estimates of thermal demand and misguided energy consumption and system sizing. To address this, a physiological thermal comfort model was developed in MATLAB to dynamically assess human body thermal behaviour and evaluate the impact of comfort on building energy consumption. This multi-node model was integrated into the DETECT 2.4 building energy simulation tool, enabling three dynamic control strategies for regulating indoor thermo-hygrometric conditions. These strategies optimize relative humidity and air temperature hourly, maximizing occupant comfort while minimizing energy use. A case study of an office space demonstrates the model's potential. Compared to standard set-points (20°C, 45% for heating; 26°C, 50% for cooling), the proposed approach—by dynamically adjusting for thermal comfort—led to increased energy consumption (2-16%) but eliminated the discomfort experienced in the reference case.

Keywords

Physiological thermal comfort models, building energy performance simulation tools, human-body thermal sensation, human body thermal adaptability, HVAC system dynamic control, optimal comfort and energy saving control of thermo-hygrometric property.

Nomenclature

Acronymous

<i>A</i>	surface area [m ²]	<i>p</i>	pressure [Pa]
<i>B</i>	body	<i>Q</i>	thermal power [W]
<i>CE</i>	caloric equivalent [W/(kg/s)]	<i>r</i>	radius [m]
<i>CR</i>	core layer	<i>R</i>	thermal resistance [K/W]
<i>f</i>	enhancement of skin surface [-]	<i>SK</i>	skin
<i>F</i>	view factor [-]	<i>t</i>	time [s]
<i>h</i>	heat transfer coefficient [W/(m ² ·K)]	<i>T</i>	temperature [°C]
<i>HR</i>	heart rate [bpm]	<i>U</i>	internal energy [J]
<i>I</i>	clothing resistance [clo]	<i>v</i>	velocity [m/s]
<i>k</i>	thermal conductivity [W/(m·K)]	<i>V</i>	volume [m ³]
<i>m</i>	flow rate [kg/s]	<i>w</i>	moisture [-]
<i>M</i>	metabolism [W/kg]	<i>W</i>	work of the human body [W/kg]
<i>MR</i>	rate of metabolic heat [W/kg]		

Greek letters

Δ	variation
ε	emissivity [-]
η	efficiency of human body [-]
ρ	density [kg/m ³]
σ	Boltzmann constant [W/(m ² ·K ⁴)]
ϕ	relative humidity [%]

Subscripts

<i>b</i>	body	<i>res</i>	respiration
<i>c</i>	convective	<i>rs</i>	regulatory sweating
<i>cl</i>	clothing	<i>s</i>	sensible heat
<i>dif</i>	diffusion	<i>S/G</i>	signal
<i>ev</i>	evaporative	<i>sw</i>	sweating
<i>f</i>	forced	<i>tot</i>	total
<i>in</i>	indoor	<i>va</i>	vapor air
<i>I</i>	latent heat	<i>vap</i>	vaporization of water
<i>mr</i>	mean radiant	<i>w</i>	wall
<i>n</i>	natural		
<i>op</i>	operative		
<i>p</i>	pressure		
<i>r</i>	radiative		

2.1 Introduction

In developed countries, people spend most of their time in indoor spaces [89]. For this reason, there is growing attention to the thermal comfort of the occupants both in commercial and residential spaces, with an impact on the associated energy demands. In this regard, the energy demand of buildings represents about 35% of the global energy consumption and of over 38% of the CO₂ emissions[90]; a large proportion of this energy is necessary for occupants' thermal comfort needs [91]. Consequently, there is a need of enhancing existing thermal comfort models [92] toward more reliable approaches [93]. In this framework, the current standards, largely adopted for building design aims, uses constant temperature setpoint [94], and the comfort zones are generally defined by air temperatures limits (available ranges are: 21-23°C for office building by CIBSE [95]; 20-24.2°C by OSHA [96]; 21.5 - 24°C by ASHRAE 55 [97]; imposes these set point of temperature in the range 20 – 26 °C by EN ISO 7730 [98]). Nevertheless, with the recent advancement of energy efficiency technologies and HVAC systems for cutting energy consumption – while increasing demands for heating and cooling are being observed - advanced thermal comfort models are required as also demonstrated by the raising attention of the scientific community on this topic in the last decade [99].

2.1.1 Thermal sensation and comfort assessment

Predicting the thermal comfort in indoor environment is a complex phenomenon and, as reported in the available literature [100], many are the thermal comfort models developed to perform this task; however, only few of them are used in international standards. Among them, the Fanger's model (on which the ASHRAE-55 and ISO 7730 standard are based) is the main adopted adaptive thermal comfort model [101]. As a result, as a function of the metabolic rate and clothing thermal resistance, the optimal thermal comfort for the occupants is determined according to the operative temperature range and two comfort indexes, the predicted mean vote (PMV) and the predicted percentage of dissatisfied (PPD) are derived [102]. Despite its large adoption, diverse works available in the literature point out several limits of the Fanger's model [103], such as considering occupants as passive to the thermal sensation and neglecting their adaptation potentials linked to physiological and cultural aspects [104]. In fact, by this model the effect of dynamic human activities, occupant age, ethnicity, thermal memory, and climate, on the comfort sensation is neglected [105]. The thermal sensation of people is, in fact, also conditioned by all these variables and, clearly, by the climatic peculiarities of the geographical area in which one lives [106]. In addition, it is also demonstrated that non-measurable socio-psychological and physiological factors should be also considered for the proper assessment of thermal sensation of occupants in indoor spaces [107]. Thus, many other models and surveys have been carried

out to study the behaviours and the actions that would be performed by occupants when they experience adverse thermal sensations [108]. Finally, the thermal sensation of occupants depends of diverse variables and factors, often impacting one another, so that a multi-domain approach to human perception in indoor spaces is advisable [93].

2.1.2 Thermoregulation mechanism of human body

Since the thermal sensation varies over time, the steady-state assumption, on which standard thermal comfort models for building design are based, does not allow for considering the effective human body thermal adaptation and thus the actual perceived comfort. The variation of thermal sensation is due to the thermoregulation mechanisms that the human body undergoes when interacting with the surrounding environment and it plays a significant role in maintaining physiological homeostasis both during rest and physical exercise. Diverse studies highlight that these mechanisms are triggered by the activity of the nervous system [109] (i.e. sympathetic nerve), which sends signals from the thermoreceptors [110], stimulating the response of the circulatory system [111]. Additionally, the metabolic rate, which is driven by the thermoregulatory system [112], should be considered as a variable (and extremely dependent on the biophysical aspects of the human body) rather than constant [113]. Consequently, the temperature of the body and of the skin are affected by these mechanisms [114]; in this regard, the use of intelligent prediction methods [115] and wearable sensors [116] have becoming pivotal to predict the impact of such physiological parameters (e.g., metabolic rate) for thermal comfort assessment. To model the peoples' dynamic thermal behaviour– by assessing all physical phenomena occurring within the human body responsible for its heat dissipation [117] - it is necessary to know its geometric, morphological, physiological and thermal properties, such as conductivity, heat capacity, emission coefficient [118]. Several works propose mathematical models where the human body is generally idealized as made of spherical or cylindrical segments [119], representing several part of the body [120]. In several cases, the segments consist of diverse layers, such as core, muscle, fat and skin, whereas other papers proposes much simplified lumped models [121]. In this regard, the use and spread of common instruments such as wearable devices and infrared cameras [122], more and more available in buildings also for prevention and monitoring of infectious diseases and epidemics, and in general for public health control [123], can support the development and implementation of more reliable and accurate thermal comfort models.

2.1.3 Thermo-hygrometric smart control for indoor spaces

Due to the dynamic pattern of the described thermoregulatory phenomena, suitable smart control strategies are required to satisfy the thermal comfort needs [124]. Nevertheless, at the state of the art, most of the available models are suitably developed for

the strict temperature and humidity control [125] of specific indoor spaces (offices [124], hospitals [126], museum [127], etc.); advanced control strategies are also derived by combining intelligent techniques exploiting data collections from IoT devices [128]. Through building control approaches and techniques [129], researchers aim at simultaneously providing optimal building energy performance without compromising the occupant thermal comfort [130]. Moreover, when considering the actual variability of human body physiological parameters, the seasonal set points (imposed by the standards on building design) are inevitably no longer able to guarantee comfort for the occupants. Thus, considering the transiency of the human body due to the thermoregulatory phenomena, new control strategies are required. In this regard, several works, based on advanced methodology such as artificial neural network applications, propose variable temperature setpoints according to the thermal sensation votes of the occupants assessed either through predictive algorithms [131] or in real time by means of smart devices [132]. However, as a limit of these approaches, the influence of physiological parameters of occupants is neglected, in addition, the possibility to change the indoor air temperature set-point according to them, limits the prediction potential of the HVAC system energy demands and its proper sizing [133]. Thus, there is still a need for building energy performance simulation tools, capable to test the effects of diverse thermal comfort models on the building energy consumptions [134].

2.1.4 Aim and contributions

As shown in the previous sections, several works in literature highlight that the thermal comfort sensation strongly depends on the action of the thermoregulatory mechanisms (e.g. sweating, vasodilation, vasoconstriction) that are activated by the dynamic changes in physiological parameters (e.g. heart rate, skin temperature). However, the works dealing with adaptive comfort models neglect the dynamic impact of thermoregulatory mechanisms giving an improper assessment of the occupant's thermal sensation. This chapter has the twofold aim to provide additional knowledge to the thermal comfort research field by estimating the effect of a novel human physiological model-based smart thermo-hygrometric control on the energy consumption of buildings due to heating and cooling. Specifically, this research work proposes a novel approach for modelling the dynamic impact of the human body's physiological parameters on the thermal sensation and on thermo-hygrometric control of indoor spaces. The thermal interaction between the occupant and the surrounding building space is solved in transient regime overcoming the limits of the steady-state assumption, allowing for ensuring the optimal comfort of occupants according to the dynamism of their thermoregulatory system. Specifically, the calculation of physiological parameters is, thus, obtained by modelling the human body with a personalized multi-node thermal model, capable to consider the dynamisms of phenomena related to thermal comfort. This model is able to estimate the thermal interactions between the building space

and the human body of the occupants by taking into account the thermoregulatory responses of the human body in a dynamic way. It worth noticing that the development and implementation of advanced thermal comfort model – such as the one presented in this research – will instead take advantage from the smartness of modern buildings (smart buildings) - equipped with appropriate sensor devices and control units of the HVAC system – necessary to implement predictive actions to properly control the thermos-hygrometric properties of an indoor space. In this regard, and as an example, the proposed methodology, later described in detail, requires as input several data that can be measured thanks to intelligent devices (e.g. wearable devices such as smartwatches for the heartbeat assessment, sensors for the skin temperature and wall surfaces temperature, etc.).

With the aim to understand the influence of occupant thermal comfort needs on the heating and cooling demand, three strategies for the dynamic control of the thermohygrometric parameters are evaluated and compared with a reference case. The three implemented strategies are based on the dynamic regulation of the indoor air temperature and relative humidity, determined with a two-step optimization. In the first step, the comfort of the occupants is maximized by estimating it through appropriate comfort indices for each of the three strategies: 1) the predicted mean vote (PMV) by Fanger [101], 2) the discomfort index (DISC) by Pierce [135], and 3) the thermal sensation index (TSV) by KSU [136]. Subsequently, the second step of the optimization process provides the solution among those that maximize comfort by at the same time minimizing the heating and cooling demands. A comparison among the heating and cooling demands calculated for all three thermal comfort strategies vs the standard one is conducted by means of the developed dynamic simulation tools (human body combined with building energy simulation tool), capable to assess the thermoregulatory response of the occupant in terms of the variation of body temperature and the building energy consumption to satisfy the related thermal comfort needs. The proposed research aims at improving the knowledge about the impact of comfort models on building thermal energy consumptions, towards energy efficiency and sustainability, as well as well-being and comfort of occupants. From this point of view, the next generation of buildings is required to be smart and sustainable and capable to actively adapt to human needs (energy, comfort, safety, etc).

2.2 Methodology

This section describes the mathematical model, and the methodologies proposed in this study. The objective is to conduct a comprehensive analysis of thermal comfort strategies and their influence on heating and cooling needs, through a new methodology that involves:

- The implementation of a multi-node thermal model of the occupant to evaluate its energy interactions with the building and the consequent thermal responses to which the body is subjected;

- New temperature and humidity control strategies aimed at guaranteeing the thermal comfort of the occupants fitted to the physiological responses investigated in the model of the human body.

As mentioned, the physiological model of the human body evaluates the thermal interaction between the occupant and the surrounding environment, abandoning the hypothesis of steady state adopted in the majority of works available in the literature [101]. The human body is modelled as a set of 4 concentric cylinders layers (core, muscle, fat, skin) crossed by small ducts (schematization of the circulatory system) in which the blood flow is responsible for the convective heat exchange within the organic tissues of the human body. Note that, part of the thermal power produced by the human body through metabolic processes is converted into work (necessary to execute activities) and part is dissipated to ensure suitable functioning of the vital organs. The heat exchange inside the human body occurs by conduction between the various layers that compose it, and by convection due to the blood circulation; the heat is dissipated through convection with the ambient air, radiative heat exchange with the surrounding walls, and evaporation of sweat and respiration. The geometrical and thermodynamic properties for modelling the human body are selected according to Fiala's [59] work. It is worth noticing that one of the main improvements to the Fiala's model, introduced in this chapter, refers to the possibility to dynamically relate the thermal energy produced by the human body to the heartbeat and the body mass. Such enhancement allows for the assessment of building thermal loads and demands on the effective dynamic thermal sensation of the human body. Such model enhancement represents a step forward towards the development of advanced comfort models based on the impact of different physical and physiological parameters, human behaviour features, and environmental conditions on the multi-domain comfort of occupied indoor spaces.

The human body model, representing the occupant for whose thermal comfort heating and cooling power must be provided, is implemented in a suitable validated BEPS tool, developed in-house and called DETECt [88], suitable developed for modelling and simulating the impact of innovative technologies [137, 138] and control strategies on the whole-building energy demand [139]. Such BEPS tool, based on the finite difference method considering as one-dimensional the thermal domain, consists of a high order resistive-capacitive RC thermal network obtained by distributed parameters allowing for the calculation of indoor air temperature and humidity and for the internal surfaces' temperatures. For the purpose of this study, the tools was suitably enhanced to properly accounts for the radiative heat exchanges among the indoor space surfaces and the human body [140].

As previously mentioned, this work shows the comparison of the thermal load and thermal comfort requests for three different indoor air temperature (T_{in}) and humidity (RH) control strategies, compared to a reference one for which the building HVAC controls are equipped with dual set point thermostats and humidistats. Specifically, as suggested by

many international or national standards (CIBSE [95], ASHRAE [97], OSHA [96]) indoor spaces are kept to the constant conditions of $T_{in} = 20^{\circ}\text{C}$, $RH = 45\%$ and $T_{in} = 26^{\circ}\text{C}$, $RH = 50\%$, during the heating and cooling season, respectively. The other three proposed strategies implement a dynamic control of temperature and relative humidity as a function of physiological parameters (e.g. temperature of the occupant's skin) predicted by the multi-node model of the human body; to guarantee the thermal well-being of individuals by diverse parameters must fall within the comfort indices acceptability ranges. Subsequently, the comfort and energy results of the three investigated strategies are compared with those obtained for the reference case. Further investigation was focused on the effect of the investigated strategies on the sizing of the HVAC.

2.2.1 Physiological thermal model

The *physiological thermal model* allows for the resolution of the human body's temperature field in a one-dimensional transient regime. To accomplish the goal of the proposed methodology, it is necessary to know the dynamic variation of occupant' skin temperature, the variation of the thermal sensation, and the occupant's thermal heat gain. In Figure 4, the shape of the human body assumed as a single cylinder consisting of four different layers (i.e. core, muscle, fat, and skin) is sketched. The geometrical and thermodynamic properties of the human body are selected according to Fiala's [141] work, as reported in Table 1.

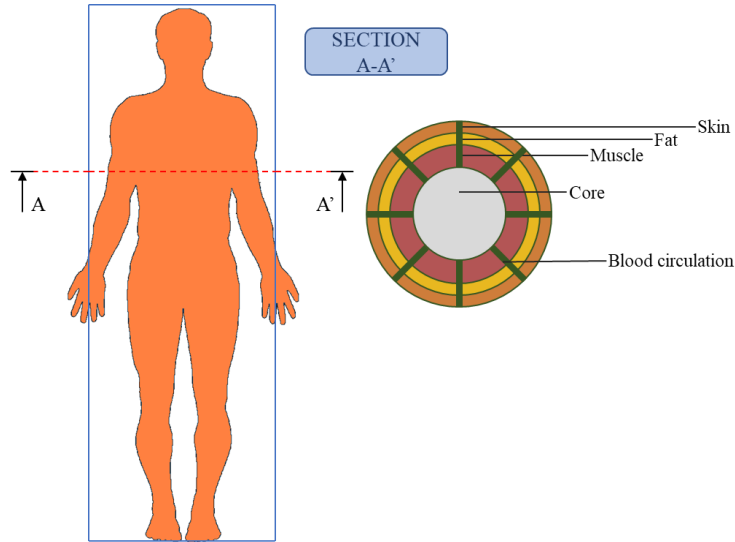


Figure 4. Discretisation procedure for human body simulation.

The radius of the cylindrical layers of the developed *physiological thermal model* (r_i) is expressed with a weighting average of the 16 cylinders considered in Fiala's model.

$$r_i = \frac{\sum_{i=1}^4 \sum_{j=1}^s r_{i,j} \cdot \frac{V_{i,j}}{V_{i,tot}}}{\sum_{i=1}^4 \sum_{j=1}^s \frac{V_{i,j}}{V_{i,tot}}} \quad \text{Eq. (1)}$$

where i is the i -th layer of cylinder i , j is the j -th layer of cylinder j , s is the number of body segments considered in Fiala's models, $V_{i,j}$ is the volume of the cylinder between the two layers i and j , and $V_{i,tot}$ is the total volume.

The *height* of the cylinder, associated to the shape of human body, is evaluated as:

$$height = \frac{A_{skin}}{2 \cdot \pi \cdot r_{skin}} \quad \text{Eq. (2)}$$

where A_{skin} is the surface of the human body' skin and r_{skin} is the radius of the skin layer. The main limitations of the reduced model of the human body are connected to the assumption of assimilating the shape of the human body to that of a single cylinder. As a consequence, only an average value of the skin temperature can be assessed, whereas more detailed model could return also the spatial distribution of such parameter. Nevertheless, for the purposes of this study this type of simplification does not affect the accuracy of the results.

Table 1. Human body thermal properties.

parameter	r	k	ρ	c
unit	m	$W/(m \cdot K)$	kg/m^3	$J/(kg \cdot K)$
core	0.059	0.504	1096	3304
muscle	0.081	0.504	1096	3304
fat	0.095	0.160	850	2300
skin	0.097	0.470	1085	3680
blood	-	-	1069	3650

2.2.2 Heat transfer within the human body tissues

According to the discretisation procedure reported in the previous section, the human body is schematized by considering a suitable resistive-capacitive RC thermal network (Figure 5). Thus, the RC thermal network is solved by considering the mechanism of heat dissipation occurring in the human body. This mechanism is described by the following bio-physiological partial differential equation:

$$\frac{1}{r} \frac{d}{dr} \left(r \frac{dT}{dr} \right) + \frac{MR \cdot \rho_{inside}}{k_{inside}} \times \frac{V_{inside}}{V_{body}} + \frac{\dot{m}_{blood} \cdot c_{p,blood}}{k_{inside} \cdot V_{body}} \times (T_{inside} - T_{skin}) = \frac{\rho_{body} \cdot c_{p,body}}{k_{body}} \frac{\partial T}{\partial t} \quad \text{Eq. (3)}$$

where r is the radius, which is the only dimension in which the temperature varies, MR is the net metabolic rate, representing the amount of the metabolic rate to be dissipated, ρ_{inside} , k_{inside} , and V_{inside} are the density, thermal conductivity, and volume relative to the inside layer - from this point on, the core and muscle layers are merged into a single layer called inside, both being characterized by the presence of thermal generation -, whereas ρ_{body} , k_{body} , and V_{body} are respectively the density, thermal conductivity, and volume related to entire human body, $c_{p,blood}$ is the heat capacitance of blood at constant pressure, T_{inside} is the temperature of the inside layer of human body, T_{skin} is the skin temperature, $c_{p,body}$ is the heat capacitance of human body, and t is the timestep of the simulation.

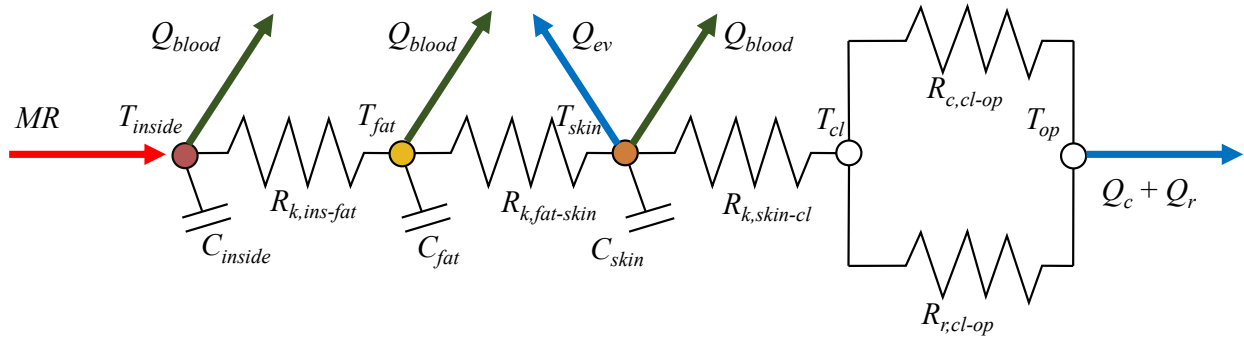


Figure 5. Resistive-capacitive thermal network of human body.

The heat conduction term in this differential equation considers the temperature variation in the radial direction, neglecting the heat flows through the other two polar coordinates. In this regard, the angular heat flow is equal to zero due to the hypothesis of symmetrical boundary conditions; whereas the heat flow along the height of the cylinder is negligible compared with the total amount of the heat conducted radially.

The heat generation term of the differential equation is represented by MR . The production of metabolic energy within the body cells is converted into mechanical work and heat, which represents about 50-80% of the metabolic energy [142]. The metabolic rate is generally proportional to the rate of oxygen consumption (V_{O_2}) and to the caloric equivalent per litre of oxygen consumed (CE_{O_2}). The volume of oxygen breathed by a person (V_{O_2}) can be measured through appropriate instruments such as the metabolimeter. However, according to a correlation provided by the work of Nelson [143], it is determined from the heart rate (HR) as:

$$V_{O_2} = ((0.3 \cdot HR - 16.44) \cdot mass) \times (10^{-3} / 60) \quad \text{Eq. (4)}$$

The volume of oxygen is estimated as a function of the individual heart rate (HR) and bodyweight ($mass$), in this way the model is personalized to the investigated person. The rate

of metabolic heat accumulated in core and muscle layers (MR) can be estimated as the difference between the production of metabolic energy (M) and mechanical work (W).

$$MR = M - W = \frac{CE_{O_2} \cdot V_{O_2}}{mass} \times (1 - \eta) \quad \text{Eq. (5)}$$

where η is the energetic efficiency of the human body.

The convective contribute, represented by the blood circulation, is of vital importance for the dissipation of heat within the human body. The heat exchanged by the blood circulation is expressed as a function of the temperature difference of adjacent bloodstreams, blood perfusion and heat capacitance (see Table 1). The blood's temperatures, with the hypothesis of negligible heat flow along the height of the cylinder, are assumed to be the same as the body's layer. Whilst, the blood perfusion is evaluated according to the correlation of Kaynakli and Kilic [144], where the thermoregulatory mechanisms of vasoconstriction and vasodilation are considered through the following core and the skin signals:

$$\begin{cases} CR_{SIG} = T_{inside}(t) - T_{inside}(t=0) \\ SK_{SIG} = T_{skin}(t) - T_{skin}(t=0) \end{cases} \quad \text{Eq. (6)}$$

Specifically, when actual temperatures of the body (core and skin) are greater or smaller than neutral temperatures, warm or cold signal are sent, respectively. Numerical values of these signals are calculated as difference of actual and neutral temperatures, and they only take on positive values [135]. Therefore, the blood perfusion is equal to:

$$\dot{m}_{blood} = \left[\left(\frac{6.3 + 200 \cdot CR_{SIG}}{1 + 0.5 \cdot (-SK_{SIG})} \right) \times \frac{1}{3600} \right] \quad \text{Eq. (7)}$$

The boundary conditions adopted to solve the body temperature field are represented by the thermal fluxes exchanged with the environment. Firstly, the external body layer exchanges heat with the clothing according to the following equation:

$$Q_{cl} = \frac{A_{skin} \cdot (T_{skin} - T_{cl})}{I_{cl} \cdot 0.155} \quad \text{Eq. (8)}$$

where T_{cl} is the temperature of the clothing layer, and I_{cl} is the clothing resistance according to ASHRAE standards [97]. Moreover, the human body exchanges sensible heat (Q_s) with the surrounding environment by convection with the ambient air (Q_c), by radiation with the walls' surfaces (Q_r), and latent heat of evaporation of moisture from the skin (Q_{ev}).

The heat exchanged by convection and radiation is equal to:

$$Q_s = Q_c + Q_r = \frac{(T_{cl} - T_{in})}{R_{c,cl-op}} + \frac{(T_{cl} - T_{mr})}{R_{r,cl-op}} = h_{global} \cdot f_{cl} \cdot A_{skin} \cdot (T_{cl} - T_{op}) \quad \text{Eq. (9)}$$

where $R_{c,cl-op}$ and $R_{r,cl-op}$ are respectively the thermal resistances due to the heat exchanged by convection with the indoor air and by radiation with the surrounding walls, f_{cl} is the enhancement factor of the skin surface of the human body due to clothing, T_{op} is the operative temperature, and h_{global} is the global heat transfer coefficient linked to the convective and radiative heat exchanges.

The latent heat, exchanged with the indoor space environment, due to the sweat production is referred to the work of Kaynakli and Kilic [144]. The evaporative heat loss from the skin depends on the difference between water vapor pressure at the skin and the water vapor pressure of indoor air room, the amount of moisture on the skin (w) and the evaporative resistance (R_{ev}), according to:

$$Q_{ev} = \frac{w \cdot (p_{skin} - p_{va})}{R_{ev}} \quad \text{Eq. (10)}$$

The evaporative resistance depends on evaporative exchange coefficient (k_c) and skin surface (A_{skin}), as:

$$R_{ev} = \frac{1}{k_c \cdot A_{skin}} \quad \text{Eq. (11)}$$

$$k_c = 2 \cdot (h_{c,f} + h_{c,n})$$

Total skin moisture (w) includes the contributes due to regulatory sweating (w_{rsw}) and to diffusion through the skin (w_{dif}), w_{rsw} and w_{dif} are given by:

$$w_{rsw} = \frac{\dot{m}_{sw} \cdot \Delta h_{vap}}{k_c \cdot A_{skin} \cdot (p_{skin} - p_{va})} \quad \text{Eq. (12)}$$

$$w_{dif} = 0.06 \cdot (1 - w_{rsw})$$

where m_{sw} is the sweat flow rate and Δh_{vap} is the heat of vaporization of water. The sweat flow rate is a function of the body and skin signal:

$$\begin{cases} B_{SIG} = T_{body}(t) - T_{body}(t=0) \\ SK_{SIG} = T_{skin}(t) - T_{skin}(t=0) \end{cases} \quad \text{Eq. (13)}$$

Therefore, the sweat flow rate (m_{sw}) according to the reference work of Kaynakli and Kilic [144] is estimated as follow:

$$m_{sw} = 4.7 \cdot 10^{-5} \cdot B_{SIG} \cdot e^{\frac{SK_{SIG}}{10.7}} \quad \text{Eq. (14)}$$

Once the boundary and initial conditions are defined, the implicit finite volume numerical method is adopted for solving the differential bio-physiological equation (Eq. 3).

2.2.3 Indoor air temperature and relative humidity control strategies

The thermal demands assessment for building heating and cooling is necessary for the proper design of HVAC systems. Establishing the temperature and humidity set points of an air-conditioned environment is the first step to conduct a detailed energy simulation analysis. Once defined, such variables are used to estimate both the sensible and latent thermal loads. In this chapter a smart control strategy based on well-known comfort indices, predicted by means of a novel personalized multi-node human body model, is presented. Specifically, temperature and humidity set points are dynamically adjusted to maintain the considered occupants' thermal comfort indices within the acceptability range (a work-flow schematization is depicted in Figure 6). The three strategies proposed to assess the optimal dynamic control of the indoor temperature and humidity are evaluated by considering a bilevel-objective: a two-step optimization analysis is aimed firstly at maximizing the thermohygrometric comfort of the occupants and then at minimizing energy consumption (see Figure 7). These three strategies differ in the comfort or thermal sensation index used to quantify the thermal well-being of the occupants in the simulation analysis. The comfort indicators considered are among the main ones used in commercial BEPS tools (e.g., TRNSYS and EnergyPlus).

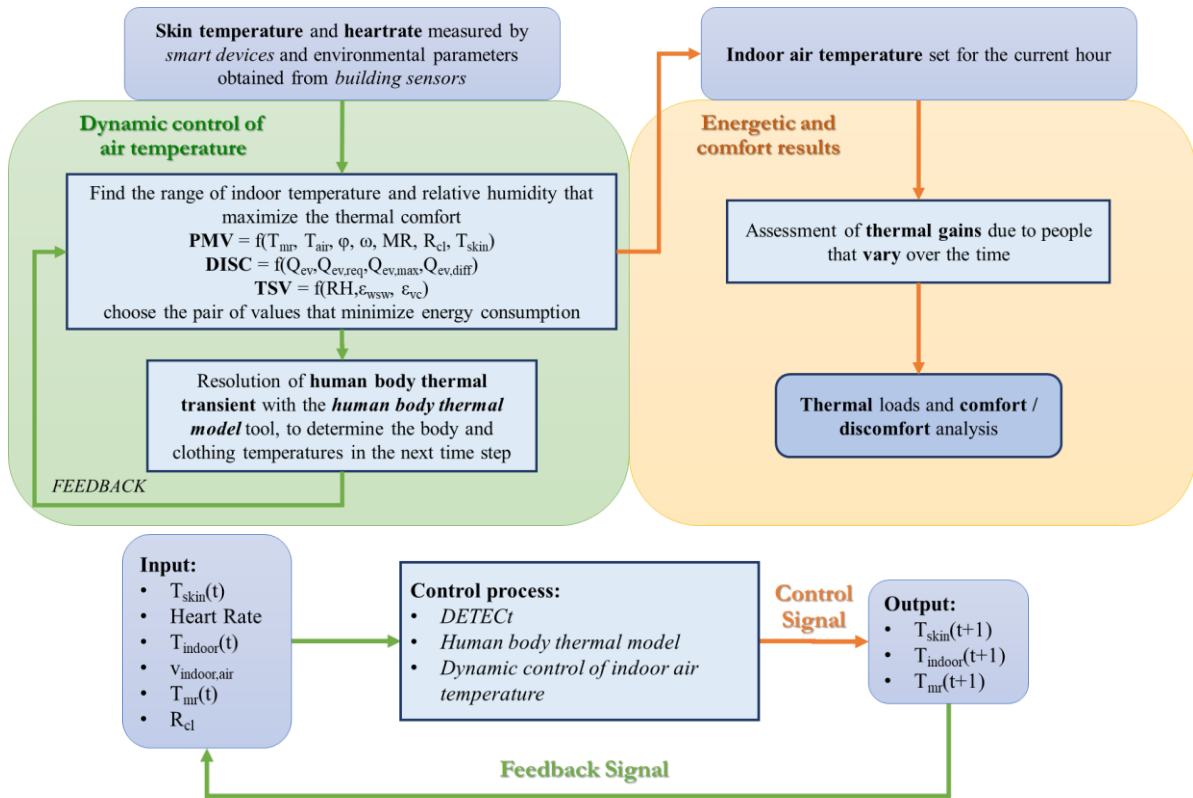


Figure 6. Synoptic block diagram of the developed control strategies.

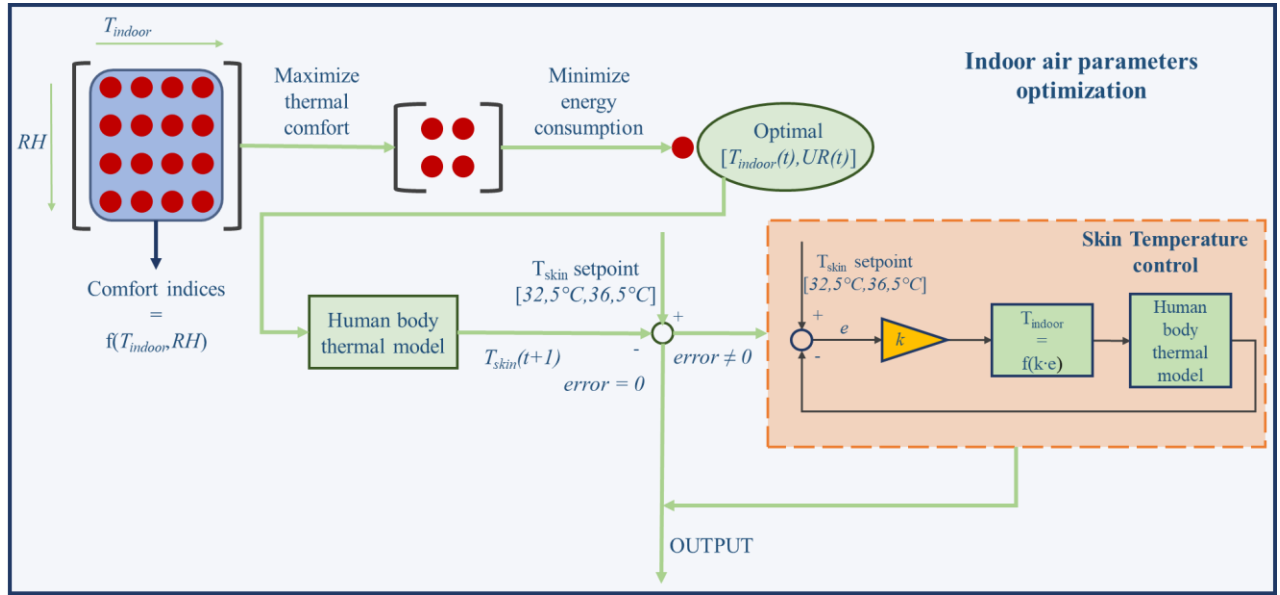


Figure 7. Synoptic block diagram of the optimisation procedure.

Therefore, as shown in the diagram of Figure 6, the control strategies are based on the knowledge of physiological parameters of the occupant (body surface temperature and heartbeats) when the system is switched on, and of building's thermophysical parameters (e.g., mean radiant temperature, an average of the walls temperatures) during its operation. In order to implement these strategies in an existing physical building, there is a need of sensors to capture its thermal properties, as well as the use of smart devices (such as thermo-scanners and smart watches) to detect skin temperature and heartbeats.

Instead, in the proposed simulation tool, with the initial aim to perform a comfort-energy analysis, the individual's skin temperature is considered as known only in the daily instant in which the system is switched on (considered as evaluated through a thermo-scanner located at the entrance of the indoor space), while the heartbeat, considered as assessed by wearable devices, is considered as equal to an average value depending on the rate of physical activity and fixed as constant over the calculation time interval. Environmental parameters are evaluated through the DETECT [140].

Once the initial and boundary conditions are set, the thermal transient of the human body can be evaluated by the developed tool to predict the temperatures of the human body in the following time steps, their knowledge is necessary to determine the dynamic control strategies for the indoor air temperature and humidity.

The process followed to determine the optimal thermohygrometric setpoint is schematized in Figure 7. By varying the indoor air temperature and relative humidity, the values of the comfort indices resulting from all their possible combinations are determined. Afterward, downstream of the first optimization step, the combinations that maximize thermal comfort is

assessed. Finally, the determination of the only combination ($T_{indoor} - RH$) that minimizes energy consumption is conducted. The subsequent step to this analysis is the evaluation of the next instant T_{skin} , simulating the thermal interaction of the human body with the surrounding environment. If T_{skin} falls within the range of admissible amounts [32.5 °C, 36.5 °C], the process stops, otherwise a new temperature control is carried out, allowing for a next step T_{skin} value until it falls within the admissible range.

Once the optimal combination of parameters to be set inside the room is determined for a typical time step, the occupant, perceiving the thermohygrometric changes related to the resulting control, begins a thermal interaction with the surrounding environment dictated by convective and radiative heat exchanges. Consequently, the thermal transient, to which he is exposed, leads the individual to reach a surface temperature (at the beginning of the next time step different from the previous one).

Thus, changing the physiological characteristics of the occupant and in particular of the body surface temperature, it becomes essential to set a different indoor air temperature, to the previous one, that satisfies the new comfort needs of the occupant. With the new skin temperature value predicted by the multi-node model of the human body, the new optimal combination of relative humidity and internal temperature to be set in the next time step can be determined with the same optimization criteria previously described.

This procedure will be iterated for all the hours of operation of the system throughout the day, resulting in dynamic and time-step control of the properties that pursue the thermal well-being of the occupants. Based on this new control strategy, an analysis of the thermal loads for heating and cooling will be carried out.

2.3 Case study

To show the capabilities of the developed thermal comfort model based on the detailed modelling of the human body and to compare the proposed strategies for the air temperature and humidity control necessary to compare the effectiveness of the investigated indices, a suitable case study is conducted. Specifically, simulations are performed for a single office space (48 m², 129.6 m³ with all thermally dispersing walls bordering on the outside and a single window area disclosed to the south), located in Naples (for which Meteonorm weather data are used). Note that the investigated single office space features the BestTest case 600 geometrical and thermophysical properties, reported in Table 2.

The choice of an office building allows for the adoption of “standard” use of the indoor space, whereas the adoption of a different building (e.g. residential) could have led to results more influenced by the considered scheduling. Specifically, the adoption, as boundary conditions of the simulation, of “well-known” operational schedules for office spaces (e.g. internal heat gain due to appliances and lights, occupational scheduling, operating

conditions of the HVAC system, etc.) allows for making a close-to-reality evaluation of the building's thermal loads. Concerning the strategies investigated in this chapter, proposing an innovative indoor air temperature and relative humidity control in function of occupant's physiological parameters, these require the use of suitable sensors, such as thermo-scanners for detecting the occupant's body surface temperature upon entering the room, and wearable devices for a dynamic measurement of the person's heartbeat. For this reason, the office building indeed use makes these control strategies more feasible for a real application with respect to other types of buildings (e.g. residential, commercial, etc.).

Table 2. Geometrical and thermal properties of test room.

component [-]	density [kg/m ³]	Capacity [J/(kg·K)]	conductivity [W/(m·K)]	thickness [m]
wall	1400	1000	0.51	0.100
	10	1400	0.04	0.062
	530	900	0.14	0.009
floor	1400	1000	1.13	0.08
	10	1400	0.04	0.08
	840	840	0.20	0.10
roof	12	840	0.04	0.11
	530	840	0.20	0.10
glass	2500	750	1.06	0.003
Geometry				
width [m]	length [m]	height [m]	window area [m ²]	
6.0	8.0	2.7	12	

According to office space usages, the HVAC system operates for 10 hours per day (from 8 a.m. to 5 p.m.) for the entire week. The energy contributions related to thermal gains of lights and appliances are respectively equal to 6 W/m² and 350 W, and these loads are assumed as constant when the HVAC is on. Furthermore, and the intake of the occupant of the single office space is evaluated through the developed human body multi-node model. The hypothesized physiological parameters necessary to evaluate the dynamical thermoregulatory response of the individual are initial skin temperature, T_{skin} , set equal to 33.7°C, the heart rate, HR , at 70 bpm, and the clothing resistance I_{cl} is 1.01 clo and 0.5 clo respectively in the heating and cooling season.

Furthermore, the parameters adopted to simulate the human body with the developed multi-node model are those reported in Table 1. Inside the thermal zone, for all the control strategy, v_{air} and the hourly air exchange rate are set at 0.4 m/s and 0.6 Vol/h (according to

UNI EN 15251), respectively. For the reference case, T_{in} is considered as equal to 20°C and 26°C and RH to 45% and 50%, respectively, during the heating and cooling season. The three dynamic control strategies return hourly set point values depending on the methodology described in the previous section and depicted in the diagram of Figure 7.

2.4 Main findings

This section includes simulation results and their discussion regarding the case study in terms of space heating and cooling demands, thermal comfort assessment, and individual thermoregulatory responses. For the sake of clarity, two specific weekly intervals (1st week of January and 1st week of July) are considered as sample time horizon to show the dynamic trends of:

- Indoor air temperatures and relative humidity to be set in the indoor space;
- Physiological parameters of the occupant (e.g. skin temperature T_{skin} and relative energy inputs $Q_{gain,people}$);
- Thermal loads and estimation of investigated comfort indices.

Results are discussed by means of a suitable comparison of the mentioned 4 dynamic control strategies: 3 proposed plus the reference one.

Simulation results aim at showing the impact of the occupant's physiological adaptation, affected by the hourly regulation of T_{in} and RH , on the space heating and cooling demands. They give an estimation of the hourly skin temperatures (decision-making variable in the process that determines the ambient set points) resulting from the energy interaction with the room in the thermophysical conditions of the previous hour. In this way, the occupant's waste energy can be obtained, to consider the thermal load that affects the building. Finally, the results of energy analysis and thermal comfort of the occupants will be illustrated.

2.4.1 Physiological adaptation of the human body

In this chapter, the conventional standards adopted for the building energy simulation are abandoned and dynamic conditions are assumed for the control of the main parameters (indoor air temperature and humidity) influencing the energy demands for space heating and cooling.

Specifically, the proposed control strategies, which adjust the thermohygrometric parameters of indoor space predicting the occupant's physiological response, are articulated in the following steps:

- evaluate the optimal thermohygrometric conditions (following the optimization procedure outlined in Figure 7) to be set in the generic simulation hour (h), once the body surface temperature of the same hour ($T_{skin}(h)$) is known;

- predict the body surface temperature in the next hour ($h+1$), due to the thermohygrometric conditions of the previous hour determined as seen above;
- iterate the procedure assuming the previously predicted skin temperature as the current value.

As an example of the model potential, in Figure 8 and Figure 9 the occupant's body temperature time histories are shown. Note that these temperatures are influenced by both thermoregulation processes and thermohygrometric conditions of the room resulting from the control (aimed at ensuring comfort for the occupant). The charts at the top of Figure 8 provide an example of how the optimization procedure works to determine the optimal combination, for all strategies, of indoor temperature and relative humidity which ensure first the thermohygrometric comfort and then energy saving. The settings at 9 a.m. on January 1st are represented by the red circles on the contour diagrams of Figure 8, used to highlight the variation of the three comfort indices with T_{in} and RH for each investigated thermal comfort indices (PMV , $DISC$, and TSV). These optimal values are (T_{in} equal to 25°C, 18°C, 18°C and RH to 35%, 35%, 35% for the 1st, 2nd, and 3rd control strategies correspondingly).

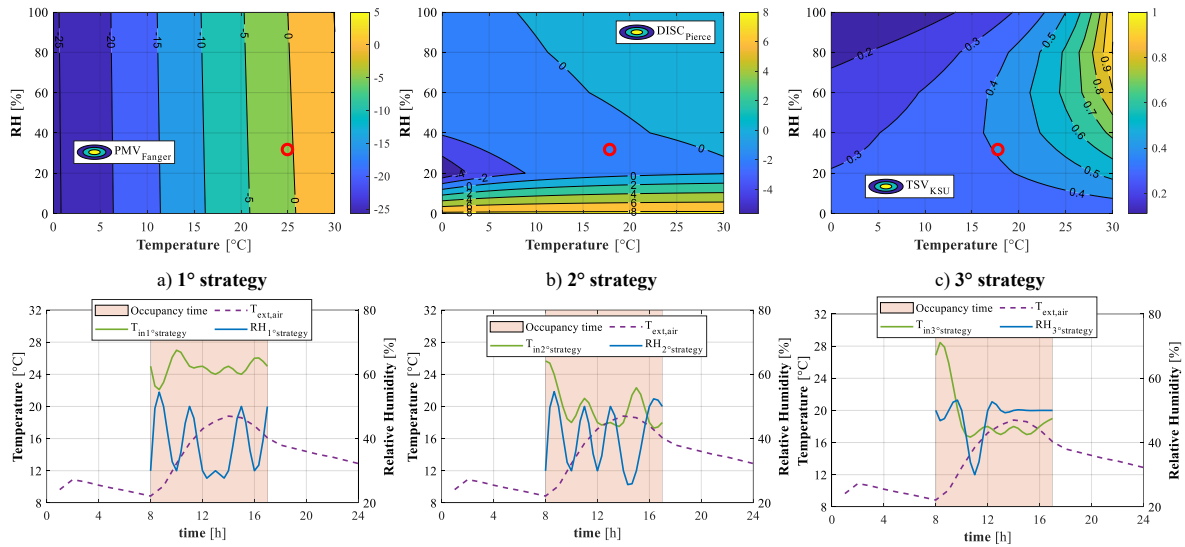
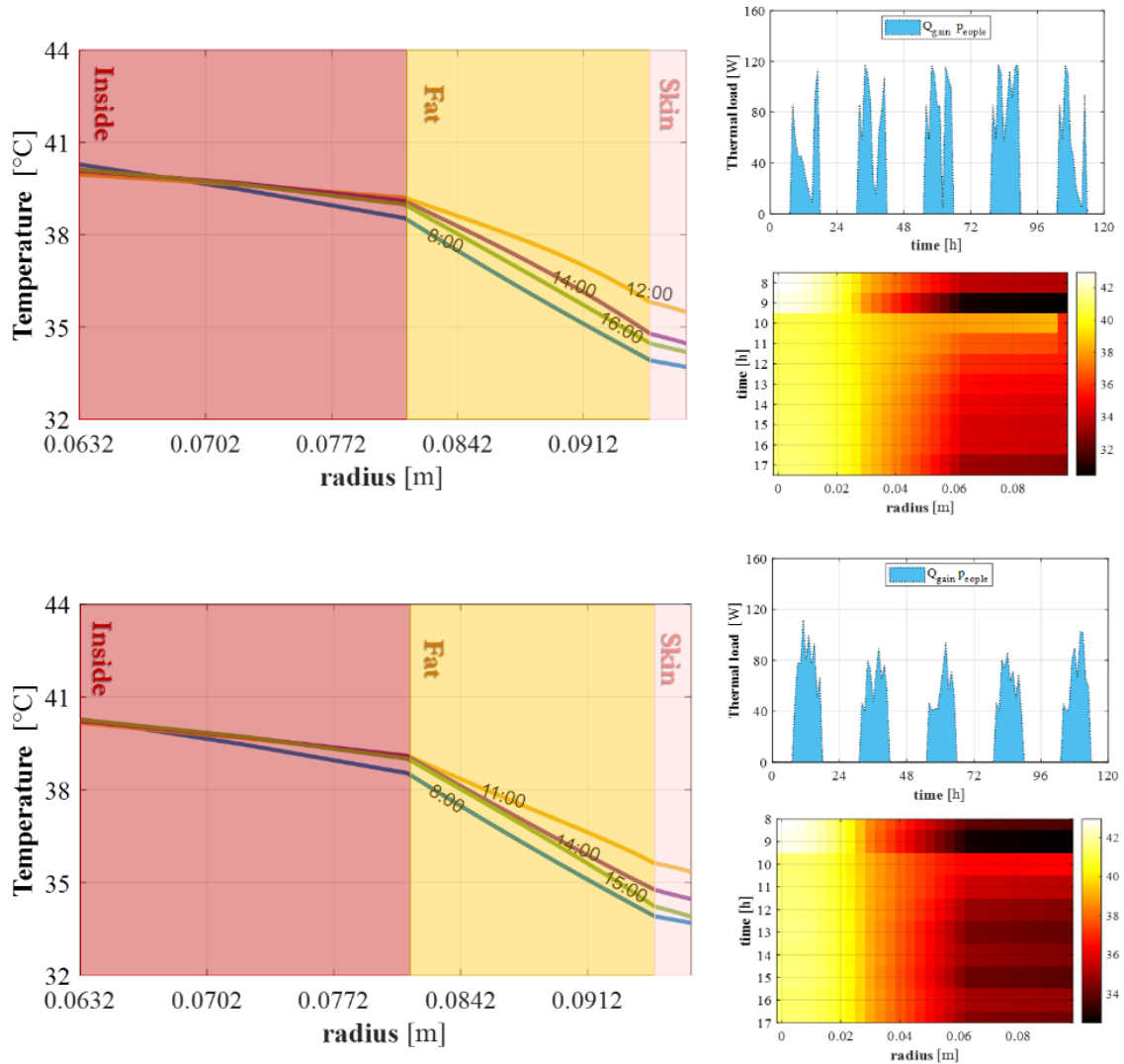


Figure 8. Thermohygrometric parameters resulting from the dynamic control strategies.

The dynamic variations of T_{in} and RH , for the three proposed strategies in relation to January 1st, observed in Figure 8, show that the thermal comfort needs, when the occupant is considered as an active subject and in thermal interaction with the surrounding environment, cannot be encountered by stationary thermohygrometric conditions. In this regard, by considering the same day, Figure 9 shows for each investigated strategy, the temperature trend through the organic tissues in certain hours of the day, whose dynamism is conditioned by the thermoregulatory responses of the organism and affects the dynamic thermohygrometric room control in order to ensure the optimal thermal sensation for the

occupant. The occupant thermal gains (depicted in Figure 9) are also time variable due to the dynamism of thermoregulatory system, since they depend on the surface temperature (T_{skin}), and on the body rate wettedness (w) linked to sweating (m_{sw}), evaluated by means of the body and the skin signal (B_{SIG} , SK_{SIG}).

From the comparison of the results regarding the various proposed strategies, it can be highlighted that– the Fanger theory (maximizing comfort by minimizing energy accumulation in the body) is the strategy that requires the highest temperature setpoint, resulting in a lower heat gain from the occupant, as well as in the smallest changes in body temperature.



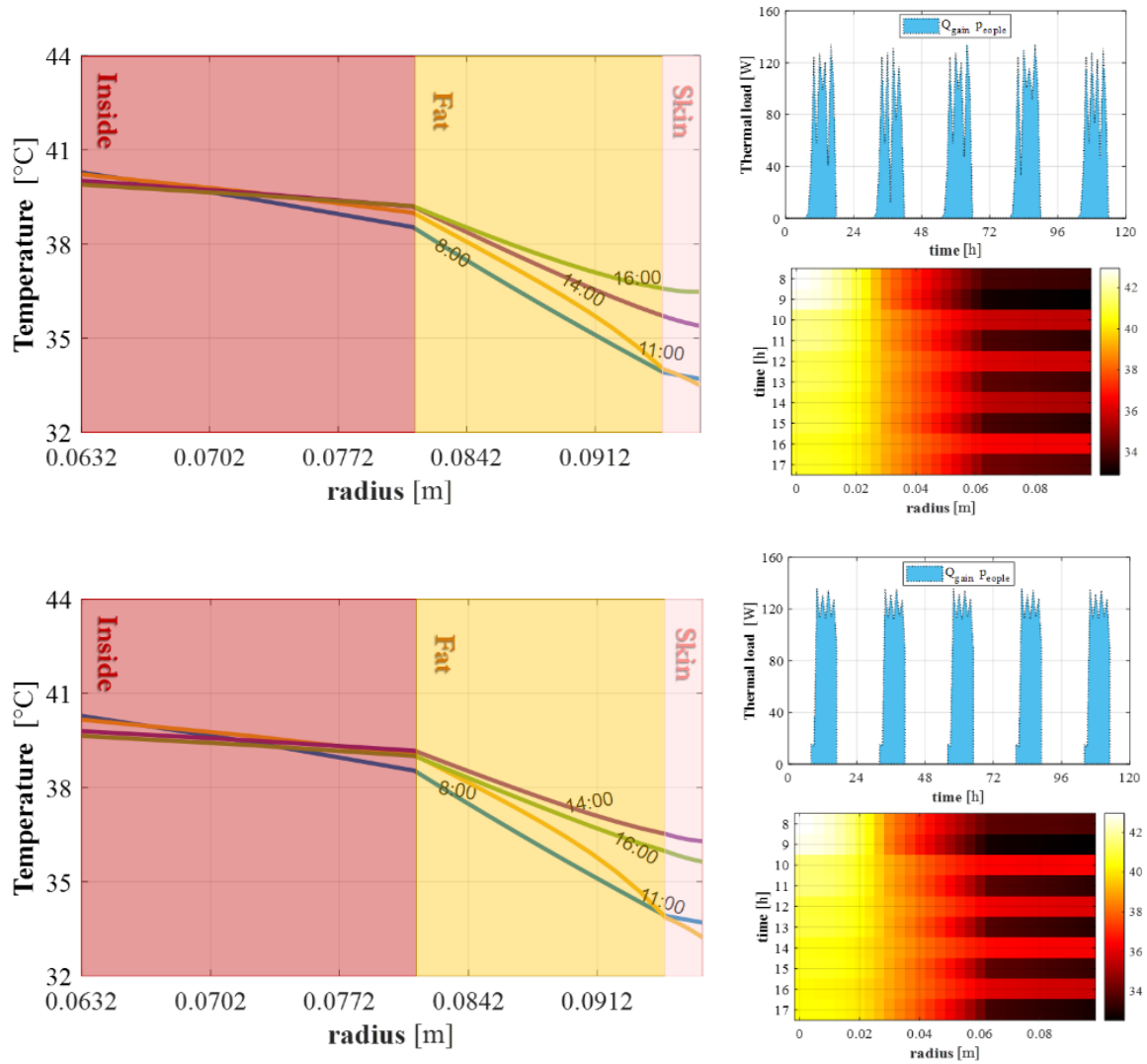


Figure 9. Physiological response due to thermoregulatory process: a) reference case, b) 1st strategy, c) 2nd strategy, d) 3rd strategy.

Conversely, for the other two strategies (based on the theories of Pierce and KSU, maximizing comfort by minimizing the thermoregulatory mechanisms of vasoconstriction and vasodilation), the one that requires lower temperatures is the KSU model, with consequent higher energy supplies by the individual. However, what is most evident is that their control strategies subject the individual to more noticeable changes in human body temperature. Nevertheless, by comparing all investigated strategies with the reference one the latter (i.e., Figure 9 d) shows the highest heat gains from the occupants.

2.4.2 Building energy simulation and comfort analysis

The aim of the proposed analysis is to compare the energy demands for heating and cooling, as well as the optimal size of HVAC system, resulting from the implementation of each investigated control strategy. In this regard, in Figure 10 and Figure 11 the thermal loads time histories for two considered sample weeks, the first of January and the first of July, are presented.

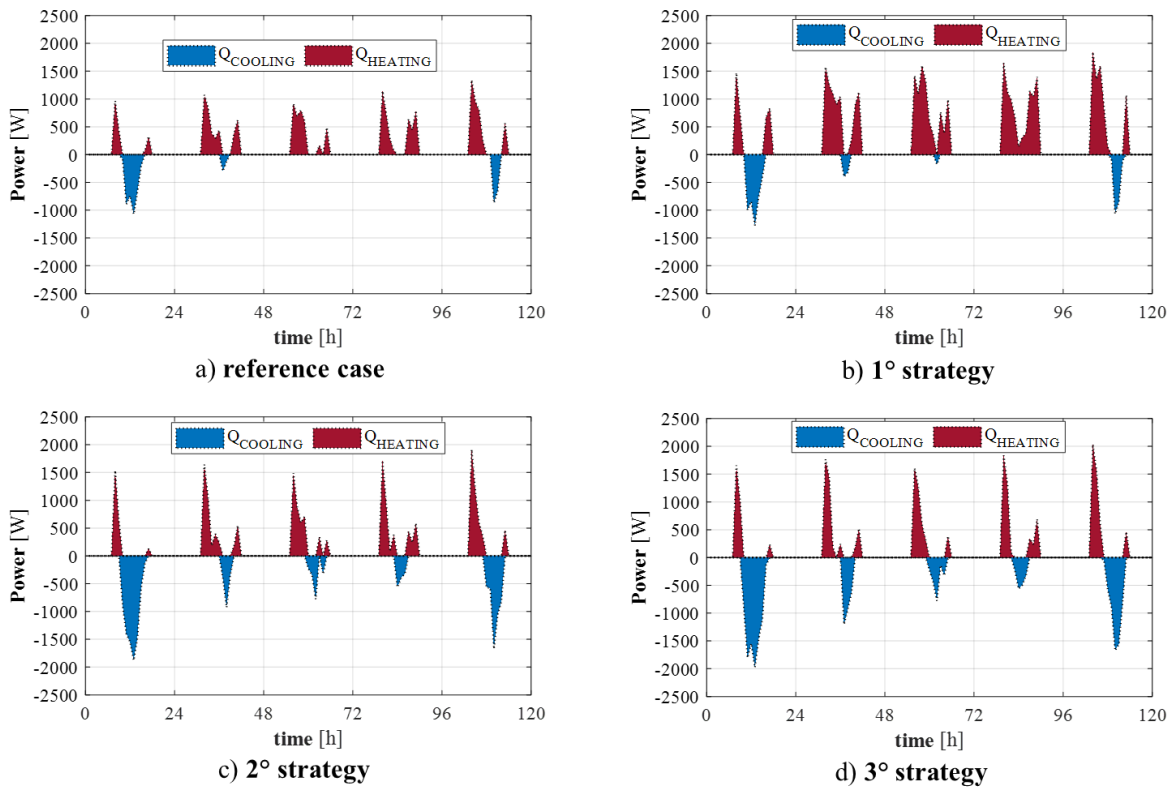


Figure 10. Dynamic trend of thermal loads and energy consumption for the 1st week of January.

For the winter week, it is interesting to note that for all strategies, in certain days, there are both heating and cooling request (due to the weather zone characteristics). From the figure it is possible to notice that the strategy that requires the greatest amount of thermal energy for space heating is, as before noticed, the one based on Fanger's theory, since it maximizes the occupant thermal comfort during the winter season reducing the body heat dissipation. As a consequence, to reach this condition the HVAC system controller acts by minimizing the temperature difference between the occupant surface and the surrounding air. In fact, as seen in Figure 8, controlling the indoor air temperature to guarantee thermal comfort according to the PMV is the strategy that requires the highest temperature set points. Conversely, the 2nd and 3rd strategies respectively based on the theories of Pierce

and KSU, propose actions to control the thermohygrometric properties of the room that stimulate the thermoregulatory activities of the human body (such as vasoconstriction to reduce the thermal sensation of cold) resulting in lowest temperature levels of T_{in} (see Figure 8). On the other hand, although the plots in Figure 10 refer to the winter season, there are high cooling requests in case of the adoption of the second and third strategies (which could be satisfied by exploiting free cooling strategies).

As regards to the sample summer week (July, Figure 11), the cooling requests are comparable for all the investigated strategies. However, in few cases, the Fanger's one are lower than those obtained by the adoption of the dynamic control strategies.

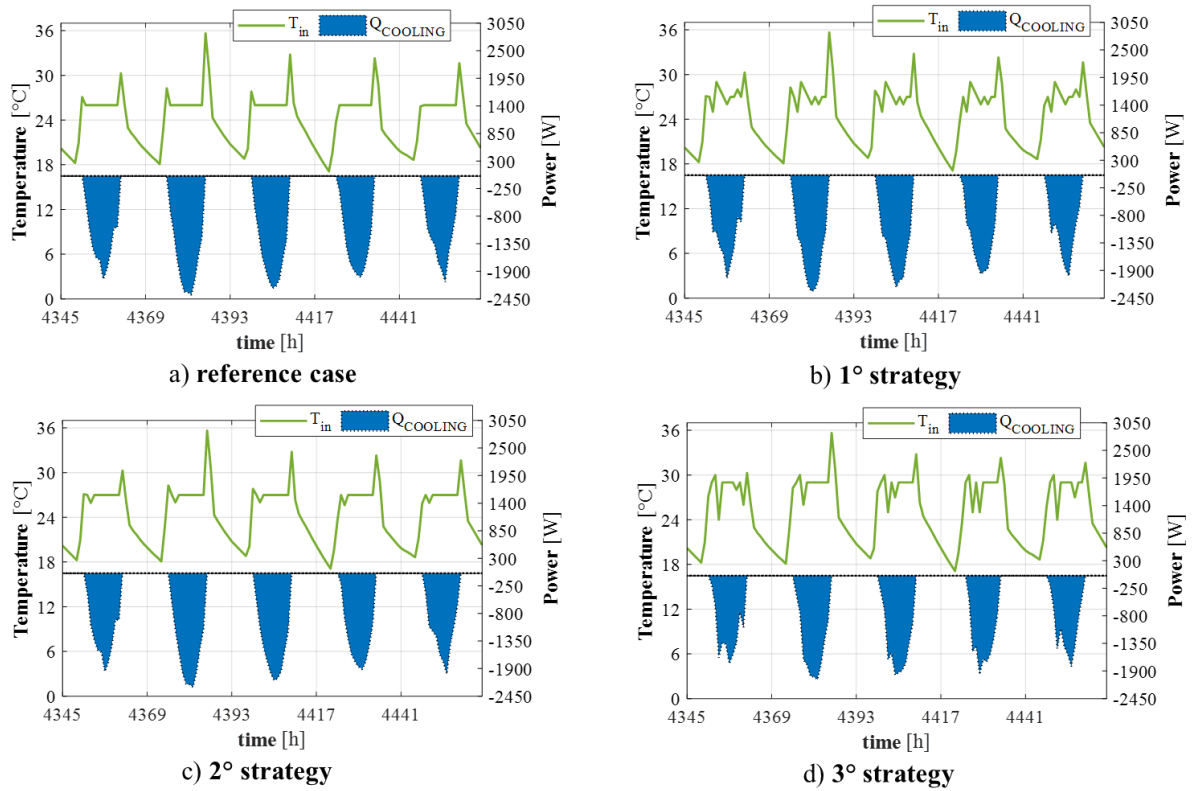


Figure 11. Dynamic trend of thermal loads, energy consumption, and indoor air temperature for the 1st week of July.

It worth noticing that the T_{in} fluctuations, most evident for strategy 1st and strategy 3rd in Figure 11, are affected by the sweating phenomenon. In fact, the occupants' too hot thermal sensation is a consequence of the increase in his sweating rate m_{sw} . Such condition will lead to a higher cooling demand to keep satisfactory thermohygrometric conditions. Once these conditions are reached, the human body begins to dissipate greater thermal energy with the surrounding environment, also due to the evaporative cooling of sweat. In this way, the occupant will once again experience a thermal sensation of mild cold justifying the T_{in} and

RH increase occurred in the next indoor regulation. The dynamic trend of T_{in} from 5:00 pm to 9:00 am for each day, when the HVAC system is off, follows the trend of the external air temperature.

The thermal comfort of the occupant, for the case study under examination, as previously mentioned, is evaluated by means of the three indices of Fanger, Pierce and KSU adapted to the thermoregulatory responses simulated with the multi-node model of the human body. In the dynamic results (see Figure 12 and Figure 13) of the thermal comfort assessment, for the same sample weeks, the proposed strategies respect the corresponding values in the acceptability ranges (Figure 12 and Figure 13, right) as a consequence of the optimal proposed control strategies. Whereas, for the reference case, by calculating the comfort indices (PMV, DISC, TSV) by considering steady state conditions, the calculated values (Figure 12 and Figure 13, left) fall outside the admissible values and highlight that the reference strategy is not optimal for the occupant's thermal comfort requirements.

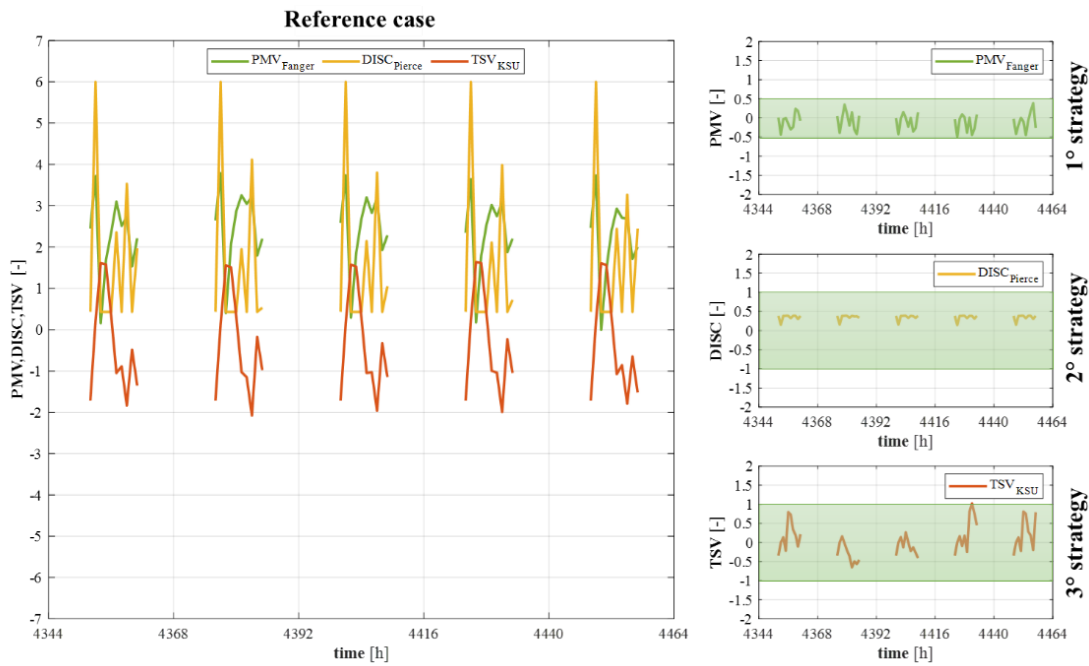


Figure 12. Comfort analysis in the 1st week of January.

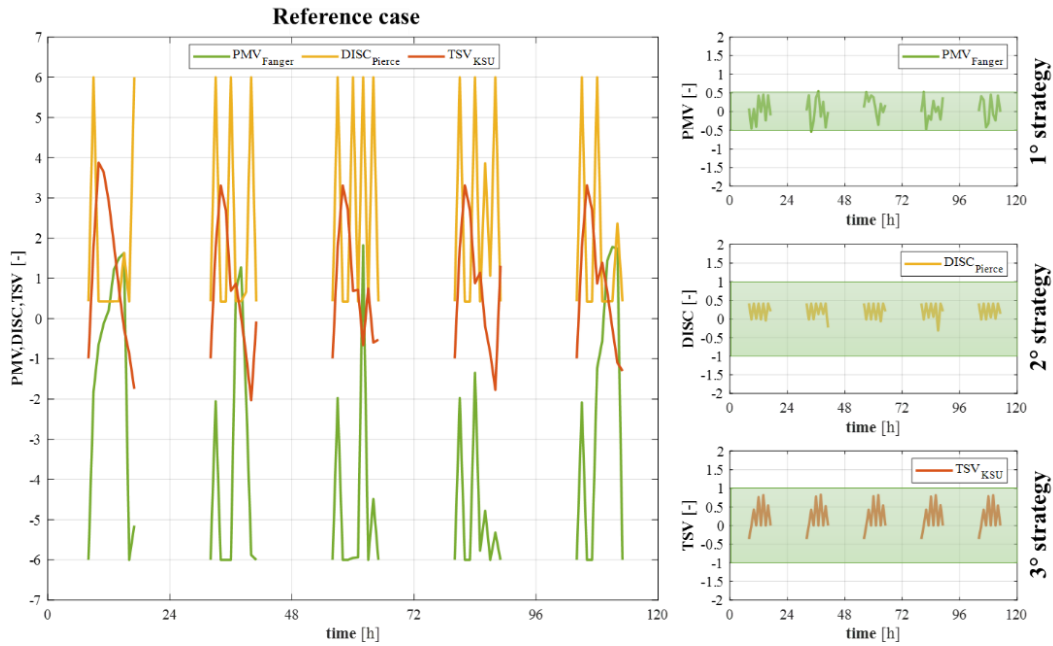


Figure 13. Comfort analysis in the 1st week of July.

2.4.3 Further remarks

In order to better estimate the energy expenditure related to each implemented strategy, a further analysis was conducted on a monthly and annual basis. The thermal energy requirements for heating and cooling for each of the investigated case study are shown in Figure 14. These results allow for the comparison of the energy expenditures for the air conditioning of indoor space when thermohygrometric parameter control strategies are performed according to the comfort requests of the occupants. From the figure it can be noted that the proposed strategies are overall more energy-intensive than the reference case. Still, it is interesting to note in Table 3 that the first strategy returns the lowest overall cooling energy demand. In contrast, the overall energy expenditure for the second and third control strategy are very close to the reference one. These results can be seen in Table 3 showing the results of annual thermal energy required for heating and cooling expressed in relation to the room's floor area. Compared to the reference case, it is possible to appreciate an annual energy consumption relating to heating of 116% higher for the first strategy, 32% higher for the second strategy, and 62% for the third. For cooling needs, the energy consumption of the proposed strategies is closer to those of the reference case. In particular, the first strategy has a consumption of 5% less, the second and third respectively of 16% and 2% more.

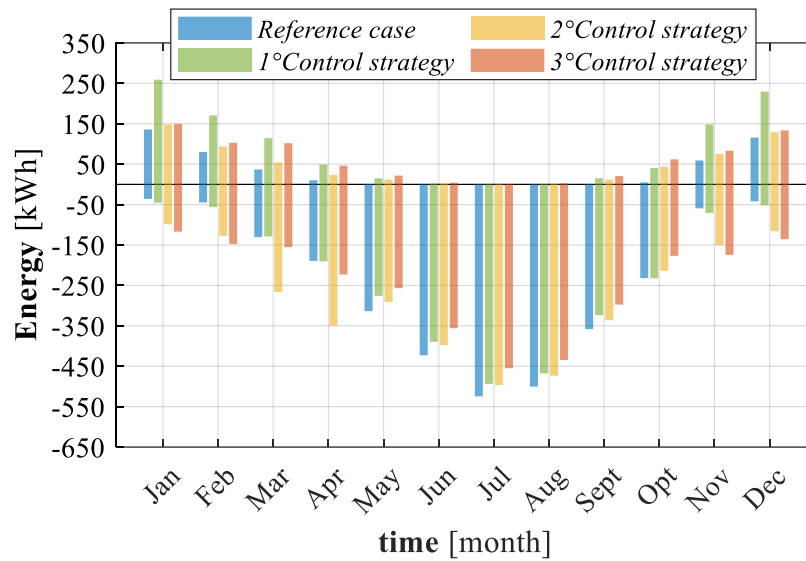


Figure 14. Monthly energy consumption for heating and cooling needs.

Table 3. Annual energy analysis for each strategy.

Control strategy	Heating demand [kWh/m ² y]	Cooling demand [kWh/m ² y]	Heating load [kW]	Cooling load [kW]
Reference case	9.3	59.3	1.5	2.9
1 st strategy	20.0	56.3	2.3	2.9
2 nd strategy	12.2	68.9	2.3	2.8
3 rd strategy	15.1	60.7	2.5	3.0

Table 4. Annual discomfort analysis for reference case strategy.

Control strategy	discomfort hour PMV [h/y]	discomfort hour DISC [h/y]	discomfort hour TSV [h/y]
Reference case	2124	2813	984

The maximum loads for heating and cooling are reported to estimate the sizing of the systems (Table 3). The data linked to the discomfort hours (Table 4) underlines the need to

overcome the reference standards that very often do not guarantee the needs of comfort. The reference case energy consumption, for cooling, is comparable and in some cases lower than that of the proposed strategies that differently offset the hours of discomfort.

The scatters plots, reported in Figure 15 show the indoor air relative humidity and temperature values set during the year for all proposed dynamic control strategies. These scatters are reported on appropriate psychrometric diagrams.

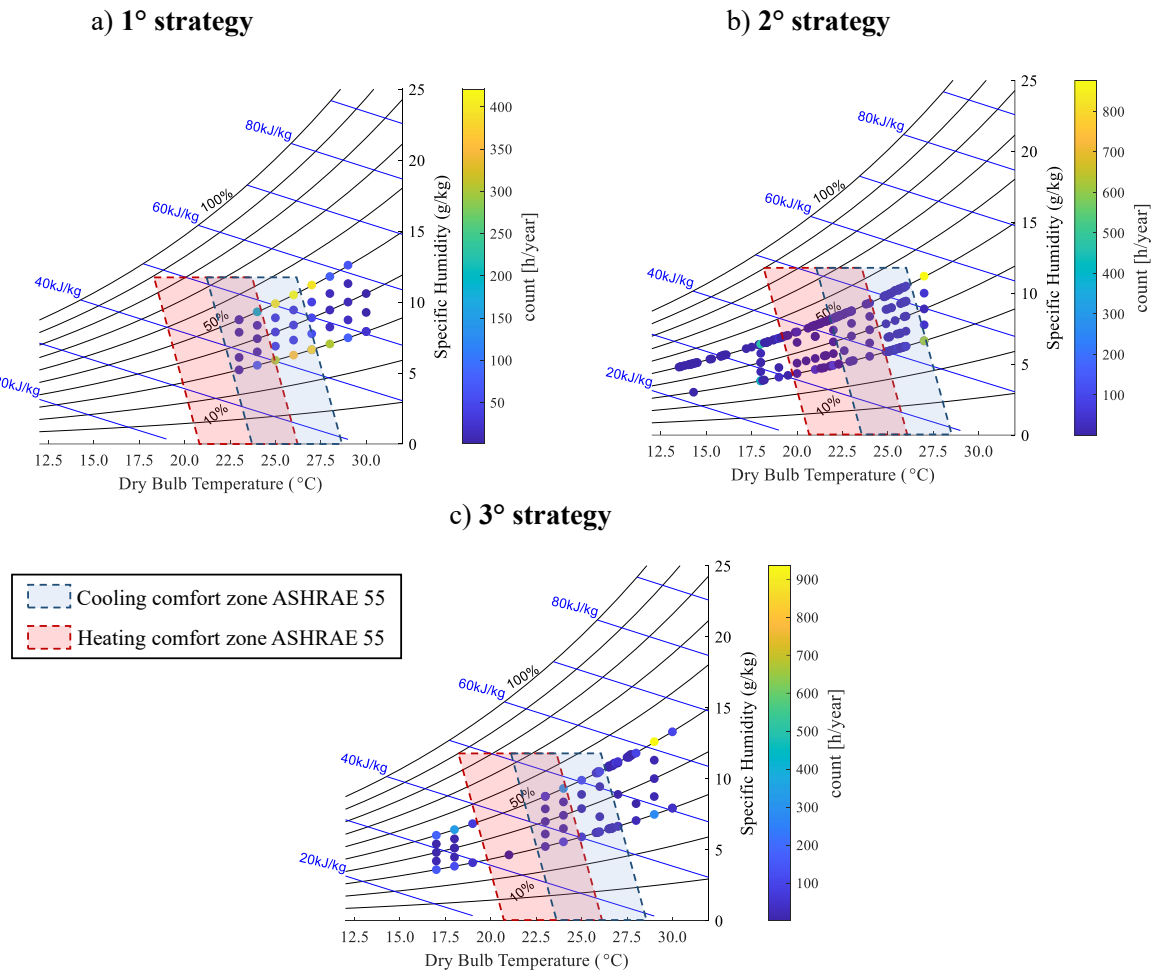


Figure 15. Scatter plot of recurring temperature and relative humidity over the year.

As can be seen from the Figure 15, the ranges of thermohygrometric well-being are produced for all the investigated strategies. They are obtained from the correlations of the respective comfort indices analysed and adapted to the multi-node model of the human body implemented in this work. Furthermore, it is possible to obtain further information from these scatter plots, such as the recurrence of air temperature and relative humidity pairs throughout the year. As clearly shown, the use of the PMV index (1st strategy) calls for higher indoor air temperatures (the relative humidity doesn't show a remarkable difference among all investigated cases). In addition, the comfort areas, referred to the ASHRAE 55 standard,

were traced as a function of the same v_{air} and I_{cl} (1.01 clo during the heating season and 0.5 clo during the cooling one) adopted in the case study. In this way, it can be possible to underline that the hourly thermohygrometric conditions of the whole year fall for 49%, 57%, and 52% within the acceptability ranges of ASHRAE 55 for the 1st, 2nd, and 3rd strategies respectively.

Finally, Figure 16 shows the recurrence of the temperature values during heating and cooling needs. It can be noted that for the cooling needs, which are predominant in the selected case study, the most recurrent temperatures are: 27°C, 27°C, and 29°C respectively for the 1st, 2nd and 3rd strategy. The obtained results show that the indoor thermal comfort, for relevant hours of the cooling season, is reached for controlled indoor air temperatures (set-points) much higher than the 26°C of the reference case achieving lower energy consumption.

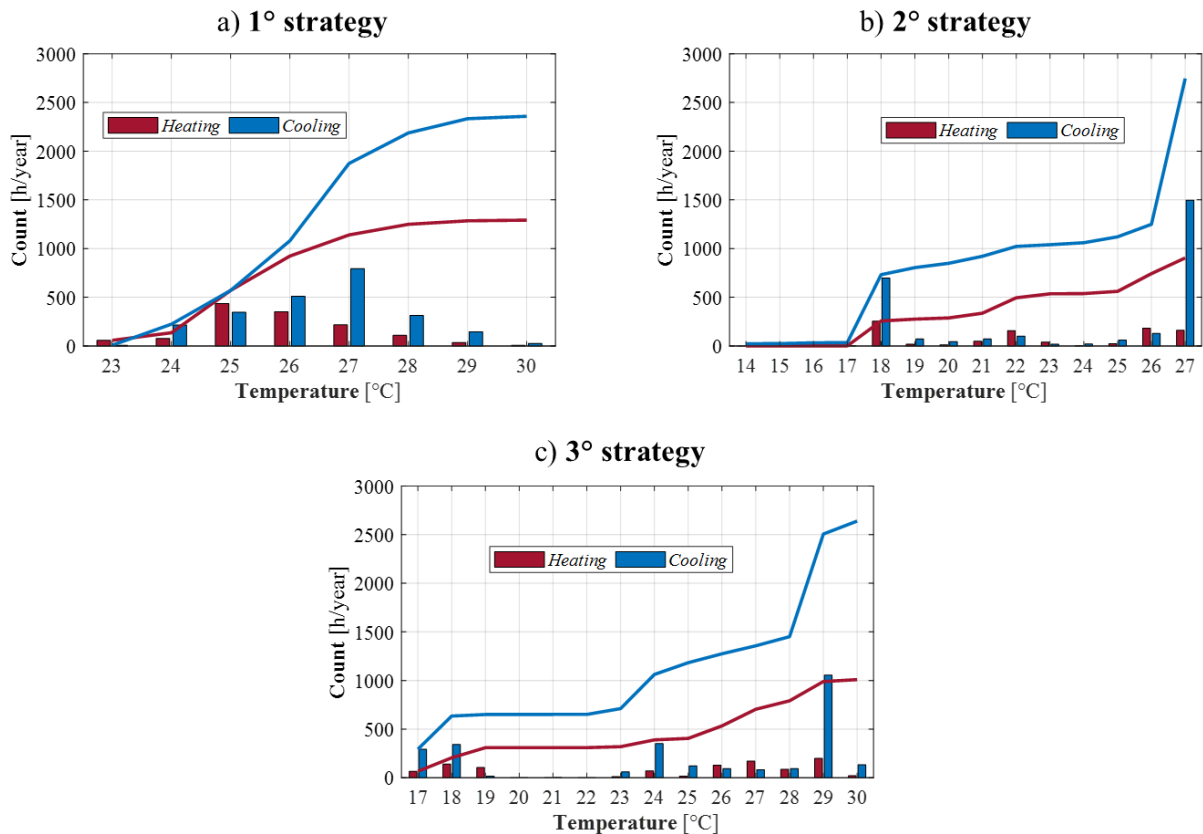


Figure 16. Cumulation of temperature values that occur throughout the year.

2.5 Conclusions

This study proposed a multi-node thermal model of the human body to perform accurate calculations of the thermal comfort of occupants in indoor spaces. Three dynamic control strategies of the thermohygrometric parameters of the indoor space are proposed and assessed through simulations. The case study analysis, based on the BestTest building features, thought the indoor spaces is considered as located in Naples. The physiological parameters of a single office space occupants were simulated by means of the cylindrical multi-node model of the human body. The three strategies maximize occupant comfort each based on an investigated comfort index (PMV, DISC, TSV). Comfort was updated and adapted to variable parameters (such as skin temperature) dependent on the thermoregulatory mechanisms that are taken into account in the simulation model. Subsequently, after the first optimization aimed at maximizing thermal comfort, the parameters to be set were chosen to optimize energy consumption. For the considered building, the energy consumption linked to cooling appears to be preponderant compared to that of heating, and in particular: about 6 times higher in the reference case and in the second strategy proposed, while are higher about 3 times for the first, and about 4 times for the third strategy. Compared to the reference case, it is possible to appreciate an annual energy consumption relating to heating of 116% higher for the first strategy. For cooling needs, the energy consumption of the proposed strategies is closer to those of the reference case, and in particular the first strategy has a consumption of 5% less.

This energy expense can be seen as the price to be paid to maximize the comfort of the occupants who, on the other hand, in the reference condition provides the following hours of discomfort: 2124 h/y respect to PMV index, 2813 h/y with DISC and 984 h/y for TSV, compared to the 3650 per year in which the system is switched on. By means of these implemented strategies, new areas of well-being are proposed on the psychrometric diagram.

Among the future perspective, there is the aim of validating the multi-node model of the human body by conducting appropriate experimental works. Once validated, a correlation between body surface temperature and ideal thermohygrometric parameters that restore comfort to the occupants could be obtained. Thus, thanks to the use of suitable fuzzy controllers, it will be possible to model, simulate, and regulate the HVAC system in order to return those values of temperature and relative humidity that are optimal for comfort, according to the skin temperature measured by means of fitting devices.

Chapter 3

Occupant-centric control for enhancing building energy efficiency

This chapter was previously published as:

Buonomano A., Forzano C., Gnecco V.M., Pigliautile I., Pisello A.L., Russo G. (2024). Enhancing energy efficiency and comfort with a multi-domain approach: Development of a novel human thermoregulatory model for occupant-centric control. *Energy and Buildings*, 303, 113771.

Summary

Occupant-Centric Control (OCC) strategies focus on creating a more personalized and comfortable indoor environment by aligning HVAC operation with occupants' comfort needs. This approach uses a multi-level, non-linear optimization process to identify optimal thermohygrometric setpoints, aiming to minimize heating and cooling demands while addressing comfort factors such as thermal sensation and perceived air quality. A novel Personal Comfort Model (PCM), incorporating physiological variables, is introduced to predict thermal sensations and CO₂ intake, validated with experimental data from a test room at the University of Perugia. The PCM is then integrated into DETECT, a simulation tool developed by the University of Naples Federico II, to support the design of advanced control algorithms and energy-efficient strategies. A model predictive control strategy utilizes these optimized setpoints to manage HVAC operations, achieving substantial comfort improvements (reducing thermal discomfort by 40% and 60% for two tests) and energy savings of 12.8% and 7.8% in HVAC electricity consumption compared to reference scenarios. This study highlights the potential of OCC in developing more occupant-centric and energy-efficient buildings.

Keywords

Physiological thermal comfort models. Building energy performance simulation tools. Human-body thermal sensation. Occupant centric control. Multi-level nonlinear programming; MPC control for HVAC; Multi-domain comfort model. Perceived indoor air quality.

Nomenclature

Abbreviations:

ANN – Artificial Neural Network	HVAC – Heat, Vent and Air Conditioning
BMR - Baseline Metabolic Rate	PCM – Personal Comfort Models
CNN – Convolutional Neural Network	PIAQ - Perceived Indoor Air Quality
GHG – Greenhouse Gas	PMV – Predicted Mean Vote
IEQ – Indoor Environmental Quality	PPD – Percentage of People Dissatisfied
IoT – Internet of Things	OCC – Occupant-Centric Control

Acronyms

A	surface area [m^2]	p	pressure [Pa]
ACC	acceptability index [-]	$\dot{Q}$	thermal power [W]
CE	caloric equivalent [$\text{W}/(\text{kg}/\text{s})$]	r	radius [m]
CR	core layer	R	thermal resistance [K/W]
f	enhancement factor of skin surface [-]	SK	skin
F	view factor [-]	t	time [s]
h	enthalpy [kJ/kg]	T	temperature [$^{\circ}\text{C}$]
HR	heart rate [bpm]	U	internal energy [J]
l	clothing resistance [clo]	v	velocity [m/s]
k	thermal conductivity [$\text{W}/(\text{m}\cdot\text{K})$]	V	volume [m^3]
$\dot{m}$	flow rate [kg/s]	w	moisture [-]
M	metabolism [W/kg]	W	work of the human body [W/kg]
MR	rate of metabolic heat accumulated [W/kg]	x	decision variables

Greek letters

Γ	control horizon	Λ	prediction horizon
Δ	variation	ρ	density [kg/m^3]
ε	emissivity [-]	σ	Boltzmann constant [$\text{W}/(\text{m}^2\cdot\text{K}^4)$]
η	energetic efficiency of human body [-]	ϕ	relative humidity [%]

Subscripts

b	body	p	pressure
c	convective	r	radiative
cl	clothing	res	respiration
dif	diffusion	rsw	regulatory sweating
ev	evaporative	s	sensible heat
f	forced	S/G	signal
in	indoor	sw	sweating
l	latent heat	tot	total
mr	mean radiant	va	vapor air
mv	manipulated variables	vap	vaporization of water
n	natural	w	wall
op	operative		

3.1 Introduction

People typically spend about 90% of their time indoors [145], that have a significant impact on their well-being and quality of life, and on the energy use. This has led to dedicated efforts to improve occupants' comfort perception, especially considering the narrow relationship between indoor environmental quality (IEQ) and people's health, well-being, productivity and social interactions [146]. Particularly, building active systems are being more demanded to maintain acceptable levels of satisfaction, which increases buildings' energy use even with the energy efficiency trends demonstrated in recent reports and standards [147]. Designers, architects, engineers, and construction managers must work together and set shared commitments to create healthier, sustainable and energy efficient indoor spaces by continuously improving the design, operation, and user engagement to achieve a harmonious equilibrium between energy consumption and occupants' comfort.

3.1.1 Managing Occupant-Centric Control through physiological information

Occupant-centric control (OCC) systems take advantage of monitoring data from occupants, indoor and outdoor environments, and human-building interaction to build operation patterns, such as occupancy schedules, shading configuration, and thermostat settings [148]. Basically, OCC is a process able to incorporate monitored data to a control method managed by algorithms, that seek to ensure occupant comfort and energy efficiency [27]. OCC strategies can deal with the conflicting occupant-systems relationship, considering the energy costs to maintain adequate comfort levels, hardly obtained on traditional manual control strategies [149].

Great energy saving opportunities can be found only by coordinating the HVAC systems accordingly to the occupants' presence, such as the study carried out by Pang et al. [150] found out by comparing different climate zones, building sizes and standards. O'Neill et al. [151], on the other hand, presented a method that dynamically adjust the minimum air flow rate to guarantee adequate levels of CO₂ concentration in each calculated zone thus also introducing the air quality dimension in addition to the thermal one.

However, the scientific body of knowledge concerning multi-domain interaction in the indoor environment is still incipient, while the single-domain analysis presents already a considerable number of works [152]. This asymmetry rises probably because the difficulty to measure and analyse multi-domain data, leading to inconclusive or contradictory outcomes [93]. However, in the last years, researchers have been more engaged in explored multi-domain approaches, particularly focusing on two factors thermal conditions and indoor air quality [153].

In addition to these agents, occupants' behaviour is, in turn, a personal response, varying due to individual preferences and occasional influences. Furthermore, it is crucial to acknowledge that occupants play a significant role in shaping their own behaviour within a given environment. These variations in behaviour can be attributed to a range of factors, such as personal inclinations, cultural backgrounds, external influences, and occasional motivations [154]. It is challenging to fully identify tailored solutions and human-centric variables by means of general models fed by building-related sensors and targeting the average response. Personalised monitoring signals can overcome this challenge, by the proposal of data-driven models to the decision-making of conditioning systems setpoint, ventilation use, lighting adjustments.

Despite its popularity in the last years among human-centric comfort researchers, OCC operation lacks real application with empirical data, obtained by clear experimental design and models capable of emulate the real human experience [148]. Experiences in test rooms can be a starting point to implement and test OCC techniques, bringing simulation suppositions to the real-world application, when new approaches are investigated [153].

Physiological data from the occupants can also assist in the determination of building operation metrics, minimising the subjective and randomness aspects of human' control [155]. Li and Chen [156] trained a convolutional neural network (CNN) capable of identify the mean facial skin temperature and relate to thermal sensation votes. From that, a system which controls the HVAC setpoint was proposed, obtaining more than 90% of acceptability when implemented. Deng and Chen [157] measured skin temperature through wristbands and indoor environmental conditions achieving savings of 90% for heating and 30% for cooling systems. However, the adoption of black-box modelling for predicting skin temperature and thermal response can rise to several issues, such as a lack of interpretability in the mechanisms which influence the predictions. Moreover, black-box models may encounter difficulties in generalizing to different scenarios. These OCC strategies are capable to unravel people's comfort preferences based on analytical information, unlocking an uncertain point in human centred studios, the dependency on personal judgments of occupants.

3.1.2 Building energy performance tools implementing personal comfort models

The integration of PCMs in BEPS tools was explored by researchers and software developers to incorporate more accurate comfort models into building simulation tools, better representing the physiological response of occupants, as well as to assess the impact of OCC strategies on the building energy use [158].

Commonly used commercial tools, such as EnergyPlus, IDA ICE, DesignBuilder, and OpenStudio, TRNSYS, incorporate personal comfort models to provide more realistic assessments of occupant comfort [159]. Most comfort models implemented in commercial BEPS are based on conventional Fanger's theory or on adaptive approaches implemented in standards [99]. The only exception is represented by Design Builder, which implements additional approaches, such as the Pierce and the KSU ones [160].

The integration of PCM in commercial BEPS tool may require additional development and customization. Moreover, PCM can be computationally demanding, particularly when considering dynamic occupant responses and real-time interactions with occupied building. This can result in longer simulation times and makes the models highly sensitive to assumptions, complexity and input data quality [161].

To address these issues, especially with respect to flexibility, PCM are now being developed and implemented into in-house BEPS tools. These tools offer greater flexibility and customization options compared to widely used commercial software, and they also allows for implementing custom or advanced control algorithms for specific application [125]. In-house BEPS tools allow researchers to tailor the simulation environment to their specific needs, to fine-tune the model to match specific research objective or indoor spaces scenarios, and to test and prototype new comfort models and update theme [45].

The PCM integration in BEPS tools, commercial or in-house, comes with several challenges basically linked to i) the way the dynamic response of the human body to environmental conditions is modelled [162], ii) the need for detailed occupant data, also necessary for calibration and validation purposes [163].

The first one can be approached integrating PCM in BEPS tools to add complexity to the simulation process. Specifically, diverse, simple, and complex, methods for the assessment of the modelling of the effective human body thermal adaptation and the actual perceived comfort can be available in the literature [164].

Among these, numerous studies have proposed different approaches to enhance comfort and energy efficiency in buildings through simulations and optimization methods, many still relying on Fanger's theory [165, 166]. Some investigations have explored alternative methods to improve comfort and energy efficiency. Anand et al. [167] presents a simplified tool for designing building layouts based on thermal comfort simulations, yet it also depends on PMV as the decision variable. Another research effort proposes an enhancement to Rohles' equation to account for different clothing thermal insulation ranges [168], while a different study [169] develops a meta-data model for optimizing building envelope design with a balance between energy-savings and thermal comfort. Moreover, researchers have delved into data-driven models for thermal comfort and indoor air quality perception [170]. Additionally, a model-free reinforcement learning algorithm is employed in

another study [171] to optimize HVAC systems based on the thermal sensation state and CO₂ concentrations in indoor space. Lei et al. [172] developed a deep reinforcement learning model that integrates personalized thermal comfort and occupants' presence, followed by a pre-train in a virtual space and an online deployment in real office space. The model guarantee about 10% improvement of thermal acceptability and around 15% of reduction in cooling energy use. Despite the diversity of analyses conducted, all these works, including those with in-house developed BEPS, continue to rely on standard comfort approaches.

A good BEPS tool integrating PCM must be capable to simulate the human comfort depending on various factors, physiological and environmental, including air temperature, humidity, air velocity, clothing insulation, metabolic rate, and radiant temperature. Capturing the interactions between these factors is essential for realistic comfort modelling and reliable results [173]. Simultaneously, as environmental conditions and occupant behaviour evolve, the human body's comfort perception also changes over time. To ensure accurate building energy performance simulations, it is crucial for advanced tools to capture the dynamic nature of thermal comfort. These tools should be capable of considering two essential factors: i) individual variability in human comfort perception, accounting for diverse needs and preferences based on factors such as age, sex, and culture, and ii) localized comfort, which allows for optimizing indoor air control strategies, system component sizing, and operation [174].

Concerning the second class of challenges, it is worth noticing that the need of data such as activity patterns, metabolic rates, etc., are often unknown and, additionally, considered as static assumptions / parameters for dynamic simulation purposes. For validation and calibration aims, extensive data collection and controlled experiments to ensure model's accuracy and reliability are not easily available [175]. Moreover, since the accuracy of PCM can vary based on the model's complexity and the quality of input data, developed models may not fully capture individual variations in comfort preferences and physiological responses due to low accuracy. Validating and calibrating personal comfort models against real-world data and human subject experiments is essential to ensure their accuracy and reliability, whereas gathering high quality data can be challenging and resource-intensive [141].

From this point of view, recent advances in sensing technologies, data analytics, and computational methods are facilitating more accurate and realistic representations of occupants' comfort [176]. Nevertheless, the research in this field continues and the integration of personal comfort models in building simulations is still an on-going research area, that clearly holds great promise for the energy-efficient building design and operation and for creating occupant-centric and comfortable indoor environments [177].

3.2 Objectives and contributions

Several scientific literatures pointed out the dependency of the thermal comfort sensation on the action of thermoregulatory systems, which in turn influence on dynamic changes in physiological information. Considering the limitations presented in classical thermal comfort models, to merge physiological and environmental data for describing analytically thermal preferences and then controlling building systems can lead to energy savings and improvement of thermal comfort satisfaction. More than that, it is necessary to start to contemplate environmental domains not in an isolate approach, but in multi-domain analysis, appealing to the complexity of human sensation of their surroundings. Buildings' operation and management process is facilitated by the integration of different sensing technologies, promoted by the Internet of Things (IoT) connectivity, finding place in the new challenges rose for human liveability in urban environments.

Based on the information presented above, the objective of this study is to develop an Occupant-Centric Control system that focuses on both thermal and air quality comfort domains. This system is based on a dynamic human body simulation model, which utilizes physiological signals from individuals and environmental data to simulate the body's response and understand thermal sensation under various conditions and metabolic rates. The collection of physiological signals is done using non-intrusive sensors, allowing occupants to freely engage in activities. To this aim, the developed simulation model addresses the limitations of traditional thermal comfort models, which rely on steady-state assumptions to define satisfaction guidelines. To ensure the reliability of the model, a validation process was conducted through a multi-domain experimental campaign taking place in the NEXT, a test room facility designed to realise highly controlled environmental conditions, at the University of Perugia. The developed model is implemented into an in-house BEPS tool to be used for the design of HVAC controls and setting strategies for more occupant centric and energy efficient buildings. The tool enables a comprehensive analysis of the interaction between humans and the built environment, facilitating the establishment of optimal setpoint values for the HVAC system in terms of temperature, relative humidity, and ventilation rate.

Overall, the study aims to address the interaction between the *indoor environment, the human body, and the HVAC system*, as well as to bridge the gap between human demands and the built environment by turning occupant comfort criteria into actual environmental conditions. The primary contributions of this study can be outlined as follows:

- Development of a highly flexible Personal Comfort Model (PCM) capable of predicting thermal sensations and CO₂ intakes of occupants, with the ability to adapt to diverse individual characteristics.

- Implementation of the PCM within DETECt, an in-house Building Energy Performance Simulation (BEPS) tool developed by the University of Naples Federico II [88, 178]. This integration enables comprehensive energy analyses, taking into account the impact of occupants' subjective comfort preferences.
- Introduction of a multi-level non-linear programming optimization procedure, aimed at determining optimal thermo-hygrometric setpoint conditions. The objective is to minimize space heating and cooling requirements, while addressing multi-domain comfort concerns related to thermal sensations, skin temperature, and perception of air quality.
- Adoption of a Model Predictive Control (MPC) strategy for HVAC system management, designed to attain the determined setpoints and ensure mechanical ventilation while achieving economic savings. The MPC strategy involves a non-linearly constrained optimization problem, manipulating supply air enthalpy and mass flow variables while adhering to technological limitations and minimum air quality requirements.

Overall, this study aims to enhance our understanding of occupant comfort by developing an advanced control system that considers both thermal and air quality factors. By utilizing a dynamic human body simulation model and real experimental data, this research contributes to the optimization of HVAC control strategies for smart buildings.

3.3 Methodology

A holistic approach for the design and operation of building systems is developed to provide occupants' comfort and energy saving by considering the dynamics of indoor spaces conditions and the human perception and adaptation. To reach this goal, the proposed methodology follows several steps:

- i) development of a HVAC control logic based on a model predictive control (MPC) approach; it aims at regulating key system parameters such as mass flow, temperature, and humidity of the treated supply air. This will allow the achievement of desired reference conditions while ensuring energy savings.
- ii) implementation of a multi-level nonlinear programming (MLNLP) optimization process, within the MPC algorithm, used to determine the thermo-hygrometric setpoints for the occupied space. This optimization process seeks to maximize occupant comfort while minimizing energy consumption.
- iii) Implementation of previous algorithms in an in-house BEPS tool with an appropriate human body thermal model for estimating comfort requirements based on occupants' dynamic physiological response.

Figure 17 provides a detailed overview of the study framework, illustrating the various components and their interconnections. By employing this methodology, the performance of HVAC systems is enhanced by ensuring that occupants experience optimal thermal comfort and air quality and focusing on efficient building operations.

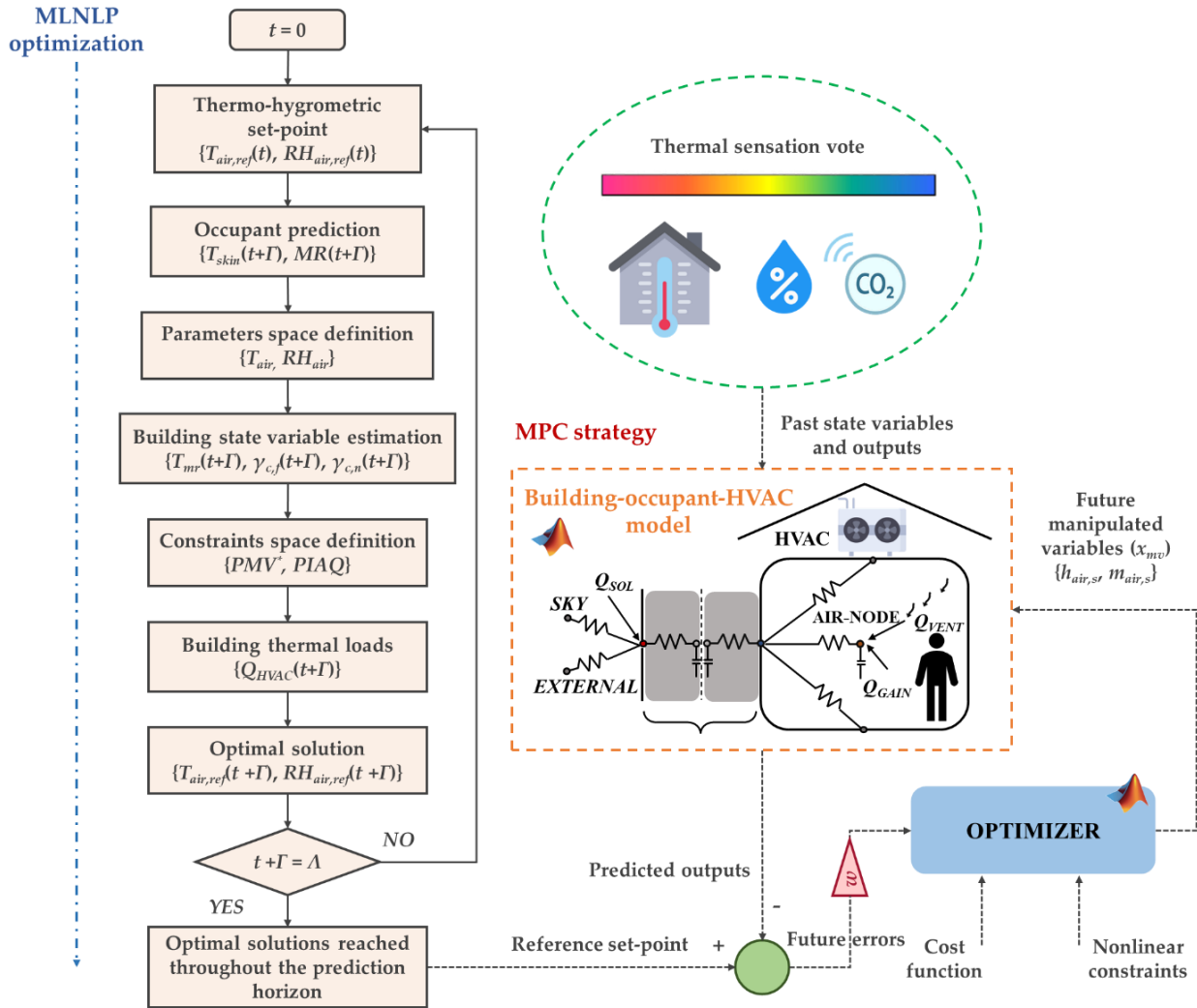


Figure 17. Research framework.

Figure 17 illustrates the workflow of the developed methodology which was developed in Matlab R2022b version. The optimization procedure for evaluating the setpoints is iterated at regular intervals, matching the control horizon of the MPC controller for the HVAC system. This iterative process generates outputs, specifically the optimal setpoint of indoor air temperature and relative humidity, for the entire prediction horizon. These outputs are then utilized to enhance the control of building systems. By incorporating both the thermal model of the human body and the energy model of the building, a comprehensive forecast of the variables that greatly impact the optimization problem under investigation is achieved. This approach enables a more precise and effective management of the building's environment.

The physical model of the building enables the dynamic evaluation of thermodynamic quantities that impact the energy requirements ($\dot{Q}_{HVC}$) of the internal space and occupant well-being. These quantities include the temperatures of the air node and envelope surfaces,

as well as heat transfer resulting from transmission and radiative exchanges, such as solar and long-wave radiation. The physiological model of the occupants (described in the previous chapter 2) facilitates the prediction of their skin temperature (T_{skin}), and CO₂ generation rate which is influenced by thermal interactions with the surrounding environment and controlled by thermoregulatory mechanisms.

After predicting the values of interest for the subsequent time interval, the optimization problem of the MLNLP type is performed to determine the optimal solutions for the decision variables. The resulting MLNLP outputs serve as reference values for the MPC regulation of the system. The primary objective of MPC is to minimize the costs associated with HVAC system operation by adjusting the manipulated variables, specifically the enthalpy and flow rate of the supply air. Therefore, by ensuring that these values comply with the energy balance of the conditioned space, overall costs related to the fan and heat pump are reduced. In this case as well, the energy model of the building is utilized as MPC predictor model to make forecasts of the system's state variables. Finally, this process is repeated at every control horizon, taking into account the updated state variables of the building-occupant-plant system based on the regulations made in the previous time step.

3.3.1 Building energy model

DETECT, an in-house BEPS tool, was created to achieve flexibility in designing and optimizing custom or advanced control algorithms, new building envelope integrated technologies, new or not yet commercialized materials/technology, and novel operating energy saving techniques. [88]. The tool, developed in-house by the Federico II University, it is meant to be used in this study to estimate the thermal demands of the indoor space and building state variables for the proposed HVAC control strategy. The model on which the tool is based relies on the finite difference method, by considering the thermal domain as one dimensional. More specifically, it implements a high order resistive-capacitive (RC) thermal network, obtained by distributed parameters, that enables the calculation of both the internal surfaces' temperatures as well as the mean radiant temperature T_{mr} . Equation **Errore. L'origine riferimento non è stata trovata.** represents the differential equation of the RC thermal network used to assess the thermal load of the structure and the temporal evolution of the air node properties [88]:

$$C_{air} \frac{dT_{air}}{dt} = \sum_{i=1}^N \frac{T_{in,i} - T_{air}}{R_{in,i}^{conv}} + \dot{Q}_{gain,sens} + \dot{m}_{vent} c_p (T_{out} - T_{air}) \pm \dot{Q}_{HVAC,sens} \quad \text{Eq. (1)}$$

Where C_{air} is the internal air node's thermal capacity and the terms to the right of Eq. (1) stand for the thermal power fluxes that the air temperature node T_{air} exchanges with the surroundings. The first term describes the energy transmitted due to convection between the thermal nodes of $T_{in,i}$ (i.e., the interior surface of the i -th wall of the building envelope)

and T_{air} , and function of $R_{in,i}$ convective thermal resistance. It can be noted that the radiative heat exchanges with the corresponding surrounding walls and the solar gains from transparent components were taken into consideration while calculating $T_{in,i}$ [124]. The thermal sources of people, lights, and equipment are also regarded as $\dot{Q}_{gain,sens}$ among the thermal inputs of the inside zone. The mass flow rate $\dot{m}_{vent}$ of outside air and the outside temperature T_{out} affect the sensible ventilation heat load. Finally, $\dot{Q}_{HVAC,sens}$ reflects the thermal power required to balance the flows that weigh on the thermal zone and cause the internal temperature T_{in} to deviate from the setpoint temperature. In addition, the latent thermal power $\dot{Q}_{HVAC,lat}$ is calculated in Equation (2):

$$\begin{cases} \mu_{in} \frac{d\omega_{in}}{dt} = \dot{m}_{w,gain} + \dot{m}_{vent} (\omega_{out} - \omega_{in}) \\ \dot{Q}_{HVAC,lat}(t) = \Delta h_{vs} \cdot [\mu_{in} (\omega_{in}(t) - \omega_{sp}(t))] \end{cases} \quad \text{Eq. (2)}$$

Where μ_{in} is the indoor dry air mass, ω_{out} and ω_{in} are the outdoor and indoor air specific humidity, respectively. The right side of the first equation represents the inlet water vapour mass flow rate due to occupants and ventilation. Consequently, the latent thermal power $\dot{Q}_{HVAC,lat}$ is evaluated as a function of water latent evaporation heat Δh_{vs} and the difference between ω_{in} and ω_{sp} which is the setpoint value of specific humidity.

The tool needs the following inputs to run energy simulations: the climate-relevant location, the shape and orientation of the building, the thermophysical characteristics of the materials, the internal heat gain schedules, the building air change profile, and the setpoint temperature and humidity. More details, also concerning the tool experimental validation, are reported in [179].

3.3.2 MLNLP optimisation for indoor setpoint evaluation

For the determination of thermo-hygrometric setpoints in the occupied space, a multi-level nonlinear programming (MLNLP) optimization procedure was employed. Figure 18 shows a schematization of the optimization problem investigated, identifying the constrained spaces and the search space for the optimal solution.

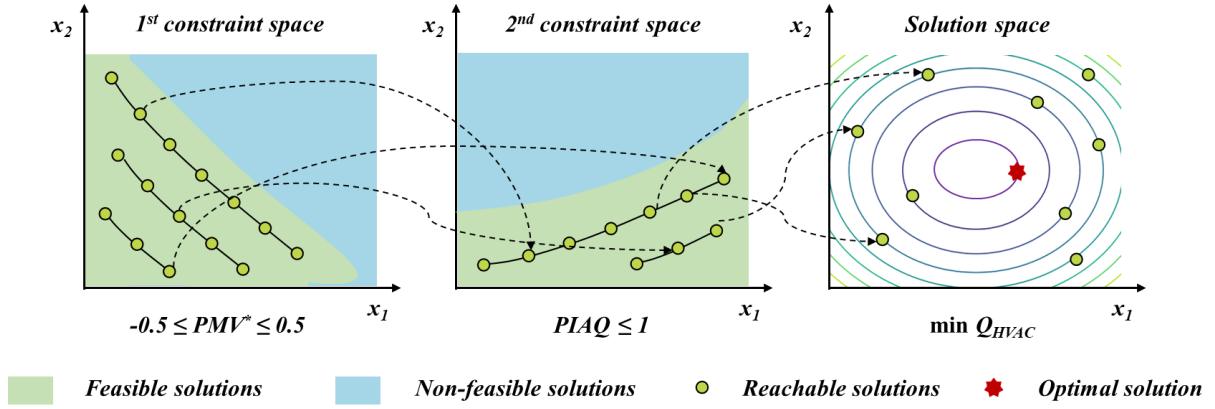


Figure 18. Optimisation procedure of MLNLP problem.

The decision variables x , which are subject to optimization, include the temperature $T_{air,ref}$ and relative humidity $RH_{air,ref}$ of the air within the indoor space. The optimization problem is defined as follows:

$$\begin{aligned} \min_x \dot{Q}_{HVAC} &= f(x) \\ \begin{cases} x(1) = T_{air,ref} \\ x(2) = RH_{air,ref} \\ -0.5 \leq PMV^* \leq 0.5 \\ PIAQ \leq 1 \end{cases} \end{aligned} \quad \text{Eq. (3)}$$

The main objective is to minimize the thermal energy demand for space heating and cooling, denoted as $\dot{Q}_{HVAC}$. To assess individual thermal sensation accurately, the comfort index PMV^* (modified version of the Fanger comfort index [180]) takes into account the skin temperature T_{skin} as a significant parameter. This allows for the evaluation of the first constraint space for the decision variables, ensuring they fall within acceptable ranges. PMV^* can be expressed as described in Equation (4):

$$PMV^* = \left(\frac{0.0303}{e^{0.036M}} + 0.028 \right) \times \begin{Bmatrix} (M_w) - 3.05 \times 10^{-3} [5733 - 6.99(M_w) - x(2)p_{v,sat}] \\ -0.42[(M_w) - 58.15] - 1.7 \times 10^{-5} M(5867 - x(2)p_{v,sat}) \\ -0.0014M(34 - x(1)) - 3.96 \times 10^{-8} f_{cl}[(T_{cl} + 273)^4 - (T_{mr} + 273)^4] \\ -f_{cl}(\gamma_{c,f} + \gamma_{c,n})(T_{cl} + x(1)) \end{Bmatrix} \quad \text{Eq. (4)}$$

Here, M and M_w represent the energy quantity associated with the metabolic rate and mechanical work performed by the occupant. The clothing temperature T_{cl} is dependent on T_{skin} , while the heat exchange surface increase factor f_{cl} estimates the influence of clothing on the occupant's heat exchange with the surrounding environment. The saturation pressure

of vapour $p_{v,sat}$, heat transfer coefficients $\gamma_{c,f}$ and $\gamma_{c,n}$, and the mean radiant temperature T_{mr} are used to evaluate the rates of latent, convective, and radiative heat transfer, which impact the occupant's thermal perception.

Subsequently, the *PIAQ* [181] is employed to define the second constraint space, linked to a new comfort domain. It quantifies the levels of air quality perception experienced by occupants in indoor environments. This perception is influenced by various environmental factors. Fanger [182, 183] demonstrated a strong correlation between *PIAQ* and indoor air temperature and humidity. His experiments involved exposing occupants to a spectrum of indoor environments, ranging from clean to polluted (e.g., environments with factors such as wall paint, carpet, floor detergents, etc.). These experiments help to observe how air enthalpy can significantly impact the perception of air quality, even in settings with strong odours.

This domain requires values of *PIAQ* lower than 1 decipol to ensure high acceptability (*ACC*) of air quality and a percentage of dissatisfied (*PD*) which is lower than 15%. The *ACC* and *PD* can be evaluated as reported in Equation (5):

$$\begin{cases} ACC = -0.0143h_{air,ref} + 0.895 \\ PD = \frac{\exp(-0.18 - 5.28 \cdot ACC)}{1 + \exp(-0.18 - 5.28 \cdot ACC)} \cdot 100 \end{cases} \quad \text{Eq. (5)}$$

Here, $h_{air,ref}$ represents the enthalpy of the air setpoint, which is a function of the decision variables in the optimization problem.

3.3.3 MPC for HVAC operation

The optimization of HVAC system operation is crucial to achieve the desired thermo-hygrometric conditions while minimizing operating costs. In this regard, a MPC strategy has been developed to optimize the manipulated variables x_{mv} , specifically the supply air enthalpy ($h_{air,s}$) and flow rate ($\dot{m}_{air,s}$). This allows for finding the optimal trade-off between fan energy consumption due to pressure drop balancing and the heat pump's cooling and heating requests.

The use of MPC in HVAC systems offers several advantages over traditional control strategies. MPC considers the system dynamics and predicts future behaviour, enabling better response to changing environmental conditions and load variations, resulting in improved energy efficiency and occupant comfort [184].

The prediction of the building-occupant-plant system's state variables is obtained by means of the DETECT tool, by adopting the mathematical models described in the previous subsections. This includes the assessment of surface and air node temperatures, as well as

the $\dot{Q}_{HVAC}$ thermal load, while accounting for variations in external climatic conditions and internal energy inputs. Incorporating these models enhances the accuracy of predictions and enables proactive adjustment of setpoints and control actions.

The selection of the control horizon Γ and prediction horizon Λ in MPC is crucial for achieving desired system performance. The control horizon determines the length of sample time t_s over which control actions are computed, while the prediction horizon defines the duration for which future system behaviour is predicted. These horizons are carefully chosen based on system dynamics, time delays, and computational complexity considerations.

The analysed HVAC system is an air handling unit equipped with cooling and heating coils respectively for dehumidification and relative humidity control of indoor space during the cooling season. In the heating season, heating coils and a liquid humidifier are used. The coefficient of performance (COP) for the heat pump is calculated using the UNI-TS 11300 method, considering partial load operation.

$$COP_{PLR} = COP_{nom} \times \left[1 - C_d \cdot \left(1 - \frac{\dot{Q}_{HVAC}}{\dot{Q}_{nom,HP}} \right) \right] \quad \text{Eq. (6)}$$

Considering the C_d coefficient equal to 0.25 as referred to air/air heat pumps.

To evaluate fan energy consumption, pressure drops are calculated based on flow properties (air velocity v_{air} and density ρ_{air}).

$$\Delta p_{HVAC} = \frac{f_{duct} \rho_{air} L_{duct} v_{air}^2}{2 D_{h,duct}} + \frac{K_{coil} \rho_{air} v_{air}^2}{2} + \frac{K_{filter} \rho_{air} v_{air}^2}{2} \quad \text{Eq. (7)}$$

Where the first term on the right of the equation represents the pressure drop distributed through the ducts and depends on its geometric (hydraulic diameter $D_{h,duct}$ and length L_{duct}) and construction characteristics which influence the friction factor f_{duct} . The remaining two terms express the concentrated pressure drops due to the main components of the system, coils, and filters. K_{coil} and K_{filter} express the resistance coefficients that depend on the construction characteristics of the components.

3.3.4 MPC optimisation problem

For the MPC a constrained nonlinear optimization technique is used. The implemented algorithm is designed to iteratively search for the optimal control inputs while satisfying specified constraints. Specifically, an interior-point algorithm is implemented to find the solution within a feasible region defined by the constraints and to iteratively adjust the control inputs to minimize a cost function by taking into account both control objectives and system constraints. Thus, the algorithm is able to systematically optimize control inputs in real-time,

while considering both current system states and future predictions, allowing us to make decisions that balance performance and constraints. Specifically, the cost function (J_{HVAC}) to be minimized is evaluated as follows.

$$\min_{x_{mv}} J_{HVAC} = \left(\int_t^{t+\Lambda} \frac{x_{mv}(1)(x_{mv}(2) - h_{air,ext})}{COP_{PLR}} + \int_t^{t+\Lambda} \frac{x_{mv}(1) / \rho_{air,s} \cdot \Delta p_{HVAC}}{\eta_{FAN}} \right) \cdot c_{el} \quad \text{Eq. (8)}$$

$$\{x_{mv}(1) = \dot{m}_{air,s} \mid x_{mv}(2) = h_{air,s}\}$$

The cost function equation represents the cumulative sum of costs over the prediction horizon Λ . It is influenced by the efficiencies of the heat pumps and fans (η_{FAN} and COP_{PLR}) as well as the unitary electrical costs (c_{el}).

The manipulated variables, $h_{air,s}$ and $\dot{m}_{air,s}$, are determined subject to the following conditions:

$$\begin{cases} x_{mv}(1)x_{mv}(2) = x_{mv}(1)h_{air,in} + \dot{Q}_{HVAC} \\ x_{mv}(1) \in \{\dot{m}_{air,min} = f(\dot{V}_{CO_2}); \dot{m}_{air,max} = f(\dot{V}_{fan,max})\} \\ x_{mv}(2) \in \{h_{air,nom,cc}; \min(h_{air,ext}; h_{air,in})\} \rightarrow \text{cooling} \\ x_{mv}(2) \in \{\max(h_{air,ext}; h_{air,in}); h_{air,nom,hc}\} \rightarrow \text{heating} \end{cases} \quad \text{Eq. (9)}$$

The first nonlinear equation ensures the heat balance in the building's control volume. $\dot{Q}_{HVAC}$ is assumed negative for cooling requests and positive for heating requests. The second condition defines lower and upper limits for the air mass flow processed by the air handling unit. The minimum value depends on the occupant's $\dot{V}_{CO_2}$ generation rate, estimated using the human body model. The upper limit is determined by the 'fan's maximum range constraints.

The third and fourth conditions set the lower and upper limits for $h_{air,s}$ during cooling and heating requests. For cooling, $h_{air,s}$ falls between the minimum enthalpy from the cooling coil ($h_{air,nom,cc}$) and the minimum value between $h_{air,in}$ and $h_{air,ext}$. Conversely, for heating, $h_{air,s}$ falls between the maximum value of the two previous quantities and the maximum achievable $h_{air,nom,hc}$ from the heating coil.

The x_{mv} variables are normalized to facilitate the search for the optimal solution since they have different orders of magnitude. Once the constrained optimization problem is solved, the x_{mv} values that minimize the cost function for all prediction horizon moves are obtained. Only the moves within the control horizon will be implemented.

By utilizing this control strategy, the HVAC system can optimize its operation and minimize costs while achieving the desired thermo-hygrometric conditions.

3.4 Experimental setup

An experimental procedure was carried out to validate the proposed human-physiological simulation model. Tests were conducted in a test room facility to gather data of subjects in different activity levels and with different personal intrinsic characteristics, such as gender and Body Mass Index (BMI). The information collected was used as input for the model reliability verification. The subsequent sections provided comprehensive descriptions regarding the methodology, the test room, and the participants involved.

3.4.1 NEXT.ROOM: targeting human-centric and multi-domain investigation

The NEXT.ROOM is a highly controlled environment located inside the Environmental Applied Physics Lab, at the Engineering campus of the University of Perugia, in central Italy [185]. The test room was constructed specifically to perform multi-disciplinary and multi-domain studies within the human well-being scope. To this end, the installed systems allow to reproduce different environmental conditions and stimuli, accordingly to the research purposes.

The facility (Figure 19) was built entirely with dry technologies, easily enabling adaptation if required. Regarding the technical systems, a radiant system serving all the NEXT.ROOM surfaces and a mechanical ventilation and air-conditioning (HVAC) system manage the thermal domain; the lighting system is composed of four LED panels and two RGB reflectors, providing different conditions of illuminance spatial distribution and correlated colour temperature (CCT). A detailed characterization of the design and decision process, materials dimensions technical specifications of the NEXT.ROOM was provided by Vittori et al. [185].

On the other hand, a monitoring system is dedicated to gather all environmental information in the different testing scenarios. The fixed sensors enable the continuous measurement of (i) air temperature in four different (and adjustable) heights; (ii) relative humidity; (iii) superficial temperature in different surface points; (iv) air velocity; (v) CO₂ concentration; (vi) globe temperature; (vii) net radiation on the three main directions; (viii) heat flux through the envelope surfaces; (ix) illuminance level. Wearable sensors are also available to monitor physiological signals such as skin temperature, Electrodermal Activity (EDA), electrocardiogram (ECG) and electroencephalography (EEG).

For this study, collect data of mean radiant temperature and indoor CO₂ concentration are used for model verification [186]. In other words, the monitoring data was implemented as input in the simulation model with the aim at reducing the source of discrepancy and focusing on the proposed human-body thermal model.

3.4.2 A study approach for assessing human physiological information

To reproduce different metabolism conditions, an experimental procedure was handled with two young subjects, one male and one female. Ten-points were selected to place skin temperature sensors, following the indications of Liu et al. [109], focused on human thermal comfort studies. The iButton Hygrochron was adopted to proceed with the measurements, using a time step of one minute. The heart-rate frequency was measured through the Empatica E4 wrist band, i.e. an equipment validated by many authors investigating physiological signals to human comfort preferences modelling [187], collecting data each second.

Concerning the environmental sensors, the CO₂ monitoring was executed by three sensors, positioned (1) near the top discharge outlet; (2) the bottom discharge outlet; (3) in the centre of the room at the desk height. Air temperature sensors were located in the centre of the room, in different heights: 10cm, 50cm, 110cm, and 170cm. Additionally, superficial temperature sensors were located in all walls, ceiling and floor. All environmental sensors gathered data using a one-minute timestep. Figure 19 describe the position of the sensors inside the NEXT.ROOM.

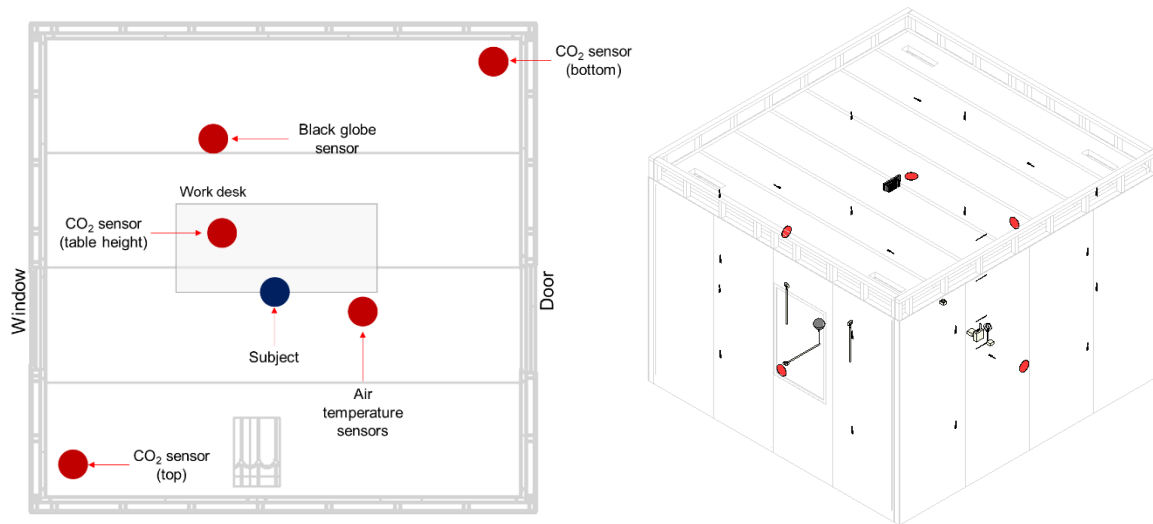


Figure 19. Sensors' representation inside the NEXT.ROOM facility: (a) plan view with sensors and subject disposition in the test room, (b) 3D view.

Two different experiment paths were adopted, focusing on the exposure of recruited subjects to different activity conditions in two operative phases of the HVAC system. The first one (Figure 20) carried out a test with a male subject for 150 minutes, from 9:00 AM to 11:30 AM, with a subject performing sedentary activities in a seated position, such as studying. The air velocity was set at the 4th level (maximum) during the first hour of test, and then maintained constant at the 2nd level until the end. Table 5 describes technical

specifications of the HVAC system. The temperature setpoint was 21°C at the first test hour, 24°C in the following hours, until the end of the experiment. The conditions changes allow the model to understand the body response because of environmental fluctuations in sedentary conditions.

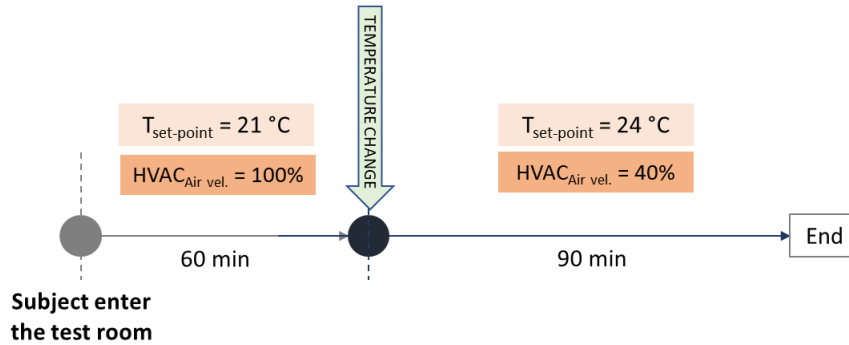


Figure 20. First experimental path.

The second procedure (Figure 21) involved a female subject, in different activity levels, for 150 minutes, starting at the 10:00 AM. Three operative phases were comprised in the experiment: acclimatization phase, consisting of 30 minutes of acclimatization stage, with the subject seated in neutral conditions, the first air flow condition, that maintain all the setpoint, visual and acoustics characteristics but specifying the 2nd level of HVAC system air velocity and the second air flow condition, also keeping the acclimatization characteristics, but changing HVAC system air velocity for the 4th level. Setpoint value was maintained constant at 24°C during the whole test, searching to follow ASHRAE 55-2020 general comfort recommendations [97]. Two activity levels were established: the first condition (light) consists in walking in a treadmill at 1.2km/h velocity; the second condition (moderate), uses a 4km/h velocity in the treadmill. The systems characteristics were described in Table 5, applicable for both experiment paths.

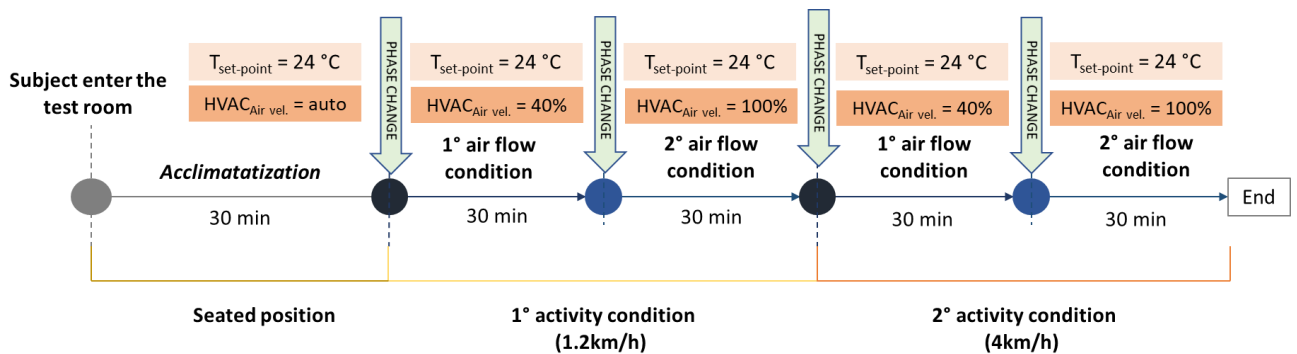


Figure 21. Second experimental path.

Table 5. NEXT.ROOM lighting and HVAC systems characteristics.

Visual characteristics	Illuminance on the desk plan (lx)	Illuminance at the sight level (lx)	Light Correlated Colour Temperature (CCT) [K]	
	~ 500	~ 300	~4000	
HVAC technical features	Air velocity level	Equipment's flow rate (m ³ /h)	Flow rate in the air outlets (m ³ /h)	Air exchange (vol/h)
	2 (40%)	128	87	0.7
	4 (100%)	320	230	1.8

The two subjects, despite their similar age, present very different body compositions. A summary of their personal characteristics considered in the model, i.e., weight, height, clothing level etc, is given in Table 6.

Table 6. Body data and clothes – subject 1 and 2.

Parameter	Subject 1	Subject 2
Weight (kg)	78.4	55
Clothing level (clo)	0.41	0.61
Height (m)	1.80	1.57
Age (years)	23	26
Gender	Male	Female
Drank water (kg)	0.125	No
Test date	22/09/2021	17/10/2022

3.5 Proof of concept

The proposed study seeks to analyse the potentials of the proposed PCM implemented in a BEPS tool with the aim at addressing the interaction among *indoor environment - human body – HVAC system*. To this aim, the *proof of concept* for the developed methodology involves simulating the previously described experimental tests by exploiting the thermal model of the human body and the new facility management system. The simulation aimed to verify the accuracy of the physiological model by recreating the operating conditions of the HVAC system shown in Figure 20 and Figure 21, specifically to evaluate the predictive performance of the model in tracking the occupant's skin temperature. The simulation also demonstrated the flexibility of the model, as it successfully adapted to different subjects and various metabolic activity conditions in the two tests.

After validation of the physiological model, the tests were further simulated using the proposed system management methodology to evaluate its impact on occupant comfort and

energy consumption, and a comparison with the reference scenario was provided. The reference scenario is rooted in real-world, measured data from experimental tests, while the proposed scenario is evaluated with a simulation. However, the simulation aspect involves predicting how occupants' physiological properties would behave under different environmental conditions based on the same characteristics of the subjects from the reference scenario (e.g., body weight, skin surface, metabolic rate, etc.).

As previously mentioned, the proposed scenario involved determining the thermo-hygrometric setpoints (Table 7) through an MLNLP optimization procedure, aimed at minimizing thermal energy demands for space heating and cooling while maximizing thermal comfort and air quality perception. The HVAC system was then managed through an MPC control strategy, optimizing its operation by manipulating the mass flow rate and thermodynamic properties of the air supplied to the room. The MPC controller's choice of mass flow rate ensured the minimum ventilation rate necessary for efficient CO₂ removal in the room, estimated based on the occupant's CO₂ generation rate. Meanwhile, the enthalpy of the air delivery flow was adjusted to comply with the technological limits of the HVAC system. For the MPC controller's characteristics, a control horizon of 15 minutes was chosen, considering the transient behaviour of the HVAC system, and a prediction horizon of 60 minutes (equal to 4 control horizons) was used (Table 7).

To evaluate the J_{HVAC} cost function, a unit cost of electricity (c_{el}) value of 0.22 cents [188] per electric kilowatt-hour was considered. This allowed the MPC controller to optimize the HVAC system's performance efficiently, balancing energy consumption and occupant comfort. The simulations demonstrated the potential effectiveness of the proposed methodology in achieving energy savings and enhancing indoor thermal comfort while considering occupants' specific needs and dynamic environmental conditions.

Table 7. Characteristics of investigated scenarios.

Parameter	Reference scenario		Proposed scenario	
	Test 1	Test 2	Test 1	Test 2
T_{indoor}	23°C	25°C	$f(\text{occupant}, PMV^*, PD, Q_{HVAC})$	$f(\text{occupant}, PMV^*, PD, Q_{HVAC})$
HR_{indoor}	40%	50%	$f(\text{occupant}, PMV^*, PD, Q_{HVAC})$	$f(\text{occupant}, PMV^*, PD, Q_{HVAC})$
Air velocity	fixed	fixed	$f(\text{occupant}, \dot{V}_{CO_2})$	$f(\text{occupant}, \dot{V}_{CO_2})$

After the simulations, the observed and simulated PMV^* and PD percentages were compared, as well as the energy use for each scenario.

3.6 Results

3.6.1 Accuracy of the physiological thermal model

The tests were carried out in 2022 on September 15th of 2021 for subject 1 and on October 17th of 2022 for subject 2, both with the same 150 minutes of duration. Table 6 provides data relative to the investigated subjects (weight, height, clothes); their consent for personal data was previously obtained. Figure 22 shows the trends of the air temperature measured near the workstation of the investigated subjects, and the average radiant temperature T_{mr} measured by the globe-thermometer. Additionally, the trends of air velocities measured near the workstation are shown. Figure 22 refers to a constant value of indoor air relative humidity within the room (equals to 50%).

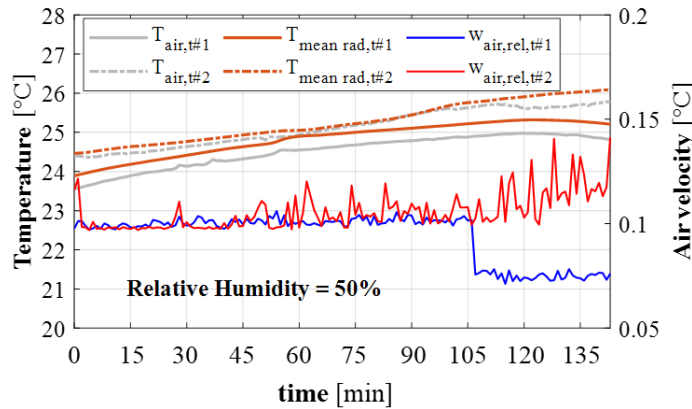


Figure 22. Room air temperature and velocity near the workstations of the two subjects.

To assess the accuracy of the model, the simulated skin temperature ($T_{skin,evaluated}$) is compared with the measured skin temperature ($T_{skin,measured}$) for both subjects (subject 1 and subject 2) during the test period. The comparison is reported in Figure 23 (left for subject 1 and subject 2 Figure 23 right). In the Figure 23, the two green lines relative to Upper and Lower limits refer to a comparison band set between $T_{skin,measured} + 0.7$ °C and $T_{skin,measured} - 0.7$ °C. This error band is related to a temperature deviation which involves error bands of $\pm 3\%$. Please note that the heart rate is equivalent to the average heart rate, which is measured over the same interval of skin temperature sampling. The results of both tests show a strong agreement between the simulation and experimental data, indicating that the developed model is reliable and suitable for conducting thermal comfort and building energy performance analyses based on the dynamic thermal sensation of occupants. It is worth mentioning that, in the case of subject 2 engaging in light and moderate activities, the model demonstrates improved performance when activity levels change. However, there is a slight delay in the simulation model's ability to capture the impact of activity levels at the beginning of the simulation. This delay occurs because the initial background data conditions, such as

the environment and subjects, are essential for the training process. Despite this initial delay, the model maintains its accuracy throughout the main duration of the occupation. When considering longer occupation times, the initial conditions may have a negligible influence on the occupant's thermal sensation. Therefore, they can be safely disregarded without significantly affecting the overall validity of the model's predictions. It is important to note that the first phase of the experiment is typically an acclimatization phase. The findings therefore demonstrate the reliability and suitability of the developed model for analysing thermal comfort and building energy performance based on occupant's dynamic thermal sensation. The model's performance is particularly notable when activity levels change, and any initial delay in capturing the impact of activity levels is outweighed by the model's accuracy during the main duration of the occupation.

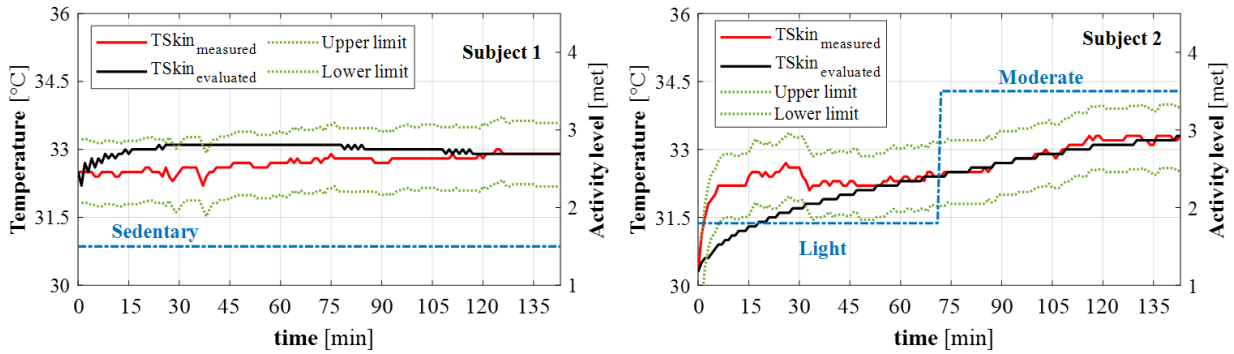


Figure 23. T_{skin} comparison between measured and simulated for (left) subject 1 and (right) subject 2.

Figure 24 shows for each test (Figure 24left for the 1st test, Figure 24right for the 2nd test), the simulated temperatures of the organic tissues of the two subjects. Different temperatures are observed due to the dynamism of thermoregulatory system and diverse activity levels.

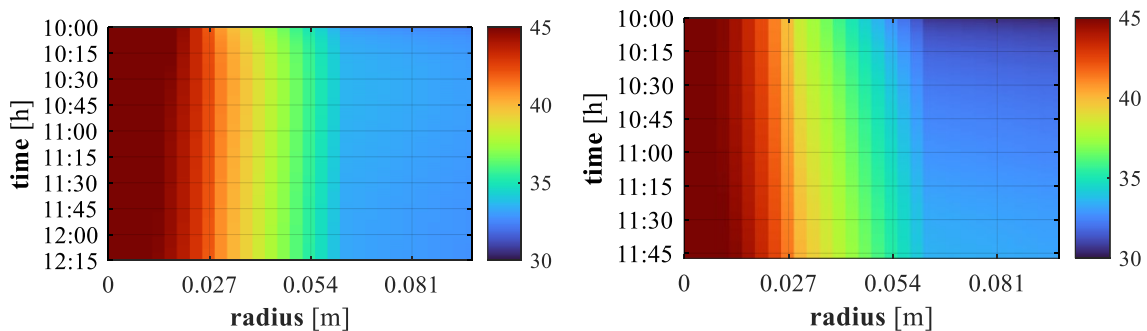


Figure 24. Temperature of the human body tissues vs. radius and time for (left) subject 1 and (right) subject 2.

Figure 25 compares the investigated subjects' body surface temperature, T_{skin} , simulated (y-axis) and measured (x-axis), by considering their deviations for the considered sampling interval. Almost all simulation results are included into the error band range of $\pm 3\%$ (red dashed lines) for both tests, whereas in test 2 a larger error is observed during the initial occupation time intervals. The 97% and 84% of simulation results ($T_{skin,evaluated}$), respectively for test 1 and test 2, are included in the confidence interval $\pm 2\%$ (green dashed lines) and the 66% (test 1) and 79% (test 2) in the narrower interval given by $\pm 1\%$ (orange dashed lines).

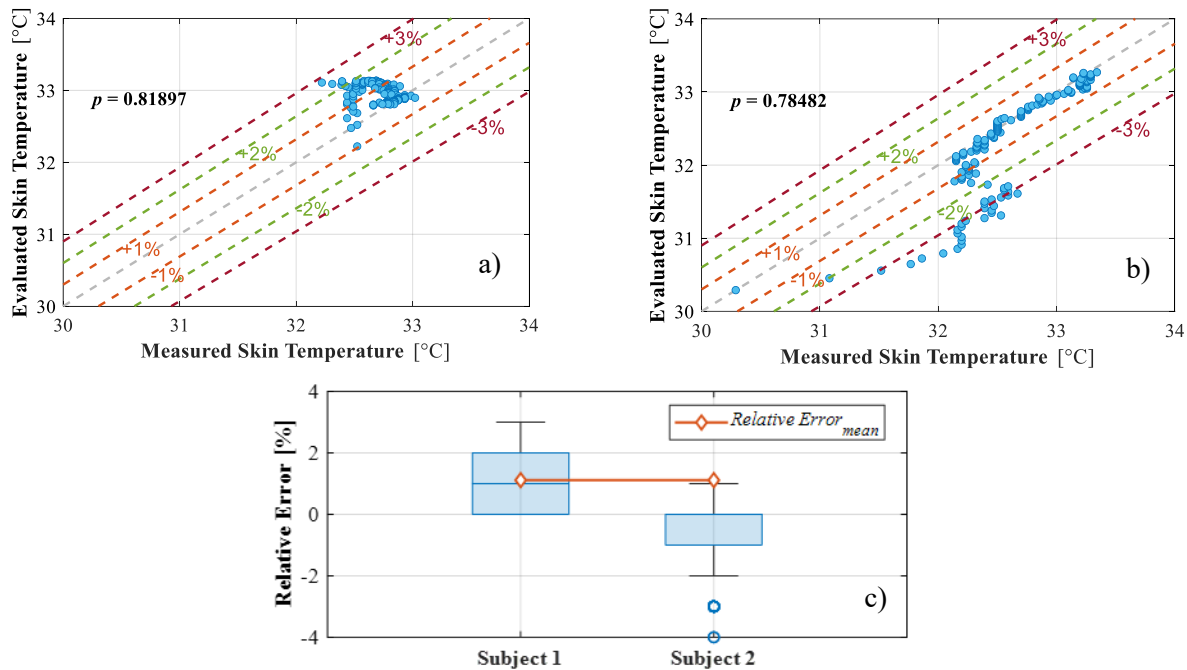


Figure 25. T_{skin} temperature –simulated versus measured for test subject 1 (a) and test subject 2 (b); boxplot for assessment of distribution of percentage relative error (c).

To assess the model's response more comprehensively, two statistical indices, namely the Pearson index (p) and the relative percentage error, were utilized. The Pearson index, which ranges from -1 to 1, provides a measure of the match between the simulated and experimental values. A value close to 1 indicates a strong agreement between the two datasets (see Figure 25a and Figure 25b). In Figure 25c, a boxplot representation illustrates the distribution of relative percentage errors resulting from the comparison. The orange diamonds represent the average error, which is found to be approximately 1% for both tests. For the first test, the boxplot shows that the median value aligns closely with the average value, and the Interquartile Range (IQR) is confined within 2%. In contrast, for the second test, the relative percentage errors predominantly gather around negative values, indicating an underestimation of the simulated values. The median value for this case is 0%,

suggesting a reasonably accurate representation on average. The outliers in the boxplot refer to the few data points where the deviation exceeds the 3% error band, indicating slight discrepancies in those instances.

The IAQ within the test room is plotted in Figure 26, focusing on test 2, characterized by diverse activity levels of the human body. Figure 26(left) shows *i)* the ppm of CO₂ of outside the test cell (CO_{2,ext}, measured near the inlet vents), and *ii)* the ppm of CO₂ inside the room, including the occupant generation (CO_{2,room}, measured near the discharge outlets). The right axis shows the survey conducted by the occupant that could rank the indoor air quality on a scale of 1 to 7. The coloured areas refer to the ASHRAE IAQ ranges as a function of the ppm of CO₂ in the environment. Finally, Figure 26(right) shows the measured and simulated CO₂ production of the human body for test 2, considering the different occupant activity levels.

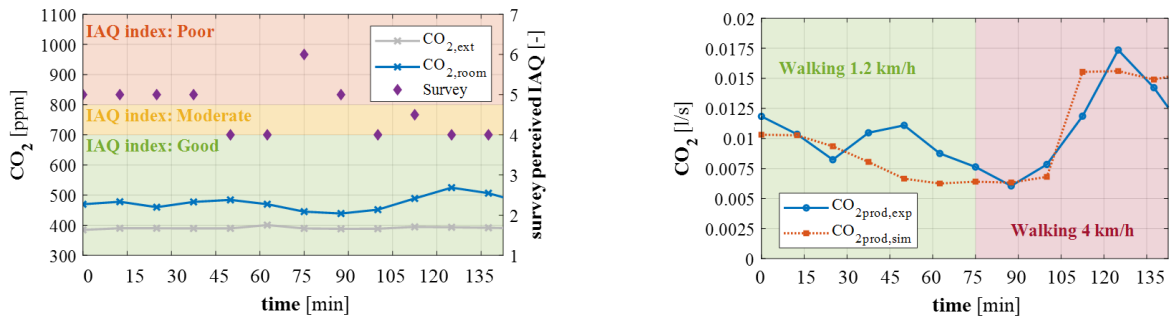


Figure 26. (left) CO₂ and IAQ for test 2 and (right) CO₂ emissions during test 2.

3.6.2 Proposed HVAC control strategies

This section presents the results of the related *proof-of-concept study*, which aims to demonstrate the advantages of an optimized HVAC control strategy in terms of both occupant comfort and energy efficiency. In this section, the effects and potential benefits of the optimized OCC control strategies implementation are checked. Utilizing the developed simulation tool, the behaviour of the HVAC system was assessed under the optimized control strategy, considering various factors such as external climate conditions, thermal properties of the building, and occupancy patterns.

The results related to the MLNLP optimization problem were reported in Figure 27. The optimization procedure was iterated for each time step, equal to the control horizon, to provide the best setpoint values for the whole prediction horizon. This process relied on the forecasting capabilities of the developed model, which enabled precise assessment of the occupant's physiological features and the building's thermodynamic properties, ensuring accurate evaluation of the output variables for successive time steps.

Figure 27 illustrates the combined criteria evaluated to determine the thermo-hygrometric setpoints ($T_{air,ref}$ and $RH_{air,ref}$) for the first test, with reference to the procedure performed after four steps of the control horizon, equivalent to 60 minutes of occupation. The Figure 27top shows all possible combinations of T_{air} and RH_{air} that guarantee a PMV^* within the acceptable range based on the predicted T_{skin} of the occupant at the analysed time instant. Additionally, Figure 27middle further investigates all those combinations which, in addition to the first constraint condition, also comply with the ones dictated by the ACC index of perceived indoor air quality. Furthermore, Figure 27bottom represents the solution space by analysing the values, shown in red, of the $\dot{Q}_{HVAC}$ objective function assumed by the achievable combinations. The optimal combination that minimizes HVAC energy demands is highlighted in green.

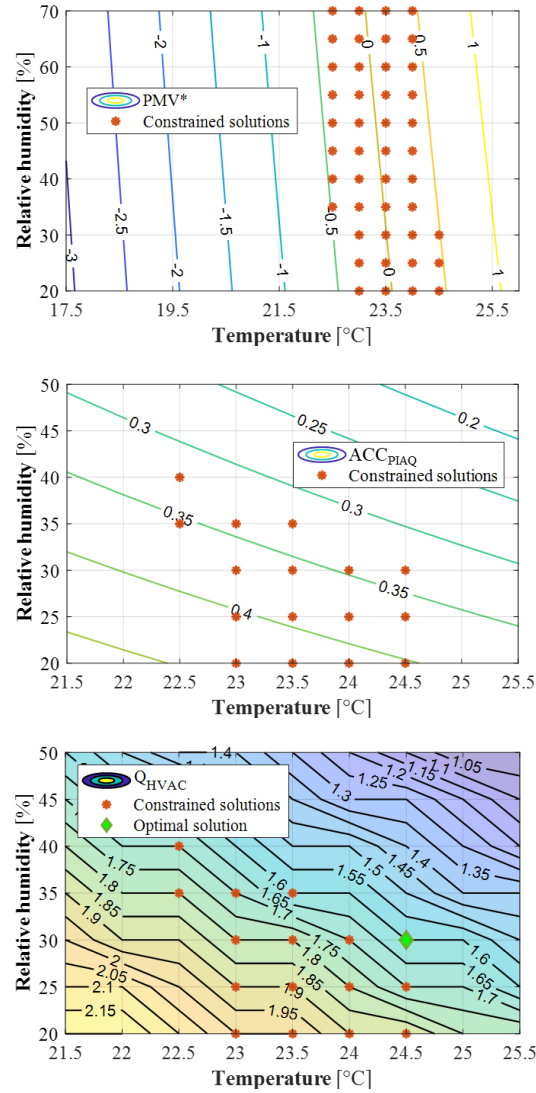


Figure 27. Optimisation procedure to determine optimal indoor setpoints for test 1: (top) PMV^* constraint space; (middle) $PIAQ$ constraint space; (bottom) solution space of $\dot{Q}_{HVAC}$.

Once the reference setpoints were selected, an MPC-type control strategy was adopted to reduce operating costs associated with the HVAC system. Figure 28 demonstrates the MPC controller operation using the proposed scenario of test 1 as reference. The results refer to a current time instant of two steps forward of the control horizon, which corresponds to 30 minutes from the start of occupation. In Figure 28top, the trend of the manipulated variables $h_{air,s}$ and $\dot{m}_{air,s}$ is reported.

The grey area depicts the values assumed in the actions passed to the current instant, while the next four steps (corresponding to the duration of the prediction horizon) show the actions envisaged to minimize the J_{HVAC} cost function. Furthermore, the result reports the action that will be implemented by the controller in the next control horizon. The manipulated variables combinations presented are essential for validating the energy balance equation applied to the control volume of the air-conditioned environment. These results are consistent with the technological limitation of the specific plant, as well as the constraints imposed by external and internal thermodynamic conditions, and the minimum ventilation rate requirements. By examining the manipulated variables, we can ensure that the energy balance equation is accurately verified within the control volume. These combinations were carefully selected to comply with the technological limitations of the plant, as well as the various thermodynamic conditions both inside and outside the system. Additionally, they meet the minimum ventilation rate requirements necessary for optimal performance. It is crucial to consider the interplay between these manipulated variables and their impact on the energy balance equation. By doing so, we can guarantee that the air-conditioned environment operates within the prescribed limits, ensuring efficient and effective functioning of the system. These results not only demonstrate compliance with the technological limits of the plant but also reflect a comprehensive understanding of the external and internal thermodynamic conditions. By carefully considering these factors, we may optimize the performance of the air-conditioning system while maintaining the required minimum ventilation rates. Moreover, Figure 28bottom displays the value of the reference enthalpy guaranteed in previous steps and those evaluated by the MLNLP optimization procedure for subsequent steps of the prediction horizon. Additionally, the value of the J_{HVAC} objective function in the prediction horizon resulting from optimized actions of the manipulated variables is shown.

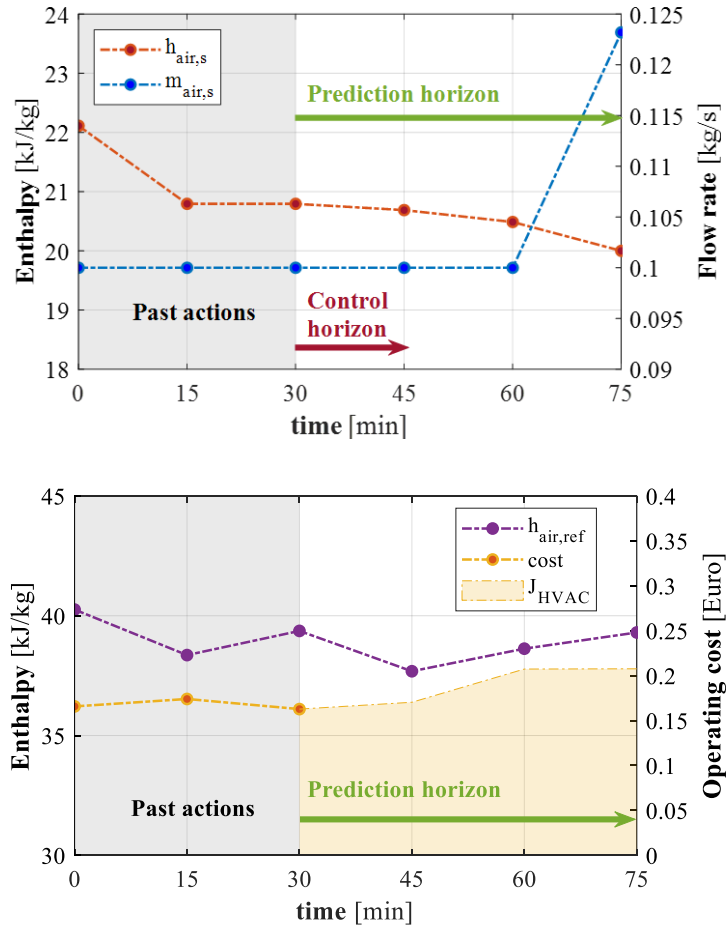


Figure 28. MPC strategy for test 1: (top) manipulated variables prediction; (bottom) prediction of reference variable $h_{air,ref}$ of the system and cost function optimisation.

Subsequently, an energy and comfort analysis are presented for the proposed scenarios of the two simulated tests. Figure 29 and Figure 30 show the energy results obtained from the simulation for both tests, focusing on energy savings while ensuring occupants' comfort requests. Figure 29top and Figure 30bottom illustrate the $\dot{Q}_{HVAC}$ thermal power requests for cooling in test 1 and heating in test 2, respectively. The green dashed line shows the dynamic trend of indoor setpoints. The reference humidity ($RH_{air,ref}$) varied between 20% and 40% due to constraints imposed by the ACC index of perceived indoor air quality, suggesting low humidity levels for improved air quality perception.

Figure 29bottom and Figure 30bottom show instead the results relating to the electrical power required by the plant and associated with the heat pump for the heating and cooling coils operation and with the fan to move the air flows and balance the drops in pressure. These electrical requests are conditioned by the convective flux supplied in the room and

shown in black dashed lines, this quantity in turn is conditioned by the $h_{air,s}$ and $\dot{m}_{air,s}$ determined by the optimization performed by the MPC controller.

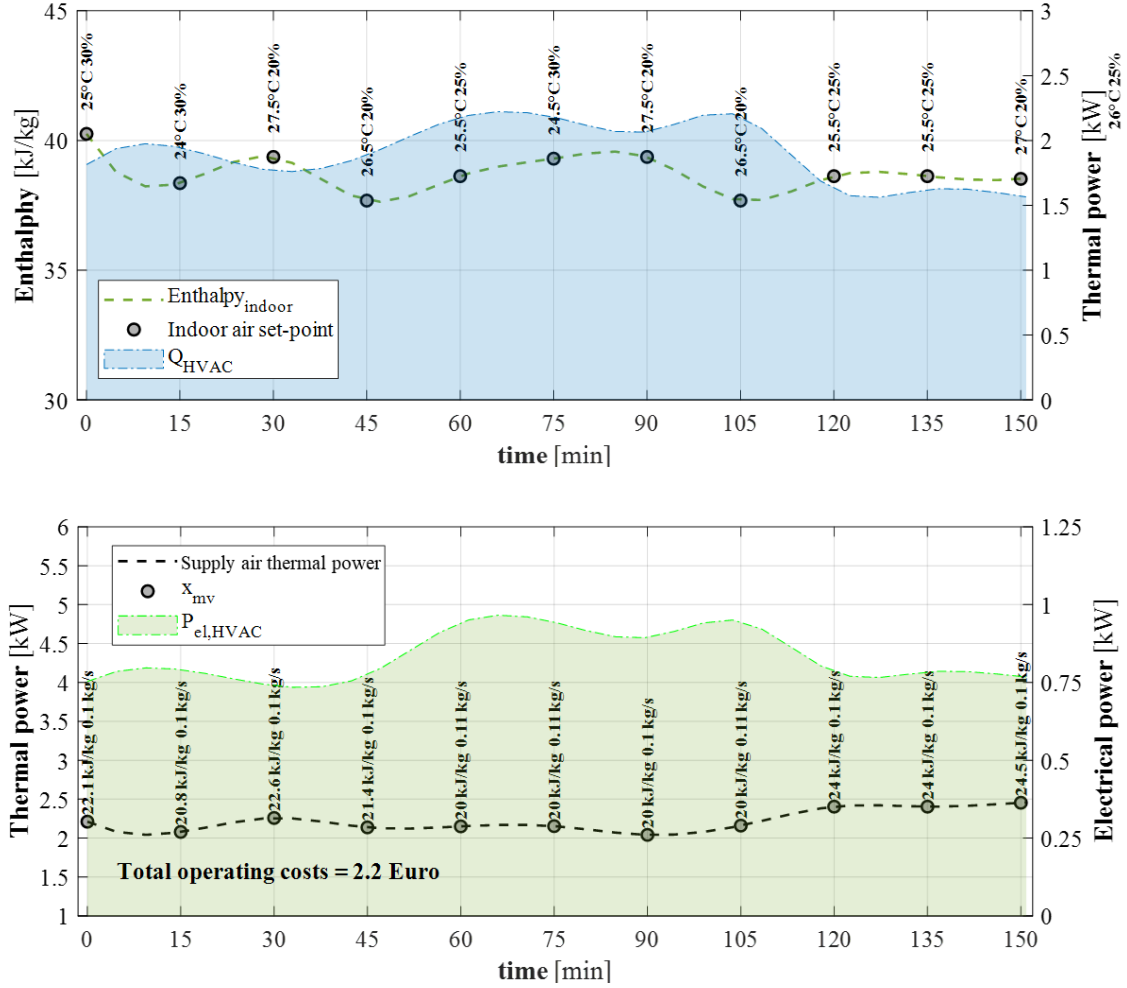


Figure 29. Energy analysis for test 1: (top) optimised setpoints and cooling thermal needs; (bottom) optimised supply air thermal power and HVAC electricity needs.

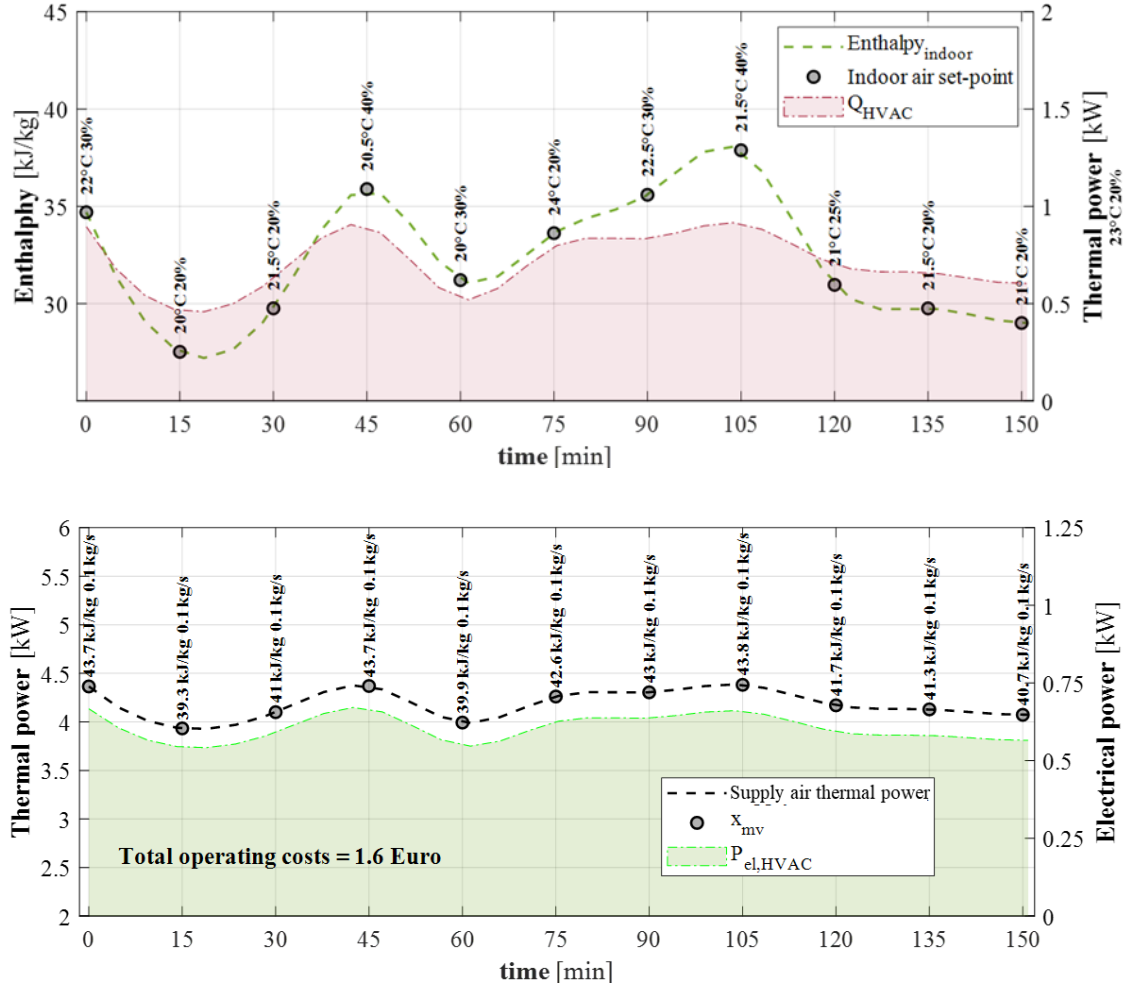


Figure 30. Energy analysis for test 2: (top) optimised setpoints and heating thermal needs; (bottom) optimised supply air thermal power and HVAC electricity needs.

Lastly, a comfort analysis highlights the benefits of the OCC strategy, ensuring both thermal comfort and air quality for the occupants. Figure 31top and Figure 32top show the PMV^* trend, demonstrating that PMV^* values fall within the acceptable ranges imposed by the index for both tests. Test 1 has PMV^* values close to the maximum limit, while test 2 has values close to the lower limit, reflecting the optimization procedure's goal to ensure comfort while minimizing energy requests.

Figure 31bottom and Figure 32bottom demonstrate that the PD values remain below the threshold of 15% at each plant control step, showcasing the effectiveness of the OCC strategy in maintaining air quality at desirable levels.

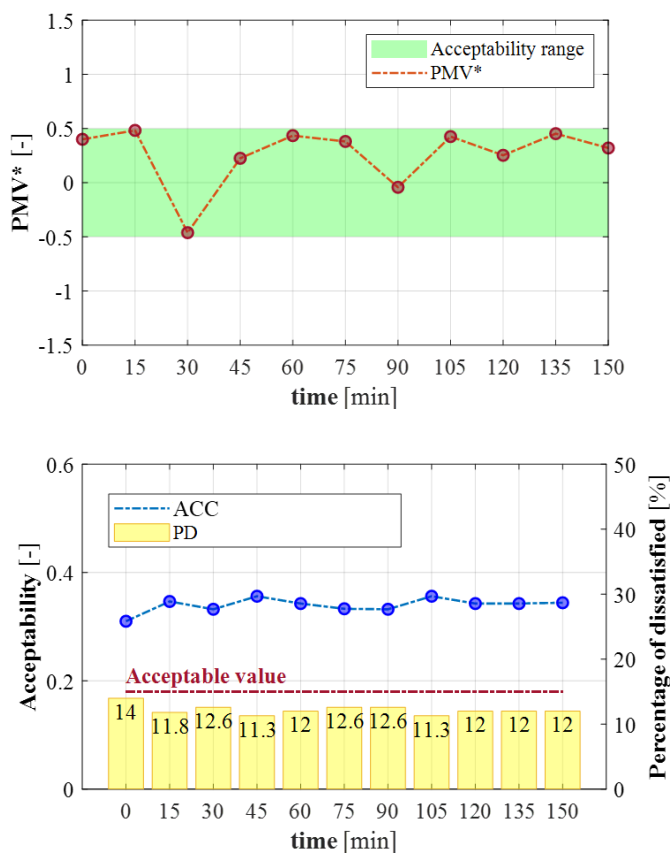
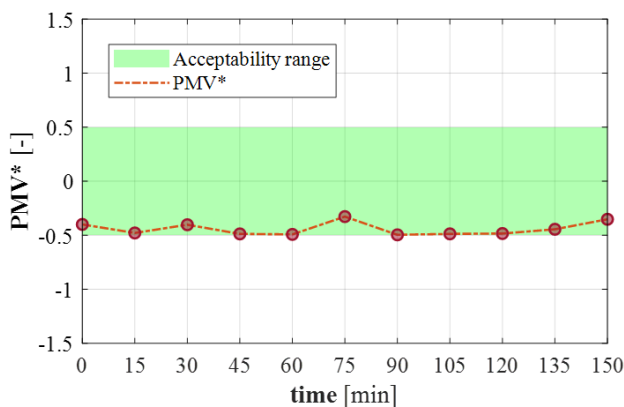


Figure 31. Comfort analysis for test 1: (top) thermal comfort; (bottom) perceived indoor air quality.



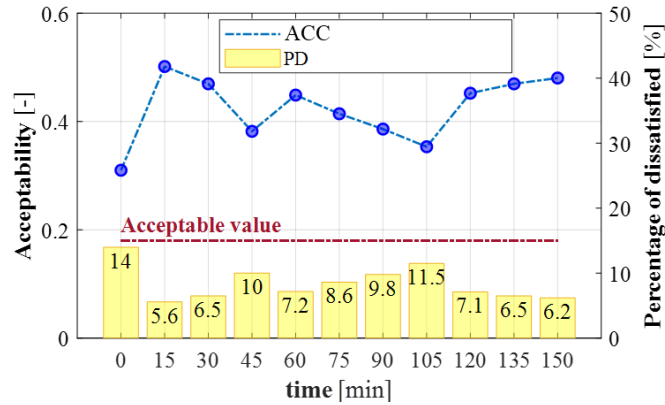


Figure 32. Comfort analysis for test 2: (top) thermal comfort; (bottom) perceived indoor air quality.

3.6.3 Results comparison

To demonstrate the benefits of the developed methodology, a complete simulation analysis was performed by comparing the reference and proposed scenarios for both tests, with a focus on comfort and energy considerations. The reference scenario involves real experimental tests conducted on the two subjects, evaluating energy consumption and comfort analysis based on the HVAC system's operating conditions, occupants' physiological response, and the thermo-hygrometric setpoints reached during the tests. This approach provided valuable insights into the actual performance of the HVAC system and its impact on occupants' comfort under real-world conditions. On the other hand, the proposed scenario represents the simulation of the same tests, but with the OCC methodology described earlier.

Initially, the comparison focused on occupants' comfort perceptions in the two scenarios. The results depicted in Figure 33 revealed that in the reference scenario for both tests, occupants experienced partial thermal discomfort, as demonstrated in the trends not entirely falling within the PMV^* acceptability band. For instance, in test 1, occupants experienced thermal discomfort for 40% of the occupation time, equivalent to 60 minutes. Similarly, in test 2, the discomfort was experienced for 60% of the occupancy time, equals 90 minutes. These findings underscored the importance of refining the HVAC control strategy to enhance occupants' thermal comfort experience.

Furthermore, Figure 33top shows that the air quality perception discomfort levels, i.e., out of the +0.5 - -0.5 range, exceed the threshold value of 15% for 90% of the occupancy time in the same reference scenario. These findings reveal flaws in the reference HVAC operation, that needs to be addressed further. On the other hand, Figure 33bottom provides insight into the PD index percentages for the evaluation of air quality perception in test 2. In

the reference scenario, the occupant experienced discomfort for only 40% of the occupation time, showing that air quality was rather well-maintained.

Overall, the proposed scenario ensured thermal comfort and air quality perception for both tests for the entire occupation time. The simulation findings demonstrate that, to maintain a comfortable indoor environment for the occupants, the HVAC control strategy could be optimized by using the developed OCC technique,

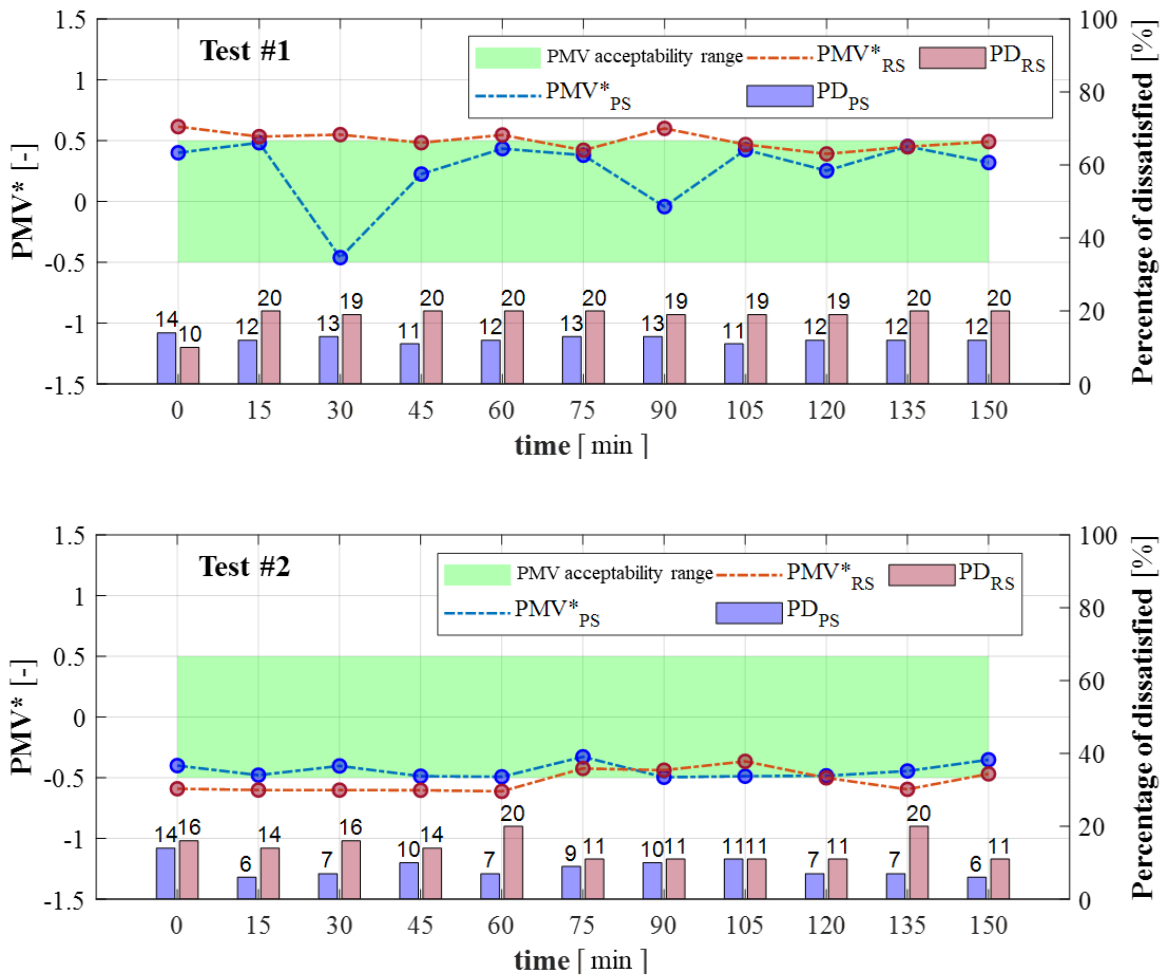


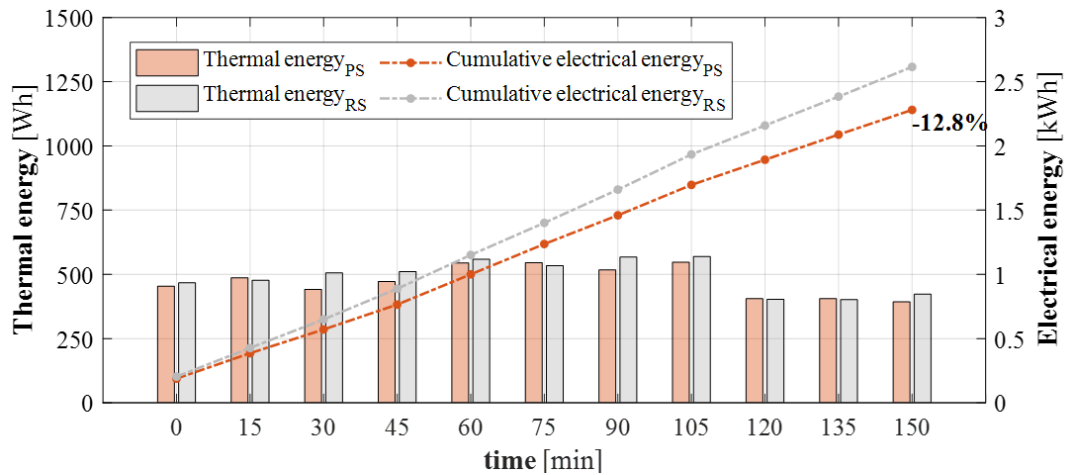
Figure 33. Comfort analysis comparison: reference versus proposed test #1 (top) and test #2 (bottom).

The comparison analysis examined the thermal energy requests for heating and cooling in both scenarios, as depicted in Figure 34. Notably, the proposed methodology achieved significant energy savings. In test 1, focused on cooling needs, the optimization strategy for determining thermo-hygrometric setpoints led to a 3.7% reduction in thermal energy consumption (see Table 8). By suitably adjusting cooling setpoints based on occupants' requirements and predicted thermal dynamics, unnecessary energy usage was minimized

while ensuring comfort. Furthermore, the MPC control strategy, as demonstrated in Figure 34top, played a vital role in further reducing energy consumption. By dynamically optimizing HVAC parameters, such as fan speed and cooling/heating intensity, the MPC controller achieved a substantial 12.8% reduction in total electricity consumed compared to the reference scenario, equivalent to 0.33 kWh (see Table 8).

In test 2, Figure 34bottom revealed that the OCC methodology resulted in 20% thermal energy savings for heating compared to the reference scenario, accomplished by fine-tuning heating setpoints based on predicted thermal conditions and occupants' activities. Moreover, the HVAC control strategy, depicted in Figure 34b, achieved a notable 7.8% reduction in energy consumption compared to the reference scenario (see Table 8). This significant reduction highlighted the potential of the OCC approach for optimizing HVAC system performance and minimizing operational costs.

In conclusion, the comparative analysis has emphasized the significant advantages of the developed OCC methodology in relation to occupant comfort and energy conservation. Through the efficient utilization of predictive models and intelligent control algorithms, the OCC strategy has enabled the HVAC system to dynamically respond to the needs of occupants, thereby creating an environment that is both comfortable and energy efficient. These promising results strongly advocate for the widespread implementation of advanced control strategies in HVAC systems, as they not only enhance the well-being of occupants but also promote sustainable practices within buildings.



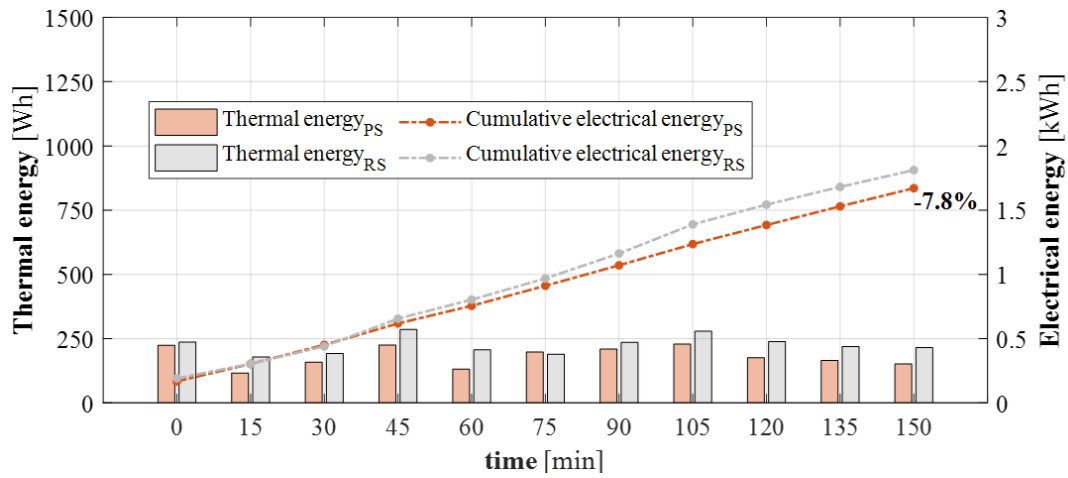


Figure 34. Energy analysis comparison: reference vs proposed test #1 (top) and test #2 (bottom).

Table 8. Comparison of energy and comfort analysis for proposed scenarios vs reference.

		Unit	Reference	Proposed	Δ [%]
Test #1	Cooling needs	[kWh]	5.40	5.20	-3.7
	Thermal discomfort ^a	[h]	1.00	0.00	-40.0 ^b
	Indoor air quality discomfort ^a	[h]	2.25	0.00	-90.0 ^b
	Electricity consumption	[kWh]	2.60	2.27	-12.8
Test #2	Heating needs	[kWh]	2.50	2.00	-20.0
	Thermal discomfort ^a	[h]	1.50	0.00	-60.0 ^b
	Indoor air quality discomfort ^a	[h]	1.00	0.00	-40.0 ^b
	Electricity consumption	[kWh]	1.77	1.63	-7.8

^a Evaluated for occupancy time of 2.5 hours

^b Percentage result of the hours of discomfort avoided compared to the reference case

3.7 Conclusions

This chapter proposes an Occupant-Centric Control technique for the design and operation of smart HVAC systems that takes into consideration the physiological response of the human body to optimize building energy performance and occupant comfort. The study aims to evaluate the potentials of the proposed PCM implemented in a BEPS tool with the goal of addressing the linkage between the *indoor environment, the human body, and the HVAC system*, as well as bridging the gap between human demands and the built environment by translating occupant comfort criteria into actual environmental conditions.

A highly flexible Personal Comfort Model was, thus, developed for the accurately predicting thermal sensations and CO₂ intakes of occupants; the model's accuracy was verified by means of an extensive multi-domain experimental campaign. The PCM based on the physiological response of the human body was modelled and implemented in a flexible dynamic simulation tool where a Model Predictive Control was developed for the design of a control strategy for HVAC systems that effectively addresses the occupants' thermal comfort and air quality requirements in indoor spaces. The developed strategy relies on a multilevel non-linear programming optimization procedure to determine optimal hygrothermal setpoints. The model's reliable predictive capabilities were effectively verified through a validation procedure conducted by using experimental data; results show that the skin temperature offset falls within the $\pm 2\%$ error band 97% and 84% of the time for the all the experimental tests. In addition, the PCM exhibited flexibility in accommodating different subjects and levels of metabolic activity.

The proposed OCC strategy employed an MLNLP optimization procedure to determine optimal hygrothermal setpoints, resulting in thermal energy savings of 3.7% and 20% for cooling and heating tests, respectively. Moreover, the strategy provided maximum comfort, with no hours of discomfort during the occupation time. The MPC strategy efficiently managed the HVAC system, resulting in operating cost savings of 12.8% and 7.8% for test 1 and test 2, respectively. The study emphasizes the significance of centralized HVAC system control to address the real and personalized comfort needs of occupants, while minimizing operating costs to achieve sustainability and building efficiency objectives. Overall, this research opens promising paths for creating energy-efficient and occupant-focused building environments. The study represents a significant advancement in the sustainable design of human-centric spaces toward energy efficiency and occupant comfort.

Future work aims to implement this strategy in real-life tests to evaluate its effectiveness in occupied environments. Additionally, conducting this analysis in different climates will provide valuable guidelines for occupant-centric control, enabling the assessment of maximum achievable savings.

Chapter 4

Predictive control of solar-assisted energy hubs in district heating systems

This chapter was previously published as:

Buonomano A., Forzano C., Palombo A., Russo G. (2023). Solar-assisted district heating networks: Development and experimental validation of a novel simulation tool for the energy optimization. *Energy Conversion and Management*, 288, 117133.

Summary

With the increasing interest in 4th and 5th generation district heating systems that operate at lower fluid temperatures, solar-assisted poly-generative networks are gaining research attention. This study aims to optimize the design and operation of individual solar thermal fields within such networks to maximize performance. A novel dynamic simulation tool for solar field design and optimization was developed and experimentally calibrated in Simulink/Simscape. This tool uniquely integrates thermal and hydraulic system behavior, critical for ensuring effective design and control strategies. A proof-of-concept analysis on Geneva's district heating network demonstrates the tool's capability, evaluating Rule-Based and Model Predictive Control strategies, and achieving notable results: primary energy reductions of up to 10.3% and CO₂ emission savings of up to 10.9 tCO₂/year. This work highlights the tool's potential to enhance the efficiency of solar-assisted district heating networks.

Keywords

Solar-assisted district heating, poly-generative district heating, multi-objective optimization, detailed thermo-hydraulic model, Model Predictive Control.

Nomenclature

Acronyms

A	surface area [m^2]
a_1	collector efficiency constant [$(\text{K} \cdot \text{m}^2)/\text{W}$]
a_2	collector efficiency constant [$(\text{K}^2 \cdot \text{m}^2)/\text{W}$]
C	thermal capacity [W/K]
C_D	valve discharge factor [-]
D	diameter [m]
f	Darcy friction factor [-]
h	heat transfer coefficient [$\text{W/m}^2 \cdot \text{K}$]
I_{tot}	total incident radiation [W/m^2]
k	thermal conductivity [$\text{W}/(\text{m} \cdot \text{K})$]
L	length [m]
m	flow rate [kg/s]
M	total heat production of metabolism [W/kg]
$MAPE$	mean absolute percentage error [%]
NTU	number of transfer units [-]
P	mechanical power [W]
p	pressure [Pa]
Q	thermal power [W]
Re	Reynolds number [-]
S	cross section [m^2]
T	temperature [K]
u	internal energy [J/kg]
UA	global thermal conductance [W/K]
V	volume [m^3]

Greek letters

Δ	variation
ε	surface roughness [-]
η	energy efficiency [-]
ρ	density [kg/m^3]
ϕ	energy flow rate [W]
ξ_p	pressure drop ratio [-]

Subscripts

$crit$	critical	sf	solar field
env	environment	t	turbulent
lin	linearly	tot	total
obj	objective		

4.1 Introduction

In this chapter, a promising solution to reduce the impact of this sector is the adoption of District Heating (DH) networks, representing an effective way to improve the efficiency of both thermal production and distribution [189]. Throughout DH systems it is possible to increase the adoption of distributed renewable energy sources [190], the utilization of waste energies [191], and in turn to improve overall energy efficiency [192]. Indeed, district heating systems are acknowledged as a central technology for decarbonization [74], especially in high-demand areas.

First district heating network commercial applications were developed in the USA during the '80s [193] and exploited high-temperature heat transfer fluid (e.g., steam) generated primarily from a single source. [73]. Nowadays, the third-generation DH systems are the most widely adopted and widespread, and are characterized by Heat Transfer Fluid (HTF) temperatures typically below 100°C [194]. Such occurrence opens to the possibility of exploiting alternative renewable energy based systems, such as geothermal, biomass, and solar [195]. Due to the still-relatively-high temperature, however, the use of solar thermal energy is restricted to systems capable of achieving high temperatures, resulting in higher capital and operational costs. [196]. Following the clear trend of temperature level reduction moving from one DH generation to another [197], 4th and 5th generation networks, which are characterized by even lower temperatures, have a greater potential for exploiting renewable energy sources.

Regarding the most recent development in the architecture of DH networks, it is important to note that the use of thermal storage has proven to be a promising solution [198]. In particular, Seasonal Thermal Energy Storage (STES) allows for excess thermal energy to be stored during low demand and high production periods and used during peak demand of heating season [199], making them a viable choice for district heating systems because it stabilises heat delivery throughout the year, despite seasonal shifts in energy supply or demand [200]. As a result, total energy costs may decrease, leading to a more efficient and sustainable energy consumption pattern [201]. There are several types of STES [202] suitable for district heating applications: aquifer thermal energy storage (ATES); borehole thermal energy storage (BTES) widely used in locations with limited space or access to underground aquifers [203]; and pit thermal energy storage (PTES) [204] which represents a low-cost and flexible option for STES but may require more space than other types of STES. Additionally, implementing advanced control strategies for the flow rates within the STES energy management system can increase the efficiency of the system by reducing heat losses and maximizing the energy supplied to the district heating network users [205]. In addition to thermal storage, a further enhancement, supported by the lower HTF working temperatures is the adoption of poly-generative DH layouts implementing renewable energy

sources (e.g. geothermal, biomass, etc.), and in particular solar thermal based ones [206]. Such trend represents a possible solution to further increase their sustainability [207]. Particularly, it is expected that the adoption of solar-based thermal systems for district heating applications will become more widespread, and that solar sources will increase their share compared to conventional ones. (e.g. fossil based energy sources) [208].

In light of what has been stated previously, the correct design and management of the diverse solar thermal fields supplying poly-generative, solar-assisted, DH networks is essential for enhancing their performance [209]. In this context, since each field serving a certain DH system could have distinctive characteristics in terms solar thermal collector technology, slope, and orientation, system layout, control logics, etc. this may imply a time-consuming optimization procedure [208]. Therefore, there is a need of powerful and accurate, yet flexible and complete, dynamic simulation tools for large solar thermal field simulation and optimization, capable of considering all the required parameters. Many works in literature present validated dynamic simulation tools for solar thermal field performance assessment and optimization [210] (not linked to DH networks). As an example, Yilmaz et al. [211] investigate a solar assisted industrial process exploiting parabolic trough solar collectors by using a previously conceived in-house developed simulation tool [212]. Similarly, a flat plate solar thermal collector field is simulatively investigated by García-Menéndez et al. [213] by adopting TRNSYS simulation environment. The dynamic optimization of a parabolic trough collector plant integrating energy storage is instead investigate by Immonen et al. [214], where an in house developed Matlab/Simulink tool is adopted. On the other hand, there are also works in literature specifically focused on solar-assisted district heating networks. As an example, Winterscheid et al. [215] studied the possibility of integrating solar thermal system in existing DH networks. Trough the adoption of purposely developed Matlab tool, they investigated the convenience in supplying a sub-system without the need of making large structural changes to the network. Another example is given in the work by Hirvonen et al. [216] presenting a techno-economic optimization of a solar assisted district heating network. Using the software TRNSYS, the authors evaluated the optimal parameters for the entire network and obtained interesting findings in terms of solar fraction achieved. In addition, they underlined the key role of solar thermal energy in DH systems, even in high latitude countries. Despite this, the majority of published works on solar-assisted DH networks concentrate on the entire system, whereas it is more difficult to identify works that provide insights and optimise individual solar fields. For instance, Tian et al. [208] carried out a thermo-economic optimization of a large scale solar field (made of both flat plate and parabolic trough collectors) serving a DH network, showing interesting outcomes in terms of potentially achievable energy and economic benefits.

In this scenario, promising improvements can be obtained by adopting Model Predictive Control techniques. Specifically, an MPC is an advanced control method that utilises a

model of the system being controlled to predict its behaviour and optimise its performance, which can be effectively applied to increase the efficiency and effectiveness of solar collectors' field operation [217]. One of the primary challenges with thermal solar fields is their highly nonlinear behaviour [218]. Factors such as solar irradiation, ambient temperature, and wind speed can all impact the performance of the system [205]. Traditional control techniques, such as proportional-integral-derivative (PID) control, are often not sufficient to account for these nonlinearities and can lead to suboptimal performance [219]. MPC overcomes these challenges by utilizing a dynamic model of the thermal solar field [220] to predict its behaviour and adjust control inputs in real-time to optimize its performance. The model can be updated based on real-time measurements of the system's state, allowing for more accurate predictions and improved control. To ensure safe and reliable operation [221] MPC can also account for constraints of the system, such as limitations on the maximum and minimum operating temperatures. This leads to more accurate tracking of setpoints, improved energy yield, and reduced maintenance costs, which proves the importance and the potential in adopting MPC control strategies for solar-based system optimization. [222].

4.1.1 Literature gap

Despite the number of works on the topic, it is still possible to identify knowledge gaps based on an analysis of the literature. First, there is a need for research focusing specifically on the function of solar fields in the context of poly-generative DH designs, as a feasible step towards enhancing the overall system's sustainability. Optimizing all the solar thermal fields serving a certain district heating system, especially in a context where the adoption of large solar based thermal power plants is going to be much more common, can have a remarkable impact on the overall performance of solar-assisted DH networks. Although there is a growing body of research on solar-assisted DH networks, most of it is concerned with the entire system rather than the influence or optimization of solar fields serving it. In this context, since each field serving a certain DH network could have different features, there is a need of a tool powerful enough to accurately simulate the system performance while being also enough flexible to considering all the different peculiarities, with the aim of carrying out comprehensive multiparameter optimizations. This need leads to the second observed knowledge gap. Specifically, while many studies have explored solar thermal fields from a simulation perspective, there is a lack of tools that can adequately account for both the thermal and hydronic factors. This is a significant drawback of many simulation tools for solar thermal fields, as the energy required to move the fluid in the circuit is not negligible and can have an effect on the way the system is operated. Such issue, which is not essential in case of small systems, become critical when simulating large solar fields (characterized by relatively greater distances covered by pipes, higher complexity of the system, a greater

number of hydraulic components, etc.), since the pressure drops caused by the resistance of fluid flow through the system's pipe and components increase as the system size and complexity does. It worth noticing that considering hydronic behaviour of the system is of particular importance especially when the tool is adopted to perform the optimization of the system design or control logics, as underlined in diverse recent works in literature [197]. For instance, Ma et al. [223, 224] investigate a parabolic trough solar thermal field, with a thermal-hydraulic dynamic simulation tool, underlining the importance of considering pressure drops to achieve more accurate results. According to Gallero et al. [222], , ignoring the system's hydronic behaviour can lead to a mistake of up to 6%. Specifically, in this work the authors emphasise that in the case of large solar fields, pressure drops are no longer negligible, and their evaluation is required to accurately optimise the operating conditions of the field. Nonetheless, despite the recognized significance of investigating hydronic aspects, the very few works taking such characteristics into consideration conduct narrow analysis (e.g. on certain collectors' typologies, using tools without enough flexibility to investigate a wide spectrum of technologies and/or variables). As a result, comprehensive multiparameter optimizations for a broad variety of solar fields serving a particular DH network, which may have very distinct characteristics, cannot be performed with the currently available tools. The third and final knowledge gap relates to the implementation of model predictive control strategies. Specifically, optimization procedures adopted to adjust the field control variable (mass flow rate) should aim at maximizing the thermal energy from renewable source supplied to the district heating network users while avoiding additional operating costs outweighing the benefits. Since hydronics aspects are rarely investigated, it is rare to find MPC strategies which account for the higher cost of pump operation and are thus able to identify the optimal cost-benefit trade-off. When investigating solar-assisted poly-generative district heating systems, all the knowledge gaps that were discovered take on a particularly important role and need to be investigated further.

4.1.2 Aim and contributions

In response to the knowledge gaps, the aim of this study is to develop a method for maximising the performance of solar-assisted poly-generative district heating networks by optimising each solar thermal field individually. To this end, an accurate, powerful, yet flexible, solar thermal collector fields simulation and optimization tool has been developed in Matlab Simulink/Simscape environment. The developed and experimentally validated tool can determine, in addition to the solar field thermal production, the energy consumption associated with fluid movement. Compared to the few other works in the literature that show tools capable of assessing the system's hydronic behaviour, the one developed for this study has two key advantages. The first is the use of Simulink/Simscape as the modelling environment, which is uncommonly used to study such applications but guarantees a high

degree of accuracy in the simulation of physical system dynamics. (e.g. pressure drops, valve flow coefficient, valve lift dynamic, etc.) making the model a valuable tool for large solar systems simulation and design. The second advantage is its flexibility, which allows for the simulation of various collectors, system layouts, control logics, etc. This capability enables the individual optimization of each solar thermal field serving a specific DH network, thereby increasing the renewable energy share of the system as a whole. The described tool is also able to perform exhaustive multi-objective optimizations (considering many of the system's key parameters) to minimise various objective functions while taking into consideration operational constraints. Finally, the tool is completed by including the option to explore various control strategies, such as traditional Rule Based (RB) or cutting-edge Model Predictive Control (MPC). Concerning the latter, the optimization process used to optimize the control variables is designed to maximize the thermal energy supplied to users of the district heating network without incurring unnecessary operating costs. In addition, the study proposes a game theory method for adjusting multiple control variables. The method addresses a bi-optimization problem by applying the Nash Equilibrium criterion, which maximises the energy delivered to DH network users while minimising the mechanical energy of the pumps. Due to its capabilities, the resulting tool can be a valuable instrument to enhance the performance of poly-generative solar-assisted district heating networks. To show the benefits potentially achievable by adopting the proposed method, and to display the capabilities of the developed simulation tool, a suitable proof-of-concept analysis was conducted on an existing solar thermal field at the service of the DH network of the city of Geneva, Switzerland. In the context of this case study, diverse control logics, including the more traditional Rule-Based Control and the more advanced Model Predictive Control, are evaluated, and compared, showing some interesting benefits in terms of the thermal energy production. These findings demonstrate the potential benefits that can be obtained at the district level by implementing the suggested approach. Indeed, higher benefits are expected in the case of comprehensive optimization carried out during the design phase and in the case of an extended analysis conducted on all the solar thermal fields serving a certain district heating network.

4.2 Methodology

In this paragraph, the adopted methodology and the developed mathematical model are described in detail. Specifically, the aim of this study is to develop a reliable and replicable method for optimising each solar field with the intention of increasing the renewable energy share of the investigated DH network. To better clarify this aspect, Figure 35 presents a schematization of a generic district heating network. Here, each node can represent a user or a producer. The latter could in turn be a fossil or renewable energy-based one. On the other hand, the dotted lines represent the connection among the DH nodes.

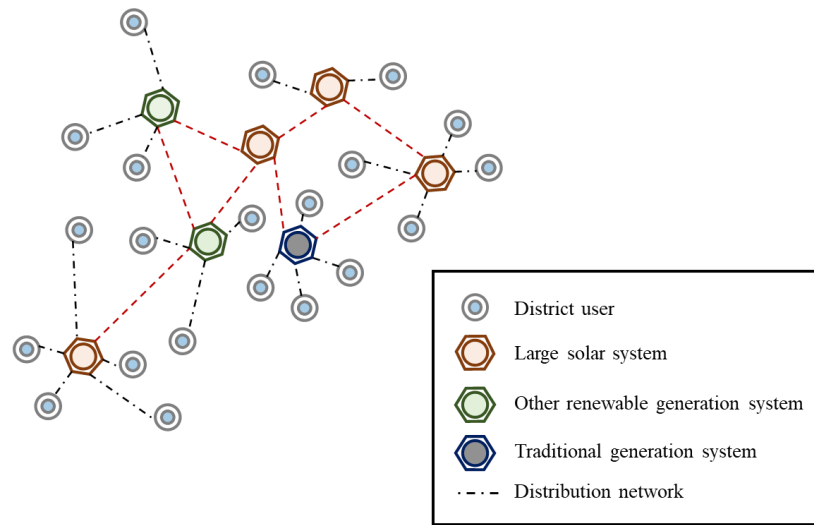


Figure 35. Scheme of a generic poly-generative district heating network.

From the figure it is clear that solar thermal generation is typically not consolidated in a single big solar field but rather spread out across the network in a number of different locations. Such occurrence implies that each field can have a whole range of different characteristics, such as the collector type, the system layout, the distribution circuit, the orientation, the slope, the working fluid, the control logic, etc. Therefore, optimizing the solar fraction at the entire network level requires a tool which is at the same time powerful enough to detailly simulate (and optimize) large fields and flexible enough to permit the investigation of a wide range of layouts. Moreover, since the solar fields that supply DH networks tend to be quite large, the impact of pressure drops on the overall energy performance is not negligible when optimising a system. Thus, to achieve the intended objectives and fill the previously identified knowledge gaps, a Matlab/Simulink-based dynamic simulation tool capable of evaluating the energy performance of a solar field while also accounting for its hydronic behaviour was developed. Specifically, the developed tool allows for the detailed modelling of the solar field's pipeline network by taking a variety of components into account (such as circulating pumps, piping, flow reducers, sharp bends, three-way valves, and safety devices such as check valves to ensure correct flow direction, ball valves to force system shutdown, expansion vessels for overpressure control, and others). Through such a tool it is also possible to execute sensitivity analyses investigating a large variety of components, system layouts, and control logics, allowing for the accurate simulation of diverse working conditions. Accurate yet adaptable, the resulting tool can be used to estimate the energy performance of existing systems or to optimise the design of new ones. In order to provide a clear understanding of the developed tool, Figure 36 shows a schematic of the software input and output.

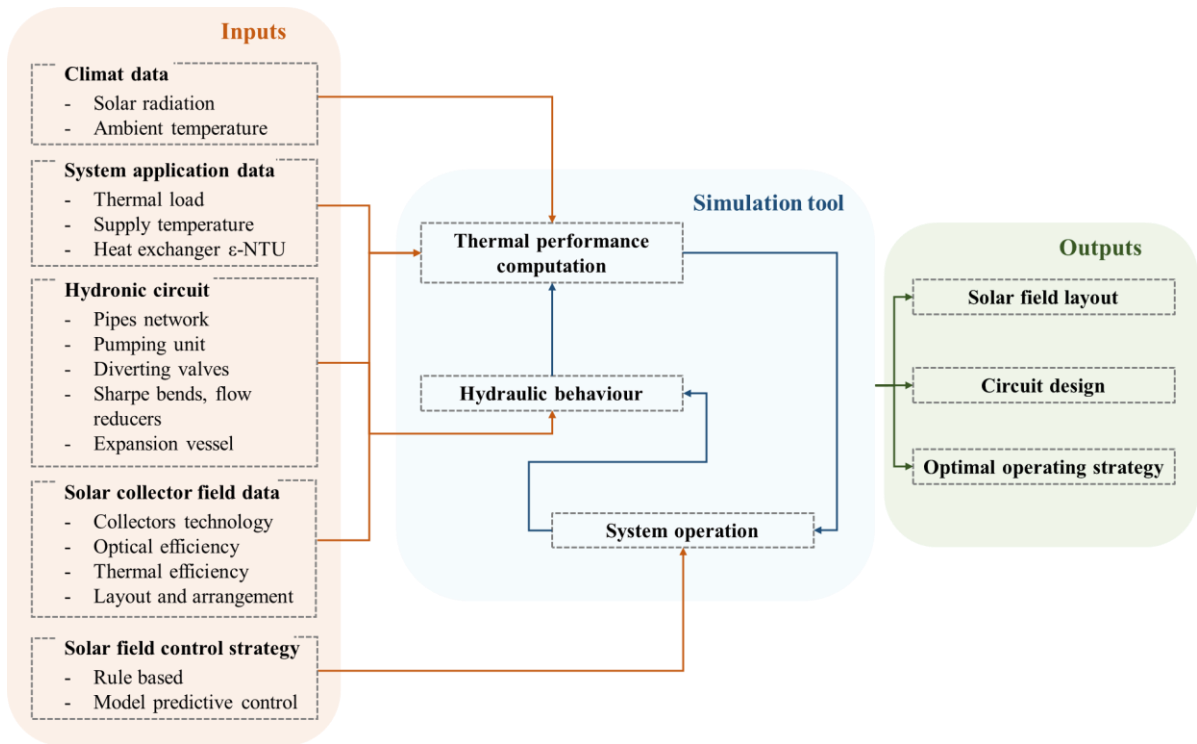


Figure 36. Schematic diagram showing the developed tool inputs and outputs.

In the following, the mathematical modelling of the solar field will be detailed described. Then, the control logic implementable will be also shown.

4.2.1 Solar field mathematical model

As was previously stated, a dynamic simulation tool has been created in a Matlab-Simulink/Simscape environment that can accurately assess the thermal and mechanical performance of solar fields, allowing for the desired investigation to be conducted. Both mechanical and thermal modelling are described in depth below.

Concerning the mechanical performance, to accurately assess the pressure drops along the piping network each component must be detailly modelled. In such a way it is possible to assess both the mechanical energy needed to move the fluid and the heat losses along the path. To reach this level of detail, the Simscape fluids library was used. Concerning the pipe network, this is modelled with the Simscape component pipe (TL) that evaluates the pressure losses along the pipe, with the hypothesis of an incompressible fluid, flow fully developed, and negligibility of gravity effect, through the following equations:

$$\Delta p_{pipe} = \begin{cases} \lambda_{pipe} \cdot u_{fluid} \times \left(\frac{L_{pipe} + L_{eq,pipe}}{2} \right) \times \frac{m_{fluid}}{2 \cdot D_{pipe}^2 \cdot S_{pipe}} & \text{if } Re < Re_l \\ f_{pipe} \times \left(\frac{L_{pipe} + L_{eq,pipe}}{2} \right) \times \frac{m_{fluid}^2}{2 \cdot \rho_{fluid} \cdot D_{pipe} S_{pipe}^2} & \text{if } Re \geq Re_t \end{cases} \quad \text{Eq. (15)}$$

where, m_{fluid} is the Heat Transfer Fluid (HTF) flow rate, λ_{pipe} is the pipe shape factor, u_{fluid} is the kinematic viscosity of the thermal liquid in the pipe, L_{pipe} is the pipe length, $L_{eq,pipe}$ is the aggregate equivalent length of the local pipe resistances, D_{pipe} and S_{pipe} are the hydraulic diameter and pipe cross-sectional area, Re is the Reynold number of the flow, Re_l and Re_t are the Reynolds numbers which determine the flow transition from laminar to turbulent, f_{pipe} is the Darcy friction factors in the pipe that are evaluated as follow:

$$f_{pipe} = \frac{1}{\left[-1.8 \cdot \log_{10} \left(\frac{6.9}{Re} + \left(\frac{1}{3.7} \times \frac{\varepsilon_{pipe}}{D_{pipe}} \right)^{1.11} \right) \right]^2} \quad \text{Eq. (16)}$$

where ε_{pipe} is the pipe surface roughness. Conversely, the thermal losses with the surrounding environment are estimated, for the same pipe length, through the energy conservation equation, as follows:

$$\rho_{fluid} \cdot V_{pipe} \cdot \frac{\partial u_{fluid}}{\partial t} = \dot{q}_{in,pipe} + \dot{q}_{out,pipe} + Q_{l,env} \quad \text{Eq. (17)}$$

With

$$Q_{l,env} = \left(\frac{1}{\left(\frac{1}{h_{air}} \right) + \frac{w_{pipe}}{k_{pipe}}} \right) \times S_{lat,pipe} \cdot (T_{air} - T_{in,wall,pipe}) \quad \text{Eq. (18)}$$

where, V_{pipe} , $S_{lat,pipe}$, w_{pipe} and k_{pipe} are respectively the volume, lateral surface, thickness and thermal conductivity of the pipe, u_{fluid} is the internal energy of the fluid, $\dot{q}_{in,pipe}$ and $\dot{q}_{out,pipe}$ are the energy fluxes of the fluid entering and exiting the control volume of the pipe, $Q_{l,env}$ is the thermal lost with the surrounding environment, $T_{in,wall,pipe}$ is the pipe internal wall temperature, and T_{air} and h_{air} are respectively the ambient air temperature and the outside convective heat transfer coefficient. Concerning the concentrated pressure drops (i.e., flow reducers, sharp bends), these are evaluated through the Simscape Flow resistance (TL) component as a function of a proportionality factor K , which depends on the friction factor of the circuit obstacles, as follows:

$$\Delta p = K \cdot m_{fluid,in} \cdot \sqrt{m_{fluid,in}^2 + m_{fluid,lam}^2} \quad \text{Eq. (19)}$$

where, $m_{fluid,in}$ and $m_{fluid,lam}$ are respectively the inlet and laminar transition mass flow rate of the fluid entering the concentrated pressure drop. Besides the distributed and concentrated pressure drops, all the hydraulic components necessary network's network proper operation are included in the model, such as check and ball valves, three-way valves, expansion vessels, heat exchangers, etc., but for sake of brevity they are not described here.

Concerning the solar field thermal energy performance, the produced heat (Q_{field}) is assessed through a purposely developed Matlab script which dynamically evaluates Q_{field} as a function of diverse operating and boundary conditions, as follow:

$$Q_{field} = f(N_{col,tot}, N_{col,par}, I_{tot}, T_{air}, m_{sf}, T_{in,sf}, T_{out,sf}) \quad \text{Eq. (20)}$$

Where $N_{col,tot}$ and $N_{col,par}$ are respectively the numbers of collectors in the entire fi and in a single row; m_{sf} , $T_{in,sf}$ and $T_{out,sf}$ are correspondingly the solar field flow rate, and the inlet and outlet temperatures of the working fluid, finally, I_{tot} and T_{air} are the incident solar radiation and the ambient air temperatures respectively. In this framework, the single collector efficiency (η_{coll}) is evaluated as follow [225]:

$$\eta_{coll} = \eta_{optical} - a_1 \times \frac{T_m - T_{air}}{I_{tot}} - a_2 \cdot I_{tot} \times \left(\frac{T_m - T_{air}}{I_{tot}} \right)^2 \quad \text{Eq. (21)}$$

Where $\eta_{optical}$ is the collector optical efficiency, a_1 and a_2 are the constants characterizing the collectors' thermal performances, and T_m is the arithmetic average between the inlet and outlet temperatures. Since the arrangement of collectors in series implies that the outlet temperature of the first collector in the row is the inlet temperature of the subsequent one, the average absorber plate temperature will be different for each collector belonging to the same row, varying the efficiency. Consequently, to correctly assess the efficiency of each collector of a given row, an iterative procedure is necessary for each timestep (t_s). In this framework, a scheme reporting the procedure performed to evaluate the thermal yield of each collector is reported in Figure 37. Specifically, for each simulation timestep (t_s), through an energy balance applied to the control volume of the single collector, the outlet fluid temperature, $T_{out,coll}$ is calculated by considering, as a first approximation, that all the incident solar radiation is absorbed by the HTF. With the estimated first attempt outlet fluid temperature, by knowing the inlet one, it is possible to evaluate the collector efficiency η_{coll} . Subsequently, by solving again the energy balance on the volume of the single collector it is possible to assess a new collector outlet temperature, which is used to evaluate a new collector efficiency η_{coll} . The procedure is iteratively carried out until the temperature of the current iteration $T_{out,coll}(it)$ and that of the previous one $T_{out,coll}(it-1)$ differ by a small quantity

ε equal to 0.01°C . At the end of this iterative procedure, the temperature of the fluid exiting the collector is finally estimated and will be adopted as the inlet temperature ($T_{in, coll}$) of the next one in the row. The described iterative procedure is then repeated for all the collectors of the row obtaining, for all the simulation time steps, the overall available thermal power of the solar field (Q_{field}).

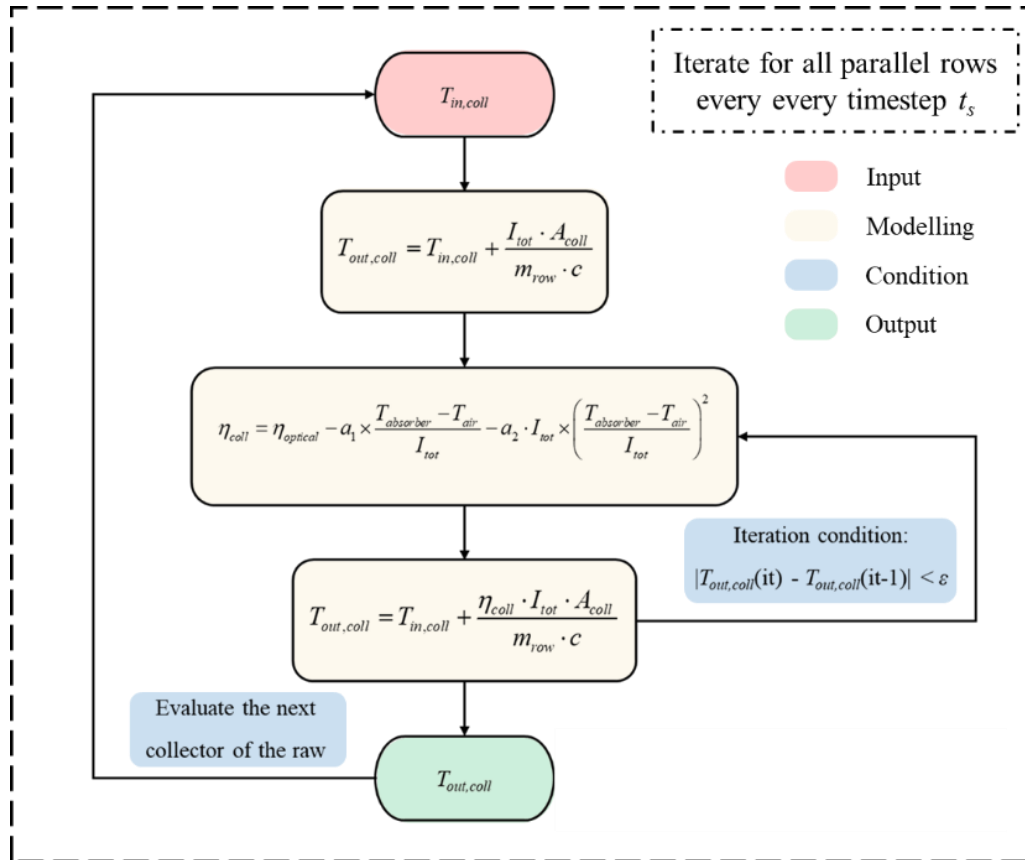


Figure 37. Iterative process to assess thermal solar production.

4.3 Control strategies

In general, when a system is affected by the action of a disturbance it is unable to reach the desired working condition. Therefore, it is necessary to adopt suitable control strategies to guarantee the achievement of the set-point condition by manipulating the system control variables. In this context, solar fields are subjected to different unexpected disturbances (such as solar radiation and external air temperature) strongly affecting their performance. Consequently, control strategies substantially influence the field's yearly yield. For such a reason, the developed dynamic simulation tool embeds the possibility of adopting diverse standard and advanced control strategies, aiming at optimizing solar field performance. Specifically, both standard Rule-Based (RB) and advanced Model Predictive Control (MPC)

strategies can be investigated by the developed tool. Concerning rule-based strategies, these affect the regulation of the controlled variable by monitoring the dynamic variation of the properties of interest according to specific control laws. Contrariwise, concerning the model predictive control strategy, this implements a prediction of the controlled variable by optimizing certain objective functions (such as the thermal yield of the solar system). In the following, the modelling behind both control strategies is described.

4.3.1 Rule-Based control strategy

In case of a rule-based control strategy, the control action begins when a certain parameter (the monitored variable) surpasses a certain threshold. Concerning solar fields, the variable usually adopted as monitored one is the incident solar radiation I_{tot} . Specifically, the control action begins when solar radiation exceeds a certain threshold value, allowing the working fluid to flow inside the pipe network. Otherwise, the HTF mass flow rate is still null. The solar radiation threshold value $I_{tot,thr}$ is determined in such a way as to ensure adequate heating of the heat transfer fluid (e.g. close to the set point temperature). To implement such control logic into the previously described dynamic simulation tool, the Matlab Control System Toolbox has been adopted. Specifically, a schematization of the implemented control algorithm is shown in Figure 38 through a block diagram.

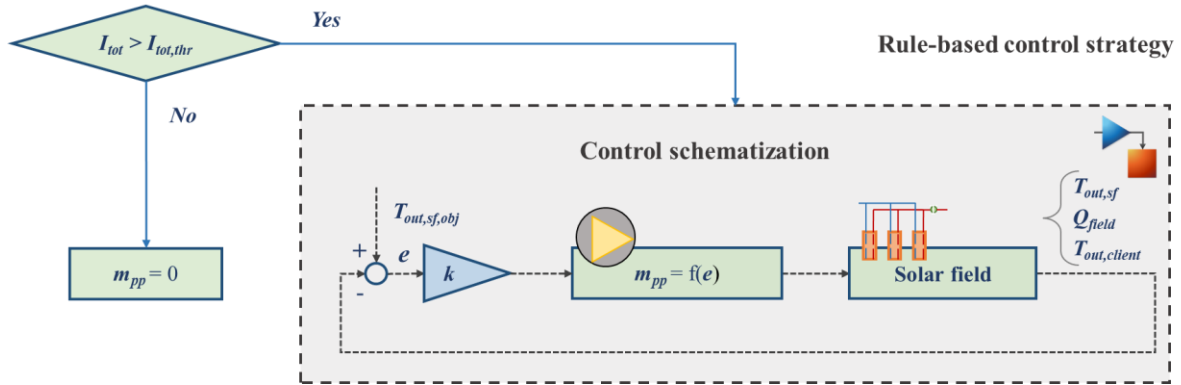


Figure 38. Scheme of rule-based control strategy.

Specifically, the output signal m_{pp} of the developed control action $f_{control}$ is evaluated through the following input signals:

$$m_{pp} = f_{control}(Q_{field}, T_{out,sf}, T_{out,client}, T_{out,sf,obj}) \quad \text{Eq. (22)}$$

where Q_{field} and $T_{out,sf}$, the feedback input signals of the controller, respectively represent the solar field thermal production and the outlet temperature of the working fluid; $T_{out,client}$ is the feedback signal of the temperature reached by the fluid returning from the heat exchange with the district heating network; $T_{out,sf,obj}$ is the set-point fluid temperature at the outlet of the solar field. Therefore, the output signal m_{pp} is evaluated in proportion to the error signal e ,

that estimates how far the temperature $T_{out,sf}$ is moving away from the desired value $T_{out,sf,obj}$, and the proportional constant K is tuned in the function of thermal power output Q_{field} and temperature $T_{out,client}$:

$$\begin{cases} K = f(Q_{field}, T_{out,client}) \\ e = T_{out,sf} - T_{out,sf,obj} \end{cases} \rightarrow m_{pp} = K \cdot e \quad \text{Eq. (23)}$$

Then, the actual solar field mass flow rate m_{sf} is adjusted accordingly to the regulation levels that can be reached by the existing pumping unit of the circuit.

4.3.2 MPC control strategy

Besides standard rule-based control logic, the developed tool embeds also novel Model-based predictive control (MPC). Specifically, an MPC strategy describes a set of advanced control methods which make use of a process model to predict the future behaviour of the controlled system [226], and determines the control laws by solving a - potentially constrained - optimization problem. To apply a predictive control strategy, it is necessary to simulate the performance of the real system through the development of an appropriate physical model. In this context, the previously presented dynamic simulation tool of large solar fields for district heating applications can be successfully adopted for this aim, being capable to make an accurate prediction of the system behaviour. A schematic diagram showing the structure of the implemented MPC strategy, developed by using Matlab libraries, is shown in Figure 39. Specifically, the previously described solar field dynamic simulation tool allows for an accurate prediction of the system behaviour by precisely estimating the state variables x_{sf} and the system outputs y_{sf} .

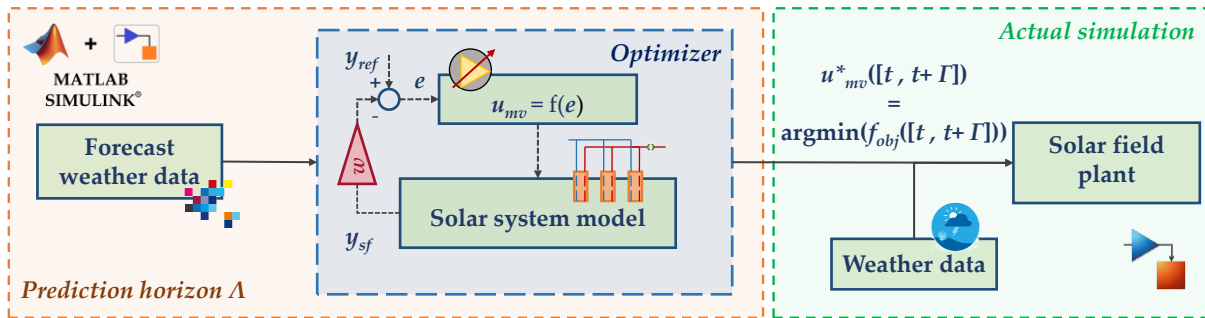


Figure 39. Scheme of MPC control strategy.

The disturbances acting on the model during the prediction horizon Δ (external air temperature, T_{air} , and incident solar radiation, I_{tot}) are estimated to predict the system behaviour and thus manipulate the control inputs u_{mv} optimizing its energy performance. The state variables x_{sf} that characterize the system (temperature and pressure at the inlet and outlet of each component of the solar circuit) are estimated through the physical model

alongside the control horizon Γ , while the values that the state variables x_{sf} assume at the beginning of a new prediction horizon Λ are equal to the real ones measured on the plant at the end of the previously control horizon Γ . In the case of large solar systems, the manipulated variables u_{mv} are represented by the mass flow rate circulating in the solar field hydraulic circuit (m_{sf}) and by collectors' tilt angle (θ_{coll}) in the case of those solar fields equipped with automatic solar tracking systems. The system outputs y_{sf} are the temperatures leaving the solar field $T_{out,sf}$ and the outlet temperature from the heat exchanger $T_{out,client}$. The reference conditions compared to the outputs y_{sf} are determined according to the technological limits and the users' demands. The optimizer of the model, which returns the manipulated variable u_{mv} in output, has been customized according to the objective functions and the control inputs. Furthermore, it has been adopted the auto-tuning of the weights w (parameter necessary to perform the model optimization procedure as reported in Figure 39). Finally, an input control variable is returned in the control horizon Γ which, together with the measured disturbances (real climatic data of the area of interest) determines the real behaviour of the plant.

4.3.3 Optimisation problem

This section describes the main aspects of the optimization processes used for MPC strategies. Specifically, in this work two different optimizers have been investigated, one adopted for the cases in which the manipulated variable u_{mv} to be controlled is represented by the mass flowrate only (m_{sf}), and the other in the case of multi-input (i.e., mass flowrate m_{sf} and inclination angle of the collectors θ_{coll}). In the first case, the optimizer performs a brute-force search to determine the optimal mass flow rate profile m_{sf}^* that minimizes the objective function in the prediction horizon Λ . This exhaustive search is performed as m_{sf} varies in the range imposed by the minimum and maximum constraints. The objective function is aimed at minimizing the costs C_{sf} for the operation of the plant, and is described by the following equation:

$$\min_{m_{sf}} C_{sf} = \int_t^{t+\Lambda} \frac{m_{sf}}{\rho_{fluid}} \times \Delta p_{sf} \cdot \lambda_{el} dt - \int_t^{t+\Lambda} m_{client} \cdot c_p \cdot (T_{in,client} - T_{out,client}) \cdot \gamma_{th} dt$$

$$\begin{cases} m_{sf,min} \leq m_{sf} \leq m_{sf,max} \\ T_{in,client,min} \leq T_{in,client} \leq T_{in,client,max} \\ T_{out,client,min} \leq T_{out,client} \leq T_{out,client,max} \end{cases} \quad \text{Eq. (24)}$$

The first term of the equation represents the operating costs for the pumping unit, whereas the second term is the revenues related to the solar field thermal production. Where Δp_{sf} is the pressure drops of the solar field hydronic circuit, c_p is the specific heat at constant pressure, and λ_{el} , γ_{th} are respectively the unitary costs of electrical energy and unitary selling

price of thermal energy to the district heating users. In addition, the constraints for the manipulated variable m_{sf} and for the time-varying system parameters of the fluid temperatures ($T_{in,client}$ and $T_{out,client}$) at the heat exchanger with the district user are also reported.

The second optimizer is based on game theory, the structure is that of a normal form game Ψ with the number of players (i.e., decision-makers) set equal to the number of variables to control u_{mv} . The strategies X_{i-th} that can be chosen by each player correspond to the set of values that can be assumed by each manipulated variable based on the fixed minimum and maximum constraints. The objective of payoff functions $f_{obj,i-th}$ will be as many as the number of players. Below are the equations of the objective functions $f_{obj,i-th}$ chosen in this case and the respective sets of strategies X_{i-th} that can be chosen by each player P_{i-th} .

$$\begin{aligned}\Psi &= \langle X_1, X_2; f_{obj_1}, f_{obj_2} \rangle \\ X_1 &= \{m_{sf,min} \leq m_{sf} \leq m_{sf,max}\}; X_2 = \{\theta_{coll,min} \leq \theta_{coll} \leq \theta_{coll,max}\} \\ f_{obj_1} &= \frac{m_{sf}}{\rho_{fluid}} \times \Delta p_{sf}; f_{obj_2} = m_{client} \cdot c_p \cdot (T_{in,client} - T_{out,client})\end{aligned}\quad \text{Eq. (25)}$$

Subsequently, the optimizer acts in such a way as to identify for each sampling time the “best reply” B_{i-th} of each player by fixing the choice of strategy of the other.

$$\begin{aligned}B_1(\bar{\theta}_{coll}) &= \left\{ \min_{m_{sf} \in X_1} f_{obj_1}; \forall \theta_{coll} \in X_2 \right\}; B_2(\bar{m}_{sf}) = \left\{ \max_{\theta_{coll} \in X_2} f_{obj_2}; \forall m_{sf} \in X_1 \right\} \\ NE(t_s) &= \{B_1(\bar{\theta}_{coll}, t_s); B_2(\bar{m}_{sf}, t_s)\}\end{aligned}\quad \text{Eq. (26)}$$

The intersection of the sets characterized by the best reply of each player for every sample time t_s determine the Nash Equilibrium (NE) point which will be of the Pareto dominated or Pareto efficiency type. When it will not be possible to identify a point of NE, the optimizer will choose as a solution the combination of optimal manipulated variables ($m_{sf,opt}$, $\theta_{coll,opt}$) of the dominant type guaranteeing the maximum payoff of the second objective function f_{obj2} .

4.4 Proof of concept analysis

To exhibit the potential of the proposed method and the capabilities of the developed simulation tool a proof-of-concept analysis has been carried out. Specifically, it refers to the District Heating system (DH) serving the city of Geneva, Switzerland, and operated by the company SIG (Services Industriels de Genève). The network, characterized by supply and return temperatures around 110°C/70°C, supplies 214 substations, for a total of 60.000

customers. Specifically, nearly two-thirds of the building surface is allocated to residential use, whereas the remaining part is used for office and commercial activities. In this context, 19% of the residential building stock consists of single-family dwellings, 4% of two-family dwellings, and 77% of buildings with at least three residences. The chosen network can currently supply up to 360 GWh/y, with 70% coming from fossil fuel sources. The rest comes from industrial thermal waste, biomass, and (to a lesser extent) solar-based thermal fields. In this context, the goal of the analysis is to verify the potential of the proposed method to increase the renewable energy share of the investigated DH network by optimising the solar thermal fields that supply it. For sake of brevity, only one field is considered and optimized. However, the same procedure can be easily extended to the other fields within the network. Specifically, the field chosen, shown in Figure 40, is the SIG SolarCAD II that supplies the SIG DH network in Geneva, and located at 46.21°N and 6.10E. The field is made of 400 cutting-edge evacuated flat plate collectors, arranged in 50 parallel strings with an inclination of 35°, covering a net field area of 784 m², with a global installed power of 222 kW, and using a mixture of water 80% and glycol 20% as working fluid (Table 9).



Figure 40. Existing Geneva solar field.

Table 9. Solar field parameters.

Solar field information					
N_{coll}	[-]	400	$UA_{dry-cooler}$	[kW/K]	21.7
Strings	[-]	50	$T_{in,client}$	[°C]	70
A_{field}	[m ²]	784	$D_{pipe,circuit}$	[m]	0.076
$D_{pipe,coll}$	[m]	0.022	V_{vessel}	[l]	200
$L_{pipe,field}$	[m]	175	$p_{max,vessel}$	[bar]	16
$k_{pipe,is}$	[W/ (m·K)]	0.04	$m_{nom,pp}$	[kg/s]	3

It worth noticing that the installed collectors' typology is an innovative flat plate collector, capable to reach outlet temperature comparable to those of a concentrating one, called MT Power and produced by the company TVP Solar. Thanks to the patented technology, they can achieve and maintain high vacuum (from 10⁻⁴ to 10⁻⁹ mbar) in all operating conditions. This collector typically uses pressurized water (up to 16 bar) as operating fluid can reach temperatures up to 200 °C. The innovative collector efficiency curve, evaluated at a solar

radiation level of 1000 W/m^2 , and further technical details are respectively reported in Figure 41 and Table 10 (see also Solar Keymark data certificate N. 011-7S1890 F).

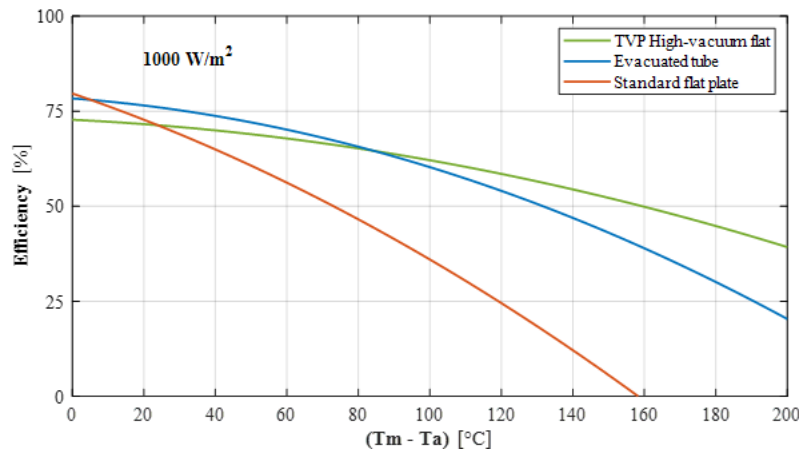


Figure 41. Innovative TVP solar MT Power collector efficiency curve vs. standard technologies.

Table 10. TVP solar MT Power vacuum collector characteristic.

Physical characteristics			
<i>A_{coll}</i>	[m ²]	1.96	
<i>weight</i>	[kg]	53	
<i>fluid_{vol}</i>	[l]	1.4	
<i>absorber</i>	[-]	Al sheet + Cu pipe	
<i>backplate</i>	[-]	AISI 441 stainless steel	
<i>glass coating</i>	[-]	Single-sided anti-reflective (interior face)	
<i>η_{optical}</i>	[-]	0.732	
<i>a₁</i>	[(K·m ²)/W]	0.504	
<i>a₂</i>	[(K ² ·m ²)/W]	0.006	
Operating conditions			
Stagnation	Max operating	Pressure	Vacuum
[°C]	[bar]	[bar]	[mbar]
302	16	0.014	2×10 ⁻⁸

It worth noticing that the adoption of these collectors represents an interesting innovation since this is a rare application of evacuated flat plate collectors supplying a DH network (usually relying on linear parabolic ones). Such occurrence has several advantages linked to lower dimensions and lower costs for maintenance while still guaranteeing high-temperature levels thanks to the exploitation of advanced vacuum technology. In addition, unlike concentrating devices, this collector is significantly less susceptible to dust accumulation and can be easily integrated into buildings, similar to any conventional flat-plate solar thermal collector. Finally, it converts both beam and diffuse radiation, contrary to

concentrating solar collectors, which only use beam radiation. Concerning the solar field layout, a schematic representation is shown in Figure 42. From the figure it is possible to notice that the solar system consists of: a pumping unit necessary to move the fluid and to overcome the pressure drops of the circuit; different safety devices such as check valves, ball valves, and expansion vessels to control fluid pressure levels; a dry-cooler for fluid heat dissipation to reduce the solar field outlet temperature when it reaches levels not technically admissible; and a counter-flow heat exchanger which supply thermal energy to the district heating network. It is important to note that, from an energy perspective, it would be preferable to use a thermal storage device instead of a dry cooler. However, this particular solar thermal field's architecture does not include such a component, and for sake of accuracy it has not been considered.

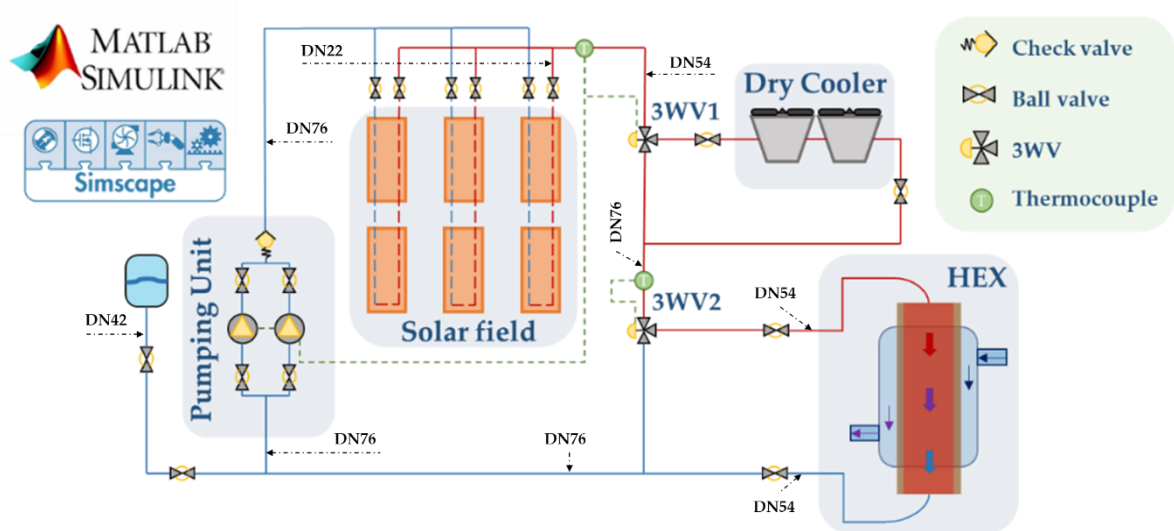


Figure 42. Schematic layout of the investigated solar field.

The described supplies to the user (i.e., district heating network) hot water at 90°C, with a temperature difference of 20°C, during the winter, and at 80°C, with a temperature difference of 10°C, during the summer. Concerning the control logic, currently, a rule-based approach is implemented. Specifically, when the measured incident solar radiation I_{tot} is greater than the threshold value $I_{tot,thr}$ (in this case equal to 212 W/m²) the control action (Rule-Based) regulates the start-up and the operation of a fixed speed pump. Concerning the operation modes, when the HTF temperature is lower than the minimum one required by the users the three-way valve (3WV2) supplying the Heat Exchangers (HEX) loop is closed (this is more common during winter operations). Thus, the HTF is recirculated in the solar field loop until it reaches the minimum supply temperature. When this condition is verified, the 3WV2 three-way valve opens, supplying the user with an HTF flow rate at the desired temperature. When the HTF temperature is higher than the maximum allowed one (in this case 100°C), more common during summer operations, the three-way valve (3WV1)

diverts the working fluid to a dry cooler. Once cooled, the HTF is sent through the second three-way valve (3WV2) to the client load Heat EXchanger (HEX). The described operating conditions are adopted during both summer and winter time (with different temperature thresholds and occurrences, as previously described). When the solar field is not able to satisfy these temperature levels, the district heating network request is met by DH auxiliary thermal sources. Note that the described field is considered as the Reference Scenario (RS) for the following analyses.

4.5 Experimental validation

To prove the reliability of the developed dynamic simulation tool, this has been validated against experimental data gathered from the previously described solar field during its real operation. The data are collected for a whole year, however only three sample winter (13th to 15th of February 2021) and three sample summer days (from 13th to 15th of June 2021) have been considered for the calibration. Specifically, the following variables are taken into account: the fluid temperature at the outlet of the solar field ($T_{sf,out}$), the fluid temperature back from the client load heat exchanger ($T_{client,out}$), the mass flow rate circulating in the hydronic circuit (m_{sf}), the mass flow rate sent to the user heat exchanger (m_{client}), the external air temperature (T_{env}), and the incident solar radiation (I_{tot}). The indexes adopted to quantitatively evaluate the goodness of fit between experimental and simulated data are the Mean Absolute Percentage Error (MAPE), and the R-squared (R^2), evaluated as follows:

$$MAPE = \frac{\sum (|y_{sim} - y_{exp}|) / y_{exp}}{N_{measures}} \times 100 \quad \text{Eq. (27)}$$

$$R^2 = \frac{\sum_{i=1}^N (y_{sim,i} - \text{mean}(y_{sim}))^2 - \sum_{i=1}^N (y_{sim,i} - a - b \cdot y_{exp,i})^2}{\sum_{i=1}^N (y_{sim,i} - \text{mean}(y_{sim}))^2} \quad \text{Eq. (28)}$$

where y_{sim} and y_{exp} are the simulated and experimental values, $N_{measures}$ is the number of measured samples, and $a_{reg,line}$ and $b_{reg,line}$ are the intercept and the angular coefficient of the regression line, respectively. Concerning the results of the calibration, these are presented in the following. Specifically, the comparison between experimental and simulated values of the temperature leaving the solar field ($T_{sf,out}$) and of the solar field mass flow rate (m_{sf}) are reported in Figure 43 and Figure 44 for the summer operations. Here, the time histories and the related errors are presented. From the figures it is possible to notice that very good agreements are almost always achieved. Specifically, concerning the temperature time histories, the greatest errors (still acceptable) occur in correspondence with the starting transients, whereas very good agreement is always achieved in the case of the flow rates.

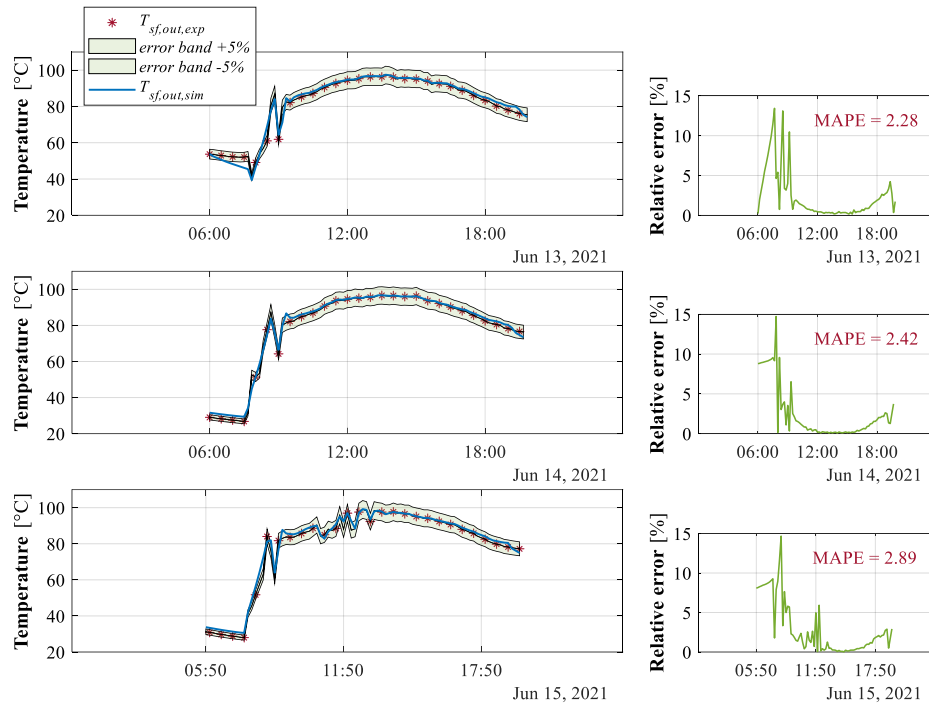


Figure 43. Validation results time histories and relative errors of $T_{sf,out}$ (from 13th to 15th of June).

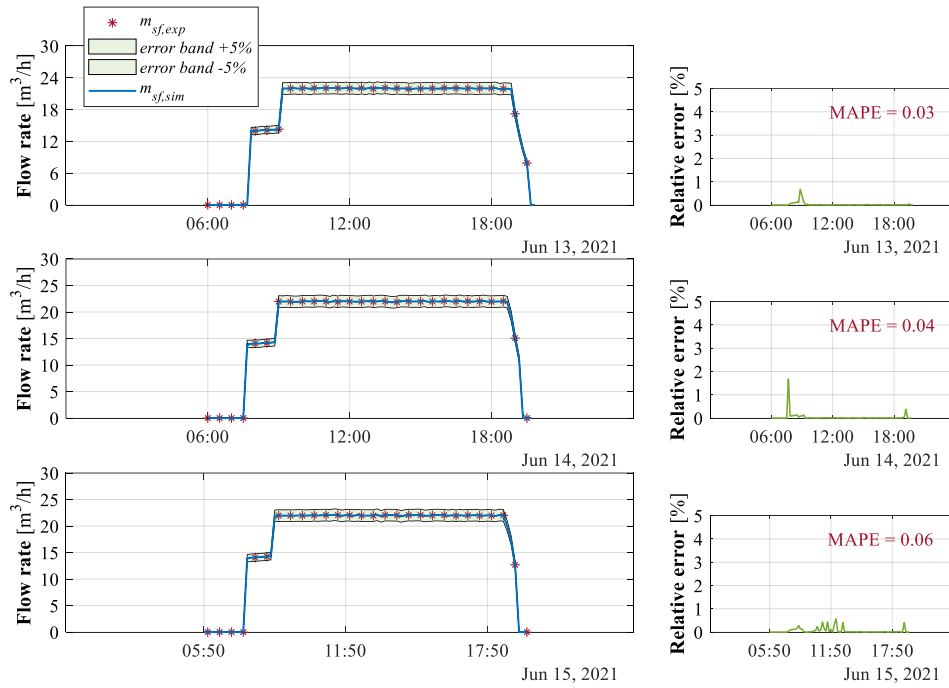


Figure 44. Validation results time histories and relative errors of m_{sf} (from 13th to 15th of June).

Finally, the complete calibration results are shown in Table 11, where the previously described indexes are presented for all the investigated parameters and all the considered days. From the table it is possible to notice that excellent agreements are achieved. Thus, from the previously shown time histories comparison, and the results presented in Table 11, it is possible to consider the developed tool as validated and reliable to be adopted for further analyses.

Table 11. Validation indices of all the investigated parameters for all the sample days.

	$T_{sf,out}$		$T_{client,out}$		m_{sf}		m_{client}	
	MAPE	R^2	MAPE	R^2	MAPE	R^2	MAPE	R^2
June 13th	2.28	0.981	1.37	0.997	0.03	0.998	0.93	0.998
June 14th	2.42	0.992	1.72	0.995	0.04	0.997	0.93	0.997
June 15th	2.89	0.987	1.93	0.993	0.06	0.996	0.96	0.996
February 13th	3.12	0.966	2.87	0.989	0.09	0.990	1.20	0.990
February 14th	3.23	0.959	2.83	0.991	0.11	0.992	1.17	0.992
February 15th	3.18	0.962	3.08	0.989	0.13	0.991	1.19	0.991

4.6 Results proposed scenarios

Once the reliability of the tool has been demonstrated, to prove its capabilities and to test the potential energy, economic, and environmental benefits achievable by adopting the proposed method, suitable enhancements to the previously described solar field have been investigated. Specifically, three different control logics have been investigated:

- **Proposed Scenario 1 (PS1):** adoption of a Rule Based (RB) control strategy which, unlike the current state, regulates a variable speed pump. In this case, the existing fixed speed pump is replaced with a variable one. It is worth noticing that this proposed scenario, even if representing an enhancement when compared to the reference system, it is a well-known and largely adopted solution, and it is investigated for the sake of completeness and to allow for a more exhaustive comparison between standard Rule-Based and innovative MPC control strategies.
- **Proposed Scenario 2 (PS2):** adoption of an MPC control strategy regulating the flow rate circulating in the solar field m_{sf} ,
- **Proposed Scenario 3 (PS3):** adoption of an MPC control strategy with a bi-objective optimization problem, solved with the game theory approach, which regulates the flow rate circulating in the solar field m_{sf} and the tilt angle of the solar collector surface θ_{coll} . In this case, a modification of the collectors' stands is required.

For each proposed scenario, the related impact on the solar field's energy performances is investigated in terms of both thermal power and yearly energy yield. It is worth noting that,

due to the features of the developed tool, aspects related to the hydraulic behaviour of the system, which is significant for large solar fields, will be taken into account. In the following, all the achieved results will be discussed in detail for each proposed system.

4.6.1 Proposed scenario 1 (PS1)

In this scenario (*PS1*), as for the existing field (*RS*), a standard rule-based control is adopted. However, differently from *RS*, a variable speed pump is considered instead of a fixed speed one. Specifically, when the incident solar radiation I_{tot} is greater than the threshold value $I_{tot,thr}$ (in case of the existing field equal to 212 W/m^2) the control action regulates the start-up and the operation of a variable speed pump. Thanks to the adoption of a variable speed pump, the flow rate of the solar field m_{sf} is continually controlled to meet the set-points temperature $T_{sf,out,obj}$ (respectively equal to 80 and 90°C during summer and winter). In such a way, the solar field flow rate m_{sf} can assume all the values included in the range of the minimum and the maximum mass flowrate that the pump can process ($m_{sf,min}$ and $m_{sf,max}$ are respectively equal to 14 and $21.35 \text{ m}^3/\text{h}$). To show the dynamicity of the flow rate achieved by adopting the proposed control logic, the related time histories are reported, along with the incident solar radiation ones, in Figure 45 for the three summer days considered (from the 13th to the 15th of June).

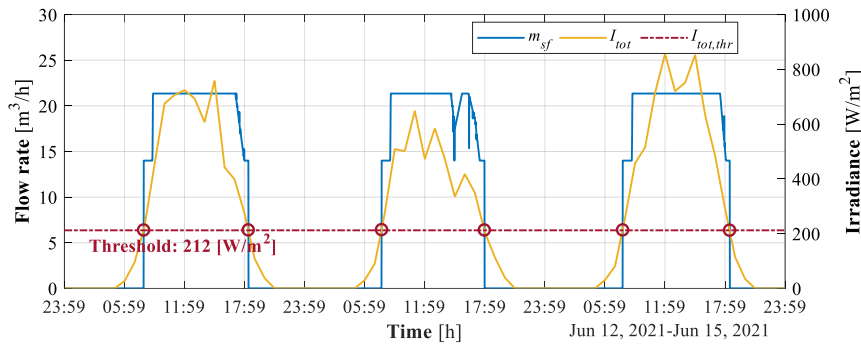


Figure 45. PS1: rule-based control strategy of m_{sf} (from the 13th to the 15th of June).

From the figure, it is possible to notice that the control strategy has been correctly implemented since the flow rate m_{sf} (blue line in Figure 45) is activated when the solar radiation I_{tot} (yellow line in Figure 45) exceeds the threshold value of 212 W/m^2 (dotted red line in Figure 45). In addition, the flow rate time histories (especially in the second part of each day) prove the ability of the software to simulate the different regulation levels of the variable speed pump (it is possible to notice that the flow rate is continuously controlled, especially when solar radiation is low). Concerning the thermal power produced and supplied to the users (Q_{client}) this is shown in Figure 46 where the related time histories are reported.

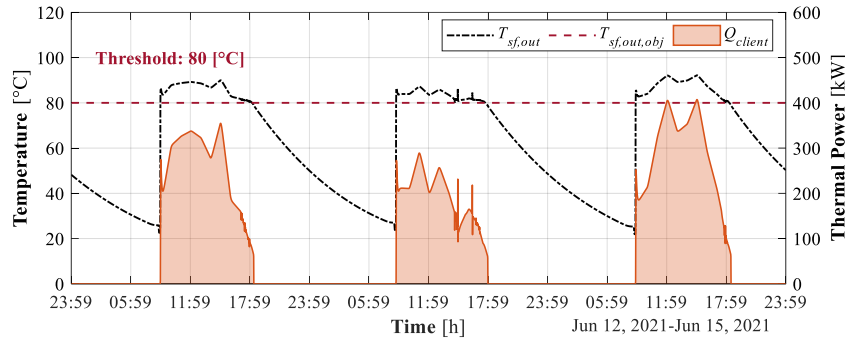


Figure 46. PS1: thermal power supplied to load (from the 13th to the 15th of June).

From the figure it is possible to notice that, as expected, the thermal energy supplied to the district heating network (orange area in Figure 46) is equal to zero when the temperature of the fluid at the outlet of the collectors ($T_{sf,out}$ – dotted black line in Figure 46) is below the summer threshold value ($T_{sf,out,obj}$ – dotted red line in Figure 46). Furthermore, from the $T_{sf,out}$ trend it is possible to notice that the adoption of the variable speed pump, with the consequent regulation of the flow rate (Figure 45), helps in reaching the desired thermal levels even when the disturbances (I_{tot} solar radiation) acting on the system are adverse. Finally, to show the capabilities of the developed simulation tool, also the circuit pressure drops, and the pump mechanical power are evaluated. Specifically, in Figure 47 the pressure drops time histories (blue dotted lines in Figure 47) and the related mechanical power expended by the pumping system (green areas in Figure 47) are reported for the three investigated days.

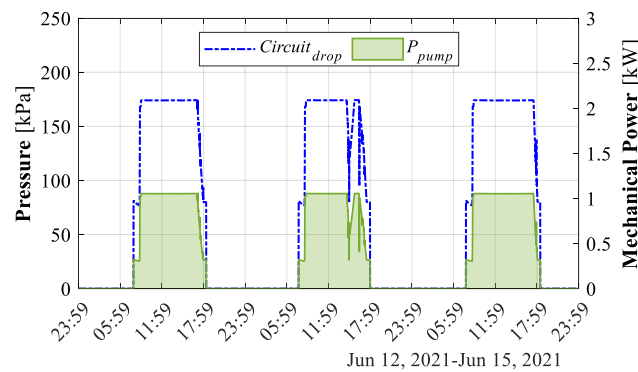


Figure 47. PS1: pressure drops and pump power (from the 13th to the 15th of June).

4.6.2 Proposed scenario 2 (PS2)

As in the case of proposed scenario 1 (*PS1*), also for proposed scenario 2 (*PS2*) a variable speed pump is considered. However, instead of a rule-based control logic, built on a threshold value of the incident solar radiation I_{tot} , an MPC control strategy to regulate the flow rate circulating in the solar field m_{sf} is adopted. Note that in this case no threshold value for the solar radiation is considered. Utilizing an MPC control logic can reduce the impact of random climatic disturbances on the energy yield of the solar field, thereby optimising energy performance. Specifically, in the case of the investigated proposed scenario (*PS2*), the following temporal conditions are considered for the MPC: i) the sampling time t_s was set equal to 10 min, which is the same timestep adopted for the real field data logging; ii) the prediction horizon Λ is equal to 24 hours, due to the higher reliability of forecasted meteorological data in this time frame; iii) the control horizon Γ is set equal to 2.5 hours – in order to guarantee robustness to the control action. It is worth noticing that as forecasted weather data (prediction horizon), Meteonorm climate file have been used. Conversely, to assess the performance of the field (control horizon) the real weather data gathered during the year 2021 have been adopted. Concerning the optimizer (objective function C_{sf}) the purchasing costs of electricity λ_{el} and the selling price of thermal energy γ_{th} were set equal to 0.30 Euro/kWh_{el} [227] and 0.04 Euro/kW_{th} [228], respectively. The resulting economic, thermal, and hydraulic outcomes for Proposed Scenario 2 (*PS2*) are illustrated in Figure 48 in the case of two sample summer days (13th and 14th of June). In the figures, the first day (13th of June, left of the grey dividing line) refers to the results obtained by simulating the solar field with the actual weather data (measured values during the year 2021) and using the flow rate profile $m_{sf,opt}$ optimized during the previous prediction time interval (here not shown). Conversely, the second day (14th of June, right of the grey dividing line), shows the flow rate, and the related thermal and mechanical power, predicted during the prediction horizon by using the Meteonorm climate data. More precisely, Figure 48a shows the time histories of the predicted (Meteonorm) and actual (measured) climatic data, Figure 48b reports the optimal and expected economic cash flow-rate, Figure 48c presents the optimal and expected mass flow rates m_{sf} and the associated pump energy consumption E_{pump} , whereas Figure 48d reports the time histories of the optimal and expected thermal energy supplied to the users. Specifically, the pump operation shown in Figure 48c, and the resultant produced thermal power (Figure 48d), are obtained by solving the optimizer C_{sf} for the highest cash-flow possible on daily basis (Figure 48b).

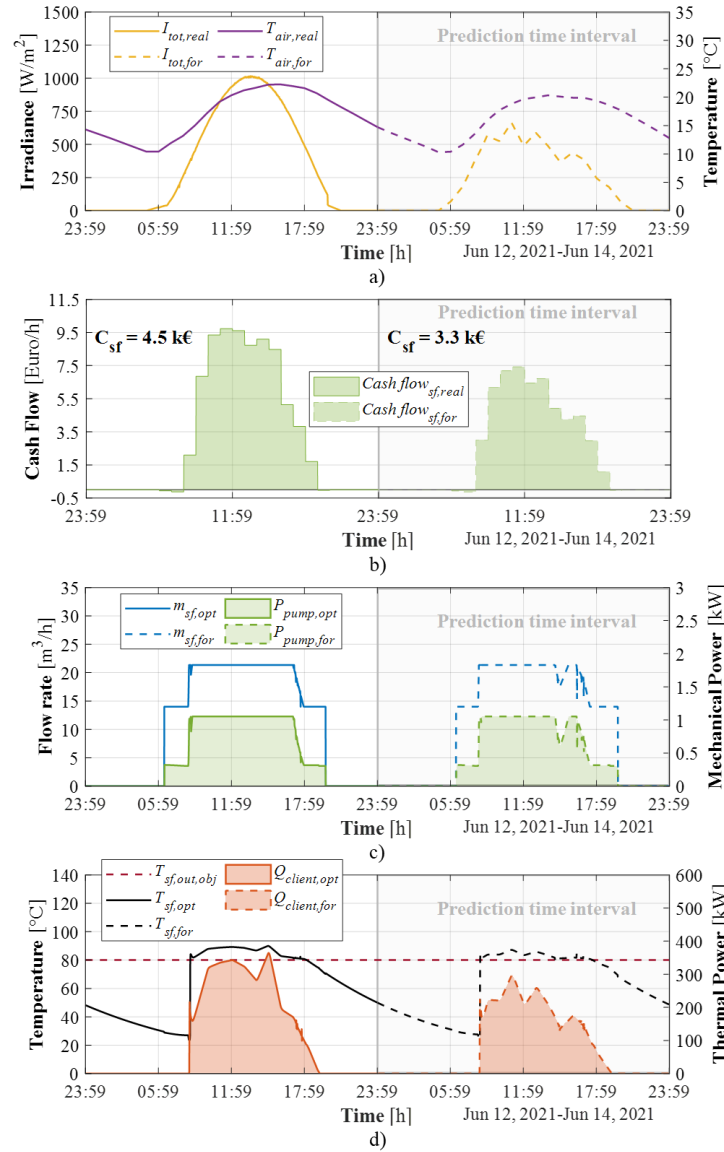


Figure 48. PS2: a) actual and foreseen weather data, b) optimised and foreseen economic results, c) optimised and foreseen mass flowrate, d) optimised and foreseen solar field output temperature - (13th and 14th June).

This is evaluated by solving Eq.(24) for the solution returning the best trade-off between thermal and pumping energy increase (Figure 48b). By comparing the results in Figure 48d (PS2) with those of Figure 46 (PS1), it is possible to notice that due to the elimination of the rule-based strategy, PS2 is capable of supplying users with thermal energy for an extended period of time than PS1, increasing the district heating renewable energy share.

4.6.3 Proposed scenario 3 (PS3)

In Proposed Scenario 3 (*PS3*) it is investigated the convenience of adopting, in addition to the variable speed pump (as in *PS1* and *PS2*), also a tracking mechanism to vary the inclination of the evacuated flat plate collectors. Specifically, the considered mechanism is a single axis system allowing for slope angles (θ_{coll}) variation. Since the control variables in this proposed scenario are two (solar field flow rate, m_{sf} , and collectors' inclination angle, θ_{coll}) a different MPC control strategy has been implemented. Specifically, the optimal combination of the two variables, u_{mv} , is determined through an optimization procedure based on game theory. The structure of the normal form game Ψ has been described in detail in the method section. In this case, the number of players P_{i-th} is equal to 2, as the number of variables to control; each P_{i-th} can choose a strategy among the sets of values that can be assumed by the variables u_{mv} . In particular, the variable m_{sf} for P_1 can assume values in the range of 14 and 21.35 m³/h with steps of 0.35 m³/h, while θ_{coll} for P_2 can assume values within the regulation range with steps of 1 deg. On the other hand, the time characteristics of the controller are the same as in the previous scenario. Concerning the payoff functions, these are reported in the method section. After determining the sets of solutions which for the first player minimize the energy required by the pump and for the second maximize the thermal yield of the solar field, the optimal combination will be determined through the Nash Equilibrium criterion. The results of the carried-out analysis are then presented in Figure 49 where the time histories of the manipulated variables and the system's outputs are presented for two sample summer days (13th and 14th of June). Similarly to *PS2*, the first 24 hours (13th of June - left of the grey dividing line) refer to the results of the solar field simulated with the actual measured weather data, and optimized as a combination of flow rate profile, $m_{sf,opt}$, and tilt inclination, $\theta_{coll,opt}$. Conversely, the following 24 hours (14th of June - right of the grey dividing line) indicate the prediction horizon Λ . Note that the time histories of the forecasted and actual climatic data are here not shown, being already reported in Figure 48a (since the weather condition are the same).

Concerning the investigated scenario results, the optimal and expected mass flow rates are reported, along with the pump's energy consumption, in Figure 49a. On the other hand, the thermal energy supplied to the DH network is shown in Figure 49b. Here it is possible to notice that *PS3* can provide thermal energy to the DH network users for a wider time interval with respect to previously investigated scenarios (*PS1* and *PS2*). This is possible thanks to the optimized tracking system (Figure 49c) which allows for the increase of the collected incident solar radiation favouring more efficient heating of the heat transfer fluid.

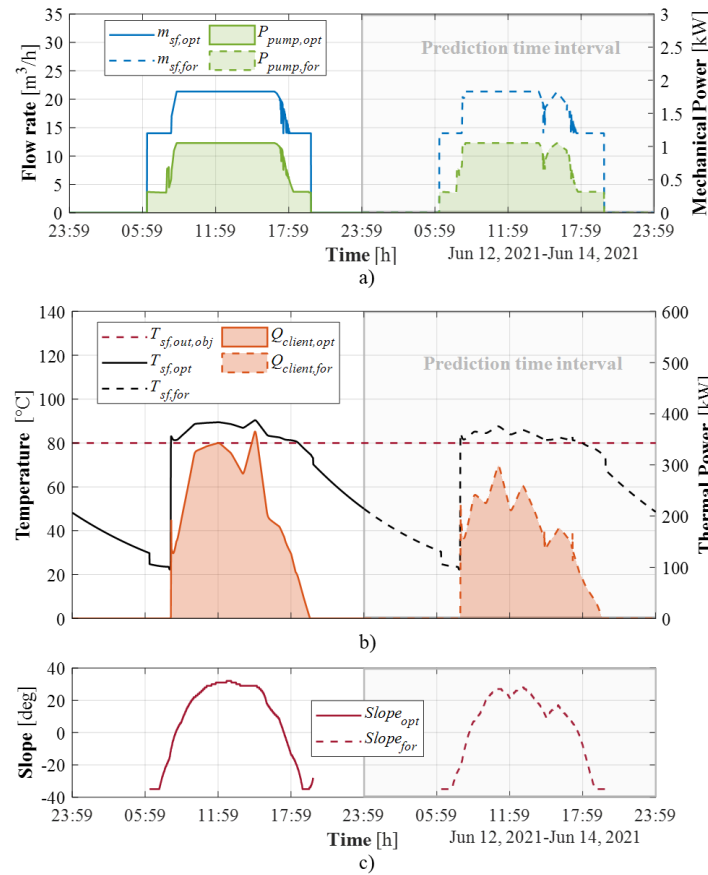


Figure 49. PS3: a) optimised and foreseen mass flowrate, b) optimised and foreseen solar field output temperature, c) optimised and foreseen tilt angle - (13th and 14th June).

4.6.4 Results comparison

In this section, a comparison is presented with the intent of highlighting the differences between the investigated case studies. In this framework, the thermal power, the elaborated flow rate, and the mechanical power time histories are reported in Figure 50.

Starting from the elaborated flow rate (Figure 50a) it is possible to notice that no remarkable variations can be detected between RS (solid blue line) and PS1 (dotted blue line). This is mainly due to the similar control logic adopted (Rule Based), and to the fact that the only difference between the two systems relies on the possibility of partializing the elaborated flow rate. In contrast, larger variations can be seen in the case of PS2 (red dotted line) and PS3 (orange dotted line), where the pump operates for a longer period of time. Such occurrence, most noticeable in the first and last hours of the day, is due to the MPC control logic forecasting the convenience of activating the pump before, and deactivating it after, the Rule-based original thresholds. This convenience can be seen in Figure 50b, which depicts the time histories of the thermal power supplied to the DH users. Here, no noticeable

difference exists between RS and PS1, whereas higher thermal power is provided by the adoption of PS2 and PS3. It is worth noticing that PS3 starts supplying thermal power to the district heating users before PS2 due to the sun tracking system. Finally, the mechanical power required by the pump system in case of all the investigated case studies is presented in Figure 50c. Here, following the results shown in Figure 20a, PS2 and PS3 require more mechanical power than PS1 and RS systems (that operate the pump for fewer hours). To determine the overall convenience of the proposed systems, a yearly based analysis is required.

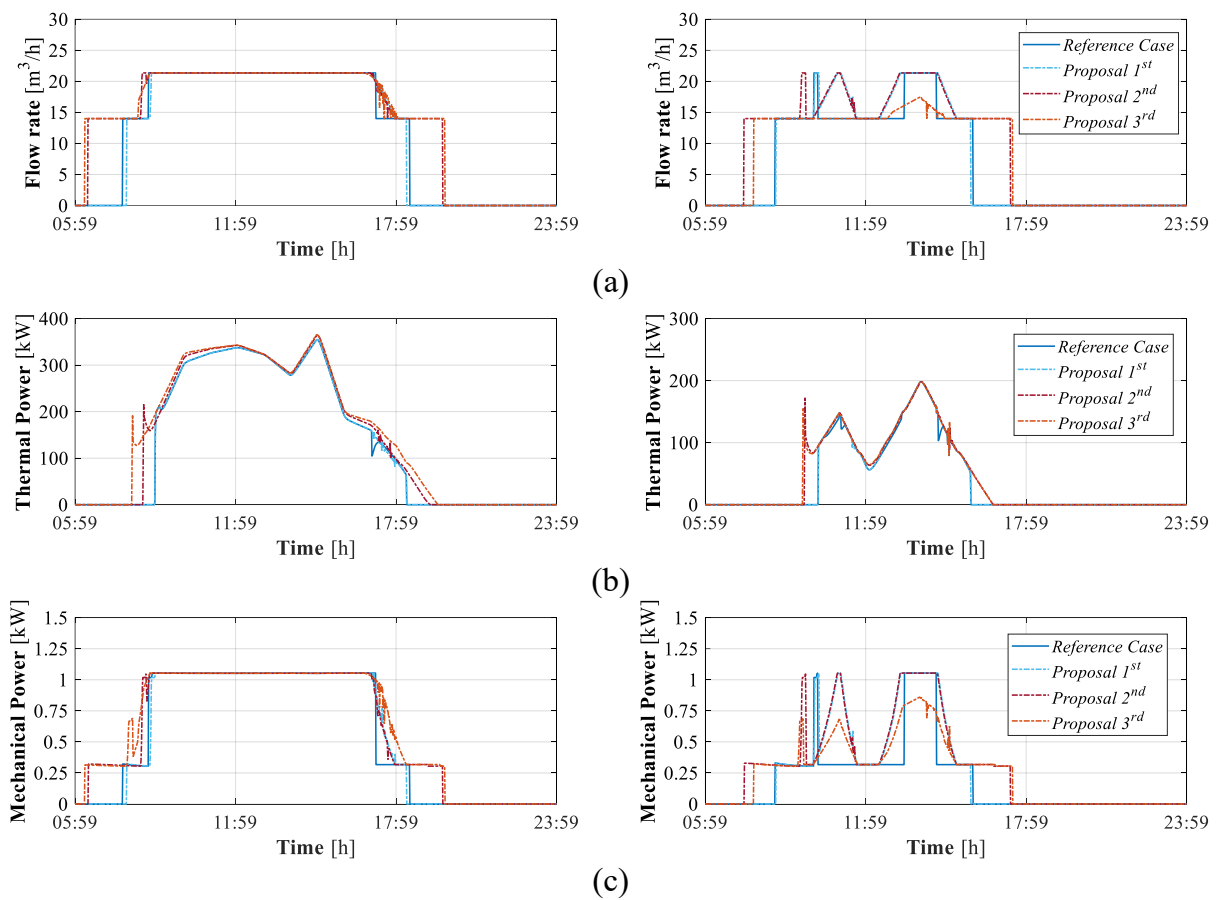


Figure 50. RS vs. PSs: a) flow rate, b) thermal power, c) mechanical power (13th February – left, and 13th June - right).

4.6.5 Yearly energy analysis

In the present section, the yearly results of the conducted analysis are reported and discussed. Specifically, to evaluate the impact of the proposed strategies on the energy supplied to the Geneva district heating network, a suitable comparison is made. Note that all the proposed scenarios require the replacement of the fixed-speed pumping unit with a

variable-speed one; the first proposed strategy (PS1) still adopts an RB control, while the second and third ones (PS2 and PS3) propose MPC control strategies. The third scenario, unlike the other two, proposes a further modification of the system by adopting a solar tracking mechanism; therefore, its control strategy differs from the second scenario due to the number of variables to control, and the adopted optimization procedure. Concerning the results, the monthly and annual thermal energy supplied by the plant to the DH network in case of *RS*, *PS1*, *PS2*, and *PS3* are reported in Figure 51, while Figure 52 shows the annual mechanical energy required to move the fluid in the hydraulic circuit.

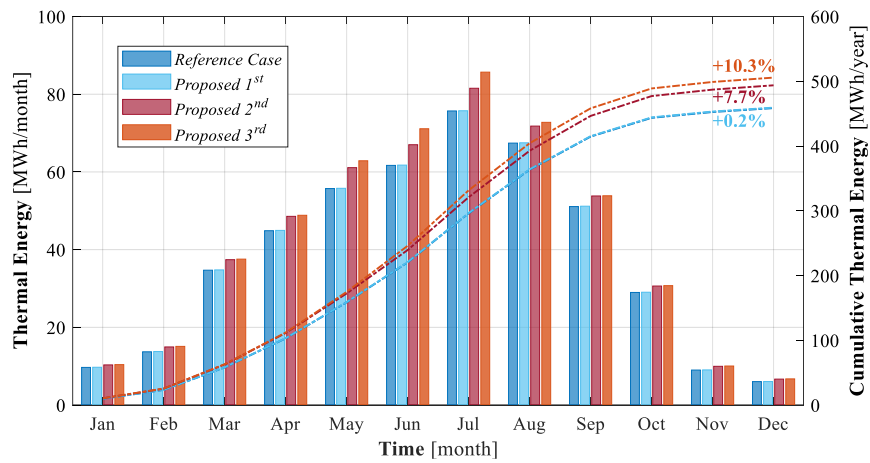


Figure 51. RS vs. PSs monthly and annual thermal energy supplied to the users.

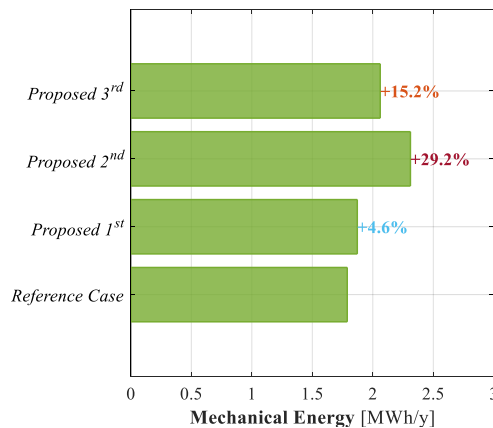


Figure 52. Annual mechanical energy of pump for reference and proposed scenarios.

From Figure 51 it is possible to notice that the first proposed scenario (*PS1* - light blue bars and dotted line) is not very profitable in terms of energy yield when compared to the reference case (only 0.2% thermal energy yield increase), especially considering that the energy expenditure of the pumping system is 4.5% higher (see Figure 52). Concerning the second scenario (*PS2* - red bars and dotted line in Figure 51) it is possible to notice that, by modifying the control strategy only, a significant benefit in terms of thermal energy yield is

detected (+7.7%). On the other hand, a 29.2% increase in the mechanical energy expended by the pumping system is also reported (see Figure 51). In terms of thermal energy yield, the third proposed scenario (PS3 - orange bars and dashed line in Figure 52) represents the optimal solution, giving the greatest increase in energy production (+10.3%). In addition, for PS3 the mechanical energy increase is less significant (equal to 15.2%) compared to PS2 thanks to the implementation of a bi-optimization procedure based on the Nash Equilibrium criterion. Moreover, it is worth noticing, from Figure 51, that the greater benefits obtained by applying the proposed strategies are always achieved during the months with elevated solar irradiation. This occurrence suggests that the same approach could return higher benefits if applied to different (hotter) climates. The overall benefits achievable by adopting of the proposed solutions are evaluated by estimating the Primary Energy Savings (PES) for all the investigated systems (PS1, PS2, and PS3 vs. RS). Specifically, since the Geneva district heating network still relies mainly on fossil based systems (e.g. gas fired heaters [229]) PES are calculated by assuming that the entire solar energy overproduction, achieved by applying the proposed solutions, represents an avoided gas consumption, as follows:

$$PES = \frac{\Delta E_{th}}{\eta_h} - \frac{\Delta E_{el}}{\eta_{el}} \quad \text{Eq. (29)}$$

here, ΔE_{th} is the higher thermal energy supplied to district heating users by the solar field, ΔE_{el} is the higher electricity required by the circulating pump, η_h is the gas fired heater efficiency (assumed equal to 0.9), and η_{el} is the Swiss national grid efficiency [230]. The results obtained by applying Eq. 15 to all the investigated case studies are presented in Figure 53.

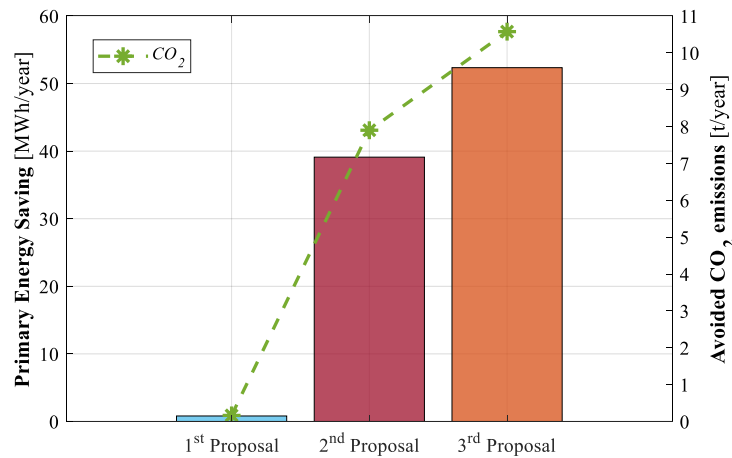


Figure 53. Primary energy savings and avoided CO₂ emissions for all the proposed solutions.

From Figure 53, it is possible to notice that the proposed solution 1 (*PS1*) returns almost negligible benefits ($<1\%$), whereas the proposed solutions 2 (*PS2*) and 3 (*PS3*) are characterized by higher energy and CO₂ emission savings (8 and 10% respectively), which are not negligible. The obtained results indicate that by adopting the proposed method to only one of the solar thermal fields supplying the Geneva district heating network, it is still possible to achieve interesting benefits. In addition, these results have been obtained by optimizing an existing field (thus, with certain constraints, such as the collector type, the layout of the system, etc.). Consequently, the proposed method can have a greater effect if it is applied to all solar thermal fields serving a given DH network, and/or if it is incorporated into the design process at the very beginning, representing an interesting option for the development of future solar-assisted DH networks.

4.7 Conclusions

Due to the decrease in working fluid temperature, large solar thermal fields will be significantly more utilised in future renewable-based poly-generative district heating networks. Therefore, optimising the design and operation of each solar field servicing a specific network will be crucial to improving its overall performance. In this context, the objective of the current research is to develop a method to maximise the performance of solar-assisted poly-generative district heating networks by optimising each associated solar system separately. To this aim, a flexible, yet detailed and powerful, dynamic simulation tool for solar thermal collector fields performance assessment and optimization has been developed in Matlab Simulink/Simscape environment. The developed tool, experimentally validated, is capable of estimating, in addition to the solar field thermal production, the energy consumption associated with the movement of the fluid, enabling a more precise optimization process. In order to demonstrate the viability of the proposed method and the capabilities of the developed simulation tool, a proof-of-concept analysis is conducted on an existing solar thermal field serving the Geneva district heating network. The following conclusions have been drawn from the analysis conducted:

- Adopting a variable-speed pump instead of a fixed-speed pump, along with a rule-based control strategy (*PS1* scenario), allows for a negligible thermal energy yield increase ($+0.2\%$). On the other hand, a 4.6% increase in the annual mechanical energy of pump occurs. Finally, almost no differences in terms of primary energy savings can be detected.
- The adoption of an MPC control strategy to regulate the flow rate circulating in the solar field (*PS2* scenario), thus overcoming the rule-based control logic, allows for a not negligible thermal energy yield increase ($+7.7\%$). Still, an increase of 29.2% in pump energy demand is detected. Still, interesting primary energy savings (up to 40 MWh/y) and avoided CO₂ emissions (up to 7 tCO₂/year) are obtained.

-
- By considering an MPC control strategy with a bi-objective optimization problem, solved with the game theory approach, which regulates the flow rate circulating in the solar field and the tilt angle of the solar collector surface (PS3 scenario), higher benefits are obtained. Specifically, primary energy savings and avoided CO₂ emissions respectively equal to 53 MWh/year and 10.9 tCO₂/year are observed.

Results indicate that even with only one solar thermal field considered, significant savings in primary energy (up to 10.3%) and avoided CO₂ emissions (up to 10.9 tCO₂/year) are possible for the entire district heating network. These outcomes prove the potential benefits achievable by adopting the proposed method and the capabilities of the developed optimization tool. Specifically, more significant outcomes can be achieved by adopting the suggested approach to all the solar thermal fields serving a certain DH network, and/or by optimizing the fields from the very early design stage.

Chapter 5

Optimisation of temperature management in 5th generation district heating and cooling systems

This chapter was previously published as:

A. Buonomano, C. Forzano, L. Mongibello, A. Palombo, G. Russo. (2024). Optimising low-temperature district heating networks: A simulation-based approach with experimental verification. *Energy*, 304, 131954.

Summary

Fifth-generation district heating and cooling (5GDHC) systems are increasingly popular for their ability to use low-temperature heat transfer fluids, facilitating more efficient renewable energy integration. However, unlocking their full potential demands both precise design and dynamic management. In this study, a novel dynamic simulation tool was developed specifically to optimize the design and operation of 5GDHC networks. This tool assesses the complex interactions within the system, capturing the effects of each building-plant system on the overall district water loop and evaluating various network configurations. The model's detailed thermohydraulic and thermophysical representations enable accurate simulation of heat pump and chiller operations, creating a holistic view of network performance. The tool was validated through comparisons with an experimental prototype network comprising a central heat pump and eight users. Subsequently, a proof-of-concept 5GDHC network was tested with an advanced predictive control strategy that dynamically adjusts the loop temperature to minimize network-wide energy demands. Results demonstrate primary energy savings of 10.3 MWh annually, underscoring the tool's effectiveness in managing 5GDHC systems for energy-efficient, sustainable urban heating and cooling solutions.

Keywords

District heating and cooling; low-temperature thermal network; fifth-generation of district heating; thermal network optimization; energy sharing.

Nomenclature

Acronymous

A	surface area [m^2]	P	electrical power [W]
C	thermal capacity [W/K]	p	pressure [Pa]
D	diameter [m]	Q	thermal power [W]
f	Darcy friction factor [-]	Re	Reynolds number [-]
h	heat transfer coefficient [$\text{W}/\text{m}^2\cdot\text{K}$]	T	temperature [K]
H	heat exchanger height [m]	t	time [s]
HEX	heat exchanger	u	internal energy [J/kg]
k	thermal conductivity [$\text{W}/(\text{m}\cdot\text{K})$]	UA	thermal conductance [W/K]
L	length [m]	V	volume [m^3]
m	flow rate [kg/s]	v	specific volume [m^3/kg]
NTU	number of transfer units [-]	w	velocity [m/s]

Greek letters

Δ	variation
ε	heat exchanger effectiveness [-]
η	energy efficiency [-]
ρ	density [kg/m^3]

Subscripts

co	critical	ref	refrigerant
$cons$	consumers	sh	<i>superheated</i>
DHC	district heating and cooling	sc	subcooled
ev	evaporator	v	vapour
liq	liquid	w	<i>water</i>
$pros$	<i>prosumers</i>	$2P$	<i>two phase</i>

5.1 Introduction

Low temperature district heating and cooling networks are considered an essential technology to reduce buildings' energy consumption, traditionally acknowledged as one of the primary contributors to greenhouse gas emissions [231]. In this framework, fifth Generation District heating and Cooling network (5GDHC), characterized by a very low thermal level of the heat transfer fluid, are increasing in popularity among researchers and practitioners. The concept of 5GDHC derives from Ground Source Heat Pump (GSHP) systems as well as Water Loop Heat Pump systems. The first is commonly used only for single buildings whereas the second is mainly widespread in commercial buildings when heating and cooling loads simultaneously occur [232]. The 5GDHC system is distinguished from the other generations by its decentralized thermal production, where each user is connected to the network via a heat pump, allowing for bidirectional thermal exchange [74]. Therefore, the piping network is often characterised by a two-pipes distribution, while three- or four-pipes designs are also employed in case of direct heat exchange with the user [233]. The temperature levels ease the integration of waste heat sources or renewable energy technologies. However, the resultant higher complexity of the network layout demands for an optimal management of these sources to simultaneously meet the users' comfort demands and energy efficiency potential [234]. Hence, distinct design approaches are needed for 5GDHC systems since their features change particularly from those of previous generation systems.[73].

5.1.1 5G district heating network modelling

As specified, 5GDHC require a fine design and a precise management to exploit their full potential. Consequently, modelling tools are essential for describing their configuration, choosing design parameters, and enhancing their management and performance [235] while favouring energy conservation, and putting control strategies into practise [236]. It worth noticing that the existing simulation tools, conceived for older generations, are not capable of correctly performing these tasks when 5th generation networks are investigated. In particular, the layout, thermal levels, and user bidirectionality of 5th generation systems demand for the development new modelling tool. These tools should account for the heat transfer fluid thermal inertia (which cannot be neglected because of the low temperatures and the absence of insulation on pipes [237]), should be able to determine the network's thermal loads to assess the potential for bidirectional exchange between a user and the network (eventually, by precisely estimating buildings thermal loads, dynamically [88]), and should accurately simulate the reversible heat pumps behaviours (by taking into account the type of heat pump, the thermodynamic properties of the refrigerant fluid, and its part-load behaviour [75]). In addition, accurate models for the central thermal station, or for the

decentralised renewable energy sources are also required [238]. In literature, diverse are the work proposing novel simulations tools for fifth generation district heating and cooling simulations, as reported in Table 12. In addition, in Table 12, the different works are categorised also based on their modelling approach (i.e., white-box, black-box, and grey-box). In this regard, it is worth noticing that simulations of network design and flexibility/peak-shaving are appropriate for white-box modelling. From the table it is possible to highlight the objectives and shortcomings of these works, with a focus on whether they consider crucial aspects for modelling 5G networks, such as:

- The hydraulic behaviour for network sizing.
- The thermal interaction of the network with the surrounding land, individual substations, and central stations.
- The thermal inertia of the network.
- The impact of buildings' thermal inertia on network users' thermal demands and overall energy performance.
- The modelling of heat pumps with a focus on their operational transients and their influence on network flexibility.

Table 12. 5GDHC network modelling approaches.

Reference	Modelling approach	Hydraulic behaviour	Thermal interaction	Network thermal inertia	Heat pumps transient operation	Buildings thermal inertia
Hirsch, H. and A. Nicolai [239]	White-box	✓	✓	×	×	×
Zheng, X., et al. [240]	White-box	✓	×	×	×	×
Bilardo, M., et al. [241]	White-box	✓	✓	✓	×	×
Hering, D., et al. [242]	Black-box	×	✓	×	✓	×
Reiners, T., et al. [243]	Black-box	✓	×	×	✓	×
Khosravi, A., et al. [244]	White-box	×	×	✓	✓	×
Wirtz, M., et al. [245]	Grey-box	✓	✓	✓	×	×

White-box modelling offers a transparent insight into the interactions among various components, providing a detailed understanding of system behaviour. This comprehension is essential for optimizing and fine-tuning system performance, serving as a robust tool for designing 5GDHC systems. The potential of employing this modelling type lies in its ability to meticulously examine various operating configurations, such as network temperature, and their impact on the actual energy performance of the entire system. Moreover, white-box models are often easier to validate and verify. Since they are based on well-known physical principles and system components, ensuring the model accurately mirrors real-world system behaviour is comparatively more manageable.

5.1.2 Optimisation and control strategies to improve efficiency

The use of thermal energy as an energy vector rather than electricity to satisfy the need for air conditioning in indoor spaces emphasises the robustness of district heating systems and their lower initial investment and ongoing operating costs [246]. Thanks to bidirectional low-temperature networks, this potential for energy and economic savings is further increased [247]. In addition, the operating temperature decrease enhances the adoption of multi-generative DH layouts using renewable energy sources (e.g., geothermal, biomass, solar based technologies, etc) [215], further boosting their sustainability [248]. Particularly, it is anticipated that large solar-based thermal power plants will be adopted more frequently for district heating applications and that solar sources will have a greater share in multi-generative 5DHC networks than traditional ones [249]. To enhance the utilization of solar energy in the global multi-generative system of low temperature district heating network, Seasonal thermal energy storage (STES) proves to be a viable solution [73], allowing for excess thermal energy to be stored during low demand and high production periods and used during peak demand of heating season [250]. Thus, STES can provide more flexibility in district heating systems by allowing for a more consistent supply of heat throughout the year, regardless of fluctuations in energy production or demand [200]. This can result in a more efficient and sustainable use of energy according to lower overall energy costs. In fact, by storing excess thermal energy generated by renewable sources, such as solar or geothermal, seasonal thermal storage can reduce reliance on fossil fuels and contribute to a more sustainable energy system [201]. The use of vapour compression heat pumps as systems for satisfying thermal demands additionally implies a significant process of electrification in the 5GDH networks. As a result, the possibility of utilising photovoltaic systems and wind turbines [251] by optimizing their sizes has been investigated in literature to ensure self-consumption to the network and providing for the possibility of integrating electrical storage systems to ensure greater flexibility [252]. In this context, it is worth noticing that supply temperature optimization in conventional district heating networks is a standard practise and has received substantial research in the literature. On the other hand,

no control strategy has been proposed for 5GDHC networks to optimize system performance and network temperatures. This represents a severe lack since 5GDHC systems' performance is significantly influenced by the network temperature [253]: high network temperatures in the summer cause unintended heat losses (excess waste heat may be dispersed for free), while low network temperatures in the winter reduce heat losses to a minimum. Moreover, heat pumps and chillers of buildings' users are significantly impacted by the network temperature in terms of their coefficient of performance (COP). It worth underlining that, since 5GDHC network can satisfy contemporary heating and cooling loads, the network temperature optimization represents a not easy task. In this framework, diverse are the works in literature dealing with the topic of 5GDHC network optimization, as synthesized in Table 13. Here, the optimized variables are listed by grouping them by category, by also citing the related work.

Table 13. 5GDHC network optimisation procedure.

Category	Optimization Procedure	Cited Work
Hydraulic and Network Design	Hydraulic sizing criteria for pipes	[254]
	Network topology and users' connection	[255]
	Coupling and sizing of energy systems within multi-generation plants	[256]
	Heat transfer fluid supply temperature	[245]
Global Pressure Drop Optimization	Optimal pipe sizing and supply temperature control	[257]
	Hydraulic control strategy for networks with multiple heat sources	[254]
DH Network Topology Optimization	Graph-based multi-objective genetic optimization algorithm	[258]
	Accurate estimation of thermal demands of buildings	[259]
	Optimization of network topology using minimal spanning tree heuristic method	[255]
Temperature Management and Control	Optimization of network temperatures, particularly for floating temperature levels	[260]
	Mixed integer linear programming (MILP) model for energy conversion and storage units	[261]
	Mathematical relationship between network temperature and heating/cooling needs	[262]
	Free-floating temperature control	[263]

With respect to the network temperature control strategies, these significantly influence the energy performance of 5GDHC systems. In particular, to ensure robust control over network temperature, selecting appropriate energy hub technologies becomes crucial, especially when dealing with fluctuating temperature levels [260]. An example is presented in the study reported in reference [261], where an optimization approach for the 5GDHC network's performance was proposed. This approach utilized a mixed integer linear programming (MILP) model, primarily focusing on optimizing the temperature of energy storage systems. The optimization aimed at enhancing the efficiency of users' heat pumps. However, in another article [262], a different network temperature control strategy was

introduced, establishing a correlation between the network temperature and individual users' heating and cooling demands. This strategy focused on maximizing the district heating system's efficiency in meeting user requests but did not consider its impact on the overall energy performance of the 5GDHC system. A floating temperature control method is presented in reference [263] proposing a straightforward yet reliable heuristic for temperature control approach. This method heats or cools the main fluid by an external source only when the network temperature is nearing predefined limits. However, this method does not address strategies to improve the efficiencies of the system's heat pumps. By focusing on the regulation and control of 5GDHC networks, the model predictive control (MPC) is often suggested as a key technique to optimize the energy performance of DH networks with relation to their control strategies [264]. The MPC potential is highlighted especially for 5GDHC that are heavily influenced by the unpredictable behaviour of renewable energy system and user thermal demands. Through the use of multi-objective optimization problems, the control variables are adjusted to maximise the system's flexibility, energy efficiency, and economic performance. In literature, the primary control variables are represented by water flow evolving in the network [242], flow rates of centralized or distributed thermal energy storage [265], the signals for the management of flexible (e.g., boilers, CHP, etc.), and non-flexible producers (e.g., photovoltaic, wind, etc.) [266]. In order to control a system, it is required to linearize the models that simulate its behaviour in order to reduce the computation needs. However, the MPC makes it feasible to retain a higher level of accuracy by not linearizing the behaviour of the model's component parts. For this reason, the necessity of developing accurate yet extremely flexible dynamic simulation models are connected to both the goals of designing, controlling, and optimizing the performance of 5GDHC systems.

5.1.3 Work contributions

Connecting consumers who have simultaneous thermal demands for heating and cooling is one of the primary features of 5GDHC systems. Network temperature is therefore an important variable for 5GDHC systems. The aim of this work is to demonstrate how significant energy savings for the entire DH system can be obtained by optimizing the temperature control of the network, when the users have simultaneous thermal needs. The multi-objective optimization has been performed maximizing the energy savings of the users of 5GDHC network, dynamically determining the loop's temperature that minimizes the objective functions using the maximum curvature point criterion. The main contribution and novelties of the work focuses on the following aspects:

- Development of a physical model that takes into account the heat dissipations of the network pipes with the ground, the thermal inertia of the heat transfer fluid, and the hydraulic aspects that influence the pressure drops.

- Modelling of the centralized thermal generation plant and of the heat pump systems of each user using a white-box approach, modelling the thermodynamic behaviour of each component, and taking into account the effects of their transients' operation on the thermodynamic quantities of interest of the 5GDHC network.
- Estimation of the thermal demands of buildings through a building energy simulation tool that considers the effects related to the thermal inertia of the building envelope and evaluates in detail the distribution of radiative heat fluxes through the glazed elements of the envelope.
- Calibration of the controllers, which regulate the operation of the centralized plant and of the distributed users' heat pumps, by considering the effects of disturbances related to the modelling integration with the DHC network and the buildings.

Finally, an energy comparison was conducted using a network temperature control strategy that fluctuated within a band of threshold values in order to assess the savings associated with the optimizer used for the network temperature management.

5.2 Methodology

To carry out the previously mentioned analysis, and to prove the convenience of the conceived method, a dynamic simulation tool has been developed. In particular, the developed tool must be flexible yet for designing and optimizing the energy performance of 5GDHC systems. It worth noticing that diverse are the 5GDHC network typologies, grouped on the basis of the network layout [247]:

- Direct cooling and heating with four-pipe network distribution; branch insulation; and energy stations for regulating the temperature of the heat transfer fluid.
- Indirect heating and cooling with two-pipe distribution, a lack of insulation to increase thermal interactions with the ground, energy substations positioned between the network and users, and energy stations for balancing heat flows.
- Hybrid systems with two or three pipes for distribution. They have the potential to directly meet the thermal needs of buildings in addition to the indirect arrangement.

The method presented in this work, and the developed dynamic simulation tool, are mainly conceived for indirect systems, which seem to be among the most advantageous given the ease of the network structure, the presence of substations, which ensure greater system flexibility, and a better achievement of customers' thermal needs. With respect to the developed dynamic simulation tool, the dynamic energy modelling of the buildings for thermal loads assessment, the thermodynamic modelling of the heat pumps, and the thermo-hydraulic effects resulting from the integration of these systems with the pipeline network are just a few of the factors that have been taken into account. The key aspects of the developed tool have been schematized in Figure 54. Starting from the users' thermal

load estimation, by using clustering criteria, district users are initially categorised according to the type of building and intended use. Consequently, an in-house building energy performance simulation (BEPS) tool [88] is used to evaluate the thermal energy demand on hourly basis, and their peak loads, using appropriate building archetypes. This simulation tool takes into account thermo-physical effects such as the attenuation and phase shift of the transmitted thermal power due to the inertia of the building envelope, the solar geometry which influences the radiative heat incomes, and the behaviour of the occupants which dynamically influences the internal heat inputs.

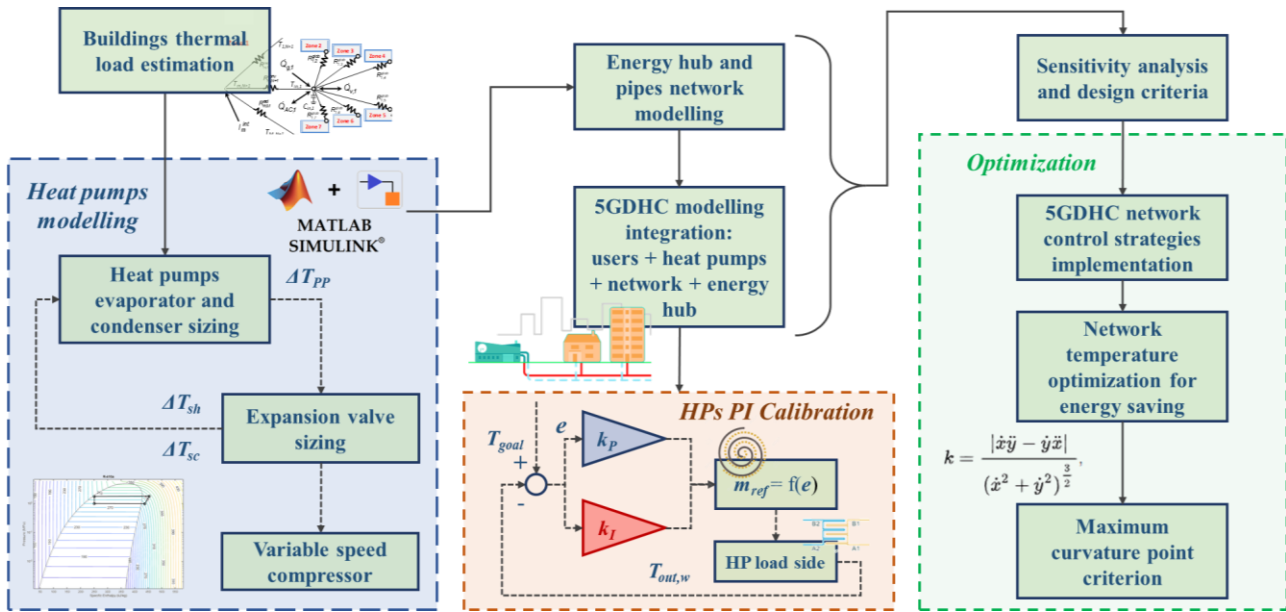


Figure 54. Overview of the developed tool for modelling and optimisation of 5GDHC systems.

The knowledge of the thermal load profiles of each user allows for the reversible heat pump (HPs) sizing. The detail modelling approach for the HPs' enables the use of control techniques, such as regulating the expansion valve opening or the compressor rpm, to simulate partial load operation and estimate the consequences of energy transients. Additionally, it is possible to assess the impact of different features (e.g., the refrigerant fluid, type of heat exchangers, type of compressor, geometric characteristics, etc.) on the energy efficiency of the HPs by carrying out sensitivity analysis. Subsequently, in order to size the energy hub used for the network's thermal balancing, a preliminary analysis is performed on the energy flows from the HPs' thermal sources serving the 5GDHC system's users. The distribution and morphology of the network, as well as a wide range of components (e.g., flow reducers, sharp bends, check valves, ball valves, expansion vessels, and pumping units), are all taken into account in the thermo-hydraulic modelling of the pipe loop. Furthermore, heat dissipations with the ground, pressure drops, and the thermal inertia of

the heat transfer fluid are estimated. The users' heat pumps systems are individually sized before being combined into a single thermo-hydraulic model, whose dynamic evolution is influenced by the one-to-one interactions of each phenomenon (i.e., thermal load fluctuation, network temperature fluctuation, and HP operation transients). As a result, it will be necessary to undertake a new tuning of the controllers to increase their robustness. Finally, as last step of the developed model, network operation optimization procedures are carried out to guarantee energy savings for the entire 5GDHC system. In particular, the Pareto front's optimal solutions for the investigated parameters, are then found using the maximum curvature criterion.

5.2.1 Heat pumps substations modelling

The components of the Simscape Fluid library (Matlab/Simulink) were used to perform the thermodynamic modelling of the substation HPs of the 5GDHC network's consumers. The characteristics of the software tool used enable a white-box modelling, which allows for a detailed analyses of the sizing and design of the individual thermodynamic components, while also supporting the development of standard and advanced control systems. The schematic representation of the electrical compression HPs is shown in the Figure 55.

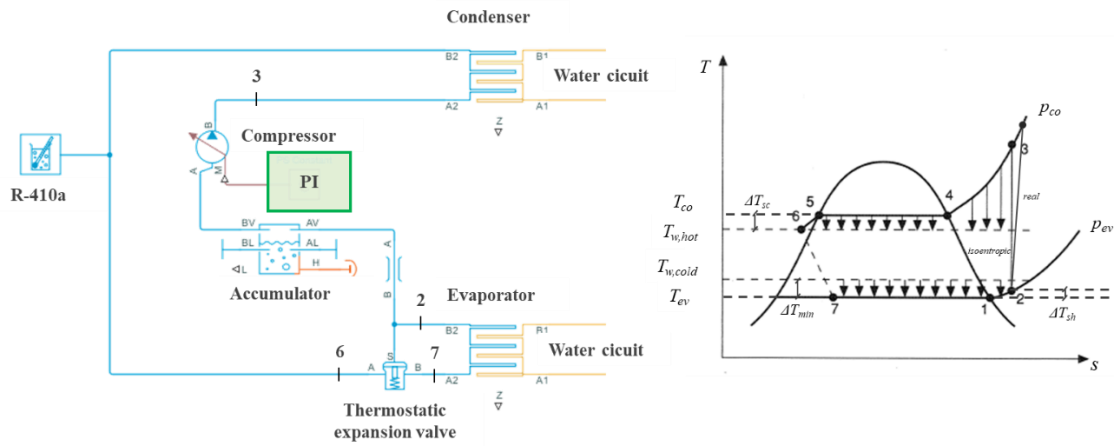


Figure 55. Heat pump layout schematisation and representation of T-s diagram.

It should be noted that the heat exchangers (evaporator and condenser) interact with the hydraulic circuit of the building's HVAC units, or the heat transfer fluid of the 5GDHC network depending on whether they act as load or source side of the HPs. It has additionally been contemplated the presence of an accumulator (as shown in Figure 55) positioned between the evaporator and the compressor to store the volume of refrigerant while HP operates at partial loads. With respect to the adopted modelling approach, each component of the heat pump (evaporator/condenser, thermostatic expansion valve, compressor, and control system) has been singularly and detailed modelled. However, for sake of brevity, the

adopted mathematical modelling is not reported, and detailed description of the heat pump components modelling can be checked in Simscape mathematical reference [267].

5.2.2 Central thermal station modelling

The 5GDHC network energy plant, which consists of a fuel boiler and a chiller respectively for heating and cooling the network's heat transfer fluid, is required to balance the heat flows and to control the network temperature. The building-plant model's dynamic simulation makes it possible to estimate the hourly profile of the thermal flows that each user directs to the network:

$$\begin{aligned} Q_{DHC, network}(t) &= \sum_{i=1}^{N_{b, cool}} Q_{ev, i}(t) \left(1 + \frac{1}{\eta_{HP, cool, i}(t)} \right) - \sum_{j=1}^{N_{b, heat}} Q_{co, j}(t) \left(1 - \frac{1}{\eta_{HP, heat, j}(t)} \right) \\ Q_{ch, nom} &= -\max(Q_{DHC, network}(t)) \\ Q_{fur, nom} &= -\min(Q_{DHC, network}(t)) \end{aligned} \quad \text{Eq. (1)}$$

Where $Q_{ch, nom}$ and $Q_{fur, nom}$ are the peak heat fluxes resulting from the dynamic simulation and used for sizing the chiller and the furnace, and $N_{b, cool}$ and $N_{b, heat}$ are respectively the number of buildings in the district that have cooling and heating requests. Similar to how the HPs were modelled in the earlier sections, the central plant chiller was also modelled. On the other hand, the estimation of the furnace's efficiency, which is dependent on the fuel type and partial load factor, forms the basis of the modelling:

$$\eta_{fur}(t) = f \left(fuel, \frac{Q_{DHC, network}(t)}{Q_{fur, nom}} \right) \quad \text{Eq. (2)}$$

Finally, it is reported the formula for calculating the primary energy used by the energy plant to balance the network's temperature:

$$PE_{hub} = \frac{Q_{ev, ch}}{\eta_{ch}} \eta_{el, grid} + \frac{m_{DHC, w} \cdot c_{p, w} (T_{DHC, set} - T_{DHC, in})}{\eta_{fur}} \quad \text{Eq. (3)}$$

It is important to note that the primary energy of the chiller (PE_{ch}) is correlated with the effectiveness of the electricity grid ($\eta_{el, grid}$), whereas the thermal power provided by the furnace is a function of the flow rate of water circulating in the network ($m_{DHC, w}$) and its set-point temperature ($T_{DHC, set}$) imposed by the examined operating strategy.

5.2.3 Pipes thermal network

Concerning the DHC thermal network, to accurately assess the thermodynamic behaviour of the heat transfer fluid along the piping network, each component must be

detailly modelled. In such a way it is possible to assess both the mechanical energy needed to move the fluid and the heat losses along the path. Concerning the pipe network, the distributed pressure drop is modelled with the hypothesis of an incompressible fluid, flow fully developed, and negligibility of gravity effect, through the following equations:

$$\Delta p_{pipe} = \begin{cases} \lambda_{pipe} \cdot u_{DHC,w} \times \left(\frac{L_{pipe} + L_{eq,pipe}}{2} \right) \times \frac{m_{DHC,w}}{2 \cdot D_{pipe}^2 \cdot S_{pipe}} & \text{if } Re < Re_l \\ f_{pipe} \times \left(\frac{L_{pipe} + L_{eq,pipe}}{2} \right) \times \frac{m_{DHC,w}^2}{2 \cdot \rho_{DHC,w} \cdot D_{pipe} S_{pipe}^2} & \text{if } Re \geq Re_t \end{cases} \quad \text{Eq. (4)}$$

where, λ_{pipe} is the pipe shape factor, $u_{DHC,w}$ is the kinematic viscosity of the thermal liquid in the pipe, L_{pipe} is the pipe length and influenced by the topology of district, $L_{eq,pipe}$ is the aggregate equivalent length of the local pipe resistances, D_{pipe} and S_{pipe} are the hydraulic diameter and pipe cross-sectional area, Re is the Reynold number of the flow, Re_l and Re_t are the Reynolds numbers which determine the flow transition from laminar to turbulent, and f_{pipe} is the Darcy friction factors. Concerning the concentrated pressure drops (i.e., flow reducers, sharp bends), these are evaluated through the Simscape Flow resistance (TL) component. Please note that besides the distributed and concentrated pressure drops, all the network hydraulic components are included in the model, such as check and ball valves, three-way valves, expansion vessels, heat exchangers, etc., but for sake of brevity they are not described here, and more information can be found in reference [https://it.mathworks.com/help/pdf_doc/hydro/index.html]. With respect to the thermal losses with the surrounding environment are estimated, for the same pipe length, through the energy conservation equation, as follows:

$$\rho_{DHC,w} \cdot V_{pipe} \cdot \frac{\partial u_{DHC,w}}{\partial t} = m_{DHC,w} c_{p,w} (T_{in,pipe} - T_{out,pipe}) + Q_{l,soil} \quad \text{Eq. (5)}$$

With

$$Q_{l,soil} = \frac{(D_{pipe,ext} - D_{pipe,in})}{k_{pipe} S_{lat,pipe}} \cdot (T_{soil} - T_{in,wall,pipe}) \quad \text{Eq. (6)}$$

Where, V_{pipe} , $S_{lat,pipe}$, and k_{pipe} are respectively the volume, lateral surface, and thermal conductivity of the pipe, $u_{DHC,w}$ is the internal energy of the heat transfer fluid, $Q_{l,soil}$ is the thermal lost with the surrounding ground, $T_{in,wall,pipe}$ is the pipe internal wall temperature, and T_{soil} is the soil temperature.

5.2.4 Optimisation problem

As previously mentioned, the thermal power exchanged at the load side of the substation ($Q_{HEX,load}$) has a significant impact on the delivery temperature of the water ($T_{load,w,out}$) to the heat exchange terminals of the user. On the other hand, changes in the building thermal load (Q_{HVAC}) have an impact on the return water temperature from the user ($T_{load,w,in}$). The pressure drops and heat dissipation of the network with the ground are related to the thermodynamic characteristics of the secondary fluid at the inlet of the HEX source side of the substations. The interaction between the substation and the building affects the heat flows exchanged by the HEX source side with the network return manifold, conditioning the temperature of the heat transfer fluid. Therefore, it is clear that the energy efficiency of substations and stations are dependent on the network temperature, which is a significant variable for 5GDHC systems. For this reason, this research presents an innovative optimization procedure with the aim of determine the optimal working temperature of the 5GDHC network. In particular, the developed optimization tool adopts a predictive strategy (with a prediction interval of Δt equal to twenty-four hours and a sampling time t_s of five minutes) that determines the value of the optimal temperature that minimizes the functions of a multi-objective problem. In particular, the HPs electricity consumption of prosumers ($E_{el,pros}$) and consumers ($E_{el,cons}$) are the investigated objective functions:

$$\begin{aligned} f_1 = f(T_{DHC}) = E_{el,pros} &= \int_t^{\Delta t} \sum_{i=1}^{N_{pros}} \frac{Q_{co,pros,i}(t)}{\eta_{HP,cool,i}(t)} dt \\ f_2 = f(T_{DHC}) = E_{el,cons} &= \int_t^{\Delta t} \sum_{j=1}^{N_{cons}} \frac{Q_{ev,cons,j}(t)}{\eta_{HP,heat,j}(t)} dt \end{aligned} \quad \text{Eq. (7)}$$

The intersection of the value ranges that ensure high HP efficiency during both winter and summer operation yields the definition set for the decision variable T_{DHC} . The maximum curvature point criterion is used to determine the best T_{DHC}^* value:

$$\begin{cases} T_{DHC}^* = \arg \max(\gamma) \\ \gamma = \frac{|\dot{f}_1 \ddot{f}_2 - \dot{f}_2 \ddot{f}_1|}{(\dot{f}_1^2 + \dot{f}_2^2)^{\frac{3}{2}}} \end{cases} \quad \text{Eq. (8)}$$

5.3 5GDHC model validation

For validation purposes, the developed dynamic simulation tool was adopted to simulate an existing 5GDHC prototype with the aim of comparing the obtained results to the

experimentally gathered data. Regarding the prototype, this is built at the Italian research centre ENEA (Figure 56, left), and its network layout is schematized in Figure 56, right.

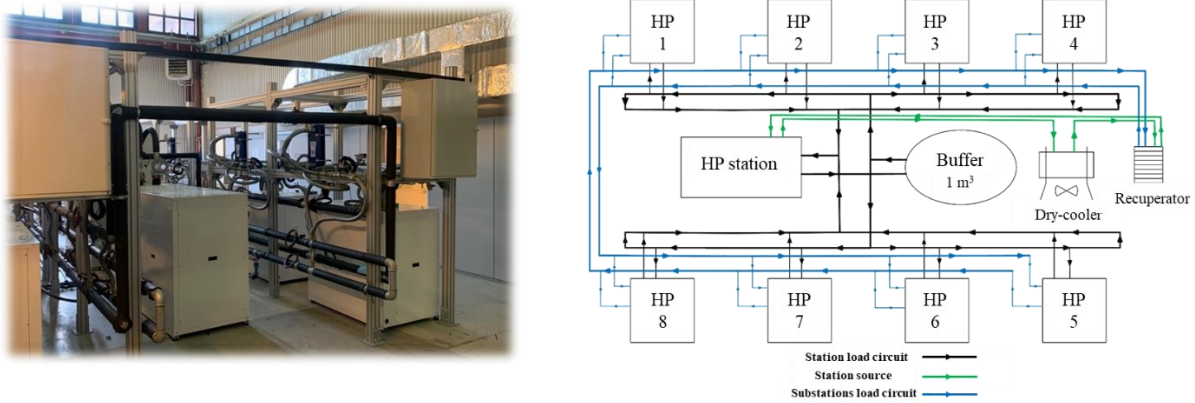


Figure 56. 5GDHC prototype developed at the ENEA research centre (left) and related system layout (right).

The system is made of eight substations, a station for balancing the heat flows from the HEX source of the HPs, and a water ring circuit appropriately insulated to avoid dispersions with the outside air. The prototype plant's key features are reported in the Table 14. The described set-up was adopted to conduct a test with the substations operating in cooling mode. In particular, during the test the central HP raises the network's set-point temperature by interacting with the condensers of the satellite HPs through the water ring's heat transfer fluid. A plate HEX recovers from the secondary fluid of the condenser of the central HP in order to simulate the thermal load on the substation evaporators. Finally, a dry cooler, positioned between the heat recovery unit and the plant condenser, ensures a modulation of the thermal substations' simulated load.

Table 14. 5GDHC network prototype characteristics.

Heat pumps					
Typology	$Q_{ev,nom}$	$P_{el,nom}$	EER	$m_{co,w}$	mev,w
[-]	[kW]	[kW]	[-]	[kg/h]	[kg/h]
Station	93.5	20	4.67	19330	16014
Substation	10.5	2.2	4.76	2178	1797
Recuperator HEX					
Typology	Flow arrangement	UA	$A_{th,exch}$	$Q_{HEX,nom}$	
[-]	[-]	[W/K]	[m²]	[kW]	
Plate	Counter flow	10034	2.2	84.2	
Network pipes					
Typology	D_{ext}		D_{int}		
[-]	[mm]		[mm]		
primary	41		33		
secondary	33		26.5		

The same test conducted with the experimental set-up is simulatively replicated with the developed dynamic simulation tool previously described. The model's accuracy is then verified by comparing the experimental data sampled during the test and the simulated ones, as reported in Figure 57. Here are presented i) the experimental vs. simulated inlet and outlet temperatures of i) the station evaporator (Figure 57a); ii) the substation evaporator (Figure 57c); and iii) the plant's condenser, the dry-cooler, and the heat recovery unit, (Figure 57a). The results shown in the Figure 57 demonstrate a very good agreement between the temperatures obtained by using developed model and the experimental data. Discrepancies no higher than $\pm 2\%$ error range are detected. From these outcomes it is possible to state that the model accurately depicts the dynamic evolution of each component, which contributes to its accuracy in simulating the thermal transients of the investigated system.

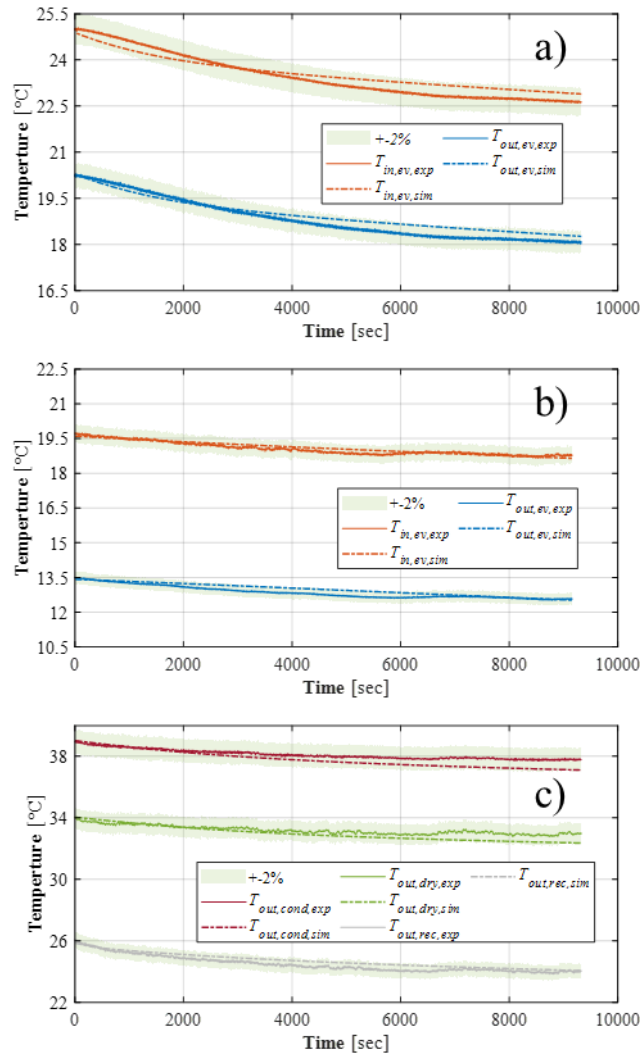


Figure 57. Temperature comparison among simulated and measured values: a) station evaporator; b) substation evaporator; c) condenser, dry-cooler, recuperator.

To further prove the model reliability the relative percentage errors for each quantity examined are reported in Figure 58 along with the median values. Also, from this analysis it is possible to notice a very good agreement between simulated and experimental data.

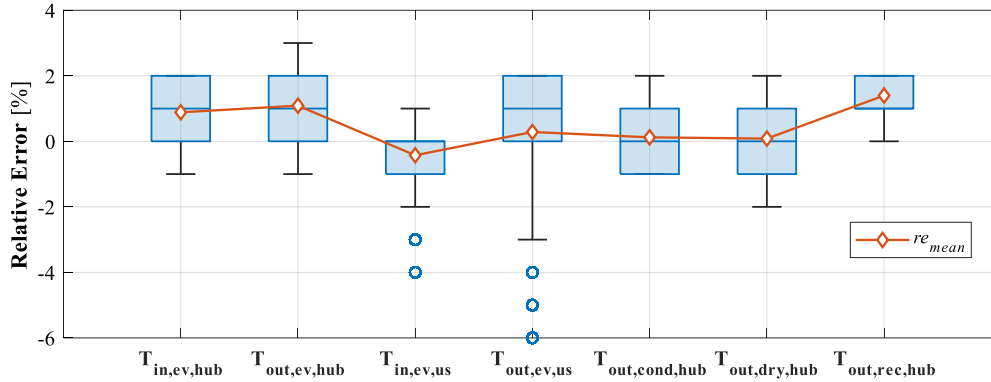


Figure 58. Percentage relative error of temperatures comparison among simulated and measured values.

Finally, the graph reported in Figure 59 compares the energy efficiency ratios (EER) of the measured and simulated substations; deviations are kept within the $\pm 5\%$ error range, and the R-square of 0.995 underlines the precision of the modelling of white-box HPs.

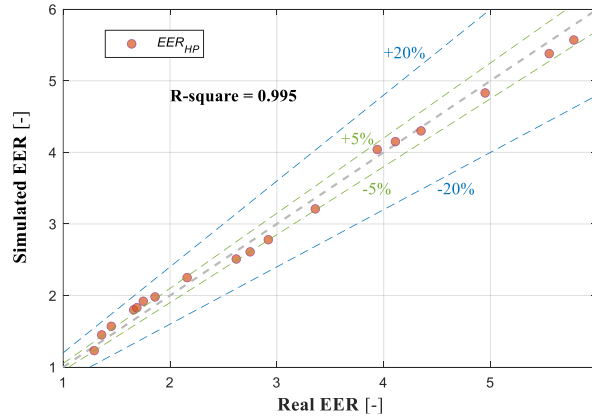


Figure 59. Comparison among simulated and measured EER of HP substation.

5.4 Proof of concept

To show the potential benefits achievable by adopting the proposed optimisation strategy, and to simultaneously prove the capabilities of the developed dynamic simulation tool, a suitable proof-of-concept analysis has been carried out. Such analysis is referred to a hypothetical 5GDHC network supplying a buildings cluster located in the urban area of Milan. In particular, the investigated configuration of the 5GDHC system is depicted in Figure

60. The primary distribution pipeline consisted of two manifolds - one for supply line and the other for return line - while the secondary distribution's hydraulic components allow the heat transfer fluid to be drawn from the thermal substations.

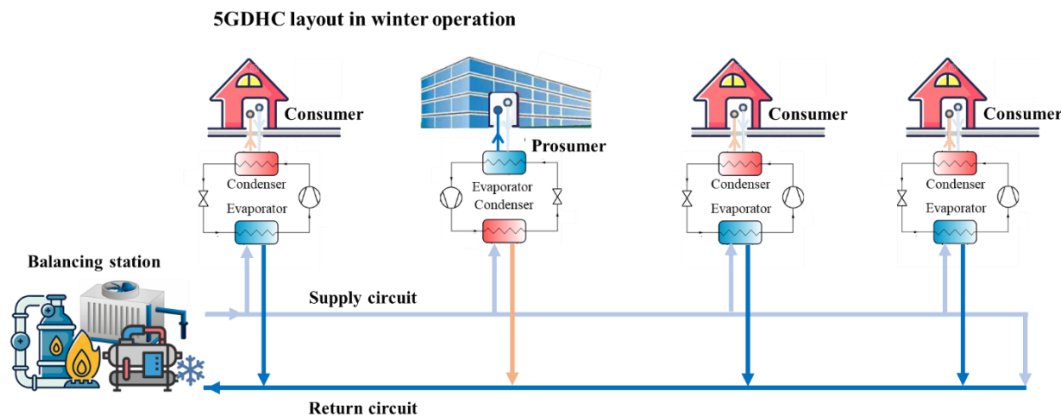


Figure 60. Scheme of 5GDHC network configuration.

Additionally, it should be emphasised that users are categorised as consumers or prosumers depending on whether the heat inputs from their substations satisfy the network's heat requirements. For the specific case study, the investigated buildings cluster is made of a data centre (prosumer), three residential buildings (consumers), and two offices (consumers), whose details of different buildings characteristics, such as the geometry, the envelope feature, and the HVAC system parameters, are shown in Table 15. The heating station and cooling station, that serve as the energy hub, operate only when the soil, which acts as waste heat source, is unable to maintain the network's thermal equilibrium. The energy hub is implemented to maintain the thermal network's equilibrium by precisely controlling its temperature. This ensures that the thermal requirements of both consumers and prosumers are satisfied without the necessity of storage or reservoirs.

Table 15. Cluster buildings characteristics.

Buildings energy modelling					
Characteristic	Parameter	m.u.	Data center	Residential	Office
Building geometry	A_{floor}	[m ²]	350	200	350
	$height$	[m]	4.5	2.8	3.1
	WWR	[%]	5	15	30
Building envelope	U_{wall}	[W/m ² K]	0.3	0.32	0.26
	U_{win}	[W/m ² K]	1.5	1.5	1.2
Ventilation	$Vent_{rate}$	[Vol/h]	8	2	6
Internal gain	$Gain_{light}$	[W/m ²]	3	2.5	5
	$Gain_{app}$	[W/m ²]	300	25	20
HVAC operation	$Set\ point$	[°C]	18	20	20

For sake of brevity, and due to the frequent simultaneous loads between buildings acting as consumers and producers, the analysis of the described cluster is conducted only for the winter season. Starting from the cluster energy demand, this has been estimated through the building energy modelling tool described in paragraph 2 by simulating each building singularly. The obtained thermal power demand time histories are reported in Figure 61 for a sample winter week (from 16th to 22nd of January). It worth noticing that, by knowing the thermal power demand time histories for all the buildings of the network, it is possible to size each building sub-station (the heat pumps) and, as a consequence, the main thermal power plant (balancing station). In this regard, Table 16 shows the key HP characteristics for the investigated case study.

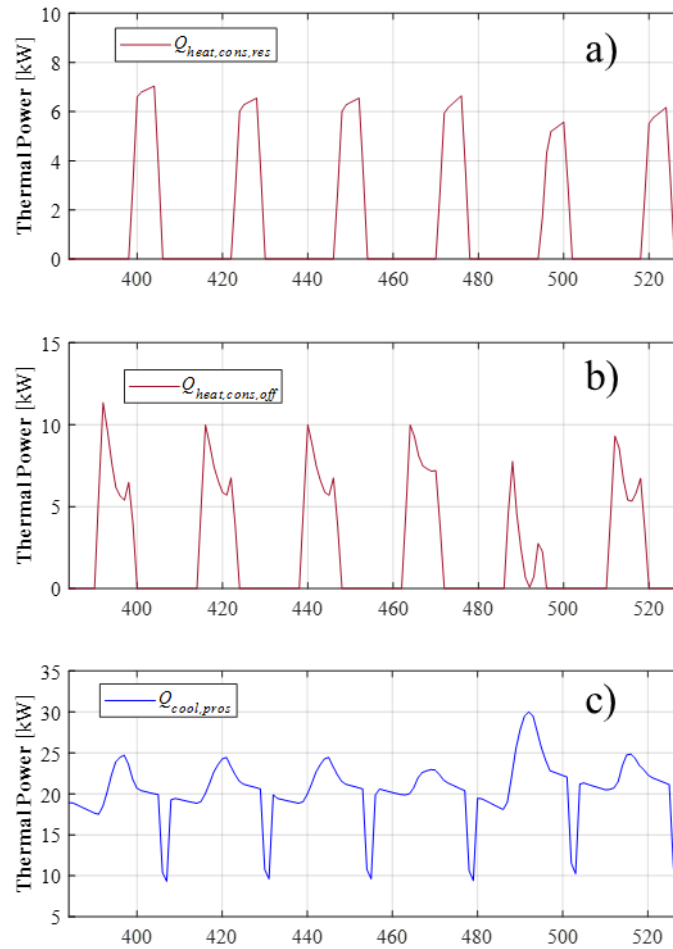


Figure 61. Buildings thermal loads: a) residential; b) office; c) data center.

From the table it is possible to notice that the nominal load of the furnace ($Q_{fur,nom}$) is 15 kW and that of the chiller of the energy hub ($Q_{ev,nom}$) is 25 kW. The location of the users being considered, as well as the flow rates needed by each substation, are taken into consideration when sizing the fifth-generation district heating network.

Table 16. Substations HPs characteristics.

Substation heat pumps				
Parameter	m.u.	Data center	Residential	Office
<i>fluid</i>	[-]	R-410a	R-410a	R-410a
$Q_{load,nom}$	[kW]	30	10	15
ΔT_{min}	[°C]	3	3	3
ΔT_{sc}	[°C]	2	2	2
ΔT_{sh}	[°C]	5	5	5
$T_{w,set}$	[°C]	7	45	45
$m_{w,load}$	[kg/h]	5155	859	1289
$m_{w,source}$	[kg/h]	6305	750	1095

Once the features of the investigated 5GDHC network have been presented, it is then necessary to determine its working conditions. As previously mentioned, to ensure good energy performance for both the substations in cooling mode (for prosumers) and those in heating mode (for consumers), it is crucial to establish a range of temperatures for the heat transfer fluid of the network. Temperature is in fact an important variable for 5GDHC systems, and significant energy savings can be obtained by optimizing the network temperature, especially when the users have simultaneous thermal needs. In this context, aiming at proving the significance of an accurate network operating temperature, two different control strategy have been analyzed for the investigated 5GDHC network:

- **Proposed System 1 (PS1 - standard control logic):** in case of Proposed System 1, a free-floating network temperature control strategy has been investigated. Here, the energy hub only activates to heat and cool the heat transfer fluid in order to return it to the respective reference values of the bandwidth swing, $T_{DHC,network,min}$ and $T_{DHC,network,max}$. This control strategy helps to limit the energy balancing station's operation due to the network temperature's wide permissible range. However, the energy efficiency of each 5GDHC user's substation heat pumps depends on the network temperature. As the network temperature cannot be precisely controlled in this strategy, it results in increased electricity consumption for the heat pumps.
- **Proposed System 2 (PS2 – innovative control logic),** in case of Proposed System 2, a multi-objective optimization procedure has been investigated. Specifically, it relies on a predictive control strategy with the goal of identifying the temperature value during the Δt 24-hour analysis period that minimizes the functions relating to prosumers' and consumers' energy consumption. In contrast to the previous strategy, this approach focuses on optimizing the operation of users' substation heat pumps. The electricity consumption from these systems significantly influences the overall electricity usage of the entire 5GDHC system. However, this strategy necessitates longer operation hours for

the energy balancing station. Its aim is to accurately control the network temperature based on the set-point values derived from the predictive control optimization procedure.

The dynamic results from the simulation of the two suggested scenarios, analysing the annual energy savings, are presented in the next paragraph.

5.5 Results

The results of the conducted analyses are shown in this section. In particular, first it will be presented the results of how it is performed the 5GDHC's temperature optimization in case of PS2 system adoption. Then, an energy-based comparison will be conducted between the investigated scenarios PS1 and PS2.

5.5.1 5GDHC network daily optimal temperature

In case of 5GDHC network, the partial load ratio, and the temperatures of the secondary fluid on the load and source sides have a significant impact on the efficiency of heat pumps, and consequently, on the efficiency of the entire system. The partial load ratio and load temperature are linked to the building thermal needs and cannot be controlled. It is instead possible to regulate the HP's source temperature, represented by the DHC network temperature ($T_{DHC, network}$), to improve the overall efficiency of the system.

This paragraph presents the results obtained through the optimization method applied to control the temperature in the DHC network (i.e., PS2 system). The PS2 system relies on a predictive control strategy with the goal of identifying the temperature value, during the Δt 24-hour analysis period, that minimizes the objective functions relating to prosumers' and consumers' energy consumption. It is worth noting that the 24-hour interval was chosen because of the substantial variation in the substations' load factors. A shorter time interval would lead to considerable variability in the optimized quantity, potentially affecting the robustness and stability of the controller responsible for regulating the energy hub's operation.

Figure 62 illustrates an example of how the multi-objective optimization process is applied to the investigated 5GDHC network. In particular, the top graph in Figure 62 shows the optimal daily temperature for the first month of the year. On the other hand, the bottom graphs in Figure 62 presents the results of the optimization method applied to two sample days. Here, the objective functions are represented by the daily electricity spent by the prosumer $E_{el, pros}$ and by all the consumers $E_{el, cons}$. As depicted in Figure 62 bottom, this situation refers to cases where a minor enhancement in one objective results in a significant deterioration of the other. Therefore, the optimal solution of the Pareto front is evaluated adopting the maximum curvature criterion, and this solution returns the daily network temperature that minimize the electricity consumption of both prosumer, and consumers.

Finally, it is worth noticing that the daily optimal working temperature for the network has been calculated for the entire year.

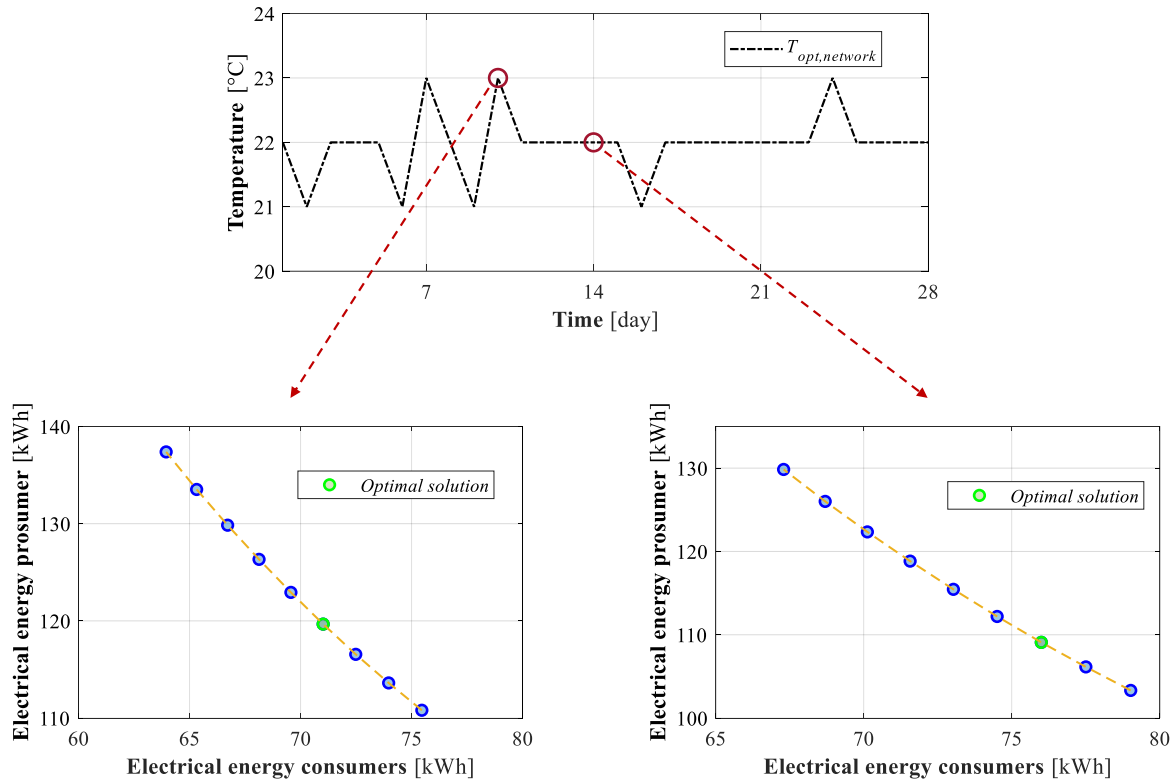


Figure 62. Optimisation procedure to assess the optimal daily temperature of the DHC network.

5.5.2 Comparison of proposed scenarios

In the present paragraph, a comparison between PS1 and PS2 systems performance is presented to investigate their influence on the energy efficiency of the 5GDHC system. Initially, a comparison was conducted to assess the impact of the proposed strategies on the operation of the balancing station. Following this, the investigation delved into the effect of these strategies on the efficiency of the heat pumps for each type of user. Lastly, a comprehensive annual energy comparison was performed to analyze the respective advantages of each strategy.

It is worth noting that, as there are no simultaneous loads during the summer season in the considered case study - only users functioning as consumers - it was preferred to conduct the analysis solely for the winter months.

As previously described, the energy balancing station consists of a traditional boiler and an electric refrigerant compression chiller. It is important to note that the aim of this study was not to explore technologies promoting energy savings. Rather, the focus was on

examining how, within a 5GDHC system, energy savings can be achieved solely through an effective management and control strategy while considering traditional technologies.

The two investigated control strategies, PS1 and PS2, dictate the temperature set-points of the thermal network, consequently affecting the operation of the central energy balancing station. As previously outlined, under the PS1 strategy, the temperature is allowed to fluctuate between a minimum setpoint of 20°C and a maximum of 28°C. In contrast, PS2 employs a predictive control approach, solving a multi-objective optimization problem to derive the optimal daily set-point value aimed at minimizing overall users' HPs energy consumption. Through a comparison between the return temperature of the 5GDHC thermal network and these specified set-point values, it becomes feasible to determine the thermal demands to be met by the energy balancing station for both proposed strategies (i.e., PS1 and PS2). At the same time, the return temperature of the network is influenced by the thermal powers of the heat exchangers situated on the source side of the users' heat pumps. Specifically, prosumers contribute thermal power in heating from the condenser, whereas consumers provide thermal power in cooling from the evaporators.

To emphasize the impact of control strategies (PS1 and PS2) and the heat inputs from the source side of users' heat pumps on the energy balancing station's operation, a three-day duration from January 2nd to January 4th was considered. In Figure 63a, the blue area represents ($Q_{ev,cons}$) - the thermal powers from consumer evaporators, while the red area represents ($Q_{cond,pros}$) - the thermal powers from prosumer condensers. This figure also illustrates the network's return temperature ($T_{w,in,cent}$) as a red dotted line, influenced by previous user heat inputs, and the supply temperature ($T_{w,out,cent}$) as a blue dotted line, determined by the set-points of the two strategies. The left graph in Figure 63a corresponds to the results of PS1, while the right graph pertains to PS2. In Figure 63b, the graphs depict the corresponding primary energy needs of the energy hub (PE_{hub}).

Observing both the PS1 and PS2 systems in the figures, it becomes evident that activation of the energy hub chiller (depicted as the grey area in Figure 63b) is necessary to cool the heat transfer fluid of the network. This need arises from the higher heat input of the prosumer's condenser compared to the cooling input of the consumer evaporators. In particular, in case of PS1 system, the temperature $T_{w,out,cent}$ stands below 28°C (maximum value for PS1 – see proof of concept paragraph for details), whereas the temperature $T_{w,out,cent}$ in case of PS2 system is cooled to 22°C (optimized temperature for the days under investigation).

These different operations of the central energy balance imply different primary energy demand of the energy hub's chiller and therefore different COP (depicted with black dotted lines). Specifically, Figure 63b highlights that the PS2 system, for the investigated time-period, requires a higher primary energy equal to an increase of 5% respecting to PS1. Furthermore, it is noteworthy that the determination of primary power considers a national electricity grid efficiency ($\eta_{el,grid}$) of 0.476 [268].

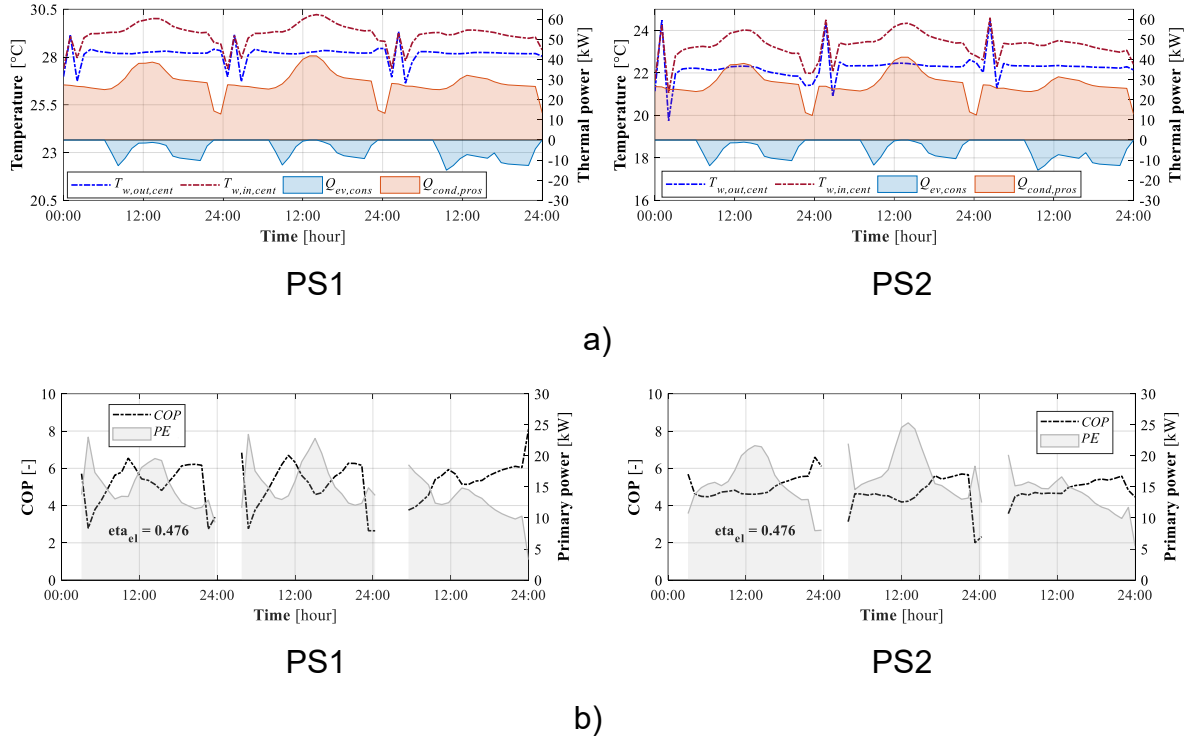


Figure 63. PS1 vs. PS2: time histories of a) inlet, and outlet water temperature, and network thermal gain; and b) primary energy and energy efficiency ratio of energy hub.

The objective of this analysis is to assess the impact of strategies PS1 and PS2 on the energy performance of individual users' heat pumps. The temperature of the heat transfer fluid within the thermal network affects both the efficiencies of the heat pumps and their electricity consumption.

To emphasize the influence of these strategies, Figure 64 compares the *EER* and *COP* indices of the users' heat pumps along with the electrical energy demands of the compressors ($P_{el,c}$). The period analysed corresponds to the three-day period from January 2nd to January 4th, matching with the range of Figure 64.

Here, for the three network users typologies (data centre - Figure 64a, residential building - Figure 64b, office - Figure 64c), the data obtained from the adoption of PS1 and PS2 system are presented. Starting from the data centre (Figure 64a), that is the building type behaving as a prosumer, it is possible to notice from the figure that adopting PS2 is particularly beneficial due to the significant increases in the *EER* (black dotted lines in the figure) and decreases of required electrical power (green areas in the figure). On the other hand, with respect to the residential and office buildings (that behave as consumers), there are no appreciable differences between *PS1* and *PS2* (see Figure 64b and Figure 64c).

For this specific case, the enhanced energy performance observed in the prosumer's heat pump is due to the network temperature in the PS2 scenario that is equal to 22°C,

respecting to 28°C experienced in the PS1 scenario (see Figure 63a). Indeed, this temperature difference, between PS1 and PS2 strategies, affects the source side of the prosumer's heat pump, narrowing the gap between the condenser and evaporator temperatures. As a result, there's a reduction in the electrical power required by the compressor. Conversely, for consumer heat pumps operating in heating, the higher temperature in the PS1 scenario favors a reduction in compressor electrical consumption. However, the substantial difference between the source and load temperatures, in heating operation of the heat pump, limits the benefits of increasing consumer evaporator temperatures compared to the prosumer scenario.

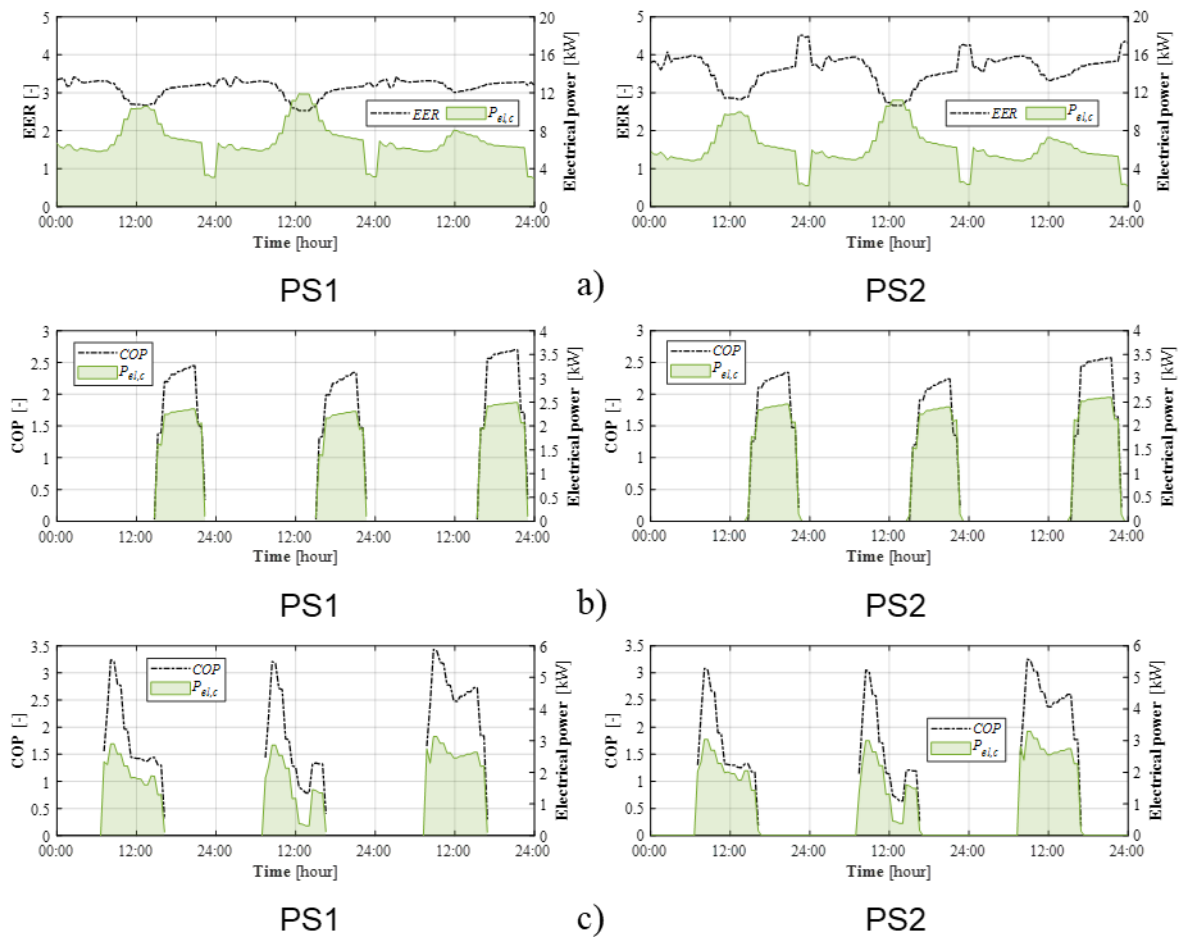


Figure 64. PS1 vs. PS2: HPs performance and electrical power for three sample days in case of a) data centre; b) residential building; c) office.

5.5.3 Energy performance analysis

To assess the overall energy performance achieved by the 5GDHC system under the two investigated strategies, PS1 and PS2, an analysis was conducted throughout the entire

cooling season. At first, a comparison between the heat pumps' efficiency obtained in the two different scenarios was undertaken. The histograms in Figure 65 demonstrate how the data are distributed and the probability density of the observations that fall within the range of COP values that were under investigation.

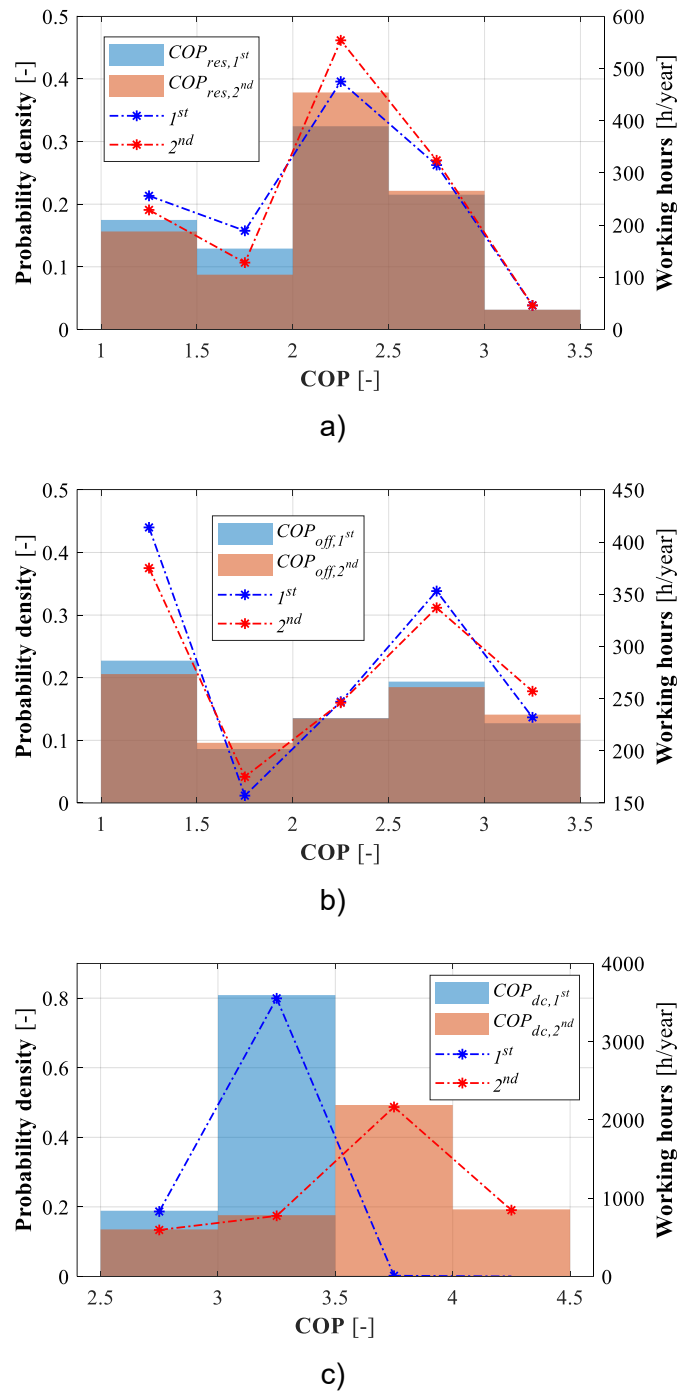


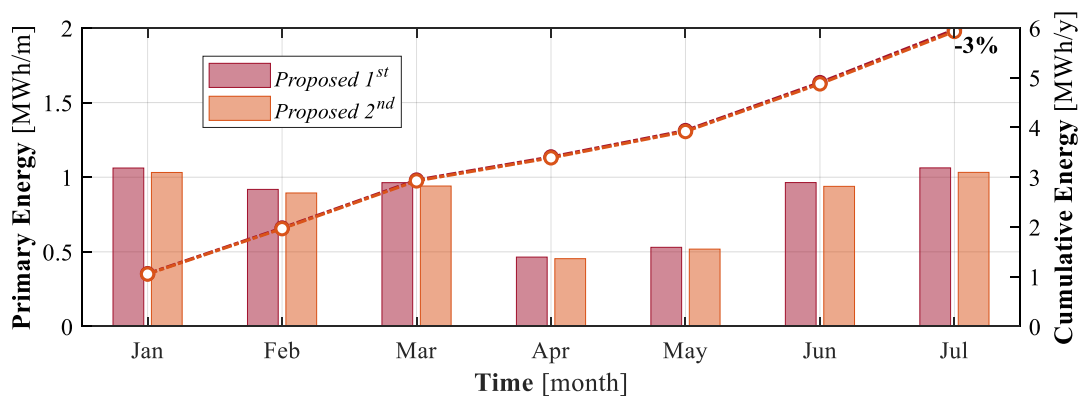
Figure 65. PS1 vs. PS2: users' heat pumps COP probability density: a) residential; b) office; c) datacentre.

In the cases of the consumers buildings, the HPs work in more efficient conditions as it is highlighted in Figure 65a and Figure 65b. Regarding the residential users, it was obtained a higher probability to work with high efficiencies in the second proposed strategy respecting to the reference free-floating temperature control. Indeed, this is demonstrated in Figure 65a where the observations for the second proposed strategy in the COP bins of 2 – 2.5 and 2.5 – 3 are greater than the reference case. Whilst the offices' HPs, as reported in the graph Figure 65b, experience a higher probability in the COP range 3 – 3.5 with the optimized control strategy PS2. The same analysis was conducted for the prosumer of the network. As it can be seen from the histogram in Figure 65c, the optimized strategy PS2 allows the HP to work in conditions which achieve efficiencies higher than 3.5 that cannot be reached by the reference scenario PS1.

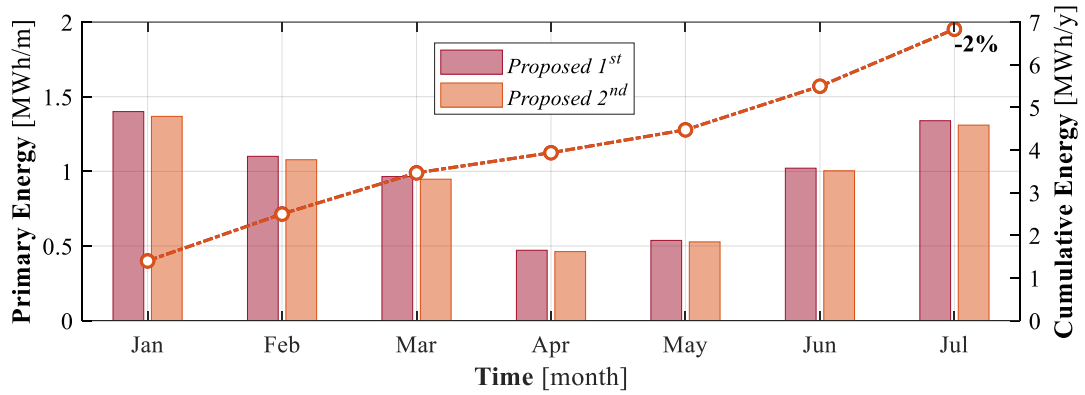
Starting from this analysis of users' heat pump efficiencies, a comparative study is presented in Figure 66, illustrating the monthly primary energy consumption differences between the two proposed strategies. As previously reported for the assessment of the primary energy it was considered an efficiency of the electricity grid equal to 0.476 [268].

In Figure 66a, and Figure 66b, the primary energy consumption for the residential building and office, respectively, is depicted. It's noticeable that the discrepancy between the analysed scenarios is minimal, consistent with the findings described in the previous Figure 65a, and Figure 65b. For the residential building, the annual primary energy consumption under PS2 amounts to 5.82 MWh/year, indicating a 3% reduction compared to PS1. Conversely, for the office, the annual consumption under the PS2 strategy totals 6.68 MWh/year, showcasing a 2% reduction compared to PS1.

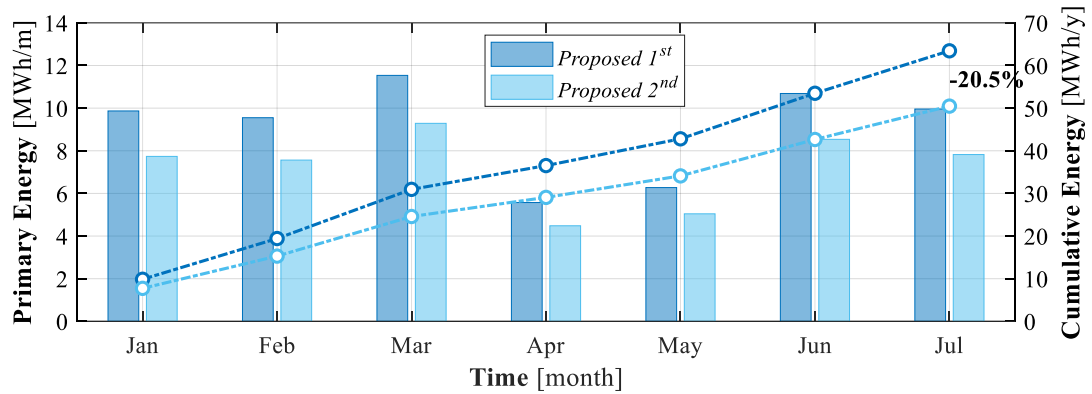
Figure 66c emphasizes the comparison between the PS1 and PS2 systems, highlighting the energy advantage of PS2 for the district's prosumer. The reduction in energy requests is evident across all examined months, as indicated by the total energy value (right axis). With the adoption of PS2 (blue dotted line), there is a significant 20.5% energy savings compared to PS1 (blue dotted line).



a)



b)



c)

Figure 66. PS1 vs. PS2 primary energy consumption on yearly and monthly basis: a) residential building; b) office; c) data centre.

The same analysis presented for the prosumer and consumers in Figure 66 have been conducted for the energy hub and reported in Figure 67. The PS2 strategy, employing predictive temperature control for the thermal network, seems more energy-demanding compared to the free-floating strategy of PS1. This discrepancy arises from the difference in approach between the two strategies. Unlike PS2, PS1 allows the network to function within a broader temperature range (i.e., 20–28°C), minimizing the need for frequent activation of the energy hub systems. Consequently, this limitation leads to reduced energy consumption compared to the PS2 case, which conversely necessitates adherence to a specific temperature set-point.

PS2 system shows a convenience over PS1 only in January and December (Figure 67), and the associated primary energy consumption is 5.4% higher than the PS1 strategy.

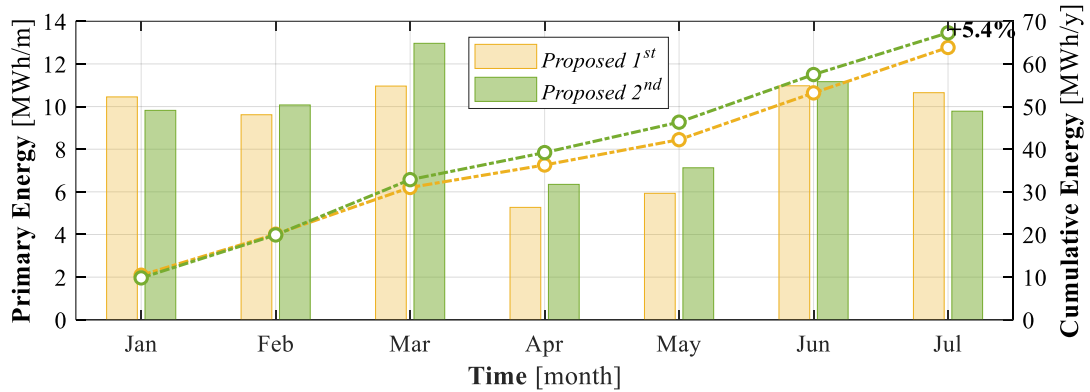


Figure 67. PS1 vs. PS2: energy hub primary energy consumption on yearly and monthly basis.

Finally, the comparison of the total primary energy used by the 5GDHC system was then done. According to a community perspective, the case study under investigation envisions the substations and station being combined, along with centralized management. The Figure 68 demonstrates how cost reduction at the prosumer substation ensures system-wide savings that balance and overcome the energy hub's excessive consumption. The fact that the data centre substation uses more energy than the power station explains this outcome. A total saving of 6.5% is possible overall under the network temperature optimization scenario using daily predictive logic.

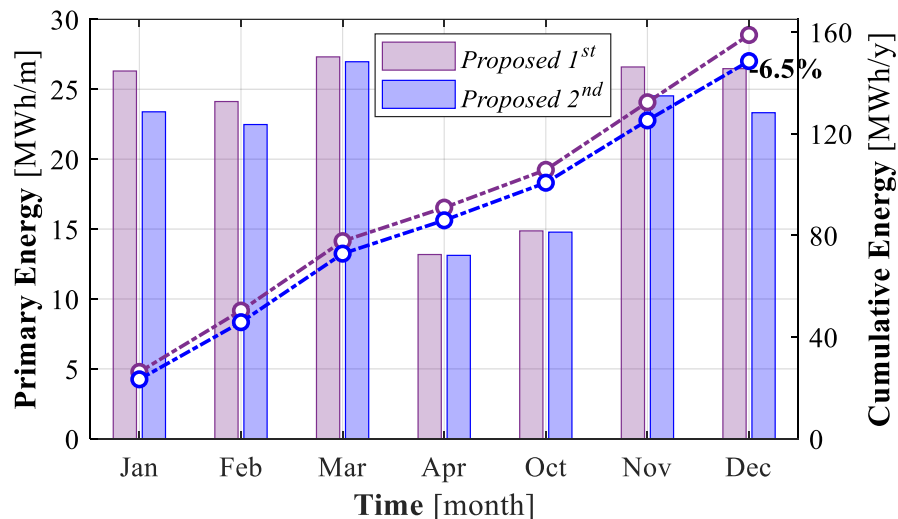


Figure 68. PS1 vs. PS2: overall 5GDHC system primary energy consumption on yearly and monthly basis.

5.6 Conclusions

The advancement of generations has resulted in a decrease of the heat transfer fluid temperature in district heating and cooling networks, which has increased the possibility in poly-generative, renewable based, district heating and cooling network. In turn, such occurrence has raised the need in the creation of powerful yet adaptable tools for the sizing, optimization, and management of these systems. Among the others, an ideal setup that ensures greater flexibility and potential for exploitation of waste and renewable energy sources is the indirect 5GDHC. Given the above, in this work a comprehensive simulation model for 5GDHC systems energy assessment has been developed and experimentally validated. In particular, the developed simulation tool adopts a white-box modelling approach allowing for high-accuracy analyses and fine controls. To verify the tool reliability, it underwent an experimental validation procedure by exploiting the data collected from an existing prototype built at the ENEA national research centre (Italy). To verify the developed tool potential, it is adopted to test a novel control strategy for the 5GDHC network temperature management. In particular, optimizing the network working temperature can result in higher system efficiency and convenience. To guarantee the stability and robustness of the control system, the optimal temperature value is determined every 24 hours. A multi-objective problem was used in the optimization process in order to find the best solution that simultaneously minimizes prosumers' and consumers' daily electricity costs. The convenience of such novel control method is verified through a proof-of-concept analysis consisting of a 6 buildings 5GDHC network in Milan (that included 1 prosumer building and 5 consumer ones). For comparison purposes, a standard free-floating network temperature approach is also investigated. The results of the proposed optimization scenario demonstrated a saving of 13 MWh/year of primary energy for the prosumer buildings. On the other hand, the balancing energy plant uses 3.8 MWh/year more primary energy, but the entire 5GDHC system is 6.5% (equal to 10.3 MWh/year of primary energy saved) more energy efficient overall than in the reference scenario, proving the potential benefits in adopting the proposed methodology. The implementation of a clustering methodology may be investigated in the future in order to find the best network configuration for increased thermal self-balancing capabilities. Future research will also look into how to incorporate renewable energy sources to increase energy efficiency and lower CO₂ emissions.

Chapter 6

Designing aggregation methods for peer-to-peer energy communities

This chapter was previously published as:

G. Barone, A. Buonomano, G. Cipolla, C. Forzano, G.F. Giuzio, G. Russo. (2024). Designing aggregation criteria for end-users integration in energy communities: Energy and economic optimisation based on hybrid neural networks models. *Applied Energy*, 371, 123543.

Summary

This study develops innovative methods for real-world implementation of energy communities, focusing on Peer-to-Peer (P2P) networks where prosumers share surplus energy with consumers to meet demand. The approach optimises connections between users by enhancing energy interactions and introducing pricing strategies that balance supply and demand for fair unit costs. The study proposes new aggregation criteria to maximise economic benefits and renewable self-consumption, based on a bi-level optimisation model. At the first level, prosumers and consumers are grouped to increase self-sufficiency and savings. The second level identifies the optimal community configuration to enhance overall self-consumption. Addressing data limitations, a Hybrid Neural Network predicts users' electrical needs for accurate demand assessment. A case study in Caserta, Italy, demonstrates the methodology's effectiveness, achieving 1.6%–19.5% consumer savings and rapid returns for prosumers (ROI under 3 years) compared to standard grid-only connections. The optimised configuration also raises annual self-consumption to 89%, up from 64%, significantly improving community energy efficiency and grid stability.

Keywords

P2P Energy Community; Energy Community aggregation criteria; Hybrid Neural Network model for electrical loads estimations; Bi-level optimisation problem to design Energy Community; Local energy market; P2P Cluster Archetype; Building Archetype.

Nomenclature

Symbol		Abbreviations	
A	surface area [m ²]	CA	cluster archetype
c	costs of energy [Euro/kWh]	DER	distributed energy resources
C	energy market curves [Euro/kWh]	DL	dispatching layer
COP	coefficient of performance [-]	EC	energy community
E	energy [kWh]	HNN	hybrid neural network
f	usage probability factor [-]	$MILP$	mixed integer linear programming
G	global radiation [W/m ²]	$P2P$	peer-to-peer
$NOCT$	nominal operating condition temperature [°C]	RES	renewable energy resources
P	power [kW]		
Q	thermal power [kW]		
SC	self-consumption [%]		
T	temperature [°C]		
Subscripts			
av	available	nom	nominal
BOP	balancing of plant [-]	occ	occupancy
$cons$	consumer	$prod$	production
d	demand	$pros$	prosumer
el	electrical	s	supply
eq	equipment	sur	surplus
Nomenclature optimisation model			
Set			
X	set of optimal cluster archetypes		
Γ	set of EC subgroups' combinations		
Variables			
$E_{load,j}$	j-th user energy need		
$E_{P2P,cons,j}$	j-th user energy need satisfied by P2P mechanisms with prosumers		
$E_{PV,sc,pros,i}$	Energy self-consumed by prosumers		
$J_{pros,i}$	cash-flow for the i-th prosumer		
$P2P_{CA}$	optimal configuration of a specified cluster archetype		
$pC_{pros,CA,m}$	percentage of prosumers in the m-th cluster archetype		
$pros_{type,CA,m}$	type of prosumers in the m-th cluster archetype		
$SPB_{pros,i,thr}$	threshold of Simple Pay-Back time for the i-th prosumer		
$SS_{CA,m}$	self-sufficiency of the m-th cluster archetype		
Parameters			
n	number of building archetypes of the community		
N	number of user for a specified building archetype		
Indices			
$CA_{pros,i}$	cluster archetype which include i-th prosumer		
$combCA$	combinations of cluster archetype		
$combCA_{pros}$	combinations of cluster archetype including i-th prosumer		
i	index type of prosumer		
j	type of building users		
m	number of optimal cluster archetype including i-th prosumer		

6.1 Introduction

The need to mitigate greenhouse gas emissions has prompted a simultaneous increase in policies aimed at encouraging the development and implementation of renewable energy technologies [17]. The NextGenerationEU plan has set a key goal of reducing emissions at least 55% by 2030 compared to the level achieved in 1990 [269]. In light of this, urgent action is needed to transition sectors still dependent on fossil fuels towards a renewable and sustainable energy mix. Decreasing costs of renewable technologies, supportive government policies and incentives, rising awareness of environmental issues, and the desire for greater energy independence are driving the increase in installation of renewable Distributed Energy Resources (DER) [270]. However, this is associated with issues related to the balance and stability of the conventional centralized electricity grid [271]. As a result, there has been a marked shift towards the development of methodologies that optimise the management of these energy systems. Among these, the concept of energy community (EC) represents a useful tool for achieving the set objectives [272], also considering that the installation of RES-based technologies, such as photovoltaic (PV) panels, has occurred significantly on buildings that have contributed to the decentralization of the RES system. As a result, despite the positive benefits of the RES integration in buildings and in our communities, new challenges – such as intermittency, storage, and the need of policies and infrastructures, as well as novel energy management frameworks / paradigms – remain and call for advancements in technology and regulatory environment to maximize the benefits of decentralized RES installations [273]. From this point of view, the adoption of energy communities has become increasingly concrete as an effective measure to achieve multiple aims [274]: reduce the impact of RES on the traditional grid (e.g. alleviating grid congestion and enhancing the overall grid efficiency), increase the self-consumption of RES production, support the integration of RES, and pursue just energy transitions [275]. Indeed, the European Renewable Energy Directive II (RED II) emerged with the aim of increasing the adoption of energy communities reflecting a growing awareness for promoting collective self-consumption, thus maximizing the effectiveness of the use of renewable energy, and aligning with broader sustainability aims [276]. To this aim, energy communities foster community engagement, encouraging citizen to actively participate in the transition to sustainable energy toward common economic, social, and environmental goals [277].

With the aim to increase the knowledge and the awareness of energy communities toward their evolution and adoption, various innovative solutions mainly regarding the topology and market models of energy-sharing systems, have been extensively explored in literature [278]. These energy-sharing systems are broadly classified into off-grid and on-grid types, each serving distinct purposes and settings [279]. Off-grid energy communities typically exist in remote areas without access to the central electricity grid. These independent communities are designed to achieve complete self-sufficiency and energy

autonomy by optimising the technologies mix of energy hub [280]. In these configurations, analysing the impact of different RES [281], integrating storage systems [282] to optimise the energy dispatch [283], and implementing energy flexibility actions [284] are pivotal to ensure the total coverage of energy demands from the electricity production mix [285]. On the other hand, on-grid energy communities consist of user aggregates categorized as consumers and prosumers [286]. They operate based on energy-sharing mechanisms while remaining interconnected with the central electricity grid. The primary aim of these systems is to maximize self-consumption investigating different Power-to-X strategies [287] while mitigating voltage and frequency imbalances that could impact the overall grid stability [288].

With the aim to contribute to this research field, this work aims to introduce a method to optimise the design configuration of on-grid energy communities, implementing aggregation criteria where the users are grouped in building clusters able to optimally interact with central grid, by exploiting local renewable energy systems, and by adopting energy sharing management strategies [275, 289].

To discover the research-gaps, the following paragraph will delve into a literature review, concentrating on methodologies, optimisation procedures and the electricity market strategies employed for the management of energy communities.

6.1.1 Literature review

Energy communities operate based on the fundamental principle of sharing energy among users. When electricity production systems are owned by users, they become primary contributors to the EC local energy market [290]. Conversely, when cooperatives manage these facilities, the energy market revolves around these entities coordinating the community's production systems and the users' requests within the same smart grid [291]. A centralized control strategy is envisaged for this configuration; conversely, for the first one where prosumers provide electricity to the local market, it is also possible to implement decentralized control strategies where each end-user has an independent energy and economic management.

Since the early implementation of energy communities or aggregators, how the exchange of energy is managed among all actors (prosumers and consumers, grid operators and users, etc.) and how the portfolio of energy production plants is coordinated have been highly investigated in literature [78]. In particular, efforts have been made for the creation of business and trading prices models [292] and for deriving control strategies and energy management schemes for the energy demand forecasting and flexibility [293], as discussed further.

Gao et al. [294] studied a cascade methodology for managing a community's energy resources. This methodology employs initial centralized control governing interactions

between user requests and electricity production. Subsequently, an aggregator within the building cluster manages energy sharing among users. The proposed method was applied to a specific case study comprising four buildings with electrical requests simulated with assumptions made on the rated power of the equipment (e.g., HVAC, electrical vehicles, etc.). The aim was to achieve a net-zero energy cluster by minimizing reliance on the grid, leveraging both distributed resources and energy hubs owned by cooperatives. Similarly, Braeuer et al. [295], proposed a centralized control approach for an energy community characterised by four different single multifamily buildings classified based on the building age and number of occupants. The goal was to optimise the prosumer's energy system design through Mixed Integer Linear Programming (MILP) to minimize return on investment [296]. Centralized control strategies are also applicable to energy communities characterised by smart homes employing flexibility actions governed by demand-side management (DSM) strategies [297]. In this context, Lokeshgupta et al. [298] suggested a coordinated energy sharing mechanism, among 10 smart homes that include electric vehicles in their electrical appliances, adopting a centralized control. This strategy effectively manages user requests and prosumer storage functioning to minimize overall energy purchase costs. Implementing centralized control strategies becomes crucial, especially in scenarios lacking viable platforms and tools to connect users and facilitate information exchange regarding their requests and availability [299].

In energy communities characterized by decentralized control, the management focus shifts towards trading strategies [300]. Li et al. [301] conducted an economic analysis aimed to estimate the economic return for domestic users while exploring various methodologies determining the unit cost of exchanged electricity. These methods considered factors like peak and off-peak power hours, user electrical demands, and grid electricity costs. Alonso Pedrero et al. [302] developed a market strategy for an EC of 50 neighbouring households based on determining the energy sales price from the previous day, relying on forecasting methodologies to evaluate influences on energy prices. Xia et al. [303] proposed a methodology to aggregate users of the EC into subgroups, demonstrating that employing trading mechanisms for electricity sharing among these subgroups could yield greater economic benefits. Furthermore, game theory, notably Nash equilibrium and Stackelberg games, widely applied in literature, allows determining user interactions to maximize economic benefits for both user categories [304].

However, transitioning to a peer-managed market remains challenging due to economic-social conditions and the absence of specific management systems [290]. Consequently, centralized control solutions aimed at optimising the collective behaviour of energy communities are among the most prevalent. Further approaches involve hybrid control models, granting peers freedom to trade within the community but under the management of a balancing service provider, defining the trading rules [305].

Energy communities comprising individual electricity production plants, like micro-wind or photovoltaic systems, can be managed using rule-based control systems. However, when the system complexity increases, more efficient control mechanisms, such as model predictive control (MPC), become necessary in case studies. Both control types rely on forecasting models to accurately estimate electrical demands and energy production of these systems [306]. Houben et al. [307] studied a MPC control strategy to regulate demand/response events, optimising CO₂ emissions. This strategy leverages heating systems and electrical storage to enhance system flexibility, ensuring user requests are met. To bolster collective self-consumption and reduce dependence on the grid, electric vehicles were employed as storage sources, alongside heat pump thermal systems coupled with thermal storage [308] to enhance community flexibility [309].

Energy flexibility within these systems serves as a crucial property, maximizing self-consumption and self-sufficiency [292], especially in remote areas and in areas significantly impacted by extreme climate events. However, implementing these strategies may face challenges, particularly when users are reluctant to alter their energy behaviour [310].

The conducted review of the literature underscores the significance of energy communities in advancing sustainability goals through optimal utilization of renewable energy resources. Some of the investigated works in the literature review are categorized in the Table 17. It is evident that the outcomes and results of many studies are tailored to the specific choice of users that compose the case studies. Replicating and applying these case studies in real-world scenarios requires the presence of the same investigated boundary conditions, which are often challenging to attain. Therefore, this highlights a significant research gap: the absence of standardized criteria to effectively apply and fully leverage the benefits associated with energy community mechanisms. Addressing this gap necessitates taking a step back and prioritizing the design of energy community configurations by establishing aggregation criteria among users based on energy and economic objectives. While the literature has explored the role of aggregating users in an EC, the primary emphasis has often been on analysing the social impact on citizens [311], rather than considering the energy and economic implications.

Moreover, providing inputs to fill this gap has a recognized twofold aim, encompassing the research and development of energy communities, and the formulation of policy and legal frameworks for enabling the effective implementation of energy community share models [312].

Table 17. Taxonomy of literature review.

Study	Energy community research field	Case study characteristics	Aim of the work
[23]	Energy flexibility strategies to manage each electricity production and requests of the single user. Centralised control strategies governing energy sharing among users.	4 prosumers equipped with PV systems, wind turbine, batteries, and EVs	Net-zero energy cluster to maximize grid-independency
[24]	Optimising prosumer's energy system design.	4 different types of prosumers buildings equipped with PV systems, batteries, combined heat and power, and thermal storage.	Minimize return of investment
[25]	Centralized control strategies based on demand-side management of smart homes.	16 prosumers classified in 14 residential units, 1 office and 1 restaurant, equipped with PV systems, and batteries.	Minimize fossil fuel consumption.
[26]	Coordinated centralized home energy management (HEM) model with neighbourhood power sharing.	6 prosumers equipped with PV systems, wind turbines, and batteries. 4 consumers classified based on occupancy patterns.	Maximize the local renewable energy utilization, minimizing the electricity bills of all smart homes.
[29]	Economic feasibility of energy communities with two investment options: self-investment and third party investment.	10 prosumers of residential type equipped with PV systems and batteries.	Minimize pay-back time for investors.
[30]	Optimisation of the power to purchase in the day-ahead retailers market in EC.	17 prosumers with PV systems, 10 prosumers with wind turbines and 23 households consumers.	Assess the effect of self-sufficiency of EC consumers on the retailers' profit losses.
[31]	Energy sharing among communities (C2C).	9 prosumers equipped with PV systems and 24 households consumers.	Development of a platform to manage the energy sharing among peers of different ECs.
[35]	Regulation of demand/response events using a model predictive control strategy.	9 consumers (residential and offices) and 1 central energy hub with PV and batteries.	Optimisation to minimise CO2 emissions related to EC energy requests.
[33]	P2P energy trading among users adopting hybrid control models with market constraints dictated by a balance service provider	90 residential prosumers and 12 commercial prosumers equipped with PV and batteries.	Maximize economic revenues of energy balance service provider
[34]	Residential energy community load estimations with probabilistic and machine learning techniques	39 residential buildings classified based on floor area and number of occupants	Increase the accuracy of electrical load estimation of EC users.

6.1.2 Contributions

This study focuses on addressing the critical issues arising from the application of energy communities in real contexts by proposing innovative methodologies. The challenges identified with the literature review concern the influences that specificity of case

studies have on the energy and economic performance of energy communities. Indeed, most of the conducted analyses are very case specific, preventing the adoption of the achieved results for different applications. These characteristics are very often linked to the energy demand of users and the typology of energy production technologies integrated into the community. Therefore, to overcome this limitation, the present work introduces a method to optimise the design configuration of energy communities, employing end-users' aggregation criteria for real implementation by stakeholders. This approach involves selecting the type and number of users – both consumers and prosumers – to be aggregated in an EC using a bilevel optimisation procedure. Initially, this procedure aggregates different types of end-users into subgroups to enhance self-sufficiency and ensure economic benefits for each member of the community. Subsequently, it prioritizes solutions that maximise self-consumption by aggregating these subgroups, thereby obtaining the optimal configuration for the EC. Furthermore, this aggregation approach is based on several key aspects:

- Development of a novel hybrid model to estimate demand curves of energy community users. This model integrates the strengths of both physical building models and neural networks, categorizing users based on building archetypes. This building classification considers not only their geometry and thermophysical properties but also the electrical usage habits of occupants conditioned by factors – working hours, age-related consumption preferences, etc. – which significantly influence the dynamism and amplitude of electrical demand. Furthermore, statistical analyses have been adopted to assess the impact of user types on the usage frequencies of equipment, lighting, and air conditioning systems.
- Implementation of a peer-to-peer energy sharing strategy between consumers and prosumers within the community. This approach relies on centralized control logic to optimize user connections, maximizing energy interactions while minimizing reliance on the central grid. Electricity market prices among peers are determined through the balancing of supply and demand curves.

6.2 Methodology

The procedure implemented for the design and management of EC is focused on specific *end-user aggregation criteria*. The aim of this procedure is maximizing the economic return of each end-user and optimising the management of the EC's distributed energy resources. The investigated EC is of the community prosumerism type [279] where end-users are differentiated into prosumers and consumers. The prosumers act as investors, while the consumers join the energy sharing mechanisms to enhance the efficiencies of the EC. This EC is connected to the central grid both to satisfy end-user requests that are not covered by distributed production systems and to sell the excess energy produced. The sharing mechanism is P2P type, EC users participate in a *local energy market* in which

prosumers and consumers can directly trade electricity among themselves [300]. The analysed negotiation type relies on the national grid infrastructure for energy sharing purposes among the EC users. Furthermore, it has been demonstrated that this type of energy exchange may help the grid infrastructure in reducing losses associated with power transmission conversion and mitigating imbalances caused by undesired energy injection into high-voltage transmission lines [313]. A centralized control system governs this P2P model, applying logical rules to ensure the community's energy equilibrium. Figure 69 provides a schematization of the proposed methodology to optimise the design and configuration of an EC. The proposed methodology is structured as follows:

- Development of predictive models to estimate the electrical loads and electricity production of EC users.
- Implementation of P2P energy sharing algorithms based on centralized control logics within ECs models.
- Definition of user aggregation criteria to investigate different EC configurations.
- Implementation of optimisation procedures aimed at determining the optimal design.

The first step of this methodology involves the identification of potential prosumers and consumers. Since it is not always possible to use real datasets relating to the dynamic measurement of end-users' energy demands, a predictive procedure has been developed. This procedure employs statistical analyses and a hybrid energy model of buildings to *forecast dynamic electricity demands*. To carry out this prediction, end-users are classified into building archetypes defined according to the socio-behavioural characteristics of the occupants and the geometric and thermo-physical characteristics of the building.

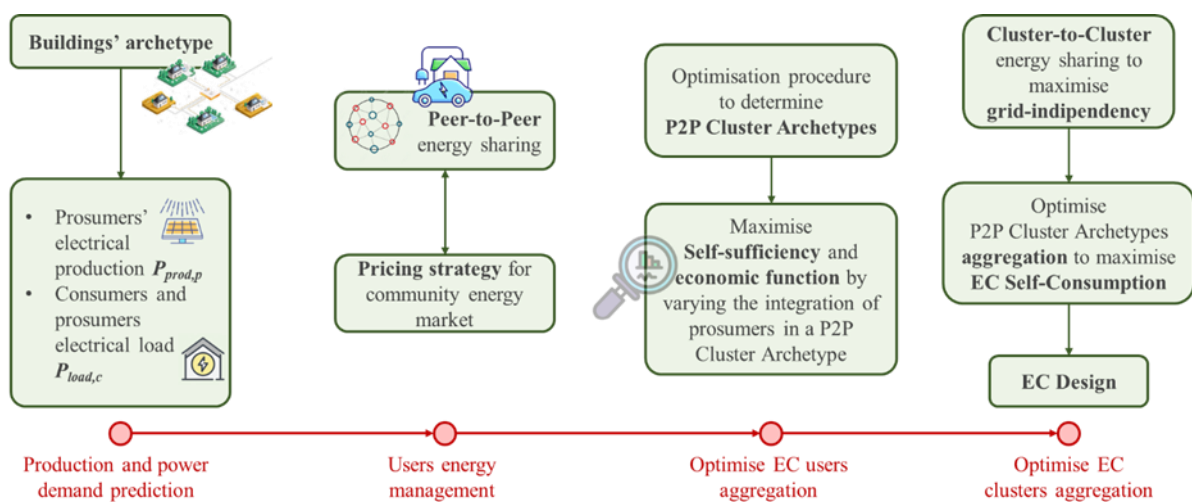


Figure 69. Overview of the developed methodology for designing and optimising the management of energy communities.

Once the typologies of potential EC users have been characterized, the next step involves defining *end-user aggregation criteria*. The first aggregation criterion consists of grouping the end-users into subgroups representing small energy communities. The second criterion is aimed to design the global EC by interacting the subgroups generated through the first aggregation criterion. Subsequently, these criteria have been adopted to develop a bi-level optimisation problem.

The first level of the optimisation problem aims to maximize the annual self-sufficiency of each EC's subgroup, observing economic constraints, while accounting for variations in the number and types of prosumers. These EC's subgroups are characterized by a first dispatching layer (1st DL) of P2P type where the end-users of a single subgroup can share energy only among them. This optimisation problem is addressed using the MILP algorithm, and the optimised EC's subgroups are defined as *P2P cluster archetypes*.

Subsequently, the second level of optimisation involves aggregation between P2P cluster archetypes ($P2P_{CA}$) and is focused to determine the optimal design configuration of the whole EC. This optimisation seeks to maximize the entire EC's annual self-consumption. This stage involves implementing a second P2P dispatching layer (2nd DL) among users of different $P2P_{CA}$, performed in series with the earlier established P2P mechanisms.

Finally, this holistic approach employed in the design and management of the EC, focused on *end-user aggregation criteria*, emphasizes the maximization of economic benefits and the efficient management of distributed energy resources, showing a structured methodology oriented towards optimising community-based energy systems.

6.2.1 Building archetypes for EC users' energy modelling

The estimation of the electricity demands and the production of the decentralized systems for each EC user, considered as all-electric – occur through an energy modelling of the building archetypes. As previously explained, end-users are categorized into these archetypes considering both the socio-behavioural attributes of occupants and the thermo-physical characteristics of the building, that contributing to its electric load.

EC prosumers are assumed as equipped with PV systems. Their sizing has been performed with the aim of determining the number of panels $N_{PV,i}$ that ensure an annual energy production equivalent to the annual energy demand of each i -th prosumer of the community. However, if the requested surface area is greater than the available one $A_{PV,av,i}$, the system sizing adheres to this constraint, as outlined in Eq. (30):

$$N_{PV,i} = f \left(\int_{year} P_{PV,prod,i} = \int_{year} P_{load,i} \right) \quad \text{Eq. (30)}$$

$$s.t. \rightarrow N_{PV,i} \leq A_{PV,av,i} / A_{PV}$$

Here, $P_{load,i}$ represents the electrical power demanded by the i -th prosumer, A_{PV} is the surface area of a single photovoltaic module, and $P_{PVprod,i}$ [314] denotes the power produced by the PV systems, calculated using Eq. (31):

$$\begin{cases} P_{PV,prod,i} = (G \times A_{PV,tot}) \cdot \eta_{PV} \cdot \eta_{BOP} \cdot \eta_{shading} \\ \eta_{PV} = f \left(P_{MPP,STC}, C_{t,P}, T_{cell}, \frac{1}{G_{STC}} \right) \end{cases} \quad \text{Eq. (31)}$$

Eq. (31) introduce terms such as η_{PV} , η_{BOP} , $\eta_{shading}$ referring respectively to single module efficiency, global plant efficiency accounting for transmission losses, and efficiency considering shading losses. $P_{MPP,STC}$ and G_{STC} stand for the maximum power production and incident radiation in standard test conditions. $C_{t,P}$, and T_{cell} represent the coefficient for power variation under conditions different from STC and the cell temperature [315]. This term is a crucial parameter to estimate the PV module efficiency [316] and it is expressed in Eq. (32):

$$T_{cell} = T_{air} + G \times \frac{NOCT - 20}{800} \times \left(1 - \frac{\eta_{cell}}{\alpha \cdot \tau} \right) \quad \text{Eq. (32)}$$

Here, $NOCT$ is the cell temperature in nominal operating condition, while α , and τ denote the absorbance and transmittance of the PV glass cover.

6.2.2 Electrical load estimation: equipment and lights

As regard the evaluation of electrical load $P_{load,j}$ for each end-user type, it was assessed by considering the electric demands associated with equipment, lighting, and air conditioning, as represented in Eq. (33):

$$P_{load,j} = P_{lights,j} + \sum_{k=1}^{N_{eq}} P_{eq,j,k} + P_{HVAC,j} \quad \text{Eq. (33)}$$

Here, $P_{lights,j}$ denotes the lighting demand of the j -th end-user, $P_{eq,j,k}$ accounts for equipment (such as computers, TVs, ovens, washing machines, etc.), and $P_{HVAC,j}$ is associated with the building's space heating/cooling thermal needs.

A predictive method employing probability factors derived from statistical analyses was utilized to model dynamic electricity usage profiles for lights and equipment. These profiles

can be obtained by knowing the nominal electrical power and determining the hourly frequency of use [317].

The electrical load related to the operation of k -th electrical equipment for the j -th user is estimated as described in Eq. (34):

$$P_{eq,j,k} = f_{occ,j} \cdot f_{use,eq,k} \cdot P_{nom,eq,k} \quad \text{Eq. (34)}$$

Where $P_{nom,eq,k}$ represents the nominal electrical power of equipment, and $f_{use,eq,k}$ the operation probability factor that is derived by the work of Paatero et al. [317]. While $f_{occ,j}$ represents the probability factor derived from occupancy patterns. Its role is fundamental in assessing how the number of occupants influences the electrical consumption of equipment during specific time periods.

For lighting, the electrical load $P_{lights,j}$ is calculated as reported in Eq. (35):

$$P_{lights,j} = f_{occ,j} \cdot f_{use,lights,j} \cdot P_{lights,density,j} \cdot A_{floor,j} \quad \text{Eq. (35)}$$

The nominal power of the lights is derived from the product of the power density $P_{lights,density,j}$ and the floor area $A_{floor,j}$ of the j -th building archetype. While the dynamism of the usage profile is estimated based on $f_{occ,j}$, and the lightning operation probability factor $f_{use,lights,j}$ which is influenced by the contributions from natural sunlight during the years.

Lastly, the prediction of the electrical load associated with the air conditioning demands of buildings is estimated through a hybrid model, further detailed in the subsequent paragraph.

6.2.3 Sequential HNN model for heating / cooling demands

The sequential hybrid neural network (HNN) model combines a building energy performance simulation tool with a feed-forward artificial neural network (FFANN) to assess the HVAC electrical load profile of EC users building archetypes. This sequential approach exploits a feedforward connection between the physical building model and the FFANN, represented by the error signal generated from comparing the simulated energy demand of the physical model with the actual demand. By incorporating this additional input/information from the physical model, the accuracy of the FFANN model is improved while avoiding the complexities associated with integrating physical laws directly into the FFANN architecture.

A schematization of developed hybrid model is reported in Figure 70. The input data for both building energy simulation models are represented by the climatic conditions, geometric properties of the archetypal building, thermophysical properties of the building envelope, heat inputs from equipment and lighting, as well as the occupancy profile of the occupants.

The physical modelling of the building consists of geometric and energy modelling. The geometric modelling was developed using Google Sketchup version 8 software. This geometric model was then imported into TRNSYS version 17 software and, by using its building energy modelling libraries, it was possible to simulate the thermal energy requests for each type of building in the EC. Once the thermal demands $Q_{th,load,j}$ were estimated, the following correlation was employed to determine the electrical consumption linked to the operation of the HVAC, denoted as $P_{HVAC,j}$:

$$\begin{cases} P_{HVAC,j} = Q_{th,load,j} \cdot COP_{hp,j} \\ COP_{hp,j} = f\left(hp_{type}, \frac{Q_{th,load,j}}{Q_{th,load,j,max}}, T_{hp,source}, T_{hp,sink}\right) \end{cases} \quad \text{Eq. (36)}$$

Where the efficiency of the heat pump $COP_{hp,j}$ was estimated based on factors such as the type of heat pump (e.g., air-to-air, air-to-water, water-to-water, etc.), the fraction of the required heat load on the maximum one, as well as the temperatures on the source and sink sides of the heat pump [232].

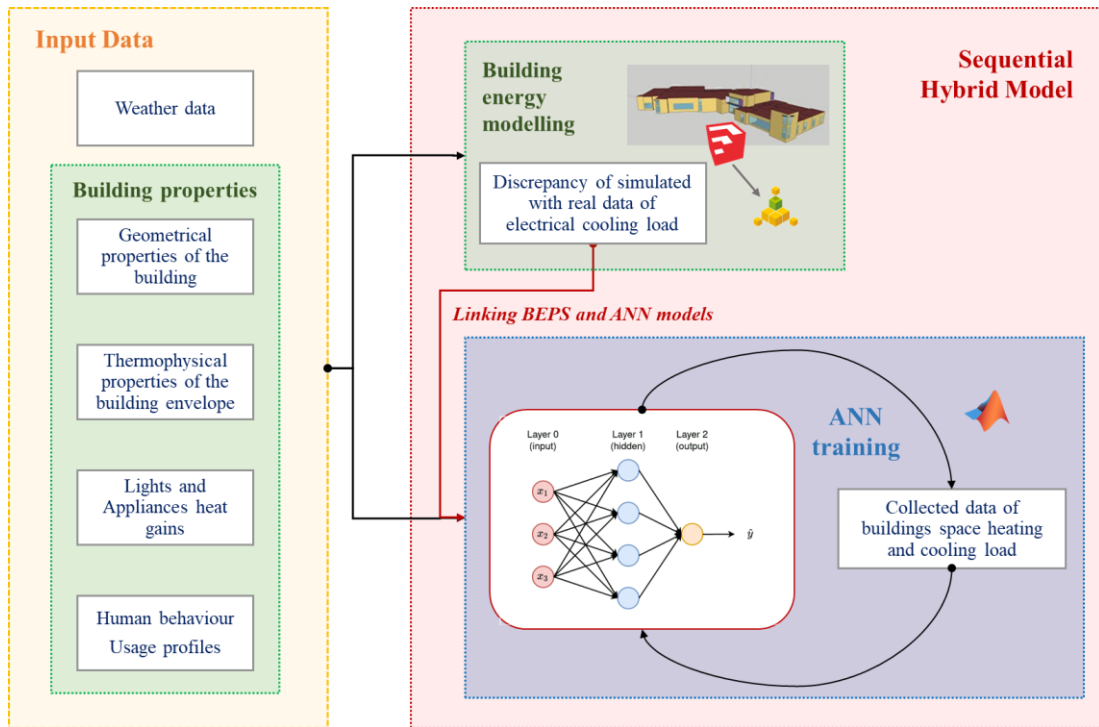


Figure 70. Schematisation of sequential Hybrid Neural Network model.

The FFANN employed within the hybrid model was developed by using MatLab functions. It consists of an input layer corresponding to various input variables (e.g., weather conditions, building characteristics, occupancy patterns, etc) and an output layer representing the electrical loads requiring prediction. The number of neurons in the hidden

layer is determined by averaging the number of neurons in the input and output layers, and it utilizes the Rectified Linear Unit (ReLU) activation function, typically used in artificial neural networks [318]. During the network's training phase, the Adaptive Gradient Algorithm (Adagrad) serves as the optimiser. This algorithm adjusts the learning rates for each weight (i.e., parameter) based on the square root of the sum of squared gradients [319].

The structure of the HNN model used to predict the electrical load associated with end-user air conditioning demands is described below. First, the difference between the real data and that obtained from the physical model of the building is estimated. This discrepancy is then incorporated as an input to the FFANN model to fine-tunes its training process, thus defining the hybrid HNN model. The HNN model training was performed with real data sets normalized to their respective maximum values on the time string to enhance the accuracy of the HVAC electrical load prediction. Subsequently, multiple HNN models are developed for each archetypal building, utilizing data sets that mirror its thermophysical and socio-behavioural characteristics of the occupants.

Finally, this sequential hybrid model capitalizes on the strengths of both approaches – the accuracy of physics-based models and the adaptability of ANN models – to enhance prediction accuracy while capturing intricate relationships and learning from available data.

6.2.4 Peer-to-Peer model for users' energy sharing

The P2P energy sharing mechanism, implemented in the proposed and developed EC model, adopts a centralized control strategy. This strategy aims to regulate the connections between prosumers and consumers, maximizing energy interaction for each end-users coupling, while reducing dependence on the central grid. The procedure adopted to determine the price of shared energy is based on the equilibrium point criteria between *consumers demand curve* and *prosumers supply curve*.

Figure 71 depicts a flowchart illustrating the algorithm used to model the P2P energy exchange within the community.

The initial step of this mechanism involves evaluating the surplus of energy generated by each prosumer's PV systems. Once the availability of electricity from a single prosumer for sharing purposes has been identified, the methodology is engaged in establishing the rules governing the *local energy market*. These rules aim to evaluate the connections among end-users that maximize their energy match. The function adopted to assess these connections is expressed in the following Eq. (37):

$$\Lambda_{opt[i]} = \arg \min_{j \in cons_{type}} (P_{sur,pros,i} - P_{load,cons,j}) \quad \text{Eq. (37)}$$

In this equation, Λ_{opt} represents a matrix with rows equal to the number of prosumer types within the investigated EC. The matrix elements are obtained through the arguments of the minimum of the function represented by the difference between the prosumer's surplus $P_{sur,pros,i}$ and the consumer's request $P_{load,cons,j}$. Consequently, each element of the matrix Λ_{opt} establishes the best coupling between the i -th prosumer and the j -th consumer.

The power exchanged by prosumers with consumers is determined by Eq. (38):

$$P_{exch,P2P_{[ix]}} = \min \left\{ P_{sur,pros,i}, P_{load,cons,\Lambda_{opt}(i)} \right\} \quad \text{Eq. (38)}$$

This equation calculates the exchanged power $P_{exch,P2P,i}$ by each prosumer as the minimum value between the available surplus and the consumer request. Where $P_{load,cons,\Lambda_{opt}(i)}$ represents the electrical load of the consumer that maximizes the energy interaction with the i -th prosumer surpluses $P_{sur,pros,i}$, as determined in Eq (37). Following this, it is possible to determine the residual surplus of each prosumer and the unmet demand of consumers.

Finally, this process is iterated to couple the community's end-users until either the surplus of prosumers or the requests from consumers have been entirely shared or satisfied.

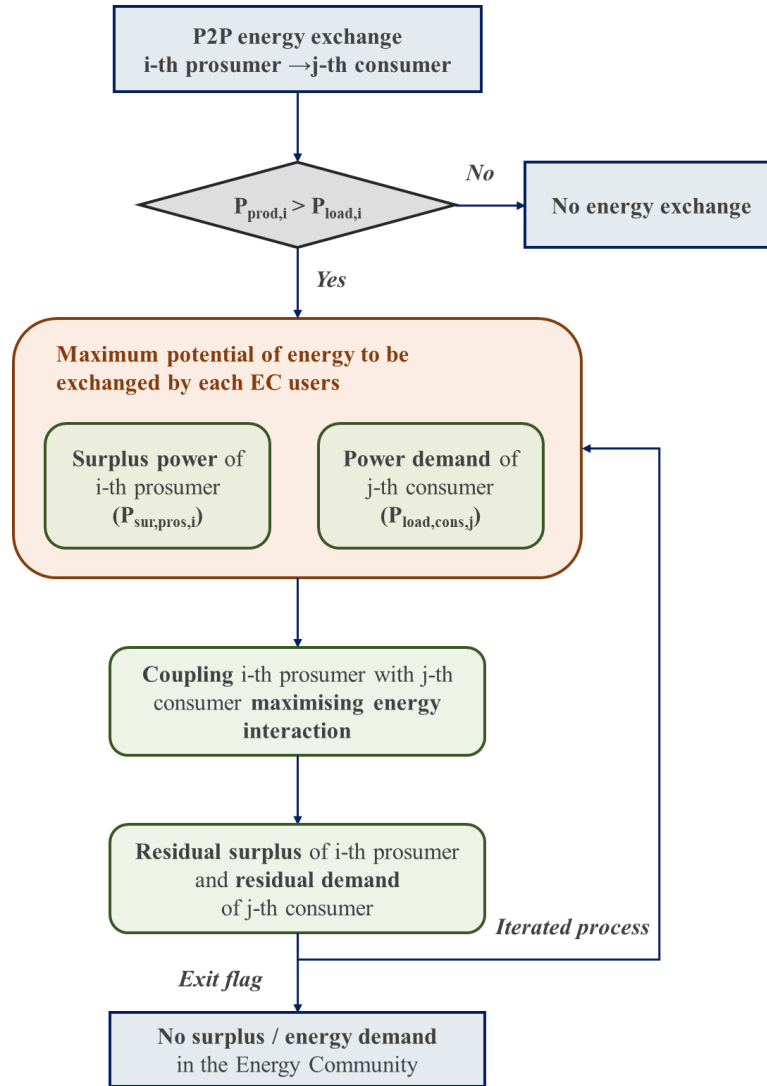


Figure 71. Algorithm used to model the P2P energy exchange mechanism.

6.2.5 Pricing strategy

The pricing strategy for the P2P energy community relies on balancing supply and demand curves to determine the market price for exchanged energy.

The demand curve, relating to consumers, expresses their willingness to pay for electricity as the quantity of energy requested varies. This curve is obtained from the utility curve, reflecting consumers' satisfaction or utility from consuming energy [320]. It is expressed with this equation:

$$\begin{cases} C_d = \frac{dU(E_d, c_{el,max})}{dE_d} = c_{el,max} - a_j \cdot E_d \\ U(E_d, c_{el,max}) = c_{el,max} \cdot E_d - \frac{a_j}{2} E_d^2 \end{cases} \quad \text{Eq. (39)}$$

Where the demand curve C_d is evaluated as the derivative of the utility curve U . C_d is a function of the quantity of requested energy, denoted as E_d , and considers the maximum cost of electricity $c_{el,max}$ that the consumer is willing to pay. In this strategy, the maximum cost aligns with the purchase cost from the central grid. Additionally, the demand curve is influenced by a calibration constant a_j which depends on the j -th consumer type, which, in this case, is impacted by factors such as the number of occupants [320].

The supply curve C_s demonstrates the price at which prosumers are willing to sell energy as the exchanged quantity varies.

$$C_s = f(a_j, E_s, rsp_{el,max}) \quad \text{Eq. (40)}$$

As expressed in Eq. (40) the supply curve is determined as a function involving the calibration constant a_j , the offered supplied energy E_s , and the maximum retail selling price, $rsp_{el,max}$, from the grid.

The intersection between the demand and supply curves enables the determination of the market's equilibrium point, thus establishing the unit cost of electricity, $c_{el,P2P,j}$, for the j -th consumer participating in the *local energy market*.

This strategy for determining the unit price of energy was aimed to establish a fair criterion that guarantees the right trade-off between consumer savings and prosumers revenues compared to the reference scenario of purchasing and selling from/to the central grid.

6.2.6 EC design methodology

This paragraph offers an overview of the aggregation criteria that have been suggested to identify different EC configurations. These configurations will be the focus of a bi-level optimisation analysis to assess the best possible P2P energy community design.

The intermittency of PV production can be noted as a critical consideration in the optimisation routine. It acts as a key variable influencing the optimal aggregation among users, selecting consumers whose energy demand profiles can minimize or mitigate the effects of this intermittency and fluctuating production on the national grid infrastructure.

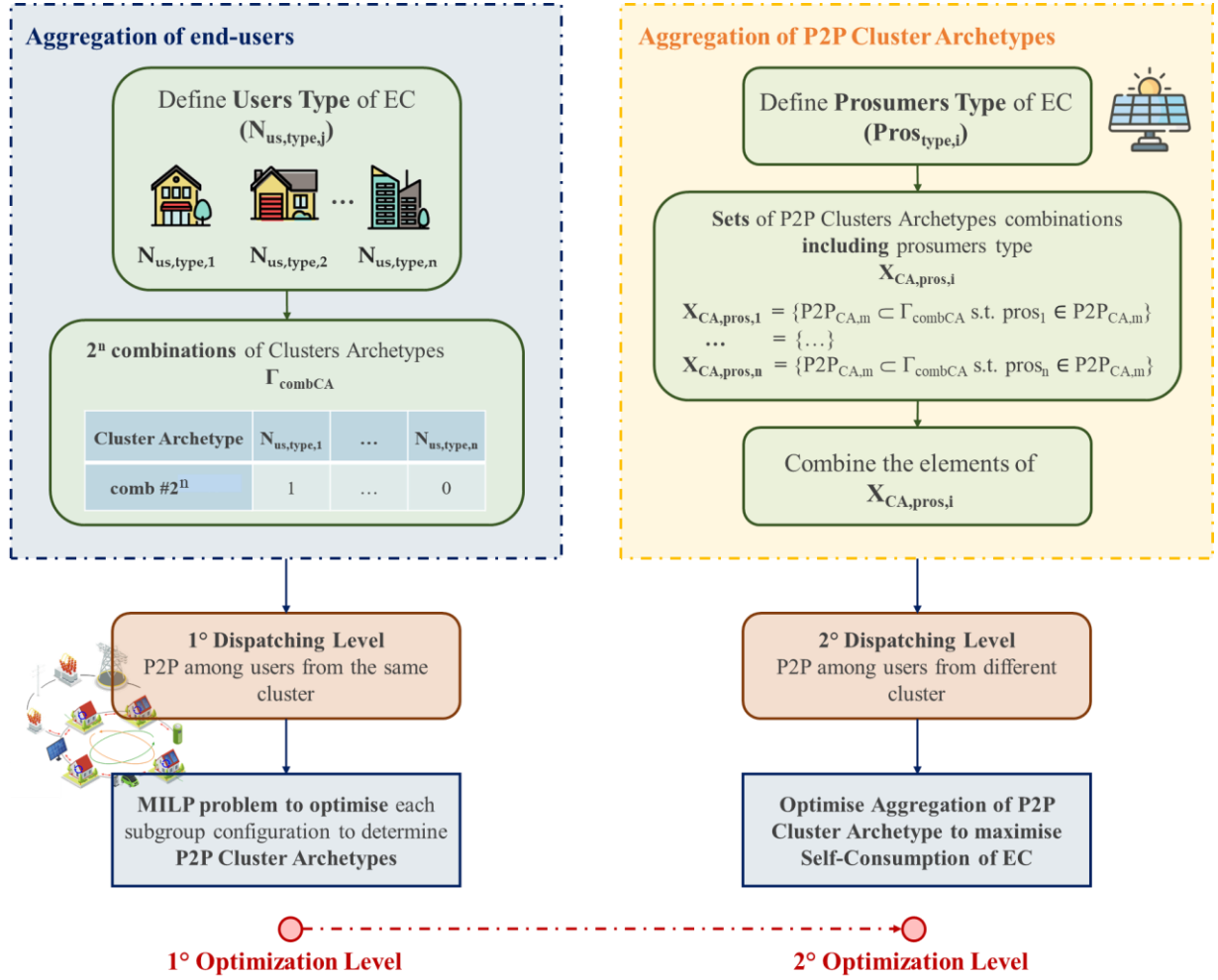


Figure 72. Synoptic diagram related to the aggregation criteria for EC design.

As illustrated in the synoptic diagram of Figure 72, the aggregation criteria are categorized into two classes, respecting the bi-level structure of the optimisation procedure. The two levels of the optimisation problem are executed sequentially, making the second aggregation criterion dependent on the results obtained from the first optimisation level.

The primary objective of the first optimisation level is to identify subgroups among community end-users, optimised in accordance with economic and energy indices. Furthermore, within each EC's subgroup, the implementation of the first dispatching layer (1st DL) of the P2P model is executed. This dispatching layer involves energy sharing mechanisms among peers of the same cluster.

The second level focuses on the aggregation of these optimised subgroups to obtain the best EC configuration that optimises the management of the EC's energy resources. Within this optimisation process, for each investigated EC configuration, the second level of P2P

dispatching (2nd DL) is implemented. This level operates in sequence with the 1st DL, enabling energy sharing among users associated with different optimised subgroups.

Further details regarding the aggregation criteria, optimisation procedures and objective functions employed for the development of the two-level problem will be described below.

6.2.7 Aggregation criteria

Establishing precise end-user aggregation criteria stands as a pivotal procedure in determining the design of energy communities. This study introduces and elaborates two aggregation levels to perform this process.

The primary step of the first aggregation criterion involves identifying and categorizing all types of end-users within the EC (see Figure 72). Therefore, an analysis is conducted to assess all potential combinations for grouping them into subgroups. These combinations are referred to as *cluster archetypes* within this manuscript. For each *cluster archetype*, the assumption is that at most one end-user belonging to each type will be considered. Subsequently, the combinations were evaluated as follows:

$$\Gamma_{combCA}^{[N_{comb,CA} \times N_{us,type}]} = combinations(N_{us,type,1}, \dots, N_{us,type,n}) \quad \text{Eq. (41)}$$

This equation defines Γ_{combCA} as the set that includes all combinations of elements derived from the input arrays denoted as $N_{us,type,j}$. This array corresponds to the j-th set of end users, where its elements indicate the presence or absence of the same user type within the *cluster archetype* (refer to Eq. (42)).

$$N_{us,type,j} = \{0,1\} \quad \text{Eq. (42)}$$

The number of rows of Γ_{combCA} , hence the number of combinations, is determined by the product of the elements within each set $N_{us,type,j}$, as indicated in Eq (43):

$$N_{comb,CA} = \prod_{j=1}^n size(N_{us,type,j}) \quad \text{Eq. (43)}$$

Meanwhile, the number of columns in Γ_{combCA} corresponds to the total number (denoted as n) of end-user types within the EC. The elements of Γ_{combCA} matrix were obtained through the Cartesian product of the elements of the n sets $N_{us,type,j}$. It is worth noting that combinations resulting in a total number of users fewer than two were not investigated, as it is impossible to create a subgroup of ECs under such circumstances.

Subsequently, the configurations of *cluster archetypes*, previously defined, are optimised through a MILP-type procedure, taking into account the variation of prosumers based on their types and numbers. The resulting optimised configurations of EC subgroups are referred to as P2P cluster archetypes ($P2P_{CA}$).

Regarding the second aggregation criterion, the focus lies on determining all the possible configurations of the entire EC obtained by combining the $P2P_{CA}$ (see Figure 72). Initially, after identifying the quantity and types of prosumers within the investigated EC, the $P2P_{CA}$ obtained from the first level of optimisation are chosen. Specifically, this selection considers $P2P_{CA}$ that include at least one type of prosumer from the investigated EC. These selected $P2P_{CA}$ are grouped into sets according to the following definition:

$$X_{CA,pros,i} = \left\{ P2P_{CA,m} \subset \Gamma_{combCA} \rightarrow s.t. pros_i \in P2P_{CA,m} \right\} \quad \text{Eq. (44)}$$

$$\begin{cases} i \in pros_{type} \\ m \in [1, 2^n] \end{cases}$$

Where $X_{CA,pros,i}$ denotes the sets formed by the m-th $P2P_{CA,m}$ elements contained in Γ_{combCA} , which encompass the i-th type of prosumer. At this stage, the elements within the sets $X_{CA,pros,i}$ are combined using the same procedure outlined in equations Eq (41) and Eq. (43). The resultant set of combined elements from $X_{CA,pros,i}$ is defined as $\Gamma_{combCA,pros}$.

Once the sets of potential end-user subgroups $X_{CA,pros,i}$ are defined and combined to assess all possible aggregation scenarios $\Gamma_{combCA,pros}$, an iterative optimisation procedure is executed. This procedure aims to identify the optimal EC configuration which maximizes the annual self-consumption.

In conclusion, these criteria have been employed to delineate sets of subgroups within the EC and configurations for the entire EC. The subsequent description details the procedures utilized to determine the optimal scenarios within these defined sets.

6.2.8 Optimisation of P2P cluster archetypes

The first optimisation level aims to determine the best configuration of each m-th *cluster archetype*, defined in the matrix Γ_{combCA} using Eq (41).

This optimisation procedure, as previously reported, was solved with a MILP-type algorithm. The decision variables investigated for the optimisation of each *cluster archetype* are the number and type of prosumers, and were defined as follows:

$$\begin{cases} pc_{pros,CA_m} = n_{pros} / n_{CA_m} \\ pros_{type,CA_m} = combinations \left(\begin{pmatrix} n_{CA_m} \\ n_{pros} \end{pmatrix} \right) \end{cases} \quad \text{Eq. (45)}$$

The variable $pc_{pros,CA,m}$ denotes the percentage of prosumers within the *cluster archetype* (CA) under investigation. This percentage ranges from a minimum value which ensure the presence of at least one prosumer, to a maximum value equal to half the number of users (i.e., $n_{CA,m}$) in the CA. Meanwhile, the second variable, $pros_{type,CA,m}$, is determined

by computing all the binomial coefficient's combinations of the $n_{CA,m}$ user types taken n_{pros} at a time. This variable's role is to determine all the potential configurations of the m-th CA, that can be obtained by varying the type of prosumer for a fixed $pc_{pros,CA,m}$ percentage.

The objective function adopted to discover the best involvement of prosumers within the m-th CA, considering both their quantity and type, is the annual self-sufficiency $SS_{CA,m}$. By modifying the variables $pc_{pros,CA,m}$ and $pros_{type,CA,m}$, the parameter space determines all feasible configurations for the CA. These potential solutions are subject to constraints related to an economic function that incorporates prosumers' revenues.

Formally, the optimisation problem is defined as follows:

$$\begin{cases} \max \left(SS_{CA,m} = \left(\sum_{i \in pros_{type,CA,m}} E_{PV,sc,pros,i} + \sum_{j=1}^{n_{CA,m}} E_{P2P,cons,j} \right) / \sum_{j=1}^{n_{CA,m}} E_{load,j} \right) \\ s.t. \rightarrow J_{pros,i} = c_{el,P2P,j} \cdot E_{P2P,cons,j} + c_{el,g} \cdot E_{PV,sc,pros,i} \geq J_{pros,i,thr} = f(SP_{B_{pros,i,thr}}) \end{cases} \quad \text{Eq. (46)}$$

Hence, as depicted in this equation, the goal is to identify the optimal solution that maximizes the annual $SS_{CA,m}$, calculated as the ratio between the sum of photovoltaic-produced energy self-consumed ($E_{PV,sc,pros,i}$) and shared by each i-th prosumer ($E_{P2P,cons,j}$), and the total energy demanded by the users ($E_{load,j}$). While, the solution set is constrained by the condition that the cash-flow $J_{pros,i}$ for each prosumer must exceed or be equal to its threshold value $J_{pros,i,thr}$, determined as a function of the minimum required pay-back time $SP_{B_{pros,i,thr}}$.

Finally, this optimisation procedure is performed for each m-th CA with the aim of determining all the optimal $P2P_{CA}$ configurations, which can be exploited for the next step related to the EC design.

6.2.9 P2P cluster archetypes aggregation

The second optimisation level is performed in series with the previous one, and as described in the previous paragraphs, is aimed at determining the optimal design of the EC.

The first step consists in determining the quantity of each type of prosumers of the investigated EC. The next step involves the implementation of an iterative procedure to obtain the EC configuration for each combination of the set $\Gamma_{combCA,pros}$.

As seen previously, the elements of each combination will be represented by $P2P_{CA,m}$ which contain at least one of the types of prosumers of the investigated EC. Through this iterative process, the goal is to determine the count of each $P2P_{CA,m}$ contributing to the EC configuration. The method (expressed in Eq. (47)) is constrained by the objective of including all the prosumers $N_{pros,i,EC}$ within the configuration EC_{conf} while simultaneously

considering the maximum availability of each consumers type $N_{us,j,conf}$ present within the EC under investigation.

$$EC_{conf} = N_{P2P_{CA,m}} \rightarrow \forall \text{ element of } \Gamma_{combCA,pros} \quad \text{Eq. (47)}$$

$$s.t. \rightarrow \exists N_{us,j,conf} \wedge N_{pros,i,EC} \subset EC_{conf}$$

The configurations generated through this iterative process for each $\Gamma_{combCA,pros}$ combination are evaluated and compared. The most favourable configuration is determined based on its ability to maximize self-consumption, defined as follows:

$$SC_{EC} = \left(\sum E_{PV,sc,pros,EC} + \sum E_{P2P,cons,EC} \right) / \sum E_{load,EC} \quad \text{Eq. (48)}$$

Here, the self-consumption of the overall EC configuration (SC_{EC}) is determined by calculating the ratio between the total energy self-consumed by all EC prosumers and the energy shared among all consumers within the investigated EC configuration, divided by the total load of the EC users.

6.3 Proof of concept

The suggested methodology's potential was assessed through a concept analysis targeting the design of an energy community, considered as case study, situated in a residential zone adjacent to the park of the Royal Palace of Caserta, Italy. Initially, the users of this area were categorized on the basis of occupant types and the geometric, thermophysical properties of their respective buildings. This classification allowed the establishment of building archetypes, enabling the energy simulation of the users. Table 18 presents the characteristics of the six identified building archetypes.

This table delineates the building characteristics and occupancy types for each user category, providing essential parameters used as inputs for estimating their electrical demands. The predictive methodology, relying on statistical analyses and the HNN hybrid model described in the previous sections ("*Building archetypes for EC users' energy modelling*" and "*Sequential HNN model*"), was employed to assess the electrical loads linked to equipment, lighting, and HVAC systems for these users. Additional inputs, necessary for this energy simulation, include occupancy profiles patterns sourced from analyses conducted by the national statistics institute (ISTAT) [321], as well as equipment and lighting usage frequency factors obtained from this specified reference [317]. Moreover, the weather data impacting the buildings' air conditioning demands - such as external air temperature, humidity, and solar radiation - were taken from Meteonorm version 8 software datasets [322].

For a comprehensive analysis of the estimated electrical demands for the users within the investigated case study, refer to "*Appendix A*".

Table 18. Users building archetypes properties.

Properties		Building archetype					
Class	Subclass	#1	#2	#3	#4	#5	#6
Type of occupants	Age range [years]	18-64	>64	18-64	>64	18-64	18-64
	Number of employee	1	0	2	0	2	2
	Number of no employees	0	1	0	2	0	0
	Number of children	0	0	0	0	2	3
Building geometry	Floor area [m ²]	67	67	100	100	134	167
	Ceiling height [m]	2.8	2.8	2.8	2.8	2.8	2.8
	Windows to wall ratio [%]	18	18	20	20	25	25
Building thermophysical properties	U-value of walls [W/m ² K]	1.4	1.4	1.4	1.1	1.1	1.1
	U-value of windows [W/m ² K]	2.5	3.8	3.8	2.5	2.5	2.5

The prospective users within the surveyed residential area willing on deploying a photovoltaic system belong to types #1, #4, and #5 (refer to Table 18 for specific categorizations). The primary parameters considered for sizing the systems tailored to these user types, alongside the user count per type are outlined in Table 19. The results related to the dynamic performance and producibility of the photovoltaic systems of the investigated users are reported in “*Appendix B*”.

The design of this case study's energy community aims to optimise the energy resources management of these users equipped with a PV system (i.e., prosumers) by aggregating them with specific consumer types. This aggregation minimizes interactions with the central grid and maximizes energy exchanges among end-users (as described in paragraph “*EC design methodology*”).

Table 19. PV systems characteristics, type and count of prosumers.

PV systems sizing					
Prosumer		Type #1	Type #4	Type #5	
Rating power [kW]		0.7	1.75	2.98	
Number of PV module [-]		4	10	17	
Surface [m²]		5.2	13	22.1	
Number of end-users [-]		1	7	9	
Technological characteristics of PV polycrystalline module					
$P_{MPP,STC}$ [W]	G_{STC} [W/m²]	$T_{cell,STC}$ [°C]	$C_{t,P}$ [1/°C]	η_{BOP} [-]	$\eta_{shading}$ [-]
175	1000	25	-0.0043	0.79	0.75

The initial step in the methodology adopted for the EC design involves introducing an end-user's aggregation scheme to create subgroups within the EC. The configurations of these subgroups were optimised using the first-level optimisation procedure described in the previous section ("*Optimisation of P2P cluster archetypes*"). This criterion aims to outline opportunities for each prosumer to align with specific consumer categories, emphasizing maximal self-sufficiency while minimizing investment pay-back time. As previously mentioned, subgroup configurations are characterized by a maximum of one user per user type. Subsequently, in order to enhance the self-consumption levels of the prosumers' PV systems and reduce dependence on the central electricity grid, a second level of aggregation was proposed. Finally, this criterion aims to offer guidelines for globally aggregating users and determining the optimal EC design.

The next section presents the results concerning energy management, as well as the energy and economic performance indices of the EC derived from the applied methodology.

6.4 Results

This section presents the main results concerning the performance and energy management of the EC designed in accordance with the proposed methodology and implemented for the analysed case study. The saving obtained by the proposed methodology have been evaluated comparing it with a reference scenario characterised by the users (both consumers and prosumers) acting independently and connected only to the national electricity grid.

The results section, aimed to investigate the reliability of the developed methodology, is organized as follows:

-
- i) Evaluation of the performance and accuracy of the innovative HNN hybrid model for estimating electrical loads associated with users' air conditioning demands.
 - ii) Assessment of energy inputs that encompass the electrical load profiles of the identified end-user types and estimates of electricity production from PV systems owned by users acting as prosumers (the results concerning the determination of these inputs are detailed in “*Appendix A*” and “*Appendix B*” respectively).
 - iii) Results concerning to the proposed bi-level optimisation procedure aimed at determining the optimal configuration and design of the energy community.
 - iv) Analysis of the energy management for each end-user, taking into account the effects associated with the adoption of a P2P energy sharing mechanism.
 - v) Economic analysis conducted on individual EC users.
 - vi) Assessment of the overall energy performance of the EC.

6.4.1 HNN model prediction accuracy

As documented in the literature, air conditioning requests often contribute significantly, sometimes up to 40%, to the total electrical demand of buildings [323]. Therefore, this study endeavours to address this by developing a precise model for predicting the electrical load linked to HVAC system requirements.

This hybrid model integrates the strengths of black-box neural network models with those of physical models used in Building Energy Performance Simulation (BEPS) tools, as previously mentioned. The resultant sequential HNN uses the gap between real and simulated data from the physical model as input for the neural network model. This approach enables the neural network to encompass all building physical effects, such as thermal inertia, solar exposure, and optical properties of window components. Concurrently, it retains the advantages of the black-box model in capturing events unattainable by the physical model, such as socio-behavioural influences of the occupants on HVAC system operation.

Six distinct hybrid models were developed for the various building archetypes identified in the analysed case study. Notably, these buildings rely on an air conditioning system (i.e., air-to-air heat pump) solely during the cooling season. The training process of the model was conducted using datasets associated with building typologies exhibiting similarities to those under examination, as outlined in Table 18. It is important to highlight that these datasets, obtained from open-source platforms [324], pertain to climatic locations distinct from those observed in the studied case. The robustness and the accuracy of the model were assessed by comparing the simulated electrical energy needs due to the HVAC operations with the actual data extracted from the aforementioned datasets. It is important to note that the data used for the model testing analysis came from a different time period than the ones used for the training process.

The results pertaining to the accuracy assessment of the developed model are shown in the following figures; for the sake of brevity, results relative to for the building type #1, characterized by a single occupant under the age of 64, are selected. In Figure 73, a comparison of the dynamic electrical demand of HVAC systems is depicted (Figure 73a: July 29th to August 4th, Figure 73b: October 7th to October 12th), showcasing the simulation by the HNN model (red dotted line) against the actual data [324] (blue line). The comparison demonstrates a notable alignment between the predicted and dataset values.

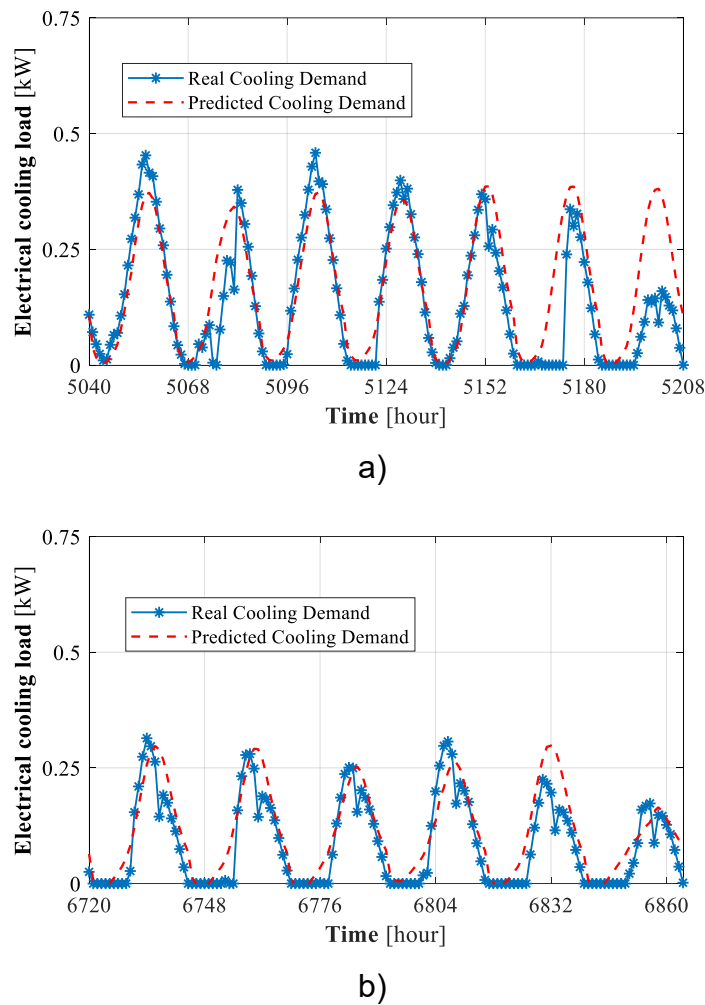


Figure 73. Comparison between the real and predicted electrical cooling demand for building archetype 1: a) comparison from July 29th to August 4th; b) from October 7th to October 12th.

Figure 74 illustrates the deviation between simulated and actual data throughout the entire cooling season. In Figure 74a, the relative error of the time series of electrical load $P_{HVAC,1}$ for the archetype building #1 consistently falls within the range of $\pm 20\%$ across all data points, demonstrating a high R-square value of 0.96. This observation is supported in

Figure 74b, displaying the analysis of actual versus predicted monthly electricity demands for cooling (E_{cool}). The histogram reveals an increase in space-cooling electrical demands, particularly from July to October, and indicates the model's accuracy in estimating these demands. Notably, minimal absolute energy deviations are observed, with relative error values within the $\pm 10\%$ range for the months of June, August, September, and October.

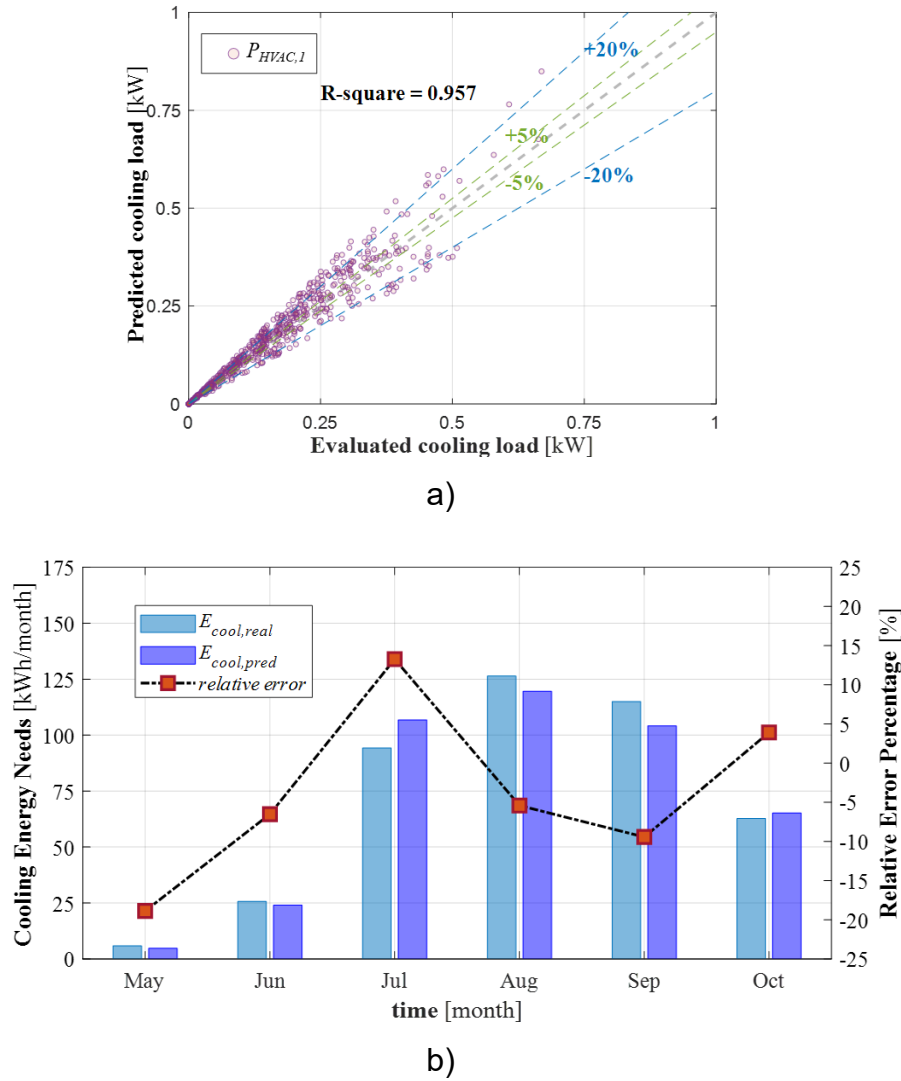


Figure 74. Relative percentage deviation between simulated and real data: a) time series comparison of electrical load P_{HVAC} ; b) monthly comparison of electrical cooling energy needs E_{cool} .

After demonstrating the accuracy of this model and utilizing it to estimate the electrical load linked to HVAC systems for each archetype building type, it became feasible to determine the energy inputs concerning the overall electrical demands of the EC end-users, as detailed in “Appendix A”.

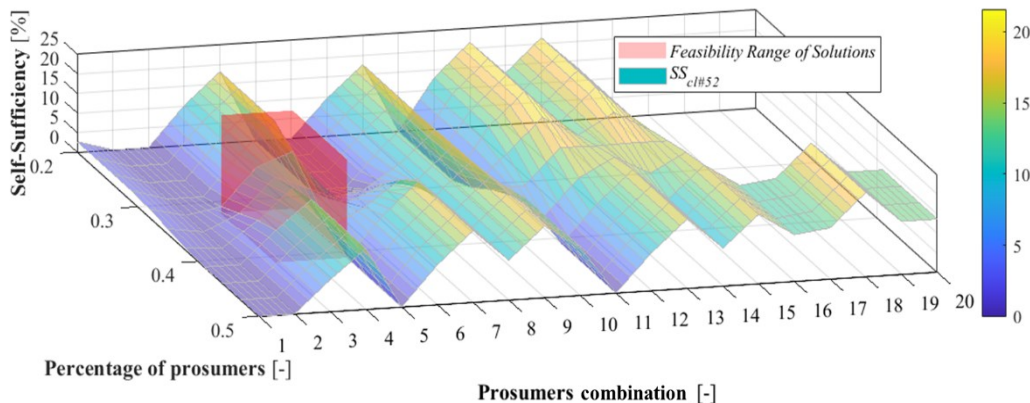
6.4.2 EC design

This paragraph delves into the implementation results of the proposed bi-level optimisation procedure aimed at determining the optimal EC configuration for the investigated case study.

As initial step, the first user aggregation criterion is implemented. This stage aims to establish all end-users' connection combinations (referred to as *EC subgroups* or *cluster archetypes* within this manuscript) by adhering to the assumption of allocating a maximum of one building per type of end-user (as detailed in paragraph "Aggregation criteria"). Consequently, with the identification of six distinct end-user types within the studied residential area, the total possible combinations of EC subgroups amount to 64. However, out of these 64 combinations, seven will be excluded as they consist of fewer than two users.

The first level of the optimisation problem focuses on determining the optimal configuration for each of the 57 cluster archetypes, maximizing annual self-sufficiency as the number and type of prosumer varies (refer to "Optimisation of P2P cluster archetypes"). The problem is solved using a MILP-type algorithm that adopts a linear function to constrain the choice of the optimal solution. This function is aimed at determining the range of configurations that ensure revenues for each prosumer greater than or equal to the minimum threshold that guarantees a return on investment of the PV system of less than 3 years. The energy sharing model between users of the cluster archetypes investigated is based on P2P mechanisms (explained in paragraph "Peer-to-Peer model for users' energy sharing").

Figure 75 shows the results of this first optimisation level. To streamline the analysis, investigation was solely conducted for the cluster archetype of the #52 combination, which includes users of types #1, #2, #5, and #6. Figure 75top illustrates the annual self-sufficiency of all configurations by varying both the percentage of prosumers and the prosumer type. The red-highlighted area outlines the feasibility range of solutions, representing the set of configurations adhering to the constraints imposed within the optimisation problem.



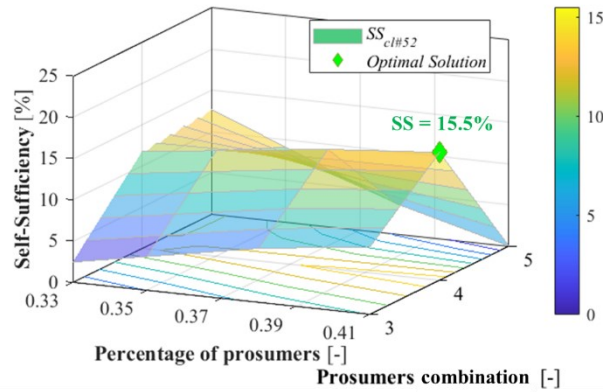


Figure 75. Results of the first optimisation level referred to cluster archetype #52: top) self-sufficiency of all investigated solutions; bottom) choice of the optimal configuration within the feasibility range.

Figure 75bottom is focused on investigating all the feasible solutions. Among these, the optimal configuration, indicated by the green diamond, achieves maximum annual self-sufficiency. This configuration involves 40% of prosumers, specifically represented by the building types #1 and #5.

The process of establishing optimal configurations (referred to as $P2P_{CA}$ in the manuscript) was conducted for all 57 combinations. Upon determining these configurations, each prosumer is offered various subgroup possibilities to unite with other residential area users, aiming to minimize their return on investment through energy sharing. Figure 75 presents all the $P2P_{CA}$ configurations that include the types of prosumers in the case study, namely types #1, #4, and #5.

Table 20. Optimal configuration of cluster archetypes.

Cluster Archetype configuration	User type #1	User type #2	User type #3	User type #4	User type #5	User type #6	Self-sufficiency
#35	prosumer	consumer	*	*	prosumer	*	10.5 %
#52	prosumer	consumer	*	*	prosumer	consumer	15.5 %
#55	prosumer	consumer	*	consumer	prosumer	*	12.7 %
#56	prosumer	consumer	*	consumer	prosumer	consumer	10.1 %
#60	prosumer	consumer	consumer	*	prosumer	consumer	11.5 %
#6	*	*	*	prosumer	*	consumer	11.1 %
#7	*	*	*	prosumer	consumer	*	12.3 %
#14	*	*	consumer	prosumer	*	consumer	10.2 %
#15	*	*	consumer	prosumer	consumer	*	14.3 %
#29	*	consumer	consumer	prosumer	*	*	16.7 %
#45	consumer	*	consumer	prosumer	*	*	9.9 %
#11	*	*	consumer	*	prosumer	*	12.2 %
#19	*	consumer	*	*	prosumer	*	24.4 %
#27	*	consumer	consumer	*	prosumer	*	14.2 %
#28		consumer	consumer		prosumer	consumer	11.1 %
#32		consumer	consumer	consumer	prosumer	consumer	10.2 %
#51	consumer	consumer			prosumer		25.1 %

As indicated in Table 20, $P2P_{CA}$ are categorized into subsets that present the same type of prosumer in their cluster configuration.

Following this categorization, the subsequent stage of the optimisation problem concentrates on defining the optimal design for the entire EC. The second aggregation criterion (detailed in paragraph “*Aggregation criteria*”) aims to connect the previously determined subgroups to enhance the management of community energy resources. This aggregation involves implementing a secondary layer of P2P energy sharing mechanism, this time among different $P2P_{CA}$ users.

By combining all the subsets outlined in Table 20, a total of 180 potential EC configurations can be determined. An iterative procedure is performed for all these combinations to ascertain the number of $P2P_{CA}$ occurrences required to encompass the entire prosumers of the case study within the EC. It will also ensure conformity with constraints related to the number of consumers by type present in the investigated residential area.

The second level of optimisation aims to identify the configuration that maximizes annual self-consumption from the available options. The reference self-consumption value,

depicted by the red dotted line in Table 20(64%), corresponds to the scenario without EC implementation.

The investigated EC configurations are then categorized based on the types of consumers they incorporate, with each coloured band in Figure 76 characterised by solutions with different number of consumers. Subsequently, comparing all investigated EC configurations, each comprising the same number and type of prosumers, reveals that the optimal configuration achieves an annual self-consumption level of 89%, represented by the green diamond in Figure 76. This configuration includes consumers of types #1, #2, #3, #5, and #6.

This categorization underscores the significance of appropriately grouping consumers with prosumers within an EC. The optimal energy community configuration attained through the exploitation of the proposed methodology is expressed in Table 21.

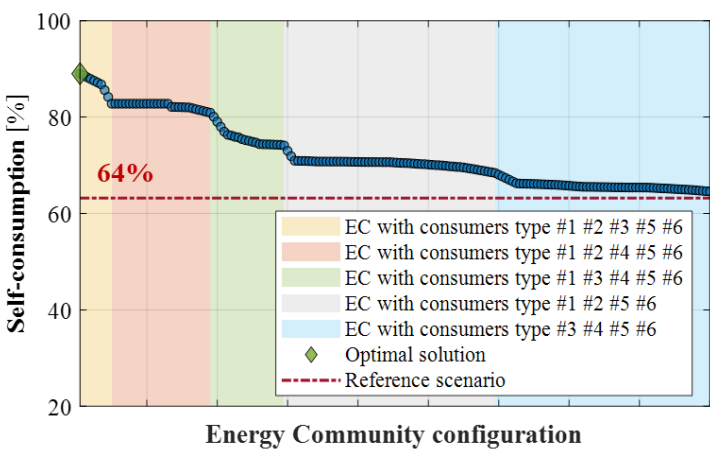


Figure 76. Selection of the optimal energy community configuration maximising the global self-consumption.

Table 21. Optimal configuration of Energy Community.

Aggregation of Cluster Archetypes						
Cluster Archetype				Number		
#52				1		
#15				7		
#19				3		
#51				5		
Number of prosumers by type						
Cluster Archetype	N _{pros,type,#1}		N _{pros,type,#4}		N _{pros,type,#5}	
#52	1		x		1	
#15	x		7		x	
#19	x		x		3	
#51	x		x		5	
Number of consumers by type						
Cluster Archetype	N _{cons,type,#1}	N _{cons,type,#2}	N _{cons,type,#3}	N _{cons,type,#4}	N _{cons,type,#5}	N _{cons,type,#6}
#52	x	1	x	x	x	1
#15	x	x	7	x	7	x
#19	x	3	x	x	x	x
#51	5	5	x	x	x	x

In the next sections, the energy performances obtained, the potential economic benefits of individual users will be analysed.

6.4.3 Users' energy management

The energy management results presented in this section refer to each end-user type of the $P2P_{CA}$ subgroups aggregated in the optimal EC configuration. It's important to note that the energy analysis investigated for each $P2P_{CA}$ is identical for all the subgroups belonging to the same $P2P_{CA}$ type. Figure 77 illustrates the dynamic trends of end-user energy management. To streamline the analysis, only one prosumer and one consumer were examined, specifically, prosumer type #5 from cluster archetype #19 and consumer type #6 from cluster #52. In Figure 77a, the distribution of surplus energy generated by the prosumer PV system is showcased. Initially, any surplus is shared with users from the same cluster archetype (for this specific case represented by the consumer type #2) according to the 1st DL of the P2P mechanism. Subsequently, the remaining surplus is available for sharing with users from other clusters, as stated with the P2P 2nd DL mechanisms. The coloured bars in

Figure 77top precisely delineate the quantities of excess energy shared within the cluster (P_{1stDL}), shared with other clusters (P_{2ndDL}), and sent to the central grid ($P_{to,grid}$).

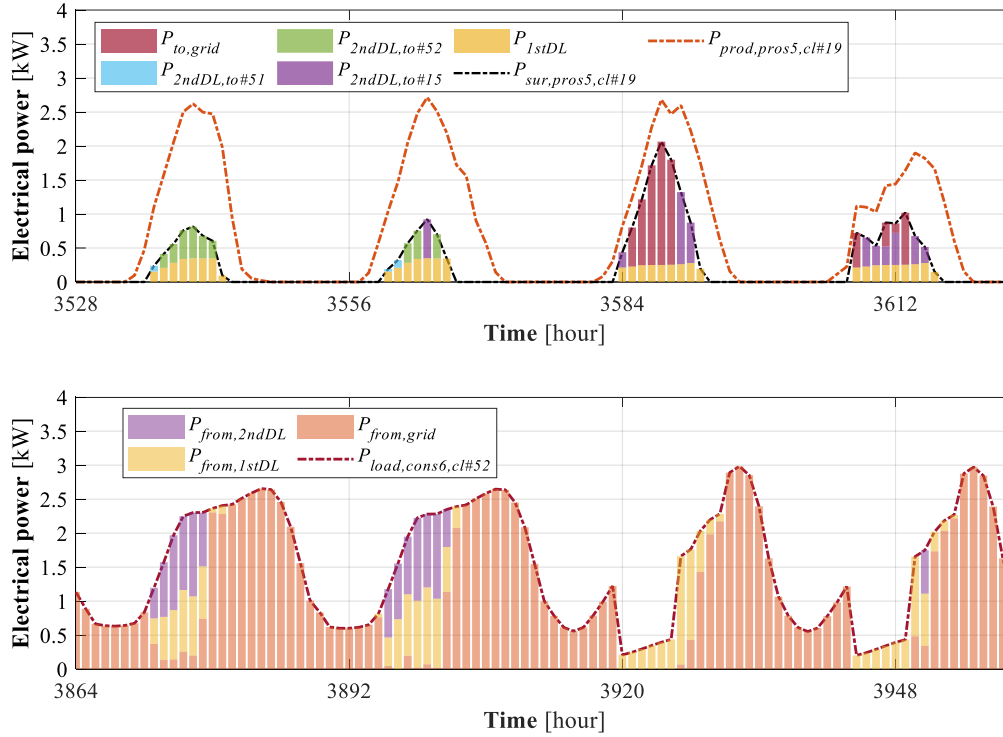


Figure 77. Dynamic trend of single user energy management from 10th to 13th of June: top) PV production dispatching of prosumer #5 of cluster #19; bottom) electrical load of consumer #6 of cluster #52.

Figure 77bottom demonstrates the fulfilment of the electrical load for the investigated consumer. The figure highlights that during periods of peak solar radiation, the consumer's load is effectively met by the excess energy generated by prosumers. The coloured bars in the figure represent the quantified energy acquired by the consumer: sourced from the EC prosumers in the 1st DL, from prosumers of other clusters via the 2nd DL, and from the grid.

On the annual basis, PV production management for each prosumer type of the EC's cluster archetypes is reported in Figure 78. Additionally, it is assessed how self-consumption levels are influenced by P2P mechanisms. For example, among the prosumers under investigation, the one of type #4 in cluster #15 achieves the highest levels of self-consumption, which is equivalent to 75% of the energy produced, even before taking into consideration the energy shared with the P2P system. Additionally, it uses the P2P sharing mechanism of the 1st DL to its advantage to sell energy to consumers inside its cluster, increasing the self-consumption rate to 98%. Otherwise, the prosumers in clusters #51 and #19 with a self-consumption rate of 60% enhance their levels to 84% and 76% respectively, further benefiting from P2P energy sharing across other clusters.

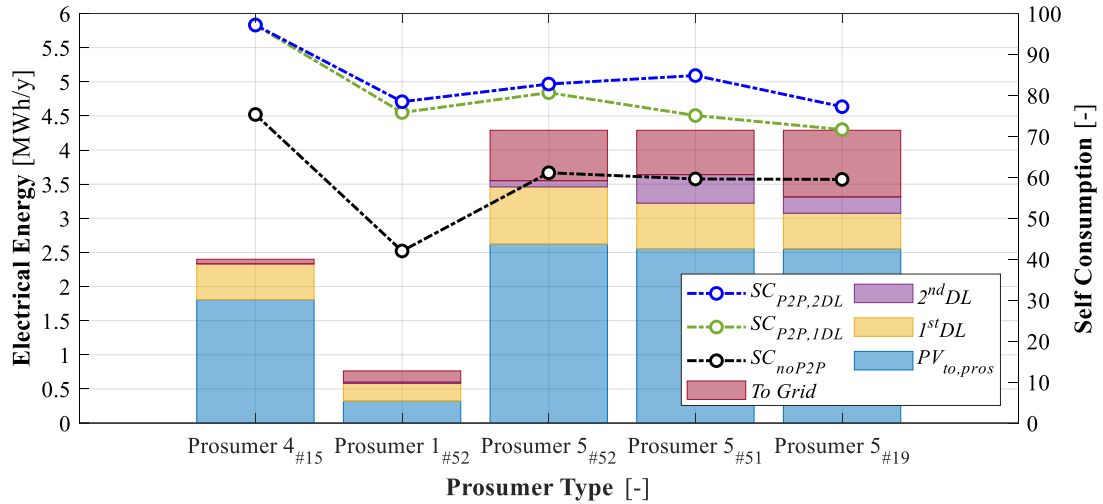
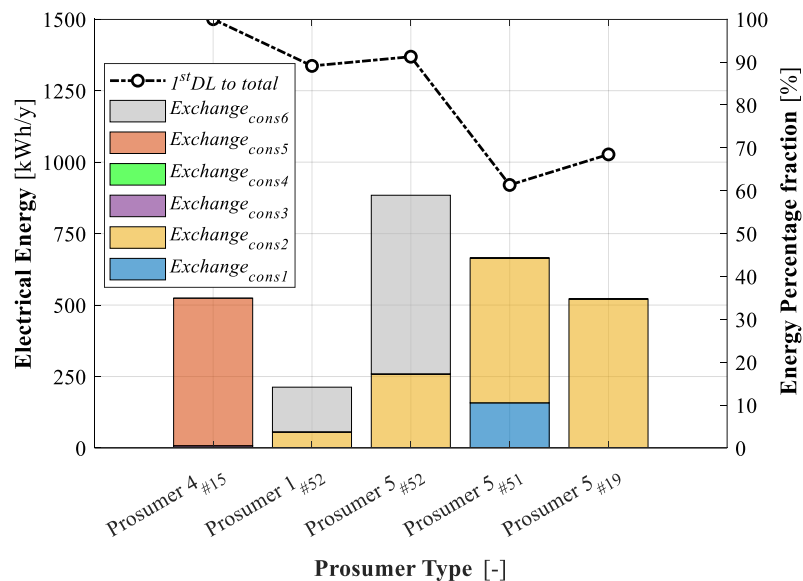


Figure 78. Annual PV production management for each prosumer type of the EC's cluster archetypes.

Figure 79 provides an in-depth analysis of how each prosumer distributes its energy, quantifying the energy shared with the six types of consumers. Figure 79a is referred to the 1st DL mechanism, while Figure 79b focuses on interactions with members from other EC clusters. Notably, prosumers from clusters #51 and #19 emerge as the primary contributors in the 2nd DL, sharing approximately 410 kWh/year and 235 kWh/year respectively. Moreover, both Figure 79top and Figure 79bottom depict a dotted black line, estimating the percentage contribution of energy shared in each of the two dispatching layers compared to the total energy sold to consumers.



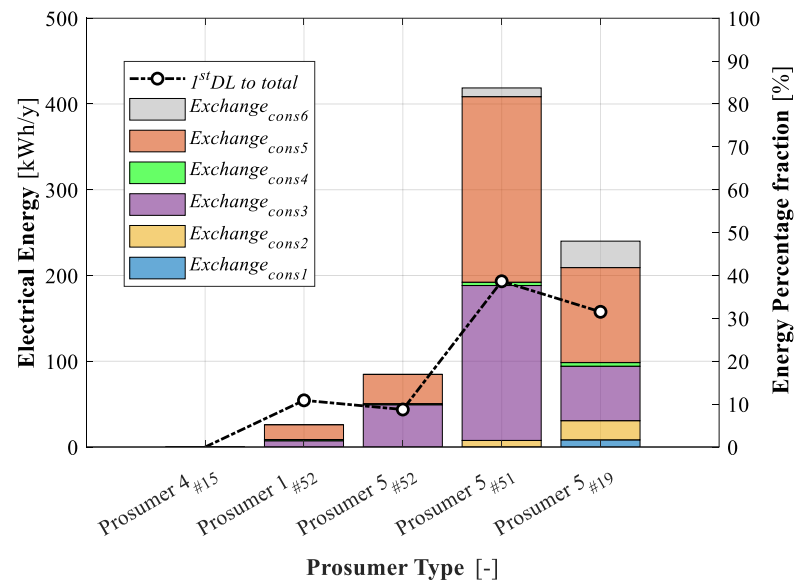


Figure 79. Rates of energy exchanged with the different types of consumers: top) 1st DL; bottom) 2nd DL.

Finally, Figure 80 analyses how the annual requests of each EC consumer and prosumer are satisfied. Additionally, it reports the annual self-sufficiency value for each user, highlighting the percentage of the load covered by the renewable energy source.

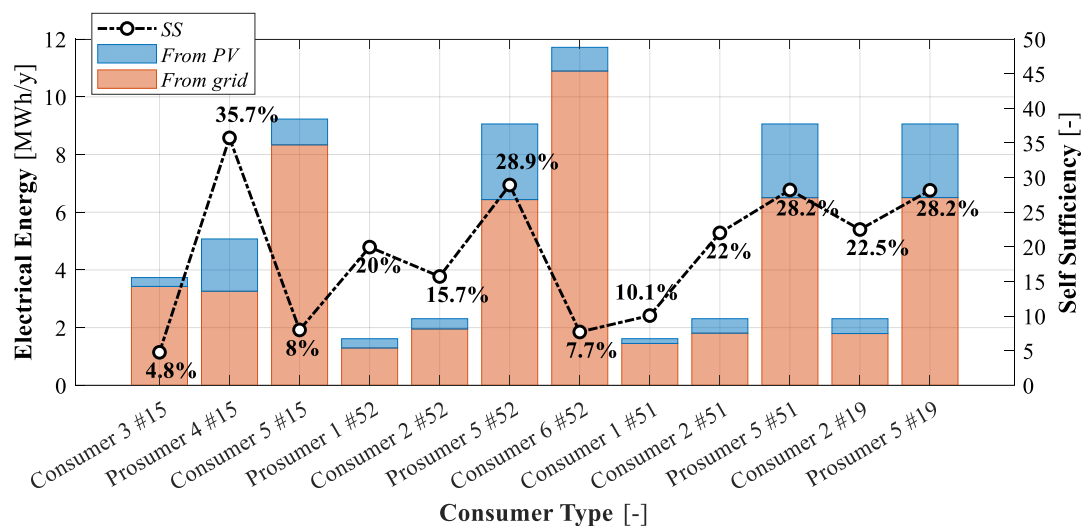


Figure 80. Annual analysis of coverage of electricity needs and self-sufficiency by type of EC user.

6.4.4 Cost analysis: prosumers and consumers

The method employed to calculate the cost of electricity shared by prosumers with consumers is founded on the balancing of the supply and demand curves (refer to paragraph “Pricing strategy”). Figure 81 describes the strategy used to determine the price within the *local energy market*. Notably, the purchase price is influenced by the building's occupancy and the quantity of electricity requested or offered. Additionally, as previously outlined, the demand curve is impacted by the maximum cost of electricity sourced from the grid, set at 0.31 Euro/kWh [325] for this case study (according to the Italian energy market price). Conversely, the offer curve is influenced by the maximum retail selling price from the grid, fixed at 0.10 Euro/kWh [325]. The results indicate purchase prices for users consisting of 1, 2, 4, and 5 occupants at 0.02, 0.05, 0.10, and 0.15 Euro/kWh respectively.

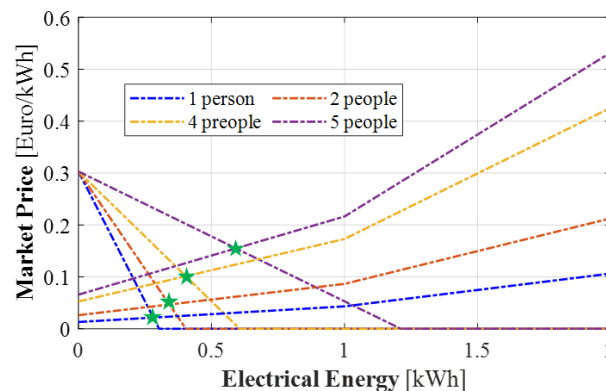
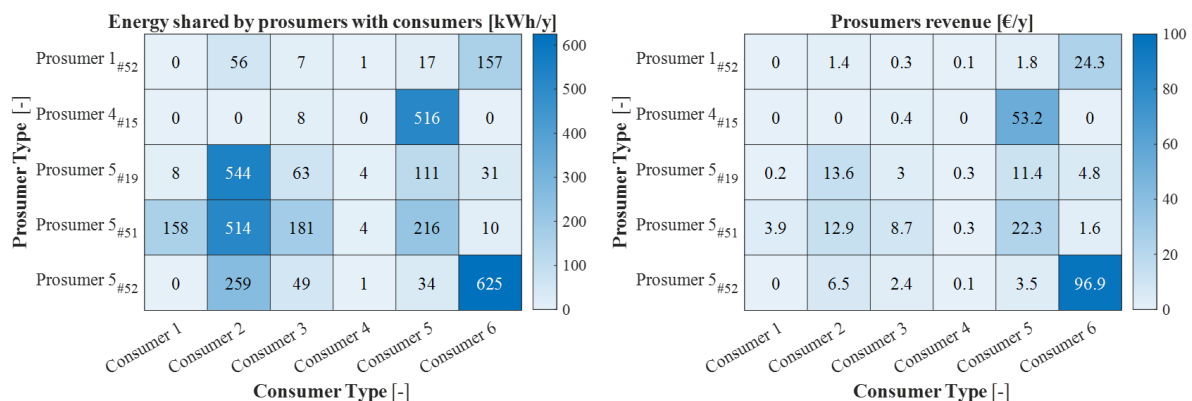


Figure 81. Energy pricing strategy, balancing of demand and supply curves.

Figure 82 presents the economic analysis concerning prosumers' revenues, derived from energy sales, and the savings obtained by consumers. Figure 82top displays the bi-matrices depicting the quantity of shared energy and the respective revenues for each type of prosumer, considering the interaction with the six distinct types of EC's consumers.



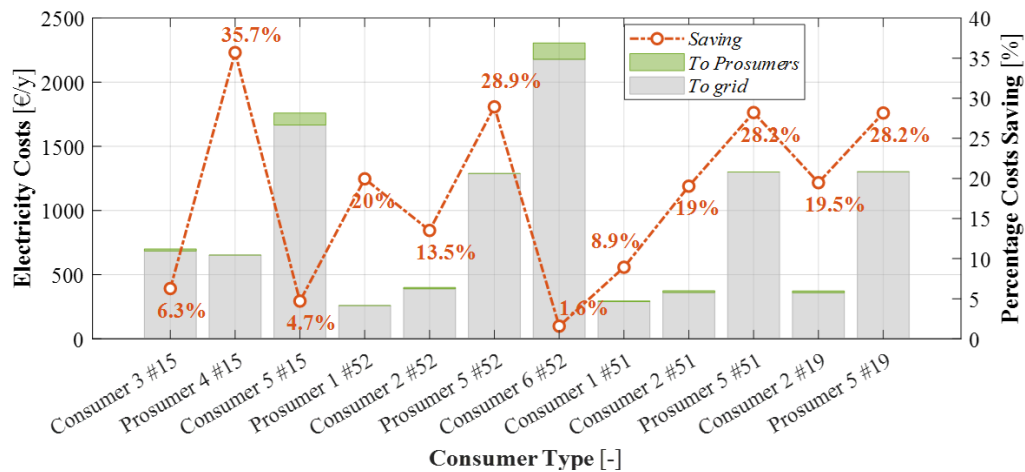


Figure 82. Economic analysis: top) prosumers' revenues; bottom) users saving.

Figure 82bottom delves into the costs associated with electricity purchases for both consumers and prosumers of the EC. The grey and green bars represent the annual costs of energy purchased respectively from the grid and prosumers. Notably, even prosumers themselves, when acting as consumers, procure energy from other prosumers. The percentage savings depicted in Figure 82bottom indicate the economic advantages gained by each user through the procurement of energy from prosumers. These saving have been evaluated in comparison with the reference scenario where the consumers and prosumers are connected only to the national electricity grid.

Finally, Table 22 presents the pay-back time estimation for each prosumer, considering a unit investment cost of 600 Euro/kW_{PV} for the purchase and installation of polycrystalline PV systems. The calculation of payback time includes considerations for costs avoided by purchasing electricity from the grid, revenues from selling electricity to users within the same cluster, and those related to sharing with users from other clusters within the EC. Additionally, it's assumed that surplus energy sent to the grid does not yield any remuneration. The results outlined in Table 22 underscore that the proposed methodology for optimising end-user aggregation allows for investment returns of fewer than 3 years for each prosumer.

Table 22. Pay-back time of prosumers investments.

Prosumer Type	Prosumer 4 CA#15	Prosumer 1 CA#52	Prosumer 5 CA#52	Prosumer 5 CA#51	Prosumer 5 CA#19
Cost of Investment [Euro]	990	320	1780	1780	1780
Pay-back time [year]	2.2	2.7	2.4	2.6	2.8

6.4.5 Energy performance of EC

The investigation aimed at assessing the benefits resulting from the application of the proposed aggregation criteria involved conducting an energy analysis of the optimised EC configuration. The outcomes depicted in Figure 83 pertain to the energy management of the EC. In Figure 83top, a monthly analysis illustrates how the requested electricity is fulfilled. This analysis includes the quantity self-consumed by the prosumers, that met through energy sharing mechanisms of the 1st DL and 2nd DL, and the portion purchased from the central grid. The dashed black line represents the self-sufficiency levels, which notably peak during the summer months. Additionally, self-consumption, depicted in blue dotted line, exceeds 75% for each month. The annual self-consumption and self-sufficiency indices for the entire EC stand at 89% and 21% respectively. As regard the reference case scenario where photovoltaic systems were solely used to fulfil individual prosumer demands and they are connected only to the national electricity grid, the self-consumption is 64%.

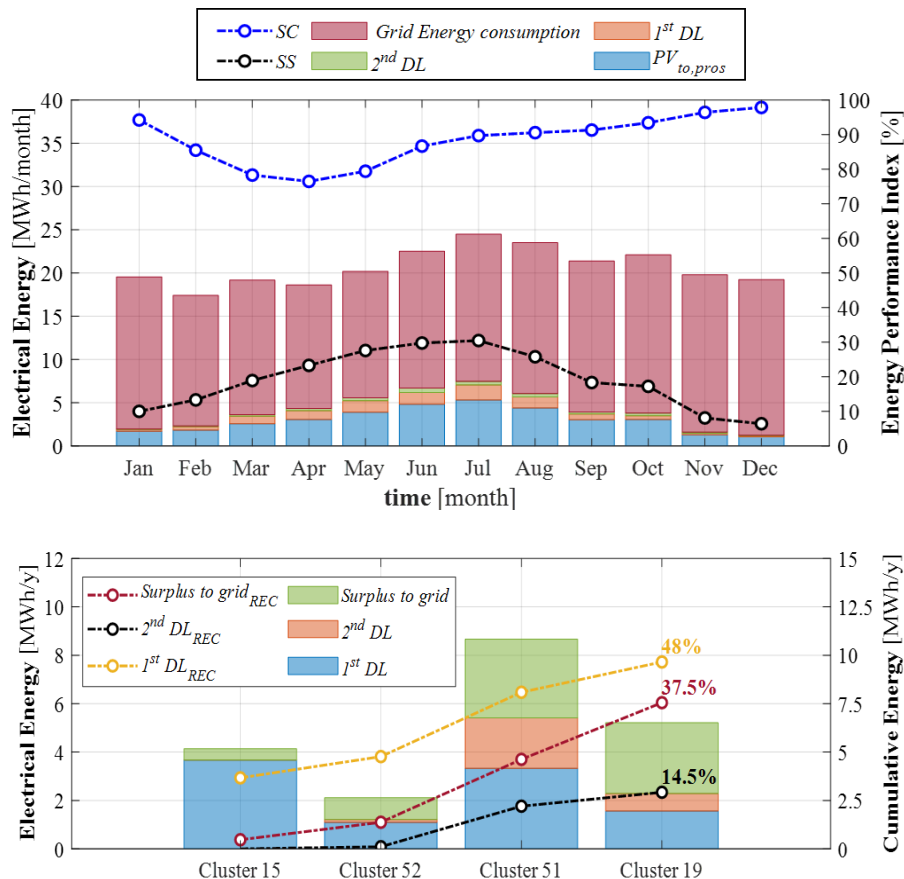


Figure 83. Results of the first optimisation level referred to cluster archetype #52: top) self-sufficiency of all investigated solutions; bottom) choice of the optimal configuration within the feasibility range.

Figure 83bottom assesses the management of surpluses generated by the global photovoltaic systems of the community, grouped based on their archetype cluster types. The cumulative analysis underscores that 48% of the surplus is allocated for sharing within users of the same cluster, while 37.5% continues to be directed to the grid. Additionally, 14.5% of the surplus is designated for sharing energy with users across different clusters. Overall, the proposed strategy facilitated a transition from the reference case (with users connected only to the national electricity grid), where grid injections amounted to 20.1 MWh/year, to the proposed scenario yielding 7.5 MWh/year, resulting in a reduction of 62%.

6.5 Conclusions

This chapter focuses on pioneering methodologies developed for the establishment of energy communities, with a specific emphasis on Peer-to-Peer (P2P) models. The devised P2P strategy employs a centralized control logic to optimise connections between prosumers and consumers, aiming to maximize the energy exchange within the community. Furthermore, the pricing strategy in the energy market is formulated based on balancing supply and demand curves, thereby determining electricity unit costs tailored to individual user characteristics.

This research has yielded a precise model for predicting the electricity demands of users within the community. This model is pivotal when energy behaviour information about users is unavailable for designing energy communities. The developed model is a sequential hybrid neural network (HNN), integrating aspects of both white-box and black-box models. Respecting to white-box models, it incorporates physical attributes and defines building archetypes, while from black-box models exploits the peculiarity of predicting how occupant behaviour impacts electrical demands.

Subsequently, criteria for user aggregation were proposed to optimise the energy community configuration through a bi-level optimisation process. The first optimisation level focuses on grouping users into subgroups, aiming to maximize self-sufficiency by varying the integration of prosumers based on quantity and type. The subsequent optimisation level determines the global configuration of the energy community by aggregating the previously identified subgroups, thereby maximizing the community's self-consumption.

To demonstrate the efficacy of this methodology, a case study was conducted in a residential area of Caserta, Italy. The study identified six user types within the community, classified their building archetypes, and predicted their electricity demands using the HNN model. By identifying the number of prosumers in each residential area type, the optimisation methodology was applied to determine the optimal EC configuration. The obtained results facilitated an estimation of economic benefits for each user. Compared to the reference scenario where the users are connected only to the national electricity grid, the consumers

achieve economic savings ranging from 1.6% to 19.5%, thanks to the partial fulfilment of their energy needs from prosumers' surplus. Prosumers, benefiting from avoided energy purchase costs and revenues from energy sales, realized a return on investment (SPB) in less than 3 years. Additionally, through optimised user aggregation, the energy matching between prosumers' surplus and consumer requests maximized annual self-consumption to 89% compared to 64% of the reference scenario (represented by the absence of energy community mechanisms). The achieved collective annual self-sufficiency is equal to 21%, where the amount of the available surpluses generated by the global photovoltaic systems of the community is shared for a rate of 48% among users of the same cluster, while 14.5% is exploited for sharing energy with users of different buildings clusters. Overall, it results in a reduction of the energy amount send back to the grid equal to a rate of 62% compared to the reference scenario.

Finally, this optimisation effectively mitigates risks associated with voltage and frequency imbalances in the network resulting from frequent surpluses injected by prosumers.

Appendix A

The users' electrical loads were estimated considering the rates due to lighting, equipment, and the HVAC system, as indicated in Eq. (33). The calculations for the electrical powers consumed by equipment (Eq. (35)) and lighting (Eq. (34)) are based on probability factors, $f_{use,eq}$, and $f_{use,lights}$, sourced from ISTAT (Italian National Statistics Institute) datasets [321].

Figure 84c and Figure 84d illustrate the dynamic trend of these probability factors, differentiated by weekdays and weekends, depicting the typical statistical behaviour of residential users at the investigated location. Additionally, Figure 84a displays a table presenting nominal powers obtained from the research of Paatero et al. [317], outlining commonly used utilities in these residential buildings.

Finally, Figure 84b exhibits occupancy pattern profiles that influence the daily usage of household appliances.

This analysis enables the determination of dynamic electrical absorption profiles for various user types within the community. Concerning the users' air conditioning-related electricity consumption, it was assessed using the hybrid model detailed in the section ("*Sequential HNN mode*"). In the context of the case study, users are assumed to have an electrical absorption system solely for cooling needs.

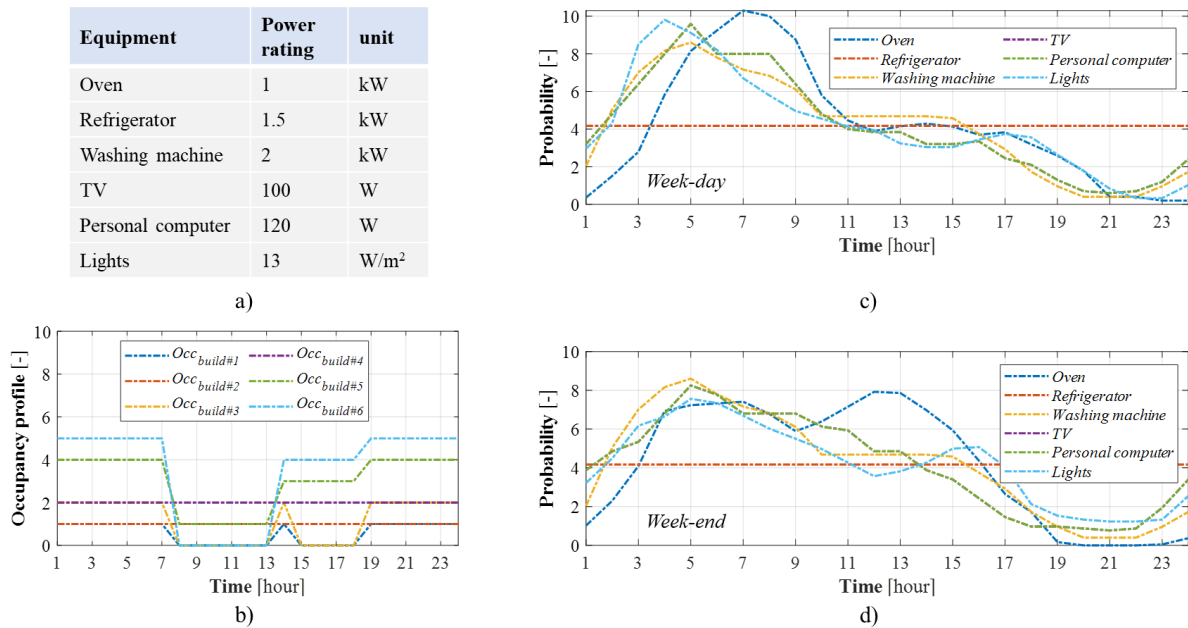
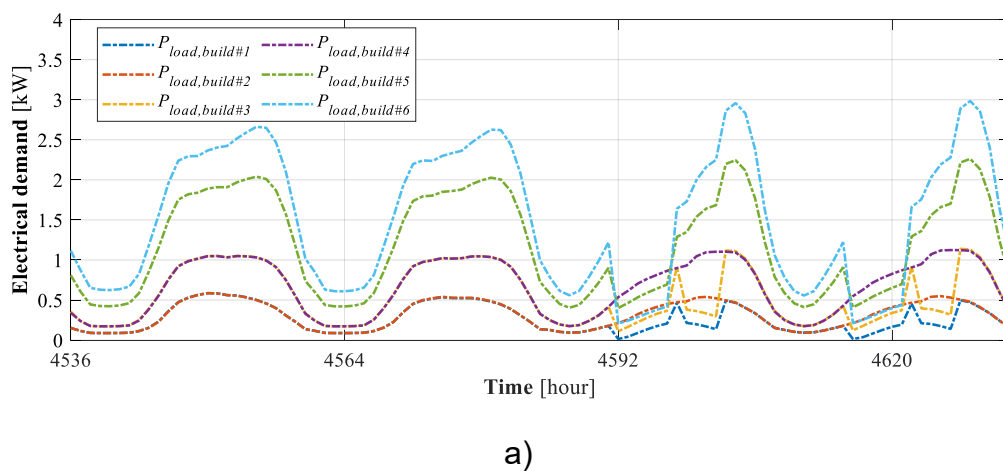
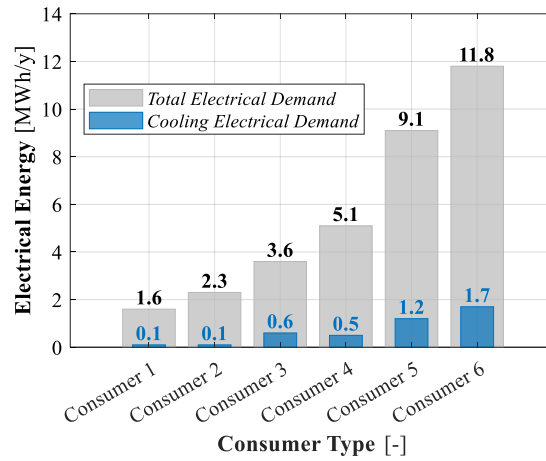


Figure 84. Equipment and lights electrical load: a) power rating; b) occupancy profile pattern of the 6 buildings archetypes of investigated EC; c) usage probability factor of equipment and lights during weekdays; d) usage probability factor of equipment and lights during week-end days.

Figure 85a presents a dynamic illustration of the global electrical load profile from July 8th to July 11th for the six user types identified within the investigated community. Figure 85b highlights the annual electricity consumption for each user type. Notably, the building's electricity consumption increases with the number of occupants, and the occupants' age also plays a significant role, impacting electricity consumption due to socio-behavioural characteristics.





b)

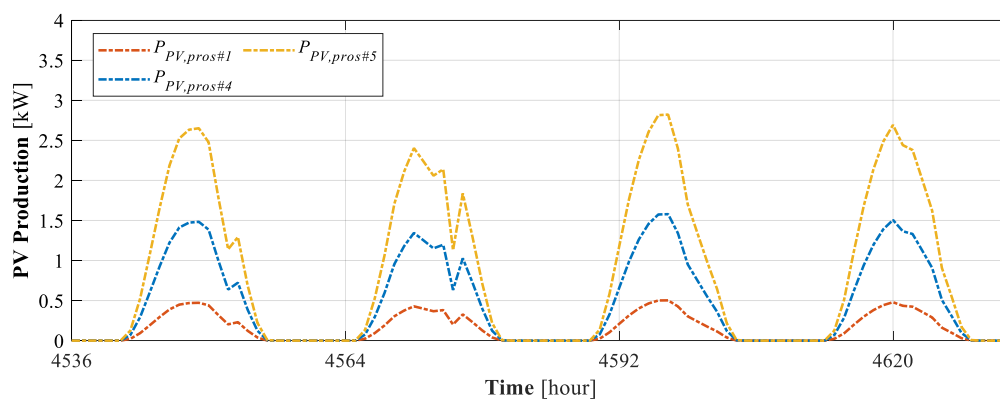
Figure 85. EC's users electrical load: a) dynamic profile of total electricity consumption from July 8th to July 11th; b) annual electricity consumption for different users' types.

Appendix B

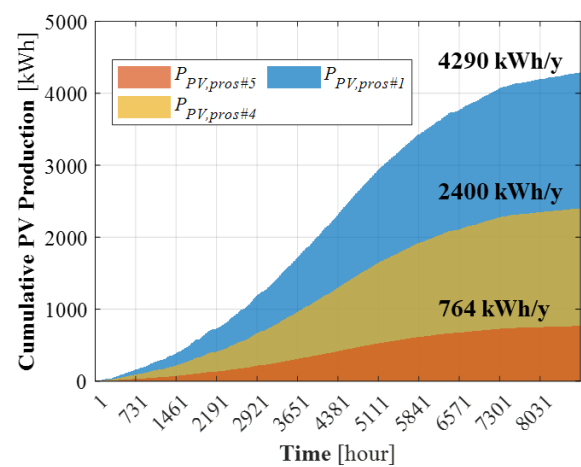
The PV systems producibility of the energy community's users acting as prosumers was determined using the mathematical modelling outlined in the section "Building archetypes for EC users' energy modelling".

Figure 86a depicts the dynamic trend observed during a simulation period from July 8th to July 11th. Notably, the obtained power values correspond to the size of the installed systems. The weather characteristics affecting producibility, such as air temperature and solar radiation, were sourced from Meteonorm datasets.

Additionally, Figure 86b presents cumulative annual data showcasing the electricity production from these PV systems of each prosumer type.



a)



b)

Figure 86. PV systems production for each prosumer type: a) dynamic profile of electricity production from July 8th to July 11th; b) cumulative annual electricity production for different prosumer's types.

Chapter 7

Predictive strategies for energy communities in grid flexibility and balancing

This chapter was previously published as:

G. Barone, A. Buonomano, C. Forzano, A. Palombo, G. Russo. (2023). The role of energy communities in electricity grid balancing: A flexible tool for smart grid power distribution optimization. *Renewable and Sustainable Energy Reviews*, 187, 113742.

Summary

This chapter presents a comprehensive methodology for enhancing grid stability in the context of renewable energy fluctuations through a peer-to-peer energy community model. The developed simulation tool enables decision-makers to explore effective energy management strategies by structuring the energy community into multiple control volumes, representing prosumers, consumers, energy storage systems, and electric vehicles. Through detailed energy balancing for both individual users and the community as a whole, the model investigates optimal configurations for distributed energy resources and frequency regulation. A key feature of the tool is its predictive function, allowing day-ahead forecasting of electricity demand, which enables proactive coordination of renewable energy generation and storage, thereby flattening demand profiles and reducing reliance on the grid. Employing objective functions such as self-consumption, self-sufficiency, and grid balancing, the model is validated in a case study, achieving a substantial increase in renewable self-consumption from 59.4 to 83.9 MWh/year. Additionally, it secures grid stability, contributing 1.46 and 7.71 MWh/year towards upward and downward frequency regulation. These results underscore the tool's potential in managing renewable dispatch, supporting grid resilience, and encouraging sustainable energy community practices.

Keywords

Energy sharing; grid stability; smart grid; power regulation; energy management; energy optimization; self-consumption; self-sufficiency; grid balancing factor; P2P; V2G; V2C; C2V.

Nomenclature

Abbreviations

<i>C2V</i>	Cluster to Vehicles
<i>DERs</i>	distributed energy resources
<i>EV</i>	electric vehicle
<i>GBF</i>	grid balancing factor
<i>P2P</i>	peer to peer
<i>RES</i>	renewable energy system
<i>SC</i>	self-consumption index
<i>NOCT</i>	cell temperature in nominal conditions
<i>ord</i>	priority dispatching order
<i>SOC</i>	battery state of charge
<i>SS</i>	self-sufficiency index
<i>V2C</i>	Vehicles to Cluster

Symbols

<i>C</i>	battery capacity [kWh]
<i>c</i>	load weight factor [-]
<i>E</i>	energy [kWh]
<i>I</i>	incident solar radiation [W/m ²]
<i>P</i>	power [kW]
<i>p</i>	surplus weight factor [-]
<i>t</i>	time [h]
<i>T</i>	temperature [°C]
<i>v</i>	electric vehicle velocity [km/h]

Greek letters

γ	community proportion factor of power [-]
η	efficiency [-]
λ	availability signal [-]

Subscripts

<i>av</i>	availability for grid regulation	<i>PV</i>	photovoltaic system
<i>bat</i>	battery	<i>res</i>	residual power
<i>c</i>	consumer	<i>reg</i>	grid regulation
<i>com</i>	community	<i>STC</i>	standard condition
<i>char</i>	charge	<i>sur</i>	surplus of electricity
<i>d</i>	downward	<i>u</i>	upward
<i>disch</i>	discharge		
<i>f</i>	forecast		
<i>g</i>	grid		
<i>MPP</i>	maximum power point		

7.1 Introduction

The growing creep of renewable energy resources into the productive electricity pools has led to well-known advantages in terms of energy efficiency and atmospheric pollutants reduction, replacing the traditional thermal power plants [326]. However, the disadvantages caused to the electricity grid systems are equally significant [327]. The unpredictability of these renewable energy systems (RES) [328] is the main cause of damaging phenomena for the electricity grid such as congestion, frequency, and voltage imbalances [329]. Consequently, preventive, and corrective actions are required, aimed at the optimal management of these distributed energy resources (DERs).

7.1.1 Sharing mechanisms in energy communities

Energy sharing mechanisms play a crucial role in addressing key challenges faced by energy communities in their transition toward sustainable and decentralized energy planning [300]. These mechanisms are effective in optimizing the utilization of renewable energy resources, bolstering community resilience, promoting energy autonomy, and fostering active interactions among community members. In the context of energy communities, peer-to-peer (P2P) energy trading represents a paradigm shift in the electricity sector. It involves the direct exchange of electricity among users within a localized community, bypassing the centralized electricity grid [290]. Prosumers, who generate electricity using renewable sources like solar PV panels, wind turbines, or small-scale hydroelectric generators, can share their surplus energy with other community members [330]. This sharing process can occur in real time or through predetermined agreements facilitated by digital platforms, smart contracts, or energy management systems [331]. Notably, decentralization of energy production and consumption distinguishes P2P energy sharing, promoting energy independence and reducing reliance on centralized power generation infrastructure [332]. Moreover, P2P energy sharing empowers prosumers to optimize their energy usage models, enabling greater self-consumption and reduced dependence on external energy sources [333]. By actively participating in energy sharing, individuals assume a more engaged role in energy decision-making and become stakeholders in the energy system [334]. P2P strategies often incorporate game theory approaches, providing a framework to understand and optimize user interactions in a self-interested manner [335]. Game theory encompasses both cooperative and non-cooperative approaches. Cooperative game theory [336] addresses situations where users collaborate to achieve common goals, while non-cooperative game theory [337] analyses scenarios where users act independently to optimize their outcomes. These approaches apply to various aspects of P2P energy sharing, including energy trading, resource distribution, and load balancing [338]. In the context of P2P energy trading, game theory helps determine optimal prices for energy exchanges,

often relying on concepts like the Nash equilibrium. Cooperative game theory becomes particularly relevant when considering the formation of coalitions or energy-sharing communities within larger energy communities [310]. By collaborating, users can achieve mutual economic benefits and enhance their energy self-sufficiency [339]. Furthermore, game theory approaches address challenges related to load balancing and resource distribution in P2P energy-sharing systems [340]. In addition to game theory, the integration of artificial intelligence and optimization techniques enhances the performance of P2P energy-sharing systems. Machine learning algorithms learn user preferences, predict energy demand, and generation, and optimize energy distribution strategies [341]. Reinforcement learning algorithms adaptively adjust energy trading or resource allocation policies based on system feedback, thereby improving efficiency and effectiveness in P2P energy sharing [342]. However, implementing P2P energy sharing requires advanced technologies such as smart metering systems, energy management systems, and digital platforms for secure and transparent energy transactions. Establishing appropriate regulatory frameworks and market mechanisms is crucial to address legal and economic considerations associated with P2P energy sharing within energy communities. Additionally, P2P energy trading can introduce uncertainties in the electricity grid, particularly when dealing with intermittent renewable energy sources. The variability of generation and energy consumption within a P2P trading framework can entail challenges for grid management, necessitating advanced grid monitoring, control, and stability measures [343].

7.1.2 Electric vehicles as sharing technology

Vehicles-to-everything (V2X) technology represents a promising avenue for implementing energy-sharing mechanisms. EVs serve as a crucial energy vector for power supply and ancillary services [344]. Through bidirectional interface capabilities, known as vehicle-to-grid (V2G) technology, EVs can actively participate in the energy network by both supplying and drawing electricity [345]. This functionality enables EVs to contribute to various objectives such as peak shaving and voltage regulation [346]. To analyse the potential of EVs in providing valuable services to the electricity grid, it becomes essential to simulate management strategies for EV charging and discharging [347] and develop control algorithms that optimize real-time electricity utilization [348]. However, it is important to consider the impact of increased charge-discharge cycles on the operational integrity of EV batteries [349]. Frequent cycling can lead to degradation and compromise their performance. To mitigate this issue, it is crucial to adopt solutions that preserve the battery's lifecycle [350]. Additionally, adjusting the maximum and minimum charging capacities of the batteries [351] can help extend their lifespan. Furthermore, electric vehicles have found applications as energy dispatching tools in building energy communities [352]. In this context, EVs are utilized to directly distribute electricity to end-users or store surplus energy

generated by building-based renewable energy systems. This vehicle-to-building (V2B) or building-to-vehicle (B2V) approach promotes community independence from the traditional grid infrastructure [353].

7.1.3 Models for energy dispatching mechanisms

Another crucial aspect in modelling energy communities is the simulation of energy sharing and dispatching mechanisms [354]. Various methodologies have been adopted in this regard, including graph theory, optimization techniques, and market-based approaches [355]. Graph theory provides a powerful tool for modelling the interconnected relationships between prosumers and consumers within an energy community [356]. By representing the community as a graph, nodes can represent individual users or groups of users, while edges indicate the energy flows or sharing relationships between them [357]. Graph-based models enable the analysis of energy flows, optimal dispatching strategies, and identification of critical nodes or pathways within the community [358]. This study [359] employs a graph theory-based approach to model user interactions within an energy community. By utilizing a cooperative game methodology, it determines the optimal connections between community members, aiming to achieve a Nash equilibrium solution that maximizes economic revenues for each user and minimizes electricity dissipation caused by user distances. However, it overlooks the potential negative impacts on the central electricity grid resulting from unutilized energy surpluses and insufficient coverage of energy demands within the community. Generally, these models may face challenges in capturing the dynamic and stochastic nature of energy exchange and may require simplifying assumptions. Optimization techniques, such as linear programming (LP), mixed-integer linear programming (MILP), and evolutionary algorithms, are widely used for energy community modelling [360]. These approaches aim to optimize energy sharing and dispatching decisions by considering various objectives, constraints, and preferences of community members [296]. Optimization models can account for factors such as energy demand, generation capacity, storage capacity, transmission limits, and cost considerations. This work adopts a MILP optimization model to favour the penetration of renewable energy sources into an energy community [361]. However, the study does not account for potential uncertainties and variations in renewable energy generation and demand patterns, which could impact the effectiveness of the proposed optimization approach. Finally, optimization models may suffer from computational complexity, especially when dealing with large-scale energy communities or considering real-time operation. Several studies have employed energy community models that incorporate demand side management (DSM) techniques [362]. DSM encompasses strategies aimed at actively managing and controlling electricity demand on the consumer side. This study [297] focuses on implementing a price-based demand response mechanism within an energy community framework. While this research

[363], has highlighted the significant potential of DSM in optimizing energy consumption, reducing peak loads, and improving grid stability, it is important to acknowledge certain limitations associated with its implementation.

One primary limitation of DSM is the challenge of achieving widespread consumer participation [364]. Encouraging individuals and businesses to modify their energy usage patterns or adopt new technologies can be a complex task, as it often necessitates altering established habits and making investments in new equipment or systems. Factors such as limited awareness, resistance to change, and perceived inconvenience can impede the adoption of DSM programs and hinder consumer engagement. In conclusion, it is important to note that the choice of modelling methodology depends on the specific objectives, size, complexity, and available data of the energy community.

7.1.4 Objective functions and optimisation procedures

In the modelling of energy communities, defining appropriate objective functions is crucial to guide the development of optimization procedures. The selection of objective functions depends on the specific priorities and requirements of the community. Some common objective functions include:

- Collective self-consumption: maximizing the self-consumption of locally generated energy within the community [365], thereby reducing reliance on external sources, and promoting energy independence [366].
- Self-sufficiency from the grid: minimizing the dependency on the main electricity grid by optimizing local generation [367], storage [368], and consumption, aiming to achieve a high degree of self-sufficiency [369].
- Economic benefit: optimizing energy management strategies to minimize costs [370], considering factors such as electricity prices, tariffs [371], and operational expenses [297].
- Environmental benefit: minimizing the carbon footprint and environmental impact of the community by prioritizing the use of renewable energy sources, reducing energy waste [372], and promoting sustainable practices [373].
- Flattening the electricity demand: smoothing out the peak electricity demand within the community [374], which can help reduce strain on the grid infrastructure and enable more efficient use of energy resources.

To optimize these objective functions, various optimization procedures are employed. These include mathematical optimization techniques such as LP, MILP, and evolutionary algorithms.

7.1.5 Aim and contributions

This research aims to address the challenges associated with energy management in prosumer communities by proposing an innovative methodology. The primary focus is on maximizing self-consumption and self-sufficiency within the community through the development of a new energy sharing mechanism. The methodology explores the potential interaction between electric vehicles and building clusters (V2C and C2V), alongside peer-to-peer energy sharing, to optimize energy utilization. One key aspect of the methodology involves the management of prosumers' batteries for community purposes. Surplus energy generated by a prosumer can be stored in the batteries of other community members, enabling efficient utilization of resources and satisfying the electrical needs of other users. To achieve higher levels of self-consumption and self-sufficiency, a centralized control system is proposed to implement optimal dispatching strategies at each time step. The other objective of this work is to investigate *the role of energy communities in electricity grid balancing*. To accomplish this, the energy management of the community is optimized to mitigate load fluctuations that may compromise grid stability. The study explores the potential of energy communities to contribute to grid frequency regulation. The methodology proposed to carry out the mentioned analyses follows a structured approach. Firstly, a predictive action is developed to determine the residual load of the community after implementing energy sharing mechanisms. This allows for the characterization of a load profile without fluctuations. Subsequently, dispatching strategies are optimized to ensure maximum regulation and grid stability. Two optimization methods are developed within the framework of this research: i) the first is a bi-objective approach that aims to maximize self-consumption and self-sufficiency; ii) the second method focuses on a single objective, which is to maximize the grid balancing factor (*GBF*). The *GBF* serves as an index to assess the capacity of energy communities in providing balancing services to the grid. The objective of this work is to emphasize the importance of grid stability and balancing in energy communities and provide valuable insights and recommendations for optimal community operations. The aim is to contribute to the development of sustainable energy communities that prioritize local energy utilization while ensuring grid stability.

7.2 Methodology

This work proposes a novel methodology to optimize the energy management of prosumer communities. The systems modelling was performed in the MatLab R2022b environment, and the developed algorithm flexibly optimizes the energy performance of prosumer communities by considering different boundary conditions and system typologies. The investigated optimization problems aim to maximize the self-consumption, self-sufficiency, and behaviour of energy communities in providing balancing services for the electricity grid. To this aim the exploitation of energy sharing mechanisms such as P2P and

V2C/C2V was properly implemented in the mathematical model. In the following sections, a detailed description of the energy modelling of the users (i.e., consumers and prosumers), the power dispatching mechanisms, and the investigated optimization problems will be provided.

7.2.1 User level energy dispatch

This section describes the power balance in cases where users operate individually.

The power balance for consumers is represented by the power purchased from the electricity grid $P_{g \rightarrow c}$ to meet their respective load demands $P_{load,c}$:

$$P_{g \rightarrow c}(t) = P_{load,c}(t) \quad \text{Eq. (1)}$$

Conversely, when users operate as prosumers, the power balance is characterized by several factors, including power production P_{prod} , power consumption $P_{load,p}$, the exchange of power with the electricity grid (purchased power in deficit $P_{g \rightarrow p}$ and sold surplus $P_{p \rightarrow g}$), and the accumulation term that determines the power charged or transferred from the battery.

$$P_{prod}(t) + P_{g \rightarrow p}(t) = P_{load,p}(t) + P_{p \rightarrow g}(t) + \frac{dE_{batt}(t)}{dt} \quad \text{Eq. (2)}$$

Regarding EVs, their power balance is characterized by several elements, including the power utilization term $P_{disch,EV}$ representing the discharge of batteries during EV driving, the purchased power term $P_{load,EV}$ required for charging EV batteries from the grid, and the accumulation term that determines the power involved in charging and discharging processes.

$$P_{load,EV}(t) = P_{disch,EV}(t) + \frac{dE_{batt,EV}(t)}{dt} \quad \text{Eq. (3)}$$

The power dispatching balances discussed in this section apply to reference cases, where users operate individually and interact exclusively with the electricity grid. In contrast, the following sections will outline the optimal solutions based on the mechanism of peer-to-peer energy sharing.

7.2.2 Strategies for community sharing

The primary investigated aspect to optimize energy management in prosumer communities involves the implementation of an energy-sharing strategy among peers. The aim of this dispatching mechanism (depicted in Figure 87) is to increase the global self-consumption and self-sufficiency of the community. However, it is crucial to note that in situations where the PV production and energy stored in batteries are insufficient to meet

the house load, the electricity cannot be shared within the energy community. During these periods, the grid plays a vital role in supporting the consumption requirements of the community.

The proposed sharing strategy follows a cooperative approach including the exploitation of batteries and electric vehicles to satisfy the community requests. In this case, the peers are represented by the community energy aggregators (i.e., prosumers, consumers, batteries, and electric vehicles) and centralized management logics determine the optimal energy dispatching adopting a priority-based approach. The following power balances have been adopted to model energy sharing strategies and evaluate the power exchanged between users.

$$\begin{pmatrix} P_{prod_1}(t) \\ \vdots \\ P_{prod_j}(t) \end{pmatrix} = \begin{pmatrix} P_{load,p_1}(t) \\ \vdots \\ P_{load,p_j}(t) \end{pmatrix} + \begin{pmatrix} P_{sur,p_1 \rightarrow c}(t) \\ \vdots \\ P_{sur,p_j \rightarrow c}(t) \end{pmatrix} + \begin{pmatrix} P_{sur,p_1 \rightarrow EV}(t) \\ \vdots \\ P_{sur,p_j \rightarrow EV}(t) \end{pmatrix} + \begin{pmatrix} \frac{dE_{batt_1}(t)}{dt} \\ \vdots \\ \frac{dE_{batt_j}(t)}{dt} \end{pmatrix} + \begin{pmatrix} P_{p_1 \rightarrow g}(t) \\ \vdots \\ P_{p_j \rightarrow g}(t) \end{pmatrix} \quad \text{Eq. (4)}$$

with

$$\begin{pmatrix} \frac{dE_{batt_1}(t)}{dt} \\ \vdots \\ \frac{dE_{batt_j}(t)}{dt} \end{pmatrix} = \begin{pmatrix} P_{sur,p_1 \rightarrow bat}(t) \\ \vdots \\ P_{sur,p_j \rightarrow bat}(t) \end{pmatrix} - \begin{pmatrix} P_{sur,batt,p_1 \rightarrow c}(t) \\ \vdots \\ P_{sur,batt,p_j \rightarrow c}(t) \end{pmatrix} \quad \text{Eq. (5)}$$

The left side of the equation $P_{prod,j}$ represents the PV production of each prosumer; while, the power consumption $P_{load,pj}$, the power shared with consumers $P_{sur,pj \rightarrow c}$, the power to charge the stationary batteries dE_{batt}/dt and electric vehicles $P_{sur,pj \rightarrow EV}$, on the right side of the equation.

$$\begin{pmatrix} P_{sur,com \rightarrow c_1}(t) \\ \vdots \\ P_{sur,com \rightarrow c_i}(t) \end{pmatrix} + \begin{pmatrix} P_{batt,com \rightarrow c_1}(t) \\ \vdots \\ P_{batt,com \rightarrow c_i}(t) \end{pmatrix} + \begin{pmatrix} P_{EVs,com \rightarrow c_1}(t) \\ \vdots \\ P_{EVs,com \rightarrow c_i}(t) \end{pmatrix} + \begin{pmatrix} P_{g \rightarrow c_1}(t) \\ \vdots \\ P_{g \rightarrow c_i}(t) \end{pmatrix} = \begin{pmatrix} P_{load,c_1}(t) \\ \vdots \\ P_{load,c_i}(t) \end{pmatrix} \quad \text{Eq. (6)}$$

The electrical demand of consumers $P_{load,ci}$ to the right of the equation is met by P2P power from prosumers $P_{sur,com \rightarrow ci}$, batteries $P_{batt,com \rightarrow ci}$ and electric vehicles $P_{EVs,com \rightarrow ci}$.

$$\begin{pmatrix} P_{sur,com \rightarrow EV_1}(t) \\ \vdots \\ P_{sur,com \rightarrow EV_k}(t) \end{pmatrix} + \begin{pmatrix} P_{load,EV_1}(t) \\ \vdots \\ P_{load,EV_k}(t) \end{pmatrix} = \begin{pmatrix} P_{EV_1 \rightarrow c}(t) \\ \vdots \\ P_{EV_k \rightarrow c}(t) \end{pmatrix} + \begin{pmatrix} P_{disch,EV_1}(t) \\ \vdots \\ P_{disch,EV_k}(t) \end{pmatrix} + \begin{pmatrix} \frac{dE_{batt,EV_1}(t)}{dt} \\ \vdots \\ \frac{dE_{batt,EV_k}(t)}{dt} \end{pmatrix} \quad \text{Eq. (7)}$$

The charging power of electric vehicles is separated into the rates of power coming from the electricity grid P_{load,EV_k} and P2P mechanisms $P_{sur,com \rightarrow EV_k}$, conversely, the discharge power in the right side of the equation is due to the route P_{disch,EV_k} of the vehicle and $P_{EV_k \rightarrow c}$ the power shared with the buildings of the clusters.

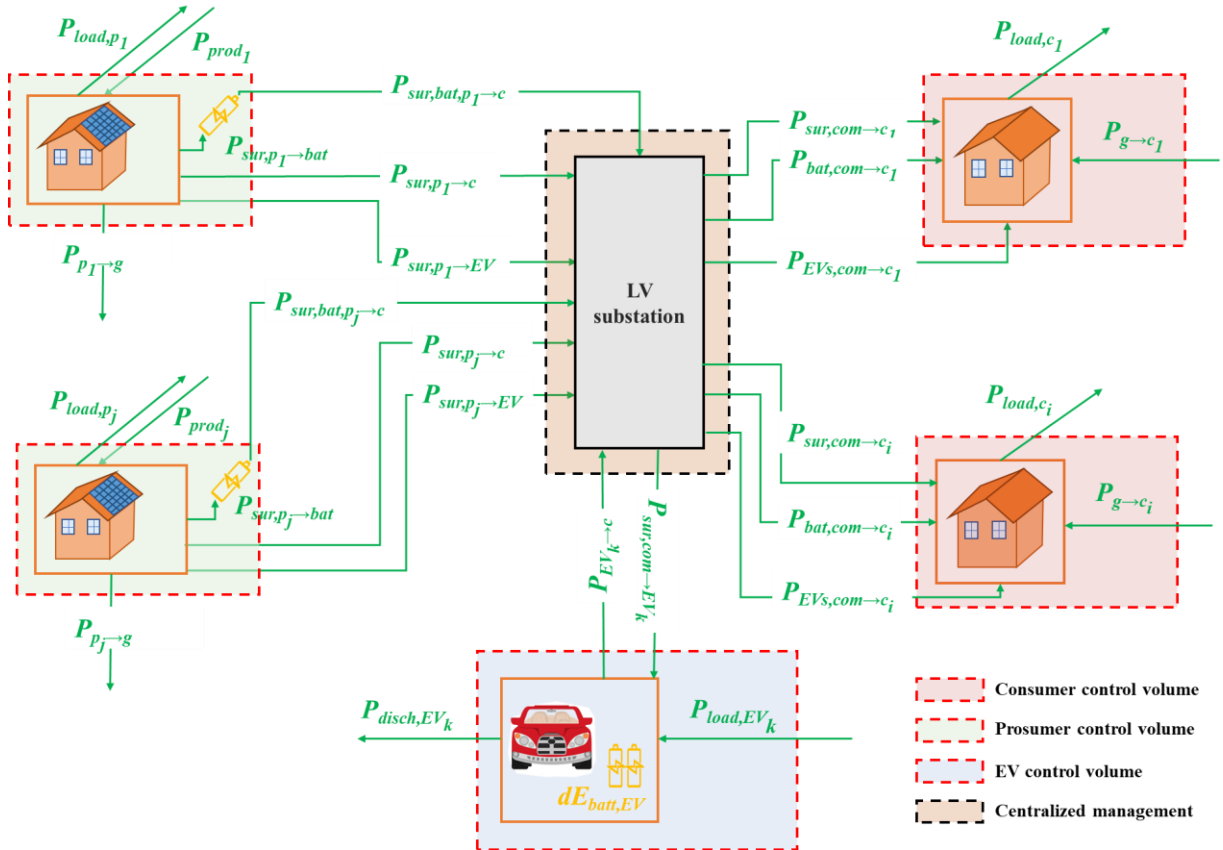


Figure 87. Energy balances for consumers, prosumers, and EVs in P2P sharing.

For every time step, the priority-based dispatching strategy (highlighted in Figure 88) begins with determining the surplus of each prosumer and the electrical requests of the users acting as consumers. The priority levels determine the dispatching order of global surplus power among the three aggregators (i.e., consumers, batteries, and electric vehicles). The six possible dispatching combinations will be a variable to optimize. Subsequently, the methodology employed to evaluate the shared power will be elucidated, considering the priority order determined by consumers, batteries, and electric vehicles.

To meet the demands of the consumers, the surpluses are sent to a two-way low voltage substation, which, regulated by proper control logic, distributes them to the community aggregators. If the resulting amount of surplus exceeds the total electrical demands, then the additional surpluses will be sent first to the stationary batteries and then to those of the electric vehicles (i.e., C2V). Conversely, when the total demands of consumers exceed the available power production, the energy stored in the stationary and EVs batteries (i.e., V2C) will be exploited. Finally, the grid will act as a backup system to satisfy further electrical needs.

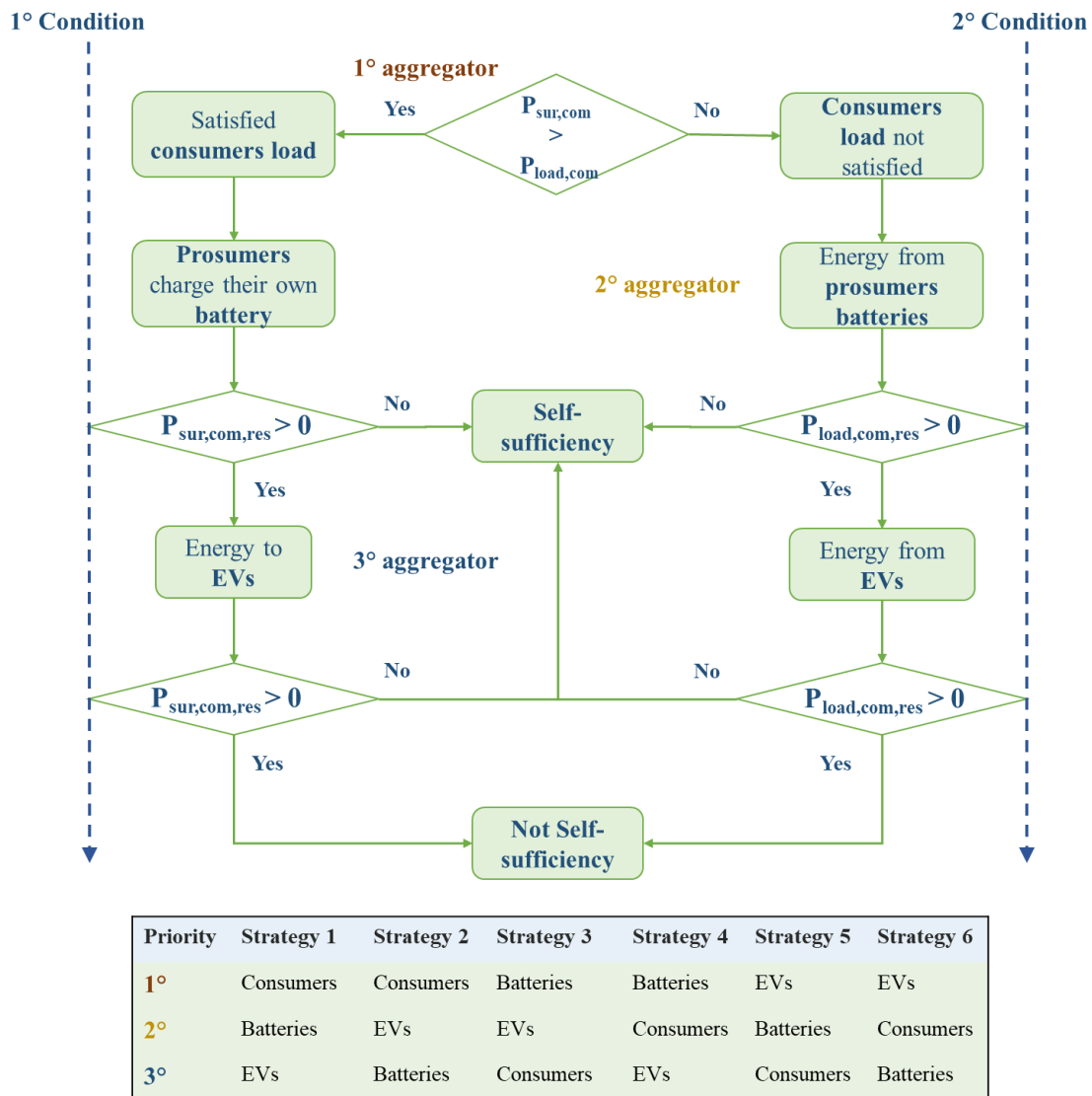


Figure 88. Schematisation of priority-based dispatching strategy.

This strategy was modelled through a matrix approach, to assess the energy interaction of each single user. At 1st priority level of the strategy and 1st condition, the vector $P_{sur,com \rightarrow ci}$ of surplus power shared to each consumer from prosumers is defined as:

$$\underline{P}_{sur,com \rightarrow c_i}(t) = \underline{P}_{load,c_i}(t) \quad \text{Eq. (8)}$$

Where $\underline{P}_{load,c,i}$ is the electrical load of i-th consumer. Therefore, to evaluate the power that each prosumer have been shared with consumers, the vector $\underline{P}_{sur,pj \rightarrow c}$ is defined as:

$$\underline{P}_{sur,pj \rightarrow c}(t) = \underline{P}_{load,com}(t) \times \underline{p}_{sur_j}(t) \quad \text{Eq. (9)}$$

with

$$\underline{p}_{sur_j}(t) = \underline{P}_{sur,p_j}(t) / \underline{P}_{sur,com}(t) \quad \text{Eq. (10)}$$

$\underline{p}_{sur,j}$ expresses the surplus weight factor of j-th prosumer. Regardless of the 2nd condition with a total amount of community surpluses $\underline{P}_{sur,com}$ less than community demands $\underline{P}_{load,com}$, the vector $\underline{P}_{sur,com \rightarrow c_i}$ is assessed as follows:

$$\underline{P}_{sur,com \rightarrow c_i}(t) = \underline{P}_{sur,com}(t) \times \underline{c}_{load_i}(t) \quad \text{Eq. (11)}$$

Where:

$$\underline{c}_{load_i}(t) = \underline{P}_{load,c_i}(t) / \underline{P}_{load,com}(t) \quad \text{Eq. (12)}$$

$\underline{c}_{load,i}$ is the load weight factor of i-th consumer, and in this way is possible to estimate the power supplied to each consumer.

In the 2nd priority level and 1st condition, the residual surplus energy is stored in the batteries. The vector $\underline{E}_{sur,pj \rightarrow batt}$ of energy stored in batteries is:

$$\underline{E}_{sur,pj \rightarrow batt}(t + \Delta t) = \min \left(\sum_{j=1}^{N_p} \left(\underline{P}_{sur,p_j}(t) - \underline{P}_{sur,p_j \rightarrow c}(t) \right) \cdot \Delta t, \sum_{j=1}^{N_p} \underline{C}_{bat,p_j} \cdot \left(1 - \underline{SOC}_{bat,p_j}(t) \right) \right) \times \underline{p}_{sur_j} \quad \text{Eq. (13)}$$

$\underline{C}_{bat,pj}$ and $\underline{SOC}_{bat,pj}$ are capacities and state of charge vectors of j-th prosumers batteries. Otherwise, in 2nd condition the batteries energy is exploited, due to an incomplete balance of the consumers' electrical load, and the power shared to consumers $\underline{P}_{batt,com \rightarrow c_i}$ is equal to:

$$\begin{cases} \underline{P}_{batt,com \rightarrow c_i} = \underline{P}_{batt,com} \times (\underline{c}_{load_i}) & \text{if } \underline{P}_{batt,com} < \underline{P}_{load,com,res} \\ \underline{P}_{batt,com \rightarrow c_i} = \underline{P}_{load,c_i,res} & \text{if } \underline{P}_{batt,com} \geq \underline{P}_{load,com,res} \end{cases} \quad \text{Eq. (14)}$$

with

$$\underline{P}_{load,com,res} = \left(\underline{P}_{load,com} - \sum_{j=1}^{N_p} \underline{P}_{sur,p_j \rightarrow c} \right) \quad \text{Eq. (15)}$$

$$P_{batt,com} = \sum_{j=1}^{N_p} C_{bat,p_j} \cdot (SOC_{bat,p_j}) \quad \text{Eq. (16)}$$

The power $P_{batt,pj \rightarrow c}$ that each prosumer's battery share with consumers is determined as follow:

$$\begin{cases} \underline{P}_{batt,p_j \rightarrow c} = P_{load,com,res} \times \underline{p}_{sur_j} & \text{if } P_{batt,com} \geq P_{load,com,res} \\ \underline{P}_{batt,p_j \rightarrow c} = \underline{C}_{bat,p_j} \cdot (\underline{SOC}_{bat,p_j}) & \text{if } P_{batt,com} < P_{load,com,res} \end{cases} \quad \text{Eq. (17)}$$

Finally, with 3rd priority level of the strategy and 1st condition (i.e., C2V), when the remaining community surpluses $E_{sur,com,rem}$ turn out to be greater than or equal to the total EVs storage capacity $E_{tot,load,EVs}$, the vector $E_{sur,com \rightarrow EVk}$ of energy stored in each EV from remaining prosumers surpluses is defined in the same way of Eq. 13.

The other condition of 3rd priority level is characterized by the possibility to exploit the EVs to satisfy the load profiles of the consumers (i.e., V2C); the vector $P_{EVs,com \rightarrow ci}$ of EVs electrical power shared to i-th consumer is evaluated as the vector $P_{batt,com \rightarrow ci}$ in Eq. 14. The power $P_{EVk \rightarrow c}$ sent from the k-th EV batteries to consumers, is assessed in the same way of the vector $P_{batt,pj \rightarrow c}$ in Eq. 17.

Finally, the 4th strategy level evaluates the residual power sold or the deficit requests covered by the electricity grid.

7.2.3 Energy community for electricity grid balancing

A further analysis concerns the implementation of innovative energy management strategies to guarantee the electricity grid balancing services. To this aim, the community's demand profile $P_{load,com}$ was initially flattened to address issues related to power fluctuations. Additionally, the community makes available its surplus power $P_{sur,com}$ and its storage capacity (i.e. stationary batteries, and EVs batteries) acting as a grid regulator for frequency and voltage imbalances. To determine the flattened daily load $P_{load,com,flat}$ a predictive analysis is performed (Figure 89). The analysis, carried out at the beginning of each day, requires as input the electrical load expected of each community's user and the current state of charge of stationary and moving batteries. The previously described energy sharing dispatching strategy (Figure 88) is adopted to evaluate the deficit load requests of the community $P_{load,com}$. The output of this first analysis is the flattened profile of the simulated demand $P_{load,com,flat}$, calculated as integral mean of $P_{load,com}$.

$$P_{load,com,flat}(day_{time}) = \frac{\int_{day_{start}}^{day_{end}} P_{load,com}(t) dt}{day_{time}} \quad \text{Eq. (18)}$$

The electricity grid uses a forecast analysis to predict the total load $P_{load,g,f}$ it must meet for a given day. The deviations between the real load $P_{load,g}$ and the expected one $P_{load,g,f}$ determine the grid's requirement for regulation $P_{g,reg}$. When $P_{g,reg}$ is positive (i.e., downward regulation power $P_{g,reg,d}$), a rise of grid frequency occurs, for this reason it is necessary an extra load to stabilize it. When $P_{g,reg}$ is negative i.e., upward regulation power $P_{g,reg,u}$), an additional energy production is required. Regularly, the fulfilment of these requests will be ensured by the regulatory stations. However, the aim of this study is to assess the feasibility of utilizing energy communities as regulatory stations.

The power distributed for grid balancing services, denoted as $P_{g,reg,com}$, is determined accordingly:

$$P_{g,reg,com}(t) = P_{g,reg}(t) \cdot \gamma_{com} \cdot \lambda_{av} \quad \text{Eq. (19)}$$

Where λ_{av} is the signal that determines the community's willingness to contribute to grid regulation phenomena, and γ_{com} expresses the proportion factor of community pick power over the maximum grid power:

$$\gamma_{com} = \frac{\max(P_{load,com})}{\max(P_{load,g})} \quad \text{Eq. (20)}$$

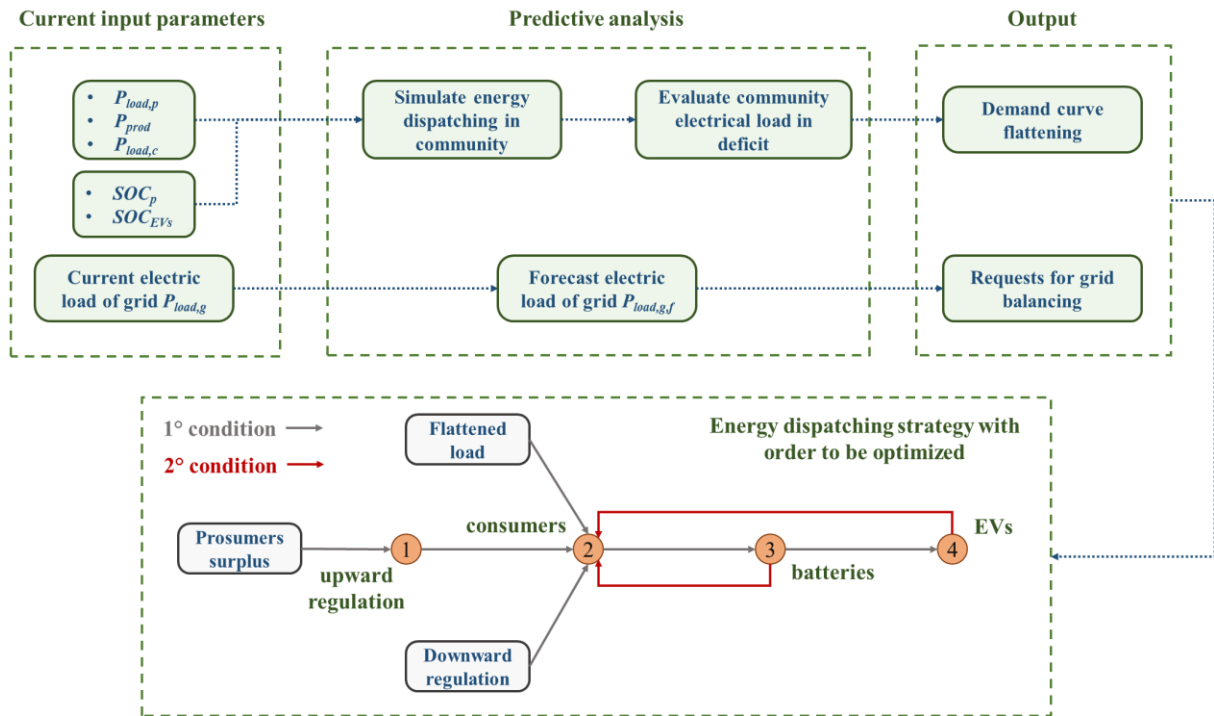


Figure 89. Work-flow schematisation of proposed strategy with community acting as grid regulator.

This time the dispatching strategy is aimed at managing not only the power $P_{sur,pj}$ of the prosumers' surplus, but also the power of the flattened optimized load $P_{load,com,flat}$ and the power $P_{g,reg,com,d}$ for the downward regulation of grid frequency. Furthermore, the electrical demands of the consumers are added to $P_{g,reg,com,u}$ for upward frequency regulation, while the community's accumulation systems will always be used as backup systems. As shown in Figure 89, the upward frequency regulation power can only be satisfied by the PV production surpluses. The excess power of the three input terms (i.e. $P_{sur,pj}$, $P_{load,com,flat}$, $P_{g,reg,com,d}$) can be used to charge stationary batteries and EVs. Whereas the deficit demands of consumers will be satisfied by the accumulated energy. Compared to the 1st optimization problem, the priority-based dispatching strategy provides for twenty-four possible combinations due to the addition of the required grid regulation power to the three aggregators of consumers, batteries and EVs. Finally, these combinations will be determined as a variable to be optimized.

7.2.4 Optimisation problem

The proposed dispatching strategies need to be optimized to maximize the energy performance of prosumer communities. Unlike the state of the art, this research considers aspects related to grid stability, including services for frequency balancing. Consequently, the proposed optimization procedure aims to maximize not only self-consumption and self-sufficiency, but also the exploitation of energy resources for grid frequency balancing and minimize community demand fluctuations. To highlight the advantages of the proposed methodology, it has been compared with a bi-objective problem that evaluates only the maximization of self-consumption and self-sufficiency.

The variable to be optimized in the energy management models is the dispatching priority order among the community aggregators. The optimization was performed on a time interval of 24h, thus determining the best priority strategy to be implemented for the investigated day. The objective functions for the two compared problems are evaluated as follows.

- The bi-objective problem is based on energy sharing mechanisms only (i.e., P2P and V2C/C2V), and the SC and SS functions to be maximized are.

$$SC(ord) = \frac{\sum_{j=1}^{N_p} P_{PV \rightarrow p_j}(t) + \sum_{j=1}^{N_p} P_{sur,p_j \rightarrow c}(t) + \sum_{j=1}^{N_p} P_{sur,p_j \rightarrow batt}(t) + \sum_{j=1}^{N_p} P_{sur,p_j \rightarrow EV}(t)}{\sum_{j=1}^{N_p} P_{PV,p_j}(t)} \times \Delta t_{24h} \quad \text{Eq. (21)}$$

$$SS(ord) = \frac{\sum_{j=1}^{N_p} P_{PV \rightarrow p_j}(t) + \sum_{j=1}^{N_p} P_{sur, p_j \rightarrow c}(t) + \sum_{j=1}^{N_p} P_{sur, p_j \rightarrow EV}(t) + \sum_{j=1}^{N_p} P_{batt, p_j \rightarrow c}(t) + \sum_{k=1}^{N_{EVs}} P_{EV_k \rightarrow c}(t)}{\sum_{j=1}^{N_p} P_{load, p_j}(t) + \sum_{i=1}^{N_c} P_{load, c_i}(t) + \sum_{k=1}^{N_{EVs}} P_{load, EV_k}(t)} \times \Delta t_{24h} \quad \text{Eq. (22)}$$

- The proposed optimization problem is based on energy sharing mechanisms, the reshaping of community demands, and the provision of regulation services. In fact, a new function - Grid Balancing Factor *GBF* - has been implemented and introduced in this work to take these objectives into account.

$$GBF(ord) = \left(1 - \frac{|P_{load, com}(t) - P_{load, com, flat}(\Delta t_{24h})|}{P_{load, com, flat}(\Delta t_{24h})} \right) \times \frac{P_{g, reg, com}(t)}{P_{g, reg, com, req}(t)} \times \frac{P_{PV, tot}(t) - P_{PV, sold}(t)}{P_{PV, tot}(t)} \times \Delta t_{24h} \quad \text{Eq. (23)}$$

7.3 Proof of concept

To demonstrate the potential of the proposed methodology a prosumer community considered as located in Naples (Italy) with PV systems and stationery/moving batteries is modelled. The total number of households N is set as thirteen with seven prosumers N_p and six consumers N_c ; whereas the number of EVs is equal to eight. The types of users differ in residential buildings with small dimensions, large dimensions, and offices (this classification is reported in Table 23).

Table 23. Characteristics of energy community users.

Maximum peak load power for user [https://doi.org/10.1016/j.est.2019.100791]			
<i>Residential small</i>	<i>Residential large</i>	<i>Office</i>	
3 kW	4.2 kW	5.8 kW	
Number of community user type			
<i>User</i>	<i>Residential small</i>	<i>Residential large</i>	<i>Office</i>
Consumers	3	2	1
Prosumers	1	4	2

The Figure 90a shows the electricity demand profile, and Figure 90b the yearly energy required for the three user types investigated such as residential small (*res,s*), residential large (*res,l*), and office (*off*). For residential buildings the load peaks occur outside working hours, the opposite occurs for office buildings. The weekly variability of the electrical load is

due to disturbances in climatic conditions which influence the buildings' thermal load, while the base load is due to the presence of always active users. Finally, the annual electricity needs of each consumer are reported.

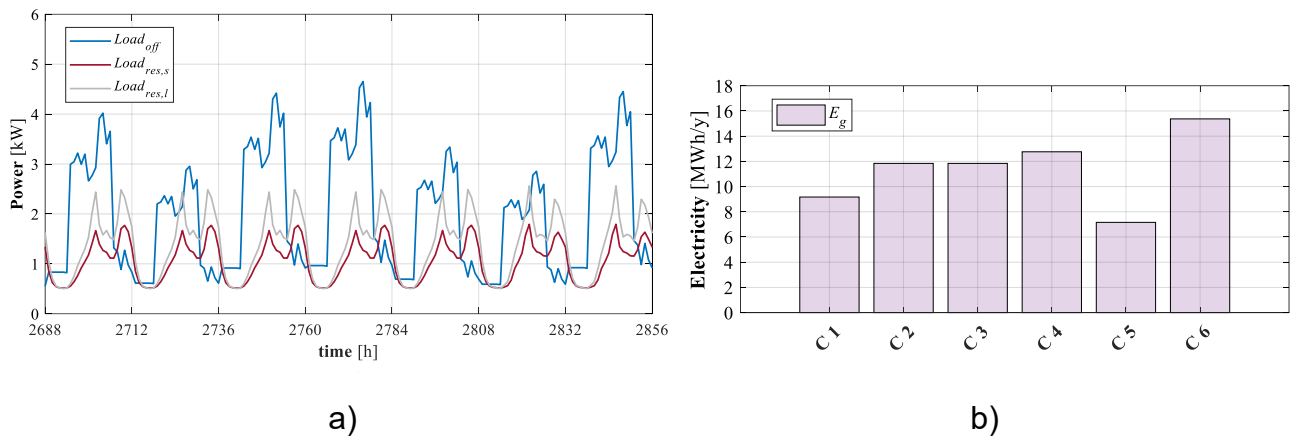


Figure 90. Consumers' electrical loads: a) weekly dynamic trend; b) annual needs.

The prosumers are equipped with a photovoltaic system coupled to a battery to maximize the self-consumption of renewable production. The global nominal installed power of the renewable production plants, and the size of the batteries are respectively 33 kW and 134 kWh. The characteristics of the power system configuration of the individual prosumer are shown in Table 24, as well as their technological characteristics.

Table 24. Characteristics of community power systems.

PV systems for user type					
	Residential small	Residential large	Office		
Installed power [kW]	3	4.5	6		
Surface [m ²]	11.4	17	22.8		
Battery capacity [kWh]	12	20	24		
Technological characteristics of PV systems					
$P_{MPP,STC}$ [W]	G_{STC} [W/m ²]	$T_{cell,STC}$ [°C]	$C_{t,P}$ [1/°C]	η_{BOP} [-]	$\eta_{shading}$ [-]
175	1000	25	-0.0043	0.79	0.75
Technological characteristics of the battery					
C_{cell} [Ah]	V_{cell} [V]	$I_{char,cell}$ [A]	$I_{disch,cell}$ [A]		
9	11	5	5		

The energy management of the prosumer shown in Figure 91a highlights the balance of its requests from PV production, from energy stored in the battery, and from the grid. Excess energy is either stored in the battery or sold to the grid (negative areas in orange and purple). The annual cumulative demonstrates that prosumers 3rd and 5th are self-sufficient but self-consumption is not guaranteed by selling many excesses to the network as highlighted by the purple dotted line in the Figure 91b. Furthermore, prosumers 2nd, 4th and 6th are the ones most grid dependent.

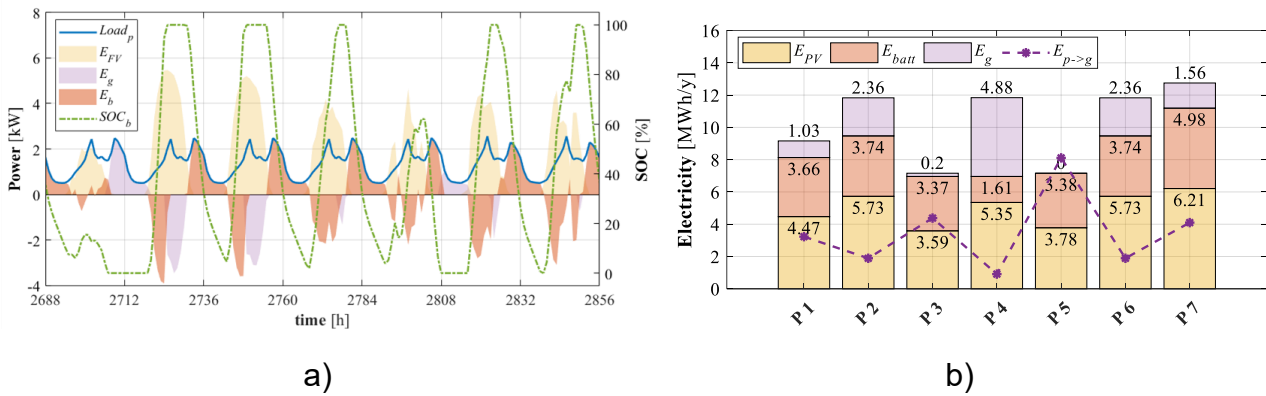


Figure 91. Prosumers energy management: a) weekly dynamic trend; b) annual needs.

To simulate the dynamic behaviour of electric vehicles, assumptions were made about their daily route:

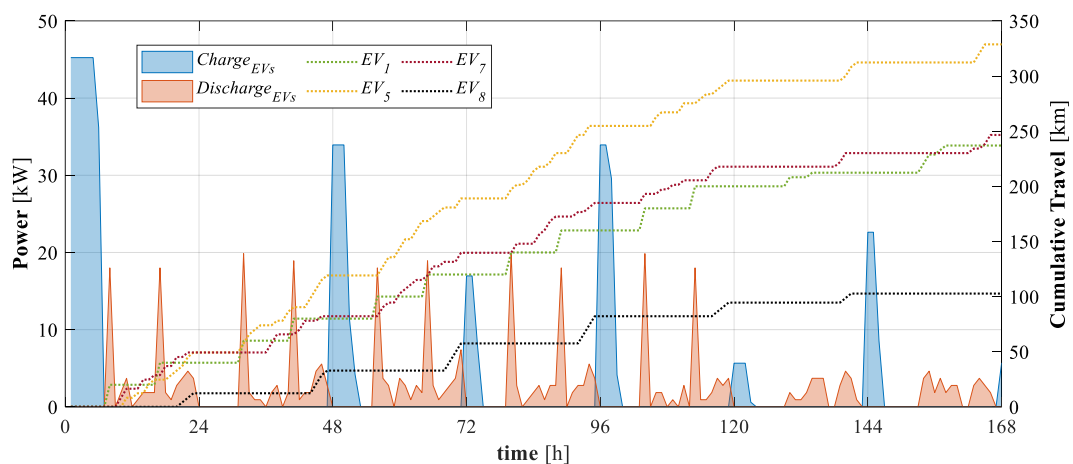
- Four vehicles operate with a random path profile from 8 a.m. to 5 p.m.
- Two vehicles operate with a random path profile from 8 a.m. to 11 p.m.
- Two electric vehicles exclusively travel in the evening, from 5 p.m. to 10 p.m. with a constant path profile.

Additional details regarding the assumptions utilized for estimating the electricity requirements of electric vehicles are provided in Table 25.

Once the total kilometres travelled in a week were determined and the assumptions for the timetable of EV movements were established, the dynamic profiles of kilometres travelled were evaluated (depicted in Figure 92). Notably, the value of $P_{u,disch}$ allows for the determination of discharging power profiles. Regarding the charging $schedule_{char}$ of the EVs, it was assumed to take place from 12 a.m. to 7 a.m. or during the hours when the vehicles are stationary in the pits.

Table 25. Characteristics of EVs.

EV characteristic			
C_{EV} [kWh]	$P_{u,disch,sum}$ [Wh/km]	$P_{u,disch,wint}$ [Wh/km]	$I_{nom,char,EV}$ [A]
41	153	225	32
Charging wall-box characteristic			
Type [-]	Charging time [h]	Power [kW]	
Slow charge	7.25	7.4	
Fast charge	2.67	32	
Weekly trips of EVs			
$EV_1 EV_2$ [km/week]	$EV_3 EV_5$ [km/week]	$EV_4 EV_7$ [km/week]	$EV_6 EV_8$ [km/week]
240	330	249	103

**Figure 92.** Global charging and discharging profile of EVs and cumulative kilometres travelled individually.

This recharge occurs only if the vehicle has a SOC_{EV} level lower than 50% (as highlighted in Figure 93a, and Figure 93b for EV 5th and EV 7th), and if so, it will be carried out with a single-phase wall box. The bar graph in Figure 93c shows the cumulative energy required by each electric vehicle.

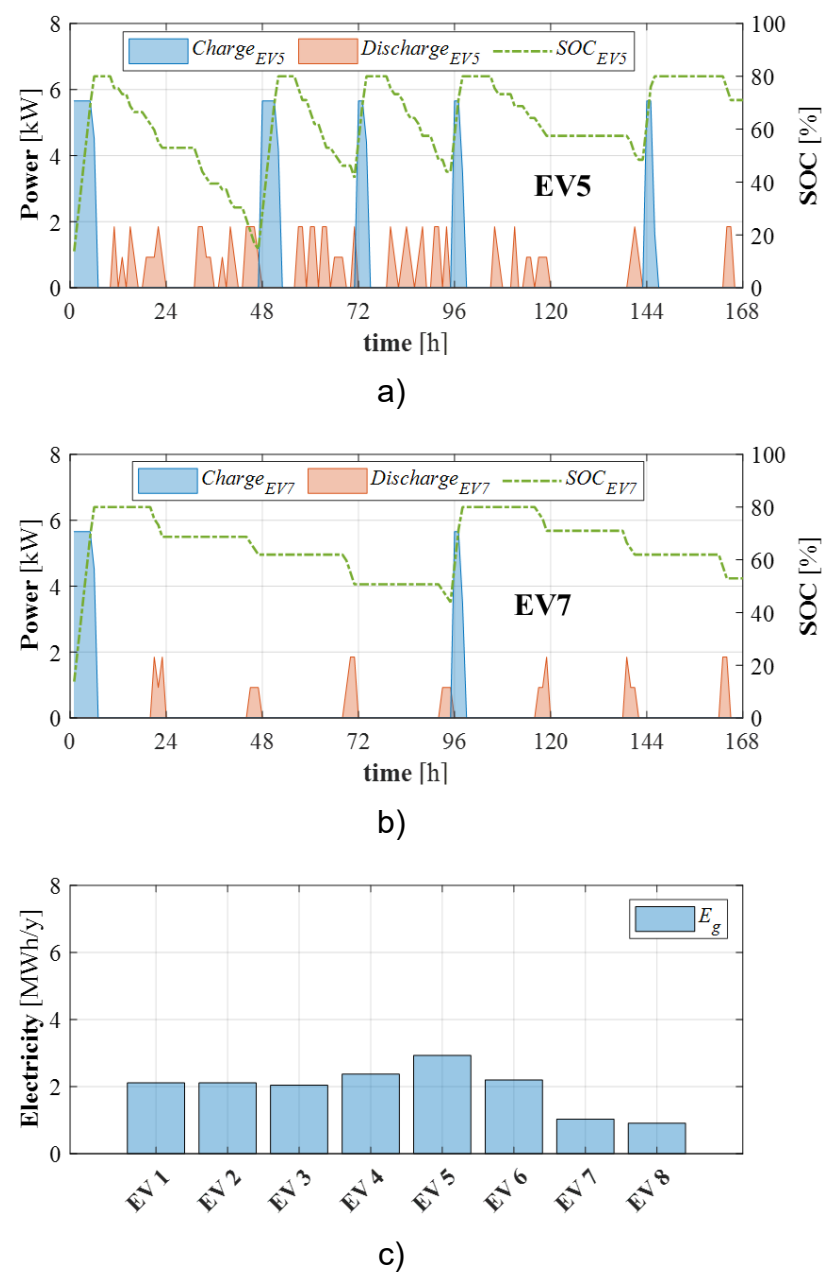


Figure 93. EVs load: a), b) charging discharging profiles of EV5 and EV7; c) individual annual needs.

Furthermore, the possibility of recharging vehicles with fast-charging columns was also evaluated when SOC_{EV} levels reached values below 20%.

7.4 Results

The energy management of the community has been optimized through the described dispatching strategies. In fact, as shown in Figure 91b, the global surpluses sold by prosumers are approximately equal to 25 MWh/year. Furthermore, the unpredictability of PV system production, and the resulting fluctuating demands of the prosumer community can compromise the grid stability. For this reason, improvement actions have been investigated to counteract these phenomena. The main results related to the implementation of strategies based on energy sharing among peers (P2P) and between electric vehicles and the building cluster (V2C/C2V) are reported. Finally, the results of the innovative optimization toward the goal of electricity grid balancing are analysed.

7.4.1 Energy sharing optimisation analysis

Energy sharing mechanisms are implemented to limit community interaction with the electricity grid. Through a bi-objective optimization, the combination of the priority-based strategy, which simultaneously maximizes self-consumption SC and self-sufficiency SS , is determined. As shown in Figure 94, the optimization of the ord variable was performed for every twenty-four hours.

In fact, the result of Figure 94 highlights in green the optimal dispatching strategy which guarantees a SC equal to 1 and an SS equal to 0.35. Once the priority strategy has been determined, it is possible to individually estimate the powers exchanged between the peers and the electric vehicles.

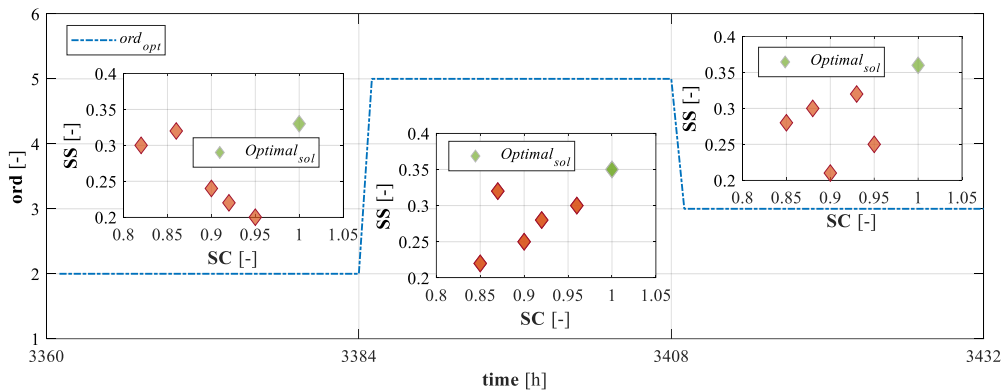


Figure 94. Optimisation procedure of priority dispatching strategy.

7.4.2 P2P energy sharing

The priority-based dispatching strategy will imply new energy management of the community users. The power surplus of the prosumers $P_{sur,pj}$ will be shared with users acting as consumers $P_{sur,pj \rightarrow c}$ or stored in stationary batteries $P_{sur,pj \rightarrow batt}$ and electric vehicles $P_{sur,pj \rightarrow EVs}$ according to the optimized order. The energy production management of prosumer 5th is shown in Figure 95, where the simulation analysis was carried out from 20 to 22 May. It can be noted that the production $P_{prod,pj}$ in yellow line exceeds the power demand in blue $P_{load,pj}$. Therefore, the prosumer mainly shares the surplus energy with the consumers (depicted with grey areas in the graph), and with the community batteries (in orange). The largest amount of energy exchanged with electric vehicles (green area of Figure 95) occurs on the second day of the investigated time interval. In fact, as obtained in the Figure 94, the optimal order is the one that determine the distribution of the surpluses first to the electric vehicles, then to the batteries and lastly to the consumers. With this strategy the maximum self-consumption is achieved.

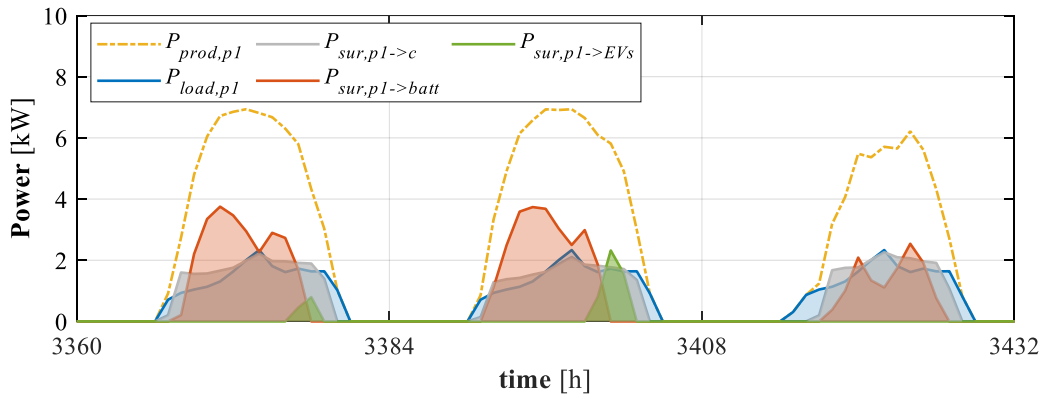
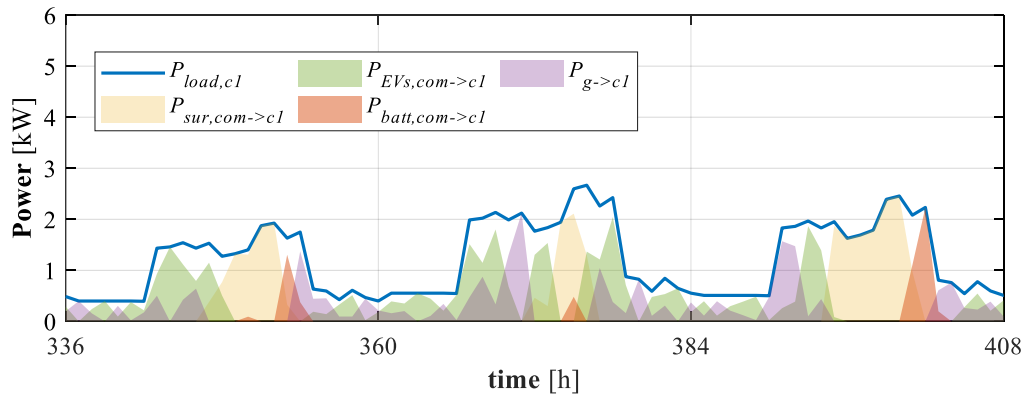


Figure 95. Energy management of PV production of prosumer #5.

The charge and discharge of the batteries will no longer be managed by the single prosumer but by the centralized logic of the community. In fact, the energy stored in the batteries is made available to all users acting as consumers.



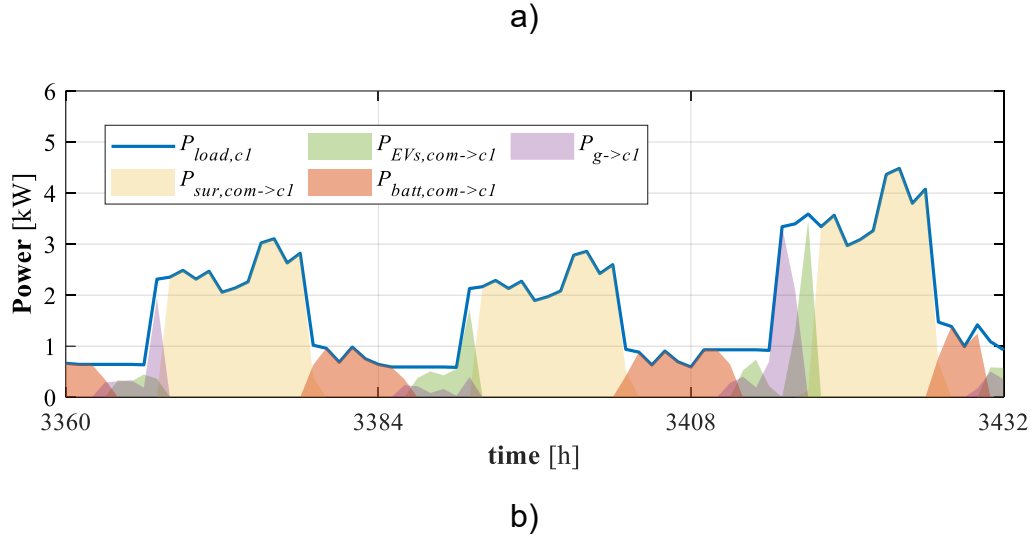


Figure 96. Energy balance of electrical load of consumer #6, a) 14-16 January; b) 20-22 May.

Figure 96 shows the electrical needs balance of consumer 6th, and this analysis was conducted for three days in January (Figure 96a) and three days in May (Figure 96b). Contrary to the reference case, this time the consumer sees his requests satisfied also by the power shared by the prosumers $P_{sur,com \rightarrow ci}$ in yellow, by the batteries $P_{batt,com \rightarrow ci}$ in orange, by electric vehicles $P_{EVs \rightarrow ci}$ in green and the residual load in deficit in purple $P_{g \rightarrow ci}$ will be satisfied by the electricity grid. In this graph, it can be noted that the consumer's self-sufficiency on summer days is greater thanks to the large amount of PV production.

7.4.3 Vehicles-to-Clusters / Clusters-to-Vehicles

The energy sharing strategy has also been extended to electric vehicles which, during their shutdown phases, are connected bidirectionally to the community's microgrid. The Figure 97 shows the charge and discharge profile of the EV 5th. In blue and orange, the charge from the electricity grid and the discharge during the EV path are represented. Whereas, in yellow the energy stored by the surplus of prosumers and in orange that shared with the consumers of the community. It can be noted that V2C/C2V strategy particularly stresses the batteries of electric vehicles by exposing them to additional charge and discharge cycles.

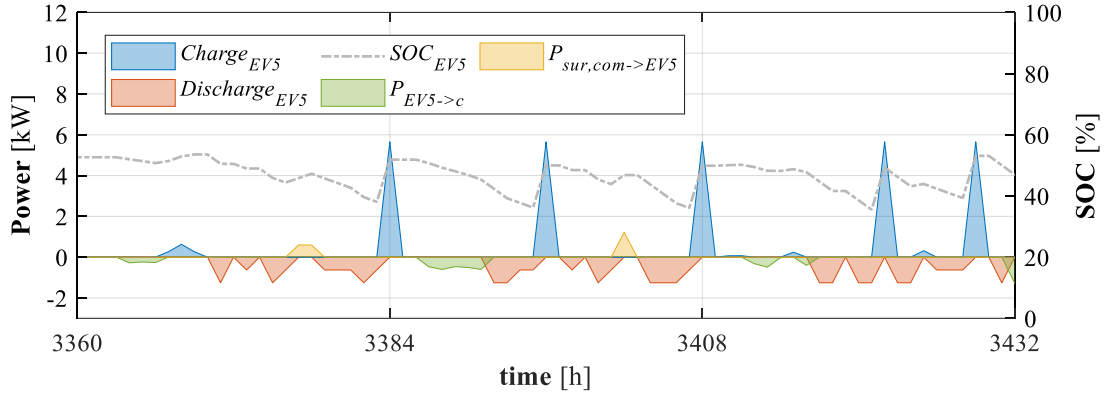


Figure 97. Charging/discharging profile of EV #5 for V2C/C2V strategy.

7.4.4 Energy community for grid balancing

The implementation of the energy sharing strategy has led to a total self-consumption and a significant increase in the community's self-sufficiency. Despite this, the stability of the electricity grid remains compromised due to greater load fluctuations. For this reason, a further optimization procedure is considered necessary, it is aimed at improving the performance of the community in providing grid balancing services. The proposed mechanisms of energy dispatching within the community are the same. However, respecting to the 1st optimization analysis, the excess power of the flattened load $P_{load,com,flat}$ and of the upward regulation of the frequency $P_{g,reg,com,u}$ are added to the surplus power $P_{sur,pj}$ of the prosumers. Furthermore, the prosumers' surplus must also balance the demands for $P_{g,reg,com,d}$ downward frequency regulation. Finally, the dispatching priority order will be optimized according to a new *GBF* index which considers the balancing role of the community.

7.4.5 Community load flattening for grid stability

As reported in the previous sections, predictive analysis is necessary to estimate the load that the community requires from the electricity grid $P_{load,com}$, and as can be noted from the blue trend of Figure 98a it would have been fluctuating and therefore potentially harmful for grid stability. The first optimization action is aimed at determining a new load profile $P_{load,com,flat}$ (orange trend in Figure 98a) that can be free of fluctuations and therefore constant throughout the day. As highlighted in Figure 98b, there will be time intervals in which the blue curve is higher than the orange one and vice versa, in these cases the energy availability and the electrical storage capacities will be exploited respectively. Finally, as depicted in Figure 98a, the optimization of energy dispatching mechanisms allows to satisfy the demands of consumers $E_{g \rightarrow com}$ and to properly store the surplus $E_{g \rightarrow bat}$ of the $P_{load,com,flat}$

in the community batteries which will satisfy the remaining cluster requests when they exceed the flattened demand.

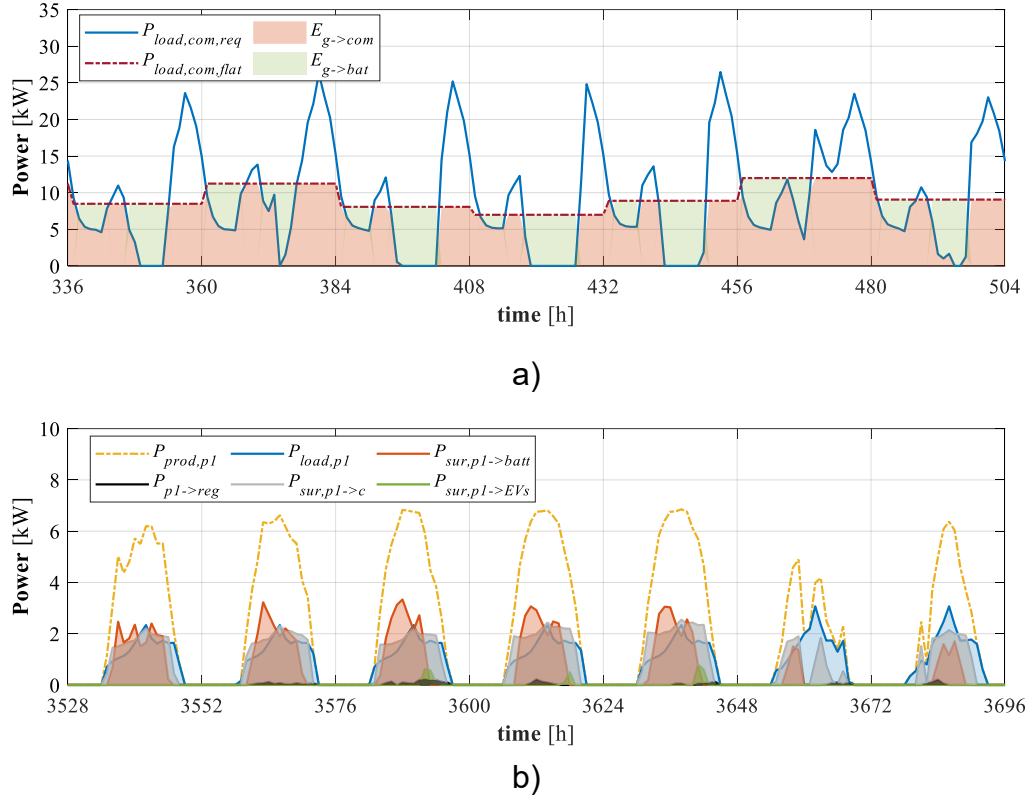


Figure 98. Grid balancing optimisation: a) energy management of community's flattened demand profile; b) energy management of PV production of prosumer #5.

The optimization of the priority dispatching strategy according to the *GBF* index guarantees at the same time the self-consumption of the community. In fact, as can be seen from the Figure 98b, the excess energy of the photovoltaic system of the prosumer 5th, is stored in the batteries and the EVs, and then is suitably used to satisfy the upward regulation requests $P_{pj \rightarrow reg}$ of the grid (represented in black) and $P_{sur,pj \rightarrow c}$ of consumers.

7.4.6 Power grid regulation services

The dynamic trend of the total power load to be satisfied by the grid is provided by Terna dataset [375]. The expected $P_{load,g,f}$ and real $P_{load,g}$ are represented in Figure 99a and refer to a time horizon from 27 May to 2 June. The power required by the grid $P_{g,reg}$ for frequency regulation, and shown in yellow in Figure 99a, is a function of the difference between the expected and actual demand. In this way, the resulting power profile that the grid would require from the community $P_{g,reg,com}$ is also determined (Figure 99b). When it assumes positive values, it refers to the power that the grid requires for the downward regulation of

the frequency, conversely for upward regulation when it is negative. Therefore, in the same way as the flattened load management, the optimization of the dispatching strategy allows to suitable exploit the surplus power from the PV systems to guarantee the upward frequency regulation requests $P_{g,reg,com,u}$ (yellow area of Figure 99c).

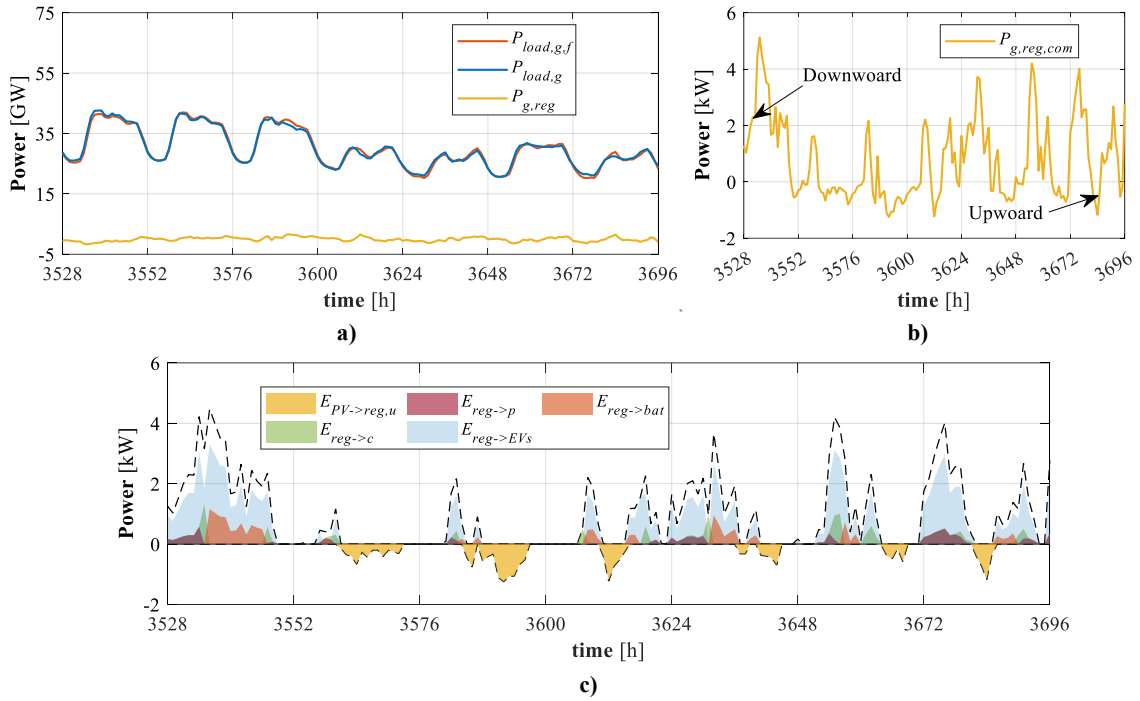


Figure 99. Power grid regulation from energy community: a) foreseen and real load of entire electricity grid; b) Power grid regulation required from community; c) Optimised energy management of community for grid regulation.

While the downward regulation power $P_{g,reg,com,d}$ is distributed to users (prosumers in red and consumers in green) or stored in community batteries (orange area) and electric vehicles (light blue area). Finally, these results show that the following strategy achieves the objectives set for grid regulation and stability.

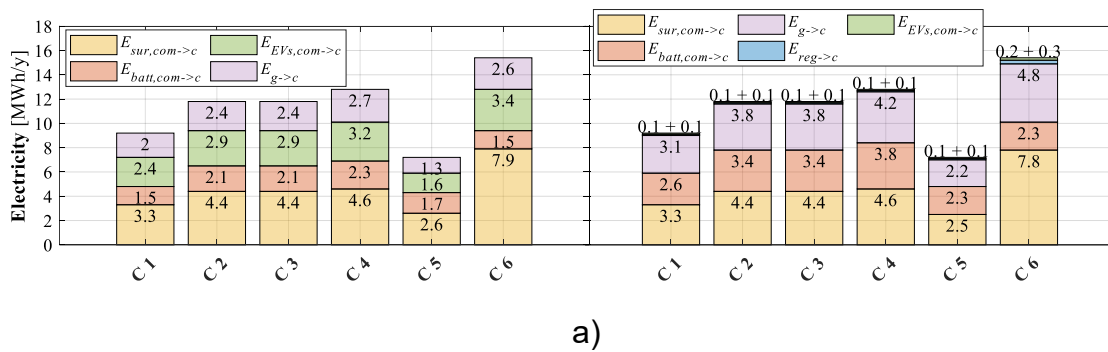
7.4.7 Comparison between optimisation strategies

A comparison was made between the two proposed methodologies. In this analysis, the management of the energy balance of each user of the community and the distribution of surpluses were highlighted.

Consumer requests covered by the excesses of prosumers $E_{sur,com \rightarrow c}$ are almost the same with 0.2 MWh/year less for the 2nd proposal. This deviation is due to the dispatching strategy, which is performed with a different objective function, and in addition, is characterized by the further request of the power $P_{g,reg,com,u}$ for upward grid regulation. The

needs of consumers covered by batteries $E_{bat,com \rightarrow c}$ in 2nd proposal are 6.6 MWh/year more than in the 1st proposal. This condition is due to the excesses of $P_{load,com,flat}$ and $P_{g,reg,com,d}$, which increase the charging. Furthermore, in the 2nd proposal, consumer requests are also met directly by the downward regulation of energy $E_{reg \rightarrow c}$ for a total amount of 0.8 MWh/year (represented by the term to the right of the addition in Figure 100a). Finally, the interaction with electric vehicles $E_{EVs,com \rightarrow c}$ is greater in the 1st proposal, in fact, the total energy exchanged is equal to 16.4 MWh/year compared to the 0.7 MWh/year (represented by the term on the left of the addition of Figure 100a) of the proposed case 2.

To satisfy the prosumers' requests, in reference and proposed cases, the energy produced by the PV systems, which directly used $E_{PV \rightarrow pj}$ is equal to 35.3 MWh/year. The load satisfied by the batteries $E_{batt,com \rightarrow p}$ for 2nd proposal is higher than the 1st by 103%. The energy purchased directly from the electricity grid $E_{g \rightarrow p}$ in 1st proposal turns out to be -0.1% lower than the reference, while in 2nd proposal it turns out to be 30% higher corresponding to a further expenditure of 3.8 MWh/year. However, the 1st proposal faces an additional expense $E_{EVs,com \rightarrow p}$ of 13.8 MWh/year from electric vehicles. As regards the sale of surpluses, in the reference case they are equal to 24 MWh/year. In the 1st proposed case 27.2 MWh/year (red line in Figure 100b) are sold to consumers and 0.2 MWh/year to EVs (at a unit selling price higher than that recognized by the grid in reference case). Instead, 2nd proposal will be characterized by the sale of 27 MWh/year to consumers and 1 MWh/year to electric vehicles (green values in Figure 100b), furthermore the energy recognized to the grid for frequency regulation (blue values in Figure 100b) is 1.5 MWh/year. It should be noted that for both proposals, although the energy purchased by prosumers is higher, the sale of P2P and C2V shared energy guarantees higher net revenues than in the reference case.



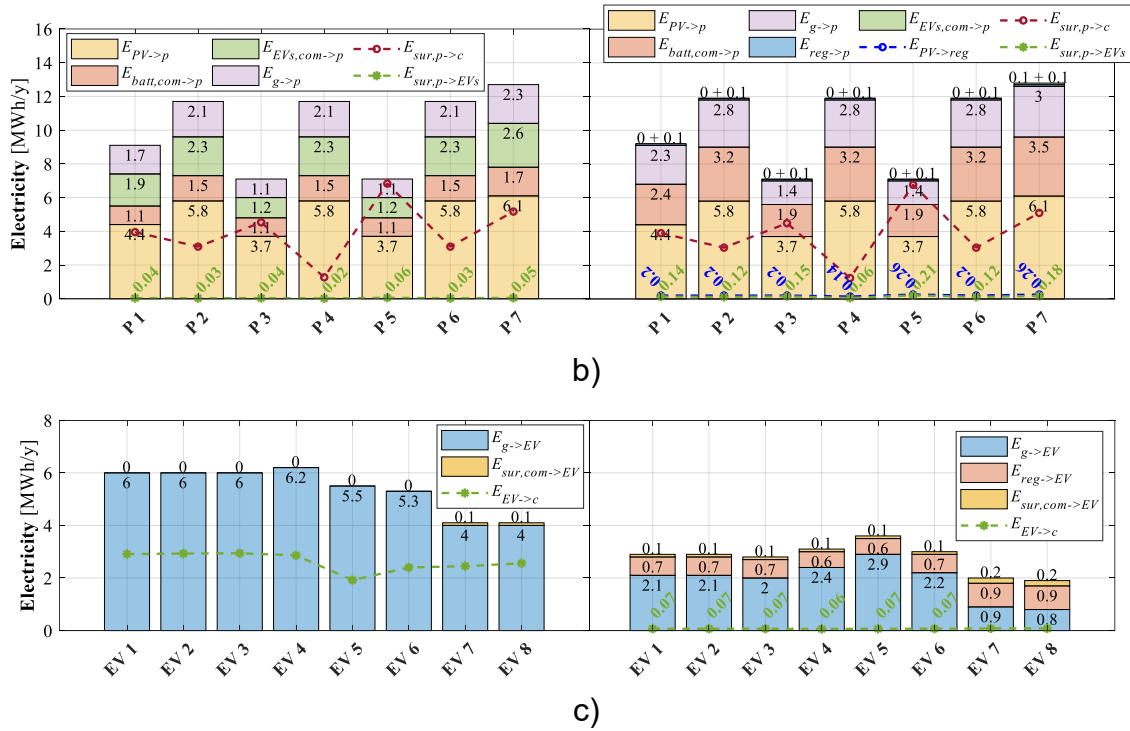


Figure 100. Comparison between 1st proposed strategy on the left and 2nd one: a) energy balance of consumers; b) energy management of prosumers; c) EVs energy management.

Finally, as regard the EVs, in the 1st proposal the greater interaction with the buildings cluster led to an increase in the charge energy purchased from grid $E_{g \rightarrow EV}$ equal to 179% respecting the reference case. While, in the 2nd proposal the electric vehicles do not face an excess expense but the energy interactions with the cluster are balanced by $E_{reg \rightarrow EV}$ equal to 5.8 MWh/year (depicted in orange in Figure 100c) and by $E_{sur,com \rightarrow EV}$ (depicted in yellow).

To highlight the advantages of the proposed dispatching strategies, a further comparative analysis was conducted considering the results obtained by the whole community. As shown in Table 26, both strategies achieve the goal of self-consumption through energy sharing mechanisms. Although the energy purchased from the electricity grid for the balance of the cluster requests with the 1st proposal turns out to be 26.8 MWh/year lower than the 2nd proposal, the requests of electric vehicles increase by 27.6 MWh/year due to the greater interactions with the clusters. Consequently, as shown in Figure 101, both proposals achieve self-sufficiency of 55% compared to 38% of the reference case. Having highlighted that the energy advantages of both strategies are comparable, a further analysis of the global discharge cycles of batteries and electric vehicles has been made in Table 26. It can be noted that the greater use of the batteries in the 2nd proposal, due to the storage of $P_{load,com,flat}$ excesses, leads to an increase in the discharge cycles of 42% and 65% compared to the reference case and the 1st proposal.

Conversely, the 1st proposal affects the life cycle of EVs batteries, causing a 173% increase in discharge cycles. Finally, the 2nd strategy by storing 14.3 MWh/year of energy from the grid guarantees a non-fluctuating load, and by providing 1.46 and 7.71 MWh/year for upward and downward frequency regulation, it acts as a regulator ensuring grid stability. In fact, as shown in Figure 101, 2nd strategy is the only one to achieve a *GBF* of 100%.

Table 26. Comparison of the results obtained by the optimisation strategies.

		Reference [MWh/y]	PS1 [MWh/y]	PS2 [MWh/y]	$\Delta(\text{PS2-REF})$ [%]	$\Delta(\text{PS2-PS1})$ [%]
PV	Cluster	34.9	62.5	62.3	+78%	-0.3%
	Battery	24.5	21.1	20.6	-15%	-2.5%
	EVs	0	0.27	1.00		
Grid	Cluster	80.5	25.9	38.4	-52%	+48%
	Battery	0	0	14.3		
	EVs	15.7	43	15.4	-2%	-64%
	$E_{reg,u}$	0	0	1.46		
	$E_{reg,d}$	0	0	7.71		
Dis_{cycle}	Battery	183	157	260	+42%	+65%
	EVs	48	131	47	-2%	-64%

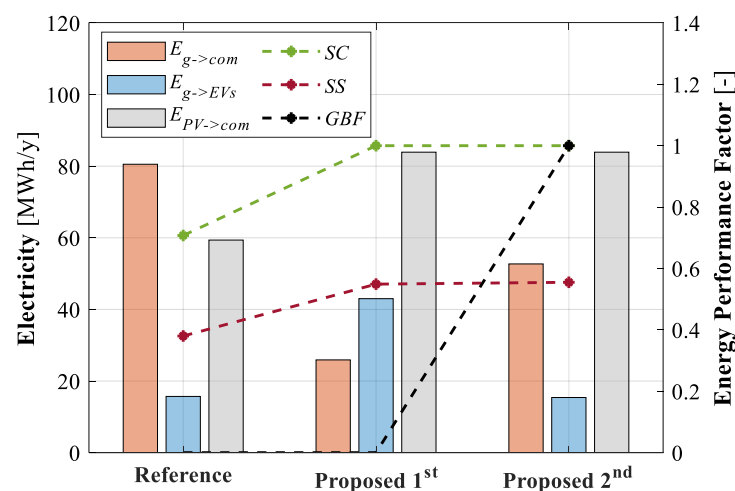


Figure 101. Energy performance comparison between reference case 1st, and 2nd proposals.

7.5 Conclusions

This study investigates the management of energy communities comprising prosumers, consumers, and electric vehicles, with a focus on optimizing energy sharing mechanisms and grid stability. The rapid growth and cost reduction of clean energy technologies have enabled decentralized energy production, but they also introduce challenges such as voltage and frequency imbalances in the electricity grid.

To address these challenges, the concept of energy communities emerges as a crucial component for efficient dispatching services. In this work, a community model is developed and simulated using MatLab. Two optimization strategies are proposed: the first maximizes self-sufficiency and self-consumption through energy sharing mechanisms, while the second incorporates the GBF as an objective function to ensure grid stability.

The first strategy achieves a self-sufficiency rate of 55% and 100% self-consumption, but it lacks grid stability. The second strategy, which considers GBF, maintains comparable levels of self-consumption and self-sufficiency while successfully balancing the grid. The results demonstrate the benefits of optimal energy management in communities, providing economic advantages to community members and mitigating balancing issues for the electricity grid. Notably, the objective of grid balancing was achieved by ensuring a non-fluctuating load and providing 1.46 MWh/year and 7.71 MWh/year for upward and downward grid frequency regulation, respectively.

The following key findings and considerations emerged from the study:

- The study demonstrates that implementing optimal energy management strategies allows for the maximization of self-consumption and self-sufficiency within energy communities.
- By incorporating a GBF-based strategy, the study successfully achieves grid balancing objectives while maintaining high levels of self-consumption and self-sufficiency.
- The implemented community model serves as a valuable tool for evaluating the energy performance of communities and optimizing dispatching services.

The objective of this work is to highlight the significance of preserving grid stability and balancing in energy communities. By emphasizing the importance of proper behaviour and management, the aim is to provide valuable insights for optimizing energy community operations.

Chapter 8

Discussions and main findings

This chapter presents a comprehensive discussion and summary of the main findings from this dissertation. As examined throughout the previous chapters, the urban sector is a complex, multi-domain environment composed of interdependent sub-systems that significantly influence energy performance, economic efficiency, and environmental impact. This dissertation has identified three primary domains within the urban landscape – **end-user**, **building systems**, and **district systems**.

The research presented in this dissertation introduced innovative methodologies and modelling tools designed to address key challenges in urban energy management, with objectives to optimise energy use, increase renewable energy integration, and support sustainable urban development. Each chapter contributes towards these goals, offering insights into how various urban subsystems can be effectively modelled, optimised, and controlled to advance the energy transition.

This final discussion synthesises these contributions, illustrating how the findings collectively enhance the understanding of multi-scale energy management in urban contexts. A central aim of this research is to capture the dynamic interactions between different elements of urban systems, providing a more accurate representation of real-world complexities. Notably, the role of the end-user has been recognised as a pivotal factor in managing and influencing the interactions across urban subsystems, reinforcing the importance of occupant-centric strategies in achieving energy efficiency and system integration.

The chapter concludes with reflections on the implications for future research and policy, underscoring the importance of integrated urban energy models as essential tools for supporting cities in their transition towards more sustainable, and efficient energy systems.

Discussions

The urban sector, accounting for 75% of global energy consumption, has a significant impact on energy demand and environmental sustainability. In recent years, primary initiatives have focused on promoting renewable energy systems, electrifying high-demand sectors such as buildings and transportation, and enhancing energy efficiency to reduce cities' environmental impact. However, the rapid, uncoordinated spread of these measures has led to unforeseen challenges. The unpredictability of renewable energy production, fluctuating energy demands from end-users, and the widespread adoption of electric vehicles are contributing to voltage and frequency imbalances within the central power grid.

In response, current efforts are increasingly oriented toward smart energy management. These efforts aim to integrate, control, and optimise urban energy systems to achieve higher self-consumption of renewable energy, limit grid surplus, enhance energy savings, reduce fossil fuel dependency, and support economic benefits. Modelling tools play a crucial role in investigating, designing, and implementing such solutions. Initially, research in this area focused on a broad, macroscopic perspective to address the urban sector's energy challenges. However, as this dissertation emphasises, the focus has now shifted toward understanding the unique characteristics and interactions of each subsystem within urban multi-domain frameworks. This shift is fundamental to accurately capturing the energy dynamics of urban systems and proposing practical solutions applicable to real-world scenarios.

This dissertation underscores the importance of considering each urban subsystem's individual interactions to develop actionable solutions that support a sustainable urban energy transition. The identified urban scales and their respective components include:

- **End-user scale:** This scale is centred around the consumption patterns, energy utilisation, and energy management practices of the end-user. End-users are key players in the urban context, yet their role in optimising urban energy performance is often overlooked, resulting in less accurate analyses. End-users can be classified as occupants, prosumers, and/or consumers. Occupants influence building energy consumption through their comfort needs and usage habits. When acting as prosumers or consumers, their behavioural decisions affect the management of building systems (such as storage systems and electric vehicles), potentially amplifying mismatches between energy demand and renewable energy production, which can, in turn, affect the central grid.
- **Building scale:** This scale connects end-users with district systems and encompasses the building infrastructure along with its HVAC systems, distributed renewable energy sources, storage systems, and electric vehicles. Although these systems are

controlled by end-users, their efficiency and performance have a broader impact on total energy consumption and generation capacity.

- District scale: This level captures the larger-scale interactions among various end-users and building systems. District systems comprise clusters of buildings, renewable energy hubs, and both thermal and electrical network infrastructures. The energy performance of each building system, shaped by end-user influence, impacts the overall operation of district systems.

The aim of this dissertation has been to develop energy-efficient and economically viable solutions that are applicable to real-world urban contexts. Through advanced modelling techniques, this work seeks to capture the interactions and dependencies across urban scales. The first objective was to examine how each subsystem influences the others, with particular attention to the unique factors often neglected in urban energy analyses. With these interactions identified, the focus shifted to exploring optimisation strategies that could guide urban energy systems toward sustainable development, with improved control and management of the systems that constitute them.

Figure 102 illustrates the interactions among urban scales as modelled in the works presented in this dissertation's chapters. The blue connections represent the influence that each subsystem has on others across different domains. Key effects from these interactions include:

- Occupant-driven comfort needs: Individual occupant behaviours and thermoregulatory responses significantly impact a building's space heating and cooling requirements, allowing for an estimation of HVAC energy consumption that reflects the real applications that are far from the projections suggested by the standards.
- Behavioural impact on building equipment: End-users' behaviours directly influence the energy use intensity and dynamic operation of building systems, such as electrical equipment, storage systems, and electric vehicles.
- Renewable energy demand matching: The end-user's occupancy and behaviour patterns affect the alignment between renewable energy production and building demand, often resulting in undesired surplus energy being injected into the grid, causing potential energy losses.
- Building energy demand on district clusters: Variations in the energy demand intensity and fluctuations across individual buildings collectively shape the energy profile of building clusters, impacting overall district energy performance.
- Renewable energy unpredictability on centralised energy hubs: Variability in renewable energy generation affects the operational stability of centralised energy hubs, underscoring the importance of adaptable control strategies.

- Thermal interactions within district heating and cooling systems: The hydronic and thermal dynamics of building HVAC systems influence the overall performance of district heating and cooling networks, affecting energy efficiency at the district scale.
- Impact on energy communities: The combined effects of variable renewable production, fluctuating building energy needs, and resulting mismatches influence energy sharing within energy communities, affecting their self-consumption, grid independence, and flexibility.

These interactions form a foundation for accurately assessing energy system performance within urban environments. Such assessments are essential for optimising the design and operational control of these systems, ultimately aiming for sustainable, decarbonised urban energy management. Figure 102 also highlights, in green, some proposed solutions that address these objectives:

- Occupant-centric control: This strategy minimises the energy impact of occupant comfort needs while maintaining a comfortable indoor environment, ensuring that energy efficiency does not compromise occupant well-being.
- Predictive control of solar systems: By implementing predictive management, large solar systems can optimise self-consumption, meeting building energy demands within shared network infrastructures.
- Optimised district heating and cooling temperature management: By facilitating thermal exchanges among users, district heating and cooling systems can achieve self-balancing, enhancing the electrification of heating and cooling demands in interconnected buildings.
- Aggregation criteria for energy communities: This dissertation emphasises the importance of recognising the unique characteristics of each building and end-user behaviour in forming energy communities. Considering these singularities enhances both energy and economic benefits.
- Energy management strategies of energy communities for grid flexibility: Effective sharing mechanisms leverage building systems, electric vehicles, and storage to maximise grid independence, provide flexibility, and offer balancing services, thereby mitigating the impact of high renewable penetration within districts.

Following this, an in-depth discussion, for the topics investigated in the previous chapters, will examine these interactions and proposed solutions, underscoring their contributions to a sustainable urban energy transition and identifying potential areas for further research.

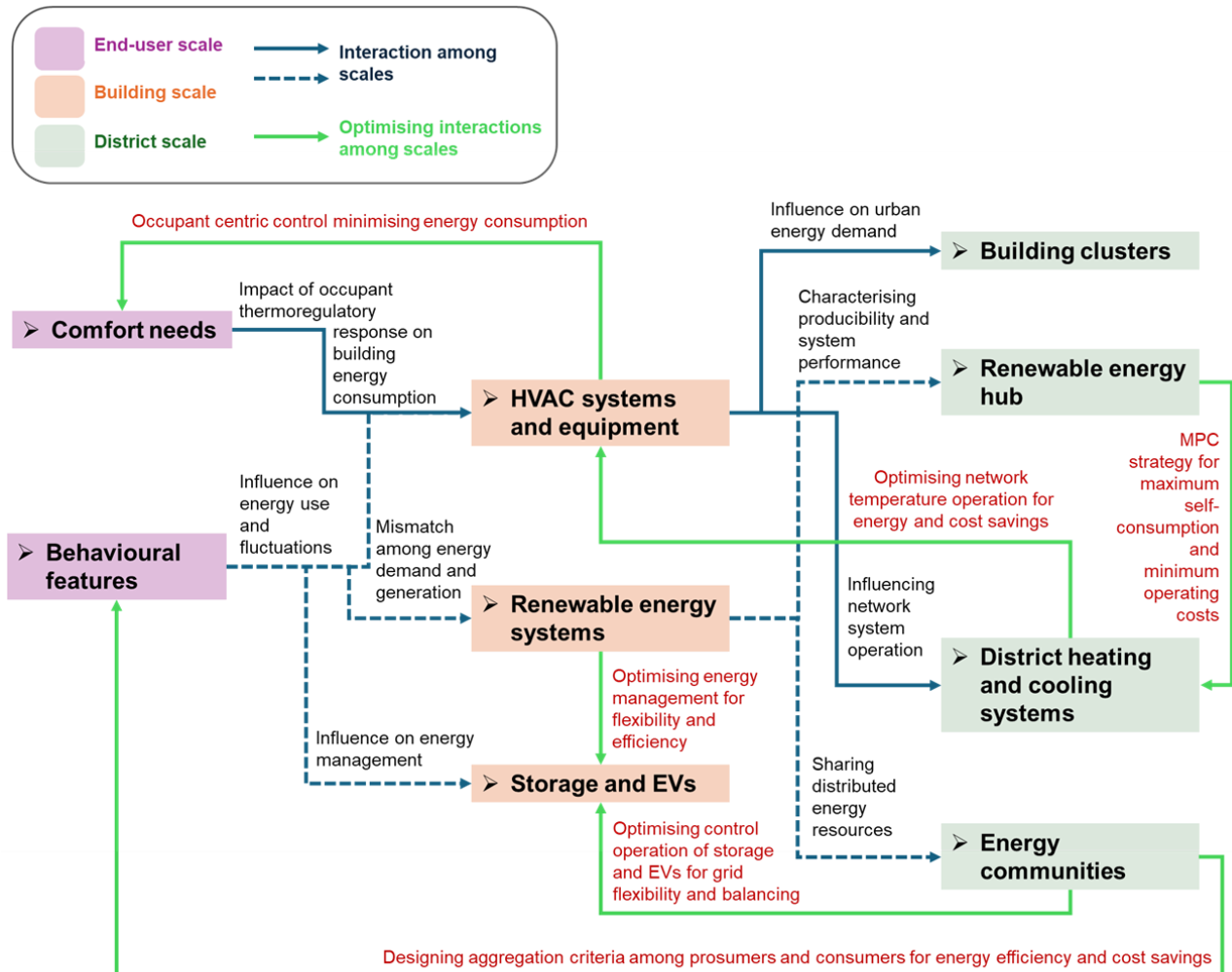


Figure 102. Framework for modelling interactions and influences between urban scales, enabling optimised solutions across subsystems.

Chapters 2 & 3

International standards, such as CIBSE, ASHRAE 55, and EN ISO 7730, often set fixed indoor comfort conditions based on classical comfort models, assuming steady-state conditions that do not account for occupants' thermal adaptation. These standards define specific temperature ranges, such as 21–23°C, 21.5–24°C, and 20–26°C, respectively, as optimal for comfort. In contrast, the physiological thermal model proposed in these chapters incorporates individual data under varied conditions, gathered through experimental testing, to establish personalised settings. This approach not only enhances liveability in built environments by addressing thermal and air quality domains but also aims to reduce energy use.

Crucially, **Chapter 2** reveals that accurately predicting and meeting the real comfort needs of occupants can significantly impact energy demand, as these needs are directly linked to the heating and cooling requirements of buildings, which in turn shape the energy profile of the broader district area. Simulation findings showed that accounting for true comfort needs led to an increase in energy consumption of 115% for heating and 16% for cooling, compared to fixed standard settings. This underscores the importance of developing strategies to optimise this interaction between comfort and energy use, as meeting actual occupant needs could otherwise lead to considerable energy expenditure.

To address this, the proposed occupant-centric control (OCC) strategy in **Chapter 3**, was developed to ensure occupants' real comfort needs are met while simultaneously minimising energy consumption. By employing an advanced simulation and optimisation tool that captures the relationship between the indoor environment, human physiological responses, and the HVAC system, the OCC strategy offers a balanced approach. It efficiently managed the HVAC system through Model Predictive Control (MPC), resulting in more efficient energy use without compromising comfort. The strategy demonstrates its potential as a key tool for sustainable, human-centric design in urban buildings and districts, where energy demands must align with real occupancy patterns.

The economic and comfort considerations are also interconnected. Meeting occupant comfort preferences can often increase energy use and costs, especially when compared to standard operation. The OCC strategy thus also addresses the economic dimension, demonstrating that achieving savings is possible by carefully balancing comfort requirements across multiple domains. Additionally, using specialised HVAC control methods that adjust the thermodynamic properties of supply airflow offers pathways to achieve both energy and economic savings.

However, limitations remain. Although participants had diverse body compositions and activity levels, they shared similar lifestyles, occupations, and age ranges. Future studies should incorporate a more representative sample to assess the model's robustness across broader demographics. Additionally, visual comfort should be explored to optimise lighting, comfort perception, and physiological responses.

Moving forward, implementing automated building system regulation based on model outputs in real-world environments is essential. This would allow for direct comparisons between actual energy use and occupant comfort outcomes with simulation predictions. Furthermore, enhancing the model to account for scenarios with multiple occupants, such as shared office spaces, would expand its practical applications. While further advancements are possible, this analysis provides a foundational framework for occupant-centric control, addressing critical aspects of urban energy management that remain underexplored within the scientific community.

Chapters 4 & 5

District heating and cooling (DHC) systems represent complex infrastructure where interconnected components, from both thermal and hydronic perspectives, directly influence system performance and the broader urban energy sector.

Chapters 4 and 5 focus on two critical advancements in DHC systems: the integration of large solar fields as energy hubs for district heating and the adoption of low-temperature 5th-generation district heating and cooling (5GDHC) systems. Both solutions address key aspects of urban decarbonisation, particularly as space heating alone can account for up to 50% of the global energy consumption of the urban areas. These chapters explore how optimised control strategies and comprehensive modelling are essential to harness the full potential of these innovative systems while managing the challenges posed by fluctuating renewable energy sources.

Solar energy hubs in district heating applications present significant opportunities for reducing carbon emissions in the urban sector by meeting the heating demands of buildings with renewable sources. However, the intermittent nature of solar energy introduces complexities in maintaining reliable energy supply and maximising efficiency. In this chapter, the analysis centres on optimising the solar field's energy output and self-consumption rates. Recognising that a solar field's effectiveness extends beyond its thermal capacity, the chapter highlights the necessity of accounting for hydronic factors, such as piping configurations and circuit layout, which have often been underexplored in existing literature. These hydraulic elements can significantly impact the system's energy efficiency and stability.

An optimised energy management strategy is proposed, aiming to balance the solar energy generated with district heating demands, while minimising operating costs. The strategy acknowledges that there are instances when the operational cost of the solar field may exceed its energy benefit, emphasising the need for a traded off energy management strategy that adapts to daily fluctuations.

The **Chapter 4** underscores the role of comprehensive modelling tools capable of capturing both thermal and hydronic dynamics within these systems. Such tools not only optimise solar energy utilisation but also support the broader decarbonisation objectives by aligning renewable energy availability with building demands within a district heating network.

The electrification of heating and cooling is a pivotal solution in the drive for energy efficiency in urban areas, but it comes with potential drawbacks, such as increased stress on central grids due to fluctuating demand. Here, the adoption of 5GDHC systems addresses these challenges, enabling an electrified, low-temperature network that can dynamically balance energy demands across users. The increased complexity of 5GDHC systems arises from the integration of advanced subsystems, including water-to-water heat pumps, which interact with the central pipe network and the building-level systems of

individual users. These interactions can affect both individual user efficiency and the overall performance of the district's central balancing station.

The **Chapter 5** presents the development of advanced modelling tools tailored to capture the thermal and hydraulic interactions within 5GDHC systems. Supported by prototype testing, these tools facilitate an in-depth understanding of how these systems function in real-world conditions. By analysing thermal exchanges between consumers and prosumers, the chapter explores configurations that promote a self-balancing thermal network, which reduces reliance on the central thermal station. An optimisation strategy for network temperature control is also introduced, adjusting temperatures dynamically to enhance the performance of each heat pump. This strategic approach to temperature management enables a trade-off that simultaneously maximises system efficiency, reduces grid dependence, and supports flexibility requirements, positioning 5GDHC as a viable solution for resilient urban energy systems.

Chapters 4 and 5 demonstrate the transformative potential of renewable integration and optimised control strategies in district heating and cooling applications. By examining the thermal, hydronic, and economic dimensions of DHC systems, these chapters illustrate how, through careful design and control, it is possible to achieve substantial energy savings and emissions reductions. This integrative approach highlights the synergy of DHC components, showing that optimising these interactions is not only technically feasible but essential for driving urban decarbonisation.

Chapters 6 & 7

With the ongoing shift towards decentralised renewable energy systems, energy communities (ECs) have become a focal point for urban energy resilience. Through incentive policies and technological advancements, ECs aim to optimise energy resource management, self-sufficiency, and economic benefits while supporting broader grid stability. **Chapters 6 and 7** address two primary goals for energy communities: enhancing self-consumption and self-sufficiency through innovative sharing mechanisms and contributing to grid flexibility. These chapters establish a comprehensive approach for designing energy communities capable of addressing local energy needs while mitigating demand fluctuations that stress the central grid, thereby contributing ancillary services to the electrical network.

The first focus of this analysis is on designing ECs through a robust, flexible methodology that aligns with real-world needs, particularly for collective self-consumption groups. Unlike approaches in existing literature that focus on optimising energy sharing and trading within already established communities, the **Chapter 6** proposes a proactive methodology for structuring energy communities by aggregating diverse users and balancing energy supply and demand at the design phase.

A critical challenge in community design is accurately predicting users' energy demands. To address this, Chapter 6 introduces a sequential hybrid neural network (HNN) model that combines physical principles with machine learning to simulate a building's electrical demands. This approach uses statistically derived inputs, such as weather conditions, occupancy patterns, and appliance usage frequencies, to accurately model demand profiles. To account for variability in user behaviour, a classification into archetypes based on common behavioural patterns is included, ensuring more accurate demand estimations.

Once demand patterns are established, a bi-level optimisation strategy is implemented to maximise self-sufficiency and economic benefits. The first optimisation level focuses on aggregating prosumers and consumers into subgroups to enhance localised energy sharing and reduce dependency on the central grid. This step provides prosumers with insight into the most beneficial aggregation configurations, ensuring balanced energy demand and supply across the community. The second optimisation level considers the perspective of grid stakeholders (e.g., grid operators), striving to limit grid injection by forming optimal community configurations with high internal self-consumption.

This chapter fosters a smart urban planning through the development of an innovative approach to aggregate energy objects within a buildings district by properly exploiting the potential of renewable energy sources. This approach is aimed at providing guidelines to stakeholders based on the development of a modelling tool capable of predicting the electricity demand of users of building clusters, implementing innovative energy sharing schemes and market strategies, as well as optimising the EC design considering proper aggregation methods.

Beyond local energy optimisation, **Chapter 7** extends the capabilities of energy communities to support grid stability and flexibility. Energy communities can contribute to balancing energy demands through shared storage solutions, such as prosumer-owned batteries and electric vehicles (EVs), which enable flexible responses to grid needs. This chapter details how ECs can be configured to provide ancillary services, such as demand flattening and upward/downward regulation, contributing to overall grid stability.

The chapter explores optimised control strategies that drive the interactions and energy-sharing mechanisms within the community. These strategies enable ECs to balance fluctuations in renewable generation by intelligently managing storage and demand response resources. The objective is to maximise renewable energy consumption within the community while ensuring that storage assets, such as batteries and EVs, contribute to grid needs when not in use. This bidirectional energy management system helps flatten peak demand, thereby reducing strain on the central grid, and offers ancillary services that aid in frequency and voltage regulation.

A critical component of this approach is an advanced energy-sharing scheme that dynamically adjusts to maximise internal self-consumption, self-sufficiency, and economic benefits for all users within the community. This control strategy also supports broader urban planning objectives, providing stakeholders with actionable guidelines for integrating renewable energy sources and optimising EC configurations. By facilitating renewable energy production sharing, the community enhances its autonomy and contributes to urban decarbonisation goals.

Chapters 6 and 7 demonstrate the transformative role of energy communities in achieving sustainable, efficient urban energy systems. By combining accurate demand modelling, strategic user aggregation, and optimised control, these chapters provide a framework that enables ECs to operate as self-sufficient, grid-supportive entities. The proposed modelling and optimisation tools offer stakeholders practical insights into developing ECs that not only meet local energy needs but also contribute ancillary benefits to the grid. This holistic approach aligns with smart urban planning, paving the way for resilient energy solutions that enhance the sustainability, flexibility, and economic viability of urban districts.

Main findings

In summary, the key findings from each chapter showcase the interconnectivity of urban energy scales, highlighting how occupant comfort, efficient building systems, and advanced district systems contribute to sustainable energy transitions in urban areas. This integration underlines the importance of optimising multi-scale energy interactions for achieving climate and energy goals. Below, the main findings of each chapter, with specific emphasis on quantitative results and their relevance to the thesis topic. A schematisation is also provided in Figure 103.

Chapter 2

This chapter presents a multi-node thermal model of the human body to enhance thermal comfort in indoor spaces through dynamic HVAC control strategies. The model assesses three comfort indices: PMV, DISC, and TSV, by simulating physiological responses. Results indicated that cooling energy consumption is notably high across all strategies, approximately 6 times greater than heating in the reference and second strategies, about 3 times greater in the first strategy, and 4 times in the third. Annual heating energy consumption was 116% higher in the first strategy, but the first strategy also reduced cooling demand by 5% compared to the reference. Discomfort hours were significantly lowered, with only 2124, 2813, and 984 h/y based on PMV, DISC, and TSV, respectively, out of 3650 operational hours. These results show the potential to enhance both comfort and energy efficiency by tailoring HVAC operation to physiological needs, a key aspect of occupant-centric, energy-efficient urban systems.

Chapter 3

This chapter advances occupant comfort through a Personal Comfort Model (PCM) coupled with an Occupant-Centric Control (OCC) strategy for HVAC systems, validated by extensive experimentation. The PCM accurately predicts thermal sensations, keeping skin temperature within a $\pm 2\%$ error for 97% and 84% of tests, indicating high model reliability. The OCC approach led to thermal energy savings of 3.7% for cooling and 20% for heating, while maintaining zero discomfort hours. Additionally, HVAC operating costs decreased by 12.8% and 7.8% in two different tests, showing significant economic and comfort benefits. By bridging human demands and built environments, this strategy underscores the potential of occupant-centric approaches for urban energy efficiency.

Chapters	Key Findings	Connection to Urban Scales	Obtained Outcomes
Ch. 2	Proposed a multi-node thermal model of the human body to accurately assess thermal comfort in indoor spaces. Three dynamic control strategies were evaluated.	Highlights the importance of occupant comfort within buildings, a key aspect of urban energy systems, impacting overall energy demand and consumption patterns.	Cooling energy consumption was significantly higher, with a ratio of about 6 times compared to heating in the reference case related to the building standards. Annual heating energy consumption increased by 116% for the first strategy, while the first cooling strategy consumed 5% less than the reference . The strategies reduced discomfort hours to -2124 h/y (PMV), -2813 h/y (DISC), and -984 h/y (TSV) .
Ch. 3	Developed an Occupant-Centric Control technique for HVAC systems, based on physiological responses to optimise energy performance and comfort.	Bridges the gap between human demand and the built environment, linking indoor comfort to urban energy systems through effective HVAC management.	Achieved thermal energy savings of 3.7% (cooling) and 20% (heating) . No discomfort hours during occupancy; operating cost savings of 12.8% and 7.8% for tests 1 and 2 , respectively.
Ch. 4	Optimised the performance of solar-assisted polygenerative district heating networks through a dynamic simulation tool.	Emphasizes the integration of renewable energy sources at a district level, illustrating how solar thermal fields can enhance urban energy systems.	Notable improvements were observed with MPC control: +7.7% thermal energy yield , leading to primary energy savings of 53 MWh/y and avoided CO₂ emissions of 10.9 tCO₂/year . Overall, significant savings in primary energy (up to 10.3%) for the district heating network .
Ch. 5	Developed a comprehensive simulation model for 5th generation district heating and cooling (5GDHC) systems.	Focuses on flexibility and adaptability in urban energy systems, highlighting the importance of smart controls in managing resources at the district level.	Achieved a saving of 13 MWh/year of primary energy for prosumer buildings ; overall energy efficiency of the 5GDHC system improved by 6.5% (10.3 MWh/year saved) compared to the reference scenario.
Ch. 6	Established methodologies for creating energy communities, emphasising Peer-to-Peer (P2P) energy exchange models.	Connects user behaviour and community dynamics to urban energy systems, illustrating how localised energy solutions can enhance resilience and efficiency.	Economic savings for consumers ranged from 1.6% to 19.5% . Optimised user aggregation led to a maximum annual self-consumption of 89% (up from 64% in the reference scenario) and a collective annual self-sufficiency rate of 21% . A reduction in energy sent back to the grid by 62% was achieved.
Ch. 7	Investigated energy community management focusing on prosumers, consumers, and electric vehicles. Proposed optimisation strategies for energy sharing and grid stability.	Addresses the decentralised nature of urban energy systems and the significance of energy communities in enhancing grid stability and operational efficiency.	Achieved a self-sufficiency rate of 55% and 100% self-consumption with the first strategy. The second strategy maintained self-consumption and self-sufficiency while balancing the grid, providing 1.46 MW h/year for upward and 7.71 MW h/year for downward grid frequency regulation . Demonstrated economic advantages for community members while mitigating balancing issues.

Figure 103. Comparative diagram of key findings, modelling connections between urban scales, and outcomes across the dissertation chapters.

Chapter 4

The findings here underscore the role of solar thermal fields in renewable district heating, using a newly developed simulation tool validated against an existing Geneva network solar field. The analysis revealed that a variable-speed pump achieved a slight thermal yield increase (+0.2%) with a 4.6% rise in pumping energy. Employing an MPC strategy (PS2) enhanced thermal output by 7.7% but required a 29.2% increase in pump demand, yielding primary energy savings up to 40 MWh/y and CO₂ reductions of 7 t/y. The bi-objective PS3 strategy achieved primary savings of 53 MWh/y and 10.9 tCO₂/year. Extending these strategies across multiple solar fields could yield significant energy and emissions savings, illustrating the scalability of district-level renewables within urban energy systems.

Chapter 5

Chapter 5 examines a flexible 5th Generation District Heating and Cooling (5GDHC) network model, validated with real-world data from ENEA's prototype. Testing a control strategy for temperature management in a Milan network of 6 buildings, it achieved primary energy savings of 10.3 MWh/year across the network, with a 13 MWh/year gain specifically for prosumer buildings. The method enhances system efficiency by 6.5%, illustrating how optimised temperature control in district systems can improve urban energy flexibility. Future research into network configuration and renewable integration could further boost system efficiency, supporting a transition to low-emission urban areas.

Chapter 6

This chapter introduces innovative methodologies for establishing energy communities, emphasising Peer-to-Peer (P2P) models. Using a centralised control system, the P2P approach optimises prosumer-consumer connections to maximise energy exchange within the community. The energy market pricing strategy is based on matching supply-demand curves, customising electricity costs for individual users. A sequential hybrid neural network (HNN) was developed to predict electricity demands, incorporating physical attributes from white-box models and behavioural predictions from black-box models. When direct data is unavailable, this HNN model accurately anticipates user demands, essential for designing energy communities. A bi-level optimisation approach further refines the community structure. The first level groups users to maximise self-sufficiency by optimising the mix of prosumer types and quantities. The second level aggregates these groups into a cohesive community, enhancing self-consumption. A case study in Caserta, Italy, illustrates the model's effectiveness. Six user types, categorised by building archetypes and predicted demand profiles, informed the optimal community configuration. Economic savings for

consumers ranged from 1.6% to 19.5% over grid-only connections. Prosumers saw less than three-year returns on investment through energy sales and cost savings. Optimised configurations raised annual self-consumption to 89% (versus 64% without community mechanisms), achieving 21% collective self-sufficiency. Energy surpluses were redistributed, with 48% utilised within user clusters and 14.5% shared across clusters, reducing grid feed-in by 62% from baseline levels.

Chapter 7

This chapter focuses on managing energy communities with prosumers, consumers, and electric vehicles, addressing optimal energy sharing and grid stability. The decentralisation of energy production introduces challenges, including potential voltage and frequency imbalances. Two optimisation strategies are proposed: one maximises self-sufficiency and self-consumption through energy sharing, and the other integrates a grid balancing factor (GBF) to enhance grid stability. While the first strategy achieved a 55% self-sufficiency rate and 100% self-consumption, the GBF-enhanced strategy also balanced the grid. The model demonstrated significant economic and grid stability benefits, providing 1.46 MWh/year and 7.71 MWh/year for upward and downward frequency regulation, respectively.

Final observations

This thesis presents a significant advancement in urban energy management by developing an integrated approach that meticulously considers the singularities of each energy subsystem across identified urban scales – end-users, building systems, and district systems. Traditional methodologies often rely on standardised models and assumptions that overlook the unique characteristics and behaviours inherent in individual subsystems and their deciders (i.e., end-users). This work diverges from convention by focusing on these specificities (singularities) and the intricate interactions between them, providing a more accurate and realistic representation of urban energy dynamics.

The core novelty of this research lies in its recognition that urban energy consumption and performance are profoundly influenced by the distinct features and behaviours of each subsystem, which cannot be adequately captured using generic standards or homogeneous models. For instance, the energy consumption associated with occupant comfort is not merely a function of standardised comfort parameters but is intricately linked to the actual physiological responses and behaviours of individuals. By acknowledging and modelling these singularities, the thesis delves deeper into understanding how each subsystem operates and interacts within the urban domain.

To effectively study the complexities arising from these singularities and their interactions, the thesis introduces advanced modelling tools capable of simulating the detailed behaviours and interdependencies of each subsystem. These tools transcend conventional modelling approaches by incorporating specific data and parameters unique to each subsystem, thus capturing features often overlooked in standard models. The models are designed to mirror real-world scenarios with greater fidelity, reflecting the true energy demands and operational characteristics of urban energy systems.

A pivotal aspect of the thesis is the implementation of optimisation strategies, such as model predictive control (MPC), within this advanced modelling framework. By integrating MPC, the research enables proactive and dynamic optimisation of energy use across different scales, considering the temporal and spatial interactions and singularities of each subsystem. This results in more efficient energy management strategies that are tailored to the specific needs and behaviours of the urban environment, rather than relying on static or averaged assumptions.

Overall, the global contribution of this thesis is the development of a comprehensive methodology that bridges the gap between standardised modelling practices and the complex realities of urban energy systems. By focusing on the singularities of each subsystem and their interactions, and by providing sophisticated tools to simulate and optimise their management, the work offers a more accurate, efficient, and realistic approach to urban energy modelling and optimisation.

This approach has profound implications for urban planning, policy-making, and the design of energy systems that are responsive to the actual needs and behaviours of urban populations. It underscores the necessity of moving beyond generic standards to embrace models that reflect the diversity and complexity of real-world conditions. By advancing the understanding of how individual subsystems contribute to and interact within the larger urban energy framework, the thesis provides valuable insights that can lead to improved energy efficiency, enhanced occupant comfort, and more sustainable urban environments.

In essence, this work sets a new precedent for future research and practice by demonstrating the critical importance of considering the unique characteristics of each subsystem. It highlights the necessity of integrated modelling and optimisation approaches to effectively address the multifaceted challenges of urban energy systems, ultimately contributing to the development of smarter, more resilient, and sustainable cities.

References

- [1] IEA. A global target to double efficiency progress is essential to keep net zero on the table. 2023.
- [2] NASA. Global temperature. 2024.
- [3] IEA. Empowering Urban Energy Transitions. 2024.
- [4] Commission E. The European Green Deal. 2024.
- [5] IEA. Net Zero by 2050. 2021.
- [6] Klemm C, Wiese F. Indicators for the optimization of sustainable urban energy systems based on energy system modeling. *Energy, Sustainability and Society*. 2022;12:3.
- [7] Nations U. World urbanization prospects: the 2003 revision: UN; 2004.
- [8] Ribeiro HV, Rybski D, Kropp JP. Effects of changing population or density on urban carbon dioxide emissions. *Nature Communications*. 2019;10:3204.
- [9] Zheng Z, Shafique M, Luo X, Wang S. A systematic review towards integrative energy management of smart grids and urban energy systems. *Renewable and Sustainable Energy Reviews*. 2024;189:114023.
- [10] Zhang X, Lovati M, Vigna I, Widén J, Han M, Gal C, et al. A review of urban energy systems at building cluster level incorporating renewable-energy-source (RES) envelope solutions. *Applied Energy*. 2018;230:1034-56.
- [11] Tian X, An C, Chen Z. The role of clean energy in achieving decarbonization of electricity generation, transportation, and heating sectors by 2050: A meta-analysis review. *Renewable and Sustainable Energy Reviews*. 2023;182:113404.
- [12] Zhang Q, Yan J, Gao HO, You F. A Systematic Review on power systems planning and operations management with grid integration of transportation electrification at scale. *Advances in Applied Energy*. 2023;11:100147.
- [13] Mussawar O, Mayyas A, Azar E. Energy storage enabling renewable energy communities: An urban context-aware approach and case study using agent-based modeling and optimization. *Sustainable Cities and Society*. 2024;115:105813.
- [14] Swan LG, Ugursal VI. Modeling of end-use energy consumption in the residential sector: A review of modeling techniques. *Renewable and Sustainable Energy Reviews*. 2009;13:1819-35.
- [15] Hong T, Chen Y, Luo X, Luo N, Lee SH. Ten questions on urban building energy modeling. *Building and Environment*. 2020;168:106508.
- [16] Nutkiewicz A, Yang Z, Jain RK. Data-driven Urban Energy Simulation (DUE-S): A framework for integrating engineering simulation and machine learning methods in a multi-scale urban energy modeling workflow. *Applied Energy*. 2018;225:1176-89.
- [17] Dabirian S, Panchabikesan K, Eicker U. Occupant-centric urban building energy modeling: Approaches, inputs, and data sources - A review. *Energy and Buildings*. 2022;257:111809.
- [18] Yazdanie M, Orehounig K. Advancing urban energy system planning and modeling approaches: Gaps and solutions in perspective. *Renewable and Sustainable Energy Reviews*. 2021;137:110607.
- [19] Javanroodi K, Perera ATD, Hong T, Nik VM. Designing climate resilient energy systems in complex urban areas considering urban morphology: A technical review. *Advances in Applied Energy*. 2023;12:100155.
- [20] Gunatilake H, Grundy J, Hoda R, Mueller I. The impact of human aspects on the interactions between software developers and end-users in software engineering: A systematic literature review. *Information and Software Technology*. 2024;173:107489.
- [21] Ren J, Zhou X, Jin X, Ye Y, Causone F, Ferrando M, et al. A systematic review of occupancy pattern in urban building energy modeling: From urban to building-scale. *Journal of Building Engineering*. 2024;95:110307.
- [22] Derkenbaeva E, Halleck Vega S, Hofstede GJ, van Leeuwen E. Positive energy districts: Mainstreaming energy transition in urban areas. *Renewable and Sustainable Energy Reviews*. 2022;153:111782.
- [23] Sola A, Corchero C, Salom J, Sanmarti M. Multi-domain urban-scale energy modelling tools: A review. *Sustainable Cities and Society*. 2020;54:101872.
- [24] Bi C, Little JC. Integrated assessment across building and urban scales: A review and proposal for a more holistic, multi-scale, system-of-systems approach. *Sustainable Cities and Society*. 2022;82:103915.
- [25] Al-Mumin A, Khattab O, Sridhar G. Occupants' behavior and activity patterns influencing the energy consumption in the Kuwaiti residences. *Energy and Buildings*. 2003;35:549-59.
- [26] Yan D, Hong T, Dong B, Mahdavi A, D'Oca S, Gaetani I, et al. IEA EBC Annex 66: Definition and simulation of occupant behavior in buildings. *Energy and Buildings*. 2017;156:258-70.
- [27] O'Brien W, Wagner A, Schweiker M, Mahdavi A, Day J, Kjærgaard MB, et al. Introducing IEA EBC annex 79: Key challenges and opportunities in the field of occupant-centric building design and operation. *Building and Environment*. 2020;178:106738.

-
- [28] Pisello AL, Castaldo VL, Piselli C, Fabiani C, Cotana F. How peers' personal attitudes affect indoor microclimate and energy need in an institutional building: Results from a continuous monitoring campaign in summer and winter conditions. *Energy and Buildings*. 2016;126:485-97.
- [29] Haas R, Auer H, Biermayr P. The impact of consumer behavior on residential energy demand for space heating. *Energy and Buildings*. 1998;27:195-205.
- [30] Stokes M, Rylatt M, Lomas K. A simple model of domestic lighting demand. *Energy and Buildings*. 2004;36:103-16.
- [31] McLoughlin F, Duffy A, Conlon M. Characterising domestic electricity consumption patterns by dwelling and occupant socio-economic variables: An Irish case study. *Energy and Buildings*. 2012;48:240-8.
- [32] Sovacool BK, Ryan SE, Stern PC, Janda K, Rochlin G, Spreng D, et al. Integrating social science in energy research. *Energy Research & Social Science*. 2015;6:95-9.
- [33] Süsser D, Martin N, Stavrakas V, Gaschnig H, Talens-Peiró L, Flamos A, et al. Why energy models should integrate social and environmental factors: Assessing user needs, omission impacts, and real-word accuracy in the European Union. *Energy Research & Social Science*. 2022;92:102775.
- [34] Gaetani I, Hoes P-J, Hensen JLM. Occupant behavior in building energy simulation: Towards a fit-for-purpose modeling strategy. *Energy and Buildings*. 2016;121:188-204.
- [35] Alagoz BB, Kaygusuz A, Karabiber A. A user-mode distributed energy management architecture for smart grid applications. *Energy*. 2012;44:167-77.
- [36] Schwidtal JM, Piccini P, Troncia M, Chitchyan R, Montakhabi M, Francis C, et al. Emerging business models in local energy markets: A systematic review of peer-to-peer, community self-consumption, and transactive energy models. *Renewable and Sustainable Energy Reviews*. 2023;179:113273.
- [37] Filho WL, Trevisan LV, Salvia AL, Mazutti J, Dibbern T, de Maya SR, et al. Prosumers and sustainable development: An international assessment in the field of renewable energy. *Sustainable Futures*. 2024;7:100158.
- [38] Angelidis O, Ioannou A, Friedrich D, Thomson A, Falcone G. District heating and cooling networks with decentralised energy substations: Opportunities and barriers for holistic energy system decarbonisation. *Energy*. 2023;269:126740.
- [39] Fleschutz M, Bohlayer M, Braun M, Murphy MD. From prosumer to flexumer: Case study on the value of flexibility in decarbonizing the multi-energy system of a manufacturing company. *Applied Energy*. 2023;347:121430.
- [40] Zhao Y, Song J, Liu M, Zhao Y, Olympios AV, Sapin P, et al. Thermo-economic assessments of pumped-thermal electricity storage systems employing sensible heat storage materials. *Renewable Energy*. 2022;186:431-56.
- [41] Cai S, Gou Z. Defining the energy role of buildings as flexumers: A review of definitions, technologies, and applications. *Energy and Buildings*. 2024;303:113821.
- [42] Goncearuc A, De Cauwer C, Sapountzoglou N, Krieking GV, Huber D, Messagie M, et al. The barriers to widespread adoption of vehicle-to-grid: A comprehensive review. *Energy Reports*. 2024;12:27-41.
- [43] Barone G, Buonomano A, Calise F, Forzano C, Palombo A. Building to vehicle to building concept toward a novel zero energy paradigm: Modelling and case studies. *Renewable and Sustainable Energy Reviews*. 2019;101:625-48.
- [44] Buonomano A. Building to Vehicle to Building concept: A comprehensive parametric and sensitivity analysis for decision making aims. *Applied Energy*. 2020;261:114077.
- [45] Barone G, Buonomano A, Forzano C, Giuzio GF, Palombo A, Russo G. A new thermal comfort model based on physiological parameters for the smart design and control of energy-efficient HVAC systems. *Renewable and Sustainable Energy Reviews*. 2023;173:113015.
- [46] Gao K, Yang Y, Gil J, Qu X. Data-driven interpretation on interactive and nonlinear effects of the correlated built environment on shared mobility. *Journal of Transport Geography*. 2023;110:103604.
- [47] Wilke U, Haldi F, Scartezzini J-L, Robinson D. A bottom-up stochastic model to predict building occupants' time-dependent activities. *Building and Environment*. 2013;60:254-64.
- [48] Zhou Y. Low-carbon urban-rural modern energy systems with energy resilience under climate change and extreme events in China—A state-of-the-art review. *Energy and Buildings*. 2024;321:114661.
- [49] Huang G, Ng ST, Li D, Zhang Y. State of the art review on the HVAC occupant-centric control in different commercial buildings. *Journal of Building Engineering*. 2024;96:110445.
- [50] Varghese AM, Menon N, Ermagun A. Equitable distribution of electric vehicle charging infrastructure: A systematic review. *Renewable and Sustainable Energy Reviews*. 2024;206:114825.
- [51] Lamnatou C, Cristofari C, Chemisana D, Canaletti JL. Building-integrated solar thermal systems based on vacuum-tube technology: Critical factors focusing on life-cycle environmental profile. *Renewable and Sustainable Energy Reviews*. 2016;65:1199-215.
- [52] Liu Z, Zhang Y, Yuan X, Liu Y, Xu J, Zhang S, et al. A comprehensive study of feasibility and applicability of building integrated photovoltaic (BIPV) systems in regions with high solar irradiance. *Journal of Cleaner Production*. 2021;307:127240.

-
- [53] Moulakhnif K, Ait Ousaleh H, Sair S, Bouhaj Y, El Majd A, Ghazoui M, et al. Renewable approaches to building heat: exploring cutting-edge innovations in thermochemical energy storage for building heating. *Energy and Buildings*. 2024;318:114421.
 - [54] Lu ML, Sun YJ, Kokogiannakis G, Ma ZJ. Design of flexible energy systems for nearly/net zero energy buildings under uncertainty characteristics: A review. *Renewable and Sustainable Energy Reviews*. 2024;205:114828.
 - [55] Balali Y, Chong A, Busch A, O'Keefe S. Energy modelling and control of building heating and cooling systems with data-driven and hybrid models—A review. *Renewable and Sustainable Energy Reviews*. 2023;183:113496.
 - [56] Pan Y, Zhu M, Lv Y, Yang Y, Liang Y, Yin R, et al. Building energy simulation and its application for building performance optimization: A review of methods, tools, and case studies. *Advances in Applied Energy*. 2023;10:100135.
 - [57] Olympios AV, Song J, Ziolkowski A, Shanmugam VS, Markides CN. Data-driven compressor performance maps and cost correlations for small-scale heat-pumping applications. *Energy*. 2024;291:130171.
 - [58] Guo Y, Wang N, Shao S, Huang C, Zhang Z, Li X, et al. A review on hybrid physics and data-driven modeling methods applied in air source heat pump systems for energy efficiency improvement. *Renewable and Sustainable Energy Reviews*. 2024;204:114804.
 - [59] Li Y, O'Neill Z, Zhang L, Chen J, Im P, DeGraw J. Grey-box modeling and application for building energy simulations - A critical review. *Renewable and Sustainable Energy Reviews*. 2021;146:111174.
 - [60] Masoumi-Verki S, Haghighat F, Eicker U. A review of advances towards efficient reduced-order models (ROM) for predicting urban airflow and pollutant dispersion. *Building and Environment*. 2022;216:108966.
 - [61] Serasinghe R, Long N, Clark JD. Parameter identification methods for low-order gray box building energy models: A critical review. *Energy and Buildings*. 2024;311:114123.
 - [62] Liguori A, Quintana M, Fu C, Miller C, Frisch J, van Treeck C. Opening the Black Box: Towards inherently interpretable energy data imputation models using building physics insight. *Energy and Buildings*. 2024;310:114071.
 - [63] Al Sayed K, Boodi A, Sadeghian Broujeny R, Beddiar K. Reinforcement learning for HVAC control in intelligent buildings: A technical and conceptual review. *Journal of Building Engineering*. 2024;95:110085.
 - [64] Esrafilian-Najafabadi M, Haghighat F. Occupancy-based HVAC control systems in buildings: A state-of-the-art review. *Building and Environment*. 2021;197:107810.
 - [65] Li Z, Ma J, Tan Y, Guo C, Li X. Combining physical approaches with deep learning techniques for urban building energy modeling: A comprehensive review and future research prospects. *Building and Environment*. 2023;246:110960.
 - [66] Maghami MR, Pasupuleti J, Ekanayake J. Energy storage and demand response as hybrid mitigation technique for photovoltaic grid connection: Challenges and future trends. *Journal of Energy Storage*. 2024;88:111680.
 - [67] Shen P, Wang H. Archetype building energy modeling approaches and applications: A review. *Renewable and Sustainable Energy Reviews*. 2024;199:114478.
 - [68] Mostafavi Sani M, Mostafavi Sani H, Fowler M, Elkamel A, Noorpoor A, Ghasemi A. Optimal energy hub development to supply heating, cooling, electricity and freshwater for a coastal urban area taking into account economic and environmental factors. *Energy*. 2022;238:121743.
 - [69] Garau M, Torsæter BN. A methodology for optimal placement of energy hubs with electric vehicle charging stations and renewable generation. *Energy*. 2024;304:132068.
 - [70] Chen Y, Tian M, Xue J, Zhang L, Ying J. Data-driven approaches to achieve energy transition: Statistical analysis of demand-side management and smart decision making in urban energy hub networks. *Sustainable Cities and Society*. 2024;101:105150.
 - [71] Fichera A, Frasca M, Volpe R. Complex networks for the integration of distributed energy systems in urban areas. *Applied Energy*. 2017;193:336-45.
 - [72] Balaban G, Dumbrava V, Lazaroiu AC, Kalogirou S. Analysis of urban network operation in presence of renewable sources for decarbonization of energy system. *Renewable Energy*. 2024;230:120870.
 - [73] Lund H, Østergaard PA, Nielsen TB, Werner S, Thorsen JE, Gudmundsson O, et al. Perspectives on fourth and fifth generation district heating. *Energy*. 2021;227:120520.
 - [74] Gjoka K, Rismanchi B, Crawford RH. Fifth-generation district heating and cooling systems: A review of recent advancements and implementation barriers. *Renewable and Sustainable Energy Reviews*. 2023;171:112997.
 - [75] Gong Y, Ma G, Jiang Y, Wang L. Research progress on the fifth-generation district heating system based on heat pump technology. *Journal of Building Engineering*. 2023;71:106533.
 - [76] López I, Goitia-Zabaleta N, Milo A, Gómez-Cornejo J, Aranzabal I, Gaztañaga H, et al. European energy communities: Characteristics, trends, business models and legal framework. *Renewable and Sustainable Energy Reviews*. 2024;197:114403.
 - [77] Gorbacheva A, Watson N, Schneiders A, Shipworth D, Fell MJ. Defining characteristics of peer-to-peer energy trading, transactive energy, and community self-consumption: A review of literature and expert perspectives. *Renewable and Sustainable Energy Reviews*. 2024;202:114672.

-
- [78] Barabino E, Fioriti D, Guerrazzi E, Mariuzzo I, Poli D, Raugi M, et al. Energy Communities: A review on trends, energy system modelling, business models, and optimisation objectives. *Sustainable Energy, Grids and Networks*. 2023;36:101187.
 - [79] Lilliu F, Reforgiato Recupero D. A cooperative game-theory approach for incentive systems in local energy communities. *Sustainable Energy, Grids and Networks*. 2024;38:101391.
 - [80] Trčka M, Hensen JLM, Wetter M. Co-simulation of innovative integrated HVAC systems in buildings. *Journal of Building Performance Simulation*. 2009;2:209-30.
 - [81] Wetter M. Co-simulation of building energy and control systems with the Building Controls Virtual Test Bed. *Journal of Building Performance Simulation*. 2011;4:185-203.
 - [82] Jie P, Su M, Gao N, Ye Y, Kuang X, Chen J, et al. Impact of urban wind environment on urban building energy: A review of mechanisms and modeling. *Building and Environment*. 2023;245:110947.
 - [83] Vassiliades C, Kalogirou S, Michael A, Savvides A. A roadmap for the integration of active solar systems into buildings. *Applied Sciences (Switzerland)*. 2019;9.
 - [84] Savvides A, Vassiliades C, Michael A, Kalogirou S. Siting and building-massing considerations for the urban integration of active solar energy systems. *Renewable Energy*. 2019;135:963-74.
 - [85] Allegrini J, Orehounig K, Mavromatidis G, Ruesch F, Dorer V, Evins R. A review of modelling approaches and tools for the simulation of district-scale energy systems. *Renewable and Sustainable Energy Reviews*. 2015;52:1391-404.
 - [86] Fatemi S, Ketabi A, Mansouri SA. A four-stage stochastic framework for managing electricity market by participating smart buildings and electric vehicles: Towards smart cities with active end-users. *Sustainable Cities and Society*. 2023;93:104535.
 - [87] Ali U, Shamsi MH, Hoare C, Mangina E, O'Donnell J. Review of urban building energy modeling (UBEM) approaches, methods and tools using qualitative and quantitative analysis. *Energy and Buildings*. 2021;246:111073.
 - [88] Buonomano A, Palombo A. Building energy performance analysis by an in-house developed dynamic simulation code: An investigation for different case studies. *Applied Energy*. 2014;113:788-807.
 - [89] Leech JA, Burnett R, Nelson W, Aaron SD, Raizenne M. Outdoor air pollution epidemiologic studies. *American Journal of Respiration and Critical Care Medicine*. 2000;161:A308.
 - [90] Terés-Zubiaga J, Bolliger R, Almeida MG, Barbosa R, Rose J, Thomsen KE, et al. Cost-effective building renovation at district level combining energy efficiency & renewables – Methodology assessment proposed in IEA EBC Annex 75 and a demonstration case study. *Energy and Buildings*. 2020;224:110280.
 - [91] Yang L, Yan H, Lam JC. Thermal comfort and building energy consumption implications—a review. *Applied energy*. 2014;115:164-73.
 - [92] Jung W, Jazizadeh F. Human-in-the-loop HVAC operations: A quantitative review on occupancy, comfort, and energy-efficiency dimensions. *Applied Energy*. 2019;239:1471-508.
 - [93] Schweiker M, Ampatzis E, Andargie MS, Andersen RK, Azar E, Barthelmes VM, et al. Review of multi-domain approaches to indoor environmental perception and behaviour. *Building and Environment*. 2020;176:106804.
 - [94] Shaikh PH, Nor NBM, Nallagownden P, Elamvazuthi I, Ibrahim T. A review on optimized control systems for building energy and comfort management of smart sustainable buildings. *Renewable and Sustainable Energy Reviews*. 2014;34:409-29.
 - [95] Davies MG. The thermal response of an enclosure to periodic excitation: The CIBSE approach. *Building and Environment*. 1994;29:217-35.
 - [96] Handbook A. HVAC systems and equipment: chapter; 1996.
 - [97] de Dear RJ, Brager GS. Thermal comfort in naturally ventilated buildings: revisions to ASHRAE Standard 55. *Energy and Buildings*. 2002;34:549-61.
 - [98] Olesen BW, Parsons KC. Introduction to thermal comfort standards and to the proposed new version of EN ISO 7730. *Energy and buildings*. 2002;34:537-48.
 - [99] Karyono K, Abdullah BM, Cotgrave AJ, Bras A. The adaptive thermal comfort review from the 1920s, the present, and the future. *Developments in the Built Environment*. 2020;4:100032.
 - [100] Mansi SA, Barone G, Forzano C, Pigliautile I, Ferrara M, Pisello AL, et al. Measuring human physiological indices for thermal comfort assessment through wearable devices: A review. *Measurement*. 2021;183:109872.
 - [101] Fanger PO. Thermal comfort. Analysis and applications in environmental engineering: Copenhagen: Danish Technical Press.; 1970.
 - [102] Fanger PO. FUNDAMENTALS OF THERMAL COMFORT. In: Bloss WH, Pfisterer F, editors. *Advances In Solar Energy Technology*. Oxford: Pergamon; 1988. p. 3056-61.
 - [103] Khovalyg D, Kazanci OB, Halvorsen H, Gundlach I, Bahnfleth WP, Toftum J, et al. Critical review of standards for indoor thermal environment and air quality. *Energy and Buildings*. 2020;213:109819.
 - [104] Höpfe P. Different aspects of assessing indoor and outdoor thermal comfort. *Energy and buildings*. 2002;34:661-5.
 - [105] Ganesh GA, Sinha SL, Verma TN, Dewangan SK. Investigation of indoor environment quality and factors affecting human comfort: A critical review. *Building and Environment*. 2021;204:108146.

-
- [106] Luo M, Wang Z, Brager G, Cao B, Zhu Y. Indoor climate experience, migration, and thermal comfort expectation in buildings. *Building and Environment*. 2018;141:262-72.
 - [107] Castaldo VL, Pigliautile I, Rosso F, Cotana F, De Giorgio F, Pisello AL. How subjective and non-physical parameters affect occupants' environmental comfort perception. *Energy and Buildings*. 2018;178:107-29.
 - [108] Raja IA, Nicol JF, McCartney KJ, Humphreys MA. Thermal comfort: use of controls in naturally ventilated buildings. *Energy and buildings*. 2001;33:235-44.
 - [109] Liu W, Lian Z, Deng Q, Liu Y. Evaluation of calculation methods of mean skin temperature for use in thermal comfort study. *Building and Environment*. 2011;46:478-88.
 - [110] Tansey EA, Johnson CD. Recent advances in thermoregulation. *Advances in physiology education*. 2015.
 - [111] Joshi A, Wang F, Kang Z, Yang B, Zhao D. A three-dimensional thermoregulatory model for predicting human thermophysiological responses in various thermal environments. *Building and Environment*. 2022;207:108506.
 - [112] Lim CL, Byrne C, Lee JKW. Human thermoregulation and measurement of body temperature in exercise and clinical settings. *Annals Academy of Medicine Singapore*. 2008;37:347.
 - [113] Luo M, Wang Z, Ke K, Cao B, Zhai Y, Zhou X. Human metabolic rate and thermal comfort in buildings: The problem and challenge. *Building and Environment*. 2018;131:44-52.
 - [114] Yeom DJ, Delogu F. Local body skin temperature-driven thermal sensation predictive model for the occupant's optimum productivity. *Building and Environment*. 2021;204:108196.
 - [115] Chaudhuri T, Soh YC, Li H, Xie L. Machine learning driven personal comfort prediction by wearable sensing of pulse rate and skin temperature. *Building and Environment*. 2020;170:106615.
 - [116] Nižetić S, Pivac N, Zanki V, Papadopoulos AM. Application of smart wearable sensors in office buildings for modelling of occupants' metabolic responses. *Energy and Buildings*. 2020;226:110399.
 - [117] Xu J, Psikuta A, Li J, Annaheim S, Rossi RM. Evaluation of the convective heat transfer coefficient of human body and its effect on the human thermoregulation predictions. *Building and Environment*. 2021;196:107778.
 - [118] Kang Z, Wang F, Udayraj. An advanced three-dimensional thermoregulation model of the human body: Development and validation. *International Communications in Heat and Mass Transfer*. 2019;107:34-43.
 - [119] Hannouch A, Habchi C, Lemenand T, Khoury K. Numerical evaluation of the convective and radiative heat transfer coefficients for preterm neonate body segments inside an incubator. *Building and Environment*. 2020;183:107085.
 - [120] Kobayashi Y, Tanabe S-i. Development of JOS-2 human thermoregulation model with detailed vascular system. *Building and Environment*. 2013;66:1-10.
 - [121] Kang Z, Shou D, Fan J. Numerical modeling of body heat dissipation through static and dynamic clothing air gaps. *International Journal of Heat and Mass Transfer*. 2020;157:119833.
 - [122] Čulić A, Nižetić S, Šolić P, Perković T, Čongradac V. Smart monitoring technologies for personal thermal comfort: A review. *Journal of Cleaner Production*. 2021;312:127685.
 - [123] Gupta D, Bhatt S, Gupta M, Tosun AS. Future Smart Connected Communities to Fight COVID-19 Outbreak. *Internet of Things*. 2021;13:100342.
 - [124] Buonomano A, Montanaro U, Palombo A, Santini S. Temperature and humidity adaptive control in multi-enclosed thermal zones under unexpected external disturbances. *Energy and Buildings*. 2017;135:263-85.
 - [125] Buonomano A, Montanaro U, Palombo A, Santini S. Dynamic building energy performance analysis: A new adaptive control strategy for stringent thermohygrometric indoor air requirements. *Applied Energy*. 2016;163:361-86.
 - [126] Yuan F, Yao R, Sadrizadeh S, Li B, Cao G, Zhang S, et al. Thermal comfort in hospital buildings – A literature review. *Journal of Building Engineering*. 2022;45:103463.
 - [127] Turhan C, Simani S, Gokcen Akkurt G. Development of a personalized thermal comfort driven controller for HVAC systems. *Energy*. 2021;237:121568.
 - [128] Chegari B, Tabaa M, Simeu E, Moutaouakkil F, Medromi H. Multi-objective optimization of building energy performance and indoor thermal comfort by combining artificial neural networks and metaheuristic algorithms. *Energy and Buildings*. 2021;239:110839.
 - [129] Rouleau J, Gosselin L, Blanchet P. Robustness of energy consumption and comfort in high-performance residential building with respect to occupant behavior. *Energy*. 2019;188:115978.
 - [130] Halhoul Merabet G, Essaïdi M, Ben Haddou M, Qolomany B, Qadir J, Anan M, et al. Intelligent building control systems for thermal comfort and energy-efficiency: A systematic review of artificial intelligence-assisted techniques. *Renewable and Sustainable Energy Reviews*. 2021;144:110969.
 - [131] Jiang L, Yao R, Liu K, McCrindle R. An Epistemic-Deontic-Axiologic (EDA) agent-based energy management system in office buildings. *Applied Energy*. 2017;205:440-52.
 - [132] Konis K, Annavaram M. The Occupant Mobile Gateway: A participatory sensing and machine-learning approach for occupant-aware energy management. *Building and Environment*. 2017;118:1-13.
 - [133] Kalogirou SA. Artificial neural networks in energy applications in buildings. *International Journal of Low-Carbon Technologies*. 2006;1:201-16.

-
- [134] Vidhyashankar R, Vinze R, Nagarathinam S, Natrajan VK. Modelling spatial variations in thermal comfort in indoor open-plan spaces using a whole-building simulation tool. *Journal of Building Engineering*. 2022;46:103727.
 - [135] Doherty T, Arens EA. Evaluation of the physiological bases of thermal comfort models. *ASHRAE transactions*. 1988;94.
 - [136] Azer NZ, Hsu S. THE PREDICTION OF THERMAL SENSATION FROM A SIMPLE MODEL OF HUMAN PHYSIOLOGICAL REGULATORY RESPONSE. 1977.
 - [137] Barone G, Buonomano A, Forzano C, Palombo A. Building Energy Performance Analysis: An Experimental Validation of an In-House Dynamic Simulation Tool through a Real Test Room. *Energies*. 2019;12.
 - [138] Forzano C, Baggio P, Buonomano A, Palombo A. Building integrating phase change materials: A dynamic hygrothermal simulation model for system analysis. *Journal of Sustainable Development of Energy, Water and Environment Systems*. 2019;7:325-42.
 - [139] Buonomano A, De Luca G, Montanaro U, Palombo A. Innovative technologies for NZEBs: An energy and economic analysis tool and a case study of a non-residential building for the Mediterranean climate. *Energy and Buildings*. 2016;121:318-43.
 - [140] Buonomano A. Code-to-Code Validation and Application of a Dynamic Simulation Tool for the Building Energy Performance Analysis. *Energies*. 2016;9.
 - [141] Fiala D, Lomas KJ, Stohrer M. A computer model of human thermoregulation for a wide range of environmental conditions: the passive system. *Journal of Applied Physiology*. 1999;87:1957-72.
 - [142] González-Alonso J. Human thermoregulation and the cardiovascular system. *Experimental Physiology*. 2012;97:340-6.
 - [143] Nelson RR, Gobel FL, Jorgensen CR, Wang K, Wang Y, Taylor HL. Hemodynamic predictors of myocardial oxygen consumption during static and dynamic exercise. *Circulation*. 1974;50:1179-89.
 - [144] Kaynakli O, Kilic M. Investigation of indoor thermal comfort under transient conditions. *Building and Environment*. 2005;40:165-74.
 - [145] American Society of Heating R, Air-Conditioning E. ASHRAE, Guideline 10-2016 - Interactions Affecting the Achievement of Acceptable Indoor Environments. 2016.
 - [146] Marin-Restrepo L, Trebilcock M, Porras-Salazar JA. Adaptation by coexistence: contrasting thermal comfort perception among individual and shared office spaces. *Architectural Science Review*. 2020;63:235-47.
 - [147] Roumi S, Zhang F, Stewart RA, Santamouris M. Weighting of indoor environment quality parameters for occupant satisfaction and energy efficiency. *Building and Environment*. 2023;228:109898.
 - [148] Park JY, Ouf MM, Gunay B, Peng Y, O'Brien W, Kjærgaard MB, et al. A critical review of field implementations of occupant-centric building controls. *Building and Environment*. 2019;165:106351.
 - [149] Wang Z, Calautit J, Tien PW, Wei S, Zhang W, Wu Y, et al. An occupant-centric control strategy for indoor thermal comfort, air quality and energy management. *Energy and Buildings*. 2023;285:112899.
 - [150] Pang Z, Chen Y, Zhang J, O'Neill Z, Cheng H, Dong B. Nationwide Energy Saving Potential Evaluation for Office Buildings with Occupant-Based Building Controls. *ASHRAE Transactions*. 2020;126:273-81.
 - [151] O'Neill ZD, Li Y, Cheng HC, Zhou X, Taylor ST. Energy savings and ventilation performance from CO₂-based demand controlled ventilation: Simulation results from ASHRAE RP-1747 (ASHRAE RP-1747). *Science and Technology for the Built Environment*. 2020;26:257-81.
 - [152] Heydarian A, McIlvennie C, Arpan L, Yousefi S, Syndicus M, Schweiker M, et al. What drives our behaviors in buildings? A review on occupant interactions with building systems from the lens of behavioral theories. *Building and Environment*. 2020;179:106928.
 - [153] Pisello AL, Pigliautile I, Andargie M, Berger C, Bluysen PM, Carlucci S, et al. Test rooms to study human comfort in buildings: A review of controlled experiments and facilities. *Renewable and Sustainable Energy Reviews*. 2021;149:111359.
 - [154] Dong B, Liu Y, Mu W, Jiang Z, Pandey P, Hong T, et al. A Global Building Occupant Behavior Database. *Scientific Data*. 2022;9:369.
 - [155] Berger C, Mahdavi A, Ampatzi E, Bandurski K, Hellwig RT, Schweiker M, et al. The role of user controls with respect to indoor environmental quality: From evidence to standards. *Journal of Building Engineering*. 2023;76:107196.
 - [156] Li X, Chen Q. Development of a novel method to detect clothing level and facial skin temperature for controlling HVAC systems. *Energy and Buildings*. 2021;239:110859.
 - [157] Deng Z, Chen Q. Development and validation of a smart HVAC control system for multi-occupant offices by using occupants' physiological signals from wristband. *Energy and Buildings*. 2020;214:109872.
 - [158] Wu Y, Fan J, Cao B. Comparison among different modeling approaches for personalized thermal comfort prediction when using personal comfort systems. *Energy and Buildings*. 2023;285:112873.
 - [159] Ahamed MS, Guo H, Tanino K. Modeling heating demands in a Chinese-style solar greenhouse using the transient building energy simulation model TRNSYS. *Journal of Building Engineering*. 2020;29:101114.
 - [160] Dzyuban Y, Ching GNY, Yik SK, Tan AJ, Banerjee S, Crank PJ, et al. Outdoor thermal comfort research in transient conditions: A narrative literature review. *Landscape and Urban Planning*. 2022;226:104496.

-
- [161] Wang L, Dalgo DA, Mattise N, Zhu S, Srebric J. Physiological responses and data-driven thermal comfort models with personal conditioning devices (PCD). *Building and Environment*. 2023;236:110290.
 - [162] Chen K, Xu Q, Leow B, Ghahramani A. Personal thermal comfort models based on physiological measurements – A design of experiments based review. *Building and Environment*. 2023;228:109919.
 - [163] Rewitz K, Müller D. Influence of gender, age and BMI on human physiological response and thermal sensation for transient indoor environments with displacement ventilation. *Building and Environment*. 2022;219:109045.
 - [164] Cheong KH, Teo Y, Koh J, Acharya UR, Yu S. A simulation-aided approach in improving thermal-visual comfort and power efficiency in buildings. *Journal of Building Engineering*. 2019;27:100936.
 - [165] Habibi S. The Promise of BIM for Improving Building Performance. *Energy and Buildings*. 2017;153.
 - [166] Buonomano A, Forzano C, Kalogirou SA, Palombo A. Building-façade integrated solar thermal collectors: Energy-economic performance and indoor comfort simulation model of a water based prototype for heating, cooling, and DHW production. *Renewable Energy*. 2019;137:20-36.
 - [167] Anand P, Deb C, Alur R. A simplified tool for building layout design based on thermal comfort simulations. *Frontiers of Architectural Research*. 2017;6:218-30.
 - [168] Buratti C, Moretti E, Belloni E, Cotana F. Unsteady simulation of energy performance and thermal comfort in non-residential buildings. *Building and Environment*. 2013;59:482-91.
 - [169] Hawila AA-W, Merabtine A, Troussier N, Bennacer R. Combined use of dynamic building simulation and metamodeling to optimize glass façades for thermal comfort. *Building and Environment*. 2019;157:47-63.
 - [170] Lu S, Wang W, Lin C, Hameen E. Data-driven simulation of a thermal comfort-based temperature set-point control with ASHRAE RP884. *Building and Environment*. 2019.
 - [171] Valladares W, Galindo M, Gutiérrez J, Wu W-C, Liao K-K, Liao J-C, et al. Energy optimization associated with thermal comfort and indoor air control via a deep reinforcement learning algorithm. *Building and Environment*. 2019;155.
 - [172] Lei Y, Zhan S, Ono E, Peng Y, Zhang Z, Hasama T, et al. A practical deep reinforcement learning framework for multivariate occupant-centric control in buildings. *Applied Energy*. 2022;324:119742.
 - [173] Vosoughkhosravi S, Jafari A, Zhu Y. Application of American time use survey (ATUS) in modelling energy-related occupant-building interactions: A comprehensive review. *Energy and Buildings*. 2023;294:113245.
 - [174] Malik J, Bardhan R. A localized adaptive comfort model for free-running low-income housing in Mumbai, India. *Energy and Buildings*. 2023;281:112756.
 - [175] Tian X, Xu R, Liu W. Facial skin temperature and overall thermal sensation of sub-tropically acclimated Chinese subjects in summer. *Journal of Thermal Biology*. 2023;112:103422.
 - [176] Yang Z, Du C, Xiao H, Li B, Shi W, Wang B. A novel integrated index for simultaneous evaluation of the thermal comfort and energy efficiency of air-conditioning systems. *Journal of Building Engineering*. 2022;57:104885.
 - [177] Li L, He Y, Zhang H, Fung JCH, Lau AKH. Enhancing IAQ, thermal comfort, and energy efficiency through an adaptive multi-objective particle swarm optimizer-grey wolf optimization algorithm for smart environmental control. *Building and Environment*. 2023;235:110235.
 - [178] Buonomano A. Code-to-Code Validation and Application of a Dynamic Simulation Tool for the Building Energy Performance Analysis. 2016;9:301.
 - [179] Barone G, Buonomano A, Forzano C, Palombo A. Building Energy Performance Analysis: An Experimental Validation of an In-House Dynamic Simulation Tool through a Real Test Room. 2019;12:4107.
 - [180] Shaw EW. Thermal Comfort: analysis and applications in environmental engineering, by P. O. Fanger. 244 pp. DANISH TECHNICAL PRESS. Copenhagen, Denmark, 1970. Danish Kr. 76, 50. Royal Society of Health Journal. 1972;92:164-.
 - [181] Pei J, Qu M, Sun L, Wang X, Yin Y. The relationship between indoor air quality (IAQ) and perceived air quality (PAQ) – a review and case analysis of Chinese residential environment. *Energy and Built Environment*. 2022.
 - [182] Fang L, Clausen G, Fanger PO. Impact of Temperature and Humidity on Perception of Indoor Air Quality During Immediate and Longer Whole-Body Exposures. *Indoor Air*. 1998;8:276-84.
 - [183] Fang L, Clausen G, Fanger PO. Impact of Temperature and Humidity on the Perception of Indoor Air Quality. *Indoor Air*. 1998;8:80-90.
 - [184] Maturo A, Vallianos C, Buonomano A, Athienitis A. A novel multi-level predictive management strategy to optimize phase-change energy storage and building-integrated renewable technologies operation under dynamic tariffs. *Energy Conversion and Management*. 2023;291:117220.
 - [185] Vittori F, Chiatti C, Pigliautile I, Pisello AL. The NEXT.ROOM: Design principles and systems trials of a novel test room aimed at deepening our knowledge on human comfort. *Building and Environment*. 2022;211:108744.
 - [186] Doherty TJ, Arens E. Evaluation of the physiological bases of thermal comfort models. *ASHRAE Transactions*. 1988;94:1371-85.
 - [187] Feng Y, Wang J, Wang N, Chen C. Alert-based wearable sensing system for individualized thermal preference prediction. *Building and Environment*. 2023;232:110047.

-
- [188] Cutore E, Volpe R, Sgroi R, Fichera A. Energy management and sustainability assessment of renewable energy communities: The Italian context. *Energy Conversion and Management*. 2023;278:116713.
- [189] Werner S. International review of district heating and cooling. *Energy*. 2017;137:617-31.
- [190] Olsthoorn D, Haghighat F, Mirzaei PA. Integration of storage and renewable energy into district heating systems: A review of modelling and optimization. *Solar Energy*. 2016;136:49-64.
- [191] Matak N, Tomić T, Schneider DR, Krajačić G. Integration of WtE and district cooling in existing Gas-CHP based district heating system – Central European city perspective. *Smart Energy*. 2021;4:100043.
- [192] Lake A, Rezaie B, Beyerlein S. Review of district heating and cooling systems for a sustainable future. *Renewable and Sustainable Energy Reviews*. 2017;67:417-25.
- [193] Lund H, Werner S, Wiltshire R, Svendsen S, Thorsen JE, Hvelplund F, et al. 4th Generation District Heating (4GDH): Integrating smart thermal grids into future sustainable energy systems. *Energy*. 2014;68:1-11.
- [194] Barone G, Buonomano A, Forzano C, Palombo A. A novel dynamic simulation model for the thermo-economic analysis and optimisation of district heating systems. *Energy Conversion and Management*. 2020;220.
- [195] Novosel T, Feijoo F, Duić N, Domac J. Impact of district heating and cooling on the potential for the integration of variable renewable energy sources in mild and Mediterranean climates. *Energy Conversion and Management*. 2022;272:116374.
- [196] Winterscheid C, Holler S, Dalenbäck JO. Integration of solar thermal systems into existing district heating systems. *Energy Procedia*. 2017;116:158-69.
- [197] Sorknæs P, Nielsen S, Lund H, Mathiesen BV, Moreno D, Thellufsen JZ. The benefits of 4th generation district heating and energy efficient datacentres. *Energy*. 2022;260:125215.
- [198] Dominković DF, Stunjek G, Blanco I, Madsen H, Krajačić G. Technical, economic and environmental optimization of district heating expansion in an urban agglomeration. *Energy*. 2020;197:117243.
- [199] Čulig-Tokić D, Krajačić G, Doračić B, Mathiesen BV, Krklec R, Larsen JM. Comparative analysis of the district heating systems of two towns in Croatia and Denmark. *Energy*. 2015;92:435-43.
- [200] Egging-Bratseth R, Kauko H, Knudsen BR, Bakke SA, Ettayebi A, Haufe IR. Seasonal storage and demand side management in district heating systems with demand uncertainty. *Applied Energy*. 2021;285:116392.
- [201] Veyron M, Voirand A, Mion N, Maragna C, Mugnier D, Clausse M. Dynamic exergy and economic assessment of the implementation of seasonal underground thermal energy storage in existing solar district heating. *Energy*. 2022;261:124917.
- [202] Mahon H, O'Connor D, Friedrich D, Hughes B. A review of thermal energy storage technologies for seasonal loops. *Energy*. 2022;239:122207.
- [203] Guo F, Zhu X, Zhang J, Yang X. Large-scale living laboratory of seasonal borehole thermal energy storage system for urban district heating. *Applied Energy*. 2020;264:114763.
- [204] Dominković DF, Čosić B, Bačelić Medić Z, Duić N. A hybrid optimization model of biomass trigeneration system combined with pit thermal energy storage. *Energy Conversion and Management*. 2015;104:90-9.
- [205] Saloux E, Candanedo JA. Model-based predictive control to minimize primary energy use in a solar district heating system with seasonal thermal energy storage. *Applied Energy*. 2021;291:116840.
- [206] Nielsen JE, Sørensen PA. Renewable district heating and cooling technologies with and without seasonal storage. *Renewable heating and cooling: Elsevier*; 2016. p. 197-220.
- [207] Perez-Mora N, Bava F, Andersen M, Bales C, Lennermo G, Nielsen C, et al. Solar district heating and cooling: A review. *International Journal of Energy Research*. 2018;42:1419-41.
- [208] Tian Z, Perers B, Furbo S, Fan J. Thermo-economic optimization of a hybrid solar district heating plant with flat plate collectors and parabolic trough collectors in series. *Energy Conversion and Management*. 2018;165:92-101.
- [209] Guelpa E, Deputato S, Verda V. Thermal request optimization in district heating networks using a clustering approach. *Applied Energy*. 2018;228:608-17.
- [210] Untrau A, Sochard S, Marias F, Reneaume J-M, Le Roux GAC, Serra S. Analysis and future perspectives for the application of Dynamic Real-Time Optimization to solar thermal plants: A review. *Solar Energy*. 2022;241:275-91.
- [211] Yılmaz İH, Söylemez MS, Yumrutaş R. Experimental analysis and dynamic simulation of a solar-assisted industrial process using parabolic trough solar collectors under outdoor conditions. *Energy for Sustainable Development*. 2023;72:212-29.
- [212] Yılmaz İH, Söylemez MS. Thermo-mathematical modeling of parabolic trough collector. *Energy Conversion and Management*. 2014;88:768-84.
- [213] García-Menéndez D, Ríos-Fernández JC, Blanco-Marigorta AM, Suárez-López MJ. Dynamic simulation and exergetic analysis of a solar thermal collector installation. *Alexandria Engineering Journal*. 2022;61:1665-77.
- [214] Immonen J, Powell KM. Dynamic optimization with flexible heat integration of a solar parabolic trough collector plant with thermal energy storage used for industrial process heat. *Energy Conversion and Management*. 2022;267:115921.
- [215] Winterscheid C, Dalenbäck J-O, Holler S. Integration of solar thermal systems in existing district heating systems. *Energy*. 2017;137:579-85.

-
- [216] Hirvonen J, ur Rehman H, Sirén K. Techno-economic optimization and analysis of a high latitude solar district heating system with seasonal storage, considering different community sizes. *Solar Energy*. 2018;162:472-88.
 - [217] Masero E, Frejo JRD, Maestre JM, Camacho EF. A light clustering model predictive control approach to maximize thermal power in solar parabolic-trough plants. *Solar Energy*. 2021;214:531-41.
 - [218] Pataro IML, Gil JD, Americano da Costa MV, Guzmán JL, Berenguel M. A nonlinear control approach for hybrid solar thermal plants based on operational conditions. *Renewable Energy*. 2022;183:114-29.
 - [219] Lizárraga-Morazán JR, Picón-Núñez M. Optimal sizing and control strategy of low temperature solar thermal utility systems. *Energy*. 2023;263:125835.
 - [220] Yang M, Wang Z, Chen L, Tang W. Dynamic heat transfer model of flat plate solar water collectors with consideration of variable flow rate. *Solar Energy*. 2020;212:34-47.
 - [221] Zhao D, Wang Z, Xu E, Zhu L, Lei D, Xu L, et al. Yanqing solar field: Dynamic optical model and operational safety analysis. *Applied Thermal Engineering*. 2017;110:275-89.
 - [222] Gallego AJ, Sánchez AJ, Escaño JM, Camacho EF. Nonlinear model predictive control for thermal balance in solar trough plants. *European Journal of Control*. 2022;67:100717.
 - [223] Ma L, Xu E, Li J, Xu L, Li X. Analysis and validation of a thermal hydraulic dynamic model for the parabolic trough solar field. *Energy*. 2018;156:430-43.
 - [224] Ma L, Wang Z, Lei D, Xu L. Establishment, Validation, and Application of a Comprehensive Thermal Hydraulic Model for a Parabolic Trough Solar Field. *Energies* 2019.
 - [225] Sabiha MA, Saidur R, Mekhilef S, Mahian O. Progress and latest developments of evacuated tube solar collectors. *Renewable and Sustainable Energy Reviews*. 2015;51:1038-54.
 - [226] Schwenzer M, Ay M, Bergs T, Abel D. Review on model predictive control: an engineering perspective. *The International Journal of Advanced Manufacturing Technology*. 2021;117:1327-49.
 - [227] Truong NL, Gustavsson L. Costs and primary energy use of heating new residential areas with district heat or electric heat pumps. *Energy Procedia*. 2019;158:2031-8.
 - [228] <https://www.swissgrid.ch/en/home/customers/topics/tariffs.html>.
 - [229] Quiquerez L, Lachal B, Monnard M, Faessler J. The role of district heating in achieving sustainable cities: comparative analysis of different heat scenarios for Geneva. *Energy Procedia*. 2017;116:78-90.
 - [230] Lienhard N, Mutschler R, Leenders L, Rüdisüli M. Concurrent deficit and surplus situations in the future renewable Swiss and European electricity system. *Energy Strategy Reviews*. 2023;46:101036.
 - [231] International Energy Agency IEA. Sustainable Energy for All 2013-2014: Global Tracking Framework Report: The World Bank; 2014.
 - [232] Buonomano A, Calise F, Palombo A. Buildings dynamic simulation: Water loop heat pump systems analysis for European climates. *Applied Energy*. 2012;91:222-34.
 - [233] Jebamalai JM, Marlein K, Laverge J. Design and cost comparison of district heating and cooling (DHC) network configurations using ring topology – A case study. *Energy*. 2022;258:124777.
 - [234] Hiltunen P, Syri S. Low-temperature waste heat enabling abandoning coal in Espoo district heating system. *Energy*. 2021;231:120916.
 - [235] Abugabbara M, Javed S, Bagge H, Johansson D. Bibliographic analysis of the recent advancements in modeling and co-simulating the fifth-generation district heating and cooling systems. *Energy and Buildings*. 2020;224:110260.
 - [236] Zhao A, Dong F, Xue X, Xi J, Wei Y. Optimal control for hydraulic balance of secondary network in district heating system under distributed architecture. *Energy and Buildings*. 2023;290:113030.
 - [237] Jakubek D, Ocloń P, Nowak-Ocloń M, Sułowicz M, Varbanov PS, Klemeš JJ. Mathematical modelling and model validation of the heat losses in district heating networks. *Energy*. 2023;267:126460.
 - [238] Alsagri AS, Arabkoohsar A, Khosravi M, Alrobaian AA. Efficient and cost-effective district heating system with decentralized heat storage units, and triple-pipes. *Energy*. 2019;188:116035.
 - [239] Hirsch H, Nicolai A. An efficient numerical solution method for detailed modelling of large 5th generation district heating and cooling networks. *Energy*. 2022;255:124485.
 - [240] Zheng X, Xu B, Wang Y, You S, Zhang H, Wei S, et al. Hydraulic transient modeling and analysis of the district heating network. *Sustainable Energy, Grids and Networks*. 2021;25:100409.
 - [241] Bilardo M, Sandrone F, Zanzottera G, Fabrizio E. Modelling a fifth-generation bidirectional low temperature district heating and cooling (5GDHC) network for nearly Zero Energy District (nZED). *Energy Reports*. 2021;7:8390-405.
 - [242] Hering D, Cansev ME, Tamassia E, Xhonneux A, Müller D. Temperature control of a low-temperature district heating network with Model Predictive Control and Mixed-Integer Quadratically Constrained Programming. *Energy*. 2021;224:120140.
 - [243] Reiners T, Gross M, Altieri L, Wagner H-J, Bertsch V. Heat pump efficiency in fifth generation ultra-low temperature district heating networks using a wastewater heat source. *Energy*. 2021;236:121318.

-
- [244] Khosravi A, Laukkanen T, Vuorinen V, Syri S. Waste heat recovery from a data centre and 5G smart poles for low-temperature district heating network. *Energy*. 2021;218:119468.
 - [245] Wirtz M, Neumaier L, Remmen P, Müller D. Temperature control in 5th generation district heating and cooling networks: An MILP-based operation optimization. *Applied Energy*. 2021;288:116608.
 - [246] Fitó J, Vallée M, Ruby A, Cuisinier E. Robustness of district heating versus electricity-driven energy system at district level: A multi-objective optimization study. *Smart Energy*. 2022;6:100073.
 - [247] Buffa S, Cozzini M, D'Antoni M, Baratieri M, Fedrizzi R. 5th generation district heating and cooling systems: A review of existing cases in Europe. *Renewable and Sustainable Energy Reviews*. 2019;104:504-22.
 - [248] Perez-Mora N, Bava F, Andersen M, Bales C, Lennermo G, Nielsen C, et al. Solar district heating and cooling: A review. *International Journal of Energy Research*. 2018;42:1419-41.
 - [249] Nielsen JE, Sørensen PA. 9 - Renewable district heating and cooling technologies with and without seasonal storage. In: Stryi-Hipp G, editor. *Renewable Heating and Cooling*: Woodhead Publishing; 2016. p. 197-220.
 - [250] Köfinger M, Schmidt RR, Basciotti D, Terreros O, Baldvinsson I, Mayrhofer J, et al. Simulation based evaluation of large scale waste heat utilization in urban district heating networks: Optimized integration and operation of a seasonal storage. *Energy*. 2018;159:1161-74.
 - [251] Nourollahi R, Zare K, Mohammadi-Ivatloo B, Vahidinasab V, Moghadam AA. Continuous-time optimization of integrated networks of electricity and district heating under wind power uncertainty. *Applied Thermal Engineering*. 2023;225:119926.
 - [252] Wirtz M, Kiviliip L, Remmen P, Müller D. 5th Generation District Heating: A novel design approach based on mathematical optimization. *Applied Energy*. 2020;260:114158.
 - [253] Revesz A, Jones P, Dunham C, Davies G, Marques C, Matabuena R, et al. Developing novel 5th generation district energy networks. *Energy*. 2020;201:117389.
 - [254] Wang Y, You S, Zhang H, Zheng W, Zheng X, Miao Q. Hydraulic performance optimization of meshed district heating network with multiple heat sources. *Energy*. 2017;126:603-21.
 - [255] Allen A, Henze G, Baker K, Pavlak G. Evaluation of low-exergy heating and cooling systems and topology optimization for deep energy savings at the urban district level. *Energy Conversion and Management*. 2020;222:113106.
 - [256] Dorotić H, Pukšec T, Duić N. Economical, environmental and exergetic multi-objective optimization of district heating systems on hourly level for a whole year. *Applied Energy*. 2019;251:113394.
 - [257] Jie P, Zhao W, Li F, Wei F, Li J. Optimizing the pressure drop per unit length of district heating piping networks from an environmental perspective. *Energy*. 2020;202:117681.
 - [258] Su L, Nie T, On Ho C, Yang Z, Calvez P, Jain RK, et al. Optimizing pipe network design and central plant positioning of district heating and cooling System: A Graph-Based Multi-Objective genetic algorithm approach. *Applied Energy*. 2022;325:119844.
 - [259] von Rhein J, Henze GP, Long N, Fu Y. Development of a topology analysis tool for fifth-generation district heating and cooling networks. *Energy Conversion and Management*. 2019;196:705-16.
 - [260] Boesten S, Ivens W, Dekker SC, Eijdens H. 5th generation district heating and cooling systems as a solution for renewable urban thermal energy supply. *Adv Geosci*. 2019;49:129-36.
 - [261] Prasanna A, Dorer V, Vetterli N. Optimisation of a district energy system with a low temperature network. *Energy*. 2017;137:632-48.
 - [262] Bünning F, Wetter M, Fuchs M, Müller D. Bidirectional low temperature district energy systems with agent-based control: Performance comparison and operation optimization. *Applied Energy*. 2018;209:502-15.
 - [263] Zarin Pass R, Wetter M, Piette MA. A thermodynamic analysis of a novel bidirectional district heating and cooling network. *Energy*. 2018;144:20-30.
 - [264] Vandermeulen A, van der Heijde B, Helsen L. Controlling district heating and cooling networks to unlock flexibility: A review. *Energy*. 2018;151:103-15.
 - [265] Hermansen R, Smith K, Thorsen JE, Wang J, Zong Y. Model predictive control for a heat booster substation in ultra low temperature district heating systems. *Energy*. 2022;238:121631.
 - [266] Maurer J, Tschuch N, Krebs S, Bhattacharya K, Cañizares C, Hohmann S. Toward transactive control of coupled electric power and district heating networks. *Applied Energy*. 2023;332:120460.
 - [267] MathWorks. https://it.mathworks.com/help/pdf_doc/hydro/index.html. 2023.
 - [268] isprambiente.it. Efficiency and decarbonization indicators for total energy consumption and power sector. 2023.
 - [269] European Commission's Communication COM(2021) 550 final. "Fit for 55": delivering the EU's 2030 Climate Target on the way to climate neutrality. <https://eur-lexeuropa.eu/legal-content/EN/TXT/?uri=CELEX:52021DC05502022>.
 - [270] Rosales-Asensio E, Diez DB, Sarmiento P. Electricity balancing challenges for markets with high variable renewable generation. *Renewable and Sustainable Energy Reviews*. 2024;189:113918.

- [271] Kataray T, Nitesh B, Yarram B, Sinha S, Cuce E, Shaik S, et al. Integration of smart grid with renewable energy sources: Opportunities and challenges – A comprehensive review. *Sustainable Energy Technologies and Assessments*. 2023;58:103363.
- [272] Reis IFG, Gonçalves I, Lopes MAR, Antunes CH. A multi-agent system approach to exploit demand-side flexibility in an energy community. *Utilities Policy*. 2020;67:101114.
- [273] Buonomano A, Barone G, Forzano C. Latest advancements and challenges of technologies and methods for accelerating the sustainable energy transition. *Energy Reports*. 2023;9:3343-55.
- [274] Buonomano A, Barone G, Forzano C. Advanced energy technologies, methods, and policies to support the sustainable development of energy, water and environment systems. *Energy Reports*. 2022;8:4844-53.
- [275] Diezmartínez CV, Zhang A. Powering just energy transitions: A review of the justice implications of community choice aggregation. *Energy Research & Social Science*. 2023;103:103221.
- [276] Haji Bashi M, De Tommasi L, Le Cam A, Relaño LS, Lyons P, Mundó J, et al. A review and mapping exercise of energy community regulatory challenges in European member states based on a survey of collective energy actors. *Renewable and Sustainable Energy Reviews*. 2023;172:113055.
- [277] Commission E. Renewable Energy – Recast to 2030. https://joint-research-centre-europe.eu/welcome-jec-website/reference-regulatory-framework/renewable-energy-recast-2030-red-ii_en2022.
- [278] Wu Y, Wu Y, Cimen H, Vasquez JC, Guerrero JM. Towards collective energy Community: Potential roles of microgrid and blockchain to go beyond P2P energy trading. *Applied Energy*. 2022;314:119003.
- [279] Neska E, Kowalska-Pyzalska A. Conceptual design of energy market topologies for communities and their practical applications in EU: A comparison of three case studies. *Renewable and Sustainable Energy Reviews*. 2022;169:112921.
- [280] Lu X, Liu Z, Ma L, Wang L, Zhou K, Feng N. A robust optimization approach for optimal load dispatch of community energy hub. *Applied Energy*. 2020;259:114195.
- [281] Groppi D, Feijoo F, Pfeifer A, Garcia DA, Duic N. Analyzing the impact of demand response and reserves in islands energy planning. *Energy*. 2023;278:127716.
- [282] Liu J, Zhou Y, Yang H, Wu H. Net-zero energy management and optimization of commercial building sectors with hybrid renewable energy systems integrated with energy storage of pumped hydro and hydrogen taxis. *Applied Energy*. 2022;321:119312.
- [283] Mazzoni S, Ooi S, Nastasi B, Romagnoli A. Energy storage technologies as techno-economic parameters for master-planning and optimal dispatch in smart multi energy systems. *Applied Energy*. 2019;254:113682.
- [284] Ponnaganti P, Sinha R, Pillai JR, Bak-Jensen B. Flexibility provisions through local energy communities: A review. *Next Energy*. 2023;1:100022.
- [285] Zabihinia Gerdroodbari Y, Khorasany M, Razzaghi R, Heidari R. Management of prosumers using dynamic export limits and shared Community Energy Storage. *Applied Energy*. 2024;355:122222.
- [286] Rodríguez-Vilches R, Martín-Martínez F, Sánchez-Miralles Á, Gutiérrez de la Cámara JR, Muñoz Delgado S. Methodology to assess prosumer participation in European electricity markets. *Renewable and Sustainable Energy Reviews*. 2024;191:114179.
- [287] Pastore LM, Lo Basso G, Ricciardi G, de Santoli L. Smart energy systems for renewable energy communities: A comparative analysis of power-to-X strategies for improving energy self-consumption. *Energy*. 2023;280:128205.
- [288] Barone G, Buonomano A, Forzano C, Palombo A, Russo G. The role of energy communities in electricity grid balancing: A flexible tool for smart grid power distribution optimization. *Renewable and Sustainable Energy Reviews*. 2023;187:113742.
- [289] F.G. Reis I, Gonçalves I, A.R. Lopes M, Henggeler Antunes C. Business models for energy communities: A review of key issues and trends. *Renewable and Sustainable Energy Reviews*. 2021;144:111013.
- [290] Xia Y, Xu Q, Li F. Grid-friendly pricing mechanism for peer-to-peer energy sharing market diffusion in communities. *Applied Energy*. 2023;334:120685.
- [291] Van Cutsem O, Ho Dac D, Boudou P, Kayal M. Cooperative energy management of a community of smart-buildings: A Blockchain approach. *International Journal of Electrical Power & Energy Systems*. 2020;117:105643.
- [292] Petrucci A, Ayevide FK, Buonomano A, Athienitis A. Development of energy aggregators for virtual communities: The energy efficiency-flexibility nexus for demand response. *Renewable Energy*. 2023;215:118975.
- [293] Plaum F, Ahmadihangar R, Rosin A, Kilter J. Aggregated demand-side energy flexibility: A comprehensive review on characterization, forecasting and market prospects. *Energy Reports*. 2022;8:9344-62.
- [294] Gao H, Cai W, He S, Jiang J, Liu J. Multi-energy sharing optimization for a building cluster towards net-zero energy system. *Applied Energy*. 2023;350:121778.
- [295] Braeuer F, Kleinebrahm M, Naber E, Scheller F, McKenna R. Optimal system design for energy communities in multi-family buildings: the case of the German Tenant Electricity Law. *Applied Energy*. 2022;305:117884.
- [296] Nastasi B, Mazzoni S. Renewable Hydrogen Energy Communities layouts towards off-grid operation. *Energy Conversion and Management*. 2023;291:117293.

-
- [297] Dal Cin E, Carraro G, Volpato G, Lazzaretto A, Danieli P. A multi-criteria approach to optimize the design-operation of Energy Communities considering economic-environmental objectives and demand side management. *Energy Conversion and Management*. 2022;263:115677.
 - [298] Lokeshgupta B, Ravivarma K. Coordinated smart home energy sharing with a centralized neighbourhood energy management. *Sustainable Cities and Society*. 2023;96:104642.
 - [299] Gbadega PA, Sun Y. Centralized peer-to-peer transactive energy market approach in a prosumer-centric residential smart grid environment. *Energy Reports*. 2022;8:105-16.
 - [300] Zhou Y, Lund PD. Peer-to-peer energy sharing and trading of renewable energy in smart communities – trading pricing models, decision-making and agent-based collaboration. *Renewable Energy*. 2023;207:177-93.
 - [301] Li N, Okur Ö. Economic analysis of energy communities: Investment options and cost allocation. *Applied Energy*. 2023;336:120706.
 - [302] Alonso Pedrero R, Crespo del Granado P. Assessing the impact of energy communities on retailers' balancing positions in the power market. *Energy*. 2023;283:128384.
 - [303] Xia Y, Xu Q, Fang J, Tang R, Du P. Bipartite graph-based community-to-community matching in local energy market considering socially networked prosumers. *Applied Energy*. 2024;353:122245.
 - [304] Alizadeh A, Esfahani M, Dinar F, Kamwa I, Moeini A, Mohseni-Bonab SM, et al. A cooperative transactive multi-carrier energy control mechanism with P2P energy + reserve trading using Nash bargaining game theory under renewables uncertainty. *Applied Energy*. 2024;353:122162.
 - [305] Wang Z, Yu X, Mu Y, Jia H, Jiang Q, Wang X. Peer-to-Peer energy trading strategy for energy balance service provider (EBSP) considering market elasticity in community microgrid. *Applied Energy*. 2021;303:117596.
 - [306] Massidda L, Marrocu M. Total and thermal load forecasting in residential communities through probabilistic methods and causal machine learning. *Applied Energy*. 2023;351:121783.
 - [307] Houben N, Cosic A, Stadler M, Mansoor M, Zellinger M, Auer H, et al. Optimal dispatch of a multi-energy system microgrid under uncertainty: A renewable energy community in Austria. *Applied Energy*. 2023;337:120913.
 - [308] Pompei L, Nardecchia F, Miliozzi A. Current, Projected Performance and Costs of Thermal Energy Storage. *Processes*2023.
 - [309] Frapin M, Roux C, Assoumou E, Peuportier B. Modelling long-term and short-term temporal variation and uncertainty of electricity production in the life cycle assessment of buildings. *Applied Energy*. 2022;307:118141.
 - [310] Volpato G, Carraro G, Cont M, Danieli P, Rech S, Lazzaretto A. General guidelines for the optimal economic aggregation of prosumers in energy communities. *Energy*. 2022;258:124800.
 - [311] Fikru MG, Canfield C. Choosing both/and: Encouraging green energy purchases in community choice aggregation. *Energy Policy*. 2024;185:113949.
 - [312] Paiho S, Kiljander J, Sarala R, Siikavirta H, Kilkki O, Bajpai A, et al. Towards cross-commodity energy-sharing communities – A review of the market, regulatory, and technical situation. *Renewable and Sustainable Energy Reviews*. 2021;151:111568.
 - [313] Schiavo LL, Galliani A, Rossi A. 6 - The “virtual” model for collective self-consumption in Italy. In: Löbbe S, Sioshansi F, Robinson D, editors. *Energy Communities*: Academic Press; 2022. p. 95-106.
 - [314] Alkharusi T, Huang G, Markides CN. Characterisation of soiling on glass surfaces and their impact on optical and solar photovoltaic performance. *Renewable Energy*. 2024;220:119422.
 - [315] Alkharusi T, Alzahrani MM, Pandey C, Yildizhan H, Markides CN. Experimental investigation of nonuniform PV soiling. *Solar Energy*. 2024;272:112493.
 - [316] Aste N, Del Pero C, Leonforte F, Manfren M. A simplified model for the estimation of energy production of PV systems. *Energy*. 2013;59:503-12.
 - [317] Paatero JV, Lund PD. A model for generating household electricity load profiles. *International Journal of Energy Research*. 2006;30:273-90.
 - [318] Gong Q, Kang W, Fahroo F. Approximation of compositional functions with ReLU neural networks. *Systems & Control Letters*. 2023;175:105508.
 - [319] Saab S, Saab K, Phoha S, Zhu M, Ray A. A multivariate adaptive gradient algorithm with reduced tuning efforts. *Neural Networks*. 2022;152:499-509.
 - [320] Feng C, Wen F, You S, Li Z, Shahnian F, Shahidehpour M. Coalitional Game-Based Transactive Energy Management in Local Energy Communities. *IEEE Transactions on Power Systems*. 2020;35:1729-40.
 - [321] ISTAT INdS-. <http://dati.istat.it/?lang=en>. 2023.
 - [322] 8 MV. <https://meteonorm.com/en/meteonorm-version-8>. 2023.
 - [323] Berardi U, Manca M, Casaldaliga P, Pich-Aguilera F. From high-energy demands to nZEB: the retrofit of a school in Catalonia, Spain. *Energy Procedia*. 2017;140:141-50.
 - [324] HVAC building datasets <https://trynthink.github.io/buildingsdatasets/>. 2023.
 - [325] ARERA. <https://www.arera.it/dati-e-statistiche?ambito=55&keyword=&setto=4&orderby=>. 2023.

-
- [326] Alam MR, St-Hilaire M, Kunz T. Peer-to-peer energy trading among smart homes. *Applied energy*. 2019;238:1434-43.
 - [327] Impram S, Nese SV, Oral B. Challenges of renewable energy penetration on power system flexibility: A survey. *Energy Strategy Reviews*. 2020;31:100539.
 - [328] Olatomiwa L, Mekhilef S, Ismail MS, Moghavvemi M. Energy management strategies in hybrid renewable energy systems: A review. *Renewable and Sustainable Energy Reviews*. 2016;62:821-35.
 - [329] Makolo P, Zamora R, Lie T-T. The role of inertia for grid flexibility under high penetration of variable renewables - A review of challenges and solutions. *Renewable and Sustainable Energy Reviews*. 2021;147:111223.
 - [330] Long C, Wu J, Zhou Y, Jenkins N. Peer-to-peer energy sharing through a two-stage aggregated battery control in a community Microgrid. *Applied energy*. 2018;226:261-76.
 - [331] Piselli C, Salvadori G, Diciotti L, Fantozzi F, Pisello AL. Assessing users' willingness-to-engagement towards Net Zero Energy communities in Italy. *Renewable and Sustainable Energy Reviews*. 2021;152:111627.
 - [332] Hahnel UJJ, Herberz M, Pena-Bello A, Parra D, Brosch T. Becoming prosumer: Revealing trading preferences and decision-making strategies in peer-to-peer energy communities. *Energy Policy*. 2020;137:111098.
 - [333] Kang J, Yu R, Huang X, Maharjan S, Zhang Y, Hossain E. Enabling localized peer-to-peer electricity trading among plug-in hybrid electric vehicles using consortium blockchains. *IEEE Transactions on Industrial Informatics*. 2017;13:3154-64.
 - [334] Alam MS, Al-Ismail FS, Salem A, Abido MA. High-level penetration of renewable energy sources into grid utility: Challenges and solutions. *IEEE Access*. 2020;8:190277-99.
 - [335] Churkin A, Bialek J, Pozo D, Sauma E, Korgin N. Review of Cooperative Game Theory applications in power system expansion planning. *Renewable and Sustainable Energy Reviews*. 2021;145:111056.
 - [336] Moniruzzaman M, Yassine A, Benlamri R. Blockchain and cooperative game theory for peer-to-peer energy trading in smart grids. *International Journal of Electrical Power & Energy Systems*. 2023;151:109111.
 - [337] Amin W, Huang Q, Afzal M, Khan AA, Umer K, Ahmed SA. A converging non-cooperative & cooperative game theory approach for stabilizing peer-to-peer electricity trading. *Electric Power Systems Research*. 2020;183:106278.
 - [338] Morstyn T, Farrell N, Darby SJ, McCulloch MD. Using peer-to-peer energy-trading platforms to incentivize prosumers to form federated power plants. *Nature Energy*. 2018;3:94-101.
 - [339] Paudel A, Chaudhari K, Long C, Gooi HB. Peer-to-peer energy trading in a prosumer-based community microgrid: A game-theoretic model. *IEEE Transactions on Industrial electronics*. 2018;66:6087-97.
 - [340] Lee W-P, Han D, Won D. Grid-Oriented Coordination Strategy of Prosumers Using Game-theoretic Peer-to-Peer Trading Framework in Energy Community. *Applied Energy*. 2022;326:119980.
 - [341] Zahedi R, Ghodusinejad Mh, Aslani A, Hachem-Vermette C. Modelling community-scale renewable energy and electric vehicle management for cold-climate regions using machine learning. *Energy Strategy Reviews*. 2022;43:100930.
 - [342] Kang H, Jung S, Jeoung J, Hong J, Hong T. A bi-level reinforcement learning model for optimal scheduling and planning of battery energy storage considering uncertainty in the energy-sharing community. *Sustainable Cities and Society*. 2023;94:104538.
 - [343] Nastasi B, Markovska N, Puksec T, Duić N, Foley A. Renewable and sustainable energy challenges to face for the achievement of Sustainable Development Goals. *Renewable and Sustainable Energy Reviews*. 2022;157:112071.
 - [344] Tan KM, Ramachandramurthy VK, Yong JY. Integration of electric vehicles in smart grid: A review on vehicle to grid technologies and optimization techniques. *Renewable and Sustainable Energy Reviews*. 2016;53:720-32.
 - [345] Lund H, Kempton W. Integration of renewable energy into the transport and electricity sectors through V2G. *Energy policy*. 2008;36:3578-87.
 - [346] Bokopane L, Kusakana K, Vermaak HJ. Energy management of a grid-intergrated hybrid peer-to-peer renewable charging station for electric vehicles. *IEEE*. p. 275-80.
 - [347] Aryanezhad M, Ostadaghaee E, Joorabian M. Management and coordination charging of smart park and V2G strategy based on Monte Carlo algorithm. *IEEE*. p. 1-8.
 - [348] Tomasso G, Di Monaco M, D'Arpino M, Abronzini U. Progettazione di un convertitore modulare per infrastrutture di ricarica con accumulo integrato. Report RdS/PAR. 2013;99.
 - [349] Li J, Murphy E, Winnick J, Kohl PA. Studies on the cycle life of commercial lithium ion batteries during rapid charge-discharge cycling. *Journal of Power Sources*. 2001;102:294-301.
 - [350] Kejun Q, Chengke Z, Yue Y, Allan M. Temperature effect on electric vehicle battery cycle life in Vehicle-to-grid applications. *CICED 2010 Proceedings*2010. p. 1-6.
 - [351] Uddin K, Jackson T, Widanage WD, Chouchelamane G, Jennings PA, Marco J. On the possibility of extending the lifetime of lithium-ion batteries through optimal V2G facilitated by an integrated vehicle and smart-grid system. *Energy*. 2017;133:710-22.
 - [352] Barone G, Buonomano A, Forzano C, Giuzio GF, Palombo A. Increasing self-consumption of renewable energy through the Building to Building approach applied to multiple users connected in a virtual micro-grid. *Renewable Energy*. 2020;159:1165-76.

-
- [353] Barone G, Buonomano A, Forzano C, Giuzio GF, Palombo A, Russo G. Energy virtual networks based on electric vehicles for sustainable buildings: System modelling for comparative energy and economic analyses. *Energy*. 2022;242:122931.
 - [354] Huang Z, Yu H, Peng Z, Zhao M. Methods and tools for community energy planning: A review. *Renewable and Sustainable Energy Reviews*. 2015;42:1335-48.
 - [355] Ahmad S, Naeem M, Ahmad A. Low complexity approach for energy management in residential buildings. *International Transactions on Electrical Energy Systems*. 2019;29:e2680.
 - [356] Ding Y, Wang Q, Tian Z, Lyu Y, Li F, Yan Z, et al. A graph-theory-based dynamic programming planning method for distributed energy system planning: Campus area as a case study. *Applied Energy*. 2023;329:120258.
 - [357] Qamar A, Iqbal S, Ahmad S, Kouzani AZ, Mahmud MAP. Configuration Detection of Grounding Grid: Static Electric Field Based Nondestructive Technique. *IEEE Access*. 2021;9:132888-96.
 - [358] Berrou Y, Soulier E. A Methodology to Analyze the Development of Local Energy Communities Based on Socio-Energetic Nodes and Actor-Network Theory. *Procedia Computer Science*. 2023;219:439-46.
 - [359] Malik S, Duffy M, Thakur S, Hayes B, Breslin J. A priority-based approach for peer-to-peer energy trading using cooperative game theory in local energy community. *International Journal of Electrical Power & Energy Systems*. 2022;137:107865.
 - [360] Klemm C, Vennemann P. Modeling and optimization of multi-energy systems in mixed-use districts: A review of existing methods and approaches. *Renewable and Sustainable Energy Reviews*. 2021;135:110206.
 - [361] Cosic A, Stadler M, Mansoor M, Zellinger M. Mixed-integer linear programming based optimization strategies for renewable energy communities. *Energy*. 2021;237:121559.
 - [362] Gupta S, Maulik A, Das D, Singh A. Coordinated stochastic optimal energy management of grid-connected microgrids considering demand response, plug-in hybrid electric vehicles, and smart transformers. *Renewable and Sustainable Energy Reviews*. 2022;155:111861.
 - [363] Zhao F, Li Z, Wang D, Ma T. Peer-to-peer energy sharing with demand-side management for fair revenue distribution and stable grid interaction in the photovoltaic community. *Journal of Cleaner Production*. 2023;383:135271.
 - [364] Casalicchio V, Manzolini G, Prina MG, Moser D. From investment optimization to fair benefit distribution in renewable energy community modelling. *Applied Energy*. 2022;310:118447.
 - [365] Nguyen S, Peng W, Sokolowski P, Alahakoon D, Yu X. Optimizing rooftop photovoltaic distributed generation with battery storage for peer-to-peer energy trading. *Applied Energy*. 2018;228:2567-80.
 - [366] Fangjie G, Jianwei G, Yi Z, Ningbo H, Haoyu W. Community decision-makers' choice of multi-objective scheduling strategy for integrated energy considering multiple uncertainties and demand response. *Sustainable Cities and Society*. 2022;83:103945.
 - [367] Maturo A, Petrucci A, Forzano C, Giuzio GF, Buonomano A, Athienitis A. Design and environmental sustainability assessment of energy-independent communities: The case study of a livestock farm in the North of Italy. *Energy Reports*. 2021;7:8091-107.
 - [368] Chang H-C, Ghaddar B, Nathwani J. Shared community energy storage allocation and optimization. *Applied Energy*. 2022;318:119160.
 - [369] Bakhtavar E, Prabatha T, Karunathilake H, Sadiq R, Hewage K. Assessment of renewable energy-based strategies for net-zero energy communities: A planning model using multi-objective goal programming. *Journal of Cleaner Production*. 2020;272:122886.
 - [370] Zhang C, Wu J, Zhou Y, Cheng M, Long C. Peer-to-Peer energy trading in a Microgrid. *Applied Energy*. 2018;220:1-12.
 - [371] Yaqub R, Ahmad S, Ahmad A, Amin M. Smart energy-consumption management system considering consumers' spending goals (SEMS-CCSG). *International Transactions on Electrical Energy Systems*. 2016;26:1570-84.
 - [372] Ebrahimi M. Storing electricity as thermal energy at community level for demand side management. *Energy*. 2020;193:116755.
 - [373] Javadi MS, Gough M, Nezhad AE, Santos SF, Shafie-khah M, Catalão JPS. Pool trading model within a local energy community considering flexible loads, photovoltaic generation and energy storage systems. *Sustainable Cities and Society*. 2022;79:103747.
 - [374] Petrucci A, Barone G, Buonomano A, Athienitis A. Modelling of a multi-stage energy management control routine for energy demand forecasting, flexibility, and optimization of smart communities using a Recurrent Neural Network. *Energy Conversion and Management*. 2022;268:115995.
 - [375] TERNA. Forecast of Italian electricity demand. 2022.