University of Naples Federico II

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PhD Thesis

MULTI-OBJECTIVE OPTIMIZATION FOR COST-OPTIMAL ENERGY RETROFITTING: FROM THE SINGLE BUILDING TO A STOCK

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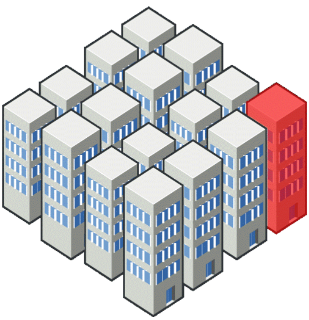

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*“Anything else you're interested in is not going to happen
if you can't breathe the air and drink the water.
Don't sit this one out. Do something. Make it sustainable. “*

CHAPTER 1. Introduction

1.1. Background

The sustainable development and the effort towards a green, low-carbon economic represent some of the most crucial challenges of our generation. The admirable purpose is a better world, in which healthy environment, economic prosperity and social justice are pursued simultaneously to ensure the well-being of present and future generations.

Within this context, the 'Roadmap for moving to a competitive low carbon economy in 2050’ (EU COM112/2011 [1]) establishes the target of reducing greenhouse gas emissions by 80–95% by 2050 in comparison to the levels of 1990. This goal cannot be reached without a substantial effort for the improvement of building energy performance. Indeed, the building sector is very energy-intensive – mainly because of the physical and functional obsolescence of the existing stock – by accounting for around 40% of primary energy consumption in the European Union (EU) [2] and 32% in the world [3]. This scenario has generated a great interest in projecting new nearly zero-energy buildings (nZEBs) in order to reduce the energy demand of the future building stock. Nevertheless, it is well known that the building turn-over rate is quite low, especially in the industrialized countries, which are responsible of a wide part of world consumption; for instance, most EU states extend their stock by less than

1% per year [4]. Thus, the impact of the new nZEBs is quite limited, whereas the energy retrofitting of the existing building stock is a key-strategy to achieve tangible results in the reduction of energy consumption and, thus, polluting emissions. However, the path is very challenging. The renovation rate in the EU, currently around 1%, should be more than doubled in order to realize, by 2050, a complete refurbishment of the European building stock [4], which would give a large contribution to the achievement of the ambitious targets pursed by the 'Roadmap for moving to a competitive low carbon economy in 2050'. It's clear that, as perfectly outlined by Ma *et al.* [5]:

"there is still a long way for building scientists and professionals to go in order to make existing building stock be more energy efficient and environmentally sustainable".

The design of the building energy retrofit is a complex and arduous task, which requires a holistic and integrated team approach [6], since it involves two distinct perspectives: the collective (state) one, interested in energy savings, and the private (single building) one, interested in economic benefits. How to find out the set of energy retrofit measures (ERMs) that ensures the best trade-off between such perspectives?

The Energy Performance of Buildings Directive (EPBD) Recast (2010/31/EU) [7] answers this question, by prescribing the cost-optimal analysis in order to detect the best packages of energy efficiency measures (EEMs) to apply to new or existing buildings. More in detail, a new comparative methodology framework has been introduced to assess the building energy performance "with a view to achieving cost-optimal levels". The recommended package of EEMs is the one that minimizes the global cost – which takes into accounts both investment and operation – evaluated over the entire lifecycle of the building, according to the European Commission Delegated Regulation [8] that supplements the

EPBD Recast. It should be noted that the proposed thesis is focused on building retrofitting, because, as aforementioned, this can ensure huge energy saving potentials. Therefore, the measures for the improvement of building energy performance are indifferently denoted either with EEMs or ERMs.

The cost-optimal analysis is a complex procedure that requires numerous simulations of building energy performance in correspondence of well-selected combinations of EEMs. In order to obtain reliable results, such simulations must consider the dynamic behavior of the system over the year, and thus the use of appropriate building performance simulation (BPS) tools – e.g., EnergyPlus [9], TRNSYS [10], ESP-r [11], IDA ICE [12] – is highly recommended. This results in a large amount of the required computational time that can assume an order of magnitude from days, for simple buildings, until months, for quite complex ones. Definitively, because of both high computational burden and complexity of BPS tools, the assessment of the cost-optimality for every building is a prohibitive goal, if the standard procedure is adopted. That's why the EPBD Recast demands the Member States (MSs) to define a set of reference buildings (RefBs) in order to represent the national building stock, and to perform the cost-optimal analysis only on these representative buildings. The RefBs should cover all the categories of new and existing buildings, where a category is meant as a stock of buildings, which share climatic conditions (location), functionality, construction type. The results achieved for each RefB about the cost-optimal configurations of EEMs should be extended to the other buildings of the same category.

The described procedure for the detection of the cost-optimal energy retrofitting, introduced by the EPBD Recast, yields a series of critical, still-open questions that have aroused a heated discussion in the scientific community. Among them, the main questions, identified in this study, can be outlined as follows:

q1. How to perform a reliable cost-optimal analysis of the retrofit measures for a single building?

q2. How to achieve global indications about the cost-optimality of energy retrofitting the existing building stock?

q3. How to evaluate the global cost of a building with a minimum computational time and a good reliability?

A definitive and robust answer to these questions is fundamental to overcome the main obstacle to the large diffusion of the cost-optimal retrofitting practice. Such obstacle can be summarized in a last crucial question that includes the previous ones:

q4. How to perform a reliable, fast, 'ad hoc' cost-optimal analysis of the retrofit measures for each building of the stock?

So far, the scientific literature did not propose a full and complete response to such critical questions.

1.2. Aims and originality

This thesis aims to provide a thorough answer to the aforementioned questions, by means of an original approach that handles all the issues involved in a robust and reliable cost-optimal analysis, achievable for every single building with an acceptable computational burden and complexity.

Three novel methodologies (CAMO, SLABE, building energy simulation by ANNs) have been developed for proposing a complete response to the first three questions and, then, they are coupled in a macro multi-stage methodology (CASA) that solves the final fundamental question, which represents the last step towards a wide-spread cost-optimal building retrofitting. The methodologies are delineated in the following lines and schematized in figure 1.1 that highlights the combination and role of CAMO, SLABE and ANNs inside CASA.

CAMO means Cost-optimal Analysis by the Multi-objective Optimization of energy performance. This methodology answers to question q1, by proposing a new procedure for the evaluation of the cost-optimality, by means of the multi-objective optimization of building energy performance and thermal comfort. The optimization is performed through the coupling between MATLAB [13] and EnergyPlus [9], by implementing a genetic algorithm (GA), and it allows the evaluation of profitable and feasible packages of energy efficiency measures applied to buildings. Then, following the adoption of these packages, the global cost over the lifecycle of the building is calculated in order to identify the cost-optimal solution.
Compared to the standard approach for cost-optimal analysis, CAMO allows to consider the thermal comfort in a more rigorous way and to reduce the computational burden, because a limited number of EEMs, properly selected by the GA, is explored. Nevertheless, computational time and complexity are still too high for the application to every building. This represents the main limit of CAMO.

SLABE means Simulation-based Large-scale sensitivity/uncertainty Analysis of Building Energy performance. This methodology answers to question q2, by providing a robust cost-optimal analysis of energy retrofitting solutions for a building stock. It is based on uncertainty and sensitivity analysis, carried out by means of MATLAB that handles

EnergyPlus simulations and outcomes. SLABE explores the effects of some ERMs on primary energy consumption and global cost related to a sample of buildings representative of a category. The aim is to detect the package of measures that represents the cost-optimal solution for most buildings of the category. The explored retrofit actions include energy measures for the reduction of energy demand, new efficient HVAC systems, renewable energy sources (RESs). Furthermore, SLABE allows to evaluate the effectiveness of current policy of state incentives directed to such actions and to propose possible improvements.
The main limit of SLABE is the impossibility of obtaining detailed indications on the cost-optimal ERMs for each single building, because only global recommendations about the explored category are provided.

ANNs means Artificial Neural Networks, which are surrogate models (or meta-models), commonly used for 'subrogating', i.e., replacing, quite complex functions. The developed methodology answers to question q3, by consisting in the adoption of ANNs for the assessment of primary energy consumption and thermal comfort of each building belonging to a considered category. Two families of ANNs are generated respectively for the existing building stock and for the renovated building stock in presence of ERMs. The ANNs are developed in MATLAB environment, by using EnergyPlus outcomes as targets for training and testing the networks. Finally, the created surrogate models can replace the BPS tools in the evaluation of transient energy performance and, thus, of global cost, of each building of the considered category, both in absence and in presence of ERMs. The benefit consists of a drastic reduction of computational time and complexity. Also the impact of the ERMs on thermal comfort can be investigated, since this latter is set as a further output of the ANNs. This allows the possible coupling between CAMO

and ANNs, which can replace EnergyPlus in the optimization routine. Different families of networks can be generated for covering all the categories of the whole building stock, in such a way that the performance of each building can be assessed with a minimum computational time and a good reliability. In this way, in the proposed macro-methodology such surrogate models take place of the RefBs. Indeed, each building category is no more represented by a reference building but by a family of ANNs.
It is noticed that ANNs are an effective tool, but they are not sufficient for the cost-optimal analysis, since they need to be implemented in another methodologies (e.g., CAMO), in which they can 'subrogate' the traditional BPS tools.

CAMO, SLABE and ANNs can be used either as stand-alone procedures for pursuing the aims summarized, respectively, in the questions q1, q2 and q3 or as stages of the macro-methodology denoted as CASA.
The acronym CASA has a double meaning. On one hand, it expresses the combination among **CA**MO, **S**LABE and **A**NN. On the other hand, it refers to the core of the methodology, that is the Cost-optimal Analysis by multi-objective optimiSation and Artificial Neural Networks. Furthermore, this appellative has a suggestive meaning, since the Italian translation of the word 'casa' is 'house'. In the same way as the different components of a house have different functions but contribute to the ultimate goal, which is the occupants' well-being, so CAMO, SLABE and ANN can be adopted independently for pursuing worthwhile targets, but their combination in CASA allows to reach the ultimate crucial goal. This is represented by a reliable, fast, 'ad hoc' cost-optimal analysis of the retrofit measures for each single building. Therefore, CASA provides a thorough response to question q4, by proposing a multi-stage procedure that can be applied to each building category and, thus, to each building of the

stock. More in detail, by referring to an established category, CASA is articulated in the following stages:

STAGE I. SLABE is implemented to investigate the building category by detecting the parameters (related to existing stock and energy retrofit measures) that most affect energy performance and thermal comfort.

STAGE II. ANNs are developed for assessing thermal comfort, energy consumption, and thus global cost of the buildings that belong to the category. The most influential parameters, identified in stage I, are adopted as Inputs.

STAGE III. CAMO is performed by using the ANNs instead of EnergyPlus in order to find the cost-optimal package of energy efficiency measures for any building of the category.

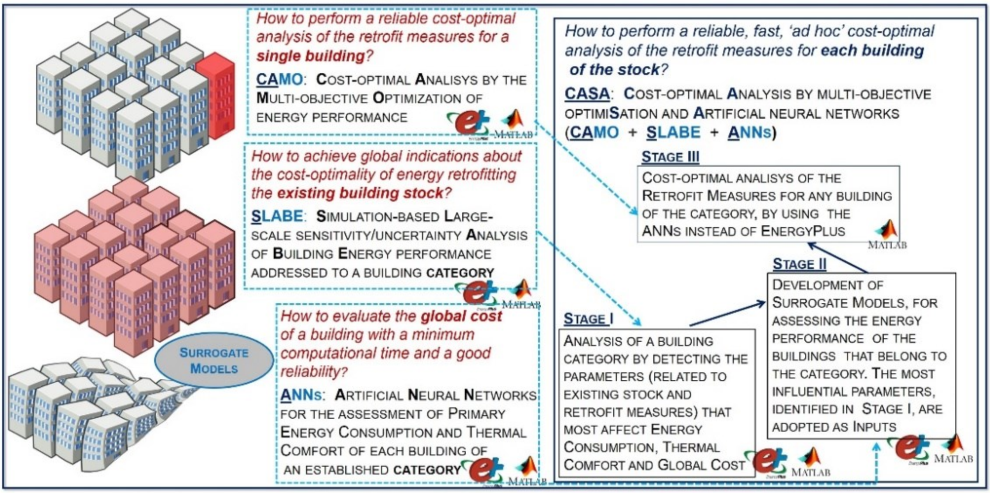

Figure 1.1. Scheme of the proposed methodologies and their coupling for the cost-optimality of building energy retrofitting: from a single building to stock

CASA allows to overcome the main aforementioned limits of CAMO, SLUSABE and ANNs, by providing a powerful tool for a reliable and fast cost-optimal analysis of every building.

1.3. Organization of the thesis

After the present Introduction (*chapter 1*) and before the Conclusions (*chapter 7*), the thesis is articulated in the following *chapters*:

CH. 2. A roadmap for efficient building retrofitting is proposed, by focusing on the state-of-art of scientific literature in such field and on the guidelines of EPBD Recast [7, 8] for identifying cost-optimal ERMs.

CH. 3. The state of art in the field of simulation-base optimization of energy performance is presented. Then, CAMO is detailed, and applied to a residential existing building located in Naples (South Italy).

CH. 4. The state of art related to the implementation of uncertainty and sensitivity analysis in the study of building energy behavior is presented. Then, SLABE is detailed, and applied to a specific category: office buildings built in South Italy in the period 1920-1970. This building category is considered also in the next two *chapters*.

CH. 5. The state of art related to the adoption of surrogate models in the analysis of building energy performance is presented. Then, the ANNs methodology is detailed, and applied to the cited category.

CH. 6. CAMO, SLABE and ANNs are combined inside CASA, which is described in detail, and applied to a building of the cited category.

It’s noted that the description of each methodology is followed by the application to a case-study, which acts as a sort of validation procedure.

"Energy efficiency is the most powerful renewable source"

CHAPTER 2. Roadmap for efficient building energy retrofitting

2.1. Introduction

In recent years, a great effort has been made, at international level, for reducing the energy consumption of buildings. Indeed, the construction sector represents one of the main challenges to deal with in order to guarantee a sustainable development for our sons and, more in general, compatible with a suitable common future.

At the European level, starting from 2002, with the entrance into force of the EPBD (Energy Performance of Building Directive – 2002/91/CE [14]), for the first time in the history, all Member States of an entire continent decided to establish common guidelines for improving the energy performance of buildings, concerning both new and existing architectures. In this regard, at national level, several laws have been formulated for receiving the European mandatory trends, by taking into account the local peculiarities of the building stock, technology and construction activities.

Some years later, the EPBD Recast (2010/31/EU [7]) has been enacted. Really, this was only a further step of a continuous process aimed at reducing, with targets increasingly more ambitious, the impact of human activity on climate change. This Directive introduces the goal of nearly zero-energy buildings (nZEB), by underlining both the high-required performance as well as the economic feasibility of the 'building system', by means of the new concept of cost-optimality. In this respect, the EPBD Recast establishes that the Member States (MSs) have to define local regulations in order to fulfil the standard of nearly zero-energy building:

- starting from January 2021, for all new buildings;
- starting from January 2019, for new buildings owned and/or occupied by public administration and public authorities.

As it is clear, we are talking of a very near future.

Diversely from the net zero-energy building (NZEB), a nZEB has not an established energy performance to satisfy. More in detail, as specified in the EPBD Recast, it is "a building that has a very high energy performance. The nearly zero or very low amount of energy required should be covered to a very significant extent by energy from renewable sources, including energy from renewable sources produced on-site or nearby". However, such definition is quite vague. Globally, a nearly zero-energy building should ensure higher energy performance compared to the cost-optimal configuration of the building.

In spite of the importance of new green and efficient buildings, the energy refurbishment of existing buildings offers much larger opportunities for reducing energy consumption and polluting emissions, as argued in the Introduction of this thesis.

In light of this, the EU guidelines establish that a great attention should be given to the energy retrofit of existing buildings. More in detail, the EPBD Recast and the delegated regulation N. 244/2012 of the European Council [8] introduce the cost-optimal analysis for assessing the most effective packages of energy retrofit measures (ERMs); this procedure is detailed in *section 2.3*, since it is adopted in the next *chapters*.

Furthermore, the EU Directive 2012/27/EU [15], underlines the necessity, for all MSs, to support "a long-term strategy for mobilizing investment in the renovation of the national stock of residential and commercial buildings, both public and private”. In this regard, the Directive promotes “cost-effective approaches to renovations, relevant to the building type and climatic zone” as well as “policies and measures to stimulate cost-effective deep renovations of buildings, including staged deep renovations". Moreover, the same document suggests “an evidence-based estimate of expected energy savings and wider benefits". In this frame, the public role should be exemplary, since “each Member State shall ensure that, as from 1 January 2014, 3% of the total floor area of heated and/or cooled buildings owned and occupied by its central government is renovated each year to meet at least the minimum energy performance requirements”.

A great effort for improving the energy performance of the existing building stock has been made also at international levels. This is shown by the number of Annex projects, developed by the International Energy Agency (IEA) in recent years, for promoting the energy efficiency of existing buildings, such as:

- Annex 46 – Holistic assessment tool kit on energy efficient retrofit measures for government buildings;
- Annex 50 – Prefabricated systems for low energy renovation of residential buildings;
- Annex 55 – Reliability of energy efficient building retrofitting;
- Annex 56 – Energy & greenhouse gas optimized building renovation [16].

These projects provided policy guidance, financial and technical support for the implementation of ERMs. As highlighted by Ma *et al.* [5], building energy retrofitting offers many challenges and opportunities. The substantial challenges, in any sustainable refurbishment project, are due to the presence of several uncertainties, such as climate change, human behavior, state policy, which have a large impact on the project success.

Furthermore, the building is a very complex system, consisting of highly interactive components. Therefore, the evaluation of the effects induced by ERMs on the building behavior is much critical, and the selection of the best retrofit strategy becomes very complex. Indeed a rigorous approach generally requires the solving of a multi-objective optimization problem (see *chapter 3*). On the other hand, the huge opportunities, provided by an efficient energy retrofitting of the existing stock, involve the reduction of pollution, operating cost and maintenance needs as well as increment of thermal comfort and an improvement of national energy security.

2.2. State of art

The scientific community supports the necessity of acting on the existing stock, in order to promote a drastic reduction of energy consumption and green-house gas emissions of the building sector. In this regard, the current literature provides a large number of studies on the huge potentials of building energy refurbishment.

2.2.1. Key elements for an efficient energy retrofit

In an admirable effort, Ma *et al.* [5] proposed a detailed review and analysis of the main methodologies adopted for designing an efficient energy retrofit, thereby identifying some key elements. Figure 2.1, which is taken from the referred-to study, depicts such elements that consist of: policies and regulations, client resources and expectations, building specific information, human factors, retrofit technologies and other uncertainty factors.

Renovation policies and regulations impose the minimum levels of energy performance that should be achieved in case of refurbishment.

Furthermore, they can also offer a financial support, namely incentives, for the implementation of efficient ERMs, as provided, for instance, by the Italian Government [17]. Baek and Park [18] presented an interesting review on the impact of such regulations on the promotion of housing renovation. The most recent public policies addressed to energy retrofit are represented by the EPBD Recast in the EU and by the Standard 189.1 in the US, as summarized in [19].

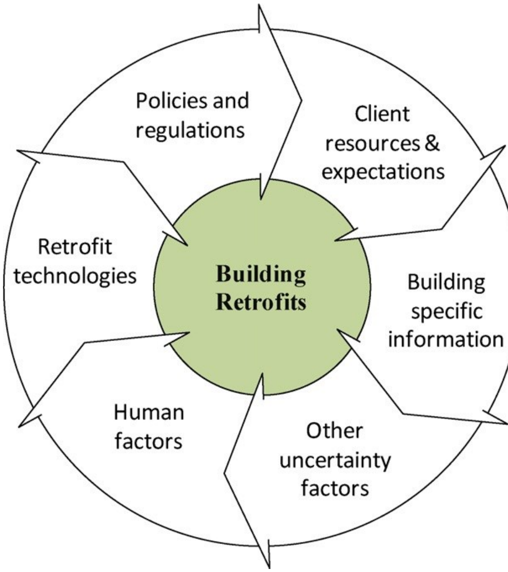

Figure 2.1. Key elements influencing building retrofits. (*from Ma et al. [5]*)

Client resources and expectations define the main goals to pursue by the retrofit project, as well as the available economic budget. Therefore, this element is crucial because it substantially affects objective functions and constraints of the multi-objective optimization problem represented by the finding of the best retrofit strategy.

A further key element for an effective retrofit is the exploitation of building-specific information, such as geographical location, geometry, size, age, intend use, occupancy profiles, operation schedules, energy sources, type of HVAC system and so on. This information should be considered in order to propose the most appropriate ERMs.
Human factors constitute another relevant element for the success of the refurbishment. They involve the occupants' behavior, in terms of comfort needs, activity schedules, and access to controls, thereby implying a deep influence, characterized by a significant uncertainty, on the final outcomes of a retrofit project [20]. Several studies showed that a proper and smart occupants' behavior can produce substantial energy savings, with no or low investment and without penalizing thermal comfort. For instance, Owens and Wilhite [21] demonstrated, for Nordic countries, a saving of domestic energy use until 20%, while Santin *et al.* [22] showed that the impact of people behavior on the energy use for heating is close to 5% in the Netherlands.
The retrofit technologies correspond to the energy retrofit measures (ERMs). They represent renovation actions aimed at the reduction of building primary energy consumption. In their paper, Ma *et al.* [5] proposed a possible classification of the retrofit measures in three categories – depicted in figure 2.2 (taken from the mentioned study) – consisting of:

a) supply side management;
b) demand side management;
c) change of energy consumption patterns.

The category a) includes the implementation of efficient primary heating/ cooling systems as well as of renewable energy sources (RESs), such as thermal solar collectors, photovoltaics (PV) generators, wind turbines, biomass systems, and so on. The purpose is providing the building with innovative and efficient energy supply systems. In recent years, the interest in RESs is more and more increasing, mainly because of the rising concern to environmental issues and of the decreasing investment cost for such systems, also thanks to very favorable national policies of financial support. The use of renewables, above all PV generators, can be particularly effective for office buildings, by virtue of the high electricity demand. This observation is proved in this thesis, by the outcomes proposed in *chapter 4*.

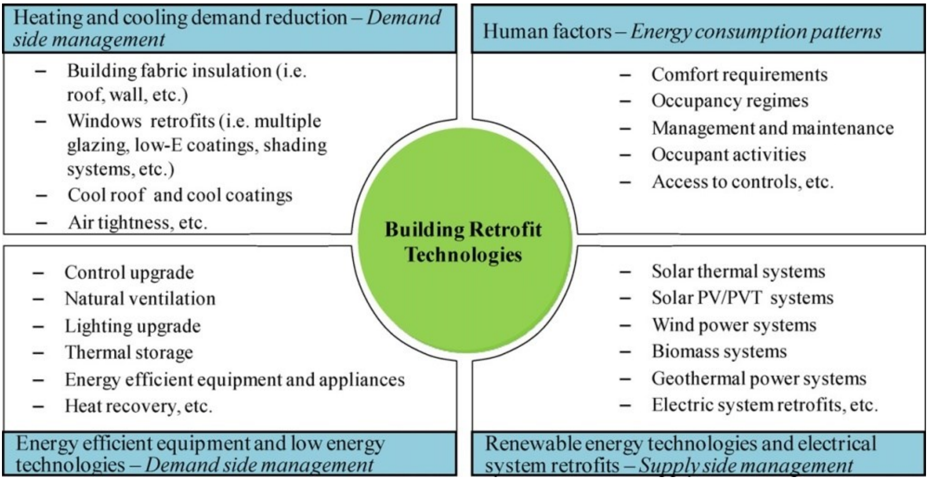

Figure 2.2. Main categories of building retrofit technologies. (*from Ma et al. [5]*)

The category b) (demand side management) collects different energy measures for the reduction of heating and cooling demand, such as the renovation of the building fabric, efficient windows, solar shading systems, natural ventilation, heat recovery, thermal storage systems, and many other efficient technologies.

The category c) (energy consumption patterns) considers the ERMs, generally with no or low investment cost, that point to properly address the human factors. In fact, as aforementioned, a smart and appropriate occupants' behavior can induce high energy savings, until 20%.

A further crucial issue for the success of energy retrofitting strategies concerns the reliable and accurate estimation of the building energy and thermal performance. This is fundamental in order to faithfully assess the impact of the proposed ERMs on energy consumption and thermal comfort, thereby providing all the energy and economic indicators – e.g., saving of energy demand, pay-back period, global cost – required for identifying the best solution. Therefore, simple steady-state methods are inadequate, whereas the recommended choice is the adoption of proper BPS tools that perform reliable dynamic energy simulations. There are several whole building energy simulation programs, such as EnergyPlus, TRNSYS, ESP-r, IDA ICE that provide an accurate investigation of the energy effects induced by the considered retrofit measures. These programs are widely used in the scientific community, because of their high capability. However, the development of whole building energy models is, generally, a complex task, which requires the calibration with experimental data for achieving a robust accuracy. Hence, also other methods can be used for estimating the energy and thermal benefits produced by retrofit measures. In this regard, Richalet *et al.* [23] delineated three approaches for assessing building energy performance, consisting of: the computational-based approach by means of BPS tools, calibrated through data deriving from energy audits; the performance-based approach, founded on exploiting the information coming from building utility bills; the measurement-based approach, founded on in-situ experimental measures. On the same track, Poel *et al.* [24] proposed an overview of the most popular methods and programs for the energy analysis of existing dwellings. Several software and tools are available, thus the best choice, for a specific project, is not trivial and depends on different factors, such as client requirements, required level of accuracy, available time and budget and so on.

2.2.2. Worthy retrofit studies

Ma *et al.* [5] also proposed a detailed review of worthy studies provided by the current scientific literature in the field of building energy retrofitting. Such studies are subdivided in two groups: those focused on residential buildings and those focused on commercial office buildings. This distinction is made because the best ERMs for heterogeneous building types and uses, e.g., dwellings vs offices, generally differ, as also shown in this thesis that investigates two different case-studies related to the mentioned categories: CAMO is applied to a residential building (*chapter 3*), whereas SLABE, ANNs and CASA are tested on office buildings (*chapters 4, 5, 6*). It is noticed that the attention is directed to these two categories because they cover the vast majority of the building stock of any country.

In the following lines, some worthy retrofit studies belonging to the referred-to groups are briefly described. For a deeper overview of the current state-of-art the reader is invited to refer to [5].

Residential buildings

The energy retrofitting of the residential sector assumes a fundamental role, because a large part of the building stock is composed of dwellings. For instance, in Italy there are 13.6 million of buildings, of which 11.7 million (more than 87%) are residential buildings [4]. Furthermore, concerning this category, as shown by Nemry *et al.* [25] at the EU level, the potential reduction of the environmental impact of new buildings can be neglected compared to that of existing ones. Thus, an efficient energy retrofitting policy assumes a huge importance.

Some interesting studies are focused on the investigation of ERMs for the reduction of heating and cooling demand (demand side management). On this track, Cohen *et al.* [26] explored the effectiveness of individual ERMs, thereby concluding that, generally, the insulation of the opaque building envelope is convenient, while the windows replacement isn't, because of the small normalized annual energy saving. However, this conclusion is valid only for heating-dominated climates (e.g., Northern Europe), whereas in presence of cooling-dominated climates (e.g., Mediterranean area) a deeper analysis is required in order to take into account that the issue of overheating in summertime. The selection of retrofit measures, aimed at a good trade-off between heating and cooling needs, is deeply examined in *section 2.2.3*. Stovall *et al.* [27] carried out an experimental analysis for exploring different wall retrofit options, thereby finding that that the external insulant sheathing exercises a high influence in the reduction of the heat transfer through the wall. Nabinger and Persily [28] considered an unoccupied house for exploring the impact different ERMs for improving the building air-tightness on ventilation rates and energy consumption.

Other worthwhile studies are focused on the investigation of ERMs addressed to the supply side management, by the adoption of efficient energy conversion systems and RESs. Hens [29] studied a two-storey house built in 1957, showing that the benefits induced by solar thermal and PV panels are minimal compared to the adoption of higher levels of thermal insulation, energy efficient windows, improved ventilation, and central heating. Goodacre *et al.* [30] performed a cost-benefit analysis of retrofit measures aimed at improving the primary heating and DHW systems in the English housing stock; they highlighted the high influence of uncertainty. Boait *et al.* [31] investigated the installation of domestic ground source heat pumps (GSHPs) in UK dwellings; they showed that the seasonal performance of such efficient system, highly affected by the time constant of the building, was worse compared to that estimated in other European studies.

Recently, Kuusk *et al.* [32] proposed a detailed study on the energy retrofitting of brick apartment buildings in Estonia (cold climate). Most notably, they examined the energy usage of such dwellings by performing simulations for four reference building types, representative of the stock. The outcomes showed that the energy renovation of old apartment buildings can allow to reach the same energy performance requirements as in new apartment buildings. On the same track, Dodoo *et al*. [33] analyzed the retrofit of a four-storey wood-frame apartment to a passive house and Xing *et al*. [34] proposed a hierarchical path towards zero carbon building refurbishment, based on the improvement of the building envelope thermal characteristics, the use of more efficient building equipment, and micro generation.

The last mentioned studies show that the energy retrofit of existing buildings to passive, low, nearly zero-energy buildings is possible in cold climates. Nevertheless, it is much more complicated in warm (cooling-dominated) climates, because contrasting phenomena are generated by the ERMs, as outlined in *section 2.2.3*. Furthermore, in most cases, a similar extreme energy retrofit strategy is not cost-effective, also in heating-dominated climates. That’s why the EPDB Recast has introduced the concept of cost-optimality.

Commercial office buildings

The main peculiarity of office buildings, compared to dwellings, is represented by a higher demand for lighting and various electric uses, as well as by a much larger endogenous heat gain that increases the energy demand for space cooling. Therefore, also in heating-dominated climates, the main components of annual primary energy consumption, i.e., space heating, space cooling, lighting, electric equipment, are more balanced compared to residential buildings, whose consumption is highly affected by space heating. This determines major issues in the design of the refurbishment strategy.

Indeed, as outlined by Rey [35], office building energy retrofitting is influenced by a large number of parameters, thereby implying the necessity of a structured multi-criteria approach, which simultaneously should take into account environmental, sociocultural and economic criteria. In the same vein, Roulet *et al.* [36] developed a multi-criteria rating methodology, denoted as Office Rating MEthodology (ORME), in order to rank retrofit scenarios according to energy demand for heating, cooling and other appliances, environmental impact, indoor comfort and cost. Arup [37] proposed a detailed guide for the refurbishment of existing office buildings, through a six-step plan, consisting of: determining the baseline, establishing goals, reviewing building maintenance, housekeeping and energy purchase strategy, crunching time: establish or demolish, selecting the optimal ERMs and getting started.

The implementation of whole building retrofits for commercial buildings was discussed by Olgyay and Seruto [38] and Fluhrer *et al.* [39], who compared the adopted approach with the typical retrofit approach commonly used by ESCOs, thereby obtaining an increase of energy saving of around 40%. Hestnes and Kofoed [40] investigated ten existing

office buildings, by exploring the impact of different retrofit strategies, including measures addressed to building envelope, HVAC system and lighting. The outcomes confirmed the complexity of designing energy retrofit for the considered building category, since the optimal strategy significantly depends on the very specific building energy characteristics. The effectiveness of multiple ERMs on the energy consumption of office buildings was also examined by Chidiac *et al.* [41]. Dascalaki and Santamouris [42] investigated the potentials of energy saving induced by well-selected ERMs for five office building types in four different European climatic zones. The retrofit measures included the improvement of building envelope, HVAC system, artificial lighting systems, and the integration of passive components for heating and cooling. Cooperman *et al.* [43] argued that the renovation of the building fabric, mainly oriented to the adoption of efficient windows, is a key action for improving the energy performance of commercial buildings. In the same vein, Chow *et al.* [44] showed that an energy conservation up to 40% can be achieved by means of a retrofit strategy directed to the building enclosure, for existing public buildings in China.
However, these outcomes are not valid for any climate. Indeed, for cooling-dominated climates, the improvement of HVAC system efficiency ensures huger potentials of energy savings compared to retrofit measures on the envelope. This is proved in the *chapter* 4 of this thesis.

Barlow and Fiala [45] showed how the application of adaptive thermal comfort theories could play an important role for future refurbishment strategies for existing office buildings.

Finally, different interactive decision support tools have been designed [46-48] for quickly identifying optimal energy retrofit measures in office buildings, on the basis of the trade-off among different performance indicators, such as investment cost, improved building performance, and environmental impacts.

2.2.3. The trade-off between heating and cooling needs

For both reasons of indoor comfort and limitation to the use of energy systems, a new issue, mainly in cooling-dominated climates (as the Mediterranean one), has to be considered. In this regard, a too high level of thermal insulation, as required by the recent regulations, can lead to a substantial increase of the energy demand for cooling in summertime, because of the phenomenon of indoor overheating. Therefore, the proper choice of the envelope thermal resistance should be made contextually to overall evaluations and other parameters, such as the annual energy performance, the thermal capacity of the building thermal envelope, the radiative characteristics of external coatings. Moreover, the potential of indoor free cooling, mainly during nighttime, should be carefully investigated by considering various heat transfer phenomena, and thus the emission to the sky and to the external environment, and/or the nocturnal ventilation, preferably natural in order to avoid the electricity demand of fans. All told, the combined effects of insulation, thermal capacity, radiative behaviors of the surfaces, free cooling, climatic conditions and building use have to be explored. A primary role is played by the building envelope, which has to mitigate the heat transfer between the external environment and the internal one, due to the high external temperatures during the central hours of the day and, above all, due to the solar radiation. This latter highly affects the cooling load, because: a) it is incident on the external surface (and thus rises the sol-air temperature), b) enters into the environment directly through the windows, c) is reflected into the building because of the reflection of the surrounding elements. By means of the selection of proper levels of thermal insulation and thermal capacity of the envelope, appropriate external coatings for optimizing the sol-air temperature (which affects the heat transfer through the opaque structures), window shadings and controls, an effective design of the building shell can give a huge contribution in improving the building thermal performance. Really, when the target is, beyond the thermal comfort, the achievement of low energy buildings from a point of view of the global performance (heating, cooling, lighting and other uses), the best compromise among the aforementioned characteristics should be found out. In this regard, some choices can have contrasting effects, for instance:

- too high levels of thermal insulation, even if surely beneficial during the heating season, can induce phenomena of indoor overheating in summer. Indeed, when solar gains and endogenous loads are significant, low values of the envelope thermal transmittance can deprecate the useful heat losses (heat dissipation), also during the nighttime, so that a common hyper-insulation phenomenon occurs;
- high levels of thermal capacity can provide useful time lags and attenuation of the heat wave transferred between the external and internal environments. Nevertheless, they can also imply a long inertia of the indoor environment for reaching the desired temperatures when the HVAC system is turned on (mainly if with radiant terminals).
- highly reflective coatings, even if suitable for keeping cool the outer building surfaces (by reducing the sol-air temperature), can yield too cold surfaces in wintertime, above all in presence of high values of thermal emissivity that can cause a significant cooling of the building shell, because of the radiative heat transfer with the surrounding environment and the sky (during nighttime).

Of course, the windows exercise a substantial influence on the building energy performance. Indeed, their thermal transmittance highly impacts on the heat transfer phenomena through the envelope. Furthermore, the adoption of different coatings (low emissive, reflective, selective and so on) and/or different shading systems (internal, external, managed by manual operation or based on the incident solar irradiance) greatly affects, in all seasons, the amount of favorable (heating season) or penalizing (cooling season) solar gains.

All told, in presence of temperate/ warm climates, a deep care is fundamental in defining the best solutions for optimizing the behavior of the envelope. Indeed, diversely from the consolidated approach for cold climates, where the main need is the reduction of energy demand for space heating, a different design activity is required in warm climates because of the aforementioned contrasting phenomena. In this regard, a very interesting study was carried out by Kolokotroni *et al*. [49], who investigated the indoor overheating in summertime, by also considering climate projections for the next years. Jenkins *et al*. [50], on the same track, developed a surrogated model, by integrating dynamic energy investigations and probabilistic climate forecasts for the future. Recently, worthwhile studies of Santamouris and Kolokotsa [51, 52] and Santamouris *et al*. [53] discussed the impact of the progressive overheating of urbanized areas on the energy demand and health conditions in civil European buildings. The attention towards the next decades has been evidenced also by Porritt *et al*. [54], who highlighted how the progressive increasing frequency of extreme weather events could affect the indoor comfort in residential buildings of the United Kingdom. The authors showed that measures for managing solar gains and external insulation of the envelope can be effective. On the other

hand, thermal insulation, placed on the internal side, can increase the indoor overheating phenomenon during the warm season.
Really, as evidenced by Ascione *et al*. [55] for various European climates, the right combination of insulation, thermal mass and radiative peculiarities of the external coatings depends on both climate and potentials of summer free cooling by means of ventilation. In this regard, beyond the thermal mass, even new technologies, for instance based on the adoption of phase change materials (PCMs), can be successfully adopted [56], even if the costs have to be carefully evaluated.
In general, two macro-strategies can be identified for reducing the cooling need and improving, at the same time, the thermal comfort during the warm season:

a) the reduction of the heat gains that, instantaneously or shifted, become cooling load;
b) the adoption of techniques for discharging the building envelope and operate a passive cooling of the indoor spaces.

With reference to the point a), the use of solar shadings and their effectiveness [57, 58] as well as the adoption of reflective coatings [55, 59], also by taking into account the interrelation among buildings [60, 61], have been largely studied in recent years by authoritative authors. In particular, Bellia *et al*. [57] investigated the suitability of various kinds of windows' screens, for several climates, while Katunský and Lopušniak [58] analyzed the influence of shading systems on cooling demand and on the phenomenon of indoor overheating in low-energy buildings. About cool colors and cool paints, Ascione *et al*. [55] proposed an index for orienting the choice of solar reflectance and thermal emissivity deepening on winter degree-days and solar irradiance in summertime. Furthermore, Cotana *et al*. [59] evaluated how the albedo of the building envelopes, at urban scale, can contribute in reducing the global warming. Some of the

same authors, in previous works [60, 61], analyzed what happens because of the mutual reflection among buildings.
With reference to the point b), a wide review has been recently proposed by Kamali [62], who discussed the potentiality of PCMs in reducing the cooling load of buildings. Diversely, Inard *et al*. [63] verified the free cooling potential of natural ventilation in low-energy office buildings. Really, free cooling represents a powerful technique for improving the building energy performance in summertime, without penalizing the heating season, as investigated also by Shaviv *et al*. [64] and Cheng and Givoni [65].

Finally, we can conclude that the design of building energy retrofitting is a critical task that requires a multi-objective approach because of the presence of contrasting targets, subject to several constraints, related to building characteristics and economical considerations. The optimal solution is a trade-off among energy related and non-energy related objectives, such as the minimization of energy consumption, thermal discomfort, investment cost, polluting emissions and so on. The EPBD Recast condenses most of these targets in the concept of cost-optimality.

2.3. Cost-optimality

As already mentioned, the EPBD Recast [7] introduces the cost-optimal analysis for detecting the best EEMs to apply to new or existing building "with a view to achieving cost-optimal levels". More in detail, he EU Commission Delegated Regulation n. 244/2012 [8], supplements the Directive, by establishing a "comparative methodology framework for calculating cost-optimal levels of minimum energy performance requirements for buildings and building elements". The cost-optimality is an innovative and powerful concept that ensures the best trade-off between the two distinct perspectives involved in the building world: the collective (state) one, interested in the reduction of energy consumption and polluting emissions, and the private (single building) one, interested in the reduction of economic disbursement.

The cost-optimal analysis should be applied to the design of both new buildings and energy retrofits. In any case, it allows to identify ‘best’ packages of energy efficiency measures (EEMs) that minimize the global cost over the entire lifecycle of a building. The global cost takes into account investment costs, replacement costs and operating costs and should be calculated according to the procedure delineated in the mentioned delegated regulation. More in detail, the cost-optimal analysis requires to compare the global cost (GC) and the primary energy consumption (PEC) in correspondence of different packages of EEMs. Such measures should range from those in compliance with current regulations to those required by nZEBs, thereby including RES systems. The final outcome is a predicted cost-optimal curve that depicts the value of GC (ordinate) in function of PEC (abscissa) for all the investigated combinations of commonly used and advanced EEMs, as shown in figure 2.3. This curve presents a minimum that identifies the cost-optimal package of energy efficiency measures. The part of the curve to the right of the cost-optimality represents solutions that underperform in both environmental and financial aspects. Diversely, the part of the curve to the left identifies low and nearly zero-energy buildings. Finally, the figure shows the distance to the target of nZEBs prescribed by the EPBD Recast for new buildings, starting from 2021.

This kind of analysis cannot be applied to each single building for reasons of computational complexity and, therefore, a set of reference buildings (RefBs) must be defined [8] in order to represent the national stock [66].

This approach has been already proposed in many studies, such as the one of the BPIE for Germany, Poland and Austria [67], but also in recent scientific papers, concerning the design of new buildings [68, 69] or the refurbishment of existing ones [70, 71].

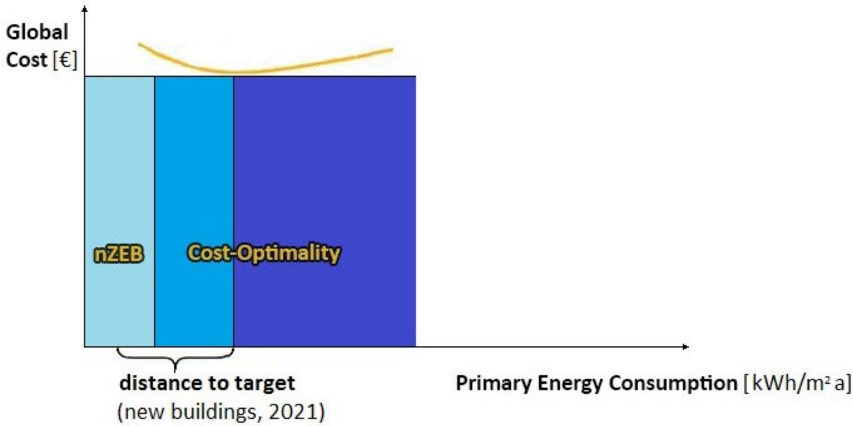

Figure 2.3. Cost-optimal curve

The detection of cost-optimal levels and nZEB solutions is an arduous task, since it requires to explore a huge number of design solutions (combinations of EEMs). Therefore, the adoption of optimization procedures is highly recommended, as shown in the next *chapter*.

How to perform a reliable cost-optimal analysis of the retrofit measures for a single building?

CHAPTER 3. Cost-optimal Analysis by Multi-objective Optimization (CAMO) of building energy performance

3.1. Introduction

The cost-optimal analysis prescribed by the EPBD Recast for the detection of the 'best' energy efficiency measures (EEMs) for new or existing buildings is a complex task. Indeed, how can the cost-optimal technologies be detected? Moreover, how can the most proper packages of EEMs be chosen in order to obtain the cost-optimality? This *chapter* aims to solve such issues, by proposing CAMO, a new methodology for performing the Cost-optimal Analysis by means of the Multi-objective Optimization of energy performance and thermal comfort.

After the coming into force of the EPBD Recast, the scientific community involved in building energy modeling is animated by a new crucial discussion, concerning the modalities for performing the cost-optimal study in order to have rigorous outcomes. Surely, suitable optimization methods, based on energy simulations and aimed at tailored and reliable evaluations of the energy performance of buildings, are a possible solution [72]. The designers often adopt building performance simulation (BPS) tools for analyzing the energy behaviors of buildings, as well as for achieving specific scopes, like – for instance – the reduction of the energy request or the improvement of indoor comfort. In order to improve the energy performance of buildings, one of the first developed approaches has been the ‘parametric simulation method’. This approach makes variable, within a proper range, some design parameters, in order to see their effects on some objective functions, while other variables are constant. Under the point of view of computation, this method is very expensive and not completely reliable because of the non-linear interactions among the design variables. Therefore, starting from the 1990s, numerical optimizations and/or simulation-based optimizations [73] are being adopted more and more frequently, also thanks to the very rapid diffusion of the computer science. A numerical optimization methodology can be defined as an iterative procedure that provides progressive improvements of the solution until the achievement of a sub-optimal configuration (the ‘actual optimal’ is normally unknown) [74-76]. In the last years, many studies focused on the combination of BPS tools and optimization programs, in order to improve the optimization algorithms, above all for reducing the required computational time and CPU resources. Presently, several algorithms are available, typically classified like local or global methods, heuristic or meta-heuristic methods, derivative-based or derivative-free methods, deterministic or stochastic methods, single-objective or multi-objective algorithms and many more. The research community involved in the topic of building energy performance often prefers the use of derivative-free optimization routines [77], because a continuous or differentiable objective function does not exist and the gradient information, even if obtained numerically from the model, is not accurate in many cases. With reference to the derivative-free methods, genetic algorithms (GAs) are the most popular. Indeed, these concern a class of mathematical optimization approaches which reproduce the natural biological evolution, as long as the processes of inheritance, selection, mutation and crossover provide an optimal population after a number of iterations (generations). Genetic algorithms have had a good diffusion in the building simulation community, because these can manage black box functions as those provided by BPS tools. Moreover, these methods have a quite low probability of converging to local minima, without ensuring the optimal solution, but producing a good solution (sub-optimal), close to the optimal one, in a reasonable time. Furthermore, with reference to the building sector, GAs allow multi-objective optimizations that are more appropriate compared to the single-objective ones. Indeed, generally, there are conflicting goals at the same time. Therefore, high performance buildings require a holistic and integrated team approach [6]. Even with well-coordinated researches, it is difficult to find a meeting point that allows the optimal solution for all necessities. Thus, the multi-objective optimization is generally required in building applications. The main purpose is to identify the so-called 'Pareto front', and thus the set of non-dominated solutions. With reference to the building efficiency, in order to avoid too complex problems, the researchers usually define only two objective functions to minimize, such as carbon dioxide equivalent emissions and investment cost [78], carbon dioxide equivalent emissions and life cycle cost [79], energy demand and thermal discomfort [71, 80-83]. In few cases, some studies propose the minimization of three functions, like energy demand, carbon dioxide equivalent emissions, investment cost [84], or energy demand, thermal discomfort and investment cost [85].

CAMO is a new methodology for performing the cost-optimal analysis of EEMs, suitable for the application to new or existing buildings, on which the present thesis is focused. In detail, CAMO provides the multi-objective optimization of energy demand and thermal comfort. The optimization procedure implements a GA and is based on the combination between EnergyPlus and MATLAB. As shown in the following *sections*, after the presentation of the coupling strategy, the methodology is used for assessing the cost-optimal energy retrofitting of an existing building located in the Italian city of Naples (Southern Italy, Mediterranean climate). The correspondent IWEC weather data file (available at [86]) is used in the energy simulations.

It is recalled that CAMO can be adopted either as a stand-alone methodology for the investigation of a single building or as a part (stage III) of the macro-methodology (CASA) proposed in this thesis (see *chapter 6*).

3.2. Methodology

The new approach, based on the multi-objective optimization, is proposed for the evaluation of the cost-optimal solution with reference to the energy refurbishment of existing buildings. Analogously, CAMO is suitable also to be applied to new buildings, by considering RefBs. The method combines EnergyPlus and MATLAB. EnergyPlus has been chosen like BPS tool for two main reasons: a) on one hand, this program allows reliable modeling of both building and HVAC systems, and, secondly, b) it works with text-based inputs and outputs, and these facilitate the interaction with optimization algorithms. According to [73], EnergyPlus is probably the most widely “whole building energy simulation program” [9] used for the research in matter of building optimization. A number of studies testify its reliability in predicting energy performance of buildings and facilities. Obviously, a proper definition of the models and expertise in the assignment of all boundary conditions (starting from the selection of the solution algorithms of the heat transfer) are required. Analogously, with reference to the optimization ‘engine’, MATLAB has been chosen for the following two main reasons: a) the program has a very strong capability, which enables the multi-objective optimization by means of

GAs and, moreover, b) this can automatically launch EnergyPlus as well as manage files of both input and output.

The methodology, fully described in the following paragraphs, like a generic optimization process [73], can be subdivided in three main phases: 1) pre-processing phase, 2) optimization phase and 3) multi-criteria decision making phase.

3.2.1. Pre-processing

The combination of BPS tool and optimization program is here developed and structured, by defining also the formulation of the optimization problem. That phase is very significant, because this concerns the boundaries between building science and mathematical optimization, by requiring a satisfactory expertise in both the fields. Initially, the existing building or the reference building (i.e., in case of new constructions) is defined in EnergyPlus, both with reference to the thermal envelope and the HVAC system, by means of the creation of a text-based format input file (.idf). Then, the parameters that most affect the energy performance are identified like design variables. This selection can be performed after a proper sensitivity analysis [87] or can be derived from a detailed study of the system. However, it requires a satisfactory expertise in matter of energy efficiency in buildings.

The value assumed by each variable corresponds to design decisions and these concern the envelope (e.g., insulation thickness, type of windows), the heating and cooling systems (e.g., kind of heat emitters, boilers, chillers) or the operation (e.g., usage of the building, defined through a set of schedules). Examples of schedules are the set points of indoor temperatures for both heating and cooling or the definition of the hourly profiles of the building occupancy along the year. Some parameters cannot be selected like design variables, because the designer has not a reliable capability in predicting these, even if these can affect greatly the building performance. An example is the active and passive effect deriving from the occupants' behavior.

Then, each selected design variable is parameterized in the aforementioned .idf file, by replacing the current unique value, defined for the base building, with a set of values depending on the designer decisions. In order to ensure a proper coupling between EnergyPlus and MATLAB, the i-th parameter is encoded with a string of n_i bits, and thus this can assume 2^{n_i} different discrete values. For example, if the thickness of vertical wall insulation is identified as design variable and there are four available values, this variable will be encoded with a string of two bits. Thus, a generic configuration of the system, defined by a number of values of the parameters, is represented by a vector $\underline{\mathbf{x}}$ of $\sum_{i=1}^{N} n_i$ bits, where N is the number of design variables. The formulation is reported in the equation (1).

$$\underline{\mathbf{x}} = \Big[\underbrace{x_1, \dots, x_{n_1}}_{\substack{\textit{encoding of the}\\ \textit{first decision}\\ \textit{variable}}}, \dots \dots, \underbrace{x_{(\sum_{i=1}^{N} n_i)-n_N+1}, \dots, x_{\sum_{i=1}^{N} n_i}}_{\substack{\textit{encoding of the}\\ \textit{last decision}\\ \textit{variable}}}\Big] \quad \textit{with} \; x_j = \begin{cases} 0 \\ 1 \end{cases} \; \textit{for} \;\; j = 1, \dots \dots, \sum_{i=1}^{N} n_i \qquad (1)$$

It should be noted that the discrete values, assumable by the chosen parameters, must be selected carefully, depending on energy and economic considerations deriving from an appropriate expertise and this aspect is particularly important. The use of proper discrete variables allows a faster convergence of the optimization algorithm, without affecting the accuracy and the generality of the method. Moreover, the adoption of discrete selections is more realistic, because a limited number of design solutions - depending on the commercial availability - usually characterizes the construction sector.

The aim of the proposed methodology is the finding of the set of the values that the decision variables should assume for optimizing various objective functions. The multi-objective approach has been considered more suitable and relevant compared to the single-objective one, because the building design has to take into consideration, simultaneously, different competitive criteria, such as the energy consumption, the thermal comfort, the investment costs and the emissions of $CO_{2\text{-equivalent}}$ during the building operation. Some of these objectives are conflicting. In this regard, this study will consider both the energy requests for the microclimatic control and the thermal comfort, even if the developed method can be applied to various other objective functions.

In our investigation, the first objective is the minimization of the primary energy required by the air-conditioning system, per unit of conditioned area, indicated with the acronym EP [kWh/m^2a] and calculated through equation (2).

$$EP = EP_h + EP_c \qquad (2)$$

In the equation (2), EP_h and EP_c are the annual primary energy demands for the space heating and cooling respectively, per unit of conditioned area

With reference to the thermal comfort, the criterion of the weighted under- or overheating hours [88] and of the weighted under- or overcooling ones, based on the Fanger theory, is used, because this provides a function that has to be minimized. More in detail, the second objective function concerns the percentage of annual occupied hours characterized by indoor thermal discomfort. In particular, this objective is identified by using the acronym DH [%] and is calculated like in equation (3).

$$DH = \frac{dh}{h} \bullet 100 \qquad (3)$$

In the equation (3), h is the number of the yearly-occupied hours and dh is the number of these hours characterized by thermal discomfort. This last term is given by the occupied hours in which the average Predicted Mean Vote (PMV), in the considered thermal zones of the building, does not fall in the range -0.85÷0.85, and thus the Predicted Percentage of Dissatisfied (PPD) is higher than 20%. This range of acceptation of the PMV has been chosen according to the ASHRAE [89], on the basis of the minimum level of thermal comfort required in a building. However, even more conservative can be used if a higher level of comfort is required (e.g., for particular applications like, for instance, health care facilities).

Furthermore, the initial investment cost (IC) has been adopted as constraint, because the total cost of the proposed solutions has to be respectful of an established budget. Therefore, with reference to each value assumable by a design variable, an initial cost (if present) is assigned and the sum of these costs, for each solution $\underline{\mathbf{x}}$, must comply the budget constraint. This approach finely corresponds to the real building design, quite always characterized by a budget that the actor (designer, owner, constructor) does not want or cannot exceed.

Finally – once defined design variables, objective functions and constraints – the proposed multi-objective programming problem assumes the mathematical formulation proposed in the following scheme.

$$\mathit{min}\ \underline{\mathrm{F}}(\underline{\mathrm{x}}) = [\mathrm{EP}(\underline{\mathrm{x}}), \mathrm{DH}(\underline{\mathrm{x}})]$$

$$\mathit{subject\ to}$$

$$\sum_{i=1}^{N} \mathrm{IC_i}(\underline{\mathrm{x}}) \leq \mathrm{B}$$

$$\underline{\boldsymbol{x}} = \left[\mathrm{x_1}, \dots, \mathrm{x_{n_1}}, \dots \dots, \mathrm{x}_{(\sum_{i=1}^{N} n_i)-n_N+1}, \dots, \mathrm{x}_{\sum_{i=1}^{N} n_i}\right]$$

$$\mathit{with}\ \ \mathrm{x_j} = \begin{cases} 0 \\ 1 \end{cases}\ \ \mathit{for}\ \ \mathrm{j} = 1, \dots \dots, \textstyle\sum_{i=1}^{N} \mathrm{n_i}$$

In the above reported formulation, B is the available budget and IC_i is the initial investment cost associated to the value assumed by the i-th decision variable, that is encoded by a string of bits in the vector $\underline{\mathbf{x}}$.

3.2.2. Optimization

The multi-objective programming problem is solved by means of proper setting and running of the optimization program, which provides the Pareto front. This is a very delicate phase because it affects both reliability and accuracy of results.

Since the optimization algorithm is implemented in MATLAB while the evaluation of the objectives needs the use of EnergyPlus, a communication between these two programs is required. Therefore, a coupling function (shown, schematically, in figure 3.1) has been written in MATLAB environment, in order to convert the vector of encoded decision variables $\underline{\mathbf{x}}$ into an EnergyPlus input file (.idf) and proper also for converting an output file of EnergyPlus (.csv) into the vector of the objectives $\underline{\mathbf{F}}$. In this way, the communication is achieved and the optimization problem can be solved.

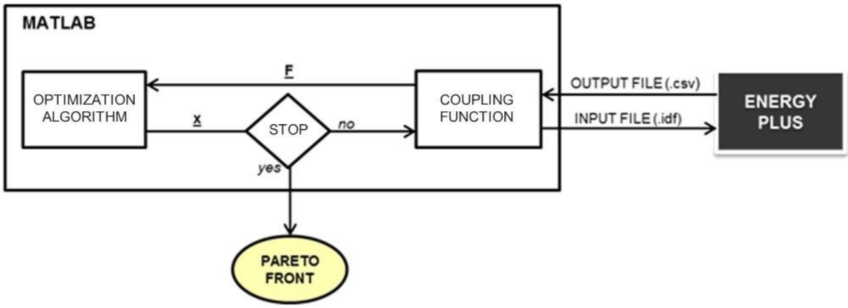

Figure 3.1. Scheme of coupling between MATLAB and EnergyPlus

It should be noted that MATLAB sees EnergyPlus as a generator of black box functions, and thus the gradient information is not available [90]. Thus, the use of heuristic and iterative optimization algorithms is recommended. These methods do not ensure that the true Pareto front will be obtained after a finite number of iterations, even if these allow to achieve a proper sub-optimal Pareto front, with reasonable computational times and required CPU resources. The proposed methodology adopts a controlled elitist genetic algorithm for optimizing the aforementioned objective functions. This algorithm is a variant of NSGA II [91] and, compared to the original, allows a more reliable evaluation of the Pareto front, by ensuring a higher diversity in the population. More in detail, this consists of a stochastic evaluation-based method, based on the iterative evolution of a population of individuals: the so-called chromosomes. These are, with reference to our scopes, the various possible building configurations. Therefore, each chromosome corresponds to a possible building layout and it is encoded by means of a set of values of the vector $\underline{\mathbf{x}}$, whose components are called 'genes'. At each iteration (called 'generation'), the genes of some chromosomes are combined and/or mutated, in order to obtain new chromosomes, characterized by improved values of the objective functions. The procedure goes on as long as 'a stop criterion' is satisfied. The ultimate result is the Pareto front. In particular, the optimization algorithm performs the procedure proposed in the following scheme, where τ denotes the number of generations.

$\tau = 1$
Create the initial population $P^{(1)} \equiv \{ \underline{\mathbf{x}}_i^{(1)} \}_{i=1,\ldots,s}$ of s individuals
Calculate $\underline{\mathbf{F}}(\underline{\mathbf{x}}_i^{(1)})$ for i=1, ...,s
Evaluate the rank value and the average crowding distance for each individual of $P^{(1)}$
DO UNTIL at least one stop criterion is satisfied
  $\tau = \tau + 1$
  Select the parents from $P^{(\tau-1)}$
  Generate $P^{(\tau)} \equiv \{ \underline{\mathbf{x}}_i^{(\tau)} \}_{i=1,\ldots,s}$ from crossover and mutation of the parents: elite parents survive
  Calculate $\underline{\mathbf{F}}(\underline{\mathbf{x}}_i^{(\tau)})$ for i=1, ...,s
  Evaluate the rank value and the average crowding distance for each individual of $P^{(\tau)}$
END
Return the Pareto front

A creation function randomly generates an initial population of s individuals, by fulfilling the budget constraint. Then, with reference to each individual, the objective functions are evaluated. A non-dominated ranking, based on the values assumed by the objectives, and a mean crowding distance is assigned to each individual. An individual has a lower ranking than another one if the first dominates the second. In addition, the crowding distance of an individual is a measure of how much this is distant from another one in the space of the objective functions (phenotype): the higher the distance, the higher the diversity in the population. Some individuals, called 'parents', are chosen within the population by applying a binary tournament selection that uses the low ranking number as first criterion and the high crowding distance as second one. In this way, the diversity of the population is guaranteed. The next generation of individuals is composed by the best parents, that form the so-called 'elite', and by the 'children', that derive in part from the crossover and in part from the mutation of the parents. The composition of the new generation is function of the values of the elite count (c_e), that is the number of surviving parents, and of the crossover fraction (f_c), that is the fraction of the population created by means of the crossover. In particular, a crossover function has been written in order to allow that each child randomly inherits some design variables (i.e., some strings of bits) from one parent and the other ones from the second parent. In addition, a mutation function has been written for obtaining a mutated child from a random parent, by changing each bit with a mutation probability f_m. It should be noted that the mentioned functions are defined in order to assure that the offspring respects the budget constraint (which is included in such functions). The 'Darwinian' evolution of the population goes on as long as at least one of the following 'stop criteria' is satisfied:

- the maximum number of generations (g_{max}) is reached;
- the average change in the spread of the Pareto front is lower than the tolerance tol.

In the present study, the discussed control parameters of the GA are set as shown in table 3.1. These values have been chosen on the basis of the expertise of the authors, previous authoritative studies [92, 93] and according to some tests carried out for obtaining the best trade-off between the computational time and reliability of the Pareto front.

Table 3.1. Setting of the control parameters of the Genetic Algorithm

s	c_e	f_c	f_m	g_{max}	tol
25	2	0.6	0.1	30	0.001

The optimization procedure is implemented for n_b different values of the available budget B. As previously said, this is the constraint concerning the maximum investment cost of the sum of the EEMs represented by the design variables. In this way, for each one of the n_b budgets, the Pareto front is defined, and this is the set of the optimal packages of solutions. This approach ensures clearer and more easily-interpretable results and this requires lower computational effort and time compared to a method with three objective functions, where the third criterion is the investment cost [84, 85]. Moreover, the defined method can support the cost-optimal analysis, introduced in the EPBD Recast, by providing a tool very suitable for finding out ‘optimal’ packages of EEMs, without operating by means of an empirical approach.

3.2.3. Multi-criteria decision making (MCDM)

In the next step, the Pareto fronts have to be analyzed and interpreted in order to select a solution, and thus the set of values that the design variables should assume for satisfying all stakeholders. In our case, this phase concerns the definition of the cost-optimal solution.

More in detail, for each of the n_b Pareto fronts obtained by means of the optimization phase, a recommended solution is identified. This process is known as ‘multi-criteria decision-making’ and can be carried out by recurring to different techniques [73]. In this study, two of these techniques are used and compared: a) the so-called ‘utopia point criterion’ and b) the ‘minimum comfort level criterion’. Moreover, even other techniques could be easily implemented in the proposed methodology. In the first case, the ‘best’ set of design variables is the closest, in the phenotype, to the ideal point that minimizes both objective functions: this method is frequently adopted [73] in engineering applications, because it gives an equal 'weight' to all objectives. In the second case, a maximum value of admitted discomfort (DH) is fixed and the 'best' solution is the one that satisfies this constraint and minimizes the energy demand (EP). This second method seems very suitable for building applications, because a minimum level of comfort is usually required.

As said, n_b sets of design variables are achieved and these consist of the recommended packages of EEMs for the n_b budgets. Moreover, with reference to each package – representative of a certain budget –, the global cost for the entire lifecycle of the building is calculated, according to the aforementioned Regulation, published after the EPBD Recast (see *section 2.3*). According to the indications provided for residential buildings, a calculation period of 30 years is used. The package characterized by the lowest value of the global cost identifies the cost-optimal solution.

Definitively, the proposed procedure allows the identification of the most proper budget and shows the 'best' way (i.e., the cost-optimal package) for investing this, by using firstly the utopia point and then the comfort criterion for the decision-making. However, once identified the best budget as previously explained, the designer could also use another criterion in order to select the desired solution (package) from the Pareto front concerning that budget.

In order to show an example, the developed methodology for the cost-optimal evaluation is applied to a case study analyzed in the next *section*. Moreover, the authors would underline that the proposed approach is useful also when the scope is not the cost-optimal analysis, but the optimization of energy performance and thermal comfort of new or existing buildings, in presence – as commonly happens – of a budget constraint. In this case, the optimization procedure is performed only for the identified budget and the specific Pareto front is determined. Then, the designer can select a point of the front (that is a package of EEMs), by recurring to the desired criterion.

3.3. Application

3.3.1. Presentation of the case study

Before the description of the case study, some lines are necessary to explain our choices. The European countries of the eastern, central and southern areas, in the period between the end of the Second World War and the first energy laws enacted after the Kippur crisis, extensively recurred to lightweight building technologies based on the use of reinforced concrete like structural frames (figure 3.2).

Figure 3.2. Italian building stock per construction period and European examples of building technologies based on reinforced concrete

These architectures are not equipped with thermal insulation, and this concerns the large part of the present building stock, and thus these buildings are characterized by quite high energy demands, above all for the space heating in wintertime. With reference to the case study here proposed, the considered building geometry (figure 3.3) is very similar to those represented in figure 3.2. Indeed, the model has been designed in order to be expressive of the aforementioned building stock.

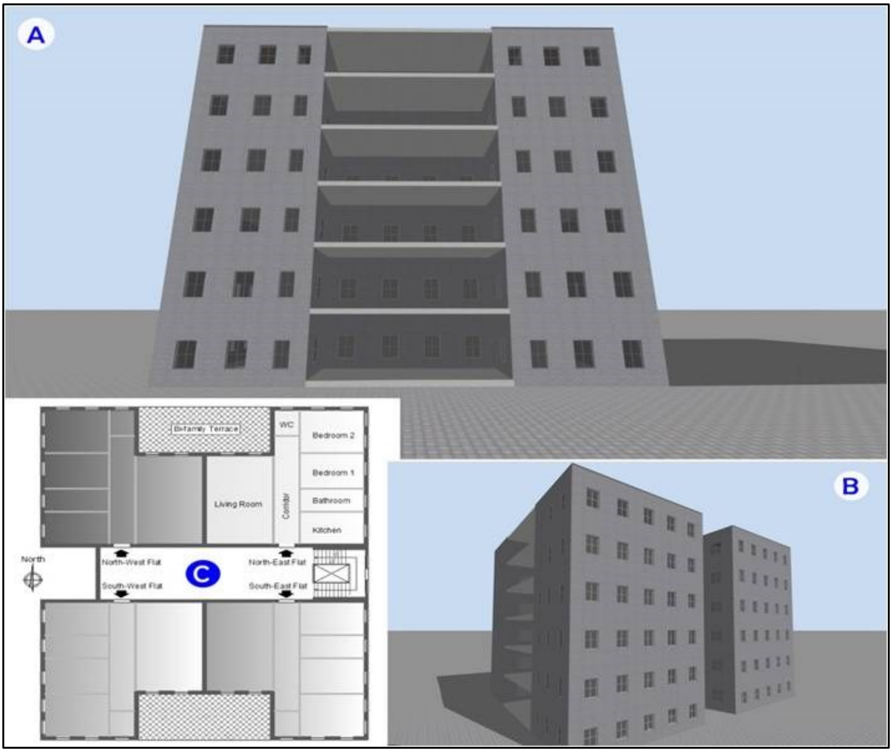

Figure 3.3. The modeled residential building: a) prospectus b) axonometric c) floor plan

The building is supposed to be located in the Italian city of Naples. The building is used for apartments and has an overall length, width and height respectively equal to 24.8 m (north-south façade), 23.7 m (east-west façade), 22.8 m (overall height). The entire architecture has six floors, with four apartments at each one (i.e., 24 dwellings), each one of 110 m^2. Two contiguous flats have a common balcony. As previously said, the structural frame is made in reinforced concrete, with vertical walls in hollow blocks (U_v = 1.4 W/m^2K) and mixed 'hollow brick-reinforced concrete' ceilings and roofs (U_r = 1.5 W/m^2K). The windows have single glasses, equipped with aluminium frames (U_w = 5.8 W/m^2K).

All flats have been parted in an appropriate number of rooms, each one equipped with a four-pipe fan-coil. The single apartment has two exposures, being located at a building corner. The active system for the microclimatic control supplies to the fan-coils:

- hot water (45 °C, ΔT = -5 °C between supply and return pipes) in the heating season,
- chilled water (7 °C, ΔT = 5 °C) during the cooling season.

The heat and cold generations are guaranteed respectively by means of a hot water boiler (low calorific value efficiency, η = 0.85) and an air-cooled chiller (energy efficiency ratio, EER = 3.5). The inner height of the single apartment is 3.3 m, the gross one is 3.8 m. All indoor spaces are conditioned, and thus also the staircase. The global net conditioned area is 3262 m^2, the gross heated volume is 12396 m^3.

EnergyPlus has been used for the creation of the model, firstly for the definition of geometry and thermal zones, by means of the third-party interface DesignBuilder [94], and then for the modeling of thermo-physical properties of the building envelope, for the assignment of the schedules of occupancy, lighting, set-point temperatures and, obviously, for the entire modeling of the HVAC system.

The building, in the starting configuration and thus before the energy retrofit, is characterized by the following values of the objective functions (note that the subscript BB means ‘base building’).

EP_{BB} = 139 kWh/m^{2}a DH_{BB} = 34%

Then, the methodology previously presented has been applied and described in the next lines of this *chapter*, in order to identify the cost-optimal solution, in case of an energy-oriented refurbishment. After a preliminary study of the existing building and of the possible ERMs, the following measures of energy refurbishment have been taken into account in the optimization study, because these are the ones that affect, more than the others, the energy performance of the building:

- Installation of a new external coating of the roof, by changing the radiative characteristics, in order to reduce the heat gains.
- Installation of external insulation of the roof, by means of installation of rockwool panels.
- Installation of external insulation of the vertical envelope, by means of expanded polystyrene (EPS).
- Installation of a mechanical ventilation system, for achieving a free cooling when the temperature of the ambient air is lower compared to the indoor. The system starts when, in the cooling season, there is a minimum temperature difference between indoor air and ambient air, equal to 2°C. Note that the adjective ‘free’ intends that the system is not equipped with a chiller, and thus the energy consumption concerns the mere fans.
- Variation of the set points of indoor temperature, during both the heating and cooling seasons.
- Replacement of the single glazed windows with systems equipped with low-emissive double glasses.

- Replacement of the present standard boiler with a condensing one (η = 1.05).
- Replacement of the air-cooled chiller with a water-cooled one (COP = 5.0), with the consequent installation of a well-sized cooling tower.

The design choices comply with the local construction standards. Therefore, the following design variables (please, note that the number is in the order of 10, as recommended by Wetter [95]) have been identified:

- absorption coefficient of solar radiation of the roof (a). Note that the thermal emissivity is commonly quite high for all construction materials, with the exception of metallic ones;
- thickness of the roof insulation (t_r);
- thickness of the insulation of vertical walls (t_v);
- free cooling by means the new mechanical ventilation system: yes/ no;
- set point temperature of indoor air during the heating season (T_{heat});
- set point temperature of indoor air during the cooling season (T_{cool});
- window: single/double glazed;
- boiler: old standard / condensing one;
- chiller: air- or water-cooled.

The values assumable by each variable and the investment costs (if present) associated with these values are reported in table 3.2, where the configuration of the base building is also shown. The values of the investment costs have been obtained through quotations from suppliers and according to the typical Italian market.
It is worthy to note that the number of energy simulations with EnergyPlus, required for investigating all possible building configurations, would be 16384, while the optimization procedure takes a maximum of 750

simulations, with a consequent saving of 95.5% of the computational time.

In order to achieve the cost-optimal solution, since the maximum total investment cost of the retrofit actions is 583573 €, the optimization study has been performed for the following six budgets: 100000 €, 200000 €, 300000 €, 400000 €, 500000 €, 600000 € (n_b = 6).

Table 3.2. Option values and investment cost (IC) of the design variables

DESIGN VARIABLES	OPTION VALUES	BASE BUILDING	IC [€]
a	0.05		31938
	0.30		31938
	0.70	●	-
	0.95		31938
t_r	0 cm	●	-
	3 cm		11023
	6 cm		16886
	9 cm		22750
t_v	0 cm	●	-
	3 cm		152911
	6 cm		174533
	9 cm		196155
free cooling	no	●	-
	Yes		30112
T_{heat}	19°C		-
	20 °C	●	-
	21 °C		-
	22 °C		-
T_{cool}	24 °C		-
	25 °C		-
	26 °C	●	-
	27 °C		-
window type	single glazed (U_w = 5.8 W/m²K)	●	-
	double glazed low-e (U_w = 1.9 W/m²K)		209711
boiler type	old	●	-
	condensing		32982
chiller type	air-cooled	●	-
	water-cooled		59925

Please note that, as known, the energy efficiency of a building can be achieved by means of: a) a proper design of the thermal envelope, b) efficient systems and equipment for the microclimatic control (equipped with suitable thermal generation devices for both heating and cooling) and c) by means of a proper energy conversion in-situ by renewable energy sources. For an existing building, the third strategy, and thus the installation of renewable energy systems, is postponed to the refurbishment of building envelope and of the heating/cooling system. Indeed, the use of renewable would be a way for compensating, by means of a clean energy conversion, the high energy demand of the present building, without solving the waste of energy due to the poor performance of the building itself. On the other hand, applied to refurbished architectures, the clean energy conversion from renewables could be used for other scopes, such as the indoor lighting or the functioning of electrical devices. Therefore, in the present case study, the attention has been focused on the renovation of the envelope and the HVAC system, being these a priority also because of the effect on the thermal comfort. In any case, a following optimization of the installable renewables is recommended. The methodology here proposed can be used also for this scope

3.3.2. Results and discussion

Figure 3.4 shows the Pareto fronts obtained for the six aforementioned budgets. Here, the 'best' solution, with reference to each budget and using the utopia point criterion, is highlighted by means of a bigger black marker. The values assumed by the design variables in correspondence of these best packages and the relative investment costs are listed in table 3.3, where the packages are respectively indicated with the symbols B1, B2, B3, B4, B5, B6 (from the lowest to the highest budget).

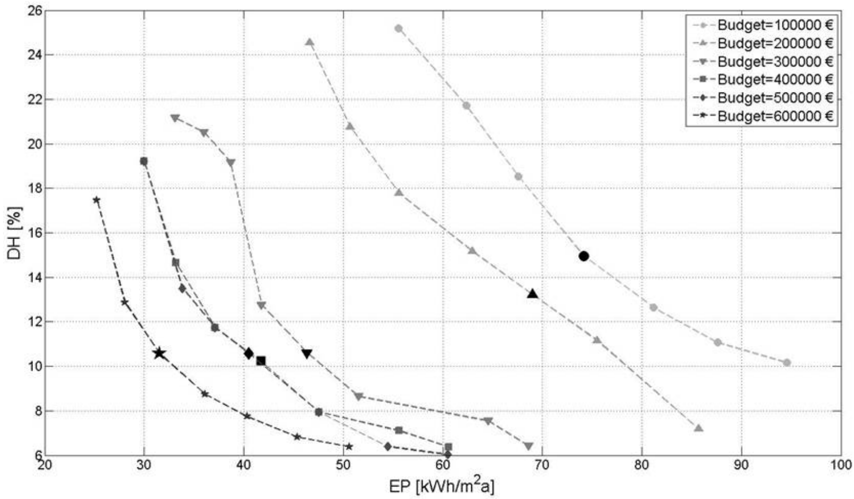

Figure 3.4. Pareto fronts for the six budgets: the recommended packages using the utopia point criterion are highlighted through bigger black markers

Table 3.3. Design variables and investment costs (IC) for the recommended packages related to the six budgets according to the utopia point criterion

PACKAGES	**BUDGETS** 100 k€ **B1**	200 k€ **B2**	300 k€ **B3**	400 k€ **B4**	500 k€ **B5**	600 k€ **B6**
a	0.7	0.05	0.7	0.05	0.7	0.05
t_r	9 cm	9 cm	9 cm	9 cm	9 cm	9 cm
t_v	0 cm	0 cm	3 cm	9 cm	6 cm	9 cm
free cooling	yes	yes	yes	yes	yes	yes
T_{heat}	20°C	21°C	19°C	19°C	19°C	19°C
T_{cool}	25°C	25°C	24°C	24°C	25°C	25°C
windows	single glazed	single glazed	single glazed	single glazed	double glazed	double glazed
boiler	condensing	condensing	condensing	condensing	condensing	condensing
chiller	air-cooled	water-cooled	water-cooled	water-cooled	air-cooled	water-cooled
IC	85844 €	177707 €	298680 €	373862 €	470088 €	583573 €

It is well evident that all solutions (i.e., each point of the Pareto fronts) determine a significant improvement compared to the base building (EP_{BB}=139 kWh/m^{2}a, DH_{BB}=34%). This underlines that the behavior of the present building is unacceptable from both the point of views of energy demand and thermal comfort.

Furthermore, figure 3.4 and table 3.3 show that the proposed optimization procedure permits original and relevant remarks, by allowing the definition of a ranking of the retrofit energy measures based on the intervention priority. In other words, the ERMs that more influence the objectives have a higher priority and a lower ranking.

As the budgets increase, the fronts obviously move left, and thus the reliability of the optimization algorithm is confirmed. In detail, the most significant shift occurs in the transition from 200000 € to 300000 €, which corresponds to the introduction of the thermal insulation for the vertical opaque walls. This measure highly influences both EP and DH.

The recommended solutions for the six budgets, summarized in table 3.3, are deeply analyzed in the following lines. In correspondence of all these solutions, three energy efficiency measures are always applied, and thus the maximum insulation of the roof, the replacement of the boiler and the introduction of the mechanical ventilation system. Therefore, these ERMs have the lowest ranking, that means the highest priority. Hereafter, the package of these three actions will be denoted with the adjective ‘basic’, exactly because this is always present. In particular, B1 is characterized by the application of the mere basic package, while in correspondence of B2 also the water-cooled chiller and the low-a coating of the roof are implemented. The low-a coating induces an increase of T_{heat}, since the mean radiant temperature of the roof decreases. The vertical insulation is not yet introduced, although this action, as aforementioned, highly affects both objectives, with an investment cost lower than 200000 €. This means that the basic package has the priority, and the application of this annuls the economic possibility of applying also the wall thermal insulation. Diversely, if the budget admits an investment of around 300000 € or more, the vertical insulation is always chosen, being possible, according to the economic capacity, its adoption together with the basic package. The vertical insulation produces a reduction of T_{heat} and an increment of T_{cool}, since this has an effect of increase of the mean radiant temperature of the inner surfaces of the vertical opaque envelope. In this way, the vertical insulation has a strong influence on the thermal comfort, as shown in figure 3.5, where the trend of the recommended solutions is depicted by means of a cubic polynomial fitting. It is evident that, after the introduction of the vertical insulation (starting from B3), the values of DH undergo small variations, and thus these tend to a horizontal asymptote.

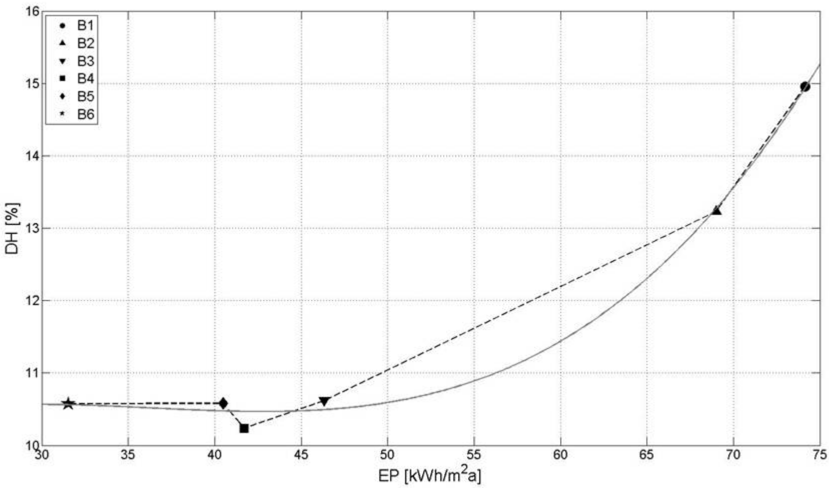

Figure 3.5. Trend of the recommended solutions according to the utopia point criterion by means of cubic polynomial fitting

Again, with reference to the recommended packages, the difference between B3 and B4 is merely the adoption of the low-a coating of the roof and the increased thickness of the vertical insulation, allowed because of the increment in the money availability. The installation of new windows with double and low-emissive glasses concerns only B5 and B6. Surely, this induces lower thermal losses in winter and thus an increment of the mean radiant temperature, by allowing a reduction of T_{heat}. In summer, contrasting effects happen. Indeed, the new glazed systems reduce the entering solar radiation, even if also the thermal losses from the indoor environment to the external one, in some hours (mainly in the intermediate seasons), are lowered. Definitively, T_{cool} is improved (i.e., higher) compared to B3 and B4, even if it is at the same value of B1 and B2. This retrofit measure has a lower priority compared to both the basic package and vertical insulation, and, thus this is adopted only for high economic availabilities. Moreover, B5 contemplates double glasses without replacing the air-cooled chiller. Thus, the replacement of the windows seems to have a higher priority compared to the adoption of a new water-cooled chiller. The Pareto fronts for the budgets 400000 € and 500000 € are almost overlapped, and thus we could conclude that, under these boundary conditions (e.g. kind of building, climate, etc.), the replacements of chiller and windows have the same ranking with regards to the considered objective functions, even if the first action is more advantageous in a mere economic perspective.

Generally, under an economic point of view, the Pareto front at 500000 € is worse than the one at 400000 €, and thus it could be excluded, 'a priori', from the cost-optimal analysis. Moreover, it can be observed that, for B5, the thickness of the vertical insulation is set to the value of 6 cm, even if also the value of 9 cm is economically feasible. This could appear strange but, actually, it is a relevant proof of the reliability of the methodology.

Indeed, a higher thickness of the insulation would induce an increment of EP, caused by a higher energy demand for the space cooling in summer, because of the occurring of an indoor overheating phenomenon induced by the hyper-insulation effect. About it, the air-cooled chiller does not mitigate this negative impact. Finally, in this case, an increment of the investment cost would determine a negative increment of the energy demand. Diversely, for the other budgets, the maximum thickness of vertical insulation is profitable. Indeed, the water-cooled chiller is adopted and thus the energy demand during the cooling season has an effect on the EP lower compared to the energy demand for the space heating. Moreover, it is noted that the external coating of the roof, with a low-absorption coefficient, is implemented only if part of the budget is still available. It means that this energy efficiency measure has the lowest priority. All told, the following ranking of the above-described retrofit actions has been achieved:

1. basic package, and thus combination of external insulation of the roof, replacement of the boiler with a condensing one and installation of a mechanical ventilation system;
2. installation of external insulation of the vertical envelope;
3. replacement of the air-cooled chiller with a water-cooled chiller; replacement of the single glazed windows with new system equipped with double glasses, low-emissive;
4. installation of a new low-a coating (i.e., high-reflective) for the roof.

Finally, the designer should select the retrofit actions, depending on the available budget, according to the shown priority.

After the optimization study above-reported in matter of energy performance and thermal comfort, a further economic analysis is necessary in order to detect the cost-optimal package and thus ‘the best budget' that should be invested. Therefore, the global cost is calculated for the solutions listed in table 3.3 and with reference to the base building, in both cases of absence of incentives and in presence of a capital grant (e.g., funding measures of the Governments according to policies of sustainability), which covers the 50% of investment costs, as shown in figure 3.6. The considered time is 30 years, as indicated in [7] for residential applications.

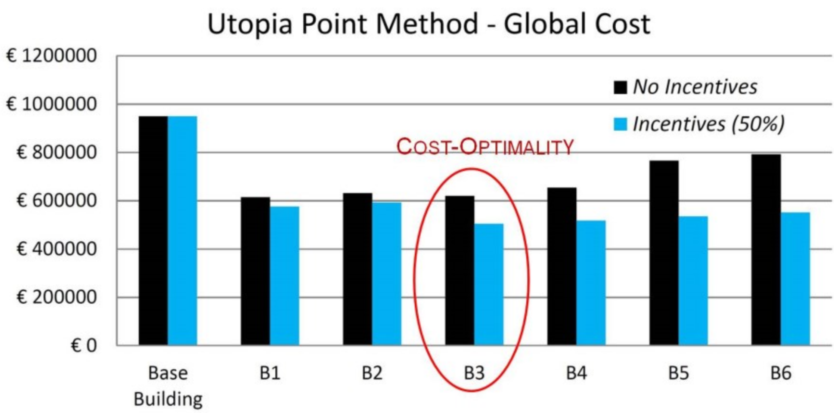

Figure 3.6. Global costs of the recommended packages according to the utopia point criterion in absence of incentives and in presence of a capital grant that covers 50% of investment costs

If incentives are not available, the cost-optimal packages are B1 and B3. These allow an economic saving of about 330000 € compared to the base building. In presence of an economic funding equal to 50% of the investment costs, the best solution is clearly B3, with a saving of about 445000 €. As predicted, the solution B5 is worse than B4 under the point of view of the cost-optimality.

In the next study, the post-processing phase is performed by adopting the comfort method for the multi-criteria decision-making. In particular, the maximum acceptable value of percentage discomfort hours (DH_{max}) is set at 10%. Really, depending on the required level of thermal comfort (related to the building use), the methodology here proposed allows the choice of the most proper level of comfort. Figure 3.7 and table 3.4 show the recommended packages according to this different criterion of choice. These are indicated with the symbols B1’, B2’, B3’, B4’, B5’, B6’. The results are similar to those obtained by, using the utopia point method, with some exceptions. First of all, it is noted that the budget 100000 € does not provide acceptable solutions. This is a relevant result, showing that a high level of thermal comfort requires a certain initial investment.

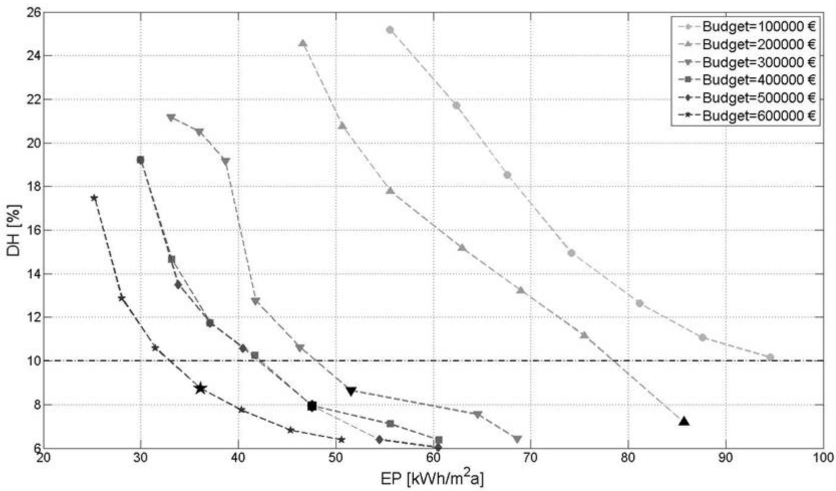

Figure 3.7. Pareto fronts for the six budgets: the recommended solutions using the comfort criterion (DH_{max}= 10%) are highlighted through bigger black markers

Table 3.4. Design variables and investments costs (IC) or the recommended packages according to the comfort criterion (DH_{max}= 10%)

PACKAGES	BUDGETS 100 k€ B1'	200 k€ B2'	300 k€ B3'	400 k€ B4'	500 k€ B5'	600 k€ B6'
a		0.7	0.7	0.05	0.05	0.05
t_r		6 cm	9 cm	9 cm	9 cm	9 cm
t_v		3 cm	3 cm	9 cm	9 cm	9 cm
free cooling		yes	yes	yes	yes	yes
T_{heat}		22°C	20°C	20°C	20°C	20°C
T_{cool}		24°C	24°C	24°C	24°C	24°C
windows		single glazed	single glazed	single glazed	single glazed	double glazed
boiler		old	condensing	condensing	condensing	condensing
chiller		air-cooled	water-cooled	water-cooled	water-cooled	water-cooled
IC		199909 €	298680 €	373862 €	373862 €	583573 €

Furthermore, as expected, in order to satisfy the comfort requirement, higher values of T_{heat} and lower values of T_{cool} are needed. In correspondence of B2', the vertical insulation is preferred to the replacement of the boiler, since this affects the mean radiant temperature, and thus the comfort, as previously demonstrated. The recommended packages for 300000 €, 400000 € and 600000 € (and thus B3', B4', B6', respectively) are the same achieved by using the utopia point method (B3, B4, B6), with the exception of the set point temperatures. Diversely, B5' doesn't match B5 but is equal to B4', because the minimum thermal comfort criterion makes the replacement of the chiller more suitable compared to the replacement of the windows.

Finally, the ranking of the ERMs, in this second study that adopts the comfort criterion, is the following one:

1. installation of external insulation of the roof;
   installation of external insulation of the vertical envelope;
   installation of a mechanical ventilation system;

2. replacement of the hot water boiler with a condensing one; replacement of the air-cooled chiller with a water-cooled chiller;
3. replacement of the single glazed windows with new system equipped with double glasses, low-emissive;
   installation of a new low-a coating (i.e., high-reflective) for the roof.

Therefore, the utopia point criterion favors the replacement of the boiler in order to obtain a greater reduction of EP, while, diversely, the comfort criterion prefers the insulation of the envelope for achieving a relevant reduction of DH.

Now, the global cost is calculated also for the solutions listed in table 3.4, in both cases of absence of incentives and achievement of a capital grant that covers 50% of the investment costs. The histograms are reported in figure 3.8. The cost-optimal package, in both cases of absence and presence of incentives, is B3'. This allows respectively an economic saving of about 310000 € and 413000 € compared to the base building. The designer can choose the utopia point or the comfort criterion for the decision-making, depending on the need to assign the same importance for EP and DH or, diversely, to obtain a certain level of thermal comfort.
However, in both cases, the proposed methodology allows the evaluation of actual cost-optimal solutions, by ensuring, at the same time, that a thermal comfort criterion is satisfied. This is one of the original aspects of this study. Indeed, standard approaches for the cost-optimal analysis contemplate the thermal comfort only in a generic way. Moreover, these assume that the packages of energy measures are chosen empirically, by trial, and thus the entire domain of possible solutions is not exhaustively investigated. Consequently, a reliable cost-optimality is not guaranteed.

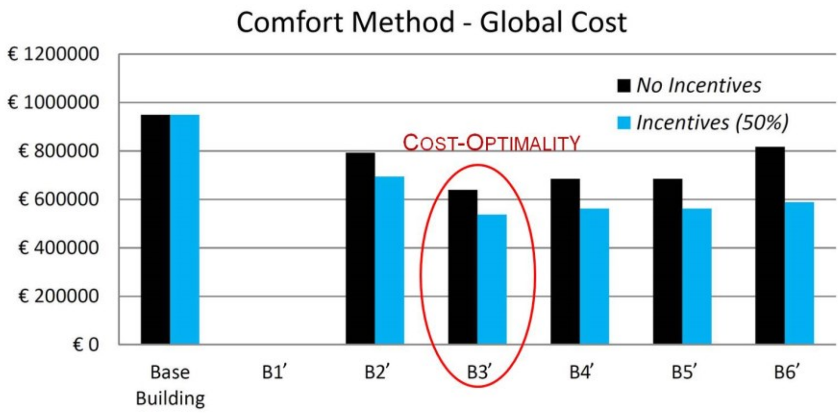

Figure 3.8. Global costs of the recommended packages according to the comfort criterion (DH_{max}= 10%) in absence of incentives and in presence of a capital grant that covers 50% of investment costs

Again with reference to the proposed case study, it can be observed that both methods for the multi-criteria decision-making provide the same cost-optimal package, with the exception of the set point temperature during the space heating. This cost-optimal package corresponds to the budget of 300000 €, which can be thus defined as the 'cost-optimal budget'. This is a very relevant result, which shows that, in this case, the methods provide equivalent information about the individuation of the best solutions for the following cost-optimal analysis. Moreover, it should be noted that the cost-optimal budget is the one that, by increasing the money availability of the same amount (increment of 100000 €), produces the highest left shift of the Pareto front compared to the previous one (see figures 3.4 and 3.7). This is justified by the strong correlation between the reduction of EP and the cost-optimality.

Two different points (namely B3 and B3') of the Pareto front of the budget 300000 € identify the cost-optimal solutions, obtained by means of the application of the two methods. After the evaluation of the cost-optimal budget and the relative Pareto front, the designer can analyze the different solutions on the front and then he can choose according to his own needs and purposes. About it, eight solutions, identified with the numbers from 1 to 8, are available, as shown in figure 3.9 and table 3.5.

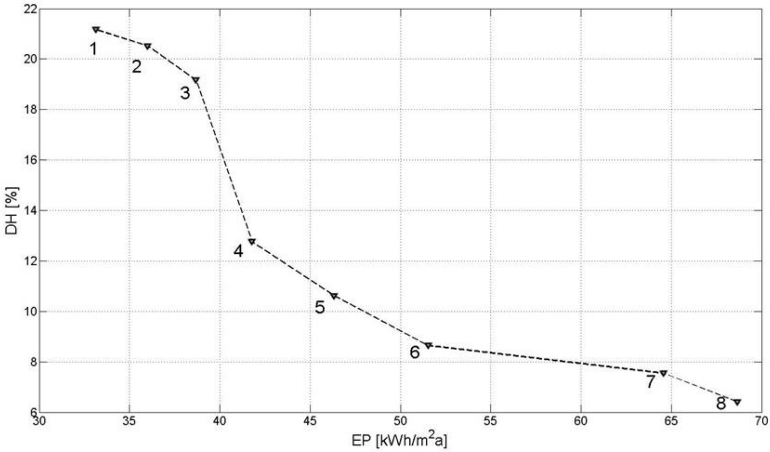

Figure 3.9. Pareto front in correspondence of the cost-optimal budget (300 k€)

Table 3.5. Design variables and investments costs for the points on the Pareto front relative to the cost-optimal budget (300000 €)

	Points on the Pareto front relative to the budget of 300000 €							
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
a	0.7	0.7	0.7	0.7	0.7	0.7	0.05	0.05
t_r	9 cm	9 cm	9 cm	9 cm	9 cm	9 cm	9 cm	9 cm
t_v	3 cm	3 cm	3 cm	3 cm	3 cm	3 cm	6 cm	6 cm
free cooling	yes	yes	yes	yes	yes	yes	yes	yes
T_{heat}	19°C	19°C	20°C	19°C	19°C	20°C	21°C	22°C
T_{cool}	27°C	26°C	26°C	25°C	24°C	24°C	24°C	24°C
windows	single glazed	single glazed	single glazed	single glazed	single glazed	single glazed	single glazed	single glazed
boiler	condensing	condensing	condensing	condensing	condensing	condensing	condensing	condensing
chiller	water-cooled	water-cooled	water-cooled	water-cooled	water-cooled	water-cooled	air-cooled	air-cooled
IC	298680 €	298680 €	298680 €	298680 €	298680 €	298680 €	292315 €	292315 €

It should be noted that these packages are very similar, with the exception of the values of set point temperatures, which influence consistently the objectives. Moreover, the solutions with lower values of EP (i.e., 1, 2, 3) are characterized by the water-cooled chiller and 3 cm of vertical insulation, while those with lower values of DH (i.e., 7 and 8) have the air-cooled chiller and 6 cm of vertical insulation. Thus, the EEM that mainly affects the EP is the replacement of the HVAC generation systems, while the one that has a more significant impact on the DH is the vertical insulation. However, the recommended packages are those that ensure a good trade-off between the objectives, and thus the solutions 4, 5 (the 'best' according to the utopia point criterion, B3) and 6 (considering the comfort criterion, B3'). These give the same retrofit actions, by differing only in the set point temperatures. Finally, the cost-optimal set of actions is identified, and the designer has only to select one of these three points (i.e., the values of T_{heat} and T_{cool}), according to the desired level of thermal comfort.

In conclusion, the cost-optimal solution is characterized by the following ERMs:

- installation of external insulation of the roof, with a thickness of 9 cm;
- installation of external insulation of the vertical envelope, with a thickness of 3 cm;
- implementation of a mechanical ventilation system, for the space free cooling (when available depending on the temperature difference between ambient and indoor airs);
- T_{heat} = 19 / 20 °C, depending on the required comfort level in winter;
- T_{cool} = 24 / 25°C, depending on the required comfort level in summer;
- replacement of the old boiler with a condensing one;
- replacement of the air-cooled chiller with a water-cooled chiller.

The achieved economic saving varies between the aforementioned values, depending on the chosen set point temperatures and the absence or achievement of economic incentives for the energy refurbishment of buildings. Finally, it should be noted that the CAMO can be easily extended to more complex buildings and new constructions, allowing original conclusions and in-depth investigations concerning all the available EEMs, in order to evaluate the cost-optimal package of the energy actions for both existing and new buildings, by taking into account also thermal comfort.

Final remarks

All told, the computational burden and complexity required by CAMO impedes the application of this powerful methodology to each single building. This represents the main weakness of CAMO. Therefore, the purpose of achieving global indications about the cost-optimal mix of ERMs fora group of buildings has led to the development of SLABE, as discussed in the next *chapter*.

How to achieve global indications about the cost-optimality of energy retrofitting the existing building stock?

CHAPTER 4. Simulation-based Large-scale uncertainty/ sensitivity Analysis of Building Energy performance (SLABE)

4.1. Introduction

Since the cost-optimal analysis can't be performed to each building, for reason of complexity, reference buildings (RefBs) have to be defined to represent the national building stock. They should cover all the building categories, where a category is meant as a stock of buildings, which share climatic conditions (location), functionality, construction type. Therefore, the cost-optimal analysis should be applied to these RefBs, in order to detect cost-optimal packages of energy measures [32, 66]. Then, the results achieved for a RefB should be extended to the other buildings of the represented category [96]. However, does this procedure ensure reliable results for all the buildings of the category? Otherwise, how to investigate, in a more rigorous way, energy performance and cost-optimality of a building category?

The energy analysis of a building stock, rather than of single buildings, is essential when the purpose is to quantify the global potential of energy savings [97] or to give general indications about cost-optimal packages of energy measures. The scientific literature shows different methods for assessing the energy performance of a building stock. However, most of these studies just provide a picture of the existing stock starting from data collections [97-101], and/or explore the potential saving induced by few energy measures in a simplified manner, without considering the cost-optimal analysis [97, 99].

This *chapter* attempts to solve the mentioned issues by proposing a novel multi-stage methodology, which provides a robust analysis of energy performance and cost-optimal retrofit solutions for a building category. The methodology is denoted as ‘Simulation-based Large-scale uncertainty/sensitivity Analysis of Building Energy performance’ (SLABE). Indeed, it is based on uncertainty analysis (UA) and sensitivity analysis (SA) of building performance, which are performed by means of the coupling between EnergyPlus and MATLAB. SLABE investigates the influence of well-selected retrofit actions on energy consumption and global cost related to a sampling set of buildings representative of a category. The main goals are:

GOAL I. to detect the package of actions that represents the cost-optimal solution for most buildings of the category.

GOAL II. to evaluate the effectiveness of current policy of state incentives directed to such actions and to propose possible improvements for achieving the best ratio between energy savings and state disbursement.

In the following lines, the methodology is first described and then applied to a specific category: *office buildings built in South Italy in the period 1920-1970*.

Alike CAMO, SLABE can be adopted either as a stand-alone methodology for the investigation of a building category or as a part (stage I) of the macro-methodology (CASA) proposed in this thesis (*chapter 6*).

4.2. Methodology

This study proposes a novel methodology for providing a robust cost-optimal analysis of energy retrofitting solutions for a building stock. The cost-optimality is estimated in line with EPBD Recast, but the developed approach introduces an original aspect that regards the simultaneous investigation of different buildings belonging to the same category. The methodology presents a multi-stage framework, which allows to assess the influence of some energy retrofit measures on primary energy consumption (PEC) and global cost (GC) related to a representative sample of buildings; this should be large enough to represent the considered category significantly. The outcomes are investigated and collected by means of UA and SA, which provide general conclusions for the whole stock. In particular, such analysis allows to detect the retrofit actions that have the strongest effect on PEC and GC savings, in order to reach the two ultimate aims mentioned in the introduction.

It is emphasized that UA and SA are generally carried out for a single building [83, 88, 102, 103], in order to assess how the variations of some uncertain parameters affect energy performance. On the contrary, this study performs UA and SA on a large scale, since the uncertainty in the parameters is generated by the investigation of several buildings belonging to the same category. Thus, the developed methodology is denoted as Simulation-based Large-scale Uncertainty/Sensitivity Analysis of Building Energy performance (SLABE).

SLABE is based on the coupling between EnergyPlus and MATLAB. EnergyPlus is chosen as BPS (building performance simulation) tool because: it’s a whole building energy simulation program that allows a detailed evaluation of each term of PEC; it works with text-based format inputs (.idf) and outputs (.csv), which facilitate the interaction with mathematical tools. MATLAB is chosen for UA, SA and post-processing because: it has a very strong capability; it can automatically launch EnergyPlus as well as manipulate EnergyPlus input and output files.

The UA is performed by means of Monte Carlo analysis (MCA), which is widely applied to BPS [83, 88, 102–104]. As aforementioned, the UA is carried out on a large scale in order to investigate the distributions of some performance indicators within a sample of buildings, representative of a certain category. Thus, the ranges of uncertainty of the parameters are wider than when the UA is applied to a single building [83, 88, 102, 103]. As regards the SA, a global approach is used through the assessment of the standardized rank regression coefficients (SRRCs). In building energy analysis, the global approach is more reliable than the local one [73, 87] and regression methods are the most used [87]. Moreover, BPS tools generally generate nonlinear, multi-modal, discontinuous outputs [105, 106]. Thus, the SRRCs are selected as sensitivity indices, since they are fine for non-linear (but monotonic) functions between inputs and outputs. This choice is largely shared in the BPS community [107, 108]. In particular, the SRRC provides a measure of how influential a parameter is on an output, based on the effect of moving such parameter away from its expected value while retaining all other parameters constant. It can vary from –1 to 1; a positive value indicates that the parameter and the output change with the same sign, while the opposite occurs for a negative value.

SLABE consists of two main stages, which are subdivided respectively in two and three steps, as shown in figure 4.1 and described in the following *subsections*.

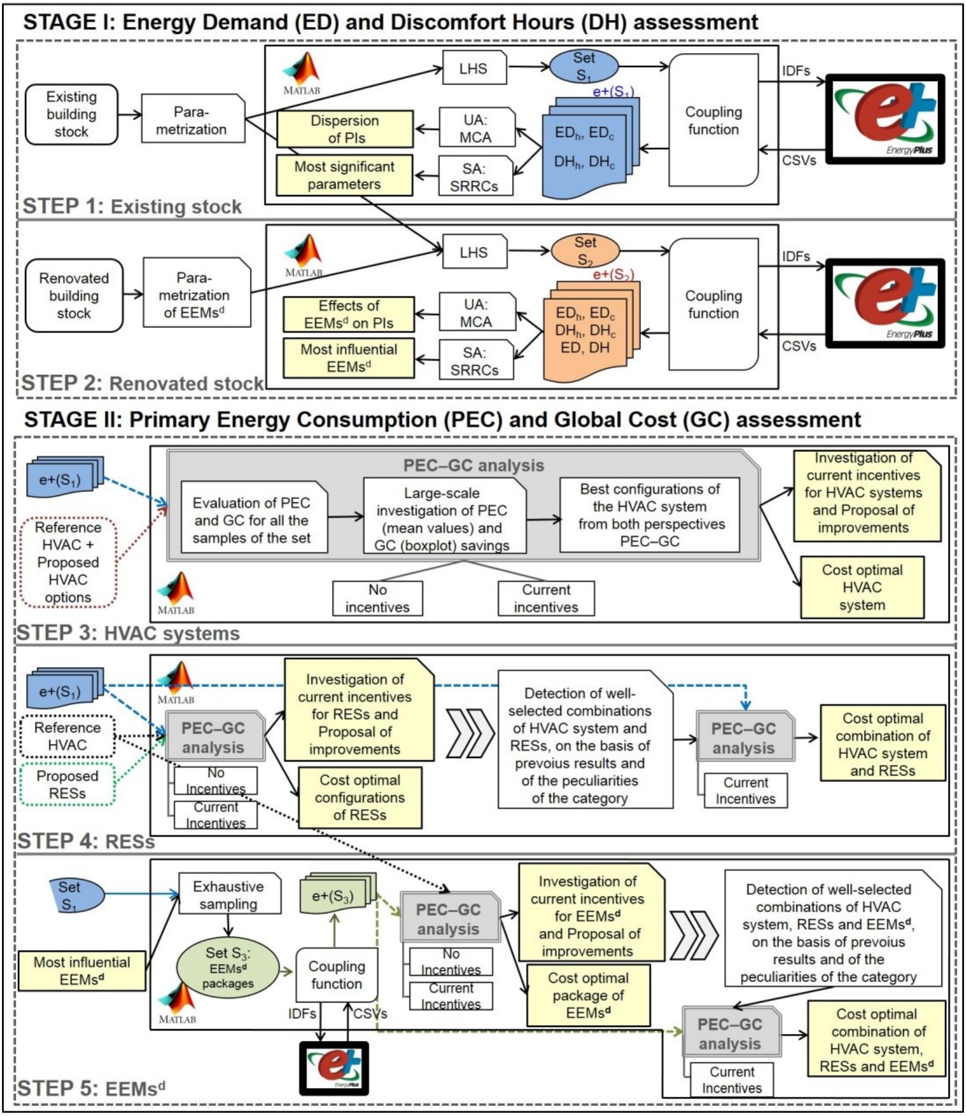

Figure 4.1. Framework of the developed methodology (SLABE). The symbol e+ indicates the data provided by EnergyPlus and handled by MATLAB, required for the evaluation of PEC (and so GC)

4.2.1. Stage I. Assessment of energy demand and thermal comfort (discomfort hours)

Energy demand and thermal comfort are investigated, by means of UA and SA. In particular four performance indicators (PIs) are considered:

- annual energy demand for heating, ED_h [kWh/m²a];
- annual energy demand for cooling, ED_c [kWh/m²a];
- percentage of discomfort hours on occupied hours, during the heating season, DH_h [%];
- percentage of discomfort hours on occupied hours, during the cooling season, DH_c [%].

The energy demand is the annual request of energy for micro-climatic control per unit of conditioned area.
As regards the assessment of the discomfort hours (DH), the weighted under- or over-heating [88]/ cooling hours criterion, which is described in *section 3.2.1*, is used.
The four PIs are first investigated for the existing building stock (step 1) and then for the renovated building stock (step 2), namely in presence of energy efficiency measures for the reduction of energy demand ($EEMs^d$). In the second case, also the annual values of energy demand (ED) and discomfort hours (DH) are considered in order to explore the overall effects of the $EEMs^d$.

Step 1. Analysis of the existing building stock

The existing building stock is characterized by detecting n key parameters relevant to energy demand and thermal comfort. A range of variability and a probability distribution (e.g., uniform or normal) are assigned to each parameter in order to represent the whole building category. A reference building (RefB) related to the investigated category can be exploited to set the mean values of such distributions, as shown in *section 4.3.1*. The selected parameters are classified in three groups, respectively related to geometry (form and orientation), envelope (thermo-physical characteristics of materials) and other parameters that can't be placed in the first two groups (e.g., set point temperatures, internal loads, people density). SLABE is limited to rectangular buildings. This choice facilitates the parameterization process [104], and it's proper for most building categories because of the high percentage of rectangular shapes.

The three groups of parameters and their correlated ranges define the sample space to investigate. Latin hypercube sampling (LHS) is applied to these parameters within a Monte Carlo framework, in order to generate N samples, which correspond to N building model instances and, thus, to N EnergyPlus simulations. These samples constitute S_1, representing the existing building stock. LHS is used because it ensures uniformity and coverage in the sample space, thanks to its efficient stratification properties [109, 110]. Indeed, it's widespread in the scientific literature concerning BPS [88, 102, 108, 111, 112]. It is noted that the value of N must be chosen carefully, in order to thoroughly represent the building stock, as argued in *section 4.3.2*.

The N building model instances are then run in EnergyPlus, by means of the coupling with MATLAB, obtaining N sets of values of the four PIs. Thus, the UA and the SA (assessment of the SRRCs) are performed respectively to explore the distributions of such indicators and to detect which parameters have the most/least influence.

Step 2. Analysis of the renovated building stock

After studying the existing building stock, an analogous analysis is performed on the renovated building stock. In particular, some EEMs[d] are introduced. Each EEM[d] is parameterized through a boolean parameter, which assumes the value of 0 if the relative measure is absent, 1 if present. These new parameters vary according an uniform distribution, so that the probability that one EEM^d occurs is equal to the 50%. Furthermore, the implementation of the EEMs^d generally requires the introduction of other parameters (e.g., the thermo-physical characteristics of thermal insulation), for a total of new e parameters.

Therefore, the renovated building stock is defined by (n + e) parameters – n for the existing buildings and e for the EEMs^d – whose sampling leads to the second set S_2, consisting of N samples alike S_1. In particular, a correspondence between S_1 and S_2 is established, as shown in table 4.1. Each element of S_2 provides the same values of the first n parameters assumed by the homologous element of S_1, while the remaining e parameters are sampled by LHS. In light of this, S_2 gathers the same building instances of S_1, but in presence of one or more EEMs^d. This expedient allows the direct comparison between the two sets (sample by sample), by detecting the effects of some EEMs^d on each building instance.

Table 4.1. Framework of the sampling set S_2, which represents the renovated building stock

SAMPLING SET S_2		PARAMETERS DESCRIBING THE EXISTING BUILDING STOCK					PARAMETERS DESCRIBING THE ENERGY EFFICIENCY MEASURES				
		p_1	p_2	…	p_{n-1}	p_n	p_{n+1}	p_{n+2}	…	p_{n+e-1}	p_{n+e}
SAMPLES	1										
	2										
	…			set S_1					LHS		
	N - 1										
	N										

The N building model instances, gathered in S_2, are run in EnergyPlus in order to evaluate the new sets of values assumed by the four PIs. At this point, the UA allows the estimation of the effects induced by the EEMs^d on energy demand and thermal comfort in the heating and cooling seasons. In addition, the values of the SRRCs are assessed for the boolean parameters representing the EEMs^d, in correspondence of ED_h, ED_c, DH_h, DH_c, ED, DH. Thus, the SA allows to detect the most influential EEMs^d on the seasonal and annual values of energy demand and discomfort hours.

4.2.2. Stage II. Assessment of primary energy consumption and global cost

The potential savings in PEC and GC induced by well-selected energy retrofit measures are investigated. Since the sampling sets reliably represent the building stock, the outcomes are valid for the whole category. It is recalled that the methodology deals with two perspectives, respectively related to collectives interests (PEC savings) and private interests (GC savings). On one hand, it aims to evaluate the effectiveness of the policy of state incentives for ERMs and to provide possible improvements. On the other hand, it points to detect a package of ERMs, which represents the cost-optimal solution for most buildings of the analyzed category.
The PEC is an appropriate metric according to EPBD Recast. It represents the sum of the different components of the building energy use, which are converted by means of primary energy factors. Heating, cooling, ventilation, pumps and fans, domestic hot water (DHW), lighting, electrical equipment are considered. If RESs are present, produced and used energy must be subtracted to the previous terms, in a consistent way. SLABE calculates the PEC through the post-process performed in MATLAB, after EnergyPlus simulations. This expedient allows the reduction of the computational time [72]. More in detail, EnergyPlus

provides the hourly values of the energy demand for heating, cooling, DHW and electricity (which gathers the remaining components of building energy use). These values are handled in MATLAB. First, heating, cooling and DHW demands are turned into hourly demand of electricity or fuel (depending on the type of HVAC system) through the hourly performance curves of the HVAC system. Then, the overall values of electricity and fuel demand are converted in primary energy, by means of primary energy factors. The PEC is so calculated. In presence of RESs, EnergyPlus also yields the hourly values of produced energy. If produced energy is consumed according to a hourly balance, it represents a subtractive term in PEC evaluation.

The GC over the lifecycle of the buildings is calculated in MATLAB, according to the guidelines of EPBD Recast. The real interest rate and the energy price escalation rate are respectively set equal to 3% and 2%. The annual energy demand is assumed constant during the calculation period.

The exploration of the achievable savings in PEC and GC is carried out in three steps, in order to consider the effects produced by three distinct groups of energy retrofit measures: replacement of the primary heating/cooling system (step 3), installation of RESs (step 4), implementation of EEMs[d] (step 5).

Step 3. Replacement of the primary heating/cooling system

The replacement of the primary heating/cooling (HVAC) system is initially considered as the only possible measure, in order to detect the impact of new efficient systems on PEC and GC. In fact, this generally represents the most influential retrofit action on energy and economic savings [72].

The PEC-GC analysis is performed (see figure 4.1). Specifically, the values of PEC and GC are calculated for each sample of S_1 (existing building stock) in correspondence of the reference HVAC system and of different new efficient options. The potential savings are then evaluated. Hence, the best configurations of the HVAC system are identified, as regards respectively energy and cost perspectives. In the first case, the best solution is the one that ensures the highest PEC saving in the building stock. In the second case, it is the one that leads to the highest number of buildings (samples) with positive GC savings; this represents the cost-optimal configuration. The best compromise between these two perspectives is investigated, by means of the concurrent representation of PEC and GC savings:

- mean values are considered for PEC savings, because they are proportional to the energy saving in the whole stock;
- the box plot is chosen for the representation of GC savings, because it allows to estimate, qualitatively, the percentage of buildings characterized by cost savings.

The described analysis is carried out in absence and in presence of state incentives in order to examine the effect of the current policy of grants addressed to energy retrofit actions. The cost-optimal solution refers to the presence of current incentives.

Eventually, a new incentive strategy is devised to obtain a better congruence between the two investigated perspectives (PEC and GC savings). The aim is to harmonize them, in such a way that the best solution for the single building corresponds to the best solution for the collectivity. The best configurations of the HVAC system are identified also in this in case.

In order to compare the two strategies of current and proposed incentives, some reasonable hypothesis are assumed. First, only the HVAC system which ensures the highest values of GC savings for the whole category can be implemented. Secondly, each building implements such HVAC system only if the latter provides an economic benefit (positive value of GC saving); otherwise it keeps its reference system. In particuar, the percentage of samples with positive GC savings is denoted with p. In these assumptions, the actual values of PEC savings and of state disbursement for incentives can be calculated by multiplying by p the values obtained for the whole sampling set. In order to point out the advantages induced by proposed incentives, the two incentive strategies are analyzed through the following indicators:

- actual value of the average saving in primary energy consumption per building, $dPEC_b$ [kWh/a];
- actual value of the average state disbursement per building, D_b [€];
- ratio between $dPEC_b$ and D_b, π [kWh/€ a]; it's a sort of state profit, representing the potential energy saving in correspodence of an unitary disbursement.

Therefore, this step allows to:

- ➢ detect the cost-optimal HVAC system, when the replacement of such system is the unique implemented EEM;
- ➢ evaluate the effectiveness of current incentives directed to HVAC systems and to provide a more efficacious strategy.

Step 4. Installation of RESs

The potential savings in PEC and GC induced by the installation of RESs are investigated for S_1.

First, the PEC-GC analysis is performed in presence of the reference HVAC system, in order to assess how the mere implementation of a RES influence PEC and GC. The best configurations of the RES (e.g., area of PV panels), as for PEC and GC savings, are detected in absence and in presence of current state incentives Furthermore, A new incentive strategy is conceived for the considered RES, and the best configurations are detected also in this case. This procedure allows to:

- determine the cost-optimal configuration of the RES;
- evaluate the effectiveness of incentives directed to the considered RES and to provide a more efficacious strategy.

If more RESs are examined, the same procedure is repeated for each of them.

Then, well-selected combinations of HVAC system and RESs are investigated by assessing PEC and GC savings in presence of current incentives. These combinations are identified on the basis of:

- previous results achieved in correspondence of the mere implementation respectively of new HVAC systems (step 3) and RESs (first part of step 4);
- pecularieties of the explored building category in terms of energy performance.

Eventually, this step identifies:

- the cost-optimal combination between the replacement of the HVAC system and the installation of RESs, when merely these energy measures are implemented.

Step 5. Implementation of $EEMs^d$

The effects of $EEMs^d$ on PEC and GC are explored. In this regard, the SA performed in stage I (step 2) identifies the $EEMs^d$ which have a significant influence on the annual value of energy demand. This step considers only these $EEMs^d$, since the remaining ones are not convenient from both analyzed perspectives. Thus, a new set S_3 is generated through exhaustive sampling, in order to represent all the n_p possible packages (combinations) of the contemplated $EEMs^d$. S_3 has a framework similar to S_2. More in detail, it collects $n_p \cdot N'$ samples, which are composed of n_p

groups of N' samples. N' denotes the minimum number of samples required to significantly describe the building stock. It can be identified only after the UA performed in stage I (step 1); that's why it generally doesn't coincide with N. Each of the n_p groups of S_3 gathers the same buildings, represented by the first N' samples of the set S_1, in presence of one of the n_p possible $EEMs^d$ packages, so that all packages are covered.

Hence, the potential savings in PEC and GC induced by the $EEMs^d$ are investigated, by referring to S_3. The analysis follows the logical order used in step 4.

First, the reference HVAC system is considered. The best packages of $EEMs^d$, as for PEC and GC savings, are detected in absence and in presence of state current incentives. Furthermore, new incentives are devised for the considered $EEMs^d$ and the best packages are found out also in this case. This procedure allows to:

- identify the cost-optimal package of $EEMs^d$, when only these energy measures are applied;
- evaluate the effectiveness of incentives directed to the considered $EEMs^d$ and to provide a more efficacious strategy.

Then, PEC and GC savings are evaluated in correspondence of well-selected combinations of HVAC system, RESs and $EEMs^d$, in order to find the cost-optimal package of retrofit actions. Likewise step 4, the examined combinations are chosen on the basis of previous results and energetic characteristics of the building category. Eventually, this step identifies:

- the cost-optimal package of ERMs, including replacement of the HVAC system, installation of RESs and implementation of $EEMs^d$; if different packages ensure similar values of GC savings, the thermal comfort can be used as discriminating criterion, on the basis of the results achieved in stage I (step 2).

4.3. Application

4.3.1. Presentation of the case study

The methodology is applied to a building category with a large amount of available data. In detail, *Office buildings built in South Italy in the period 1920-1970* are investigated. A research study performed by ENEA [113] (Italian national agency for new technologies, energy and sustainable economic development) provides a deep statistical analysis of structural characteristics and plant conditions of the Italian office building stock. This study defines two RefBs respectively for office buildings built in the period 1920-1970 and from 1971 until now. Buildings built in the period 1920-1970 are considered in this study, because they are characterized by worse energetic performance compared to more recent ones. Thus, the energetic retrofit of these buildings can induce high energy savings. Moreover, they represent a significant percentage (32.4%) of the national office building stock.

South Italy is chosen as geographical location for two main reasons. First, the scientific literature concerning the study of office buildings in South Italy is quite meager. Secondly, a high percentage (around 60%) of such building dates back before 1970 [113]. Thus, investigated buildings cover a wide segment of office buildings in South Italy and ensure high energy saving potentials, as aforementioned.

The IWEC weather data file [86] of the city of Naples is used in EnergyPlus simulations, because it is the second district in South Italy regarding the number of office buildings. The first district is Lecce, but Naples is preferred because of its climatic conditions, which are close to average conditions in South Italy. Therefore, the results obtained for Naples can be extended to many other cities of South Italy with an acceptable approximation.

Reference building (RefB)

The considered RefB has a rectangular shape, thus perfectly fits to the developed methodology. The structural frame is in reinforced concrete; the vertical walls are made of two layers of bricks separated by an air gap; a structure in mixed brick-reinforced concrete characterizes floor and roof. Table 4.2 shows information about the stratigraphy of these elements. The composition of internal walls and ceilings are not indicated by ENEA; thus, they are supposed to be made of 0.15 m of concrete. The windows are made of singles glasses and wooden frames (U_w=5.0 W/m^{2}K). Their height is equal to 1.5 m. There is no solar shading.
All the other characteristics related to geometry, envelope and operation are reported in table 4.3, in the column denoted with RefB; the other columns are explained in the next *subsection*.
The defintion of the HVAC system is not explicit, since only statistical data are reported by ENEA. Thus, this study is based on the following assumptions. Fan coils and hot water radiators are alternately considered as heating terminals; indeed the presence of one or the other can significantly affect energy performance and thermal comfort. Cooling terminals always consist of fan coils, which allow to investigate different options of the primary cooling system. The primary heating system is a natural gas boiler, with nominal efficiency (η, related to the low calorific value) equal to 0.85, indicated with reference boiler (RB). The primary cooling system is an air-cooled chiller, with nominal energy efficiency ratio (EER) equal to 2.2, indicated with reference chiller (RC). There aren't RESs.

Table 4.2. Reference building: stratigraphy of floor, external walls and roof. The values of solar absorptance (a) are indicated only for the external layers

	t [m]	k [W/m K]	d [kg/m^3]	c [J/kg K]	R^T * [m^2 K/ W]	a
FLOOR						
Cobblestone	0.18	0.70	1500	880	-	-
Floor Block	0.18	0.66	1800	840	-	-
Clay	0.06	0.12	450	1200	-	-
Screed	0.03	0.90	1800	840	-	-
Tiles	0.02	1.00	2300		-	-
EXTERNAL WALLS						
External Brick	0.12	0.72	1800	840	-	0.5
Air Gap	0.20	-	1.03	1010	0.156	-
Internal Brick	0.08	0.90	2000	840	-	-
Plaster	0.02	1.4	2000	820	-	-
ROOF						
Cement	0.03	1.40	1000		-	0.5
Screed	0.03	1.40	400	1000	-	-
Expanded Clay	0.05	0.27	900	1000	-	-
Roof Block	0.22	0.66	1800	840	-	-
Plaster	0.02	0.70	800	1000	-	-

*R^T is the thermal resistance

Table 4.3. Parameters describing the building stock: value in the RefB; distribution in the stock; mean value (μ) and standard deviation (σ) for normal distributions; range of variability

PARAMETERS			RefB	DISTRIBUTION	μ	σ	RANGE
GEOMETRY	p_1	Orientation (North Axis)	0°	uniform	-	-	0; ±30; ±60; 90
	p_2	Area of each Floor [m²]	216	uniform	-	-	100 ÷ 500
	p_3	Form Ratio	1.5	uniform	-	-	1 ÷ 5
	p_4	Floor Height [m]	3.4	uniform	-	-	2.7 ÷ 4.2
	p_5	Window to Wall Ratio: S	29%	uniform	-	-	10 ÷ 40
	p_6	Window to Wall Ratio: E	33%	uniform	-	-	10 ÷ 40
	p_7	Window to Wall Ratio: N	17%	uniform	-	-	10 ÷ 40
	p_8	Window to Wall Ratio: W	33%	uniform	-	-	10 ÷ 40
	p_9	Number of Floors	2	uniform			1; 2; 3; 4; 5
ENVELOPE	p_{10}	Air Gap R^T [m² K/W]	0.156	normal	RefB	0.01	0.116 ÷0.196
	p_{11}	Roof a	0.5	normal	RefB	0.2	0.1 ÷ 0.9
	p_{12}	External Walls a	0.5	normal	RefB	0.2	0.1 ÷ 0.9
	p_{13}	Thickness of Concrete [m]	0.15	normal	RefB	0.05	0.05 ÷ 0.25
	p_{14}	Type of Glass	Single	uniform	-	-	Single/Double
	p_{15}	Type of Frame	Wood	uniform	-	-	Wood/Aluminum
	p_{16}	Clay t [m]	0.06	normal	RefB	0.2 μ	(μ – 3σ) ÷ (μ + 3σ)
	p_{17}	Clay k [W/m K]	0.12	normal	RefB	0.2 μ	(μ – 3σ) ÷ (μ + 3σ)
	p_{18}	Clay d [kg/m³]	450	normal	RefB	0.2 μ	(μ – 3σ) ÷ (μ + 3σ)
	p_{19}	Clay c [J/kg K]	1200	normal	RefB	0.2 μ	(μ – 3σ) ÷ (μ + 3σ)
	p_{20}	Expanded Clay t [m]	0.05	normal	RefB	0.2 μ	(μ – 3σ) ÷ (μ + 3σ)
	p_{21}	Expanded Clay k [W/m K]	0.27	normal	RefB	0.2 μ	(μ – 3σ) ÷ (μ + 3σ)
	p_{22}	Expanded Clay d [kg/m³]	900	normal	RefB	0.2 μ	(μ – 3σ) ÷ (μ + 3σ)
	p_{23}	Expanded Clay c [J/kg K]	1000	normal	RefB	0.2 μ	(μ – 3σ) ÷ (μ + 3σ)
	p_{24}	External Brick t [m]	0.12	normal	RefB	0.2 μ	(μ – 3σ) ÷ (μ + 3σ)
	p_{25}	External Brick k [W/m K]	0.72	normal	RefB	0.2 μ	(μ – 3σ) ÷ (μ + 3σ)
	p_{26}	External Brick d [kg/m³]	1800	normal	RefB	0.2 μ	(μ – 3σ) ÷ (μ + 3σ)
	p_{27}	External Brick c [J/kg K]	840	normal	RefB	0.2 μ	(μ – 3σ) ÷ (μ + 3σ)
	p_{28}	Floor Block t [m]	0.18	normal	RefB	0.2 μ	(μ – 3σ) ÷ (μ + 3σ)
	p_{29}	Floor Block k [W/m K]	0.66	normal	RefB	0.2 μ	(μ – 3σ) ÷ (μ + 3σ)
	p_{30}	Floor Block d [kg/m³]	1800	normal	RefB	0.2 μ	(μ – 3σ) ÷ (μ + 3σ)
	p_{31}	Floor Block c [J/kg K]	840	normal	RefB	0.2 μ	(μ – 3σ) ÷ (μ + 3σ)
	p_{32}	Internal Brick t [m]	0.08	normal	RefB	0.2 μ	(μ – 3σ) ÷ (μ + 3σ)
	p_{33}	Internal Brick k [W/m K]	0.9	normal	RefB	0.2 μ	(μ – 3σ) ÷ (μ + 3σ)
	p_{34}	Internal Brick d [kg/m³]	2000	normal	RefB	0.2 μ	(μ – 3σ) ÷ (μ + 3σ)
	p_{35}	Internal Brick c [J/kg K]	840	normal	RefB	0.2 μ	(μ – 3σ) ÷ (μ + 3σ)
	p_{36}	Roof Block t [m]	0.22	normal	RefB	0.2 μ	(μ – 3σ) ÷ (μ + 3σ)
	p_{37}	Roof Block k [W/m K]	0.66	normal	RefB	0.2 μ	(μ – 3σ) ÷ (μ + 3σ)
	p_{38}	Roof Block d [kg/m³]	1800	normal	RefB	0.2 μ	(μ – 3σ) ÷ (μ + 3σ)
	p_{39}	Roof Block c [J/kg K]	840	normal	RefB	0.2 μ	(μ – 3σ) ÷ (μ + 3σ)
OTHER	p_{40}	People Density [peop./m²]	0.12	normal	RefB	0.2 μ	(μ – 2σ) ÷ (μ + 2σ)
	p_{41}	Light Load [W/m²]	15	normal	RefB	0.2 μ	(μ – 2σ) ÷ (μ + 2σ)
	p_{42}	Equipment Load [W/m²]	15	normal	RefB	0.2 μ	(μ – 2σ) ÷ (μ + 2σ)
	p_{43}	Infiltration Rate [h⁻¹]	0.5	normal	RefB	0.2 μ	(μ – 2σ) ÷ (μ + 2σ)
	p_{44}	Heating Set Point T [°C]	20	normal	RefB	1	19 ÷ 22
	p_{45}	Cooling Set Point T [°C]	26	normal	RefB	1	24 ÷ 27
	p_{46}	Heating Terminals	Fc(1)/Rad(2)	uniform	-	-	Fc/Rad

(1)Fan Coils; (2)Hot Water Radiators

Existing building stock

As aforementioned, investigated buildings are supposed to have a rectangular shape (figure 4.2a), constituted by equal height storeys. Each floor is subdivided into five thermal zones in order to contemplate the different sun exposures, as shown in figure 4.2b. Hereinafter, the term building North axis denotes the oriented direction perpendicular to the two widest façades of the building, which forms with the true North axis an angle inferior to 90°. In addition, the longest and the shortest sides of the plan view are indicated with the letters L_M and L_m.

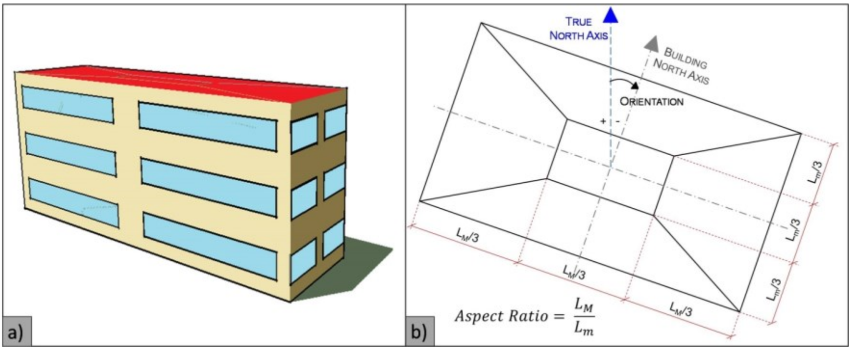

Figure 4.2. An example of the investigated rectangular geometries: a) Axonometric view; b) Plan view with specification of orientation and thermal zones

In these assumptions, the building geometry is defined by the following nine parameters: *orientation*, *area of each floor*, *aspect ratio*, *floor height*, *window to wall ratio (S, E, N, W)*, *number of floors*. These parameters are explained below, where necessary. The *orientation* is specified by the angle between the true North axis and the building North axis (see figure 4.2b). It can vary in the range -90°÷90°, respectively for anti-clockwise and clockwise rotations. The *area of each floor* is preferred to the *total building area* (used in [104]) as investigated parameter, since it's independent from the other parameter *number of floors*; indeed, the presence of correlated parameters compromises the reliability of the SA [109]. The *aspect ratio* is the ratio between L_M and L_m. The *window to wall ratio* is defined for each of the four façades, constituting the building. Each floor is characterized by eight windows, namely two for each façade, which are placed symmetrically (see figure 4.2a). The vertical center of the windows is located at half height of the related floor. The height of each window is equal to 1.5 m (alike the RefB), if sufficient to reach the corresponding *window to wall ratio*, or 2.4 m otherwise, while the width is automatically derived from height and *window to wall ratio*.

All told, the existing building stock is defined by the 46 parameters reported in table 4.3: 9 for geometry, 30 for envelope and 7 other parameters. They are assumed as the most influencing energy performance and thermal comfort of the stock. Thus, other possible parameters (e.g., thermo-physical characteristics of plasters, screeds, tiles) are not contemplated, since they are considered insignificant. The thickness of the concrete of internal walls and ceilings (parameter p_{13}) is included in order to represent the internal thermal inertia.

The ranges and distributions assigned to the parameters (table 4.3) are based on the statistical survey of ENEA and on the experience of the authors. Also previous studies on UA applied to single buildings [83, 88, 102, 103] have been taken into account, but ranges and distributions are different for a building stock. The uniform distribution is chosen when the probability that the parameter assumes a certain value is supposed constant for all the values of the range (e.g., geometry parameters). Instead, when the parameter has a higher probability to take the value assumed in the RefB (e.g., most envelope parameters), a normal distribution centered on the value in the RefB is used. The ranges of variability are such to cover a huge segment of the stock.

Proposed energy retrofit measures

The energy retrofit of the existing building stock is based on three gorups of measures: EEMs for the reduction of energy demand ($EEMs^d$), replacement of the HVAC system, RESs. These measures are detailed below. Also the relative investment costs, needed for the evaluation of GC are indicated. They have been obtained through quotations from suppliers. For the thermal insulants, the same cost of the material has been considered respectively for roof, wall and floor, while the surcharge due to the installation has been assumed slightly different.

After a preliminary analysis of the possible $EEMs^d$, which is supported by the results achieved in step 1 and by the characteristics of the category, the eight $EEMs^d$ reported and described in table 4.4 are investigated. They are denoted with the letters from *a* to *h*. These $EEMs^d$ introduce 18 new parameters, delineated in table 4.4.

In particular, the presence or absence of the eight $EEMs^d$ is encoded by the first eight boolean parameters. Other nine parameters represent the thermo-physical characteristics of the thermal insulants. The values of k, d and c of the three insulants ($EEMs^d$ *a*, *b*, *c*) vary according normal distributions and cover a great part of most used thermal insulants in building application. The insulation thicknesses are automatically deduced, in such a way to ensure the U values prescribed by Italian law to obtain state incentives, in case of refurbishment [17]. The last new parameter is related to the solar shading (EEM^d *g*). Indeed, shading is active if beam plus diffuse solar radiation incident on the window exceeds the solar set point, which varies according to an uniform distribution in the range 300÷600 W/m^2, chosen to represent a broad segment of occupants' behavior. Therefore, the renovated building stock is defined by 64 parameters.

Table 4.4. EEMs for the reduction of Energy Demand and related parameters

EEM[d]	Description	IC	Boolean Parameters[(1)]		Additional Parameters		
					Description		Distribution
a) **Insulation of the vertical walls**	the thickness (t_v) ensures U=0.34 W / m² K	[500 – (3000 x t_v)] x 1.6 €/m³	p_{47}	0			
				1	p_{55}	k [W/m K]	normal[(2)], μ =0.04
					p_{56}	d [kg/m³]	normal, μ =15
					p_{57}	c [J/kg K]	normal, μ =1400
b) **Insulation of the roof**	the thickness (t_r) ensures U=0.32 W / m ² K	[500 – (3000 × t_r)] x 1.5 €/m³	p_{48}	0			
				1	p_{58}	k [W/m K]	normal, μ =0.04
					p_{59}	d [kg/m³]	normal, μ =15
					p_{60}	c [J/kg K]	normal, μ =1400
c) **Insulation of the floor**	the thickness (t_f) ensures U=0.40 W / m² K	[500 – (3000 × t_f)] x 1.7 €/m³	p_{49}	0			
				1	p_{61}	k [W/m K]	normal, μ =0.04
					p_{62}	d [kg/m³]	normal, μ =15
					p_{63}	c [J/kg K]	normal, μ =1400
d) **Low-a plastering of the vertical walls**	the absorption coefficient to solar radiation (a) is 0.05	20 €/m²	p_{50}	0			
				1			
e) **Low-a plastering of the roof**	the absorption coefficient for solar radiation (a) is 0.05	20 €/m²	p_{51}	0			
				1			
f) **Replacement of the windows**	double-glazed low-e windows with PVC frame (U_w=1.8 W/m² K)	250 €/m²	p_{52}	0			
				1			
g) **External solar shading**	diffusive blinds, solar and visible transmittances equal to 0.5	50 €/m²	p_{53}	0			
				1			
h) **Free cooling by means of mechanical ventilation**	in the cooling season (nights), ACH = 2 h⁻¹	10 €/m²	p_{54}	0			
				1	p_{64}	shading set point [W/m²]	uniform within the range 300÷600

[(1)]Each boolean parameter assumes the value of 0 if the relative EEM[d] is absent, 1 if present.
[(2)]All the normal distributions are characterized by σ = 0.1μ and range ≡ (μ – 2σ) ÷ (μ + 2σ)

Regarding the replacement of the HVAC system, the investigated options are discrebed in table 4.5, which also recalls the characteristics of the reference systems. These options mainly derive from local constructive standards. The hourly performance curves of these systems – provided by suppliers – are implemented in MATLAB.

Table 4.5. Options of HVAC system

Heating System		**Description**	**IC** [€]
RB	Reference Boiler	Existing natural gas boiler, nominal LCV(1) efficiency equal to 0.85	-
EB	Efficient Boiler	New natural gas boiler, nominal LCV efficiency equal to 0.95	$45 \cdot kW_p$ + 1500
CB	Condensing Boiler	Condensing natural gas boiler, nominal LCV efficiency ($T_w^{(2)}$=35/55 °C) equal to 1.06	$80 \cdot kW_p$ + 1900
HP	Heat Pump	Air-water heat pump, nominal COP (T_w=40/45 °C; $T_e^{(3)}$=7°C) equal to 3.5	$150 \cdot kW_p$ + 5000
Cooling System		**Description**	**IC** [€]
RC	Reference Chiller	Existing air-cooled chiller, nominal EER (T_w=12/7°C; T_e=35°C) equal to 2.2	-
ACC	Efficient Air-Cooled Chiller	New air-cooled chiller, nominal EER (T_w=12/7°C; T_e=35°C) equal to 3.0	$150 \cdot kW_p$ + 5000
WCC	Water-Cooled Chiller	Water-cooled chiller with cooling tower, nominal EER (T_w=12/7°C; $T_c^{(4)}$=28°C) equal to 4.5	$250 \cdot kW_p$ + 8000

(1) Lower Calorific Value; (2) Water inlet/outlet temperatures;
(3) External Temperature; (4) Water inlet temperature to condenser

Finally as for RESs, photovoltaic (PV) panels are considered, since solar energy is one of the most advantageous RESs in Europe [114], and particularly in Italy because of favorable climatic conditions. PV panels are preferred to solar thermal, because they are more cost-effective [72], in particular for office buildings. In fact, the demand of electricity is predominant, so that PV panels ensure high energy saving potentials. On the other hand, the demand of DHW is very low; thus, the best application of solar thermal is limited. In this study, PV panels are characterized by

34° tilt angle and 0° azimuth angle (orientation to south), in order to achieve the maximum annual production of electricity, as verified bt means of PV-GIS Software [115]. They have conversion efficency equal to 14% (polycristalline silicon) and investment cost (including inverter and installation) equal to 5 €/W.

4.3.2. Results and discussion

The results are organized in *sections* and *subsections* – which follow the steps described in the *Methodology*– in order to provide a clear and systematic study of the building stock.

4.3.2.1. Energy demand and thermal comfort (**stage 1**)

Energy demand and thermal comfort (more precisely, the percentage of discomfort hours) are investigated for both heating and cooling seasons, by means of UA and SA, in two steps:

- step 1: analysis of the existing building stock;
- step 2: analysis of the renovated building stock, by means of EEMs[d].

Existing building stock (**step 1**)

The proposed methodology is tested on office buildings built before 1970 located in Naples. LHS is applied to the 46 investigated parameters related to the considered buildings in order to generate the sampling set S_1. S_1 is composed of 500 building model instances and represents the existing building stock. The resulting ratio r between the number of samples and the number of parameters is equal to 10.9, whereas it is lower (r=2÷5) in most studies on UA and SA applied to buildings [83, 88, 102, 103]. However, the current study deals with wider ranges of variability – since it concerns a building stock – and thus 500 simulations have been carried out in order to detect the minimum number of samples (simulations), which ensures the stability of mean value and standard deviation of all performance indicators (PIs). It is recalled that the PIs investigated in this stage are four, namely the values of energy demand and percentage of discomfort hours respectively in the heating season (ED_h and DH_h) and in the cooling season (ED_c and DH_c).

Figure 4.3 shows that the stabilization of the PIs starts to occur after 100 simulations, demonstrating that a r-value just higher than 2 is sufficient for the representation of the considered building category. Therefore, the minimum number of samples required for the study of a restricted building category seems to correspond to the value recommended for a single building [83, 88, 102, 103]. However, the proposed study considers all the 500 samples, since the simulations have been already performed: thus, higher accuracy and reliability are ensured.

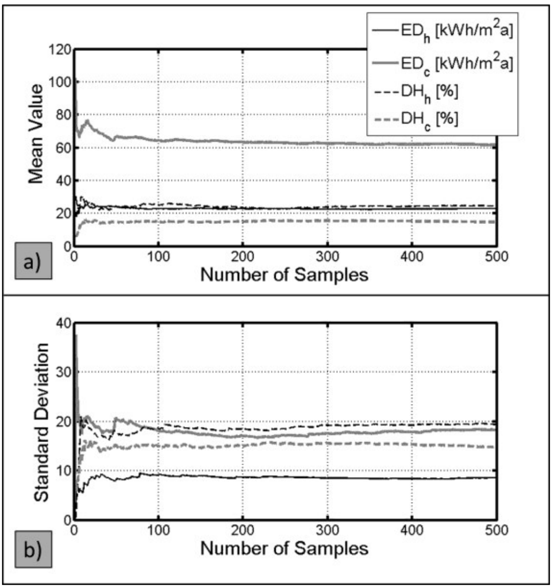

Figure 4.3. Mean Values (a) and Standard Deviations (b) of the PIs, in function of the number of samples

The values assumed by the four PIs in correspondence of the 500 simulations are depicted in the histograms of figure 4.4, where the dots represent the values obtained for the RefB. In particular, the distinction between the presence of hot water radiators (rectangular dot) and fan coils (circular dot) is made as regards the heating season (figures 4.4a and 4.4c). Moreover the normal distributions that approximate the four sets of PI values are reported.

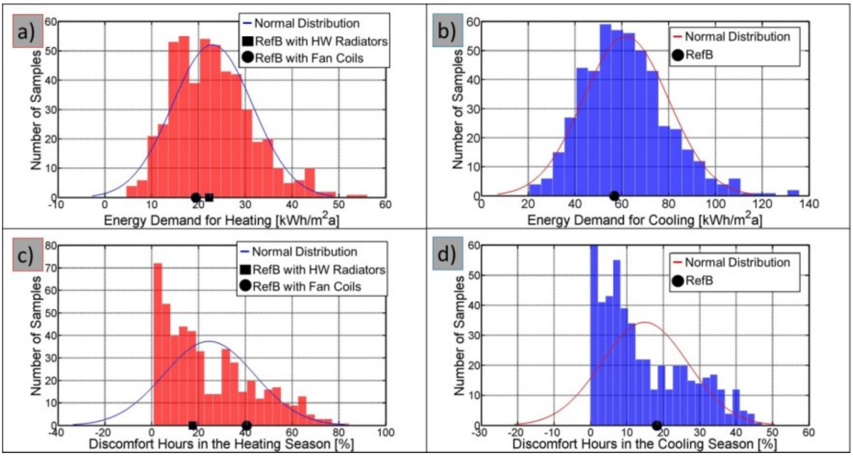

Figure 4.4. Distributions of the values assumed by the PIs in the existing building stock (S_1): a) Energy Demand for Heating (ED_h); b) Energy Demand for Cooling (ED_c); c) Discomfort Hours in the Heating Season (DH_h); d) Discomfort Hours in the Cooling Season (DH_c)

The values of the PIs for the RefB are very close to the mean values of the distributions, showing that the RefB is able to gather the average characteristics of the building category. However, a strong dispersion of results occurs in each case, so that the RefB can represent only a very limited part of the stock, although the HVAC system is not even considered yet. In fact, an error higher than 100% can be committed, by using the RefB to evaluate energy demand and thermal comfort for other buildings belonging to the category. Furthermore, figure 4.4c confirms that the type of hydronic terminals mainly affects DH_h, since a discontinuity in the distribution of such PI occurs, due to the alternation between radiators and fan coils.

The performed UA is followed by the SA, in order to detect the most relevant parameters. The values of the SRRC are calculated for the three groups of parameters in relation to the four PIs. These sensitivity indices are shown in figures 4.5, 4.6, 4.7 respectively for geometry, envelope and other parameters: figures a refer to the energy demand, figures b refer to the discomfort hours.

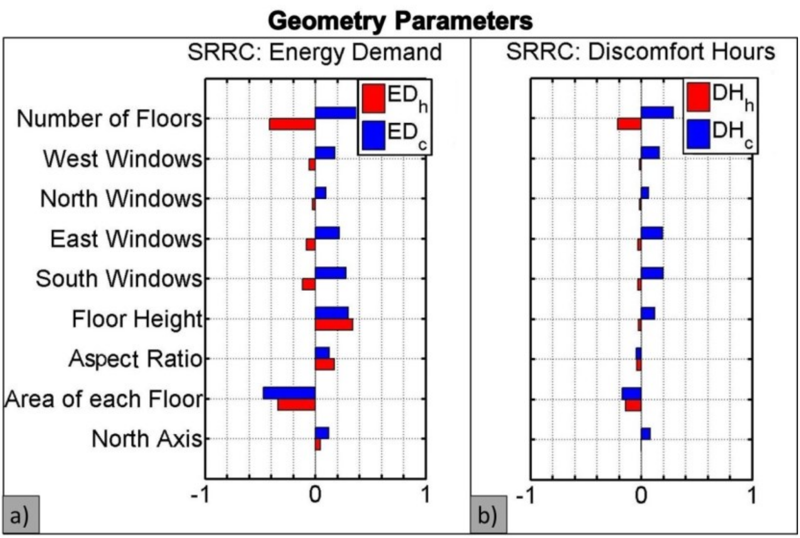

Figure 4.5. Standard Rank Regression Coefficients (SRRCs) for the geometry parameters in relation to: a) Energy Demand (ED_h and ED_c); b) Discomfort Hours (DH_h and DH_c)

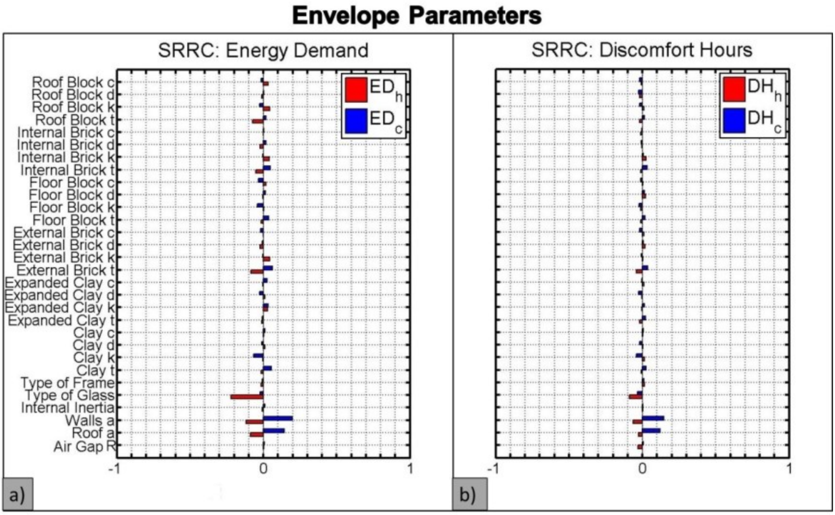

Figure 4.6. Standard Rank Regression Coefficients (SRRCs) for the envelope parameters in relation to: a) Energy Demand (ED_h and ED_c); b) Discomfort Hours (DH_h and DH_c)

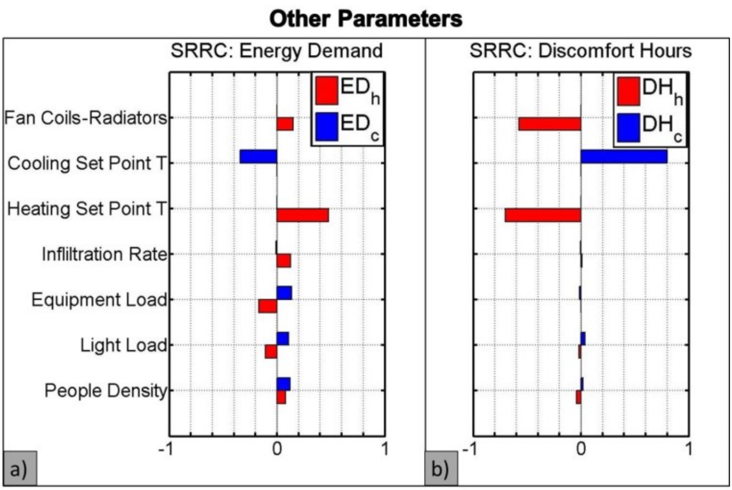

Figure 4.7. Standard Rank Regression Coefficients (SRRCs) for the other parameters in relation to: a) Energy Demand (ED_h and ED_c); b) Discomfort Hours (DH_h and DH_c)

First, it should be noted that the SRRCs achieved for all groups are consistent with thermo-physical considerations, as argued below for some parameters.

Geometry parameters exercise the strongest influence on PIs*;* among them, the highest values of the SRRCs (figure 4.5) occur in correspondence of *number of floors* (N_F) and *area of each floor* (A_F). This happens because these two parameters greatly affect the ratio S/V between the external surface and the conditioned volume as well as the entity of solar gain. In particular, S/V decreases when N_F increases, considering the other parameters constant. This represents a clear benefit during the heating season, confirmed by the negative values of the SRRCs related to ED_h and DH_h. This phenomenon, on the contrary, is adverse in the cooling season (SRRC>0 for ED_c and DH_c), since it reduces the rate at which the high internal gain is dissipated. As regards A_F, when it increases, two main effects occur: both the ratio S/V and the incidence of solar gain decrease with conflicting consequences on the PIs. The first effect prevails in the heating season, the second one during the cooling season; this explains the negative values assumed by all the SRRCs in correspondence of this parameter.

Envelope parameters have the lowest influence on PIs; in fact only the *roof solar absorptance*, the *walls solar absorptance*, the *thickness* and *conductivity of internal brick*, *external brick*, *roof block* and *clay*, as well as the *type of glass*, are significant (figure 4.6), while the other parameters can be neglected in further analyses (ISRRCI<0.05 for all PIs). However, the mentioned envelope parameters – albeit not negligible – provide quite lower values of the SRRCs, compared to the other two groups of parameters. This outcome is mainly due to the high ventilation rate required in office buildings, which covers a wide part of energy demand, so that building energy performance is slightly affected by the envelope.

The *specific heat* of materials and the *thermal internal inertia* provide the lowest SRRCs, because of the characteristics of examined buildings, notably the lightweight structure and the high *window to wall ratio*.
At last, most parameters belonging to the third group (figure 4.7) present not negligible values of the SRRCs. As expected, among these, the *set point temperatures* have the greatest influence on energy demand and thermal comfort. The positive value of the SRRC based on ED_h for *people density* could appear strange: actually, it occurs because the required ventilation rate increases when this parameter increases.

Renovated building stock (**step 2**)

The following energy efficiency measures (EEMs[d]) are investigated for the reduction of energy demand, as described in *section 4.3.1*:

a) insulation of the external vertical walls;
b) insulation of the roof;
c) insulation of the floor;
d) low-a plastering of the external vertical walls;
e) low-a plastering of the roof;
f) installation of double-glazed low-e windows with PVC frame;
g) implementation of external shading of the windows;
h) achievement of night free cooling, by means of mechanical ventilation.

When these EEMs[d] are considered, the renovated building stock is characterized by 64 parameters. Specifically, in addition to the 46 ones describing the existing buildings, there are eight boolean parameters (one for each EEM[d]), nine parameters related to the characteristics of thermal insulants and one parameter related to the shading set point. The sampling (LHS) of these 64 parameters generates S_2, consisting of 500 samples alike S_1. In particular, S_2 represents the same building instances of S_1, but in presence of one or more of the eight EEMs[d]. This expedient allows the direct comparison between the two sets (sample by sample), by detecting the effects of some EEMs[d] on each building instance. The authors have verified that the minimum number of simulations required for the stabilization of PIs is around 100 also for S_2. Anyway, 500 simulations have been performed in order to not waste the simulations carried out for S_1, thus more reliable outcomes are ensured.

The histograms of figure 4.8 show the comparison between the values assumed by the four PIs respectively in the existing building stock (S_1) and in the renovated stock (S_2).

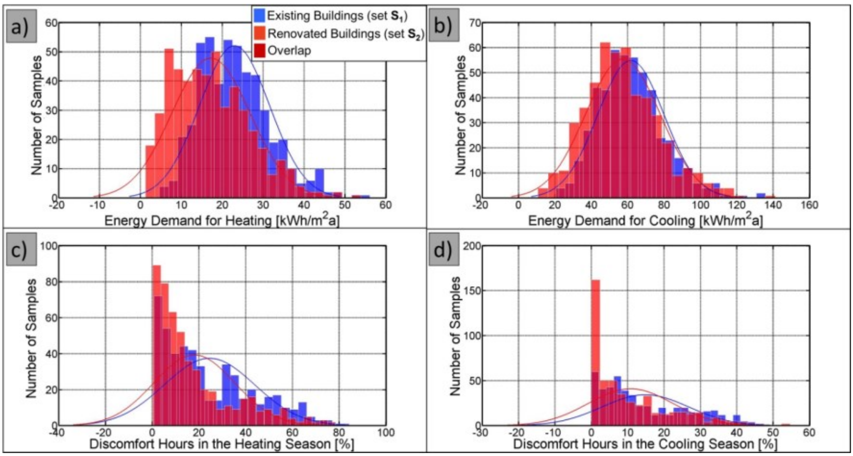

Figure 4.8. Distributions of the values assumed by the PIs in the existing building stock (S_1) and in the renovated stock (S_2): a) Energy Demand for Heating (ED_h); b) Energy Demand for Cooling (ED_c); c) Discomfort Hours in the Heating Season (DH_h); d) Discomfort Hours in the Cooling Season (DH_c)

As expected, the EEMs[d] induce a desired reduction of the mean values of all PIs. However, the improvement related to ED_c is very slight compared to the other PIs. The reason is that some EEMs[d] – mainly those related to thermal insulation (*a, b, c*) – have a negative effect on the cooling demand (see figure 4.8b) because of the magnitude of internal gain. Thus, most $EEMs^d$ produce insignificant benefits on the annual values of energy demand, by virtue of the high relevance assumed by the cooling season for the considered case study.

These observations are confirmed by the values of the SRRCs evaluated for the 8 boolean parameters representing the described $EEMs^d$, in correspondence of ED_h, ED_c (figure 4.9a), DH_h, DH_c (figure 4.9b) and of the annual values (figure 4.9c) of energy demand (ED) and discomfort hours (DH). Indeed, the $EEMs^d$ *a*, *b*, *c* induce unfavorable effects in the cooling season, since they provide positive SRRCs for ED_c and DH_c; the opposite occurs for the $EEMs^d$ *e*, *f*, *g*, *h*, which yield negative SRRCs in correspondence of these two PIs. These conflicting effects are balanced as for ED_c, while the benefits prevail as for DH_c. That's why the $EEMs^d$ lead to a significant improvement of DH_c (figure 4.8d) and not of ED_c (figure 4.8b). On the other hand, the advantages induced by thermal insulation of external walls and roof ($EEMs^d$ *a*, *b*) during the heating season are predominant for both energy demand and thermal comfort. This is demonstrated by the high absolute values of the SRRCs (which are negative), related to ED_h and DH_h, in correspondence of these $EEMs^d$. That's why the $EEMs^d$ lead to a significant improvement of both ED_h (figure 4.8a) and DH_h (figure 4.8c).

Overall, the $EEMs^d$ most affecting the four seasonal PIs are the insulation of walls and roof, but they have conflicting effects in the heating and cooling seasons; in fact, only new low-e windows ensure a positive result in both seasons, since they simultaneously induce an increase of thermal resistance and of reflectance to solar radiation.

Therefore, as predicted, figure 4.9c shows that the proposed $EEMs^d$ don't have a strong influence on the annual values of thermal comfort and, mainly, energy demand. This occurs for two aforementioned reasons, here recalled: first, in most cases, there are opposite seasonal repercussions and, secondly, a significant percentage of energy demand for office buildings is affected by ventilation, independently of the characteristics of the envelope.

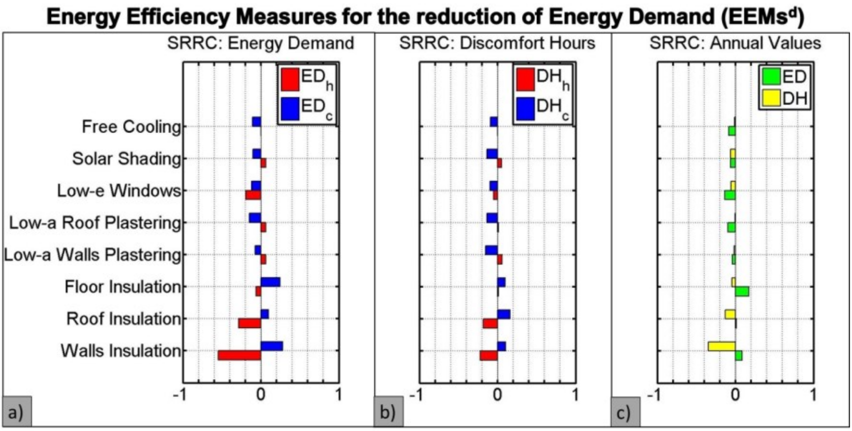

Figure 4.9. Standard Rank Regression Coefficients (SRRCs) for the proposed EEMs in relation to: a) Seasonal Energy Demand (ED_h and ED_c); b) Seasonal Discomfort Hours (DH_h and DH_c); c) Annual values of Energy Demand (ED) and Discomfort Hours (DH)

In particular, only the four EEMs^d *e, f, g, h* – namely low-a roof plastering, low-e double glazed windows, solar shading and free cooling – have a not negligible advantageous effect on annual energy demand. On the other hand, among these, only *f* and *g* induce an improvement – albeit slight – of the annual value of discomfort hours, while *e* and *h* are irrelevant. In fact, the annual assessment of thermal comfort is mainly affected by the thermal insulation of the envelope (see figure 4.9c), since this measure has a positive effect on the mean radiant temperature of the walls, not only in the heating season but also during the intermediate seasons.

4.3.2.2. Primary energy consumption and global cost (**stage 2**)

The achievable savings in PEC and GC compared to the current configuration of the building stock are investigated. As described in *section 4.2.2*, the exploration follows three steps:

- step 3 contemplates the mere replacement of the primary heating/ cooling system ;
- step 4 introduces the installation of renewable energy sources (RESs), in particular PV panels;
- step 5 introduces the implementation of EEMs for the reduction of energy demand, in order to find the cost-optimal package of energy retrofit actions.

For PEC evaluation the primary energy factor is set equal to 1 for natural gas and to 2.18 for electricity, according to Italian standards. For GC evaluation, a calculation period of 20 years is used, as prescribed by the guidelines of the EPBD Recast for non-residential buildings. The prices of electricity and natural gas, considered constant, are respectively set equal to 0.25 €/kWh_{el} and 0.90 €/Nm^3 [116].

Replacement of the primary heating/cooling system (**step 3**)

The analysis of savings in PEC and GC is initially carried out considering the mere replacement of the primary heating/cooling (HVAC) system.

Therefore, the sampling set S_1 – which represents the existing building stock – is considered in this stage. As aforementioned, the RefB is characterized by a natural gas boiler (reference boiler: RB) and by an air-cooled chiller (reference chiller: RC), while the proposed options for the replacement of the system (see table 4.5) are listed below:

- efficient boiler (EB), condensing boiler (CB), heat pump (HP) for heating generation;

- efficient air-cooled chiller (ACC), water cooled-chiller (WCC) for cooling generation.

Thus, twelve configurations of the HVAC system are investigated, including RB and RC. Figure 4.10 shows mean value and standard deviation of the achievable PEC savings, in correspondence of these configurations. Two different metrics are used: *energy per building* [MWh/a] and *energy per area* [kWh/m^2 a]. The second one is more used in building applications and recommended by EPBD Recast, but the first one is more appropriate for this study, because it allows a rapid estimation of the potential PEC saving in the whole stock. Furthermore, figure 4.10 indicates that the trends are similar, so that the observations made for *energy per building* are generally also valid for *energy per area*. Thus, the second metric is used hereinafter. The adption of efficient systems can induce significant energy savings in the stock, up to a mean value around 26 MWh/a per building (33 kWh/m^{2}a) in presence of WCC and CB or HP (see figure 4.10). The replacement of the cooling system ensures higher potential savings, by virtue of the magnitude of cooling demand.

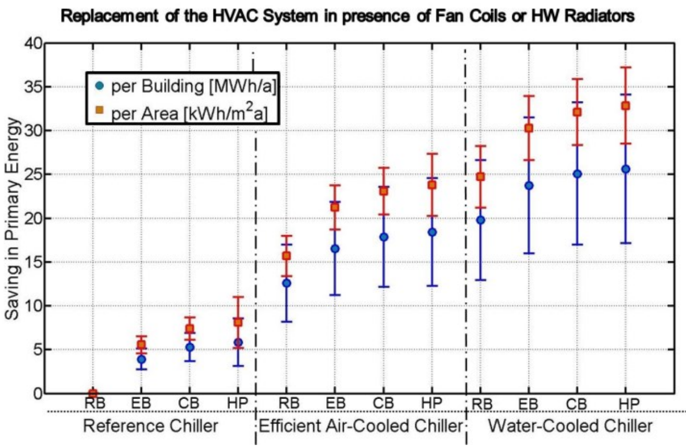

Figure 4.10. Mean Value and Standard Deviation of the of the achievable savings in PEC for S_1, in correspondence of the investigated HVAC configurations

More in detail, figure 4.11 shows the potential savings in PEC and GC, respectively in presence of fan coils (figure 4.11a) and hot water radiators (figure 4.11b). The results are analyzed separately for these two subsets – characterized by 250 samples each – since the type of terminal highly affects the performance of the heat generation system. The observations on the cooling system are obviously the same for the two subsets, since only a type of cooling terminal is considered, namely fan coils. The figure confirms that both PEC and GC are highly influenced by the type of cooling system, since the cooling demand is predominant for office buildings in Naples. Thus, the best cooling system from both perspectives is the most efficient one, which is the WCC. On the contrary, the congruency between the two analyzed perspectives is not always ensured as for the heating system, as argued below for the two subsets.
As expected, the presence of fan coils leads to higher values of energy savings, mainly in correspondence of CB and HP, which ensure the greatest savings in PEC. This occurs because of the lower temperature of inlet hot water of fan coils compared to radiators. On the contrary, GC savings are maximized by RB and EB. In fact, cost savings are ensured for about 75% of buildings using one of these two boilers together with the WCC, so that the probability that one of these two configurations will be implemented is very high. In this way, the larger potential energy savings guaranteed by CB and HP will be wasted. On the other hand, the radiators induce lower values of energy savings and ergo cost savings. The higher temperature of inlet hot water causes a deterioration of system efficiency mainly for CB and HP. This leads to a greater congruence between the energy and cost perspectives, in presence of radiators. Indeed, the EB represents an optimal compromise, since it is very close to both the best solutions respectively related to PEC (CB) and GC savings (RB).

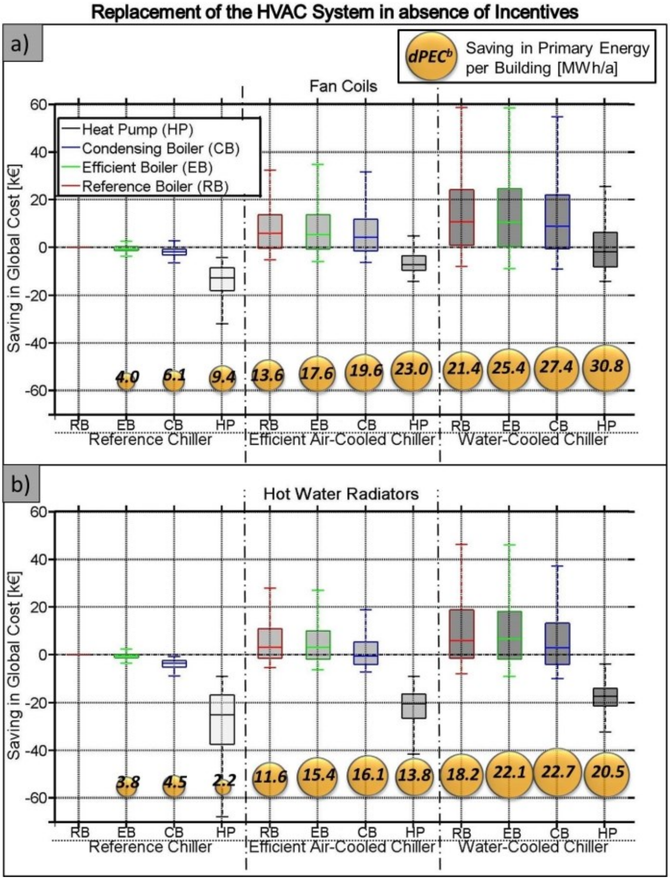

Figure 4.11. Savings in PEC (mean values) and GC in case of the mere replacement of the HVAC system with no incentives, respectively in presence of fan coils (a) and hot water radiators (b)

At this point, the same analysis is carried out in presence of current state incentives. The current incentives provided by Italian Government modify, significantly, the values of GC savings in presence of CB and HP (figure 4.12), which benefit from a capital grant, accorded in ten years, covering the 65% [17] of the investment cost. Instead, there are no incentives for cooling systems, so that the WCC remains the best solution from all the points of view. Thus, the attention is hereinafter focused on the heating system. Obviously the values of PEC savings do not change compared to the case of absence of incentives.

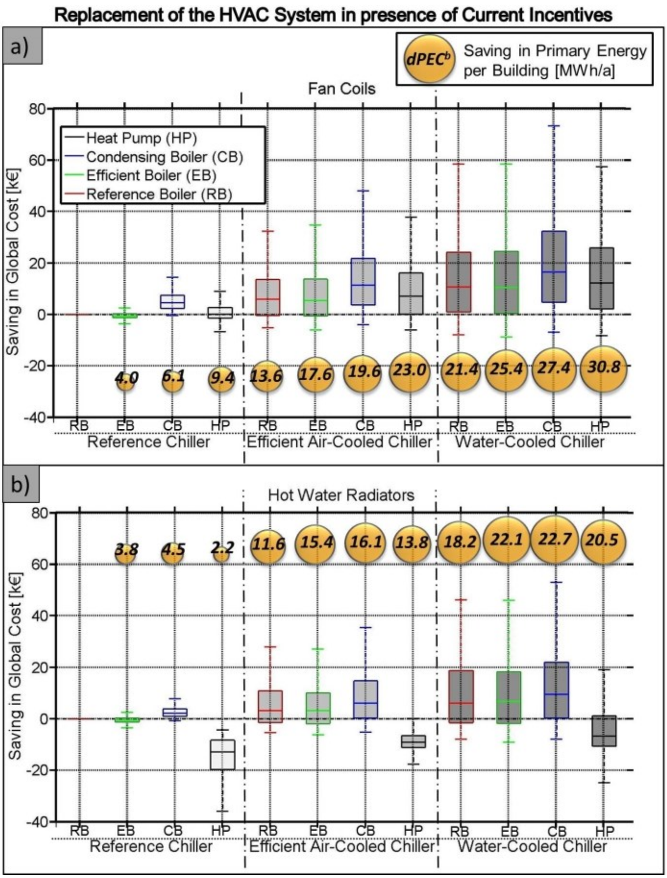

Figure 4.12. Savings in PEC (mean values) and GC in case of the mere replacement of the HVAC system with current incentives, respectively in presence of fan coils (a) and hot water radiators (b)

The cost-optimal HVAC system is composed by WCC and CB, both in presence of fan coils (figure 4.12a) and radiators (figure 4.12b), while the highest PEC savings occur in correspodence of WCC–HP for fan coils and WCC–CB for radiators. Thus, current incentives are fine in the case of radiators since the two solutions match, but they are not effective in the case of fan coils, because they don't support enough the heat pumps: in fact, the CB – which ensures a higher money saving – will be preferred in most cases.

Therefore, this study tests a different incentive strategy in order to get more satisfactory results. It consists of a capital grant, accorded in ten years, that covers:

- the 70% of the investment cost of heat pumps, if the building is heated by fan coils;
- the 65% of the investment cost of new efficient boilers, if the building is heated by radiators.

Condensing boilers are not contemplated. This strategy aims at the following objectives:

- to encourage the use of heat pumps in presence of fan coils, since they induce huge energy savings;
- to encourage the use of new efficient boilers in presence of radiators; this heating system is preferred to the condensing boiler, because – compared to the latter – it induces a just slightly smaller energy saving, in spite of a much lower investment cost.

The new values assumed by GC savings for fan coils and radiators are depicted in figure 4.13. As expected, the best heating system with proposed incentives is HP in presence of fan coils and EB in presence of radiators. Thus, the harmonization between the two perspectives is ensured.

Therefore, the cost-optimal HVAC systems consist of:

- WCC in all cases;
- CB in presence of current incentives, in both cases of fan coils and radiators;
- HP in case of fan coils and EB in case of radiators, in presence of proposed incentives

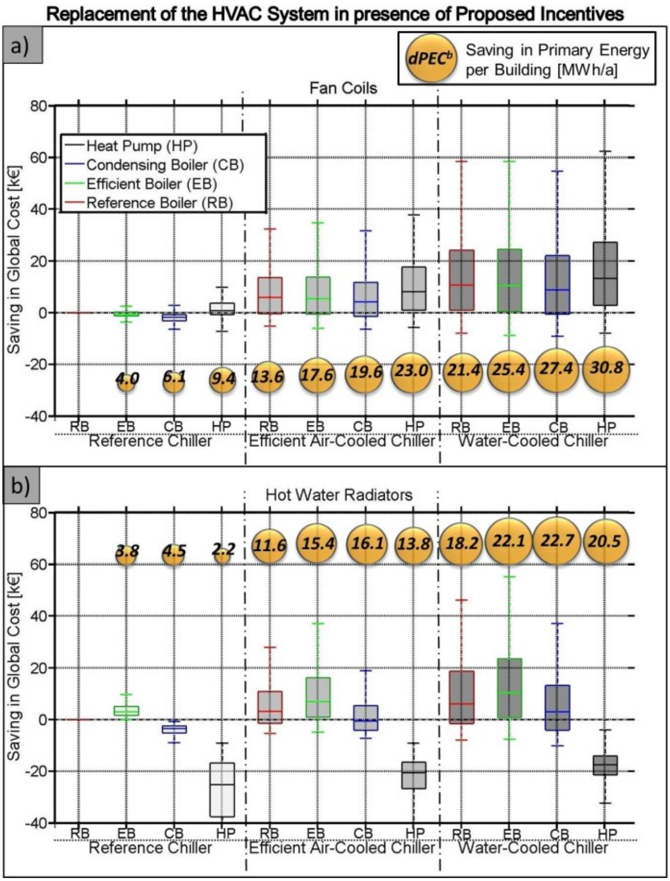

Figure 4.13. Savings in PEC (mean values) and GC in case of the mere replacement of the HVAC system with proposed incentives, respectively in presence of fan coils (a) and hot water radiators (b)

All told, the two strategies of current and proposed incentives for HVAC systems are compared in table 4.6, through the indicators (p, $dPEC_b$, D_b, π), described in *section 4.2.2*. It is recalled that such indicators are evaluated in the assumption that only the cost-optimal HVAC system (which ensures the best values of GC savings) can be implemented.

Table 4.6 Comparison between current and proposed incentive strategies, directed to the mere replacement of the HVAC system

Replacement of the HVAC system	p	$dPEC_b$ MWh/a per building	D_b k€ per building	π kWh/€
Current Incentives	0.79	19.8	5.63	3.52
Proposed Incentives	0.78	20.9	6.97	3.00

Proposed incentives are penalized by the highest value of actual state disbursement D_b – due to the substantial support to heat pumps – resulting in a lower value of the state profit π; in spite of this, they ensure a higher actual energy saving $dPEC_b$ (5.6% more) and they encourage the spread of heat pumps, stimulating the reduction of the investment cost of this efficient system. Thus, in the long term, proposed strategy appears more effective.

RESs: Installation of PV Panels (**step 4**)

Once the best configurations of the primary heating/cooling system are identified, the implementation of PV panels is investigated. At first, the savings in PEC and GC are assessed in presence of RB and RC, in function of the percentage of PV power (area fo PV panels) compared to the maximum installable power (maximum area) on the buildings' roofs. In particular, these savings are represented in figure 4.14, in the cases of:

- absence of incentives (figure 4.14a);
- presence of current state incentives, which cover (in ten years) the 50% [17] of the investment cost for PV panels (figure 4.14b);
- presence of proposed incentives, which cover (in ten years) the 40% of the investment cost for PV panels (figure 4.14c).

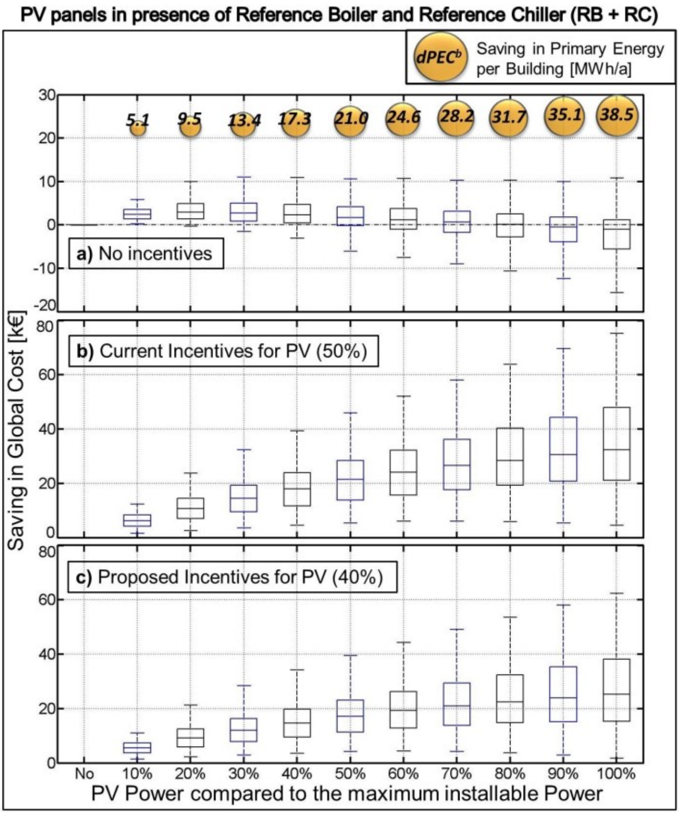

Figure 4.14. Savings in PEC (mean values) and GC in function of the percentage of PV power compared to the maximum installable power, in presence of RB and RC, respectively with no incentives (a), current incentives (b), proposed incentives (c)

The implementation of PV maximum power induces huge energy savings – an average of 38.5 MWh/a per building – but it's very likely that, in absence of incentives, most buildings will install only a limited part (20-30%) of the available power, in order to achieve a major money saving. Thus, incentives are necessary to harmonize the two so-far-examined perspectives. However, current incentives are excessive. Indeed, the proposed ones are sufficient to support the implementation of the maximum PV power, by ensuring positive values of the saving in GC for the whole building stock. Therefore, the best option from both private and collective perspectives is the installation of the maximum PV power (100%), with both current and proposed incentives.

As regards the explored building category, the greatest part of electricity produced by the PV panels is absorbed by lights and electrical equipment, since these provide a significant energy demand in office buildings. That's why, in this case study, the replacement of the HVAC system and the implementation of PV panels can be considered as independent from an energetic point of view. In other words, in presence of current and proposed incentives, the installation of the maximum PV power represents the best option in correspondence of all the twelve investigated HVAC configurations, as shown for the reference HVAC system. Moreover, it induces similar GC savings for these HVAC configurations. Thus, the cost-optimal combination of PV and HVAC systems is provided by the installation of the maximum PV power and of the cost-optimal HVAC option identified in the case of mere replacement of the HVAC system.

More in detail, the following cost-optimal combinations are achieved:

- in presence of current incentives: maximum PV power, WCC, CB in both cases of fan coils and radiators;

- in presence of proposed incentives: maximum PV power, WCC, HP in presence of fan coils and EB in presence of radiators.

The savings in PEC and GC provided by these cost-optimal solutions are depicted in figure 4.15.

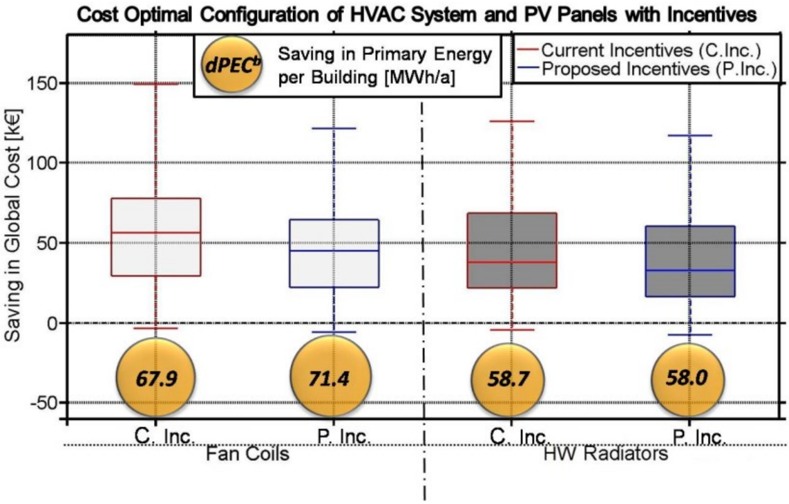

Figure 4.15. Savings in PEC (mean values) and GC for the cost-optimal configurations of HVAC system and PV panels (100%) in presence of current incentives (WCC+CB for fan coils and radiators) and proposed incentives (WCC+HP for fan coils and WCC+EB for radiators)

Proposed incentives produce slightly lower GC savings for both kinds of heat terminals. Nevertheless, they ensure money savings for almost the whole building stock, as well: 96% of samples (against 99% in presence of current incentives). On the other hand, the proposed strategy leads to higher PEC savings for fan coils (~5% more) and similar PEC savings for radiators compared to the current one. This rewards the devised choices for incentives, by confirming that:

- in presence of fan coils, heat pumps provide significant energy savings;
- in presence of radiators, new efficient boilers and condensing boilers provide analogous energy savings; however the first ones are less expensive and so more convenient.

In more detail, the two overall incentive strategies for HVAC and PV systems are compared in table 4.7.

Table 4.7 Comparison between current and proposed incentive strategies, directed to the replacement of the HVAC system and to the implementation of PV panels

Replacement of the HVAC system + PV panels	p	$dPEC_b$ MWh/a per building	D_b k€ per building	π kWh/€
Current incentives	0.99	62.7	44.6	1.41
Proposed incentives	0.96	62.8	37.8	1.66

They induce similar values of $dPEC_b$, but the proposed incentives lead to a significantly lower D_b and, consequently, to a higher profit π. Thus, the proposed strategy better achieves the purpose of incentives, that is the harmonization of private and collective interests.

Implementation of $EEMs^d$ (**step 5**)

As shown by SA, only four $EEMs^d$ have a positive impact on annual energy demand (figure 4.9c), so that they can improve PEC and GC. Thus, only these $EEMs^d$ are here considered. In particular, they consist of:

e) low-a plastering of the roof;

f) installation of double-glazed low-e windows with PVC frame;

g) implementation of external shading of the windows;

h) achievement of night free cooling, by means of mechanical ventilation.

It's recalled that two sampling sets have been generated so far:

- S_1, representing the existing stock, characterized by 46 parameters and 500 samples;
- S_2, representing the renovated stock in presence of the eight EEMs^d, characterized by 64 parameters and 500 samples.

At this point, a new sampling set S_3 is needed to consider the implementation of the 15 packages deriving from the combination of the four aforementioned EEMs^d *e*, *f*, *g* and *h*. Involved parameters are here 51, including 46 for buildings' description, 4 (boolean parameters) for EEMs^d and 1 for shading set point. The exhaustive sampling of these 51 parameters generates the set S_3 of 1500 samples, which are composed of 15 groups of 100 samples. Each group corresponds to a EEMs^d package. 100 samples are sufficient to obtain reliable results in correspondence of each package, since they ensure the stability of mean value and standard deviation of energy demand and percentage of discomfort hours. This occurs in correspondence of both S_1 (see figure 4.3) and S_2 (as verified by the authors), and so it must occur also for each of the 15 groups of S_3, since the latter presents a number of parameters intermediate between S_1 and S_2. Hence, the potential savings of PEC and GC refer to S_3. At first, these savings are assessed for all the considered pakages of EEMs^d in correspondence of RB and RC, respectively:

- in absence of incentives (figure 4.15a);
- in presence of current incentives (figure 4.15b); among the considered EEMs^d, only the installation of low-e windows (EEM^d *f*) is supported by a capital grant that covers the 65% (in ten years) [17] of the investment cost.

No incentives are proposed for the EEMs^d because they are not effective, as argued below.

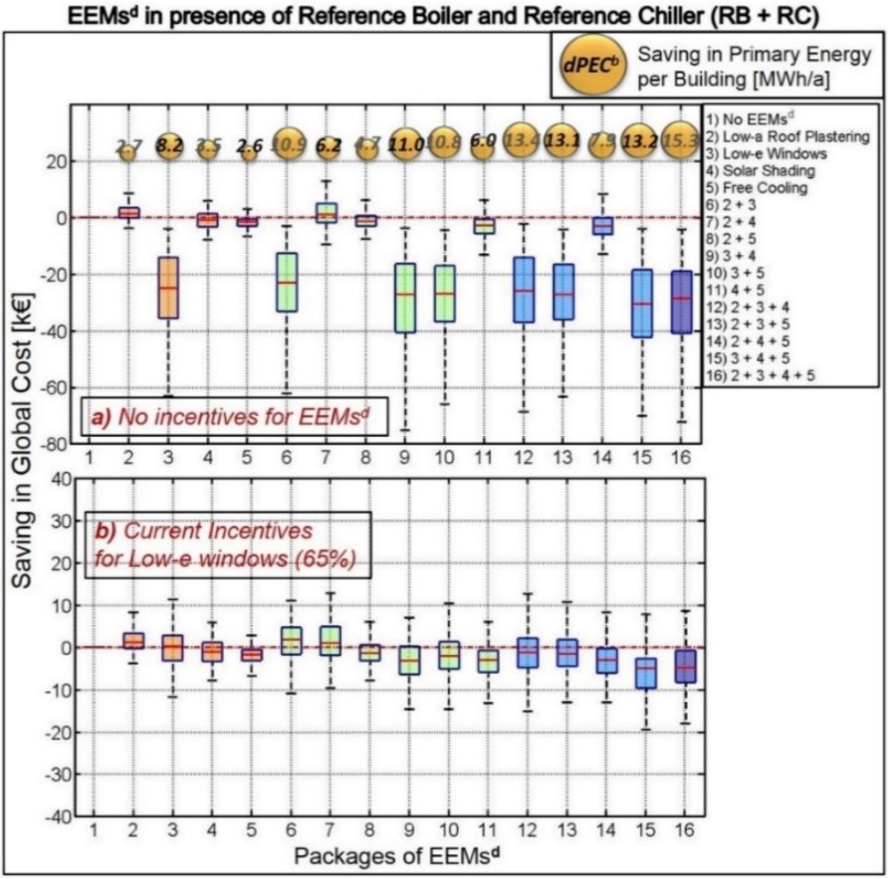

Figure 4.15. Savings in PEC (mean values) and GC provided by the packages of EEMs^d in presence of RB and RC, respectively with no incentives (a) and current incentives (b)

The mere implementation of EEMs^d packages induce lower PEC savings compared to the other retrofit actions, because of the discussed characteristics of the building category. The EEM^d most affecting PEC is the installation of low-e windows, followed by the solar shading, the roof low-a plastering and the implementation of free cooling. This confirms the

results of the sensitivity analysis: the EEMs^d with higher absolute values of the SRRC related to annual energy demand (see figure 4.9c) have a higher influence on PEC. This outcome is not obvious, since energy demand causes only a part of PEC. In fact, the replacement of the windows and the solar shading have very close values of the considered SRRC but the first EEM is much more influential on PEC; this occurs because solar shading induces an increase of energy comsumption for lighting, which represents another part of PEC.
Although the installation of low-e windows is the EEM^d that induces the highest energy savings, it is not cost-effective in absence of incentives. Instead, current incentives ensure GC savings for about the 50% of buildings that implement only this energy measure. However, the resulting PEC saving in the stock is much slighter than that produced by new efficient HVAC systems and RESs. Thus, it doesn't justify the huge state disbursement required by such grants. For this reason, current incentives addressed to new insulating windows are considered not effective, in relation to the investigated building category.
The GC savings provided by the packages of EEMs^d decrease with increasing the number of measures. Most packages are not cost-effective for the majority of explored samples. In particular, in presence of incentives, only low-e windows, low-a roof and their combination ensure cost savings for more than half of the samples. The cost-optimal package includes only the low-a plastering of the roof, which induces cost savings for the 75% of the stock.
Since the EEMs^d have a slight influence on PEC compared to the previous retrofit actions, their implementation does not alter the cost-optimal combination of HVAC system and PV panels, which includes CB, WCC and maximum PV power. Thus, the potential savings in PEC and GC provided by the packages of EEMs^d are calculated in correspondence

of such combination, applied to the building instances gathered in S_3. The outcomes, related to the existence of current incentives, are depicted in figure 4.16.

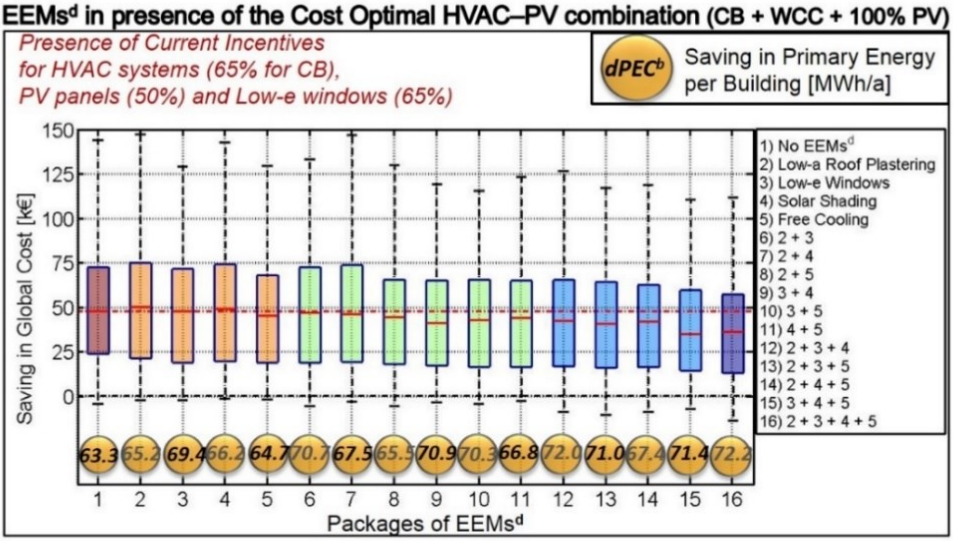

Figure 4.16. Savings in PEC (mean values) and GC for the cost-optimal combination of HVAC system (CB+WCC) and PV panels (100%), with current incentives, for the investigated packages of EEMs[d]

As anticipated, the mean increase of PEC saving per building (maximum value of 8.9 MWh/a) is insignificant compared to the mean saving induced by the replacement of the HVAC system and the implementation of PV panels (63.3 MWh/a). This shows that the EEMs[d] don't lead to substantial energetic benefits, once improved the heating/cooling/electricity generation system.

Furthermore, none of the EEMs[d] introduces evident GC savings, so that the best choice for the buildings' owners is to not implement them. Thus, the cost-optimal package of energy retrofit actions for most buildings of the stock is represented by the mere installation of the cost-optimal combination of HVAC system and PV panels, namely CB, WCC and maximum PV power.

Moreover, the considered incentives are not convenient from the collective perspective, even in the hypothetical case that the replacement of the windows is implemented, although this does not guarantee sufficient GC savings. Indeed, these incentives determine a significant state disbursement (~16 k€ per building), in spite of a small increase of the mean value of PEC saving (~6 MWh/a per building). More in detail, table 4.8 shows how the incentives directed to EEM[d] *f* affect the values of p, $dPEC_b$, D_b and π evaluated for the overall current incentive policy.

Table 4.8. Indicators of the overall current incentive strategy, respectively in absence and in presence of incentives for the replacement of the windows

Overall Current Incentives	p	$dPEC_b$ MWh/a per building	D_b k€ per building	π kWh/€
NO incentives for Windows	0.99	62.7	44.6	1.41
Incentives for Windows	1.00	69.3	60.6	1.14

They cause an evident decrease of the state profit π, since the increase of D_b is much more significant than the increase of $dPEC_b$. It is clear that the situation gets worse if such incentives are raised in order to more encourage the single buildings, since $dPEC_b$ remains constant (p=1) while D_b increases. Thus, state incentives for new windows are not advantageous, and similar considerations are valid for the other EEMs[d] aimed at the reduction of energy demand. In fact, the potential energy savings induced by these measures are not such as to justify the state intervention, as regards the investigated case study.

In conclusion, once improved the heating/cooling/electricity generation system, the implementation of EEMs[d] is not convenient from both collective and private perspectives. Thus, the proposed incentive strategy doesn't support such EEMs[d], since the two perspectives don't need to be harmonized. These considerations are valid for office buildings in Naples and in other localities of South Italy with similar climatic conditions, where the energy demand for cooling is predominant.

Final remarks

All told, it is emphasized that the implementation of SLABE provides worthy global indications on the cost-optimal package of energy retrofit measures for a building category SLABE. However, the main weakness of the methodology is the impossibility of obtaining detailed information on the cost-optimality of retrofitting each single building. This has led to the development of ANNs that exploit the outcomes of UA and SA performed in SLABE, as discussed in the next *chapter*.

How to evaluate the global cost of a building with

a minimum computational time and a good reliability?

CHAPTER 5. Artificial Neural Networks (ANNs) for the prediction of building energy performance

5.1. Introduction

The cost-optimal analysis prescribed by the EPBD Recast is a computationally expensive procedure, because it requires several transient energy simulations, generally performed in BPS tools. This results in a large amount of the required computational time that can assume an order of magnitude from days, for simple buildings, until months, for quite complex ones. This *chapter* aims to handle this issue by proposing the development of surrogate models, i.e. artificial neural networks (ANNs), for the assessment of building energy performance. The benefit is represented by a substantial reduction of computational time and complexity.

A surrogate model (or meta-model) is a “model of the model” [117], that is a function of the design variables that emulates a more complex one, generally based on expensive computer models, thereby approximating the objective functions (Sacks *et al*. 1989). The surrogate models are built from the data gathered in several evaluations of the objective functions realized by means of the original model. Therefore, their development involves a long procedure. However, once built, the meta-model is highly advantageous, because, compared to the original one, it is much faster in the evaluation of the objectives. Common meta-modeling techniques are Multivariate Adaptive Regression Splines (MARS), Kriging (KG), Radial Basis Function (RBF), Artificial Neural Networks (ANNs), and Support Vector Regression (SVR). A crucial issue in meta-modeling is the selection of a proper surrogate model type under a given condition.

The most used techniques for the prediction of the energy and thermal behavior of buildings are, essentially, KG [118, 119], SVR [83, 123, 124] and ANNs [81,125-140] that represent the most popular method. In several cases, such meta-models are adopted for replacing a BPS tool inside an optimization procedure, in order to reduce the computational time. In this regard, an interested review and comparison of metamodeling techniques for simulation optimization in Decision Support Systems is provided by Li [141].

Actually, a perfect meta-model technique does not exist and the correct choice depends on the characteristics of the problem. ANNs are particularly widespread in the building sector because they ensure a good performance with large-size problems, as those typical of building energy studies. Concerning building applications, ANNs have been widely used for the prediction of hourly energy demand for space conditioning [126-133], daily heating and cooling load [134, 135], annual energy consumption [81, 136, 137] and average thermal comfort (PMV) [81, 137, 138]. Furthermore, ANNs have been also used for modeling the energy behavior of a whole building stock [139, 140], instead of single buildings. In all mentioned cases, the networks ensure optimal performance, by providing a regression coefficient (R) around (higher in most cases to) 0.9.

It is emphasized that the development of meta-models for the evaluation of building energy performance is a long and critical process, since it requires several simulations performed through BPS tools. That’s why the generation of surrogate models that are valid merely for a single building

is generally pointless, except for some cases characterized by the implementation of optimization algorithms that needs a higher number of BPS simulations, compared to that required by the surrogate models [81, 83, 118, 119, 137]. On the other hand, the generation of surrogate models that can be used to investigate several buildings appears particularly worthwhile. Indeed, in this case, the powerful capability of such models is thoroughly exploited with a consequent huge benefit. A meta-model can be compared to a Swiss knife. As the adoption of a Swiss knife is useful only if most blades are used, so the development of a surrogate model is worthwhile only if it can be fully exploited. In other words, if only one blade is needed, a simple knife is more convenient, because less expensive; similarly, if the energy behavior of a simple building should be investigated, the use of BPS tools is generally more convenient, because it ensures a higher accuracy and a lower computational cost.
Starting from this consideration, the methodology proposed in this *chapter* consists in the generation of ANNs for the assessment of energy consumption, thus global cost, and thermal comfort of any building belonging to an established category, in absence and presence of energy retrofit measures (ERMs). The ANNs are developed in MATLAB environment, by using EnergyPlus outcomes, post-processed and handled in MATLAB, as targets for training and testing the networks.

In the following lines, the methodology is first described and then applied to the category explored in the previous *chapter*, namely *office buildings built in South Italy in the period 1920-1970*.
Alike CAMO and SLABE, the developed ANNs can be adopted either as a stand-alone tool or as a part (stage II) of the macro-methodology (CASA) proposed in this thesis (see *chapter 6*).

5.2. Methodology

The methodology is based on the use of ANNs for the simulation of building energy and thermal behavior. Artificial neural networks have been chosen among the aforementioned meta-modeling techniques, for two main reasons, reported also in [81]: firstly, they have shown their efficiency and strong capability in a number of previous studies on building energy performance [81,125-140]; secondly, they are pre-programmed in many programs, such as MATLAB.

An ANN is a processing data system that learns the relationship between inputs and outputs by studying previously recorded data, obtained from the original model. It consists in a “network of elementary computation units called neurons, as a reference to the human brain function” [142]. The neurons are connected to each other by a number of weighted links, denoted as synaptic connections (synapses), over which information is transmitted and manipulated. Each neuron receives input data from the previous ones by means of synapses, handles such data and combines them, through a transfer function, in order to generate output data that are sent to the following neurons. The net learns from the provided inputs and outputs through the training. More in detail, the training is an iterative procedure that is finalized to properly set the weights of the synaptic connections, by optimizing a certain parameter, for instance the sum of squared errors (SSE) [81] or the root mean squared error (RMSE) [137]. The training is stopped when a criterion is satisfied; for example, when an established maximum number of iterations, denoted as epochs, is reached (no-stop training method).

The most popular and simple ANN architecture is the feed-forward multi-layer perceptron (MLP), which is characterized by the presence of different neuron layers: one input layer, one or many hidden layers and one output layer (see figure 5.1). The input layer receives data (independent variables) from outside, while the output layers provides the outcomes (objective functions) of the net. Between these two layers, a network can have one or more intermediate hidden layers. The number of such layers should be properly chosen: too many hidden layers lead to an over-fitting of the model; not enough layers can hinder the robustness and reliability of the ANN learning process [136].

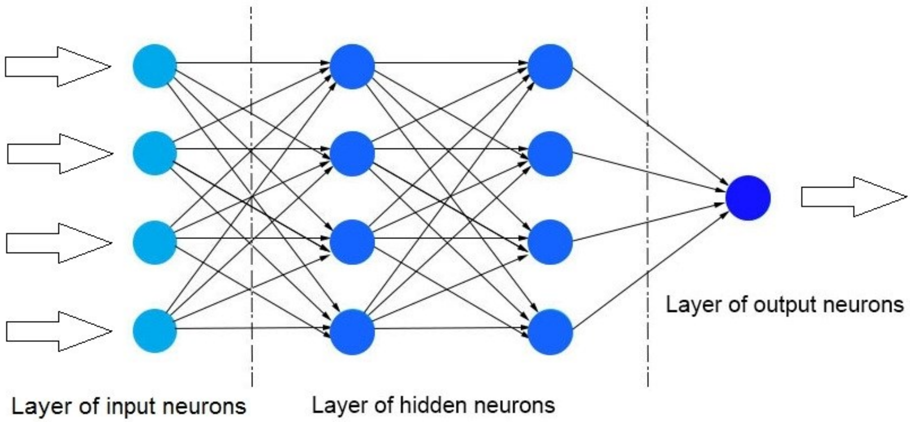

Figure 5.1. Architecture of a feed-forward multi-layer ANN, with one hidden layer

The performance of an ANN significantly depends on input and output data, as well as on its architecture and parameters [136], which must be chosen carefully.

The ANN model used in this study is a feed-forward MLP, composed of three layers and thus with only one hidden layer. The number of hidden neurons is detected by trial-and-error. This parameter highly influences the ANN performance: when it increases, the training data set error decreases at the cost of compromising the generalization ability of the model. The network is trained with Levenberg–Marquardt back-propagation algorithm coupled with Bayesian regularization. A sigmoidal function for the hidden layer and a linear function for the output layer are used as transfer function. A similar configuration of the net has been adopted in previous worthwhile building studies with optimal results [81, 133, 137, 139, 140]. The training of the ANN is stopped when either the RMSE stabilizes over a certain number of epochs or the maximum number of epochs, set equal to 1000 as in [133], is reached. Then, the network is tested on a second sample of input and output data by considering as performance indicators the coefficient of regression (R) and the distribution of the relative error between the ANN outputs and the 'original' ones. EnergyPlus simulations provide the data that, after a post-process in MATLAB, are exploited for ANN training and testing. The number of samples gathered in the training set should be selected properly according to architecture and dimensions of the network; for instance, according to Conraud [143], the minimum value of this number for achieving reliable results is equal to 5 × number of inputs × number of outputs. The ratio between the sizes of training and testing sets is set equal to 9/1 in agreement with previous studies [81, 137]

By adopting the described ANN model, two families of networks are built in order to assess energy performance and thermal comfort of each building belonging to an established category. The first family refers to the existing building stock, whereas the second one refers to the renovated stock, in presence of well-selected ERMs.
More in detail, the first family of ANNs consists of three independent networks, all characterized by a single output, finalized to assess respectively:

- the primary energy demand for heating (ANN for EP_h [kWh/m^2 a]);
- the primary energy demand for cooling (ANN for EP_c [kWh/m^2 a]);

- the percentage of annual discomfort hours as defined in *section 3.2.1* (ANN for DH [%]).

The inputs of the networks are represented by the parameters, related to the whole 'building system', that affect the considered outputs. These parameters can concern building geometry, envelope, operation and HVAC system. The three ANNs are developed and verified by using the same training and testing sets, whose size is imposed by the network with more inputs (characterized by the highest value of the minimum acceptable size of the training set). The use of different networks with only one output neuron, instead of a single network with more output neurons, determines a reduction of the computational burden required by the nets' learning, as well as an improvement of meta-modeling reliability, as suggested by Boithias *et al*. [144]. Indeed, if a single ANN with three outputs – namely EP_h, EP_c, and DH – is used, all the parameters that influence one or more of these three objectives should be included in the (unique) group of the ANN's inputs. Diversely, if three independent ANNs are used, three smaller groups of inputs, chosen ad 'hoc' in correspondence of each output, can be adopted. This induces a reduction of the required size of the training set, compared to the case of a single ANN, and thus a lower computational burden. Indeed, the number of EnergyPlus simulations, needed for the nets' training, decrease, with a consequent shortening of the most computationally-expensive phase of the procedure. Furthermore, the generation of independent ANNs for the three outputs ensures higher reliability, because only the parameters that actually affect a certain output are considered as inputs of the network associated to that output. In this regard, EP_h and EP_c have been preferred, as ANNs' outputs, to the total primary energy demand for space conditioning ($EP = EP_h + EP_c$) because there are some building parameters (e.g., the heating set point temperature) that affect EP_h

without influencing EP_c, and viceversa (e.g., the cooling set point temperature). Therefore, this choice allows to reduce the number of the nets' inputs, with the aforementioned benefits.

The final goal of the ANNs is to provide, besides DH, the primary energy consumption (PEC [kWh/a]) and the global cost (GC [€]) for any building of the category. In particular, diversely from *chapter 4*, here and in the next *chapter*, the PEC per unit of conditioned area, denoted with PEC' [kWh/m^2 a], is considered, since this metric is more suitable when the interest is focused on the energy saving achieved for whichever building and not for the whole stock. PEC' and GC are calculated by means of a post-process performed in MATLAB. It is recalled that PEC' doesn't include only EP_h and EP_c, but also energy consumption for DHW (EP_{dhw} [kWh/m^2 a]) and electric uses (EP_{el} [kWh/m^{2}a]). In this study, EP_{dhw} and EP_{el} are evaluated in MATLAB, in a simplified manner, by considering typical schedules of DHW and electricity demand. The author opted for this choice because the interest is focused on the impact of some ERMs on building energy performance; generally, a reliable quantification of such impact on EP_{dhw} and EP_{el} does not need the use dynamic energy simulations with BPS tools. Nevertheless, in more complex cases, further ANNs for the evaluation of EP_{dhw} and EP_{el} can be developed.

Similar considerations are valid for the assessment of GC, which is calculated according to the guidelines of the EPBD Recast. It is noted that, in addition to the aforementioned motivation, the choice of setting EP_h and EP_c as ANNs' outputs, instead of EP, also derives from the will of evaluating the global cost. Indeed, the procedures for deriving the operating cost, respectively for space heating and space cooling, from the primary energy consumption can differ, because different conversion systems can be used. A typical example is represented by the presence of a gas boiler for heating end of an electric chiller for cooling.

The second family of ANNs consists of other four independent networks, related to the renovated building stock, characterized by a single output because of the reasons previously argued and finalized to assess respectively:

- the primary energy demand for heating (ANN for EP_h [kWh/m^2 a]);
- the primary energy demand for cooling (ANN for EP_c [kWh/m^2 a]);
- the percentage of annual discomfort hours (ANN for DH [%]);
- the thermal/ electric energy produced by in-situ renewable energy sources (RESs) and consumed by the facility (ANN for E_{RES} [kWh/m^{2}a]).

This family includes one more network, compared to the first one, in order to take into account the energy produced by in situ RES systems, e.g., photovoltaic (PV) generators and solar thermal collectors, and consumed by the building on the basis of hourly energy balances. This ANN is introduced because the implementation of RESs represents a possible ERM, which is very influential on building energy performance.

The four new ANNs aim to investigate the applications of ERMs. Therefore, the inputs of the networks include both the parameters that define the energy performance of existing buildings – i.e., the inputs of the first three ANNs – and the parameters describing the energy retrofit measures. As previously explained for the first family of networks, here too, the four ANNs are independent. Indeed, they accepts different groups of inputs in order to optimize and speed up the generation of such surrogate models.

PEC' and GC are derived from as previously explained, by taking into account also the amount of energy that is produce by RESs and consumed by the facility.

Finally, it is emphasized that a rigorous implementation of the proposed methodology requires the combination with SLABE (see *chapter 5*), as shown in the application reported below. Indeed, SLABE allows to carry out a propaedeutic investigation of an established building category by means of uncertainty and sensitivity analysis. Such procedure yields the detection of the most influential parameters on each output of the seven described ANNs, concerning both the current configuration of the stock and the proposed ERMs. Thus, these parameters are used as networks' inputs, thereby ensuring the aforementioned benefits produced by a proper, 'ad hoc' development of each ANN.

5.3. Application

5.3.1. Presentation of the case study

The methodology is applied for exploring the energy and thermal behavior of the buildings that belong to the category investigated by means of SLABE in *chapter 4*, namely: *Office buildings built in South Italy in the period 1920-1970*. For a detailed description of the case study the readers are invited to refer to the *section 4.3.1*, which outlines the characteristics of the examined buildings as well as the proposed ERMs. The information gathered by means of SLABE allows to optimize the development of the seven ANNs, three for defining the existing building stock and four for assessing the impact of ERMs. It is recalled that the energy and thermal behavior of the existing stock is defined by 46 parameters (see table 4.3): 9 for geometry, 30 for envelope and 7 other parameters. They are assumed as the most affecting thermal energy demand and comfort. In order to contemplate also the primary energy systems, two additional parameters are here considered, namely the efficiency (η) of the heating primary system (parameter p_{65}) and the energy efficiency ratio (EER) of the cooling primary system (parameter p_{66}). The energy conversion systems are, respectively, set equal to a gas hot water boiler and to an air-cooled chiller, because these represent the most popular HVAC configurations in the explored building stock. In order to cover the vast majority of such stock, the boiler η (based on the low calorific value) is varied within the range 0.7÷0.9, whereas the chiller EER is varied within the range 1.5÷3. The two referred-to parameters are taken into account in ANNs' development for ensuring a more accurate and reliable estimation of primary energy consumption and global cost for each building of the stock. Indeed, the efficiency of the HVAC system is a very influential parameter on the mentioned outputs. Diversely, SLABE did not considered the variation of the two parameters, because it did not aim to the analysis of each building, but to the achievement of global indications for the cost-optimality of retrofitting the whole category. Therefore, the adoption of average values for these parameters ensured satisfying and reliable outcomes. Finally, the existing building stock is represented by 48 parameters. Among these, the parameters that exercise a non-negligible influence on each output of the three ANNs, respectively for the assessment of EP_h, EP_c, and DH, are detected. In particular, if the sensitivity index, namely the standardized rank regression coefficient (SRRC) evaluated in *section 4.3.2,* is less than 0.05, the parameter is considered negligible on the output and ignored in the generation of the corresponding ANN. This threshold value has been chosen by observing a cutoff in the number of influential parameters vs. the sensitivity index amplitude, as also done in [103]. It should be noted that the SRRCs have been calculated, in *chapter 4*, in reference to the demand of thermal energy (ED) and not of primary energy (EP). However, this does not prejudice the reliability of the procedure, since a parameter that is not negligible for ED, reasonably, will be not negligible for EP too.

This screening leads to the establishment of three groups of significant parameters, used as inputs in the development of the three mentioned ANNs. These groups are outlined in table 5.1.

The same procedure is applied for identifying the inputs of the four ANNs, representing the renovated stock, in presence of ERMs. Among these, the unique RES system consists of PV panels, and thus the denotation E_{RES} is replaced with E_{PV}, in order to indicate the electricity produced by the photovoltaic generators and consumed by the building.

The renovated building stock is characterized by 64 parameters (see table 4.3 and 4.4). Specifically, in addition to the 46 ones describing the existing buildings, there are eight boolean parameters (one for each ERM for the reduction of energy demand), nine parameters related to the characteristics of thermal insulants and one parameter related to the shading set point. However, here, the thicknesses of the thermal insulants are varied in the range 0÷12 cm, whereas in the application of SLABE, they were fixed for ensuring the U values prescribed by Italian law to obtain state incentives [17]. The upper value of the range, i.e., 12 cm, has been established by virtue of local construction standards that take into account the strong impact of energy demand for space-cooling in the Mediterranean area, among all for office buildings, which are characterized by a significant internal heat gain. Indeed, too high values of insulant thickness would induce an increment of EP, caused by a strong increase EP_c, as also shown in *chapter 3*. The insulation thickness is considered variable in the networks' development, because this parameter can highly affect both energy demand and thermal comfort. Diversely, it has been considered fixed in the implementation of SLABE in order to facilitate the interpretation of the results.

Therefore, the Boolean variables encoding the presence/ absence of the insulation are replaced by continuous variables representing the thickness of the insulation layers. This choice is justified, again, by the different aims of the methodologies, consisting of the detailed analysis of each building and retrofit action for the ANNs, and of a global investigation of the building category for SLABE. Of course, the two additional parameters (p_{65} and p_{66}) that refer to the primary energy systems are considered also in this case. Their ranges of variability should include both the presence of existing and new efficient devices. Most notably, the application of SLABE (see *section 4.3.2*) showed that the largely most effective retrofit measures directed to the HVAC system consist of the implementation of a condensing boiler (η = 1.06) and of a water-cooled chiller (EER = 4.5). Hence, only these options are included in the in ANNs' development, in such a way that the range of variability is set equal to 0.7÷0.9; 1.06 for boiler η and to 1.5÷3; 4.5 for chiller EER. Eventually, a last parameter is introduced (p_{67}) in order to express the percentage of the building roof covered by polycrystalline PV Panels. As argued in *section 4.3.1*, they are selected as RES because solar energy is one of the most advantageous RESs in Europe [114], and particularly in Italy because of favorable climatic conditions. PV panels are preferred to solar thermal, because they are more cost-effective [72], in particular for office buildings. In this study, they are characterized by 34° tilt angle and 0° azimuth angle (orientation to south), in order to achieve the maximum annual production of electricity, as verified bt means of PV-GIS Software [115]. They have conversion efficency equal to 14%.

Finally, the renovated building stock is represented by 67 parameters. Among these, the non-negligible parameters on each output of the four ANNs, respectively for the assessment of EP_h, EP_c, DH, and E_{PV}, are detected by using the previously explained procedure, in which the threshold value for the SRRC is set equal to 0.05. The resulting four groups of ANNs' inputs are outlined in table 5.2.

Table 5.1. Parameters selected as ANNs' inputs for the existing building stock

Parameters			ANN for EPh	ANN for EPc	ANN for DH
Geometry	p_1	Orientation (North Axis)	●	●	●
	p_2	Area of each Floor [m^2]	●	●	●
	p_3	Form Ratio	●	●	
	p_4	Floor Height [m]	●	●	●
	p_5	Window to Wall Ratio: S	●	●	●
	p_6	Window to Wall Ratio: E	●	●	●
	p_7	Window to Wall Ratio: N		●	●
	p_8	Window to Wall Ratio: W	●	●	●
	p_9	Number of Floors	●	●	●
Envelope	p_{10}	Air Gap R^T [m^2 K/W]			
	p_{11}	Roof a	●	●	●
	p_{12}	External Walls a	●	●	●
	p_{13}	Thickness of Concrete			
	p_{14}	Type of Glass	●		●
	p_{15}	Type of Frame			
	p_{16}	Clay t [m]		●	
	p_{17}	Clay k [W/m K]		●	
	p_{18}	Clay d [kg/m^3]			
	p_{19}	Clay c [J/kg K]			
	p_{20}	Expanded Clay t [m]			
	p_{21}	Expanded Clay k [W/m K]			
	p_{22}	Expanded Clay d [kg/m^3]			
	p_{23}	Expanded Clay c [J/kg K]			
	p_{24}	External Brick t [m]	●	●	●
	p_{25}	External Brick k [W/m K]	●		
	p_{26}	External Brick d [kg/m^3]			
	p_{27}	External Brick c [J/kg K]			
	p_{28}	Floor Block t [m]			
	p_{29}	Floor Block k [W/m K]			
	p_{30}	Floor Block d [kg/m^3]			
	p_{31}	Floor Block c [J/kg K]			
	p_{32}	Internal Brick t [m]	●	●	
	p_{33}	Internal Brick k [W/m K]	●		
	p_{34}	Internal Brick d [kg/m^3]			
	p_{35}	Internal Brick c [J/kg K]			
	p_{36}	Roof Block t [m]	●		
	p_{37}	Roof Block k [W/m K]	●		
	p_{38}	Roof Block d [kg/m^3]			
	p_{39}	Roof Block c [J/kg K]			
Other	p_{40}	People Density [peop./m^2]	●	●	
	p_{41}	Light Load [W/m^2]	●	●	
	p_{42}	Equipment Load [W/m^2]	●	●	
	p_{43}	Infiltration Rate [h^{-1}]	●		
	p_{44}	Heating Set Point T [°C]	●		●
	p_{45}	Cooling Set Point T [°C]		●	●
	p_{46}	Heating Terminals	●		●
HVAC	p_{65}	Boiler η (**0.7 ÷ 0.9**)	●		
	p_{66}	Chiller EER (**1.5 ÷ 3**)		●	

Table 5.2. Parameters selected as ANNs' inputs for the renovated building stock

Parameters			ANN for EPh	ANN for EPc	ANN for DH	ANN for E_{PV}
Geometry	p_1	Orientation (North Axis)	●	●	●	
	p_2	Area of each Floor [m^2]	●	●	●	
	p_3	Form Ratio	●	●		●
	p_4	Floor Height [m]	●	●	●	
	p_5	Window to Wall Ratio: S	●	●	●	
	p_6	Window to Wall Ratio: E	●	●	●	
	p_7	Window to Wall Ratio: N	●	●	●	
	p_8	Window to Wall Ratio: W	●	●	●	
	p_9	Number of Floors	●	●	●	●
Envelope	p_{11}	Roof a*	●	●	●	
	p_{12}	External Walls a	●	●	●	
	p_{14}	Type of Glass**	●	●	●	
	p_{16}	Clay t [m]		●		
	p_{17}	Clay k [W/m K]		●		
	p_{24}	External Brick t [m]	●	●		
	p_{25}	External Brick k [W/m K]	●			
	p_{32}	Internal Brick t [m]	●	●	●	
	p_{33}	Internal Brick k [W/m K]	●			
	p_{36}	Roof Block t [m]	●			
	p_{37}	Roof Block k [W/m K]	●			
Other	p_{40}	People Density [peop./m^2]	●	●		
	p_{41}	Light Load [W/m^2]	●	●		
	p_{42}	Equipment Load [W/m^2]	●	●		
	p_{43}	Infiltration Rate [h^{-1}]	●			
	p_{44}	Heating Set Point T [°C]	●		●	
	p_{45}	Cooling Set Point T [°C]		●	●	
	p_{46}	Heating Terminals	●		●	
EEMs^d	p_{47}	Walls Insulation (**tv = 0 ÷ 12 cm**)	●	●	●	
	p_{48}	Roof Insulation (**tr = 0 ÷ 12 cm**)	●	●	●	
	p_{49}	Floor Insulation				
	p_{50}	Low-a Plastering of the Walls	●	●	●	
	p_{51}	Low-a Plastering of the Roof*	●	●	●	
	p_{52}	Low-e double Windows**	●	●	●	
	p_{53}	External Solar Shading	●	●	●	
	p_{54}	Free Cooling		●	●	
	p_{55} - p_{64}	Additional parameters				
HVAC	p_{65}	Boiler η (**0.7÷9; 1.06**)	●			
	p_{66}	Chiller EER (**1.5÷3; 4.5**)		●		
RES	p_{67}	Percentage of the Roof covered by polycrystalline PV Panels (0 ÷ 100 %)				●

*The low-a plastering of the roof is contemplated by means of the variation of the roof a
** The low-e windows are contemplated by means of the variation of the type of glass

5.3.2. Results and discussion

All the developed networks are characterized by ten hidden neurons, because this number ensures a good compromise between accuracy and generalization ability of the models for the investigated case study.

Existing building stock

Three ANNs are developed for simulating the performance of the existing building stock, respectively for the assessment of EP_h, EP_c, and DH. For training and testing these networks, the sampling set S_1 of 500 building instances, generated by means of Latin Hypercube Sampling (LHS) for the application of SLABE (see *section 4.3.2*), is considered. More in detail, the performed EnergyPlus simulations, have provided for each one of the mentioned 500 samples the following relevant data:

- the hourly values of the predicted mean vote (PMV) for all the thermal zones for the building;
- the hourly values of thermal energy demand for heating and cooling.

From the values of PMV, the target DH is calculated in MATLAB. Diversely, the evaluation of EP_h and EP_c requires an intermediate step, since the LHS that leads to S_1 involves only the parameters affecting the demand of thermal energy (from p_1 to p_{46}), thereby not considering those related to the primary energy systems (p_{65} and p_{66}). Therefore, a further LHS is needed in order to sample the parameters p_{65} and p_{66}. In other words, two sets of 500 values respectively of boiler η and chiller EER are generated. Such values are used in order to obtain the values of EP_h and EP_c from the hourly values of thermal energy demand provided by EnergyPlus. This post-process is performed in MATLAB.

Eventually, a set of 500 values is achieved for each output, i.e., EP_h, EP_c and DH, thereby representing the targets of the three respective ANNs. The training set is composed of 450 cases (90% of cases), fulfilling the minimum value proposed by Conraud [143], randomly picked from the 500 available samples. The testing test includes the remaining 50 ones. The performance of the networks are evaluated by considering the regression as well as the distributions of the relative errors between ANN's outputs and targets provided by EnergyPlus. The outcomes of the testing are summarized in table 5.3 and in figure 5.2.

Table 5.3. Testing of the developed ANNs related to the existing building stock

ANNs		Epochs	R	Number of cases with Relative Error					Average |Relative Error|
				<1%	<2.5%	<5%	<10%	<25%	
Existing Stock	EP_h	387	0.982	18	26	50	76	100	6.1%
	EP_c	336	0.975	10	22	44	76	100	6.9%
	DH	394	0.966	12	18	38	70	100	8.4%

The average relative errors are quite good, respectively 6.1% for EP_h, 6.9% for EP_c and 8.4% for DH. The ANN for DH prediction is less accurate because the estimation of thermal comfort is ruled by more complicated phenomena, which are hardly predictable (e.g., radiation heat transfer between walls and people, heat transfer between heating terminals and people, and so on). The same conclusion was provided by previous studies on the adoption of ANNs for the simulation of building energy performance [81, 137]. It should be noticed that the values of relative errors between ANNs' outputs and targets are globally higher compared to those achieved in similar worthy studies referred to a single building [81, 137], since the analysis of a building stock is obviously much more complicated, because of much wider ranges of parameters' variability. On the other hand, a similar approach for the investigation of energy and thermal behavior of a whole building category is quite new; thus, the current scientific literature does not provide many comparable studies for a deeper investigation of the goodness of the proposed methodology.

The regressions between the ANNs' predictions and the simulated targets (see figure 5.2), also show a good agreement with regression coefficients (R) very close to 1.

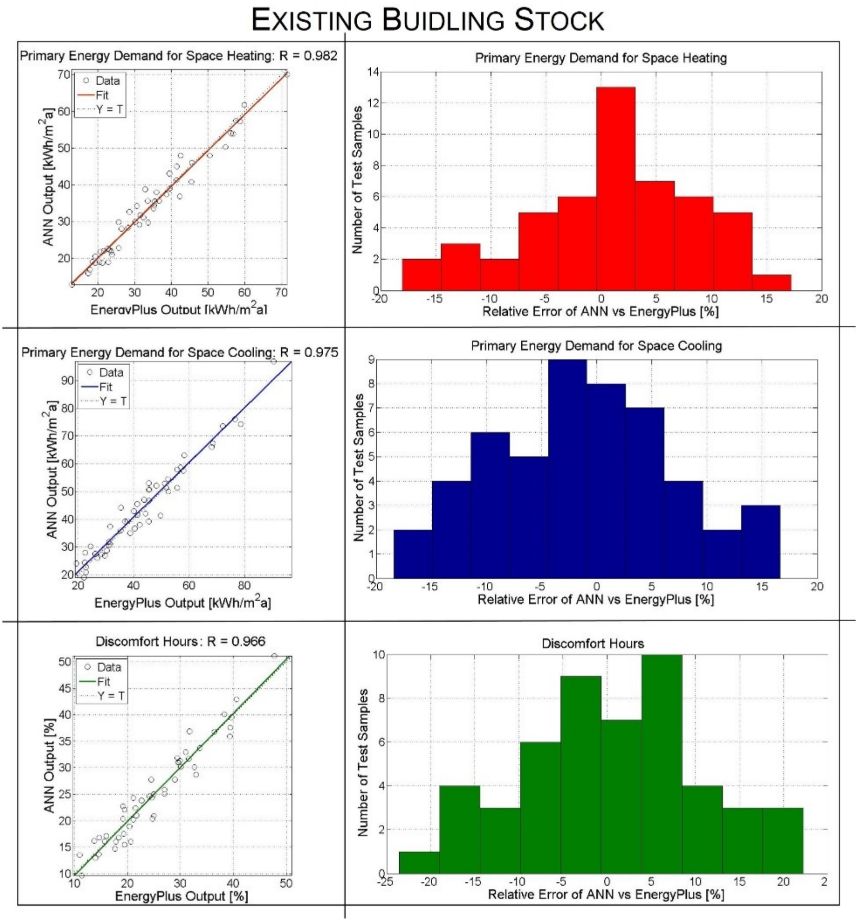

Figure 5.2. Meta-models of the existing building stock. ANNs vs EnergyPlus: regression between ANNs' outputs and simulated (EnergyPlus) targets and distributions of relative error

Renovated building stock

Four ANNs are developed for simulating the performance of the renovated building stock, respectively for the assessment of EP_h, EP_c, DH and E_{PV}. For training and testing these networks, a new sampling set, S_4, is generated by means of LHS. The sample space is defined by the parameters (and their correlated ranges) reported in table 5.2 that are included in the inputs of at least one network, i.e. all the referred-to parameters except for the floor insulation (p_{49}) and the additional parameters defining the ERMs (p_{55} - p_{64}). The set S_4 collects 1000 building instances, which are run in EnergyPlus, by means of the coupling with MATLAB. The outcomes of the simulations are post-processed in MATLAB, as explained in the previous *section*, in order to achieve a set of 1000 values for each output, i.e., EP_h, EP_c, DH and E_{PV}, thereby representing the targets of the four corresponding ANNs. By adopting the aforementioned subdivision of the sampling set (90% vs 10%), the training set is composed of 900 cases (fulfilling the minimum value proposed by Conraud [143]), randomly picked, and the testing one includes the remaining 100. A higher number of cases is used for the developed of the ANNs, compared to the first networks' family (existing stock), because additional parameters are introduced for defining the ERMs, which make the energy and thermal behavior of the buildings much more heterogeneous. Thus, in order to ensure reliable outcomes the number of cases is doubled.

The regression as well as the distributions of the relative errors between ANN's outputs and targets provided by EnergyPlus simulations are summarized in figure 5.3 and in table 5.4.

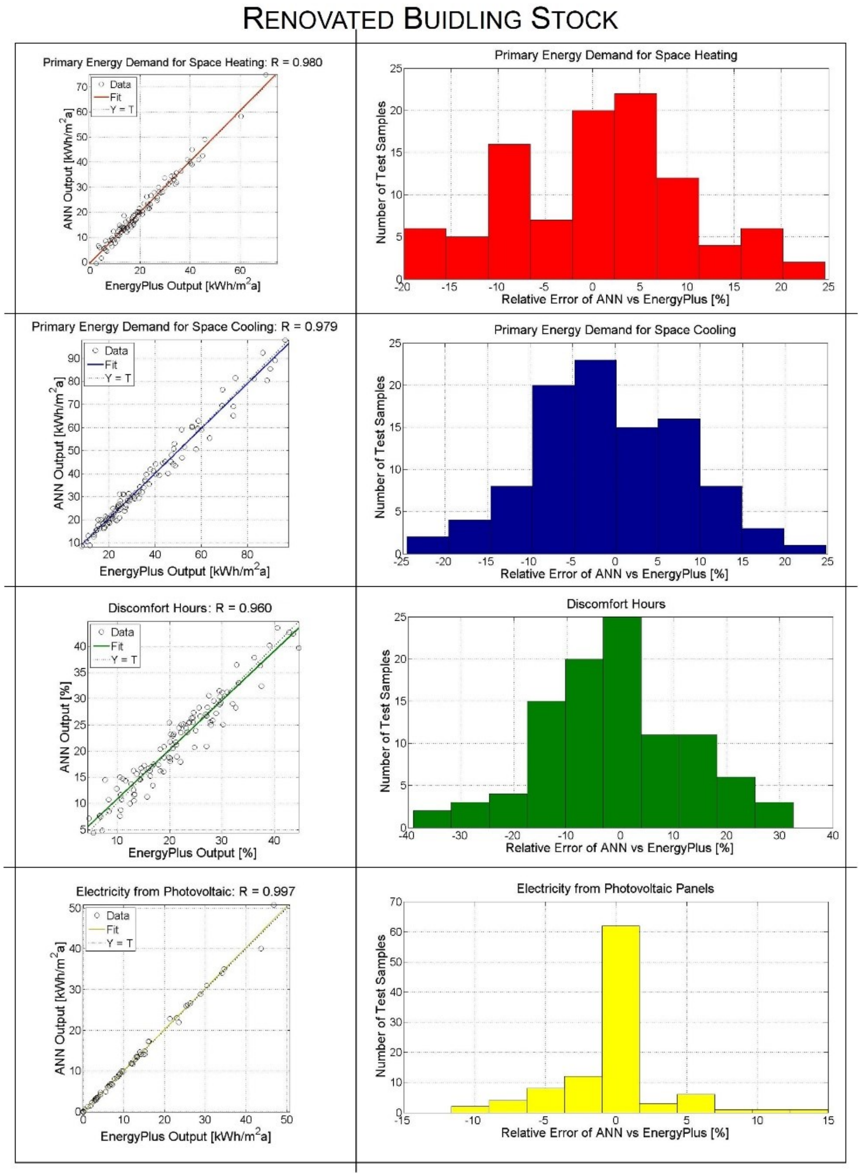

Figure 5.3. Meta-models of the renovated building stock. ANNs vs EnergyPlus

Table 5.4. Testing of the developed ANNs related to renovated building stock

ANNs		Epochs	R	Number of cases with Relative Error					Average|Relative Error|
				<1%	<2.5%	<5%	<10%	<25%	
Renovated Stock	EP_h	695	0.980	6	21	36	75	100	8.0%
	EP_c	655	0.979	7	22	37	76	100	8.1%
	DH	384	0.960	11	17	33	54	90	11%
	PV	479	0.997	60	75	85	96	100	2.0%

The performance of this second family of networks for EP_h, EP_c and DH is quite similar, albeit a slight worsening, to that of the first family. Indeed, the average absolute relative errors are respectively equal to 8.0% for EP_h, 8.1% for EP_c and 11% for DH, as well as the regression coefficients are lower, but still very close to one. This outcome is quite obvious because the ANNs related to the renovated stock aim to predict the behavior of a more complex, wide and various system. As already argued, the ANN for DH assessment is the one with the worst performance. On the other hand, the fourth network, that is the one for the prediction of E_{PV}, behaves very well (R = 0.997, average absolute relative errors = 2.0%) because it is characterized by only three inputs, consisting of building *form ratio*, *number of floors* and *percentage of the roof covered by polycrystalline PV panels.* The first two parameters affect the ratio between the electricity produced by the PV generator and that required by the facility, and thus the percentage of the produced energy that is consumed, while the third parameter obviously exercises a huge influence on the absolute value of electricity produced by the PV generator.

In order to perform a further verification of the reliability and accuracy of the two networks' families, both of them are applied for predicting the performance of the reference building related to the investigated category. The building is detailed in *section 4.3.1*. It doesn't present a PV system, so that the ANN for E_{PV} assessment (second family) is not used. The comparison between ANNs' predictions and EnergyPlus simulated targets are reported in table 5.5.

Table 5.5. Comparison between ANNs' outputs and EnergyPlus simulated targets in relation to the reference building (in absence of ERMs)

Reference Building	**EnergyPlus**	ANNs related to the Existing Stock		ANNs related to the Renovated Stock	
		value	error [%]	value	error [%]
EP_h (Fc) [kWh/m^{2}a]	**25.4**	24.9	0.74	25.5	0.43
EP_h (Rad) [kWh/m^{2}a]	**28.8**	28.2	-2.2	27.5	-4.7
EP_c [kWh/m^{2}a]	**47.8**	49.0	2.5	48.1	0.62
DH (Fc) [%]	**35.5**	35.4	-0.28	33.6	-5.7
DH (Rad) [%]	**26.7**	26.9	0.74	24.7	-8.1

The results are very satisfying for both families, with a maximum absolute error of the networks equal to 2.5% (ANN for EP_c assessment) for the family related to the existing stock, and to 8.1% (ANN for DH assessment) for the one related to the renovated stock. As expected, the first family performs better because it is built on data concerning only the existing buildings. However, the outcomes show that also the second family is able to predict with a good approximation the energy behaviour of existing buildings. This is an important target because it ensures that the impact of the retrofit measure is properly estimated.

Finally, it is highlighted that, by using a processor Intel® Core™ i7 at 2.00 GHz speed, the computational time required by a simulation performed in EnergyPlus for the reference building is around 50 s, whereas that required by the implementation of an ANNs' family is around 1 s.

Therefore, the adoption of the developed surrogate models allows a saving of the computational time around 98%.

Of course, this benefit is amplified when the ANNs either are used for the simulation of more complex buildings or are implemented in optimization procedures, e.g., CAMO, that require a high number of energy simulations (of the order of 1000).

Final remarks

Most notably, ANNs provide an effective tool, but they have a weakness: they are not sufficient for a robust cost-optimal analysis, since they need to be implemented in other methodologies, in which they can ‘subrogate’ the traditional BPS tools. This happens in CASA, which is illustrated in the next *chapter*.

How to perform a reliable, fast, 'ad hoc' cost-optimal analysis of the retrofit measures for each building of the stock?

CHAPTER 6. CASA: a new methodology for Cost-optimal Analysis by multi-objective optimiSation and Artificial neural networks

6.1. Introduction

CASA is the macro-methodology proposed in this thesis. It allows to achieve the ultimate, crucial and original goal of this study, that is a reliable, fast, 'ad hoc' cost-optimal analysis of the retrofit measures for each single building of a stock. It is recalled that the acronym CASA has a double meaning. On one hand, it reveals the combination among **CA**MO, **S**LABE and **A**NN. On the other hand, it points out the core of the methodology, that is the Cost-optimal Analysis by multi-objective optimiSation and Artificial Neural Networks. In addition, the acronym is something suggestive, since the Italian translation of the word 'casa' is 'house'. As the different components of a house have different functions but they all contribute to the ultimate occupants' well-being, so CAMO, SLABE and ANN can be applied independently for achieving important targets, but their combination in CASA allows to reach the ultimate crucial goal. CAMO, SLABE and the adoption of ANNs for modeling the energy behavior of any building of a certain category, as discussed in the previous *chapters*, are original and worthy methodologies. However, they provide a response to questions (q1, q2, q3 in *section 1.2*) to which other authors have already tried to answer. Diversely, CASA is an absolute novelty because the current scientific literature is devoid of studies that aim to answer the final question, on which this thesis is founded:

q5. How to perform a reliable, fast, 'ad hoc' cost-optimal analysis of the retrofit measures for each building of the stock?

CASA is the solution.

6.2. Methodology

CASA is a novel multi-stage methodology that can be applied to each building category and, thus, to each building of the stock, for the assessment of the cost-optimal package of energy retrofit measures (ERMs) with a low computational burden. It includes the other three methodologies proposed in this thesis, namely CAMO, SLABE and building energy simulation by ANNs, that represent the three complementary parts of CASA. In more detail, by referring to an established category, CASA is composed of three stages, reported in figure 1.1 (here revived) and described below:

STAGE I. SLABE is implemented to investigate the building category by means of uncertainty analysis and sensitivity analysis in order to detect the parameters (related to existing stock and energy retrofit measures) that most affect thermal energy demand and thermal comfort. The most cost-effective ERMs are identified. (*chapter 4*)

STAGE II. Seven ANNs are developed for assessing thermal comfort, energy consumption, and thus global cost of the buildings that belong to the category. More in detail, two families of networks are generated. The first family aims to predict the primary energy consumptions for heating (EP_h) and cooling (EP_c), as well as the annual percentage of discomfort hours (DH) of the existing building stock (3 ANNs). The second family aims to predict EP_h, EP_c, DH and the energy produced by renewable energy sources (E_{RES}) of the renovated building stock, in presence of ERMs (4 ANNs). The most influential parameters, identified in stage I, are adopted as networks' inputs. Furthermore, the most effective ERMs detected in stage I are investigated. (*chapter 5*)

STAGE III. CAMO is performed by using the ANNs instead of EnergyPlus in order to find the cost-optimal package of energy retrofit measures for any building of the category. Once developed the ANNs through the information provided by SLABE, the implementation of CAMO is much faster and 'user-friendly' compared to the case that a BPS tool is adopted.

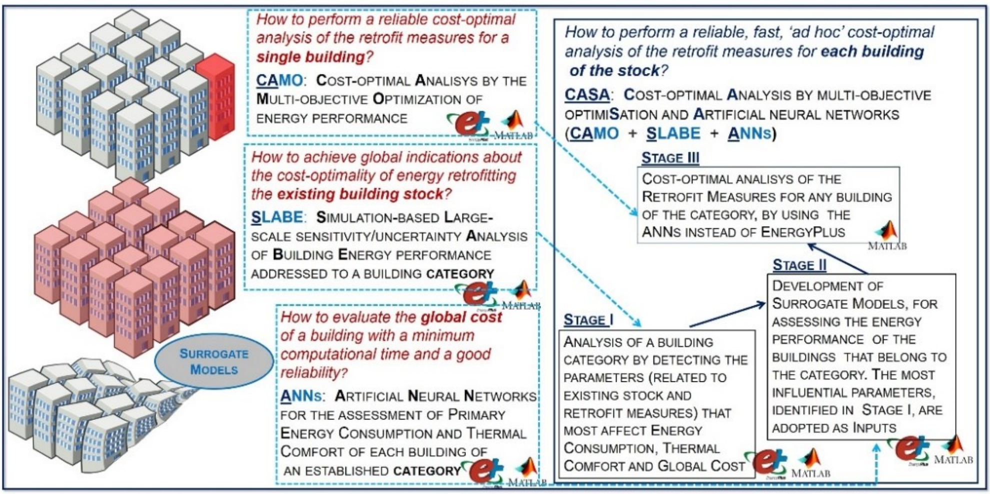

Figure 1.1. Scheme of the proposed methodologies and their coupling for the cost-optimality of building energy retrofitting: from a single building to stock

6.3. Application

6.3.1. Presentation of the case study

CASA is applied for assessing the cost-optimal energy retrofitting strategy of a building belonging to the category investigated by means of SLABE and ANNs, namely: *Office buildings built in South Italy in the period 1920-1970.* More in detail, the methodology is implemented to the reference building (RefB) related to such category, detailed in *section 4.3.1*.
Therefore, the first two stages of CASA have been already applied in the previous part of this thesis. Indeed, SLABE has been performed to the considered category in *chapter 4*, and the ANNs related to the examined buildings have been developed in *chapter 5*, by exploiting the data provided by SLABE. In the following lines, the application of the final stage of CASA is carefully described and the cost-optimality is assessed.

In particular, CAMO is applied to the building, by using the ANNs instead of EnergyPlus, in order to investigate the following ERMs:

- installation of a new external coating of the roof, characterized by a low solar absorptance (a);
- installation of external thermal insulation of the roof;
- installation of external thermal insulation of the vertical envelope;
- installation of a mechanical ventilation system, for achieving free cooling when the outdoor temperature is lower than the indoor one in summertime;
- variation of the set points of indoor temperature, during both heating and cooling seasons;
- replacement of the single-glazed windows with low-emissive double-glazed ones;
- replacement of the present standard boiler with a condensing one (η=1.06);

- replacement of the air-cooled chiller with a water-cooled one (EER=4.5), with the consequent installation of a cooling tower;
- installation of polycrystalline PV panels on the roof.

These ERMs have been selected on the basis of the outcomes provided by SLABE for the considered category. Indeed, they are the most affecting the building energy and thermal behavior. For a detailed description of such retrofit measures, the readers are invited to refer to *section 4.3.1*. Of course, only these measures have been considered in the generation of the four ANNs related to the renovated building stock.
Eventually, the following design variables (the number is of the order of 10, as recommended by Wetter [95]) can be identified:

- absorption coefficient of solar radiation of the roof (a);
- thickness of the insulation of roof (t_r);
- thickness of the insulation of vertical walls (t_v);
- free cooling by means the mechanical ventilation system;
- set point temperature of indoor air during the heating season (T_{heat});
- set point temperature of indoor air during the cooling season (T_{cool});
- window: single/double glazed;
- boiler: old standard / condensing one;
- chiller: air- or water-cooled;
- percentage of the roof covered by PV panels.

Each design choice can assume different discrete values, since CAMO operates with discrete variables (see *section 3.2.1*). These allowable values and the associated investment costs (IC), if present, are reported in table 6.1, where the configuration of the reference building is also shown. The of IC are taken from *chapter 5* (see tables 4.4 and 4.5).

It is noted that, diversely from the previous application of CAMO to e residential building (see *chapter 3*), also a RES system, i.e., photovoltaics, has been investigated, because PV panels exercise a huge impact on the energy performance of office buildings, characterized by high electric uses.

Table 6.1. Option values and investment cost (IC) of the design variables

DESIGN VARIABLES	OPTION VALUES	REFERENCE BUILDING	IC [€]
a	0.05 0.50 0.95	 ● 	4320 - 4320
t_r	0 cm 3 cm 6 cm 9 cm	● 	- 4059 6336 6783
t_v	0 cm 3 cm 6 cm 9 cm	● 	- 5495 8578 9182
free cooling	no Yes	● 	- 7610
T_{heat}	19°C 20 °C 21 °C 22 °C	 ● 	- - - -
T_{cool}	24 °C 25 °C 26 °C 27 °C	 ● 	- - - -
window type	single glazed (U_w = 5.8 W/m^{2}K) double glazed low-e (U_w = 1.9 W/m^{2}K)	● 	- 21600
boiler type	old condensing	● 	- 8100
chiller type	air-cooled water-cooled	● 	- 21500
PV: roof coverage	0 – 100% with a step of 10%	0%	3 €/W_p

CAMO is applied to the delineated case study, in conjunction with ANNs, by adopting the parameters of the GA reported in table 6.2. The GA performs the multi-objective optimization of primary energy consumption per unit of conditioned area (PEC’) and annual percentage of discomfort hours (DH), in presence of the aforementioned design variables that represent ERMs. PEC’ and DH are evaluated by means of the second family of ANNs, developed for investigating the ERMs (see *chapter 5*). It is noted that PEC’ is preferred, as objective, to the primary energy demand for space conditioning (EP), used in the previous application of CAMO, in order to contemplate the benefits induced by the PV panels.

Table 6.2. Setting of the control parameters (see *section 3.2.2*) of the GA

s	c_e	f_c	f_m	g_{max}	tol
50	2	0.6	0.1	200	0.001

The values of the population size (s) and of the maximum number of simulations (g_{max}) is quite higher compared to the application of CAMO proposed in *chapter 3*. Indeed, the adoption of ANNs (50 vs 25 for s, 200 vs 30 for g_{max}), instead of EnergyPlus simulations, allows to save around 98% of the computational time for energy simulations, as argued in the previous *chapter*. Therefore, the implementation of the networks in CAMO yields a double benefit, because it ensures a more reliable Pareto front in a time much lower.

It is also worthy to note that the number of energy simulations, required for investigating all possible retrofit strategies, would be 122880, while the optimization procedure takes a maximum of 10000 simulations. Thus, an exhaustive analysis carried out by means of EnergyPlus would involve a computational time around 70 days, while the adoption of CAMO coupled with ANNs (inside CASA) would imply a computational time lower than 3 hours. It’s clear that the capability of CASA is enormous.

6.3.2. Results and discussion

It is recalled that the first phase of CAMO involves the multi-objective optimization of PEC’ and DH, in correspondence of different available economic budgets. In this case study, since the maximum total investment cost of the retrofit actions is 120000 €, the optimization procedure has been performed for the following four budgets: 30000 €, 60000 €, 90000 €, 120000 € (corresponding to an unlimited availability).

The Pareto fronts achieved for these four budgets are depicted in figure 6.1, where the ‘best’ solution, with reference to each budget and using the minimum comfort criterion (DH_{max} = 20%), is highlighted by means of a bigger black marker. The values assumed by the design variables in correspondence of these best packages and the relative investment costs are listed in table 6.3, where the packages are respectively indicated with the symbols P1, P2, P3, P4, (from the lowest to the highest budget).

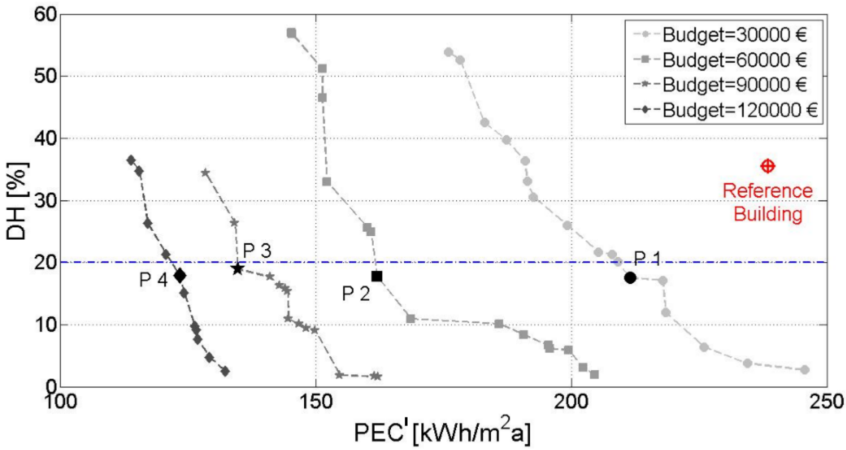

Figure 6.1. Pareto fronts for the four budgets: the recommended packages using the comfort criterion are highlighted through bigger black markers

Table 6.3. Design variables and investments costs (IC) of the recommended packages

PACKAGES	BUDGETS 30 k€ P1	60 k€ P2	90 k€ P3	130 k€ P4
a	0.5	0.5	0.5	0.05
t_r	0 cm	0 cm	9 cm	9 cm
t_v	0 cm	3 cm	9 cm	9 cm
free cooling	yes	no	yes	yes
solar shading	no	no	yes	yes
T_{heat}	21 °C	20 °C	20 °C	20 °C
T_{cool}	25 °C	24 °C	26 °C	25 °C
windows	single glazed	single glazed	single glazed	low-e double glazed
boiler	condensing	old	old	condensing
chiller	air-cooled	water-cooled	water-cooled	water-cooled
PV coverage	40%	80%	100%	100%
IC	28020 €	58195 €	86346 €	120000€

Unlike in the first application of CAMO (*chapter 3*), only the method of the minimum acceptable thermal comfort is here used for the multi-criteria decision making (MCDM), since this criterion is more relevant to the study of building energy performance. Furthermore, the outcomes of *chapter 3* has shown that the comfort method and the utopia point method lead to similar results. The maximum acceptable value of percentage discomfort hours (DH_{max}) is set at 20%. A higher threshold value has been chosen, compared the previous application to a residential building (DH_{max} = 10%), because this case studies is globally characterized by higher values of DH, as clear in the comparison between figure 6.1 and figure 3.7. This is mainly due to the high internal heat gains that penalize the comfort in summer time. Really, depending on the occupants' needs, the methodology here proposed allows the choice of the most proper DH_{max}. Most solutions on the Pareto fronts determine a significant improvement compared to the reference building, whose performance is indicated in figure 6.1 by a red cross. This underlines that the behavior of the present

building is unacceptable from both the point of views of energy consumption and thermal comfort. All told, figure 6.1 and table 6.3 yield to original and relevant remarks, founded on physical considerations.
As the budgets increase, the fronts obviously move left without overlapping, thereby providing a first verification of CASA reliability.
The recommended packages of ERMs for the four budgets (P1, P2, P3, P4), summarized in table 6.3, do not include a retrofit measure that is always present, except for PV panels. This shows that the considered ERMs are quite interactive as argued in the following lines. As said, the photovoltaic technology is always present because it ensures a huge PEC’ saving. However, when the budget is quite limited (see P1 and P2) the maximum size of PV panels compatible with the economic limit is not implemented. Indeed, when the size increases, the energy benefit induced by photovoltaics grows more slowly (see figure 4.14). Thus, other ERMs are preferred to the adoption of a higher number of PV panels, in order to improve also the second objective, that is DH, which is not affected by photovoltaics. Besides the installation of PV panels, each of the recommended solutions includes a mix of ERMs that aims to ensure a trade-off between the needs of wintertime and summertime.
P1 is characterized by the presence of free cooling and condensing boiler. This latter is preferred to the water-cooled chiller that would be more influential on PEC’ by virtue of the magnitude of cooling demand (see figure 4.11). This could appear strange but, actually, it is a proof of the reliability of the methodology because the choice of replacing the chiller, instead of the boiler, would be more expensive, thereby reducing the size of photovoltaics and avoiding the adoption of ERMs for the other (heating) season. Diversely, P1 provides a more balanced and effective mix of measures directed to all the energy uses of the building, i.e., heating, cooling and electricity. Moreover, it includes more comfortable

set point temperatures in both season compared to the reference building, while nevertheless ensuring a lower PEC'.

P2 provides a higher size of photovoltaics, albeit still lower than the maximum one, as well as a 3 cm thick insulation of the vertical walls and the water-cooled chiller. In this case, the replacement of the chiller is preferred to that of the boiler, because the higher budget allows the implementation of the insulation, which produces a reduction of heating demand and DH. Indeed the value of DH is significantly influenced by the levels of thermal comfort during winter and intermediate seasons (summer covers a small period), which benefit from the presence of an insulated building envelope because of higher values of the mean radiant temperature. Consequently, an increment of this parameter allows a reduction of T_{heat} compared to P1 (20°C vs 21°C), which obviously is convenient from the energy and economic points of view. Diversely, the thermal comfort in summertime is penalized, by requiring a reduction of T_{cool} compared to P1 (24°C vs 25°C), not convenient from the aforementioned points of view. All told, also this package of measures contemplates all the energy uses of the building.

P3 implements all the considered ERMs, except for the low-a plastering of the roof, the low-e windows and the condensing boiler. PV panels cover the whole roof surface; so the maximum power is installed. Both roof and vertical walls are insulated, by adopting the maximum insulant thickness, i.e., 9 cm. This determines a strong reduction of energy demand for heating and a substantial improvement of thermal comfort during winter and intermediate seasons. On the other hand, the implementation of free cooling and external solar shading yields substantial benefits on cooling demand and thermal comfort in summertime. Thus, the ERMs are balanced and provide an optimal trade-off among the different building need. In fact, there isn’ t the necessity of modifying the set point temperatures compared to the reference building.

P4 implements all the investigated ERMs. This is possible by virtue of an unlimited available budget. In general, this result is not obvious (for instance, see the previous application of CAMO) but, in this case, it was expected because the ERMs have been properly chosen by means of SLABE. The main differences between P4 and P3 consist in the presence of the low-a roof plastering, low-e windows and condensing boiler. These measures have different effects. Indeed, the low-a plastering is beneficial for energy demand and thermal comfort in the cooling season, while the opposite occurs for the heating season. The condensing boiler, obviously, determines a reduction of energy demand for heating. Eventually, the installation of new windows with double and low-emissive glasses induces lower thermal losses in wintertime, whereas contrasting effects occur in summertime. Indeed, the new glazed systems reduce the entering solar radiation, although also the favorable thermal losses from the indoor environment to the external one, in some hours (mainly in the intermediate seasons), are lowered. Finally, also P4 collects a balanced mix of retrofit measures. However globally, compared to P3, such mix slightly penalizes the thermal comfort in summertime, thereby requiring a lower T_{cool} (25°C vs 26°C).

It’s quite difficult to draw up a ranking of the retrofit energy measures based on the intervention priority as done in *section 3.3.2* because of the high synergy among them. However, it is noted that the low-a plastering of the roof and the installation of low-e windows are implemented only if an unlimited budget is available. It means that these energy efficiency measures have the lowest priority, because their impact on the objectives is less positive compared to the other measures. On the other hand, the installation of PV panels, the achievement of free cooling by means of mechanical ventilation and the implementation of efficient HVAC systems represent the ERMs with the highest priority. Concerning the HVAC system, in absence of an insulated building envelope, the priority belongs to the replacement of the boiler with a condensing one, otherwise it belongs to the replacement of the air-cooled chiller with a water-cooled one. The thermal insulation of both vertical walls and roof represents a further effective retrofit measure. Indeed, in most cases when the budget is sufficient, the maximum thicknesses are implemented. This outcome seems to be partially in disagreement with the results of the sensitivity analysis performed by means of SLABE (see figure 4.9). Indeed, the standardized rank regression coefficients (SRRCs) show that the insulation of both walls and roof determines a significant improvement of DH, while they exercise a slight influence on the demand of thermal energy for space conditioning because of the contrasting effects occurring in wintertime and summertime (see *section 2.2.3*. for a detailed description). Actually, the disagreement does not subsist. In fact, in CASA's outcomes the presence of the thermal insulation is always coupled with the adoption of the efficient water-cooled chiller, which reduces the impact of energy demand for cooling on PEC', thereby making the insulation effective. Furthermore, CASA tends to pick this retrofit measure because it exercise a huge positive impact on DH, whereas PEC' can be 'adjusted' by means of photovoltaics.

As done in *chapter 3*, after the optimization study in matter of energy performance and thermal comfort, an economic analysis is performed for detecting the cost-optimal package and thus 'the best budget' that should be invested. Thus, the global cost (GC) is calculated for the packages listed in table 6.3 and for the reference building. It is noticed that in *chapter 3*, two cases have been investigated, namely the absence of state incentives and the presence of a hypothetical capital grant that covers the 50% of the investment cost (IC) for ERMs. Here, in order to realize an evaluation closer to reality, only the presence of current incentives provided by the Italian Government is considered. They consist of a capital grant, according in ten years, that cover the 50% of IC for PV panels and the 65% of IC for condensing boiler, efficient windows and thermal insulation that allows to fulfill the U values prescribed by the law (in this case, for both walls and roof, the incentive is accorded only in presence of a 9 cm thick insulant). These incentives are not contemplated during the optimization procedure for assessing IC related the ERMs packages, which should fulfill the economic budget, because they are differed in ten years and so they are not perceived by the users as an actual reduction of the initial disbursement, for which the constraint is conceived. For GC evaluation, a calculation period of 20 years is used, as prescribed by the guidelines of the EPBD Recast for non-residential buildings. The prices of electricity and natural gas, and primary energy factors assume the values shown in *section 4.3.2*.

The values of DH, PEC' and GC – which are the main objectives of this study – in correspondence of P1, P2, P3, P4 and RefB are shown in table 6.4, where the results achieved by means of ANNs are compared to those provided by EnergPlus in order to further verify the reliability of CASA. The percentage relative error committed by the newtorks is reported for each of the mentioned objectives. Finally, the values of GC for the four recommended packages (P1, P2, P3, P4) and the RefB are depicted in figure 6.2, where the cost-optimal package of ERMs is highlighted. In this figure, the solutions are put in order of increasing PEC', for recalling the typical cost-optimal curve (see figure 2.3) where the point of minimum represents the cost-optimality.

Table 6.4. Values of objective functions and global cost for recommended packages and reference building: comparison between ANNs and EnergyPlus

	Packages	Budgets 30 k€ P1	60 k€ P2	90 k€ P3	130 k€ P4	Reference Building
ANNs	PEC' [kWh/ m^2 a]	211.5	162.0	134.8	123.4	239.1
	DH [%]	17.5	17.8	19.0	18.1	33.6
	GC [€]	148615	140180	**133130***	137260	152720
EnergyPlus	PEC' [kWh/ m^2 a]	212.5	164.3	134.5	124.4	238.5
	DH [%]	19.0	21.8	23.6	22.0	35.5
	GC [€]	149320	140470	**131750***	135900	152320
Error of ANNs	PEC'	-0.5%	-1.4%	0.2%	-0.8%	0.3%
	DH	-8.6%	-22.0%	-24.0%	-22.0%	-5.7%
	GC	-0.5%	-0.2%	1.0%	1.0%	0.6%

*Cost-optimal solution

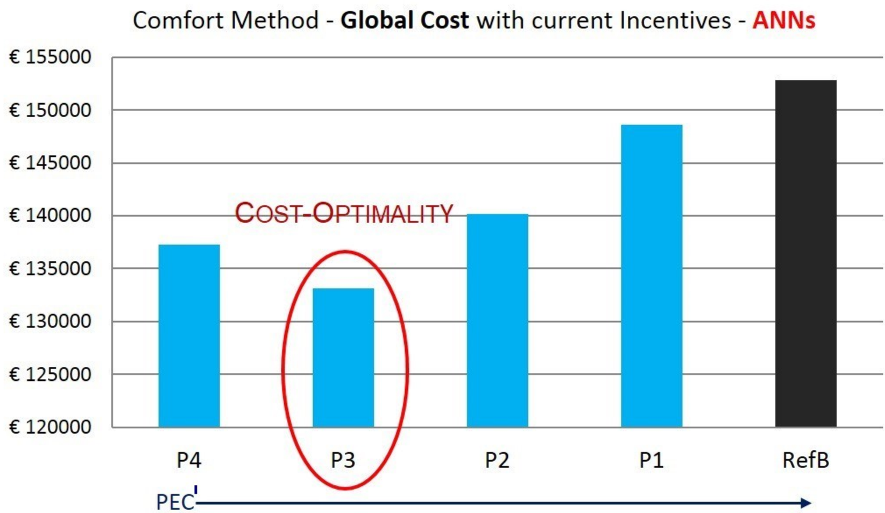

Figure 6.2. Global cost of the recommended packages in presence of Current Incentives and cost-optimal solution

Table 6.4 shows that the results provided by ANNs are very reliable as for PEC' and GC predictions, since the maximum absolute relative error related to EnergyPlus simulations is respectively equal to 1.4% for PEC' and 1% for GC. On the other hand, the network for the assessment of DH is less accurate, as already noticed in *section 5.3.2*, because thermal comfort is ruled by more complicated phenomena, which are hardly predictable. The maximum absolute relative error is equal to 24% However, such ANN is able to predict the trend of DH. Indeed, both the network and EnergyPlus outputs determine that $DH_{RefB}>DH_{P3}> DH_{P4}> DH_{P3}> DH_{P1}$. This is the most important feature concerning thermal comfort that the network must own in order to achieve a faithful comparison between different ERMs packages. Indeed, the calculation of the precise value of DH is quite aleatory and also the number given by EnergyPlus is not completely credible. That's why, the main thing is the capability of predicting the increasing or decreasing trend of DH. Therefore, also the performance of the ANN for DH assessment is considered satisfying.

The cost-optimal package is represented by P3, and thus the 'cost-optimal' budget to invest is equal to 90000 €. This yields a GC saving of around 19600 € in the building life-cycle, compared to the reference building.

This output differs from the cost-optimal package identified by means of SLABE for most buildings of the category (see figure 4.16) because CASA gives a greater importance to thermal comfort, which is an objective whereas in SLABE it is a secondary criterion for selecting ERMs. Therefore, the cost-optimal solution by CASA includes the thermal insulation of roof and external walls, while that by SLABE doesn't. On the other hand, the two cost-optimal packages present the same HVAC system and size of PV panels.

Finally, CASA can be applied to any building for detecting the cost-optimal package of energy retrofit measures by means of a reliable, fast, ‘ad hoc’ procedure. This induces both a saving of global cost, thus of money, and a reduction of energy consumption, thus polluting emissions, of the building sector.

Therefore, a double ‘optimum’ is achieved: an economic ‘optimum’ for the buildings’ owners/ occupants; an environmental ‘optimum’ for the community.

This means multi-objective optimization.

CHAPTER 7. Conclusions

The recast version of the Energy Performance of Building Directive (2010/31/EU) underlines the necessity of a building activity aimed at the most proper levels of energy efficiency “with a view to achieving cost-optimal levels”. More in detail, it prescribes the cost-optimal analysis for detecting the best package of energy efficiency measures (EEMs) to apply to new or existing buildings. This study is focused on the energy retrofitting of existing constructions because it is a key-strategy to achieve tangible results in the reduction of energy consumption, and thus polluting emissions, of the building sector.

All told, the cost-optimal analysis is a complex and time-consuming procedure that requires several dynamic energy simulations by building performance simulation tools. Thus, it cannot be applied to each single building. That’s why the EPBD Recast demands the Member States to define a set of reference buildings (RefBs) in order to represent the national building stock, and to perform the cost-optimal analysis only on these representative buildings. The results achieved for each RefB about the cost-optimal configurations of EEMs should be extended to the other buildings of the same category, where a category is meant as a stock of buildings, which share climatic conditions (location), functionality, construction type. However, it’s clear that this procedure cannot ensure reliable results for each building. Therefore, a crucial question arises:

How to perform a reliable, fast, ‘ad hoc’ cost-optimal analysis of the retrofit measures for each building of the stock?

This thesis aims to answer this question by proposing a novel multi-stage methodology, denominated CASA, which represents an absolute novelty for the current scientific literature.

CASA represents the combination and ultimate fulfillment of other three original methodologies proposed in this study, namely CAMO, SLABE and the simulation of building energy and thermal behavior by means of ANNs. Indeed, the acronym CASA has a double meaning. On one hand, it reveals the combination among **CA**MO, **S**LABE and **A**NN. On the other hand, it points out the core of the methodology, that is the Cost-optimal Analysis by multi-objective optimiSation and Artificial Neural Networks.
CAMO, SLABE and ANNs can be used either as stand-alone procedures for pursuing worthy aims or as stages of CASA for reaching the final goal expressed by the aforementioned question.
In the following lines, the purpose and the main outcomes obtained from the independent application of CAMO, SLABE and ANNs are first described. Then, the framework of CASA and the final results of this study are proposed.

CAMO is a new methodology for the Cost-optimal Analysis by Multi-objective Optimization, which aims at the identification of the cost-optimal package of EEMs for new or existing buildings. Since this study is focused on energy retrofitting, only existing buildings are considered and thus the EEMs consist of energy retrofit measures (ERMs). The methodology is based on the multi-objective optimization of energy demand for microclimatic control and indoor thermal comfort. The optimization procedure is performed through the coupling of EnergyPlus and MATLAB, in which a genetic algorithm is implemented. Various economic budgets, available for the energy refurbishment, should be identified as constraints regarding the investment cost. Then, for each one of these economic availabilities, the application of the methodology allows the definition of the Pareto front, which represents the set of ‘best’ packages of ERMs. Among the different combinations shown on the Pareto front, for each budget, the most suitable can be selected by using various criteria. In the present study, both the ‘utopia point method’ and the ‘minimum comfort level method’ are used for the multi-criteria decision making (MCDM), although the second one is more relevant to building studies. In this way, recommended packages of ERMs – that would be otherwise determined empirically by trial – are achieved. Then, the one characterized by the lowest value of global cost represents the cost-optimal solution. Finally, the methodology permits a strong support to the cost-optimal analysis.

The proposed optimization procedure has been applied to a case study, concerning the design of the energy retrofit of a residential building located in Naples, Southern Italy (Mediterranean area). The outcomes show that the most proper economic budget for the refurbishment is 300000 €. The cost-optimal package of ERMs, which complies with this constraint, includes the thermal insulation of walls (9 cm thick insulant) and roof (3 cm thick insulant), the installation of a water-cooled chiller and of a condensing boiler, and the implementation of free cooling by means of a mechanical ventilation system. This package provides the following savings of global cost (GC), evaluated according the guidelines of the EPBD Recast:

- 330000 €, without incentives and by adopting the utopia point criterion;
- 445000 €, with incentives equal to 50% of the investment cost and by adopting the utopia point criterion;
- 310000 €, without incentives and by adopting the comfort criterion;
- 413000 €, with incentives equal to 50% of the investment cost and by adopting the comfort criterion.

Furthermore, in all cases, also a substantial improvement of thermal comfort occurs, because the annual discomfort hours (DH) are reduced

of around 25 percentage points, compared to the base configuration of the building.
Finally, CAMO ensures the evaluation of the actual cost-optimal solutions. Diversely, standard approaches, with packages of energy retrofit measures chosen empirically by trial, cannot guarantee the same accuracy and feasibility, because the entire domain of possible solutions is not completely explored. Moreover, the method provides an effective and flexible tool for managing the thermal comfort and for understanding its impact on the energy demand. It is noted that CAMO can be also used when the purpose is not the cost-optimal analysis, but the definition of incentive policies, or the optimization of energy performance and thermal comfort of a new or existing building in presence of a budget constraint.
Nevertheless, computational time and complexity are still too high for the application to each single building. This represents the main limit of CAMO. Therefore, in order to achieve global indications about the cost-optimal energy retrofitting of a group of buildings, SLABE has been developed.

SLABE is a new multi-stage methodology aimed to investigate the implementation of some ERMs to buildings belonging to the same category. It is based on uncertainty and sensitivity analyses, carried out by means of the coupling between EnergyPlus and MATLAB. Thus, it is denoted as Simulation-based Large-scale uncertainty/sensitivity Analysis of Building Energy performance (SLABE). The effetcs of such ERMs on primary energy consumption (PEC) and global cost (GC) are explored in other to achieve two main objectives:

- to detect a package of ERMs that represents the cost-optimal solution for most buildings of the analyzed category (private perspective);

- ➢ to provide the policy of state incentives for ERMs that ensures the best ratio between energy savings and state disbursement (collective perspective).

SLABE consists of two main stages, which are subdivided respectively in two and three steps.

- Step 1 (stage I): the existing building stock is investigated and the most influential parameters (related to geometry, envelope and other) on energy demand for micro-climatic control and on thermal comfort (specifically, discomfort hours) are identified.
- Step 2 (stage I): some EEMs for the reduction of energy demand ($EEMs^d$) are selected on the basis of the results achieved in step 1 and of the characteristics of the category; their impact on energy demand and thermal comfort is evaluated and the most influential measures are detected.
- Step 3 (stage II): the implementation of new efficient HVAC systems is investigated, by assessing the effect on PEC and GC; this step detects the best policy of state incentives for HVAC systems, and it identifies the cost-optimal HVAC configuration, when the replacement of the HVAC system is the only implemented ERM. This cost-optimal solution is found out respectively in presence of current and proposed incentives.
- Step 4 (stage II): the implementation of renewable energy sources (RESs) is investigated, by assessing the effect on PEC and GC; this step detects the best policy of state incentives for RESs and it identifies the cost-optimal combination of HVAC system and RESs .
- Step 5 (stage II): the implementation of the most influential $EEMs^d$, identified in step 2, is investigated, by assessing the effects on PEC and GC; this step defines the best overall policy of state incentives for

different EEMs and it identifies the cost-optimal package of ERMs, including HVAC system, RESs and EEMs[d].

As a case study, the methodology has been applied to a specific category: *office buildings built in South Italy in the period 1920-1970*. The weather data file related to Naples is used in EnergyPlus simulations, because this city is one of the main districts in South Italy regarding the number of office buildings and its climatic conditions are close to average conditions in this region. Therefore, the results obtained for Naples can be extended to many other cities of South Italy with an acceptable approximation.

Therefore, the results obtained for Naples can be extended to many other cities of South Italy with an acceptable approximation.

The outcomes imply the following main conclusions.

- A strong dispersion of the values assumed by energy demand and thermal comfort occurs; thus, the reference building cannot provide reliable results for all the buildings of the category (an error higher than 100% can be committed), although the investigated category is quite restricted.
- The energy performance is mainly affected by geometry parameters (in particular *number of floors* and *area of each floor*) and other parameters (in particular *set point temperatures*), while most of the envelope parameters are neglible. This occurs because of the magnitude of the ventilalation load.
- The most inflluential EEMs[d] on annual energy demand are: the low-a plastering of the roof, the installation of double-glazed low-e windows, the implementation of external shading of the windows, the achievement of night free cooling by means of mechanical ventilation. On the other hand, they are almost irrelevant to the annual value of discomfort hours, which is mainly reduced by the thermal insulation of the envelope. However, this latter EEM[d] even produces a slight

increase of energy demand, by virtue of the high relevance assumed by the cooling season.

- The package of ERMs, which represents the cost-optimal solution for most buildings of the analyzed category, does not include EEMs[d] in both cases of current and proposed incentives. More in detail, the following cost-optimal combinations are achieved:
  - in presence of current incentives: maximum photovoltaic (PV) power on the buildings' roofs, water-cooled chiller, condensing boiler in both cases of fan coils and radiators;
  - in presence of proposed incentives: maximum PV power on the buildings' roofs, water-cooled chiller, heat pump in presence of fan coils and new efficient boiler in presence of radiators.

  It is recalled that concerning the investigated ERMs:
  - current incentives provide a capital grant, accorded in ten years, that covers:
    - the 65% of the investment cost of condensing boilers, heat pumps, new efficient windows and thermal insulation that allows to fulfill the U values prescribed by the law;
    - the 50% of the investment cost of PV panels;
  - proposed incentives provide a capital grant, accorded in ten years, that covers:
    - the 70% of the investment cost of heat pumps, if the building is heated by fan coils;
    - the 65% of the investment cost of new efficient boilers, if the building is heated by radiators;
    - the 40% of the investment cost of PV panels.
- Proposed incentives, compared to current incentives, would induce a similar actual value of the average saving in primary energy consumption, $dPEC_b$ (62.8 vs. 62.7 kWh/a per building), in

correspondence of a significantly lower average state disbursement, D_b (37.8 vs. 44.6 k€ per building). Thus, they would ensure a higher state profit π, ratio between $dPEC_b$ and D_b (1.66 vs. 1.41 kWh/€).

The main limit of SLABE is the impossibility of obtaining detailed indications on the cost-optimal package of ERMs for each single building, because only global recommendations about the investigated category are provided. However, the outcomes of the uncertainty and sensitivity analyses performed in SLABE can be exploited for the development of meta-models, such as artificial neural networks (ANNs).

In this study, ANNs are adopted for the assessment of primary energy demand and thermal comfort of each building belonging to a considered category. Two families of ANNs are generated respectively for the existing building stock and for the renovated one in presence of ERMs. The ANNs are generated in MATLAB environment, by using EnergyPlus outcomes as targets for training and testing the networks. The developed surrogate models can replace the BPS tools in the evaluation of transient energy performance and, thus, of GC, of each building of the considered category, both in absence and in presence of ERMs. The benefit consists of a drastic reduction of computational burden and complexity. As aforementioned, SLABE can provide a significant support to the development of reliable ANNs. Indeed, SLABE allows to perform a propaedeutic investigation of the considered building category by means of uncertainty and sensitivity analysis. Such procedure yields the detection of the most influential parameters on energy and thermal behavior of the buildings, concerning both the current configuration of the stock and the renovated one characterized by the presence of ERMs. Thus, these parameters are used as inputs of the networks, thereby ensuring a proper, reliable, 'ad hoc' development of each ANN.

The methodology is applied to the buildings that belong to the category investigated by means of SLABE. The information gathered by means of SLABE allowed to optimize the generation of seven ANNs, three for defining the existing building stock and four for assessing the impact of ERMs. More in detail, the first family of ANNs consists of three networks, all characterized by a single output, aimed to assess respectively:

- the primary energy demand for heating (ANN for EP_h);
- the primary energy demand for cooling (ANN for EP_c);
- the percentage of annual discomfort hours (ANN for DH).

The second family of ANNs consists of other four networks, related to the renovated building stock, characterized by a single output and finalized to assess respectively:

- the primary energy demand for heating (ANN for EP_h);
- the primary energy demand for cooling (ANN for EP_c);
- the percentage of annual discomfort hours (ANN for DH);
- the electricity produced by PV panels (unique RES investigated in this case study) and consumed by the facility (ANN for E_{PV}).

The ANNs' energy outputs can be post-processed in MATLAB in order to calculate the values of PEC and GC for each building of the category.

The performance of the networks are estimated by considering the regression as well as the distributions of the relative errors between ANN's outputs and targets provided by EnergyPlus simulations. The following main results about ANNs' reliability are achieved.

- For the first family of ANNs, the average relative errors are quite good, respectively 6.1% for EP_h, 6.9% for EP_c and 8.4% for DH. The regressions between the ANNs' predictions and the simulated targets, also show a good agreement with regression coefficients (R) very close to 1.

- The performance of the second family of ANNs for EP_h, EP_c and DH is quite similar, albeit a slight worsening, to that of the first family. Indeed, the average absolute relative errors are respectively equal to 8.0% for EP_h, 8.1% for EP_c and 11% for DH, as well as the regression coefficients are lower, but still very close to one. This outcome is quite obvious because the ANNs related to the renovated stock aim to predict the behavior of a more complex, wide and various system. The network for the prediction of E_{PV}, performs very well (R = 0.997, average absolute relative errors = 2.0%) because it is characterized by only three inputs, consisting of building *form ratio*, *number of floors* and *percentage of the roof covered by polycrystalline PV panels.*

The networks for the assessment of DH are less accurate because the evaluation of thermal comfort is ruled by more complicated phenomena, which are hardly predictable.

It is noticed that ANNs represent an effective tool, but they have a limit: they are not sufficient for a robust cost-optimal analysis, since they need to be implemented in other methodologies (e.g., CAMO), in which they can 'subrogate' the traditional BPS tools.

CASA is the macro-methodology that combines CAMO, SLABE and ANNs in order to answer the question on which this thesis is focused. It allows to overcome the mentioned limits of CAMO, SLUSABE and ANNs, by providing a powerful tool for a consistent, reliable and fast cost-optimal analysis of each single building.

By referring to an established category, CASA can be subdivided in the following three stages.

I. SLABE is implemented to explore the building category by detecting the parameters (related to existing stock and renovated stock) and the

ERMs (renovated stock) that most affect energy performance and thermal comfort.

II. Two families of ANNs are developed for assessing thermal comfort, energy consumption, and thus global cost of the buildings that belong to the category. The first family refers to existing buildings, whereas the second one refers to renovated buildings. The most influential parameters, identified in stage I, are adopted as Inputs and only the most significant ERMs, also identified in stage I, are investigated.

III. CAMO is performed by using the ANNs instead of EnergyPlus in order to find the cost-optimal package of ERMs for any building of the category, with a low computational effort and time for the users.

As case study, CASA has been applied to a building belonging to the same category investigated by means of SLABE and ANNs. More in detail, the methodology is implemented to the reference building related to such category. Only the 'minimum comfort level method' has been adopted for MCDM because it is considered more relevant to building applications. The outcomes show that the cost-optimal package of ERMs is achieved in correspondence of the economical budget of 90000 €. It includes the thermal insulation of walls (9 cm thick insulant) and roof (9 cm thick insulant), the installation of a water-cooled chiller, the implementation of free cooling by means of a mechanical ventilation and of an external solar shading system, as well as of the maximum size of PV panels installable on building roof. The economic analysis is carried out in presence of the aforementioned current incentives provided by the Italian Government. The cost-optimal package of retrofit measures produces the following main benefits compared to the reference building:

- the GC over the building life-cycle is reduced of around 19600 €;
- the value of DH is reduced of around 15 percentage points.

Finally, the reliability of CASA has been verified by comparing the values of PEC, DH and GC provided by the ANNs for the recommended packages, with those obtained by means of EnergyPlus simulations.

- The results are very good for PEC and GC predictions, since the maximum absolute relative error committed by the networks is equal to 1.4% for PEC and 1% for GC. On the other hand, the ANN for the assessment of DH is less accurate (maximum absolute relative error equal to 23.6%), as expected. However, such network is able to predict the increasing or decreasing trend of DH, therefore its performance is considered satisfying.

In conclusion, CASA can be applied to any category, and thus to any building for achieving a reliable, fast, 'ad hoc' cost-optimal analysis of the ERMs. In other words, CASA allows each single building to know and implement the cost-optimal package of retrofit measures. In this way, a double benefit is reached: a benefit for the buildings' owners/occupants, who obtain the maximum economic saving, and a benefit for the community/environment, because a wide diffusion of cost-optimal energy retrofits would determine a huge reduction of energy consumption and polluting emissions of the building sector.

This means sustainability.

Nomenclature

A	Conditioned building area	m^2
a, b,.., h	Labels of the EEMs[d]	---
a	Absorption coefficient of solar radiation	---
B	Budget	€
Bz	Recommended package according to the utopia point criterion for the budget of z00000 €	---
Bz'	Recommended package according to the comfort criterion for the budget of z00000 €	---
COP	Coefficient of performance of a heat pump	W_{TH}/W_{EL}
c	Specific heat	J/kg K
ce	Elite count	---
DH	Percentage of annual discomfort hours	%
DH_{max}	Maximum value of DH, using the minimum comfort level criterion	%
D_b	Actual value of average state disbursement per building	€
d	Density	kg/m^3
dh	Annual discomfort hours	h
$dPEC_b$	Actual value of the average saving in primary energy consumption per building	kWh/a
ED	Annual thermal energy demand	kWh/m^2a
EP	Annual primary energy demand	kWh/m^2a
EER	Energy Efficiency Ratio of a chiller	W_{TH}/W_{EL}
EP_{PV}	Electricity produced by PV panels and consumed	kWh/m^2a
EP_{RES}	Energy produced by RESs and consumed	kWh/m^2a
e	Number of parameters describing the EEMs[d]	---
$\underline{\mathbf{F}}$	Vector of objective functions	---
f_c	Crossover fraction	---
f_m	Mutation probability	---
GC	Global cost	€
g_{max}	Maximum number of generations	---
h	Annual occupied hours	h
IC	Initial investment cost	€
k	Thermal conductivity	W/m K

Nomenclature

N	Number of decision variables	---
n	Number of parameters describing the existing stock	---
n_b	Number of budgets	---
n_i	Number of bits encoding the i-th decision variable	---
PEC	Annual primary energy consumption	kWh/a
PEC'	Annual primary energy consumption per unit of conditioned area	kWh/m²a
p	Percentage of samples(buildings) with GC savings	---
p_i	i-th parameter	---
R	Coefficient of regression	---
R^T	Thermal resistance	m²K/W
r	Ratio between the number of samples and the number of parameters	---
S	Sampling set, collecting building instances	---
SRRC	Standardized rank regression coefficient	---
s	Population size	---
T_{heat}	Set point temperature during the heating season	°C
T_{cool}	Set point temperature during the cooling season	°C
t	Thickness	m
tol	Tolerance in the average change of the Pareto front	---
U	Thermal Transmittance of opaque components	W/m²K
U_w	Thermal transmittance of the windows (glass+fame)	W/m²K
$\underline{\mathbf{x}}$	Vector of decision variables	---
Greek symbols		
η	Nominal efficiency of a gas boiler related to the low calorific value	W_{TH}/W_P
μ	Mean value	---
π	State profit, ratio between $dPEC_b$ and D_b	kWh/€ a
σ	Standard deviation	---
Subscripts		
BB	Base Building	
c	Referred to the cooling season	

h	Referred to the heating season
r	Referred to the roof
v	Referred to the vertical opaque walls
Acronyms	
ACC	Efficient air-cooled chiller
ANN	Artificial neural networks
BPS	Building performance simulation
CAMO	Cost-optimal analysis by multi-objective optimization
CASA	Cost-optimal analysis by multi-objective optimisation and artificial neural networks (CAMO+SLABE+ANN)
CB	Condensing boiler
DHW	Domestic hot water
EEM	Energy efficiency measure
EEM^d	Energy efficiency measure for the reduction of energy demand
ERM	Energy retrofit measure
GA	Genetic algorithm
HP	Heat pump
HVAC	Heating, ventilating and air conditioning
MCDM	Multi-criteria decision making
MLP	Feed-forward multi-layer perceptron
nZEB	Nearly zero-energy buildings
PI	Performance indicator
PV	Photovoltaic
RB	Reference boiler
RC	Reference chiller
RefB	Reference building
RES	Renewable energy source
RMSE	Root mean squared error
SA	Sensitivity analysis
SLABE	Simulation-based large-scale uncertainty/sensitivity analysis of building energy performance
UA	Uncertainty analysis
WCC	Water-cooled chiller

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