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Thesis for the Degree of Doctor of Philosophy

Development of I4.0 paradigms and methodologies for product recovery

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A nonna Maria

Ai miei Genitori

Abstract

The thesis explores the concept of sustainability, with a focus on the role of maintenance, wear and tear, and end-of-life product recovery in promoting sustainable practices, specifically in the context of Industry 4.0. Industry 4.0 is the fourth industrial revolution, characterized by the integration of advanced technologies such as the Internet of Things (IoT), Digital Twin (DT), and Cyber Physical System (CPS).

The research includes an analysis of current industry trends and best practices in several areas. The study shows that Industry 4.0 technologies, such as IoT-enabled predictive maintenance, can significantly improve the efficiency of maintenance and repair programs, reducing downtime and prolonging the life of equipment. Furthermore, the integration of DT and CPS can enable more effective end-of-life product recovery systems, by providing insights into the most valuable components to recover and recycle. For instance, IoT sensors can be used to monitor the condition of products and components in real-time, enabling the prediction of component failures and reducing the need for inventory.

The Product 4.0 model is proposed as the fourth generation of product innovation, characterised by the integration of advanced technologies such as IoT, DT and CPS into the product design, development and manufacturing process. Furthermore, the Product 4.0 approach enables products to be easily disassembled, repaired and recycled. It enables the integration of smart sensors and connectivity into products to monitor wear and tear and schedule maintenance and repair activities in real time.

Keywords: Industry 4.0, Sustainability, Maintenance, Tool wearing, End-of-Life recovery process, Product 4.0.

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Chapter 1

Introduction

1.1 Industry 4.0

Industry 4.0, also known as the Fourth Industrial Revolution, refers to the current trend of automation and data exchange in manufacturing and other industries. It involves the use of advanced technologies such as Artificial Intelligence (AI), the Internet of Things (IoT), and Cloud Computing (CC) to improve the efficiency and flexibility of production processes.

Manufacturing technology advancement has always been a result of industrial evolution throughout history. The "1st Industrial Revolution - Energy Generation" began with the invention of the mechanical loom in 1784 and was marked by the mechanization of industrial processes as well as the transportation and processing of goods (Cipolla 1965). With the advent of the Fourth Industrial Revolution industrial production has become more autonomous and "intelligent".

As a result, the Fourth Industrial Revolution is currently in full swing, and all manufacturing sectors around the world are searching for novel approaches and techniques to implement the new paradigms that the Industrial Revolution has brought to various production fields.

The evolution of these concepts in Korea, Germany, and the US was emphasized by Kang et al. (2016). In fact, Manufacturing Innovation 3.0, Industrie 4.0, and Smart Manufacturing (SM) have all emerged in Korea, Germany, and the United States, respectively. These philosophies are always being researched and developed, and they are in full evolution.

The most notable of the three paradigms is undoubtedly Industry 4.0 (I4.0). This innovative industrial idea is built on cutting-edge technology tools that can enhance and boost the productivity of production processes.

The Internet of Things (IoT), Cloud Computing (CC), Big Data (BD), Digital Twin (DT), Artificial Intelligence (AI), Machine Learning (ML), Augmented Reality (AR), Virtual Reality (VR), and Human-Machine Cooperation (HMC) are the most commonly used advanced technologies in I4.0, according to a literature review.

Furthermore, Industry 4.0 is based on the use of Cyber-Physical Systems (CPS) production and the integration of heterogeneous data and knowledge and its main features are: digitisation, automation, optimisation, customisation and adaptation of production; Human-Machine Interaction (HMI); value-added services and businesses and automatic data exchange and communication (Posada et al. 2015).

Internet of Things (IoT) devices are connected devices that can collect and transmit data, allowing for real-time monitoring and control of production processes.

Big Data Analytics: Advanced analytical tools are used to analyze and interpret large amounts of data generated by IoT devices and other sources, to gain insights into production processes and optimize them.

Artificial Intelligence (AI) and **Machine Learning (ML)** are used to automate decision-making and control processes, as well as to analyze data and identify patterns.

Cloud Computing (CC): Industry 4.0 systems often rely on cloud-based platforms to store and process data, as well as to provide access to software and other resources.

Robotics and Automation systems are used to perform tasks that are dangerous or difficult for humans, as well as to improve the efficiency and flexibility of production processes.

Cybersecurity: Industry 4.0 systems rely heavily on connectivity and data sharing, so it's crucial to have robust cybersecurity measures in place to protect against cyber threats.

Augmented Reality (AR) and **Virtual Reality (VR)** are increasingly being used for training, maintenance and repair, and remote assistance in Industry 4.0

Human-Machine Cooperation (HMC) refers to the integration of advanced technologies such as robotics, automation, and Artificial Intelligence (AI) into work environments, in order to improve efficiency and productivity, while also enhancing the safety and well-being of human workers.

Industry 4.0 is expected to have a significant impact on several aspects of manufacturing and other industries, including:

- Productivity and efficiency: Industry 4.0 technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and automation are expected to improve the efficiency and flexibility of production processes, leading to increased productivity and lower costs.
- Customization and personalization: Industry 4.0 systems allow for greater customization of products, enabling manufacturers to quickly respond to changing market conditions and customer demands.
- Innovation: Industry 4.0 technologies can facilitate faster and more efficient innovation, by allowing manufacturers to quickly test new ideas and designs.
- Supply chain coordination: Industry 4.0 systems can help to improve supply chain coordination, by providing real-time visibility into production processes and inventory levels.
- Job displacement: Industry 4.0 technologies, particularly automation and robotics, have the potential to displace jobs in certain sectors, particularly in manufacturing. However, it may also create new jobs in areas such as software development, data analytics, and maintenance of the systems.
- Environmental impact: Industry 4.0 has the potential to reduce the environmental impact of manufacturing, by increasing the efficiency of production processes and reducing waste and emissions.
- Business model: Industry 4.0 is also expected to change the way businesses operate, by creating new business models, such as on-demand manufacturing, that rely on advanced technologies to quickly respond to customer demands.

- Security: As Industry 4.0 systems are highly connected, it's important to have robust cybersecurity measures in place to protect against cyber threats.

Overall, Industry 4.0 is expected to bring about significant changes in the way we manufacture and work, with the potential to improve efficiency, productivity, and innovation. However, it also implies new challenges such as job displacement and security threats, so it's important to consider the impacts of these changes and plan accordingly.

Examining how Industry 4.0 affects lean manufacturing systems is doable; in fact, Wagner et al. (2017) work created a matrix of the impact of Industry 4.0 on lean manufacturing systems and offered a framework to start the design and development of integrated Industry 4.0 applications.

After identifying the capabilities of 12 advanced technologies, García & García (2019) evaluated the potential impact that each technology could have on maintenance management, returning a road map for businesses that want to apply these tools in the maintenance area. Maintenance management is another area where I4.0 tools can be used.

Environmental sustainability is another area where Industry 4.0 has significant benefits. The goal of work of Bonilla et al. (2018) is to offer a perspective on how Industry 4.0's fundamental traits and the changes they foster effect the flow of raw materials, energy, products, waste, goods, and information, and how that transformation ultimately affects whether or not the environment is sustainable. By assisting stakeholders and governments in advancing technological and policy solutions to address the outcomes that will follow from the widespread deployment of these technologies, our effort can help us identify potential pathways towards more sustainable societies.

More broadly, we might say that the idea of supply chain management can encompass all of these factors. We can declare with certainty that Industry 4.0 has a significant impact on the supply chain and the whole management of the product life cycle. According to Fatorachian & Kazemi (2021), Industry 4.0's extensive integration and connectivity can enable a supply chain management strategy and enhance performance. The main advantages of Industry 4.0 and its enabling technologies can be realized at the supply chain level primarily through greater integration, automation, and digitization, which result in the development of innovative analytical capabilities and, as a result, performance enhancements at the level of individual supply chain processes.

1.2 Sustainable practices and recovery options

Sustainability refers to the responsible management of the environmental, social and economic impact of the sourcing, production and logistic of products. This includes minimising resource use, reducing waste and emissions, ensuring fair labour practices and promoting community and environmental well-being.

Environmental, social and economic aspects are brought together within a model referred to as the Triple Bottom Line (TBL). It is a framework that assesses the performance of a company or organisation in terms of three key elements: economic, social and environmental.

The **economic bottom line** refers to the financial performance of the organisation, including factors such as revenue, profit and return on investment.

The **social bottom line** assesses the organisation's impact on people and communities, including factors such as employee welfare, workers' rights and community engagement.

The **environmental bottom line** considers the organisation's impact on the environment, including factors such as resource use, waste generation and pollution.

The TBL framework is designed to provide a more comprehensive view of organisational performance, as it takes into account not only the financial success, but also the social and environmental impact of an organisation. It helps organisations assess their sustainability performance and identify areas for improvement.

The triple bottom line is often used as a framework for measuring the sustainability performance of organizations. It can be used to evaluate the overall sustainability of an organization, as well as to identify areas for improvement. Some organizations will use the TBL framework to set sustainability targets and to track their progress over time.

One of the key benefits of using the TBL framework is that it helps organizations to consider the potential trade-offs between economic, social, and environmental goals. For example, an organization may need to invest in new equipment to reduce its environmental impact, but this may initially increase costs and decrease profits. By considering the trade-offs between economic, social, and environmental goals, organizations can make more informed decisions that are better aligned with their overall sustainability objectives.

Additionally, more and more companies are using TBL to report their performance to stakeholders, such as investors, customers, employees, suppliers, and regulators. This helps to increase transparency, accountability, and trust. Overall, the triple bottom line is a powerful tool for organizations looking to improve their sustainability performance, providing a framework for evaluating performance, setting goals, and tracking progress over time.

The second aspect of sustainability is that the factory must have sustainable production. In fact, sustainable production refers to the practice of producing goods and services in a way that is environmentally friendly and socially responsible, while also being economically efficient. This can include using renewable energy, reducing waste and emissions, and implementing fair labor practices. The goal of sustainable production is to minimize the environmental impact of production activities, while also ensuring that products are produced in a socially responsible way and that they can be sold at a reasonable price.

There are many ways to achieve sustainable production. Some examples include:

- Implementing energy-efficient technologies and processes
- Using sustainable materials, such as recycled or biodegradable materials
- Reducing water usage
- Implementing closed-loop production systems that minimize waste and pollution
- Implementing fair labor practices, such as safe working conditions and fair wages
- Implementing sustainable packaging and transportation

- Adopting sustainable business models, such as shared economy, circular economy, and collaborative consumption
- Creating closed-loop systems for product recovery and recycling

Sustainable production is important because it can help to minimize the environmental impact of production activities, while also promoting social and economic sustainability. This can lead to economic benefits, such as cost savings from reduced resource use and increased efficiency, as well as social and environmental benefits, such as reduced pollution and improved working conditions.

Another element that characterises sustainability is logistics. Sustainable logistics refers to the practice of managing the transport and distribution of goods in an environmentally friendly, socially responsible and economically efficient manner. This may include using more fuel-efficient vehicles and transport methods, reducing emissions and waste, and implementing fair labour practices.

It is clear that sustainability is not limited to these areas but it extends to include also supply chain. In fact, Shekarian et al. (2022) created a paradigm that emphasises the key factors of sustainability throughout supply chain management. A literature analysis led to the identification of a number of aspects of supply chain sustainability. Specifically, they identified 11 main categories, each of which was reclassified in order to create sub-categories for the elements with the most similarities.

These classifications were set based using common supply chain structures and principles. The first and second categories concerned with supply chain beginning points, or activities connected to the production process. The points that form a circle connecting the customer to the chain were the focus of the third category (C). Based on the material supplied by suppliers, the fourth category (D) was created. The software abilities required to manage the supply chain were found in the fifth category (E). The measuring of quality in the context of sustainability was the subject of the sixth category (F). The seventh category (G) dealt with safety and risk considerations. The eighth category (H) looked into how to promote sustainability through human relations. The eighth area, financial difficulties, was taken into consideration (I). In categories J and K, respectively, incentive techniques and supply chain management were covered. A total

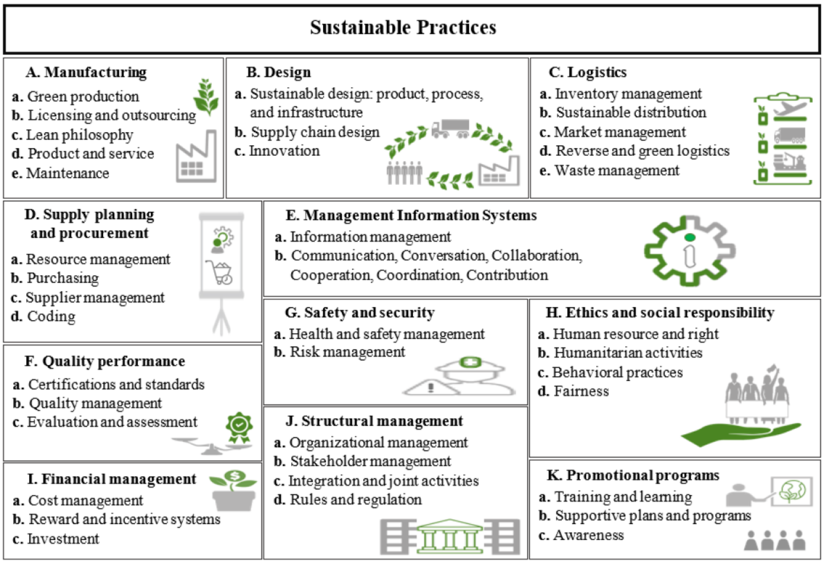

Figure 1.1. Suggested framework for sustainable practice of Shekarian et al. (2022)

of 38 categories were used to summarize sustainable options (see Fig. 1.1).

In order to develop sustainable practices, we must not only pay attention to management policies but also to the elements that make up the production line. This leads us to consider the product from the initial processing of raw materials to delivery to the customer. Sustainability must also integrate issues concerning: product design, manufacturing by-products, by-products produced during product use, product life extension, product end-of-life and end-of-life recovery processes (Linton et al. 2007).

Product life extension refers to the practice of extending the useful life of a product through various means. This may include designing more durable and repairable products, regular maintenance, upgrading or retrofitting products, recycling or reusing products at the end of their useful life. The objective of product life extension is to maximise the use of resources by extending the useful life of products, reducing the need to produce new ones and minimising waste. It thus becomes an important aspect of sustainable production and consumption, as it can help reduce the environmental impact of product production and disposal. It also helps reduce costs and increase the efficiency of production operations.

1.2.1 Sustainable and Smart maintenance

Sustainable maintenance refers to the practice of maintaining buildings, infrastructure, and equipment in a way that is environmentally friendly and economically efficient, while also ensuring their continued functionality and safety (Hami et al. 2020). This can include using energy-efficient techniques and materials, practicing preventative maintenance, and incorporating green technologies. The goal of sustainable maintenance is to minimize the environmental impact of maintenance activities, while also reducing costs and ensuring that assets continue to function properly.

Following a review of the literature, Franciosi et al. (2020) develops a framework that gives a comprehensive overview of all effects of maintenance activities on sustainability aspects. It also develops clearly defined performance indicators that assist in measuring and monitoring impacts to spot potential discrepancies between the actual and desired sustainable performance of maintenance and other company departments. By pointing them in the direction of specific maintenance procedures and the reduction of their impact in order to satisfy corporate objectives, this work may be of interest to businesses that seek to close the gap between maintenance and sustainability.

Instead, other authors consider how Industry 4.0 will impact maintenance's position in the manufacturing industry. Roda et al. (2018) focuses in particular on how maintenance may profit from new opportunities brought about by the continuous digitalization of industrial processes. The analysis pinpointed the key problems that would define maintenance in the Industry 4.0 paradigm going forward. Data and the human aspect emerged as the two essential components for the successful digitalization of maintenance activities. The study also attempted to collect empirical data on how manufacturing firms are actually handling the maintenance phase of digital transformation. Relevant problems also surface in this context, including organizational and technological ones.

Smart maintenance, on the other hand, is a proactive approach to maintenance that leverages Industry 4.0 technologies such as predictive analytics, the Internet of Things (IoT), and Artificial Intelligence (AI) to optimize maintenance tasks (Bokrantz et al. 2020). This approach helps to reduce downtime, extend the lifespan of equipment, and improve overall efficiency. When combined, sustainable and smart maintenance can lead to a more efficient and environmentally responsible approach to maintenance. The integration of Industry 4.0 technologies can provide real-time data and predictive insights to help companies identify potential maintenance issues before they become problems, allowing for more proactive and environmentally friendly maintenance practices.

Moreover, smart maintenance can also help to reduce the need for excessive spare parts and resources, as maintenance tasks can be performed with greater accuracy and efficiency. This can lead to a reduction in waste, as well as cost savings for the company. In addition, the use of sensors, IoT, and AI in smart maintenance can also provide valuable data on equipment usage and performance, which can be used to identify areas for improvement and optimize maintenance schedules. This results in more informed decision-making and helps to minimize the environmental impact of maintenance activities. Overall, sustainable and smart maintenance are complementary approaches that can help companies to minimize waste, conserve resources, and reduce their negative impact on the environment, while also improving efficiency and cost-effectiveness.

1.2.2 Preventive measures and useful life extension

One of the impacts of Industry 4.0 on predictive maintenance is the use of technology to monitor tool wear and predict when tools will need to be replaced, thus helping to further reduce the impact of tool wear. For example, sensors can be used to collect tool usage data, which can be analysed to identify wear patterns and trends. This can help manufacturers identify the tools most prone to wear and take measures to reduce it.

This integration brings numerous benefits to the industry, including the ability to extend the life of tools and machinery through predictive maintenance (Begüm et al. 2021). Constant monitoring of tool and machine performance enables Industry 4.0 systems to detect signals of wear and deterioration, prompting timely maintenance and repairs. This proactive approach increases tool efficiency and ultimately results in cost savings for manufacturers.

Preventive measures, including regular maintenance, proper use and storage, timely repair of defects and damage, and upgrading equipment with new technologies, can help extend the life of tools and equipment. The use of protective equipment can also reduce wear and tear. Regular monitoring and inspection play an important role in identifying potential problems before they develop into serious issues that reduce equipment life. Predictive maintenance programs that collect and analyse data to predict equipment failures can enable proactive maintenance and repair, further extending the life of tools and equipment.

The implementation of Industry 4.0 technologies not only benefits the manufacturing industry, but also contributes to a more environmentally conscious society. Indeed, Industry 4.0 has the potential to increase efficiency, cost savings and sustainability by extending the life of tools and equipment (Aivaliotis et al. 2019). By reducing the need to frequently replace tools and machinery, the production process can produce fewer waste materials, resulting in a reduction of industry's overall carbon footprint. In addition, the use of predictive maintenance can help reduce energy consumption, as equipment that operates efficiently is less likely to consume excess energy.

In conclusion, the integration of Industry 4.0 technologies into the manufacturing process has the potential to significantly extend the lifespan of tools and equipment, leading to greater efficiency, cost savings and sustainability. By reducing waste and energy consumption, manufacturers can contribute to a more sustainable and environmentally conscious society.

1.2.3 End of Life product recovery options

Sustainable product recovery is an important aspect of product design and refers to the practice of recovering value from products at the end of their useful life in an environmentally responsible and socially just manner. It includes recycling products, reusing product materials, reducing the environmental impact of waste and conserving resources.

Product recovery can include the following steps:

- Collection: Products are collected from consumers and businesses, either through organized recycling programs or through informal means such as curbside pickup.

- Transportation: The collected products are transported to a processing facility where they will be sorted and prepared for recovery.
- Sorting and Processing: Products are sorted by type and processed to remove any contaminants or hazardous materials.
- Recycling or Reuse: Recyclable products are processed further to extract materials that can be used to make new products, while non-recyclable products are sent to a landfill or incinerated.
- Final Disposition: Products that have been recycled or reused are either used to make new products or are permanently removed from the waste stream.

Several end-of-life product recovery options for a generic product exist in the literature. Among the most relevant are reuse, remanufacturing, recycling, cannibalisation and disposal (Ziout et al. 2014).

Reuse involves using a product again for its original intended purpose or for a different purpose. In fact, it is considered to be an operation whereby a few non-destructive improvements are made in order to bring the product back to its initial state. Examples include refurbishing electronics, reselling used clothing, and re-purposing building materials.

Remanufacturing involves fixing a product so it can be used again; it is a more complex operation where the product is disassembled and worn or broken components are replaced. This can include simple repairs such as patching a hole in clothing or replacing a broken part, as well as more complex repairs such as rebuilding an engine or repairing electronics.

Recycling involves processing products to extract materials that can be used to make new products. This can include traditional recycling methods such as paper, plastics, and metals, as well as more advanced methods such as chemical recycling and mechanical recycling.

Cannibalization involves in a process in which parts products that are still functional are removed and used as replacement parts in similar products or equipment still in use. This is also known as "part harvesting" or "part reuse" and is often used in industries such as automotive, electronics and aerospace.

Disposal involves disposing of products that cannot be recycled or otherwise recovered in a landfill; it is the last possible operation, where

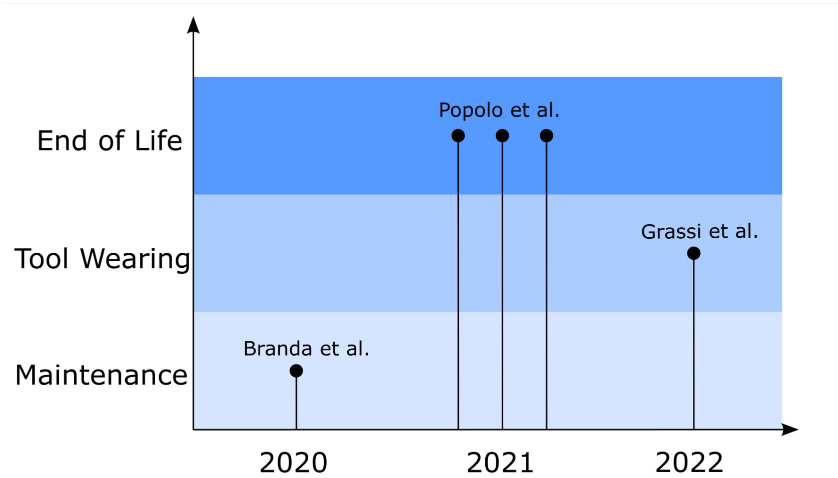

Figure 1.2. Relationship between the different articles submitted in different years and the topics of the thesis

nothing can be recovered from the product and it is therefore thrown away.

The best end-of-life recovery option for a product will depend on a variety of factors, including the product's composition, the cost of recovery, and the availability of recycling and recovery infrastructure.

1.3 Research outline and contributions

This thesis is structured in the form of a "three-paper" thesis, with several published and forthcoming scientific papers in which I significantly contributed. The work that guided this thesis was developed and submitted over several years, as shown in Fig. 1.2.

The first paper (Chapter 2) is a research on a scheduling issue for flow shops when machines aren't always available and faults happen randomly during periods of downtime. They undergo both corrective maintenance and planned maintenance procedures because they are prone to malfunctions in order to increase their availability. Therefore, the best plan takes into account both maintenance tasks and activities. Finding the best integrated maintenance work-planning sequence that reduces the makespan and the early-delay penalty is the objective. In order to do this, we suggest two novel meta-heuristic algorithms that were created by tweaking the conventional Genetic Algorithm (GA) and Harmonic Search (HS).The suggested Harmony Search algorithm and genetic algorithm are effective in addressing the problem of integrated task scheduling and maintenance, according to numerical findings from trials taking varied problem sizes and configurations into account.

The second paper (Chapter 3) studies the field of intelligent production from the complex optimisation problem Flexible Job-Shop Scheduling Problem (FJSP), which seeks to allocate production jobs to machines at particular times in order to minimise makespan. Despite major advancements in this area, current methods do not sufficiently take into consideration the issue of tool wear, which can result in higher costs and waste. In this article, we suggest a novel method that takes tool wear into account while optimizing scheduling. The method adjusts the extension rate by taking into account the tool's age and the length of time it has been in use. By doing this, we hope to increase tool utilization, decrease scrap, and eventually create production processes that are more effective and sustainable. Our studies' findings demonstrate that our strategy performs better than other approaches in terms of waste reduction and tool utilization. Our strategy is also very adaptable and scalable, making it appropriate for shifting consumer demands and manufacturing needs.

The third paper (Chapter 4) investigates whether and how it is possible to better support product lifecycle management by exploiting the enhanced product capabilities resulting from an I4.0 ecosystem. To this end, the new concept of 'Product 4.0' (P4.0) is proposed, a product archetype that combines the functionalities of an intelligent product with those enabled by I4.0 technologies. Since Product 4.0 has the potential to benefit from the various stages of the product life cycle, this paper also provides further details on the end-of-life recovery options of this new product archetype, through an explanatory case related to a laserjet printer. Next, the speed at which new technology products are brought onto the market and old ones are discarded was investigated. This is generating a twofold negative effect: an exponential increase in electrical and electronic waste and an unsustainable exploitation of non-renewable natural resources. This situation may in turn have significant effects on the economic sustainability of our societies, due to the rising costs of waste disposal and the increasingly limited availability of raw materials. Therefore, the main variables at play and their interconnections when considering smart products were investigated. To analyse the effects of these variables, a Causal Loop Diagram (CLD) is developed and discussed in detail. The proposed CLD highlights the sustainability aspects of smart products. Furthermore, it highlights how the introduction of the so-called 'Product 4.0' can be a solution to improve the triple bottom line of sustainability.

Chapter 2

Metaheuristics for the flow shop scheduling problem with maintenance activities integrated

2.1 Introduction

In the current competitive environment, production scheduling plays a crucial role in the survival of a company in the market (Pinedo 2012). Since the mid-twentieth century, planning problems have caught the interest of many researchers (Ahmadizar 2012, Chen et al. 2012, Ekşioğlu et al. 2008, Laha & Gupta 2018, Saricicek & Celik 2011, Yuce et al. 2017). The flow shop is a plant layout extensively studied in the literature. The Flow Shop Scheduling Problem (FSSP) deals with the sequencing of a set of jobs that visit a defined number of machines, always in the same order. In most research about FSSP, it is assumed that machines are available during the whole planning horizon. In a real environment, the machines are not always available during the entire planning horizon (e.g., due to breakdown or preventive maintenance). This availability problem may have a significant impact on a variety of performance aspects such as productivity, reliability, and profitability (Lee & Kim 2017).

The problem is that the maintenance planning is commonly not integrated with the production scheduling activities (Liu et al. 2018). Instead, the production scheduling activity and the maintenance planning must be done jointly to balance the utilisation and availability of the resource (Wang & Liu 2014). To this extent, there are two research classes of the problem within the literature. The first one assumes that preventive maintenance are performed periodically, ignoring unexpected failures. That is the unavailable periods of the machine are known in advance and, therefore, it represents a deterministic problem. The second one assumes that machines can fail randomly. This last class belongs to the stochastic programming problem and is entirely different from the first class (Cui et al. 2018).

Most prior research - focused on the deterministic problem - can serve as modelling tools for planned breaks such as lunch breaks, days off, holidays etc (Kubzin & Strusevich 2006). Lee (1997) studied a two machine FSSP under a deterministic environment in which the unavailability time of the machine is known in advance. He develops a pseudo-polynomial dynamic programming algorithm to solve the problem optimally. Breit (2006) and Wang & Cheng (2007) investigated a two-machine flow shop where the first machine is not available for processing during a given time interval. They propose a Polynomial-Time Approximation Scheme (PTAS) for this problem. Hadda (2014) developed a PTAS to solve a particular case of two machine FSSP with several availability constraints on the second machine known in advance.

Regarding the second class of research, Kubzin & Strusevich (2006) investigated a two-machine FSSP in which each machine must be serviced exactly once during the scheduling period. The duration of the maintenance interval depends on the start time. This means that the start time and the duration of the maintenance interval are not fixed in polynomial solvable by dynamic programming. Ruiz & Stützle (2007) have developed three different policies to define when to carry out Preventive Maintenance (PM) tasks in the FSSP. The first policy is based on the principle that the PM tasks are processed at fixed time intervals, known in advance. The second policy, instead, aims to maximise the machine's availability, calculating the optimum period for PM. In the third policy, the criterion used is to maintain a minimum reliability threshold for a given production period t. The reliability of a machine is the probability that the machine will work during a certain period. Xiao et al. (2016) proposed a key-random GA for the joint optimisation of the scheduling of jobs and machine group preventive maintenance to minimise the sum of production, preventive maintenance, minimal repair for unexpected failures and tardiness costs.

Assia et al. (2018) have discussed, analysed and developed the resolution of the joint scheduling of jobs and variable maintenance activities in an FSSP scenario in their survey.

This paper belongs to the above-mentioned second FSSP research classes and includes the maintenance planning activity taking into account a stochastic environment. A flow shop production system made of not identical, failure-prone machines is considered. It is assumed that the time to process a single job, the time to carry out a corrective or preventive maintenance task, and setup times are deterministic. Machines are supposed to fail randomly according to a Weibull distribution. Hence, the time to process a given job-maintenance sequence on a certain machine is random. We consider the problem of finding the job planned maintenance sequence that minimizes the expected makespan or the expected earliness tardiness penalties, evaluated taking into account the expected value of job-maintenance sequence processing times on each machine.

This problem has been addressed similarly by Zammori et al. (2014). However, while they dealt with the problem on a single machine, we propose a more general model valid for multimachine problems in flow shop settings. To approach the problem, we propose two novel meta-heuristic algorithms obtained by modifying a standard Genetic Algorithm (GA) and Harmony Search (HS).

The rest of paper is organized as follow: Section 2.2 introduces the basic notation, describing the problem statement. Section 2.3 and 2.4 present the proposed metaheuristic algorithm for finding a quasi-optimal solution. Then, in Section 2.5, the proposed algorithms are evaluated. To this aim, a comprehensive set of scheduling problems was generated and benchmarked with the solution of an exhaustive search method. Lastly, in Section 2.6 conclusions and directions for future works are given.

2.2 Problem description

2.2.1 Notations

To facilitate the problem description and formulation, the notations variables used in this paper are summarised below:

Indices

i (i = 1,2,...,N) is the job indicator.

m (m = 1,2,...,M) is the machine indicator.

Parameters

N denotes the number of jobs.

M denotes the number of machines.

$p_{\pi_i,m}$ indicates the processing time of the ith job in a sequence (i = 1,2,...,N) on the mth machine (m = 1,2,...,M).

$s_{\pi_{i-1},\pi_i,m}$ denotes the setup time between jobs on the machine m.

R_m time to perform a single corrective maintenance activity on the machine m.

V_m time to perform a single planned maintenance activity on the machine m.

β_m denotes the shape parameter of the Weibull probability distribution on machine m (m = 1, 2,...,M).

η_m denotes the scale parameter of a Weibull probability distribution on machine m (m = 1, 2,...,M).

d_{π_i} denotes the due date of job π_i.

Decision variables

π is the vector that represents the jobs orders according to their processing sequence.

π_i (i = 1,2,...,N) is the ith job order in a sequence.

Variables derived from decision variables

Z_m is the number of maintenance actions for the mth machine.

D_m is the downtime of the mth machine.

μ_m (m = 1,2,...,M) represents the vector whose generic element is the job that precedes the generic $j_m th$ planned maintenance activity on the mth machine: $\mu_m = \mu_{1m}, \mu_{2m}, ..., \mu_{jm}, ..., \mu_{Zm}$.

$\delta(m, \pi_i)$ is a binary variable $\delta(m, \pi_i) = \begin{cases} 1, & if \pi_i \in \mu_m \\ 0, & otherwise \end{cases}$
$\mathscr{I}_I^m \equiv \{i \leq I : \delta(m, \pi_i) = 1\}$ (I = 2, 3, ...,N) (m = 1, 2, ...,M)
$j(m, I) = \begin{cases} max \mathscr{I}_I^m, & if \mathscr{I}_I^m \neq \emptyset \\ 1, & if \mathscr{I}_I^m = \emptyset \end{cases}$

C_{π_i} denotes the completion time of the ith job in a sequence (i = 1,2,. . . ,N).

$E\left[C_{\pi_i}\right]$ denotes the expected completion time of the ith job in a sequence (i = 1,2,. . . ,N).

2.2.2 Problem assumptions

Main assumptions of the problem can be described as:

- When the machine begins processing a job, it cannot be interrupted. If a failure occurs, consider a longer job order processing time. This includes the time needed to restore the machine, reset the machine, and complete the machining;

- Setup times are deterministic and dependent of the job sequence;

- When calculating the number of planned maintenance activities, it is considered that each of these requires a fixed and constant time value (may be different for each machine);

- The planned maintenance operations cannot be at the beginning or at the end of a certain sequence of jobs. If q* is the optimal number of scheduled maintenance operations and P is the total time required to process all the jobs in the sequence, it is possible to demonstrate that the optimal positioning of planned maintenance interventions, to minimise the expected number of breakdowns, is one every (see Zammori et al. (2014)):

$$\frac{P}{q^* + 1} \tag{2.1}$$

- The processing time of each job on a certain machine is deterministic and may be different from the one needed on another machine;

- Machine failures occur randomly and according to a Weibull distribution. The failure rate of a given machine may differ from that of the others;
- We consider an average time to carry out a corrective or a preventive maintenance tasks (i.e., this time is supposed to be deterministic) and its value may vary among the various machines;
- Planned and corrective maintenance are carried out when the machine is not operating. Planned maintenance has to be carried outwith no order job on the machine, i.e., planned maintenance is considered as a maintenance job to be scheduled among order jobs. On the contrary, corrective maintenance can be performed with an order job on the machine;
- Corrective maintenance and preventive maintenance interventions follow the minimal repair and perfect repair approach, respectively;
- When the job leaves machine m and machine m + 1 is busy, the job is hosted in a buffer of unlimited amplitude;
- All jobs are independent and available for their process at time 0;
- Each machine m can process only one job j at the time;
- Each job j can be processed only in one machine m at the time;
- The transportation time to move a job between two consecutive machines is neglected.

2.2.3 Problem description

Initially, we consider the problem in which the machines do not fail, then we will consider the case in which the machines are subject to breakdowns, and we will see how the equations are modified. In this problem, we want to find the best sequence for n jobs that must be processed in a set of M machines that minimises the objective function. Each job requires a deterministic processing time on each machine m. N jobs must be processed on M machines in the same order. The objective of scheduling is to find a production sequence of the jobs in the machines so that an established criterion is optimised. The most common optimisation criterion are the minimisation of the total manufacturing time, called makespan or C_{max}, and the minimisation of the Earliness Tardiness Penalties (ETP).

The makespan is defined as the maximum job completion time:

$$C_{MAX} = \max_i \{C_{\pi_i}\} \tag{2.2}$$

Similarly to Zammori et al. (2014), who consider more general, not strictly complementary cost factors a_{π_i} and b_{π_i} weighting the importance of earliness and tardiness, respectively, the ETP criterion is:

$$ETP = \sum_i (a_{\pi_i} E_{\pi_i} + b_{\pi_i} T_{\pi_i}) \tag{2.3}$$

where

$$E_{\pi_i} = |min\{0, C_{\pi_i} - d_{\pi_i}\}| \tag{2.4}$$

represents the advance of the job, being his due dates;

$$T_{\pi_i} = max\{0, C_{\pi_i} - d_{\pi_i}\} \tag{2.5}$$

represents the job delay. Note that the above defined objective functions are deterministic, as job processing times are deterministic by assumption and machines are supposed to be completely failure-free.

The completion time of each job on the m-th machine is obtained by solving a series of recursive equations.

If we consider the machine 1:

$$C_{\pi_1,1} = p_{\pi_1,1} \tag{2.6}$$

$$C_{\pi_i,1} = C_{\pi_{i-1},1} + p_{\pi_i,1} + s_{\pi_{i-1},\pi_i,1}; \qquad i = 2, ..., N \tag{2.7}$$

for the generic machine m:

$$C_{\pi_1,m} = C_{\pi_1,m-1} + p_{\pi_1,m}; \qquad m = 2, ..., M \tag{2.8}$$

$$C_{\pi_i,m} = max\{C_{\pi_i,m-1}, C_{\pi_{i-1},m} + s_{\pi_{i-1},\pi_i,m}\} + p_{\pi_i,m};$$
$$i = 2, ..., N; m = 2, ..., M \tag{2.9}$$

If the goal is the minimisation of the makespan, being a flow shop the machines arranged in series, and therefore the maximum completion time of the jobs coincides with the completion time of the last job on the last machine. So, the goal is to minimise $C_{\pi_N,M}$.

2.2.4 Integrated maintenance planning

We now consider the case in which machines are prone to fail according to a Weibull distribution. The failure rate of the mth machine, λ_m, is thus expressed as follows

$$\lambda_m(t) = \beta_m \eta_m^{-\beta_m} t^{\beta_m - 1} \tag{2.10}$$

The failure rate $\lambda_m(t)$ is decreasing when $\beta < 1$, constant when $\beta = 1$, and increasing when $\beta > 1$. In this paper, we consider the case in which the failure rate is increasing (i.e., $\beta > 1$). Given the failure rate $\lambda_m(t)$, the expected number of failures in [0, t] for the mth machines is

$$\Lambda_m(t) = \int_0^t \lambda_m(\tau) d\tau = \left(\frac{t}{\eta_m}\right)^{\beta_m} \tag{2.11}$$

If we regard a generic machine m, with m = 1, 2, . . . , M, the criterion for determining the optimal number of planned maintenance operations for each machine is that of minimising the expected downtime. Let $P_m = \sum_i p_{\pi_i,m}$, Z_m be the number of planned maintenance tasks on the mth machine and D_m be the downtime of the mth machine. Then, using the rational policy of placing planned maintenance activities every $\frac{P_m}{Z_m+1}$ time units after the beginning of the job processing sequence (placing a planned maintenance activity before the first job in the sequence is clearly not appropriate), the expected downtime of machine m is given by

$$E\left[D_m\right] = Z_m V_m + R_m (Z_m + 1) \Lambda_m \left(\frac{P_m}{Z_m + 1}\right) = Z_m V_m + v_m (Z_m + 1)^{1-\beta_m} \tag{2.12}$$

where

$$v_m \equiv R_m \left(\frac{P_m}{\eta_m} \right)^{\beta_m} \tag{2.13}$$

is the average time to make corrections to failure between two planned maintenance operations.

Since the expression of $E\left[D_m\right]$ is convex in Z_m, the optimal number of planned maintenance operations for the machine m can be calculated by solving the equation:

$$\frac{d}{dZ_m} E\left[D_m\right] = V_m - v_m \frac{\beta_m - 1}{(Z_m + 1)_m^{\beta}} = 0 \tag{2.14}$$

From which it is obtained:

$$Z_m^* = \left[\frac{v_m(\beta_m - 1)}{V_m} \right]^{\frac{1}{\beta_m}} - 1 \tag{2.15}$$

Since Z_m^* must be an integer, it is necessary to take the integer closer to Z_m^* (greater or less than Z_m^*) which minimizes $E\left[D_m\right]$.

Since we are now considering machine breakdowns (which is the only source of randomness considered in our model), the time to complete a job-planned maintenance sequence is not deterministic, but random. Hence, the optimization criteria introduced in Section 2.2.3 (i.e., Eqs. 2.2 and 2.3) are random as well. Similarly to Zammori et al. (2014), we consider the expected value of the time to process a job-planned maintenance sequence. We can therefore extend the formulas presented in Section 2.2.3 to the case of failure-prone machines as follows:

$$C_{MAX} = \max_i \{E\left[C_{\pi_i}\right]\} \tag{2.16}$$

$$E_{\pi_i} = |min\{0, E\left[C_{\pi_i}\right] - d_{\pi_i}\}| \tag{2.17}$$

$$T_{\pi_i} = max\{0, E\left[C_{\pi_i}\right] - d_{\pi_i}\} \tag{2.18}$$

$$E\left[C_{\pi_{1,1}}\right] = p_{\pi_{1,1}} + R_1 \Lambda_1(p_{\pi_{1,1}}) \tag{2.19}$$

$$E\left[C_{\pi_i,1}\right] = E\left[C_{\pi_{i-1},1}\right] + V_1\delta(1,\pi_{i-1}) + p_{\pi_i,1} +$$
$$R_1\left(\Lambda_1\left(\sum_{k=j(1,i)}^{i} p_{\pi_k,1}\right) - \Lambda_1\left(\sum_{k=j(1,i)}^{i-1} p_{\pi_k,1}\right)\right) + s_{\pi_{i-1},\pi_i,1}; \qquad i = 2,...,N \tag{2.20}$$

$$E\left[C_{\pi_1,m}\right] = E\left[C_{\pi_1,m-1}\right] + +p_{\pi_1,m} + R_m\Lambda_m(p_{\pi_1,m}); \qquad m = 2,...,M \tag{2.21}$$

$$E\left[C_{\pi_i,m}\right] = max\{E\left[C_{\pi_i,m-1}\right], E\left[C_{\pi_{i-1},m}\right] + V_m\delta(m,\pi_{i-1}) + s_{\pi_{i-1},\pi_i,m}\} + p_{\pi_i,m}$$
$$+R_m\left(\Lambda_m\left(\sum_{k=j(m,i)}^{i} p_{\pi_k,m}\right) - \Lambda_m\left(\sum_{k=j(m,i)}^{i-1} p_{\pi_k,m}\right)\right); \qquad i = 2,...,N; m = 2,...,M \tag{2.22}$$

The previous expressions permit us to calculate the expected completion time of a given job-planned maintenance sequence in a flow shop production system, and hence the expected makespan and earliness tardiness penalties as well. Our objective is to find the job-planned maintenance sequence that minimizes the expected makespan or the expected earliness tardiness penalties. To this aim, we adopt two well-known metaheuristic algorithms, a genetic algorithm and a harmony search algorithm, whose features will be presented in the next sections.

2.3 Genetic algorithm

In order to solve the scheduling problem in the flow shop environment, a Genetic Algorithm (GA) has been developed. This type of algorithm is based on the Darwinian principle according to which the individuals who are better suited to the environment have a greater chance of surviving and passing on their characteristics to their successors. The population of individuals evolves from generation to generation through mechanisms very similar to sexual reproduction and gene mutation.

The GA was implemented using Optimization Toolbox in Matlab®. The steps of the developed GA can be summarized in the diagram in Fig. 2.1.

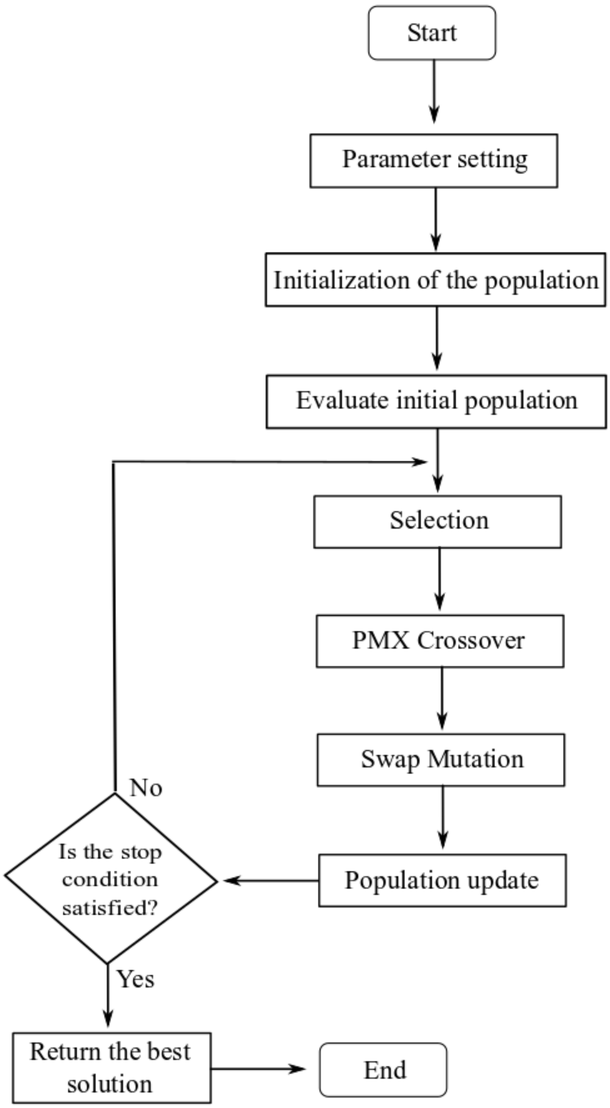

Figure 2.1. Flow chart of Genetic Algorithm

Table 2.1. Fine-tuned parameters of GA

GA Parameters	Value
Population Size	50
Crossover rate	0.8
Mutation rate	0.15
Elite count	0.05*Population Size
Number of seconds without improving the best solution	900

For the choice of the parameters used in Table 2.1, we started from the values used by Wang & Liu (2016) and then modified them to adapt them to our algorithm. In particular, they apply the mutation and the crossover on the same chromosomes, instead we apply one or the other exclusively. In the proposed algorithm, some chromosomes of the current population that have the best fitness are chosen as elite. These elite individuals are passed to the next population. Then we select from the previous population the chromosomes (parents) according to the crossover rate. We generate children from the parents. Children are produced either by making random changes to a single parent (mutation), according to the mutation rate, or by combining the vector entries of a pair of parents (crossover) (Goldberg 1989).

2.3.1 Representation of the solutions

The solution representation is a key factor for the algorithm efficiency. Each chromosome X represents a possible solution to the problem and to each chromosome corresponds value of the objective function. The X_i takes value in [1:N] if it is a job order, otherwise it takes value in $[N + 1 : N + \sum_m Z_m]$ if it is maintenance job. So, if we consider a problem with 5 job orders, 2 machines, and 2 maintenance operations on each machine, then the jobs orders will be: $X_1 = 3$, $X_4 = 1$, $X_5 = 4$, $X_7 = 5$, $X_9 = 2$; maintenance on first machine are: $X_2 = 6$, $X_8 = 7$; maintenance on the second machine are: $X_3 = 8$, $X_6 = 9$ (see Figs. 2.2 and 2.3).

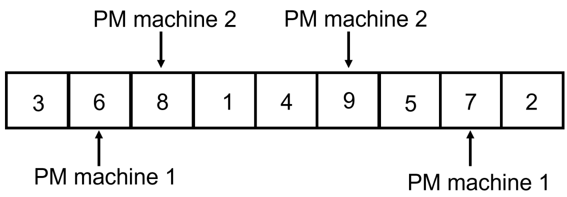

Figure 2.2. Coding solution

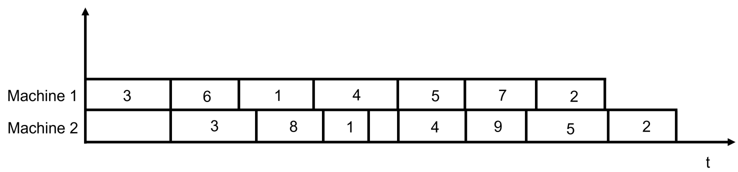

Figure 2.3. Solution Gantt chart

2.3.2 New solutions generation

An initial population of 50 individuals is set, and this dimension is assumed to remain constant with each generation. The individuals that will give life to the new generation are selected with the roulette method that selects individuals with a probability proportional to their fitness, according to the law of natural evolution.

The GA implemented creates three types of children for the next generation:

- Elite children are individuals in the current generation with the best fitness values. These individuals automatically survive to the next generation. They compose 5% of the next population. The elitism allows to emphasize the currently best solutions in subsequent generations. In this way, the good solutions previously found have the possibility of moving on to subsequent generations (Alexandre et al. 2015).

- Crossover children are created by combining the vectors of a couple of parents through the PMX rule (Fig. 2.4). These children compose 80% of the next population.

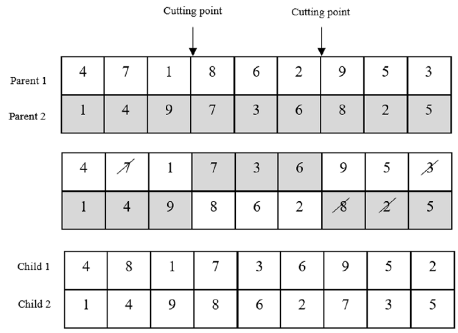

Figure 2.4. Partially matched crossover

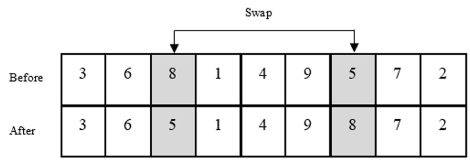

Figure 2.5. Swap mutation

- Mutation children are created by introducing mutations in a single parent and they will be the remaining part of the population. As a mutation operator, the swap mutation was chosen (Fig. 2.5).

Crossover operator

The crossover operator couples two parents, to generate two children presenting a genetic heritage deduced from that of their parents. The crossover operator is applied with a probability equal to Pc, whose value is generally very high (Pc $\geq$ 0.80). Since the solution is represented by permutations, we have chosen to use Partially Matched Crossover (PMX). In the PMX the values of the genes are not crossed but the order in which they appear is crossed, this eliminates the generation of children who violate the constraints of the problem.

Mutation operator

The mutation operator randomly modifies the value of an allele within a string. The mutation helps to prevent the algorithm from being trapped in a local minimum, and it is responsible for recovering lost genetic information. It is an operator used to maintain genetic diversity in the population.

2.4 Harmony Search

Harmony Search (HS) is a meta-heuristic algorithm proposed by Geem et al. (2001). It is inspired by the improvisation process that musicians follow to create new melody with their instruments and to collectively achieve the correct harmony or the state of equilibrium of the system. Just like the musical harmonies that are improved by the comparison and the improvisation of the single musicians creating each time new harmonies to improve the melodies, similarly the solutions to the problem become even better iteration after iteration.

2.4.1 Proposed changes

To explore the more significant parts of the solution space, the traditional HS has been modified, introducing additional features inspired by human nature. Specifically, we decided not to use the classic pitch adjusting which perturbs the generic elements X_i (the single allele of the string) of a certain quantity, as done by Zammori et al. (2014) and Wang et al. (2010) for similar problems, but we use the pitch adjusting rule used by Maythaisong & Songpan (2018) in the mutation-based harmony search algorithm (MBHS) to solve a different type of problem. With this method, we apply the mutation operator to the whole string.

In Fig. 2.6 the New Candidate Harmony Vector (NCHV) is the new solution that is created with each iteration of the algorithm. The Harmony Memory (HM) is a memory location where all the solution vectors are stored. This HM is similar to the population in the GA (Geem et al. 2002) (see Fig. 2.7).

For the calculation of PAR we used the formula of Mahdavi et al. (2007):

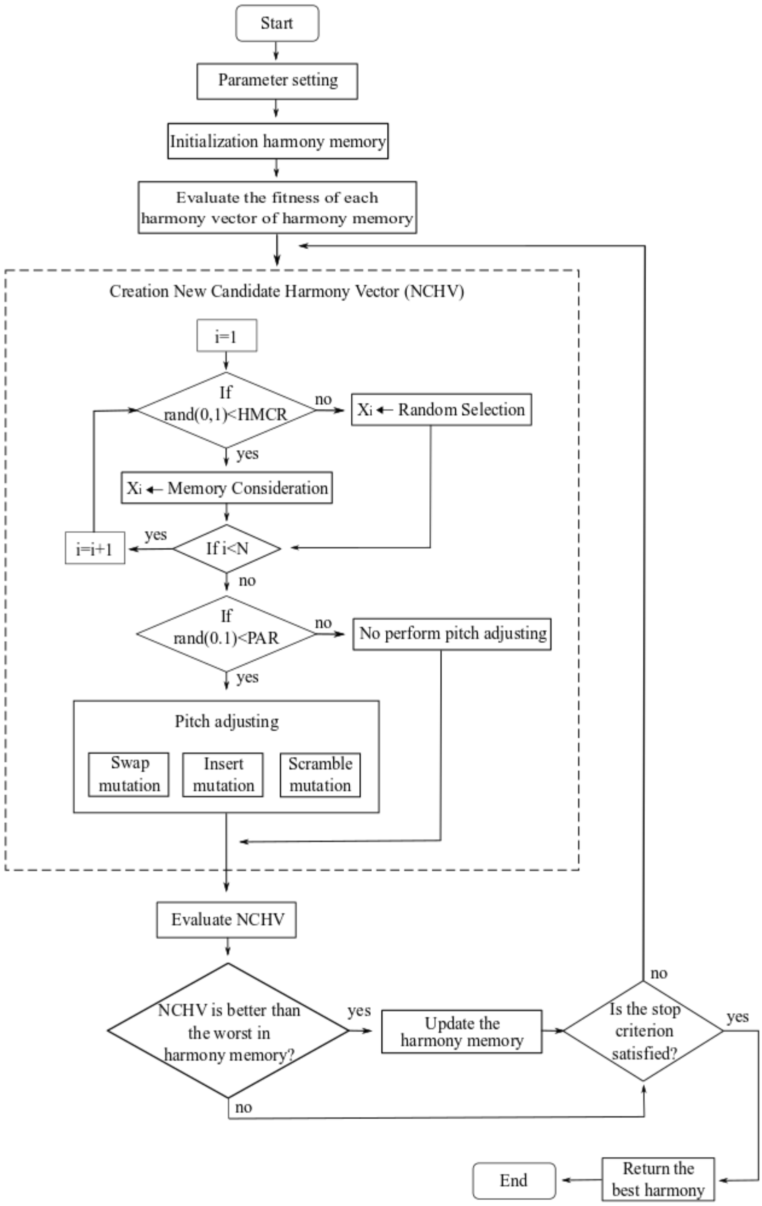

Figure 2.6. Flow chart of harmony search

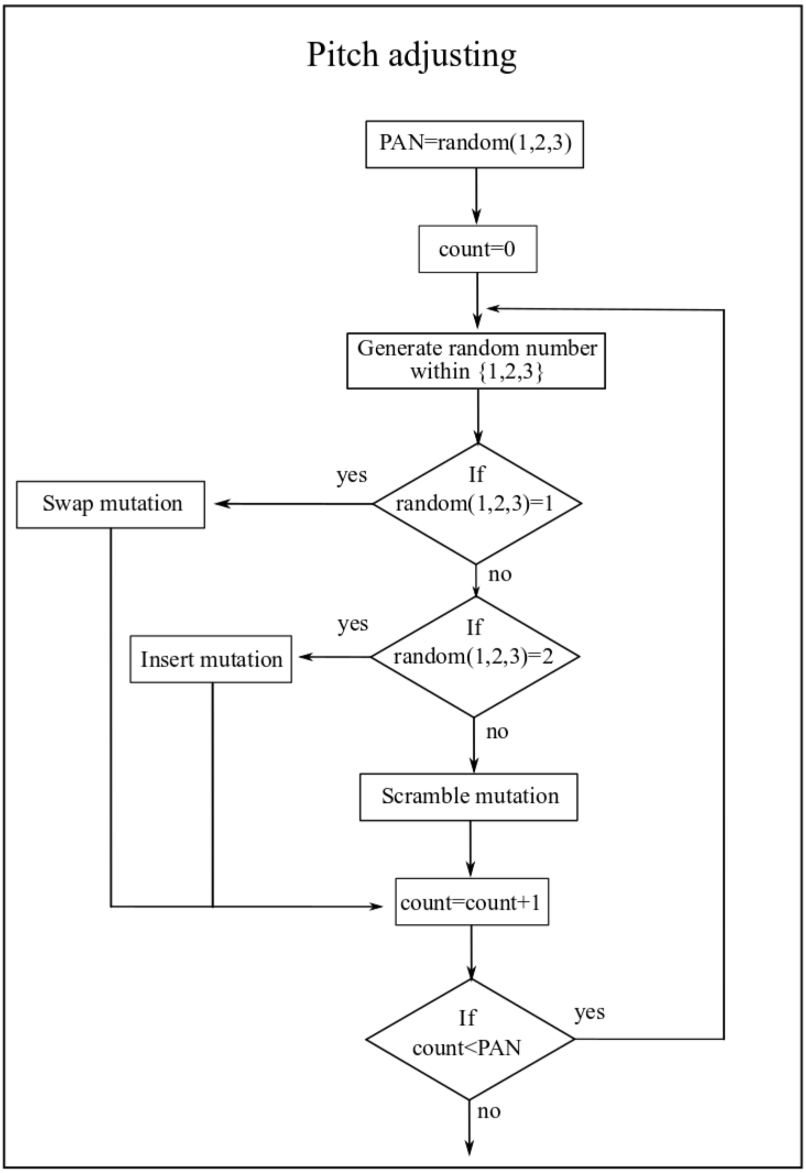

Figure 2.7. Pitch adjusting

Table 2.2. Fine-tuned parameters of HS

HS Parameters	Value
Harmony Memory Size	Same as the GA
Harmony Memory Consideration Rate	0.9
Minimum Pitch Adjusting Rate	0.4
Pitch Adjustment Rate (PAR)	0.4
Pitch Adjustment Number (PAN)	Random within {1,2,3}
Number of seconds without improving the best solution	Same as the GA

$PAR(Iteration) = \frac{PAR_{max} - PAR_{min}}{MaxItr} * Iteration + PAR_{min}$

In our case, the maximum number of iterations is infinite since we impose a maximum stall time of 15 min as a stop condition (i.e., if the solution does not improve for 15 consecutive minutes, then the algorithm will stop). Consequently $PAR = PAR_{min}$.

For the choice of the parameters in Table 2.2 we started from the values used by Zammori et al. (2014) and we modified them since in our problem the maximum number of iterations is infinite and therefore PAR is constantly equal to PAR_{min} and does not increase. So we chose a higher PAR_{min} value.

Following, once all the elements X_i of the new harmony have been obtained, a random number is extracted between 0 and 1 and, if this number is less than PAR for a number of times equal to PAN, the harmony vector is modified according to the following rule:

A new integer value is extracted between 1 and 3,

- If the value extracted is equal to 1, then the Swap Mutation is carried out: two genes are selected, and their alleles are simply exchanged (Fig. 2.8 (a));
- If the value extracted is equal to 2, then the Insert Mutation is performed: two genes are selected, and one of them is moved to be adjacent to the other moving the others accordingly (Fig. 2.8 (b));
- If the value extracted is equal to 3, then the Scramble Mutation is performed: in this case, a portion of the chromosome chosen at random sees its genes scrambled (Fig. 2.8 (c)).

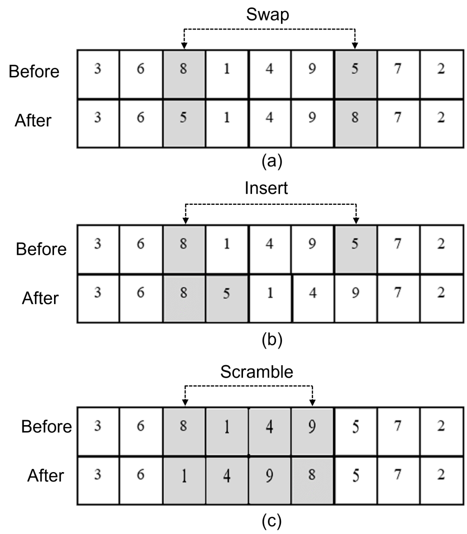

Figure 2.8. Mutation operator

Therefore the main difference between the Insert Mutation and the Scramble Mutation is that in the former after the displacement of an adjacent gene to another the rest of the genes keep the same order, in the latter the selection of the two genes identifies a portion of chromosome that is shuffled.

The same encoding used for GA is used to represent the solution in HS.

The following pseudo-code gives a better understanding of how the algorithm works.

HS PSEUDO-CODE

```
Begin
Define objective function
{*Initialization of constant parameters*}
Define HMCR Harmony Memory Consideration Rate
Define HMS Harmony Memory Size
Define PARmin minimum pitch adjusting rate
Define PARmax maximum pitch adjusting rate
Define NVAR number of variables
{*Variables and matrices population*}
Termination_condition = false
Generate the initial Harmony Memory
{*Execution of Harmony Search*}
  While (Termination_condition = false)
    For (i = 1:NVAR)
      If (rand(0,1) < HMCR) then
        Perform Harmony Memory Consideration to generate X_i;
      Else
        Perform Random Selection to generate X_i;
      end if
   end for
   If (rand(0,1) < PAR) then
      PAN = Random(1,2,3);
      For (i = 1:PAN)
        Mutation operator: Random(Swap, Insert, Scamble);
        X^new ← Mutation operator;
    End for
  End if
  If (fitness X^new < fitness X^worst) then
X^worst = X^new ;
    Update Worst, Best;
   End if
End while
Return X^best = the best solution in Harmony Memory
End
```

2.5 Computational experiments

In order to compare the performance of a Genetic Algorithm (GA) and Harmony Search (HS), an extensive set of planning problems was examined. First of all, for small problems, the two heuristics were evaluated by comparing them with an exhaustive search method able to find the optimal solution for relatively small problems in a reasonable time. Subsequently, for more significant problems, the two heuristics were compared considering different scheduling scenarios created according to different optimization and problem generation criteria.

2.5.1 Proposed generation

The problems are generated using the following rules used by Zammori et al. (2014):

- Job processing time is distributed according to a normal distribution with a mean of 100 and standard deviation 25.
- The setup times are uniformly distributed between 0 and 19.
- Weibull eta (η) is set at 100.
- The average time required to carry out corrective maintenance is evenly distributed between 15 and 25.
- The average time required to carry out the planned maintenance is evenly distributed between 30 and 50.

For the problems related to the minimisation of the ETP, these additional parameters are defined:

- Earliness penalty (a): equal to 1.
- Lateness penalty (b): equal to 8.
- Tardiness factor (TF): uniformly distributed between 0.3 and 0.6.
- Relative two date range (RD): equal to 0.4.

Table 2.3. Simulated scenario

Problem dimension	Job number (N)	Machine number (M)	Maintenance's number (PM)	Problem size (CL = N + PM)	β	Schedule complexity	Problem ID
Small	8	5	3	11	1.3	Low	SL1
Small	8	5	5	13	1.4	High	SH1

For the generation of due dates in a scheduling problem on a single machine the rule proposed by Tan et al. (2000) has been modified to be adapted to the scheduling problem with multiple machines:

$$\mu_{DD} = \frac{p}{N} * M * N * (1 - TF) \tag{2.23}$$

$$R_{DD} = \frac{p}{N} * M * N * RD \tag{2.24}$$

Due dates are uniformly distributed with average $\boldsymbol{\mu_{DD}}$ and range $\boldsymbol{R_{DD}}$.

Hence, the value of these parameters in individual problems are deterministic. To create various different problems (each relating to machines and jobs characterized by different parameters), the aforementioned random procedures have been adopted.

2.5.2 Comparison with the exhaustive search method

To evaluate the performance of the proposed meta-heuristic algorithms in terms of solution quality only for the problems concerning makespan minimization, two experiments have been carried out: a first one in which the machines are more reliable (i.e., they require fewer maintenance activities resulting in a low scheduling complexity), and a second one in which machines are less reliable (i.e., they fail more easily and require more maintenance resulting in a high scheduling complexity). The parameter that distinguishes the two cases is β, i.e., the shape parameter of the Weibull distribution. Since the exhaustive search method requires very high calculation times, the size of the problems considered is relatively limited (see Table 2.3).

We solved the proposed problems exhaustively on a Google Cloud virtual instance with the following features: 72vCPU Intel Skylake and 270 GB of memory. The same has been done for the two heuristic algorithms on a different virtual instance with the following features: 4vCPU Intel Skylake and 15 GB of memory.

The Stop condition in both heuristic methods has been set at 15 min of stall time (i.e., if the solution does not improve for 15 consecutive minutes, then the algorithm will stop).

In Table 2.4, the computation results of the proposed heuristics versus the exhaustive one are shown. The execution times of the exhaustive algorithm have been multiplied by 72 to make the times of the exhaustive comparable with the heuristic times. This calculation is justified by the fact that, while the exhaustive method exploits the parallel calculation, the meta-heuristic algorithms work with one core at a time. As revealed, increasing β from 1.3 to 1.4 provides a negative effect on the performance of the algorithms.

Table 2.4 shows that the result of HS has an average error, compared to the solution found with the exhaustive algorithm, which is lower than the GA. The performance of HS, in terms of average percentage error, is more significant in SH1 type problems, while we can consider it limited for SL1 type problems. In any case, both heuristics (HS and GA) have an average error lower than 0.2% and therefore provide a good result for these types of problems. Finally, in terms of computational time, Table 2.4 shows that HS, in SL1 problems, takes significantly less time to find the solution than GA (about 35% less time). While GA, in SH1 problems, takes slightly less time than HS (about 7% less time). In any case, both heuristics (HS and GA) have significantly less computational time than the time spent by the comprehensive algorithm. It is even more relevant in SH1 type problems.

2.5.3 Comparison of meta-heuristics

Six classes of problems were solved for each objective function (Makespan minimisation and ETP minimisation) to compare the performances of GA and HS: three with a low scheduling complexity and three with a high scheduling complexity. For each class, 100 problems were solved for a total of $600 \times 2 \times 2 = 2400$ experiments. For the classification of the

Table 2.4. Computational results of GA and HS algorithms on small-sized test instances

Problem		Exhaustive Algorithm	Genetic Algorithm		Harmony Search	
ID	Size	Average time [s]	Average time [s]	Average error [%]	Average time [s]	Average error [%]
SL1	11	$6,86x10^3$	121,53	0,05	79,43	0,03
SH1	13	$9,18x10^5$	146,8	0,16	157,61	0,04

Table 2.5. Simulated scenario

Problem dimension	Job number (N)	Machine number (M)	Maintenance's number (PM)	Problem size (CL = N + PM)	β	Schedule complexity	Problem ID
Medium	20	5	5	25	1,15	Low	ML1
Large	40	5	10	50	1,15	Low	LL1
Large	45	5	12	57	1,15	Low	LL2
Medium	20	5	10	30	1,2	High	MH1
Large	40	5	20	60	1,2	High	LH1
Large	45	5	24	69	1,2	High	LH2

problems in Table 2.5 we have chosen the same notation and definitions used by Zammori et al. (2014).

To evaluate the performances of GA and HS, we have used the relative percentage deviation (RPD) over the best solution found in the experiment:

$$relative\ percentage\ deviation\ (RPD) = \frac{Alg_{sol} - Min_{sol}}{Min_{sol}} x100 \quad (2.25)$$

where Alg_{sol} is the C_{max} obtained for a given algorithm and instance, and Minsol is the best solution obtained for each instance by any of the algorithms. The ARPD is the average RPD obtained on one hundred problems. Table 2.6 and Table 2.7 show the computational results of GA and HS for solving the six classes of problems.

In particular, the showed average times have been obtained by considering and subtracting the stall time (equal to 15 min in the considered scenario). As revealed from Table 2.6, the meta-heuristics show very similar results in terms of Average RPD, whereas the average time is doubled for the HS. Only for the simplest case ML1, the execution times are com-

Table 2.6. Obtained results in case of makespan objective

Problem		Genetic Algorithm			Harmony Search			Draws (%)
ID	Size	Average time [s]	Wins (%)	Average RPD (%)	Average time [s]	Wins (%)	Average RPD (%)	
ML1	25	725,73	38	0,12	963,45	59	0,05	3
LL1	50	856,35	92	0,01	1577,39	8	0,46	0
LL2	57	785,8	94	0,01	1523,99	6	0,66	0
MH1	30	825,75	37	0,17	1635,42	63	0,14	0
LH1	60	799,72	100	0,00	1360,42	0	1,08	0
LH2	69	978,74	97	0,01	1323,89	3	1,19	0

Table 2.7. Obtained results in case of ETP objective

Problem		Genetic Algorithm			Harmony Search			Draws (%)
ID	Size	Average time [s]	Wins (%)	ARPD (%)	Average time [s]	Wins (%)	ARPD (%)	
ML1	25	442,14	19	0,06	654,26	80	0,01	1
LL1	50	1265,7	62	0,05	1803,06	38	0,07	0
LL2	57	2368,75	70	0,03	2081,42	30	0,11	0
MH1	30	443,81	15	0,09	1397,11	84	0,01	1
LH1	60	2978,53	72	0,03	3011,56	28	0,12	0
LH2	69	5497,91	85	0,01	3501,62	15	0,18	0

parable. We may, therefore, conclude that, for this type of problem, which aims at minimising the makespan, the GA seems to perform better when the problem size increases.

For the ETP minimisation problem, the Table 2.7 reveals that, only in the case of medium-sized problems, the GA takes less time than the HS. For large problems, instead, the execution times of the meta-heuristics are comparable whereas both algorithms almost have no percentage deviation.

2.5.4 Impact of problem size on the heuristics

To further analyse the performance of GA and HS, concerning different problem sizes, Fig.2.9 depicts the ARPD yielded by GA and HS on all test instances. Specifically, the problem size is given by the sum of the number of machines, the number of jobs and the number of maintenances. Note that, as the problem size increases, ARPD values of GA decrease gradually, and the values of HS increase.

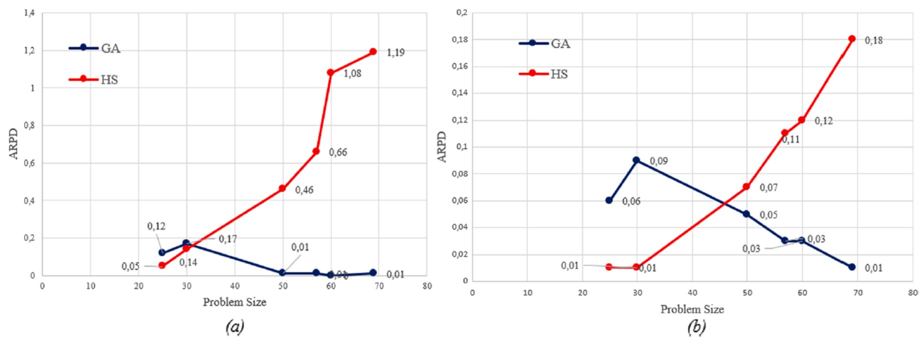

Figure 2.9. Performance of GA and HS with respect to different values of problem size. (a) Makespan objective. (b) ETP objective

2.5.5 Trend of heuristics over time

The graphs in Fig.2.10 shows the trend over time of the two heuristics: both for medium-sized problems than for large problems, GA tends first to the optimal compared to the HS. As time increases, the area between the two curves decreases in accordance with the results of Table 2.6 in which it is seen that the two heuristics give very similar results.

If we compare the graphs obtained aiming at minimizing the makespan (Fig.2.10) with those obtained aiming at the minimisation of the ETP (Fig.2.11) it is possible to see that in this last case the area between the two curves is smaller. Moreover, it is possible to observe that HS tends first to the optimal solution than GA.

2.6 Conclusions and future research

This work has investigated a Flow Shop Scheduling Problem (FSSP) integrated with preventive maintenance and stochastic breakdown. The time to failure of each machine is subject to a Weibull distribution with $\beta > 1$, i.e. the machines are characterised by a time increasing failure rate, considering both reactive and planned maintenance tasks.

The paper solves two minimisation problems separately: (i) the minimisation of makespan; (ii) the minimisation of the ETP. Considering the practical relevance of the problem and its complexity, we developed and

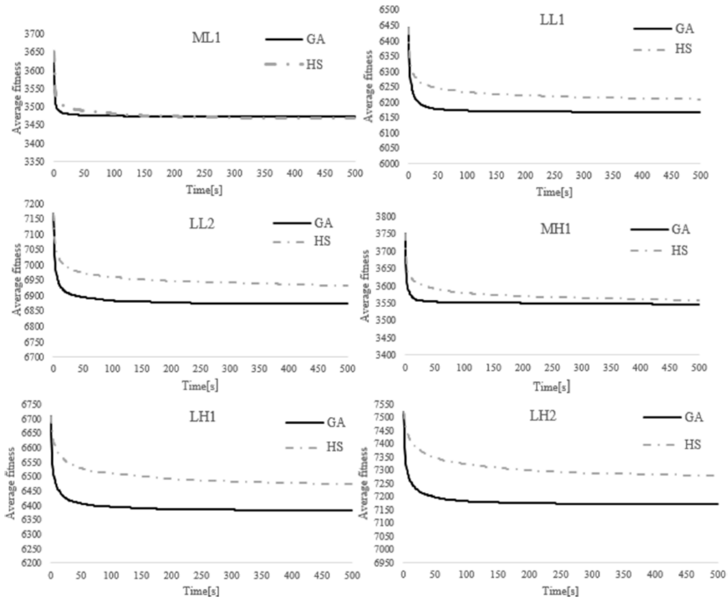

Figure 2.10. Average fitness on 100 problems in function of time

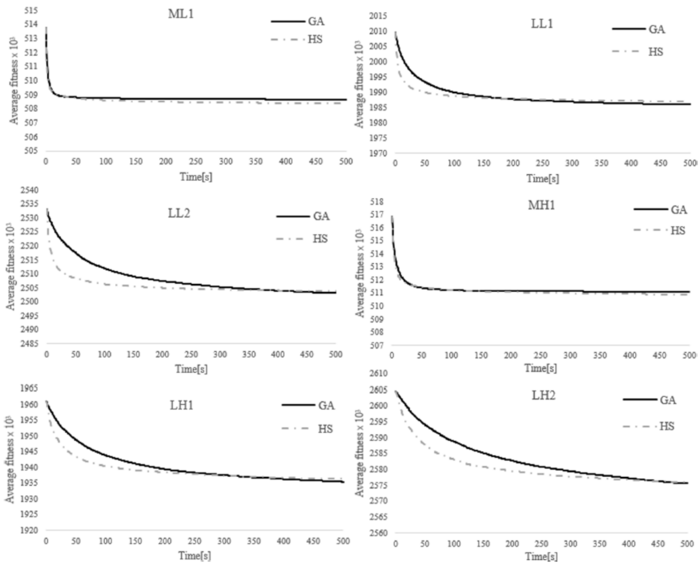

Figure 2.11. Average fitness on 100 problems in function of time

tested two meta-heuristic algorithms for solving the FSSP in a reasonable time, finding practicable and fulfilling schedules in industrial applications. Specifically, we have modified two widespread metaheuristics: GA and HS. To evaluate the performance of the proposed algorithms, we performed a series of computational experiments. For small problems, we have compared the two heuristics with an exhaustive search method, which can find the optimal solution. The computational results show the time benefits of using these heuristics. Moreover, to make a comparison between the proposed meta-heuristic algorithms, we have considered scenarios with different scheduling complexities and instance sizes. The results recorded show that, as the size of the problem increases, GA tends to perform better than HS.

For future research, it could be interesting to study the considered problem in the hypothesis of absent buffers. An additional exciting line of investigation would be to improve the proposed HS going to guide memory consideration to prefer solutions within harmony memory that have better fitness.

Chapter 3

Optimizing Scheduling in Flexible Job-Shop Manufacturing with Tool Wearing Effect

3.1 Introduction

In recent years, there has been a shift in the manufacturing industry towards more flexible and efficient production systems, and the Flexible Manufacturing System (FMS) has emerged as the leading solution. FMSs have grown in importance in the aerospace, automotive, and electronics industries as a result of their capacity to produce multiple products simultaneously and quickly adapt to production changes (Liaqait et al. 2021). These systems are composed of interconnected workstations, automated material handling and storage systems, and an integrated computer system for control and coordination (Shivanand et al. 2006, Kostal & Velisek 2017). This enables FMSs to adapt to changing market demands and production requirements, ultimately leading to increased efficiency and competitiveness in the manufacturing industry.

FMSs can be divided into three main categories based on their job processing orders: open shops, flow shops, and job shops (Haupt 1989). The job shop system is the most commonly used FMS due to its flexibility and adaptability, where each job is processed on available machines within a specified processing time, with the constraint that each machine can only process one operation per job. This system is known as the Job Shop Flexible Manufacturing System (JS-FMS), and it requires more complex scheduling algorithms to handle the flexibility and variety of jobs involved. This problem is known in the literature as the Job Shop Scheduling Problem (JSP), which seeks to assign production jobs to machines at particular times to optimize multiple objectives such as makespan, flow time, tardiness, etc. (Meilanitasari & Shin 2021, Dornhöfer et al. 2020). As a classic problem in operational research, the JSP is known to be NP-hard, and this means that it is computationally difficult to solve, requiring advanced algorithms and techniques to find efficient solutions (Zhang et al. 2019).

To address the complexity of scheduling JS-FMSs, researchers have proposed different optimization techniques to solve the JSP, both with exact methods (e.g. mixed-integer models) and approximate methods (e.g., simulation, neural networks, genetic algorithms, simulated annealing, etc.) (Xie et al. 2019, Mohan et al. 2019). One critical issue in the scheduling of an FMS is tool deterioration that has been widely addessed from the scientific literature (Xu & Randhawa 1998, Altumi & Taboun 2001, Braglia & Zavanella 1999, Liu et al. 2001, Tian et al. 2023). For example, Hirvikorpi et al. (2007) developed a genetic algorithm to solve the Job Scheduling with Stochastic Tool Lifetime (JSSTL) problem and showed that the proposed algorithm outperformed the traditional Short Processing Time (SPT) method. On the other hand, Xiuli et al. (2019) proposed a Multi-Objective Hybrid Pigeon-Inspired Optimization and Simulated Annealing (MOHPIOSA) algorithm to tackle the FJSP by simultaneously considering the effects of tool deterioration and energy consumption. In recent work, Salama & Srinivas (2021) proposed a similar sustainability-oriented approach to scheduling with tool deterioration in order to minimize the weighted costs of energy consumption, integrating the information about tool costs and production delays.

However, the analysed approaches still do not adequately take into account the phenomenon of tool wear from an operational point of view. As a matter of fact, operators often change tools prematurely to avoid breaking them during a shift, resulting in suboptimal tool utilization and increased costs (Waydande et al. 2016). This is a significant problem especially in the production of high-value materials such as those in the aerospace sector that require costly tools, where optimization of their utilization is of utmost importance to minimize production costs (Aamir et al. 2020, Barni et al. 2020, Nabhani 2001). Additionally, in the production of small series products, reducing the makespan while improving tool utilization is essential to meet customer demand and maintain competitiveness (Tanvir et al. 2020). Thus, there is a pressing need for advanced scheduling algorithms that can optimize both the makespan and the tool utilization concurrently. An optimal work sequence can improve tool utilization and reduce the number of partially used tools, making scheduling an FMS a challenge.

To fill this gap, the proposed approach takes into account the impact of tool wearing on scheduling optimization. Specifically, the approach considers the residual useful life of tools conservatively estimated by manufacturers. Using this information, the approach models and allocates a set of jobs with specific processing times and tooling requirements on identical parallel machines, taking decisions on job and tool assignment. Two metrics are introduced to evaluate these decisions and optimize the scheduling process, with the goal of maximizing tool utilization and minimizing production makespan. Balancing these objectives is challenging, as they often conflict. This problem is then addressed by searching for a set of optimal solutions on the Pareto front that offer the best possible balance between the two objectives, resulting in a trade-off that achieves the optimal local performance in terms of both makespan and tool utilization.

The proposed approach has been implemented with a customized genetic algorithm and validated on a real case study from a company located in Naples (Italy) and operating in the aerospace sector. The algorithm, as it is conceived, provides practitioners with quantitative insights about the optimal configuration of the FMS with respect to the management of the tool warehouse, whether it should be centralized or decentralized, also supporting the optimal scheduling process by both increasing tool utilization and makespan reduction in JS-FMSs.

The remainder of the paper is organised as follow. Section 3.2 describes the hypothesis on the problem under consideration; Section 3.3 introduces the proposed genetic algorithm architecture; Section 3.4 presents the experimental scenario and the discussion of the results; Section 3.5 concludes the paper.

3.2 Problem Formulation

The optimization of production scheduling for flexible manufacturing systems (FMS) is a crucial task in industrial settings, especially in highly demanding industries like aerospace, automotive, and electronics (Yadav & Jayswal 2018). The efficient allocation of jobs to parallel machines and the management of tools are essential to ensure productivity, minimize costs, and maintain competitiveness (Balogun & Popplewell 1999). As mentioned in Section 3.1, current approaches available in the literature do not adequately consider the phenomenon of tool wear, leading to suboptimal tool utilization, increased costs, and waste of tool residual life (Waydande et al. 2016, Braglia & Zavanella 1999). The problem is even more pressing when dealing with high-value materials, which require the use of costly tools (Buyurgan et al. 2004). Therefore, there is a clear need for advanced scheduling algorithms that can optimize both the makespan and the tool utilization concurrently, while taking into account the phenomenon of tool wear. Such an algorithm could potentially reduce costs, improve efficiency, and increase competitiveness for industries that rely on FMS.

The Identical Parallel Machines Problem with Tooling Constraints is the problem explored in this paper. The scenario involves different jobs, each requiring specific tools for machining. Processing time varies for each job and is not dependent on the machine they are performed on. Each machine has a tool warehouse with limited capacity and automatic tool changer, allowing it to process multiple jobs without significant setup times, as long as the required tools are distinct. A constraint of this problem is that each machine can only process one operation at a time. If a job requires multiple operations and different tools, these operations must be performed in sequence on the same machine. However, interrupting an operation is not feasible as the process cannot be resumed from its interruption point. The production system includes a double pallet that eliminates the wait for setup times between operations on the same machine.

The goal is to find the best possible sequencing of jobs allocated to different machines in order to (i) maximize the utilization of the tools useful life and avoiding having tools that remain with a residual useful life that cannot be used for next operations, and (ii) keeping the makespan at the minimum possible with respect to the production plan. The proposed approach aims to solve this multi-objective optimization problem by minimizing the two target variables which measure the balancing of machines and the effectiveness of tool utilization. To achieve this, a measure of the two target variables and a genetic algorithm has been developed. It can provide non-dominated optimal solutions on the Pareto front, allowing for a better balance between the two proposed objectives.

The problem statement of this work is based on a real case of an aerospace industry company that produces titanium parts using FMSs for production. The company requires effective scheduling of production machines, particularly during unsupervised night shifts. Due to the high cost of tooling and the risk of tool breakage during machining, the company estimates the residual useful life of tools in a conservative manner, taking the advised value from the tool manufacturer. The problem they face is to optimally schedule jobs among different machines in the FMS station, which all have independent automated tool warehouse. The proposed algorithm aims to identify the optimal configuration of the considered FMS with respect to the management of the tool warehouse, determining the tool to be loaded on each machine for dealing with the scheduled job.

3.3 The proposed approach

The proposed approach considers two target variables to optimize: the balancing of machines, the so-called "Smoothness Index" (SX), and the "Effectiveness Utilization Tool" (EUT). SX is a traditional measure of the assembly line theory and represents a measure of the workload assigned to the various machines. It assumes a value of zero when production is perfectly balanced among FMS machines and the maximum value equal to the sum of all jobs processing time when all machining time is concentrated on one machine. EUT is a dimensionless measure of how effective the job allocation was in the use of the tools, and assumes a value of zero for an ideal situation in which tools are not wasted and positive values when tool residual life is wasted. Therefore, we understand that SX and EUT are interrelated quantities. A solution that minimizes the value of SX minimizes the umbalancing between the machines in terms of process-

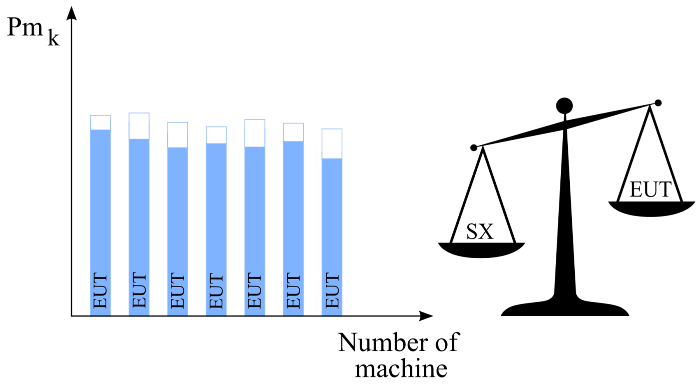

Figure 3.1. Machine Load Balance - Solution minimizing SX

ing time (as shown in Figure 3.1), resulting in a lower makespan for the scheduled operations, but will result in higher tool waste due to suboptimal scheduling of the tools at the machines. On the other hand, a solution that minimizes the value of EUT (as depicted in Fig. 3.2) leads to more efficient tool utilization but creates a strong imbalance in the distribution of machining times across the machines, increasing the overall makespan value of the production system. This problem is a classic example of multi-objective optimization.

Using Graham notation $(\alpha|\beta|\gamma)$, we can classify the problem considered in this paper as follows:

$$\alpha = P \tag{3.1}$$

$$\beta = \emptyset \tag{3.2}$$

$$\gamma = SX, EUT \tag{3.3}$$

Eq. 3.1 indicates that the problem involves parallel machines; Eq. 3.2 means that the jobs do not have any characteristics specified by Graham (e.g. preemption is allowed, presence of limited resources, precedence relations between jobs, release dates, processing time has a lower and upper

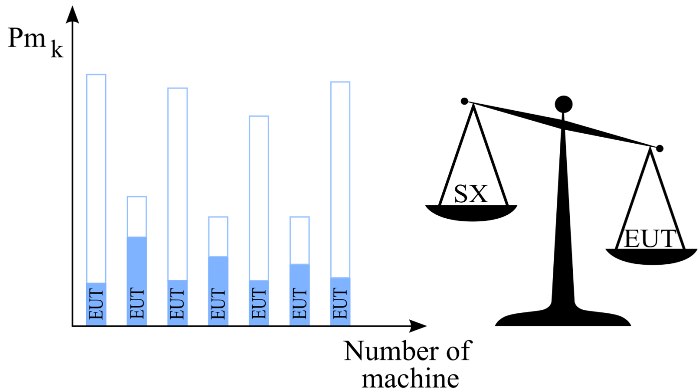

Figure 3.2. Tool Utilization Efficiency - Solution minimizing EUT

bound); Eq. 3.3 indicates that the optimal criteria are the minimization of the unbalancing of processing times between machines (SX) and the efficient use of tools (EUT).

Let us introduce the following notation:

- n is the number of jobs to be processed;
- m_c is the number of parallel machines;
- t is the number of different types of tools required to produce the job orders;
- j_i is the i-th job, $i = 1, \ldots, n$;
- m_k is the k-th machine, $k = 1, \ldots, m$;
- J_{m_k} is the set of jobs assigned to the machine m_k;
- T_v is the v-th type of tool, $v = 1, \ldots, t$;
- UL_v is the useful life of the v-th tool (in machining minutes);
- RUL_v is the residual useful life of the v-th tool (in machining minutes);

- $h_{i,b}$ is the b-th tool required to process the job i;
- $h_{i,b} \in H_i \subset T$, where H_i is the set of different types of tools required to produce the job i and T is the set of different types of tools required to produce all the jobs;
- $p_{H_i,i}$ is the machining time (in minutes) of the job i using the set of tools H_i;
- P_{m_k} is the total machining time of the jobs assigned to the machine m_k;
- $\overline{P}$ is the average machine processing time.

Given the introduced notation, it is possible to calculate SX as in Eq. 3.4 and EUT as in Eq. 3.5.

$$SX = \sqrt{\sum_{m_k} (P_{m_k} - \overline{P})^2} \qquad \forall k \in \{1..m_c\} \tag{3.4}$$

$$EUT = \sum_{v} EUT_v \tag{3.5}$$

where

$$EUT_v = \sum_{v} BestUT_v - UT_v \quad \forall v \in \{1..t\}$$

where $BestUT_v$ (Eq. 3.6) is the utilization of the v-th tool type in the best (ideal) solution.

$$P_{m_k} = \sum p_{H_i,i} \qquad \forall i \in J_{m_k} : \overline{P} = \frac{\sum_{k=1}^{m_c} P_{m_k}}{m_c}$$

$$BestUT_v = \sum_{i} \frac{p_{i,v}}{UL_v} \quad \forall i \in 1..n \tag{3.6}$$

To address the introduced multi-objective optimization problem, we propose a genetic algorithm that can generate optimal solutions to the scheduling problem. The genetic algorithm follows the traditional structure of such algorithms, including the representation of solutions in the form of chromosomes, the crossover operator for generating offspring chromosomes, and the mutation operator for introducing variation into the population. This choice is motivated by genetic algorithm's ability to efficiently explore the solution space, find optimal or near-optimal solutions, and handle multi-objective problems through the use of Pareto front analysis. In the following sections, we will describe each of these components in detail and discuss how they are used in the proposed algorithm.

3.3.1 Chromosome

As the objective is to determine the optimal sequence of operations to be performed on various machines, it is imperative that the chromosome accurately represents this information. With this in mind, the chromosome was designed to represent the sequence of operations scheduled on each machine. It is worth noting that the allocation of jobs to machines and the sequencing of those jobs on each machine are two important aspects of the scheduling problem. These aspects are captured in the chromosome through its positional encoding, where the position of each gene represents the machine to which the job has been assigned, and the sequencing of the job on that machine. The chromosome was designed with a fixed length, which is determined by the number of machines, the number of jobs, and the number of scheduling days considered in the problem. In the example shown in Figure 3.3, the chromosome was designed to allocate a maximum of 4 different jobs per day on the machines, and consider a total of 2 scheduling days. As such, the first 4 allocations of the chromosome represent the jobs assigned to the first machine on the first day, the next 4 represent the jobs assigned to the first machine on the second day, and so on. It is also worth mentioning that, once the chromosome is defined, its dimensionality cannot be changed during the execution of the algorithm. To account for this, the presence of 0s was taken into consideration in the chromosome design, allowing solutions to be identified even if not all possible allocation slots are occupied. In this context, the 0s are simply skipped, as shown in the example in Fig. 3.3.

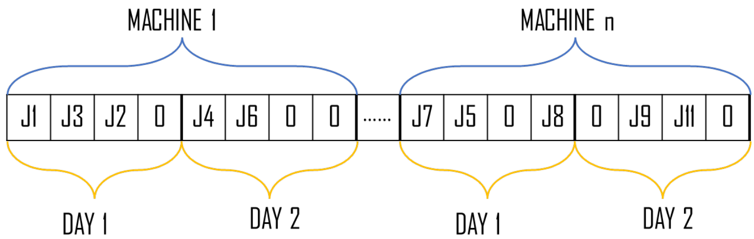

Figure 3.3. Example of Chromosome Representation in the Genetic Algorithm Solution Space

3.3.2 Crossover operation

The Crossover operation in a genetic algorithm is the process of generating a child solution by combining the genetic information of two parent solutions. The purpose of this operation is to create offspring that are fitter and more diverse than their parents, thereby enriching the population with better individuals. The crossover operator is modeled after biological reproduction, where genetic information is passed from one generation to the next. In this study, the Partially Mapped Crossover (PMX) method has been adopted to generate the child chromosome. This method is advantageous as it preserves the order and interconnections within the chromosome and ensures that the offspring respects the rules of permutation.

The process of PMX starts with the random selection of two parent chromosomes (P1 and P2) and two crossover sites. As illustrated in Figure 3.4, the first parent (P1) segment between the two sites is directly copied to the same position of the second child (O1). Then, the elements that are present in the middle segment of the second parent (P2) but not in P1 (elements 1, 9, 6 in the illustration) are placed in the corresponding positions of the child chromosome. For instance, the element 9 in P2 is positioned at 5 in O1, so the next step is to place the element 9 in the available position from the previous 5 in P2. This process continues for the elements 6 and 1 in a similar manner. Finally, the remaining elements of parent P2 are copied to the corresponding positions of the child chromosome. This approach ensures that the offspring chromosome inherits traits from both parents while maintaining the order and interconnections of the solution. By doing so, the PMX method helps maintain the diversity of

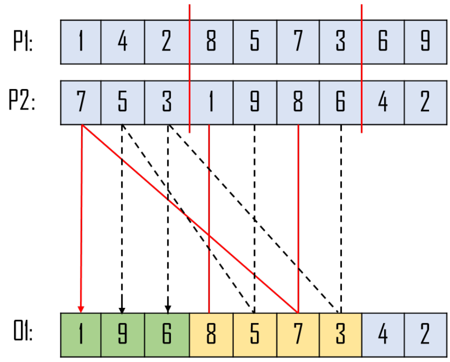

Figure 3.4. Example of Partially Mapped Crossover (PMX) operation between two parent chromosomes to generate a child chromosome

the population and improves the chances of finding an optimal solution.

3.3.3 Mutation operation

The purpose of mutation in genetic algorithms is to introduce new genetic information into the population, breaking away from the constraints imposed by the current solutions. This helps the algorithm escape from being trapped in a local minimum and aids in exploring the entire search space. Mutation is crucial in maintaining the genetic diversity of the population, thereby increasing the chances of discovering better solutions. In the present work, Random Resetting is used as the mutation method. This method is equivalent to binary mutation, where each gene has a fixed probability p_m of being replaced by a random value, calculated within a predetermined range. This approach ensures that the mutation rate is independent for each gene, allowing for a more nuanced exploration of the search space.

3.4 Results and Discussion

The proposed approach for the Identical Parallel Machines Problem with Tooling Constraints has been tested and validated in a real-world case study of a manufacturing company in the aeronautical supply chain. As previously stated, the company must schedule production machines during unsupervised shifts while efficiently using costly tools with conservative estimates of their residual useful life. To assess the approach's ability to optimize machine balancing and tool utilization, a genetic algorithm was implemented in Python, taking into account the chromosome configuration and genetic operators described earlier. The experimental methodology was designed to evaluate the approach's effectiveness, with levels of the considered factors based on their relevance to the company's real-world scenario.

In Section 3.4.1 the design used to evaluate the proposed approach and the performance measures used to assess the solutions' quality are explained, along with the rationale behind the selection of factors and their levels. In Section 3.4.2, instead, the results of the experiments are analyzed, and implications for practitioners are discussed. The discussion section highlights the importance of considering tool residual life when scheduling production machines and the potential impact of the proposed approach in reducing tool-related costs and improving tool utilization in similar real-world scenarios. Additionally, the results suggest that the optimal configuration of the FMS tool warehouse, whether centralized or decentralized, may vary depending on the specific scenario being considered.

3.4.1 Experimental Methodology

The experimental methodology aims to evaluate the proposed approach by testing it on a simulated scenario inspired by a real-world scenario from the aerospace industry. The company's production system is made up of fully autonomous FMS units, equipped with an internal tool warehouse. These machining operations require efficient scheduling, and the SX and EUT parameters play a crucial role in understanding the type of solution identified by the proposed approach. Minimizing the SX parameter results in a solution with the lowest makespan, where each of the plant's productive FMS unit has an equal distribution of work. This represents the fastest solution to complete the scheduling, but with the use of tools dispersed and replicated among the various machining units, leading to higher EUT values. On the other hand, solutions that minimize the EUT value result in a situation where some machining units are occupied for

Table 3.1. Factorial scenario plan

Experimental Factor	Levels	Unit
Machines	3	[machine]
Job	200	[job]
Total Operation	1400	[operation]
Operation Time Distribution	triangular$(15, 391, 98)$	[minutes]
Type of Tool	56-75-94	[different tool]
Tool Type Distribution Scenario	00-03-06	[]

much longer than others, with a unbalanced load between machines and a longer overall makespan, saving the waste of tool life.

To validate the proposed algorithm, production scenarios of 200 total jobs composed of 1400 operations were generated. The operation processing times were extracted from a triangular distribution with a minimum value of 15 minutes, a maximum value of 391, and a modal value of 98. The experimental scenarios were generated varying two factors: the number of different tools used in the machining cycles and the distribution of the different types of tools in the machining cycles. Table 3.1 shows the three distinct values for the first factor, with the central value being representative of the case study. These values simulate scenarios in which 56, 75, and 94 tool types are used in the machining cycles. Three levels were also determined for the second factor, with the central value always representative of the case study. The three values represent the frequency distribution of the specific tool type within the generated processing cycles. A value of 00 is representative of a situation in which the use of tools within the machining cycles is uniform, meaning that the generated operations technological cycle presents shared tool among them. Figure 3.5 depicts the frequency distribution probability, where the type of tool is represented on the x-axis and the frequency distribution on the y-axis. On the other hand, both the 03 and 06 values represent a damped exponential tool frequency distribution. However, the 03 value indicates a less pronounced damped exponential distribution, meaning that it is closer to a uniform situation than the distribution represented by the 06 value, as shown in Figure 3.6.

To ensure the robustness of the proposed approach, the experimental

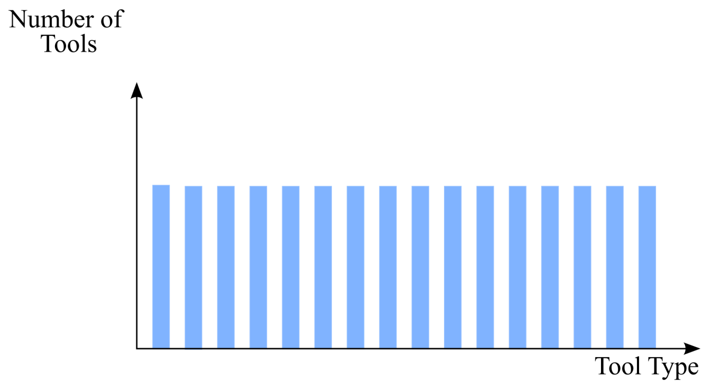

Figure 3.5. Uniform tool utilization distribution - Tool Type Distribution Scenario 00

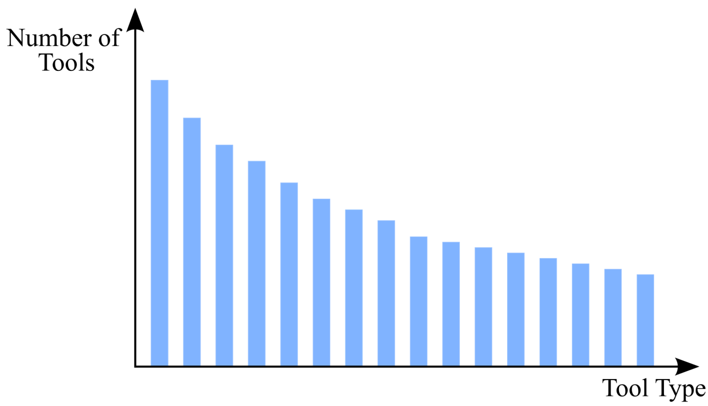

Figure 3.6. Unevenly increasing tool utilization distribution Tool Type Distribution Scenario 03

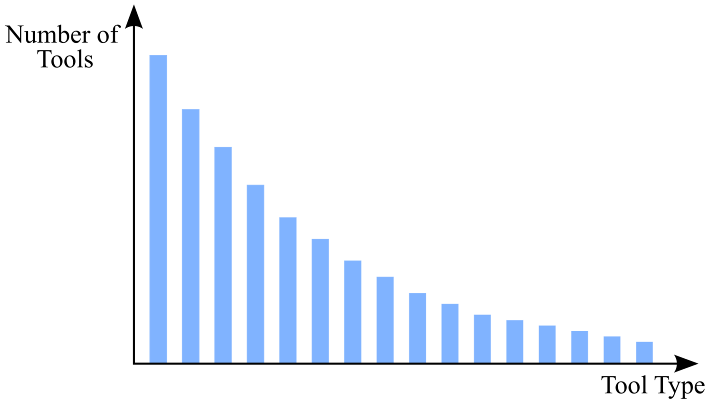

Figure 3.7. Damped exponential tool utilization distribution - Tool Type Distribution Scenario 06

methodology involved generating a sufficient number of problems for each combination of factors. For the proposed factor and level, with a full factorial experimental plan 9 different scenario are identified. Specifically, a generation problem algorithm has been built for generating 10 different problems for each combination, resulting in a total of 90 runs. To evaluate the proposed approach, the genetic algorithm discussed in Section 3.3 was applied to each of the resulting scenarios, and the solutions were analyzed to gain insight into the algorithm's performance in terms of distribution and resilience.

3.4.2 Results and Discussion

In this section, we present the most relevant results obtained from our experiment. The results are shown through scatter plots, with the x-axis representing the value of the objective function EUT and the y-axis representing the value of the objective function SX. As a reminder, the goal of the proposed genetic algorithm is to minimize the weighted sum of these two objective functions, obtaining a Pareto front of optimal solutions that allow the decision-maker to choose among them the appropriate solution depending on the situation at hand. The results will be presented in two steps: first, the results obtained by keeping the distribution of the tool type constant while allowing the number of tools to vary; second, the results obtained by keeping the number of tools constant while observing what happens when the distribution of the tool type varies.

Figures 3.8, 3.9, 3.10 show the first three distinct scenarios, respectively: Figure 3.8 represents scenarios where the tool type distribution in technological cycles is uniform; Figure 3.9 represents scenarios where the imbalance is depicted in Figure 3.6; and Figure 3.10 represents scenarios where the imbalance is depicted in Figure 3.7. The results show that as the number of tools type increases, with the same distribution of tools among the technological cycles, the Pareto front rises and the slope of the front increase. This trend is repeated in all the various distribution scenarios analyzed, although it should be noted that this impact is stronger in the situation with uniform tool distribution and gradually decreases in the situations with increasing imbalance. This means that with the same SX, the respective EUT value increases, making it more difficult to optimize tool utilization as the number of tools increases. Conversely, as the EUT remains the same, the imbalance between the machines increases significantly (the SX value identified by the optimal solution increases).

From these results, we can highlight a practical conclusion: as the number of tool types required for machining operations increases, it becomes increasingly complex to optimize machining cycles while minimizing the makespan and safeguarding the tool life wastage. In such scenarios, it may be more convenient to organize the FMS unit to use central tool warehouse rather than decentralized on-board machine warehouse, to allow for combined optimizations with respect to both the makespan (SX) and the residual useful life of the tools (EUT). This consideration is not necessary if the distribution of tools in the machining cycles is uneven, as the gain from centralizing the tool warehouse becomes significantly reduced with increasing imbalance and the number of tools.

Finally, we focus on the results obtained when the number of tools type is fixed and the distribution of tool types vary. Figures 3.11, 3.12, 3.13 depict, respectively, the three distinct scenarios: Figure 3.11 depicts a scenario in which the number of tool type is at its lowest value (56), Figure 3.12 depicts a scenario in which the number of tool type is 75, and Figure 3.13 depicts a scenario in which the number tool type is 94. The

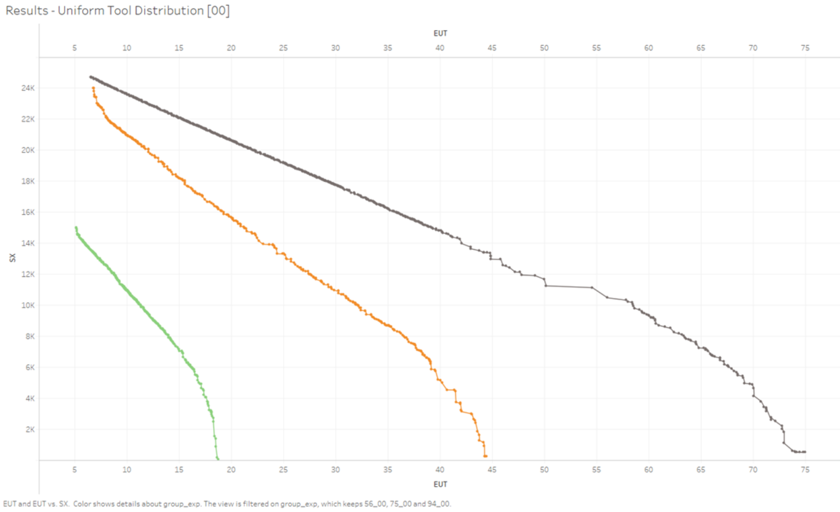

Figure 3.8. Domain Solution - Uniform Tool Distribution [00]

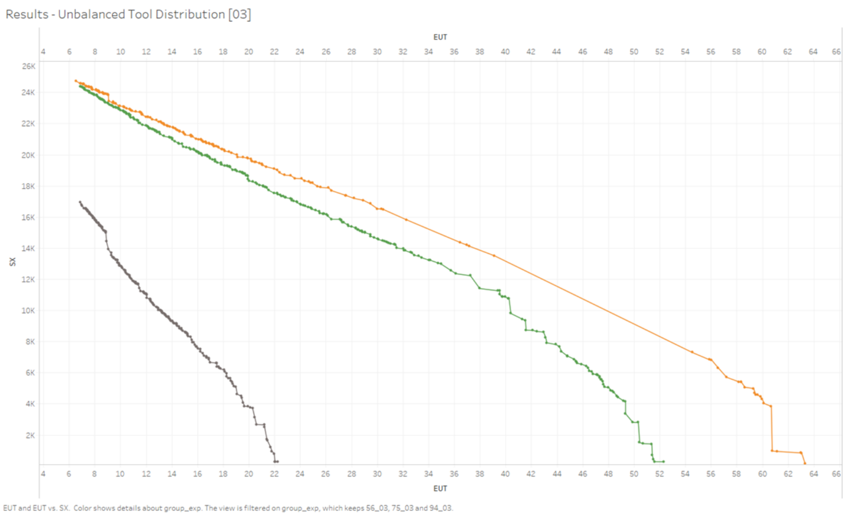

Figure 3.9. Domain Solution - Unbalanced Tool Distribution [03]

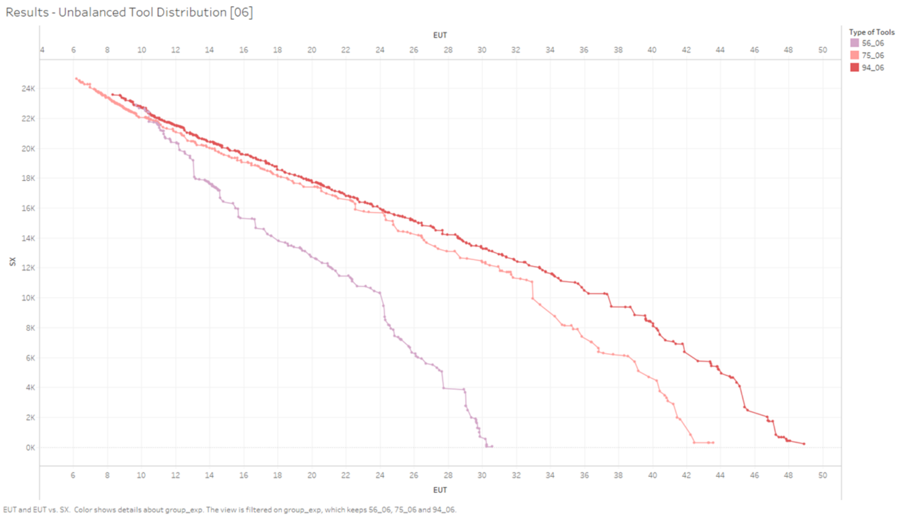

Figure 3.10. Domain Solution - Unbalanced Tool Distribution [06]

results show that, with a fixed number of possible tools to be used, as the distribution of the tools between the technological cycles changes, better results are obtained in scenarios with a large number of tools and a uniform distribution between the machines (i.e. solutions with decentralised tool warehouse). This consideration becomes less important as the number of different tools increases and reverses in scenarios involving 94 distinct types of tools. On a practical level, we can conclude that if a small number of tools are predominantly used in the technological cycles, it is advantageous to use on-machine warehouse, while a centralised warehouse is more advantageous in the case where the number of tools is large.

3.5 Conclusion

In this paper, a novel approach to address the Job Shop Scheduling Problem in the context of Job Shop Flexible Manufacturing Systems with the consideration of tool wear has been presented. The proposed approach takes into account the residual useful life of tools conservatively estimated by manufacturers and allocates a set of jobs with specific processing times

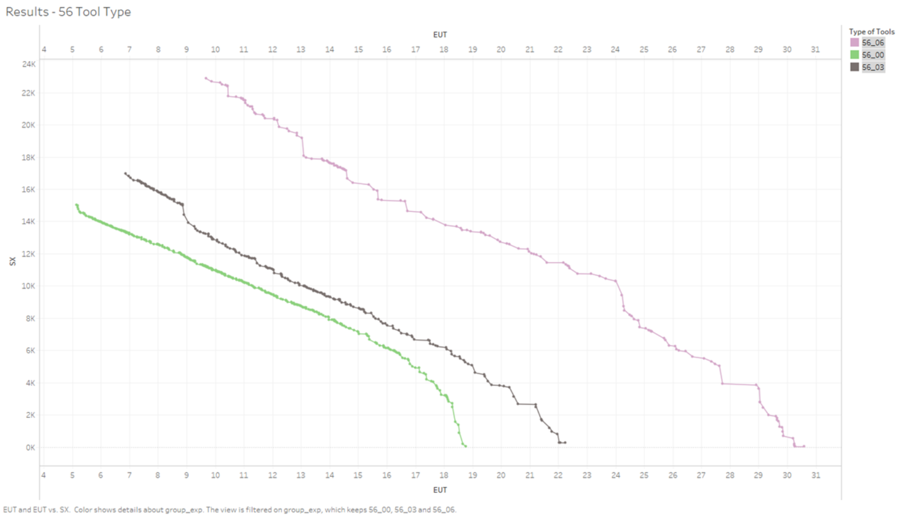

Figure 3.11. Domain Solution - Fixed Tool Type at 56

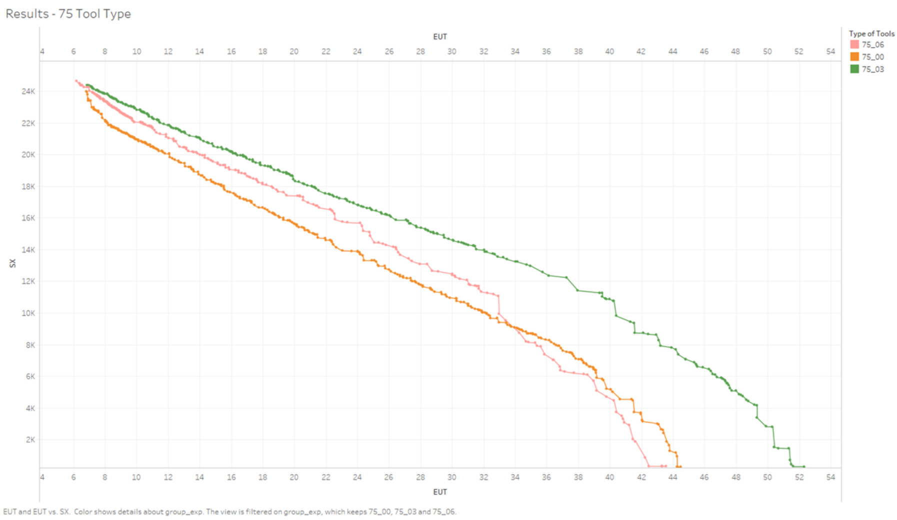

Figure 3.12. Domain Solution - Fixed Tool Type at 75

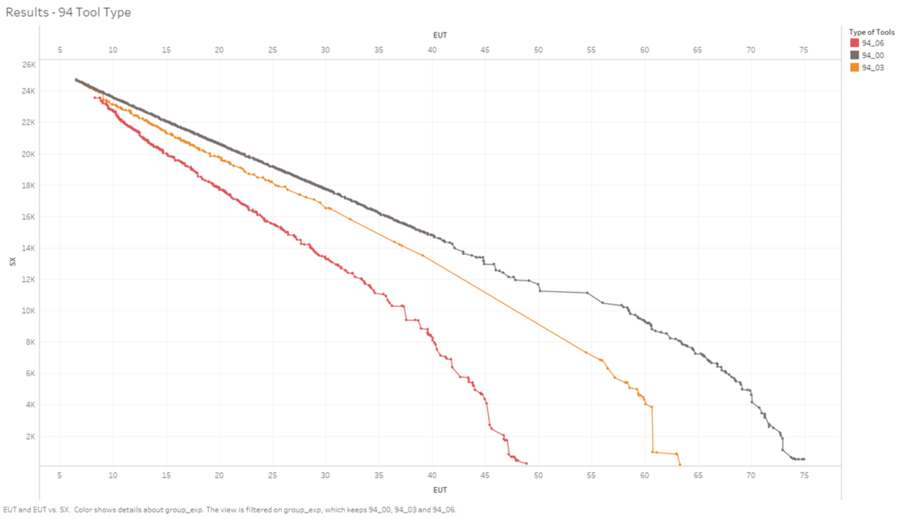

Figure 3.13. Domain Solution - Fixed Tool Type at 94

and tooling requirements on identical parallel machines. We introduced two metrics to evaluate the scheduling decisions and optimize the scheduling process, with the goal of maximizing tool utilization and minimizing production makespan. To address the trade-off between these two objectives, the proposed approach searches for a set of optimal solutions on the Pareto front that offers the best possible balance between them, achieving optimal local performance in terms of both makespan and tool utilization. We implemented this approach with a customized genetic algorithm and validated it on a real case study from a company operating in the aerospace sector, which confirmed the effectiveness of the approach in increasing tool utilization and reducing the makespan.

The results obtained from the considered experiment show that, as the number of tool types increases, it becomes increasingly complex to optimize machining cycles while minimizing the makespan and safeguarding tool life wastage. In such scenarios, it may be more convenient to organize the FMS unit to use a central tool warehouse rather than a decentralized on-board machine warehouse to allow for combined optimizations with respect to both the makespan and the residual useful life of the tools. However, if the distribution of tools in the machining cycles is uneven, the gain from centralizing the tool warehouse becomes significantly reduced with increasing imbalance and the number of tools.

The proposed approach has significant practical implications for the manufacturing industry, particularly in the production of high-value materials such as those in the aerospace sector that require costly tools. By optimizing tool utilization, the proposed approach can help reduce production costs, improve production efficiency, and maintain competitiveness. Additionally, in the production of small series products, the proposed approach can help meet customer demand by reducing the makespan while improving tool utilization. Moreover, the solutions found by the proposed algorithm can be chosen by the production manager by selecting the solution that best satisfies the contingent requirement of the moment, for example by choosing the one with the lowest makespan in hectic contexts or the others that preserve tool useful life waste.

Future research may focus on extending the proposed approach to include more complex scheduling scenarios, such as considering the stochastic tool life and the uncertainty of processing times. Moreover, combining the proposed approach with other optimization techniques may lead to more advanced algorithms and better performance. Finally, applying the proposed approach to other manufacturing sectors and scenarios may provide further insights into the effectiveness and efficiency of the approach.

Chapter 4

Exploiting the full potential of I4.0 Technologies for Products EOL Recovery Process in the triple bottom-line of Sustainability

4.1 Introduction

The manufacturing sector's environmental impact is steadily growing, and ambient pressures related to waste and resource consumption are increasingly being examined as a result of sustainability concerns (Yusup et al. 2014, Kayikci 2018, Jamwal et al. 2021). Manufacturing still remains one of the world's largest sources of contamination, and manufacturers have been working hard to reduce their environmental impact (Khan et al. 2021). To help with this transition, factories may take advantages from the recent advancements of Industry 4.0 (I4.0). Under these conditions, I4.0 technologies offer interesting opportunities to address the challenges of sustainability at the factory and value chain level. I4.0 should also contribute to the environmental dimension of manufacturing sustainability by reducing waste in value creation activities and promoting cleaner energy and material resources (Machado et al. 2020). Regarding the social sustainability dimensions, Industry 4.0 is expected to improve working conditions and customer experience and create new job opportunities (Sartal et al. 2020). As a results, a connection between the three dimensions of sustainability and smart manufacturing emerged (Bai et al. 2020).

In the scientific literature there are several works that investigates this connection. The Triple Bottom Line (TBL) of sustainability represents the most widely accepted dimensions of sustainable manufacturing among industrial communities, consisting of three dimensions: Social, Environmental and Economic (Jamwal et al. 2021). Among them, Nicoletti Junior et al. (2018) proposed a conceptual model to associate sustainability and performance in a manufacturing system, taking into account all of the correlations between the TBL concept's dimensions. From the other side, Machado et al. (2020) refers to sustainable manufacturing as the integration of processes and systems that can produce high quality products and services using less and more sustainable resources (energy and materials), being safer for employees, customers and surrounding communities, and being able to mitigate environmental and social impacts throughout its life cycle. With the integration of sustainable processes and resources, different strands of Sustainable Smart Manufacturing has been developed, with applications in different areas, such as in the supply chain, innovative products and, among other, on the Product Life Management (PLM) (Manavalan & Jayakrishna 2019).

The potential of I4.0 technologies is apparent in various aspects of industrial operations, such as sustainability, smart products, End of Life (EoL) and remanufacturing.

Kamble et al. (2018) propose a sustainable I4.0 framework that includes three main components: I4.0 technologies, process integration and sustainable outcomes. The authors also suggest future research developments investigating the implementation of I4.0 technologies for better man-machine and machine-to-equipment integration through the use of sensors. Another important impact of these technologies is on the design of efficient supply chains, which through information gathered from products themselves, logistics and production operations and a seamless integration between the physical and digital worlds could further improve product's lifecycle permitting also a more effective and efficient product recovery at its End of Use (EoU) and/or End of Life (EoL).

Nowadays products are not exclusively composed of mechanical and electrical parts, they have become complex systems that combine hardware, sensors, data storage, microprocessors, software and connectivity capabilities Porter & Heppelmann (2014). Classifying smart products allows a clearer their definition and application. The Raff et al. (2020) archetypes are an example of the classification of smart products according to their features.

Kerin & Pham (2020) identify Remanufacturing as a key strategy for the full achievement of Circular Economy, which, in turn, represents an important research area for many companies worldwide and for our societies as a whole. This "smart remanufacturing" review focuses on the remanufacturing industry and the sustainable application of I4.0 enablers. The results are used to create a framework that links to the research agenda needed to fully achieve smart remanufacturing. Other authors have tried to define the types of intelligent recovery options. Alcayaga et al. (2019) detailed the characteristics that intelligent reuse, intelligent remanufacturing and intelligent recycling must have in relation to smart products.

In light of the above, there are a lack of articles dealing with these topics in the current literature. Few authors deal with smart products as aggregation systems of innovative technologies. Recovery options exploiting I4.0 tools are little studied in the literature.

According to these premises and within the outlined context, the first aim of this work is to propose the novel concept of "Product 4.0" (P4.0). This concept builds upon product archetypes and explores the augmented capabilities of an intelligent product in a I4.0 environment. In fact, we highlighted the aspect of the smart product with the use of I4.0 tools. Furthermore, this paper has the aim of investigating the possibilities that arise when recovering an intelligent product, at its EoU or EoL, in a I4.0 environment.

A further aspect of this work is to assess the impact that the introduction of such a Product 4.0 may have on society, specifically on the TBL of sustainability (in terms of advantages in environmental, economic and social aspect). To that end, a Causal Loop Diagram (CLD) model that relates sustainability aspects to increased product demand is here proposed and discussed in depth.

The remaining part of this paper is as follows. Section 4.2 presents the literature review of the I4.0 tools and the recovery options. After defining Product 4.0 in section 4.3, deals with the recovery options with respect to Product 4.0 in section 4.4. Section 4.5 deals with the proposed CLD and the implications of P4.0; the benefits of the model are discussed in Section 4.6; Finally, section 4.7 draws conclusions and future development.

4.2 Literature Review

In this section, the relevant literature is presented in two parts. The first part describes the I4.0 tools that can be used in smart products, and the second part will analyse aspects of the different recovery options.

A notable starting point when dealing with so called *Smart Products* and their possible classification is represented by the work carried out by Raff et al. (2020). The authors classify smart products according to 4 archetypes based on 16 criteria/characteristics of the products themselves. The proposed archetypes are classified as follows: *Digital Product, Connected Product, Responsive Product, Intelligent Product.*

The so called smart products are the most used technological products today. The capabilities of these products can be expanded by the integration of more advanced I4.0 tools and with the aspects of the different end-of-life recovery options.

4.2.1 Suitable Industry 4.0 Technologies

From a literature review, we identified those advanced technologies that could be included as additional features to the archetypes proposed by Raff et al. (2020) and briefly described above. In particular, we found out that the main tools are: Internet of Thing (IoT), Cloud Computing (CC), Big Data (BD), Digital Twin (DT), Machine Learning (ML) and Human-Machine Cooperation (HMC). The previous innovative tools and technologies were chosen because they are the most representative for an innovative product. Although the IoT technology was swiftly mentioned by Raff et al. (2020), any other of the above cited technologies was explicitly considered in the proposed archetypes.

In order to proper ascribe to the various archetypes the different I4.0

tools, we will start this discussion from their very definition. For the IoT, we adopt the same definition as Xu et al. (2014) who argues that virtual 'things' have virtual identities, physical attributes and virtual personalities.

The BD technology has been largely investigated in scientific literature and, among its different definitions, we consider that provided by Hashem et al. (2015) who argues that Big Data is a set of techniques and technologies that require new forms of integration to discover great hidden values from large datasets.

According to Mell & Grance (2011), CC can be defined as "a model for enabling ubiquitous, affordable, on-demand network access to a range of configured computing resources".

Bottani et al. (2017) define the DT as a simulation technology available for use in the real system, allowing the equipment's self-adaptive behaviour. The machine can simulate the different environment, establishing the best decision to make in a particular situation

ML is a subject that studies how to use computers to simulate human learning activities and to study methods of self-improvement of computers to obtain new knowledge and new skills, identify existing knowledge and continuously improve performance and results Wang et al. (2009). From a practical point of view, machine learning allows automatic data processing and can be considered an advanced analysis tool for intelligent production.

We decided to include also HMC as another important advanced technology that features an I4.0 environment. According to Pacaux-Lemoine et al. (2017), HMC is a technology that allows to incorporate more and more decision-making capabilities in both material (e.g. machines, products) and immaterial (e.g. production orders) elements, transforming them into efficient assistance systems to help human beings improve their performance.

Finally, Cyber Physical System (CPS) can be seen as systems of systems, which emerge through complex networking, integration of embedded systems, application systems and infrastructures, made possible by human-machine interaction Thoben et al. (2017).

4.2.2 EoL Recovery Options

Literature reports on several different EoL recovery options for a generic product. Morseletto (2020) grouped these options into ten recovery strategies, including Recovery, Recycle, Repurpose, Remanufacture, Refurbish, Repair, Reuse, Rethink, Reduce. Lee et al. (2001) considered only seven recovery options, while distinguishing for recycling between a primary and a secondary type. Sitcharangsie et al. (2019) in their review of key regeneration activities grouped the recovery options into Reconditioning, Dismantling/Disassembly, Refurbishment, Repair, Salvage, Incineration, Resale, Cannibalisation. In addition, the authors interestingly classified extant research papers, according to the level of decision, i.e., whether the recovery option is applied to the entire product or components. Desai & Mital (2003), while tackling the disassembly problem, identified five options for product recovery, in particular they assigned to each level of disassembly also which elements could be recovered from the product itself, i.e. product, module, part and material level.

For the purpose of this research, we decided to focus only on the main EoL options, i.e. reuse, remanufacturing, recycling, cannibalization and disposal. In accordance with the relevant literature, we adopted the following definitions for the recovery options mentioned above. Reuse is considered to be an operation whereby a few non-destructive improvements are made in order to bring the product back to its initial state. Remanufacturing, on the other hand, is a more complex operation where the product is disassembled and worn or broken components are replaced. Recycling is the operation where raw materials are recovered and a complete conversion is carried out. Disposal is the last possible operation, where nothing can be recovered from the product and it is therefore thrown away. Finally, cannibalisation is the operation that allows us to recover from a product only the components that are still functional and then reuse them on another product as replacement components.

4.3 Conceptualization of Product 4.0

In a I4.0 environment, we argue that the product, as a whole, along with its parts and components can "interact" with the various resources it encounters during its lifecycle. These interactions turn out to be greatly enhanced or augmented by the implementation of I4.0 technologies. Needless to say, that this enhancement strongly depends upon the embedded capabilities of the product and its parts and components.

As a consequence of the previous considerations and according to the tools of I4.0, we can extend the archetypes of product of Raff et al. (2020) in a I4.0 perspective (see Fig. 4.1). Based on the definitions previously given, we decided to suitably attribute the I4.0 tools among the different archetypes. In fact, the possibility to make different decisions in different situations makes DT a suitable element for the fourth archetype, i.e. Intelligent product. Depending on the definition of IoT and taking into account that most of current products are equipped with Radio Frequency Identification (RFID), sensors and communication technologies Ivanov et al. (2013), the archetype that could exploit at most this advanced technology is the second one, i.e., Connected product. By taking into account the considerations made about BD, we expect that Responsive product is the archetype that could have more advantages stemming from BD technology. It is worth noting here that, although the first archetype, i.e. the Digital product, already has data archiving capability, the BD technology has not been linked to it as the data involved in this case are not complex or various. Still according to the definitions given above, we can attribute the tools of CC in the third archetype and ML and HMC in the fourth archetype. Once defined, categorized and imputed to the appropriate archetype the various I4.0 tools in a separated way, it can be argued that all these technologies epitomize what literature defines as CPS. This object turns out to be the union of different technological systems, for this reason we decided to group all the I4.0 tools within the umbrella term of CPS.

Fig. 4.1, turns out to be an extension of the image originally proposed by Raff et al. (2020) to pictorially represent the various archetypes of products. We give a three-dimensional representation of the various archetypes by adding an axis, labelled as I4.0 Technologies, along which the innovative tools and technologies of I4.0 are shown in relation to the various archetypes. By jointly considering the capabilities of the fourth archetype proposed by Raff et al. (2020), i.e. the Intelligent product, along with the new ones available in the so called CPS while interacting in an I4.0 environment, we could introduce the new concept of *Products 4.0*.

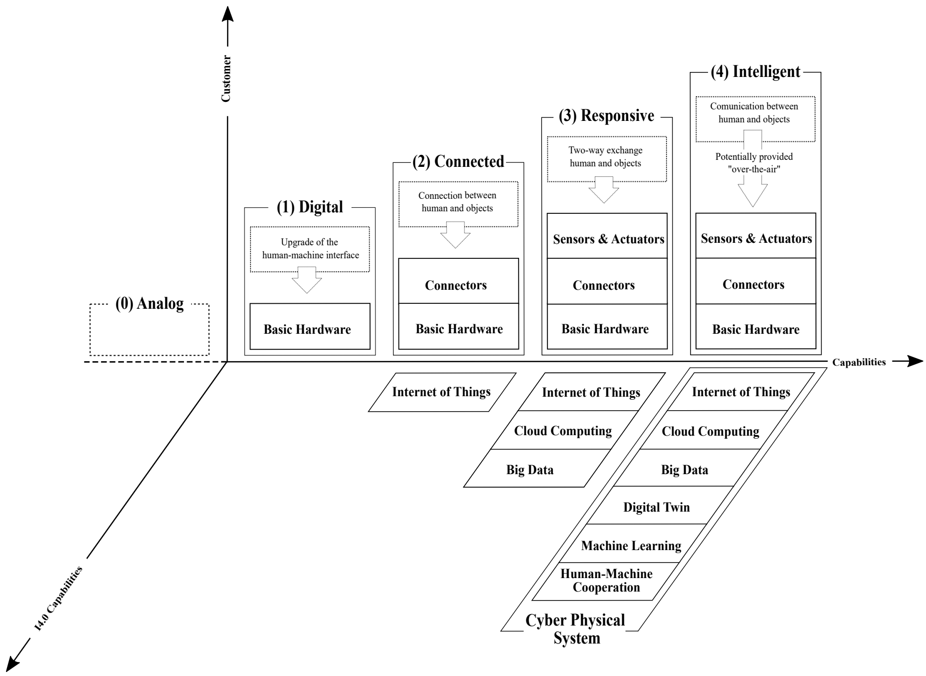

Figure 4.1. Extension of Raff et al. (2020) archetypes with I4.0 technologies

As a consequence of the previous definition, we can argue that the Product 4.0 concept involves not only the product itself but also the ecosystem where the product life cycle takes place. In fact, it includes *a smart product that can communicate with humans and objects as well, having basic hardware and intrinsic characteristics (sensors, actuators and connections) and implementing I4.0 technologies (IoT, CC, BD, DT, ML and HMC).*

The enhanced capabilities of Product 4.0 have the potential to deliver several benefits during the product lifecycle. It can also effectively support logistic and production activities and, in general, all the activities involved from product's conception to its EoU or EoL.

In this perspective, P4.0 may represent the hinge upon which circular economy models could rest. In fact, it would lead to a better investigation of product recovery options. In the next section we will investigate and discuss how a P4.0 prototype could be recovered at the end of its life cycle.

4.4 Enhanced Recovery Capabilities of P4.0

In this section we will show and discuss how the Product 4.0 archetype may heavily revolutionize and streamline the recovery process of a generic product at its end of life. In fact, many factors still prevent the remanufacturing business from reaching its full development Vogt Duberg et al. (2020) and one of these factors is the cumbersome inspection activity required to diagnose the product's health status also identified as product's *quality* in remanufacturing jargon Ridley et al. (2019).

Traditionally, recovery operations start when the collected product returns to the factory Gaspari et al. (2017), King et al. (2007), Ma et al. (2011).

In order to optimise the recovery of the product, it must necessarily pass through several stages to analyse and investigate its possible problems. These steps are typically: Inspection, Cleaning, Analysis and Verification. Most of these activities are time-consuming for the company involved in the recovery operation.

This recovery process takes place if it is not possible to exploit the product's capabilities inherent to I4.0 technologies. Fig. 4.2 shows a possible flow chart for product's collection that fully take advantage of I4.0 technologies. Under a P4.0 scenario the use of I4.0 tools and technologies allow us, in general, to reduce and/or greatly simplify many steps of the recovery process if compared to that of "traditional" products. With the capabilities inherent to P4.0, a smart product that interact with a smart environment, we can take advantage of available technologies to collect detailed information about product's health even before it returns to the factory for recovery purposes.

In general, it is possible to gather and exploit two types of data. A first set of information is that pertaining the various products belonging to the installed base and sent by products themselves to a cloud platform. This data usually refer to the average behaviour of the products of the installed base. A second set of information is the product-specific data collected once the product enters the factory and, therefore, it is able to communicate with the Industry 4.0 system. Thanks to the combined use of these data sets, the diagnostic phase of the recovery process is noticeably simplified and sped up, in fact there is no need to carry out the various levels of inspection and problem analysis as we already know in advance the health and usage status of the product, which can then go straight to the cleaning stage.

As a consequence, Inspection and Analysis phases may not appear in the flowchart of the recovery process. In order to identify the more appropriate recovery option for the specific product, it is possible to make use of product's status and use data. Depending on product's "health state" and "use" parameters, the different recovery options can be properly chosen. Once defined the product category, it is crucial to identify the "use" parameters and "health state" to better address recovery operations. Specifically, in the case of intensive use of the product and a good health state, it would be viable to first cannibalize the still valuable components, then materials recovery from parts and components, and, finally, the disposal of remaining parts. If the "use" parameters and "health state" are appropriate, product could undergo the reuse option provided that minor repairs and replacements are carried out. If, despite the low values of "use" parameters, the "health state" is not adequate, the product could conveniently undergo the remanufacturing process where it is disassembled at component level, and relevant parts of the product are replaced.

It is worth noting that, because of the augmented capabilities of P4.0, it could perform by itself the verification phase that conclude the reman-

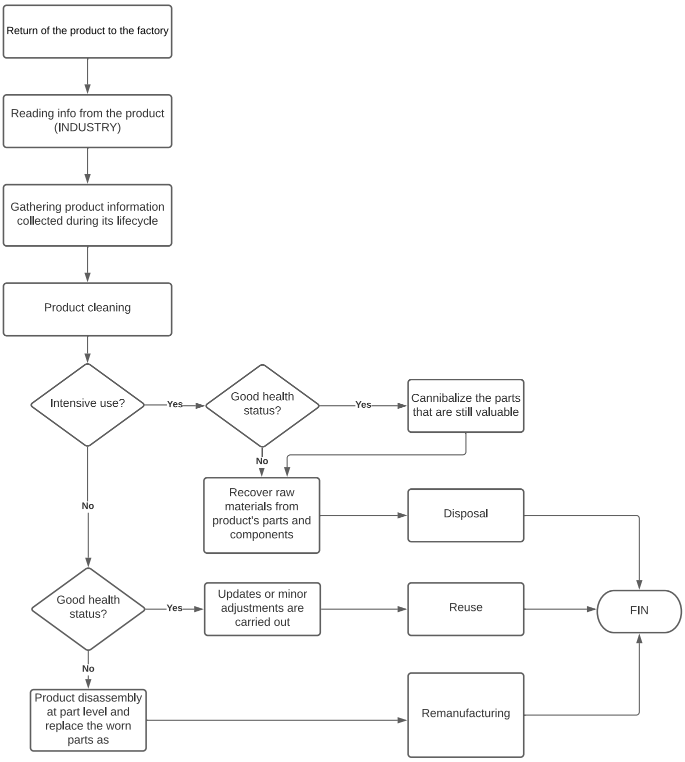

Figure 4.2. Example of a flowchart diagram of a recovery process exploiting I4.0 technologies

ufacturing process.

In order to show the potential of P4.0 in terms of its recovery process, we provide the readers with a simple but effective example. We considered here the case of a consumer electronics product, that is, a multi-function laser jet printer. This kind of products are usually capable of and actually share many information on product use and product performance with Original Equipment Manufacturer (OEM) on the basis of sharing agreements. These agreements are usually framed within a win-win Product Service System logic and are mainly intended to gather information on the installed base in order to deliver more customer value during the product use and, at the same time, to allow the OEM to sell secondary products and ancillary services. In our use case, both the aggregated information about the installed base and the product-specific data may be used to support a more efficient and environmental friendly recovery process.

In fact, some data related to product's operation (e.g., number of printed pages, number of scans on the glass) as well as data coming from product's event log (e.g., document feeder jam, paper jam, supplies status, double feed error) could be put into relation with the general health state of the product and its main modules, parts and components in a cause-effect logic. It is worth noting that, in general, this type of products is made of two types of modules, parts and components: the first type, such as toner cartridges, drums and fuser, are to be classified as "consumables" as they are purchased recurrently during product's lifecycle as part of its regular maintenance. Another type of parts, such as scan unit, transfer module, sheet feeder, edge guides, electric motors and gears, imaging unit are those more likely to be recovered from discarded products provided that a reliable assessment on their status can be performed.

For example, a malfunctioning of the printer's transfer module may be signalled by an abnormal consumption of electrical power of its motors, that can be obtained by minor product's design changes as well as cheap additional sensors to collect those data. While the data related to the "use" parameters (i.e., the number of printed pages, number of scans on the glass) could be already exchanged via a cloud platform during product's life-cycle, when the printer returns to the factory to be recovered, it is also able to exchange stored data of its components with its environment. By jointly exploiting the data related to "use" parameters and those stored in the printer, it is possible to assess the health state of its components in a more reliable manner, thus better supporting the identification of the more appropriate recovery options.

4.5 The Implication of Product 4.0 on Sustainability

In order to assess the impact that the introduction of the Product 4.0 may have on the triple bottom-line of Sustainability, a Causal Loop Diagram, which features the main relationships between the system parameters, has been exploited. The choice of the CLD is not casual as it represents a diagram that aids in visualizing how different variables in a system are causally interrelated and here used to present a clearer view of the underlying mechanisms and their impact of the Product 4.0 on the different aspects of sustainability (Zamagni 2012). To this end, we started from the work by Onat et al. (2016) in which the authors tried a similar approach for identifying the impact of the electric vehicles on the triple bottom-line of sustainability. The authors, in fact, identified the keywords of the three aspects of sustainability and created relationships among them. Having applied this methodology to them in the case of electric cars, which differ from traditional cars, they exploited their CLD in another field of application. In this regard, our work starts from the considerations made by Onat et al. (2016) and, exploiting the keywords and relationships they identified, to assess the impact of the Product 4.0 compared to a normal product.

The proposed CLD is presented in Fig. 4.3 and includes the main submodels and the causal relationships between each variable or submodel. It should be stressed that the CLD is an overview of the observed system where complex relationships are explained in a simplified form. As known, a typical CLD consists of loops that can be reinforcing (an increasing impact of a cause on an effect is an increase) or balancing (an increasing impact of a cause on an effect is a decrease), while the causal link is represented by arrows and has a polarity that can be, respectively, positive (+) or negative (-) (Inghels 2020).

In the proposed model, 6 Balancing loops and 3 Reinforcing loops have been identified. The reinforcement and balancing loops are briefly ex-

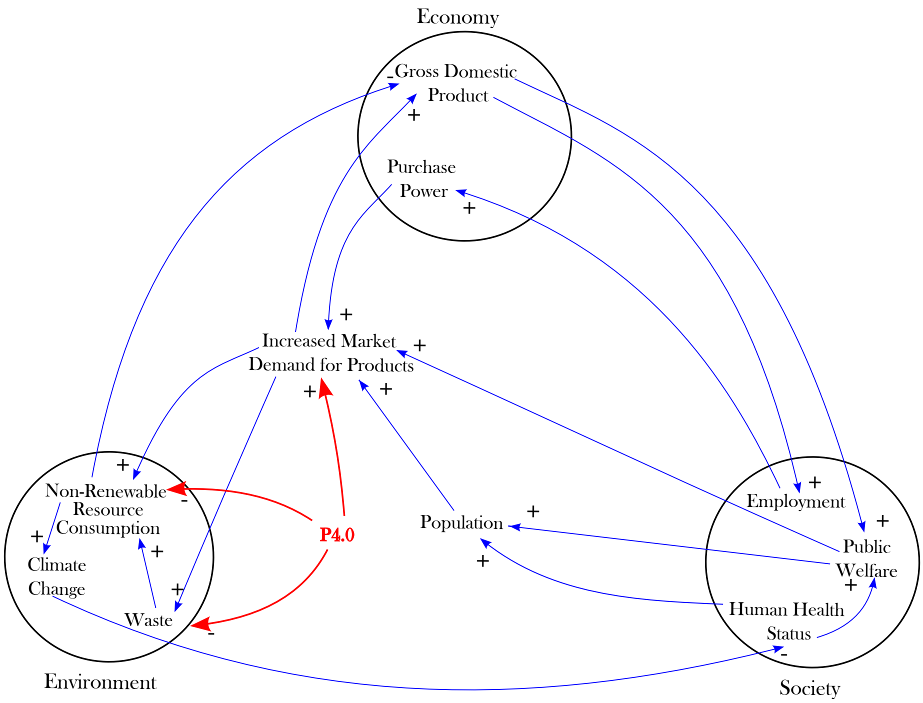

Figure 4.3. The Proposed Causal Loop Diagram with the Product 4.0

plained as follows:

Balancing loop 1, 2, 3

(1) Increased Market Demand of Product – Waste – Non-Renewable Resource Consumption – Climate Change – Human Health Status – Population – Increased Market Demand of Product

(2) Increased Market Demand of Product – Waste – Non-Renewable Resource Consumption – Climate Change – Human Health Status – Public Welfare - Increased Market Demand of Product

(3) Increased Market Demand of Product – Waste – Non-Renewable Resource Consumption – Climate Change – Human Health Status – Public Welfare – Population – Increased Market Demand of Product

The demand for new products on the market leads to climate-related disadvantages. The increase in the demand for new products creates a high level of consumer interest, but this increases waste. Very often products that are still in good condition are thrown away. This creates a balancing loop that affects the consumption of non-renewable resources for the creation of new products. Climate change suffers great damage from the consumption of these resources, and this also leads to human health impacts, which affects the population through life expectancy. Climate change degrades public wellness which in turn affects sales of new products; in fact a population that has a good level of wellness is more inclined to buy new products. A low level of human health status negatively affects public welfare, which can lead to a decrease in birth rate and therefore to a reduced sale of products.

Balancing loop 4, 5, 6

(4) Increased Market Demand of Product –No-Renewable Resource Consumption – Gross Domestic Product (GDP) – Public Welfare – Increased Market Demand of Product

(5) Increased Market Demand of Product –No-Renewable Resource Consumption – Gross Domestic Product (GDP) – Public Welfare – Population – Increased Market Demand of Product

(6) Increased Market Demand of Product –No-Renewable Resource Consumption – Gross Domestic Product (GDP) – Employment – Purchase Power – Increased Market Demand of Product

As the demand for new products increases, the consumption of non-renewable resources damages the economy by reducing the growth rate of GDP. This loss can lead to two different consequences, i.e. there could be a reduction in public welfare through a change in income that would cause a decrease in population, or there could be a loss of jobs that would decrease the purchasing power of individuals. In balancing loop 5, any change in public welfare affects population through birth rates. This impact can be either reinforcing or balancing depending on income level.

Reinforcing loop 1, 2, 3

(1) Increased Market Demand of Product – GDP – Public Welfare – Increased Market Demand of Product

(2) Increased Market Demand of Product – GDP – Public Welfare – Population – Increased Market Demand of Product

(3) Increased Market Demand of Product – GDP – Employment – Purchase Power – Increased Market Demand of Product

With the increase of demand for products and the consecutive sale of those products, aggregate expenditures also increase. Increased consumption accelerates economic growth through the contribution of industries associated with the production and operation of products. This growth has a reinforcing effect. In fact, as productive activities increase there is an increase in employment by workers which increases the purchasing power of individuals. To this there is an increase in public welfare through individual income and thus an increase in population. Both public welfare and employment change people's demand for new products.

It is worth highlighting that the previous CLD represents the cause effect relations for a generic product. In fact we want to analyze how the increase in market demand for products influences and can be influenced by the three aspects of sustainability. Once identified the relationships for a generic product, this work aims to evaluate if and how these relationships are modified by the presence of new generation products, i.e. Product 4.0, with enhanced inherent capabilities. Let us consider the previous CLD with the addition of cutting-edge technologies: in fact, as we know from the literature, smart products are becoming increasingly common in the market, and their demand is growing by the day. This could result to an increase of the demand for these products, which could be reflected in the proposed CLD, affecting the proposed balance loops on the three aspects of sustainability. In fact, Product 4.0 having the technologies and capabilities would have a positive impact on the various aspects of sustainability (economic, environmental and social benefits) that has to be investigated. With sensors and data analysis capabilities that the Product 4.0 can do throughout its useful life, it may helps us to analyze the product's health status while extending its useful life. The P4.0, in fact, has the potential to monitor and keep track of its components and, then, to know if they need repair, if they could be recycled or if they must be sent to landfill. This would greatly reduce technological waste that impacts climate change. With the use of P4.0 we could go to recover even just the raw materials of which it is composed, this leads us to have a reduction in the consumption of non-renewable resources that impact on GDP. Having less waste and less consumption of resources brings advantages both for the environment and the economy of the country. If there is less climate change and GDP growth, public welfare increases, as people have better health and more employment that allows them to have greater purchasing power and therefore also increases the demand for new innovative products.

4.6 Discussion of CLD

Research shows that sustainability is a multifaceted problem. As already analysed, sustainability can be investigated on three main perspectives: social, economic and environmental. As clearly stated in literature and consistently represented in Fig 4.3, all the facets of sustainability are strongly interacting either directly, by means of a direct link, or indirectly by means of the identified loops. This latter type of interactions is the more difficult to detect, but also the more important to investigate as they may lead to unexpected dynamics of the system under consideration.

The complex interplay among the various variables involved in the sustainability concept suggested us to analyse the problem under a systemic perspective, hence, it was decided to use a very effective graphical tool that is essential for any System Dynamics analysis, that is, Causal Loop Diagrams (Swanson 2002). In fact, the systemic analysis stemming from the CLD of Fig 4.3 permits us to draw the readers' attention on some crucial aspects which are worth being discussed.

1. All the variables involved in one of the sustainability dimensions can be interacting among each other and, more importantly, can influence and be influenced by variables under the other dimensions. This is the case, as an instance, of the environmental dimension that has 'Non-Renewable Resource Consumption', 'Climate Change' and 'Waste' as its relevant variables. These variables clearly interfere but have also not negligible impact on the economic dimension as well as on the social dimension.

2. The presence of mutual influence among the various variables featuring the sustainability aspects, allows us to identify several loops which regulates the dynamics of the system as a whole. Unfortunately, the final effect of these loops, without considering the effect of new technologies like the analysed Product 4.0, is to: *i*) limit the economic growth of our societies on the long period due to existing balancing loops; *ii*) deteriorate the social dimension of sustainability as a consequence of worst human health conditions, a diminishing employment rate and cost cut on public welfare policies; and *iii*) produce irreversible damages to the natural environment mainly ascribable to unrestrained waste generation and non-renewable resource consumption.

3. The introduction of P4.0 in the proposed CLD is to be intended as a sort of external variable which can be leveraged by the analyst while performing scenario analysis. Hence, we assume that P4.0 can influence the dynamics of the system but not the other way around. In this perspective, a future simulation model may be of help in developing what-if analysis in which the P4.0 variable can be used to play different roles depending on the context. For example, the variable P4.0 could be intended the amount of effort companies put into redesign existing product families or designing new ones from scratch.

In a similar fashion, the variable P4.0 could be used to represent the economic incentive private companies or public institutions may give to potential buyers on the market to purchase new generation products. P4.0, thanks to its positive effects on the three dimensions of sustainability, may completely alter the dynamics of the system towards more positive outcomes. In fact, P4.0, while permitting a more environmental conscious life-cycle management, it does influence sustainability also on the social and economic perspective. Beyond the expected result of stimulating demand for new products, it can also have an indirect effect by creating brand-new opportunities on the job market related to new skills and professional figures. Moreover, it can have a positive social impact by providing less affluent people with access to new products and technologies, as in the case of consumer electronics, through secondhand or secondary market options as well as charitable organizations.

4.7 Conclusion

The first goal of this paper was to combine advanced industrial technologies with the product archetypes identified by Raff et al. (2020) in order to propose the new concept of Product 4.0. To this aim, the tools with the highest potential for implementation in smart products have been analysed. This analysis identified as the main tools IoT, CC, BD, DT, ML and HMC. The concept of Product 4.0 stems from the combination of the I4.0 technologies with the fourth archetype proposed by Raff et al. (2020).

A second goal of this paper was to conduct an exploratory analysis of product recovery scenarios in presence of a Product 4.0 prototype. In particular, the most common product recovery options were presented. We highlighted the potential advantages of recovering P4.0s in comparison with those products not exploiting I4.0 technologies. An explanatory case dealing with laser jet printer allow us to exemplify these benefits.

Finally, a graphical representation of the relationships that exist between sustainability aspects and increased product demand has been proposed with the use of CLD technique. Aspects such as the importance of waste and consumption of non-renewable resources for the environmental aspect, GDP for the economic, and public welfare for the social aspect has been analysed. Within the proposed model, these elements are at the centre of several hubs and we showed, how the demand for products is a variable strongly influenced by the TBL of sustainability.

Following that, an innovative element that resulted in a variety of different balances has been added and discussed: the Product 4.0. In fact, the addition of P4.0 may leads to a changes into the proposed relationships that it may be useful to quantify. To this end, it should be noted that, as such an innovative element as P4.0, with its inherent technological aspects can bring about strong improvements, especially in the reduction of waste and consumption of non-renewable resources. Reducing these aspects leads to a double advantage, an increase in the welfare of the population and an increase in global GDP. This benefit of allowing people to stay healthy and have jobs translates into a further increase in demand for products, probably innovative products.

Future development of this research could focus on the other phases of Product Lifecycle Management, such as Beginning of Life (BoL) and Middle of Life (MoL). With reference to the BoL, the main aspects of product design, creation and verification could be analyzed. In fact, Product 4.0, in order to deliver specified functionalities and to suitably interact with its environment, has to be designed with proper hardware and software features. A further aspect to investigate would be that of properly addressing the design process in order to widen as much as possible the recovery options to which Product 4.0 could undergo at its end of life.

Chapter 5

Conclusions

The technological advancement of the fourth Industrial Revolution (I4.0) is bringing major changes to manufacturing and service industries through the integration of advanced technologies, including Internet of Things (IoT), Digital Twin (DT) and Cyber Physical Systems (CPSs). The potential of I4.0 technologies is evident in various aspects of industrial operations, involving all the facets of sustainability, with a special focus on the role of maintenance, wear and tear and end-of-life product recovery.

The possibility of leveraging Industry 4.0 technologies in different areas of production allows us to make better use of resources. For example, IoT-enabled predictive maintenance can significantly improve the efficiency of maintenance and repair programs, reducing downtime and extending equipment life-cycle. Furthermore, the integration of DT and CPS can enable more effective end-of-life product recovery systems, providing guidance on the most valuable components to be recovered and/or recycled. As an instance, IoT sensors can be used to monitor the condition of products and their components (even in real time), anticipating component failures or product malfunctioning and, therefore, permitting a better product's life cycle management as well as, for example, reducing the need for inventory.

All the above considerations led us to the analysis of 4.0 tools' capabilities, particularly in the area of maintenance. In fact, recognizing a machine's maintenance need before its imminent failure can assist in preventing further damages to the machine and,as a consequence, in avoiding to repair more substantial parts of the product. Additionally, it may be helpful to eliminate or shorten the waiting period while the damaged portion is being repaired.

In fact, the situation of a flow shop production system with N parallel machines was analysed in Chapter 2, where a production system consisting of non-identical, failure-prone machines was considered. It was assumed that the time to process a single job, the time to carry out a corrective or preventive maintenance task, and setup times were deterministic. Machines were supposed to fail randomly according to a Weibull distribution. Hence, the time to process a given job-maintenance sequence on a certain machine was random. We considered the problem of finding the job-planned maintenance sequence that minimizes the expected makespan or the expected earliness tardiness penalties, evaluated taking into account the expected value of job-maintenance sequence processing times on each machine. With this objective, a model was developed for multi-machine problems for planning preventive maintenance taking into account a stochastic environment. To address this problem, we proposed two new meta-heuristic algorithms obtained by modifying a standard Genetic Algorithm (GA) and Harmony Search (HS).

In this research we solved two minimisation problems separately: (i) the minimisation of makespan; (ii) the minimisation of the ETP. Considering the practical relevance of the problem and its complexity, we developed and tested two meta-heuristic algorithms for solving the FSSP in a reasonable time, finding practicable and fulfilling schedules in industrial applications. Specifically, we modified two widespread meta-heuristics: GA and HS. To evaluate the performance of the proposed algorithms, we performed a series of computational experiments. For small problems, we compared the two heuristics with an exhaustive search method, which can find the optimal solution. The computational results showed the time benefits of using these heuristics. Moreover, to make a comparison between the proposed meta-heuristic algorithms, we considered scenarios with different scheduling complexities and instance sizes. The obtained results showed that, as the size of the problem increases, GA tends to perform better than HS (Branda et al. 2021).

After having planned maintenance activities of machines as if they were jobs to be scheduled, the thesis work focused on a further aspect of operation planning. Once extended the useful life of the machines by appropriately planning their operations, we decided to adopt the same logic to their components, particularly to those equipment and tools that are worn out due to continuous use. In the literature, few researches addressed the problem of tool wearing, nevertheless it is essential to analyse this aspect, especially when the tools are expensive. The aim was to try to extend tool life by determining the sequence of jobs to optimise tool useful life. Better use of tools means determining a sequence of jobs having fewer tools consumed almost completely (90% of tool life), rather than many tools consumed partially.

In Chapter 3, we proposed an approach which took into account the age of the tool and the duration of its operation to adjust the extension rate. The problem addressed by this approach was the modelling and allocation of a set of jobs with specific machining times and tooling requirements on a set of identical parallel machines. Decisions to be made included the allocation of jobs to machines and the allocation of tools on each machine. The purpose of the proposed algorithm was to identify the best possible sequencing of jobs allocated to different machines in order to maximise the utilisation of the tools' useful life, while avoiding having tools that remain with a residual useful life that cannot be used for the next operation and at the same time avoiding excessively increasing the overall makespan of the scheduled production plan.

This is a typical multi-objective optimisation problem, which seeks to minimise the wasted useful life of the tools (by shifting production to a single machine that can sequence operations efficiently) and minimise the overall production time of the batch (by temporally balancing the jobs on all available parallel machines, without having to discard tools that could still be partially used). To evaluate the effectiveness of the proposed approach, we conducted a series of experiments on a real-world dataset. The results of these experiments showed that our approach outperforms existing methods in terms of tool utilisation and waste reduction. Furthermore, our approach was able to adapt to changes in demand and production requirements, making it highly flexible and scalable. In conclusion, the paper aimed to find an optimal solution to the Identical Parallel Machines Problem with Tooling Constraints through the use of a genetic algorithm. The algorithm aimed to minimize the two target variables which measure the balancing of machines and the effectiveness of tool utilization respectively. As said, this was a multi-objective optimization problem where the trade-off between the two objectives will be analyzed through the Pareto front, a set of optimal solutions that are non-dominated and offer a better balance between the two objectives.

Both in the case of machine maintenance and tool wear, 'solutions' to prolong product's useful life were evaluated. Preventive methods were proposed to avoid or rather delay the end-of-life phase. However, sooner or later, the product will approach its end of life which requires to implement possible recovery options.

In fact, after having analysed two examples of useful life extension, the thesis also aimed to explore the concept of a smart product, which, by exploiting Industry 4.0 technologies, can gather information during the use stage of its life cycle and, therefore, enhance recovery options (Chapter 4). The research then focused on the development of a 'Product 4.0' model, which combines the concept of a smart product with typical I4.0 tools. This type of product can implement a monitoring system to optimise the product's recovery options. In fact, during the various phases of the product life cycle, the information gathered could be exploited to understand the product's 'health' status in real time. This information, both at the end-of-life and during operational phases, will be used to extend the product's useful life and to improve its end-of-life recovery process.

The implementation of Product 4.0 brings about a significant shift in the way products are managed at the end of their life. The traditional recovery systems were found to be inefficient and often result in the waste of valuable resources. This is why the study aimed to explore the impact of the new technologies on the end-of-life recovery phases and to propose a new and improved solution. The proposed flowchart took into account the health status and level of use of the product to determine the best recovery option. The health status was evaluated by examining the individual components of the product and determining their functionality. The level of use was analyzed to determine the extent to which the product has been utilized and its overall wear and tear.

The new technologies integrated in Product 4.0 allowed us for the efficient and accurate analysis of these parameters, leading to a more informed decision on the type of recovery that should be pursued. This ensures that the product is handled in a way that is sustainable and maximizes the recovery of valuable resources. Whether the product is to be recovered, recycled, reused or discarded, the new flowchart helps to ensure that the right decision is made. Overall, the work highlights the importance of implementing new technologies in product management and the positive impact they can have on the environment and the efficient use of resources.

Finally, a further objective of this work was to assess the impact of Product 4.0 on sustainability, using the Triple Bottom Line (TBL) concept. To this end, we decided to use a Causal Loop Diagram (CLD) as an analysis method. The CLD provides a visual representation of the interconnections between system variables and their impact on different aspects of sustainability, allowing a clearer understanding of the mechanisms involved in the introduction of smart products. The analysis focused on the impact of technology products on the three main aspects of sustainability, namely the economic, social and environmental dimensions. The CLD helped us to demonstrate the relationship between the different variables, such as increased efficiency, reduced waste and improved sustainability, and their overall impact on TBL. In conclusion, after the CLD analysis, it was shown how the inclusion of P4.0 within the sustainability stream can benefit waste reduction, reduction of non-consumable resources while increasing market demand for new products. The study thus provided a comprehensive examination of the sustainability impact of technology products, highlighting the importance of considering all three dimensions of sustainability in the development and implementation of new products.

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