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Master Degree Thesis

A general cost model to assess the implementation of collaborative robots in an assembly line.

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Abstract

In the realm of assembly processes, collaborative robots (cobots) are recognized as valuable assets for enhancing production performance, encompassing assembly time, product quality, and worker satisfaction. Nonetheless, there's a noticeable absence of models that effectively assess cobot integration and assist decision-makers in selecting the most economically efficient assembly setup. This study aims to bridge this gap by proposing an innovative cost evaluation model, facilitating a practical comparison among various assembly configurations to aid in choosing the most optimal one. The proposed model accounts for diverse cost dimensions such as manufacturing, setup, prospective, retrospective, product quality, and worker well-being. Furthermore, it incorporates the influence of learning effects on assembly time and quality, which is particularly pertinent in scenarios of low-volume and mass-customized productions. Alongside the model description, the study presents three real-world manufacturing case studies.

Furthermore, this thesis conducts an in-depth examination of an industrial assembly line, scrutinizing its throughput across different production setups. Contrary to conventional wisdom, the analysis suggests that the conventional average production batch size might not always yield the most efficient balance between production costs and line throughput. The throughput analysis underscores the necessity of considering specific production attributes and assembly strategies to optimize operational efficiency and profitability

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Chapter 1

Introduction

Significant advancements in robotics have revolutionized manufacturing processes, enabling the substitution of human labor with automated systems across various industries. In the past, manufacturing managers often aimed to establish automated factories, where automated equipment would execute all production operations under human supervision. This approach yielded favorable outcomes in contexts focused on high-volume production of standardized goods. The investment in automated production lines translated into lower production costs and increased capacity, making it economically viable over time.
Cobots have demonstrated exceptional performance in assisting humans with assembly tasks, executing precisely repeatable and monotonous activities such as bolting, nut driving, and part fitting. This collaboration reduces the physical and mental strain on operators while improving productivity and quality outcomes. Despite their benefits, the widespread adoption of cobots in manufacturing processes with high collaboration potential remains constrained by technological immaturity and a lack of supportive design tools.

While collaborative robots offer significant advantages, their use in manufacturing processes with high collaboration potential remains limited due to technological immaturity and a lack of supportive design tools. Assembly processes, in particular, could benefit greatly from collaborative robotics, but their adoption is hindered by these factors. Manufacturers often struggle with deciding which assembly configuration to adopt, yet there are insufficient tools available to guide decision-makers towards efficient choices. To address this gap, this study aims to answer two research questions:

- When is it cost-effective to introduce a cobot in an assembly process?
- What are the main components of assembly costs that decision-makers need to consider?

To address these questions, this thesis presents a cost model that captures the key factors influencing the selection of the most cost-effective assembly configuration for an assembly line.

The subsequent sections of this thesis are structured as follows: The first chapter provides an overview of the conceptual background in the industrial sector, emphasizing its significance for Europe's economy, with a focus on innovation and efficiency. It introduces Industry 5.0 as an evolution of Industry 4.0, placing greater emphasis on sustainability and worker well-being. The integration of collaborative robots (cobots) into manufacturing processes is highlighted as a key trend, enhancing productivity across various tasks. Industry 4.0 is characterized by principles such as interconnectivity, decentralized decision-making, and smart technology, driving the transformation of traditional industries into more efficient and flexible systems. Cobots facilitate human-robot collaboration, offering advantages like ease of programming and cost-effectiveness. The market for collaborative robots is expected to expand significantly due to increasing labor costs and the demand for higher efficiency, although efforts are needed to make cobots more accessible to smaller enterprises.

The second chapter describes the proposed cost model. The general cost model considers various components, including retrospective costs linked to operational disruptions and unused inventory, and costs related to product quality, such as inspections and detection errors. Automation of production systems can reduce inspection errors but not eliminate them completely. The research conducted in this thesis proposes a general cost model aimed at assessing the implementation of cobots within assembly lines. By examining various cost components, including but not limited to manufacturing costs, setup costs, and the costs associated with product quality and worker wellbeing, this study endeavors to provide a comprehensive evaluation framework.

The thrid chapter offers recommendations for production throughput analysis. Theoretical computation involves analyzing throughput across multiple assembly stations, focusing on meeting demand while optimizing efficiency. It considers factors like batch size and annual production volume. Utilizing FlexSim software, simulation models are developed for assembly stations. The case study illustrates how different assembly configurations affect efficiency and cost-effectiveness. Utilization rates and queue dynamics between stations are analyzed, highlighting the need for synchronization to minimize idle time. The comparison between maximum and required throughput reveals potential mismatches between production capacity and market demand, prompting adjustments to optimize operations and meet customer needs effectively. This underscores the importance of balancing cost optimization with fulfilling demand for sustainability and competitiveness.

In the last chapter, the Stellantis case is analyzed where the mathematical model developed in chapter two for multiple stations is implemented on two real cases of production plants.

Finally, the concluding section summarizes the contributions, limitations, and potential avenues for future research.

Chapter 2

Conceptual framework

2.1 Industry 4.0

The industrial sector stands as a pivotal economic and social cornerstone in any region, and Europe is no exception. Industry not only contributes to the region's revenue and future prospects but also promote stability and economic growth. To enhance global competitiveness, regions must fight for elevated levels of industrial efficiency and innovation. While the European Union is in the process of transitioning to Industry 5.0, the current emphasis remains on Industry 4.0. Industry 5.0 builds upon Industry 4.0, placing a significant stress on research and innovation as catalysts for a shift toward a sustainable, human-centric, and resilient European industry [1]. This innovative industry prioritizes worker well-being, utilizing advanced technologies to promote prosperity beyond mere job creation and economic growth, while also respecting the Earth's production constraints.

The unique aspect of Industry 5.0 lies in its focus on the worker's centrality in the production process, utilizing cutting-edge technologies inherited from Industry 4.0 but with a distinctive orientation. Rather than concentrating on specific technologies or tools, Industry 5.0 can be interpreted as an approach, highlighting the need to research into the concepts and technologies integral to Industry 4.0.

Understanding the concepts and technologies that constitute Industry 4.0 is thus more compelling. Historically, technological advancements and discoveries have given rise to various "industrial revolutions" that have fundamentally transformed existing paradigms [7]. The First Industrial Revolution introduced steam power and mechanization, reducing production times and increasing human productivity. The Second Industrial Revolution harnessed electric energy and assembly line production, leading to even greater efficiency and reduced production times. The 3rd Industrial Revolution emerged with the widespread digitalization, computers, and the use of robots. Following these, the 4-th Industrial Revolution, often referred to as ”Industry 4.0,” began in Germany in 2011, characterized by the application of information and communication technology in industry. The ”4.0” terminology alludes to software versioning, digitization, and the "smart" concept [7].

Defining Industry 4.0 is challenging, so it’s more helpful to outline its key principles [3]:

- **Smart Technology:** Involves the use of sensors, actors, and autonomous systems in factories, integrating technologies like the Internet of Things (IoT) and artificial intelligence to create "smart factories."

- **Cyber-physical Systems:** This principle represents the convergence of the physical and digital worlds, where physical objects are digitally recorded, and the real conditions of a system are determined by digital process parameters.

- **Self-organization:** Industry structures are shifting towards decentralized systems, promoting individualization, increased autonomy in activities, and the breakdown of traditional hierarchies.

- **New distribution and procurement systems:** These systems are becoming more personalized and individualized, aligning with the trend towards customization and tailored approaches.

- **New product and service development systems:** Adaptation to innovation is vital to stay competitive, pushing for more flexible and responsive product and service development.

- **Adaptation to human needs:** Industry 4.0 aims to place humans at the center of processes, satisfying their needs and enhancing collaboration with technology rather than replacing human operators.

- **Corporate Social Responsibility:** Emphasizes resource efficiency and sustainability to ensure resources are safeguarded for future generations, contributing to ethical and sustainable practices within industries.

These principles collectively represent the ethos of Industry 4.0, guiding the integration of advanced technologies and methodologies within the industrial landscape to enhance productivity, efficiency, and sustainability. Industry 4.0, also known as the Fourth Industrial Revolution, is characterized by several key principles and concepts that define its approach to modernizing and enhancing industrial processes. These principles include [3]:

- **Inter connectivity:** Devices, machines, and systems are interconnected and communicate with each other in real-time. This allows for seamless data sharing and collaboration between different components of the production process

- **Information transparency:** : All relevant information is made visible and accessible to decision-makers. This transparency enables better decision-making and optimization of processes.

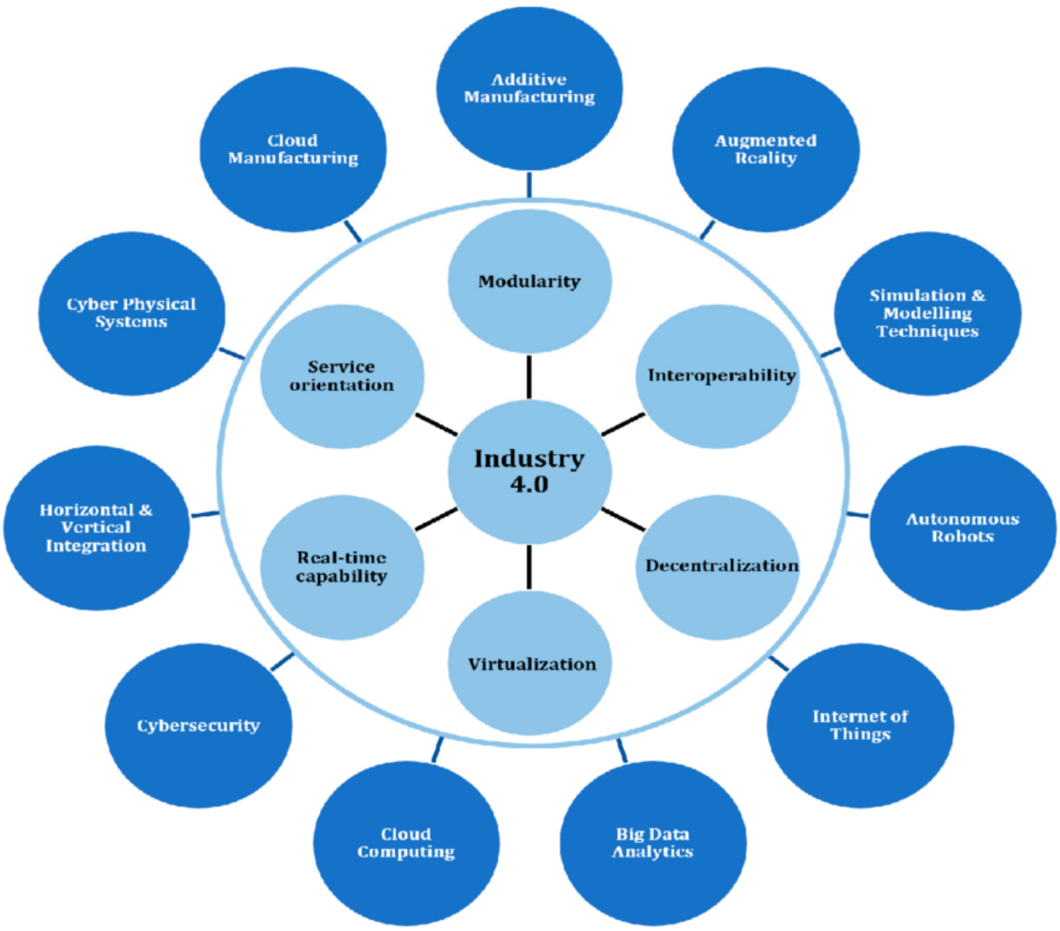


Figure 2.1. Industry 4.0 technology trends and design principles

- **Decentralized Decision-Making:** Industry 4.0 promotes decentralized decision-making, where intelligent systems and devices can make decisions autonomously. This reduces the need for central control and allows for quicker responses to changing conditions.

- **Technical Assistance:** Human workers are assisted by smart systems and technologies, which can offer guidance, suggestions, and alerts. This enhances the capabilities of human workers and improves overall productivity.

- **Smart Products and Services:** Products are designed with embedded sensors and connectivity, making them "smart." These products can collect data and provide valuable insights throughout their life cycle, leading to better customer experiences and service.

- **Digital Twins:** Digital replicas of physical systems, products, or processes are created. These digital twins allow for real-time monitoring, simulation, and analysis, enabling better control and optimization.

- **Cyber-Physical Systems (CPS):** These systems bridge the gap between the physical and digital worlds. They integrate physical components (e.g., machinery) with digital technologies (e.g., sensors and software) to improve performance and efficiency.

- **Big Data and Analytics:** Large amounts of data are collected from various sources, and advanced analytics and machine learning are used to extract meaningful insights, identify trends, and predict future events.

- **Additive Manufacturing (3D Printing):** 3D printing and additive manufacturing technologies are used to create customized and complex components, reducing waste and increasing flexibility in production.

- **Cloud Computing:** Cloud-based systems provide a platform for data storage, processing, and analysis, making it easier to access and share information across organizations.
- **Internet of Things (IoT):** IoT devices are widely used to connect physical objects and systems to the internet, enabling remote monitoring, control, and data collection.
- **Artificial Intelligence (AI) and Machine Learning:** AI and machine learning algorithms are applied to make sense of data, improve decision-making, and automate tasks.
- **Augmented Reality (AR) and Virtual Reality (VR):** AR and VR technologies are used to enhance training, maintenance, and troubleshooting processes by providing real-time, interactive information.
- **Sustainability and Resource Efficiency:** Industry 4.0 emphasizes sustainability by optimizing resource usage, reducing waste, and promoting energy efficiency.

These key principles collectively drive the transformation of traditional industries into more efficient, flexible, and intelligent systems, fostering innovation, competitiveness, and resilience in the digital age.

In recent years, the integration of robotics, particularly collaborative robots (cobots), has become widespread in manufacturing, aligning with the goals of Industry 4.0. The benefits include relieving workers of repetitive tasks, ensuring precision, and achieving higher product quality. Striking the right balance between automation and flexibility is crucial for achieving manufacturing goals in mass customization. This has led to the emergence of Human-Robot Collaboration (HRC), a discipline focused on enabling robots and humans to work collaboratively [8].

Collaborative robots play a vital role in making manufacturing lines more flexible and breaking down the traditional separation between robots and human operators. They offer advantages such as ease of programming, speed of setup, flexibility, safety, and cost-effectiveness. The collaborative robot market is expected to witness significant growth, driven by factors such as the need for automation due to a lack of skilled labor, rising labor costs, complex demands, and the requirement for higher efficiency [3].

The research and adoption of collaborative robots have garnered attention in both industry and academia. The increasing number of articles on this topic underscores its relevance and potential to surpass traditional robots in various applications. However, the market for collaborative robots is currently dominated by a small number of companies, emphasizing the need for market expansion to encourage competition and innovation, making these robots more accessible to smaller enterprises.

2.2 What are Cobots?

The application of Human-Robot Collaboration (HRC) in manufacturing systems has increased in recent years, aligning with the growing significance of Industry 4.0-related technologies. Collaborative robots, also known as cobots, are complex devices defined as machines that support and assist human operators in shared work processes. In simpler terms, cobots are robots designed to collaborate with humans, sharing a workspace to ease human efforts [8].

The term ”Cobot” is a contraction of ”collaborative robot”. The Institute for Occupational Safety and Health of the German Statutory Accident Insurance (IFA) defines Cobots as "complex machines which work hand in hand with human beings.

In a shared work process, they support and relieve the human operator.” In simplified terms, a cobot is a robot that collaborates with humans, sharing a workspace to alleviate human efforts. Instead of replacing humans with autonomous counterparts, Cobots augment and enhance human capabilities with super strength, precision, and data capabilities so that they can do more and provide more value to the organization.” [8]

Drawing an analogy with the software context, cobots can be considered as the hardware counterpart of augmented intelligence. Rather than replacing humans with autonomous counterparts, cobots enhance human performance by providing strength, precision, and data capabilities, thereby adding value to organizations.

Quality control of products is widely acknowledged as a crucial factor in the production process to minimize defective parts reaching end-users. Given the high customer demands in today’s market, there is a continuous search for new control systems and technologies to make quality control processes as efficient and effective as possible, posing a significant challenge for academia and industry.

In the context of Industry 4.0, cobots equipped with various sensors have gained prominence, cooperating with humans in the quality control of finished or semi-finished products. Cobots play a pivotal role in Quality 4.0, a paradigm emphasizing the adaptation to technological innovations by updating traditional quality approaches in the modern era of Industry 4.0 [9]. Quality 4.0 offers benefits such as real-time process monitoring, big-data collection, and predictive maintenance supported by analytics, contributing to enhanced enterprise efficiencies, performance, innovation, and improved business models.

The market for cobots is rapidly expanding due to their flexibility, ease of use, and affordability. In industrial contexts, cobots are deployed for various tasks such as packing, assembling, palletizing, welding, material handling, parts and product inspection, machine loading/unloading, part cleaning, bin picking, and kitting. However, the collaborative features of cobots are not fully exploited; they are often used for simple repetitive tasks with limited interactions with human operators. One possible reason for this under utilization may be the lack of practical and quantitative tools capable of demonstrating the benefits of the technology in new application contexts [5].

In manufacturing lines, robots traditionally undertake activities that humans cannot physically accomplish, are unsafe to perform, or are not preferred by humans. Robots are typically used for "3D jobs," referring to "Dirty, Dangerous, or Dull jobs." However, to ensure human safety and prevent accidents, these industrial robots must work physically separated from human operators while performing these activities. For human operators to collaborate with robots safely, the means to interact with them need to be available. Human-Robot Interaction involves the exchange of information between humans and robots and can be implemented using different concepts. A high-level classification of interaction modes includes direct physical interaction with the robot or the part being processed by both human and robot, remote contactless interaction, tele-operation, and message/information exchange through human-machine interfaces or other IT systems.

Remote contactless interaction employs interfaces such as voice or gesture recognition software and 3D cameras to translate human input into actions for the robot. Tele-operation involves the operator directly driving the robot through an interface like a joystick, determining its position and velocity without the need for intermediate software/controller translation. Message/information exchange through human-machine interfaces or other IT systems involves the robot exchanging information with the use of digital I/O signals, transmitted through a PLC or physical buttons in the cell [5].

Standards have been developed to regulate the interaction between humans and automation. ISO 10218 Part 1 and Part 2 address workplace safety requirements for assisting robots working in a collaborative workspace with users. The standards include requirements for safety-related control system performance, robot stopping functions, speed control, operational modes, collaborative operation requirements, and axis limiting. The more recent ISO/TS 15066 provides guidelines for collaborative robot operation in shared work spaces with humans, including establishing minimum separation distance, establishing maximum safe speed, tracking operator position and velocity, determining and avoiding potential contact, avoiding potential collision, operator controls, power and force limiting, technological, medical/bio mechanical requirements, and ergonomic requirements. [11]

Many manufacturing industries aspire to introduce collaborative robots into their production lines using these standards as guidelines. Companies like BMW, Volkswagen, and Audi have integrated collaborative robots to work alongside human operators, taking over tasks that could cause repetitive strain injury or optimizing ergonomic issues and automating routine operations. These applications demonstrate the lifting of safety barriers as system integrator find ways to meet the requirements set by standards. However, some significant gaps persist in current practice:

- In the majority of collaborative applications, lightweight robots are used, which are easier and safer to work with but may not fully exploit the capabilities of high-powered industrial robots capable of undertaking strenuous tasks.

- Safety functionalities should not obstruct the workflow, and protective functions should minimize the need for recovery even in the presence of human error.

- Approaches replacing physical barriers with laser scans or light barriers are insufficient, and a more dynamic monitoring approach is needed to adjust the workspace according to the robot's actual status and task.

- There is a lack of efficient means to integrate human operators into the collaboration workflow, with current interaction relying on warning lights and human-machine interfaces that may not be designed for non-expert operators.

In conclusion, the collaboration between humans and robots in manufacturing is evolving rapidly, driven by advancements in collaborative robot technologies and Industry 4.0-related innovations.

2.3 Difference between cobots and robots

There exist two significant distinctions between traditional industrial robots and Cobots. Firstly, as previously mentioned when discussing Cobots, the interaction between robots and humans is absent in traditional robots, as they often operate autonomously without human presence. In contrast, Cobots are trained by humans directly manipulating their arms and learning by example through demonstrations and reinforcement learning. These robots are both autonomous and capable of collaborating with humans in the same physical environment, equipped with a range of sensors and standardized interfaces. Autonomous and collaborative robots are a fundamental component of Industry 4.0 and are increasingly preferred over traditional industrial robots due to their ability to function in diverse settings, offering several advantages, such as [7]:

- They are user-friendly, enabling programming accessibility to a wide range of individuals, including those without prior programming expertise. Additionally, they can quickly adapt their programming to suit various applications, enhancing versatility.

- They have a rapid setup process, requiring only a few hours as opposed to the weeks often needed for traditional robots.
- They are flexible and occupy minimal space, allowing for quick deployment in various settings.
- They prioritize safety, collaborating with humans without posing risks through environmental awareness and sensor-equipped capabilities for detecting various factors.

In summary, collaborative robots are typically a more cost-effective and efficient choice compared to traditional industrial robots, especially in suitable contexts. Their lighter weight and increased mobility make them easier to relocate within the factory or industry where they are installed. The flexibility and affordability of collaborative robots render them a suitable option for a wide range of industries and applications. Presently, collaborative robots find applications in numerous industries, including automotive, electronics, general manufacturing, metal fabrication, packaging, plastics, food, agriculture, pharmaceuticals, chemicals, and scientific research. As collaborative robot technology advances, and more companies recognize the productivity benefits they offer, sales volumes in this sector are expected to rise [7].

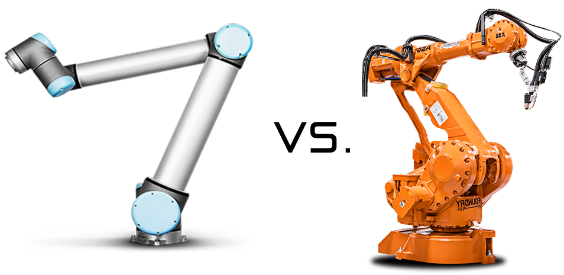


Figure 2.2. Collaborative robots vs Traditional robots

2.4 Application of HRC system in manufacturing

In contemporary times, the utilization of collaborative robots in manufacturing systems is extensive and continually evolving. The manufacturing industry, particularly the automotive sector and assembly lines, heavily relies on Cobots for a diverse range of tasks such as picking, packing, palletizing, welding, assembly, material handling, product inspection, and more [5].

The evolving market dynamics and heightened customer expectations have compelled the industry to enhance efficiency and flexibility. Hence, collaborative robots, with their numerous advantages outlined in Chapter 1.2, are now being integrated into factories not only for assembly and basic tasks but also for comprehensive involvement in both production and non-production processes. Within the reviewed literature, various application domains for collaborative robots were identified, and these are summarized as follows [7]:

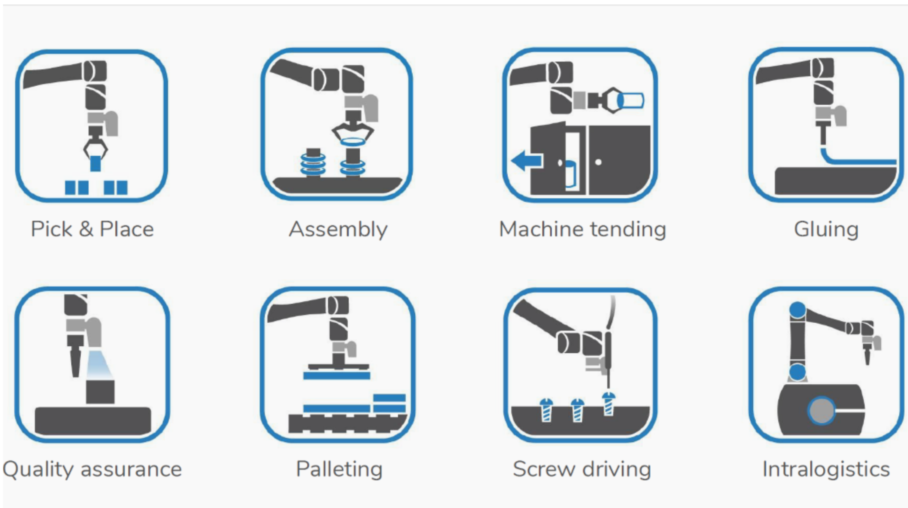


Figure 2.3. Application of collaborative robots

- **Welding:** Collaborative robots excel in precision and speed when it comes to welding tasks. They can operate independently with high precision or assist human welders as needed. These Cobots incorporate features such as vision sensing, automatic programming, guiding, tracking, and real-time intelligent control of the welding process. The collaboration system depends on human skills, with the robot functioning under a robot-as-tool approach and limited autonomy or cognitive capabilities.

- **Material Handling:** Material handling represents one of the most significant applications of collaborative robots today. These robots efficiently transport materials within manufacturing units and across factory floors, reducing the physical strain on workers involved in lifting and moving materials. Collaborative robots are particularly useful when handling materials that are unsuitable for human handling due to hygiene, safety, or weight constraints. It's important to note that this application entails cooperation rather than direct collaboration between human workers and the robot, and the robot operates under a robot-as-tool approach, leaving most cognitive tasks to the user. A wide variety of palletizing and material-handling robots with different payloads and gripper tools are available in the market.

- **Machinery:** Collaborative robots are employed as machinery, primarily following a robot-as-tool approach. Similar to welding applications, they excel in high-precision and high-speed tasks, whether it's cutting, deburring, drilling, foundry work, grinding, material removal, milling, polishing, refueling, routing, sanding, spindle operations, or water jet cutting.

- **Assembly:** Cobots play a significant role in lean industrial processes, expanding production capabilities in manufacturing. They are integrated into what's known as hybrid assembly robotic cells, using their capabilities in part handling, high-speed picking, and assembly to assemble parts into subassemblies. This, in turn, allows human operators to focus on more value-added tasks at the assembly line, increasing productivity for simple assembly tasks. Cooperative assembly workstations are particularly well-suited for sequential assembly, where the robot handles simpler tasks, while human operators complete complex, often varied tasks at the end of the line. Effective timing and coordination between humans and robots are crucial for the success of Human-Robot Collaboration (HRC).

- **Quality Inspection:** Robots consistently and accurately follow precise processes, making them more precise than human operators. They can perform quality inspections with high accuracy and repeatability, without suffering from fatigue or boredom. A common application involves combining a vision system with a Cobot to inspect products for quality and immediately remove defective items from the production line. This approach minimizes human errors and introduces a new level of quality control and assurance for end customers.

- **Picking, Packing, and Palletizing:** Many industries, particularly those requiring extensive packaging, have turned to robots for these tasks. Manual execution of these activities can be labor-intensive and time-consuming. Collaborative robots excel in tasks like shrink-wrapping, box assembly, loading, box collation, and pallet placement for shipping.

- **Automotive:** The automotive industry warrants a separate category due to its significant interest in collaborative robot applications, both in industrial settings and academic research. These applications primarily focus on assembly tasks, where collaborative robots play a crucial role in producing lines, ensuring high-precision operations.

As technology and collaborative robot capabilities continue to evolve, these robots are expected to find even broader applications, enhancing productivity and efficiency across various industries.

Chapter 3

General cost model

To facilitate the integration of cobots into assembly production lines, this section introduces a comprehensive cost model intended for estimating unit assembly costs and than implement it into an assembly line. The purpose of the model is to assist decision-makers in selecting the most cost-effective assembly configuration, incorporating key factors that define the overall assembly cost for a single unit. Specifically tailored for production settings marked by small lot production, the model takes into consideration the learning processes of human operators, addressing both productivity and product quality aspects. However, it is versatile enough to be effectively employed in mass production scenarios characterized by large volumes of standardized products.

3.1 Notation

The following notations are used in the remainder of the thesis:

i	Assembly configuration (i = manual, collaborative, automated)
C_m	Unit manufacturing costs (€/unit)
c_0	Cost of operative assembly time (€/hours)

t_a	Operative assembly time (hours)
$t(n)_i$	Operative assembly time for the n-th lot unit(hours)
$t(1)_i$	Operative time for the 1st lot unit (hours)
b_i	Productivity leaning factor
θ_i	Productivity learning percentage ([0;1])
C_{si}	Unit setup costs (€/unit)
c_{si}	Cost of setup time (€/hour)
t_{si}	Setup time attributable to the individual assembly operation (hours)
C_{PC}	Unit prospective costs (€/unit)
K_i	Total life-cycle cost of investments (€)
v_i	Service life of the equipment (years)
N	Estimated lot size (unit)
L	Estimated number of lots processed in a year
RC_{TOT}	Total annual retrospective costs (€)
C_{qi}	Unit quality costs (€/unit)
d_i	Average defectiveness ([0;1])
c_{di}	Average cost of a defective unit (€/unit)
$d(n)_i$	Defectiveness related to the n-th lot unit ([0;1])
$d(1)_i$	Defectiveness related to the 1^{st} lot unit ([0;1])
CW_{TOTi}	Unit well being costs (€/unit)

$CW_{TOT\ MAX}$	Maximum well being costs (€)
γ_i	Well being costs reduction factor ([0;1])

3.2 Model formulation

The proposed assembly cost model takes into account six distinct cost components:

- **Manufacturing costs (C_m):** This pertains to the expense associated with the time spent by human operators while conducting assembly operations.
- **Setup costs (C_s):** This involves the cost incurred during the time in which the human operator sets up the assembly station between one production lot and the next.
- **Prospective costs (C_{PC}):** This refers to the expenditure related to acquiring the necessary equipment essential for executing the assembly process.
- **Retrospective costs (C_{RC}):** These are costs that will persist even if the current assembly configuration is modified.
- **Product quality costs (C_q):** This encompasses costs arising due to defects in the assembly process, affecting the quality of the final product.
- **Wellbeing cost (C_w):** This includes costs resulting from the physical and cognitive workload imposed on operators, reflecting the impact on their well-being.

In summary, the model provides a comprehensive framework by considering these six cost components to estimate the overall assembly costs. [4]

The unit cost of assembly in the i-th assembly configuration can be expressed by the following formula [4]:

$$C_{Ai} = C_{mi} + C_{si} + C_{PCi} + C_{RCi} + C_{qi} + C_{wi} \tag{3.1}$$

3.2.1 Manufacturing cost

The first cost that we take into account is the manufacturing cost, that is referring to the cost of the time during which the human operator performs assembly operations. We can assume that it can be expressed by the following formula:

$$C_m = c_o \cdot t_a \tag{3.2}$$

Where c_o is the cost of operative assembly time and t_a is the required operative assembly time. The time required for operative assembly (t_a) is influenced by the complexity and number of tasks involved in the assembly process. Two production types are considered: mass production, where assembly time tends to stabilize as a constant, converging to a specific standard time (t_{std}) with increasing units produced, and low-volume production (small lots), where assembly time is heavily influenced by learning processes, and the standard time is not attained. In smaller production lots, the impact of learning processes on average assembly time becomes more pronounced.

The substantial impact of learning processes on average assembly time is often characterized by the concept known as the learning curve. The learning curve illustrates the relationship between cumulative production quantity and the average time required to complete a task or produce a unit. Key points highlighting how learning processes affect average assembly time include [2]:

- **Learning Curve Effect:** Workers or a production team, gaining experience with a specific task or assembly process, become more efficient over time - a phenomenon known as the learning curve effect. While there may be an initial slower production pace, accumulated experience leads to a decrease in average assembly time.

- **Increased Efficiency:** Repeated practice and exposure to the assembly process make workers more familiar with the steps, fostering better coordination, reduced errors, and a smoother workflow-contributing to a decrease in assembly time.

- **Skill Development:** Learning processes involve the acquisition and refinement of specific skills and techniques. As workers develop these skills, they can perform tasks more rapidly and accurately, ultimately reducing assembly time.

- **Process Optimization:** Learning processes often include the analysis and optimization of assembly methods. This encompasses identifying and implementing more efficient tools, streamlining workflows, and adopting best practices-contributing to a reduction in assembly time.

- **Technology and Automation:** Learning processes can integrate new technologies or automation in the assembly line. Automated processes, being more consistent and faster than manual ones, result in decreased average assembly time.

- **Training Programs:** Well-designed training programs significantly impact the learning curve. Effective training accelerates the learning process, enabling workers to quickly understand assembly intricacies and minimizing the time to achieve optimal performance.

- **Feedback Loops:** Learning processes benefit from feedback loops where performance data is analyzed, and improvements are implemented. Continuous improvement based on feedback refines processes, enhancing efficiency, and reducing assembly time.

In summary, learning processes positively influence average assembly time through skill development, increased efficiency, process optimization, and the integration of technology and automation. A well-managed learning curve contributes to more cost-effective and streamlined assembly operations [2].

Wright is widely acknowledged as the first individual to observe and delve into the study of the learning curve within the realm of production and operations management. His pioneering work sparked a multitude of articles exploring both the practical application of learning in production and its theoretical foundations. The advantages of incorporating the learning curve concept into production and operations management are manifold. A comprehensive grasp of these benefits by managers can lead to favorable and valuable managerial implications and insights.

At the granular planning and operations levels, these benefits encompass establishing more precise labor standards and monitoring achievable production objectives [16]. Additionally, the application of learning curves facilitates the forecasting of the available working time of a process [13], as well as predicting production output [14] and the occurrence of non-conforming units [10].

On a strategic level, the utilization of learning curves, sometimes referred to as "experience" curves in this context, extends to optimal decisions related to new product introductions, competitive pricing strategies, determining investment levels to drive process and product innovations, decisions regarding vertical integration, and the selection of organizational design structures [12].

The Wright (1936) learning curve (WLC) is of the form:

$$t(n)_i = t(1)_i \cdot n^{-bi} \tag{3.3}$$

The formula express the time required to produce the n-th lot unit in the i-th assembly, where:

- n is the cumulative unit number
- $t(1)_i$ is the operative time required to assembly the 1st lot unit
- b_i is the learning productivity factor in the i-th assembly configurations.

The learning productivity factor can be related to the learning productivity percentage ϕ by the following:

$$b_i = -log2(\phi_i) \tag{3.4}$$

The smaller is the value of ϕ_i, the larger is the value of b_i and the higher is the productivity learning effect. We can assume standard value of ϕ:

- 0.98 for manual assembly
- 0.95 for collaborative assembly
- 1 for automated assembly

It can therefore be deduced that the support of cobots allows for shorter assembly times and faster learning with respect to manual configuration.

The average unit assembly time ($\overline{t_{ai}}$) is influenced by the lot size, and it can be calculated as follows:

$$\overline{t_{ai}} = \frac{\sum_{n=1}^{\overline{N}} t(1)_i \cdot n^{-bi}}{\overline{N}} \tag{3.5}$$

where $\overline{N}$ is the estimated production lot size. Considering this, the unit manufacturing costs in the i-th assembly configuration can be calculated as follows:

$$C_m = c_o \cdot \overline{t_a} \tag{3.6}$$

3.2.2 Setup cost

We are examining another cost known as the setup cost, which pertains to the expenditure of time when a human operator arranges the assembly station between consecutive production lots.

The unit setup costs (C_s) arise from the inactive time needed to reorganize the workstation according to production requirements. When transitioning from one batch to the next, it is crucial to consider the passive time required to change tools, reprogram robotic systems, or modify the workstation layout. In a practical context, it is imperative to recognize that this cost cannot be disregarded.

In instances of manual configuration, setup times are generally brief. However, the scenario differs significantly when implementing robotic systems. Currently, robotic systems lack the ability to autonomously reprogram their actions, necessitating human involvement in tasks such as selecting trajectories, reprogramming task sequences and allocation, and changing tools and grippers [15].

Cobots demonstrate remarkable flexibility, enabling swift movement and intuitive, rapid reprogramming. Reprogramming cobots often does not necessitate extensive expertise. Conversely, traditional industrial robots are typically stationary, and their reprogramming is intricate and time-consuming.

Utilizing cobots in the assembly line introduces enhanced flexibility, as a single cobot can undertake various tasks by adapting different tools. While tool changes can be automated, it is important to note that this process incurs setup time. In simpler terms, altering the tools on the cobot initiates the setup time. Aghajani formulated a model for the design of a robot-based assembly line that considers setup time; however, this model does not align with the trajectory of human-robot collaboration, as the setup time is activated by traditional setup activities associated with conventional robots. Cobots exhibit remarkable flexibility, showcasing both agility in movement and intuitive, rapid reprogramming.

The setup cost can be expressed by the following formula [4]:

$$C_{si} = c_{si} \cdot t_{si} \tag{3.7}$$

Here, C_s denotes the cost of setup time, which may significantly differ from the cost of operative time due to the potentially heightened skill requirements for workstation setup. The value t_{si} represents the time needed to set up the assembly station for an individual unit produced.

It is given by:

$$t_{si} = \frac{T_{si}}{\overline{N}} \tag{3.8}$$

where T_{si} is the total time required to setup the workstation in the i-th assembly configuration.

This time is linked to the specific assembly operation and is influenced by the estimated lot size.

3.2.3 Prospective cost

Costs linked to the acquisition of new tools, equipment, operator support systems, and robotic systems need to be considered in the projected costs. These projected costs should cover any expenditure that the current decision on assembly configuration has the potential to alter. The projected costs for an individual unit in the i-th assembly configuration can be calculated as follows [4]:

$$C_{PC} = \frac{K_i/v_i}{\overline{N} \cdot L} \tag{3.9}$$

Here, K_i represents the comprehensive life-cycle cost of investments essential for executing the i-th assembly configuration, v_i signifies the operational lifespan of the equipment measured in years within the i-th assembly configuration, N denotes the projected production lot size, and L indicates the estimated number of lots processed in a year.

Projected costs for an individual unit should specifically consider the costs that are affected by the current decision, and what is commonly known as sunk costs should be disregarded. Sunk costs, which refer to expenditures that have already been incurred and are irrecoverable, should not be factored in. For instance, in the scenario where a workstation is newly arranged, all investments made in equipment fall into the category of sunk costs. This term is typically used to describe money that has already been spent and cannot be recuperated.

A manufacturing company, for instance, may have various sunk costs, including machinery expenses, equipment costs, and lease payments for the factory space. When making decisions related to selling a product as is or processing it further, sunk costs are excluded. This concept applies to situations where a product can either be sold in its current state or subjected to further processing. Similarly, in cases where the workstation undergoes a reorganization, all equipment investments fall under the umbrella of sunk costs.

3.2.4 Retrospective cost

On the flip side, retrospective costs emerge when the assembly systems are already established, and the decision-maker is faced with the task of deciding whether and how to introduce modifications. In these situations, there may be ongoing costs resulting from past decisions that need to be taken into account when making future choices. A typical example of retrospective costs is the expenditure linked to employees who cannot be terminated or redeployed to different tasks. The retrospective costs for an individual unit in the i-th assembly configuration can be computed as follows [4]:

$$C_{RC} = \frac{RC_{TOT}}{N \cdot L} \tag{3.10}$$

Where RC_{TOT} are total annual retrospective costs in the i-th assembly configuration.

In the manufacturing context, retrospective costs denote expenses incurred due to past decisions or actions, becoming relevant when contemplating changes or enhancements to existing processes or systems. These costs are tied to decisions made in the past and can significantly influence future choices. Retrospective costs are contrasted with prospective costs, which are forward-looking and relate to anticipated investments and decisions.

Illustrative examples of retrospective costs in manufacturing encompass:

- **Costs of Existing Equipment:** If a manufacturing facility has previously invested in machinery or equipment that remains functional but may require modification or replacement for process improvements, the costs associated with the existing equipment become retrospective.

- **Labor Costs:** Expenses related to employees, particularly those with specific skills or expertise not easily transferable to other tasks, are considered retrospective. For instance, if specialized workers were hired for a particular manufacturing process, their salaries and benefits contribute to retrospective costs when contemplating changes in the process.

- **Training Costs:** If specialized training was provided to employees or operators for a specific manufacturing process that might undergo changes, the training costs incurred in the past become part of retrospective costs.

- **Operational Disruptions:** Costs linked to disruptions or downtime resulting from past decisions, such as implementing new technology or reconfiguring production lines, fall into the category of retrospective costs.

- **Unused or Surplus Inventory:** In cases of overproduction or excess inventory stemming from past decisions, the costs associated with storing, managing, or disposing of unused materials or finished goods are considered retrospective.

Recognizing retrospective costs is pivotal for decision-makers in manufacturing when assessing the feasibility and implications of altering existing processes. This understanding aids in evaluating the complete financial repercussions of past decisions on current and future operations.

3.2.5 Product quality cost

Quality inspections typically aim to verify compliance with specified and functional requirements, as well as to detect potential defects or anomalies in a product. These inspections may be guided by either strict or lenient rules, such as periodic checks or fixed-percentage controls, employing statistical or heuristic approaches.

Key considerations when developing inspection procedures include [6]:

- **Collection of Information:**Gathering relevant data on the process under examination.

- **Definition of Tasks and Parameters:** Clearly outlining the tasks and parameters essential for the inspection process.

- **Activity and Responsibility of Operators/Inspectors:** Specifying the roles and responsibilities of the individuals conducting the inspection.

- **Identification of Inspection Costs:** Determining the associated costs involved in the inspection process.
- **Identification of Possible Inspection Errors:** Recognizing potential errors in the inspection, such as false positives or false negatives, and understanding their consequential impact.

Recent advancements in the automation of manufacturing systems contribute to a reduction in inspection errors, although complete elimination remains unattainable. Additionally, due to budget constraints, not all manufacturing systems can be automated, underscoring the crucial role of inspector skills. It's noteworthy that, in numerous production environments, the impact of inspection errors on quality costs is substantial. This is particularly evident when there are relatively low inspection costs, high repair costs, significant penalty costs, or a high probability of defects. Unfortunately, these errors are frequently overlooked.

The construction of a probabilistic model involves two main phases:

1. **Estimating the Probability of (Not) Detecting Defects:**This phase involves assessing the likelihood of detecting or failing to detect defects in each manufacturing step.
2. **Combining Probabilities into a Model:**The probabilities determined in the first phase are integrated into a model that portrays the overall effectiveness and cost of the inspection procedure.

During each process step (i-th step), various types of quality control activities may be conducted, depending on the specific defect type. For each of these activities, there is a risk of detecting a defect when it is not present (type I error) and a risk of not detecting it when it is actually present (type II error). While sophisticated quality monitoring techniques (manual and/or automatic) can minimize these risks, complete elimination remains unachievable.

An inspection is associated with two types of errors [6]:

1. Type I Error (α): This occurs when a good part is misclassified as defective.
2. Type II Error (β): This happens when a defective part is misclassified as good.

Each step (i-th step) in the production process is represented by a Bernoulli distribution, characterized by three parameters:

1. p_i: The probability of a defect occurring in the i-th step (parameter of the Bernoulli distribution).
2. α_i: The probability of (erroneously) detecting a defect when it is not present in the i-th step (Type I inspection error or false positive).
3. β_i: The probability of not detecting a defect when it is present in the i-th step (Type II inspection error or false negative).

The index i ranges from 1 to m, representing the total number of steps. The first parameter (p_i) pertains to the defectiveness or, alternatively, the quality of the i-th step. On the other hand, the other two parameters (α_i and β_i) relate to the quality of the corresponding inspection(s). The following probabilities can be calculated for each generic i-th step.

The probability of detecting the defect in the step i P_1 is:

$$P_1 = p_i \cdot (1 - \beta_i) + (1 - p_i) \cdot \alpha_i \tag{3.11}$$

The probability of non detecting the defect in the step i P_2 is:

$$P_2 = p_i \cdot \beta_i + (1 - p_i) \cdot (1 - \alpha_i) \tag{3.12}$$

where i is included between 1 and m, i.e., the total number of steps.

In the case the defect is detected, it will be authentic with a probability p_i · (1 - β_i) or false with a probability (1 - p_i) · α_i. On the other hand, in the case no defect is detected, there can be an inspection error (false negative), with a probability p_i · β_i, or due to the real absence of any defect, with a probability (1 - p_i)·(1 - α_i) Regarding the i-th step, the total inspection cost may be expressed, as a first approximation, as follows [6]:

$$C_{TOT} = c_i + NRC_i \cdot p_i \cdot (1 - \beta_i) + URC_i \cdot (1 - p_i) \cdot \alpha_i + NDC_i \cdot p_i \cdot \beta_i \qquad (3.13)$$

where:

- c_i is the cost of the specific inspection activity (e.g., manual or automatic inspection activities).
- NRC_i is the necessary-repair cost, i.e. the cost for removing the defect when it is present.
- URC_i is the unnecessary repair cost, i.e., the cost incurred when identifying false defects, e.g., although there is no repair cost, the overall process can be slowed down or interrupted, with a consequent extra cost.
- NDC_i is the cost of undetected defect, i.e., the cost related to the missing detection of defects.

Expenses linked to product quality are a result of errors or malfunctions occurring in the assembly process, leading to imperfections in the final product. These costs significantly impact production expenses across diverse industries. For instance, in sectors such as aerospace or precision manufacturing, where product defects can have severe consequences, the existence of defects can result in substantial economic repercussions. Product quality costs can manifest due to various factors, encompassing expenditures related to re-manufacturing, costs linked to discarded products, harm to the brand image, and expenses associated with after-sales repairs.

As an initial estimate [4], the computation of product quality costs for the i-th assembly configuration can be determined by multiplying the average defectiveness (d_i) - representing the proportion of defective assembled units - by the average cost of a defective unit (c_{di})

$$C_{qi} = d_i \cdot c_{di} \tag{3.14}$$

The defectiveness, as a first approximation, can be assumed constant for large-volume productions. However, similarly to productivity, defectiveness is also influenced by a learning process; consequently, the observed average defectiveness can be affected by the size of the assembled lot.

The defectiveness related to the assembly of the n-th unit in the i-th assembly configuration can be calculated as follows:

$$d(n)_i = d(1)_i \cdot n^{-qi} \tag{3.15}$$

where:

- n is the cumulative unit number
- $d(1)_i$ is the defectiveness related to the 1st unit, i.e. the initial quality performance, in the i-th assembly configuration
- q_i = -log2(φ_i) is the quality learning factor
- φ_i is the quality learning percentage in the i-th assembly configuration. The smaller is the value of φ_i, the larger is the value of q_i and the higher is the quality learning effect

So the equation for the product quality cost becomes [4]:

$$C_{qi} = \overline{d_i} \cdot c_{di} \tag{3.16}$$

where $\overline{d_i}$ is

$$\overline{d_i} = \frac{\sum_{n=1}^{\overline{N}} d(1)_i \cdot n^{-qi}}{\overline{N}} \tag{3.17}$$

3.2.6 Wellbeing cost

To enhance both the physical and mental well being of individuals and overall system performance, the design of contemporary workplaces should incorporate considerations of physical and mental ergonomics. From this standpoint, it is vital to include costs related to worker well being when assessing an assembly configuration. The incorporation of human support systems in repetitive and physically demanding tasks is often intended to enhance the operator's well being and can serve as valuable assistance in alleviating the physical and mental burden on human operators. Although the literature offers highly advanced and quantitative well being cost models, a preliminary analysis can provide a rough estimate of well being costs in the i-th assembly configuration using the following approach [4]:

$$CW_{TOTi} = CW_{TOT\ MAX} \cdot \gamma_i \tag{3.18}$$

where $\gamma_i \in [0;1]$. If, for example, the implementation of cobots allows a 30% reduction in well being costs with respect to the manual assembly configuration (considered the most onerous configuration), then $\gamma_{collaborative\ assembly} = 0.7$

3.3 Overall assembly cost

The overall assembly cost resulting from the proposed model is a function of (i) the specific input parameters of the process, (ii) the assembly configuration and

(iii) the estimated lots size processed by the assembly station ($\overline{N}$). The cost curves highlighted by the model clearly show the potential of collaborative robotics to make small lot assembly processes more efficient.

3.3.1 Model extension for multiple stations

The extension of the model [4] was made through the following assumptions:

- The assembly line's operational time is computed as the highest value between the operational times of the two stations. This is due to the operator being remunerated for the entirety of the work session, not just the time when the station is actively involved in production activities.
- Upon establishing the operational time for the assembly line, manufacturing costs are derived by directly multiplying this duration by the corresponding operational expenses.

Given this extension of the model, it is possible to verify at both cost and throughput levels what the optimal configuration is for two in-line stations as the average production lot size varies.

Chapter 4

Theoretical computation

In this chapter we will analyze, graphically, the variation of the average optimal production lot size through cost curve analysis and production capacity through a simulative approach using FlexSim software.

After this initial analysis and estimating the average lot size we will consider, we will go to see which of the costs has the greatest impact on the total cost of manufacturing and how these cost components are sensitive to changes and are therefore important to consider when seeking to optimise or minimise costs.

An examination of the suggested cost model can be carried out to identify which cost components had the greatest impact on the overall cost. In conducting this analysis, it is initially assumed that the individual cost elements are independent.

4.1 Single station

The first study we go to is on the single workstation. The calculation done is based on fictitious examples of cost curves for different assembly configurations. The assembly stations analyzed are: fully manual, collaborative and automatic.

The data considered for the cost curve analysis and evaluation of the optimal average production lot size are those summarized in Table 4.1.
The result of the analysis obtained are ranges of average lot sizes that go to minimize the costs of the corresponding assembly stations.

Parameters		**manual**	**collaborative**	**automated**
c_0	[€/hour]	30	30	0
$t_{(1)i}$	[hour]	2	1,5	0,5
θ_i		0,98	0,95	1
c_{si}	[€/hour]	30	30	60
T_{si}	[hour]	0,1	1	6
K_i	[€]	25.000 €	150.000 €	1.000.000 €
v_i	[years]	10	10	10
L	[lot/years]	150	150	150
RC_{TOT}	[€/year]	- €	- €	- €
c_{di}	[€/unit]	100	100	100
φ_i		0,97	0,95	0,99
$d_{(1)i}$		0,05	0,03	0,01
$CW_{TOT\ MAX}$	[€/year]	2.000 €	2.000 €	2.000 €
γ_i		1	0,7	0

Figure 4.1. Input for the single assembly station

The total cost that we observe as a projection of curves in Figure 4.1 is given by the following formula:

$$C_{Ai} = C_{mi} + C_{si} + C_{PCi} + C_{RCi} + C_{qi} + C_{wi} \tag{4.1}$$

As evident from the discernible trends depicted in the graphical representations, our optimization strategy revolves around three distinct average lot size ranges, each finely tuned to maximize efficiency across the spectrum of assembly stations at our disposal.
The judicious selection of manual stations comes into play when dealing with average batch sizes ranging from $\overline{N}$=1 to $\overline{N}$=5. In this scenario, the human touch and

attention to detail play a pivotal role in ensuring precision assembly.
Moving up the scale, the collaborative station seamlessly integrates into our operational framework for average batch sizes spanning from $\overline{N}$=6 to $\overline{N}$=22. This station harnesses the power of teamwork and coordinated effort, capitalizing on the collective skills and expertise of a group of operators to enhance productivity and streamline assembly processes.
For more substantial lot sizes surpassing the threshold of 22, the fully automatic station takes center stage. This state-of-the-art station leverages cutting-edge technology to handle the complexities associated with larger batches, ensuring a seamless and efficient assembly process without compromising on accuracy.

In summary, our approach is finely calibrated to align with the unique demands posed by varying the estimated lot sizes, strategically employing manual, collaborative, and fully automatic stations to optimize assembly operations and elevate overall efficiency.

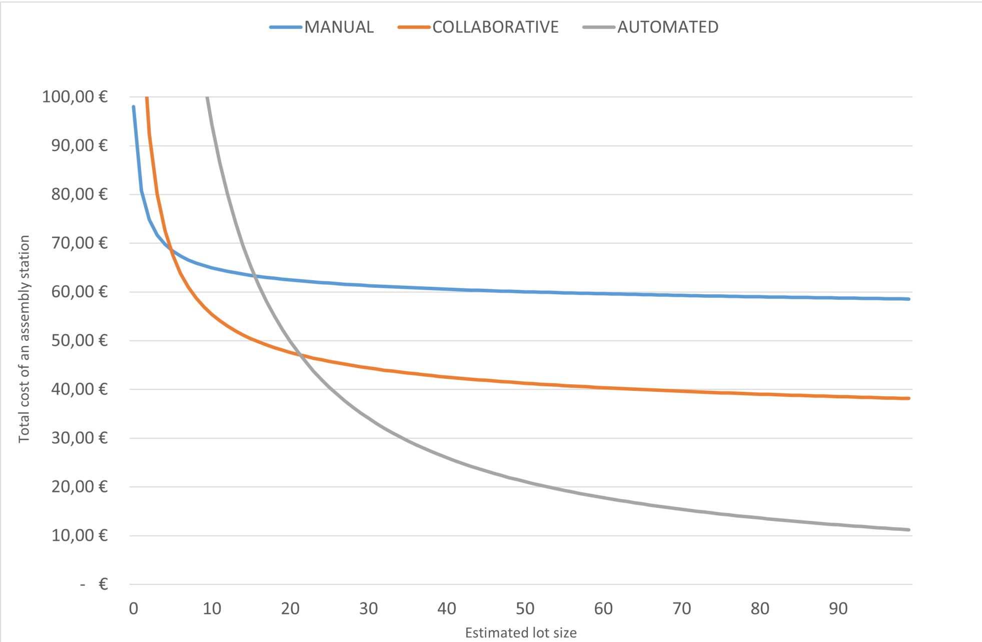


Figure 4.2. Total assembly cost curves

4.2 Multiple station

In this section, our focus will be directed towards a meticulous examination of the dynamics inherent in the sequential placement of two stations, with a comprehensive assessment encompassing both their production capacity and the fluctuation of total costs contingent upon the average lot size.

An underlying assumption integral to our analysis is that the tandem operation of these two sequentially arranged stations is exclusively dedicated to the assembly process under scrutiny. Furthermore, it is postulated that any idle time within a station is not diverted for the execution of alternative operations.

Parameters		manual 1	manual 2	collaborative 1	collaborative 2	automated 1	automated 2
c_0	[€/hour]	30	30	30	30	0	0
$t_{(1)i}$	[hour]	3	2	1,5	1,8	0,5	0,2
θ_i		0,98	0,98	0,95	0,95	1	1
c_{si}	[€/hour]	30	30	30	30	60	60
T_{si}	[hour]	0,1	0,15	1	1,2	6	5
K_i	[€]	25.000 €	25.000 €	150.000 €	150.000 €	1.000.000 €	1.000.000 €
v_i	[years]	10	10	10	10	10	10
L	[lot/years]	150	150	150	150	150	150
RC_{TOT}	[€/year]	- €	- €	- €	- €	- €	- €
c_{di}	[€/unit]	100	100	100	100	100	100
φ_i		0,97	0,97	0,95	0,95	0,99	0,99
$d_{(1)i}$		0,05	0,05	0,03	0,02	0,01	0,01
$CW_{TOT\ MAX}$	[€/year]	2.000 €	2.000 €	2.000 €	2.000 €	2.000 €	2.000 €
γ_i		1	1	0,7	0,7	0	0

Figure 4.3. Input for the assembly line

To ensure a comprehensive and thorough analysis, we have developed various combinations of two machines arranged in line, taking into account potential variations in operating and setup times, particularly when dealing with two stations of the same type. The total cost of the production line is determined by aggregating the individual costs associated with each station, with the exception of the manufacturing cost.

For the latter cost component, a distinct methodology is applied. Recognizing that the stations are exclusively dedicated to the desired assembly operation and acknowledging that the manufacturing operational cost is calculated based on the hourly wage of the operator, several assumptions have been formulated:

The operational time required for the assembly line is calculated as the maximum of the operational times for the two stations. This is because the operator is compensated for the entire work session, not solely for the time the station is actively engaged in production tasks. After determining the operational time for the assembly line, the manufacturing costs are calculated by simply multiplying this time by the respective operational costs.

This meticulous and systematic approach ensures a precise evaluation of the production line's performance and associated costs, facilitating effective planning and optimization of assembly operations. So the total assembly cost of the line with two consecutive stations is given by the following formula:

$$C_A = C_{m1}+C_{s1}+C_{PC1}+C_{RC1}+C_{q1}+C_{w1}+C_{m2}+C_{s2}+C_{PC2}+C_{RC2}+C_{q2}+C_{w2} \quad (4.2)$$

After calculating the various costs of the different assembly lines, the data were plotted on a graph to visualize their variation based on the estimated batch size. This graphical representation allowed for a clear understanding of how costs fluctuate with changes in the size of the batch, providing valuable insights for decision-making and optimization strategies.

Additionally, the visualization facilitated the identification of potential cost-saving opportunities and the determination of the most cost-effective estimated lot sizes for efficient production processes.

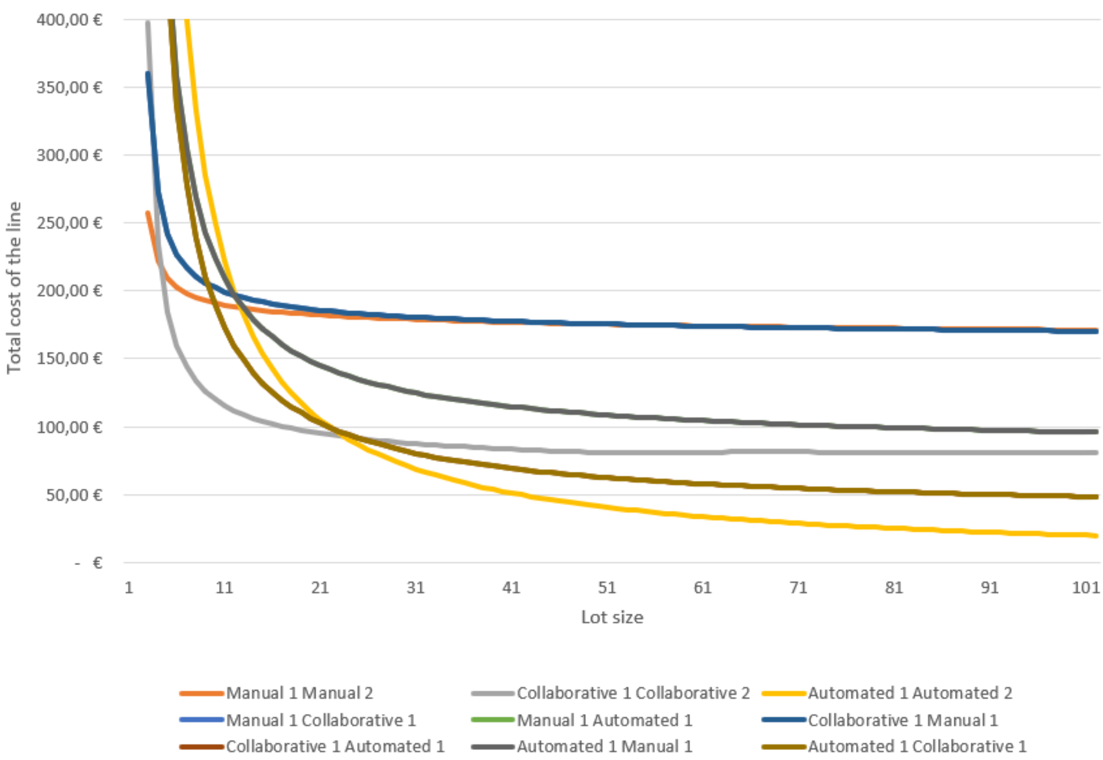


Figure 4.4. Total cost of the assembly line

The provided data presents various combinations of machines along with their associated total costs for different lot sizes. Let's break down the analysis:

- **Combination**: Refers to the specific combination of machines used in the assembly line setup. For example, "Manual 1" refers to the first manual machine, "Collaborative 1" refers to the first collaborative machine, and "Automated 1" refers to the first automated machine.

- **Variation of lot size**: Indicates the different lot sizes considered in the analysis.
- **Total Cost of the Line**: Represents the total cost incurred for a specific combination of machines and lot size.

Here's a breakdown of the data:

- **Manual Combination** (Manual 1 + Manual 2):
  - The total cost of the line decreases as the lot size increases, indicating potential economies of scale.
  - For example, for the first combination (Manual 1 + Manual 2), the total cost ranges from €257.50 for a lot size of 1 to €171.16 for a lot size of 100.
- **Collaborative Combination** (Collaborative 1 + Collaborative 2):
  - Similar to the manual combination, the total cost of the line generally decreases with increasing lot size.
  - However, the cost reduction is not as pronounced compared to the manual combination.
  - For example, for the first combination (Collaborative 1 + Collaborative 2), the total cost ranges from €397.67 for a lot size of 1 to €81.13 for a lot size of 100.
- **Automated Combination** (Automated 1 + Automated 2):
  - The total cost of the line is significantly higher compared to manual and collaborative combinations.
  - However, similar to the other combinations, the cost decreases with increasing lot size.

  - For example, for the first combination (Automated 1 + Automated 2), the total cost ranges from €1,995.33 for a lot size of 1 to €19.95 for a lot size of 100.

- **Mixed Combinations** (Manual 1 + Collaborative 1, Manual 1 + Automated 1, Collaborative 1 + Automated 1):

  - These combinations involve mixing different types of machines.
  - The total cost of the line varies based on the combination and lot size.

Overall, the data highlights the impact of lot size and machine type on the total cost of the assembly line. It suggests that larger lot sizes generally lead to lower costs per unit, while automated configurations tend to be more expensive but may offer advantages in terms of efficiency and productivity.

4.2.1 Production throughput analysis for a single station

The analysis of throughput is crucial when designing, operating, and managing production systems. This aspect must be taken into account when evaluating and selecting the optimal assembly setup. Different assembly configurations can exhibit varying levels of performance and yield different unit volumes.

It's evident that the anticipated number of units processed by the assembly station changes depending on the assembly configuration and estimated lot size. While one assembly configuration may appear more cost-effective, it might not meet the necessary demand in terms of productivity. Therefore, alongside cost analysis, it's essential to conduct a productivity analysis to ensure that the chosen assembly configuration can meet the required demand [4].

A rough estimate of the maximum annual throughput for the i-th assembly configuration can be calculated as follows:

$$maximum\ throughput = \frac{t_{ws} \cdot e_{ws} \cdot n_{ws} \cdot WD}{\overline{t_{ai}} + tsi} \tag{4.3}$$

Where:

- t_{ws} is the duration of the work session
- n_{ws} is s the number of work sessions in a working day
- e_{ws} is is the efficiency in the use of the production resources (workforce and equipment)
- WD is the number of working days in a year
- $\overline{t_{ai}}$ is average unit assembly time
- t_{si} is setup time attributable to the individual assembly operation

Parameters		manual	collaborative	automated
t ws	[hour/session]	8	8	8
n ws	[session/day]	2	2	2
e ws	[day]	0,85	0,85	0,95
WD	working days	280	280	280
t(1)i	[hour]	2	1,5	0,5
θi		0,98	0,95	1
Tsi	[hour]	0,1	1	6

Figure 4.5. Data for throughput analysis

Using the data in Figure 4.5, we can analyze various curves of maximum throughput as the estimated lot size varies. As evident from the graph in Figure 3.6, the more automated the station, the greater the increase in annual units produced with the growth of the average production lot size, highlighting a clear correlation between automation level and production scalability.

As clearly evidenced by the graph, the automatic station exhibits its maximum efficiency with very large production batches, exceeding 100 units. On the other hand, the collaborative station achieves its maximum yield with batches exceeding 50 units, while the manual station reaches its peak throughput already with batches exceeding 30 units.

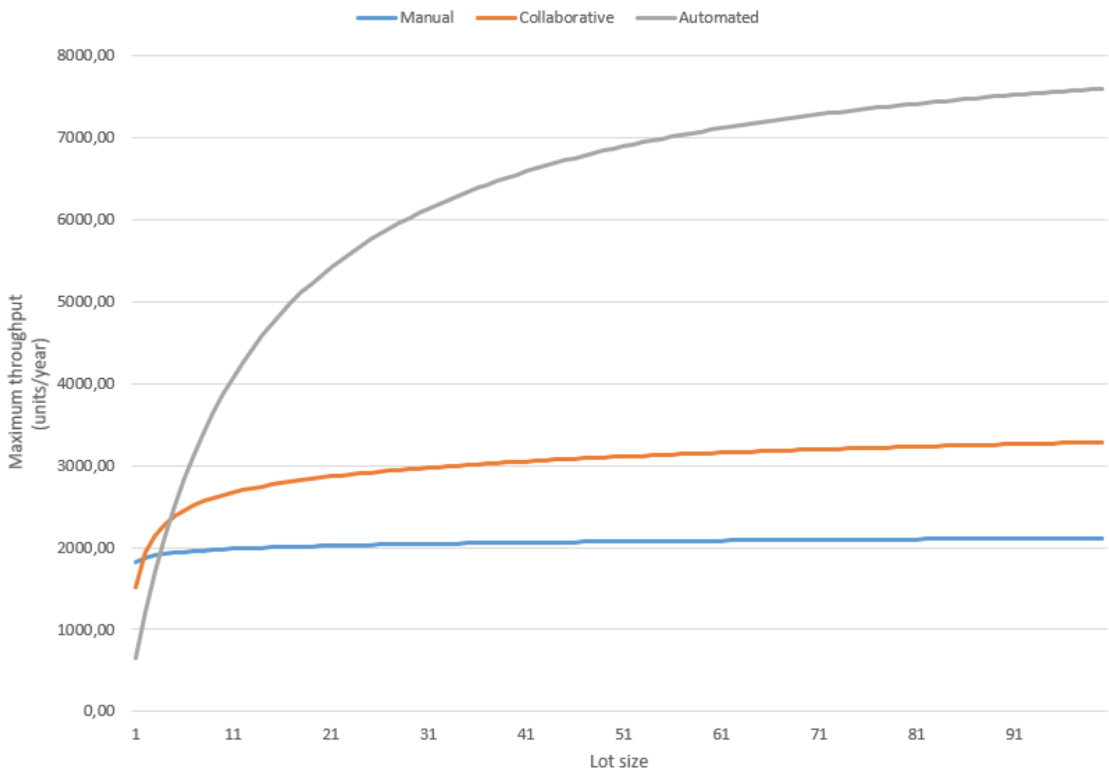


Figure 4.6. Productivity curves for different assembly configurations

The maximum annual throughput should be compared with the throughput required by the production system to ensure alignment between production capabilities and system demands, facilitating informed decision-making and optimal resource allocation:

$$Required\ throughput = \overline{N} \cdot L \tag{4.4}$$

where:

- $\overline{N}$ is the estimated lot size
- L is the estimated number of lots processed in a year

The i-th assembly configuration allows the required demand to be fulfilled, if the following condition is satisfied:

$$Required\ throughput < Maximum\ throughput \tag{4.5}$$

Where the maximum throughput is determined based on the chosen batch size and the type of assembly station used.

4.2.2 Production throughput analysis for multiple stations

When it comes to analyzing throughput for multiple stations, the approach adopted leans more towards being illustrative rather than strictly analytical. This choice is driven by the inherent challenge of accurately predefining the exact manner in which the setup time of each station will influence the overall throughput of the production line. In essence, the methodology prioritizes providing a visual representation or demonstration of the throughput dynamics, acknowledging the complexity involved in quantitatively predicting the impact of setup times on the system's performance.

To analyze the maximum throughput our production line can achieve, we look at two main things: the size of the batches we're working with and how many batches we assume we'll handle each year for our specific case. We then compare what we find using Flexsim software with what we've previously calculated as the required throughput. This helps us see if we're hitting the target we've set for our production line in terms of how much it should ideally produce. If we're not hitting that target, we can figure out where we might need to make improvements.

FlexSim is a 3D software used for 3D modeling and discrete event simulation. In our case study, two generic assembly stations were developed, subsequently made specific based on varying process times and setup times; a queue between the two assembly stations due to different production times; and a sink resource identifying the output of the line.

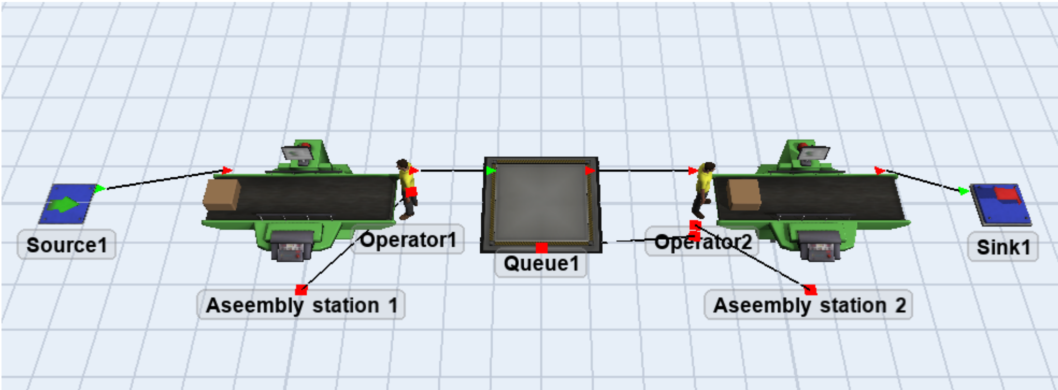


Figure 4.7. Software simulation [FlexSim]

The software furnishes the hourly throughput (th) of the production line, necessitating adjustment according to the data in the Table 4.8 to derive the yearly production volume. Subsequently, this maximum throughput of the production line is juxtaposed with the theoretically established required throughput. Should the latter fall short of the line's current annual production output, then the solution advocated by us is deemed satisfactory.

Parameters		manual	collaborative	automated
t_{ws}	[hour/session]	8	8	8
n_{ws}	[session/day]	2	2	2
e_{ws}	[day]	0,85	0,85	0,95
WD	working days	280	280	280

Figure 4.8. Annual work session data

4.2.3 Case study - application example

In conducting this assessment of throughput across multiple stations, we delve into the intricacies of our production dynamics. Here, we set our focus on an annual production scale, aiming to handle a total of L=150 batches throughout the year. Additionally, we pay close attention to the average size of each batch, which stands at $\overline{N}$=10 units. These parameters serve as foundational elements in our quest to understand and optimize the efficiency of our production processes across multiple stations. The required throughput so becomes:

$$Required\ throughput = \overline{N} \cdot L = 10 \cdot 150 = 1500\ [units/year] \tag{4.6}$$

Given that the average production batch size amounts to 10 units, we have carefully selected a configuration for our assembly line. This configuration entails the incorporation of two collaborative stations arranged sequentially. The rationale behind this decision lies in a thorough examination of cost curves, which has shed light on the most cost-effective approach to assembly.

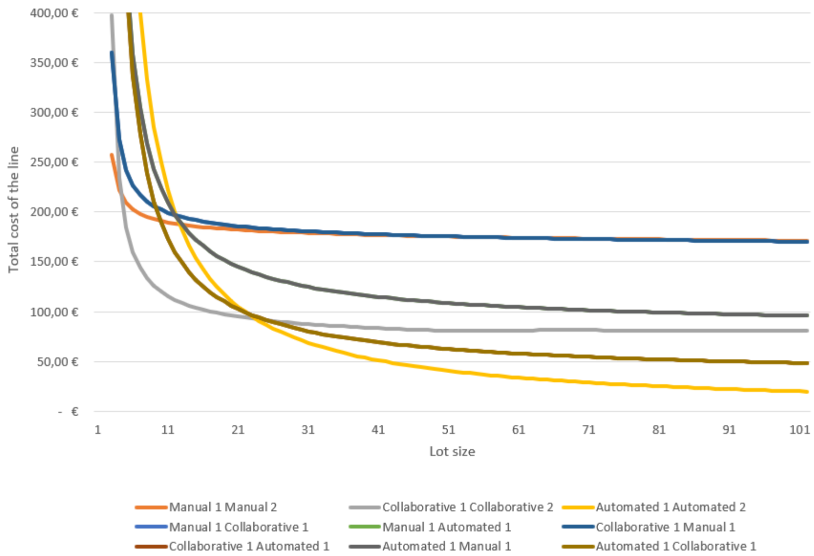


Figure 4.9. Total cost of the assembly line

By scrutinizing these curves, we have discerned that the arrangement featuring two collaborative stations in series offers the optimal balance between efficiency and cost-effectiveness. This strategic choice not only ensures the smooth flow of production but also serves to minimize assembly costs, ultimately contributing to the overall profitability and competitiveness of our operations.

The data used to implement the two collaborative stations in the software are those presented in the table.

Parameters		**collaborative 1**	**collaborative 2**
c_0	[€/hour]	30	30
$t_{(1)i}$	[hour]	1,5	1,8
θ_i		0,95	0,95
c_{si}	[€/hour]	30	30
T_{si}	[hour]	1	1,2
K_i	[€]	150.000 €	150.000 €
v_i	[years]	10	10
L	[lot/years]	150	150
RC_{TOT}	[€/year]	- €	- €
c_{di}	[€/unit]	100	100
φ_i		0,95	0,95
$d_{(1)i}$		0,03	0,02
$CW_{TOT\,MAX}$	[€/year]	2.000 €	2.000 €
γ_i		0,7	0,7

Figure 4.10. Two collaborative stations

By implementing the two stations on the software, various results useful for our analysis can be visualized on the dashboard.

The first data we analyze are the utilization rates of the stations. Following the release of the initial output from the production line, a closer examination reveals notable utilization patterns at both Station 1 and Station 2.
Station 1 exhibits a high utilization rate of 99.84%, indicating that the station

is nearly constantly occupied. This utilization is further broken down into two components: 52.79% attributed to processing activities and 47.06% to setup times. Conversely, Station 2 presents a lower utilization rate of 55.81%. Here, processing accounts for 24.14% of the utilization, while setup activities contribute 31.67%.

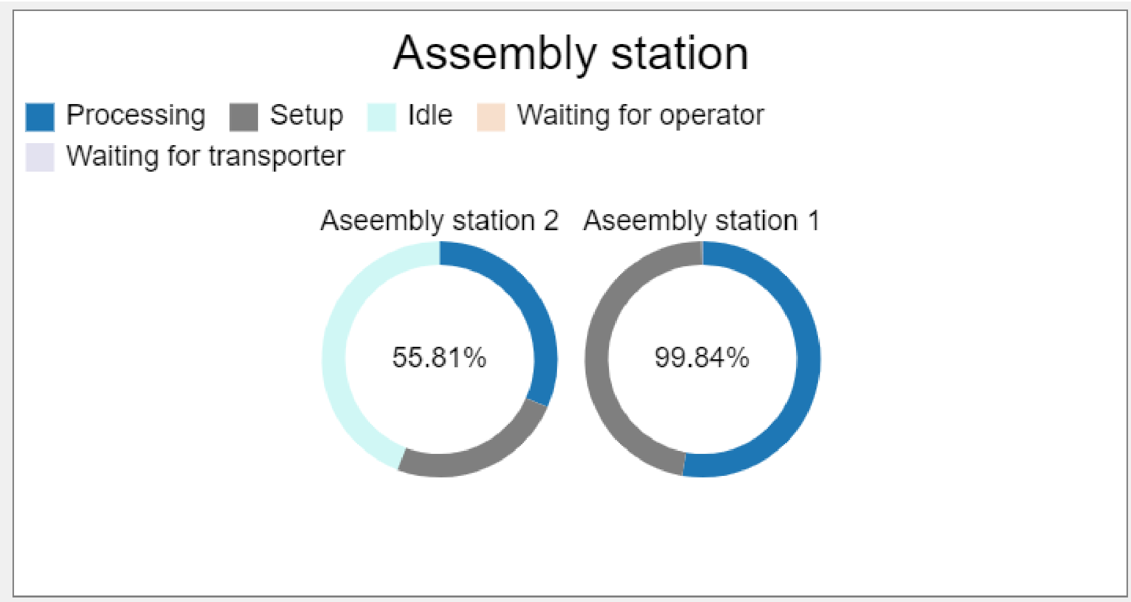


Figure 4.11. Utilization of two collaborative stations

Concerning the utilization of the queue situated between the two assembly stations, it's noteworthy to observe that after the initial cycle, its usage amounts to 8.81%. This relatively low utilization can be attributed to the variance in processing and setup times between the two stations.
The queue essentially acts as a buffer, accommodating any temporal disparities that may arise during the production process. This indicates that while the queue is indeed being utilized, its usage is not overly extensive at this stage.

This insight prompts further investigation into the dynamics of the assembly process and highlights the importance of synchronizing the activities of the two stations to minimize idle time and enhance overall efficiency.

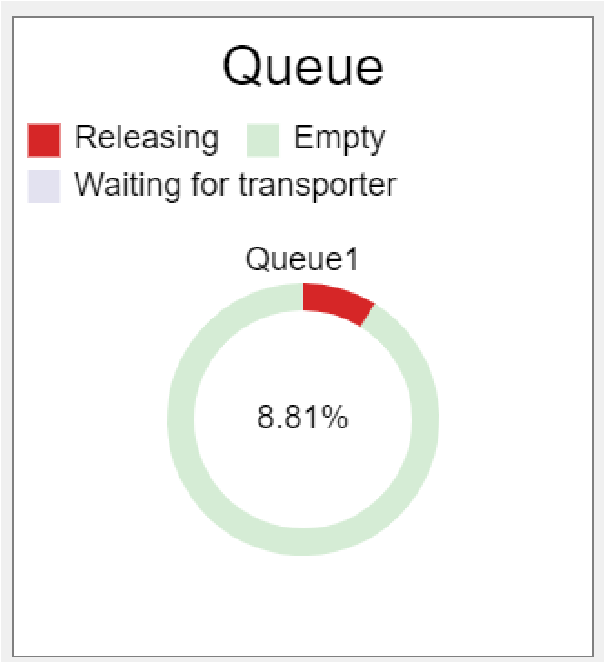


Figure 4.12. Queue between station 1 and station 2

Lastly, we can delve into the examination of the hourly output of the production line. When conducting the throughput analysis for a multi-station assembly line, the focal point of our investigation is the output recorded at the sink.This output encapsulates the cumulative result of the entire production process, reflecting the final outcome of the assembly line's operations. By scrutinizing the hourly output data from the sink, we gain valuable insights into the overall performance and efficiency of the production line.
The hourly output will need to be adjusted based on the data in Figure 4.8 in order to conduct the actual throughput analysis.

This analysis allows us to assess the effectiveness of our manufacturing processes, identify any potential bottlenecks or inefficiencies, and make informed decisions to optimize production throughput and enhance overall productivity.

Output / Hour

Object	Throughput
Sink1	4.22
Aseembly station 2	4.22
Aseembly station 1	8.45

Figure 4.13. Hourly output of a collaborative assembly line

The maximum throughput of the line is given by the following formula:

$$maximum\ throughput = \frac{t_{ws} \cdot e_{ws} \cdot n_{ws} \cdot WD}{output/hour} \tag{4.7}$$

Which then for our case study will become:

$$maximum\ throughput = \frac{8[hour/session] \cdot 0.85[day] \cdot 2[session/day] \cdot 280}{4.22[units/hour]} \tag{4.8}$$

$$maximum\ throughput = 902.37[units/year] \tag{4.9}$$

Once we have determined the maximum throughput of our assembly line, the next step is to compare it with the required throughput, which is dictated by the demand for our products. This comparison serves as a pivotal assessment to evaluate whether our production capabilities align with the needs of our customers.

If the maximum throughput exceeds the required throughput, it suggests that our production capacity surpasses demand, potentially leading to surplus inventory or underutilization of resources. On the other hand, if the required throughput exceeds the maximum throughput, it indicates a shortfall in our production capacity to meet customer demand, highlighting the need for adjustments or enhancements in our manufacturing processes.
By conducting this comparison, we gain valuable insights into the alignment between our production capabilities and market demand, enabling us to make informed decisions to optimize our operations and meet customer needs effectively.

The required throughput, as calculated earlier, stands at 1500 [units/year], surpassing the maximum throughput of the production line being evaluated. This observation leads us to a significant inference: while the chosen collaborative assembly line configuration proves cost-effective for the specified lot size, it falls short in meeting production demands.

Despite its efficiency in cost optimization, its inability to meet the required throughput underscores a critical misalignment between production capacity and market demand. This discrepancy prompts a deeper examination of our manufacturing processes and underscores the importance of ensuring that our production capabilities are sufficiently aligned with customer needs. Addressing this disparity may entail reevaluating our production strategies, exploring alternative assembly line configurations, or implementing process improvements to enhance efficiency and productivity.

Ultimately, the goal is to strike a delicate balance between cost optimization and meeting customer demand, ensuring the overall sustainability and competitiveness of our operations.

Chapter 5

Stellantis case study

The primary objective of this thesis was to showcase, through a tangible case study, the practical application of a cost model within two manufacturing facilities belonging to Stellantis. The purpose was to illustrate how various factors within the production process can influence the strategic choices made when deploying technology in assembly processes.

5.1 Melfi Plant

The first plant under analysis is Melfi, formerly known as SATA (an acronym for SocietÃ Automobilistica Tecnologie Avanzate S.p.A.). It serves as both a production site and an industrial complex within the FCA Italy group, now controlled by the multinational Stellantis. Presently, this facility is responsible for manufacturing the Jeep Renegade, Jeep Compass, and Fiat 500X.

In order to conduct the analysis utilizing the cost model that we've developed earlier, we take a closer look at two consecutive stations at a time to assess how efficiently they operate considering the different technological advancements they incorporate.

The initial examination focuses on two specific stations: one operated manually and the other in collaboration with technology.
The manual station requires human labor for assembling the left front door panel. On the other hand, the collaborative station integrates tasks such as reading traceability labels, a task performed by a cobot (a collaborative robot), along with the preparation of the rear crossmember, which is managed by an operator.

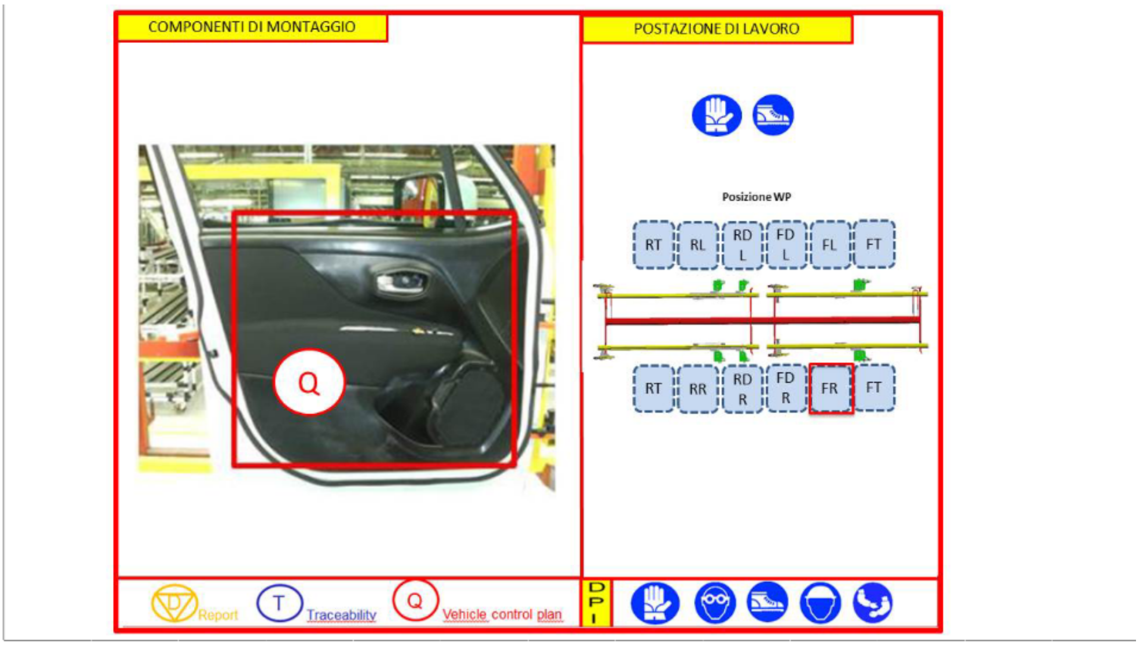


TABELLA ATTREZZATURE

ATTREZZATURA	Peso (kg.)	Prelievo/deposito	Braccio (mm)	Coppia di chiusura (Nm)
Martello in gomma		marsupio		
Marsupio con porta martello				

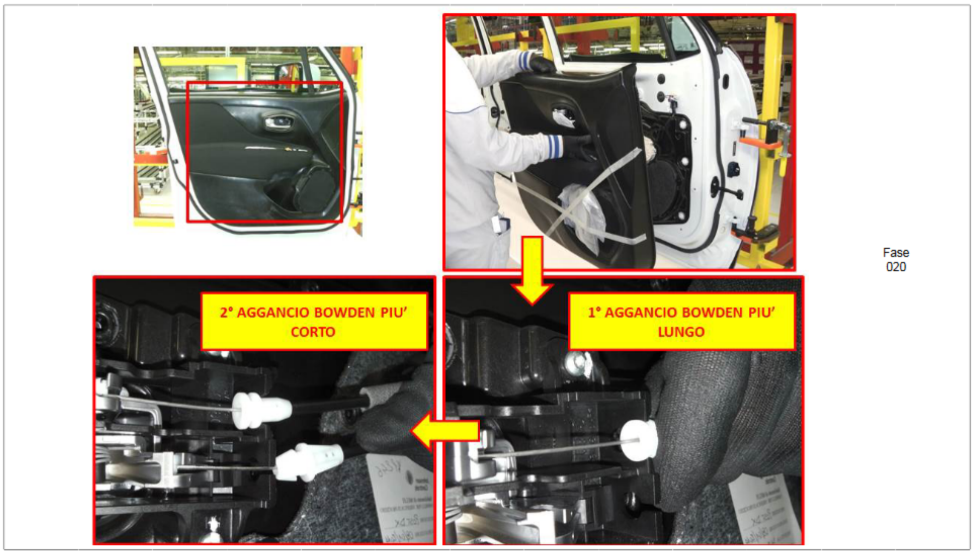
DPI

Codice	Descrizione	Note
DPI001	Calzature Di Sicurezza	
DPI002	Guanti Protettivi	

TABELLA UAS

COMPONENTE	PESO (KG.)	FORZA INSER. (N)	Ingombro:SI SE 1 lato>80 Cm SE lato>30 Cm	Presa da contenitore (cm)	Distanza da contenitore (m)
PANNELLO	3.100	NO	SI	45	1

Figure 5.1. Operational card for manual labor in assembling the left front door panel



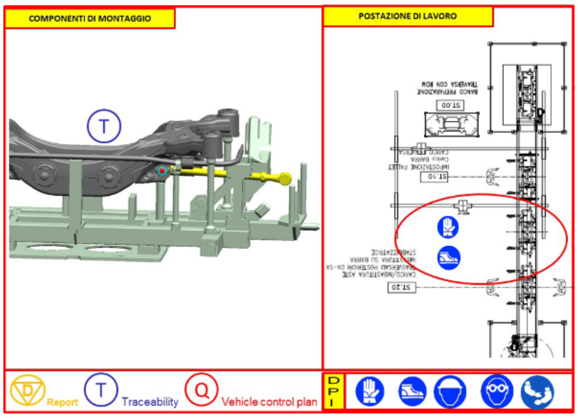
FASE 020			
Richiamo elemento		Descrizione	MES
020		• Disporsi a bordo carrello elementi sequenziati, leggere la prima sequenza per verificare la corretta corrispondenza tra pannello e la sequenza vettura, operazione da effettuare ad ogni cambio carrello, il carrello sequenziato è composto da n° 24 elementi. • Prelevare manualmente da cassone lato linea, n.1 pannello porta anteriore sx. • Accostare il pannello vicino all'ossatura porta zona superiore. • Trattenere il pannello con mano sx e con mano dx individua da carrier zona superiore N° 2 cavi bowden rimando maniglia. • Prelevare il bowden piu' lungo ed inseriscilo al rimando maniglia e successivamente agganciare mediante pressione manuale al supportino. • Prelevare il bowden piu' corto fare passare al disotto del bowden lungo ed inserire al rimando maniglia e successivamente agganciare al supportino.	

Figure 5.2. Operational card for manual labor in assembling the left front door panel

FASE 030			
Richiamo elemento		Descrizione	MES
030		• Prelevare N° 2 briglie per collegamento mostrina alzacristallo e farle fuoriuscire attraverso il foro del pannello posto su zona centrale.	

Figure 5.3. Operational card for manual labor in assembling the left front door panel

The second collaborative station has the following operational card.



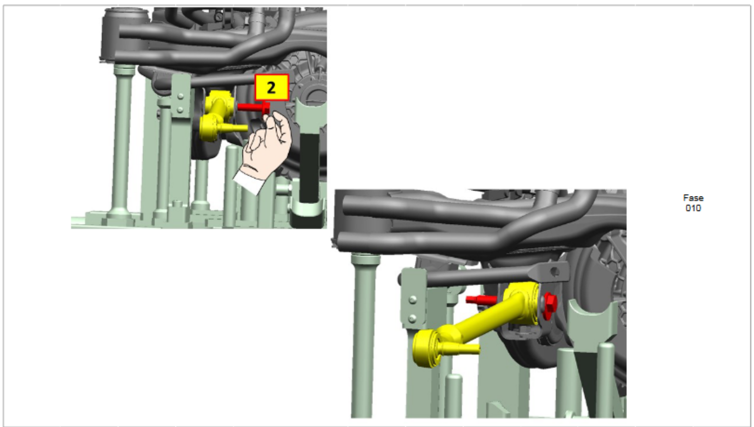
DPI

Codice	Descrizione	Note
DPI001	Calzature Di Sicurezza	
DPI002	Guanti Protettivi	

TABELLA UAS

COMPONENTE	PESO (KG.)	FORZA INSER. (N)	Ingombro:SI SE 1 lato>80 Cm SE lato>30 Cm	Presa da contenitore (cm)	Distanza da contenitore (m)
ASTA TRASVERSALE POSTER. P. SOSP. POST.	1,400	SI		0,50	1

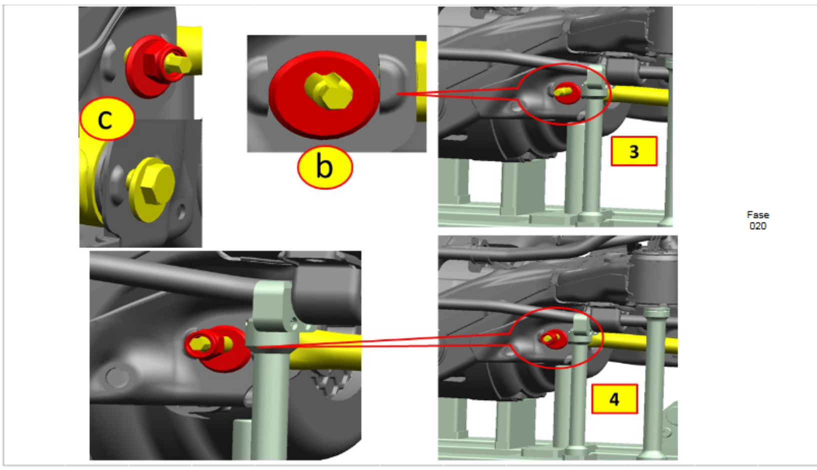
Figure 5.4. Operational card for preparation of the rear crossmember



FASE 010			
Richiamo elemento		Descrizione	MES
010		• Prelevare asta posteriore DX da contenitore sequenziato in postazione. • Prelevare da cassetta sul sag a lato linea n.1 vite fissaggio braccio oscillante a telaio. • Inserire asta dx mediante pressione manuale dal lato esterno dx verso sx fino a inserimento della boccola del braccio oscillante all'interno dello scatolato del telaio. (rif. 1) • Eseguire allineamento fori di fissaggio telaio con boccola braccio oscillante (Rif.a). • Inserire n.1 vite in apposito foro di fissaggio su telaio dall'interno verso l'esterno (Rif.2).	

ELENCO CONSUMED FASE 010					
Matricola	Descrizione	Fiat Part Number	Quantita'	A/E	Caratterizzazione
E57892	VITE(SPECIALE) - M12 X 1.75	52008200		1	TUTTI I TIPI
E57802	ASTA COMPL. POST.SOSP.POST.	52173142		2	ELTPHEV+,TTEAWD+

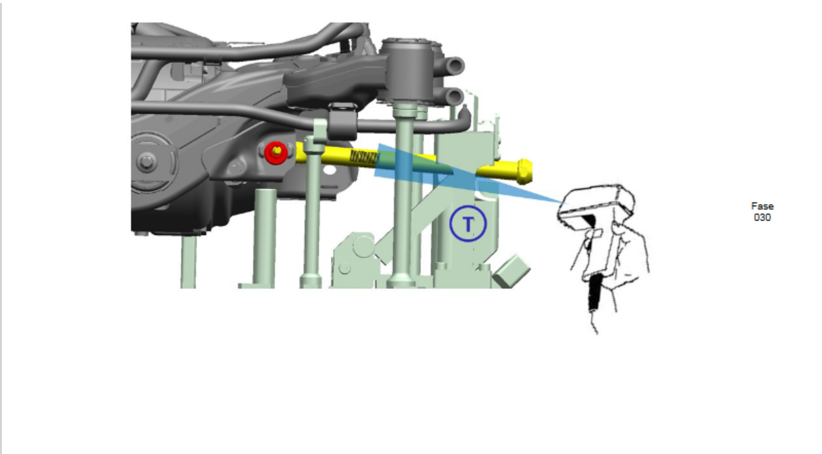
Figure 5.5. Operational card for preparation of the rear crossmember



FASE 020			
Richiamo elemento		Descrizione	MES
020		• Prelevare da cassetta sul sag a lato linea n.1 rondella eccentrica e n.1 dado fissaggio braccio oscillante a telaio, inserire n.1 rondella eccentrica sulla vite (Rif.3) rispettando l'oggettivazione della rondella con quella del perno scanalato (rif. b) . • Imbastire manualmente n.1 dado sulla vite precedentemente inserita (Rif.4) per almeno 2-3 giri di filetto rilascia l'asta su appositi riferimenti pallet. • Verificare che la rondella eccentrica della vite e la rondella eccentrica interposta al dado non siano inserite negli spallamenti presenti sul telaio per consentire il recupero giochi (rif. c).	

ELENCO CONSUMED FASE 020					
Matricola	Descrizione	Fiat Part Number	Quantita'	A/E	Caratterizzazione
E57892	DADO - - -	52008204		1	TUTTI I TIPI
E57892	RONDELLA - ECCENTRICA	52002833		1	TUTTI I TIPI

Figure 5.6. Operational card for preparation of the rear crossmember



FASE 030			
Richiamo elemento		Descrizione	MES
030	T	Quality control: Asta trasversale dx sospensione posteriore : Traceability e verifica congruenza | ELTPHEV: • In automatico , in stazione con robot collaborativo, viene eseguita la lettura del codice a barre del componente Asta posteriore DX In caso di avaria della stazione automatica l'operatore deve eseguire la lettura del codice a barre del componente come fase di Back-up sotto descritta: • Prelevare da supporto a lato linea lettore datamatrix. • Effettuare lettura codice su asta sx, visualizzare visivamente il monitor a lato linea per l'avvenuta corretta operazione. • Deporre lettore sul supporto a lato linea.	TRC

ELENCO ATTREZZATURE/IMPIANTI FASE 030				
Codice SAP	Oggetti	Codice/Descrizione	Impiego	Quantita'
	071120121638 - Lettore bar code	LETTORE BAR CODE		1

Figure 5.7. Operational card for reading traceability labels

The second analysis pertains to the following segment of the production line. Resuming from the collaborative station, we move on to the next one, which is entirely automated. Here, the focus is on the assembly of rods GOMA links, where a robot secures each side in place.

The third automated station has the following operational card.

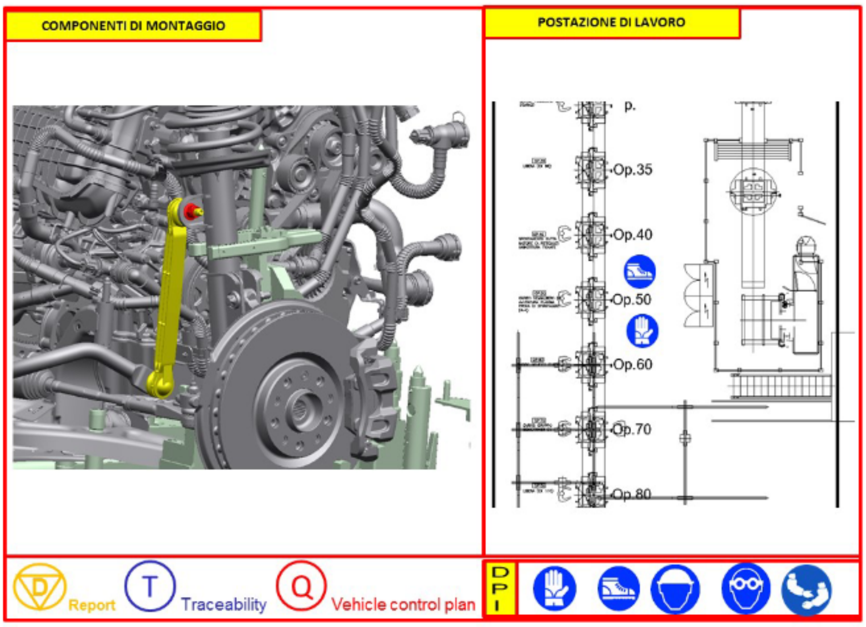


TABELLA UAS

COMPONENTE	PESO (KG.)	FORZA INSER. (N)	Ingombro:SI SE 1 lato>80 Cm SE lato>30 Cm	Presa da contenitore (cm)	Distanza da contenitore (m)
DADI FISS. BIELLETTA	<0,100	xx	NO	45	1

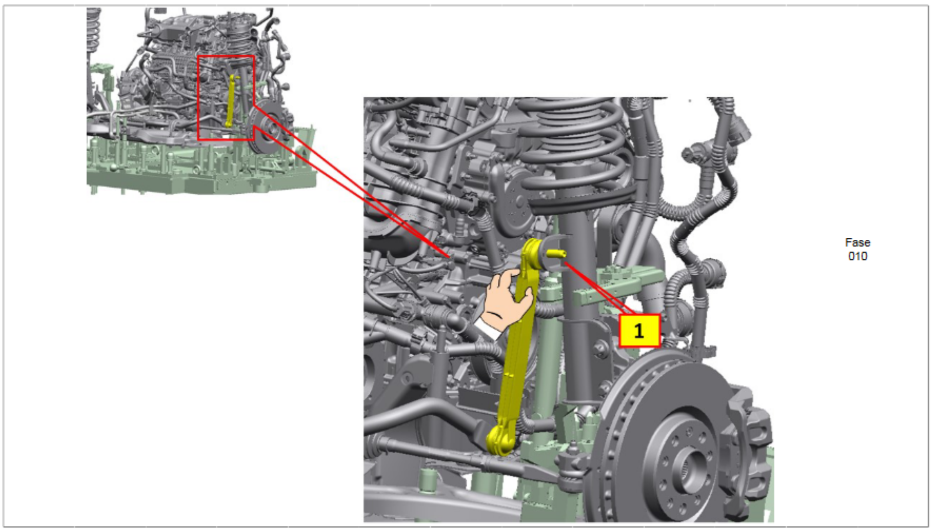
DPI

Codice	Descrizione	Note
DPI001	Calzature Di Sicurezza	
DPI002	Guanti Protettivi	

TABELLA ATTREZZATURA

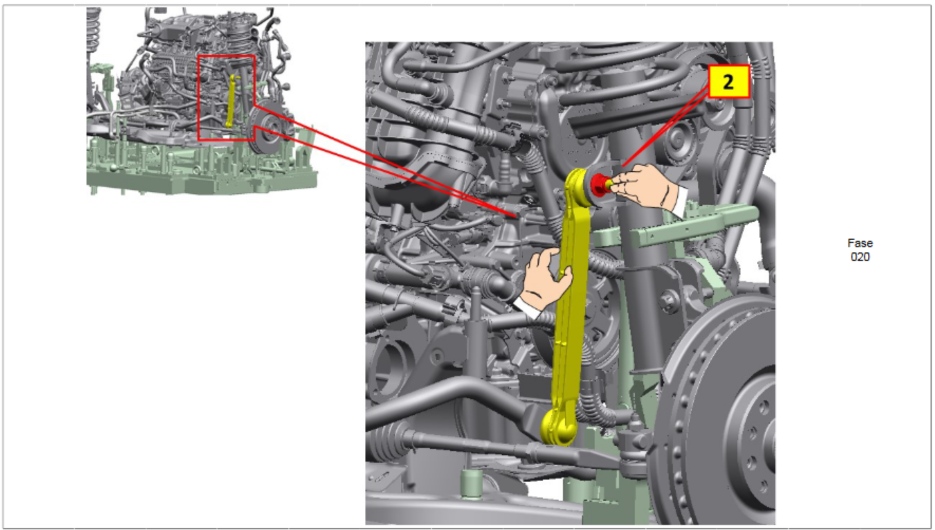
ATTREZZATURA	Peso (kg.)	Prelievo/deposito	Braccio (mm)	Coppia di chiusura (Nm)
ETD ST61-90-13-T25-AVVITATORE A CONTROLLO DI COPPIA ELETTRICO SU BRACCIO DI REAZIONE	ND	45	ND	80
BUSSOLA 18mm				

Figure 5.8. Operational card for assembly rods



FASE 010			
Richiamo elemento		Descrizione	MES
010		• Posizionare testa bielletta e piazzare il perno filettato della bielletta nel foro sulla staffa ammortizzatore DX (rif. 1)mediante orientamento della testina bielletta.	

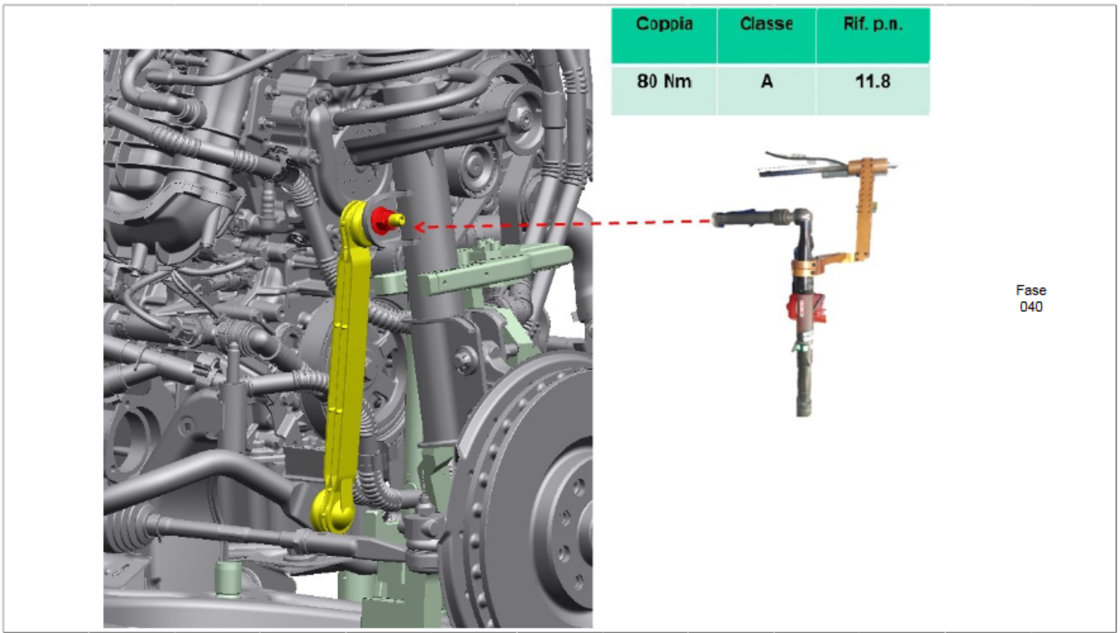
Figure 5.9. Operational card for assembly rods



FASE 020			
Richiamo elemento		Descrizione	MES
020		• Disporsi a lato linea • Prelevare da scatolo sul sag n. 1 dado fissaggio bielletta ad ammortizzatore e ridisporsi a pallet • Eseguire imbastitura manuale di n. 1 dado sul perno filettato della bielletta per almeno n. 2 giri di filetto (rif. 2). OPERAZIONE PERIODICA: ogni n. 250 dadi consumati, cestinare scatolo cartone vuoto in contenitore rifiuti a lato linea • Prelevare da sag a lato linea scatolo dadi nuovo e posizionare scatolo sul dolly.	

ELENCO CONSUMED FASE 020					
Matricola	Descrizione	Fiat Part Number	Quantita'	A/E	Caratterizzazione
E564509	DADO SPECIALE	52008203		1	TUTTI I TIPI

Figure 5.10. Operational card for assembly rods



FASE 040			
Richiamo elemento		Descrizione	MES
040		• Operazione da eseguire in caso di Back-up per mancato funzionamento stazione automatica o scarto stazione automatica: • Prelevare da lato linea avvitatore elettronico su braccio di reazione con relativa bussola specifica e ridisporsi a pallet • Eseguire fissaggio definitivo del dado bielletta ad ammortizzatore alla coppia di 80 Nm Cl A - rif. Norma TN-20002_5600 Rif. Punto Norma 11.8 • Visualizzare accensione LED VERDE su avvitatore per corretta operazione eseguita. • Portare a lato linea avvitatore elettronico con braccio articolato e ridisporsi a pallet. N.B. Nel caso l'avvitatura è KO il led è rosso e l'avvitatore passa allo stato in cui è consentito solo svitare, prendi il dado e rottamalo nella cassetta di scarto, preleva dado nuovo per imbastirlo, ed esegui serraggio a coppia prevista a norma.	

ELENCO ATTREZZATURE/IMPIANTI FASE 040				
Codice SAP	Oggetti	Codice/Descrizione	Impiego	Quantita'
	ETD ST61-90-13-T25-AVVITATORE A CONTROLLO DI COPPIA ELETTRICO SU BRACCIO DI REAZIONE	AVVITATORE A CONTROLLO DI COPPIA ELETTRICO SU BRACCIO DI REAZIONE		1
	BUS-3/8-18	BUSSOLA Q. 3/8" ES. 18		1

Figure 5.11. Operational card for assembly rods

The Melfi assembly line operates based on a predetermined cycle time of 1 minute. Considering a target output of 60 pieces per day, working for 21 hours daily across three shifts, and accounting for 235 working days in a year, the subsequent analyses have produced the following outcomes:

Parameters		manual station	collaborative station
c_0	[€/hour]	27,36	27,36
$t_{(1)i}$	[hour]	0,0167	0,0167
θ_i		0,98	0,95
c_{si}	[€/hour]	0	0
T_{si}	[hour]	0	0
K_i	[€]	- €	25.000 €
v_i	[years]	6	6
L	[lot/years]	5000	5000
RC_{TOT}	[€/year]	- €	- €
c_{di}	[€/unit]	100,00	100,00
φ_i		0,97	0,95
$d_{(1)i}$		0	0,06
$CW_{TOT\ MAX}$	[€/year]	2.000 €	2.000 €
γ_i		1	0,7

Figure 5.12. Manual + Collaborative stations input data

Parameters		collaborative station	automated station
c_0	[€/hour]	27,36	0
$t_{(1)i}$	[hour]	0,01667	0,01667
θ_i		0,95	1
c_{si}	[€/hour]	- €	- €
T_{si}	[hour]	0	0
K_i	[€]	25.000 €	125.000 €
v_i	[years]	6	6
L	[lot/years]	5000	5000
RC_{TOT}	[€/year]	- €	- €
c_{di}	[€/unit]	100	100
φ_i		0,95	0,99
$d_{(1)i}$		0,06	0,03
$CW_{TOT\ MAX}$	[€/year]	2.000 €	2.000 €
γ_i		0,7	0

Figure 5.13. Collaborative + Automated stations input data

When we analyze the situation with a fixed lot size of L=5000 lots per year, several key insights emerge. For lot sizes smaller than 15 units, it becomes evident that the optimal strategy for cost efficiency involves a combination of manual and collaborative stations in the assembly process. However, as lot sizes grow larger, the dynamics shift accordingly.
In these cases, it becomes more advantageous to lean towards a predominantly automated assembly setup, which integrates both collaborative and automatic stations. This transition underscores the potential advantages of embracing automation, particularly in larger-scale production settings, where the pursuit of efficiency gains and cost optimization becomes increasingly paramount.

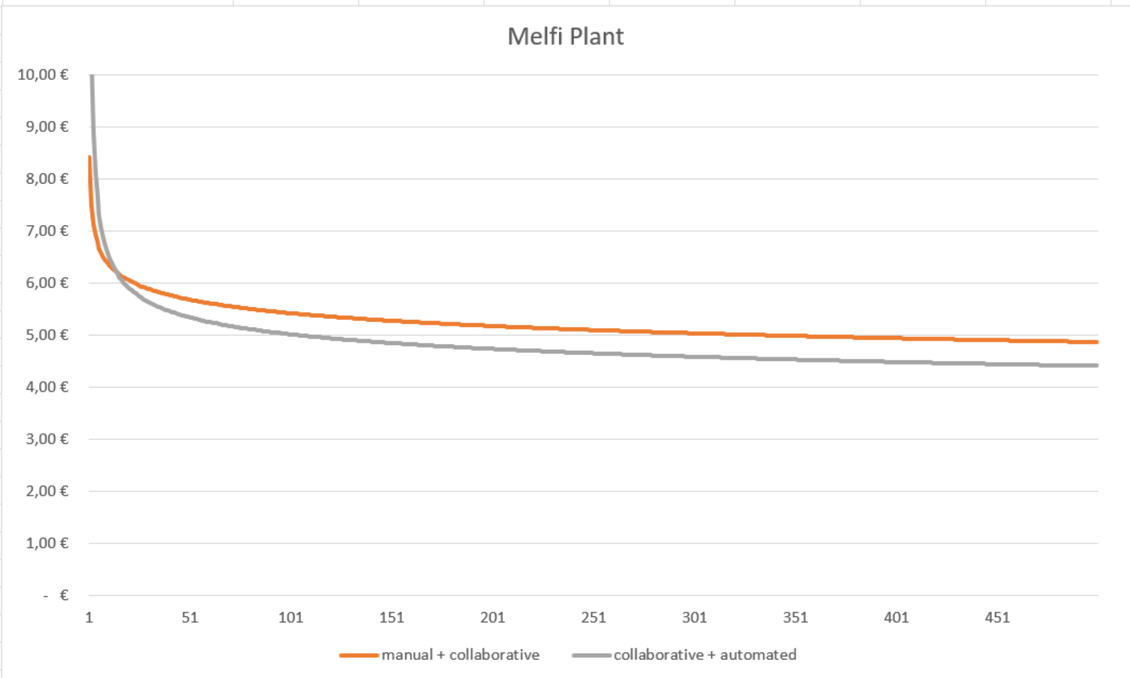


Figure 5.14. Cost curves for Melfi Plant

5.2 Mirafiori Plant

Similar to the approach taken with the Melfi plant, we will now delve into examining a segment of the production line at Mirafiori, which comprises three stations. Unlike the setup at Melfi, however, the operations at Mirafiori are confined to a single shift, and there isn't a predetermined cycle time governing the entire production line.

The three stations under analysis are:

- Homologation VIN labels: At this manual station, there's a printer dedicated to producing homologation labels tailored for the specific markets across various regions where the cars are destined to be shipped. These labels are then carefully affixed to different areas of the vehicle body, including the electric motor, engine hood, and bumper. Each label is crucial as it contains the vehicle identification number (VIN), ensuring that every car has its unique identifier, making them distinguishable from one another.

- Marriage: this station is a fully automated stage where the mechanical components of the vehicle, including the electric motor, battery, and two axles, come together with the vehicle chassis. This union between the two components is achieved through the fastening action carried out by screwdrivers controlled by two fully automated carts.

- Fluid Filling Plant Startup: This station serves as a collaborative workspace within the fluid filling area. It's where vehicles are filled with various fluids essential for operation during the shift, including brake fluid, windshield washer fluid, engine coolant, and air conditioning gas. Unlike fully automated setups, this station operates semi-automatically, utilizing both a cobot system and a human operator. Each morning before the shift begins, a startup routine is performed to prepare the system. This involves warming up the equipment, purging the lines, and ensuring that all plant parameters, such as temperature, flow rate, and sensor readings, are within the correct operational ranges.

We begin our analysis by examining the first two stations in sequence along the production line. The initial station is manual, followed by a collaborative station. Moving further down the line, we encounter a succession of collaborative stations before reaching an automatic one.
The input data used for this analysis are as follows:

Parameters		manual station	collaborative station
c_0	[€/hour]	0,86	0,00
$t_{(1)i}$	[hour]	0,031	1
θ_i		0,98	0,95
c_{si}	[€/hour]	0	38,64
T_{si}	[hour]	0	0,5
K_i	[€]	- €	- €
v_i	[years]	5	5
L	[lot/years]	5000	5000
RC_{TOT}	[€/year]	- €	- €
c_{di}	[€/unit]	0,35	70,00
φ_i		0,97	0,95
$d_{(1)i}$		0,007	0,25
$CW_{TOT\ MAX}$	[€/year]	2.000 €	2.000 €
γ_i		1	0,7

Figure 5.15. Manual + Collaborative stations input data

Parameters		collaborative station	automated station
c_0	[€/hour]	0,00	0,97
$t_{(1)i}$	[hour]	1	0,028
θ_i		0,95	0,95
c_{si}	[€/hour]	38,64	0
T_{si}	[hour]	0,5	0
K_i	[€]	- €	300.000 €
v_i	[years]	5	5
L	[lot/years]	5000	5000
RC_{TOT}	[€/year]	- €	- €
c_{di}	[€/unit]	70,00	0,20
φ_i		0,95	0,99
$d_{(1)i}$		0,25	0,008
$CW_{TOT\ MAX}$	[€/year]	2.000 €	2.000 €
γ_i		0,7	0,7

Figure 5.16. Collaborative + Automated stations input data

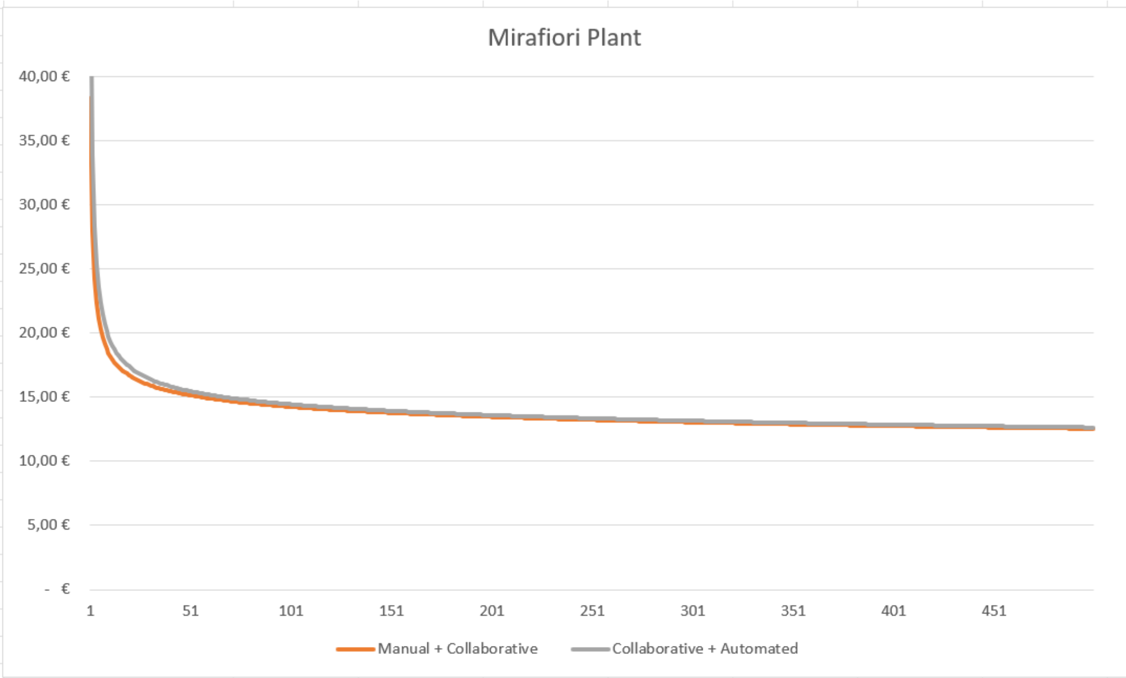


Figure 5.17. Cost curves for Mirafiori Plant

In contrast to the Melfi plant, it's evident that when cycle times aren't defined for the entire line, opting for automation in assembly lines is consistently preferable over relying mainly on manual processes, even when dealing with small production batch sizes.

Chapter 6

Conclusion

This thesis embarked on a comprehensive exploration of the integration of collaborative robots (cobots) within assembly lines, particularly focusing on the automotive industry, represented by the case studies of Stellantis' Melfi and Mirafiori plants. Through the development of a general cost model, the study systematically assessed various configurations of manual, collaborative, and automated assembly processes. Key findings include the economic efficiency of cobots, their impact on worker well-being, improvements in quality and throughput, and the adaptability and learning curve associated with their deployment.

The findings of this thesis carry profound implications for the manufacturing sector. Manufacturers should consider cobots as a viable solution for optimizing production lines, especially where flexibility and rapid adaptation to changing market demands are critical. Emphasizing the development of ergonomic and intuitive interfaces can further harness the potential of human-cobot collaboration, optimizing production efficiency and worker satisfaction. The study advocates for enhanced industry standards and policies that facilitate the integration of cobots into manufacturing systems, ensuring safety, interoperability, and efficiency.

While this study offers valuable insights into cobot integration in manufacturing, several limitations warrant further investigation. Future research could explore the application of the developed cost model across different industries to validate its universality and adaptability. An in-depth analysis of the long-term economic implications of cobot integration, including return on investment and total cost of ownership, would provide a more comprehensive understanding. As cobot technology continues to evolve, future studies should examine the impact of technological advancements on cobot capabilities and the corresponding training needs of the workforce.

The integration of collaborative robots into assembly lines represents a paradigm shift towards more flexible, efficient, and human-centric manufacturing processes. This thesis has laid a foundational framework for assessing cobot implementation in manufacturing, offering valuable insights for industry practitioners and paving the way for future research in this burgeoning field.

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