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Digital Twin Application for Dynamic Speed Regulation in Collaborative Robots

Supervisor:
Bruno Giulia

Candidate:
Casaletto Pierpaolo

Abstract:

This thesis explores the potentialities deriving from the integration of Digital Twin (DT) technology with collaborative robots (cobots) in manufacturing framework, focusing on the energy consumption optimization, improving operational efficiency and economic profitability. Digital Twin, the virtual representation of physical systems made possible by a continuous exchange of data, allows for real-time data monitoring and collateral adjustment based on a continuous performance evaluation, facilitating the dynamic adaptation of cobots based on real-world conditions. This approach is helpful for manufacturers who increasingly aim to balance productivity with sustainability goals.

The study comes from the recent evolution and implementation of the Digital Twin technology in the manufacturing field. This evolution also addresses key challenges for further development, including the lack of standardization and the complexity of integrating real-time data into virtual models. Moving from this point, this research examines the role and the possible interaction of collaborative robots, contrasting them with traditional industrial robots. Unlike conventional robots, cobots are designed to collaborate safely with humans, enhancing flexibility and enabling dynamic responses to changes in production demands. From a social point of view, this would allow humans to have a key role in the process, defining a new anthropocentrism, based on a strict relationship between the human and the machine.

While taking up a critical vision, this thesis explores potential integration of cobots and Digital Twin technology, assuming the hypothesis of a more efficient energy management in the full process. In fact, mirroring cobots in a virtual environment, real-time adjustments can be made to their operating parameters, optimizing energy consumption based on factors such as payload and changes in dynamic parameters. The study provides a detailed case study conducted at Mind4Lab of Politecnico di Torino, where simulations using the FlexSim software were employed to assess different energy optimization strategies, as the dynamic speed regulation. This case study serves as a practical example of how Digital Twin and cobots can work together to reduce energy usage, starting from a strict comparison with the data gathered in a Digital Shadow framework without the intervention of the virtual workspace.

Presenting the results of various simulation scenarios, the research wants first to evaluate the energy consumption across different speed settings for cobots, revealing the optimal conditions for balancing speed and energy use, while demonstrating that dynamic speed regulation can significantly enhance energy efficiency, without renouncing to the productivity dimension.

Therefore, this work is an opportunity to emphasize the potentiality of integrating Digital Twin with cobots as a pathway to achieve both operational and sustainability objectives in modern manufacturing. By leveraging advanced simulation techniques and real-time data integration, this thesis contributes to the growing body of research focused on sustainable industrial automation, offering a framework for future developments in energy-efficient collaborative robotics.

1. Introduction

In recent years, the adoption of collaborative robots (cobots) has reshaped industrial automation by allowing human operators and machines to interact in synergy. Differently from traditional industrial robots, typically segregated from human workers through cages or other delimitations due to safety concerns and operational hazards, cobots are designed to collaborate with humans in shared workspaces, offering increased flexibility, adaptability, and safety. The possibility to work side by side with human operators is granted thanks to the presence of advanced sensors along the body of the collaborative robots and the possibility to integrate them with AI-driven control systems, and adaptive algorithms. The augment in adoption of collaborative robots in manufacturing context marks a turning point towards a more human-centric and collaborative manufacturing, where robots complement and enhance human capabilities, giving them the possibility to perform high-value activities only, rather than just replacing them in tedious and not added value tasks.

In a world where the customers' demand for products varies frequently, based on new trends and new discoveries, and the research by customers for personalized products is arising, the adoption of cobots may respond to these issues, since it represents the right instrument to be applied for its dynamicity offering unprecedented levels of adaptability to changing production demands. In fact, unlike traditional robotics where a change in demands require a significative change in the layout of the machines and even in the programming phase, among the key features of the collaborative robots emerge the easiness of programming and the adaptability, which make them flexible to every change. Their ability to be easily reprogrammed and adapted for different tasks makes them suitable for small and medium-sized enterprises (SMEs) that require agility in their production processes. Furthermore, cobots are often designed with user-friendly interfaces that allow operators with little or no programming experience to set up and operate them through the interaction with a screen, called teach pendant. In this way, even the need for skilled employees suitable to manage industrial robotics which require programming skills may be overcome.

However, related to the advancement of the adoption of collaborative robots in manufacturing, a new challenge arises: managing energy consumption effectively, meeting simultaneously both the operational efficiency and the sustainability goals.

After 2015, when the United Nations established the set of seventeen global goals aimed at promoting sustainable development by 2030, the attention towards efficiency in resource usage has increased. Referring to the *goal #9,* a series of initiatives have been promoted so far for minimizing the environmental impact of the technological progress, focusing on the reduction of CO_2 emissions and a better usage of resources. The *goal #12*, instead, poses greater attention to promoting resource and energy efficiency across all industries.

The impact of industrial robotics and automation machines in terms of energy consumption is disruptive, since more than 70% of the total power consumption in manufacturing industry is accountable to them. [11]

The optimization of energy consumption in collaborative robots is a critical area of research that holds significant potential for improving the sustainability and cost-effectiveness of industrial automation. Energy costs contribute significantly to the total operating costs of manufacturing facilities, and inefficiencies in energy usage can lead to higher production costs, lower profit margins, and negative environmental impacts. The rising costs of energy and the increasing emphasis on reducing carbon footprints are driving companies to seek innovative ways to enhance energy efficiency and collaborative robots may represent one of the viable solutions, despite the high number of limitations they still have. Among the crucial limitations regarding their possible applications, it is important to mention the lower payload collaborative robots are able to carry on with respect to the traditional robotics, and in addition even the constraint on the throughput, thus cobots are more indicated for low-volume production requiring high levels of precision and customization.

Several are the techniques which may be applied to optimize the energy consumption of cobots, including *efficient motion planning* and *adaptive control system*.

Concerning *efficient motion planning* strategy, cobots can lower the time and energy required to complete tasks, minimizing useless movement, and optimizing trajectories, reducing the number of excessive accelerations and decelerations, and selecting energy-efficient routes. While adaptive control system can dynamically adjust the cobot's operating parameters based on real-time conditions. This allows the cobot to operate at optimal efficiency, reducing energy consumption during periods of low demand and increasing it when higher performances are required.

To adopt adaptive control system strategy, a connection of the cobot to a Digital Twin is required to collect and monitor real-time data and make predictions about potential future patterns. Thanks to Digital Twin is possible to develop real-time model able to gather data from the real environment, transfer them to the virtual world and through the elaboration of the real-time data with the historical ones, make the cobots to align to the instructions given by the Digital Twin.

This thesis aims to explore the various techniques for optimizing the energy consumption of collaborative robots. The objective of this thesis is to find a right trade-off among processing speed and energy consumption, dealing with the fact that, as every form of automation, cobots consume energy in both the states of processing and idle, hence it would not be optimal to have always a low speed to try to compensate decreasing the idle state time interval, but in the meantime, frequent variations of speed may result in additional energy consumption. Understanding the relationship between task requirements and energy consumption is essential for developing effective optimization strategies. After a deep research phase about the actual framework of collaborative robots, in which the research gap of the missing of a model which analyse the possible correlation among processing speed and energy consumption, this thesis tries to catch the optimal speed to obtain the lowest energy consumption possible, considering the possibility of speed variations due to machine failures or change in the interarrival rate at the source. The proposed model is an example of *efficient motion planning* which seeks to minimize the energy required to execute a given task by optimizing the robot's path, velocity, and acceleration. To adopt such a model, the introduction of Digital Twin is mandatory since it is required to transfer real-time data for monitoring performance metrics, including energy consumption and make the model responsive to any possible above-mentioned changes.

Furthermore, the study will focus on the sustainability impact of the case study conducted, not only in terms of dissipated power, representing for every scenario analysed how different payloads and different speeds influence the impact on the environment.

2. Digital Twin

2.1 Historical Background, Key Definitions and Applications

The advent of digital twin technology marks a turning point in the realm of digitalization and data integration, profoundly impacting diverse industries from manufacturing to healthcare.

In manufacturing, Digital Twins facilitates the construction of virtual factories which can be monitored and optimized remotely, reducing downtime, predicting potential future faults, and enhancing the productivity based on the usage and analysis of historical data.

The origin of digital twin needs to be researched in the 1960s when the NASA pioneered the idea of examining a physical object using a digital twin. [21] During NASA's Apollo 13 space mission, two identical space vehicles were built so that the space vehicle on earth can mirror, simulate, and predict the conditions of the other one in space. The vehicle that remained on earth was the twin of the vehicle that executed mission in the space. [4]

Despite the first usage in 1960s, the first definition of such a deep and disruptive concept was provided in 2002 by Michael Grieves during an industry presentation concerning product lifecycle management (PLM). [32]

For the first time, Digital Twin has been introduced as the virtual representation of a physical product or system throughout its lifecycle. The disruption of the PLM was imaginable, people could not even imagine what the importance of this concept would have meant for the following years and that a century of discovery in this field was about to depart.

Grieves' definition of PLM extended beyond a static depiction of the product. It emphasized the dynamic integration between the physical and virtual realms, guaranteed by continuous data exchange. This integration ensured that the digital twin was a precise and faithful representation of the physical system within a cyber space, from inception through to recycling.

The virtual system, at that stage, was classified as a mirror of the real product, hence it was named, at first instance, as Mirrored Space Model.

During the last years, the concept of Digital twin has been developed and changed.

According to the more precise definition given by researchers from NASA, the digital twin can be considered as "an integrated multi-physics, multi-scale, probabilistic simulation of a complex product and uses the best available physical models, sensor updates, etc., to mirror the life of its corresponding twin." [79] Even though more complete with respect to the one given by Grieves a decade before, the latter definition lacks some features: the bidirectional data flows description between the physical and virtual entities.

Digital twinning is way more than just the simulation of the physical entity in a virtual world, using the term ''simulation'' to define digital twin does not exhaustively describe its capabilities and is not accurate enough to describe the bi-directional information and data flow between physical object and its virtual twin. [16]

As mentioned by Grieves in 2015 [33], the concept of digital twin can be easily summarized in three main components, namely:

- The physical twin.
- The virtual twin.
- The connection between the real and cyber spaces through which the data are transferred.

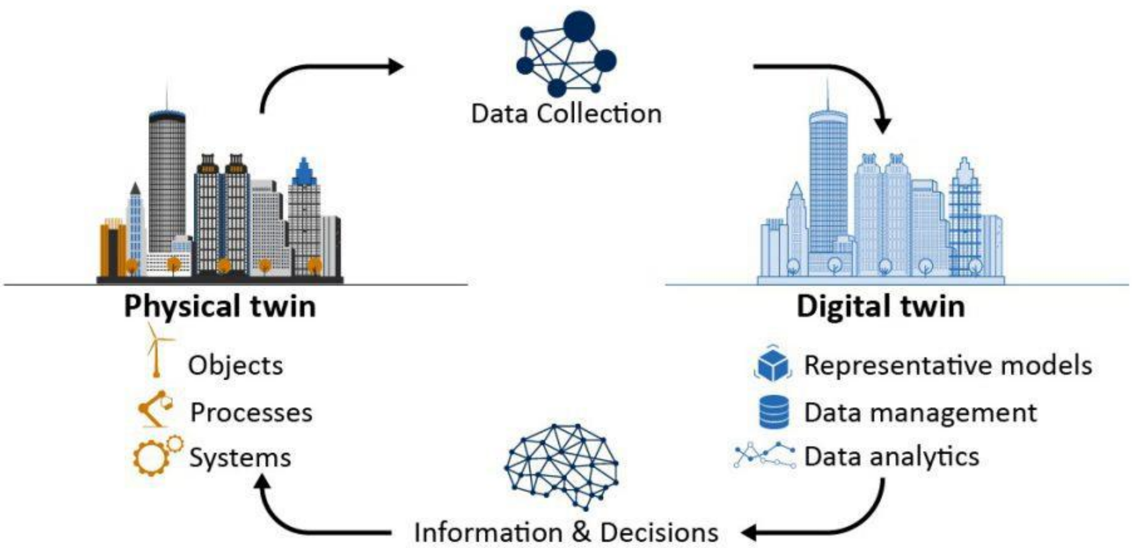


Figure 1 - Digital Twin conceptual representation [https://www.gao.gov/products/gao-23-106453]

These are the three key pillars that have been considered as starting points in all the following definitions. The physical twin represents the real object under exam. The virtual twin is the representation of the physical twin in a digital environment through the usage of some software.

Moreover, of major importance is the constant linkage between real and cyber space which makes the digital twin a unique tool, thanks even to the huge quantity of data exchanged over time.

Differently from Grieves in 2015, authors of [26] in 2022 identified the constituent parts of Digital Twin as:

- Physical entity, namely a machine or a group of them.
- Data-driven simulation model, among which there exist machine learning algorithms and data mining for the extraction of data.
- Data generated by the real-world entity.

The main difference among the two definitions relies on the missing description by the latter authors of the existing connection among the physical and virtual entities, giving major emphasis on the data generated, gathered, and examined, which are the main components of the Digital Twin definition introduced by [26].

In fact, whilst in the definition given by Grieves, the existence of an infrastructure among the two entities were described, in [26] the concept of digital twins can be thought as "a natural extension of traditional simulation modelling coupled with increased data availability, connectivity, and evolving needs of end users."

Based on ISO23247 [42], Digital Twin may be defined as "a virtual representation of manufacturing elements such as personnel, products, assets and process definitions, a living model that continuously updates and changes as the physical counterpart changes to represent status, working conditions, product geometries and resource states in a synchronous manner".

In the latter definition, the interdependence among physical and virtual models has been highlighted. One of the key characteristics of Digital Twin is the ability to update autonomously as soon as the physical entity changes. Whenever one of the conditions surrounding the physical world is altered, the digital twin will respond to the same change.

Authors in [84], after a thorough literature review, propose a consolidated and generalized definition for a Digital Twin as ''a virtual representation of a physical system (and its associated environment and processes) that is updated through the exchange of information between the physical and virtual systems''.

This definition seems to be the most complete and effective in terms of simplicity because it contains all the crucial elements which make unique the DT: the possibility of updating it automatically and the exchange of information among the systems.

After a brief presentation of some related definitions presented above, the first problem arises: the lack of a formal definition of digital twin has not been standardized, despite the increasing research.

The abovementioned definitions are only some of the several existing. This lack of consistency has led to a breadth of characterizations and definitions for digital twins and the digital twinning process that leads to a risk of diluting the concept and missing the benefits that the Digital Twin was originally devised to deliver. [44]

Despite the increasing interest in the topic, as declared above, there is still a misalignment among all the researchers. A standard and concise definition of digital twin recognized by the global community has not been found yet. Surely, the various application areas of Digital Twin have caused the existence of numerous definitions, but the absence of an established definition has led people to misuse the term of DT, often confusing it with some related concepts like Digital Model and Digital Shadow.

For this reason, [48] study aims to distinguish between the various digital forms categorizing them as digital model, digital shadow and digital twin based on the level of integration. A digital model, in essence, is a fundamental replica of the physical object without any transfer of data between the real object and the digital one.

Thus, in a digital model, an operator is needed to mediate all information exchange among the two objects as shown in *figure 2*. [14]

The digital model needs a manual integration among the physical and digital entities, hence each change in the real environment needs to be reported and adjusted manually in the digital counterpart.

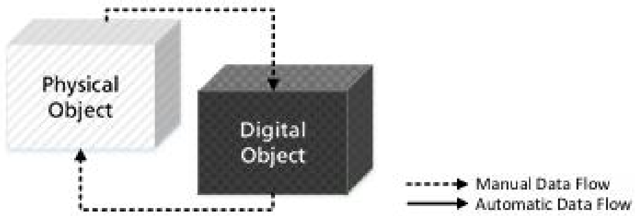


Figure 2 - Data flow in Digital Model [48]

Whilst, if there further exists an automated one-way data flow between the state of an existing physical object and a digital object, one might refer to such a combination as Digital Shadow.

In a digital shadow, as shown in *figure 3*, real-time information flows automatically from the physical to the digital entities, but it requires an operator intervention for the opposite flow. Due to its characteristics, a DS can monitor, analyse, and optimize data but cannot interact with the physical system.

Thanks to the automatic linkage among the physical and digital objects, a change in physical space will be directly reflected in the virtual space.

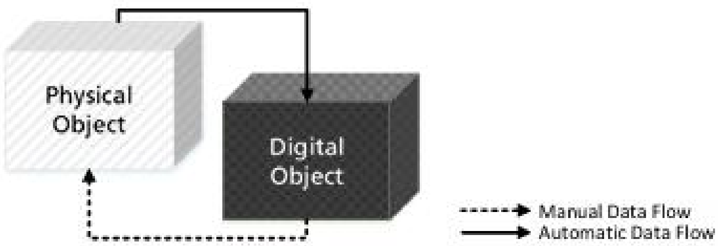


Figure 3 - Data flow in Digital Shadow [48]

The digital twin is the faithful representation of the physical model in a virtual way. It should contain all the process information and acquire all the operational and technical information through the automatic flows of data among the virtual and real system. As shown in recent years' research, digital twin is something that evolves and changes overtime, but the key concept is the constant convergence and interaction between the virtual and real space. [22]

The flow of data is bidirectional and automatic, from the physical object to the digital and other way around.

At the heart of the differences among these three concepts lies the dynamicity of the Digital Twin. The dynamic data stream constantly updates the DT [5] through the existence of sensors spread worldwide. DTs transcend the limitations of static simulations, embracing the inherent dynamism of the real world. The combination of data and digital representation is a powerful tool for comprehending, predicting, and optimizing the things we care about most.

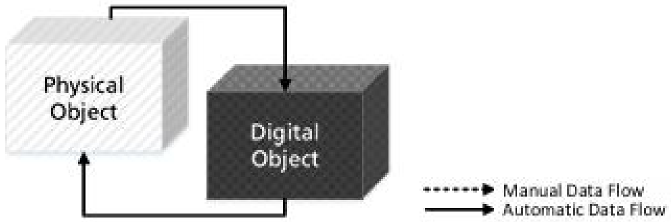


Figure 4 - Data flow in Digital Twin [48]

So far, the DT has been described as the faithful virtual representation of the physical counterpart, but to evaluate its fidelity, it may be important to introduce some characteristic unit of measurement.

The concept of identicality, introduced by [77], is a way to evaluate the DT in terms of completeness, trueness, precision, and latency.

The completeness aims to assess how comprehensively a DT represents its physical entity; hence it is the sum of purpose-based weights associated with all representative information in the digital twin, which can be mapped from the physical space to the virtual space.

The trueness is a measure of how closely the DT aligns with its corresponding physical counterpart.

Then, regarding the precision measures how realistic the DT is, a higher value indicates a smaller standard deviation among output values.

Real time is a key feature of DT, it is important to reduce the delay of communication between the two states. For this purpose, the concept of latency is relevant in evaluating the performance of identicality of each DT.

2.2 Supporting Technologies

Internet of Things (IOT) development in the first years of the 21st century has laid the groundwork for the exploitation of the Digital Twin potentialities. The term IOT, coined by Ashton in 1999, refers to a network where sensors connect physical objects to the Internet. [54]

Sensors installed within an intelligent factory enable IoT to acquire, process, and analyse real-time data. Regarding DT technology, it enables Industry 4.0 to replicate or represent physical machines, processes, or people in cyber space. Hence, IoT is an essential strategic element and a foundational necessity to unlock the complete potential of DT. By continuously updating data, IoT enables DT applications to create a real-time virtual representation of a physical object. Therefore, IoT is the primary technology used in all DT applications. [5]

Cloud technologies admit the huge amount of data exchanged among the digital and real world to be stored via the Internet. Cloud computing allows DT, with large volumes of data, to store data in the virtual Cloud, reduce the computation time, and easily access the required information from any location without the need of direct connection, overcoming the necessity of storing and accessing the data from local server.

Artificial Intelligence (AI) gathers data collected from IOT devices, operates alongside real-world manufacturing systems, identifying improvement areas, and supporting strategic decision making. Recent research suggests that integrating AI can boost the adaptability of DTs to dynamic changes in factories and workshops. This enhanced adaptability opens valuable applications, particularly in production planning, control, and quality assurance.

Extended Reality (XR) is an umbrella term for any technology that alters reality by adding digital elements to the *physical* or *real-world environment* to any extent and includes augmented reality (AR), mixed reality (MR) and virtual reality (VR). Generally speaking, XR refers to all real-and-virtual combined environments and human-machine interactions generated by computer technology and wearables.

Finally, the last of the technologies presented in *figure 5* is the blockchain. The latter concept can be defined as “a distributed ledger of transactions implemented as data batched into blocks that use cryptographic validation to link the blocks together. Each block references and identifies the previous block using a hashing function which forms an unbroken chain (i.e., blockchain).” [6]

Blockchain may be useful for the standardization of the protocols for the exchanging of the data among various Digital Twin, augmenting the interoperability across different industries.

It enhances DT reliability and secures all the data streams, increasing confidence both in the accuracy and speed of transmission.

In addition, Blockchain deletes the need of a centralized structure for the data collection and storage, reducing the risk of a single point of failure and enabling all the stakeholders to verify and audit the transactions independently.

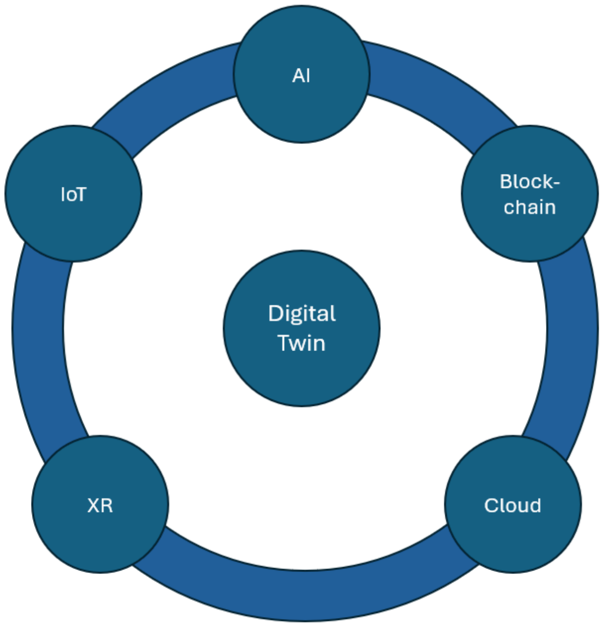


Figure 5 - Digital Twin related technologies (personal elaboration)

Furthermore, additional technologies are necessary to develop consistent Digital Twin. Among these, it is crucial to mention Machine Learning, for predictions and feedback, as well as to identify effective mitigation strategies, in exceptional circumstances. [71]

Machine Learning is strictly related to artificial intelligence (AI) that focuses on the development of algorithms and statistical models and hence it enables computers to perform specific tasks without explicit instructions. Using the large amount of data gathered and leveraging the patterns of these data, machine learning systems can improve their performance over time through experience.

Machine Learning joined with Digital Twin may be implemented for many different purposes, namely:

- Data integration and analysis, where ML algorithms can be used for detecting anomalies and defining specific patterns of the copious amounts of data gathered with the aim of taking reliable decisions.
- Simulation and optimization, where ML models are exploited for predicting future different scenarios, testing hypothesis without incurring the risk associated with the real experiments on the physical prototype.
- Real Time decision making, ML capabilities enable real-time decision making adapting the responses based on the changing conditions.

2.3 Research trend

A first research phase has been implemented with the objective of finding all the possible existing gaps and discover which direction the research is undertaking in the last few years.

The main issue of Digital Twin, namely the absence of a unified and agreed definition worldwide, has been discussed in the previous paragraph with the presentation of many of the most relevant definitions provided in the last decade.

Moreover, other research questions have been identified, for instance the need for a clear development guideline and unified framework that not only defines the components of a DT but also provides an implementation path for consistent conception, standardization, establishment, and management. [49]

Knowing what standard components should be included in every Digital Twin will enhance its acceptance and make it easier for widespread adoption.

Despite the importance of augmenting the possibilities of interoperability between different Digital Twin has been already treated in the previous paragraph, it represents still a research gap.

Thus, extensive research was applied to analyse all the potential issues.

For identifying relevant articles in the field of study, query-based searches are used. To commence the identification of relevant studies for this review, we initiated the formulation of appropriate search queries, reducing the number of articles out of scope or too old.

The data shown in the graph below are taken by Scopus, which is the source from where the main part of the academic articles have been taken from using "*Digital twin AND (manufacturing OR production OR process)"* as keywords to perform a deeper search. The research was restricted by a lower time set at 2018 and the research period is extended up to April 2024.

Furthermore, an additional filter was added to the research avoiding, in this way, all the conference texts or unprofessional contents, and giving major relevance to research article or review article.

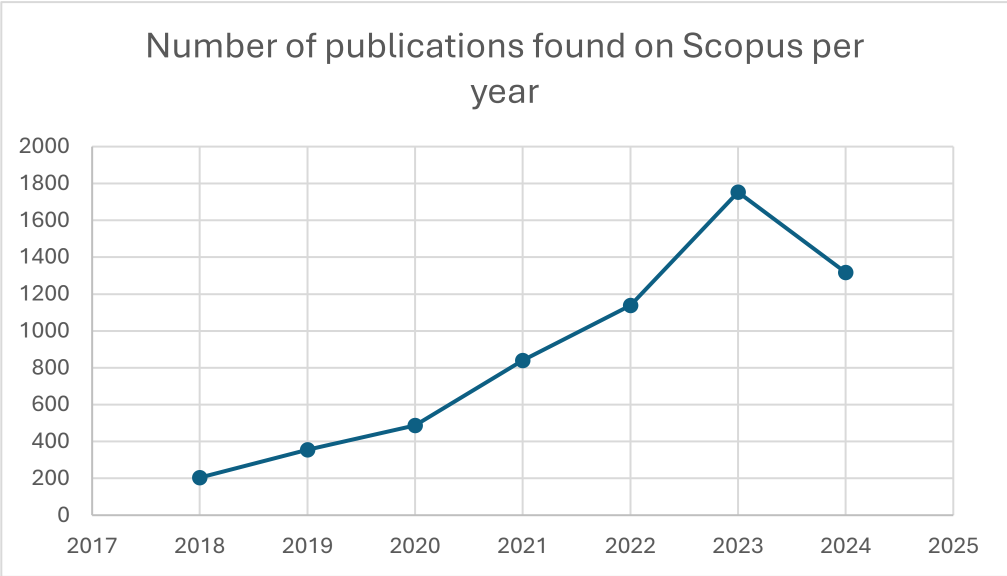


Figure 6 - Number of publications per year January 2018 - April 2024 (personal elaboration)

Thanks to this approach, it will be possible to evaluate the gap existing among the theoretical background and the practical implementations nowadays.

As easily observable from the chart above, the trend in research in this field is increasing yearly, as well as the interest and the potential implementation of this technology.

The drop of publication is clear, passing from around 200 papers found published in 2018 with the selected keywords to 1314 publications in the first few months of the current year.

It is important to remark that for the data of the current year, 2024, just articles published up to April are taken into consideration, here explained the fact that the number of publications is lower than the previous year, but still significative considering a 4 months' timeframe.

Upon completion of the research, several gaps have been identified. Notably, one of the primary gaps, as previously discussed, is the absence of a unified and widely accepted definition within the scientific community. It can lead to a general sense of confusion in the scientific community and going forward even the application may sometimes be inexact.

Additionally, other significant gaps have been recognized, including ambiguities in the characteristics of digital twins [70], terminological inconsistencies [46] and the diverse forms and outputs associated with the concept. [25]

2.4 Threats and challenges

Implementing a Digital Twin, despite all the benefits and advantages presented so far, has still some threats and challenges.

In a company, digital maturity is more important than technology investments, with high-quality data infrastructure and motivated and skilled employees being the key factors in the first stage. Digital Maturity is the predictor of success for companies launching a digital transformation. [12]

In fact, Digital Maturity represents a key milestone to be reached prior to the implementation and the investments since it reflects the organization's ability to effectively leverage digital technologies. Digital Maturity is defined as the extent to which a company has integrated digital tools and processes into its operations and culture, enabling it to respond adeptly to changes and opportunities in the digital landscape.

The level of digital maturity in a company is enhanced, in first instance, by the presence of a stable data infrastructure, which allows that the data can be gathered, exchanged and processed, then the presence of expertise employees who need to be proficient in using digital tools and technologies, and be capable of examining data, and adept at adapting to new digital workflows.

Continuous training and development programs are necessary to keep the workforce up to date with the latest technological advancements.

So far, the basic requirements for an adequate level of digital maturity to assess a digital twin implementation has been presented, but there exist other entry barriers to be defeated prior to obtaining satisfying result from a DT.

Nevertheless, real-time data collection/processing demands the extensive integration of sensors, processors, networks, and other devices. [27] All these instruments require initial significant investments by the companies, which can even be discouraged by the initial entry barriers, especially the SMEs which are less confident in making these kinds of investments.

The first and highest costs to face in order to implement such infrastructure are the acquisition of high-performance servers, cloud storage space, and data processing capabilities, [80] without forgetting the costs of labour, for the hiring of well specialized personnel and for their formation. Even the costs for the data collection cannot be neglected: many sensors and monitoring equipment must be installed and costs for their maintenance and subsequent substitution may be taken into consideration.

Despite the witness presented in the previous paragraph about the increasing trend in terms of investments by the large companies, SMEs with tight budgets still see DT technology as a financial burden rather than a cost-effective investment.

The lack of digital maturity for SMEs worldwide is straightforward evidence. However, SMEs should start investing more in integrating their production with digitalization to reach cost effectiveness, efficiency, and scale economies to reduce the large gap generated with the large companies, if they want to survive in the long term.

To overcome the investment challenge, SMEs can utilize public initiatives for digital integration, such as the “Digital SMEs Manifesto” [20] launched by the European Commission. This initiative aims to make 90% of EU SMEs fully digitally integrated by 2030, offering funding programs to support digital transformation.

Another possibility regards the possibility of using Digital Twin in outsourcing, avoiding the initial investments, with the possibility of exploiting all the benefits paying a periodic fee to the service provider.

In conclusion, while these entry barriers may seem daunting, the long-term benefits the companies will enjoy, namely increased efficiency, cost optimization, and enhanced decision-making, underscore the value of overcoming these obstacles. To exploit the full potential of Digital Twin, companies must prioritize digital maturity, make thoughtful investments, and prepare their workforce to adapt to these emerging digital landscapes.

2.5Actual implementation

Many are the fields in which Digital Twin has been diffused over time, as well as many are even the advantages that its use may involve.

Based on the Grand View Research [31] report published at the end of 2023, the global digital twin market size was estimated at USD 16.75 billion in 2023 and is projected to grow at a compound annual growth rate (CAGR) of 35.7% from 2024 to 2030.

This is unambiguous evidence that not only the research is dropping fast, but the investments, specially made by large companies, are doing the same. This alignment between research and practical application grow is really representative of the comprehension by companies worldwide of the importance of adopting Digital Twin for various scopes in their organizations, which is increasing during the last years, and it is supposed to grew even more aggressively in the further years. The adoption of the Digital Twin in companies processes may vary based on the industries they compete, shifting from Product Digital Twin to Process Digital Twin to System Digital Twin.

The disruption of Digital Twin will evolve over the next decade, where the trend of the amount of money invested by the companies worldwide and even the market share will drop yearly, reaching in around five years by now the market value of one hundred billion dollars.

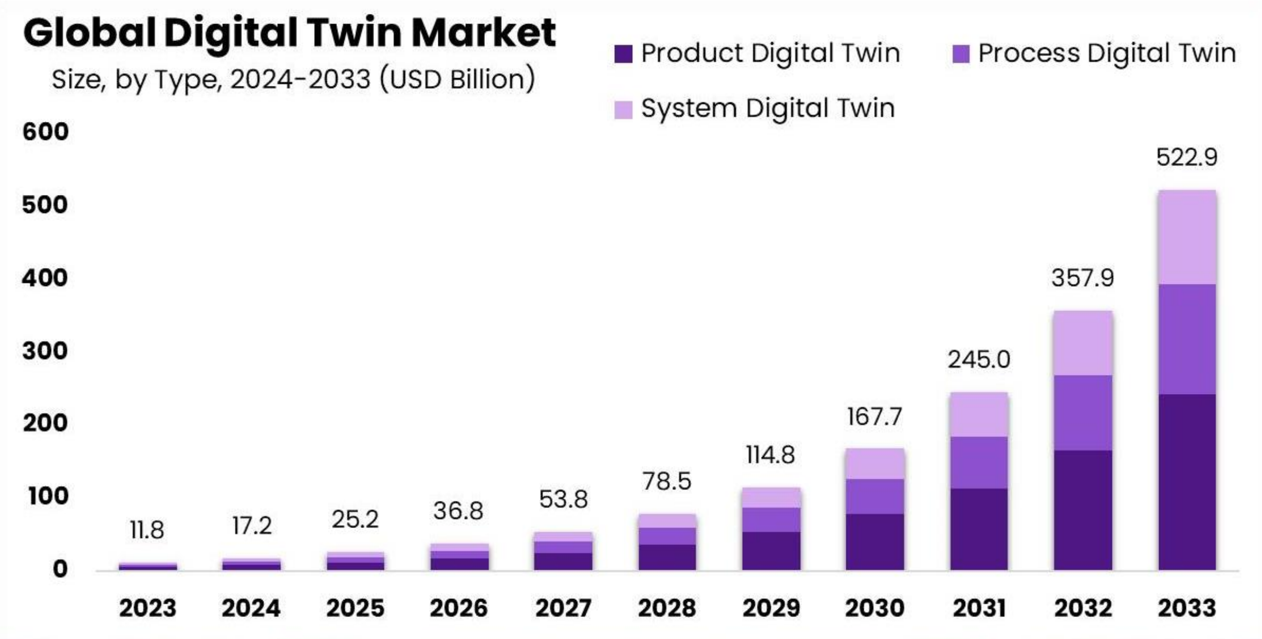


Figure 7 - Focus on global Digital Twin market size [31]

A Gartner survey, in 2019 [29], revealed that by 2027, more than 40% of large companies worldwide will adopt the Digital Twin in their project to increase revenues. Growing demand for digital twin solutions is encouraging industry players to improve their product portfolio and geographic expansion to achieve higher profitability from the market.

The way Digital Twin may help companies increase their revenues are several.

A concise and comprehensive summary of the advantages of Digital Twin in economic terms is presented above.

- Waste reduction guaranteed by a higher accuracy in production.
- Time to market decreases through the quickening in product development, especially in the design stage. Digital twins may allow rapid iterations of product designs - faster than physically evaluating every single prototype. By simulating the product throughout the manufacturing process, it is easier to identify flaws in the design earlier.
- Decision making improvements about resource distribution, scheduling and predictive maintenance avoiding spare time.

Particularly related to the second step described above, the advantage of testing a product without the necessity of realizing some expensive prototype [71] bring many benefits to the companies, since it is crucial for decreasing time, waste and money. Rather than spending time and money for building multiple prototypes for testing a product, digital twin offers a much more efficient and cost-effective solution.

Others are the advantages from the environmental point of view, related to the optimized resource usage, decreased greenhouse gas emissions and sustainable product development.

Sustainable manufacturing is defined by the U.S. Department of Commerce as ‘‘the creation of manufactured products that use processes that minimize negative environmental impacts, conserve energy and natural resources, are safe for employees, communities, and consumers and are economically sound.’’

Digital Twins significantly enhance sustainability practices by enabling organizations to measure and improve the performance of physical systems, thereby diminishing their environmental impact. In the virtual domain, they are particularly valuable for simulating new product designs, alternative packaging solutions, and manufacturing configurations aimed at reducing energy and water use, as well as waste production.

DTs are an emerging technology to significantly improve the sustainability performance of products and processes by providing information across the entire lifecycle. [69]

Thanks to its strict correlation with Product Lifecycle Management (PLM), DT is able to track all the phases of the product it is referring to, from the Beginning of Life (BoL) till the recycle and reuse phase. However, since the ability of the DT to save on material scraps in the BoL, avoiding the usage of physical prototype, has been aforementioned, the focus will be more on the recycling and reuse phase, a clou topic in recent times.

The impact of Digital Twin on CO_2 emissions reduction may be disruptive as clearly presented by a quantitative analysis presented by Accenture, a consultancy company, which in 2021 predicted the total possible reduction to 7.5 Gt CO_2 emissions. [2]

The reduction in terms of CO_2 emissions may derive not only from a better usage of materials, avoiding scraps and waste, but even from a higher degree of attention in sustainable manufacturing where the construction of Digital Twins allows energy consumption management and possible waste detections.

By creating virtual models of manufacturing systems, companies can monitor energy consumption in real-time and identify areas where energy is wasted. This enables the optimization of energy use, leading to significant reductions in CO_2 emissions.

According to [93], an important case study is represented by Schneider Electric which uses a Digital Twin application to optimize energy management (-25%), reduce material waste (-17%), and minimize CO2 emissions (-25%).

While the digital twin is helping Schneider Electric reach its goal of net zero by 2025, it is also more cost-effective and creates more efficient processes.

Furthermore, manufacturers can utilize digital twins to streamline their production processes and enhance sustainability. However, manufacturers are overlooking a crucial opportunity by treating production digital twins and sustainability-focused digital twins as separate entities.

Ignoring the integration of all production aspects results in an incomplete model. [92]. By adopting an integrated approach that encompasses both production and sustainability elements, manufacturers can achieve a more comprehensive and accurate understanding. This enables them to reach higher levels of operational efficiency and environmental stewardship. Thus, only through a unified and holistic approach manufacturers can fully exploit the potential of digital twins for continuous and sustainable process improvement.

Many companies worldwide have gained major benefits combining both the willingness to reach productive efficiency and sustainability optimality.

A clear example is the LG Electronics factory in Changwon, Korea where its assembly line visual simulation tool, in 2022, was transformed into a digital twin by continuously integrating real-time production data, with updates occurring every 30 seconds. This integration led to a 17% improvement in productivity, a 70% enhancement in product quality, and a 30% reduction in energy consumption. [52]

These results underscore the potential benefits of a unified approach. By adopting an integrated digital twin strategy that encompasses both production and sustainability dimensions, manufacturers can achieve higher levels of operational efficiency and environmental responsibility.

In conclusion, the research in the Digital Twinning made huge progress in the last few years, giving the possibility to align the theoretical background with the physical implementation, but as shown in the latter paragraph the research is not yet in a maturity stage, since there are still several unexplored field which can gain benefits from possible implementation of the Digital Twin.

In a world where things go faster, it is crucial not only for the people but even for the technologies to adapt even faster and, as aforementioned, the adaptability is one of the key features of the Digital Twin which make it one of the turning points of the recent history.

3. Collaborative Robots

3.1Introduction and definition:

The term human-robot collaboration, or HRC, refers to an industrial context where, as suggested by the name, employees and robots collaborate working alongside, increasing the productivity rate, improving the quality of the products and consequently reduce the unit production costs even through some savings in terms of waste. HRC represents a meaningful shift in the industrial paradigm where the synergy among human workers and robots brings unprecedent levels of efficiency, safety and innovation granted through sophisticated sensors, machine learning algorithms and adaptive controls.

Traditional robotics are designed for high speed and intensive processes, where the risk of potential injuries is significant partly due even to the material of the components. As a result, these robots often require a safety system which cannot guarantee humans to work side by side with them. The inherent danger of operating in such productive intensive context necessitates physical barriers or other safety measures, which effectively isolate robots from human workers. Consequently, these robots are primarily used in repetitive, heavy-duty tasks where human interaction is minimal, focusing on maximizing efficiency and output (Colgate et al., 1996)

Different from traditional robotics, collaborative robots, commonly known as cobots, represent a significant evolution in the field of robotics, designed specifically to work alongside human operators in a shared workspace to boost productivity, ensure safety, and liberate humans from labour-intensive activities [57] speeding up the manufacturing processes. [65]

Prior to the discovery and the application of collaborative robots, the concept of human– robot interaction (HRI) was partially put aside due to the necessity of making safety a key requisite for cobots, granted through the presence of cages, physical barriers and light gates as previously adapted in the traditional robotics context. The latter safety measures protected human workers, but, on the other hand, they made the environment bulky and inflexible preventing true collaboration and augmenting even more the realization cost of the cobots. [90]

The origin of the collaborative robots may be traced back in the late 1990s, when two researchers at Northwestern University, Michael Peshkin and J. Edward Colgate, introduced for the first time the term cobots to describe “a robotic device which manipulates objects in collaboration with a human operator”. [17]

The figure below is a photography of one of the first prototype of a unicycle cobot which “consists of a single steerable wheel that rolls on a horizontal plane.” A unicycle cobot can constrain motion in x and y axis, but the orientation is not constraint.

Some components are clearly recognizable, like the handle through which the operator can move it or the wheels which make the movement possible or finally the steering motor and transmission.

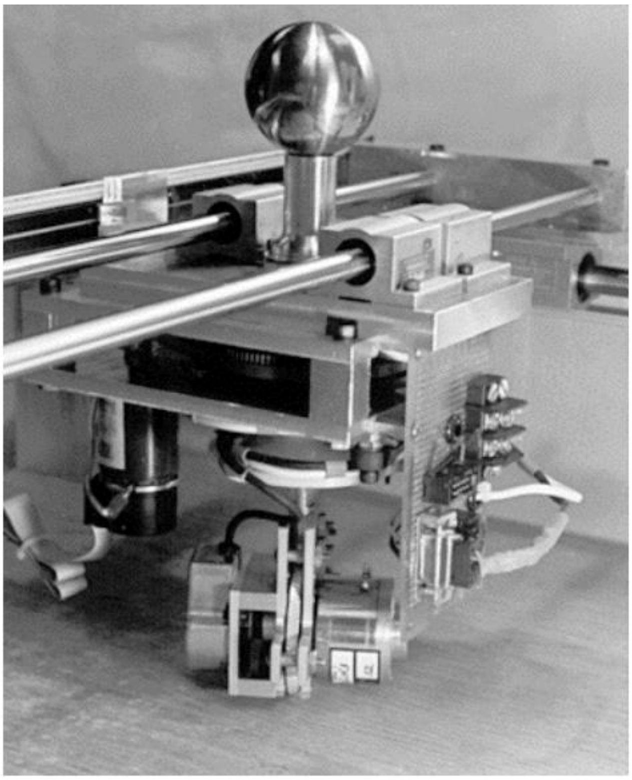


Figure 8 - A picture of the first unicycle cobot prototype [17]

The one presented in *figure 9*, taken from [65], is one of the first cobot applications ever presented realized by the two researchers of the Northwestern University aforementioned in collaboration with General Motors. In this frame, a cobot and a worker work together in the same environment, accelerating the process of testing the quality of the “door opening” process of a car in an assembly line.

When the worker pushes the payload against the virtual surface, a generalization of the straightedge which provides a physical guidance, the payload motion is constrained to follow the virtual surface to speed up the process.

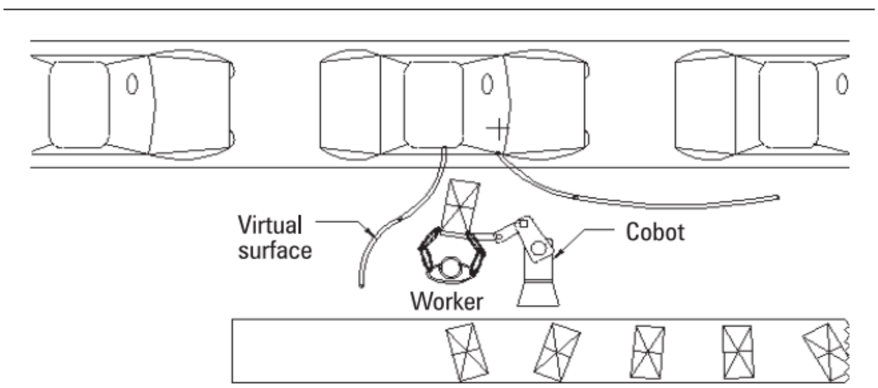


Figure 9 - Application of cobots in automotive assembly line [65]

Picture 10 shows the General Motors' door-unloader cobot which provides virtual surfaces assuring that the door does not collide with the car body. The choice of this task as first application was made consciously by Colgate and Peshkin: based on their experience, removing the doors from the vehicle is a labour-intensive activity and sometimes is difficult for workers to remove a door without marrying the surface.

This example of cobot has a passive mechanism as soon as it did not have any form of propulsion, but it used mechanical transmissions to guide the motion of the door being manipulated by the operator.

Figure 10 - Application of cobots in automotive assembly line [17]

As discussed so far, despite the first implementations of the collaborative were far away from the actual imaginary, since they were passively guided by a human operator, the impact, and the success of the first version of the cobot shown before paved the way for further research and development.

In the first year of this century, many firms, such as Universal Robot, started implementing and producing the first example of cobots with advanced features playing a pivotal role in the evolution and industrialization of cobots. The first version of cobots launched in 2008 by Universal Robot is UR5, a lightweight, flexible, with a payload of 5kg, the ancestor of the most recent and advanced currently in use.

The technological progress of the last years had an impact even over the cobots, which nowadays through the integration of machine learning, artificial intelligence and advanced sensors have enabled cobots to become more autonomous and capable to perform complex and labor-intensive tasks.

The industrial robot market has shown a consistent upward trend in recent years, further accelerated by the advent of Industry 4.0. According to a 2023 European Parliament study, the global stock of operational industrial robots rose to 3.5 million units in 2021, marking a 15% increase from the previous year. Although collaborative robots represent a smaller segment of this market, their adoption is rapidly growing, with a 31% increase in 2022. (*figure 11*) [23]

The impact of the collaborative robotics in manufacturing is disruptive, as witnessed by the data about their adoption, presented in *figure 11,* where is clearly observable how in the period between 2020 and 2022, the units of collaborative robots worldwide is more than doubled, from 26000 units in 2020 to more than 55000 units in 2022, and the trend suggests an even more confident increase in the next few years.

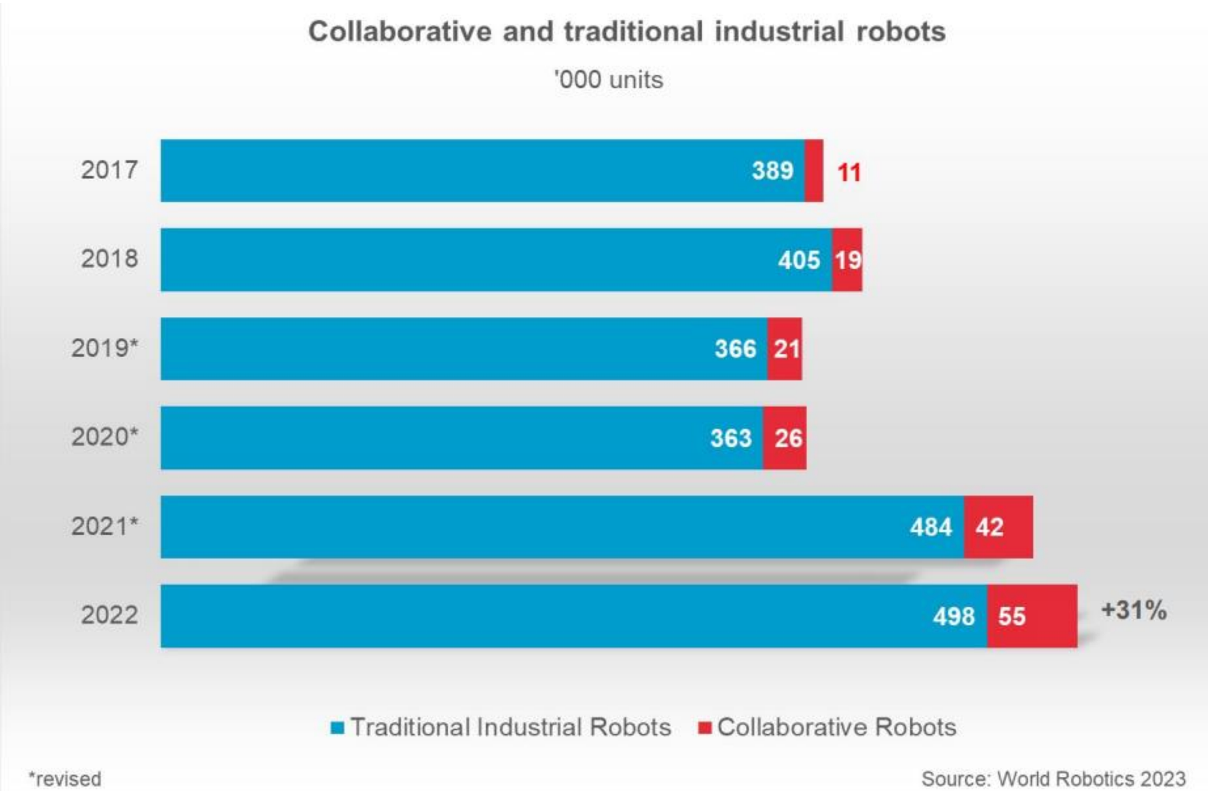


Figure 11 - Collaborative and traditional industrial robots' units [41]

According to a study conducted in 2024 by Markets and Markets which foresaw the expansion expectation of the Collaborative Cobots industry, a compound annual growth rate (CAGR) of 35,2% from 2024 to 2030 is expected, reaching the maximum peak of USD 11.6 billion. [58]

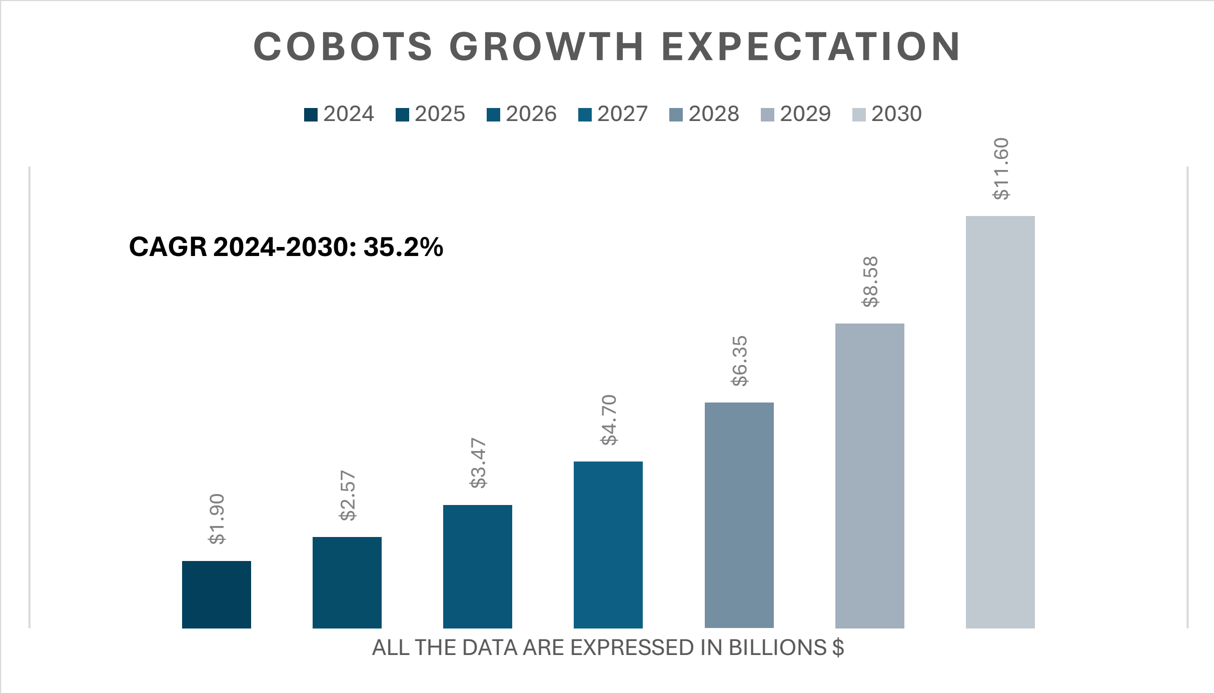


Figure 12 - Cobots growth expectations (personal elaboration)

One of the probable causes of the trend analysed in the chart above may be the evolving dynamicity of the demand by the customer and the rise of "mass-personalization" phenomenon in the market. [24] The main challenge of current globalization is represented by the need to match the market dynamics while ensuring all three aspects of sustainability: economic, environmental, and social. [43]

Therefore, manufacturers need easily adaptable solutions, such as collaborative robots, which may quickly respond to variations in the demand, without the need for further transformation of the plant or reworking the whole layout of the manufacturing system.

3.2 An In-Depth Analysis of Collaborative Robots Benefits

Differently from traditional industrial robots which operate separately from humans, often behind barriers for safety, a cobot is an artificially intelligent robot [15] programmed for working and collaborating with humans to perform tasks avoiding difficulty, danger, or dullness. [61]

Cobots signify a transformative shift in the realm of automation. Unlike traditional robots programmed to operate in isolation, cobots are engineered to work alongside human operators, enhancing their capabilities, and reducing the overall risks rather than replacing their roles. In this way, humans do not disappear from production, but cooperate in the production line alongside the cobots, which guarantees flexibility and dynamicity and relieving humans of arduous tasks reaching the combination of the precision, endurance, and power of industrial robots with the individual skills and ability inherent to humans.

The major difference among collaborative and traditional robots lies in the way safety is managed. While in traditional robots, workers are excluded from the workstation in order to preserve safety and avoid potential accidents, collaborative robots open the possibility of optimal human-robot collaboration, without separation and without barriers, and in this way, it is possible to automate new applications.

Furthermore, in traditional robotics, the safety measures, like the existence of cages or barriers are used for pre-emptive concern, trying to avoid in advance the occurrence of injuries and damages in the work environment, the adaptability of the cobots allows them to work in an open and cageless environment, but a high standard of safety is preserved due to the presence of force sensors triggering hard stops to deactivate the cobots as soon as a collision occurs represent an example of adaptive safety contrast. [59]

The two figures below are representative of how safety is managed. On the left the operator is collaborating with the cobots in the same environment, enhancing productivity, exploiting the advantage of combining the automation with the flexibility and cognitive skills of human workers without the necessity of any cages and any safety measures overcoming the classical division of work [87]. In this case, safety is ensured through a series of sensors, located along the cobots' arm, which detect humans' motion and prevent harming humans moving around, taking track of possible collision.

While, on the right, a frame of a traditional robots operating within the manufacturing system without any interaction with human workers which are kept far away by the presence of a cage. The latter prevents the occurrence of any kind of failures and damage caused by the interaction with human workers, which can lead to slow down the process causing economic and timing losses, but in the meantime all the benefits just described in matter of flexibility and humans' involvement are avoided.

In addition, the presence of the cage makes the layout less versatile since for any changes in production, the whole plant should be renewed which imply additional costs and less dynamicity.

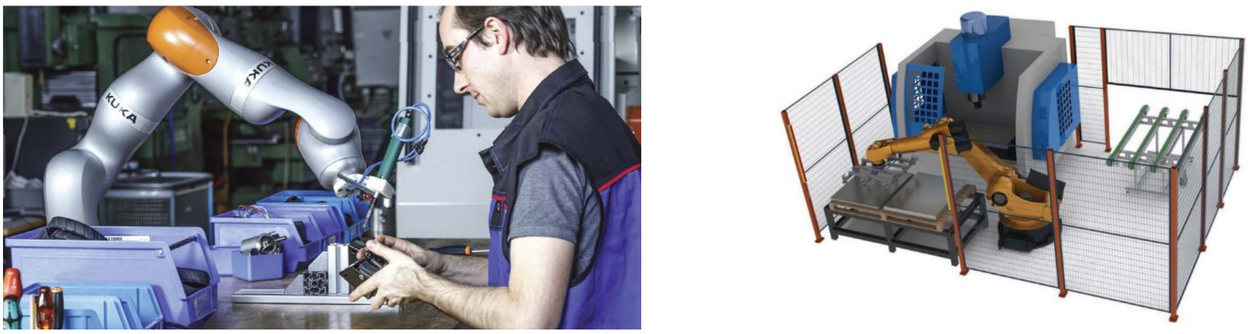


Figure 13 - A comparison of collaborative robots (on the left) and traditional robots (on the right) working environment.

Surely, collaborative robotics represent a revolution even in the way employees participate in the productive processes. They will not be involved anymore in repetitive tasks as it happened in past centuries with the mass production, but new types of skills are required to the new generations of intelligent employees. Skilled workers able to set up, manage and adjust digital twins and collaborative robots will be needed most. [51]

In fact, the integration of collaborative robots into industrial settings marks a transformative shift in employment dynamics in the production systems. Through the automation of routinary and physically intensive activities, cobots enable human workers to focus on more complex, creative, and added-value activities [74]. Cobot-enabled industries foster a work environment where employees are central to innovation and productivity. [3] The cobots introduction aligns with the broader trend towards human-centred automation, where technology is designed to aid rather than replace the workforce, leading to more rewarding and sustainable employment opportunities [8] while humans focus on perception-driven decisions.

Against any fears about the possibility of cobots stealing jobs, a deep analysis on the foreseeable future [39] clearly states that cobots, as aforementioned, will not substitute humans in production lines, reducing jobs opportunities, but they will be used for filling gaps in the labour market created by the labour shortage, and assist operators in enhancing productivity through a speed-up of the processes. Collaborative robots have a great impact on the productivity rates of manufacturing systems, since compared to an assembly line composed exclusively by humans, the utilization rate of the collaborative robots can be pushed even close to the limit of 1, while the presence of operators forces the utilization rate to decrease, due to the necessity of periodical break or other breakdown conditions, affecting the reduction of prolonged idle period. For this concern, [43] measures the impact of the introduction of a collaborative robot, in terms of augmented productivity and number of units processed, replacing a manual assembly line in an almost fully automated manufacturing system, where the just cited assembly line represents the bottleneck of the system. The drop in number of units processed increased by 144.8% in a working day passing from 2890 units processed with just the operators' aid, to 7074 thanks to the establishment of the collaborative arms. The augment of the productivity rate and the inherent throughput generates extra profit for the firms, due to a cost cut of 60€ per batch in the considered case study.

Combining the creativity and the ability in decision making of human workers with the repeatability of robots' results in a collaborative environment in which humans and robots collaborate in a workspace, reducing the risk of being in conflict, therefore being definable cobots. [13] Collaborative robotics represents a hybrid among the totally manual and fully automated lines, bringing all the benefits of the craftmanship, expertise and quality of the tasks managed by humans integrated with the speed in execution, the consistency, and the guide of the robotics. From the interaction among humans and robots, namely Human Robot Collaboration (HRC), not only the whole manufacturing system gains numerous benefits, as increased productivity, and quality, but even the employees enjoy various advantages, as an improvement of their performance and a reduction in the fatigue and physical strain. With the purpose of computing the performance improvements enjoyed by the working class, [19] presented a quantitative analysis based on the evaluation of the workers' performances assisted by collaborative robots. As discussed in the study, the performances of the workers in terms of productivity and ergonomics are improved thanks to the HRC highlighting a negative correlation among human performances and three subjective factors, acceptance, trust, and usability. Higher levels of workers' acceptance and trust towards the innovative technology and system usability may result in an improvement of the collaboration with the robot, whilst, on the other hand, lower levels may negatively influence their performance.

Cobots' key feature is represented by being easy programming and adaptive to simple tasks [66], ensuring minimal downtime and constant output while enabling the worker to focus on product inspection [73] and in this way granting potential benefits in terms of efficiency and costs savings.

Going more in detail, flexibility represents the adaptability of the system to a vast variety of applications guaranteeing advanced level of customization which gives the possibility to be in line with dynamic change in demand by the customers. The easiness in programming grants the possibility to use cobots even to non-expert users, differently from the prominent level of skills required for the usage of industrial robotics. [62] The small dimensions and the low weight of the cobots make them easily movable within the manufacturing system, representing a key pre-requisite for the dynamicity.

HRC can greatly benefit workers in industry by increasing efficiency and productivity while reducing the risk of workplace injuries. By partnering with robots, workers can offload repetitive or hazardous tasks to the robots, allowing them to focus on higher-value tasks that require human skills and expertise. In addition, the implementation of Human-Robot Collaboration (HRC) can extend its positive impact beyond mere efficiency gains. HRC demonstrably reduces the risk of workplace injuries, yielding a significant advantage from both financial and temporal perspectives. The occurrence of a work-related injury necessitates the cessation of the production line, incurring substantial financial losses and production delays.

Referring to [23], the main advantages of collaborative robotics include:

- Reduced commissioning costs: Cobots usually require lower initial investment and maintenance costs compared to traditional robotics.
- Complementary to human workers: Rather than replacing human workers, cobots collaborate with them, enhancing productivity without replacing the operators.
- Increased productivity: The ability of cobots to operate continuously without fatigue leads to higher overall productivity.
- Facilitate new applications and business models: The versatility of cobots has enabled businesses to explore innovative uses and revenue streams.

Moreover, the lightness, the easiness of movement and redeployment and the advantages in terms of occupied factory floor space, which is a limitation for the manufacturer firms, represent crucial gains while collaborative robots are adopted instead of traditional robotics. [40]

Whilst cobots offer several advantages, it should be clarified that they also have some limitations compared to traditional industrial robots. Cobots generally do not match the high speed, payload capacity, long reach, precision, and productivity levels that conventional robots can achieve. These limitations make cobots less suitable for applications that require high-volume production or the handling of heavy loads over long distances. As a result, industries that require rapid, high-capacity operations often still rely on traditional robots to meet these demands efficiently.

In *figure 14*, taken from Universal Robots, a possible comparison among the traditional robots' applications and cobots applications is presented.

The chart allows for evaluating both the solution based on different contexts and needs. In fact, traditional industrial robots are unmatched in scenarios requiring high-speed, high-precision operations with significant payload demands. Cobots, however, offer unparalleled flexibility, ease of use, and safety, particularly in environments that benefit from human-robot collaboration.

Traditional robots excel in high-volume and high-speed production, making them indispensable in large-scale manufacturing contexts where throughput is a critical factor. [41]

Contrarily, cobots are designed for rapid redeployment across various tasks and processes, which is a significant advantage in industries that require frequent production changes. Their flexibility is a key factor in their growing adoption in environments where agility and adaptability are crucial.

In addition, cobots may not achieve the same level of accuracy and workload replicability as human workers [95] hence this reduced accuracy can restrict their suitability for high-quality product manufacturing.

On the other hand, relying on [82], all the problems linked to repeatability and the precisions of the operations which belong to the first generations of cobots have been overcame over the last years, reaching a range of repeatability among +/- 0,03 mm which make them feasible even to process high-quality and low-error range operations.

If you need...	...consider a traditional industrial robot	...consider a collaborative robot ("cobot")
High-volume, high-speed production	☑	☐
Similar throughput as a human worker	☐	☑
High payload or very long reach, especially at high speed	☑	☐
Ability to program and set robot up in-house	☐	☑
Ability to easily redeploy robot to different processes/tasks	☐	☑
Extremely high accuracy, including at high speed	☑	☐
Minimal changes to existing production layout	☐	☑
Human workers to enter the robot cell to complete their tasks	☐	☑
Integration options with other machines and robots	☑	☑
Low initial cost and payback in under a year	☐	☑
Ability to run processes with few or no employees	☑	☑
Automation of processes or products that won't change over time	☑	☑

Figure 14 - Comparative analysis of the application context among traditional robots and collaborative robots. [82]

The chart above may be helpful to assist manufacturers in the choice of the best solution to adopt among traditional industrial robots and collaborative robots.

In conclusion, as soon as the throughput and a higher payload are critical factors, the choice falls on traditional robotics, whereas whether the limited speed, range, and payload capacity are not so critical, and the lower cost of installing a cobot worth the trade-off of lower performance, the decision falls on collaborative robotics.

3.3 *Different levels of Collaborative Robots integration*

The screen shown in *figure 15*, also called *teach pendant*, is the representation of the instrument operators use to interact directly with the collaborative robots, programming them through the setting of the parameters as the operating speed, the force, the width different for each application. The teach pendant shown in the figure belongs to a model UR3e, produced by Universal Robots, hence the characteristics which are visible through the picture may be different from other models. The user-friendliness of the programming interface allows, in case of stand-alone applications and not specific requirements, even workers with minimal robot training to easily re-deploy the robot to a new task. The existence of such device makes the cobot very simple to be used and programmed, enhancing the easiness of programming, a milestone of the cobot technology, and the intuitiveness, as mentioned in the *section 3.2*.

Figure 15 - The user interface of a UR3e Collaborative Robot.

In this paragraph, the manner Collaborative Robots and human workers interact while they share their workspace is analysed because there is still a misalignment towards the full integration of Collaborative Robots in manufacturing applications. As pointed out in [78] there are different levels of cooperation which deserves to be distinguished between employees and Collaborative Robots.

- *Coexistence*: the human workers and the robots just share their operating space, without any interaction, performing their activities separately.
- *Synchronization*: the operators and robot share the work environment with independent tasks. The robot's activities may complement human work, but the task remains distinguished.
- *Cooperation*: the human and the robot share the work environment, and the task execution is in a step-by-step procedure. In this case, cobots generally substitute human workers in executing tedious activities (i.e. material transportation, or components'

assembly), improving his productivity and leaving him focusing just on added value tasks.

- *Collaboration*: the maximum level of cooperation. The operator and the collaborative robots share the work area and the task simultaneously. Both the entities contribute to the tasks at the same moment, requiring advanced interaction and safety systems to ensure seamless and safe operations.

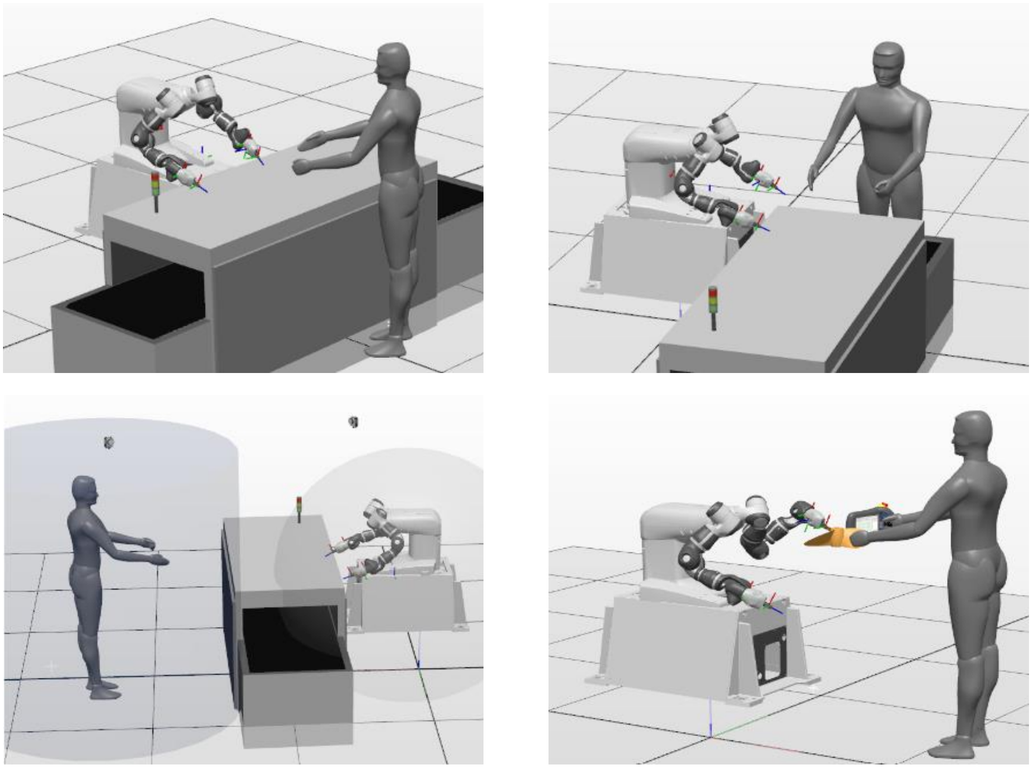


Figure 16 - Different levels of cooperation among human worker and robot. [78]

Despite the latter distinction presented above about the different levels of collaboration among the human workers and the collaborative robots seems to be one of the most complete to distinguish how each component behaves in different context, in the last few years plenty authors have pointed out several approaches based on the level of workspace sharing, interaction and cobots' movements.[67] mentioned three levels of workspace sharing levels relying on the operator safety and fatigue.

Moreover, [72] introduced three levels of collaboration based not only on the degree of workspace sharing, but also on the cobots' movements.

Similar to the scale aforementioned, [9] used three characteristics to describe the type of interaction: shared workspace, simultaneous co-work and physical contact. In this case, the forms of co-work were determined as follows:

- Coexistence, where collaborative robots and human workers are present simultaneously, but they have separate workspaces.

- Sequential cooperation, successive actions on same workpiece. The activity of the robot is interrupted when human is working on the same workspace.
- Parallel cooperation, in this case there not exists physical contact, even though they work towards a common goal.
- Collaboration, joint action, physical contact allowed and possibility for hand-guiding.

Summing up, there exists several ways to categorize collaborative works, but each study may rely on distinct factors. Many of them consider as distinctive factors the way the workspace is split among the two parts, or the timing of the operations, in case they are simultaneous, sequential, or uncorrelated.

However, since there is a misalignment among all the scale of collaboration listed above, it may be necessary to ensure a satisfactory and clear classification describing the depth of collaboration through a normative diffused and shared by the whole scientific community. It would be optimal to start classifying the levels by the lowest, the no coexistence, characterized by physical separation among the two components, arriving to the highest level, the collaboration, where the two components work simultaneously with the same goal within the same workspace, listing and highlighting all the critical elements which belong to each level in order to obtain a clear differentiation leading to an ordinal scale.

3.4 Collaborative Robots and manufacturing: an overview on the applications

The collaborative robot has become an integral part of manufacturing, making production processes more efficient, flexible, and safe. The easiness to transport, install and operate belonging to cobots make them vastly used in manufacturing performing numerous activities such as assembling (screwdriving, part insertion), dispensing, finishing (sanding, polishing), material handling (packaging, palletizing, picking and placing), and others.

Figure 17 groups together all the feasible tasks performable by Cobots in the manufacturing context. These activities include *machine-tending,* for loading and offloading operations onto CNC mills, lathes, or injection-molding machines, or *pick and place*, where items are moved from a position to another, mostly used as support for logistics and packaging, or *assembly operations*, for which cobots integration in the assembly line is required for operation of screwing and components insertion above all.

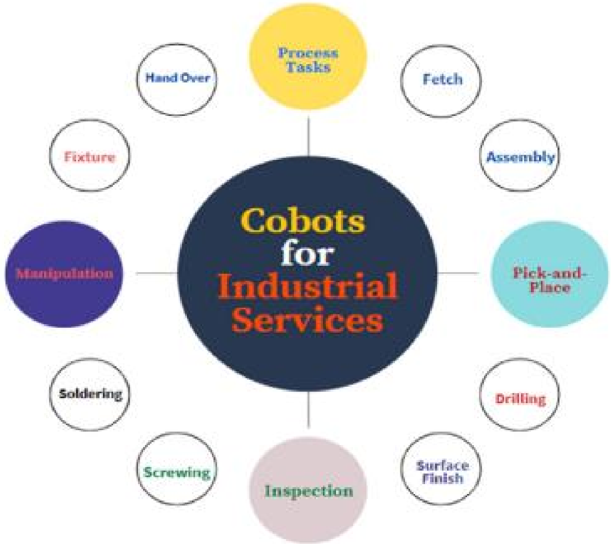


Figure 17 - Possible Collaborative Robots applications in Manufacturing. [61]

Handling probably represents the most widely used task in the collaborative robots framework, due to its diffusion among many industries, and it comprises various processes as transporting, palletizing, product testing and pick and placing. [87]

Cobotic material handling allows to reduce human workers efforts and stress deriving from labour-intensive tasks, reducing time-to-market and product life cycle, making possible for companies to gain additional advantage against their competitors. This is one of the reasons which lead the diffusion of collaborative robots to increase in the small and medium enterprises sphere. Time effectiveness and the possibility to use human workload just for added value activities, rather than using them for labour intensive and repetitive tasks, generate additional productivity which may be translated in extra revenues for the company. Under a mere financial perspective, collaborative robots represent a profitable investment for small and medium enterprises, as soon as they have a high return on investment (ROI) caused by an initial cost of investment comprised between 40000€ and 45000€, much lower than the range of investment, among 100000€ and 150000€, required for acquiring and installing an industrial robot. [50]

Nevertheless, as stated by authors in [87] cobots handling applications are still quite limited to the robot-as-tool approach, hence the level of collaboration existing among workers and cobots is low.

Nevertheless, as stated by authors in [87] cobots handling applications are still quite limited to the robot-as-tool approach, hence the level of collaboration existing among workers and cobots is low. Thus, as evidence of the several challenges still existing, which avoid the possibility of fully integrate collaborative robots and human workers within the manufacturing context exploiting higher levels of collaboration, the percentage of cobots among all the robot installations in 2023 was less than 7%. [41]

Authors in [68] pointed out several factors as the root cause of the persistence of a still scarce integration of the collaborative robots in the manufacturing context focusing on the following fields:

- Technical and technological limitations, as active collision avoidance, dynamic task allocation and efficient motion planning.
- Safety, cybersecurity, and data accuracy.
- Load division, e.g. finding the risk task allocation between human and machine.

Through a survey conducted in [59], authors were able to identify that the level of collaboration in cobots applications is still quite low, concluding that cobots are simply used as "uncaged" traditional robots, neglecting in this way the evident benefits each firm can exploit by them, as the possibility to reduce workers' payload, or the flexibility of re-deploy the activities conducted by the machines without the need of redesign the whole layout. This reluctance is due to a non-affinity to the change and a myopia in the strategic adoption of change management by the companies' managers.

Nevertheless, cobots can even take part in quality inspection and testing. Defective check, components measurements and test to verify the functionalities of the products are tasks completed by the cobots to support operators, guaranteeing a higher level of accuracy. These activities bring benefits not only under an economic perspective, but it is strictly related to the sustainable manufacturing framework which will be introduced further.

The effects of the power consumption of industrial robots should not be underestimated as they are responsible for 70% of the total industry consumption, which affect directly on the unit cost of production per item. [18] Optimizing the energy consumed per each item might result in potential economic benefits and even in cleaner production in line with the sustainability goals, namely number 9 and 15, formulated in 2015 by United Nations, which request by 2030 not only the usage of cleaner resources, but either the usage of technologically advanced processes. One of the viable solutions is represented by the usage of intelligent collaborative robots, which through sensors, artificial intelligence algorithms and digital twin can enable manufacturers to achieve their sustainability goals, improving efficiency and profitability, thus enhancing their competitive advantage.

The depletion of finite energy resources has appeared as one of the most pressing challenges of the 21st century. [38] As global populations and economies continue to grow, the demand for energy rises, placing immense strain on traditional fossil fuel reserves. The finite nature of these resources, coupled with their detrimental environmental impacts, causes a paradigm shift towards sustainable manufacturing practices.

Sustainable manufacturing encompasses a broad range of strategies aimed at minimizing environmental impact, conserving resources, and reducing waste. By adopting sustainable practices, industries can mitigate the negative consequences of conventional manufacturing methods, such as greenhouse gas emissions, pollution, and the depletion of natural resources. Moreover, sustainable manufacturing can enhance operational efficiency, reduce costs, and improve a company's reputation. Thus, a firm can be defined as sustainable if it pursues aims of reducing their environmental impact, while the financial situation and the social impact on the stakeholders are augmenting.

One of the primary drivers of sustainable manufacturing is the need to address energy scarcity. By optimizing energy consumption, industries can reduce their reliance on fossil fuels and contribute to a more sustainable energy mix. This can be achieved through various means, including the implementation of energy-efficient technologies, the adoption of renewable energy sources, and the optimization of production processes. The optimization of the production processes is the factor which leads collaborative robots to be included in the manufacturing context. Because of their financial profitability, due to lower costs compared to the traditional robotics and for their increasing return on investment (ROI) which make the collaborative robots the right instrument to be adopted by companies with strict budget constraints, and in addition because of the positive impact they have in terms of reduction of the environmental impact and the great social impact they bring, especially for the blue-collars, collaborative robots represent a sustainable friendly tool under all the three perspectives.

Authors in [75] provided some recommendations for energy consumption optimization, mainly based on the structure of the robots and on the workload of the manufacturing process. The authors focused on factors which mostly influence the choice of the adapt robots able to satisfy the process requirement, such as:

- The payload capacity should not exceed the demand, it would be useless and energy consuming to adopt a robot with 50 kg payload capacity which is assigned to pick and place lighter items.
- The arm speed should be proportional to the interarrival rate. A robot that moves too quickly consumes more energy than necessary, increasing in the meantime the idle time which is not an advantage. Thus, it would be proper to regulate the operating speed on the type of operations the robots are assigned to perform.
- Well-maintained robots typically consume less energy since maintenance avoids eventual friction and energy losses.
- Flexibility may stand for a key advantage in terms of energy optimization. Robots able to be reprogrammed or easily adapted to new tasks can lead to energy savings in the long run.

All the characteristics listed by the authors belong to cobots, therefore they represent the most energy efficient example of robots. The flexibility, the regulable arm speed and the low payload make it possible to consume lower energy compared to a traditional industrial robot.

The objective of this thesis and of the application presented further is to develop a list of critical activities crucial to optimize, both in a hardware context and even in a software one, the energy consumption of the collaborative robots to gain advantage in terms of sustainability under the economic perspective and the environmental one too.

3.5 Collaborative Robots and Energy Consumption

After a first focus on the general concept of collaborative robots, their development and the possible application in several industries, the research was mainly based on the impact collaborative robots have on sustainable manufacturing and some energy consumption optimization model.

The number of valid papers discussing among the others about, the evolution of cobots within the last few years timeframe, the challenges and the most widely used application in manufacturing is vast, hence the choice of the most useful was quite complex.

While the research on Human Robot Collaboration (HRC) in various industries was quite easy since it is in line with the increasing interest of companies in this field as demonstrated by the drop in the investments in the last years, the deep dive on the energy consumption optimization model was instead quite tricky, as clearly ascertainable by the few number of academic papers found during the research phase conducted on scientific database Scopus and IEEE.

The research was conducted mainly on Scopus and IEEE, which are two of the major academic articles repository, using as query the following prompt: *(ENERGY CONSUMPTION OR ENERGY CONSUMPTION OPTIMIZATION OR ENERGY EXPENDITURE) AND (HUMAN ROBOT COLLABORATION OR COLLABORATIVE ROBOTS OR COBOTS)* extended to abstract, title and keyword which is valid for both the websites.

As a timeframe, the research was limited to 2018-2024 horizon, without exceeding to set a too distant lower bound, which may lead to conduct imprecise research due to the continuous development presented about the topic.

Scopus presented 105 results in line with the imposed query and filters, of which around the 53% has been published in the 2023-2024 biennium, while IEEE gives it back 123 papers, of which the 50% belongs to the 2023-2024 biennium.

Firstly, all the fields not related to the research domain was discharged reaching 93 papers on Scopus and 97 papers from IEEE repository, for a total available 166 papers.

The following step requires a crossed analysis to identify possible repetitions among the two repositories and the consequent elimination of them. After this analysis, the number of remaining papers was equal to 112.

Then, an assessment based on the abstract, keywords and full-text evaluation was performed to identify which are the most appropriate papers representing the current state of art, hence all the papers classified as not in line with the thesis objectives have been discharged, obtaining a final number of valid 27 papers.

The selection phase was performed through a complete top-down analysis, starting from all the articles provided by the two repositories, reaching an almost adequate number of reliable papers, which discuss about possible mathematical optimization models, threats and opportunities linked to the resolution of this problem, literature reviews and some case studies and/or experiments conducted by others.

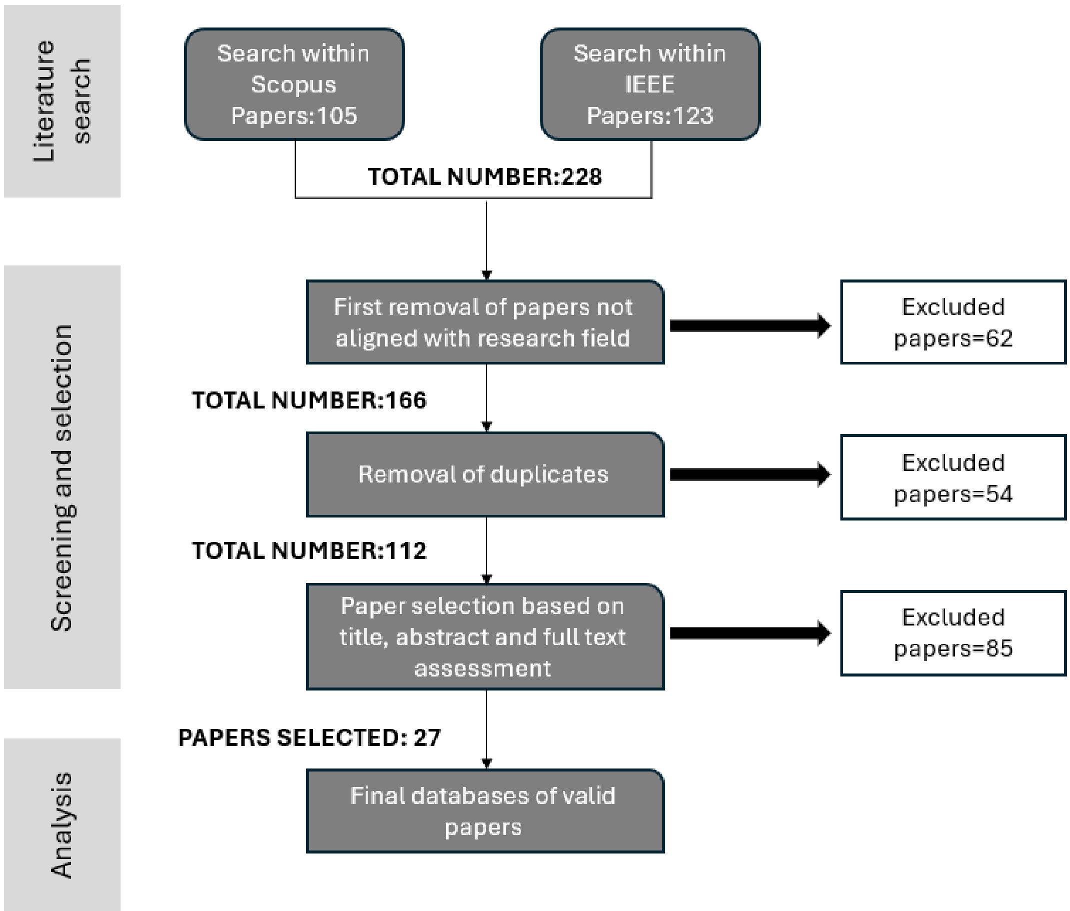


Figure 18 - Literature review methodology (personal elaboration)

The chart below shows how the list of selected papers is distributed overtime in different clusters to highlight what is the ongoing trend of research. For clarification, the sample of selected papers is reduced, hence the analysis is not significative and may lead to mistakes in the observation of the trend.

Nevertheless, it is observable that in line with the drop in the investment in cobots analysed in the paragraph above and in line with the awareness and the measures undertaken both by governments and industries about resource scarcity and sustainability goals, the interest toward resource optimization in the collaborative robotics context is augmenting.

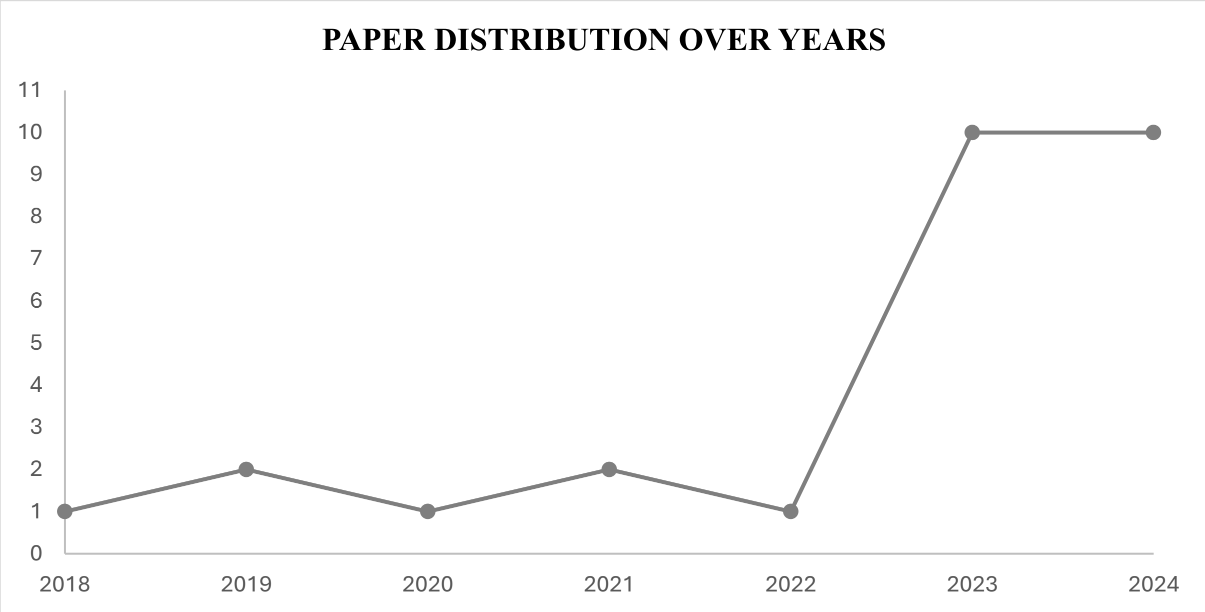


Figure 19 - Paper distribution 2018-2024 timeframe. (personal elaboration)

Since the result of the research was quite scarce, it was extended to some of the manufacturer websites, as Universal Robots which periodically post updates about the state of art or some interesting applications, which provide a more technical background to the thesis.

Going more in detail, the table below shows a synthetic review of all the papers taken into consideration for the state of art analysis, including the main topic discussed and other relevant information contained within each paper.

Title	Year	Main Topic	Summary
Going Green with Lightweight Robots: Energy Optimal Programming of Lightweight Robots	2023	Energy optimization of lightweight robots	Proposes three optimization techniques for reducing energy consumption in lightweight robots, leading to 31% energy savings.
Human-Robot Collaborative Scheduling in Energy-Efficient Welding Shop	2023	Scheduling optimization in human-robot collaborative welding environments	Focuses on minimizing makespan and total energy consumption (TEC) using a Pareto-based memetic algorithm.
Research on Multi-Objective Optimization of Grinding Robots Based on Multi-Verse Optimizer	2024	Multi-objective optimization for grinding robots	Proposes an improved Multi-Verse Optimizer for optimizing robot trajectories, reducing time and energy consumption.

Sizing up Energy Consumption in Lightweight Robots: A Comprehensive Assessment	2023	Energy consumption assessment in collaborative robots	Provides a detailed energy consumption analysis of lightweight robots, offering some optimization strategies based on joint configurations, speed, and other parameters.
Breaking Down the Energy Consumption of Industrial and Collaborative Robots: A Comparative Study	2023	Comparative analysis of energy consumption in industrial and collaborative robots	Analyses the differences in energy consumption patterns between traditional industrial robots and collaborative robots, proposing optimization strategies.
Efficiency Analysis of Cooperative Robot Based on Dynamic Parameter Identification	2023	Efficiency analysis in cooperative robots	Proposes a model for energy and efficiency optimization in cooperative robots by using dynamic parameter identification techniques.
Empowering Cobots with Energy Models: Real Augmented Digital Twin Cobot with Accurate Energy Consumption Model	2023	Digital twin modeling for energy optimization in collaborative robots	Develops a digital twin augmented with energy consumption models for real-time optimization and troubleshooting of collaborative robots.
Data-Driven Energy Estimation of Individual Instructions in User-Defined Robot Programs for Collaborative Robots	2024	Energy estimation of robot instructions	This paper develops a data-driven approach for energy estimation, emphasizing the role of specific instructions within robot programs in collaborative robotic environments. Focuses on improving energy efficiency in robotic programming.
Energy-Efficient Robotic Parallel Disassembly Sequence Planning for End-of-Life Products	2024	Energy-efficient robotic disassembly sequence planning	Focuses on improving the energy consumption during the disassembly of end-of-life products. It introduces a parallel sequence planning method that considers energy constraints and improves the overall efficiency of the robotic disassembly process.
Human-Robot Collaborative Workflows for Reconfigurable Fabrication Systems in Timber Prefabrication using Augmented Reality	2024	Human-robot collaboration in construction with augmented reality	Presents workflows integrating human-robot collaboration with augmented reality (AR) in timber prefabrication. The paper put in evidence the role of AR in improving the efficiency and accuracy of collaborative fabrication tasks.
Multi-fidelity optimization with Adaptive Optimal Sampling for Position-constrained Human-robot Collaborative Disassembly Sequence Planning	2024	Optimization for human-robot collaborative disassembly sequence planning	Proposes a high-fidelity optimization approach using adaptive optimal sampling. Focuses on position-constrained human-robot collaborative disassembly sequence planning and line balancing, aiming to improve task allocation and resource efficiency.
Optimal Energy Operation Strategy for We-Energy of Energy Internet Based on Hybrid Reinforcement Learning with Human-in-the-Loop	2024	Energy operation strategy using reinforcement learning for the energy internet	Introduces a hybrid reinforcement learning model involving human-in-the-loop for refining energy operations in the context of We-Energy. The focus is on improving energy efficiency while integrating human decision-making processes in the loop.

Reducing the energy consumption required for the disassembly process implemented on an assembly and disassembly line	2024	Energy consumption reduction in disassembly processes	Explores methods for reducing the energy required in disassembly lines. It presents optimization strategies for disassembly line operations to reduce overall energy consumption without sacrificing operational efficiency.
Research on Key Technologies of Low voltage Flexible direct system based on Station area Energy consumption optimization	2024	Energy optimization in low-voltage flexible direct systems	Investigates key technologies for optimizing energy consumption in low-voltage direct systems in station areas. The case study proposes methods for improving energy efficiency supporting the consistency of the system.
Multi-objective optimization of cycle time and robot energy expenditure in human-robot collaborated assembly lines	2024	Optimization of cycle time and energy in human-robot assembly lines	Focuses on lowering both the cycle time and energy expenditure in human-robot collaborative assembly lines using a multi-objective optimization approach.
Multi-Objective Multi-Resource Task Allocation for Collaborative Robots Systems	2023	Task allocation optimization for collaborative robot systems	This paper focuses on a multi-objective optimization approach for task allocation in collaborative robot systems. It explores the trade-offs between multiple resources such as time, cost, and energy in task allocation.
On designing cyber-physical-social systems with energy-neutrality and real-time capabilities	2021	Design of cyber-physical-social systems with energy-neutrality and real-time capabilities	This paper discusses the design of cyber-physical-social systems (CPSS) that achieve energy-neutrality while keeping real-time performance. It introduces methods to balance energy consumption with the real-time demands of CPSS.
Collaborative or Simply Uncaged? Understanding Human-Cobot Interactions in Automation	2020	Understanding human-cobot interactions in automated environments	This paper investigates the nature of human-robot interactions in automated settings. It explores whether these interactions are genuinely collaborative or simply a result of physical proximity without meaningful cooperation.
Optimization of the Energy Consumption of Industrial Robots for Automatic Code Generation	2019	Energy optimization in industrial robots through automatic code generation	The paper focuses on reducing energy consumption in industrial robots by optimizing motion parameters such as velocity and acceleration. The approach integrates with existing offline programming tools to generate energy-optimal robot code. It also highlights the significance of this optimization in terms of financial and environmental impact.
Empowering Cobots with Energy Models: Real Augmented Digital Twin Cobot with Accurate Energy Consumption Model	2023	Digital twin modeling for energy optimization in collaborative robots (Cobots)	This paper presents a real-augmented digital twin model of Cobots that accurately estimates energy consumption. The model is used for various applications such as robot optimization, commissioning, and troubleshooting. It also eases anomaly detection by comparing real-time data with the model, and it can predict energy consumption during commissioning phases before installation.

Digital Twins for Collaborative Robots: A Case Study in Human-Robot Interaction	2021	Digital twin applications in human-robot interaction	This paper explores the use of digital twins for enhancing human-robot interaction in collaborative environments. The study highlights the benefits of using digital twins for real-time monitoring, predictive maintenance, and improved safety in collaborative robotic systems.
Digital Twin Driven Human–Robot Collaborative Assembly	2019	Digital twin for human-robot collaborative assembly	This paper presents how digital twins can address human-robot collaborative assembly processes. It highlights the role of digital twins in real-time monitoring, simulation, and optimization of human-robot collaboration, focusing on enhancing flexibility and productivity in assembly systems.
Optimization of Energy Consumption in Industrial Robots, A Review	2023	Energy consumption optimization in industrial robots	This paper reviews the various techniques for perfecting energy consumption in industrial robots. It explores both hardware and software approaches, focusing on energy-efficient motion planning, control algorithms, and system design. The paper highlights the latest advancements and trends in reducing energy use, offering a comprehensive overview of methods and strategies for energy optimization in industrial robotic systems.
Survey on Human–Robot Collaboration in Industrial Settings: Safety, Intuitive Interfaces and Applications	2018	Human-robot collaboration in industrial settings	This paper provides a comprehensive survey on human-robot collaboration in industrial environments underlining key areas such as safety regulations, intuitive user interfaces, and practical applications of collaborative robots in industry. The paper highlights trends, challenges, and advancements in making human-robot interaction safer and more efficient in various industrial applications.
The Impacts of Industrial Safety on Environmental Sustainability in Human-Robot-Collaboration within Industry 5.0	2024	Balancing industrial safety and environmental sustainability in human-robot collaboration	This paper explores the balance between human-robot collaboration (HRC) safety measures and their impact on environmental sustainability within the Industry 5.0 paradigm. It presents a case study of an HRC workstation and evaluates how various safety components influence the energy consumption and carbon footprint of the system. The paper highlights a 10% reduction in energy consumption and carbon footprint when Design for Environmental Sustainability (DfES) principles are applied.

Sustainability of Human-Robot Cooperative Configurations: Findings from a Case Study	2023	Sustainability in human-robot cooperative configurations	This paper investigates the sustainability of different human-robot collaborative configurations within industrial settings. It explores the environmental and operational impacts of these configurations, focusing on factors such as energy consumption, efficiency, and ergonomic improvements. The case study presented evaluates the trade-offs between sustainability and productivity, offering insights into refining human-robot interactions for better sustainability outcomes.

Table 1 - Summary of key findings from selected research papers on Collaborative Robots.

Although energy consumption optimization in traditional robotics has been deeply explored, the research on collaborative robotics is still limited and it leads to a small number of existing mathematical model analysing this topic due even to the complexity and dynamicity of environment in which collaborative robots operate. Despite some authors have tried to adapt the computation and the model developed for the industrial robotics framework to the cobots, the existing difference in the size and in the configuration witness a different amount of energy consume. The result on the analysis conducted in [36] put in evidence how not only the amount of dissipated energy is different, but even the way energy is consumed is different, showing that up to 48% of the total amount of energy for cobots is spent in their electronic components, against just the 6% for the industrial robots, which instead consume a larger amount for mechanical operations.

Dealing with a blank field in process of expanding gives the possibility to identify several gaps existing either in the application context and in the research phase.

The opportunities of using a digital twin to address the complexity of collaborative production systems [57] and to support the design, build and control of human machine cooperation [10] have already been explored, but the evaluation of the benefits as well as criticalities of applying digital twins and cobots for sustainable applications within manufacturing is still lacking and requires an in-depth quantitative analysis. Authors in [36] agreed on the fact that, despite the presence of some studies ongoing integrating cloud technologies and digital twin in the cobots framework, none of the DT-enabled multi-robot collaborative manufacturing system have incorporated an energy consumption evaluation. Despite an increasing trend in incorporating DT with collaborative robotics in various fields there is an evident gap in literature of DTs including energy consumption. [37]

The existing literature is mostly focused on the cycle time minimization to enhance productivity through the introduction of the cobots using mathematical model with lower attention towards the energy consumption optimization, which so far represented almost a blank field. Authors in [63] introduce for the first time a mathematical model in which the objective function was to optimize the assembly line balancing problem (ALBP) considering the cycle time and the energy consumption simultaneously for an intelligent dynamic scheduling of the tasks developing an exact multi-objective approach optimization approach to minimize both CT and energy consumption costs.

The minimization of the makespan, the time required to execute the whole tasks, represents the common objective to evaluate the productivity of a manufacturing system. The model presented in [89] contains a multi-objective function, since in the meantime the authors want to minimize both makespan and energy consumption in a robotic framework. To achieve the twin goals of minimizing makespan and energy consumption, the study uses a Multiobjective Artificial Bee Colony (MOABC) algorithm applied to the phase of disassembling product at the end of life (EOL). As suggested directly in the conclusion, the authors aim to extend the presented model even to a collaborative robot's context, combining advanced technologies and more efficient energy saving strategies.

[30] and [55] focused on a multi-objective multi-resource optimization model with the aim of minimizing simultaneously the *makespan* and the *energy expenditure* utilizing different algorithms, but with the same objective of [89] overcoming the limitation of the adaptability of the model to a collaborative robotics context. Whilst the model presented in [30] consider just the amount consumed directly by the operators in terms of kcal, hence the model lacks the component of energy dissipated by the cobots and their mechanical and electronic components, in [55] a Pareto-based memetic algorithm (PMA), which merges a genetic operator and variable neighborhood search (VNS), is presented to obtain a set of tradeoff solutions between makespan and TEC for operations of welding.

Moreover, many models in literature relies on industrial robotics and in addition present significant errors as the sample limited [86] or error made directly in the analysis and gathering of the data, but authors in [28] simply justify the presence these errors as related to the academic exploration and to overcome this limitation [35] presented a data-driven model feasible for collaborative robots application with mathematical basis.

[1] presented the guidelines for the energy consumption optimization of a cobot alimented by battery, but using as reference point the mobile robot behavior, hence it becomes necessary to save on the consumption satisfying all the constraints. Certainly, the conducted research was used to enlarge the field, but in the meantime, it is not fully aligned with the objective of this thesis, as a cobot alimented through batteries disposes of a limited quantitative of energy, hence it would not be optimal to consider it as a correct benchmark in terms of quantitative result.

However, [64] focused on the effects on energy consumption deriving from optimization in robot path planning presenting how some metaheuristic computational techniques, as Ant Colony Optimization (ACO), Genetic Algorithm (GA) among many others, have lacked bringing great results in solving path optimization problems combined with energy efficiency. In fact, it results that if the energy efficiency is achieved, the traveling time of robot arms is increased, and then the throughput of may be deteriorated, sacrificing the productivity dimension. To overcome this limitation, they proposed a model capable of joining together GA, used to optimize the robot motion planning problem identifying local optimal solutions instead of global optimum, with Proportional-Integral-Differential (PID) controller gain adjustment, used to look for the optimal the best robot placement. Combining the two latter strategies in a particle swarm optimization (PSO) algorithm makes it possible to find a suitable solution even in terms of energy efficiency optimization.

Among the possible gaps identified in [59], the lack of skilled employees capable of interacting with technologically advanced equipment represents one of the crucial. Despite the easiness in programming is one of the key pillars of cobots as highlighted above, the authors in [59] highlight how there exists a substantial gap among how the research is evolving and the potential applications cobots may reach and the actual ones due to unskilled human workers. One of the solutions presented by [59] regards not only the need for advanced training, which in some cases are frequent but even a detailed identification of the needed skills by the manufacturers in order to make the employees more autonomous and ready to operate. The presence of this skill gap is contributing to lowering the level of collaboration in existing applications, limiting in this way the benefits cobots may bring.

The lack of competence in employees aforementioned is the effect of an old generation of employees and operators which did not born under the *digital era* and are more resistant to adopt new technologies. This generational gap has resulted in a significant disparity in digital skills across the workforce. Older workers often lack the familiarity with digital tools that younger generations possess, creating a barrier to adopting and effectively utilizing new technologies like cobots.

Other impactful factors deriving from the adoption of a manual assembly line, which represents a weakness of a production line governed entirely by operators without the introduction of a supportive instrument as a collaborative robot, regard both the productivity and the linkage with the energy consumption. [43] performed a comparative analysis conducted on two different scenarios to assess a quantitative evaluation of the impact of a collaborative robot within a manufacturing system which is prior almost full automated, but contains a manual assembly station, and then the latter station is substituted by a collaborative robot. The objective was to evaluate the impact both under the productivity and energy-efficiency sphere of the integration of a collaborative robot. The results are clear: despite an increase in the amount of energy consumed per hour (97 W/h of the manual assembly station against 143W/h of the automated station), the augment of the utilization (from 88% to 95%), of the whole system, since the operators represented the bottleneck, generated an overall effect of reducing the energy consumption necessary per batch, hence comparing the system under homogeneous conditions, from 2220 W to 1164W, 47.6% lower. The analysis just presented is an example of how productivity rate increases are strictly related to an overall diminishing of the energy consumption level.

The objective of this thesis is the analysis of the current state of art, highlighting and solving the existing gap, like the absence of a real-time energy consumption real-time optimization model without any missing part and without any kind of under evaluation of some parameters. In addition, the realization of a model integrated with Digital Twin capable of detecting the power consumption data of the system and adapt the production parameters based on the gathered data will be presented further.

Moreover, even the existence of a correlation between the augment of efficiency in terms of productivity and idle time reduction and the related energy consumption benefits will be tested in the case study, to evidence how collaborative robots represent the way to get closer to a sustainable production, due to their impact on the financial and environmental spheres.

The model presented in this thesis will be tested under different conditions of processing speed and payload to highlight the correlation between weight transported and energy consumption and among speed and energy consumption as well. It is clear that an augment in the payload generates an amount in the energy consumed [36], but the objective is to adapt the study [60], based on the evaluation of the % of increment relying on a traditional robotics carrying different payloads, to the collaborative robots, which instead have limited payload and the incidence even of a small augment may be significative.

It allows to fill the gap related to the absence of a complete model, capable of evaluating the percentual of savings from a baseline case in which the Digital Twin is not implemented to a more advanced and real case in which the Digital Twin, thanks to the analysis of the collected data, would be able to signal the presence of some corrective actions which may result in energy savings.

4. Collaborative Robots and Digital Twin integration

While Industry 4.0 mainly relies on the introduction of collaborative robots in manufacturing system, the promise of Industry 5.0 is the generation of production ecosystems where humans and intelligent machines can symbiotically enable one another to reach shared goals regarding productivity, quality, and sustainability. [95] The Industry 5.0 phenomenon brings the human back to the center of the manufacturing process, defining a new anthropocentrism, combining the strength of the human operators in performing high-quality tasks with the capabilities of the most advanced robots. The step forward the Human Robot Collaboration is the Human Robot Teaming in which collaborative robots are integrated in human workers teams not as mere tools, but as equal partners. HRT marks a paradigm shift in the relationship between humans and robots, where robots become active contributors to collaborative endeavour. The integration of Digital Twin technologies in a Human Robot Collaborative context gives life to the DT-HRC, a structured tool where digital twins are used to modeling and simulate HRC's, allowing engineers and researchers to analyze, optimize, and improve the performance and efficiency of the whole system. To achieve efficient and responsive collaboration, it is necessary that each entity, in this case collaborative robots, human operators, involved in collaboration is aware of the intentions and state of each of the other entities. In this way, all entities will be working towards a shared plan to achieve the common goal [45]. Digital Twin represents the right instrument capable to provide the required awareness of the surrounding context to both the actors cited before, informing the human operator of upcoming robot operations, and making the robots able to understand the operating environment.

Several authors in the past just focused on a robot hardware optimization to improve the manufacturing system efficiency, proposing strategies such as a lighter design of components or by using energy storing devices, neglecting the possible integration of software and feasible technological solution which may include a remote monitoring and control of the system in real-time during their ongoing operations.

On the other hand, integrating Human Robot Collaboration with Artificial Intelligence, Machine Learning and Digital Twin technologies enables the collaborative robots to have a deeper understanding of the environment in which it operates, enhancing its cognitive features and exploiting the perceive-reason-act paradigm. [81] The latter paradigm allows the cobots to dynamically adapt to any occurring changes perceiving the production environment, recognizing surrounding activities and events. Machine Learning is used in robotics to enable robots to learn from their experiences and through artificial neural networks give them the ability to learn from data and get better over time. [88] As previously discussed in chapter 2, a Digital Twin is the virtual replica of a physical environment characterized by the exchange of data between the two counterparts which can be used to study the impact of different environmental conditions, including the potential factors which may affect object detection, human action recognition and decision making. [90] The physical counterpart is the actual production system composed of workers, cobots and the related production equipment, whilst the digital counterpart is represented via Flexsim, the virtual simulation tool used in the experiment presented further, or any other kinds of 3D event simulation software. In fact, to exploit the capacities of DT-HRC is required to represent in the virtual environment, not only the cobots acting in the process, but even the humans, to take track of their interaction with robots and analyze how they may influence the whole system. [56]

By using simulation software, the system adaptability to certain extraneous conditions can be assessed while the real system is not altered, reducing the cost impact firms would face in case the testing would be held in the physical workspace. Necessary conditions to make the simulation software work properly regard both the quantity and quality of data, enhancing the reliability and consistency of the simulation environment which may be accustomed to the real-world environment.

Integrating cobots with Digital Twin and exploiting the potentialities of collecting and anaylzing data gathered real-time through sensors lead manufacturers to identify areas of inefficiency and waste and develop strategies to improve energy and resource efficiency [94]. The impact of the adoption of collaborative robots for pursuing energy consumption optimization is disruptive since it leads to leverage two dimensions out of three of the sustainable manufacturing. Decreasing the quantity of wasted energy brings benefits not only in terms of greener production, reducing CO_2 emissions and all the collateral effects, but also in terms of profitability cutting down the resource cost.

Moreover, a digital twin allows for continuous monitoring and analysis of the cobot's operation in real-time. [10] This can help to identify potential issues and improve the overall performance of the system. Furthermore, by integrating the digital twin with other systems such as manufacturing management software, manufacturers can gain a more comprehensive understanding of the entire manufacturing process and make data-driven decisions to improve efficiency and reduce costs.

The core components for enabling a DT-HRC can be summarized as follows:

- The collaborative robot, which is the main source of data in a production system, with a UR-Real Time Data Exchange (UR-RTDE) protocol provided. [47]
- Physical sensors: Sensors, located alongside the body of the collaborative robots, are a means by which large volumes of data can be collected.
- Virtual sensors: Virtual sensors are needed in cases where it is not possible to directly measure the data. [47]
- A data collection platform where data are sent for collection and storage in datasets.
- An event-based simulation software to virtually replicate the ongoing operations.

By using sensors to read motor speed, angle, energy consumption, processing time, and compute the optimal parameters with an efficient control scheme and fault assessment for the real system, a digital twin or virtual model can precisely recreate the state and movement of a robotic arm as they occur in the physical or real world. Through the connection among the physical entity, the collaborative robot, and the digital environment, real-time data can be exchanged and gathered, and through their analysis, significant results can be deducted and even predicted. Despite the several benefits just announced, there are still some challenges related to the amount and quality of data exchanged which might be solved for a complete and effective communication between the digital and real-world environments in HRC scenarios, thus enabling the two systems to influence each other, and allowing for adjustments and improvements to be made to the manufacturing system.

However, the detection of data and the usage of machine learning algorithms can be applied in manufacturing processes for energy efficient behaviors adapting cobots' actions on the environment and task requirements. Sensors capable to transfer data can be helpful for changing the operating condition, optimizing the speed as well. In addition, the usage of simulation tool as virtual replica of the pragmatic environment is useful to gather potential energy-intensive tasks. [96]

The effectiveness of Digital Twin combined with collaborative robots is evident in [37] where a real augmented digital-twin model that accurately estimates energy consumption has been presented. The latter model is useful for identifying feasible techniques for energy optimization and possible implementation in the manufacturing context representing a groundbreaking method for real-time tracking and optimization of energy usage. The possibility of detecting anomalies in energy consumption in real-time allows the system to be reprogrammed reducing unnecessary energy expenditure.

The width of applications of DT-HRC includes even the automotive sector, which represents not only the turning point used by Colgate and Peshkin in 1996 to introduce the first example of human-robot interaction but is even one of the industries where the combination of automatization and operators' capabilities provides better results. Due to the high volume of production and the necessity of having a flexible assembly line to quickly respond to eventual change in the production of different components, the HRC symbolizes the most suitable solution for the industry's requirements. The integration of Digital Twin technologies in the automotive industry grants the feasibility of tracing a real-time operational monitoring, evaluating the performance of the entire system, forecasting the future statistics, and enhancing users' decision-making. Furthermore, since automotive is characterized as a continuous production standing for one of the most energy intensive industries, it would be optimal to adopt some monitoring strategies to cut down the amount of energy wasted. Integrating energy consumption models into digital simulations for virtual engineering, and real-time operational monitoring helps engineers to predict power needs and optimize processes to reduce energy waste. For instance, robots and auxiliary processes like welding and gluing can be simulated in advance to forecast and control power usage accurately, thereby enhancing overall production efficiency. In addition, using Digital Twins in HRC also aids in predictive maintenance, as they can flag energy anomalies that may indicate impending component degradation or inefficiency.

By comparing the simulated energy performance with real-time operational data, the system can detect deviations that suggest maintenance needs, thus preventing excessive energy consumption and reducing the likelihood of costly breakdowns. [34]

[76] analyzed the energy consumption during some deburring operations conducing different operations. The process involves analyzing energy data from cycles where burrs were removed from workpieces, simulating situations in which further passes for the total removal were required integrating the model within a Digital Twin framework. During these simulation, eventual existing patterns between speed, payload and energy consumption were highlighted, underlining how higher payloads and very low or high speeds increase consumption. Their first aim was to put in evidence how the values of energy consumption gathered during the simulation phase were distant from the physical measurements, and through a validation process the credibility of the data of the simulation model was enhanced after a close comparison with the physically gathered ones. The study includes a data evaluation paragraph in which the pattern among the different phases of operation and the energy consumption are strictly related and how additional operations lead the total motor energy to reach values 19% greater than the baseline case.

It shows how the potentialities of Digital Twin are not limited only to a real-time evaluation of the dynamic parameters, or to enhance decision-making capabilities, but it can be used even for validation purposes. The Digital Twin model presented in the latter research study, *figure 20,* is composed by two parts, the first where data are acquired through robot sensors, and the second where data are visualizable for monitoring or decision-making purposes. The data are gathered through sensors located on the robots' body and are sent directly to the virtual counterpart, which exchanges API using the HHTP protocol via web services to a data storage. The virtual model simulates robot behavior in the real world and provides feedback since it can calculate robot motions and handle I/O signals. One of the greatest limitations of this model regards the alerts sent by a telegram bot, which may be quite obsolete to manage and may compromise the real-time process due to downtime. Then, even presence of external control dashboards may result redundant, since there exists optimized software which comprises internal features capable of solving this problem.

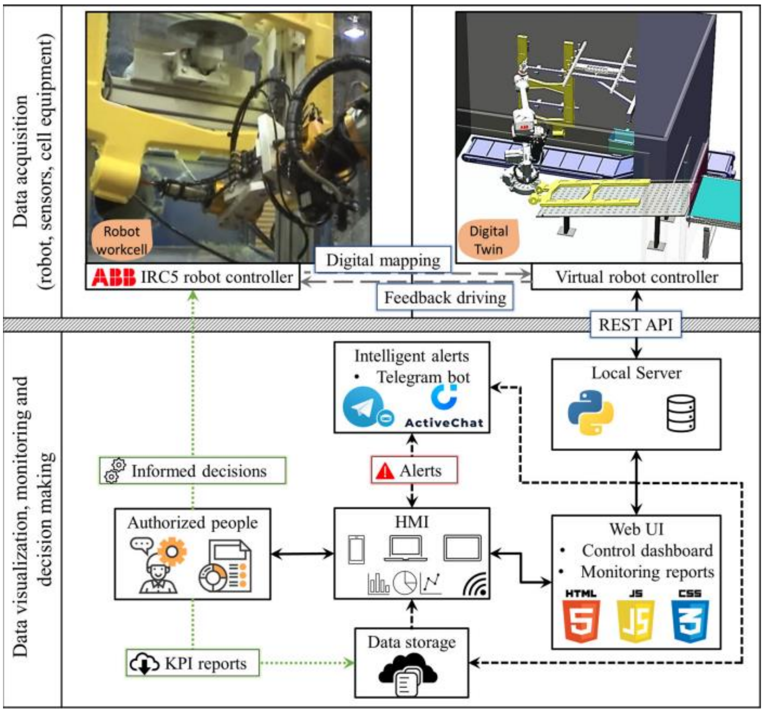


Figure 20 - Web-based manufacturing system for monitoring and control [76]

The model presented in [37] is based on a complex environment structured as follows:

- Real robot, in their case a UR3e.
- Robot manufacturer simulator which runs on an additional computer
- Mobile device communicating with the latter two elements. It computes the robot power consumption and motor currents, displays the AR DT model, and sends commands to the real robot or simulator.
- The three components are connected through a TCP/IP connection.

Analysing the presented model, it represents a deep advancement in the research field since through the interface realized with the Augmented Reality (AR) it is possible to monitor either joint measurements, such as their *velocity, position or temperature*, and robot measurements, including *power, current and voltage* thanks to which it is possible to realize an energy consumption model.

The study conducted includes an algorithm composed of two components, a dynamic model, and an energy consumption manipulator model. Through this algorithm, the total power consumption has been estimated as the sum of several elements, namely the power dissipated by the electronics components, brakes, braking resistors and mechanical components.

The model developed represents a good benchmark for future development, but it lacks analytical computation and eventual comparisons with baseline case in which Digital Twin is not implemented, hence it is not clear how the Digital Twin positively impacts on energy consumption savings and the related economic ones. It would have been optimal showing up all the scenarios, starting from the case in which Digital Twin is not integrated, identifying what are the components among the ones taken into account within the model, mostly influencing the energy consumption.

The usage of a Digital Twin in the cobots context may be useful to perform, among the long list of benefits, a more suitable Human-Robot task allocation, reducing the idle time and estimating real-time the task completion times. Thanks to these capabilities, possible modifications may be performed on the assembly scheduling to reduce the idle times and any form of non-added value timeframes and to better use each resource.

The dynamic speed and acceleration adjustment presented in [91] refers to optimizing energy consumption by adaptively adjusting the execution time of robotic operations based on the specific requirements of each movement. In contrast with linear time scaling which uniformly slows down or speeds up the robot's movements, the dynamic speed regulation proposed is a better solution since it analyzes specific segments of the trajectory and adjusts the speed optimally, considering the dynamic characteristics of each section of the robot's path. The limitations presented in the latter model refer to the absence of a digital twin which is fundamental to better understand the surrounding environment and consequently regulate the speed of the robots based on an observant dynamic parameter analysis. To overcome this restriction, this thesis aims at conducting a dynamic speed regulation integrating the Digital Twin of two collaborative robots, trying to reduce the impact of energy consumed in an idle state, combining in this manner energy consumption optimization, speed adjustment and the relative model productivity.

[85] presented a similar model based on a dynamic optimization motion planning strategy, where the impact of the speed and of the payload in a collaborative robot framework has been computed to assess how much energy consumption can be saved through the application of a Digital Twin responsible of selecting the less energy intensive path, generating a total saving of 675 kW. The case study relied on computing the energy necessary to perform 8 operations of pick and place under different conditions of speed and payload, optimizing the level of energy savings through a dynamic decision-making process which allows to select the best parameters and path for every different testing conditions, in matters of required speed and payload. The result of the case study highlights how the maximum speed necessitates higher power resulting in a higher amount of energy dissipated, since the time dimension is not taken into consideration, and in this way neither the productivity. Despite the latter model deeply inspired the application performed during the elaboration of this thesis, some gaps are clearly identifiable. In first instance, neglecting the time dimension means that the productivity and the higher throughput generated by the operations performed at higher speed are put aside and moreover that the results which have been collected are not comparable among them. It is clear that the instantaneous power for making the cobots move at higher speed is greater than the instantaneous power of the cobots moving at lower speed, but since the energy value is given by the product of power by time, the conclusion they reach are not in line with the reality.

In the 5th chapter of this thesis, a case study developed in Mind4Lab, a laboratory of Politecnico di Torino, will be introduced in which the usage of the Digital replica of a cobot will grant the possibility to collect data about the energy consumption of the cobot working in different conditions and through the historical data analysis a deep dive on the possible actions which can lead to the energy consumption optimization will be presented focusing on the velocity regulation which may result in diminishing time within a series of operation, in jargon called idle time, seeking for a joint optimization of energy consumption and productivity.

In addition, from the conclusion of the latter study above, based on a 55000 collected energy consumption samples analysis conducted on a cobot, model UR3e, the authors stated that cobot joint configuration affects the EC and the optimization of the standby cobot position may result in evident energy savings, amounting to 18% compared to the worst scenario. Thus, the cobots during the experiment will be located in the optimal location indicated by the previous authors with the aim to conduct the data collection in the best condition possible.

5. Case study in Mind4Lab

5.1 Motivation

A recent drop in the cost of electricity put the manufacturers under pressure due to an increase in the overall cost of production, representing a reduction in the demand for the produced goods.

Linked to this issue, manufacturers are seeking a solution which can avoid any kind of stress in the market share. One of the optimal solutions is represented by the cobots, which by nature consume less than traditional robots, but how much are they energy efficient and how much are they able to make producers save on utility bills?

These are the two research questions a study conducted in 2024 by Universal Robots, one of the major producers of cobots world-wide, is trying to get an answer to. [83] The study analyzes the comparison of different types of cobots with different weights and specifications with some household appliances.

In particular, the author highlighted how the UR3e cobots, the ones which will be used in the experiment conducted in Mind4Lab, consume on average 100W, the same quantity of energy consumed by a computer desktop.

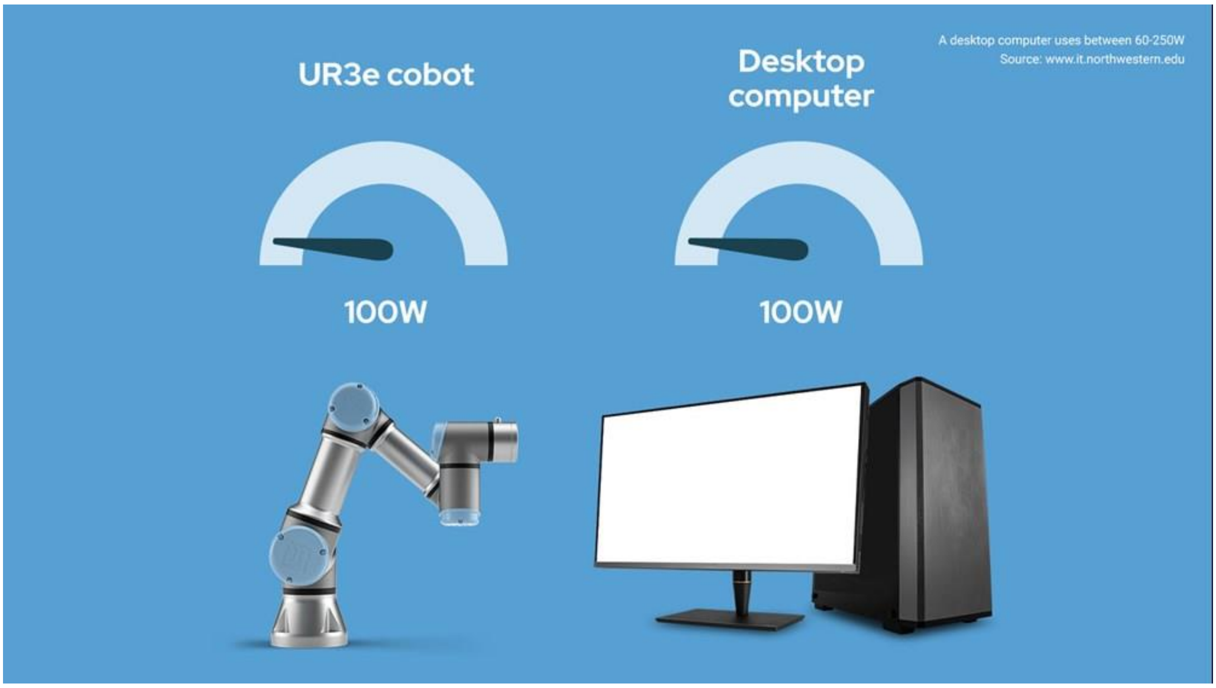


Figure 21 - Comparison among the energy consumed by the UR3e cobots and a computer desktop [83]

On the other hand, the UR20e model, the one with the highest payload of 20kg, consumes 500W on average which is the same amount of energy consumed by the most efficient washing machines, which is still neglectable compared to the consumption of industrial robots.

Figure 22 - Comparison among the energy consumed by the UR20e cobots and a washing machine [83]

The Universal Robot cobots are optimized in terms of execution time to be efficient under the energy consumption point of view, but it is crucial to reduce the amount of wasted energy for non-productive activities. As underlined by [64] the minimization of energy usage for robot motions is becoming an increasing concern in industries because of the rising costs of the energy source which effects the economic sustainability of the businesses, for their environmental impact and for the scarcity of natural resources. For these concerns, it would be profitable to define an energy saving program which aims at reducing the amount of energy spent in a useless way. A study conducted by Syddansk Universitet [35] lists the most common source of wasted energy, including long movement trajectories, wait time between operations and repetitions of movements. For reducing the amount of energy dissipated in moment which does not require energy intensive processes, for reducing the impact of the energy consumption in case of low-demand state for specific product, and for dynamically adapt the supply to market's input, this thesis aims at dynamically regulate the processing speed of the collaborative robots based on input received by a simulation environment which tries to replicate the dynamic attitude of the market. This dynamic regulation will mediate between periods of high but useless productivity, with periods of low productivity causing the generation of a supply which is much lower than the demand by the consumers due to a much lower processing speed. In this way, the amount of energy dissipated when the cobots are operating at maximum speed, but not required, would be reduced, reaching an optimization of the energy consumption with the productivity required to satisfy specific customers' needs. Companies worldwide are seeking for adaptable and flexible manufacturing system, capable to intercept dynamic changes in the external environment and adapt to them in real-time without the need of developing pre-emptive strategies. For the aforementioned reasons, this thesis tries to catch a possible trade-off between the energy consumption optimization and the productivity acting on the speed regulation which is a key factor influencing both the latter measures.

Therefore, the model which will be proposed afterwards tries to replicate a context similar to the reality where the demand for specific products varies frequently overtime, with the level of demand influencing the interarrival rate of items at the collaborative robots, which have a direct relationship with the elaboration speed. In this way, the variability component will be introduced to assess its effect over all the performance indexes. This model may represent an effective method to help manufacturers reaching environment goals, which reflect in a financial prosperity since the direct cost of resource will be reduced, without giving up the opportunity to capture their market share. The incorporation of the Digital Twin and the possibility of display the parameters change effect by using a simulator allow to identify in a relatively short time eventual problem areas and check the effectiveness of the implemented plan.

5.2 Experiment Implementation

The need for testing the energetic efficiency of the collaborative robots and the need for insights about how sustainable may be the cobots in pick and place operations have pushed to develop an experiment which may give practical evidence about the existence of a correlation pattern among the processing speed, thus the inherent process time, and the energy consumption. In the meantime, the two cobots work with different payloads, the first carrying a 3kg item, and the second carrying a 2.3kg payload to highlight the linkage among energy consumption and different payloads and point out which is the best load condition in terms of energy efficiency computed as Wh/kg for each cycle of operations under different speed setting. Despite it is already clear that higher payload generates higher energy consumption, testing different payloads has been done to evaluate if the increase in payload and the relative increase in energy consumption are proportional, i.e. how much the energy dissipated varies in terms of % changing the used payload. Further analysis about the energy consumed, in terms of Wh, will be displayed in the seventh chapter, with a greater attention towards the definition of a processing time optimal to be adopted to reduce the energy dissipated by each operation.

Figure 23 - 3kg payload transported by the UR3e collaborative robots.

The experiment was divided into two parts: the first regards the data gatherings of current and voltage under a Digital Shadow condition, in which the data were transferred from the real world to Node-RED, a platform for the data collection, and write in .csv files, while the second part regards the collection of data of current and voltage with the exchange of data from the real environment to the virtual and viceversa, requiring the implementation of a Digital Twin for a dynamic speed regulation, and the subsequent comparison with the results gathered in case of constant speed, holding the same processing conditions. Another great difference existing between the two stages regard the way the items have been created, since in the first part all the items are generated forming a batch, while the second part aims at assessing the impact of the variability in the source, which generates item one per time with different interarrival rates. Regarding the first step of the experiment, the speeds of the collaborative robots were directly managed through the teach pendant and was not influenced by the virtual environment, differently from the second part of the case study where the speed is instead managed dynamically by the establishment of the Digital Twin, in which through an input from the virtual workspace, the processing time of the collaborative robots would be regulated based on the needed conditions.

The first part was conducted not implementing a Digital Twin since it is a data-driven analysis of the energy consumption of the cobots operating under different conditions of speed. It has been assumed that no failures and interruptions occur, therefore it represents a static and ideal framework in which operates. The goal of this experiment is to evaluate the optimal speed setting, between three different: maximum speed, ½ of maximum speed and ¼ of maximum speed. In this way, the best processing speed in terms of energy efficiency was found which corresponds to operating at the maximum speed. It is crucial to clarify that speed is assumed to be constant over time, which is a strong assumption for the real world, therefore no failures have been taken into account. Thus, the two cobots work in parallel simultaneously, without any variation in time, either in speed. Furthermore, with the aim to reduce the energy consumption, the cobots follow linear motion paths, which results in lower energy amount compared to non-linear movements due to the presence of force acting on the joints and the activation of the brakes. The optimal working condition for collaborative robots in dynamic situations is to operate in a linear path, following a point-to-point movement setting. In addition, none form of variability in the source has been assumed, since the simulation has been conducted using a batch of 20 items generated at the launch of the simulation.

In this phase of the experiment, 20 operations of pick and place were conducted in series by each of the two collaborative robots. The cobots collect the items at the starting point, process them and release the items at the final position, which in a real manufacturing system may correspond to a warehouse. As soon as the item has been released and the cobots are in their idle state, they move back to the initial position to pick up a new item. Therefore, the level of utilization reaches its maximum peak, since there is no room for idle state, because the cobot switches immediately from the loaded condition movement to the unloaded movement. This cycle of operation will last till the last item has been processed.

During the case study, some of the safety features of the collaborative robots have been tested and during all the tests they respond as they should. For instance, it happens that one of the operator responsible of positioning the items in the right place to be picked, casually touch the arms of the collaborative robots simulating a crash accident among the two components, and, suddenly, the collaborative robot stops its cycle, witnessing the right functioning of the robots in preventing any type of safety issues.

From the physical point of view, the cobots were configured to start from the standstill position, *figure 24*, which is the position resulting in the lower energy consumption in standby conditions due to the lower force needed. [36] The locations of pick and place were opportunely defined after the program of the cobots operations has been launched without any load to avoid any kind of mistakes which can lead to miscalculations. Before the program has launched, several changes on the teach pendant were made, as activating the depth compensation of the cobots' hand, maximizing their force and grip since they are working with high load compared to the maximum payload, they are able to carry. Then, the operating actions conducted by the collaborative cobots will be defined through the teach pendant defining the operating loops, such as the presence of some waiting time, the joint speed and acceleration and eventually the conditions to be respected before each operation has been performed. The further step consists of setting the connection among the physical and virtual entities to establish the data transferring infrastructure, verifying the rightness of the IP addresses of the cobots in the simulation software emulation tool and the stability of the TCP/IP communication which in this step of the experiment allows the transfer of the relevant data from the physical entity to Node-RED, which organizes the date in .csv file exportable in excel to be manipulated.

Figure 24 - Collaborative Robots in standstill position prior the launch of the operations.

After the connection among the physical environment and the virtual one has been established and the data have been gathered with a resolution of one second among each other, a deep analysis of them has been conducted. First of all, all the observations which contain missing information, the inconsistent ones and the repetition were removed. Then, an analysis about the presence of outliers, like values too high of current or voltage, or zero values were removed as well in order to enhance the quality of the analysis. The data were collected in .csv files and the primitive structure of the dataset contains a column indicating the time, a second one indicating the current dissipated for each second, in terms of Ampere, and the third column containing the data about the Voltage, expressed in Volt. Through the multiplication of current by voltage, it was possible to obtain the amount of instantaneous power required. Once the instantaneous power for each second have been computed, it is possible to proceed computing the average power and multiplying it by the time required for each cycle, the result is the energy consumed in terms of Wh. All the data are rounded at the second decimal, to avoid difficulties in reading and manipulating them, aware that it may lead to some rounding problems, which were considered as neglectable.

From a theoretical perspective, as declared within the cobots' manufacturer website, one of the experts provides some suggestions on the speed to be used to obtain the lowest possible consumption a priori. Based on these suggestions, manufacturers adopting a speed and a workload equal to 70-80% of their maximum will obtain savings both on the deterioration and energy consumption. [83]

Nevertheless, the results, which will be deeply presented in the 7th chapter, witness that in the first experiment the optimal scenario is represented by the collaborative robots working at maximum speed, under both the payload conditions. However, in a real environment, which tries to replicate the market dynamics where the customer demand fluctuates overtime, it may be useless to perform all the tasks at the highest speed, since supposing that the robots operate at the highest speed, the amount of product the robots will be able to produce is greater than the one required by the customers, generating additional inventory costs, and since cobots at maximum speed state burn more energy than at minimum speed, neglecting the time dimension during which the cobots are operating, it would not be optimal to make them process at highest speed constantly. In addition, the necessity for further maintenance will raise when robots operate at highest speed and consequently the productivity rate will be affected. For this reason, a dynamic speed allocation based on the variable interarrival time represents a fair way to optimize the energy consumed in such applications trying to combine two crucial dimensions for each manufacturer, the energy consumption and the productivity. Thus, the second part of the experiment will rely on the intervention of the Digital Twin, which through the virtual space monitoring will be able to adapt the cobots' speed to the required level following the variability of the process, looking for a trade-off between productivity and energy consumed. The process variability is created simulating a different interarrival time per each item, with the interarrival rate following a uniform distribution with a minimum value, which represents the lowest time required for the flow item launch and a maximum value, which instead is the latest moment in which an object is bring to the system. The interarrival time is a variable following the uniform distribution, hence the moment in which each item is inserted within the process is unknown a priori. The parameters of the uniform distribution have been set to be in line with the collaborative robots features, hence the minimum time is 40 seconds, while the maximum is 100 seconds, thus each item may be inserted within the system in a timeframe between these two values. The dynamic speed regulation, as mentioned above, will work effectively as soon as the linkage between the manufacturing system and the virtual workspace is stable and allows to transfer a large amount of data in real-time, which are the pillar of the Digital Twin functioning, to manage any possible changes and replicate them in the real world.

The application analysed in the second part of the experiment will be very useful for continuous production, but due to time and space limitations, the experiment was conducted on the basis of 40 items in total, 20 per cobots. The collaborative robots will adapt their process time to the interarrival rate. The higher the interarrival rate, which corresponds to a higher demand for that specific product, the lower will be the process time and consequently the higher will be the processing speed, negatively related to the time. This adaptive condition was set as a prompt in the virtual replica of the collaborative robots' properties. The objective of these conditions was to create a trade-off among the energy consumption and the level of productivity, trying to restrict the idle time and the power dissipated for non-added value activities. More in details, the conditions declared in the prompt are the following and are managed through a series of if-else structure:

- If the item' interarrival time is greater than 80 seconds, the highest threshold, the collaborative robot proceeds working at the lowest move time, corresponding to the 25% of the greatest reachable speed by the collaborative robot.
- If the item' interarrival time is bounded between 60 and 80 seconds, the collaborative robot processes at medium move time, set around the 50% of the maximum speed.
- Finally, if the interarrival time is lower than 60 seconds, the collaborative robot performs the operation at the highest move time, which correspond to the maximum speed tested in the first scenario.

All these if-else conditions have been established for this experiment but may be varied and adapted to different scenarios. The chosen values have been selected after a profound evaluation of the parameters of the collaborative robots features in terms of joints' speed, tested both in load conditions and without any load.

As performed for the first scenario, even in this case, the energy consumption will be calculated starting from the current and voltage data gathered in real-time, and all the operations already mentioned with the aim to enhance the quality of the data and conduct the analysis in a proper manner has been executed.

Optimizing the energy consumption of collaborative robots and consequently of the whole manufacturing process is important not only for the economic impact, but also for the reduction in terms of environmental impact, moving close to the concept of sustainable manufacturing. The primary goal of this experiment is to witness how productivity and greener production are not so distant each other, and manufacturers may combine both the elements in the same manufacturing context, and a trade-off among both is feasible and may be reached reducing the amount of energy consumed with non-added values activities, by shrinking the process productivity as soon as the market dynamics do not demand it. As previously declared, it would be useless to work at maximum speed, if the demand for a specific product is not in line with the supply, hence this method will allow to dynamically regulate the speed in line with the demand, reducing the energy consumption if the same timeframe is considered as operative for both the maximum and minimum processing time settings.

In conclusion, the dynamic speed regulation strategy has been adopted to test the collaborative robotics' adaptability to dynamic inputs, which is one of the key advantages which bring more and more companies to adopt them in substitution of traditional robotics.

A deep insight on the findings got through the two case studies will be performed in the seventh chapter where all the data will be compared, and the optimal scenario will be highlighted.

5.3 Assumptions:

Regarding the first part of the experiment, several assumptions have been made and due to their relevance in the conduction of the case study it is crucial to mention them to make the readers fully aware of how the experiment has been taken place. The following assumptions have been a priori made to justify the results obtained:

- The initial position, where the items are picked up, and the final position, where the items are released, are chosen over the working plan, setting, through the teach pendant, the *freedrive* function, which allows the operator to move the cobots over the working plan without any resistance, selecting in this way the proper reference positions.
- The processing speed of the cobots has been set, prior the simulation starts, manually by configuring the teach pendant. An ideal case, in which the speed remains constant over the twenty series of operation, has been replicated. Moreover, no interruptions or speed slowing down have been considered. Dealing with an ideal case, it is far away from the real scenario of a manufacturing system, but this choice was made to highlight the possible existing correlation between speed and energy consumption, without the presence of variability, in a baseline scenario. In particular, I am aware of the impossibility in a real scenario of keeping the constant speed exploding the case study to a larger time interval, even because the tendency towards a more frequent maintenance increase as soon as the cobots process items at lower process time, taking the time to failure to decrease over time. The latter reduction will be reflected in a reduction of the productivity as well, but the scenario presented is limited to a small series of operations, hence I can consider as justifiable the total absence of failures.

- The two cobots carry different payloads, the first, indicated as Robot 1 further, process items of 3kg, while the second, indicated as Robot 2 further, process items of 2.3 kg. This choice was made to put in evidence the effects of the payload over the energy consumption, considering a third components for the analysis of the factors influencing the consume of energy, and highlighting in this way which one of the two cobots is more efficient, computing the efficiency as Wh/kg (watt per hour/kilograms).
- The twenty items are generated by the source simultaneously, representing a batch of twenty units, hence no variability in the interarrival time have been included in the analysis. The twenty units are generated as soon as the simulation has been started, hence the cobots do not have any spare time, waiting for the next components. When all the items have been processed, hence they have been located in the place position, which in a real manufacturing system may represent a warehouse, and the cobots have moved back to their starting position, they suddenly stop their movement.
- As mentioned above, no failure time has been considered, hence neither variability in the process time has been evaluated, therefore process time is deterministic and strictly dependent on the process speed adopted.
- The two cobots are supposed to work in parallel, with the same parameters and the same speed, therefore the cycle time for both coincides.
- Finally, regarding the final data analysis about the energy consumption, it has been derived from the multiplication of the power consumption by the cycle time. I am neglecting the energy consumption required for launching the desktop and other energy components which are insignificant, hence negligible. Comparisons, which will be shown afterwards in details, have been performed both in case of same speed, but with different weights, to highlight the component of energy consumption influenced by the change in load, and in case of same weight but different speeds, to evidence that there exists a percentage of energy influenced by the decrease of the speed.

Starting from the assumptions just presented and in order to overcome the ideal case, bringing it to a more realistic and applicable case in manufacturing context, the second part of the experiment tried to put aside all the assumptions made so far. This has been done even because the processing conditions changed, due to the introduction of the variability in the source, and the analysis is no more performed over batches, but over single items, with different interarrival times. Thus, the objective was to evaluate even in a variability scenario, which one of the speed configurations, between minimum, medium, maximum and dynamically adapted, result in the lowest possible energy consumption, suggesting the most efficient one to be adopted in a variable interarrival rate framework.

Then, the absence of variability has been overcome through the introduction of the interarrival time dependent on a uniform distribution, hence two consecutive items are not generated by the sources at the same interarrival time. It generates the variability diffused within the process, since the interarrival time is not anymore deterministic, but it varies by items in items. Since the elements are generated separately, the batch present in the first part of the experiment has been deleted, hence it is not required that all the items will be present at the beginning of the simulation as performed in the previous scenario. In addition, arrival at time 0 is not expected for any case, otherwise the unpredictability to which the model is able to adjust would collapse.

The variability in the source is then transmitted to the cobots, which with the intention of keeping high levels of efficiency and reduce the percentage of idle state, adapt their speed through a dynamic regulation, which is a strategy to contrast the variability of the process and the possible effects on the power dissipated. In this way, the cobots will regulate their speed to the interarrival rate of the items and right after a possible change in the interarrival time happens, the process time of the cobots will be adjusted too. Before the simulation has been launched, three different programs have been defined using the teach pendant, one for each different speed condition declared above. The program contains three different branches, depending on which of the if conditions, based on the interarrival time thresholds, have been satisfied and consequently the joint speed of the collaborative robots will be adapted to the assigned level. An additional branch contained in the collaborative robots' teach pendant program regards the possibility that no items will be generated for a certain timeframe and in this specific condition, the collaborative robot will be in a standby position, waiting for further instructions.

The two collaborative robots keep working in parallel, but under different conditions of speed. They are, in fact, independent each other since the items which arrives at the queue, despite they follow the same distribution, are characterized by a different interarrival time which leads the cobots to operate in different manners.

Notwithstanding the variability in the source has been introduced, dealing with a limited number of operations, possible failures or machine breakdowns have not been taken into consideration, but it would not be so complicated to adjust both the virtual model and the cobots' program to such conditions. The eventual presence of machine failures and the consequence effects can be analysed in further development and extension of this model.

Unluckily, for space and time constraint, it was not possible to extend the experiment to a more meaningful sample of operations, but as will be displayed in the 7th chapter of this thesis, the number was at least sufficient to highlight further insights about model' potential improvement under parameters optimization regarding both the energy and efficiency perspective.

The developed model is suitable to make assessment in a continuous production framework, where the items presented in this model are substituted by batches and the number of operations may be extended to a larger one, and the impact of the optimization will be more meaningful.

5.4 An insight about material components

In this paragraph, the physical elements utilized during the case study will be presented through a brief technical excursus.

The machines chosen for the pick and place operations, as mentioned above, are two collaborative robotics arms model UR3e, produced by Universal Robots, one of the biggest manufacturers in the industry.

The model UR3e is the smallest industrial collaborative robot arm in Universal Robots portfolio with a maximum payload of 3kg, a reach of action of 500mm and a footprint of 128mm. Composed entirely of aluminium, plastic and steel with a composite weight of 11.2 kg, key element for its lightness and easiness in transportation, have a high level of precision with a pose repeatability, as indicated in the user manual, of +/- 0.03 mm. As every cobots, the UR3e has six rotating joint degrees of freedom, which allows to freely move in the workspace.

Figure 25 - Example of Collaborative Robotics arm used in the case study.

The two collaborative robotics arms are allowed to move on a working cageless plan which ensure the interaction between the human operator responsible, in the physical case, to put the items to be processed in the right position to be picked up, and the collaborative robots avoid any kind of damages or injuries. The two processors require a connection to a stable connection to the electricity network to be productive since they do not dispose of the possibility to work with batteries.

As previously mentioned, the two cobots work under different conditions of payload, the first carries a 3kg payload, while the second carries a steel brick with a weight of 2.3kg. The choice was made to evidence the more efficient payload conditions of the collaborative robots, computing the percentage of additional energy consumption deriving from carrying maximum payload.

Moreover, the software used to perform the virtual simulation is FlexSim, described in detail in the sixth chapter, which have allowed to create different scenarios by the realization of a suitable process flow.

5.5 The experiment objectives

This paragraph is a recap of all the objectives which have been pursued through the execution of this experiment. The following list allows to make clear and align the readers with all the objectives and expected results of this case study:

- Monitoring the correlation between speed and energy consumption in static conditions, without the intervention and collateral adjustments of the Digital Twin, as it is a Digital Shadow, testing it through 3 different speed setting and evaluating the optimal speed in static conditions, which corresponds to the level of speed with lowest energy consumption.
- Monitoring the effects of variable payload on the energy consumption, testing the amount of energy consumed in static conditions under 2 different payload settings, computing the percentage of energy consumption surplus deriving from the incrementing payload.
- Implementing a dynamic strategy to optimize both the energy consumption and the overall efficiency, diminishing the amount of cobots' idle time, thus improving the utilization rate, through the implementation of a Digital Twin. The latter Digital Twin has been created linking together through a TCP/IP connection the virtual workspace created within the FlexSim environment and the physical entities composed by the two collaborative robots, and by creating a infrastructure capable of continuous exchange of data, the model is able to detect and implement possible changes in the whole environment. This dynamic approach is called dynamic speed regulation, with the cobots' process time depending strictly on the interarrival time, hence any changes in the interarrival time will be reflected in the process time. The main objective of the dynamic speed regulation is to find a trade-off among energy consumption and productivity, trying to monitor in a dynamic context the possible energy savings and how this implementation may bring benefits to both the economic profits and energy consumption level. It is a manner even to test the cobots' adaptability to dynamic conditions, which vary during the simulation, which represents one of core features of collaborative robots.

6. Virtual model

6.1 FlexSim: A versatile tool for Digital Twin creation

FlexSim is a sophisticated 3D simulation software renowned for its ability to model, analyse, and optimize complex systems. By creating their digital twins manufacturers can ex-ante identify eventual bottlenecks, improve and test the process and gather the impact of the change without it physically occurs.

In this way, FlexSim enhances the decision-making capabilities, assisting manufacturers in predicting whether to realize a specific investment or a layout relocation without physically testing it, hence savings on both risks and costs associated with altering actual operations.

The user-friendliness interface grants the possibility to realize even complex models by simply dragging and dropping items from a comprehensive library into a virtual workspace. Among the selectable items there are *fixed resources*, as source, queue, and processors, and even *task executers,* which are responsible of transporting and operating on the items. Once the items have been selected and moved into the virtual workspace, users may operate modifying the statistics and the parameters in order to personalize the process making it more accustomed to the one manufacturers are interested in realizing.

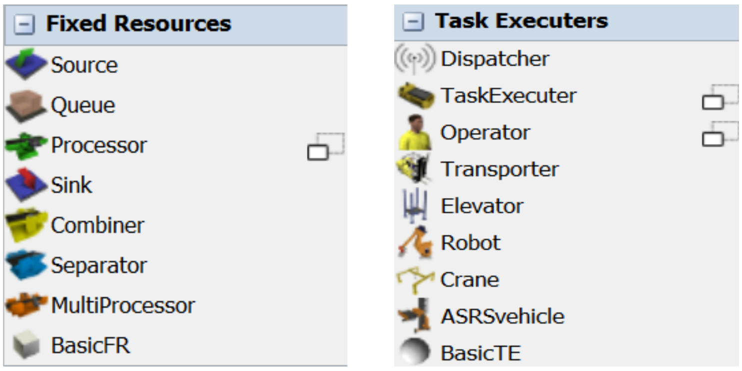


Figure 26 - List of some of selectable items in FlexSim.

Once the items have been located within the virtual workspace, the flow items should be defined through the connection among the components, which guarantees the passage from a resource to another, representing the evolution of the manufacturing system and the dynamic transition of the items towards the completion of the operations.

One of the key features of FlexSim is represented by the possibility to import directly datasets into the simulation to make the model adapt to a realistic context, or, in the other hand, export datasets containing statistics and parameters of the simulation for further analysis. The possibility of realizing dashboards, *figure 27*, allows the real-time visualization of the evolution of some critical statistics of the model, such as the average WIP, throughput and cycle time. While the simulation runs, the visualization of these parameters grants the users to make predictions about the model behaviour, understanding and identifying possible areas of improvement, and through the actuation of some changes in the model's parameters the user may test the manufacturing system without the need of implementing any physical change.

Figure 27 - An example of dashboard containing performance metrics analysis.

Furthermore, FlexSim capabilities are extended to real-time data integration with external system and data sources, a feature that opens vast possibilities for more precise data-driven simulations. These data may be gathered from sensors, IoT devices, spreadsheets or may be written directly from some data collection and processing platforms, as Node Red. In the latter way, physical entities data are sent through a TCP/IP connection to the data collection platform, they are elaborated and then sent to FlexSim. This approach makes FlexSim suitable for Digital Shadow representation, since the data flow occurs just from the physical entity to the virtual one. In line with the definition of [48], based on the level of data integration within the physical and virtual environment, FlexSim is a suitable software for the representation of Digital Model, Digital Shadow and Digital Twin. In this way, FlexSim receive dynamic data from the physical world, such as machine breakdowns, speed variations or any other changes in the baseline conditions, granting real-time simulation adjustments. Example of real-time adjustments may be dynamic speed regulations based on clear changes in the interarrival rate; in this way FlexSim will respond diminishing or augmenting the processing speed of the machineries present in the layout.

Several are the fields of application of FlexSim, but above all there is the manufacturing, where the intervention of FlexSim may lead to production line and layouts optimizations. Manufacturers leverage the software to enhance workflows, reduce cycle times, balance workloads across machines and operators, and improve overall equipment effectiveness (OEE).

Logistics and supply chain management also benefit from data integration within FlexSim. Simulations that integrate data from warehouse management systems (WMS), transportation management systems (TMS), and IoT sensors can offer real-time visibility into inventory levels, shipment status, and distribution bottlenecks.

Despite all the advantages highlighted so far, the usage of FlexSim and data integration is not without any form of challenges. The major one consists in ensuring data accuracy and consistency across the systems, which is a diffused challenge in all the Digital Twin applications. Then, going forward, the learning curve of using FlexSim is steep, especially in manufacturing context, since as discussed in the *chapter 3,* there is a lack of skilled employees in the field of programming and API integration, caused by digital skill gap.

6.1.1 Layout development

After each element has been dragged and dropped within the virtual workspace and all of them connected through their ports in order to complete the virtual counterpart of the manufacturing system under analysis, the next step consists in the configuration of the input, triggers and output of each item.

Double-clicking on each component is possible to open the properties' window, in which all the parameters may be modified making them accustomed to the configuration the user is looking for. Starting from the source, *figure 28*, responsible of the generation of the flow items, the virtual representation of the processed objects in the manufacturing system, where the interarrival time characteristics may be defined, distinguishing it in deterministic or stochastic. The interarrival time represents the time interval between two consecutive objects entering the system. The user may define the time interval as a constant value or use a statistical distribution (e.g., exponential, normal, uniform) to model variability, or can even decide to make all the items arrive at the same time in forms of batches. Furthermore, one or more labels may be inserted among the properties of the source. The label allows to take track of some relevant data while the simulation is running, as the interarrival time of each item, or the class they belong to. In the model developed, a label regarding the interarrival time has been created for the resolution of the if-else loop.

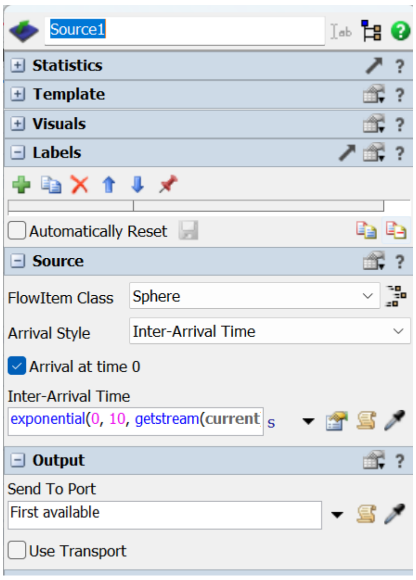


Figure 28 - Elements editable in the source setting.

After a source, it is somehow necessary the presence of a queue where all the items, before being processed by *task executers* or moved by a transporter, are stored waiting to pass to the following step. Even for the queue, the user may manipulate its parameters, regulating the state, the staytime, the maximum content and if there exists a preferred ports where the items would be sent first, based on the priority level. Regarding the model implemented for the second part of the experiment, the queue has been limited to a maximum of 10 items containable.

The presence of at least a task executer, of a robot or of a transporter, depending on the system the user would like to represent, is way more important, since it represents the machinery under examination of the manufacturing system. In this case, the users may regulate the processing speed, the trigger, the eventual presence of some failures and other elements which make it as similar as possible to the physical counterpart. In the FlexSim model realized, the robots have no set-up time and their *movetime* are deterministic, but dependent on the interarrival time of each item to be processed.

All the steps described so far are just some of the basic ones needed for the realization of a virtual workspace through FlexSim. Of course, the more elements are considered, the more faithful will be the virtual representation to the manufacturing system under evaluation.

6.1.2 Run the Simulation

The step after the virtual layout has been realized consists of launching the simulation, clicking on the button *run.* In this way, the flow items generated by the source will leave moving towards the next step. The system will evolve over time, the items will move from one part of the system to another one and the dashboard will be updated in real time based on the performance of the system' components.

Launching the simulation, the potentialities of FlexSim as a Discrete Event Simulator (DES) will be exploited since the operator is replicating in the virtual workspace what would happen in the real world, but with relevant savings in terms of time, waste and money.

Pressing the run button in the software environment will generate the launch of an input to the collaborative robots, which enables their activations and readiness in performing tasks once additional inputs are sent to the cobots. In fact, once an item has been generated by the source of the virtual environment, the input is sent to the collaborative robot, which prior to start its processing state, decodes the received input which contains relevant information about the operating mode. Practically, the input will be directed to different registers based on a first evaluation of the label assigned to each item representing the interarrival time, and according to the threshold level the interarrival time label belongs to, the output will be different both in the virtual and real environment, since they represent the decisional criteria for the speed regulation.

As soon as the conditions for ending up the simulation has been reached, pressing the button *stop* the user may decide to interrupt the process and, supported by the data collected and the dashboard elaborated directly by the software, he may conduct analysis and reach empirical conclusions which will help him in the decision-making process. Whilst in the first part of the experiment, right after the completion of the pick and place of all the items by the collaborative robots, the simulation will end up, in the second part of the experiment, once all the items have been generated by the source, a trigger *onexit* will be activated on the source itself which interrupts the output of additional units.

6.2 Virtual Representation on FlexSim for the case study

For the case study conducted in Mind4Lab, it was necessary to realize the digital counterpart of the system composed by the two cobots UR3e shown in *figure 29*. While the layout remains identical for both the scenarios, the logic beyond instead varies, to be aligned with the variations responding to the different scenes.

The real system is not complex, since it is just composed of the two collaborative robots above mentioned which are performing operations of *pick and place*, hence it was not so difficult to realize a model on FlexSim which was representative of it.

The case study is based, in a first instance, on the iteration of 20 consecutives operations of pick and place in which the cobots take the items from an initial position, and after they have been elaborated, they are moved to the final position, which represent the end of the manufacturing process.

As soon as the objects are released in the final position, the robots move back to the initial position to complete another operation till all the objects are processed.

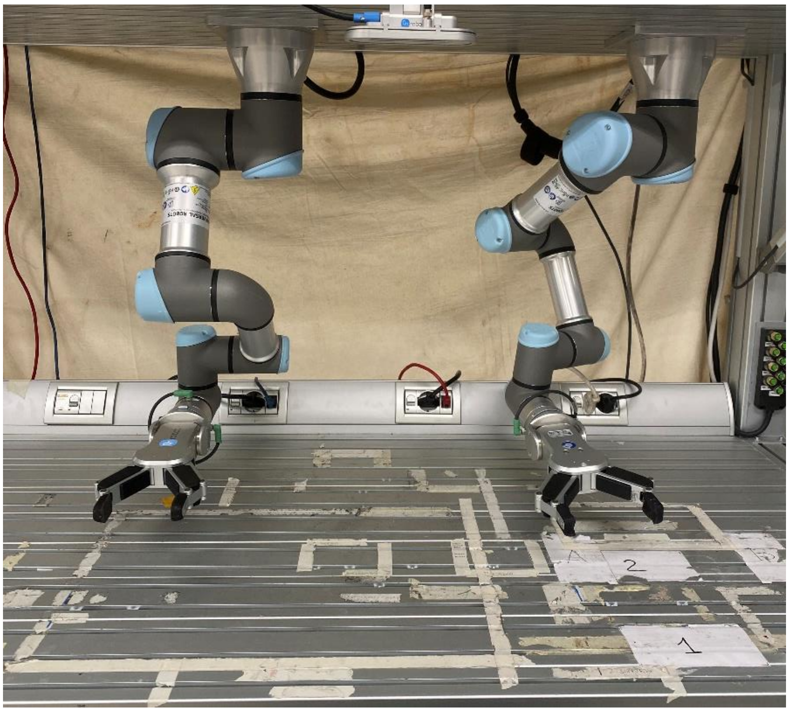


Figure 29 - Two collaborative robots adopted in the case study.

The second scenario is represented by an identical layout, but simply the items instead of being generated all simultaneously in the form of a batch in the moment the simulation is launched, they are generated in different moments unknown a priori. Therefore, what mainly changes is the configuration of the source parameters, regarding the arrival time, and the processing conditions belonging to the robots.

The representation of the system in FlexSim is presented in *figure 30.* The layout implement consists of the two productive lines which are represented as different entities. Two sources generating the flow items are located at the beginning, followed by two queues where the items are stored prior to being processed by the two cobots in parallel. The two robots are in the idle state since the simulation has not launched yet, but as soon as an item reaches the two queues behind, they react, picking it up, processing and placing the item in the final queue.

The final queue, in *figure 30* indicated as *queue3*, is the place where the items after they have been handled are stored in forms of output. In pick and place operations, which point represents the warehouse where all the outputs are stocked.

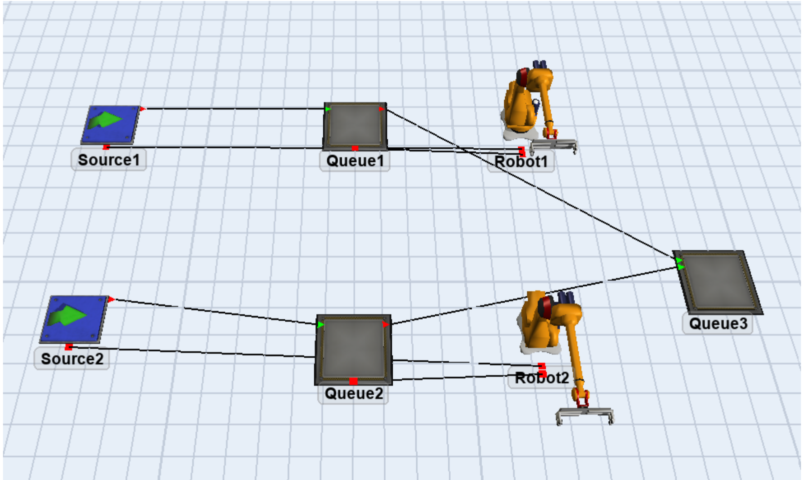


Figure 30 - Virtual replica on FlexSim of the manufacturing system.

Beyond the drag and drop function of collocating objects somewhere in virtual space, the most complex and interesting part regards the definition of the logic behind the cobots' behavior, which is graphically represented in the process flow.

Moreover, all the details on the interarrival rate distribution, the queues maximum content, the process time of the cobots should be defined prior to the simulation beginning. Regarding the interarrival rate distribution, the most appropriate one, which respects the way the flow items are generated by the source, should be defined. Then, the queue maximum content represents the maximum number of items which may be contained in the queue simultaneously. Finally, the process time of the cobots is related to the processing speed and the throughput, and even in this case we can set it as depending on a specific statistical distribution, or equal to a deterministic value.

In the experiment conducted and presented further, the presence of two different scenarios did not affect the layout organization, while both the parameters and the process flow have been varied. Regarding the sources' parameters, while in the case of digital shadow collection of data, the twenty items arrive simultaneously at the queue as if they were part of the same batch, in the second scenario, where the objective was to replicate the variability of the interarrival rate, the items are generated by a process which follows an uniform distribution for both the sources. The uniform distribution allows to replicate a scenario in which the variability is present and the interarrival time is not deterministic, but it may be a variable which falls between 40 and 100 seconds.

6.3 Process Flow Definition

The logic behind the implementation of the model may be represented in FlexSim by the realization of a process flow. The process flow realizable in FlexSim is a flow-chart consisting of activities and connections that symbolize operations, decision points, and actions, guiding the movement of entities, namely the tokens, through the system. Tokens follow pre-determined paths represented by the linkage of arrows or through the sequence of activities in column. In the model used during the case study, *figure 31*, the process flow starts with an event-triggered source, representing the launch of a token as soon as an activity in the virtual model has been accomplished. In this case, the trigger which represents the beginning of the path is the generation of the item from the source, hence right after the exit of the item, the token will appear in the process flow. To each token generated by the source, a label containing the information about the interarrival time of each item will be assigned, crucial to determine which of the three following paths to follow. In fact, based on the lists of the two decide in series, the if-else conditions presented before, can be replicated. The first decide is characterized by the statement "interarrival time>=80 seconds" and if the statement is satisfied, the token will follow the arrow entering in the *minspeed* container. Whereas the statement is not satisfied, a second decide will be imposed and the condition to be verified is "interarrival time<60 seconds" and in case the statement is true, the token will access the *maxspeed* container, otherwise the *medspeed*. This subsequence of activities replicates the evaluation phase of the interarrival time before the level of speed of the collaborative robots will be chosen. The following steps are common to every different container, what differs is simply the register to which the input from the virtual model is sent to the collaborative robots in order to adapt their motion parameters. The registers are a series of binary information which conveys to a physical output and the initial value is set to 0. The first step once the token has entered one of the three sub-containers is a *wait for event*, the logical representation of the starting of the operation, because the trigger which allows to overcome this block is represented by the item physically entering the robots. The "acquire" task stands for the logical constraint for which each cobot can process only one product per operation, hence until the robot is in a processing state, no more items will be accepted. The task "Set Variable" represented in *figure 31* consists of changing the value of the binary information from 0 to 1, which corresponds to the input sent from the virtual model to the collaborative robots to adapt their programs translating the input in a digital output, and accordingly with the specific registers activated the robots will adapt its motion status. This block of subsequential tasks is the representation of how an input regarding the start of the operation is sent from the simulation software to the physical environment in a continuous manner.

The lower part of the process flow, not contained in the bigger container, corresponds to the existing Modbus connection. The *Start and Stop* enables the real system to be reactive to the simulation, hence in the exact moment the simulation is launched, the two collaborative robots are ready to commence the processing loop. Even in this case, the connection is made possible via the input of the virtual workspace which changes the values of the correspondent register from 0 to 1 signaling the start of the operations.

The various *maxspeed*, *medspeed* and *minspeed* variables presented in the lower container represent the existing connection between the token following a specific path and the input sent to the related register. All the variables cited so far function as sensor register, hence the input is sent from the virtual workspace to the collaborative robots and the value of the sensors is manipulated directly by FlexSim. The *Control Robot 1* variable, differently from the just mentioned variables, *acts* as a control register, hence the input is sent from the collaborative robots to the FlexSim environment, to make the two environments fully aligned on the completion of the activities. Thus, as soon as the activity is completed in the physical system, a message input is delivered to the simulation environment, which suddenly completes the operation. This variable has been introduced to fully synchronize the two environments, without creating any form of delays.

The last variable shown in the lower container is the *Modbus TCP Connection* representing how the connection between the two environments is established through the usage of an emulation tool which allows to connect the two entities using their IP address and setting other features crucial to establish a real-time connection.

Figure 31 portrays only a branch of the process flow, corresponding to the Robot 1, while the second part is missing, but is identical to the one presented.

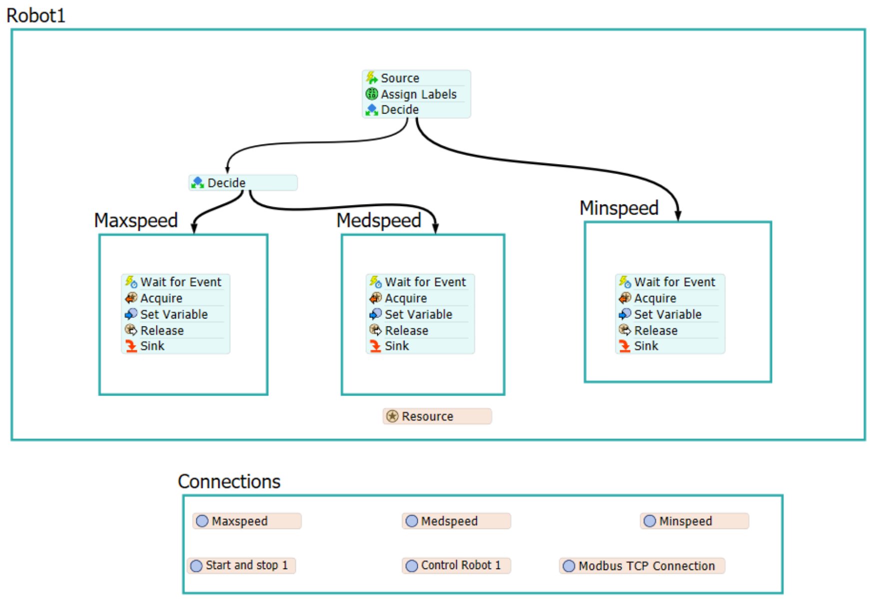


Figure 31 - Model process flow.

6.4 Collaborative Robots Offline Programming

The configuration of the collaborative robots is characterized by a user-friendly process, where the operator directly through a user interface and without any kind of programming skills can decide the list of operations the cobots are going to perform. By the usage of the teach pendant, the collaborative robots functioning program could be configured and all the condition-based actions already declared can be formalized.

In *figure 32*, the whole list of tasks the collaborative robot is going to follow are declared.

The process starts defining, in a *freemove* moving status, the target initial and positions, called waypoints, of the operations. Then, additional operations representing the whole program will be added in a loop composed of different if-else conditions, which represents the moment in which the collaborative robots will adjust its speed based on the inherent evaluation of the interarrival time. Right after the simulation starts and one of the conditions has been manifested, the simulation software sends an input to the collaborative robots register which is therefore converted on a digital output. Based on the value of the label of the interarrival time assigned to each item to be processed, the input will be sent to a different register and the digital output will be converted in a different action by the collaborative robots through a binary decoding. In fact, as soon as one of the conditions expressed in the loop statement has been satisfied, the collaborative robots will enter that specific loop and perform the specific set of operations with a different processing time.

In case momentarily no digital output has been generated, since the cobots' register did not receive any input message from the simulation software, the robots will not perform any activities awaiting any signal reception.

Getting deep with the program used for this case study, once one of the three operating branches of the loop will be activated since the condition at the basis is respected, the first activity performed is to set off the digital output 4, a register used to communicate with the simulation software indicating that the collaborative robot has just started the process. The next step is operative and regards the picking of the item to be processed and the relative movement of the arms. All the parameters, as the joint speed and acceleration, the grip and the level of the force needed to move the item will be directly configured through a series of commands. The wait activity has a different length for each path, its value is lower when the robots is operating at maximum speed, since it represents the time needed to process the item and finally locate it at the final position. Right after the completion of the placing activity, the digital output 4 will be again turned on, communicating to the simulation software that the cobot is again available for performing additional operations and the digital output register, which symbolizes the decisional criteria for the speed, will be again turned off, waiting for an additional signal. This is the way collaborative robots communicate with the FlexSim environment to make the simulation reactive for the entry of a new token in the process flow and the availability of the collaborative robots to activate the process again.

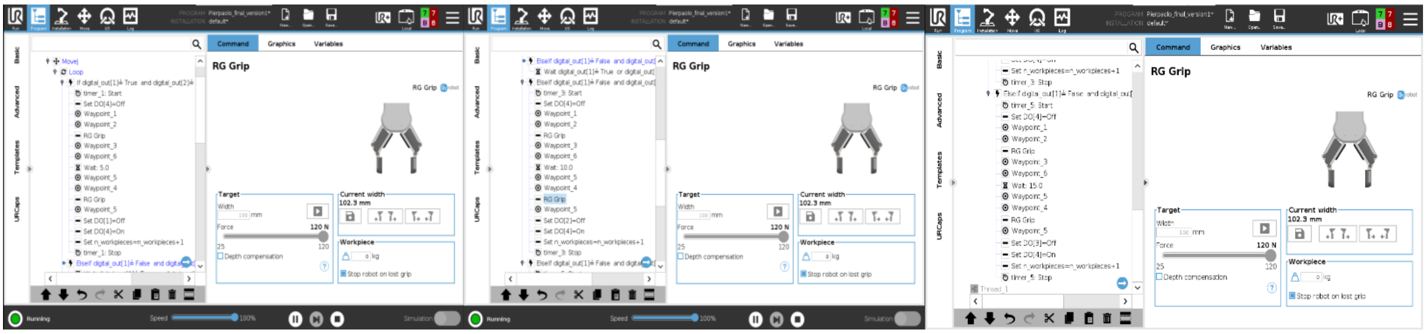


Figure 32 - Collaborative Robots programming sequence.

The entire loop will last until an additional input symbolizing that the simulation has been completed is not sent to the collaborative robots.

As briefly explained above, all the communication protocol between the virtual environment and the collaborative robots is based on inputs sent from the virtual environment to the real and vice versa and through a binary decoding these inputs are converted in physical output.

6.5 Real to Virtual Connection

Whilst in the first part of the experiment, there exists only a connection between the physical model and Node-RED, a platform for the collection of data and elaboration of datasets, in the second part is necessary to establish a reliable connection even between the virtual workspace and the real working environment. The existing connection to Node-RED represents the way the physical system sends data about current and voltage with a one second resolution and the platform will store and organize them in .csv files. In the Digital Twin implementation is somehow fundamental the existence of another connection in the counter side, from the simulation environment to the collaborative robots, which is instead required to control and adapt the manufacturing system parameters based on the ongoing simulation. Through the communication with registers belonging to the collaborative robots and the possibility to convey input via TCP/IP connection established between the two models and convert these inputs into motion outputs grant the collaborative robots to be manipulated by the virtual workspace commands. By establishing this connection, the inputs sent from the simulation framework converts the binary information, contained in the aforementioned registers, into different actions by the collaborative robots, based on the specific decoding program actuated in the collaborative robotics interface.

The linkage among the physical and virtual entities represents the fundamental part speaking about Digital Shadow and Digital Twin between the real environment and the virtual one to enhance the data exchange among the two entities occurs through a TCP/IP connection, the fundamental communication protocol useful for the transmission of data.

Internet Protocol (IP) is responsible for addressing and routing packets of data, ensuring that each packet reaches the correct destination. IP can be seen as the logistical framework for data transmission, assigning unique IP addresses to devices and directing packets accordingly.

Transmission Control Protocol (TCP) operates on top of IP to provide a reliable, connection-oriented communication channel. TCP ensures that data packets are delivered accurately and in the correct order, even if they are sent at different times or over different routes.

7. Result description

In this section, the results of the experiments conducted in Mind4lab, the facility of Politecnico di Torino, are presented graphically and numerically. First, a brief overview of the experiments, explaining how the functioning goes on. Then, the result of each scenario for the first part of the case study are explained individually, leading to a comparative analysis of the gathered data to formalize which is the optimal framework in static condition without the intervention of a Digital Twin. In conclusion, an insight about the Dynamic Speed Regulation and the consequences gained in terms of energy optimization and a comparison with the result obtained replicating the experiment using the same dynamic parameters of the first experiment adapted to the conditions of the second part of experiment is provided.

A manufacturing system composed by two collaborative robots performing pick and place operations for the final part of the assembly process has been considered for evaluating the energy performance of the two collaborative robots operating in independent conditions each other. The simulation aims to replicate, as mentioned before, the real situation of picking an item, from an intermediate warehouse, at the end of the manufacturing line, based on the customers' demand and placing it next to subsequent warehouse ready to be delivered to the market.

The objective of the experiment was based on the collection of data about current and voltage with a resolution of one second until the completion of the 20 pick and place operations, to evaluate the impact of collaborative robot on energy consumption. The first part of the experiment relies on a clear analysis of the existing pattern between energy consumption and speed, seeking for the optimal speed condition which leads to the lower energy consumed for the same amount of product processed, considering the items are organized in batches. The case study was based on testing 3 different speed settings, low, medium and high speed, under the same surrounding conditions of payload, availability of the item as soon as the simulation starts and right after the completion of one operation, without considering any spare time. Thus, the collaborative robot is always in a processing state until all the items have not been processed, perfectly balanced between loaded and unloaded movement state, without considering any form of variability, neither in the source neither in the processing time. The second part of the experiment relies on a dynamic speed regulation, in which the speed is not considered as constant as in the first scenario, but it is periodically adapted to the interarrival time threshold the item to be processed belongs to. The dynamic speed regulation strategy has been developed to respond to the variability of the source, trying to simulate the dynamics of the market, where the customers' demand changes repeatedly and to confirm the collaborative robots' adaptability to dynamic context, causing a drop in the variability of the source. The just mentioned strategy aims at solving a key challenge in the manufacturing process regarding the combination of satisfying the market demand being focused on the sustainability paradigms, which include the well-being under a financial, social and environmental point of view. The latter objective has been reachable through the inclusion of a Digital Twin in the Human Robot Collaboration framework, which has as core feature the adaptability and flexibility to variable external inputs.

Once the experiment has been concluded, a first process of data cleaning was conducted, aims at enhancing the quality of data analysed, crucial to obtain a coherent dataset to reach consistent results. After the cleaning process, through a multiplication of current, computed in Ampere, by the voltage, computed in Volt, the instantaneous power consumption was computed, in Watt. This intermediate step is fundamental, firstly to underline the influence of the speed over the power consumption, and then, to obtain an average level of power required all over the conduction of the experiment, which multiplied by the execution time provide the amount of energy required, expressed in Wh.

$$Energy\ consumption = \int_0^T I * V\, dt$$

The latter equation expresses the computation in a more compact form to reach the energy consumed from the initial moment, indicated by the lower limit of the integer 0, till the completed execution of the experiment, indicated by T, as the integer of the product of the intensity of current, I, by the voltage, V.

The transition from power to energy is somehow critical to introduce the time, a crucial dimension to be considered, to normalize the results and make them comparable. In addition, the time is a key element even regarding the productivity, since neglecting the time, the experiment will not take into consideration the change in throughput generated at different speed in the same timeframe. Considering the same timeframe, the result would be obvious, the higher speed will generate a higher consumption of energy, but since this thesis aims at finding a trade-off with productivity too, it would not make sense to exclude the throughput from the analysis. Supposing that a batch of 20 items has to be processed, the time required for processing them at lower speed is greater than the time required using a higher speed, and the same time influences even the energy dissipated in a linear way, hence prior to make hasty and obvious conclusions, another factor should be taken into consideration, which is the number of items produced.

The 7th chapter will be organized as follows: in the first paragraph the evidence of the existing correlation between the augment in payload and the relative rise of the energy consumption will be displayed, focusing on the percentage of energy savings when the collaborative robot operates at maximum payload, in the second paragraph the data collected thanks to a Digital Shadow implementation will be presented and deeply commented, aiming at finding the best speed configurations in terms of energy consumption optimization. Then, the third paragraph will move towards the introduction of the *Dynamic Speed Regulation*, a strategy implemented for this case study and easily replicable and extendable to bigger productive contexts. Finally, replicating the same speed configurations holding the same surrounding conditions of variability and organization of the single items of the second part of the experiment, the results will be compared, seeking for all the weaknesses and strengths of the latter strategy introduced and the gains in terms of energetic efficiency compared to the circumstances in which the speed is kept fixed.

7.1 Payload effect on Energy Consumption

Even though it is already clear that payload and energy consumption are positively related each other, hence an increase in the payload will cause an increase in the energy consumed for performing such operation, the goal of this part of the experiment was to test on a smaller amount of repetitions on two different collaborative robots the impact of a variable payload, thus to quantify the shift of energy consumption generated by a decrease or an increase in the payload, looking for the most energy-efficient load configuration for a UR3e collaborative arm.

For this concern, two collaborative robots were supposed to work in parallel picking and placing two different weights, of which one was equal to 3kg, equivalent to the maximum carriable weight based on the producer's indication, and the other object with a weight of 2.3 kg. As already mentioned, it is already evident that the cobot operating with maximum weight dissipates a higher quantity of energy, but the goal was to verify the existence of a common factor of proportionality between the change in the payload and the relative change in energy expenditure, and collaterally evaluate even the most energetic efficient configuration in terms of Wh/kg. To make the experiment homogeneous and gather comparable results, the surrounding conditions were the same for both the collaborative robots, without altering the environment, while 5 consecutive operations were conducted from each collaborative robot for each speed testing, to correlate another variable to the payload-energy consumption relation.

The lower payload is 23.3% lighter than the higher one. The next table resumes all the data of energy consumption for each payload under different speed conditions. On average, the collaborative robot operating at maximum payload consumes more than the case in which it operates with a payload of 2.3 kg, with a drop of 19.31% for the maximum speed scenario, 19.63% more for the medium speed scenario and 21.05% for the minimum speed case. Hence, there not exists a constant parameter influencing the change of payload and the relative change of energy consumption, since they are case-specific, but it has been witnessed, even though the data presented in this paragraph, how additional load causes additional energy consumed.

	Minimum Speed	Medium Speed	Maximum Speed
3 kg	7.819 Wh	4.095 Wh	2.347 Wh
2,3 kg	6.459 Wh	3.423 Wh	1.967 Wh

Table 2 - Energy consumption for 5 consecutive pick and place operations under different payload conditions.

However, it may be surprising, but operating at maximum payload is more efficient, computed in terms of Wh/kg, than moving items with a lower weight for all the three scenarios. For instance, the high-speed operations consume on average 0.782 Wh for each kg carried in case of maximum payload, 8.6% less than carrying a kg while operating at lower load. The same reasoning is valid for all the three speed levels. Therefore, the table below shows how the collaborative robots have been built to be optimized under extreme performances both of payload and of speed.

	Minimum Speed	Medium Speed	Maximum Speed
3 kg	2.606 Wh/kg	1.365 Wh/kg	0.782 Wh/kg
2,3 kg	2.808 Wh/kg	1.488 Wh/kg	0.855 Wh/kg

Table 3 - Energy efficiency for each scenario.

Of course, the latter parameters are dependent on the configuration of the collaborative robots, on their trajectory and on the movement, they make to conduct the item from the initial position to the final one. The efficiency factor has been computed only on those two payloads and the correlation was among the latter twos, hence it may be tested even for other payload configurations.

Certainly, the optimal results in terms of power and energy consumption occur in case of unloaded movements, but the replication of this scenario would be meaningless under a manufacturing perspective.

The objective of this section was to put in evidence how operating at maximum load results in the highest possible consumption, but in the meantime, it represents even a more energetic sustainable solution, if the possible energy savings generated by the rise of the payload have been taken into consideration.

7.2 Energy Consumption monitoring in different speed settings

In these paragraphs, the results obtained in terms of power consumption and consequently of energy consumption, in each speed conditions, will be deeply presented and commented seeking for the optimal motion configurations leading to the lower consumption. A quantitative analysis about the variability and the fluctuation around the average value will be performed, looking for the existence of a pattern which relate the speed with the energy consumed. The operating environment does not differ based on the speed adopted, thus all the other parameters have been kept constant, as the absence of idle state, the presence of a batch of same size located in a queue from which the collaborative robot draws right after the completion of the previous activity without incurring in waiting time and the total absence of variability within the process. Certainly, varying a dynamic dimension as the motion time, dependent on the speed configuration, the duration of the simulation, the *staytime* in the queue and other factors will be affected. Augmenting the speed at which the collaborative robots perform their operations, the simulation duration will drop down, as well as the average waiting time in the queue for each time, while the average content of the queue will remain constant for every speed configuration and equal to 10 items, since starting from 20 items at the launch will decrease linearly till the latter value.

Nevertheless, for each scenario, statistics performance collected directly from the simulation environment and the power consumption data gathered through the usage of Node-Red, which with a one-second resolution detect data from the real-world system, will be commented and analysed under a statistical perspective, presenting the average power required to sustain the simulation, the mode value, which represents the most common value for power consumption and finally the energy consumed for each scenario, showing how the length of the simulation, and directly the speed configuration used influence the energy consumed for the whole case.

The Node-Red platform has been configured prior to launch the simulation with the following features: with a one-second resolution, the collaborative robot sends data about the current and voltage required, and Node-Red will organize all the data in datasets, which may be manipulated through spreadsheets.

The resolution has been decided to be set to one second to evaluate how dynamically the instantaneous power evolves and how it differs second by second, based on the state in which the cobot is. It was a well-made choice to reduce the resolution to this value, since it gives the opportunity to evidence the shift of power, highlighting the most-intensive energy activities, as in absolute the moment in which the collaborative robot passes from the unloaded state to load the item and the moment in which the cobot release the item in the place position. However, as deeply discussed afterwards, the movement of the load is less power consuming than the latter described moments, with value which fluctuates around a certain value depending on the speed set.

Concluding, it is necessary to declare that all the results displayed afterwards belong to a collaborative robot UR3e carrying on a payload of 3 kg, and as shown in the *section 7.1*, the value are proper of the load configuration considered in the case study.

7.2.1 Minimum Speed

In this part, the results obtained after the data collection and processing of the minimum speed condition will be displayed. With the aim of clarifying the discussion, the minimum speed configuration used to run the simulation is not the lowest reachable speed, but it is a good approximation of it, without making the movement too low, which will not put in evidence any distinctive treats with respect to the unloaded movements. The minimum speed has been assumed to be ¼ of the maximum speed, hence it would be more correct to declare it as the

25% of the maximum speed used. However, the minimum speed configuration needs on average 40 seconds to complete a pick and place operation, leading the item from the starting position to the final one, without considering the come back from the final position, which instead would be conducted without any load. As soon as an item has been processed and released at the final position, the collaborative robot would move back to the starting position, and without any waiting time, since all the items to be processed are supposed to be immediately available in the initial batch till the end of the simulation, will process the following one. Once all the items have been manipulated, the collaborative robot will receive a trigger interrupting its motion. For the latter motivations, the possible states, as shown in *figure 33*, are only two: offset travel empty, representing the move back from the place position to the pick one, conducted unloaded, which will have a lower impact on the energy consumption, as displayed afterwards, and the offset travel loaded, consisting of the real pick and place operations under analysis.

The total absence of idle time is caused by the fact that the batch is generated at time 0 of the simulation, right after the launch of it the batch is already available, and the simulation will be halted after the completion of the last operation. Therefore, the utilization is assumed to be at maximum level, which is a strong assumption, but may be considered valid for a strict timeframe as the one considered for the case study. The absence of idle time is reached even thanks the total neglection of variability both in the source and in the process time, since in addition no interruption or setup time have been considered as present. In conclusion, as shown in *figure 33*, the possible states are only two and they are perfectly balanced.

Concerning the average content of the queue located prior to the collaborative robot, its value is stable to 10 as mentioned above, decreasing from the initial value of 20 till the final value of 0, and since the time required to complete each operation is constant, the value will decrease linearly.

The table disposed in the middle in *figure 33* indicates the average, minimum and maximum value of the stay time, corresponding to the time which each item spends in the queue prior to be elaborated. The average staytime is computed over all the 20 items, while regarding the minimum and maximum staytime, they represent the time waited in the queue by respectively the first and the last item processed.

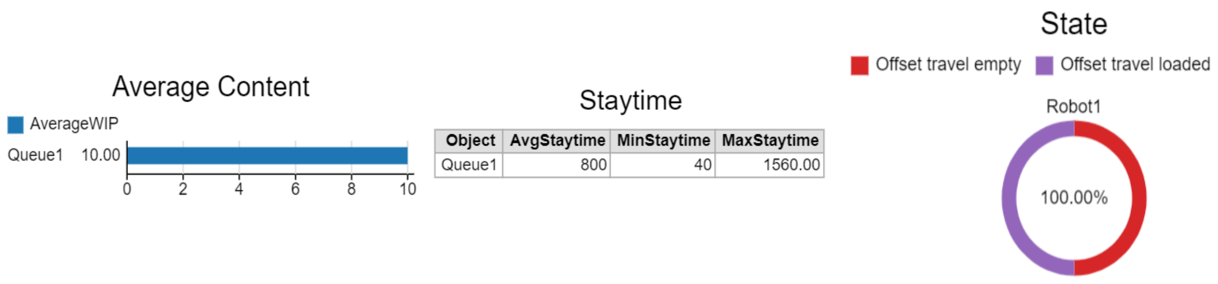


Figure 33 - Minimum Speed dashboard statistics.

Prior to analyze the mere energy consumption required for conducting the whole cycle, a brief description of the power consumption trend and its shift related to the state in which the collaborative robot is. The maximum level of power required to conduct the pick and place operation is equal to 66.12 W, occurred in the fourth observed operations, while the minimum value gathered is 36.68 W, obtained during the unloaded movement performed to recollocate the collaborative robot at the pick position, and it witness how the payload influences the power required to move the collaborative robots.

The most energy intensive moment for each repetition consists of the moment in which the collaborative robot shifts from unloaded to loaded and uplift the item to the operating height, as shown in *figure 34.* The latter mentioned figure is a representation of the instantaneous power consumption variations overtime and the shape of the power consumption trend for each operation while the cobot is in a loaded condition is similar. In fact, after the maximum reached concurrently to the starting of the operation, the power consumption drops down during the motion time, fluctuating around a value of 50 W. Once the place position has been reached, the collaborative robot arm will be opened to release the item and it represents another power intensive moment, reaching the second maximum peak of the operation, lower than the first mentioned one.

The presence of frequent oscillations generates the presence of variability in the power consumption computation, computed through the standard deviation of all the measurements, equal to 6.01 W. Computing just the standard deviation to assess the variability of the measurement is somehow meaningless, therefore it is important to compare it with the sample power average, computed as 45.9 W. The latter comparison is feasible through the introduction of the coefficient of variation (CV), an estimator of the variability, in order to make the result comparable with other cases and meaningful.

$$Coefficient\ of\ variation = \frac{standard\ deviation}{sample\ average}$$

The coefficient of variation in this case is equal to 13.09%, introducing a medium level of variability in the computation. This variability is generated by the frequent changing of state of the collaborative robot.

Regarding the unloaded movements, the value of power required to conduct them flactuate around values close to 40 W, with a lower variability compared to the latter discussion.

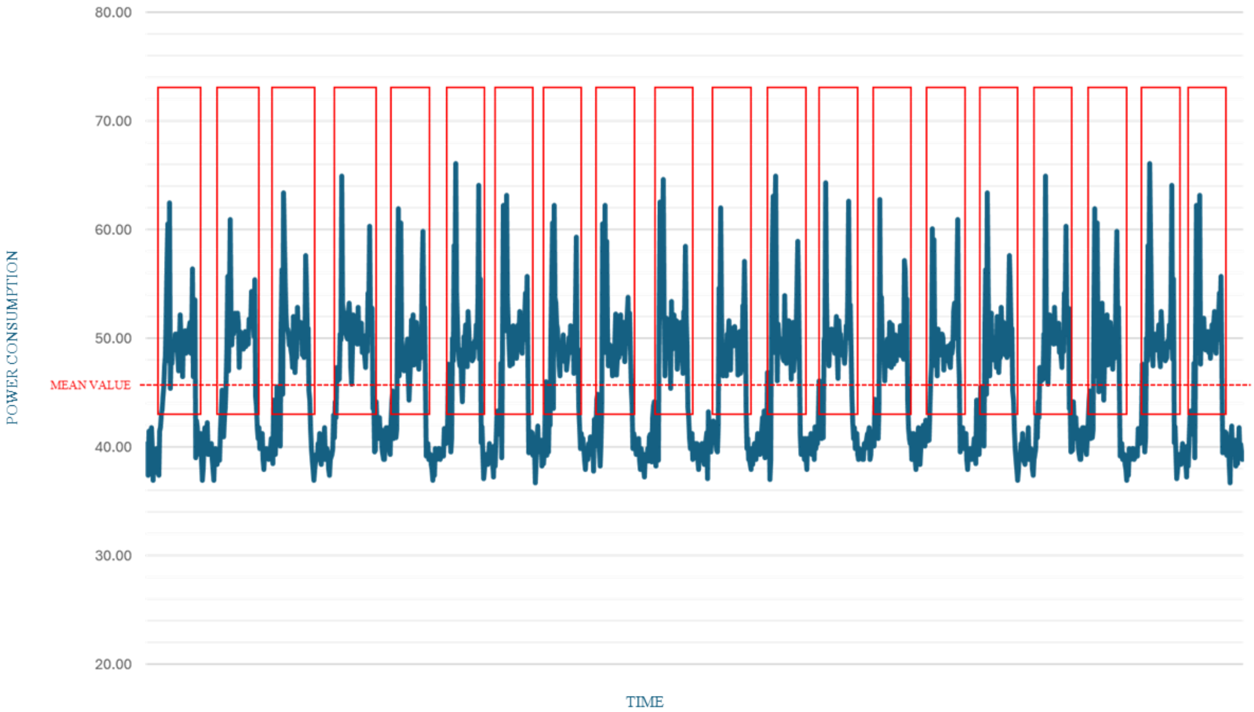


Figure 34 - Minimum Speed power variations.

The duration of the whole simulation conducted at minimum speed is equal to 1600 seconds, a deterministic value since the parameters of the simulation are not affected in any way by the variability. Multiplying the average power by the duration of the simulation, the result shows the energy consumption for conducting this simulation, just considering the collaborative robotic contribution. However, the value of power burnt over time may be subject to light variations, but the results of average power consumption used to perform the computation is the most frequent obtained.

The amount of energy needed is equal to 20.4 Wh, therefore each complete operation consumes on average 1.02 Wh, but despite the collaborative robot takes about the same time to perform the round-trip, it is not correct to split the energy consumed in two.

7.2.2 Medium Speed

Regarding the medium speed scenario, a motion time of 20 seconds for each loaded movement from the picking to the placing positions, which is exactly the half of the minimum speed.

As commented for the minimum speed case, even in this scenario, the existing state in which the collaborative robot may be are only two: travel loaded from the pick to the place position, and the journey-back to the pick position to be ready to execute a new operation.

What differs from the previous case description is just the *staytime,* strictly dependent on the processing speed of the robot. Thus, the minimum *staytime* value drops down to 20 seconds, which is the time that the first item waits till the collaborative robot pick it up. However, all the statistics about these parameters are exactly equal to half of the previous case, passing respectively from 800 to 400, for the average, and from 1560 to 780, for the maximum.

Figure 35 - Medium Speed performance statistics.

The power consumption data, plotted in *figure 36*, presents more pronounced variations, because when the cobot is unloaded, the level of power consumption remains the same, fluctuating around 40 W, while the power required in case of loaded movements increases due to the drop of the speed. In fact, while the global maximum of power consumption for the minimum speed operations was 66.12 W, in the present case, a maximum peak of 71.04 W has been reached in the 17th operation, although the minimum value remains stable, with a peak of 36.79 W, creating a gap between the maximum and minimum equal to 34.25 W, which is classified as sample range. The most frequent value, namely the mode, is equal to 41.82 W, and as mentioned above, occurs during the unloaded movement with 33 repetitions during the simulation length. Regarding the average value of power consumption is 4.2% higher than the average consumption presented for the minimum speed scenario, it is equal to 47.93 W, as plotted in *figure 36* by the horizontal red dotted line.

With the aim to evaluate the variability of the result, it is crucial to compute its standard deviation and further the coefficient of variation. The standard deviation is assessed to 6.99 W, leading to a coefficient of variation of 14.59%, slightly higher than the homolog for the minimum speed configuration.

However, the pattern is equivalent to the one analyzed before, with the shape of the power consumption trend following the same logic, with the loaded movement power consumption highlighted by the red rectangles.

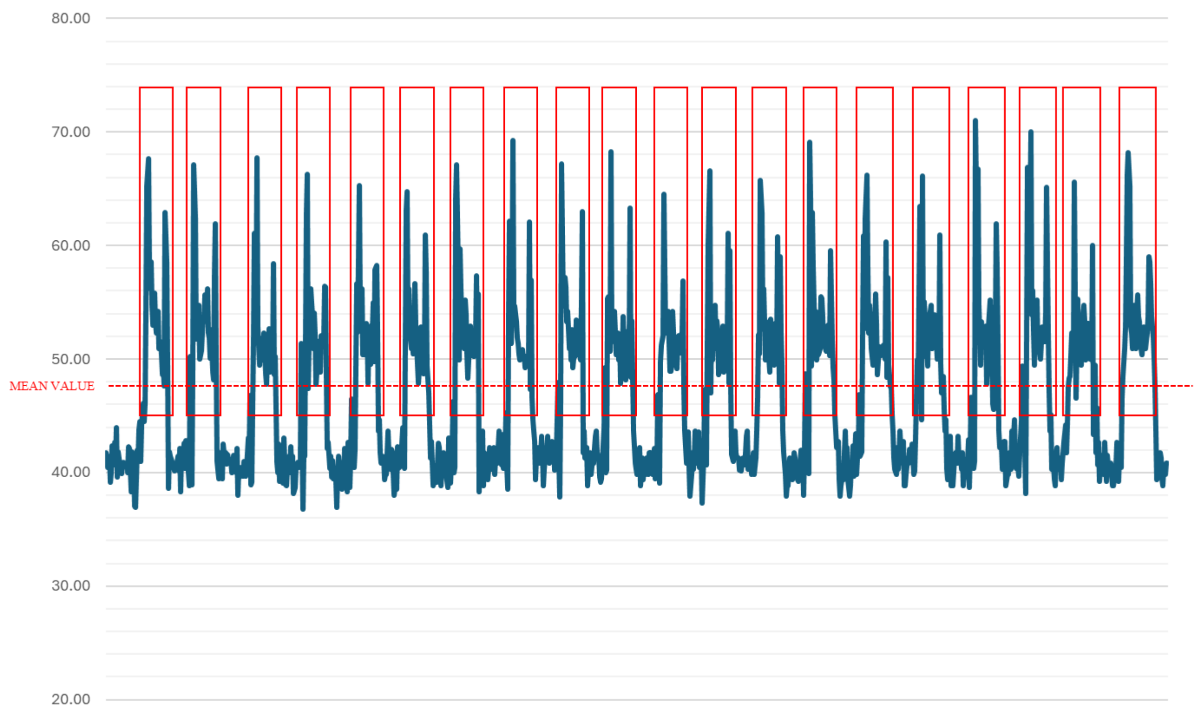
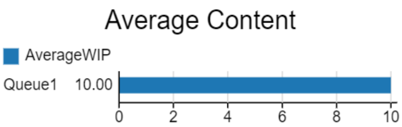


Figure 36 - Medium Speed power variations.

The length of the simulation is exactly the half of the minimum speed scenario, estimated to 800 seconds, and for estimating the energy consumption, the same approach has been used, which leads to a total energy consumption equivalent to 10.65 Wh, 47.8% lower than the minimum speed scenario. This reduction shows the importance of introducing the time dimension in the evaluation phase of the results and all the relative benefits in terms of energy consumption optimization deriving from the augment of the speed. The time dimension is crucial since it permits to compare different scenarios outcomes, making them homogenous, and allows to reach the conclusions that the increase of the speed generates benefits in terms of efficiency, not recognizable just through the evaluation of the power consumption, which instead does not include the time in its computation. Considering just the instantaneous power required, the higher the speed the higher the power, but this outcome is meaningless, since the rate of completion of each operation increases using a higher speed.

7.2.3 Maximum Speed

In this section, the last speed configuration outcome will be commented to gather further information about the optimization trend, treated in the previous paragraph, generated by a decrease in the motion time. The last speed considered is, in fact, the maximum speed, which leads the processing time to a minimum value of 10 seconds. For the seek of clarity, the maximum speed used in this scenario does not represent the maximum reachable speed, leading to a processing time of around 8 seconds, but it is the less risky avoiding the machine collapse or eventual damages. As for the medium and minimum speed scenarios, even in this case, there is a total absence of idle time, hence the utilization of the collaborative robot is assumed to be equal to 1, which represents a sort of risk in case of occurrence of unpredicted events, as failure or machine breakdowns. However, the risk has been considered as negligible, due to the restricted number of operations, therefore the assumption of the absence of idle time can be considered respectable. Taking into consideration the staytime, the trend is identic to what has been disclosed in the previous paragraph, hence all the parameters are exactly the half of the medium speed scenario and ¼ of the minimum speed. Therefore, the average content of the queue decreases in a steeper way, since the time each item is supposed to wait in the queue drops down.



Staytime

Object	AvgStaytime	MinStaytime	MaxStaytime
Queue1	200	10	390.00

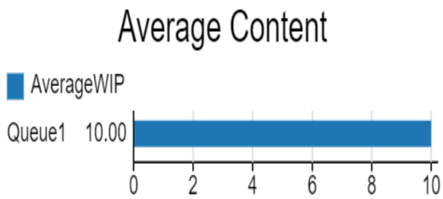


Figure 37 - Maximum Speed performance statistics.

Looking at the observations, the same considerations valid for the two previous scenarios are still valid. The shape of the trend is identical, even though the extreme points are more distant each other, generating a higher sample range and a collateral variability.

The global maximum is set at 75.36 W, occurred in the 19th operation, while the global minimum is close to the ones already presented, equal in this case to 37.54 W, creating a gap of 37.82 W. However, despite the dispersion of the values increases, it makes no sense to disclose it, without comparing it with the other case coefficient of variation. With a standard deviation of 8.39 W, and a mean value of 49.23 W, the coefficient of variation has a rate of 17.05%, moving closer to the class of high variability, based on the standard guidelines. The rate of 17.05% permits to conclude that the greater dispersion aforementioned is therefore verified and caused by a higher distance between the extreme points, represented by the maximum and the minimum peaks, gathered during the simulation.

Going more in details with the statistical analysis, the most frequent occurring value is 52.32 W, which, based on the chart below, occurs concurrently with the movement of the item and the consequent processing, with 15 repetitions in total. The two peaks tracked for each operation are relatively the moment of the pick of the item, when it has been lifted-up, and the moment in which the item is released, and the gap in terms of power intensity existing between these two moments is comprised between the 10 and 15% for all the operations.

In addition, looking at the fluctuations generated during the motion, they happen generally around a value greater than the ones detectable from the previous graphs tracking the power burnt by the minimum and maximum speed movement. This increase of the oscillations is caused by a higher intensity of the movement and a necessity of higher power to sustain and carry the item from the initial to the final position at maximum speed.

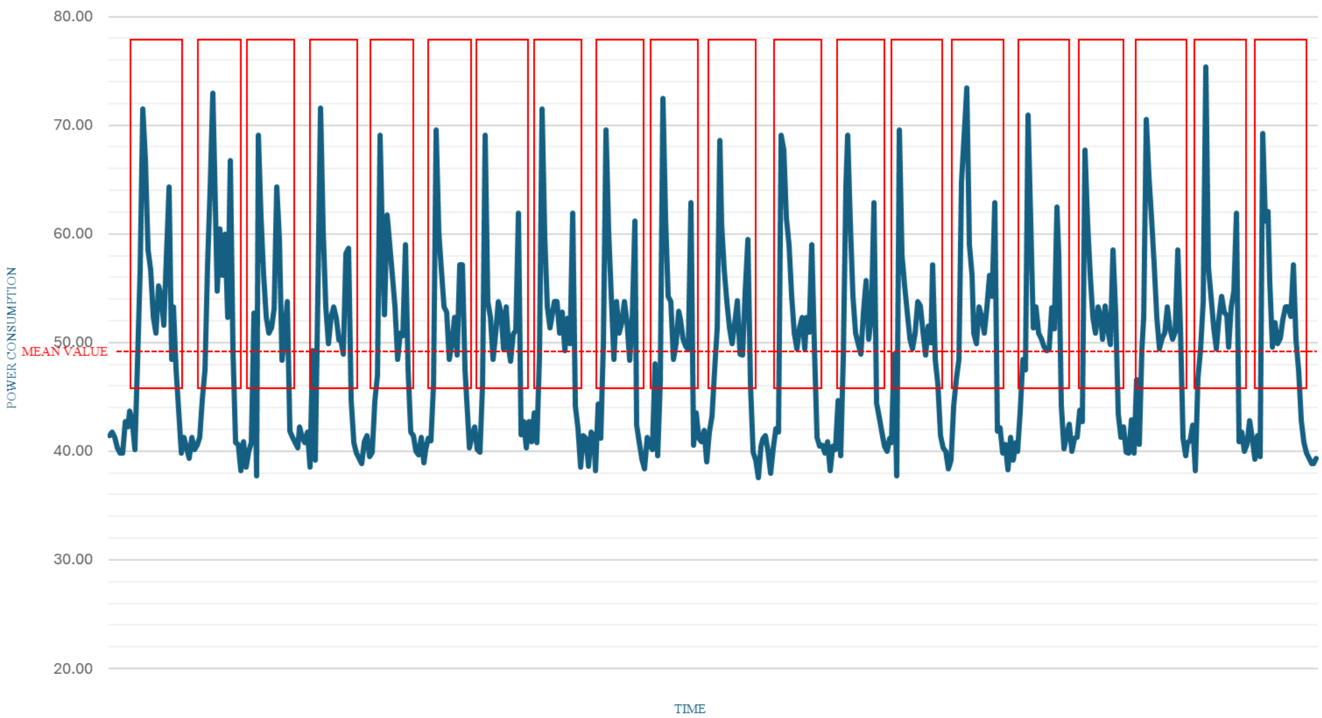


Figure 38 - Maximum Speed power variation.

However, the focus will turn onto the energy consumption over the whole cycle of operations, and computing it as the product of time by the average power level, it provides a value of 5.47 Wh, with a mean value per operation equivalent to 0.2735 Wh.

The latter result witnesses how the energy consumed for conducting the same cycle at maximum speed is 73.19% lower than conducting the same series of operation at minimum speed and is 48.63% lower than conducting them at medium speed. It clarifies the disruptive impact of the time reduction generated by performing the same activities at a speed which is 4 times and 2 times greater respectively of the minimum and medium configuration and how the related increase of mean value of power required is more than balanced by the time. Therefore, despite the instantaneous power is higher for activity performed at higher speed, reaching peak even of 15-18% more with respect to the lower speed framework, the reduction of time from the 1600 seconds needed to complete the operation at minimum level to the 400 seconds cycle time, leads to a profound contraction.

To conclude, it seems obvious to admit that the collaborative arms are energetic-friendly when operate at maximum speed, which represent the most efficient dynamic configuration.

7.3 Dynamic Speed Regulation Energy Consumption Monitoring

The Dynamic Speed Regulation is a strategy created to replicate a real manufacturing environment characterized by a variable demand for specific goods and to assess the adaptability features of the collaborative robot to different external inputs. Therefore, both for leveraging the inventory costs and to reduce the impact of unused energetic resources, especially for easily perishable goods, the latter strategy represents a valuable instrument seeking for the energy consumption optimization. For the dynamic speed regulation, for the pursuit of clarity, the speed configurations have been slightly modified and increased in order to obtain a more reactive instrument, thus there not exist the same proportionality shown in the previous paragraph among each other. The cycle time required to conduct a pick and place operation at maximum speed is supposed to be equal to 20 seconds, the medium motion time is set to 30 seconds and the minimum level of speed generates a duration of 40 seconds. The reason why the maximum and medium speed have been increased is due to the level of variability presented into the simulation. It would not make any sense to have a much lower processing time than 20 seconds, otherwise the utilization rate would drop down the 30% level, corresponding to very high level of idle state, generating a great amount of non-added value energy expenditure.

Differently from the three scenarios just presented, the following one will present distinct parameters regarding the average content of the queue, which is located just before the robot, since its average content diminishes till a value of 0.74, caused by the absence of the batch formed at the launch of the simulation in the previous scenarios, substituted by a source governed by an interarrival rate dependent on a uniform distribution. The average content decrease is directly related to the staytime in the queue diminishing, which represents the time the item spends in the queue waiting for being processed, with an average value of 33.04 seconds, significantly lower than the one presented in the previous section, witnessing the higher level of reactivity of the model, capable of adapting its motion features to the different interarrival rates, and avoid the formation of the queue.

Regarding the state of the robots, a significant drop down in the utilization is evident, passing from a 100% utilization to a 89.49%, with the collaborative robot spending on average 11.51% of its time in an idle state, while the remaining part of the pie is perfectly split between offset travel empty, corresponding to the travel made by the cobot unloaded from the place position to the initial position, and offset travel loaded. This reduction in the fraction of processing state is impactful even on the overall energy consumption, since the cobot in an idle state still burns energy, but in a lower quantity with respect to the processing phase.

Then, having the utilization rate lower than 1, but with still a considerable value, may represent an advantage even in the long-term, since supposing a machine failure, the plan may be adapted to it, and the throughput would not be affected. Hence, the idle state might be considered as a buffer for the implementation of this strategy in case of unplanned activities.

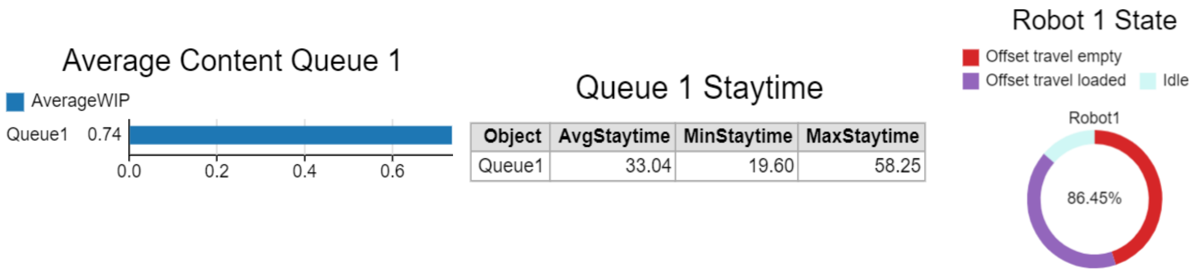


Figure 39 - Dynamic Speed Regulation performance statistics.

The choice of performing the same number of operations in every phase was not casual but has been made to have a direct comparison on the energy consumption for every case, avoiding incorrect evaluations, caused by the introduction of an average value of energy consumed per item, and the need for adding further assumptions.

Henceforth, the discussion will rely on the energy consumption deriving from the dynamic strategy adopted, emphasizing the possible divergences arising from the data presented in the previous paragraphs.

In the chart below, a clear pattern between the power consumption and the speed is displayed. All the peaks highlighted with a red rectangle represent the power consumption while the collaborative robot is processing the item. There exists a strong pattern between the power consumption and the exact moment in which the cobot brings up the load, which results in the local maximum of the observations, hence the load represents the most instantaneous energy-intensive activity performed by the robots.

Each rectangle is distinguished by another through a capital letter which corresponds to the initial of the speed used to carry the item from the initial to the final position, hence H stands for high speed, M stands for medium speed and L for low speed, which are the three levels used for conducting the experiment.

Firstly, it is clearly statable that the higher the speed, the higher the instantaneous power. It explains the high accelerations that the machine needs to reach its maximum speed as quick as possible, therefore increasing speed needs more energy to consume considering the same time horizon for all the scenarios, neglecting the impact which the speed has on the productivity.

The observations in which the power is stable around values comprised between 38 W and 42 W are representative of the idle state, when the collaborative robot waits for the following operation and based on the length of this period, it is deductible the speed adopted in the following operation.

Longer periods of inactivity of the collaborative robot correspond to period in which the demand is low or absent, hence the following item will be processed at lower speed, since there is no necessity for accelerating the process and generate a too high supply compared to the demand, due even to the corresponding higher instantaneous power required. While, when the period of inactivity of the collaborative robot is lower, or absent, it signifies that the demand for that specific good is augmenting, hence the processing rate of the collaborative robot will be adapted at greater level, to match the demand with the supply, increasing companies' revenues.

The dynamic speed regulation strategy works effectively on the basis of the variable interarrival rate, unknown a priori, thus it demonstrates the DT-HRC capabilities in adapting to dynamic conditions, since as soon as a different input is sent from the Digital Twin to the collaborative robot, it adjusts its motion program. The introduction of a dynamic strategy in a collaborative robotics framework makes the production line completely adaptable and ready to respond to external inputs, without the need for establishing a long-term plan which may lead to failure.

The maximum level of power consumption reached is 74.28 W, occurred in the second operation performed at high speed, corresponding to the moment of picking up the item, which is the most energy intensive action, since the cobot passes from an unloaded moment to suddenly pick up the item which is a stressful activity for the collaborative robot. Regarding the minimum level, all the data gathered during phases of inactivity for the cobot, while they are in stand-by waiting for a new command, fluctuate in a range comprised between 38 W and 42 W, but the lowest value corresponds to 36.9 W.

The existing gap between the highest and the lowest value of power consumption, named sample range, is 37.38 W, hence it means that the power dissipated in the idle state is less than 50% of the correspondent in a processing state at maximum speed. The sample range is an estimator of the variability in the process of measurement, given by the difference between the global maximum and global minimum, and the larger the sample range, the larger the variability. In order to compute the variability of the whole dataset and to disclose the class of variability to which the whole population of data belongs to, the standard deviation needs to be computed, and its value is 6.27 W. However, this value alone lacks context without comparison to the dataset's average power consumption, which is 44.57 W. Only by comparing the standard deviation with the average can we determine if the variability is high, moderate, or low.

The process exhibits a coefficient of variation (CV) of 14.06%, which, based on established guidelines, falls within the 10% to 20% range, and is therefore classified as moderate variability. Compared to the other coefficients computed so far, this value is slightly lower than the one observed in the medium speed static scenario, hence ranking them in a crescent order, it is the second from the bottom, after the CV gathered for the minimum speed. This level of variability suggests a noticeable degree of dispersion around the mean, reflecting the fluctuations in processing times. This moderate variability can be attributed to fluctuations in the source input, specifically the interarrival rate, which follows a uniform distribution with a maximum value of 100 seconds and a minimum of 40 seconds. This interarrival distribution yields a CV of 28.85%, indicative of a high degree of variability. Such variability in the interarrival times inherently affects processing time. Therefore, the observed moderate variability in the process CV can be partly attributed to the influence of this high variability in input rates, validating the relationship between interarrival rate fluctuations and processing time consistency, which in conclusion directly influences the power consumption value.

Furthermore, an in-depth analysis of the local maximum power consumption for each speed condition - high, medium, and low - provides valuable insights into the variability in power demand across different operational states. Examining these intervals allows us to assess the range of peak power consumption values specific to each speed, capturing the localized fluctuations that may not be evident from a global maximum alone.

From the graph below, it is possible to derive the number of operations performed at each speed setting, counting the number of repetitions for each capital letter. In particular, 9 out of 20 operations are performed at maximum speed, 7 out of 20 at medium speed, and the remaining 4 at minimum speed. These values are empirical and based on the case study under analysis, they may vary applying a different distribution, or changing the threshold deciding for the level of speed the collaborative robot is going to adopt or repeating the simulation several times.

In fact, the number of operations belonging to each class is not fixed and varies for each simulation. The following chart is used to describe one of the simulations conducted, since it was really explicative of the randomness of results, both for the sequence of class of operation and for the value of the peaks reached. Hence, even the results presented afterwards will be case-dependent, since replicating the simulation, the results obtained will change, due to the variability introduced in the source.

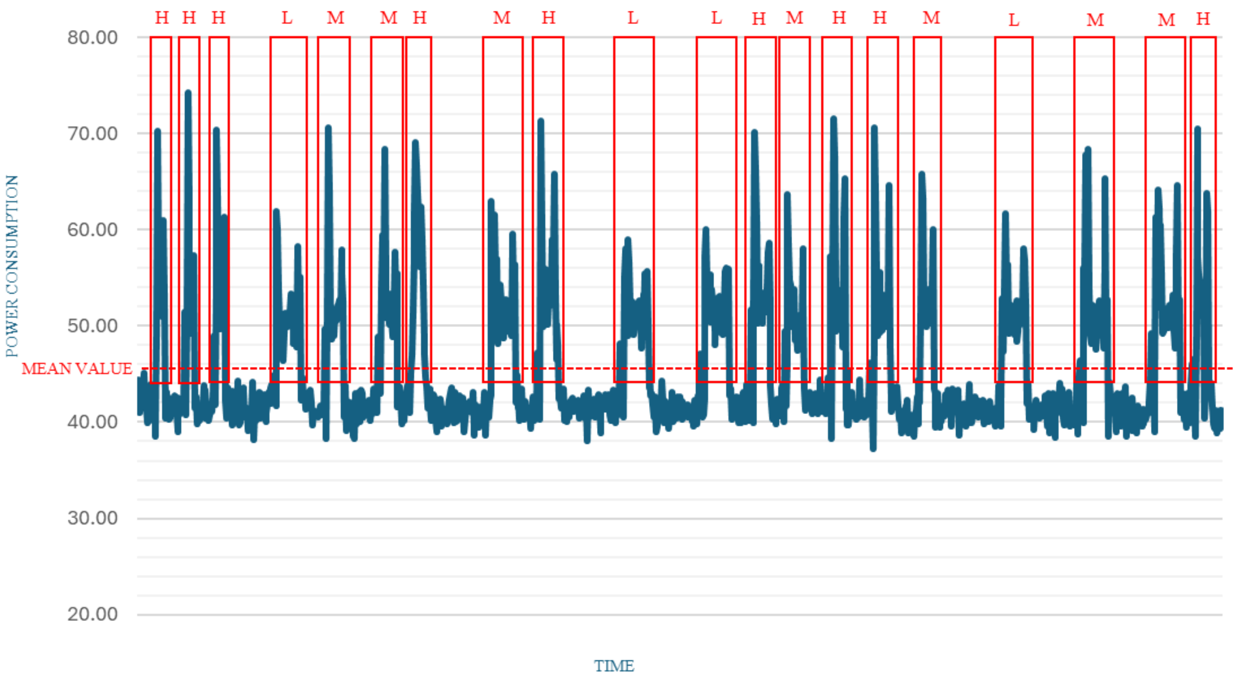


Figure 40 - Dynamic Speed Regulation power consumption variations.

After the statistical analysis just conducted, the focus turns to the evaluation of the energy consumption, computed with no distinctions from the previous scenarios. The average power needed for the whole duration of the experiment has been evaluated as 46.87 W, which multiplied by the time needed to complete the entire cycle of 20 operations, equal to 1520 seconds, of which 672.5 seconds spent during the loaded movements, 672.5 seconds spent performing the unloaded movements and the remaining 175 seconds completely in an idle state, yields the value of 19.52 Wh. Considering just the fact that around 11.5% of the total duration is spent in an idle state, it is possible to derive that the energy required to sustain the collaborative robot during its standby state is equal to 2.25 Wh. The latter approximation is not definetely true, since from an empirical computation the total amount of energy consumption in the idle state is equal to 2.82 Wh, hence a gap of 0.47 Wh is existing, which is equal to 20.27 of error, hence it may not be considered as a right rounding. This is another crucial demonstration of how the time impacts on the energy consumption, since despite the power consumed in the idle state is clearly lower than in other cases, the amount dissipated in this state is however considerable and close to the 14.44% of the overall energy expenditure.

From now on, the inspection centres on the energetic expenditure during the processing phase, reviewing all the observations gathered during the operating state, seeking for the percentage of energy consumed by each distinct speed setting.

Despite the maximum speed processes require a higher level of instantaneous power consumption, as clearly statable by the previous chart just presented, the bigger part of the pie of the overall energy consumption was occupied by the 4 tasks computed at minimum speed, due to the time dimension introduced, which affects the energy computation in a linear way. In fact, the higher the time to complete a pick and place process, the higher will be the energy consumption due to their linear proportionality. The time required to complete a pick and place operation at minimum speed is around 2 times greater than the completion time at maximum speed, even though the power variation during a high-speed task is on average 10% greater than the power variation caused by a low-speed task.

Nevertheless, the remaining part of the energy consumed during the processing state is equivalent to 16.7 Wh and is attributed to each class of speed in this way: the 9 maximum speed operations expenditure is 4.18 Wh, the 7 medium speed operations account for 5.56 Wh, while the remaining slice of the pie, equal to 6.96 Wh, representing the most impactful phase of the cycle, consumed by the 4 tasks conducted at minimum speed.

Wrapping up, *table 4* summarizes the consumption for each state. The idle state has an influence on the whole consumption, but limited to the 14.44% of the total, with a consumption of 2.82 Wh. The greatest contribution is given by the minimum speed operations, with a total energy used of 6.96 Wh and a share of 35.66%. Regarding the maximum speed, as discussed in the static scenario, it represents the most optimal case, with a share over the total consumption of 21.41%, and a value of 4.18 Wh. Concluding, the medium speed impacts for 28.49%, generating an energy expenditure of 5.56 Wh.

Idle state	Maximum Speed	Medium Speed	Minimum Speed
2.82 Wh	4.18 Wh	5.56 Wh	6.96 Wh
14.44%	21.41 %	28.49%	35.66%

Table 4 - Wrap-up of the energy consumption for each state.

Under the energetic perspective, the Dynamic Speed Regulation replicates the same path of the static analysis, with the minimum speed greatly effecting the overall consumption, despite the lower level of instantaneous power required and the lower number of operations performed, due to the time required to execute a complete operation which is 2 times greater than the one conducted at maximum speed. As shown in *figure 41*, the sum of minimum speed consumption and medium speed accounts for 64.15%, representing a consistent part of the whole pie. Although the maximum speed configuration is the most widely used in the specific case just described, with 9 observations out of 20, is responsible of only around $\frac{1}{5}$ of the total energetic requirement.

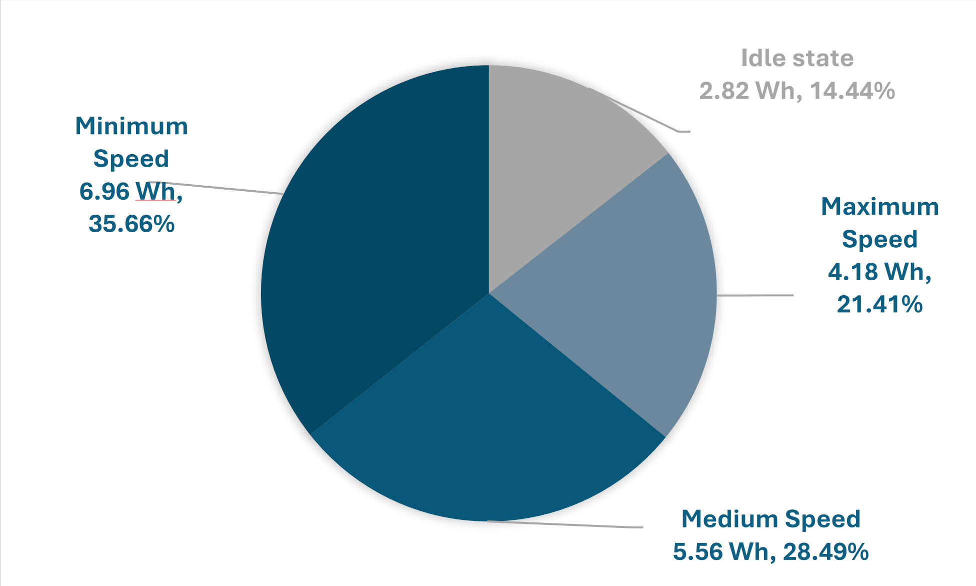


Figure 41 - Energy consumption partition.

7.4Results Comparison and Insights

With the aim of performing a comparable evaluation between the Dynamic Speed Regulation strategy and the scenario in which the speed was kept fixed overtime, it was necessary to replicate the simulation holding the same variability conditions introduced for the Dynamic Speed Regulation and all the assumptions declared as valid, while using the same level of speed used in the latter dynamic adjustment strategy, but without altering them overtime. Thus, it leads to replicate other three scenarios, one for each speed setting, where the utilization rate, the average level of power consumption, and the inherent energy expenditure has been computed. The reason behind the generation of these other scenarios was merely based on obtaining results which are comparable, since otherwise it makes no sense to use as benchmark the outcomes obtained for the first part of the case study, since in that case no variability has been considered and even the item generation process has been altered.

Table 5 summarizes all the results obtained by the several tested scenarios, displaying the time needed to complete the cycle of operation, the average power consumption, the utilization rate and finally the energy consumption, based on which the scenarios are ranked.

The most energy efficient case is the Dynamic Speed Regulation configuration, thanks to its responsiveness to adapt the processing speed to the variability and the related interarrival time of each item which is unknown a priori. Keeping the same level of speed would be useless in such a situation, especially when the maximum speed configuration is used because a great part of the energy would be consumed in an idle state. However, the dynamic strategy adopted represents the most optimal scenario even because the mean value of power is the second lowest, just behind the minimum speed. Despite the implementation of a Digital Twin can require additional energy consumption, which in this case study have been neglected, exploding the number of operations to a continuous production framework, the possible gains deriving from the dynamic strategy would be even more meaningful than the one presented in the table.

The possible cause of the energy expenditure reduction implementing such strategy can be found even in the reduction of required time needed to perform the whole cycle with respect to the case of adopting constantly a speed set to the medium or minimum value, with a reduction quantifiable respectively as 19.62% and 61.84%. This is due to the fact that the number of operations performed at maximum speed are two times greater than the operations performed at minimum speed, even though the sequence of different speed cannot be deducted prior to launch the simulation, since these features, as others, are case-specific.

Despite the energy optimization with respect to the Maximum Speed scenario could be assumed as negligible since has been generated a cut-off equal to 0.16 Wh, the adopted strategy represents the most energetic efficient especially if compared to a larger amount of operations, proper of a continuous production process, hence expanding the simulation to a larger values of tested operations, the benefits will be more consistent. Therefore, it has been proven that the dynamic adjustment strategy represents a consistent trade-off between energy consumption optimization and the market efficiency, since they are capable to gather any shifts in the demand, adapting the motion output of the collaborative robots, without sacrificing the supply, which has kept in line with the demand.

In conclusion, the lowest speed configuration stands for the worst possible scenario, hence it is not advisable to set the collaborative robotics to work at minimum. Collaborative robots are intelligent assistant for the human operators, but needs to be used in a clever way, since from how results from this thesis the collaborative robots are fine-tuned to work under extreme conditions both of payload and speed.

	Minimum Speed	**Medium Speed**	**Maximum Speed**	**Dynamic Speed Regulation**
Time per operation	60 seconds	45 seconds	30 seconds	Dynamically adapted
Utilization rate	97.25%	94.67%	83.43%	89.49%
Average Power Consumption	46.05 W	47.13 W	49.18 W	46.87 W
Cycle Time	2460 seconds	1860 seconds	1440 seconds	1520 seconds
Energy Consumption	31.47 Wh	24.35 Wh	19.68 Wh	19.52 Wh

Table 5 - A comparison of the gathered results for each configuration.

The same comparison has been performed for other scenarios, aiming at observing how the variability may impact over the energy consumption. The next results under examination regard the case in which the variability in the source follows a uniform distribution, as the latter case, but with different values, both of them lowered, the minimum to 10 seconds and the maximum to 55 seconds. In the same way, even the processing time per operation has been lowered to 10 seconds for what concerns the maximum speed, 20 seconds for what regards the medium setting and 30 seconds for the minimum level. The reason behind these additional computations was to relate the possible shift of variability to the effect over energy consumption optimization.

Both the simulations replicate the same pattern, hence the order of efficiency of each speed configuration remains unaltered, with the minimum speed scenario representing the worst setting to be adopted and the Dynamic Speed Regulation, on the opposite side, is the most efficient one.

As stated before, all the outcomes are case-sensitive. Differently from the previous outcomes just presented, the gap existing between all the scenarios is less remarkable, hence the greatest range existing between the extreme scenarios is equal to 3.36 Wh, since the variability has a lower effect over the whole process cycle time and the related element. Even in this case, the gap existing among Maximum Speed and Dynamic Speed Regulation could be assumed as neglectable, but the same considerations made above are valid, hence the results should be gathered in a larger context.

	Minimum Speed	**Medium Speed**	**Maximum Speed**	**Dynamic Speed Regulation**
Time per operation	30 seconds	20 seconds	10 seconds	Dynamically adapted
Utilization rate	92.98%	81.20%	59.74%	73.33%
Average Power Consumption	46.55 W	47.91 W	49.46 W	47.04 W
Cycle Time	1060 seconds	920 seconds	760 seconds	792 seconds
Energy Consumption	13.71 Wh	12.24 Wh	10.44 Wh	10.35 Wh

Table 6 - A comparison of the gathered results for each configuration.

Nevertheless, there are even some cases where the dynamic speed regulation does not represent the most efficient solution, hence prior to adopt this strategy is strictly recommended to perform similar simulations as performed during this thesis, trying different impact of the variability and other speed configurations, since as soon as the gap between the maximum speed and the minimum rises, the effect of the Dynamic Speed Regulation over the Maximum Speed will be delimited.

8. Conclusions

This thesis aims to assess the capability of the collaborative robot to be more reactive to external variable input compared to traditional robotics. In fact, among the key features of the collaborative robot there are the flexibility and adaptability, thereby to test these parameters, the objective was to replicate in a smaller context the dynamicity of the market, which in the last years has increased its unpredictability in the demand, due even to an increase in the concept of *mass personalization* at the expense of the *mass production*. Thus, the model presented represents a way to dynamically adapt the collaborative robotics performances based on external variable inputs, in this case regarding the variable interarrival rate, somehow simulating the variability of demand just cited, but the variable under attention may vary depending on the focus of the application. The model tries to combine both high performance in terms of productivity and customer demand satisfaction, placing emphasis on the sustainability paradigms for what regards the environmental impact, computing for each scenario the energy required and the eventual optimization feasible. Moreover, thanks to the realization of a Digital Twin infrastructure was possible to transfer data of current and voltage gathered from the collaborative robots to a data collection interface, Node-Red, responsible of collecting the data and organizing them in composite datasets. The manipulation of the latter datasets grants the possibility to compute the average power consumption, and consequently perform a quantitative evaluation of the energy consumption, highlighting the energy savings created by the different scenarios. All the data treated come from the real collaborative environment, hence the results are not simulation-based, increasing the consistency of the model. The developed case study represents a way to evaluate quantitatively the energetic impact deriving from the usage of different source configurations, passing from the batch generation to the single item generation, assessing how each assumption may influence the computation under analysis.

The Digital Twin developed links the collaborative robots with the data collection interface and the simulation software in a bidirectional way, overcoming the connection established in the first Digital Shadow framework, allowing to transfer in real time the inputs generated by the simulation environment to the collaborative robot, granting the realizability of the implemented strategy which requires the implementation of a real-time infrastructure to test the collaborative robot ability and replicate all the changes implemented in the virtual scenario even in the physical environment.

Nevertheless, the just introduced model has several limitations, regarding the introduction of it in a larger framework. Firstly, it would be optimal to expand the model to a mass production context, considering a longer timeframe, to put in evidence the advantage which can be gained, not only under the energy consumption perspective, but even in terms of inventory cost savings, which is another variable optimizable through the usage of this dynamic strategy, but was not taken into consideration during the conduction of the experiment, since the focus was mainly on the energetic footprint of each scenario. In fact, the cost of inventory is another key component which really influence the financial profitability of all the firms and using this model the latter cost will be cut down, since the manufacturer would just produce what is needed for satisfying customer needs. Thanks to its combined simplicity and efficiency, this model could be extremely useful especially for Small and Medium Enterprises, to overcome the consistent gap existing in terms of digitalization with the large companies. Another possible feature which is missing in the model is the economic perspective, evaluating all the benefits gathered in terms of process optimization, inventory cost reduction, energy bill cut down, with the costs of implementing this model ex-novo.

Then, even though the energy savings generated by the dynamic speed regulation in this experiment was not so impactful compared to the maximum speed scenario, which is the second optimal value, exploding the number of operations to a more realistic value, the little gap will rise more and more. The 20 operations posed under analysis were not so meaningful if benchmarked with the quantity of products moved in a firm operating under mass production paradigm, but was at least satisfying to evidence the existing pattern between the used processing rate and the energy consumed for a part of the production, and I had to deal with space and time constraints which did not permit me to explode the experiment to higher and more considerable values.

The model was developed for a UR3e collaborative robot, but it is adaptable to any class of collaborative robots, to detect how the others behave, hence it could represent the cue for additional perfectioning of the model, correlating the results gained using each type of collaborative robotic arm.

The occurrence of a breakdown during the simulation running has not been taken into consideration since the number of operations is quite limited and even to the risk-adverse approach used to not push the collaborative robot to deal with extreme conditions, hence any possible failures have been avoided. In addition, the dynamic speed regulation strategy may work effectively even in case of occurrence of failure, which can represent the input for correcting the speed configuration of the collaborative robot, hence further development of the model may be addressed in this way.

Another sort of limitation of the model is represented by the minimum and maximum value of the uniform distribution used, which might be not balanced and overestimated considering the execution time, but the choice was made to highlight the presence of increasing idle time and its impact over energy consumption. However, these values, as the distribution, can be easily adapted directly through the simulation environment interface to other specific needs.

In addition, on my opinion, it is not correct to treat the item as single object, but it would be more reasonable to consider batch of item arriving at different rate to make the simulation aligned with a real manufacturing system, but for software limitations, it was not possible to implement this feature.

Concluding, the data about the energy consumption relies just on the collaborative robotics during the operative phase, excluding from the computation the energy required for running the Digital Twin and all the collateral elements. Therefore, to realize a more complete model, it would be interesting to introduce even these values, and the consumption generated by the human operator located in the proximity of the robot.

9. References

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