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The Importance of Digital Twin Concepts for Industrial Process Simulation in the Manufacturing of Electronic Products

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Abstract *— The present work sets forth the development and application of a robotic manipulator arm, integrating physical prototypes (LEGO EV3 and 3D printing) with a virtual representation through a Digital Twin and an interactive dashboard. The objective of the research is to optimize industrial processes, reduce costs, and increase productivity, in accordance with the principles of Industry 4.0. The methodology employed involved the mapping of production processes in a factory located in the Industrial Hub of Manaus, utilizing an ACATECH maturity questionnaire. This classification system assigned the company a level 2 (Connectivity) ranking. The construction of the prototypes and the digital simulation enabled the analysis of behavior on the production line and the identification of improvement points, such as material selection and programming. The project demonstrated the potential of accessible tools for the development of robotic systems, with Augmented Reality being explored for the enhancement of maintenance and user-system interaction. The preliminary findings lend credence to the methodology, with the research proceeding towards the execution of comparative assessments and the development of future enhancements.*

I. INTRODUCTION

The industry is undergoing an unprecedented transformation, driven by the emergence of new digital technologies. This movement, known as Industry 4.0 or the Fourth Industrial Revolution, represents a significant evolution from previous production models, which were characterized by mechanization (1st Revolution), electrification (2nd Revolution), and IT-based automation (3rd Revolution) [1]). The concept of Industry 4.0 was formalized in 2011 in Germany, during the Hannover Messe fair, and since then has been associated with a set of enabling technologies that promise to revolutionize manufacturing [2].

The Internet of Things (IoT) is a primary technology that facilitates the interconnectedness of machines, sensors, and systems, thereby establishing an intelligent network capable of collecting and analyzing data in real-time [3]. This communication infrastructure is imperative for the integration of the physical and digital domains, thereby facilitating more efficient and adaptable processes [4]. Moreover, cloud computing and Big Data play a pivotal role in the storage and processing of substantial volumes of information, thereby enabling data-driven decision-making [5]. Another fundamental pillar of Industry 4.0 is the Digital Twin, a virtual representation of a physical system that allows for simulations and predictive analyses. This technology facilitates the early identification of failures, process optimization, and the reduction of rework costs [6]. [7] posit that the digital twin is a multifaceted entity, serving not only as a replica of an object or process but also undergoing continuous evolution based on the analysis of real data. This capacity to evolve provides a foundation for the generation of valuable insights, which can be instrumental in facilitating continuous improvements. The application of this tool is especially relevant in complex industrial environments, where precision and reliability are critical [8].

Augmented Reality (AR) also emerges as a pivotal technology in this context, assisting in tasks such as maintenance, training, and operations monitoring. The application of augmented reality (AR) involves the overlaying of digital information on a physical environment, facilitating the interpretation of complex data and enhancing human-machine interaction [9]. Furthermore, the utilization of augmented reality (AR) systems has been demonstrated to facilitate the provision of real-time instructions, thereby reducing errors and enhancing productivity [10].

Advanced robotics constitutes a pivotal component of Industry 4.0, with autonomous and collaborative robots assuming progressively sophisticated functions. These pieces of equipment, ranging from industrial manipulators to mobile systems, are designed to operate with a high degree of precision and adaptability [11]. The evolution of robotics is inextricably linked to the development of cyber-physical systems (CPS), which integrate computing, networks, and physical processes, thereby creating more flexible and intelligent manufacturing [12].

In the global context, countries such as Germany and China have spearheaded the adoption of these technologies through initiatives like the "Industry 4.0" project and "Made in China 2025," respectively [12] In Brazil, despite the nascent stage of implementation, institutions such [13] underscore the potential of digitalization to enhance industrial competitiveness.

Therefore, the objective of this study is to examine the implementation of digitalized simulation (Digital Twin) in production processes with the aim of enhancing efficiency, facilitating the execution of tasks correctly on the first attempt, reducing expenses associated with rework, and enhancing the efficiency of company growth. A promising approach to developing the Digital Twin is the utilization of augmented reality (AR), as AR-based systems have the capacity to support a range of services, including the selection of components in a warehouse or the transmission of repair instructions via mobile devices [10]. Consequently, the simulation of field maintenance information, which is often challenging to interpret and requires operator experience, can be conducted on mobile phones or tablets. This approach has the potential to reduce travel costs, prevent misinterpretations, and minimize the need for rework in maintenance actions. Furthermore, the integration of augmented reality (AR) technology with human-machine interfaces has the potential to enhance manufacturing applications and IT assets. This integration enables the display of Key Performance Indicators (KPIs) and real-time feedback on manufacturing processes, thereby facilitating enhanced decision-making processes [9]. Consequently, augmented reality (AR) emerges as a pivotal enabling technology within the ambit of Industry 4.0, facilitating enhanced information exchange between the digital and physical domains [14]. This integration fosters seamless collaboration between human operators and machine systems, thereby redefining the landscape of modern industrial operations.

The objective of the research was to apply Digital Twin simulation to investigate production processes with the aim of reducing costs and increasing productivity in companies. The research unfolded in crucial stages. The comprehensive mapping of the production process, coupled with the subsequent analysis of the collected data, furnished the requisite empirical foundation. From this standpoint, the development of a production process simulation was undertaken, with the exploration of augmented reality as a promising alternative for optimizing maintenance and decision-making. This approach enabled the visualization and experimentation of scenarios. The proposal of improvements, based on the results obtained from the simulation, closes the cycle, demonstrating how the Digital Twin approach can effectively empower industries to "do it right the first time," minimizing rework and optimizing growth time. This solidifies the potential of digitalized simulation as a strategic pillar for Industry 4.0.

II. BACKGROUND

A. Foundations of Industry 4.0 and Its Enabling Technologies

The conceptualization of Industry 4.0 as a technological and organizational paradigm is rooted in the seminal works of [5] and [1], which establish a comprehensive conceptual framework for this fourth industrial revolution. These studies reveal how the convergence of digital technologies is radically reconfiguring production systems, marking a transition from traditional automation to intelligent and interconnected manufacturing ecosystems. [5] identify nine fundamental technological pillars that underpin this transformation, including the Industrial Internet of Things (IIoT), cyber-physical systems, cloud computing, and virtual simulation. These pillars form the basis for implementing solutions such as Digital Twins and the creation of robots.

The term robot was originally presented in 1921 by the Czech playwright Karel Čapek during a theatrical play. The definition of a robot is broad and varied; some authors present their definitions, [15] a reprogrammable, multifunctional manipulator designed to move materials, parts, tools, or special devices, through[1] various programmed motions, for the performance of a variety of tasks."[2] A more complete definition is provided by the International Organization for Standardization [11], as: an automatically controlled, reprogrammable, multifunctional manipulator machine, with several degrees of freedom, that can have a fixed or mobile base for use in industrial automation applications. According to [16], the term robotics was introduced and coined by science fiction writer Isaac Asimov; this term is used to designate the science dedicated to the study of robots, which is based on three fundamental laws:

1 A robot may not injure a human being or, through inaction, allow a human being to come to harm.
2 A robot must obey the orders given it by human beings except where such orders would conflict with the First Law.
3 A robot must protect its own existence as long as such protection does not conflict with the First or Second Law.

The robotic model chosen for the research project's development was the fixed manipulator shown in Figure 1, and it is composed of the following components:

Links: Basically composed of rigid structural elements, connected to each other by means of joints (articulations) responsible for the freedom of movement, with the first link being called the base and the last one where the end effector will be attached [15].

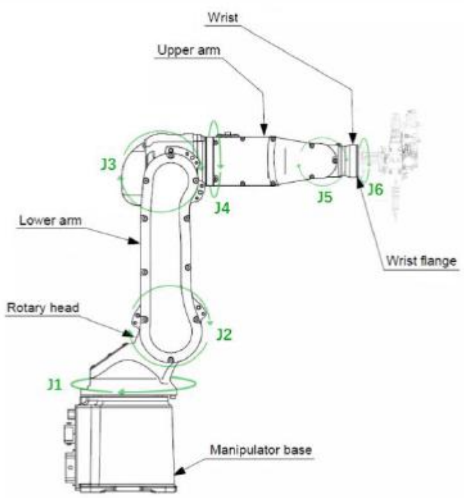

Fig.1 - Composition of a Fixed Robotic Manipulator

According to [17], joints are the mechanical devices or articulations that enable the robot's movements, allowing it to move in various directions, positions, and angles, performing both linear and rotational movements. Joints also determine the number of degrees of freedom a robot possesses and are classified into three categories:

- Sliding Joint: Named for allowing linear movement between two links. It is a piece that fits inside another and enables up and down movement as shown in Figure 2

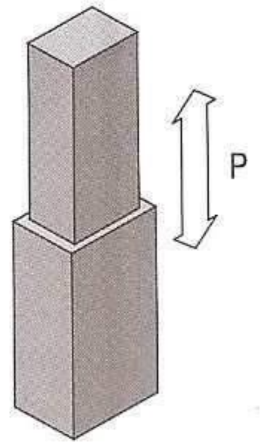

Fig.2 - Schematic of a Sliding Joint

Source: [17]

- Rotary Joint: Named for allowing rotational movement between its joints, capable of various types of movements, such as rotating, moving up and down, etc., as shown in Figure 3.

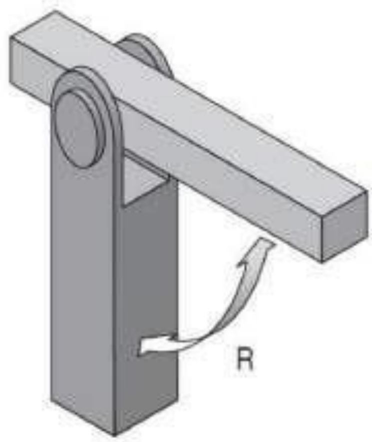

Fig.3: Schematic of a Rotary Joint

Source: [17]

- Ball and Socket Joint: Named for having a sphere at its base, allowing rotational movement as shown in Figure 4.

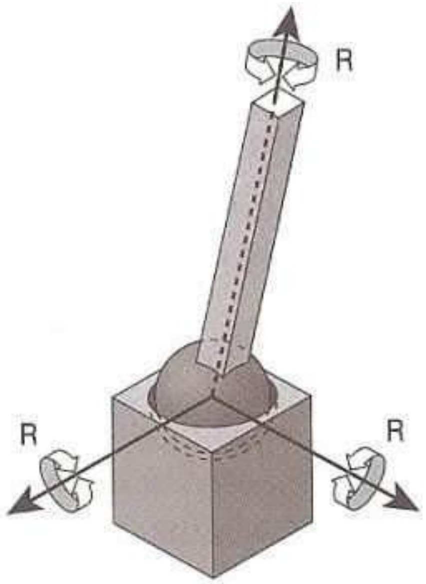

Fig.4: Ball or Sphere Joint

Source: [17]

In order to provide a more accurate contextualization of the relevance of robotics, particularly with regard to the application of fixed manipulator robots in the contemporary industrial landscape, the historical analysis proposed by [1] offers a crucial evolutionary perspective. As illustrated in Flowchart 1, each industrial revolution from mechanization driven by steam (1.0) to electrification and mass production (2.0), culminating in automation through electronics and Information Technology (3.0) paved the way for the current Fourth Industrial Revolution (4.0), characterized by digitalization and the integration of cyber-physical systems. In this transformative context, digitalized simulation, far from being an isolated innovation, emerges as a fundamental link in this evolutionary chain, enhancing the capabilities of robots and optimizing production processes. The historical analysis proposed by [1] offers a crucial evolutionary perspective, demonstrating how each industrial revolution—from mechanization (1.0) to electrification (2.0) and automation (3.0) set the stage for the current phase of integrated digitalization. This historical-technological framework is particularly valuable for the present work, as it allows us to contextualize digitalized simulation not as an isolated innovation but as part of a continuum of industrial development. The transition between these stages can be visualized through the following flowchart:

1) The Four Industrial Revolutions

<table>
<tr><td>1st Revolution (1784) | Mechanization → Steam</td></tr>
<tr><td>2nd Revolution (1870) | Electrification → Mass Production</td></tr>
<tr><td>3rd Revolution (1969) | Automation → Electronics/IT</td></tr>
<tr><td>4th Revolution (2011) | Digitalization → Cyber-Physical Systems</td></tr>
</table>

The table below synthesizes the main enabling technologies and their applications in manufacturing, as identified by [5]

Table 1: Enabling Technologies of Industry 4.0

Technology	Primary Function	Impact on Manufacturing
Internet of Things	Connect machines and systems	Real-time visibility
Big Data Analytics	Process large volumes of data	Predictive decision-making
Autonomous Robotics	Execute complex tasks	Production flexibility
Virtual Simulation	Test scenarios without risk	Reduced prototyping costs

Source: Adapted from [5]

The importance of these foundations for the present research becomes evident when examining their relationship with Digital Twins. As [8] observe, the effectiveness of digital twins directly depends on the maturity of these enabling technologies, particularly concerning IoT infrastructure and data processing capabilities. This interdependence explains why the initial mapping carried out at the factory in the Manaus Industrial Hub, which identified Stage 2 (Connectivity) in the ACATECH maturity index, is a crucial step for the successful implementation of digitalized simulation.

The concepts presented by these authors not only validate the methodological approach adopted in the Project, but also provide clear parameters for evaluating the results. The transition between levels of digital maturity, for example, finds theoretical support in the technological progression described by [1], while the selection of technologies to be implemented in prototypes aligns perfectly with the pillars defined by [5]. This solid theoretical foundation allows the research to be positioned in both academic and practical industrial contexts, demonstrating how process simulation through Digital Twins represents a natural advancement in the evolutionary trajectory of manufacturing.

A. Digital Twins and Industry 4.0 in Electronics Manufacturing

The evolution of industry towards the Fourth Industrial Revolution has been extensively discussed in the literature, with a focus on the works of [5] and [1], which establish the conceptual foundations of this transformation. These authors demonstrate how the convergence of digital technologies such as the Internet of Things (IoT), Big Data, and cyber-physical systems is redefining production paradigms. Industry 4.0, a term coined in Germany in 2011, represents not only a technological evolution but a structural change in how industrial processes are conceived and managed, combining the advantages of mass production with individualized customization [18]

At the heart of this transformation lies the concept of the Digital Twin, deeply explored by [8] and [9]. These researchers define digital twins as dynamic virtual representations of physical systems, capable of simulating behaviours, predicting failures, and optimizing processes in real time. The application of this technology in manufacturing, as demonstrated by [7], can reduce rework costs by up to 30%, in addition to significantly increasing productivity through early identification of production bottlenecks.

The practical implementation of these concepts requires a robust technological infrastructure, particularly regarding the Industrial Internet of Things (IIoT). [19] and [4] detail how machine-to-machine connectivity, combined with real-time data collection and analysis, forms the backbone for creating functional digital twins. These systems fundamentally depend on three components: sensors for data capture, cloud computing platforms for processing, and machine learning algorithms for predictive analysis [20].

In the specific context of industrial robotics, which constitutes a fundamental part of this research, the works of [14] and [11] establish the technical parameters for the development of robotic systems compatible with Industry 4.0. These studies are particularly relevant for the project in question, as they technically support the development of prototypes with LEGO EV3 and 3D printing, especially concerning the definition of degrees of freedom and motion parameters.

The assessment of the digital maturity of industries, as proposed by the German Academy of Science and Engineering [21], provides an essential framework for the initial mapping carried out at the factory. This model, complemented by the analysis of the Brazilian scenario presented by [13], allows for contextualizing the specific challenges of adopting these technologies in emerging industrial environments.

Table 2. Enabling Technologies of Industry 4.0

Technology	Application in Manufacturing	Expected Impact
Digital Twin	Process simulation	25-30% reduction in failures
IIoT	Real-time monitoring	15-20% increase in productivity
Advanced Robotics	Task automation	40% reduction in operational costs

Source: Synthesis of [5], [8]

The integration of these concepts results in a robust theoretical framework for the research, demonstrating how digitalized simulation can transform production processes in the electronics manufacturing industry. The studies by [14] on human-machine interfaces and [9] on real-time visualization systems complement this theoretical basis, providing valuable insights for the development of the simulator's interface as described in the project.

This theoretical foundation not only validates the methodological approach adopted in the research but also establishes clear parameters for evaluating the results, particularly regarding productivity gains and cost reduction. The transition from level 2 (Connectivity) to level 3 (Visibility) in the ACATECH maturity index, observed in the partial results, finds theoretical support in the works of [2] on the gradual evolution of industrial systems towards Industry 4.0.

Theoretical Framework: IoT and Cyber-Physical Systems Integration in Manufacturing 4.0

The Industrial Internet of Things (IIoT) emerges as a central element in the architecture of Industry 4.0, as demonstrated by the fundamental studies of [19] and [4].

These works establish the theoretical and practical bases for understanding how machine-to-machine connectivity enables the creation of intelligent productive ecosystems, where data flows in real-time between physical and digital systems. [19] particularly highlights the IIoT as a transformative technological paradigm that goes beyond the simple connection of devices, creating cognitive networks capable of self-diagnosis and dynamic adaptation – essential characteristics for the effective implementation of Digital Twins.

The conceptual framework proposed by [4] advances this discussion by detailing the critical components for the practical implementation of IoT in factory environments. Their model integrates three essential layers: (1) sensors and embedded devices for data capture, (2) robust communication networks for secure transmission, and (3) analytics platforms for transforming data into actionable insights, as shown in the flowchart. This structure finds direct application in the developing project, where sensors coupled to robotic prototypes (such as the light and touch sensors described) continuously feed the digital twin with operational information, as presented in the table.

FLOWCHART: Cyber-Physical Systems Architecture

Sensors → Industrial Network → Cloud Platform → Digital Twin → Decision Making

Source: Adapted from [19] and [4]

The following table offers a concise overview of the infrastructure's primary components and their association with the project:

Table 3. IoT Components for Digital Twins

Component	Function in the Project	Practical Example
Sensors	Capture physical data	Touch sensor on the LEGO robot
Gateways	Convert protocols	Arduino-ROS interface
Cloud Platform	Store and process data	Simulator database
Analytics	Generate predictive insights	Fault detection algorithms

Source: Adapted from [19] and [4]

The integration between cyber-physical systems plays an even more significant role when we examine the specific challenges of electronics manufacturing, the sector this research focuses on. [4] highlight how the heterogeneity of equipment and protocols in production lines demands robust interoperability solutions – a problem clearly evident in the development of the prototypes described in the report, where it's necessary to connect LEGO components, 3D printed parts, and conventional electronic systems.

[19] warns about the inherent security risks in these hyperconnected environments, an alert that resonates in the reported design decisions, particularly in the implementation of physical limits (via sensors) and the layered architecture of the simulation interface. This concern with cybersecurity and operational resilience emerges as a critical factor for the successful transition between the maturity levels identified in the studied factory.

The convergence between these theoretical concepts and the practical development in the project becomes evident when examining the established data flow: from capture by physical sensors, through processing on intermediate platforms, to virtual representation in the digital twin – a trajectory that precisely mirrors the models proposed by the referenced authors. This foundation not only validates the technical choices made but also provides a frame of reference for evaluating the results obtained and planning the next steps of the research.

III. METODOLOGY

The methodology developed for this study is structured into four interrelated phases, based on best practices from the literature on Industry 4.0 and process simulation. The first phase comprises the detailed mapping of production processes, which, according to [5], is a crucial step for the effective digitalization of industrial operations. This mapping is carried out through systematic evaluations in the factory environment, using instruments such as standardized questionnaires about the production line. As highlighted by [14], this approach allows for capturing not only formal workflows but also informal practices that frequently impact operational efficiency.

The data analysis phase adopts a qualitative case study approach, a methodology widely recommended by [22] for investigating complex organizational phenomena. This in-depth analysis of the mapped processes makes it possible to understand the causal relationships between different operational variables, following the framework proposed by [23] for thematic analysis of qualitative data. The triangulation of data —cross-referencing information from questionnaires, direct observations, and internal documents—ensures the validity of the results, as advocated by [24] in his works on qualitative research methods.

Process simulation represents the core of the methodology, where the collected operational parameters are transposed into a virtual environment. [8] demonstrate in their studies that the creation of digital twins requires the precise incorporation of physical and dynamic characteristics of real systems. This virtual representation, as detailed by [6] allows not only for real-time monitoring but, more importantly, for the safe experimentation of different operational scenarios. The methodology incorporates the recommendations of [7] for calibrating simulation models, ensuring that the digital twin's predictions maintain statistical fidelity with the physical system's behaviour.

The final phase of proposing improvements is based on the continuous optimization framework proposed by [19], integrating insights generated by the simulation with the practical limitations of the real industrial environment. This approach follows the principle of "evidence-based design" advocated by [9], where improvement decisions are based on quantitative and qualitative data collected throughout the previous phases. The methodology also includes an iterative validation cycle, in which proposed improvements are first tested in the virtual environment before physical implementation, reducing risks and costs as demonstrated in the case studies presented by [13]

IV. ANALYSIS OF THE RESEARCH RESULT

The analysis of the production process and the data collected at the company reveals an interesting overview of its digital transformation journey. The initial stage, focused on the detailed mapping of the production flow, was a fundamental step to understand the existing operational architecture and identify points of contact with digital technologies. The application of the Maturity Index Measurement questionnaire, based on the renowned ACATECH model, allowed for a structured assessment of the organization's digital capabilities across several crucial dimensions.

By exploring the responses obtained through the questionnaire, it was possible to outline the company's digital maturity profile in relation to digital competencies, levels of computerization, process visibility and transparency, predictive capability, and operational adaptability. Figure 5, as a visual reference point, illustrates the sequential progression of these levels, from basic computerization to the autonomous optimization characteristic of full Industry 4.0.

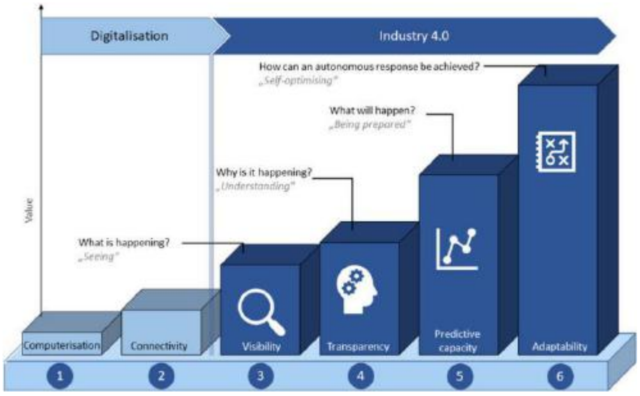

Fig.5 - Industry Maturity Levels

The in-depth analysis of the compiled data, enriched by on-site observations during technical visits, converged to the conclusion that the company is currently at Level 2, named Connectivity. This classification indicates that the organization has already initiated the digitalization process of its operations, establishing connections between systems and machines. However, it still lacks a more comprehensive data integration and analysis to reach the Visibility stage, which is the initial landmark of true Industry 4.0.

Figure 6, which presents a summary of the questionnaire responses, offers a quantitative representation of the company's position across each assessed maturity level. This detailed visualization allows for identifying areas where the company scored higher, indicating its strengths in its digital journey, as well as areas that demand greater attention and investment to drive its evolution to Level 3 (Visibility) and, consequently, to the more advanced stages of Industry 4.0. The transition to Visibility implies an enhanced capacity to collect, analyze, and interpret data in real-time, providing a deeper understanding of operational performance and paving the way for proactive optimization and more assertive decision-making.

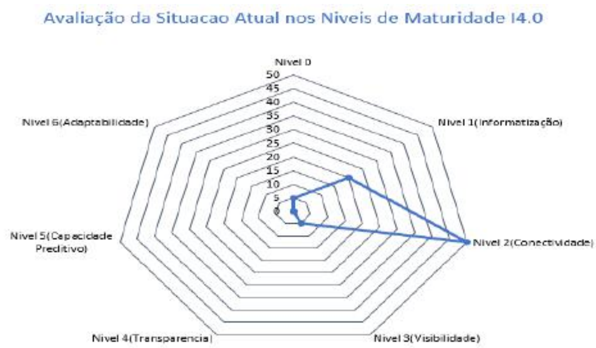

Fig.6: Current Maturity Level of the Evaluated Production Line

Source: The Authors

The construction of the prototypes for digital twin simulation was carried out using a methodological approach that integrates physical prototyping with virtual modeling, following the principles of Industry 4.0. The process began with the assembly of a robotic manipulator using a LEGO EV3 kit available in the research laboratory, based on the industrial articulated model. This prototype was designed with three main joints, all using rotary joints, which replicate the characteristic degrees of freedom of industrial robots, as described by [14]. The robot's base allows for a 180-degree rotation, while the trunk articulation enables a vertical movement of up to 90 degrees. The end effector, a pincer-type gripper, was designed to open and close at a 90-degree angle, allowing for precise object manipulation. This was necessary to understand the difficulties and functioning of a production line and identify potential improvements for the project's completion. The initial prototype, shown in Figure 7, had three joints located at the base (M1), body or trunk (M2), and gripper (M3).

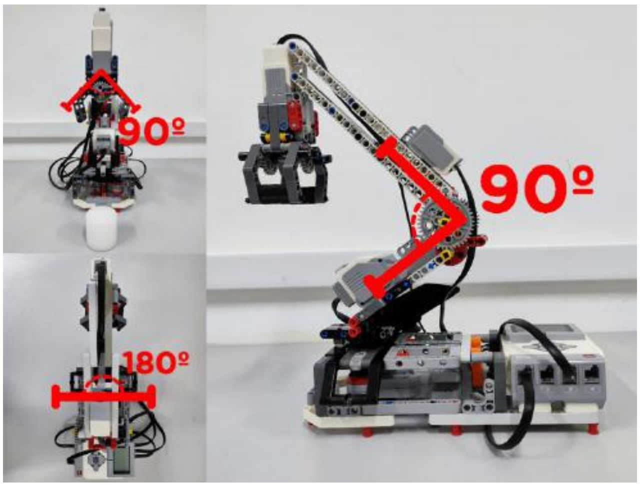

Fig.7 - Mechanical Prototype Detailed View

Source: The Authors

M1: Located at the base, providing 180 degrees of freedom for the mechanical arm.

M2: Located in the body, allowing the arm to incline up to 90 degrees.

M3: Located in the gripper, allowing it to open up to 90 degrees to pick up components from the production line.

To ensure that the physical prototype behaved similarly to a real industrial robot, light and touch sensors were incorporated. The light sensor acts as a movement limiter, stopping the mechanical arm if it detects a significant reduction in light, simulating adverse operational conditions. The touch sensor functions as a safety system, defining start and end points for the base rotation, thus preventing collisions and unnecessary wear.

After some tests with the LEGO model, it was noted that some modifications to the design would be necessary. These included:

- Replacing the LEGO robot with the MKII model, which was fabricated using an Ender 3D printer.
- Changing the programming language.
- Enabling communication via serial port.
- Replacing the EV3 board with an Arduino Mega 2560 board.
- Swapping the LEGO motors for servomotors.

While the robot configurations differ in some aspects, both models possess three articulations and the same classification. According to [14], the degrees of freedom are what classify a typical industrial robot, and these degrees of freedom are what differentiate one from another. The MKII model can be seen below in Figure 8.

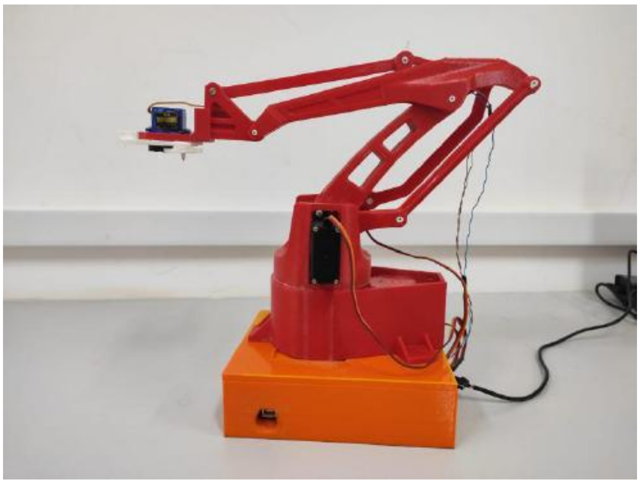

Fig.8 - 3D Printed Mechanical Prototype

Regarding the MKII model, it is a well-known model in the robotics world, primarily used for academic experiments. It is a 3D model called Arm MKII that can be created using 3D printers, equipped with three Mg995 servomotors and one Sg90 connected to an Arduino Mega 2560, arranged from pin 2 to 5 on the digital ports, corresponding respectively to the base, axis 1 (responsible for lowering or raising the gripper), axis 2 (responsible for advancing or retracting the gripper), and the gripper. The MKII model was developed by the 3D printing enthusiast known as [25]

Limits:

- Servos have a 180º rotation amplitude.

- Gears involved in the rotation around the z-axis (base): a main gear (moved by servo 1) with 25 teeth and a second with 50 teeth, which means the rotational movement around this axis only has a 90º amplitude.
- Collisions between the horizontal rod (servo 2) and the main rod (servo 1) imply that the servos that move them have the following respective limits: 60º between 45º and 105º (servo 2), and 90º between 55º and 145º (servo 1).

After replacing the LEGO model with the MKII, modifications were made to the project's architecture, as illustrated in Figure 8, and to the software used in the MKII's construction. Both **Blender** and **Unity** tools were necessary for physical materialization and digital representation. Blender is an application focused on 3D object modeling and animation, while Unity is a game engine that covers programming, animations, and other tasks related to model creation. In the context of building the digital model in Unity, it was necessary to import the 3D model previously created in Blender. In the game engine, the digital model animation and data collection from the physical prototype stages were conducted.

To execute movements in the physical prototype, the IDE provided by the Arduino platform was used. The control panel was developed using Visual Studio Code. This panel played the role of intermediary in communications between Arduino and Unity, ensuring synchronization between the models. Regarding QR code reading on the panel, two libraries available on GitHub were incorporated for this purpose.

A second prototype was developed using 3D printed parts, with reduced dimensional characteristics but maintaining the same functionality and degrees of freedom. This model was designed for future integration tests with a dedicated circuit board, which will allow for more robust communication with the simulation system.

The virtual modeling stage of the digital twin was performed using computer-aided design tools to create a precise replica of the physical prototype from Blender and animated in the Unity game engine. The task of this model was to execute all the movements that the physical model performs in the real world. To complete this task, communication was established through the serial port with Unity, where a string vector with instructions on what the physical model was doing at a given moment was passed, as shown in Figure 9. This virtual model was then integrated into a dynamic simulation environment, where parameters such as speed, acceleration, and movement limits were configured to faithfully reflect the behavior of the real robot. Communication between the physical prototype and the digital twin was established through IoT protocols, allowing data collected by the LEGO robot's sensors to feed the simulation in real-time. This approach, based on the works of [8] and [6], enables early fault identification and process optimization even before implementation in a real industrial environment.

Fig.9: 3D Model in Unity

Source: Author (2024).

In parallel with the prototype construction, a graphical interface for the digital twin simulator was developed. This interface was designed to offer a comprehensive view of the system, including a coding area for programming robot movements, a 3D visualization of the prototype in action, and a command-line tool for sending specific instructions. The interface allows not only for the simulation of predetermined tasks but also for performance analysis through key indicators such as cycle time and success rate in object manipulation, as shown in Figure 10. The integration between hardware and software follows [9] recommendations, which emphasize the importance of intuitive and interactive simulation systems for training operators and engineers.

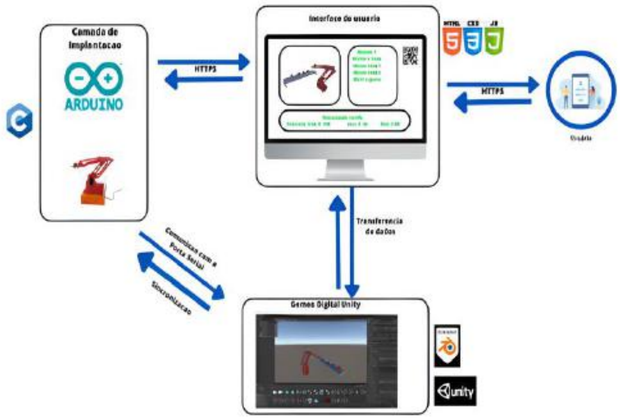

Fig.10: Project Architecture

Source: Author (2024).

At the current stage of the research, objectives 1 and 2 have been fully met, while objective 3 is in an advanced stage of development. The next steps include coding the robots for operation on a real platform available in the laboratory, as well as conducting comparative tests between the physical and virtual models. These tests will be fundamental for validating the accuracy of the digital twin and identifying possible discrepancies between the simulation and reality. Furthermore, the obtained results will be documented in a case study, which will serve as a reference for future applications in industrial environments.

The methodology employed in this work demonstrates how the combination of accessible prototyping (using LEGO and 3D printing) and advanced simulation can reduce costs and lead times in the development of robotic systems. By utilizing widely available tools and standardized protocols, the project offers a scalable solution that can be adapted for different industrial contexts, from manufacturing to logistics. This approach aligns with current Industry 4.0 trends, which value flexibility, interoperability, and integration between the physical and digital worlds.

V. CONCLUSION

This work aimed at the construction of a manipulator arm and its virtualization; it surveys a new era in human-machine interaction and the optimization of industrial processes. By integrating accessible prototyping with advanced simulation, this research not only democratizes the development of robotic systems but also redefines the role of the Digital Twin in modern manufacturing.

The methodology employed, combining design flexibility with simulation precision, offers a replicable and scalable model for industries of all sizes. The ability to predict the behavior of complex systems in a virtual environment, before physical implementation, represents a breakthrough with the potential to eliminate costly errors, drastically reduce production costs, and accelerate innovation.

More than a technical solution, this work presents a vision of the future where collaboration between humans and robots is seamless, intuitive, and efficient. By paving the way for user interaction with the manipulator arm in virtual space, this research expands the boundaries of augmented reality and paves the way for transformative applications in various sectors, from manufacturing and logistics to medicine and space exploration.

The impact of this research is multifaceted. In industry, it promises to revolutionize the design, prototyping, and operation of robotic systems, driving efficiency, safety, and sustainability. In science, it offers new tools and methodologies for the investigation of complex systems, with potential applications in areas as diverse as biology, physics, and materials science. And in society, it heralds a future where robotic technology is within everyone's reach, empowering individuals and communities to solve complex problems and create new opportunities.

In short, this research not only addresses a specific technical challenge; it offers a vision of the future and a roadmap for the next industrial revolution, with the potential to transform the way we live, work, and interact with the world around us.

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