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RESEARCH ARTICLE

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Optimization of New Project Validation Protocols in the Automotive Industry: A Simulated Environment for Efficiency and Effectiveness

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Abstract: Increasing vehicle manufacturers has led to a considerable rise in the automotive industry's competitiveness. Various research projects are being developed to devise process optimization strategies using virtual simulation. The paper discusses the importance of applying modeling and simulation strategies to optimize automotive manufacturing processes to meet the demands of a constantly evolving market. The aim is to demonstrate a strategy divided into a few stages to optimize the process of validating new projects applied in the automotive industry. The methodology employed was computer modeling and simulation, which enabled identifying and eliminating risks inherent in the validation process, thereby reducing the time required to complete new projects. The results demonstrated that implementing this strategy facilitated an efficient transition of the validation process, maintaining the quality and safety standards required in the cell. Consequently, it can be posited that the methodology developed is an efficacious instrument for expediting the implementation of novel processes in automotive manufacturing, thereby contributing to the competitiveness and innovation of the industry in the automotive segment.

Keywords: automotive industry, modeling, new projects, optimization, validation process, virtual simulation

1. Introduction

The necessity for adaptability to serve the automated systems market competitively is a persistent challenge faced by the industry. Considering the rapid technological evolution and the varying customer demands, companies must continuously adapt to remain relevant. This adaptability is not limited to the end products but also encompasses the manufacturing processes. New approaches and strategies are consistently sought to ensure efficiency and agility in production. This pursuit of adaptability is essential to keep pace with the market changes and ensure that companies remain competitive [1].

Software applications are pivotal in evaluating potential scenarios resulting from implementing new projects. Using simulation and modeling tools enables companies to anticipate the consequences of alterations to manufacturing processes, thereby minimizing risks and optimizing resources. This software enables the analysis of diverse scenarios, facilitating decision-making and strategic planning. Consequently, investment in simulation technologies is crucial for the efficiency and competitiveness of industrial operations [2].

The assessment of physical and procedural risks during the production of new products through the interaction of industrial robots represents a critical stage in the development of automated processes. Integrating robots into the production line brings a series of challenges related to safety and operational efficiency. It is therefore necessary to carefully assess the possible risks associated with the tasks performed by the robots, as well as the possible process failures that could occur. It is of the utmost importance to identify these risks early, as this allows prevention and mitigation measures to be implemented, thus ensuring the safety of workers and the integrity of the equipment [3].

The necessity to reduce the validation time for new projects involving robotic systems is a common objective among companies in the automotive sector. The validation process is pivotal in developing new products and technologies, ensuring they meet the established quality and performance requirements. However, the time needed to validate a new project fully can be considerable, which may impact on the time to market and the company's competitiveness [4].

The article presents the following problem: how can virtual modeling and simulation optimize the validation process

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of new processes applied in automobile manufacturing, reducing implementation time and, consequently, the associated costs? The research questions that guide this study are:

1) What are the specific benefits of simulation in optimizing validation time?
2) How does the implementation of robotics techniques contribute to reducing the development time of new processes?

This article contributes by exploring the application of virtual modeling and simulation to optimize the validation process of new robotic systems in automotive production, with a focus on reducing implementation time and eliminating operational bottlenecks. The research seeks to show how these techniques can improve the efficiency and competitiveness of the industry.

2. Literature Review

2.1. Modeling and simulation of industrial robots using software

The modeling and simulation of industrial robots using software plays a fundamental role in developing and optimizing automation processes [5]. The need to perform modeling and simulation is crucial to ensure the effectiveness and efficiency of robot operations in various industrial sectors [6]. Through virtual simulation, it is possible to evaluate and validate different robot control and motion strategies before implementation, significantly reducing the time and cost of developing new robotic systems [7].

Deep learning applications, such as convolutional neural networks (CNNs), and augmented reality (AR) technologies have shown great potential in optimizing industrial processes. The implementation of these technologies improves accuracy in object identification and classification, minimizes failures, and speeds up decision-making. In the automotive context, AR can be used to overlay visual instructions on the physical environment, reducing errors during product verification. Models based on CNNs, such as YOLO v8, offer high accuracy in real time, increasing the efficiency of production lines and reinforcing quality control in critical processes [8, 9].

This approach also makes it possible to identify potential problems and optimize robot performance in complex and dynamic environments [10].

When modeling and simulating industrial robots using software, it is essential to consider several specific elements and characteristics. These include the robot's geometry and kinematics, such as dimensions, joints, and motion constraints [11]. In addition, it is essential to accurately model the robot's sensors and actuators, as well as the characteristics of the working environment, such as obstacles, surfaces, and lighting conditions [12]. Proper modeling of these elements is essential to ensure the simulations' accuracy and reliability and provide realistic and valuable results for the design and development of robotic systems [13].

Some programs stand out when it comes to modeling and simulating industrial robots, such as Simulink, part of MATLAB from MathWorks [14], RobotStudio developed by ABB [15], Webots developed by Cyberbotics [16], and CoppeliaSim from Coppelia Robotics [17]. CoppeliaSim is a versatile and powerful platform for accurately modeling robots, environments, and automation processes. With its intuitive interface and wide range of features, CoppeliaSim is widely used in industrial robotics and automation research, development, and education [18].

Software to model and simulate industrial robots covers various fields and industries. These include automotive manufacturing, where CoppeliaSim simulates assembly, welding, painting, and parts handling processes [19]. In addition, robot simulation is used in logistics, healthcare, agriculture, and services sectors, where robots play an increasingly significant role in automating tasks [20]. The application of industrial robot modeling and simulation is diverse and broad, demonstrating its potential in different contexts and industries [21].

Software modeling and simulation of industrial robots have a variety of practical applications. For example, in automotive manufacturing, virtual simulation is used to optimize production line layout, define robot motion paths, and validate new assembly processes [22]. In logistics environments, robot simulation is used to plan transportation routes, optimize material flow, and maximize operational efficiency [23]. Robot simulation is also used in healthcare scenarios, where surgical robots are simulated to train surgeons and plan procedures [24]. These examples illustrate the versatility and usefulness of modeling and simulating industrial robots in various contexts and practical applications.

Despite the benefits of software-based modeling and simulation of industrial robots, significant challenges are associated with its implementation. These include the complexity of modeling and simulating robotic systems, which require specialized engineering and programming skills [25]. In addition, the validation of simulation models against real systems can be complex due to variations in the dynamics of the environment and operating conditions [26]. Integrating different software and hardware systems can also be challenging, requiring platform interoperability and compatibility [27].

Current and future market requirements reflect the growing need for software-based modeling and simulation of industrial robots. With the rapid evolution of robot technology, the demand for simulation and optimization tools is expected to grow [28]. This includes the need for more realistic and accurate simulations that consider physical interactions, material dynamics, and the behavior of complex systems [29]. In addition, integrating artificial intelligence and machine learning techniques is expected to improve the ability to predict and optimize the performance of robotic systems through simulation [30]. These trends highlight the continued importance of modeling and simulation of industrial robots as an essential tool for innovation and advancement of automation in various sectors and industries.

2.2. Robotic cells applied to automotive manufacturing processes

The use of robotic cells in automotive manufacturing is vital for increasing industrial operations' efficiency, quality, and productivity [31]. The need for robotic cells is driven by the increasing complexity of automotive manufacturing processes, which require precision, repeatability, and flexibility [32]. Robotic cells allow for the automation of repetitive and hazardous tasks, freeing workers for more skilled activities and reducing the risk of workplace accidents [33]. Integrating robotics into automotive manufacturing processes allows faster response to market demands, mass production of customized vehicles, and adaptation to changing consumer preferences [34].

The application of augmented reality (AR) in industrial environments offers an efficient means of overlaying virtual information on the physical environment in real time. In the automotive context, this technology allows rapid identification of components, improves interaction between operators and systems, and reduces operational errors during product verification. Implementing AR also makes it easier to visualize assembly steps and safety standards, optimizing processes and minimizing training time. Thus, AR can be integrated into new product validation protocols to ensure compliance and efficiency, promoting a more dynamic and safe work environment [35].

Several elements and characteristics must be considered when designing a robotic cell applied to automotive manufacturing processes to ensure its effectiveness and efficiency. Among the most critical elements to consider are industrial robots, the fixturing and transport devices, the vision and sensor systems, and the control and monitoring systems [36]. Each component of the robotic cell must be designed and sized to meet the specific requirements of the manufacturing process, ensuring integration and interoperability between the different elements [37]. Operator safety and compliance with occupational health and safety regulations must be considered at all stages of the design and implementation of the robotic cell [38].

There are numerous practical applications for robotic cells in automotive manufacturing, ranging from component assembly to quality inspection [39]. Industrial robots are used on assembly lines to precisely manipulate and position parts to ensure fast and accurate assembly [40]. Another scenario is collaborative robots, which are increasingly used in welding, painting, and inspection processes, where they work side by side with human operators to increase efficiency and quality [41]. Other applications include automated material handling, surface polishing, and the application of adhesives and sealants to automotive components [42].

It should also be noted that implementing robotic cells in automotive manufacturing also faces significant challenges. One of the main challenges is the integration of different technologies and systems, which may have different origins and interfaces, making communication and coordination between the components of the cell complex [43]. Another difficulty is that programming and optimizing the robots to meet the specific requirements of the manufacturing process can be complex and time-consuming, requiring specialized knowledge of control and automation engineering [44]. Ensuring operator safety and preventing collisions between robots and equipment are also significant challenges, requiring the implementation of advanced collision detection and prevention systems [45].

Current and future market demands highlight the continuous need to develop and improve robotic cells used in automotive manufacturing processes. As technology advances, robotic cells are expected to become even more sophisticated and intelligent, incorporating features such as computer vision, machine learning, and IoT connectivity [46]. These technologies enable closer integration between production and IT systems, allowing data to be collected and analyzed in real time to optimize cell performance and meet dynamic market demands [47]. Robotic cells are expected to be increasingly flexible and adaptable, automatically reconfiguring themselves to meet changes in product demand and production requirements [48]. The literature on process simulation and optimization in the automotive industry prioritizes reducing cycle time and increasing productivity. Studies such as that by Dias et al. [49] explore tools such as line balancing and 5S to optimize assembly lines. Mayr et al. [50] use a multidimensional approach based on historical data to identify performance scenarios and optimize process planning in the automotive sector.

The layout of workstations is also essential for efficiency and sustainability. Bag et al. [51] highlights its relevance in Industry 4.0 to promote sustainable production and the circular economy. Ebrahimi et al. [52] analyze mixed assembly line configurations and show how different layouts impact operational efficiency.

Although relevant, few studies deal with the validation of new processes, especially in optimizing trajectories to reduce implementation time and eliminate bottlenecks.

Advanced techniques such as the attention mechanism can be adapted to improve the efficiency of automated industrial systems. The application of process simulation, as demonstrated in Chen et al. [53] as well as Liao and He [54], allows the optimization of dynamic interruptions and the anticipation of failures in real time, ensuring that adjustments can be made without operational risks. The simulation offers a controlled environment to test different scenarios, which results in better resource allocation and optimization of robot trajectories, directly impacting failure management and task scheduling. In actual development, this approach reduces costs and improves time, improving security and efficiency. The combination of simulation with reinforcement learning, as proposed in Yang et al. [55], allows continuous improvement, being crucial to guarantee increasingly efficient and adaptable processes in the production environment.

The integration of modeling and simulation concepts with technologies such as machine learning and robotics allows the validation of industrial processes, optimizing trajectories and eliminating operational bottlenecks. To deepen the analysis, a synthesis of studies is presented that highlights the benefits of using these approaches in the context of robotic cells and automotive processes, which can be seen in Table 1.

Table 1
Comparative analysis of SOTA techniques in robotic process validation

Aspect	Venigandla et al. [1]	Soori et al. [2]	Murino et al. [3]	Andronas et al. [4]	Zhang et al. [5]
Focus	Robotic process automation in retail pricing	Virtual manufacturing systems	Risk assessment in cobots	Human–robot collaboration in automotive	Simulation in intelligent manufacturing
Main Methodology	AI-enhanced robotic automation	Literature review	FMEA and PRAT risk assessment	Case studies in automotive workstations	Modeling and simulation
Key Findings	AI optimization improves efficiency	Virtual systems enhance production efficiency	Cobot risk is minimized through combined methodologies	Effective human–robot collaboration in automotive	Simulation optimizes manufacturing processes
Applications	Retail pricing optimization	Industrial manufacturing	Collaborative robotics in industrial tasks	Automotive industry workstations	Intelligent manufacturing environments
Limitations	Focused on retail sector	General manufacturing focus	Limited to risk assessment in cobots	Limited automotive case studies	Focused on manufacturing
Future Work Suggestions	Explore AI in other sectors	Extend virtual systems to new industries	Further study on collaborative robot safety	Explore further human–robot integration	Apply simulation to broader industries

3. Research Methodology

The methodology used in preparing the paper was computer modeling and simulation, which focuses on detailed modeling of the robotic cell and assembly operations in both the virtual simulation and the real cell [56]. The models are validated using real data collected during the operation of the robotic cell. The models are then used to simulate different production scenarios and evaluate the impact of proposed improvements [57].

The simulation was conducted using the CoppeliaSim software, version 4.0.0, with the Lua dynamics and programming modules enabled. The layout of the robotic cell was modeled based on measurements of the physical environment, replicating the dimensions and positioning of the supports. The trajectory modeling included reference points defined as Home, P1, P2, P3, and P4, used to define the robot's trajectory. Operating times were collected through manual timing at eight cycles per movement, with data validated using mean and standard deviation to ensure consistency.

To minimize the impact of validating new projects in the robotic cell and to comply with automotive manufacturing processes, ten steps have been developed to standardize the procedure in an industrial environment:

1) Verification that the current parameters correspond to the proposed modifications, such as the robot's work area and reach, the load to be managed, the type of fixture for handling, the trajectory, and the collision analysis.
2) Select the robot manufacturer and model in the CoppeliaSim software environment.
3) Positioning of the robot in the virtual manufacturing cell.
4) Declaration and assignment of the variables involved, such as the robot's work area and reach, the load to be managed, the type of attachment for handling, trajectory, and collision analysis.
5) Simulation of the movements excluded by the new process.
6) Verification of possible collisions.
7) Creation of the program to check the trajectory followed by the robot in the virtual environment.
8) Post-processing of the program created in the virtual environment for the language of the selected manufacturing cell.
9) Controlled simulation of the new program in the actual environment.
10) Validation of the new process in the robotic cell to achieve automotive manufacturing.

3.1. 3D model of robotic cell

The initial stage involved utilizing CoppeliaSim software in version 4.0.0 to delineate the operational region, thereby enabling the newly derived process values to be implemented. The robot was configured with linear values of 3000 mm in each of the three axes,

Figure 1
Real cell x virtual cell

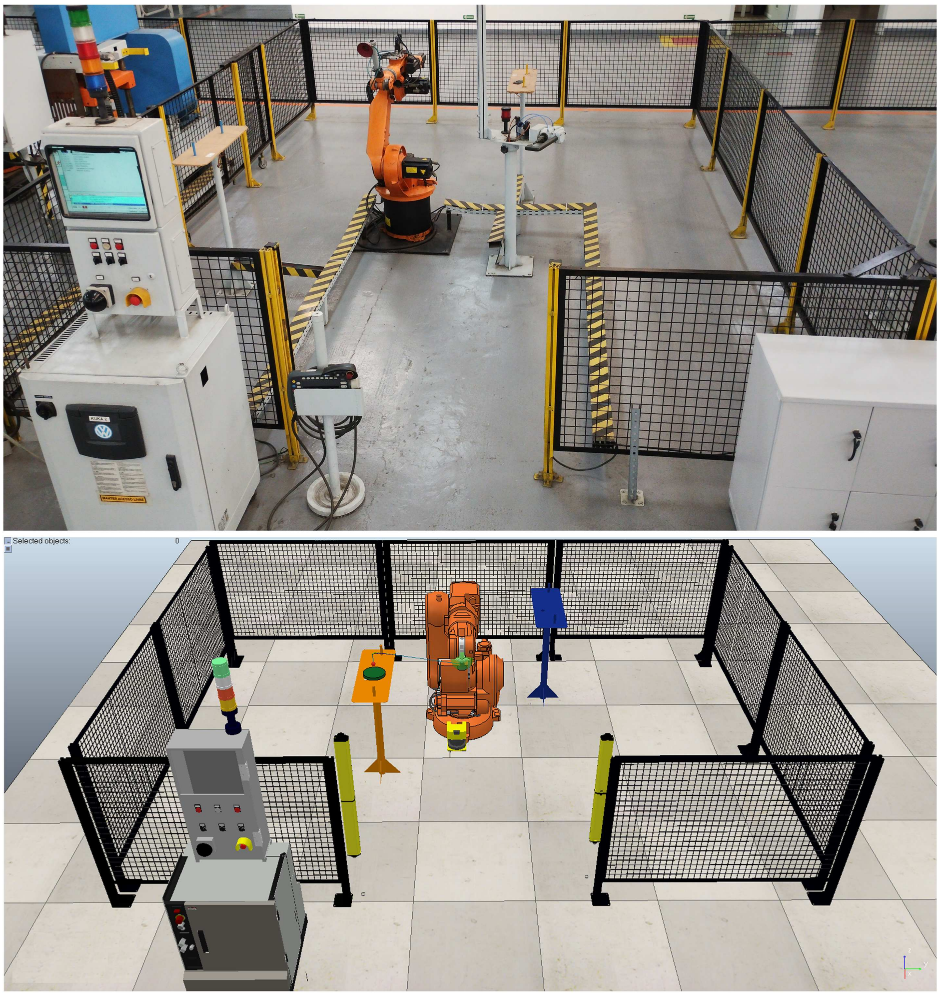


Figure 2
Cell programming

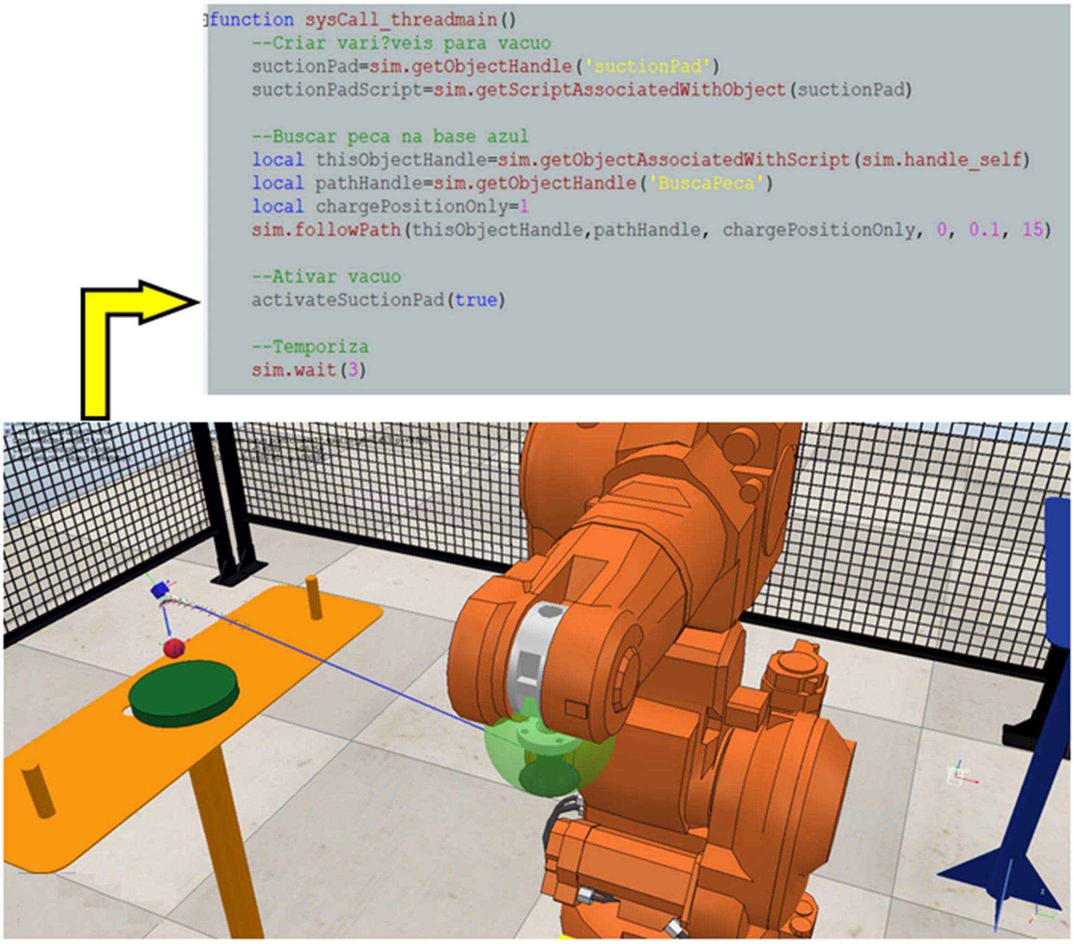
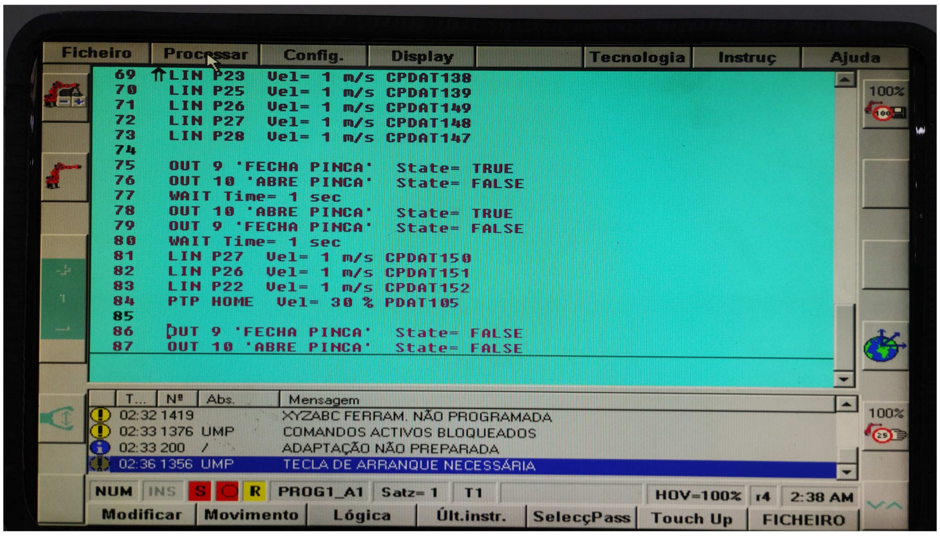


Figure 3
Real programming of the robot after validation of the virtual system

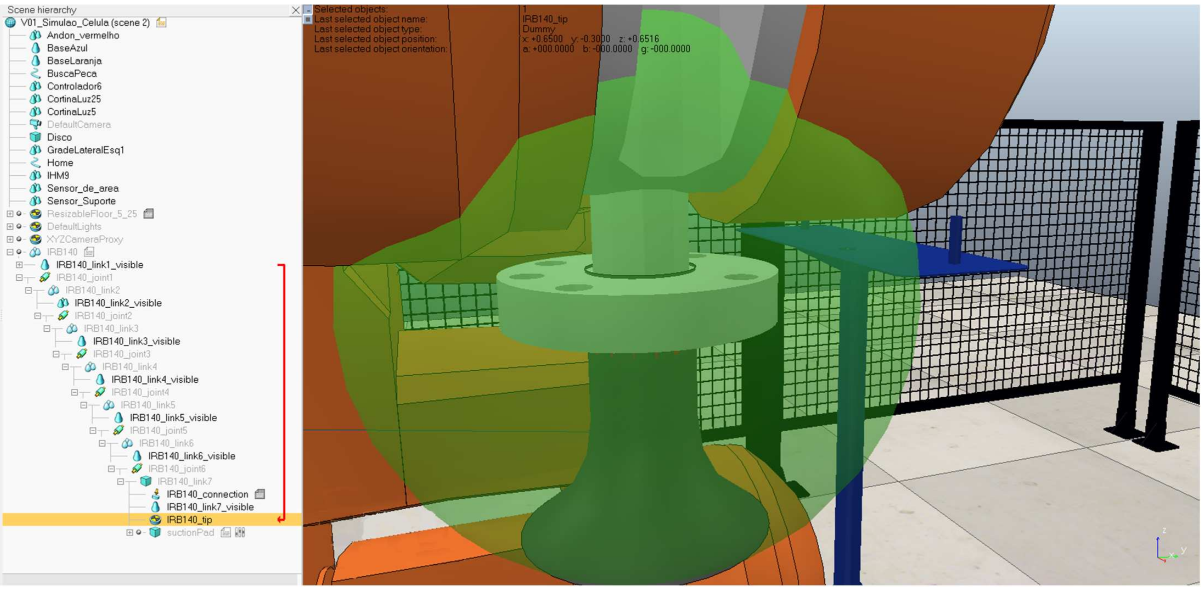


designated as X, Y, and Z, and a helpful handling area of 9000 m^3. The load to be managed weighed 700 grams, and a flat plate geometry shaped like an automotive stamping platen. Therefore, it was decided to attach them using suction cups.

Once the working region and clamping method had been defined based on the geometry, the trajectory was defined by analyzing it from point to point, from its origin, designated as P1 in the program, to the end of the manipulation cycle. The data entered the virtual environment was then simulated, and the result was that there was no risk of collision, as illustrated in Figure 1.

Subsequently, the variables to be analyzed were declared and assigned within the programming development environment using the Lua language. The robot's movements were then simulated according to the new process. After that, the absence of collisions was checked and confirmed with all the parameters declared, the trajectory defined, and the robot configured.

Figure 4
Tool center point



The next stage involved the creation of a program to define the trajectory traced by the robot. In the eighth stage, the coordinates generated by the program were post-processed to insert the values obtained into the cell. This transformation of the coordinates into ISO language commands for the actual environment enabled the robot to begin operating.

The final stage of the process involves using the actual environment in conjunction with the programming generated and validated by the virtual environment. At this point, the cell has already received all the parameters needed to start the new process, including those relating to the reference, the end-of-travel check, the program directory, and the reduction in axis speed to increase safety during the initial test. The result of this activity can be seen in Figure 2.

Once the simulated programs had been validated in the virtual environment, post-processed, and installed in the robot's directories, they were all validated individually in the cell, respecting the safety procedure. Given the success of the robot's trajectory, characterized by the absence of a collision, the cell was released to conduct the new activity, as shown in Figure 3.

3.2. Cell kinematics

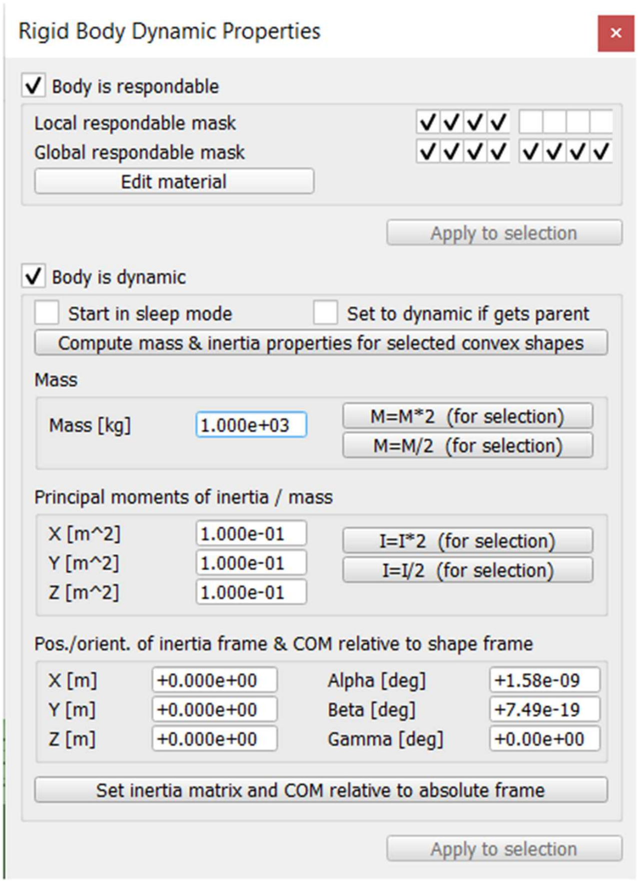
The most crucial aspect of the kinematics of the cell is the study of the robot's movements. To achieve this, it is essential to define the devices' positions, references, trajectories, velocities, and accelerations.

A fundamental procedure for ensuring the accuracy of the positions is the setting of the "TCP" (Tool Center Point), defined as the distance between the center of the flange of the robot's sixth axis and the tip of the tool.

In CoppeliaSim, the TCP is defined by parameterizing the Dummy, which, once inserted, is considered an integral part of the robot in its movements, see in Figure 4.

Another crucial configuration is the definition of the robot's mass in kg, its moment of inertia, and its orientation concerning the angle of the moment of inertia, as illustrated in Figure 5.

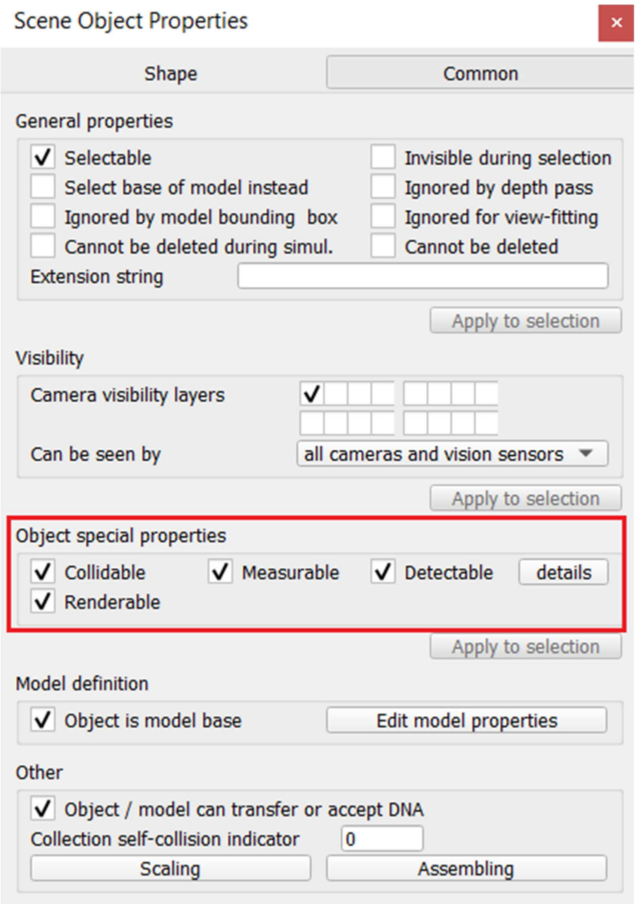
Figure 5
Moment of inertia



For the virtual simulation to correspond to the real process, it is necessary to configure the object's properties by the following specifications: collidable, measurable, detectable, and renderable, as seen in Figure 6.

Once the requisite settings have been established, an interface screen will be displayed upon simulation execution. This screen

Figure 6
Object's properties



allows the user to control the x, y, and z axes following inverse kinematics. The alpha, beta, and gamma axes may also be oriented according to the user's specifications. Furthermore, spatial speed and workspace velocity may be adjusted. Finally, each axis may be individually configured for movement. The result of this activity can be observed in Figure 7.

4. Conclusion

The results found during the project's development were divided into three stages: layout of the actual environment, chrono analysis of the steps of the new process based on the actual environment, and simulation in a virtual environment to obtain the best scenario before validating the new process. The first step involved adapting the cell's previous process to a new trajectory model established in the project. To allow a precise analysis of each movement conducted by the robot, timing was created to identify each step within the cell. The positioning process was then segmented into three parts: updating and efficient movement adjustments. The first stage of the movements involved defining the trajectory, which included leaving the initial position (Home Position) toward support 1, passing through the Home, P1, and P2 marking points. Then, from support 1, it was moved to support 2, passing through points P2 and P3, and finally, support 2 was returned to the initial position, passing through points P4, P3, and Home. These initial movements are represented in Figure 8.

In the second stage, chrono analysis was conducted, recording the eight movements of each phase of the process for visual validation and data insertion in the virtual environment. This ensured that the data provided was concrete and allowed partial analysis of the system's performance before implementation. Detailed records enabled an in-depth understanding of operations, identifying areas for improvement and refinement of the project. This procedure contributed to the precision and reliability of the results, strengthening the validity of the proposed model. This step helped verify bottlenecks and provided a solid basis for decision-making in the development of the validation process, as seen in Table 2.

The third stage began with table data insertion into the CoppeliaSim software to declare the variables, replicating the actual environment. Next, the parameters, including positioning, speeds, and collision analysis, were checked to ensure compliance with the established technical specifications. A new analysis was conducted to optimize the trajectories to achieve the ideal scenario for the new process. This refinement resulted in significant gains in efficiency and performance, adding value to the project.

After generating the favorable scenario, post-processing was conducted on the program developed in the virtual environment by the CoppeliaSim software, using the Lua language

Figure 7
Robot interface

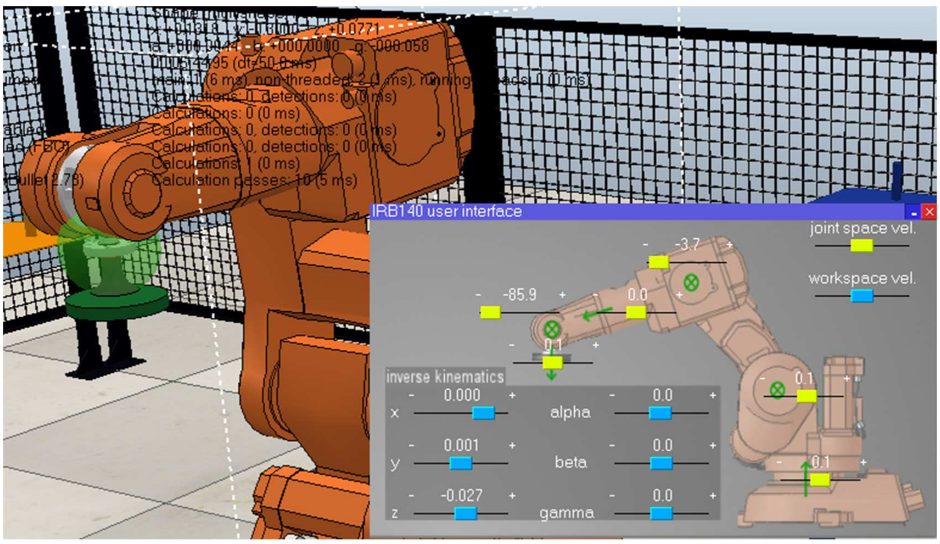


Figure 8
Robot interface

Table 2
Chrono analysis of trajectories

Position of activities	1	2	3
Description	Home Position to Support 1	Support 1 to Support 2	Support 2 to Home Position
1st timing	3.06	5.85	2.53
2nd timing	2.97	5.85	2.47
3rd timing	3.09	5.88	2.56
4th timing	2.91	5.56	2.40
5th timing	3.15	6.20	2.62
6th timing	2.97	5.67	2.45
7th timing	3.03	5.82	2.50
8th timing	3.10	6.12	2.50
Meantime (s)	3.03	5.87	2.50
Accumulated time (s)	3.03	8.09	11.4

for the KUKA Robot Language (KRL) to prepare it for insertion into the cell robot for actual manufacturing. This process involved converting code coordinates to ensure proper compatibility and functionality in the physical environment. Finally, the post-processed program was successfully inserted into the real cell, as shown in Figure 9.

Eliminating the risk of robot collisions within the manufacturing cell was one of the main advances achieved, ensuring the safety of the equipment and the integrity of the work environment. The simulation of different scenarios in the virtual environment allowed the search for the best positions, optimizing trajectories, and directly reflecting on the robot's manipulation speed.

One of the points analyzed in the study was the possibility of validating new processes derived from existing activities, which provided continuous development and improvement of industrial practices. Reducing the time and total costs involved in developing new projects was another benefit achieved, resulting in savings in financial resources and time for companies in the automotive sector. Table 3 compares the scenarios before and after the optimization, based on the times presented in Table 1 to present the impact of the improvement.

In Table 2, it is possible to visualize the result by comparing the times before and after optimizing the trajectories, highlighting the reduction obtained in each activity and the impact on the total cycle execution time.

Although the results are promising, the study has limitations. The generalization of the results is restricted, as the simulation used specific parameters and configurations, not reflecting the diversity of layouts and equipment in different factories. The complexity of optimization algorithms and the need for constant adjustments can represent challenges in the practical context of the automotive industry, especially in relation to operational demands and delivery times. Unforeseen factors, such as sensor failures and environmental variations (temperature, humidity), were not considered and may affect the applicability of the results in real scenarios.

The study demonstrated the effectiveness of trajectory optimization in validating automotive processes, reducing implementation time and eliminating operational bottlenecks.

Figure 9
Validation of the new process in the virtual environment

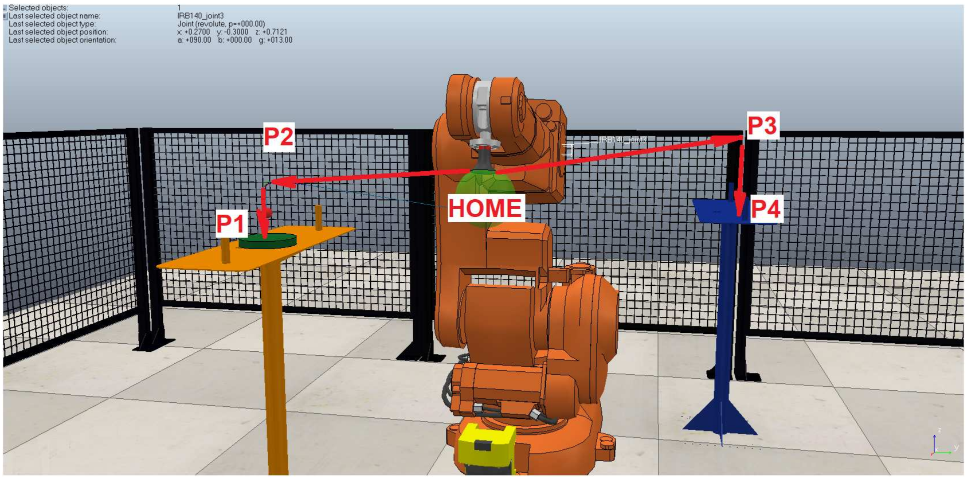


Table 3
Comparing the times before and after optimizing

Activity	Initial time (s)	Optimized time (s)	Reduction (s)	Reduction (%)
Home position to Support 1	3.03	2.80	0.23	7.59
Support 1 to Support 2	5.06	4.74	0.32	6.32
Support 2 to Home position	3.31	2.98	0.33	9.97
Total	11.40	10.52	0.88	7.72

Recommendations

The steps conducted in this study provided advances in validating new projects in the automotive industry. Eliminating the risk of robot collisions within the manufacturing cell was one of the main results obtained, ensuring the safety of the equipment and the integrity of the work environment. Furthermore, the simulation of different scenarios in the virtual environment allowed the search for the best positions and the optimization of trajectories, directly reflecting on the robot's manipulation speed.

Also noteworthy is the possibility of validating new processes derived from existing activities, which provided industrial practices' development and continuous improvement. Another positive point observed was the reduction in time and total costs involved in developing new projects, resulting in savings in financial resources and time for companies in the automotive sector.

Future research can explore the application of trajectory optimization in different factory layouts, such as in-line arrangements, production cells, or modular layouts. For example, simulations can be used to test how rearranging workstations impacts robot delivery speed and material flow. Variations in machine configurations, such as the inclusion of collaborative robots or adjustments to storage areas, can be demonstrated. Simulated data can be compared to actual cycle time and cost specifications, offering actionable insights for real-time adjustments and measurable improvements in the production environment.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data available on request from the corresponding author upon reasonable request.

Author Contribution Statement

William Aparecido Celestino Lopes: Conceptualization, Methodology, Validation, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Adilson Cunha Rusteiko:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Cleiton Rodrigues Mendes:** Conceptualization, Methodology, Software, Investigation, Resources, Writing – original draft, Writing – review & editing, Visualization. **Nicolas Vinicius Cruz Honório:** Conceptualization, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization. **Marcelo Tsuguio Okano:** Validation, Formal analysis, Data curation, Supervision, Project administration.

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