Digital and Smart Production Using Simulation Systems to Improve the Manufacturing Performance

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Abstract: The article aims to present a case study of an electronics company with a focus on automotive products, using actual production data in which computer simulation was used to analyze the efficiency and process improvement, paying attention to the indicators and reduction of labor in the process using an intelligent system for inspection of the plates. A computational tool for discrete events is used to explore the system's functionalities, aiming to provide a more comprehensive view of the manual insertion process since the software has several performance analysis tools. The method was developed through "in loco" data collection, in similar cases studied in the literature, and in learning the computational tool, thus creating a virtual environment that allowed simulation of different strategies to achieve the desired result verifying. There is excellent potential for improvement with the proposed scenario. Finally, the results obtained with the simulation proved that its use emerges as a powerful tool for evaluating the rationalization of resources and the application of digital twins, predicting a new assembly line efficiency from 76,16% to 97,24% of improvement, making clear the advantages and characteristics of using computer simulation as a competitive tool for quick decision-making in the manufacturing process.

Keywords: Discrete-Event Simulation, Digital Twin, Industry 4.0, Process Improvement.

1. INTRODUCTION

Digital transformation and Industry 4.0 are changing the data generated in the industrial and commercial processes to make the data very dense. In this way, artificial intelligence should support decision-making, especially in operation management, where organizations always seek operational excellence. In smart manufacturing, where machines are increasingly connected, there is a need to create new proposals and decision-making models to help executives, managers, engineers, and operators of Industry 4.0.

The physical layout project is essential for the excellent performance of a manufacturing process, as deployments and layout changes can entail high costs for the company experiments in the physical environment can lead to delays and even paralyze production. Thus, more and more organizations have acquired computational systems that make it possible to visualize different distributions of production cells in search of better performance.

In many cases, the transformations to be carried out involve radical changes in layout, material flow, models, production management techniques, changing machines, etc. In practice, stopping a production line to test the new process model is not feasible. Computer simulation has been widely used so that a whole set of impact analyses can only be carried out virtually, without taking any action on the actual system (de Paula Ferreira et al., 2020).

This study was developed in a company specialized in the manufacture of automotive car radios, having as its primary objective the use of a computational tool in the restructuring of the physical arrangement, using the Tecnomatix Plant Simulation® software, which is a discrete event simulation tool that allows a more excellent visualization of manufacturing through a simulated experiment, as a tool, it is possible to optimize the flow of materials, production bottleneck and make layout changes in the simulation environment, providing greater security in changes in the production process (Bangsow, 2016).

Given the above, based on some decision variables, a comparison was made between the current physical layout and the simulated scenarios, which presented indicators that made it possible to propose a manufacturing restructuring using computer simulation as an analysis tool.

Smart manufacturing attracts the attention of numerous researchers who have reported their findings in the literature. Discussed the main features of cyber-physical systems and provided an overview of Germany's Industry 4.0 initiative and manufacturing efforts undertaken in other countries (Thoben et al., 2017). An attempt has been made to identify relevant research questions. Helu et al. (2016), defined requirements for data-based decision-making in manufacturing. Based on these requirements, the leading technologies, and barriers to implementing data-driven decision-making in the industry were identified. Shafiq et al. (2015), Proposed a framework for knowledge representation of engineering objects incorporating relevant knowledge and experience.

Considering the facts presented, the importance of this study is relevant since the implementation of digital manufacturing is becoming a differential within organizations, digital manufacturing helps change the processes of companies, in which high investment costs are involved, helping in anticipating problems and finding a solution. In short, the use of technological resources helps managers in decision-making. However, a careful implementation project is essential to achieve the desired results in terms of cost, time, and quality of implementation.

Thus, to improve the manufacturing process, it is necessary to create a simulation scenario that allows control of the production process and evaluate the possibilities for improvements. The simulation environment allows forecasting of resource requirements for demand increases. Another reason is the search for the best manufacturing environment to obtain the best results with the existing equipment/resources.

2. DEFINITION & METHODOLOGY

The main objective of this paper is to provide a literature review with a categorization of the different contributions related to Simulation, Discrete Event, Industry 4.0, and Digital Twin. They are categorized in terms of their levels of integration, their area of focus and the technologies used. Therefore, this section discusses the academic and theoretical definition of the concept of Digital Twin and Simulation in Manufacturing in the context of Industry 4.0.

2.1 Bibliometric analysis on Simulation based on Event Discrete and Digital Twin

A bibliometric analysis was carried out to analyze the dynamics of research evolution considering Discrete Event-based Simulation in the context of Industry 4.0 to create a Digital Twin. The final search was carried out in April 2023 in the Scopus and Web of Science database with the keywords “Simulation,” “Discrete-Event Simulation,” “Industry 4.0” and “Digital Twin” applied in the titles, abstracts, and words key of the articles. For the portfolio, only articles with publications in journals and in English were considered.

Based on the methodology adopted, 49 articles were included in qualitative synthesis, from the articles selected for content analysis, quantitative analyzes were developed with the Bibliometrix tool of the R Studio® software, following the procedure developed by Aria & Cuccurullo (2017).

The final search string is presented as follows for Scopus:

TITLE-ABS-KEY ("simulation" AND "discrete-event" AND “Industry 4*" AND "Digital Twin") AND (LIMIT-TO (LANGUAGE, “ENGLISH”))

For Web of Science the string as follow:

TS= ("simulation" AND "discrete-event" AND "Industry 4*" AND "Digital Twin")

Figure 1 shows the temporal evolution of publications in the selected portfolio. 2017 was the first year a publication appeared in an indexed journal in the databases considered. Bottani et al. (2017) presented a prototyping of a Digital Twin that addresses the logistic behavior of a family of automatically guided vehicles (AGV), using discrete event software to simulate different application environments. Over the years, the number of publications has grown consistently. Between 2017 and 2022, publications increased steadily, with annual growth of 34.8%. This analysis shows the growing interest in discrete event simulation in the context of Industry 4.0.

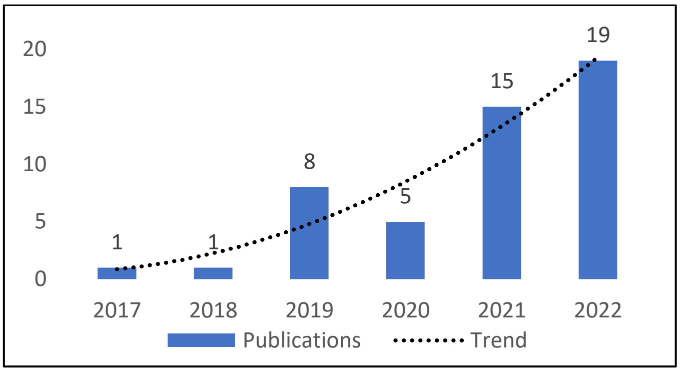

Fig. 1 Temporal evolution of publications.

Figure 2 shows a keyword co-occurrence network by multidimensional scaling (Huang et al., 2005) using the edge-betweenness centrality clustering algorithm (Qi & Tao, 2018). This analysis allows the identification of a main group of terms that deals with the intersection between the themes investigated in this research.

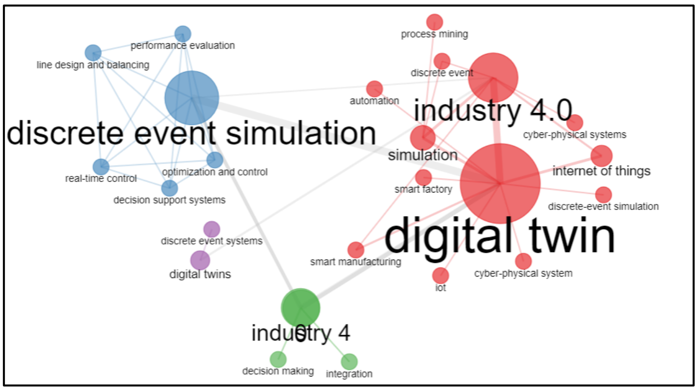

Fig. 2 Keyword co-occurrence network based on bibliometric research.

As central terms “Digital Twin”, “Industry 4.0” and “Discrete Event Simulation” appear in the co-occurrence network. Other related terms, Internet of Things and Simulation, demonstrate the connection between the research fields. Figure 3 demonstrates the map of words based on the research carried out in the databases.

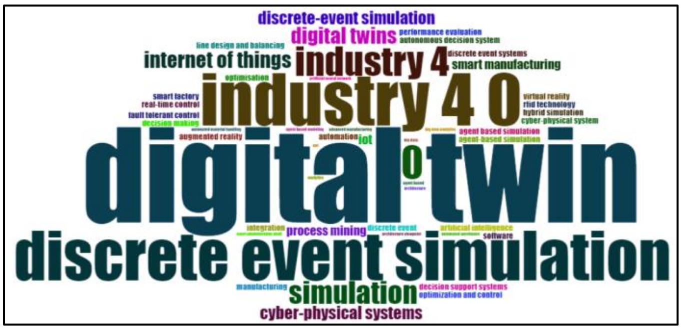

Fig. 3 WordCloud is based on bibliometric research.

2.2 Levels of Integration

Some digital representations are modeled manually and connected to any physical object, while others are fully integrated with real-time data exchange. Therefore, the authors would like to propose a classification of Digital Twins into three subcategories according to their level of data integration (Kritzinger et al., 2018; Magalhães et al., 2022).

2.3 Digital Model

A Digital Model is a computational representation of an existing model or planned physical object that does not use any form of automatic data exchange between the physical and the digital object. The digital representation may include a comprehensive description of the physical object. These models may include but are not limited to simulation models of smart factories, algorithms models of new products, or any other process models of a physical system that do not use any form of automatic data integration. Digital data from existing physical systems may still be used to develop such models, but all data exchange is done manually. Any data change in the state of a physical systems has no direct effect on the digital model (Magalhães et al., 2022). Figure 4 illustrates this model where there is no flow of information between the physical and digital environments.

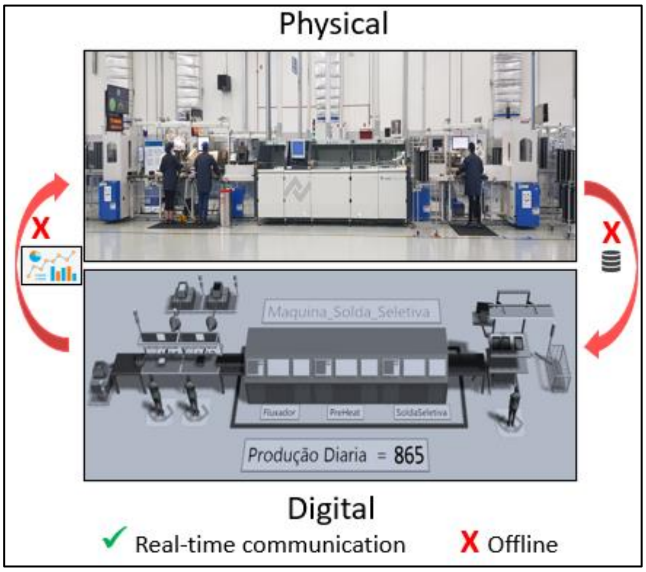

Fig. 4 Data Flow into Digital Model.

2.4 Digital Shadow

Based on the definition of a Digital Model, if there is more than one automated one-way data flow between the state of an existing physical object and a digital object, one might refer to that combination as a Digital Shadow. Any data change in the physical system's state leads to a change of state in the digital scenario, but not in the other way (Magalhães et al., 2022). Figure 5 illustrates this model where only one information path exists between the physical and digital environments.

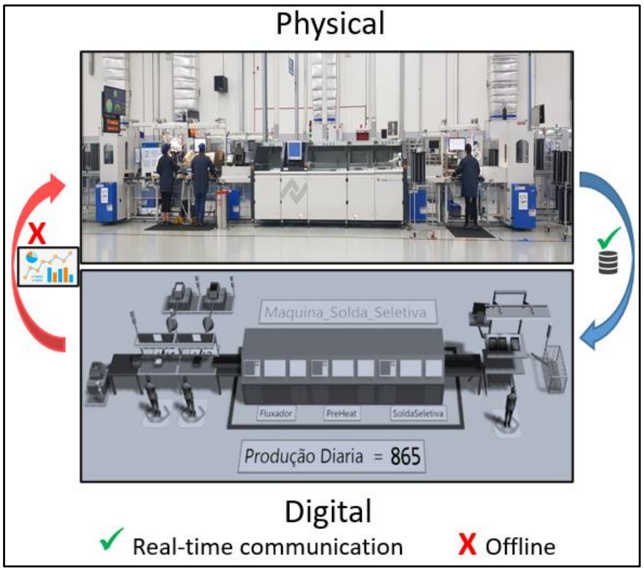

Fig. 5 Data Flow into Digital Shadow.

2.5 Digital Twin

Digital transformation is today one of the leading development trends of Industry 4.0. One of the main approaches to this concept is the "Digital Twin". Digital Twin (DT) supports virtual models of actual equipment, industrial processes, and end products. This technology provides methods for analyzing data from different types of sensors installed in equipment on manufacturing lines and updates their virtual information from the existing system (Agostino et al., 2020). For this, DT applies different mathematical models to simulate processes of interest implemented using statistical methods, data mining, and finite element methods (Zhang et al., 2020; Magnanini et al., 2021).

The DT development of an industrial process can be presented through a computational workflow composed of a set of computational services that represent models for the process steps and their interaction (Korambath et al., 2016). Each of these computational methods defines specific requirements for the necessary computational resources. A possible solution that provides a system with high flexibility, on the one hand, and high computational performance, on the other, is to use discrete event simulation technology (de Paula Ferreira et al., 2022; Bangsow, 2016).

DT is a hierarchical system of mathematical models, computational methods, and software services that provides near real-time synchronization between the state of the real-world process or system and its virtual copy (Retto Uhlmann et al., 2023).

Data flowing between an existing physical object and a digital object is fully integrated with both directions; one can refer to it as the Digital Twin. In such a combination, the digital object can also act as the controlling instance of the physical object. There may also be physical or digital objects that induce state changes in the digital object. The change in the state of the physical object directly leads to a change in the state of the digital object in the both way (Magalhães et al., 2022; Zhang et al., 2020; Krenczyk & Paprocka, 2023). Figure 6 illustrates the model with two paths of information flow between the physical and digital environments.

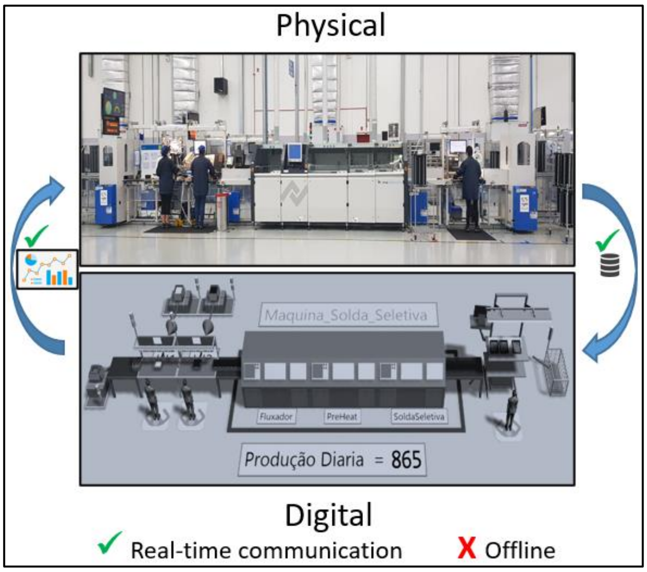

Fig. 6 Data Flow into Digital Twin.

2.6 Simulation in Manufacturing

Simulation is widely used to evaluate the performance of manufacturing systems. Historical data can be used to model manufacturing processes and activities. Managers and planners use simulation models to examine different "what-if" scenarios in decision-making and gain managerial insights. Vieira et al., (2019) developed a simulation model of a radio manufacturing facility to assess the impact on process layout and facilitate decision-making.

Johansson et al. (2015) developed a discrete-event simulation model that considered energy consumption data and conducted an analysis of datasets from three factories. Their results suggested that non-value-added activities increase energy consumption, and a discrete event simulation approach can help reduce energy use. Azadeh et al. (2015) proposed a stochastic simulation approach using historical operational data to design the layout of a workshop facility. Mousavi & Siervo (2017) adopted an approach to estimate key performance indicators (KPIs) from real-time data collected from a control system. Their approach could help managers in predicting what-if scenario outcomes. Jain et al. (2017) presented the concept of a virtual factory through simulation and data analysis tools. They applied these techniques in data generation and validation of results.

Simulation models allow decision-makers to predict outcomes and generate data for scenarios that have not been realized before. Most research on simulation modeling in manufacturing is aimed at evaluating alternatives performance and examining alternatives' benefits and tradeoffs. However, a shortcoming of simulation modeling is that the model developer must be familiar with the system.

Production Simulation is applied to anticipate strategy or improvement and define future and current production lines or cells. It can be used to determine production systems' capacity and develop and test resource operations, work time calculations, storage size determination, and control strategies.

Simulation design should be used when you want to design a new facility, optimize an existing one, or implement a ready-made design, testing different scenarios when the plant is ramped up or commissioned.

Some data need to be evaluated during the preparation phase, such as Cycle times and processes, Operation of units to be simulated, Description of the process and time (Direct Labor time), Expected Downtime percentage, and manufacturing breaks. Figure 7 illustrated the simulation stages used during the research.

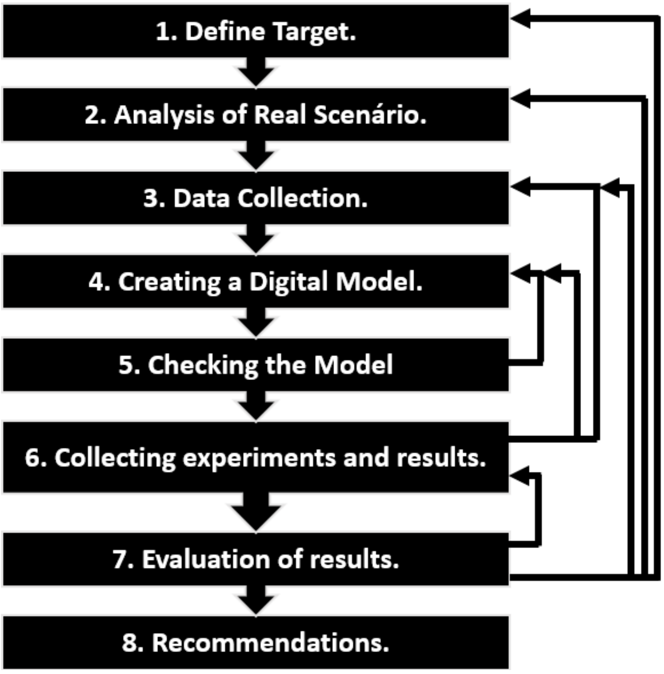

Fig. 7 Process Stages for Simulation.

3. FRAMEWORK OF HAND INSERTION PROCESS

The research was applied in the industry that designs and manufactures head-unit products for automotive companies, which sell to more than thirty brands worldwide. The company has part of its production dedicated to manufacturing and follows a lean manufacturing culture. The analyzed process is in the intermediate phase of the product, in the process of Hand-Insertion of Pin Through-Hole components (PTH), where the assembled board receives the connectors, screws, capacitors, coils, and metallic support.

Industry 4.0 is allowing new models of interaction in the value chain, and, from them, new process methods are emerging,

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proposing changes in manufacturing driven by industrial process adjustments (Kusiak, 2022).

In this industrial era, new computational tools have emerged to allow the application of other digital technologies. Following this mindset, it is possible to relate some technologies in this study, such as digital twin (DT) that support digital planning processes (Oluyisola et al., 2020)., 2020), Digital Simulation (DS) that offers a more advanced analysis study approach (de Paula Ferreira et al., 2020) and the Machine Vision (MV) where we can improve the quality assurance of processes to reduce the risks of failures due to human detection capacity (Singh & Desai, 2023).

An intelligent framework for the Manual Insertion process is proposed based on emerging manufacturing systems, scientific academia, and empirical knowledge. Initially, the idea was to add technologies in a manual manufacturing process; Figure 8 illustrates the model mapped in the study divided into three main processes: Hand-Insertion (HI), Selective-Soldering (SS), and Smart Inspection System (SIS), updated by inclusion of new digital technologies (DT, DS, MV) thus becoming an intelligent system.

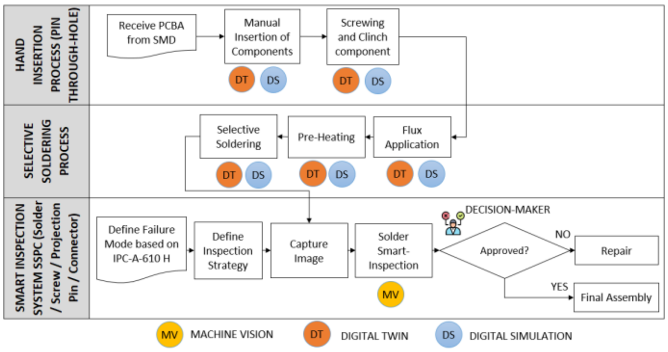

Fig. 8 Conceptual Framework.

4. RESULTS AND DISCUSSIONS

The baseline scenario represents the existing situation within the examined manufacturing system, that is, the physical model. The parameters are based on existing production conditions. A complete inspection strategy is considered in 2 other scenarios to evaluate the performance and increase the operators' efficiency. The results of the simulated scenarios are shown in Table 1.

Tab 1. Overview of results for three Scenarios.

Scenario	Type	Direct Labor (qty)	Daily Throughput (pieces)	Operator Utilization Balance Efficiency (%)
Baseline	Physical Line	3	865	76,16
Scenario 1	Digital Model	3	865	76,16
Scenario 2	Digital Model	2	879	78,61
Scenario 3	Digital Model	1	817	97,24

The system throughput is 52 pieces/hour, which works in 2 daily shifts, with a daily capacity of 865 pieces/day.

After mapping the process during the research, Scenario 1 was created, representing the system's digital model, achieving the same result as the physical model, with a process balancing efficiency of 76.16%. Figure 9 demonstrates the simulation models.

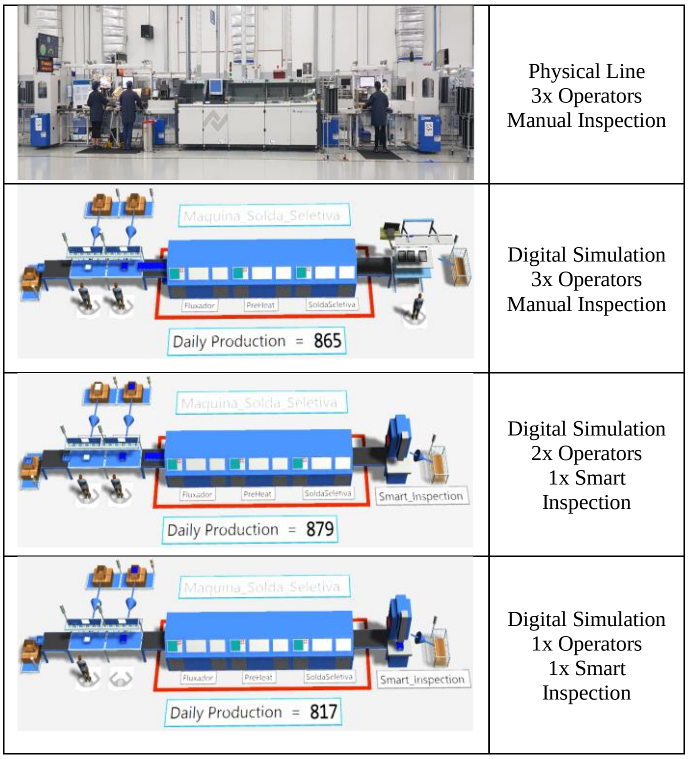

Fig. 9 Three Simulated scenarios.

In the search for process improvement, scenario two was created to improve the visual inspection process, aiming to reduce the risk of defects, as it is done visually by the process reviewer.

In Scenario 2, there is a reduction of 1 Operator in the system and an increase in daily production to 879 pieces/day, with an increase in the balancing efficiency of the two system operators to 78.61%.

Scenario 3 was elaborated after analysis of the process mapping, where it was verified that the bottleneck is the selective soldering machine in this proposal with only one operator. The assembly operations were unified, so there was a loss of 6% in daily capacity with 817 parts/day, but the balancing efficiency rose to 97.24%.

Future work will analyze the effect of implementing an intelligent inspection system based on data analysis tools to reduce failures and increase reliability. In addition, the simulation results showed some activities that do not negatively influence the system's behavior. Therefore, the intelligent system definition for quality inspection should be analyzed to optimize the overall manufacturing system. In addition, more research is needed on the allocation of inspection stations within the manufacturing system based on computer vision and machine learning.

5. CONCLUSIONS

In this research, some manufacturing simulation scenarios were developed using a computational tool because it is easy to understand; a simulation model is often simpler to justify than some analytical models. In addition, a simulation model is usually more reliable because it is compared with the existing system or because it requires slight simplification, capturing the actual characteristics of the system and showing instantaneous manufacturing results.

During the research, other opportunities for gains and improvement in the production of car radio cards were visualized, as the software includes functionalities that allow a deeper analysis. It is worth remembering that with the simulation, it became evident that it is possible to add activities to just one workstation and maintain performance, optimizing the operator's resources and increasing its level of use.

Adding an intelligent inspection system can increase process reliability and seek new approaches with suppliers and customers as the process becomes more robust and reliable.

A balancing study with the proposed scenarios is recommended, especially where the machines are over capacity, seeking new resources to combine functions and achieve better results to reduce costs and remain more competitive in the current market.

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