# A DIGITALIZATION PROCESS TO IMPROVE THE PRODUCTION SYSTEM IN THE AUTOMOTIVE INDUSTRY

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**RESUMO**

Com a intensa competição entre montadoras, esta pesquisa visa mostrar que um modelo de digitalização pode melhorar a competitividade de um sistema de produção de autopeças. Desta forma, é desenvolvido um estudo de caso real baseado em um processo de modelagem e tomada de decisão. Considerando os resultados obtidos por este estudo, a melhor proposta apresentou um Retorno sobre o Investimento de 9,22%, reduções de 23% no *lead time*, 55% em *work in process*, 38% na distância percorrida e 16% em hora/homem, com tempo estimado de implantação de quatro meses. No entanto, o investimento e a implementação dessas práticas podem ser vistos como barreiras para as empresas.

**PALAVRAS CHAVE. Indústria 4.0, Indústria de Autopeças, Simulação, TOPSIS, Eficiência Organizacional.**

**SIM – Simulação**

**ABSTRACT**

With the intense competition between automakers, this research aims to show that a digitization model may improve one auto parts production system's competitiveness. In this way, a real case study is developed based on a modeling and decision-making process. Considering the results obtained by this study, the best proposal presented a Return on Investment of 9.22%, reductions of 23% in lead time, 55% in work in process, 38% in the traveled distance, and 16%

in hour man, with an estimated implementation time of four months. However, these practices' investment and implementation can be seen as barriers for companies.

**KEYWORDS. Industry 4.0, Auto Parts, Simulation, TOPSIS, Organizational Efficiency.**

**SIM – Simulation**

## 1. Introduction

The fierce competition in the automotive industry reflects its competitiveness along the entire supply chain in the sector, resulting in pressures for cost reduction, reduction of development time for the most innovative products and products [Howell e Hsu, 2002; Rodrigues e Agostinho, 2018]. Given the complexity in which the Auto Parts Industry (part of the automotive industry supply chain) is inserted and the uncertainties that the market presents, the search for ways to improve production processes is increasingly necessary.

Defining competitive priorities represents one of the main activities in formulating the production strategy [Roh et al., 2014]. Production decisions must be integrated with the organization's strategic decisions, significantly when the pressure for competitiveness is growing [Ahlstrand, 2015]. Thus, in the automotive industry chain in which there is a highly competitive scenario, operational efficiency becomes a relevant factor. Porter e Heppelmann [2014] show that operational efficiency cannot be considered a competitive advantage but rather a minimum requirement for insertion in the market. Thus, if productivity is one of the most critical determinants for long-term growth and rising living standards, its absence, if maintained, impacts lower growth [Schwab, 2017].

In order to achieve improvements in operational efficiency, the adoption of best practices throughout the value chain is required, including, for example, updated product technologies, state-of-the-art production equipment, more modern sales approaches, information technology solutions, and supply chain management [Porter e Heppelmann, 2014]. Operational efficiency is a minimum requirement for competition worldwide. If a company is not operationally efficient and does not continuously adhere to new and best practices, its rivals will surpass cost, speed, and quality. Despite this, operational efficiency is rarely a sustainable advantage source, as competitors will adopt the same practices and eliminate this difference [Porter e Heppelmann, 2014].

In this scenario, the fourth industrial revolution (Industry 4.0 or advanced manufacturing) has been changing industry paradigms rapidly, increasing the competitiveness of organizations and expanding the availability of technologies with improved communication interfaces [Lasi et al., 2014; Prinz et al., 2016]. The decisive factor in this evolution of the industry is the fusion of technologies that make it possible to break the barriers between the physical, the biological, and the digital, expanding the range of opportunities in innovation [Schwab, 2017]. Goecks et al. [2020] highlight that the applicability of Industry 4.0 concepts has been spreading across industry and manufacturing.

The recommendation to adhere to new and better management practices is a requirement for maintaining high-quality products at affordable prices and terms. In order to meet this requirement, it is essential to design a flexible and intelligent process based on artificial intelligence, shorter innovation cycles, management of the volume of data generated, a higher level of automation, and flexibility of the production line to meet a demanding custom [Lasi et al., 2014; Faller e Feldmüller, 2015]. Thus, flexible manufacturing and fast delivery are new design techniques that emerge to address these challenges and offer a greater variety of products to customers [Porter e Heppelmann, 2015].

For this, the formation of insights for new research is opportune, as in the example of Esmaeilian et al. [2016] who present the new production paradigms, analyzing that as they become a reality, production systems must be carefully studied to explore how new technologies can influence the current infrastructure. Although new technologies have received much attention, advanced manufacturing is more than a compilation of high-performance technologies. However, new business models extract the real value that new technologies can offer [Esmaeilian et al., 2016].

Among the technologies included in Industry 4.0 is a computer simulation. Negahban e Smith [2014] provide a comprehensive review of 290 articles published from 2002 to mid-2013 on the application of discrete event simulations focusing on manufacturing. The study presents areas of application of the simulation, such as the real-time control of the production process, leveling production, and scheduling maintenance. In this way, the simulation of discrete events provides computational models with different scenarios in which it is possible to verify the resources, waste, and capacities to generate results. In the study by Gomes et al. [2012], the authors examine how a product life cycle assessment tool can complement the performance of analysis of production systems, taking into account layout planning.

Thus, when considering technological advances and their implications for business processes, there is a need to redesign processes. In which engineering actions can be responsible for the increase of gains or cost reductions for each company. Considering that the fourth industrial revolution can be considered a primary engine for process innovation. This research's main goal is to show as a digitization model may improve the competitiveness of one auto parts production system.

This objective is justified by the importance of the theme in line with industrial advances, through the fourth industrial revolution (referred to in this work as Industry 4.0) and the opportunities for gains in speed, inserted in the production system in an auto parts company. This research opportunity is reinforced by Sanders et al. [2016] who highlight Industry 4.0 as a facilitator for improvements in the production system, and by Lugert et al. [2018] from the empirical assessment of the adequacy of Industry 4.0 in the mapping of the value flow in the manufacturing industries.

Thus, this article is divided into five sections. Starting with the Introduction to contextualize the problem. Going through the Model and Conceptual and Decision Making Process sections, addressing the development process of this study. Finally, the Results and Final Considerations sections are covered.

## 2. Conceptual simulation model

With the inclusion of technologies in the production process arising from Industry 4.0, there is a need to seek information on the inclusion of these technologies in production systems to support this rise. As a simulation method, the point cloud is used, making the process more effective and realistic. The simulation allows a more in-depth analysis based on indicators and evaluation of suggestions for improvements. Several future scenarios perform this analysis. Figure 1 illustrates the general flowchart with the simulation steps.

### 2.1. Pre-Simulation

In this stage, data collection is carried out to understand the area to be investigated. Its objective is to understand the process to develop opportunities for improvement. The phase consists of process mapping activities, data collection, and construction and validation of the computational model (digitization of the factory) [Freitas Filho, 2008]. From these activities and technologies of Industry 4.0, it is possible to simulate the scenarios to improve the process. Each of these phases is described below:

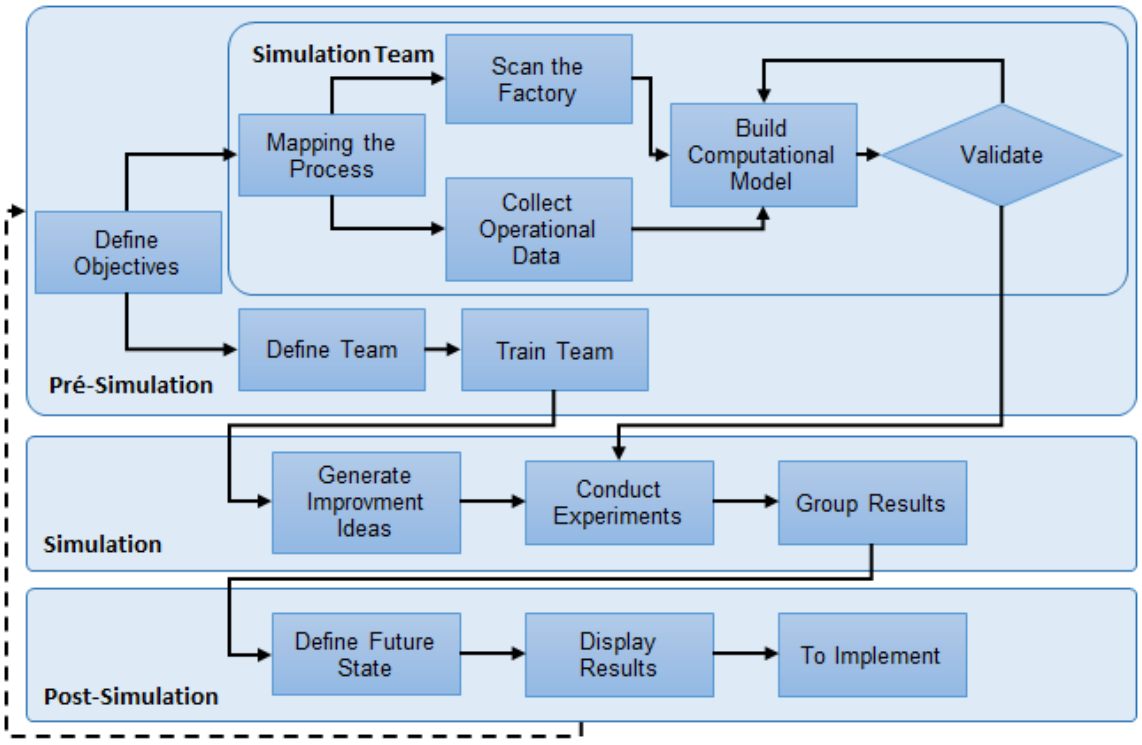



Figure 1: Simulation steps.

- Mapping the Process - aims to understand and understand how a business unit operates, representing each step of that unit's operation in terms of inputs, outputs, and actions. The objective of this step is to assist in the construction of the computational model. For a better understanding of the production processes, the process mapping is carried out by the modeling analyst;

- Scan the Factory- consists of scanning the area where the improvement project will be carried out. This activity can be performed by external actors (contracting third-party services) or by the modeling analyst;

- Collect Operational Data - a task that can be performed by the data analyst, who is responsible for collecting, processing, updating, and making available the probabilistic data. These are even treated in a format suitable for use in the simulation software;

- Build Computational Model - in this phase, the modeling analyst imports the data from the production process into the computational model. In this step, the integration with the digitalization point cloud is carried out;

- Validate - a task where a comparison is made between the simulation results and the current production process. The greater the adherence between the real and the simulated system, the more reliable the simulation model is. If the real and virtual models' adherence is greater than or equal to 90%, it means that they are aligned.

## 2.2. Simulation

This stage of the simulation process consists of three phases: the proposition of improvements, the performance of experiments, and the compilation of results [Freitas Filho, 2008].

- Generate Improvement Ideas - the phase that involves the entire project team to identify the practical implications and analyze the different points of view and ideas available. The immersion can be divided into preliminary and deepened. In the preliminary phase, there is a first contact with the problem to be analyzed. Subsequently, this is assessed in depth when the survey of needs and opportunities begins that will guide the generation of solutions in the next stage of the project;
- Conduct Experiments - with all the improvement proposals identified during the design stage, the modeling analyst simulates future state scenarios based on the suggested changes. The largest possible scenarios should be generated to ensure a broader scope of improvements. The planning of these scenarios must take into account the characteristics of the company and methods that optimize the process;
- Group Results - in the end, the results are compiled by the modeling analyst, who presents all the proposals obtained in future state scenarios' computational models. The results are discussed with the team involved in the project to identify the strengths and weaknesses of the implementation of each improvement proposal.

## 2.3. Post-Simulation

After performing the previous steps, the post-simulation stage must conclude from the experiments carried out, defining the adopted future state, presenting its results, and planning its implementation. In defining the future state and presenting the results, the project manager confronts the results obtained in the future state simulation with the target indicators. This step's output is the choice of the scenario to be implemented, based on a multi-criteria decision, such as the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). In this way, with the method employed, it will be possible to obtain the ideal solution, that is, the optimal solution [Kahraman, 2008; Hwang e Masud, 2012].

Afterward, the implementation of the action plan is carried out, and the documentation of all activities performed in the simulation's execution. All future state models and scenarios must be documented. Implementation varies according to the implementation and investment plan available [Hwang e Masud, 2012].

The inclusion of the simulation increases the improvement project's effectiveness through the insertion of technologies for future state analysis, enabling multi-criteria analysis. The implementation requires investments in technological and human resources. Without a qualified team, it is impossible to build computational models representing the reality of the production line. The use of new technologies also poses significant challenges for the development of the simulation. For scanning a production line, it is ideal that no people are circulating. Also, the data generated requires high-performance computers for processing, in addition to a modeling specialist dedicated exclusively to the project. Table 1 presents a summary of the requirements and restrictions for each of the technological resources necessary for the useful application of Industry 4.0 concepts to improve the process.

Other software can be used in addition to those described, which may have other requirements and restrictions. For this work, the selected technologies took place according to the company's adaptability to be investigated. Human and technological requirements are essential factors, as they help to replicate this knowledge in the organization's routine.

Table 1: Requirements and Constraints for Technological Resources

| Resources | Requirements | Constraints |
|---|---|---|
| *Plant Simulation*$^{TM}$ | Professional and additional license for point cloud | Only compatible with point cloud in .POD format and need for a modeling specialist with CAD knowledge |
| *Laser Scanner* | Acquisition of equipment or contracting to provide services | Number of points, colorization of points, number of scans, scanning performed outside the production shifts |
| *NX CAD*$^{TM}$ | Professional and additional cloud license | Color point cloud files are not supported, except .POD format |
| Computer | High processing and storage capacity | High investment for equipment acquisition |

## 3. Decision making process

To assist decision-makers in their unique and personal decision-making process, multicriteria decision-making methods emerged. Such methods do not aim to automate it but to integrate subjective evaluations in the search for a compromise solution that can meet not only a selection criterion [Ishizaka e Nemery, 2013]. In the literature, decision problems are classified into: choice, classification, ranking, description, elimination, and design [Ishizaka e Nemery, 2013].

Thus, an essential step in searching for the solution to a multicriterial problem is choosing the most appropriate method for the situation. None of the available methods is ideal for all situations. Each method has its particularities, limitations, and strengths. As a way to select the most appropriate method to demand, there are several approaches. One of these ways is through the format of the data to be inserted and the desired formatting in the data output [Ishizaka e Nemery, 2013]. Thus, observing the data obtained for this study and the expected output of the method, a ranked classification, the method chosen was the Technique for Order of Preference by Similarity to Ideal Solution - TOPSIS.

TOPSIS allows the adoption of an unlimited amount of criteria to evaluate an unlimited amount of alternatives [Jahanshahloo et al., 2009]. The method requires as input data the attribution of evaluation values for all alternatives concerning all evaluation criteria. If necessary, weighting criteria can also be integrated into the input data. If there is no distinction between the criteria, weights equal to all [Jahanshahloo et al., 2009; Silva e Almeida Filho, 2020] are assumed.

Its operationalization works as follows: the chosen alternative must be as close as possible to the ideal solution, and as far as possible from the anti-ideal solution, where the ideal solution is formed as a compound of the best performance values displayed (in the matrix of decision) for any alternative, as the anti-ideal solution is the combination of the worst performance values, therefore, the proximity of each of these performances is measured in the euclidean sense (for example, square root of the sum of the squared distances along of each axis in the “attribute space”) [Kahraman, 2008]. The output produced is simple to interpret, being a coefficient, in which the alternative with the highest coefficient is the alternative closest to the ideal solution and, concomitantly, the furthest away from the anti-ideal solution, thus being considered the best solution of commitment [Hwang e Masud, 2012; Jahanshahloo et al., 2009; Silva e Almeida Filho, 2020].

## 4. Application in a real case

The company’s production process under analysis has several manufacturing cells, each for a fuel tank model. It was noticed that the layout of workstations could be improved, thus reducing the distance traveled by workers and materials, consequently reducing lead time. This phase was structured based on an improvement study, which identifies opportunities to convert an existing factory into a factory of the future, including some concepts and technologies of Industry 4.0. Table 2 presents some opportunities that can be considered for the transformation of the production process, using concepts from Industry 4.0.

The proposals presented in Table 2 can be applied based on the structuring of a team according to the different departments/sectors of the company, seeking trained professionals with

Table 2: Practical application in an auto parts factory

| Steps | Description |
|---|---|
| Manufacturing layout | The manufacturing system layout must be evaluated and reorganized |
| Transport standardization | Use of automatic transport technologies (AGV's) |
| Reduce/Eliminate setup time | Improvements in the fixing structure and transport in the robotic welding station |
| Tank traceability | Track product movement at the factory and calculate lead-time (RFID, QR Code or TaggenBeacon) |
| Inventory reduction | Work on approaching the machines, directing the tanks to continuous flow (layout improvement) |
| Integrate maintenance | Inclusion of technologies for monitoring equipment to predict preventive/predictive maintenance |
| Even and balance | Planning training for the team for a continuous flow and standardized work |
| Automate manual processes | Collaborative robots to assist finishing routines, sharing the same location with operators |
| Prediction technologies | Inclusion a computational system for planning and production optimization (BD & Data Analytic) |

*Objective*: Convert an existing factory into a factory of the future (Industry 4.0).
*Phase 1*: Opportunity identification.

an innovative profile. Also, considering the opportunities previously mentioned, training was carried out to qualify the improvement project team, that is, transformation for Industry 4.0. In this way, implementing these technologies can become stable, with a qualified team and engaged in the improvement process.

Finalizing the team's selection, training, and the definition of the technologies of Industry 4.0 to be used, it is possible to start the planning of insertion of these in the industry to be investigated. To this end, the simulation phase aimed to increase the production system's efficiency by assessing the future state, using algorithms to generate scenarios. The steps presented in Figure 1 are unfolded in Figure 2.

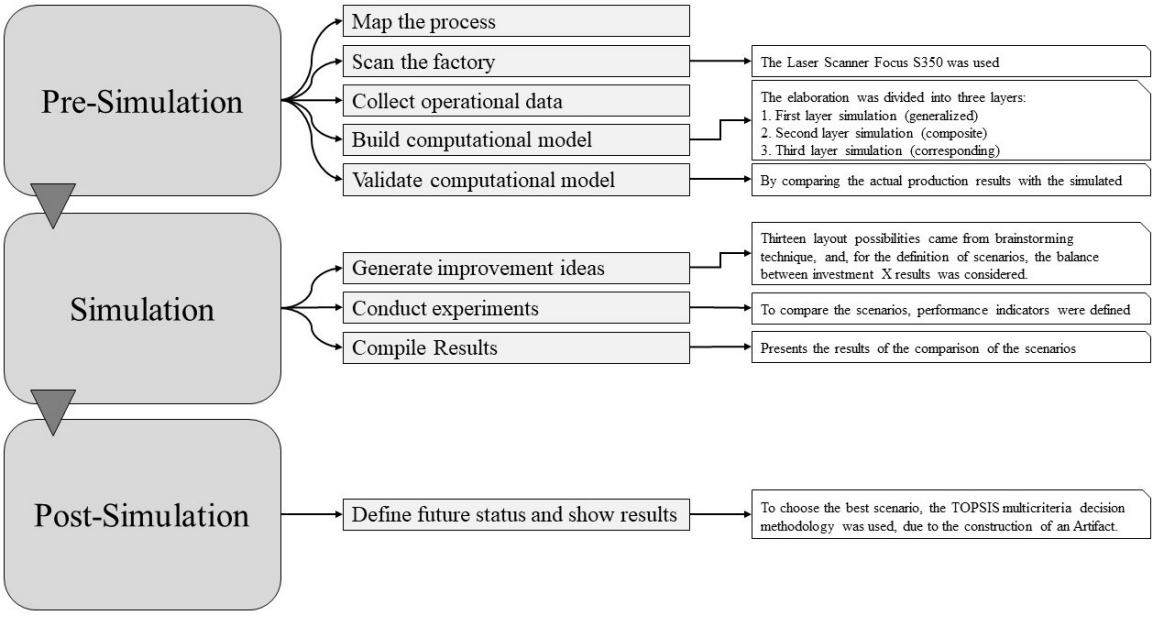



Figure 2: Simulation flow.

From Figure 2, we identified three main steps, the first of which, "Pre-simulation", can be divided into five sub-steps. In the "map the process", it was identified that the fuel tanks are made up of the parts: body, partitions, caps, and nozzle. The manufacturing process is divided into two construction sequences: the fuel tank body and the caps. As for the work cells, these are

divided into cutting, welding, and finishing/packaging. With the factory mapped, it is possible to "scan the factory". For scanning the production line, the Laser Scanner Focus S350 equipment was used, divided into three stages: planning, execution, and treatment of the point cloud. With this, the "collect operational data" used data from the company's computerized system, which are: average cycle time, minimum cycle time, maximum cycle time, setup time, availability, measurement (inspection), rework, number of resources, area occupied by the manufacturing cell, number of parts in inventories, size of parts lots (input/output), and operator efficiency. With the data adequately collected, it was possible to understand the fuel tanks' line and know the variables existing in all processes. With these data, the "build computational model" was made possible. This started with a more detailed simulation of the mapped process after complexity was more significant than the first layer. Finally, it was greater detail that the second layer was inserted. The three layers were used to develop the modeling, starting from the simplest one with the production flow. The operators were included in the second, and finally, the standard icons were replaced by 3D resources (visually exposing how the materials and facilitating the understanding of the process). Finally, the "validate computational model" was made by comparing the actual production results with the simulated ones. The adherence of the simulation to the model was 91.2%. In this way, all the information and variables considered allowed the simulated environment to represent the real system as closely as possible (Figure 3).

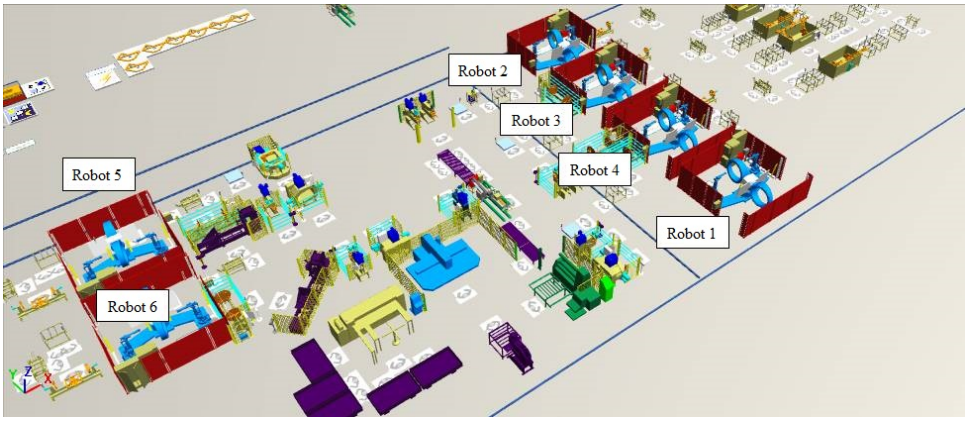



Figure 3: Layout of the current status of the fuel tanks production line.

In the "Simulation" stage, three sub-steps were developed to improve the auto parts company's fuel tank's production process. In the "generate improvement ideas", suggestions for improvements to the process were suggested during the project team's training. To define the scenarios (layout proposals), the balance between investment versus results was considered. In this, twelve layout possibilities were suggested, Table 3

Table 3: Layout proposals

| Scenario | Description | Scenario | Description |
|---|---|---|---|
| Sc1 | Optimized current state | Sc7 | Scenario 1 with less setup time |
| Sc2 | Change of positioning of robots | Sc8 | Scenario with all robots in parallel |
| Sc3 | Changes suggested by the workers | Sc9 | Scenario 8 plus reduced setup times for scenario 7 |
| Sc4 | Junction of scenarios 2 and 3 | Sc10 | Scenario 9 with the inclusion of collaborative robots |
| Sc5 | Scenario 4 with all robots grouped | Sc11 | Scenario 9 with inclusion of AGVs for materials logistics |
| Sc6 | Scenario 5 with fewer operators | Sc12 | Union of scenarios 9, 10 and 11 |

These scenarios were tested one by one, comparing the results obtained with the current scenario. To this end, performance indicators were taken into account, defined to validate which scenario is the best option – considering Industry 4.0 technologies. With these results, it was possible to conduct experiments to identify waste in operations. For comparison of scenarios, performance indicators were defined, namely: lead time (LT), work in process (WIP), total distance traveled by operators (TD), hours man / tank produced (HM), and return on investment (ROI).

After the execution of the simulations, the performance indicators measured were grouped. For the decision-making process of the best scenario, the TOPSIS multi-criteria decision-making method was used. Since it is not mandatory for each scenario built to take into account information from the predecessor scenario, in addition to the number of variables available. To standardize decision making for future replications, Table 4 represents the steps that have been followed.

Table 4: Decision-making process/steps

| Steps | Description |
|---|---|
| 1 | Initially, decision matrices definition with the scoring of alternatives concerning each criterion and weight vector (Table 5) |
| 2 | Subsequently, the matrix data has been normalized so that it is possible to compare the various criteria |
| 3 | Alternatives were selected that were close to the ideal solution and distant from the anti-ideal solution |
| 4 | The final score for each alternative was composed of the distances obtained between the alternatives and the ideal and anti-ideal solutions concerning each criterion |
| 5 | The final score of the alternatives is given between 0 and 1 |
| 6 | The ranking of the simulated scenarios were compiled in Table 5, leaving out the current scenario |

With that, the coefficients of each simulated scenario were obtained and their position in the ranking, as shown in the Table 5.

Table 5: Performance indicators, evaluation and ranking of simulated scenarios

| **Scenario** | **LEAD** | **WIP** | **TD** | **PRO** | **SETUP** | **HM** | **TOPSIS coefficient** | **Ranking** |
|---|---|---|---|---|---|---|---|---|
| Current | 6,0 | 50 | 329 | 988 | 74,5 | 3,3 | – | – |
| 1 | 5,9 | 132 | 454 | 1087 | 60,4 | 4,3 | 0,109 | 12 |
| 2 | 6,2 | 47 | 293 | 988 | 72,2 | 3,3 | 0,723 | 11 |
| 3 | 5,9 | 47 | 289 | 961 | 74,4 | 3,4 | 0,729 | 10 |
| 4 | 6,1 | 47 | 270 | 967 | 70,9 | 3,3 | 0,736 | 9 |
| 5 | 5,6 | 44 | 254 | 990 | 71,4 | 3,2 | 0,791 | 7 |
| 6 | 5,2 | 45 | 244 | 1022 | 68,5 | 3,1 | 0,823 | 6 |
| 7 | 6,1 | 41 | 331 | 1121 | 58,6 | 3,3 | 0,745 | 8 |
| 8 | 5,5 | 39 | 239 | 940 | 68,4 | 2,9 | 0,833 | 5 |
| 9 | 5,4 | 34 | 235 | 999 | 51,9 | 2,8 | 0,902 | 2 |
| 10 | 5,4 | 38 | 232 | 939 | 70,4 | 2,6 | 0,840 | 4 |
| 11 | 5,5 | 32 | 208 | 938 | 69,7 | 2,8 | 0,853 | 3 |
| 12 | 4,9 | 36 | 216 | 977 | 51,8 | 2,6 | 0,931 | 1 |

| **Indicators** | **Description** | **Weight** |
|---|---|---|
| Lead Time (LEAD) | = sum of operation times + sum of waiting times | 30% |
| Work in Process (WIP) | = raw material used - units produced | 15% |
| Travelled Distance (TD) | = sum of the distances covered by the operators | 15% |
| Production (PRO) | = number of fuel tanks produced | 15% |
| Total setup (SETUP) | = sum of setup times performed | 15% |
| Hour man per fuel tank produced (HM) | = Hour man / fuel tank produced | 10% |

It is worth mentioning that the current scenario was not considered in the multicriterial evaluation due to its obsolescence in the company; thus, it needed improvements to increase the production process's efficiency. Thus, scenario 12 obtained the best performance, followed by scenarios 09, 11, and 10, respectively. The best-evaluated scenario was constituted from the unification of scenarios 9, 10, and 11. Its conception also starts from the significant changes carried out in scenario 8, where the proposition of physical arrangement of the production line was altered, including

the gains obtained with the implementation of the fast setup of scenario 7. Both scenarios, 8 and 7, form scenario 9, which has a positive point, the reduction in setup time. Scenario 10 originates in adopting technologies, such as collaborative robots (AGV's), improving the HM indicator. Scenario 11 considers the inclusion of AGV's, obtaining the best performance in the WIP and TD indicators. The set of these scenarios forms the best performing scenario, scenario 12. Figure 4 shows this scenario, which includes technologies from Industry 4.0.

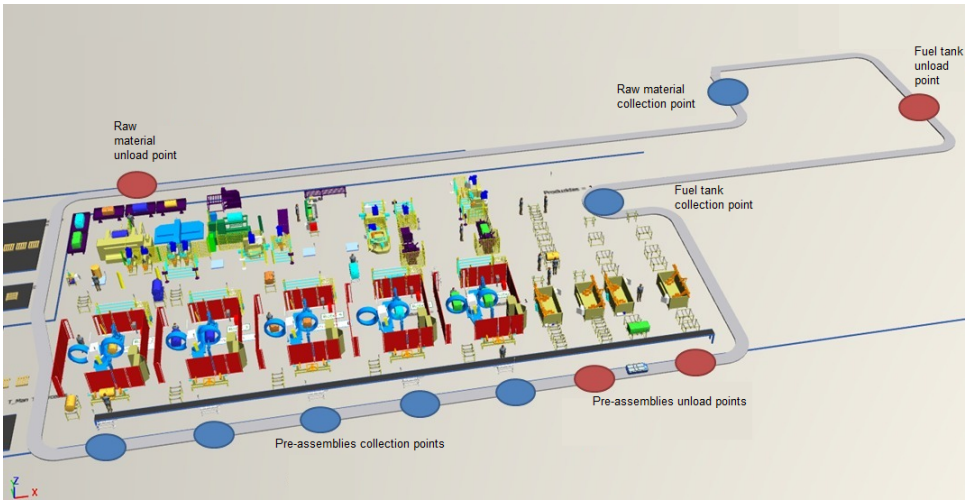



Figure 4: Scenario 12 – best TOPSIS performance.

Evaluating scenario 12, the suggested investment amount is R$ 1,452,351.00 (December/18 bases), with an estimated implementation time of four months. The return, also estimated, is R$ 45,104.00 per month, obtained through the gain of 23% in LT, 55% in WIP, 38% in TD, and 16% in HM, compared to the current operating status of the production. In the implementation year, the return is multiplied by eight months (R$ 360,832.00), with the other four months being used for the implementation. In the first two years, the estimated return is multiplied by twelve months (R$ 541,248.00), ending the return on investment in the third year, where the gain is multiplied by also eight months (closing the 40 months of amortization). Considering the annual interest rate of 15%, scenario 12 will have an ROI of 9.22%.

While looking at the other scenarios, scenario 6 draws attention due to its low initial investment and significant return. With an investment of approximately R$ 251,000.00 and two months for implementation, it presents an estimated return for the operation of R$ 8,098.00 per month. It was obtaining an ROI of 14.05% (closing 40 months of amortization) - getting better positioned than scenario 12 in the ROI aspect. In addition to obtaining gains compared to the current state, 18% in LT, 19% in WIP, and 30% in TD.

Both scenarios showed that they bring significant gains to the operation. The choice of which scenario to implement becomes an organizational strategy since scenario 12 obtains more significant gains than scenario 6 but requires more excellent investment. In the aspect related to the organization's strategy, it should be taken into account when deciding how much money is available for investment. Besides, it should evaluate the time needed to improve the products' current production, the life cycle of the products, the emerging markets, the profit on the product, the fluctuations in demand, among other factors of the market/segment.

## 5. Conclusion

The search for competitive advantage leads companies to invest in new technologies. These technologies, which were seen as something distant, are becoming increasingly present in companies with good results, regardless of the type of production. There is a need to adopt technologies according to strategic needs that are motivated by the performance indicators' results.

According to the results presented, the use of enabling technologies for Industry 4.0 tends to enhance its financial and economic gains. It is noteworthy that the research contributed to a competitive differential for the company, given the gains obtained, 23% in Lead Time, 16% in HM / Tank, 55% in WIP, 38% in total distance traveled by operators, in addition to a return on investment of 9.22%. These changes in the production process impact the company's competitiveness, presenting a shorter crossing time, increased productivity, reduced inventories, reduced costs, and better delivery performance.

From a professional perspective, studying the automotive sector has a strong relationship with technological developments, given the healthy competition between automakers. In general, it can be concluded that this research contributed to: improving the process, optimizing gains, and expanding the knowledge of the work team. As the execution of each phase required a conceptual leveling among the participants. The development of the work reinforced the interest in monitoring and managing the results through indicators that directly reflect the industrial area's behavior.

The indicators used to measure the results of applying the method were satisfactory. However, the topic of investments and implementation is still far from sufficiently addressed for the new production scenarios. The experience of applying simulation to improvement projects proved to be effective. However, to achieve maximum application potential, the proposed change would have to be incorporated into the company's culture and absorbed by its internal processes and methods.

The result obtained by the implementation of the simulation performed, with the gain of 23% reduction in crossing time, shows the importance of improving the study of adopting these technologies. There are still technological barriers to be overcome, which may include even more technologies aimed at Industry 4.0, which are not feasible to be simulated, such as Big Data analytic, internet of things, among others.

As the limitation of this research, a representative variable is the product mix, which is not always the same simulated when it comes to simulation. The demands may suffer from market fluctuations and reflect on the orders received. The lack of a planned budget for an immediate application can also be considered a limitation of the work. We opted for the lowest possible cost in this research's simulated scenarios but without a defined target. The economic and financial results were also little explored.

Finally, it should be noted that the inclusion of Industry 4.0 elements in the production environment is considered one of the trends for the future of the industry. The coming years will bring new challenges and opportunities. Given this, organizations that are better prepared for change, building the necessary organizational capacities, will have a competitive advantage and will benefit from these technologies. Future research may expand the proposed model to other production processes.

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