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Process simulation and optimization in industry 4.0: Redesigning assembly lines in an automotive industry

Simulación y optimización de procesos en la industria 4.0: Rediseño de líneas de ensamble en una industria automotriz

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Abstract

The experimental study conducted in an automotive company aimed to optimize the process flow and redesign service lines in the final assembly area, thereby creating physical space for the integration of new lines. Three pivotal tools were employed: the Guerchet methodology, lean manufacturing techniques, and process simulation before physical alterations. The outcomes revealed a substantial increase in production, ranging between 17 % and 20 %, following the implementation of the proposed changes. Furthermore, there was a reduction of 25 square meters in the physical space occupied by the final assembly service lines. This productivity enhancement signifies a significant advancement in the automotive industry, marking a milestone in service parts efficiency. In addition to the productivity impact, these changes brought about economic savings for the company. Decision-making relied on positive simulation results, allowing physical modifications solely upon their proven effectiveness in a virtual environment. This strategy not only drove productivity improvements but also positioned the company on the path towards the digitalization of its processes, as a prelude to a transition towards Industry 4.0. This strategic approach not only demonstrates enhancements in operational efficiency but also underscores the value of prior planning and the gradual adoption of digital technologies in the current manufacturing landscape. The integration of these tools offers not only immediate improvements but also a long-term vision toward a more efficient and adaptable manufacturing environment.
Keywords: Optimization, Guerchet Model, simulation, service lines, manufacturing, industrial.

Resumen

El estudio experimental llevado a cabo en una empresa automotriz se enfocó en optimizar el flujo de proceso y rediseñar las líneas de servicio en el área de ensamble final, liberando así espacio físico para la incorporación de nuevas líneas. Se emplearon tres herramientas clave: la metodología Guerchet, técnicas de manufactura esbelta y la simulación de procesos antes de implementar cambios físicos. Los resultados revelaron un incremento significativo en la producción, entre un 17 % y un 20 %, tras la implementación de los cambios propuestos. Además, se logró una reducción de 25 metros cuadrados en el espacio físico ocupado por las líneas de servicio para ensamble final. Esta mejora en la productividad representa un avance significativo para la industria automotriz, marcando un hito en la eficiencia de las partes de servicio. Además del impacto en la productividad, estos cambios generaron un ahorro económico para la empresa. La toma de decisiones se basó en los resultados positivos obtenidos en la simulación, lo que permitió implementar modificaciones físicas solo cuando se demostró su efectividad en un entorno virtual. Esta estrategia no solo impulsó mejoras en la productividad, sino que también posicionó a la empresa en el camino hacia la digitalización de sus procesos, como antesala a una transición hacia la Industria 4.0. Este enfoque estratégico no solo refleja mejoras en la eficiencia operativa, sino que también subraya el valor de la planificación previa y la adopción progresiva de tecnologías digitales en la industria manufacturera actual. La combinación de estas herramientas proporciona no solo mejoras inmediatas, sino una visión a largo plazo hacia un entorno de fabricación más eficiente y adaptable.
Descriptores: Optimización, Modelo Guerchet, simulación, líneas de servicio, manufactura, industrial.

Introduction

Mexico's position in global automotive production continues to be of great relevance on the international stage. In 2022, Mexico secured the seventh position among the world's leading vehicle-producing countries, following China, the United States, Japan, India, Korea, and Germany (AMIA, 2022). In that year alone, Mexico's auto parts industry generated a total of $107.329 billion in production, marking a substantial increase of 13.35 % compared to the previous year (INEGI, 2022). This remarkable growth not only signals the strength of the Mexican auto parts sector but also indicates a promising future. This upward trend is expected to persist through 2023 and 2024, driven in part by the introduction of new production lines by renowned manufacturers such as BMW, Audi, and Tesla (AMIA, 2022).

However, the Mexican automotive manufacturing industry faces constant challenges to maintain its competitiveness in a constantly evolving global market. Operational efficiency, adaptability, and the capacity for continuous improvement have become fundamental pillars for companies' success in this sector (Guariente *et al.,* 2017). In this context, the implementation of methodologies like Lean Manufacturing has proven essential to optimize production processes and effectively manage available resources.

A fundamental challenge confronting the automotive manufacturing industry is ensuring the effective manufacturing of parts and components for the original equipment and spare parts markets. In this scenario, service lines acquire unmatched relevance, serving as the backbone ensuring continuity and quality in the manufacturing of these critical components (Awari *et al.,* 2023). Despite being activated only for special orders, these lines must operate with the same precision and excellence as the primary production lines. The customization and specific adjustment of products demanded by customers require flexibility and efficiency achievable only through meticulous planning and process optimization (Karmokolias & Mundial, 1990).

In this context, time efficiency is crucial in manufacturing, and reducing cycle times stands as another essential challenge. Maintaining high-quality standards, and optimizing these times translates into higher productivity and the ability to swiftly respond to market demands (Piran *et al.,* 2020). Equally important is the proper management of space in the production plant. While these lines operate intermittently, the space they occupy must be maximized. Spatial optimization ensures that when demand requires, activating these lines is smooth and efficient, and it also facilitates adding lines for new models (Olhager & Feldmann, 2018).

The manufacturing industry, in response to these needs, have integrated key Industry 4.0 technologies, contributing to the improvement and application of lean manufacturing principles (Rosin *et al.,* 2020) or within their supply chains (Ghadge *et al.,* 2020). The adoption of process simulation or virtualization has become a crucial component (Zhong *et al.,* 2017), such as the specific case of Siemens (Annanth *et al.,* 2021), which has transitioned to Industry 4.0 by machine learning, process simulation, virtualization, and the Internet of Things. This strategic shift has enabled these companies to evolve toward more efficient and technologically advanced methods, thereby adapting to market demands and promoting operational effectiveness.

This paper presents a significant project conducted at a leading automotive manufacturing company in Cd. Reynosa, Tamaulipas. The primary focus of this initiative is to enhance process flow and reorganize service lines in the final assembly area. The main objective is to create additional space within the facility for implementing new service lines for final product assembly and to reduce cycle times to boost productivity. To achieve this, the Guerchet methodology was applied, leveraging solid mathematical principles to enable optimal space distribution within the production plant. This approach aims to maximize production capacity and improve operational efficiency (Arbos, 2021). Furthermore, the use of an advanced simulation tool, Promodel®, is explored to evaluate and refine service line redesigns. Simulation has become essential in the automotive industry, allowing precise forecasting and analysis of proposed changes' potential impacts on production processes. This simulation-based approach helps to identify bottlenecks, reduce cycle times, and optimize the overall performance of service lines (Pannerselvam & Senthilkumar, 2013).

This project makes a significant contribution to the literature on industrial plant design and optimization by applying the Guerchet Method within the Mexican automotive industry. Unlike prior studies focused on varied configurations, this work examines the integration of the Guerchet Method with advanced simulation tools, such as Promodel®, to enhance flexibility and efficiency in a dynamic production environment. Notably, Promodel® offers a trial version that can be downloaded and used effectively for projects like this, enabling researchers and professionals to conduct simulations and analyses.

Although the Guerchet Method has been widely documented (Cruz, 2019), this study offers an innovative perspective by examining its applicability within the Mexican automotive industry, where the market demands customization and quick adaptation. Research in industries such as metalworking (Plua *et al.,* 2023), plastics (Penafiel *et al.,* 2021), textiles (Vega *et al.,* 2023), and food (Teneda *et al.,* 2023) has highlighted the need to optimize workstation layouts for space efficiency; however, these studies do not address the critical, intermittent processes in the automotive sector, where operational efficiency and adaptability are crucial.

This paper fills these gaps by implementing the Guerchet Method, achieving optimal space allocation and cycle time reduction through precise simulations of production processes. The results demonstrate the method's effectiveness in spatial redistribution while introducing new metrics to assess its impact on efficiency. This combination of methodology and technology provides a replicable framework for other industries, thereby contributing to both theoretical and practical knowledge in industrial process optimization.

Methodology

The methodology applied in this study was meticulously designed to address the redesign of the final assembly process aimed at service lines in the automotive industry. The primary goal was to generate additional space in the industrial facility to accommodate new service lines. Alongside this objective, there was a concerted effort to significantly reduce cycle time, thus optimizing the assembly process. To achieve these aims, an approach based on simulation using the Promodel® software was employed, along with the implementation of the Guerchet method to optimize the available space in the production plant.

Guerchet method

The Guerchet method, based on robust mathematical principles, is used to accurately determine the space required for machinery and workstations within the dimensions allocated by the industry. This assessment allows for an effective distribution of service lines based on the provided space requirements (Zapata *et al.,* 2022). The Guerchet method employs the following main equation (Cruz, 2019):

$$St = Se + Sg + Scm$$

The first step involves calculating the static surface area (Se), which represents the space occupied by equipment, workstations, and required machinery on a plane based on the length, width, and total number of machines. This can be calculated using the equation (Bastidas & Aguirre, 2020):

$$Se = (L \ x \ A) \ x \ N$$

Where:

Se = static surface area
L = machine and/or workstation length
A = machine and/or workstation width
N = number of machines and/or workstations of the same measurement

Next, it is necessary to calculate the gravitational surface area (Sg), starting from the result obtained in the static surface area (Se). This type of surface corresponds to and is reserved for the movement of workers and materials around the workstation, and it can be calculated using the following equation (Kong, 2014; Perrieres *et al.,* 2013):

$$Sg = Se \ x \ N$$

Where:

Sg = gravitational surface area
Se = static surface area
N = number of working sides

To continue obtaining data for the main equation, it is necessary to calculate the common evolution surface (Scm). In our case, it was not necessary to calculate it because the equation is designed to obtain a coefficient (K) specifically when using machinery, equipment, or mobile workstations. This applies to situations were working with equipment involves more than one operational side, exceeds the dimensions of its base, or involves materials that protrude from the machine or equipment (Renna, 2012). In the context of service lines, there are no mobile stations, machines, or equipment in use. Therefore, the value of the coefficient (K) is zero, and when multiplied in the main equation, it results in a common evolution surface (Scm) equal to zero (Renna, 2012).

The Guerchet method was a significant choice for this project as it plays a crucial role in industrial plant layout design by providing a solid and quantitative basis for efficient space allocation. Rooted in robust mathematical principles, it precisely determines the spatial requirements of machinery, equipment, and workstations within an industrial setting. This methodology enables optimal resource distribution, maximizing the utilization of available space in the plant. Precisely understanding the space requirements for machinery operations, facilitates the planning of designs that optimize workflow, reduce unnecessary movements, and enhance the overall efficiency of the industrial plant.

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Identification of the area to place service lines

In collaboration with the manufacturing team, a comprehensive inspection is carried out within the industrial plant aiming to locate a suitable zone for the relocation of service lines. During this detailed analysis, an available space adjacent to the superficial assembly lines (SMD) is identified. Figure 1 illustrates the comprehensive layout of the production area, distinctly highlighting an unoccupied sector next to the SMD, indicated in green, potentially suitable for accommodating the service lines. This designated space provides the required logistical and spatial feasibility for effectively installing these lines, potentially streamlining the plant's arrangement and bolstering efficiency in industrial production. The collaborative inspection aims to optimize the plant's layout, emphasizing the importance of a detailed assessment to ensure the seamless integration of the service lines, thereby enhancing the overall operational flow and productivity within the manufacturing setup.

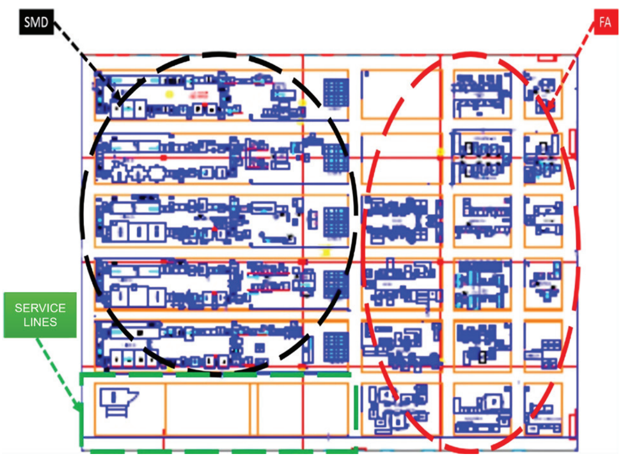

Figure 1. Layout of production lines, in green the area where the service lines are to be located (near the SMD area)

Simulation of the process in service lines

The virtualization of processes in Industry 4.0 has revolutionized operational strategies by creating digital environments that simulate real production processes. This approach enables companies to digitally model the product lifecycle, from design through to distribution, allowing for comprehensive performance forecasting and the identification of potential inefficiencies. Such simulations reduce risks and costs associated with direct production changes, streamline workflows, and improve productivity. Additionally, virtualization plays a crucial role in staff training, allowing employees to familiarize themselves with systems and scenarios safely, which enhances operational safety and efficiency (Ghadge *et al.*, 2020; Rosin *et al.*, 2020).

A prime example of successful implementation is Siemens, which leverages simulation, machine learning, and IoT to improve workflows and make data-informed decisions (Annanth *et al.*, 2021). In this project, the Promodel® software was used to create an accurate simulation of the production line, integrating data like cycle times and processing speeds. Promodel® allowed iterative testing of different conditions, pinpointing bottlenecks, and offering strategic insights for improvements. Proposed changes, including adjustments in workstations and workflow optimization, were simulated before implementation, ensuring informed decision-making and resource optimization. This preemptive approach ultimately enhances production line efficiency by virtually validating improvements across all manufactured models on the service lines.

Technical details of the simulation model

To ensure accuracy and relevance in the layout redesign process, a simulation model was developed using Promodel®, a software specialized in analyzing and optimizing industrial processes. This section outlines the data analysis methods, experimentation process, and statistical evaluation that underpin the simulation, ensuring alignment with real-world conditions and reliability in the results.

Input data analysis

The data used to build the simulation model includes production rates, transport times, and cycle times in the current layout. Data was collected over a two-month period to capture normal operational variability and seasonal fluctuations. After data collection, statistical analyses were performed to assess the accuracy and representativeness of each data category:

- *Cycle times:* Cycle times were averaged from 500 production runs, yielding an average of 24.5 minutes per cycle, with a standard deviation of 4.2 minutes.
- *Transport times*: Transport times between stations followed a normal distribution, with an average of 6.8 minutes and a standard deviation of 1.5 minutes. Outliers were removed using the interquartile range (IQR) method of 1.5 to prevent bias in the results.
- *Production rates*: Daily production rates fluctuated between 180 and 250 units. An exponential distribution model was applied, and its fit was validated using a Chi-square test with a 95 % confidence level,

ensuring the suitability of the data for simulation input.

Experimental configuration in the simulation

To accurately replicate operational dynamics, the simulation model was configured and tested in detail. Key parameters include the number of replications, the duration of each replication, and a warm-up period, as described below:

- *Number of replications*: To ensure statistical reliability, each scenario was replicated 30 times. This quantity was determined based on the desired confidence interval width, calculated to maintain a margin of error below 5 % in key performance metrics such as cycle time and production.
- *Duration of each replication:* Each replication simulated a 10-hour shift, reflecting a typical production day in the company. This approach allowed for clear comparisons with actual production data and consistency in daily performance metrics.
- *Warm-up period*: A 30-minute warm-up period was set to stabilize initial conditions and reduce the influence of initial anomalies. This period was determined through preliminary testing, where performance metrics consistently stabilized after the first 30 minutes of simulation.

Statistical analysis and validation of results

To evaluate the redesigned layout's performance, several key performance indicators (KPIs) were analyzed, including cycle times, production, and workstation utilization rates. Simulation model results underwent rigorous statistical evaluation to confirm reliability and projected efficiency improvements.

- *Cycle time reduction:* The redesigned layout was validated using a t-test conducted on cycle times from the current and redesigned layouts, confirming a statistically significant improvement ($p < 0.05$).
- *Production improvement:* Production was measured with a 95 % confidence level.
- *Utilization rates:* Workstation utilization rates were measured to identify potential bottlenecks, confirmed through an ANOVA test.
- *Statistical confidence and validation*: Simulation results were validated using confidence intervals and hypothesis testing.

Implementation and continuous monitoring

After validating the simulation, the layout was implemented gradually, starting with high-traffic areas to monitor real-time impacts on cycle times and production. Initial on-site monitoring results indicate alignment with simulation projections, confirming that the redesigned layout meets productivity goals.

This structured simulation approach, incorporating rigorous data analysis, experimentation, and statistical validation, supports the application of the Guerchet method in layout optimization and serves as a replicable model for similar industrial environments.

Layout redesign process using the Guerchet Method

To comprehensively address the layout redesign in the assembly line, a detailed process was followed, complementing the approximate space calculation provided by the Guerchet methodology with a specific analysis of flow and distribution. Each phase of the process is outlined below, integrating preliminary evaluations, simulations, and an iterative optimization process, within the context of the automotive industry. This approach seeks not only to determine the required space but also to optimize workflow efficiency and minimize cycle times:

1. *Initial analysis.* Evaluation of the current layout: A diagnosis of the existing layout was conducted, identifying areas with space limitations and transport times between stations. This analysis included an initial mapping of the workflow to detect potential areas of inefficiency. Data collection: Specific information was gathered on the size and functional requirements of each work area within the plant, including dimensions and access needs for each section.
2. *Application of the Guerchet Method***.** Estimation of required space: The Guerchet methodology was applied to calculate the necessary space based on the needs of each area, allowing for a preliminary distribution that serves as a foundation for the redesign. Preliminary layout: With the estimated space for each work area, a first version of the layout was created, focusing on optimal space allocation to meet each section's needs.
3. *Workflow redesign.* Identification of bottlenecks: Through an analysis of the material and personnel flow, bottlenecks in the workflow were identified, along with points where access routes crossed critically, affecting efficiency. Spaghetti diagram: A Spaghetti diagram was used to visualize and opti-

mize material and operator paths. This allowed for adjustments to routes and station rearrangement to reduce transport times and facilitate continuous flow in the plant.

4. *Layout optimization.* Adjustment of positions and distances: In this phase, adjustments were made to the relative positions of key workstations, aiming to minimize travel distances and improve material flow. Proposed final layout: Based on the previous observations, a final version of the optimized layout was proposed, incorporating reductions in cycle times and flow paths. This layout also underwent validation according to ergonomic and workplace safety criteria.
5. *Design validation.* Testing through simulation: Before implementation, Promodel® software was used to simulate the proposed layout. This analysis allowed for evaluating the performance of the new design in a virtual environment and predicting its impact on cycle times and workflow efficiency. Evaluation of performance indicators: Simulation results were compared with initial performance data, allowing for the observation of improvements in travel time reduction and minimization of unnecessary transfers.
6. *Implementation and continuous evaluation.* Gradual implementation: The redesigned layout was implemented gradually in the assembly area, allowing for adjustments based on actual operating conditions. Post-implementation monitoring: Once the new layout was installed, key performance indicators, such as cycle times and material flow, were monitored to verify improvements achieved and make adjustments if necessary.

This detailed redesign process, as shown in Figure 2, not only complements the initial space calculation proposed by the Guerchet Method but also provides a replicable structure in other industrial settings, adapting to the needs of each plant. Thus, it addresses the need to redesign workflows in terms of operational efficiency and adaptability to the specific requirements of the automotive industry.

Results and discussion

Firstly, relevant calculations were conducted using the Guerchet method to determine the theoretical dimensions that service lines for each model should have. It's important to note that this surface area can vary based on the specific layout of the line, potentially increasing depending on the design and arrangement of elements.

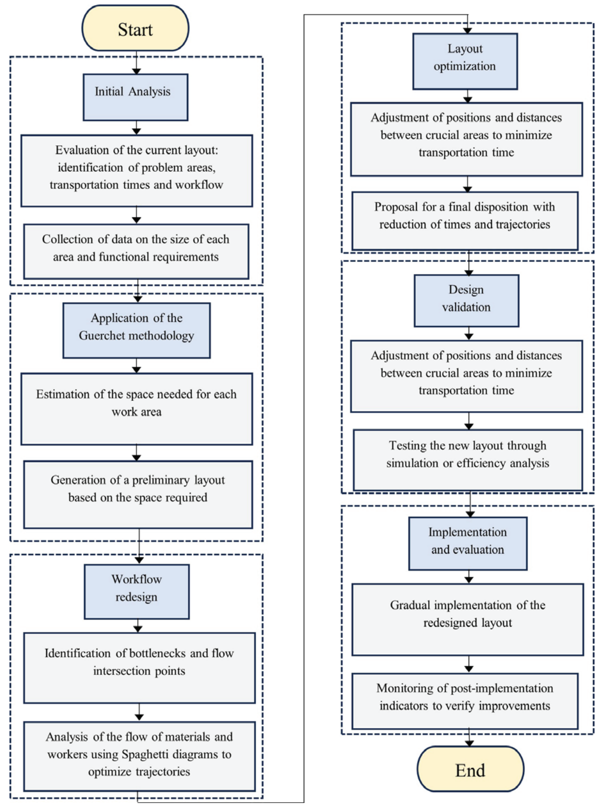

Figure 2. Layout redesign flowchart

Therefore, calculations begin with the current configuration.

Table 1 presents the dimensions of equipment, machinery, workstations, racks, tables, and containers comprising the service line for Model A. Additionally, it showcases the minimum total required surface area (*St*) in square meters to ensure the proper functioning of a production line, based on the current configuration.

Next, physical measurements of the area occupied by the service line corresponding to Model A are conducted. The findings reveal that the line occupies a space of 37.81 square meters, exceeding the requirements set by the Guerchet model. These findings indicate the necessity of adjusting achieve a more efficient and compact process, reducing the space occupied.

A similar procedure was carried out for Models B, C, and D, and the detailed results are outlined in Table 2.

In Table 2, it's evident that the current total area occupied by the assembly service lines exceeds the parameters established by the Guerchet model. This situation presents a clear opportunity for implementing improvements.

The information provided in Table 2, along with the layouts and the step-by-step process descriptions in the flow diagrams for each service line and model, is of great

Table 1. The total surface area for the service line of model A calculated using the Guerchet method

Workstation (WS)	Test equipment or Machine	Raw Material (RM), Work in Process (WIP), Containers	Large (m)	Width (m)	Number of machines and/or workstations of the same size (*N*)	Static surface in m² (*Se*)	Gravitational surface in m² (*Sg*)	Total area in m² (*St*)
N/A	N/A	RM 1&4	1.15	0.65	2	1.50	1.50	3.0
N/A	N/A	RM 2	0.90	0.76	1	0.68	0.68	1.4
WS1	N/A	N/A	1.00	0.55	1	0.55	0.55	1.1
WS2	N/A	N/A	1.08	1.80	1	1.94	1.94	3.9
WS3	N/A	N/A	0.70	0.88	1	0.62	0.62	1.2
N/A	N/A	RM 3	0.93	060	1	0.56	0.56	1.2
N/A	N/A	WIP	1.00	0.60	1	060	0.60	1.2
WS 4&5	Auto control	N/A	0.90	0.90	3	2.43	2.43	4.9
N/A	Final control	N/A	0.95	1.00	1	0.95	0.95	1.9
N/A	N/A	Scrap	0.57	0.40	1	0.23	0.23	0.5
N/A	Printer machine	Scrap	0.74	0.53	2	0.78	0.78	1.6
N/A	N/A	Packing	0.80	0.65	1	0.52	0.52	1.0
					Total surface area for model A (m^2)			22.72

Table 2. The total surface area of each service line based on the Guerchet method vs the total surface area occupied in the current assembly process

Linea	Total surface area based on the Guerchet Method (m^2)	Total surface area before the change in the assembly process (m^2)
Model A	22.72	37.81
Model B	49.48	35.46
Model C	29.84	32.08
Model D	31.03	29.85
Total surface area (m^2)	133.07	135.2

utility and importance. This information served as the basis for configuring the simulation in Promodel®, which constitutes the second phase of this project.

As previously mentioned, simulation plays a vital role in this project, allowing for comprehensive analysis, process optimization, and data collection without the need for physical modifications. For this reason, each model was simulated for each service line. During these simulations, various modifications were implemented following the principles of lean manufacturing, aiming to optimize processes and reduce the space occupied by each service line. These modifications included the elimination of raw material racks, adjustments in workstations, and some changes in functional testing equipment, among others.

Figure 3 presents the distribution and simulation of Model A using Promodel®. In Figure 3a, the current assembly process is visualized, while Figure 3b depicts

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the assembly process after the implementation of modifications. The latter illustrates a lean and optimized manufacturing approach, demonstrating a significant reduction in the occupied area.

a)

b)

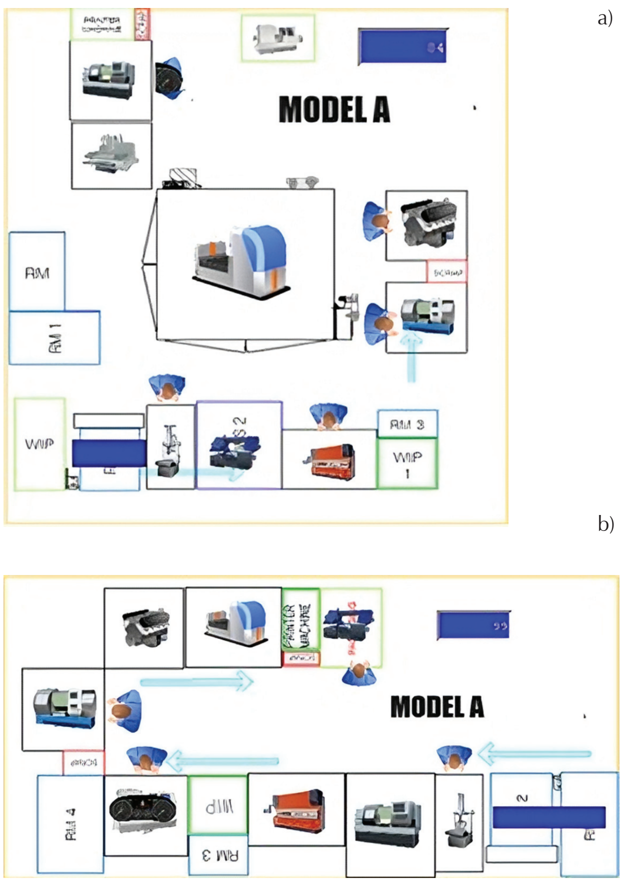

Figure 3. Distribution and simulation of the service line for final assembly of model A carried out in Promodel®. a) Current distribution of the assembly process, b) Distribution after making changes to the process to optimize assembly and reduce total occupied surface

The same procedure described earlier was carried out for models B, C, and D. Once the simulations were completed, a theoretical recalculation of the total area occupied after the proposed changes and optimization was conducted. The results are presented in Table 3, where it's observed that the changes yielded satisfactory outcomes, achieving a reduction of 25.36 m^2. It's important to note that for the lines where models B and D are manufactured, the total area they occupy remained unchanged since these models already fell within the parameters established by the Guerchet method.

Afterward, physical changes were implemented across all service lines for every model, involving essential documentation such as client approval notifications, updated process flowcharts, and work instructions, among others. Notably, alongside process optimization, time studies were conducted, imperative for determining the total production each line must generate to meet client needs. This ensures upholding the company's reputation, prestige, and quality by swiftly and effectively responding to customer demands.

In this specific case, the redistribution and optimization of space and service line processes became a critical commitment to enhancing cycle times, gaining significant importance as part of the company's investment. This improvement was only achievable by optimizing resources, processes, and their distribution, enabling operators to perform tasks efficiently, and meeting the primary goals of quality and required production.

Table 4 shows the average total time saved in the company's processes due to the optimization and reorganization of plant spaces. It is important to note that this data was obtained through simulation, assessing the time required to manufacture a product from the initial station to packaging. The results, showing cycle times before and after changes in the assembly processes, represent the mean of a total of 30 samples. The confidence interval (CI) of [122.59, 134.21] seconds for the difference in cycle times before and after the assembly process changes suggests a statistically significant reduction in cycle time following process optimization.

Table 3. The total surface area occupied by service lines with the Guerchet methodology, before and after the line optimization changes in the simulation

Linea	Total surface area based on the Guerchet Method (m^2)	Total surface area before the change in the assembly process (m^2)	Total surface area after the change in the assembly process (m^2)
Model A	22.72	37.81	22.91
Model B	49.48	35.46	35.46
Model C	29.84	32.08	21.62
Model D	31.03	29.85	29.85
Total surface area (m^2)	133.07	135.2	109.84

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Table 4. Simulated cycle times before and after assembly process optimization with statistical analysis of models A, B, C, and D

Linea	Cycle time before the change in the assembly process (mean)	Cycle time after the change in the assembly process (mean)	Difference (before-after) (sec)	Standard deviation	Confidence intervals (95 %)
Model A	436.8	369.6	67.2	10.57	[63.26, 71.14]
Model B	382.2	321	61.2	8.06	[58.19, 64.21]
Model C	267.6	267.6	0.0	5.25	[– 3.75, 3.75]
Model D	327.6	327.6	0.0	6.15	[– 4.39, 4.39]
Total (sec)	1,414.2	1,285.8	128.4	15.56	[122.59, 134.21]

This indicates that the change was effective in improving performance. Additionally, the CI indicates that, with 95 % confidence, the mean difference in cycle time falls between 122.59 and 134.21 seconds, providing a quantitative estimate of the improvement.

The same information presented in Table 4 is graphically depicted in Figure 4 to visually highlight the improvement in the process. In practical terms, this information is useful to justify implementing changes in the assembly process, supporting the decision to proceed with modifications, especially in an industry focused on enhancing efficiency and reducing costs. While the positive CI is promising, it is also essential to consider data variability and to continuously monitor the process to ensure consistent results over time and under varying conditions. The results are encouraging and suggest that the changes in the assembly process have positively impacted cycle efficiency, which could lead to an overall improvement in productivity.

Even the slightest improvement and reduction in cycle time always benefit processes, as seen in this case, where there's a 128.4 second reduction based on the previously established service line times. This reduction translates into favorable economic benefits for the company.

The data in Table 5 illustrate the effects of improvements in design and process flow on production efficiency across different models. These improvements primarily aimed to reduce cycle times, allowing for more units to be assembled per shift. Production increases are notable in Models A and B, while Models C and D show no changes due to specific workflow characteristics, which were less affected by the enhancements.

To visually illustrate the impact of process improvements in assembly across different models, we have included graphs showing the simulated production output per shift before and after workflow adjustments (Figure 5). The graphs for models A, B, C, and D reflect the variations in production, highlighting increases in models A and B following the implementation of changes, while models C and D remain stable. These visuals provide a more intuitive understanding of productivity differences before and after the improvements, supporting the results presented in Table 5.

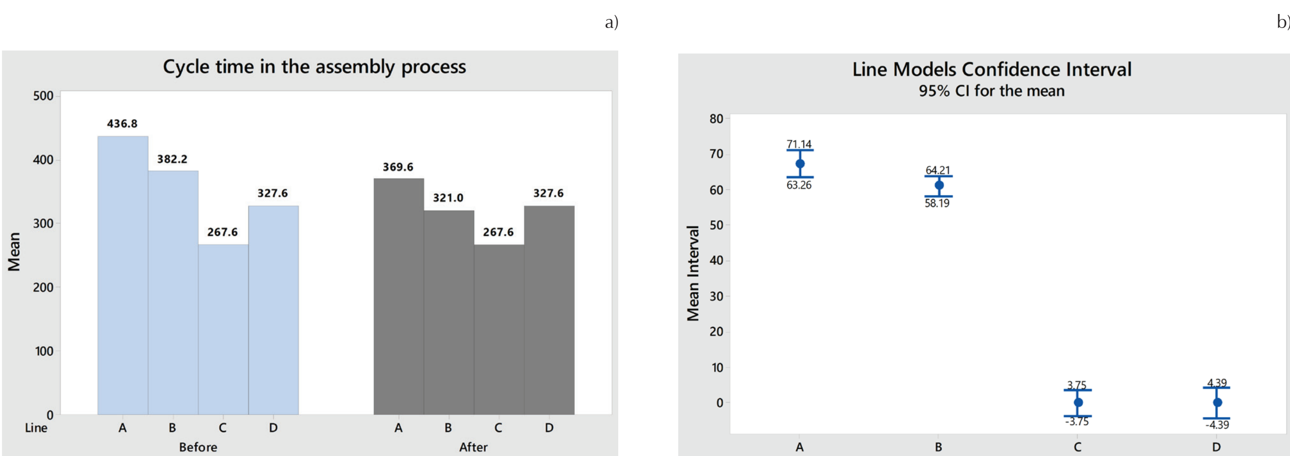

Figure 4. Cycle times and confidence intervals for assembly process optimization: a) Mean cycle times before and after changes, b) 95 % Confidence intervals for each model

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Table 5. Simulated production output per shift before and after process improvements for assembly models A, B, C, and D

Linea	Production Before (pieces/shift)	Standard Deviation Before	95 % CI Before	Production After (pieces/shift)	Standard Deviation After	95 % CI After	Production Increase (%)
Model A	100	5	[95, 105]	117	6	[111, 123]	17 %
Model B	150	8	[142, 158]	180.3	9	[171.3, 189.3]	20.20 %
Model C	130	7	[123, 137]	130	7	[123, 137]	0 %
Model D	175	10	[165, 185]	175	10	[165, 185]	0 %

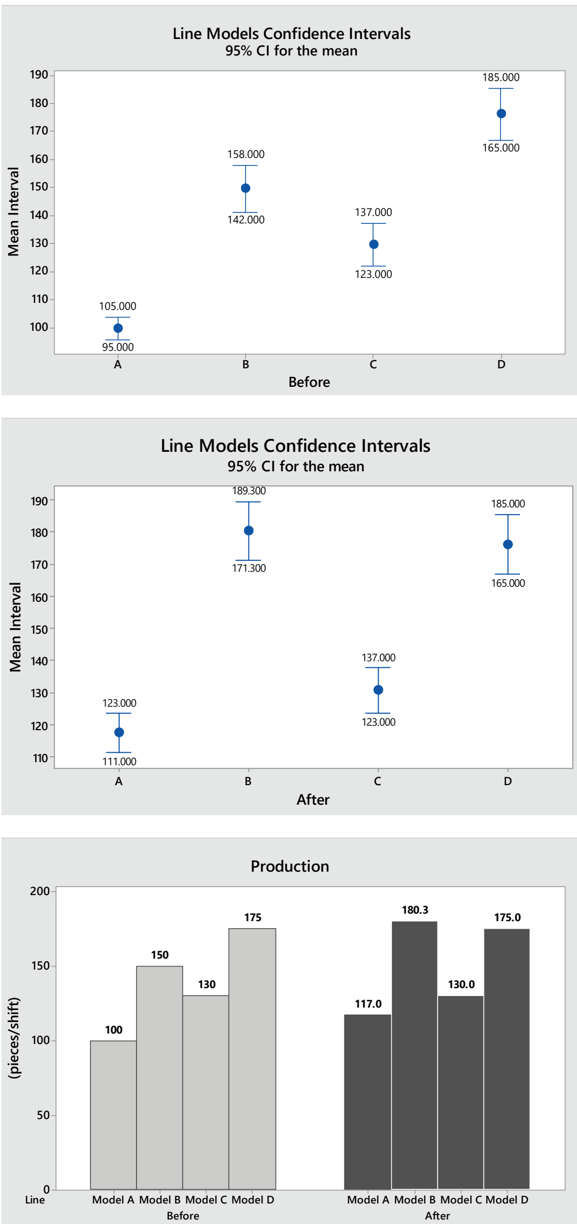

Figure 5. Simulated production output per shift and confidence intervals for assembly process optimization: a) 95 % Confidence interval of production before changes, b) 95 % Confidence interval of production after changes, c) Production before and after (pieces/shift)

In Model A, design adjustments led to a 17 % increase in production, raising the number of units produced per shift from 100 to 117. Initially, production had a standard deviation of 5, with a 95 % confidence interval (CI) of [95, 105]. After the improvements, the standard deviation slightly increased to 6, resulting in a CI of [111, 123]. This slight increase in the standard deviation likely reflects minor variations in the newly optimized process. Model B, which shows the greatest gain, experienced a production increase of 20.20 %, moving from 150 units per shift to 180.3. Production variation before the improvement was more pronounced, with a standard deviation of 8 and a 95 % CI of [142, 158]. After the improvement, the standard deviation slightly increased to 9, yielding a CI of [171.3, 189.3]. This suggests an improvement in performance, albeit with a slight increase in variability, which may be attributed to adjustments in handling and processing additional units. However, Models C and D maintained stable production rates of 130 and 175 units per shift, respectively, with no increase after the changes. Consistent standard deviations and confidence intervals before and after the improvements confirm that these models were unaffected by the design modifications. This stability is likely due to operational constraints or fixed parameters specific to these models, which limited the impact of the changes.

Therefore, the design improvements achieved productivity gains for Models A and B, benefiting from reduced cycle times and enhanced flow. On the other hand, Models C and D remained stable, indicating that a more specific analysis may be needed to identify potential improvements for these models. The use of standard deviation and confidence intervals provides a clearer understanding of production consistency, with increased variability managed within acceptable limits across all models.

Conclusions

The results obtained validate the effectiveness of reconfiguring the service lines within the plant, achieving the set objectives of improving process flow and reducing cycle times in production. Models A and B showed a significant increase in efficiency and productivity due to cycle time reduction, while Models C and D, with specific operational characteristics, did not show changes, suggesting they may require more targeted or additional adjustments to achieve similar benefits.

This study underscores the importance of simulation and optimization technologies in the manufacturing industry, providing evidence that the use of virtual modeling tools, such as ProModel® software, is crucial for evaluating design changes prior to physical implementation. This approach not only minimizes costs and risks but also enables companies to anticipate the impact of improvements without altering the actual production environment. Additionally, a reduction of 25.36 square meters in space was achieved, offering the possibility of expanding production capacity by incorporating new service lines.

Overall, the findings highlight that productivity increases can be achieved not only through infrastructure investment but also through optimizing existing resources and strategically applying digital tools. This approach aligns with the principles of Industry 4.0, facilitating the transition toward smart, digitally integrated manufacturing, where simulations and process virtualization allow companies to progress toward sustainable operational efficiency and competitiveness. Moreover, the virtual testing of production line improvements demonstrates a forward-looking model for manufacturing, where evidence-based adjustments can be systematically evaluated before implementation, making each modification grounded in data-driven insights. These results reaffirm the importance of a thoughtful, gradual implementation of advancements in manufacturing environments, where simulation and optimization provide a viable and cost-effective pathway to excellence in performance and strategic growth.

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