MODELING AND SIMULATION OF INDUSTRIAL PROCESSES

Modelado y simulación de procesos industriales

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Received: 8/01/2024| Accepted: 15/02/2024| Publication date: 6/05/2024
DOI: 10.20868/abe.2024.1.5233

HIGHLIGHTS

- Aplicación de herramientas digitales en el estudio de procesos industriales. / Application of digital tools in the study of industrial processes.
- Uso de simulaciones para entender y mejorar tiempos y costes. / Using simulations to understand and improve times and costs.
- Análisis y propuesta de optimizaciones para viabilizar sistemas de fabricación. / Analysis and proposal of optimizations to make manufacturing systems viable.
- Estudiantes de ingeniería aplican metodología en entornos industriales reales. / Engineering students apply methodology in real industrial environments.

RESUMEN

Este artículo presenta una metodología didáctica aplicada a los estudios de ingeniería. A partir del uso de herramientas digitales se desarrolla una metodología para modelar y simular un proceso de fabricación industrial. La metodología comienza con el análisis del proceso de fabricación, por lo que los estudiantes realizan una aproximación analítica al modelado del sistema productivo analizado. A continuación, se utiliza una herramienta digital para modelar dicho sistema en base a los parámetros previamente analizados. Con la simulación del modelo, los estudiantes de ingeniería analizan los resultados de tiempos y costes específicos de cada proceso y producto. En base a estos se presentan propuestas de mejora para optimizar el proceso que se modela y simula nuevamente para comprobar la eficiencia y beneficio de las mejoras propuestas en el proceso. Con esta metodología, los estudiantes de ingeniería se introducen en un contexto escalable de la industria real para realizar mejoras seguras, al mismo tiempo que desarrollan habilidades en ingeniería de procesos y herramientas digitales.

Palabras clave: *Procesos de fabricación, sistemas sostenibles, máquinas de fabricación, optimización de sistemas.*

ABSTRACT

This paper presents a didactic methodology applied to engineering studies. From the use of digital tools, a methodology is developed to model and simulate an industrial manufacturing process. The methodology begins with the analysis of the manufacturing process, so the students carry out an analytical approach to the modeling of the analyzed production system. Next, a digital tool is used to model said system based on the previously analyzed parameters. With the simulation of the model, engineering students analyze the results of specific times and costs of each process and product. Based on these, improvement proposal are presented to optimize the process that are modelling and simulated again to check the efficiency and benefit of the proposed improvements in the process. With this methodology, engineering students are introduced to a scalable context of real industry for safe improvements, while developing skills in digital tools and processes engineering.

Keywords: *Manufacturing processes, sustainable systems, manufacturing machines, system optimization.*

1. INTRODUCTION

This paper presents a didactic methodology applied to engineering studies. From the use of digital tools, a methodology is developed to model and simulate an industrial manufacturing process.

Industrial processes have long been a fundamental part of society [1], [2]. These processes are made up of different specific transformation threads where, through different tools, a resource is converted into a good, either as a product or as a service. Within these transformation processes, many variables must be taken into account [3]–[5]. Certainly, the fundamentals are focused on the raw material, which is transformed into the output product. However, both the process itself and the various agents actively influence how this transformation is carried out. The tools themselves, used in the process, are to be considered, both for their handling, as well as their affect in terms of cost, use of labor when handling, scheduled maintenance, breakdowns, etc. Precisely, failures and maintenance can also affect the process in general, either due to the quality of the input material, the handling of the operator, accidents, the transformation machinery, the output quality, among others. Likewise, these failures and maintenance stops cause a time of absence of production, which is associated with certain costs in the industrial process. The costs also cover labor, material, the replacement of machinery or, among others, the energy cost [6]–[11].

All these variables that make up a transformation process must be controlled with great precision in order to guarantee that the process is efficient and safe. Fortunately, today, digital tools allow for predictive simulations in industrial process engineering [12]. Thus, with the application of the same, both industries [13]–[15], and especially engineering students [16], [17], can carry out simulations of large processes in a totally safe environment and where a real temporality is not required to obtain scalable results, prior to implementations, or modifications in existing production systems, which entail high costs and risks..

Process optimization in industrial manufacturing is a crucial aspect that leverages both traditional engineering principles and advanced technological tools to enhance the efficiency and effectiveness of production lines. The goal of process optimization is to minimize costs, maximize output, and maintain product quality, thereby ensuring that manufacturing processes are not only economically viable but also environmentally sustainable and socially responsible.

One of the foundational techniques in process optimization is Lean Manufacturing, which originated in the Japanese automotive industry and has since permeated various sectors. Lean principles focus on the elimination of waste within manufacturing systems, where waste is defined as any process or activity that does not add value from the customer's perspective. Techniques such as Just-In-Time (JIT) production, Kaizen (continuous improvement), and 5S (Sort, Set in order, Shine, Standardize, Sustain) are commonly implemented to streamline operations and reduce unnecessary costs [18].

Furthermore, Six Sigma methodology complements Lean practices by providing a data-driven approach to minimize defects in the manufacturing process. It uses statistical methods to identify and remove the causes of defects and variability in manufacturing and business processes, aiming for six standard deviations between the mean and the nearest specification limit. This rigorous approach ensures that products meet stringent quality standards, which is particularly critical in industries such as pharmaceuticals, aerospace, and electronics, where precision and reliability are paramount [19].

Advancements in digital technologies have significantly enhanced these traditional optimization techniques. For instance, the integration of advanced sensors and data analytics tools allows for real-time monitoring and control of manufacturing processes. These technologies enable manufacturers to detect deviations from optimal performance immediately and make adjustments on the fly, thereby reducing downtime and enhancing productivity.

Moreover, the adoption of Industry 4.0 technologies, such as the Internet of Things (IoT) and big data analytics, has transformed process optimization into a highly dynamic, interconnected practice. IoT devices can collect data from multiple points across the production line, which algorithms analyze to predict potential failures or bottlenecks before they occur. This predictive maintenance ensures that machines operate at peak efficiency with minimal interruptions, significantly improving the reliability and longevity of manufacturing equipment [20].

In addition to technological innovations, process optimization also involves a strategic component—Supply Chain Optimization. By analyzing the entire supply chain, from raw material sourcing to product delivery, companies can identify inefficiencies and optimize the flow of goods and information. Advanced simulation software allows businesses to model supply chain processes and test various scenarios to determine the most efficient strategies under different conditions. This holistic approach not only reduces costs but also improves responsiveness to market changes and customer demands, thereby enhancing competitive advantage.

Environmental sustainability has also become an integral part of process optimization. As global awareness of environmental issues grows, manufacturers are increasingly adopting green manufacturing practices to reduce their ecological footprint. This includes optimizing energy use, minimizing waste through recycling and reuse programs, and selecting environmentally friendly materials. Simulation tools play a crucial role in this context by allowing companies to assess the environmental impact of their processes and explore alternative, more sustainable methods before implementing them in real life [21].

Furthermore, the role of workforce optimization cannot be overlooked. Engaging and training employees in optimization techniques is vital for fostering a culture of continuous improvement. Empowering workers with the tools and knowledge to identify inefficiencies and suggest improvements leads to a more motivated, productive workforce. This human-centric approach not only improves process efficiency but also enhances job satisfaction and retention.

The integration of process optimization techniques and continuous improvement methodologies into industrial manufacturing is a multifaceted endeavor that involves a combination of traditional practices and cutting-edge technologies. By continuously refining these processes, manufacturers can achieve higher levels of efficiency and productivity, respond more effectively to market demands, and maintain a competitive edge in a rapidly evolving industry. As these practices mature and new technologies emerge, the landscape of industrial manufacturing will continue to evolve, promising even greater efficiencies and innovations in the future.

The endeavor to optimize and improve industrial processes is not a product of modern technology alone; it has been a continual pursuit since the dawn of industrialization. In the early 20th century, the focus was primarily on mechanization and standardization of production lines, epitomized by Henry Ford's assembly line innovations. These early methods aimed at enhancing productivity through mechanical efficiencies, setting the stage for more sophisticated approaches.

As industries evolved, so did the tools at their disposal. The introduction of computers and automation in the mid-20th century marked a significant shift. Early computer-aided design (CAD) systems and manufacturing (CAM) technologies started to replace manual drafting and machining processes, introducing a new era of precision and control [22]. In the contemporary industrial landscape, digital tools are indispensable. The use of comprehensive enterprise resource planning (ERP) systems, integrated with CAD and CAM, supports complex production activities across global industries.

The integration of Internet of Things (IoT) technologies has further extended capabilities, enabling real-time monitoring and control of manufacturing processes from remote locations. These digital tools do more than just streamline operations; they allow for the simulation of industrial processes in virtual environments, providing a sandbox for innovation without the risks associated with physical trials. Tools like MATLAB, Simulink, and proprietary software specific to industries allow engineers to model scenarios and predict outcomes with a high degree of accuracy [23], [24].

Traditional manufacturing processes often struggle with inefficiencies related to scale, complexity, and adaptability. Issues such as equipment downtime, unpredictable maintenance costs, and inflexible production lines are common. The inability to predict and mitigate these issues effectively can lead to significant economic losses. In the automotive industry, for instance, a lack of efficient modeling can result in production bottlenecks that delay entire supply chains, demonstrating the critical need for robust process simulations. Traditional methods, while once effective, now require integration with advanced simulations to meet modern demands for speed, efficiency, and sustainability [25]–[27].

The realm of simulation technologies has undergone remarkable evolution, transitioning from rudimentary models to sophisticated systems capable of intricate and predictive simulations. Initially, simulations were limited to simple, static scenarios that could provide basic insights into a process under predefined conditions. However, as computing power increased and software became more sophisticated, dynamic and real-time simulations began to emerge, transforming the landscape of industrial engineering. Modern simulation tools now incorporate real-time data feeds, allowing them to adjust simulations on-the-fly to reflect changing conditions. This shift is crucial for industries where conditions change rapidly, such as in chemical processing or high-speed manufacturing. Software like ANSYS, Autodesk Simulation, and SolidWorks Simulation have made it possible to perform complex fluid dynamics, structural analysis, and thermodynamic calculations within minutes, a process that previously took days [28], [29].

At the core of process modeling lies a variety of theoretical frameworks designed to mirror the complexities of real-world systems. These models range from deterministic models, which assume a fixed set of known variables, to stochastic models that account for randomness and uncertainty in input variables. Each type of model serves a different purpose and is chosen based on the specific requirements of the process being analyzed. Static models are typically used for processes that do not change over time, ideal for scenarios where conditions are stable and predictable. Dynamic models are useful for processes that evolve over time, requiring the model to adapt to changes in system variables. Stochastic models are best suited for processes with inherent uncertainty or variability in inputs, often used in supply chain management and quality control. These models form the foundation upon which simulations are built, allowing engineers to explore how processes behave under various scenarios without the need for costly real-world experimentation.

The practical application of modeling and simulation is vast and varied. In industries like aerospace, automotive, and pharmaceuticals, simulations are critical for ensuring product safety and efficacy without the need for expensive and time-consuming physical prototypes. For instance, in the aerospace sector, simulations are used extensively to test the structural integrity of aircraft components under extreme conditions, significantly reducing the risk of failure during actual flights. Moreover, the integration of simulation into the design and development phase enables industries to accelerate innovation cycles, reduce costs, and improve product quality. By predicting how new designs will perform under real-world conditions, companies can make informed decisions earlier in the product development process, thereby enhancing their competitive edge.

The integration of machine learning (ML) into modeling and simulation represents a groundbreaking shift in how industrial processes are optimized. Algorithms can analyze vast amounts of data from simulations to identify patterns and predict outcomes, thereby enhancing the accuracy and efficiency of the simulations. With predictive maintenance, simulations can predict when a machine is likely to fail or require maintenance, thus preventing downtime and reducing maintenance costs. With optimization algorithms, models can optimize production processes by learning the best parameters for each step of the process, continuously improving efficiency and output quality [30], [31].

The Impact of IoT and Data Analytics

The Internet of Things (IoT) has revolutionized data collection in industrial environments, with sensors and connected devices providing a continuous stream of data that feeds into simulation models. This real-time data allows for more accurate and dynamic simulations that can adapt to changing conditions instantaneously. Within, real-time monitoring, IoT devices monitor critical parameters and feed this data into simulation models, allowing for real-time adjustments and predictions. Using big data analytics, the analysis of large datasets generated by IoT devices helps in refining simulation models, making them more precise and reflective of real-world conditions. By harnessing the power of IoT and data analytics, industries can achieve unprecedented levels of precision and efficiency in their process modeling and simulation efforts [32].

In today's complex industrial environment, the pivotal role of robust data management systems combined with the comprehensive integration of Internet of Things (IoT) technologies dramatically enhances the efficiency and effectiveness of process modeling and simulation. As manufacturing becomes increasingly digitized, the capture and precise analysis of data from a myriad array of sources across production facilities become critical. This extensive data collection is typically conducted using a vast network of sensors and IoT devices that continuously monitor a wide range of parameters including machine performance, environmental conditions, and energy consumption. These devices not only gather massive volumes of real-time data but also ensure that this data is immediately available for processing and analysis. Effective data management is integral to modern simulation techniques as it underpins the accuracy and reliability of the simulations. Handling such large datasets requires robust databases and advanced data processing algorithms that maintain data integrity and ensure quick access. Moreover, IoT technologies enable real-time feedback mechanisms that are essential for adaptive simulations, which adjust dynamically to reflect new data and changing conditions. This adaptability allows for more precise and predictive modeling of industrial processes, helping to anticipate outcomes under various scenarios. The integration of IoT in industrial simulations also supports proactive maintenance and operational efficiency. By analyzing data trends and patterns, the systems can predict potential failures before they occur, significantly reducing downtime and maintenance costs. This predictive capability ensures that maintenance can be scheduled during optimal times without disrupting the production process. Additionally, the analysis of this data helps in optimizing resource allocation, improving energy efficiency, and reducing waste, thereby not only saving costs but also contributing to environmental sustainability. Such advanced data-driven simulations facilitate the development of digital twins—virtual replicas of physical devices or systems that can be used to run simulations to predict how a process will operate under different conditions. Digital twins serve as a bridge between the physical and digital world, providing deep insights into system performance and potential points of failure before they manifest in the real world. This leads to a deeper understanding of the systems, enabling manufacturers to innovate faster and with less risk [33], [34].

The seamless integration of sophisticated data management systems and IoT technologies in industrial process modeling and simulation marks a transformative shift in manufacturing. This integration not only enhances the accuracy and efficacy of the simulations but also brings about a significant improvement in predictive maintenance, operational efficiency, and resource optimization. As industries continue to embrace these technologies, they unlock new potentials in productivity and cost-effectiveness, paving the way for smarter, more sustainable manufacturing practices [35].

The drive towards sustainability has become a central concern for industries worldwide, catalyzed by increasing environmental regulations and a growing awareness of the finite nature of our natural resources. Modeling and simulation play pivotal roles in enabling green manufacturing practices, helping companies to minimize their environmental footprint while maintaining or enhancing production efficiency [36], [37]. Simulations help in optimizing the use of materials and energy, reducing waste and emissions. For instance, in the automotive industry, lightweight materials can be tested through simulations to assess their performance before actual production, significantly reducing material wastage. Energy consumption models can simulate various scenarios to find the most energy-efficient processes. This is particularly relevant in industries like steel and cement manufacturing, where energy costs constitute a significant portion of total production costs. Advanced simulations are used to predict and reduce the carbon footprint of manufacturing processes by analyzing different scenarios where alternative, less carbon-intensive materials or methods are used. Simulation tools are crucial in designing systems that maximize water reuse in industrial processes, essential in industries like textiles and pharmaceuticals where water scarcity poses a significant challenge.

Regulations play a critical role in shaping how industries approach sustainability. Simulation tools help companies comply with these regulations by enabling them to predict the outcomes of regulatory changes before they are implemented. For example, simulations can help assess the impact of new environmental standards on manufacturing processes, allowing companies to adapt without significant disruptions.

This work presents a specific methodology where it makes use of modeling and simulation tools, applicable in engineering education, with the aim of providing students with an accessible environment where they can analyze previously analyzed real production systems, proposing specific improvements. The objective is to develop a methodology that meets the criteria of being intuitive, practical, scalable and industrially applicable, as well as to develop skills in students in terms of process engineering and process simulation and modeling.

2. MATERIALS AND METHODS

Industrial process modeling and simulation employ a range of sophisticated methods that vary widely depending on the specific requirements of the production environment and the goals of the study. One common approach is the use of discrete event simulation (DES), which models the operation of a system as a discrete sequence of events in time. Each event occurs at a particular instant in time and marks a change of state in the system. This method is particularly useful in industries where operations are clearly defined and occur sequentially, such as manufacturing and logistics. In addition to DES, continuous simulation is another method often used, particularly suitable for processes that change continuously over time, such as chemical production or power generation. This type of simulation uses differential equations to represent the changes in system states over time, requiring sophisticated numerical methods and computational tools for solving these equations accurately and efficiently. Another important methodology is agent-based modeling, which simulates the actions and interactions of autonomous agents (both individual or collective entities such as organizations or groups) to assess their effects on the system as a whole. This method is increasingly used in supply chain management and healthcare systems where individual behavior can significantly influence the system's performance.

System dynamics is also employed, especially for understanding the behavior of complex systems over time. It involves constructing causal loop diagrams that help visualize how different variables in a system are interrelated and how they affect each other over time. This method is particularly valuable for strategic planning and policy evaluation in industrial operations. The integration of real-world data into these simulations is crucial for their success and relevance. Data acquisition in industrial settings is typically performed through a myriad of sensors and IoT devices that collect data on various parameters such as temperature, pressure, speed, and flow rates. This data is then processed and analyzed using advanced data analytics techniques to inform the simulation models. Moreover, the use of virtual reality (VR) and augmented reality (AR) is becoming more prevalent in industrial simulations. These technologies allow engineers and operators to visualize complex processes and simulations in a more intuitive and interactive manner. VR and AR can simulate how changes in the process might impact the operation without the need to physically alter the production line, which can save significant time and resources.

Another critical aspect of the methodology is the validation and verification of the models used in simulations. Validation ensures that the models accurately represent the real-world processes they are intended to simulate, while verification checks that the models are correctly implemented. These steps are essential to ensure that the simulations can be reliably used for making decisions about process improvements and optimizations. Furthermore, the simulation environment itself must be carefully designed to ensure that it can handle the complexity and scale of industrial processes. This includes selecting the appropriate software and hardware, designing user interfaces that are intuitive and efficient, and ensuring that the system is scalable and can be integrated with existing IT infrastructure. To ensure continuous improvement and relevance of the simulation models, a feedback loop is often established where the outcomes of the simulations inform further adjustments and refinements of the process. This iterative process helps in fine-tuning the models and the decision-making processes they support, leading to more accurate predictions and more effective interventions.

The materials and methods used in industrial process modeling and simulation are diverse and complex, requiring a deep understanding of both the theoretical underpinnings and practical applications. By utilizing a combination of simulation methods, advanced data acquisition technologies, and interactive visualization tools, industries can significantly enhance their ability to analyze, predict, and optimize their operations. This comprehensive approach not only improves efficiency and productivity but also drives innovation in manufacturing practices, ultimately contributing to the industry's long-term sustainability and competitiveness.

situations that may require preventive maintenance, with which the machinery stops, or possible failures, including the replacement of certain parts, once they have been accidentally disabled. Regarding the process, the methodology proposes to analyze the transformation globally, taking into account internal variables and external agents, which respond to times and costs of resources associated with them. The analysis of the products must respond first to the estimated quantities of production. Likewise, the qualities must be quantified, taking into account types, such as acceptance factors and failures in the final production, they also consider that it is carried out with said products with different degrees of quality. In the same way, the storage, in its different variants, of each by-product is finished, including temporary, seasonal, security, waste, waiting, etc. storage. Likewise, the distribution of said products is taken into account when carrying out a movement or transport, direct or not, towards another process, which may well be transformation, or simply classification, quality analysis or transport as such, among others. In general, all times must be quantified, given that the temporary space in which it is produced, consumes resources, or stops production, finally influences both the efficiency ofthe process, by producing stops or slowness in the flow, as well as costs, associated with such stops and the unnecessary use of resources in an ineffective manner. Among others, it includes the analysis of times of production, use, use of active resources, use of

Process analysis:

- Tools: specific transformation machinery, resources consumed (time, costs, human resources), maintenance and failures.
- Processes: transformation process at a global level, taking into account internal variables and external agents, which respond to times and costs of resources.
- Products: results of each of the transformation processes, storage and distribution.
- Raw material: necessary material to obtain the product, supply, regular stock, stock breaks,
- Time costs: times of production, use, use of active resources, use of active resources, waiting times, times in failure or maintenance.
- Faults/Maintenance: preventive maintenance situations and possible failures that cannot be prevented but can be estimated.

***Fig. 1:** Process analysis methodology.*

The methodology in this work begins with the analysis of the manufacturing process, Figure 1, analyzing tools, processes, sub products, used materials, times, costs, failures and maintenance. The tools are the main element that is in charge of precisely carrying out the transformation with which to obtain the product, so the students, in this proposed methodology, analyze the necessary machinery. They also analyze the resources necessary for the tool to perform its function, including the different times, both in use and in its different states, the costs, both associated with times and, for example, energy consumption, and finally each one of the active resources, waiting times, times in failure or maintenance. Parallel to how it is analyzed in the rest of the element, it is vital to guarantee both the safety and the efficiency of the system through the analysis of possible failures and the required preventive maintenance.

Thus, preventive maintenance situations and possible failures that cannot be prevented but can be estimated are analyzed precisely. In this way, the students carry out an analytical approach to the modeling of the analyzed production system. Thus, the modeling is based on a previous, specific observation, which above all quantifies the process, so that the model phase can be carried out in the most precise and efficient way possible.

Next, a digital tool is used to model said system based on the previously analyzed parameters, Figure 2. This tool allows to specify all the previous characteristics, including estimated frequencies of maintenance and failures. In this phase, it is about transforming the specific analysis carried out in the previous phase, where the process is analyzed, and being able to introduce it as parameters for the realization of the simulation-oriented model. In this sense, the first step consists of specifically delimiting the transformation flow, including input material resources and their possible distribution to different machines, which are the ones that specifically carry out each of the possible transformations. Likewise, the result of each process is delimited, including the distribution of possible products, together with the quality analysis, waste due to defective products, etc. In addition, the rest of the resources used by the machinery must be specifically modeled, both labor, auxiliary materials, etc. Once the process flow as such has been modeled, the time of each of the phases must be concretely modeled, from the introduction of the product, its transformation, handling, classification, analysis or storage. In what refers to the process, and to the machinery or tools, all the times referred to them and to the workforce must also be modeled, or the possible stops, programmed or due to failures. Finally, it is key to quantify the costs associated with the entire process in the model, to guarantee that the results not only provide a guarantee of efficiency, in terms of time optimization, but also in terms of the use of economic resources.

The next step of the methodology entails the simulation of said process, Figure 2, which is a direct result of using the previous simulation-oriented model design. With this, engineering students can analyze the results of specific times and costs of each process and product, including different times (idle, busy, etc.). This phase makes it possible to obtain scalable results for simulation times that in reality would

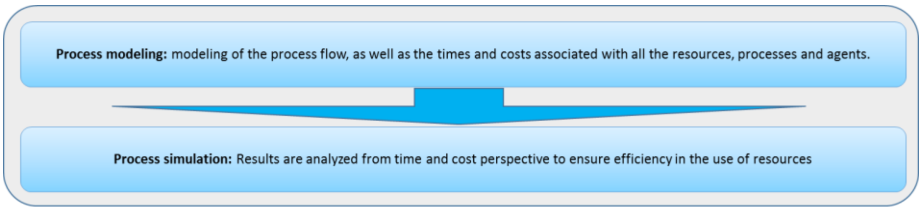

Fig. 2: *Process model and simulation.*

take too long to verify, as well as a high cost, not only due to the associated resources, but also due to the modifications in the process that it entails, extended throughout the entire on-site test.

analyzed in industries visited in person, or through telematic resources of the industries, have been quantized in a specific way, modeled and simulated following the didactic proposal designed, presented in this work. In the next phase, following this methodology, they have proposed real improvements, which have been

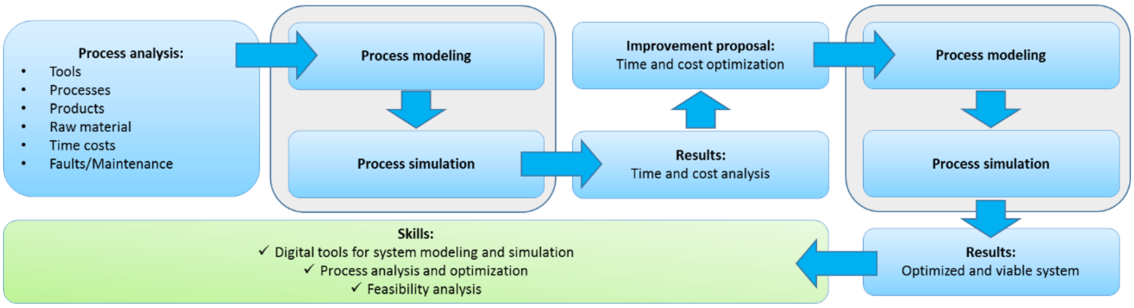

***Fig. 3:** Proposed design for modeling and simulation of industrial processes didactic methodology.*

Based on these simulation results, the critical points of the system are analyzed, based on times, considering the slowest processes. Likewise, the processes that entail the highest cost are considered. The improvement proposal analyzes how to optimize the times and costs of said process based on these previous results. The specific improvement proposal is implemented again with a new model, in which its improvement is previously estimated. The model of the proposed system is simulated again in order to analyze the improvement. The objective of this following simulation is to be able to observe a clear improvement in the optimization of time and cost, and above all to make the manufacturing process viable, if previously it was not profitable enough.

3. RESULTS AND DISCUSSION

The design carried out, in terms of the specific methodology for modeling and simulation of industrial processes, is presented in Figure 3.

This methodology has been applied in teaching engineering students within the knowledge area of process engineering. In this way, real systems, transferred to the industries analyzed at source for their feasibility analysis in terms of real implementation.

In the most relevant works, students effectively identify the main "bottlenecks" and propose alternative flows of processes or use of resources. With this, times and costs are reduced, achieving time improvements, which produce economic increases that go from even losses to highly reliable benefits, with scalability supported by the simulations carried out.

The results of the modeling and simulation methodologies applied to industrial processes, as outlined in Figure 3 and discussed throughout this work, are both substantial and multifaceted. These methodologies, which begin with a detailed analysis of existing processes and proceed through iterative simulations and optimizations, have shown to significantly impact the operational efficiency and economic viability of manufacturing systems. The implementation of these methods in real-world industrial settings has provided a wealth of data and insights, affirming the potential of simulation tools in driving process improvements.

The primary objective of applying simulation methodologies in industrial processes is to identify and eliminate inefficiencies that contribute to increased costs and extended production times. Through the use of detailed process modeling, which meticulously maps out every step of the manufacturing process, engineers and process managers can visualize not only the workflow but also the interaction between different components and variables within the system. This visualization is crucial for identifying bottlenecks—areas where delays or inefficiencies occur most frequently.

Once these bottlenecks are identified, the simulation phase allows for the exploration of potential solutions without the risk and expense associated with physical trials. Various scenarios can be tested to see how changes in the process affect overall performance. For example, adjusting the sequence of operations, changing the layout of a production line, or introducing new machinery can all be simulated to predict their impact on throughput and quality. These simulated modifications make it possible to pinpoint the most effective changes that improve flow and reduce cycle times.

The iterative nature of this methodology means that the process does not end with the first round of improvements. Each change can be further refined, and its long-term effects can be studied through subsequent simulations. This ongoing process of optimization is geared towards not only enhancing the efficiency of the manufacturing process but also reducing the consumption of resources, thereby lowering the environmental impact and operating costs.

An integral part of these results is the quantification of time and cost savings achieved through the application of these methodologies. In practical applications, the reductions in cycle times and operational costs have a direct correlation with increased production capacity and profitability. For instance, a case study involving a car manufacturer revealed that through process modeling and simulation, the company was able to reduce its assembly time by 25%, resulting in a significant increase in output and a reduction in labor costs. These economic benefits are crucial for industries operating in competitive markets where margins are often tight.

Moreover, the scalability of these simulations allows for their application in various contexts, from small-scale boutique operations to large, multinational manufacturing plants. This versatility ensures that the methodologies developed and refined through academic research and practical application remain relevant across different industries and scales of operation.

The secondary benefits of implementing these methodologies include improved product quality and consistency, enhanced worker safety, and increased customer satisfaction. By optimizing the manufacturing process, companies can ensure that the products they produce meet high-quality standards consistently. Additionally, more efficient processes typically involve less manual handling and fewer interventions, which contribute to a safer working environment.

In conclusion, the results of applying modeling and simulation methodologies to industrial processes as depicted in your article demonstrate significant improvements in efficiency, cost management, and overall productivity. These methodologies offer a systematic approach to diagnosing and resolving inefficiencies in manufacturing operations, providing a foundation for continuous improvement and innovation. As industries continue to face pressures to optimize operations and reduce costs, the role of process modeling and simulation will likely become increasingly important, offering a pathway to sustainable, profitable manufacturing practices.

4. CONCLUSIONS

With this methodology, engineering students access the scalable analysis of real industrial processes in a safe environment that allows iterating the results until optimizing the improvement proposal. With this, they acquire skills in digital tools for system modeling and simulation, in the analysis and optimization of processes, and in feasibility analysis.

5. REFERENCES

[1] A. C. Kerckhoff, "Institutional arrangements and stratification processes in industrial societies," *Annu. Rev. Sociol.*, vol. 21, no. 1, pp. 323–347, 1995.

[2] E. Abad-Segura, M. E. Morales, F. J. Cortés-García, and L. J. Belmonte-Ureña, "Industrial processes management for a sustainable society: Global research analysis," *Processes*, vol. 8, no. 5, p. 631, 2020.

[3] F. Klocke and A. Kuchle, *Manufacturing processes*, vol. 2. Springer, 2009.

[4] T. Gutowski, J. Dahmus, and A. Thiriez, "Electrical energy requirements for manufacturing processes," in *13th CIRP international conference on life cycle engineering*, Leuven, Belgium, 2006, pp. 623–638.

[5] A. J. Allen and K. G. Swift, "Manufacturing process selection and costing," *Proc. Inst. Mech. Eng. Part B J. Eng. Manuf.*, vol. 204, no. 2, pp. 143–148, 1990.

[6] J.-Y. Jung, "Manufacturing cost estimation for machined parts based on manufacturing features," *J. Intell. Manuf.*, vol. 13, pp. 227–238, 2002.

[7] E. . Shehab and H. . Abdalla, "Manufacturing cost modelling for concurrent product development," *Robot. Comput. Integr. Manuf.*, vol. 17, no. 4, pp. 341–353, Aug. 2001, doi: 10.1016/S0736-5845(01)00009-6.

[8] H. Yamashina and T. Kubo, "Manufacturing cost deployment," *Int. J. Prod. Res.*, vol. 40, no. 16, pp. 4077–4091, Jan. 2002, doi: 10.1080/00207540210157178.

[9] A. Locascio, "Manufacturing Cost Modeling for Product Design," *Int. J. Flex. Manuf. Syst.*, vol. 12, no. 2, pp. 207–217, 2000, doi: 10.1023/A:1008199714982.

[10] M. Schröder, B. Falk, and R. Schmitt, "Evaluation of cost structures of additive manufacturing processes using a new business model," *Procedia Cirp*, vol. 30, pp. 311–316, 2015.

[11] R. Creese and M. Adithan, *Estimating and costing for the metal manufacturing industries*. CRC Press, 1992.

[12] D. Ulas, "Digital transformation process and SMEs," *Procedia Comput. Sci.*, vol. 158, pp. 662–671, 2019.

[13] S. M. Afazov, "Modelling and simulation of manufacturing process chains," *CIRP J. Manuf. Sci. Technol.*, vol. 6, no. 1, pp. 70–77, 2013.

[14] R. Sinha, C. J. J. Paredis, V.-C. Liang, and P. K. Khosla, "Modeling and simulation methods for design of engineering systems," *J. Comput. Inf. Sci. Eng.*, vol. 1, no. 1, pp. 84–91, 2001.

[15] D. J. Murray-Smith, *Modelling and simulation of integrated systems in engineering: issues of methodology, quality, testing and application*. Elsevier, 2012.

[16] M. Dodgson, D. M. Gann, and A. Salter, "The impact of modelling and simulation

technology on engineering problem solving," *Technol. Anal. Strateg. Manag.*, vol. 19, no. 4, pp. 471–489, 2007.

[17] A. J. Magana, "Modeling and simulation in engineering education: A learning progression," *J. Prof. Issues Eng. Educ. Pract.*, vol. 143, no. 4, p. 4017008, 2017.

[18] S. M. Saad, R. Bahadori, C. Bhovar, and H. Zhang, "Industry 4.0 and Lean Manufacturing – a systematic review of the state-of-the-art literature and key recommendations for future research," *Int. J. Lean Six Sigma*, Apr. 2023, doi: 10.1108/IJLSS-02-2022-0021.

[19] T. Pongboonchai-Empl, J. Antony, J. A. Garza-Reyes, T. Komkowski, and G. L. Tortorella, "Integration of Industry 4.0 technologies into Lean Six Sigma DMAIC: A systematic review," *Prod. Plan. Control*, pp. 1–26, 2023.

[20] C. Marinagi, P. Reklitis, P. Trivellas, and D. Sakas, "The impact of industry 4.0 technologies on key performance indicators for a resilient supply chain 4.0," *Sustainability*, vol. 15, no. 6, p. 5185, 2023.

[21] O. Yavuz, M. M. Uner, F. Okumus, and O. M. Karatepe, "Industry 4.0 technologies, sustainable operations practices and their impacts on sustainable performance," *J. Clean. Prod.*, vol. 387, p. 135951, 2023.

[22] F. J. Alhamed, G. F. Neiva, S. Bak, E. Karl, and M. R. Inglehart, "Pre-doctoral dental students' computer-aided design/computer-aided manufacturing-related education, knowledge, attitudes and behavior: A national survey," *J. Dent. Educ.*, vol. 87, no. 4, pp. 562–571, 2023.

[23] B. DUMAN and A. A. SÜZEN, "MODELING OF IOT-BASED ADDITIVE MANUFACTURING MACHINE'S DIGITAL TWIN FOR ERROR DETECTION," *Mühendislik Bilim. ve Tasarım Derg.*, vol. 11, no. 2, pp. 486–497, 2023.

[24] V. Ngunzi, F. Njoka, and R. Kinyua, "Modeling, simulation and performance evaluation of a PVT system for the Kenyan manufacturing sector," *Heliyon*, vol. 9, no. 8, 2023.

[25] A. S. George and A. S. H. George, "Revolutionizing Manufacturing: Exploring the Promises and Challenges of Industry 5.0.," *Partners Univers. Int. Innov. J.*, vol. 1, no. 2, pp. 22–38, 2023.

[26] Z. Wu *et al.*, "Structural integrity issues of additively manufactured railway components: Progress and challenges," *Eng. Fail. Anal.*, p. 107265, 2023.

[27] A. Shah, R. Aliyev, H. Zeidler, and S. Krinke, "A review of the recent developments and challenges in wire arc additive manufacturing (WAAM) process," *J. Manuf. Mater. Process.*, vol. 7, no. 3, p. 97, 2023.

[28] A. K. Agbonkhese, "Application of Solidworks Simulation to Improve Mechanical Design Skills of Mechanical Engineering Students in the National Institute of Construction Technology and Management, Edo State, Nigeria," *Int. J. Funct. Res. Sci. Eng.*, vol. 3, no. 1, 2024.

[29] G. S. Usiagu, A. Adefemi, C. E. Okoli, C. D. Dauda, and K. A. Olu-Lawal, "Simulation techniques in industrial engineering: A USA and African perspective review," *Magna Sci. Adv. Res. Rev.*, vol. 10, no. 1, pp. 265–272, 2024.

[30] S. Kumar *et al.*, "Machine learning techniques in additive manufacturing: a state of the art review on design, processes and production control," *J. Intell. Manuf.*, vol. 34, no. 1, pp. 21–55, 2023.

[31] A. Norouzi, H. Heidarifar, H. Borhan, M. Shahbakhti, and C. R. Koch, "Integrating machine learning and model predictive control for automotive applications: A review and future directions," *Eng. Appl.*

Artif. Intell., vol. 120, p. 105878, 2023.

[32] H. Dadhaneeya, P. K. Nema, and V. K. Arora, "Internet of Things in food processing and its potential in Industry 4.0 era: A review," *Trends Food Sci. Technol.*, 2023.

[33] Q. Qi, Z. Xu, and P. Rani, "Big data analytics challenges to implementing the intelligent Industrial Internet of Things (IIoT) systems in sustainable manufacturing operations," *Technol. Forecast. Soc. Change*, vol. 190, p. 122401, 2023.

[34] M. Soori, B. Arezoo, and R. Dastres, "Internet of things for smart factories in industry 4.0, a review," *Internet Things Cyber-Physical Syst.*, 2023.

[35] O. Peter, A. Pradhan, and C. Mbohwa, "Industrial internet of things (IIoT): opportunities, challenges, and requirements in manufacturing businesses in emerging economies," *Procedia Comput. Sci.*, vol. 217, pp. 856–865, 2023.

[36] A. Haleem, M. Javaid, R. P. Singh, R. Suman, and M. A. Qadri, "A pervasive study on Green Manufacturing towards attaining sustainability," *Green Technol. Sustain.*, vol. 1, no. 2, p. 100018, 2023.

[37] A. Rashid, R. Rasheed, and A. H. Ngah, "Achieving sustainability through multifaceted green functions in manufacturing," *J. Glob. Oper. Strateg. Sourc.*, 2024.