Optimization of the Production Process through Digital Twin Simulation

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***Abstract*—With the advancement of technology and industry, customer demands have become increasingly complex, making it more challenging to anticipate and meet their needs. In this context, Industry 4.0 has introduced essential tools that facilitate the simulation of various scenarios, enabling manufacturers to anticipate customer needs without relying on highly advanced or expensive technologies. In response to this need, the concept of the Digital Twin (DT) has emerged, aiming to create a simulation that closely mirrors real-world scenarios. Its primary function is to accurately replicate, based on a set of real-life data, a piece of equipment or an industrial process without requiring physical acquisition. In this study, DT software was utilized to simulate the manufacturing process of coils for a generator rotor, in order to detect production bottlenecks, and recommend optimal solutions to improve efficiency. The main objective is to develop a scenario that accurately reflects the current state of the production line, identify critical points, and subsequently redesign the workflow to eliminate inefficiencies and improve overall productivity.**

***Keywords*—digital twin, simulation, optimization, industry 4.0, production efficiency, bottlenecks identification**

I. Introduction

The implementation of DTs has proven to be highly effective in tackling the challenges of Industry 4.0, including growing process complexity, the need to minimize downtime, and the pursuit of enhanced product quality [1].

Scientific literature has increasingly highlighted the adoption of DTs in the manufacturing industry. For example, an analysis conducted by Fantozzi et al. enhances a production line's operational efficiency by demonstrating the accuracy of replicating a production line model in the pharmaceutical industry through the implementation of a DT, identifying bottlenecks and inefficiencies on the production line. Furthermore, the primary impact of their study was to demonstrate the use of a DT as a decision-support tool, through the integration of real-time data and the execution of detailed simulations. This approach enabled managers to explore various operational strategies and select the most efficient ones, thereby improving production flow, reducing risks, and optimizing resource utilization [2].

To accurately replicate a production line and develop a DT that closely approximates the real existing system, the initial and essential step involves the systematic collection of databases or the comprehensive mapping of the targeted process. Value Stream Map (VSM) is one of the most recognized and widely used mapping methodologies in both lean manufacturing and industrial applications.

VSM specifically enables the visualization of information and material flow, facilitating the identification and analysis of inefficiencies and activities that do not add value [3]. Moreover, it enables the identification of areas that need process improvements, thereby enhancing overall efficiency and effectiveness. A compelling example is a case study conducted by Costa in which they successfully implemented a VSM for a production line in a luxury metal piece manufacturing company [3]. The results demonstrated a reduction in lead time from 336.45 h to 318.14 h, along with an increase in value-added time and overall process efficiency. The most significant improvement came from eliminating approximately 14 h of time that does not add value through flow optimization and the development of an inventory. Additionally, the study suggests future research to evaluate the applicability of VSM in similar industries and to analyze the impact of Single-Minute Exchange of Die (SMED) actions, as well as the implementation of First In, First Out (FIFO) and Kanban systems.

Chiscop *et al.* [4] studied a manufacturing architecture diagnosis designed meant to identify solutions for enhancing productivity while maintaining an optimized product cost. The economic validation was conducted based on the Cost-to-Use Value ratio.

While previous studies have addressed the individual application of DT technology or VSM in manufacturing, this research introduces a novel and integrative framework that combines both approaches in a fully operational, high-precision industrial setting. The study applies DT and VSM to the rotor coil manufacturing line of high-power generators. This is underrepresented in existing literature due to its standardization and low tolerance for variability. Moreover, the digital model was constructed using WITNESS Horizon software and validated with real production data, achieving a relative error of only 0.00425%. This exceptionally high accuracy reinforces the model's applicability for real-time performance diagnostics and scenario testing. Additionally, the research outlines a step-by-step, reproducible methodology that includes field data collection, simulation model calibration, bottleneck detection, and optimization scenario validation. These contributions demonstrate both scientific and practical novelty, offering a robust and generalizable framework for applying DT technology in structured manufacturing environments. Furthermore, the study provides a concrete demonstration of using DT as a diagnostic and optimization tool for production bottlenecks in a highly structured industrial setting, a use-case that remains underrepresented in peer-reviewed literature.

The primary objective of this article is to map the rotor coil manufacturing process for generators using a VSM and based on this mapping to implement a DT. This approach aims to identify critical points in the production flow, detect idle times, and explore optimization strategies for the overall process.

The proposed methodology includes the following steps:

- Develop a VSM incorporating equipment Cycle Times (CT).
- Build a DT based on the previously developed VSM.
- Simulation of the material flow real existing system to identify vulnerabilities and bottlenecks.
- Redesign the flow to mitigate idle times and optimize the overall process.

A DT is generated using the developed methodology that closely replicates the tangible system, providing several optimization possibilities, as follows: A substantial reduction in lead time for customer deliveries; More efficient allocation of operators across workstations, improving overall productivity; Simplified analysis of potential future scenarios, allowing for targeted actions to achieve specific goals (e.g., reduced lead time, increased operational capacity, etc.); Improved product quality by pinpointing areas with the highest rejection rates, enabling timely interventions to reduce raw material waste.

II. Materials and Methods

As previously outlined, DTs serve as virtual representations of products, processes, or services. This technology enables the simulation, prediction, and optimization of operations by using real-time data, positioning it as a critical component of Industry 4.0 [5, 6]. The integration of DTs with technologies such as the Internet of Things (IoT) and Big Data has led to notable advancements in product lifecycle management, a reduction in downtime, and improvements in predictive maintenance strategies [7, 8].

The literature indicates that, although DT technology is acknowledged for its transformative potential in industrial operations, its implementation frequently lacks a thorough, systematic approach that encompasses the entire lifecycle of production processes. This issue is especially prominent in sectors such as manufacturing, where most studies tend to concentrate on the capabilities of DTs in predictive maintenance and isolated optimizations, rather than on the comprehensive integration of processes [9].

The methodology proposed in this article seeks to bridge existing gaps by establishing a rigorous framework for the implementation of DTs, specifically designed to maintain optimal alignment between digital and real-world systems. Unlike traditional methods that focus mainly on specific study cases, this framework adopts a systematic strategy encompassing data collection, digital model development, identification of critical points, and comprehensive optimization of the production process [10].

By integrating these components, the proposed solution overcomes the limitations identified in the existing literature and introduces a scalable model applicable across multiple industries. This highlights the significance of a structured methodology for DT implementation, as it enables organizations to fully capitalize on its benefits, improve operational efficiency, and boost their competitiveness in the context of Industry 4.0.

The case study followed a structured methodological approach, divided into four main phases: (1) field observation and data collection, (2) process mapping using VSM, (3) digital modeling and simulation, and (4) validation and optimization.

Phase 1 — Field Observation and Data Collection: Data was collected directly from the production line of a rotor coil manufacturing facility. A mixed-methods approach was used, combining direct time studies, operator interviews, and consultation of production logs. Cycle times for each station were measured using stopwatch techniques across multiple shifts to capture variability. Batch sizes, waiting times, and changeover durations were also recorded. The goal was to obtain representative and statistically stable averages for each process parameter.

Phase 2 — Value Stream Mapping (VSM): Based on the collected data, a detailed VSM diagram was created to visualize material and information flows. The mapping followed standard lean manufacturing conventions, identifying process steps, inventory buffers, lead times, and processing times. This diagram served as the foundation for identifying bottlenecks and setting up the digital twin structure.

Phase 3 — Digital Modeling Using WITNESS Horizon: The digital twin model was developed using WITNESS Horizon, a discrete-event simulation platform selected for its capacity to replicate time-dependent industrial processes. The choice of WITNESS Horizon was based on its ability to model resource constraints, queueing behavior, and batch processing rules—critical features in coil manufacturing. Model inputs were calibrated using real-world measurements from Phase 1.

Phase 4 — Validation and Optimization: To ensure the model's accuracy, a validation step was conducted by comparing the simulated lead time to actual system performance, using relative error as the metric. Once validated, a series of what-if optimization scenarios were tested, including reductions in bottleneck station times. The impact of these interventions on overall throughput and process efficiency was analyzed quantitatively.

The methodology ensures repeatability, transparency, and adaptability to other structured manufacturing contexts. The structured approach also allows clear traceability from raw observations to simulation-based decision support.

III. Methodology

The methodology outlined is summarized in Fig. 1, which presents a structured representation of the fundamental phases and critical steps involved in the development of a DT.

The initial phase in the development of a DT entails a comprehensive analysis of the process to be digitally replicated.

The first step involve gathering process data that includes equipment CTs, required batch sizes at each workstation, and the raw materials processing capacity . The next step involves systematically mapping the production process and constructing a VSM. This mapping serves as a foundational framework for developing a simulation that closely replicates real-world conditions. Once both the real existing system and digital model have been established, a comparative analysis is conducted to assess their level of similarity, ensuring the accuracy and reliability of the digital representation.

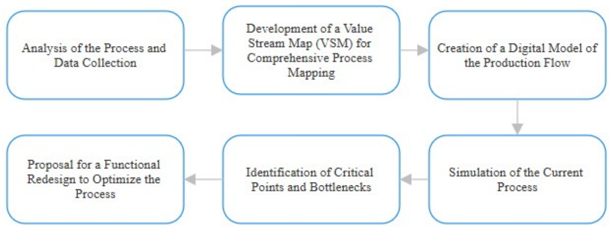


Fig. 1. Graphical representation of the method.

To validate the digital model, mathematical formulations will be utilized to quantify the accuracy of the simulation. Furthermore, a critical evaluation will be performed to determine whether the bottleneck identified in the VSM remains consistent within the simulation, thereby reinforcing the validity of the proposed model.

In a production system or process chain, the bottleneck refers to the workstation or operational phase that determines the maximum production rate, characterized by the longest CT.Mathematically, the bottleneck can be defined as the process i^* such that:

$$i^* = argmax\ CTi, \text{ where } i \in \{1, 2, \dots, n\} \quad (1)$$

Furthermore, the time associated with the bottleneck, denoted as CT_{Max}, can be expressed as:

$$CT_{Max} = max\ CT_i \text{ , where } i \in \{1, 2, \dots, n\} \quad (2)$$

For the validation of the DT, the relative error formula was used, defined as:

$$Error(\%) = \left(\frac{Dreal - Dsim}{Dreal}\right) \times 100 \quad (3)$$

where D_{real} represents the experimentally measured values, and D_{sim} is the value simulated by the DT. This formula provides an assessment of the difference between the values obtained through simulation and the real values expressed as a percentage.

Small errors (below 5%) indicate a good alignment between the theoretical models and the real-world system behavior, suggesting proper validation of the DT. Conversely, large errors (above 10%) may signal shortcomings in the simulation model, indicating the need for adjustments to better reflect reality.

IV. Case Study

Following a detailed overview of the methodology, we will demonstrate its applicability within a manufacturing environment. The focus will be on the production line specifically designed for the fabrication of rotor coils utilized in high-power generators.

We initiated this process by gathering data related to the Cycle Times (CTs) for each piece of equipment involved, along with information on the work batches and the aggregate time necessary for process execution at each workstation. This data has been compiled in Table 1 below.

Table 1. CT for each workstation

Equipment Name	Cycle Time per Coil(min)	Batch Size(pcs)	Total Processing Time(min)
Horizontal_CNC_milling	23.15	624	144.456
Cleaning_and_Deburing	28	624	174.72
Vertical_CNC_milling	27	624	168.48
Banding_90	58	624	361.92
Anneling	24	624	149.76
Cleaning_turns	30	624	187.20
Packing	36	624	224.64

To facilitate a thorough analysis of the production processes, a detailed flow chart has been developed, as depicted in Fig. 2.

Following the comprehensive collection and aggregation of requisite data, the process was meticulously mapped out, leading to the construction of the Value Stream Mapping (VSM) for the manufacturing workflow. This analysis revealed a total lead time of 141,117.6 m, equivalent to 235,196 working hours. The resultant VSM, informed by the process mapping, is presented in Fig. 3.

Fig. 2. The process flow chart.

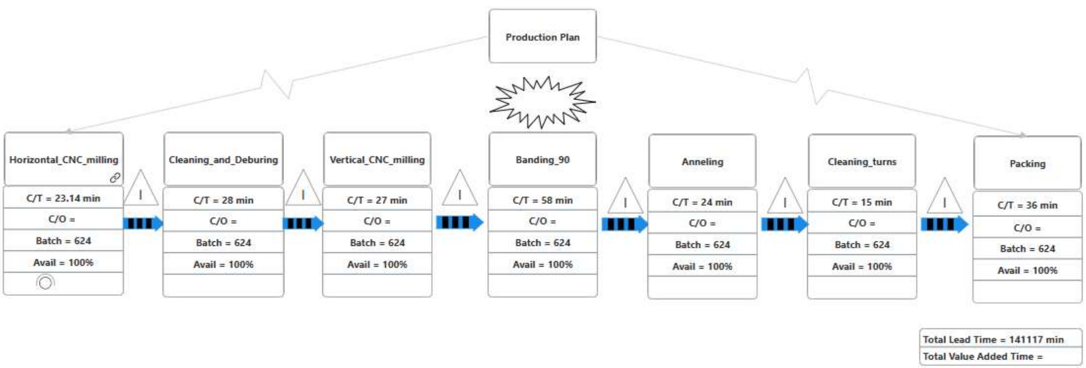


Fig. 3. VSM for the rotor coil manufacturing process.

With the process mapped, the bottleneck of the manufacturing process can now be identified to determine whether the results of the theoretical model aligns with those of the digital model in the next simulation.

In this case, the maximum CT is determined to identify the bottleneck time and the process index, allowing for the identification of the slowest equipment.

$$CT_{Max} = \max(23.15, 28, 27, 58, 24, 30, 36) = 58$$
$$i^* = argmax\,(CT1, CT2, \ldots, CT7) = 4$$

Thus, based on the calculations, we conclude the following:

Maximum CT (bottleneck time): 58

Bottleneck process: CT_4 (the fourth process)

Therefore, Process 4 is the constraining factor in the system's flow and must be optimized to enhance overall performance.

With everything well-structured and systematized, at this point, the development of the DT for the digital model represents the next essential step in creating an accurate virtual replica of the process or system, which will allow for real-time monitoring, simulation, and optimization. This way, any changes or issues can be anticipated and managed more efficiently, leading to a positive impact on overall performance and efficiency.

The digital model was created using Witness Horizon software and is illustrated below in Fig. 4.

Fig. 4. Production line modeling.

For the manufacturing of a rotor coil with 6 poles, which consists of 26 conductors per half-coil, a total of 624 conductors need to be processed. The information regarding the amount of raw material to be processed was the necessary input, followed by the definition of the processing rules for the machines and the CTs according to the VSM. The result of the simulation obtained is highlighted in Fig. 4.

As a result of simulating the digital model of the production line, information is obtained regarding the equipment load level, as well as the lead time for executing the entire process. The lead time obtained is 141,123 working hours.

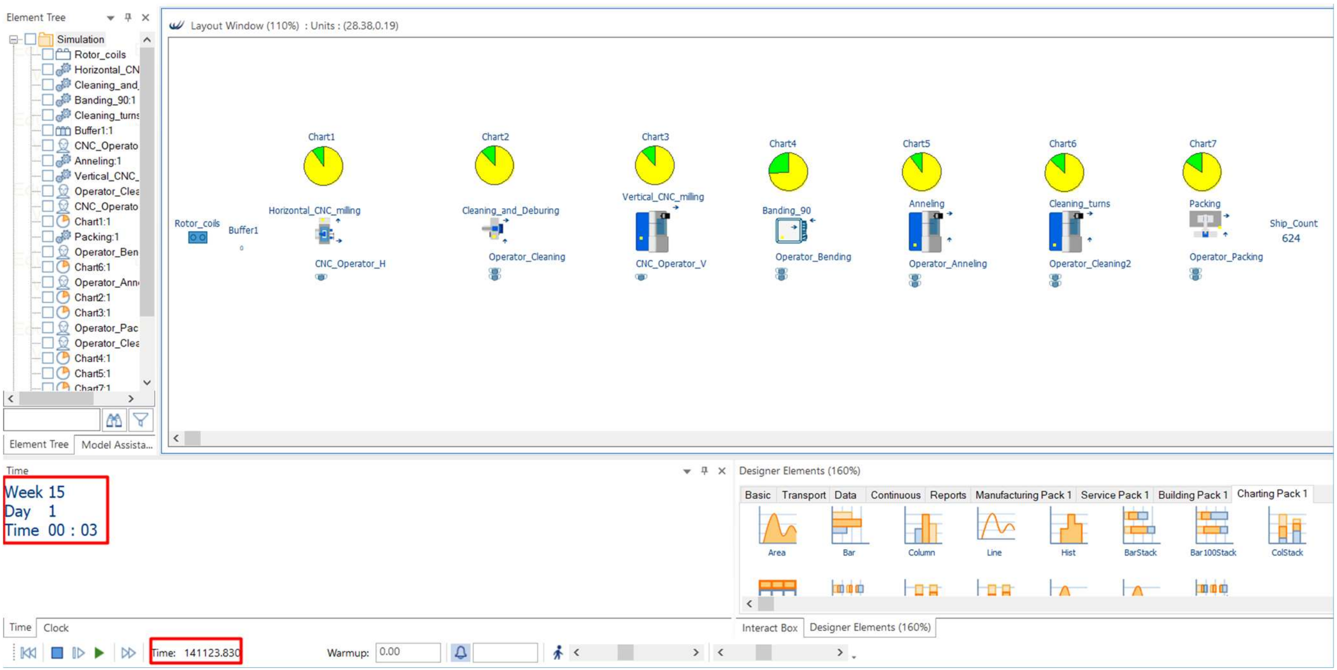


Fig. 5. Production line simulation.

To verify the actual physical model, it will be evaluated using the relative error formula.

$$Error(\%) = \left(\frac{141117 - 141123}{141117}\right) \times 100 = 0.00425\%$$

The results indicate a relative error of only 0.00425%, demonstrating an almost perfect alignment between the actual values and those simulated by the DT model. This exceptionally low value confirms the model's validity and suggests that it can be reliably used for analysis and predictions. The high accuracy achieved shows that the differences between the theoretical model and experimental data are negligible, requiring minimal further adjustments. However, for comprehensive validation, testing the model under various scenarios is essential to assess its robustness across different operating conditions.

The bar chart divides machine states into multiple categories, such as Working properly (green), Waiting for elements (yellow), Thus, in the report shown in Fig. 5, the waiting and operating times of the equipment can be observed. According to the analysis, the bottleneck is represented by Banding_90, as the upstream and downstream equipment experience reduced operating times due to the processing carried out by this machine, the machine's downtimes vary based on shift time. The report confirms that the critical point identified in the VSM corresponds with the one in the simulation. This indicates again that the real world system aligns perfectly with the digital model.

Horizontal_CNC_milling operates 10.24% of the time, remains idle for 89.76%, Cleaning_and_Deburring operates 12.38% of the time, remains idle for 87.62%.

Banding_90 operates 25.65% of the time, remains idle for 74.35%.

Cleaning_turns operates 13.26% of the time, remains idle for 86.74%.

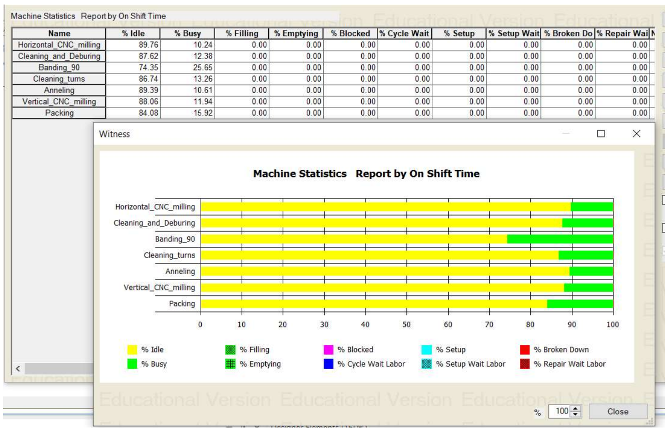
Annealing operates 10.61% of the time, remains idle for 89.39%.

Vertical_CNC_milling operates 11.94% of the time, remains idle for 88.06%.

Packing operates 15.92% of the time, remains idle for 84.08%.

Having conducted a thorough analysis of the entire process and having identified the bottleneck as well as the key critical point obstructing the efficient operation of the system, the next step involves optimizing and enhancing the system's efficiency. This will be achieved by evaluating whether the proposed solution effectively reduces waiting times and, consequently, improves overall delivery time.

Thus, for the equipment with the highest processing time, Banding 90, a 10% reduction in processing time will be applied, lowering its CT from 58 minutes to 52.2 m. The functional remodeling new obtained flow can be seen in Fig. 6, while the updated report on processing times is presented in Fig. 7.



Machine Statistics Report by On Shift Time

Name	% Idle	% Busy	% Filling	% Emptying	% Blocked	% Cycle Wait	% Setup	% Setup Wait	% Broken Do	% Repair Wai
Horizontal_CNC_milling	89.76	10.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Cleaning_and_Deburing	87.62	12.38	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Banding_90	74.35	25.65	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Cleaning_turns	86.74	13.26	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Anneling	89.39	10.61	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Vertical_CNC_milling	88.06	11.94	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Packing	84.08	15.92	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Fig. 6. Production line simulation.

The delivery time was improved by 2.56% as a result of lowering the total processing time from 141,117.6 m to 137,504 m.

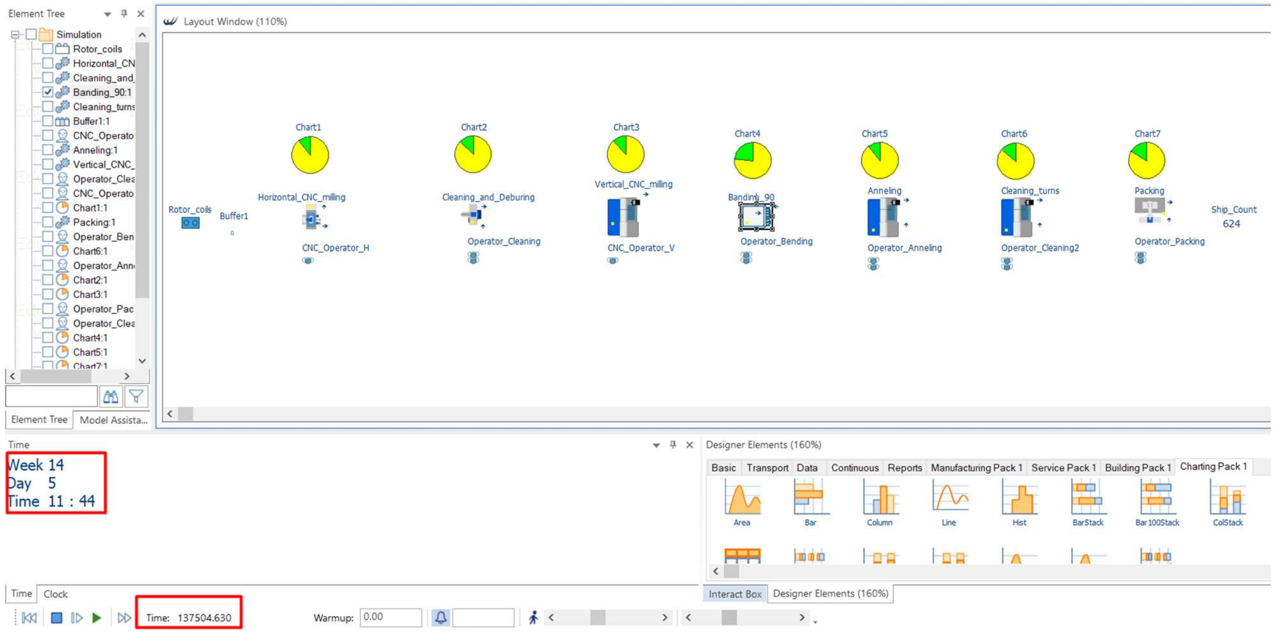
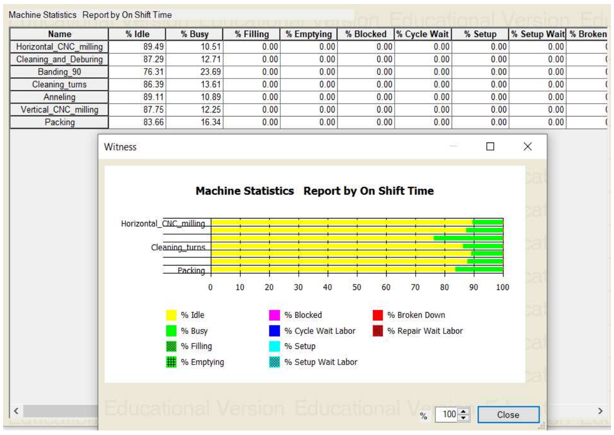


Fig. 7. Report for Equipment (RF).



Machine Statistics Report by On Shift Time

Name	% Idle	% Busy	% Filling	% Emptying	% Blocked	% Cycle Wait	% Setup	% Setup Wait
Horizontal_CNC_milling	89.49	10.51	0.00	0.00	0.00	0.00	0.00	0.00
Cleaning_and_Deburing	87.29	12.71	0.00	0.00	0.00	0.00	0.00	0.00
Banding_90	76.31	23.69	0.00	0.00	0.00	0.00	0.00	0.00
Cleaning_turns	86.39	13.61	0.00	0.00	0.00	0.00	0.00	0.00
Anneling	89.11	10.89	0.00	0.00	0.00	0.00	0.00	0.00
Vertical_CNC_milling	87.75	12.25	0.00	0.00	0.00	0.00	0.00	0.00
Packing	83.66	16.34	0.00	0.00	0.00	0.00	0.00	0.00

Fig. 8. Production line simulation (RF).

The improvements following the optimization are as follows:

Horizontal_CNC_milling now operates 10.51% of the time, compared to 10.24% previously, showing an improvement of 0.27%. The waiting time has decreased from 89.76% to 89.49%.

Cleaning_and_Deburring now operates 12.71% of the time, compared to 12.38% previously, showing an improvement of 0.33%. The waiting time has decreased from 87.62% to 87.29%.

Banding_90 now operates 23.69% of the time, compared to 25.65% previously. However, the waiting time has increased from 74.36% to 76.31%.

Cleaning_turns now operates 13.61% of the time, compared to 13.26% previously, showing an improvement of 0.35%. The waiting time has decreased from 86.74% to 86.39%.

Annealing now operates 10.89% of the time, compared to 10.61% previously, showing an improvement of 0.28%. The waiting time has decreased from 89.39% to 89.11%.

Vertical_CNC_milling now operates 12.25% of the time, compared to 11.94% previously, showing an improvement of 0.91%. The waiting time has decreased from 88.06% to 87.75%.

Packing now operates 16.34% of the time, compared to 15.92% previously, showing an improvement of 0.42%. The waiting time has decreased from 84.08% to 83.66%.

Most of the processes have shown a decrease of the waiting time and an increase in the operating time, with the exception of Banding_90, which saw a slight increase in waiting time. These improvements suggest a more efficient operation overall.

V. Limitations and Future Work

While the proposed methodology for implementing a DT in the rotor coil manufacturing process demonstrates high accuracy and practical viability, several limitations must be noted. The current DT model, built on a static representation of the production environment, does not reflect real-time variations such as operator availability, equipment failures, or supply chain disruptions. Although the relative error is very low (0.00425%), the simulation assumes constant processing conditions and uniform CT, which may not be realistic in dynamic contexts. Scalability is also a concern, as applying the approach to other systems—particularly those with high variability—would require extensive reparameterization. Moreover, the model's fidelity depends heavily on the availability and accuracy of real-time data, which may not be feasible in all manufacturing settings. Maintaining the DT over time is another challenge, as it must be continuously updated to reflect changes in equipment, workflows, or business objectives. Future work should address these issues by integrating dynamic IoT-based sensor data and adaptive machine learning algorithms to enhance real-time responsiveness and predictive accuracy.

VI. Conclusion

This study demonstrates the efficiency of implementing the Digital Twin (DT) concept in optimizing rotor coil manufacturing for high-power generators within the Industry 4.0 paradigm. DT technology enables the creation of a virtual replica of a real system which, by integrating real-time data, supports simulation, forecasting, and optimization of industrial processes with minimal costs and resources. Using the VSM method and a digital model of the production line, bottlenecks and inefficiencies were identified, offering a clear view of processes that generate downtime and waste. This mapping served as the basis for developing the DT and simulating the coil manufacturing process to optimize performance.

The created digital model was validated by comparing experimental data from the real system with simulation results, yielding an extremely low relative error of 0.00425%, which confirms an excellent match between model and reality. Through simulations, the "Banding_90" process was identified as the main bottleneck, having the highest CT. Reducing its CT by 10% resulted in a 2.56% improvement in delivery time.

Implementing the DT not only revealed process weaknesses but also allowed testing of future scenarios and assessing the impact of changes on system performance. This led to better resource allocation, reduced operational risks, and improved product quality, contributing to a faster and more sustainable production flow. In the long term, applying the presented methodologies can significantly impact the manufacturing industry, enabling more efficient and flexible processes. Combining DTs with other Industry 4.0 technologies, such as IoT and Big Data, could transform industrial process management, ensuring stronger alignment between digital and physical systems.

In conclusion, DT is a powerful tool for optimizing industrial processes—identifying and eliminating inefficiencies, shortening delivery times, improving resource utilization, and boosting overall performance. This research highlights the value of a clear methodological framework for DT implementation to address modern production challenges and advance digital transformation in industry. Certain operational parameters and layout details were anonymized to preserve confidentiality without affecting the accuracy or validity of the results.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Scarlat Andrei Daniel: Methodology, writing-original draft preparation, data analysis, the creation of the digital model and its functional redesign; Popa Cicerone Laurentiu and Florina Chiscop: Contributed to writing-original draft preparation, data analysis, supervision; Cotet Costel Emil and Parpala Radu: Conceptualization, methodology, supervision; all authors had approved the final version.

References

[1] F. Tao and M. Zhang, "DT shop-floor: A new shop-floor paradigm towards smart manufacturing," *IEEE Access*, vol. 5, pp. 20418–20427, 2017.

[2] I. C. Fantozzi, A. Santolamazza, G. Loy, and M. M. Schiraldi, "DTs: Strategic guide to utilize DTs to improve operational efficiency in industry 4.0," *Future Internet*, vol. 17, no. 41, 2025.

[3] B. Costa, J. Varejão, and P. D. Gaspar, "Development of a VSM to optimize the production process in a luxury metal piece manufacturing company," *Processes*, vol. 12, no. 1612, 2024.

[4] F. Chiscop, T. Aurite, and C. E. Cotet, "Manufacturing architecture diagnosis for a milling machine main shaft," *U.P.B. Scientific Bulletin*, vol. 73, pp. 185–194, 2011.

[5] J. F. Yao, Y. Yang, X. C. Wang, and X. P. Zhang, "Systematic review of DT technology and applications," *Visual Computing for Industry, Biomedicine, and Art*, vol. 6, no. 1, 2023.

[6] F. Tao, H. Zhang, A. Liu, and A. Y. C. Nee, "DT in industry: State-of-the-art," *IEEE Trans. Ind. Inform*., vol. 15, pp. 2405–2415, 2019.

[7] F. Caputo *et al*., "Product and process integrated design to enhance smart manufacturing systems," in *Proc. European Council for Modeling and Simulation, Caserta*, 2019, pp. 231–238.

[8] Q. Qi and F. Tao, "DT and big data towards smart manufacturing and industry 4.0," *IEEE Access*, vol. 6, pp. 3585–3593, 2018.

[9] S. Boschert and R. Rosen, *Impact of Future Digital Twins for Mechatronic Systems*, Springer International Publishing, 2016, pp. 249–265.

[10] M. Grieves and E. Y. Hua, *Defining, Exploring, and Simulating the DT Metaverses*, Springer Nature Switzerland, 2024, pp. 1–31.