Digital twin for supply chain improvement: A case study of a building company

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Abstract. In the realm of supply chain management, the rapid progression of digital technology has introduced many of challenges and opportunities. One challenge is the effective monitoring and optimization of physical assets and processes in real-time. The specific problem this research aims to address is the enhancement of supply chain performance, particularly focusing on the quality rate, a critical performance metric. To tackle this issue, we employed the digital twins, virtual replicas of physical entities, with the help of simulation models software. The research question of the study is how can a comprehensive supply chain model, informed by digital twins, be used to analyze and improve the quality rate. Through extensive simulation experiments, we test various scenarios, including reconfiguration of supply chain elements. The results show the potential for quality rate enhancement through strategic changes and provide actionable recommendations for decision-making in supply chain management based on simulation outcomes.

Keywords: Supply Chain Management, Digital Twins, Quality Rate, Simulation.

1 Introduction:

In the context of contemporary supply chains, their dynamic and complex nature calls for sophisticated strategies for surveillance, analysis, and enhancement. Conventional approaches often prove inadequate in addressing the complexities and real-time requirements of present-day global supply networks. An emerging solution is the digital twin, a virtual representation of physical processes and assets, which facilitates real-time data union and exhaustive analysis. By establishing a digital equivalent of a physical supply chain, organizations can simulate, forecast, and optimize operations, leading to notable performance enhancement.

Despite the promising potential of digital twins, a specific problem remains insufficiently explored which is their pragmatic application in improving key supply chain performance indicators, such as the quality rate. The quality rate is a pivotal metric influencing customer satisfaction, and operational expenses. Moreover, the quality rate is closely linked to other KPIs such as cycle time, and overall equipment effectiveness (OEE). By optimizing the quality rate, we indirectly influence these related KPIs, creating a ripple effect that enhances overall supply chain performance. However, multiple existing studies lack in-depth, practical demonstrations of how digital twins can be employed to improve this metric. Addressing this gap can offer valuable insights for supply chain managers aiming to enhance quality control and operational efficiency.

In order to address this issue, this paper suggests a method to model a supply chain using Arena simulation software. The digital twin will mirror the supply chain processes, enabling thorough analysis and experimentation. By executing simulation experiments, we aim to assess the impact of various process enhancements and configurations on the quality rate. This approach provides a controlled environment to test hypotheses and observe the potential outcomes of different strategies without causing disruptions to actual operations.

This research centers on the following question: How can deploying a digital twin, modeled in Arena, ameliorate the quality rate in a supply chain, and which specific alterations yield the most substantial improvements? We suggest that strategic modifications informed by the digital twin model will significantly enhance the quality rate. The outcomes of this study are anticipated to offer actionable insights into process enhancements and supply chain configurations that can drive higher performance.

The structure of this paper is organized as follows. Initially, we present a literature review encompassing the concept of digital twins and their role in supply chain management. Subsequently, we detail our methodology, including the design of the supply chain model in Arena. We then delineate the simulation experiments conducted, presenting the outcomes of the baseline scenario and various improvement scenarios. Following this, we discuss the results, underscoring key findings and their implications for supply chain management. Finally, the conclusion, in which we propose areas for future research.

2 Literature review:

[1] highlight significant gaps in the research on Digital Twins (DTs) in supply chains, particularly when compared to their application in production systems. The results indicate that DTs in supply chain management (SCM) have not advanced to the same level of autonomous control as those in production, which are moving towards fully autonomous systems. Additionally, there is a noted lack of development in shared DTs, which are still in their infancy. This gap suggests that while industrial examples of DTs are being implemented, comprehensive validation is still lacking. The perspective taken

in the research acknowledges the manifold purposes of DTs, such as visibility, optimization, prediction, and simulation, but points out that a holistic approach integrating these purposes is rare. This limitation offers sufficient opportunities for future research and development, particularly in creating DTs that provide comprehensive, integrated services and validating their effectiveness through real-world applications.

In their paper, [2] conducted a literature review on DTs for logistics and supply chain systems (LSCS). They developed a conceptual framework for DTs in LSCS, aiming to facilitate effective, efficient, transparent, and timely decision-making. Their framework focuses on three dimensions: hierarchy levels, layers, and life cycle and value stream. The authors identified gaps in the current research and practical implementations, proposed a new conceptual DT framework to address these gaps, and discussed the potential research opportunities and practical challenges. They also outlined future steps to deploy transparent, trustworthy, and resilient DTs for LSCS, emphasizing the need for advanced analytics and modeling techniques to meet the new framework's requirements.

[2] outlined several steps to build transparent, trustworthy, and resilient DTs. They emphasize integrating data-driven and data-informed value methods, where high-quality data collection, secure communication, and advanced modeling techniques are employed for decision-making. Enhancing operational and human excellence is crucial, with a focus on improving data processing and ensuring employees make informed decisions based on DTs insights. Strengthening internal communication and data security and developing reliable interpretation techniques to convert data between machine-readable and human-readable formats is vital. Finally, establishing strategies for the ongoing maintenance and management of the DTs system is essential to sustain its operations, address technology updates, and integrate new methods and techniques.

On the other hand, the paper by [3] is a systematic literature review that examines the integration of DTs and Physical Internet (PI) in SCM. The authors used a bibliometric knowledge mapping approach to analyze 518 journal articles, identifying ten key research streams: job shop scheduling, smart manufacturing design, PI-based SCM, manufacturing virtualization, information management, sustainability development, data analytics, manufacturing operations management, simulation and optimization, and assembly process planning. They also detected research frontiers and emerging trends, including production processes and systems, robotics, computer architecture, and cost. The study suggests seven future research directions, emphasizing PI/DTs-related issues such as business ecosystems, sustainability, downstream SC management, cognitive thinking in Industry 5.0, citizen twins, and SC resilience. The aim is to provide a comprehensive overview of the current research status and guide future studies in this evolving field.

The papers collectively highlight the significant potential and necessity of DTs for enhancing supply chain operations. [1] emphasize that DTs provide better visualization, analysis, simulation, and optimization opportunities for supply chains, although the research environment is currently unorganized and lacks a clear focus. [2] identify several practical challenges in DTs implementation, such as data security and standardization, and propose a comprehensive framework to address these issues, suggesting that DTs can improve decision-making and operational excellence through advanced analytics and modeling techniques. [3] provide a systematic literature review and suggest future research directions to enhance the adoption and integration of DTs in SCM. These directions include developing business ecosystems, enhancing sustainability, building resilience, focusing on downstream applications, integrating cognitive thinking, and managing costs.

In their paper, [4] clarify the differences between DTs and simulation technologies, which are often confused or used interchangeably despite having distinct capabilities and purposes. The authors propose two frameworks to categorize and better understand these technologies: the 4R framework for DTs and the 4S framework for simulation.

The 4R framework consists of four levels of capability for DTs, each representing an increasing level of sophistication and integration. The initial phase, Representation (R1), focuses on understanding the behavior of the physical system and creating a system for data collection and storage from the physical environment. The next phase, Replication (R2), involves duplicating the system in a virtual environment using the data collected in the Representation phase, allowing the virtual model to replicate the physical system's outputs when given the same inputs. At the Reality (R3) level, the DTs is used to investigate what-if scenarios, with the goal of using results from virtual runs to influence the physical system. This phase involves real-time data collection and optimization. The highest level, Relational (R4), features full synchronization between the physical and virtual systems with bi-directional data flow. This phase incorporates decision-making technologies such as AI and machine learning, enabling the DTs to learn and adapt in real time.

The 4S framework categorizes simulation capabilities into four levels, aligning with the DTs capabilities to some extent but focusing more on the simulation aspect. The basic level, Modeling (S1), involves a simulation model that virtually represents a physical system using historical data. The Analyzing (S2) level allows the simulation to analyze the system by varying model inputs and structure to provide insights. Predicting (S3) simulations can predict the outcomes of the physical system under new and different conditions, allowing for scenario analysis and performance measurement. The highest level, Prescribing (S4), involves a simulation model that evaluates the system and provides optimal solutions or recommendations to improve system performance.

The authors highlight that while simulations create virtual models using historical data to analyze, predict, and prescribe solutions, they lack the real-time data integration and bi-directional communication that characterize DTs. DTs involve continuous data flow between physical and virtual environments, using real-time data for decision-making and system optimization.

DTs have emerged as a key concept in simulation, driven by the need to manage the life cycle of complex systems. Digital twins are virtual replicas of real-world entities, offering a multidimensional perspective that integrates both the physical and informational aspects of systems. This fusion of the physical and virtual worlds is central to the ongoing industrial and social transformation globally. [5] In one of his presentations, Professor Mickael Grieves, the founder of the concept of DTs, discussed the potential of using virtual replicas of real systems to represent the various phases of their increasingly complex industrial life cycles. The goal of this information modeling, based on domain-specific and multidimensional models was to simulate the life cycle development of physical systems within their environments. These simulations would not only apply in the virtual world but, more importantly, enhance the system with evolving intelligence. This intelligence, powered by data received from the field, historical data, and future simulations, would allow the system to respond to various constraints such as quality, maintenance, and production. [6] [5] The "Digital Master" encompasses the initial stages of a complex product's life cycle to which the digital twin is associated. It involves all relevant data and information about the product, including its technical specifications, development foundations, management and commissioning procedures, deployment environment, internal structure, and interactions with stakeholders. After the product is deployed, it generates extensive operational data within its environment and through interactions with users. The "Digital Shadow" then gathers this data to provide an accurate, real-time representation of the system, minimizing communication errors between the physical and virtual worlds. This shadow uses both current and historical data to offer a clear view of the physical environment and system performance. It models ongoing, potential, past, and desired future scenarios, including performance targets set by stakeholders. The final level, the digital twin, builds on the information from the previous levels, adding a proactive layer that enhances the system's intelligence and responsiveness based on the data and outcomes from earlier stages. [7] [5] Thus, digital twin is mainly a simulation-based, integrated multiphysics and multidimensional model of a product-system, capable of representing mechanical, electrical, software, and other discipline-specific properties throughout the entire product lifecycle. [8] [5]

Several studies have aimed to establish a generic conceptual framework for digital twins, capable of overcoming the challenges posed by deploying them in critical areas that demand a more thorough exploration of the multidimensional nature of modern complex systems in industry [9] [5]. These efforts have resulted in the creation of various digital twin models that incorporate new elements, merging digital twins with technologies from digital transformation to develop and implement a hybrid and adaptive structure [10] [5].

The reviewed literature highlights the significant potential and necessity of DTs for enhancing supply chain operations, and addressing various gaps and challenges in their implementation. Incorporating DTs in supply chains is essential due to their ability to connect real and virtual spaces, enabling real-time monitoring, predictive maintenance, and proactive risk management. This integration enhances efficiency, flexibility, and resilience, allowing supply chains to adapt to disruptions and optimize operations through data-driven insights and simulations. Addressing current gaps and leveraging advanced technologies will transform supply chains into intelligent, responsive, and sustainable systems, ultimately improving performance metrics like the quality rate as it directly impacts customer satisfaction, operational expenses, and overall supply chain performance. Effective quality management ensures the production of high-quality products, minimizing waste, rework, and repair costs before delivery to customers. This, in turn, enhances customer satisfaction by consistently meeting or exceeding customer expectations for product quality. Additionally, a high-quality rate contributes to improved operational efficiency and reduced costs, which are essential for maintaining competitiveness in the global market. The emphasis on quality performance measurement systems, integrating both financial and non-financial criteria, is crucial for organizations to monitor, evaluate, and continuously improve their quality management processes. By focusing on key performance indicators such as defect rates, on-time delivery, and customer feedback, companies can identify areas for improvement and implement strategies to enhance their overall supply chain performance. Therefore, the quality rate serves as a vital indicator for assessing the effectiveness of supply chain operations and driving continuous improvement efforts. [11]

3 Methodology:

3.1 Problem design:

The first step consists of defining the specific problem to be addressed, focusing on enhancing the supply chain performance. This involves identifying the key performance metrics and setting clear objectives for the study.

3.2 Data collection:

In this step, we gather the necessary data for developing the DTs model. This includes collecting operational data such as the execution time of each process, the number of resources, and the number of defects.

3.3 Process mapping or representation (R1):

In the third phase, we model the entire supply chain process to understand the behavior of the physical system. This involves creating a detailed representation of supply chain operations.

3.4 Simulation model development or the first part of replication (R2):

This step involves developing a detailed simulation model that accurately replicates the physical supply chain using the data collected. This model should mirror the supply chain processes, enabling thorough analysis and experimentation.

3.5 Testing with fictional data or second-part of replication (R2):

In this step, we run the simulation model with various scenarios using fictional data to test the impact of different process enhancements and configurations on the quality rate. This phase aims to explore potential improvements and optimize the supply chain without affecting real operations.

3.6 Implementation and validation with real data or reality (R3):

In the last step, we implement the optimized strategies identified in the simulation experiments using real data from the actual supply chain. Continuously synchronize the physical and virtual systems with bi-directional data flow, allowing real-time monitoring and adaptation.

4 Case study:

4.1 Problem design:

The specific problem we aim to address is the enhancement of supply chain performance in a real-world building construction company based in Morocco, with a particular emphasis on improving the quality rate. To effectively tackle this issue, we will focus on indicators such as the execution time of each process, the number of resources, and the number of defects. The unit's process of the building construction company involves several stages, it begins with the transportation and preparation of raw materials, specifically cement and aggregates. Once the order is received, the quantities of cement and aggregates are measured and stored. In the manufacturing phase, these materials are mixed, homogenized, and transferred to a hopper. The mixture is pressed and compacted, and the mold is moved to form concrete products. Ejection and initial quality control follow, separating compliant products from non-compliant ones. The compliant products are transported for batch arrangement and drying. After drying, the semi-finished products are transferred to the palletizing area, where they undergo visual control, and finalization, and are then prepared for delivery. The entire process involves multiple stages of material handling, mixing, pressing, quality control, and transportation to ensure the production of high-quality concrete products.

4.2 Data collection:

Based on a significant period in the company, we successfully gathered a substantial amount of data concerning the treatment time for each process, as well as the values of various action and evaluation indicators. This data was meticulously recorded using daily data collection sheets. These sheets provide detailed insights into the operational performance and efficiency of different stages within the supply chain. The collected data includes metrics such as the execution time of each process, the number of resources, and the number of defects, machine downtime, the different types of delays, and other relevant performance indicators. This comprehensive dataset will be instrumental in feeding our simulation system, enabling us to create an accurate and dynamic digital twin model. This model will allow us to analyze the current processes, test various scenarios, and identify optimal strategies for improving the quality rate and overall supply chain performance. (See Appendix 1)

4.3 Process mapping:

In this phase, we aim to map the entire supply chain process to gain a comprehensive understanding of the physical system's behavior. The figure in the appendix 2 is an activity diagram constructed using Unified Modeling Language (UML) to illustrate the supply chain process of a unit named Unit 4 in the building construction company.

The diagram outlines key stages such as raw material preparation, manufacturing, quality control, and delivery. It starts with the initiation process, detailing the transportation and measurement of cement and aggregates. The manufacturing phase includes steps like mixing ingredients, homogenization, hopper opening, pressing and compacting, and mold movement. Quality control is performed to separate compliant products from non-compliant ones, leading to the transport and arrangement of conforming products, drying, palletization, and final delivery. This activity diagram highlights the flow of both physical materials and information, providing a clear visualization of the entire supply chain process.

4.4 Simulation model development:

The initial step involved transforming the UML activity diagram of the supply chain process into a simulation model using Arena software. This transformation is detailed in Appendix 3, where the UML model serves as a blueprint for the simulation. The Arena model captures the entire supply chain process, including the transportation and preparation of raw materials, manufacturing steps, quality control procedures, and final product delivery. Each process is meticulously represented in the simulation to reflect real-world operations accurately. This simulation model facilitates in-depth analysis and experimentation, allowing for evaluating various process configurations and their impact on performance metrics such as the quality rate.

The simulation model begins with the raw material preparation stage, where aggregates and cement arrive and are transported to storage areas. At this point, the aggregates and cement are measured and the aggregates are stored before being used in the production process. In the next phase, orders are received and processed, triggering the measurement and batching of aggregates and cement. These materials are then mixed to prepare the raw material for manufacturing. In the manufacturing process, the mixed materials undergo homogenization and are transferred to the hopper. The mixture is then pressed and compacted into molds, followed by mold movement, then the positions of molds are checked, and ejection is executed for quality control. During the quality control phase, an initial quality control is conducted. Semi-finished products are then assigned for further processing or rejection based on quality checks. In the transportation and drying stage, semi-finished products are transported, dried, and prepared for the final stages. The final steps are palletization and finalization, where dried products are palletized and subjected to visual control before being finalized and prepared for delivery.

4.5 Testing with fictional data:

To verify the functionality of the developed simulation model, we conducted a series of tests using a comprehensive set of fictional data. This step was crucial to ensure that the model operates correctly and produces reliable outputs. The fictional data encompassed various scenarios, including different execution times, duration of transport, and number of resources, reflecting a range of potential real-world conditions. By running these scenarios, we tested the model's robustness and its ability to handle diverse inputs and process flows. The results demonstrated that the simulation model accurately mirrored the expected outcomes, validating its effectiveness and readiness for further experimentation with real-world data.

4.6 Implementation and validation with real data:

In this final phase, we transition from simulation testing with fictional data to implementing the simulation model using actual operational data. This step is crucial for ensuring that the digital twin model accurately reflects and improves real-world supply chain performance.

We began by applying the Arena simulation model to real-world data collected from the building construction company. This model was carefully calibrated to replicate the actual timings of processes and the number of resources used in the production chain. By integrating real data, we ensured that the simulation mirrored the true operational environment, providing a realistic foundation for testing and optimization.

To enhance the model’s effectiveness, we utilized OptQuest, an optimization tool within Arena, to identify the optimal configuration of system variables that would maximize the quality rate. The quality rate was defined as follows:

$$\text{Quality Rate} = \text{Inspection Accuracy} \times (\text{Good Pieces}/\text{Total Pieces}) \qquad (1)$$

In the Arena model, quality control was managed through two key checkpoints. Products were directed either toward rejection or further processing based on these checkpoints. This approach ensured that non-compliant products were effectively filtered out, and only those meeting quality standards proceeded through the production process. Furthermore, implementing the model with real data significantly enhanced its accuracy and relevance. By aligning the simulation with actual operational metrics, we ensured that the optimization insights generated by OptQuest were applicable to real-world scenarios. This alignment is crucial for validating the model’s effectiveness in a practical setting. The application of OptQuest revealed that the highest achievable quality rate was 88.75%. This result was derived from analyzing 25 different feasible solutions, each representing various configurations of system variables. Key variables such as defect detection rate, inspection accuracy, and resource allocation were pivotal in achieving optimal performance. The consistency of certain settings across optimal solutions—such as the balance, conveyor, descender, hopper, and others underscore their importance in the system's performance. For instance, a balance setting of 2 was found to be crucial for maintaining high quality, indicating its significant role in the optimization process. Similarly, high defect detection rates and inspection accuracy were essential for achieving superior quality outcomes.

In this study, the bidirectional data flow between the DTs and the physical supply chain process is integral to enhancing supply chain performance. Real-time data from the physical process, including execution times, defect counts, and other performance indicators, were collected using observing process timings and recording metrics on sheets, which provided detailed insights into those indicators. This collected data is used to create a dynamic simulation model within the digital twin, reflecting the actual operations of the supply chain. This data enables the digital twin to create a dynamic and accurate simulation model of the supply chain. The model utilizes this input to analyze current processes, identify inefficiencies, and generate recommendations for improvement.

Once the digital twin identifies potential enhancements, these recommendations are sent back to the physical system. When the model suggests adjustments to the defect detection rate or changes in resource allocation, these adjustments are applied in the real-world production environment. The system then gathers feedback on the impact of these changes, including any improvements in the quality rate or process efficiency. This feedback is continuously fed back into the digital twin, which updates its simulations and recommendations accordingly. This iterative process ensures that both the digital and physical systems remain synchronized, facilitating ongoing optimization and real-time adjustments to improve overall supply chain performance. Figure 1 presents the **b**idirectional data flow between the physical process and the digital twin system.

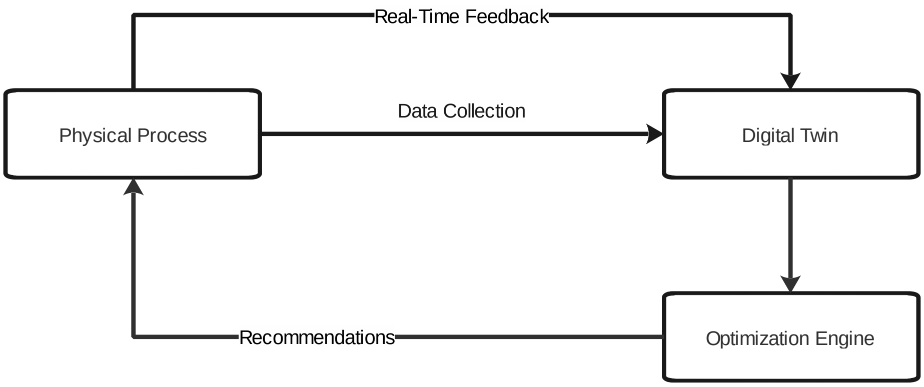

Fig. 1. Bidirectional data flow in the Digital Twin system

The figure illustrates the bidirectional data flow between the physical process, digital twin, and optimization engine within the supply chain system. Data is initially collected from the physical process, capturing real-time operational metrics, which are then fed into the digital twin. The digital twin simulates the physical process and, through the optimization engine, generates recommendations for process improvements. These recommendations are returned to the physical process, where adjustments are made, creating a continuous loop of real-time feedback and optimization. This dynamic interaction ensures that the physical process is constantly refined and optimized based on real-time data and advanced simulations.

In this phase, the application of the digital twin model extends beyond traditional simulation by incorporating real-time data synchronization and iterative feedback loops. Unlike a static simulation, the digital twin dynamically mirrors the physical supply chain, reflecting real-world changes and operational nuances. This approach allows for continuous alignment between the virtual and physical systems, enabling real-time monitoring and adjustment of processes based on actual performance data. The integration of the digital twin with real data ensures that optimization strategies are not merely theoretical but are actively refined and validated through ongoing interaction with the physical system. This capability of real-time adaptation and feedback distinguishes the digital twin from conventional simulation, providing a more robust and responsive framework for enhancing supply chain performance.

5 Discussion and results:

In this paper, we have explored the optimization of a supply chain system using a digital twin model integrated with discrete event simulation. Initially, we constructed a detailed process modeling of the supply chain operations within a building company. This involved simulating the real timings and resources for each process using Arena simulation software. We implemented a comprehensive model that included two quality control checks and various decision points, ensuring that non-compliant products were rejected while compliant products continued through the production line. Subsequently, we utilized OptQuest to identify the optimal combination of variables that maximized the quality rate. The analysis focused on understanding the influence of key variables on the quality rate and highlighted the most critical factors contributing to the system's performance. This study demonstrates the potential of digital twin technology and advanced simulation techniques in enhancing supply chain efficiency and product quality.

The results of this study indicate that the application of OptQuest on the Arena simulation model effectively identified the optimal combination of variables that maximizes the quality rate of the supply chain processes. The optimization process revealed that a combination of 22 different variables, including balance, conveyor, defect detection rate, descender, ejector, elevator, hopper, inspection accuracy, inspection time, machine scrap rate, mixer, operator 1,2, 3, 4, 5, 6 and 7, pallet, qc process efficiency, screw pump, skip, consistently led to the highest achievable quality rate of 88.75% in 25 optimal combinations of results.

The balance variable is consistently set to 2 in all the optimal solutions. Given that the balance has only two potential settings, 1 or 2, this uniformity indicates that maintaining a balance of 2 resources is crucial for achieving the highest quality rate. Any deviation from this setting might result in a lower quality rate, highlighting its significant influence. The conveyor's value is fixed at 2 across all optimal runs, illustrating that, a setting of 2 is necessary to achieve the best quality outcomes. Similarly, the descender, hopper, operators (1 to 7), and screw pump are consistently set at 2, indicating that maximum resource allocation is essential for optimal performance. This pattern also holds for the ejector, pallet, elevator, skip, and mixer, all of which require a setting of 2 to reach the highest quality rate, underscoring their significant impact on the system's efficiency.

The defect detection rate is uniformly high, close to 1.0 in the optimal solutions, with the lowest acceptable performance benchmark set at 0.75, reflecting its critical role in maintaining quality standards. Inspection accuracy is unwavering at 1.0 across all scenarios, affirming its pivotal role in achieving the highest quality rate. The inspection time is consistently set between 4.2 and 4.4, suggesting a significant impact on quality outcomes, considering that the range of this variable is between 3.6 and 4.4. The machine scrap rate, while varying from 0.01 to 0.1 as possible values, is set at 0.1, showing that this variable does critically influence the quality rate. The QC process efficiency shows some variability in the optimal solutions, ranging from 0.91 to 1.0, indicating that this variable is very crucial to achieve a higher efficiency level, and the system will perform optimally within this range.

While the case study presents a detailed simulation of the manufacturing process within an existed building construction company in Morocco, it also underscores a significant advancement in the application of DTs in supply chain management. Unlike traditional simulation models, which often rely on static representations and theoretical data, this study integrates a dynamic digital twin that continuously synchronizes with real-time operational data. This innovative approach not only enhances the accuracy of the simulation but also introduces a novel methodology for real-time process optimization and feedback. The originality of this work lies in its practical application of digital twin technology, which has been underutilized in SCM, particularly in the context of manufacturing quality improvement. By leveraging a digital twin to iteratively refine and validate supply chain processes, this study fills a gap in existing research and demonstrates a unique contribution to the field. The integration of real-time data and continuous feedback into the simulation model represents a pioneering step towards more adaptive and responsive SCM solutions, thereby addressing the identified gap and offering a new perspective on the application of DTs in manufacturing processes.

This study addressed the challenge of enhancing supply chain performance with a particular emphasis on improving the quality rate, a critical performance metric. The problem identified was the lack of pragmatic application and comprehensive validation of digital twin technology in supply chain management to improve key performance indicators like the quality rate. Despite the promising potential of digital twins, the literature review highlighted significant gaps, such as the insufficient development of shared digital twins and the lack of real-world applications demonstrating their effectiveness. To bridge this gap, we employed a digital twin model integrated with discrete event simulation using Arena software.

The results demonstrated that maintaining high inspection accuracy, defect detection rate, and optimal resource allocation were crucial for achieving and sustaining high-quality standards. This comprehensive analysis and implementation of a digital twin model showcased the potential for significant improvements in supply chain performance. The study provides valuable insights and actionable recommendations for supply chain managers, highlighting the effectiveness of digital twin technology and advanced simulation techniques in optimizing quality control and operational efficiency. Thus, this research successfully addressed the identified gap and demonstrated the practical benefits of digital twins in enhancing supply chain performance.

This approach distinctly embodies the principles of digital twin technology, even though the framework has not yet been tested in real-time within the company's operational environment. Unlike traditional simulation, which often operates in isolation and is limited to pre-defined scenarios, the digital twin framework we developed is designed as an interactive, continuously evolving model that mirrors the physical system. The key differentiator of this approach lies in the integration of real-time data and the bidirectional flow of information between the physical process and its digital counterpart. While the current implementation uses historical and operational data to validate the model, the framework is built to dynamically adapt to live data, reflecting ongoing changes in the physical environment. This positions the digital twin as more than just a simulation tool; it is a virtual replica that evolves alongside the physical system, providing real-time insights and facilitating ongoing optimization. This capability elevates this model beyond traditional simulation, offering a more robust and responsive solution for supply chain management. While simulation is a key component of the digital twin, providing the analytical engine that models various scenarios and outcomes, the digital twin itself is characterized by its continuous interaction with the physical world. This interaction is facilitated through real-time data exchange, allowing the digital twin to reflect the current state of the physical system accurately and to adapt as changes occur in real time.

6 Conclusion

This study successfully demonstrated the application of digital twin technology integrated with discrete event simulation to enhance supply chain performance, with a particular focus on improving the quality rate. By constructing a detailed process model of a building company's supply chain and employing OptQuest for optimization, we identified the optimal combination of 22 critical variables that achieved the highest quality rate of 88.75%. Key variables such as inspection accuracy, defect detection rate, and optimal resource allocation were found to be crucial for maintaining high-quality standards. This research addressed significant gaps in the literature by providing a comprehensive and practical demonstration of how digital twins can be effectively utilized to optimize supply chain operations.

While this study has successfully demonstrated the application of a digital twin framework in enhancing supply chain performance through detailed simulations and iterative optimizations, it is important to note that the framework has not yet been tested in real time within the company's operational environment. The current research has primarily focused on modeling and validating the framework using historical and fictional data to ensure its effectiveness and feasibility. Moving forward, a promising avenue for future research involves deploying the framework in a live operational setting to assess its performance and adaptability in real-time conditions. Future research could explore the integration of artificial intelligence (AI) in the optimization process to further enhance the performance of digital twin models in supply chain management. AI algorithms could be employed to analyze larger datasets and identify more complex patterns, potentially leading to even higher quality rates and more efficient resource allocation. Finally, in future research, other key performance indicators, such as overall equipment effectiveness could be incorporated into the framework to provide a more comprehensive evaluation of supply chain performance.

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Appendix 1:

Table 1. Raw data of the process

Parameter Designation	Nature	Workstation	Source
Time Between Arrivals of aggregate arrival	Action	Raw material preparation	Environment
Time Between Arrivals of cement arrival	Action	Raw material preparation	Environment
Duration of aggregates transportation	Action	Aggregates transportation	Production
Number skip for aggregates transportation	Action	Aggregates transportation	Production
Duration of aggregate storage	Action	Aggregates storage	Production
Number hopper for aggregates storage	Action	Aggregates storage	Production
Execution time of aggregates measurement	Action	Aggregates measurement	Production
Number operator1 for aggregates measurement	Action	Aggregates measurement	Production
Duration of cement transportation	Action	Cement transportation	Production
Number of screw pump for cement transportation	Action	Cement transportation	Production
Execution time of cement measurement	Action	Cement measurement	Production
Number operator2 for cement measurement	Action	Cement measurement	Production

Number balance for cement measurement	Action	Cement measurement	Production
Batch aggregate Size	Action	Ingredient mixing	Production
Batch cement Size	Action	Ingredient mixing	Production
Execution time of homogenization	Action	Homogenization	Production
Number mixer for homogenization	Action	Homogenization	Production
Execution time of hopper opening	Action	Hopper opening	Production
Number quadra12 for hopper opening	Action	Hopper opening	Production
Execution time of pressing and compacting	Action	Pressing and compacting	Production
Number quadra12 for pressing and compacting	Action	Pressing and compacting	Production
Duration of mold movement	Action	Mold movement	Production
Number operator3 for mold movement	Action	Mold movement	Production
Execution time of the ejection	Action	Ejection	Production
Number ejector for ejection	Action	Ejection	Production
Duration of the quality control	Action	Quality control	Quality control
Number operator3 for quality control	Action	Quality control	Quality control
Duration of the transport-compliant products	Action	Transport compliant products	Production
Number of conveyors for transport-compliant products	Action	Transport compliant products	Production
Batch compliant products	Action	Transport compliant products	Production
Duration of transport of semi-finished products	Action	Transport semifinished products	Production

Number elevator for transporting semi-finished products	Action	Transport semifinished products	Production
Duration of the drying process	Action	Drying process	Production
Duration of transfer to palletizing area	Action	Transfer to the palletizing area	Production
Number descender for transfer to palletizing area	Action	Transfer to the palletizing area	Production
Duration of the visual control	Action	Visual control	Quality control
Number operator4 for visual control	Action	Visual control	Quality control
Execution time of the palletization	Action	Palletization	Production
Number pallets for palletization	Action	Palletization	Production
Execution time of the finalization	Action	Finalization	Production
Number operator5 for finalization	Action	Finalization	Production
Execution time of the expedition	Action	Expedition	Expedition
Number operator6 for expedition	Action	Expedition	Expedition
Duration of the rejected product	Action	Reject product	Production
Number operator7 for the rejected product	Action	Reject product	Production
Quality rate	Evaluation		Quality control
Defect detection rate	Action	Defect detection check (decide)	Quality control
Qc process efficiency	Action	Visual control	Quality control
Inspection time	Action	Visual control	Quality control
The inspection accuracy	Action		Quality control
the machine scrap rate	Action	The machine scrap rate (assign)	Quality control

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Appendix 2:

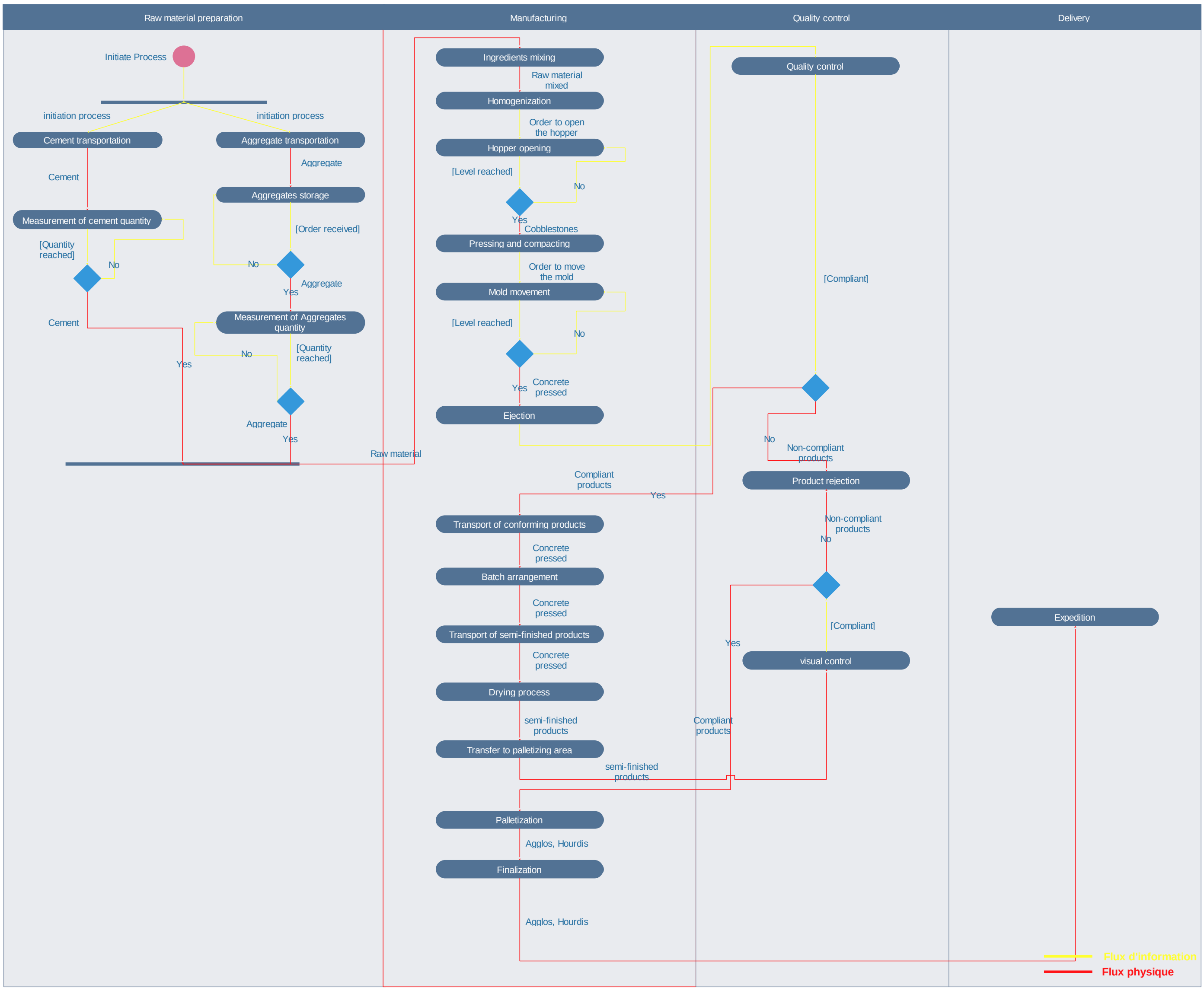

Fig. 2. UML Activity diagram

Appendix 3

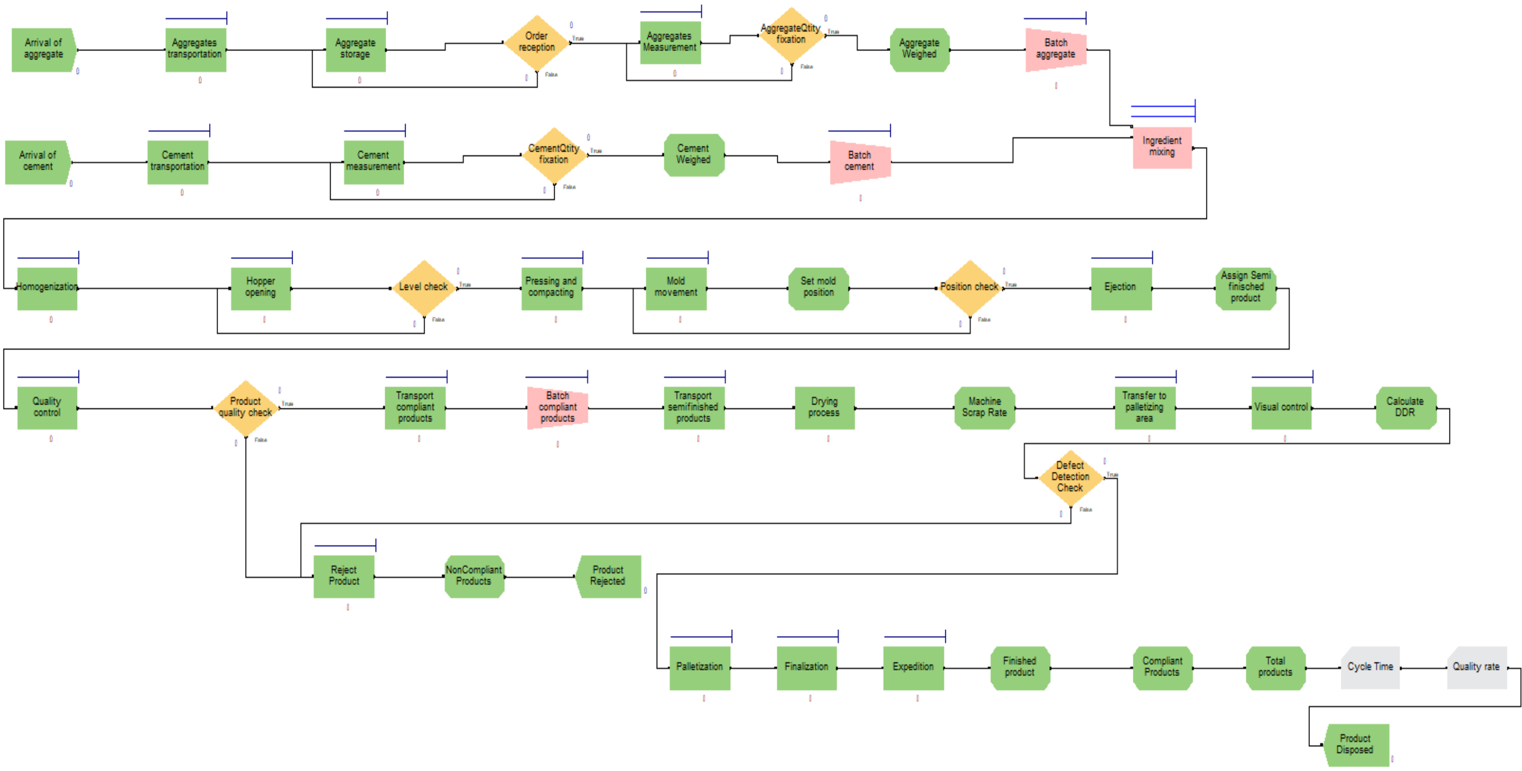

Fig. 3. Process flowchart with ARENA simulation.