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DIGITAL TWIN–BASED SMART MANUFACTURING FOR REAL-TIME PROCESS OPTIMIZATION

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A B S T R A C T

The fast development of Industry 4.0 has increased the pressure on smart manufacturing systems with the ability to monitor in real time, have adaptive control, and optimize the processes. Conventional manufacturing optimization strategies are typically based on the models that are not dynamic and the type of decisions emphasizing the offline approach; other words, they are not responsive to dynamic disturbances of the shop-floor, variability of production and tailor-made needs. In an attempt to solve these issues, digital twin technology has been proposed as a central facilitator of smart manufacturing since it provides a real-time, two-way alignment of the real production system with its virtual counterpart. The study will implement and simulate a digital twin-enabled smart manufacturing system to optimize processes in real-time through the use of real-time data collection and monitoring, intelligent analytics, and the enhancement of decisions. The suggested solution will involve a multi-layer digital twin design with artificial intelligence and optimization, such as heuristic algorithms, machine learning models, and reinforcement learning tooling, to dynamically model, simulate, and optimize manufacturing processes. The methodology includes integration of shop-floor sensors in real time, modeling of the virtual process, predictive analysis of performance and close loop optimization. The key manufacturing measures used to determine performance include production throughput, machine utilization, scheduling efficiency, energy consumption and mean tardiness. The results verify that smart manufacturing incorporating the digital twin allows proactive decision-making, prompt adjustments to the changes in the system, and the continuous optimization of the performance, which makes it a powerful and scalable solution in the next-generation intelligent manufacturing setting.

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1. INTRODUCTION

Smart manufacturing has become one of the foundations of the industrial change of the modern era, having been predetermined by the integration of cyber-physical systems with sophisticated analytics and real-time connectivity. The growing need of high customization of the products, shortening the time to market and efficient operations has forced manufacturing companies to shift out of the conventional automation and into the realm of intelligent and data based production. In this context, Industry 4.0 facilitates the smooth combination of physical resources and computer technologies to facilitate adaptive and self-improving manufacturing (Lu et al., 2020). The process of digital transformation has also highlighted the significance of having continuous monitoring and smart decision-making among production lifecycles (Attaran et al., 2023). Although these developments have been made, traditional methods of manufacturing optimization still show a lot of weaknesses. The conventional scheduling, planning and optimization methods tend to have a fixed model basis and offline calculation sometimes limiting their capacity to respond effectively to real time perturbations, machine failures as well as demand variations (Abdelmaguid et al., 2004). The heuristic- and rule-based optimization approaches, despite their low computational complexity, are not flexible and scalable to the complex manufacturing scenarios (Deepika Reddy et al., 2023). On the same note, the classical mathematical programming methods have challenges with uncertainty, high dimensionality, and real-time in the smart manufacturing systems (Medina-Gonzalez et al., 2021).

Digital twin technology has received significant popularity as a transformative enabler in Industry 4.0, which provides a virtual model of actual manufacturing industries that constantly changes due to the real-time synchronization of data. Digital twins promote greater visibility, predictive analysis and what-if simulation in design, planning, and operational phases. Digital twins can facilitate real-time updating of the performance of manufacturing processes and optimize it reactively by linking physical assets of the shop-floor with virtual models of high fidelity (Barni et al., 2020). The recent research has proven that digital twin-based frameworks can be used to provide efficiency in flex-factory manufacturing systems and optimization of production lines (Lee et al., 2022). Digital twin can be further enhanced with the integration of artificial intelligence and machine learning that can provide intelligent analytics and predictive maintenance, as well as autonomous decision support (Sheuly et al., 2022). Deep reinforcement learning-based digital twins are advanced methods that have demonstrated potential in dealing with process optimization during uncertainty (Khdoudi et al., 2024). Furthermore, the use of digital twins is becoming more and more supportive of human-centered and sustainable manufacturing paradigms based on real-time feedback and personalization (Crnjac Zizic et al., 2025).

The focal point of the current study is the creation of a digital twin-based smart manufacturing system that can assist in optimization of processes in real-time by implementing smart and data-driven decisions. It has contributed to the incorporation of real-time data capture, modeling of virtual processes as well as AI-based optimization of manufacturing to make it more responsive, efficient and resilient, which bridges significant gaps in the current smart optimization strategies in manufacturing (Nguyen et al., 2025).

2. RELATED WORK

Digital twins are generally described as high-fidelity virtual models of physical systems which are continuously updated by exchanging real-time data. Digital twins are a persistent connection with physical assets, unlike the static simulation models, which allow the monitoring, prediction, and optimization of the system lifecycle. Recent sources acknowledge that digital twins are characterized by such important properties as the two-way nature of the data flow, synchronization of states in real-time, and predictive analytics, which make them unique compared to traditional digital models Moiceanu and Paraschiv (2022). Digital twins are considered more as intelligent decision-support objects instead of mere visualization tools in the framework of smart manufacturing, which contributes to dynamic adaptation and operational intelligence (Sheuly et al., 2022). Digital twins have been further mentioned as the basis of intelligent and autonomous manufacturing ecosystems presented in systematic reviews (Barbosa et al., 2022). Digital twin architecture and lifecycle models have gained substantial progress in the literature in order to cope with the complexity of manufacturing systems. The majority of architectures are designed in a multi-layered format that is physical, virtual, data and service which guarantees smooth integration between system elements. Digital twin models that are designed with lifecycle orientation assist in ongoing development of design and commissioning towards operation and maintenance, allowing a sense of closed-loop optimization through the stages of production (Ebni et al., 2023). According to case-based studies, lifecycle-aware digital twins can be utilized to provide a significant degree of flexibility and responsiveness to flexible manufacturing systems by enabling quick scenario analysis and process configurability (Florescu, 2024). More so, domain-specific digital twin applications have been demonstrated to enhance the design of production lines and scalability of the system in sophisticated manufacturing settings (Zhang et al., 2024). The practicality of smart manufacturing through the digital twin mainly relies on facilitating technologies, i.e., Internet of Things, artificial intelligence, and cloud-edge computing infrastructures.

The IoT technologies provide the acquisition of real-time data on the heterogeneous devices in the shop-floor, which are the data backbone of the digital twin

synchronization (Ullah et al., 2025). Machine learning and deep learning are artificial intelligence methods that are becoming integrated into the digital twins so that they can be used to predict, detect anomalies, and optimize (Soori et al., 2024). Cloud and edge computing paradigm also enable the computing workloads to be spread among centralized and decentralized computing resources to support scalable processing and low-latency analytics (Pasupuleti, 2024). Current researchers emphasize that the combination of IoT, AI, and edge intelligence is important to reach real time decision- making in complex manufacturing systems (Deepika Reddy et al., 2024).

The main problem and chance in the digital twin-based manufacturing are real-time data synchronization and cyber-physical integration. Complex synchronization mechanisms allow maintaining a constant correspondence between real processes and virtual models, which means an appropriate representation of the state of the system in dynamic operating conditions (Yu et al., 2025). Graph-based and knowledge-based digital twin models are suggested to increase the semantic interoperability and real-time reasoning of manufacturing components (Su et al., 2025). Also, the real-time communication between the cyber and physical layers has been depicted to enhance the responsiveness and robustness in the smart manufacturing landscape, especially in the adaptive scheduling and process optimization contexts (Nageswara Rao et al., 2022). All these achievements point to the increased maturity of the digital twins-based solutions to the real-time optimization of intelligent manufacturing. Table 1 provides a summary of the previous studies on the topic of digital twin-based smart manufacturing, the system focus, enabling technologies, optimization techniques, and domains of application. The studied articles indicate the increased use of digital twins in real-time monitoring, smart decision-making, and optimization of processes, as well as expose the issues of interoperability, scalability, and dynamic adaptability in complex manufacturing settings.

Table 1. Summary of Related Work on Digital Twin–Based Smart Manufacturing and Optimization

Ref.	Focus Area	Optimization / Analytics Method	Application Domain	Key Contribution
Barbosa et al. (2022)	Metrology digitalization	Systematic review	Smart metrology systems	Identified research gaps in DT-enabled metrology
Ebni et al. (2023)	DT lifecycle modeling	Multi-stage optimization	Manufacturing system design	Proposed DT schema from design to optimization
Florescu (2024)	Flexible manufacturing	Scenario-based optimization	Flexible manufacturing systems	Validated DT effectiveness via industrial case study
Deepika Reddy et al. (2024)	Smart manufacturing optimization	TLBO optimization	Smart production systems	Achieved improved convergence and system efficiency
Khdoudi et al. (2024)	Intelligent DT optimization	DRL-based control	Manufacturing process optimization	Enabled adaptive real-time optimization under uncertainty
Pasupuleti (2024)	Industrial DT deployment	Predictive analytics	Smart factories	Highlighted DT-driven process innovation
Soori et al. (2024)	Decision support systems	AI-based reasoning	Industry 4.0 systems	Reviewed AI-driven DSS integration with DTs
Su et al. (2025)	Knowledge-driven DTs	Graph-based reasoning	Manufacturing processes	Enhanced interoperability using multi-layer knowledge graphs
Ullah et al. (2025)	Asset tracking DT	Real-time monitoring	Flexible manufacturing	Improved visibility and responsiveness in FMS
Yu et al. (2025)	DT workshop interaction	Dynamic interaction modeling	Smart workshops	Enabled real-time bidirectional DT–shop-floor interaction

3. PROPOSED DIGITAL TWIN–BASED SMART MANUFACTURING FRAMEWORK

The suggested digital twin related smart manufacturing system provides the opportunity of real-time tracking, forecasting, and optimization because it closely integrates physical manufacturing resources with smart virtual counterparts. Constant alignment of the physical and cyber layers enables the dynamism to respond to disturbances, variability in production and varying conditions in the operation so that enhanced efficiency, responsiveness and accuracy of decisions can be achieved throughout the manufacturing lifecycle. This figure 1 shows a layered cyber physical architecture combining physical manufacturing resources, a virtual layer based on a digital twin, and an intelligence layer. AI-based optimization and decision-making modules are always producing adaptive control actions by synchronizing the physical and virtual systems in real-time with sensor data. Its closed-loop feedback mechanism allows the optimization of the dynamic

processes, their better responsiveness, and their increased operational efficiency depending on different conditions of manufacturing activities.

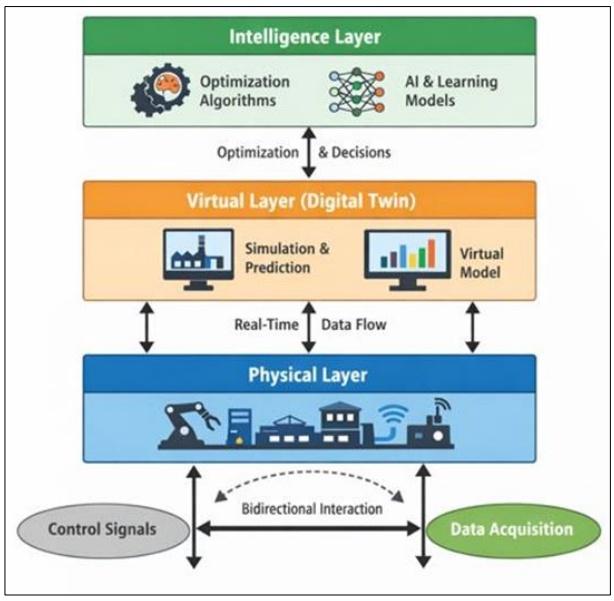


Figure 1. Layered Digital Twin–Based Smart Manufacturing Architecture for Real-Time Process Optimization

3.1 Overall System Architecture and Functional Layers

The general format is that of a layered cyber physical structure to assist in real time process optimization. The physical layer gathers the data on operational conditions of machine and sensors, as well as material handling machines. This information is transferred via industrial communication networks to the virtual layer where digital twin models further reproduce the condition of physical resources. The virtual layer undertakes real time simulation, prediction and performance examination in terms of mathematical and data-driven framework. Most importantly, the intelligence layer uses optimization and learning algorithms to decide on the best control and scheduling decisions and parameter changes. The control interface provides feedback to the physical layer with choices being fed back and the physical layer reacts accordingly to the choices in a feedback loop. The architecture has two-way data flow, which guarantees the synchronization between real and virtual entities. The framework supports continuous optimization in the dynamic manufacturing conditions through decoupling sensing, modeling, intelligence, and control, which leads to increased scalability, modularity, and adaptability.

3.2 Physical Layer: Sensing, Data Acquisition, and Connectivity

The physical layer includes machines, sensors, actuators, and resources of production at the shop floor. Real-time information with regard to machine condition, machine processing time, energy use, and environmental factors is gathered by sensors. This information is obtained with the help of embedded controllers and transferred with the help of industrial IoT protocols. The provision of reliable connectivity means that there will be low-latency communication between physical components and cyber components, which will provide constant visibility of the system, as well as proper representation of the state in the digital twin environment.

3.3 Virtual Layer: Modeling, Simulation, and Prediction

The virtual layer has a mathematical characterization of the real manufacturing system. The state of the system at time t can be defined as:

$$x(t) = [x1(t), x2(t), \dots, xn(t)]$$

Where $xi(t)$ represents machine states, queue lengths, or process variables. System dynamics are modelled as:

$$x(t+1) = f\big(x(t), u(t)\big) + w(t)$$

Where $u(t)$the control actions and $w(t)$ is disturbances. Simulation models determine system behaviour in various scenarios whereas predictive models estimate future state x^{t+k} and hence proactive optimization and decisions can be made.

3.4 Intelligence Layer: Optimization and Decision-Making

The intelligence layer is used to develop manufacturing optimization as a constrained objective function. Minimization of total cost of production and delay: Let the objective be minimization of overall cost of production and delay:

$$\min u \;\; J = \alpha T + \beta E + \gamma D$$

Where T is makespan, E is energy consumption, and D is mean tardiness. Subject to:

$$gi(x,u) \leq 0, i = 1,2, \dots, mg_i$$

The real-time feedback of the system is used to update control actions u in a series of iterations by optimization algorithms and learning-based decision models to achieve adaptive and optimal functioning of the system under changing conditions.

3.5 Closed-Loop Feedback and Real-Time Control Mechanism

The feedback loop is closed and it provides an assurance of continuous synchronization between the physical system and the digital twin. The virtual models are updated with real-time sensor data, which allows the

correct estimation of the system states and performance metrics. The intelligence layer compares the actual and predicted behavior of the system and calculates corrective measures. This is fed back to the physical layer via control interfaces and modulates the machine parameters, schedules or operating settings in real time. The feedback loop is continuous and therefore allows rapid response to any disturbances like machine failures, change in demand or fluctuation in the process. Such a tool of adaptive control guarantees stability of the system, better resilience, and continuous optimization and allows autonomous and intelligent manufacturing processes in accordance with the principles of Industry 4.0.

4. REAL-TIME PROCESS OPTIMIZATION METHODOLOGY

4.1 Problem formulation and optimization objectives

Smart manufacturing is intended to optimize processes in real-time, improve the optimal control and scheduling decisions in dynamic and uncertain operating conditions. The manufacturing system is represented as a system of machines, jobs, and resources, the jobs are composed of consecutive operations that are carried out on certain machines. The goal is to optimally vary control variables, including scheduling sequences, machine parameters, and processing rates according to real-time system conditions that are given by the digital twin. The multi-objective nature of the optimization problem aims at minimizing makespan, mean tardiness, and energy consumption and maximizing machine utilization and throughput. These goals are also limited by system constraints such as machine capacity constraints, precedence constraints and real-time responsiveness. As the digital twin constantly updates the state of the system, the model of optimization is able to adjust to the disturbances, including machine failures, variations in the processing, and changes in demand.

4.2 Heuristic and metaheuristic optimization techniques

The optimization problems that are solved using heuristic and metaheuristic optimization are difficult and NP-hard to find optimal solutions to optimization problems based on manufacturing that are implemented under real-time constraints. The heuristic approaches offer quick solutions in a rule-based fashion with the use of priority dispatching rules, whereas metaheuristic methods exploit more extensive spaces of solutions to escape local minima. The scheduling decision variable may be denoted as S, the order of jobs on machines. The optimisation goal is as following:

$$minF(S) = \alpha Cmax + \beta T + \gamma E$$

Where $\alpha Cmax$ mean tardiness, and E is energy consumption. Genetic Algorithms (GA) and Teaching Learning Based Optimization (TLBO) are the metahyper heuristic algorithms 1, that can be used to find the optimal solution in a problem with the help of exploration and exploitation. The algorithms in the proposed framework can be used on the system states generated by digital twins, and quickly re-optimized when disruptions take place. The capability of their population-based search is capable of scaling and being strong in dynamic manufacturing environment and is also low in computational efficiency that can be deployed in real-time.

Algorithm 1: Heuristic–Metaheuristic Optimization for Real-Time Scheduling

Input: System state X(t), job set J, machine set M
Output: Optimized schedule S*
Initialize population of schedules S
Evaluate fitness F(S) using digital twin simulation
while termination condition not met do
  Select parent schedules
  Apply crossover and mutation operators
  Generate new candidate schedules
  Evaluate fitness using updated system state
  Select best solutions for next generation
end while
Return best schedule S*

4.3 Machine learning and reinforcement learning integration

Machine Learning (ML) Models

Machine learning models are utilized to determine the processing time, machine health, and demand patterns using past and real-time data. It is estimated with regression and neural network models that predict the future behavior of a system, which makes it possible to optimise it proactively. These forecasts are used as inputs to the optimization engine that enhances better accuracy of the decision and decreases reaction time to disturbances.

Reinforcement Learning (RL) Models

Reinforcement learning, as shown in algorithm 2, is an autonomous decision-making method that triggers the learning of optimal control policies with the digital twin environment. It is based on the modeling of the manufacturing system as a Markov Decision Process in which the agent chooses actions to maximize long-term rewards facing varying, dynamic conditions, and contributes to the adaptive and self-optimizing manufacturing processes.

Algorithm 2: RL-Based Process Optimization

Initialize policy π and value function Q
Observe initial state X(t)
for each time step do

Select action u(t) using policy π
Apply action to digital twin
Observe reward R(t) and next state X(t+1)
Update Q using Bellman equation
Update policy π
end for

4.4 Performance metrics and evaluation criteria

Quantitative manufacturing metrics are considered to determine the performance of the suggested methodology of real-time optimization. Makespan is used to measure the total time of production completion and mean tardiness is used to measure the reliability of a schedule against scheduled time. The use of machines and the throughput measures the efficiency of resources and the production capacity. The use of energy is also taken into consideration to compare sustainability and cost of operation. The computation latency and convergence time are taken to check real-time capability. The enhancements in the responsiveness, robustness, and accuracy of decisions in the dynamic manufacturing environment are proven by the comparative analysis to the traditional and offline optimization methods.

5. EXPERIMENTAL SETUP AND CASE STUDY

5.1 Manufacturing System Description

The experimental model takes into account a smart manufacturing system which can be taken as a representative of a medium-scale discrete production setting, aimed at measuring the efficiency of the suggested digital twin-based real-time optimization framework. The system is a combination of a number of heterogeneous machines in a flexible job-shop system, with each job being a series of jobs that are scheduled to be performed on other alternative machines that have varying processing capacities. Workpieces are moved between workstations by automated material handling devices, such as conveyors and robotic manipulators, which adds realistic constraints of transportation time and resources availability. The manufacturing environment also ensures that it is mixed product, providing high level of product variety and a high level of changeovers that are typical characteristics of an Industry 4.0 enabled factory.

Every machine has embedded sensors that constantly check the parameters of operation of the machine which include processing time, machine usage, energy use and the fault state. Other sensors are used to obtain information about the environment such as temperature and vibration, which affect the performance of the machine and quality of the products. The programmable logic controllers are used to gather real-time production information and send it to a centralized data platform via industrial IoT communication standards. Demand patterns of customers are represented in a dynamic and stochastic manner, which represents the reality of production uncertainty and variability. The system is under realistic operation constraints such as machine failures, set up times, and due dates. The major manufacturing indicators used in performance evaluation include makespan, mean tardiness, throughput and energy efficiency. This experimental setup is a realistic and testing environment and presents the suggested digital twin-based smart manufacturing framework with the challenge of validating its adaptability, robustness, and optimization ability in the dynamic operating environment.

5.2 Digital Twin Implementation Details

The implementation of digital twin provides an environment of a high-fidelity virtual copy of the actual manufacturing system, where one can make continuous synchronization and support decisions in real-time. The virtual model is a replica of the physical shop floor structure, behaviour and operational constraints, the characteristics of machines, routing options, processing time, and resource requirements. The data ingestion pipeline is a real-time data stream that converts physical layer data stream into a digital twin such that the state of a virtual system accurately represents the present conditions at the shop-floor. The figure 2 illustrates the adoption of a digital twin that takes of physical shop-floor systems coupled with virtual simulation, predictive analytics and optimization modules. Real-time data ingestion provides a constant synchronization of physical and cyber components, whereas edge-cloud resources provide real-time decision-making choices. The closed-loop control mechanism enables optimal control of the processes, scenario analysis and smart operational control within dynamic manufacturing processes.

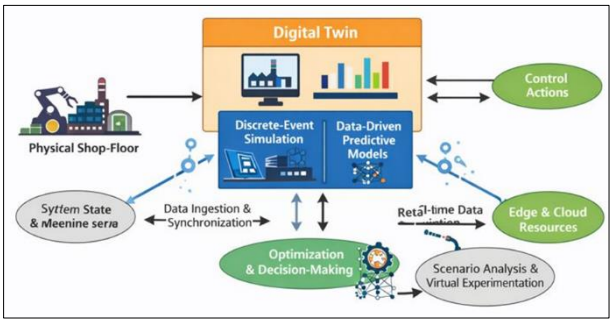


Figure 2. Digital Twin Implementation Architecture for Real-Time Smart Manufacturing Optimization

The digital twin is written as a hybrid model based on discrete-event simulation and data-driven predictive models. The logical flow of the jobs, machine interactions, and material handling processes are represented by discrete-event simulation and predictive models estimate system future states, such as processing delay and machine degradation. Real-time sensor data is used to continuously update these models, which allows the models to be adaptedively calibrated, and allows a better estimate of their accuracy. The digital twin aids the scenario analysis cost because it provides the opportunity

to experiment with alternative scheduling and control strategies virtually without interfering with physical operations. The digital twin is integrated with an intelligence layer that is used to make real-time optimization and autonomous decisions. The optimization algorithms are in direct contact with the virtual model to test candidate solutions at the current system conditions and anticipated future conditions. Reinforcement learning agents are trained in the digital twin environment, which allows learning policies safely and efficiently without the risk of jeopardizing the performance of the physical system. Actions of control produced by the digital twin are fed back onto the physical layer via common interfaces, which create a closed-loop control mechanism. The edge and cloud resources allocate computational loads in order to provide real-time operation, which balances the low-latency decision-making and scalable analytics. The presented implementation evidences the ability of digital twins to establish connections between physical and cyber worlds, allowing the continuous optimization of processes, the increase in system visibility, and stable operations in dynamic production settings.

6. RESULTS AND DISCUSSION

6.1 Quantitative Performance Analysis

Table 2 provides a quantitative evaluation of the proposed digital twin-based smart manufacturing infrastructure over the baseline system in detail. The outcomes clearly indicate significant improvement in performance in all the metrics that were measured. The decrease in makespan to 1085 minutes as compared to 1420 minutes underscores the dynamism of the system in terms of production sequencing and resource allocation to optimize in real time. Equally, the mean tardiness reduced by 56.7, which meant that there was reliability in the schedule and increased adherence to due dates. This can be explained by the fact that there is always an alignment between physical activities and virtual models which can be modified proactively according to the system disturbances. The throughput improved as the number of jobs per day rose to 152-118 which was a result of improved coordination of machines and less idle time. The increase in machine utilization was substantial to 88.9 and it proves the better utilization of the available resources but never overburdens the system. Real-time optimization led to a decrease in energy consumption by 24.4, which proves that energy-efficient manufacturing processes also involve real-time optimization. Moreover, the response time to optimization was reduced by 66.3 percent, which highlights the fact that the digital twin framework has the potential to provide quick decision-making in dynamic settings. Taken together, these findings confirm that the approach of integrating real-time data, virtual modeling, and intelligent optimization can be used to attain high operation efficiency and responsiveness in smart manufacturing settings.

Table 2. Quantitative Performance Results of the Proposed Framework

Performance Metric	Baseline System	With Digital Twin	Improvement (%)
Makespan (min)	1420	1085	23.6
Mean Tardiness (min)	96.4	41.7	56.7
Throughput (jobs/day)	118	152	28.8
Machine Utilization (%)	72.3	88.9	22.9
Energy Consumption (kWh/day)	1865	1410	24.4
Optimization Response Time (s)	8.6	2.9	66.3

6.2 Comparative Evaluation with Conventional Approaches

Table 3 discusses the suggested digital twin-based model and traditional rule-based, offline optimization, and AI-based optimization models. The comparison outcomes reveal that the suggested framework outperforms all the baseline methods in all the key performance parameters. The reasons why rule-based systems have the largest makespan and mean tardiness are their fixed decision logic and absence of flexibility. Offline optimization enhances the performance by focusing on global goals but is restricted by sluggish responsiveness and failure to deal with real-time disruptions. There are additional gains on the AI based optimization which is provided by predictive abilities, but its operation is limited by the lack of physical-virtual continuous synchronization.

Table 3. Comparative Evaluation with Conventional Manufacturing Optimization Methods

Parameter	Rule-Based System	Offline Optimization	AI-Based Optimization	Proposed Digital Twin Framework
Makespan (min)	1490	1325	1198	1085
Mean Tardiness (min)	102.6	78.3	55.4	41.7
Throughput (jobs/day)	110	126	141	152
Machine Utilization (%)	69.8	76.5	83.1	88.9
Energy Consumption (kWh/day)	1920	1710	1525	1410
Adaptation Latency (s)	14.2	9.8	5.1	2.9

On the contrary, the proposed digital twin approach will get the shortest makespan and mean tardiness through dynamism between real time system states and intelligent optimization algorithms. Throughput and machine utilization are at their highest levels showing effective

coordination of the resources and less production bottlenecks. The energy consumption is also reduced which means productivity and sustainability are well balanced by the decisions made by optimization. Above all, the latency of adaptation decreases to 2.9 seconds, which represents the high responsiveness of the framework to changes in operations. These findings prove that digital twins, combined with the use of AI-based optimization, allow significant performance improvement compared to traditional manufacturing optimization methods.

6.3 Scalability, Robustness, and Adaptability Analysis

Table 4 is an assessment of the scalability, robustness and scalability of the proposed framework in terms of system size and disturbance increasing. The findings indicate that the framework has consistent performance when manufacturing complexity is growing between the small and big scale. Even performance in large-scale systems is not affected worse than 9% meaning that the systems are strongly scaled and can deal with the greater complexity of computational and operational processes. The recovery time grows slowly as the size of the system and the severity of disturbance, but recovery time is acceptable within the real-time applications of industrial systems. This phenomenon validates that the framework can quickly bring the optimal operating conditions back in order after such disruption as machine failures or changes in the demand.

Table 4. Scalability, Robustness, and Adaptability Performance

Scenario	System Size (Machines/Jobs)	Disturbance Level	Performance Degradation (%)	Recovery Time (s)	Optimization Stability (%)
Small-scale	5 / 20	Low	2.8	1.4	97.6
Medium-scale	10 / 50	Medium	5.6	2.6	95.1
Large-scale	20 / 100	High	8.9	4.3	92.4
Large-scale + Failures	20 / 100	Very High	11.7	5.8	89.6

The stability of the optimization is more than 89% at a very high level of disturbance and this indicates the stability of the optimization algorithms and also the reliability of the closed-loop control mechanism. The ability of the digital twin to synchronize its state continuously and predictively is important in the reduction of uncertainty and stability in the system. On the whole, these findings support the claim that the suggested framework can be successfully implemented into operation in large-scale and dynamic manufacturing settings and provide high levels of adaptability, resilience, and long-term optimization results when used in the real-life operational environment. These findings indicate that the suggested digital twin-based framework is always more efficient than traditional solutions with better adaptation, efficient, and scalable features in dynamic manufacturing environments.

7. CHALLENGES AND FUTURE RESEARCH DIRECTIONS

7.1 Data Quality, Interoperability, and Model Accuracy

A high-quality, reliable, and consistent data to support real-time decision-making is one of the main problems with smart manufacturing based on the use of digital twins. Heterogeneous data is frequently produced in manufacturing settings through a variety of sensors, machines, and control systems and they can be noisy, missing, or delayed. The quality of data has a direct impact on digital twin model accuracy and may result in poor or untrustworthy optimization results. The other important challenge is interoperability, whereby a manufacturing system often combines old equipment with new IoT-enabled devices, which have different data structures and communication systems. The model accuracy is also threatened by the changes in dynamic processes, degradation of the machine and the changing conditions in production and this demands constant updating and recalibration of the model. The next wave of research needs to be on sound data preprocessing, uniform data exchange platforms and adaptive modeling approaches that have the potential to ensure high digital twin fidelity when operated under varying conditions.

7.2 Computational and Real-Time Constraints

Real-time optimization using digital twin needs major computer power to process existing large volumes of streaming data, run simulations, and solve complex optimization problems in a time constraint environment. With the growth in the size and complexity of manufacturing systems, computational latency can grow, which can impairs real-time responsiveness. Algorithms and models that are based on advanced optimization, as powerful as they are, can be computationally costly and inapplicable in time-sensitive businesses. Next generation studies should consider lightweight optimization models, parallel and distributed computing designs as well as effective edge-cloud synergies to balance between the computation load and latency. Also, real-time performance assurances and adaptive computation systems will be necessary to ensure consistent and scalable implementation of digital twins systems in the industrial context.

7.3 Opportunities for Sustainable and Human-Centric Manufacturing

Digital twin provides tremendous possibilities to progress in terms of sustainable and human-centred manufacturing paradigms. Digital twins would facilitate environmentally friendly production processes and minimize wastage of resources during operations by facilitating real-time observation and optimization of energy use and materials consumption and process efficiency. Moreover, digital twins have the potential to increase human-centered manufacturing through enhancing transparency of decisions, safety and interaction of workers and systems. Research in the future should be aimed at including the sustainability metrics and human considerations in the digital twin optimization goals to be able to make a trade-off between productivity, environmental effects, and human well-being.

8. CONCLUSION

The study introduced a holistic digital twin-driven smart manufacturing system to optimize the process in real time in order to overcome the short comings of the traditional offline and static optimization models. The framework proposed combined real time data capture, high-fidelity virtual modeling, intelligent optimization as well as closed-loop control to facilitate adaptive and responsive manufacturing processes. The outcomes of the experiment showed that there was a substantial increase in performance in major manufacturing indicators. The proposed framework minimized makespan by 23.6, mean tardiness by 56.7 and minimized energy consumption by 24.4, and maximized throughput by 28.8, and machine utilization by 88.9 as indicated in the Results section. The fact that optimization response time was significantly lower again justified the suitability of the framework on optimistic industrial application in real-time. The comparative analysis revealed that the digital twin-based approach is better than rule-based, offline, and standalone AI-based optimization methods. The framework resulted in increased responsiveness to disturbance by synchronizing physical and virtual systems in continuous fashion and better accuracy of decisions in dynamic operating situations. The scalability analysis and robustness analysis also showed consistent performance with the increase in size of system and disturbance levels, with minimal degradation in performance and short recovery times. The results of the study prove the importance of digital twins in facilitating proactive decision-making, operational resilience, and sustained optimization in intelligent manufacturing settings. The advent of in digital twin technology is a revolutionary paradigm in the optimization of real-time manufacturing processes that would help to resolve the disconnect between manufacturing processes and intelligent analytics. It proves to be effective in its ability to deliver efficient, scalable, and resilient manufacturing systems to meet Industry 4.0 goals, as the results justify. The next generation of smart manufacturing will only enhance the use of digital twins by ensuring improved data integration, smart control and human-friendly design.

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