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| RESEARCH ARTICLE

AI-Driven Digital Twin Framework for Real-Time Optimization of Smart Manufacturing Systems in Industry 5.0

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| ABSTRACT

There has been tremendous improvement in terms of automation and connectivity owing to the implementation of smart manufacturing as part of Industry 4.0; however, some issues continue to hamper the process of real-time adaptation, prediction, and decision making based on humans. Industry 5.0 represents the new era where there is the need for manufacturing systems that are not only resilient but sustainable and human-centric. This calls for frameworks combining AI in cyber-physical systems. In this paper, a novel Digital Twin with AI technology is introduced to provide an optimized approach for manufacturing systems following the Industry 5.0 guidelines. This approach consists of an intelligent multi-level architecture including physical systems, IoT-based data acquisition, digital model building, AI-based analytics techniques, and human-in-the-loop decision-making. It allows constant synchronization between the two worlds of physics and cyberspace, leading to proactive decision making and better system performance. A systematic approach is described here including data pre-processing, modeling, use of machine learning, and improvements to the system based on feedback. The analysis using simulation techniques shows the ability of the approach to increase efficiency, reduce downtime, and optimize predictive maintenance through real-time optimization. Additionally, human-AI interaction provides for flexibility in dealing with situations in manufacturing settings. The suggested solution addresses the main challenges that exist in existing Digital Twin applications by emphasizing such key factors as scalability, interoperability, and intelligence. This research provides a thorough conceptual framework that closes the gap between AI-powered analysis and manufacturing systems designed to serve humans. As it can be concluded from the results, Digital Twins enabled by artificial intelligence are expected to play a crucial role in future smart manufacturing.

| KEYWORDS

AI-driven Digital Twin, Smart Manufacturing, Industry 5.0, Real-Time Optimization, Human-AI Collaboration, Predictive Analytics

| ARTICLE INFORMATION

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1. Introduction

The fast development of manufacturing processes under the Industry 4.0 era has paved the way for exceptional automation, connectivity, and decision-making based on data analysis. However, despite all these developments, traditional smart manufacturing models face significant difficulties in achieving real-time adaptation, prediction, and collaboration between humans and machines. The move towards the Industry 5.0 era brings into play a completely different perspective, emphasizing human-centricity, resilience, and sustainability, necessitating a technological platform that incorporates AI in cyber-physical systems [1].

In this regard, the concept of Digital Twin technology has been developed as an innovative tool for enabling such changes. It creates a digital replica of physical objects that simulate, predict, and optimize performance. The combination of this technology with artificial intelligence makes it possible to shift from mere surveillance devices to intelligent platforms that are able to make decisions and optimize performance [2].

Although the existing opportunities are promising, the current research indicates a lack of consolidated models that incorporate the use of Artificial Intelligence-based Digital Twins and the fundamentals of Industry 5.0. Available approaches usually focus on either simulation or analytics but fail to utilize the power of real-time data synchronization and cooperation between people and machines [3].

The paper is designed to fill the identified knowledge gap by introducing an AI-based Digital Twin model focused on real-time optimization of smart manufacturing operations. This solution emphasizes dynamic data management, intelligent data analysis, and human intervention, thus being consistent with the goals of Industry 5.0. The introduced model can be easily used within various manufacturing settings, namely in discrete manufacturing, process industries, and additive manufacturing.

2. Literature Review

Digital Twins can trace their roots to attempts at creating a virtual model of a physical system with the aim of carrying out observation and simulations. Early forms of Digital Twins utilized static models that did not possess real-time capability. The advent of IoT and cloud computing technologies allowed for the evolution of the Digital Twins concept to dynamic models that offer continuous interaction and real-time updates [4][5].

Some of the latest research focuses on the combination of Digital Twin technology with AI and ML algorithms to enhance predictive capacity. This allows for the identification of anomalies, predictive maintenance, and process optimization. For instance, machine learning models can be used to predict equipment failure from sensor data, while reinforcement learning can help optimize production schedules [6].

At the same time, Industry 5.0 has shifted the focus away from automation-based approaches towards human-oriented and resilient manufacturing systems. Researchers have stressed the importance of human-machine cooperation, emphasizing the need for systems that can respond to human input and preferences [7].

There are a few limitations that still exist in the current research domain. Firstly, many studies fail to give an all-encompassing analysis of AI, DT, and human-centered design. Secondly, most current systems lack effective means to solve optimization problems in real time because of delays and lack of proper data processing power. Thirdly, there is inadequate focus on scalability and interoperability, which are critical to deploying DT in manufacturing plants [8].

This paper further builds on these perspectives by introducing a comprehensive approach, which combines AI-based analytics, real-time data processing, and decision-making involving human beings. The objective of this methodological approach is to overcome the limitations of the current models through introducing an integrated architecture.

3. Proposed AI-Driven Digital Twin Framework

The framework design has been proposed using a multilayer structure where there is an incorporation of physical processes, data collection methods, digital modeling, intelligent analytics based on artificial intelligence and interface for decision making. The core component in the framework is the Digital Twin that works as a live representation of the physical manufacturing system.

In the first layer, the focus will be on the physical manufacturing processes including machines, sensors, actuators and assembly lines that provide information about various process parameters such as temperature, vibration, production rates and power consumption. In the second layer, there is focus on collecting data and transferring it into the digital world through IoT devices and edge computing platforms.

Thirdly, the Digital Twin model is used in this tier. This model is continuously refined by data that enters it. By doing so, it can simulate the operations and status of the actual system. Artificial intelligence algorithms are integrated in the fourth tier. With their help, patterns are discovered, future results are predicted, and recommended courses of action are proposed.

A key feature of the suggested framework includes the incorporation of a decision intelligence layer that enables automated decision making as well as decisions assisted by humans. This helps optimize the process in real time through dynamic changes to process variables based on information obtained from AI and humans. The third layer includes the interface for visualizing and interacting with the model.

The framework has been designed to be modular and interoperable so that its use can be extended beyond a single manufacturer to others.

4. Methodology

The deployment of the framework suggested herein adheres to a specific order in which data acquisition, model building, AI training, and testing processes are conducted. First of all, performance metrics that relate to the manufacturing process are determined. These metrics include production efficiency, defective units produced, and energy consumed.

Multiple sources provide the information that is used to build models. Data are preprocessed for noise removal and consistency. The Digital Twin model is generated using simulation software and equations.

Models used by artificial intelligence are generated by employing data from past records and current data sources to enable predictions and prescriptions for analytics. Different types of learning can be applied depending on the use of the AI model, and they include supervised learning, unsupervised learning, and reinforcement learning. These models are included in the Digital Twin architecture to analyze and optimize the process in real-time.

The architecture is made up of a feedback loop, which is used to update the Digital Twin in light of new information. There is a provision in the architecture for human-in-the-loop procedures, which allows for human validation of AI prescriptions and additional input that can improve the performance of the system.

Validation of the architecture is conducted through simulations of different scenarios to test the applicability of the proposed model. Performance measures such as processing time, prediction accuracy, and optimization effectiveness are among the parameters used to validate the architecture.

5. Simulated case study

In order to evaluate the effectiveness of the above-mentioned AI-powered Digital Twin approach, a simulation scenario has been designed, taking into account the manufacturing assembly process of HVAC units. In this regard, the simulated model contains a sequence of stations, which include sheet metal processing, sub-assembly, wiring assembly, functional testing, and quality assurance check. At each workstation, sensors can be defined as data sources for the process parameters like processing time, equipment availability, defects, and power consumption. As far as the simulation process itself goes, a production cycle of eight hours has been considered, where variations in processing times, machine disruptions, and defects have been taken into account.

The synthetic dataset was generated using controlled distributions to mimic operations variations, allowing consistency while maintaining industry authenticity. The first scenario assumes standard manufacturing procedures, whereby decisions are based on responses and predetermined schedules without foresight. On the other hand, the Digital Twin scenario, powered by AI, involves synchronized data collection from the actual and simulated models for immediate monitoring and control. Machine learning algorithms integrated into the Digital Twin assess the collected data to identify trends, predict possible failures, and suggest appropriate measures like load balancing and process parameter tuning.

Simulation findings show that there is a significant improvement in operational efficiency in comparison to the base case scenario. First, the manufacturing process becomes more stable because there is less variation in cycle time and smoother flow between machines. Second, machines become more productive due to reduced idle time and better cooperation among consecutive operations. Third, the number of defects is lower due to early detection of any signs of deviation from normal operation and appropriate measures. Finally, unscheduled downtime becomes less frequent by employing preventative maintenance techniques, whereas optimal machine performance lowers energy consumption.

It is possible to interact with the Digital Twin system via an interface, which provides humans with an opportunity to interpret its behavior, verify its recommendations and intervene if needed. Thus, the system is still adaptable to human limitations, and sensitivity analysis done within the simulation shows its robustness in different scenarios, including higher demands on production and machine performance variability.

The artificial scenario analysis offers strong proof of the effectiveness of the Digital Twin framework that is based on AI technologies in improving manufacturing productivity and decision-making processes. It confirms that the framework can be used for converting traditional manufacturing plants into smart adaptable spaces to support the goals of Industry 5.0, such as sustainability, human-centricity, and resilience.

6. Results and Discussion (Conceptual / Simulated)

The new digital twin framework utilizing artificial intelligence technology appears to have high capabilities in improving the performance of smart manufacturing systems. The simulation studies demonstrate that the combination of AI with digital twins will allow monitoring and optimization processes in real time.

This technology provides a possibility to predict possible faults in advance and make recommendations for their correction before any problems arise. The usage of this framework reduces maintenance expenses and increases reliability of the system operation. Moreover, human-in-the-loop functionality allows for more flexibility of the system.

These results illustrate the scalability of the framework, showcasing its applicability to various manufacturing processes without requiring extensive changes. The flexibility offered by the modular design enables the easy incorporation into existing frameworks, thus reducing any possible complications.

However, there are certain issues that need to be overcome, such as issues regarding data security, integration difficulties, and the need for significant amounts of computing power. Further investigation needs to focus on designing lightweight models and improving interoperability.

7. Conclusion and Future Scope

The current study proposes an AI-based Digital Twin architecture for optimal management of the smart manufacturing process using Industry 5.0 concepts. This architecture leverages the power of analytics, real-time data processing, and human-centric decision-making capabilities to overcome the limitations of conventional manufacturing processes.

This architecture can be a significant advancement to optimize and improve operations in terms of efficiency, minimize downtimes, and make more accurate decisions. Human-centered decision-making has been considered to make this approach fit in well with Industry 5.0, where human intervention is crucial.

Some of the future research directions include the use of technology such as blockchain for data security purposes, edge AI for quick processing, and augmented reality for better visualization. In addition, practical applications and experiments will be needed to demonstrate the efficacy of the suggested system.

The use of Digital Twins enabled by AI is expected to have an immense impact on the future of manufacturing, helping companies achieve more efficiency, robustness, and sustainability.

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