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A DES-BASED ONLINE DIGITAL TWIN FRAMEWORK FOR FESTO'S CYBER-PHYSICAL SYSTEM: INDUSTRY 4.0

Muhammad Alfas

Department of Mechanical Engineering
Indian Institute of Technology Delhi
New Delhi, India 110016
mez208100@iitd.ac.in

Yanyan Tian

Exeter Digital Enterprise Systems Laboratory
Department of Engineering
University of Exeter
Streatham Campus, Exeter EX4 4QF, UK
yt401@exeter.ac.uk

Ahmad Attar

Exeter Digital Enterprise Systems Laboratory
Department of Engineering
University of Exeter
Streatham Campus, Exeter EX4 4QF, UK
a.attar@exeter.ac.uk

Martino Luis

Exeter Digital Enterprise Systems Laboratory
Department of Engineering
University of Exeter
Streatham Campus, Exeter EX4 4QF, UK
m.luis@exeter.ac.uk

Voicu Ion Sucala

Exeter Digital Enterprise Systems Laboratory
Department of Engineering
University of Exeter
Streatham Campus, Exeter EX4 4QF, UK
i.sucala@exeter.ac.uk

ABSTRACT

This paper proposes a digital twin framework for the Festo Cyber-Physical Factory through the discrete event simulation (DES) method. As a virtual representation of a physical system, such a twin facilitates seamless bidirectional communication between the physical and virtual components. This integration enables real-time monitoring, predictive maintenance, and process optimization, particularly in production lines. The proposed framework deploys Open Platform Communications Unified Architecture (OPC UA) to establish a reliable connection between the physical factory and its digital counterpart, ensuring effective data exchange. This paper explores the technical facets of developing this digital twin, examining its functionalities, prospective applications, and its practical contribution to improving operational efficiency and decision-making.

Keywords: Online Digital Twin, Cyber-Physical Systems, Industry 4.0, Discrete Event Simulation

1 INTRODUCTION

Industry 4.0, also known as the Fourth Industrial Revolution, aims to utilize advancements in digitalization to increase productivity, flexibility, and efficiency in the manufacturing sector. The key components of Industry 4.0 include the Internet of Things (IoT), cyber-physical systems (CPS), smart factories, and the latest advancements in technology, such as cloud computing, big data, and machine learning (Lasi et al. 2014). Smart factories are a kind of implementation of Industry 4.0 for manufacturing, which uses tools and techniques like sensors, actuators, embedded programmable logic controllers (PLCs), automated guided vehicles (AGVs), and other network-connected objects to track, monitor, and analyze the data collected from the production lines to develop more efficient and productive systems (Chen et al. 2018).

The CPS refers to a system that combines the digital and physical worlds by combining computational capabilities with real-world physical systems. Such an integrated structure enables the CPS to continuously monitor, control, and improve physical operations in real time. This fusion of computation, communication, and control provides opportunities in diverse areas like transportation, healthcare, and aerospace (Baheti and Gill 2011). In fact, CPS is the layer in smart factories that facilitates the integration of digital technologies into manufacturing through interconnectivity, data utilization, and autonomous operations; yielding better flexibility, customization, enhanced efficiency, and broader socio-economic implications (Sinha and Roy 2020). The availability of real-time data and feedback mechanisms in such CPS structures paves the way for a digital twin that is a virtual replica of physical systems that differs from the traditional simulation models by providing real-time interaction with the physical system and the potential for continuous improvements (Attar et al. 2023, 2024). The development and implementation of digital twins in a CPS lead to a more efficient system with minimal additional infrastructure requirements (Tao et al. 2019).

The major components of a digital twin include a set of physical elements (e.g., machines and related parts), a set of virtual models that mimic the physical elements, and a communication and integration layer (Grieves and Vickers 2016). Digital twins provide every advantage a typical simulation model offers, i.e., it can be used to forecast and predict possible downtime and maintenance, perform experiments and what-if scenarios, and optimize operations. Additionally, digital twins provide bidirectional communication, thus enabling continuous improvement of the physical system using feedback loops. These twins generate valuable data that may be used to enhance the performance and productivity of the real system in multiple ways. The data can be used for optimization, data analytics, simulation analysis, forecasting models, machine learning, and predictive maintenance (PdM) (Liu et al. 2023). Some PdM-related applications that would benefit from having such a digital twin are health indicators, reinforcement learning for improving maintenance schedules and predicting remaining useful life (Chen et al. 2023).

In this study, we develop a digital twin framework for a cyber-physical system by utilizing the discrete event simulation (DES) method with a special focus on Festo's cyber-physical factory (FesCPF). FesCPF is an Industry 4.0 integrated, modular, and flexible manufacturing production system with a research platform designed for academic institutes. This paper also lays out major components, development details, applications, and future extension plans of the proposed framework. The rest of the paper is organized as follows: The next section explores the major, recent, and most related studies in the domain of digital twins. Section 3 details the methodology and developmental framework of the online twin, followed by some discussion on the developed twin in Section 4. Finally, the conclusion and future research directions are provided in Section 5.

2 RELATED LITERATURE

Although the concept of creating a digital model that integrates real-time data from physical devices has existed for a long time, the term "Digital Twin" was first introduced during a Product Life-cycle Management course at the University of Michigan in early 2002 (Grieves 2014). Following that, NASA presented one of the earliest definitions of the digital twin, with their initial models found to be in the domain of aerospace engineering (Negri et al. 2017, Attar et al. 2024). Based on the idea of real-time feedback and control, digital twins have found applications in healthcare, urban planning, energy, airspace, agriculture, climate, and transportation (Rasheed et al. 2020). For instance, digital twins in the energy industry have numerous successful implementations in all stages, i.e., generation, storage, transmission, distribution, and management (do Amaral et al. 2023). In industrial settings, where real-time data can be gathered from stations and equipment, digital twins depend on these data collection and feedback systems. Nevertheless, real-time data collection is not directly implemented in many of the aforementioned fields, necessitating frequent data update mechanisms (Fuller et al. 2020).

In the mid-2010s, as a part of Industry 4.0 adoption, the manufacturing industry also started proceeding in the direction of digital twins and real-time feedback systems. Schroeder et al. (2016) are considered the pioneers of digital twin implementation in the field of CPS that integrates both virtual and physical systems through communication, computing, and control. As CPS provides a better infrastructure for real-time feedback and data collection, digital twins became the tool to leverage the data generated and acted as a decision support system (Esterle et al. 2021). Josifovska et al. (2019) presents a five-level reference framework for digital twin implementation in CPS, which starts with connecting sensors to the digital model and evolves into a plug-and-play mode in level five. This implementation also calls to look into big data handling, lifecycle perspective, and semantic modeling (Negri et al. 2017). Recently, Michael et al. (2024) discussed how digital twins can be implemented to interpret the behavior of CPS akin to how explainable artificial intelligence (AI) models work.

Among these studies, there have been a few attempts to develop a digital twin for the Festo cyber-physical factory (FesCPF) from an academic perspective. Mihai et al. (2021) developed a digital twin for the Festo CP factory using the Unity game engine. This work focuses on the two production cells in the factory and discusses the applications and challenges. Onaji et al. (2022) provides a comprehensive literature review and a framework for digital twins as well as three case studies. The case studies investigated by Onaji et al. (2022) included a FesCPF, a pharmaceutical continuous crystallization system, and a virtual x-ray of electric motors. Furthermore, a recent study by Teimoori et al. (2023) used Siemens Tecnomatix Plant Simulation (TPS) software and developed a monitoring system for a small FesCPF with only two production cells. Our study extends the existing models and digital twins for the FesCPFs to cover a more complex structure that involves three production cells, robotic assembly, and multiple products.

3 METHODOLOGY

As stated by Grieves and Vickers (2016), a digital twin comprises three core components: (i) physical objects that constitute a physical system we want to model, (ii) digital objects that constitute a virtual replica of the physical system, and (iii) connections between physical and digital objects. Besides these core components, digital twins may also have an intelligence layer, which includes databases, algorithms, and control programs to provide insights into the performance of the physical system. Figure 1 demonstrates a schematic overview of these components and their interaction. In the figure, the physical objects are connected to their digital counterparts using a layer based on a communication protocol like OPC-UA (Open Platform Communications Unified Architecture). On top of the digital objects, we can employ an intelligence layer that constitutes databases, control programs to manage manufacturing, and algorithms to predict and forecast maintenance and other activities. The proposed framework has five major stages that are summarized in Figure 2. As seen in this figure, these stages are:

1. **Conceptual design:** This step mainly focuses on planning the work, defining modeling objectives, and deciding which processes and data need to be collected.

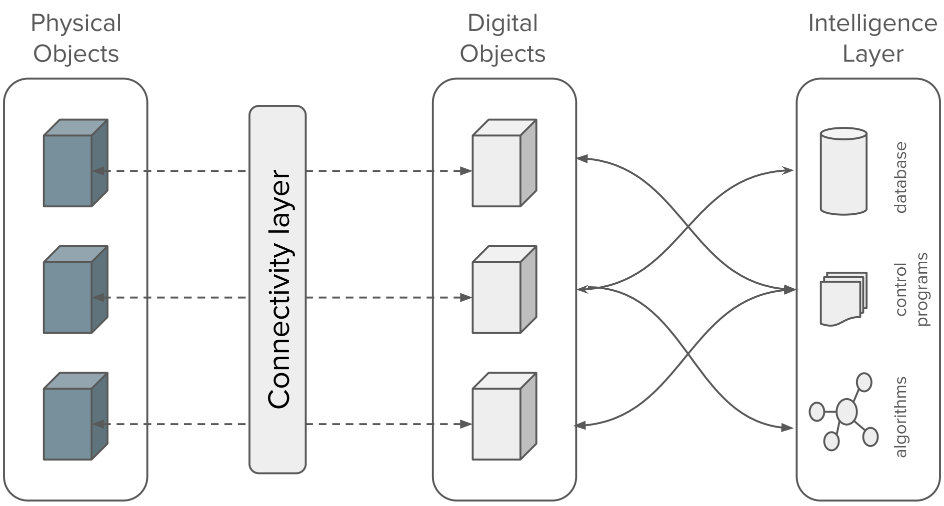

Figure 1: Overview of the digital twin components.

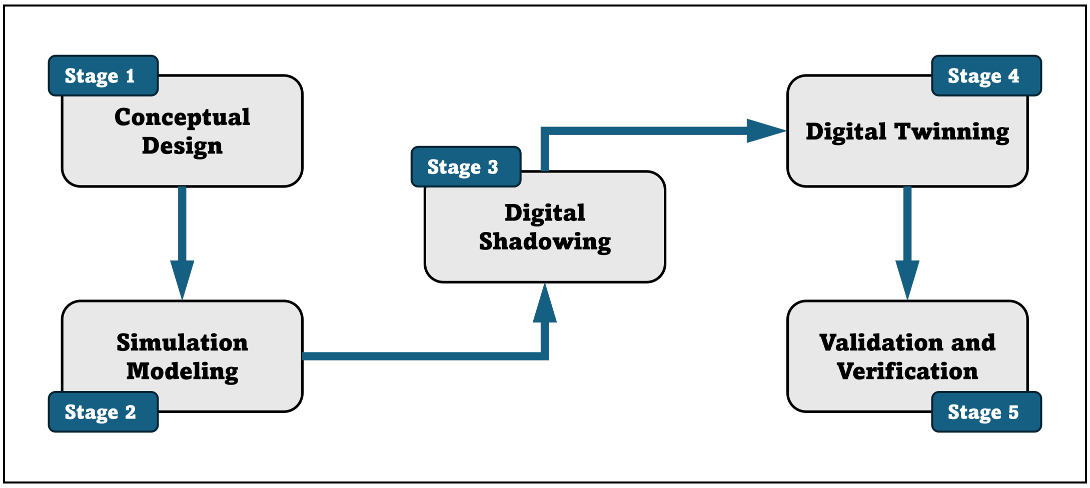

Figure 2: Summary of all stages of the applied framework.

2. **Simulation modeling:** The simulation model is the digital copy of the physical system. The simulation model is developed based on the discrete event simulation method using a simulation software. Service times of the stations, as well as the travel times of the conveyors, are collected from the Manufacturing Execution System (MES) software and provided in the model.
3. **Digital shadowing:** In this phase, the workstations and components in the simulation model are connected to the physical objects using the available communication protocols. Then, the data is collected and sent to the simulation model in real-time.
4. **Digital twinning:** In this stage, the data transfer is enabled in both directions, enabling data transfer from the simulation model to the actuators of the physical objects to control the production flow.
5. **Validation and verification:** This step ensures that the digital twin mimics the actual behaviors of the objects in the FesCPF production line.

In the following subsections, we detail the components and process sequence of the FesCPS located in the Exeter Digital Enterprise Systems (ExDES) Laboratory, Department of Engineering, University of Exeter, UK, and describe our proposed digital twin.

3.1 FesCPF System Description

The studied FesCPF system contains 13 main modules: Top Magazine Station (TM), Measuring Station (MS), Drilling Station (DS), Pressing Station (PS), Bottom Magazine Station (BS), Output Station (OS), Automatic Storage and Retrieval System (ASRS), Robot Assembly Station (RASS), Pick by Light (iP), Branches to transfer from and to the islands (B1, B2, and B3), and an automated guided vehicle (AGV) called Robotino. Please note that Branch 3 (B3) is on Island 1, and Branch 1 (B1) is on Island 3. The layout of the studied FesCPF system is schematically visualized in Figure 3, in which all transportation within the islands is carried out via conveyor belts, and the inter-island transportation is performed by the AGV. The proposed digital twin aims to monitor and control the two products of the CP factory, namely, Products A and B. In this system, production orders are sent and managed by a Manufacturing Execution System (MES) software, coupled with an AGV fleet manager software for the required communication with Robotino.

Product A production starts at Island 1 when the top magazine station (TS) loads the top cover of the product to the workpiece carrier/pallet. Then, the carrier is moved to MS to check whether the top cover is in the proper orientation. Subsequent to passing this test, the workpiece is carried to the DS via a conveyor belt to drill four holes precisely in the top cover. Then, the pallet is moved to B3, waiting for the AGV to transfer it to Island 2. The AGV, Robotino, delivers the carrier to B2 on Island 2, where the first process is the pre-assembly of the back cover of the product, carried out in BS. The final assembly of the bottom cover is performed in the PS station, where a pneumatic press assures proper attachment of all components. In all production cells of this system, the carrier's movement is possible only in one direction. That is, based on the current layout of the system in Figure 3, the pallet has to complete one loop to reach PS from the BS station. Successful pressing in the PS station concludes the production of Product A, following which it leaves the system via the output station (i.e., OS).

For Product B, however, the process starts at Island 3, where the top cover is loaded to the pallet by the ASRS from its existing stock. Then, it is transferred to Island 1 (by Robotino) for the measuring and drilling operations. Upon completion of the required operations on Island 1, the AGV carries the workpiece back to Island 3 for circuit board assembly in the RASS station. This station uses an advanced robotic arm to assemble the printed circuit board (PCB) and the required fuse units on the workpiece. The only operation remaining on this island is to fit the bottom cover of the product, which is done manually in the iP station. The product is then carried by the AGV to Island 2 for final pressing and output, and this completes one production cycle for Product B.

3.2 Proposed Digital Twin

The simulation model in this study follows a DES paradigm that involves modeling events at discrete time points. The entities in this model are machines, stations, robots, conveyors, and storage units. Events and processes in this model are the processing and transfer of the product at different stations. Occasional breakdowns and maintenance are also counted towards events and need to be considered. Throughput rate, processing times, resource utilization, bottleneck statistics, and process cost are among the performance metrics collected using these models to analyze the state of the system, providing insights for decision-makers.

The simulation model is developed using the Siemens Tecnomatix Plant Simulation (TPS) software that has been successfully used in various industries and applications (Attar et al. 2023, Cortés et al. 2021, Pekarcikova et al. 2021, Teimoori et al. 2023). This object-oriented modeling platform enables detailed representation of different segments of the production system, such as workstations, material flows, and logistical processes. In this model, the default object classes available in the software are used for modeling stations, conveyors, assembly processes, and robotic assembly. Furthermore, we use the class worker for a better representation of the autonomous behavior of Robotino in the system. While an order is running, MES tracks how much time each machine spends on processing activities and provides a preliminary comparison with the expected time. Thus, the simulation parameters (e.g., the transit times along the conveyors and the service times at each station) are collected directly from

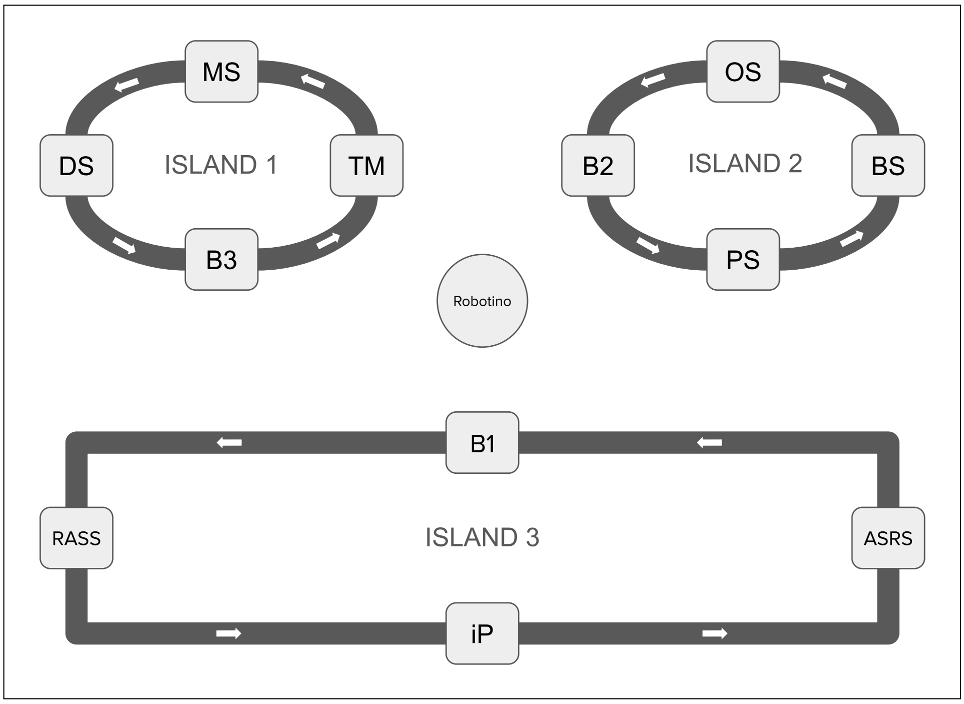

Figure 3: Layout of the studied FesCPF system.

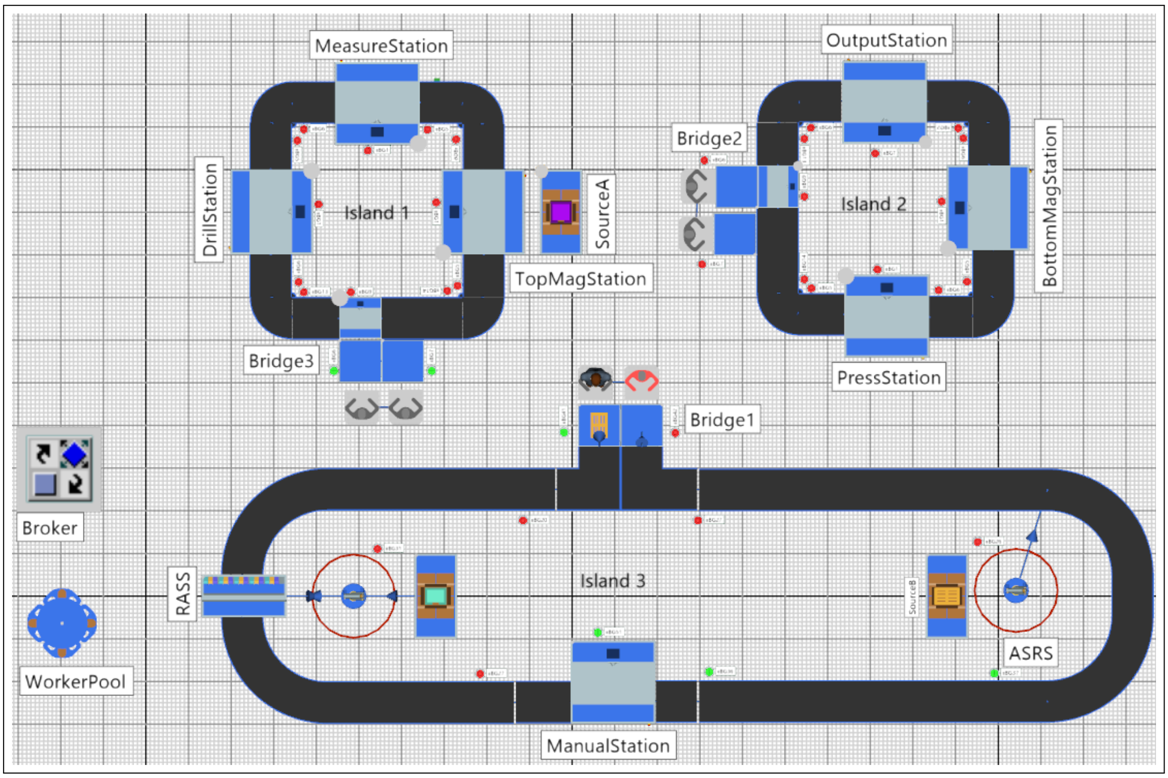

Figure 4: The 2D representation of the proposed model for the FesCPF in the TPS software.

the MES software. A snapshot of the proposed model is presented in Figure 4. Please note that the Pick by the Light station is the same as the Manual Station.

In order to transform this model into a digital shadow of the FesCPF, it should be linked to the activities of the physical system. This task is accomplished by deploying the OPC-UA available in the TPS software which creates a communication link between the simulation model and the real system. It is notable that the used OPC-UA is a widely adopted industrial communication standard known for its robust security features and ability to handle real-time data exchange between disparate systems. This fact generalizes the application of the proposed framework to a broader application area in the industry, beyond laboratory equipment. Each station and conveyor has a set of sensors and instruments that gather operational data, including machine performance, production counts, and system statuses, continuously fed into the simulation model through the OPC-UA protocol. Therefore, this digital shadow replicates the behavior of the FesCPF system realistically and can be used effectively as a monitoring and analysis tool.

The proposed shadow evolves into a proper digital twin when data transfer occurs in both directions between the simulation model and the physical system, for which we still utilize the same OPC-UA protocol. However, unlike the digital shadow, the twin uses the protocol to send control signals and commands back to the physical system. This bidirectional communication enables adjustment of production speeds, rerouting of material flows, or activation of specific workstations based on real-time data and analyses. That leads to one of the primary benefits of these digital twins, which is to facilitate ongoing enhancements to the physical system by utilizing the data generated through the application of certain decision algorithms.

4 DISCUSSION

The present model offers a wealth of opportunities for creating PdM models and identifying possible solutions for optimizing performance, thanks to the current twin's ability to simulate and capture all relevant sensor data, as well as the existing control systems. Strengthening this aspect of the proposed twin can result in a more realistic digital twin experience. As seen in Figure 4, the visual objects used in the proposed digital twin to represent the stations and equipment are not the exact representation of the real systems. With reference to the benefits highlighted by Attar et al. (2024) for 2D and 3D representation of digital twins on the management audience, this can be a potential weakness for our digital twin. This underscores a practical extension avenue for the current study that would involve importing the realistic 3D models of the machines as well as their realistic animations to the digital twin.

The major advantage of such digital twins is adding the possibility of continuous improvements to the physical system based on the generated data using some decision algorithms. However, observations during the development of this digital twin reveal that the digital model may occasionally encounter latency relative to the physical system due to the extensive data collection and computational demands. Thus, another technical aspect that might need addressing based on this finding is employing such twins on high-performance multi-core servers. This would guarantee a smooth running of the program. Such a smooth real-time connection will facilitate the above-mentioned continuous improvement process and enhance the user experience of this digital twin.

On the other hand, digital twins themselves also necessitate ongoing enhancements to keep up with system evolution, especially when dealing with a modular system like FesCPF. The modular nature of the hardware and software is one of the greatest advantages of the FesCPF, as it facilitates the installation of new machines and reconfiguration of the line. Such situations, however, call for reconfiguration and recalibration of the proposed digital twin and may necessitate further testing of the data collected from the previous version or some reevaluations before proceeding to develop the decision algorithms. With operational systems, sensors, and devices producing massive amounts of data in real-time, another aspect to address in this digital twin is the deployment of advanced data storage solutions, e.g., databases, cloud storage, or distributed storage systems, that could help speed the storage and retrieval of data from and to the physical system, the digital model, and decision algorithms.

5 CONCLUSION

The development of digital twins for modular smart production lines of well-known equipment manufacturers has long been important for both academics and industrial practitioners. This paper addresses this need by proposing a digital twin framework for a smart line from Festo's cyber-physical factory (FesCPF) class installed in the ExDES laboratory at the University of Exeter, United Kingdom. Our study outlines the methodology and components that are required in the development of such a digital twin using the Siemens Tecnomatix Plant Simulation software. The proposed procedure begins by defining the modeling objectives and developing an offline model based on the existing production data. The next stage in this framework is digital shadowing, where a real-time data collection mechanism is deployed using the OPC-UA protocol. Eventually, enabling bidirectional data transfer turns the digital shadow into a digital twin. Validation and verification experiments were also carried out to ensure the reliability of the developed model. The current twin, which simulates and captures all requisite sensor data alongside actual management systems, offers substantial possibilities for system optimization purposes.

The implementation of digital twins in a smart factory extends beyond the creation of the digital twin. An intelligence layer is also essential, which incorporates advanced data storage solutions, algorithms, and programs on top of the developed twin. However, this layer was out of the scope of this study, as we were laying the foundations for the proposed digital twin framework and its technicalities in such systems. An interesting future research avenue may involve leveraging the complete capabilities of this intelligence layer that contains data analytics, machine learning, and other algorithms and techniques to act as a decision support system. Working on this can lead to comprehensive predictive maintenance (PdM) models and performance optimization. Deploying efficient algorithms for anomaly detection, fault diagnosis, and remaining useful life prediction, as well as data analytics solutions like pattern recognition models and trend analyzers, are all among the possible future applications of the proposed framework that can be applied to similar Festo factories or other smart production lines.

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AUTHOR BIOGRAPHIES

MUHAMMAD ALFAS is a Ph.D student at the Department of Mechanical Engineering, Indian Institute of Technology Delhi, India. His research work focuses on modeling complex systems, resource allocation, and optimization using heuristics, as well as reinforcement learning.

YANYAN TIAN is a Ph.D. student at the Department of Engineering at the University of Exeter, UK. Her research focuses on predictive maintenance in the field of smart manufacturing.

AHMAD ATTAR is a postgraduate teaching associate with the Dep. of Eng., University of Exeter, UK, mainly delivering System Modeling, Simulation, and Mathematical Programming. He received his M.Sc. and B.Sc. degrees as the top student in Industrial Engineering from IAU-STB and joined Exeter in 2022 as a Ph.D. student in Engineering, focusing on the simulation of resilient, sustainable, and cost-efficient supply chains. He has about a decade of experience in the industry, and his main areas of research interest include simulation modeling, digital twinning, supply chain, reliability, airport management, inventory modeling, healthcare systems, and offshore wind energy.

MARTINO LUIS is a Senior Lecturer at the Department of Engineering, University of Exeter, UK. He holds a Ph.D. in Operations Research from Kent Business School, University of Kent. His research interests are the applications of Exact Methods, (Meta)-Heuristics optimization and a combination of both, as well as simulation modeling in manufacturing systems, facility location problems, sustainable supply chain design networks, and inventory routing problems that focus on environment and sustainable operations.

VOICU ION SUCALA is a Professor in Engineering Management and the Head of Engineering at the University of Exeter. He holds a Ph.D. in Industrial Engineering (TU Cluj-Napoca) and a Ph.D. in Social Sciences (University of Glasgow), serves as vice-chair of the Research, Innovation and Knowledge Transfer committee at Engineering Professors' Council, and leads Exeter Digital Enterprise Systems (ExDES) laboratory. His research focuses on modeling, simulation, digital twinning and optimization of manufacturing processes, technology innovation and entrepreneurship, industrial organization management, and engineering education.