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Expert Twin: A Digital Twin with an Integrated Fuzzy-Based Decision-Making Module

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ABSTRACT

Digitalization and the application of modern Industry 4.0 solutions are becoming increasingly important to remain competitive as product ranges expand and global supply chains grow. This paper presents a new Digital Twin framework to achieve robustness in manufacturing process optimization and enhance the efficiency of decision support. Most digital twins in the literature synchronously represent the real system without any control elements despite the bidirectional data link. The proposed approach combines the advantages of traditional process simulations with a real-time communication and data acquisition method using programmable logic controllers designed to control automated systems. In addition, it complements this by utilizing human experience and expertise in modeling using Fuzzy Logic to create a control-enabled digital twin system. The resulting "Expert Twin" system reduces the reaction time of the production to unexpected events and increases the efficiency of decision support; it generates and selects alternatives, therefore creating smart manufacturing. The Expert Twin framework was integrated, tested, and validated on an automated production sample system in a laboratory environment. In the experimental scenarios carried out, the method production increased production line utility by up to 28% and the number of re-schedules can be halved.

1. Introduction

Manufacturing systems undergo significant transformations due to Industry 4.0 (I4.0) [1,2] and the increasing digitization of the sector. (These industries can be considered the automotive and machine manufacturing [3–5], railway industry [6–8], mining [9], etc.) This evolution is driven by global competitiveness, necessitating manufacturers to respond quickly and adaptively to diverse and rapidly changing consumer demands. These dynamics introduce higher complexity and reduce the available time for decision-making (DM) within the manufacturing framework, thus demanding the application of intelligent and innovative technologies. The various make-to-order manufacturing strategies, such as Just in Time (JIT) and Just in Sequence (JIS), necessitate an accurate estimation of lead times (LTs) to ensure efficient and optimized utilization of resources. Additionally, reliable

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system load and performance forecasting are crucial for pricing bids on manufacturing deadlines and production management decisions. Given the challenging nature of LT estimation, there is a pressing need for new and improved methodologies that consider a broader and more precise range of system parameters influencing LTs, leveraging the extensive dataset made available by digitalization. While Discrete Event Simulation (DES) is a well-established and long-employed method in corporate environments for predicting future system states, it proves particularly time-consuming and costly for Small and Medium Industries (SMIs) due to the essential input information and logic descriptions needed for model construction. Furthermore, the continual maintenance and updating of traditional simulation models impose significant tasks on the employing company [10].

A digital twin (DT) represents a digital model of a physical asset, where the complexity of the DT – whether real-time or predictive – depends on its specific application. DTs can model various levels of system behavior and complexity tailored to user needs and can be utilized throughout all stages of the product lifecycle, from prototyping to production. In the context of manufacturing, the deployment of DTs and CPS (Cyber-Physical System) [11,12] in a production environment is referred to as a Cyber-Physical Production System (CPPS). The digitization of the shop floor has led to more accurate and timely information flow, enhancing reporting times, reducing errors, and increasing process planning flexibility. The concept of the DT has garnered considerable applications such as machine fault prediction, structural optimization design, and intelligent management and control. The DT employs sophisticated digital techniques to construct high-fidelity representations of physical entities and to simulate their characteristics and behaviors within a virtual environment. This innovation offers a novel approach to overcoming existing challenges in job shop production and enhancing production management and control. Modern production processes require integration between factory floor automation and Enterprise Resource Planning (ERP) systems, with the Manufacturing Execution System (MES) serving as the intermediary to manage production lines aligned with business strategies. The MES enhances situational awareness of the production process, and a CPPS plays a critical role in real-time DM support and predictive planning, thereby reducing unnecessary operational costs [13,14].

A fundamental element of CPS is Machine to Machine (M2M) communication, which encompasses any interaction between machines, controllers, and actuators across wired and wireless networks. M2M is integrated into the Internet of Things (IoT) networks, supported by various commercial and open-source communication protocols designed for manufacturing. OPC-Unified Architecture (OPC-UA) is a flexible implementation protocol across a broader range of industrial automation applications. In the context of CPS, the challenge lies in utilizing available data to enhance productivity, predict system responses, and minimize downtime. Real-time data from programmable logic controllers (PLC) and RFID (Radio-frequency identification) or NFC (Near Field Communication) tags on production pallets are crucial sources for updating both the MES and the DT. Tags facilitate the automatic identification and tracking of products throughout production phases, enhancing the accuracy of the MES updates through M2M communications [13].

A robustly constructed DT facilitates the iterative enhancement of production planning and process control by integrating and synthesizing all constituent elements and data. Furthermore, the DT employs a virtual model as a dynamic benchmark for detecting disturbances and provides a broader array of information for scheduling decisions. This approach potentially fosters a more efficient scheduling paradigm compared to conventional simulation-based scheduling and optimization methods.

Nevertheless, it is critical to highlight that while an increasing volume of data can be integrated into the DT system through automatic updates of model parameters using information transmitted from Programmable Logic Controllers (PLCs) overseeing automated systems and data from Manufacturing Execution Systems (MES) or ERP systems, the incorporation of human expertise and DM logic remains crucial. This paper introduces a so-called Expert Twin (ET) framework, a type of DT developed from user interactions with the observed system, which is enhanced by a DM module employing fuzzy logic (FL).

The paper is organized as follows. Section 2 presents the foundational concepts of DT and DES, examining their potential applications within industrial contexts and discussing the integration of DM support into a DT simulation framework, concluding by clearly articulating the research aims. Section 3 introduces a novel DT paradigm termed the expert twin with bilateral communication capabilities utilizing the OPC-UA protocol. This section also describes the execution of DT via DES modeling, coupled with a DM module developed using MATLAB that employs FL. Section 4 presents a case study conducted in the Cyber-Physical Manufacturing System Laboratory at Széchenyi István University. The final section offers concluding remarks contextualizing the study's contributions within a broader scholarly framework.

2. Related Works

Recent studies collectively signal an accelerating trend in adopting DT technology, spurred by its ability to merge and analyze large datasets, significantly elevating operational efficiencies and predictive capacities across various sectors. Despite the persisting challenges in data integration and system complexity, the prospective advantages of DT technology for catalyzing innovative solutions and achieving operational excellence are considerable.

Luo *et al.,* [15] extensively review how Industry 4.0 technologies, including the IoT, cloud manufacturing, blockchain, and big data analytics, reshape production planning. Their study details the transition towards DT frameworks integrating these advanced technologies with production planning systems, facilitating real-time, data-driven DM. The paper thoroughly evaluates the benefits and applications of each technology within production planning, emphasizing their contributions to enhancing adaptability and efficiency in manufacturing operations. It also offers critical insights into future research trajectories, underscoring the necessity for data-driven models capable of managing uncertainties and responding dynamically to changes in manufacturing environments.

Turner and Garn [16] investigate advancements in DES for human-centric manufacturing, emphasizing the integration of human-in-the-loop methodologies, extended reality (XR), and DTs. Their findings suggest significant DM and operational efficiency enhancements through dynamic, interactive simulation models. The study highlights the critical role of advanced DES in adapting to and predicting changes in manufacturing environments, aided by advanced data integration and machine learning.

Liu *et al.,* [17] provide a systematic review of DT technologies, focusing on integrating physical entities, virtual models, and twin data in various applications. The paper clarifies the relationship between DTs and cyber-physical systems, providing comprehensive insights into the functionalities and applications of DTs in industries such as manufacturing; it discusses the role of DTs in bridging the physical and virtual worlds, enhancing simulation, prediction, and operational management.

Tao *et al.*, [18] explore the advancements and challenges of DTs in industrial applications, particularly emphasizing the pitfalls and obstacles hindering their broader implementation. While beneficial in synchronizing physical and virtual systems for improved monitoring and DM, they note that DTs face significant challenges due to overly simplistic or overly complex models, inadequate data interactions, and underused artificial intelligence. These issues often lead to inefficiencies in model accuracy, data handling, and real-time system interactions, compromising the potential benefits of DT technologies in industrial settings. The authors call for a balanced approach to model complexity and improved data integration strategies.

Ladj *et al.*, [19] focus on improving data and knowledge management in the machining industry through a knowledge-based Digital Shadow (DS) within a DT framework. This approach merges real-time data, expert knowledge, and machine learning, showing significant operational improvements in the aeronautics machining industry by enabling precise predictions and effective system management.

Dos Santos *et al.*, [20] present a systematic literature review on applying simulation as DTs in decision support systems for productive processes, focusing on DES and Agent-Based Simulation (ABS). The review highlights the growing integration of simulation models with physical systems, enhancing their real-time operational alignment and contributing to developing advanced DTs. This evolution is part of a broader trend towards intelligent, automated systems, especially within Industry 4.0 contexts. Challenges identified include the necessity for ongoing model validation and integrating diverse model types to provide robust decision support. Furthermore, the review identifies significant research opportunities in improving the scalability and accessibility of DT technologies.

2.1 Literature review on DES-based DTs

This collection of studies highlights the pivotal role of DT technology in enhancing manufacturing processes through integrating Industry 4.0 technologies. These research efforts explore various applications of DTs, from improving operational efficiency in railway axle production to implementing dynamic scheduling in perfume manufacturing. The studies collectively demonstrate how DTs facilitate advanced DM, efficiency, and adaptability across diverse industrial settings, underscoring their significant impact on manufacturing operations.

Ricondo *et al.*, [21] introduce a DT framework that enhances manufacturing DM and efficiency by integrating simulation models and optimization engines. Highlighting the convergence of Industry 4.0 technologies, the framework facilitates advanced, data-driven manufacturing operations. Applied to railway axle production, it demonstrates significant improvements in operational efficiency and adaptability to dynamic production demands.

The article by Resman *et al.*, [22] introduces a five-step methodology for developing data-driven DTs in manufacturing systems. The study presents a framework for aligning digital models with actual manufacturing processes to enhance control and optimization. It describes how DTs can adapt to their physical counterparts via ongoing data exchange, enabling real-time operational adjustments. This method was validated through a case study, illustrating its practical implementation in managing DTs within industrial settings. The results underscore the potential of digital systems to improve the efficiency and flexibility of manufacturing operations.

Eyring *et al.*, [23] assess the efficacy of a closed-loop DT employing DES within a smart manufacturing context. The study performs three principal evaluations, throughput and bottlenecks, supplier quality, and process alignments, to gauge the performance of the closed-loop system. Results indicate that integrated with live data, the DES models significantly enhance short-term predictive accuracy and swiftly adapt to system changes. Specifically, the throughput and bottleneck analysis show a 35% improvement in predictive precision and a nearly 50% reduction in error compared to models using historical data. The supplier quality evaluation reveals the model's quick adaptation to new material variances from historical distributions. The process alignment analysis confirms the model's effectiveness in proactively predicting and responding to potential system failures, minimizing downtime and waste.

Onaji *et al.*, [24] conducted a detailed analysis of DT technology integration within manufacturing systems, illustrated through three case studies. These case studies demonstrate DTs' diverse applications and benefits in improving manufacturing processes. The results indicate that DTs substantially enhance system monitoring, control, and process optimization. Integrating real-time data within DTs promotes a dynamic and adaptable manufacturing environment, improving resource efficiency, product quality, and operational flexibility. The case studies, drawn from different sectors, underscore the versatility of DTs in adapting to and optimizing various manufacturing contexts, confirming their pivotal role in advancing Industry 4.0 initiatives.

Tliba *et al.,* [25] investigate implementing a DT-driven dynamic scheduling system in a hybrid flow shop within the perfume manufacturing industry. Their findings demonstrate that integrating DT technologies with optimization and simulation techniques markedly improves scheduling flexibility and responsiveness. This strategy effectively addresses real-time production disturbances, including urgent order arrivals or operational timing changes, ensuring the robustness and adaptability of the scheduling system to various changes. The results validate the practical utility of DTs in enhancing the agility and efficiency of manufacturing operations, aiding industries in navigating the complexities of contemporary production environments.

Negri *et al.*, [26] investigate the integration of DT frameworks with manufacturing execution systems (MES) under the umbrella of Industry 4.0, targeting improved DM and system responsiveness. The study introduces two frameworks designed to manage error states and facilitate disassembly processes related to quality issues. The MES-integrated DTs are shown to enhance production efficiency. Specifically, DT-driven error management significantly reduces downtime, and the disassembly framework proactively corrects assembly quality failures, preventing the progression of flawed production. These developments lead to greater operational efficiency and fewer interruptions, highlighting the value of DT integration in MES contexts.

Monek and Fischer [27] proposed a solution to enhance synchronization between physical and digital layers in manufacturing by using discrete-event-driven simulations for more precise DT environments. The system updates a real-time DT by integrating cheap microcontrollers and sensors with standard programmable logic controllers, accurately tracking products throughout production. This environment offers a practical testing ground for digital-twin solutions, enabling efficient simulation-driven process optimization. Monek and Fischer [28] developed a modular DT framework for real-time monitoring and optimization of manufacturing processes with minimal components. Integrated with IIoT (Industrial Internet of Things), it facilitates fault detection, reduces data collection efforts, and supports model reusability, ultimately enhancing sustainability.

2.2 Literature review on Decision support DTs

The compilation of research studies explores the innovative applications of DT technology and FL methods to enhance DM processes in various manufacturing settings. By integrating real-time data, predictive analytics, and fuzzy systems (FSs), these studies address dynamic management of manufacturing processes, resource allocation optimization, and system reliability and responsiveness improvement. The emphasis on decision support systems employing DTs and FL showcases their potential to revolutionize manufacturing workflows, enhance operational flexibility, and enable real-time adaptive responses to changing market conditions and production demands.

The study by Yu *et al.*, [29] investigates the application of DT technology in job shop scheduling, focusing on enhancing manufacturing efficiency. The technology integrates real-time data and predictive analytics to enable dynamic management of manufacturing processes, thereby improving scheduling and resource utilization. The research highlights the potential of DTs to transform manufacturing workflows.

Villalonga *et al.*, [30] present a novel DM framework for dynamic scheduling in cyber-physical production systems, focusing on leveraging multiple DTs to optimize production schedules in real-time. This framework enables decentralized, data-driven DM using FL and condition-based monitoring to predict equipment status and dynamically adjust production schedules.

Mo *et al.*, [31] devised a robust framework employing DTs and modular artificial intelligence for reconfiguring manufacturing systems. This innovative methodology enables dynamic adjustments to manufacturing systems' layout and operational parameters in response to variable market demands. The framework leverages knowledge graphs for DM and optimizes systems within an integrated simulation environment. Its efficacy was validated in a real-world application, which achieved a 10% improvement in process time, demonstrating significant enhancements in responsiveness and productivity within manufacturing contexts.

Francalanza *et al.,* [32] seek the challenges faced by manufacturing system designers in incorporating evolving product ranges. The study introduces an FL-based approach to assist designers in determining the changeability level of manufacturing systems. This approach employs an experimental intelligent ICT tool to support the creation adaptable manufacturing systems designed to accommodate future product developments. The experimental implementation underscores the importance of flexible and reconfigurable systems in effectively responding to unpredictable market demands and customer requirements.

Saraeian and Shirazi [33] analyze a DT-based fault tolerance strategy to improve reliability in CPPS, with a specific focus on the food production industry. The study employs Fault Tree Analyzer (FTA), Zero-suppressed Decision Diagram (ZDD), and Support Vector Machine-Adaptive Neuro-Fuzzy Inference System (SVM-ANFIS) to predict and manage faults effectively. This approach proactively prevents failures by identifying reliable fault signatures, thus enhancing production reliability and reducing downtime. The findings indicate that the DT-based CPPS maintains optimal operation consistently, demonstrating the method's potential to boost system reliability significantly.

Wang *et al.,* [34] explore the use of DTs for real-time resource allocation in the shipbuilding industry, specifically for hull parts picking and processing. The study documents a notable improvement in workstation utilization rates, with an increase of 17.39% and a decrease in the standard deviation of utilization by 83.31%. This enhancement is attributed to the sophisticated real-time task allocation and scheduling capabilities afforded by DT technology, which enables precise and efficient resource distribution and optimizes workstation operation throughout the production cycle. The findings corroborate the efficacy of DTs in boosting operational efficiency and resource management in complex manufacturing environments.

Tulasiraman *et al.*, [35] evaluate FL-enabled Autonomous IoT Systems (FLAIS) for proactive industrial maintenance. Their simulations demonstrate that FLAIS predicts equipment failures and advises maintenance strategies effectively, improving reliability and reducing costs. The system performs best under low uncertainty, with reduced effectiveness in high uncertainty environments, suggesting areas for improvement. This research highlights FLAIS's potential to enhance industrial efficiency within Industry 4.0 by leveraging real-time IoT data and FL.

Glatt *et al.*, [36] research implementing and validating a DT for material flow systems within a cyber-physical production environment, emphasizing the simulation of physical interactions in material handling systems. Their research demonstrates that incorporating a physics engine to simulate material flows markedly diminishes risks associated with handling disturbances, such as accidents and reduced throughput. Through scenario simulation, the DT predicts and mitigates potential disruptions, enhancing safety and efficiency in material handling. The applied use case shows that these capabilities significantly enhance system responsiveness and cost-effectiveness by proactively optimizing operational parameters for safety and productivity.

2.3 Research Gap

Following the general overview, this section of the research aimed to identify research gaps by examining specific case studies and implementations. The outcomes of this analytical assessment are summarized in Table 1. Articles were collected according to two main metrics: publications between 2020 and 2023 with a high citation count, indicating a significant impact within the field. The evaluation of these articles was conducted using a meticulously defined set of six criteria:

- Detailed components: this criterion examines the extent to which the studies address the physical and digital complexities.
- Communication: it evaluates the interconnectivity between physical and digital systems through established communication protocols.
- DES involvement: this involves defining the extent to which DES is integrated into the DT.
- FL implementation: this criterion examines whether FL is employed within the DT framework to facilitate DM processes.
- DT utilization: it considers the objectives behind the development of the DT and its practical applications.
- Validation methodology: this assesses the techniques or tools utilized for validating the developed DT.

A comprehensive review of the studies underscores the necessity for enhanced research and development to augment the operational management of cyber-physical production systems. The analysis indicates that the full potential of the Industry 4.0 paradigm, particularly regarding DTs, could be more effectively realized by establishing a well-defined framework that integrates DTs within a DM support architecture. It is evident from the research that projects deploying DTs predominantly utilize DES-based systems, with OPC-UA emerging as a commonly employed M2M communication protocol.

The review focused on the objectives of DTs and the application of FL in supporting DM processes. As delineated in Table 1, many publications incorporate these techniques concurrently, highlighting a significant interest in the synergistic application of these technologies. Nevertheless, two primary research gaps have been identified. The first concerns the scarcity of frameworks that not only propose theoretical models but also demonstrate their practical applications and validations. Furthermore, there is inadequate discussion regarding the requirements of the physical systems, the integration of real and virtual systems, and the options for action and control. The second identified gap pertains to the limited consideration given to factors influencing the performance of the observed systems, which are typically informed by human expertise and experience. For instance, the anticipation of resource reduction due to unforeseen failures or insights regarding unstocked yet received items remains underexplored.

This paper aims to design and implement a DT to enhance DM in error handling and scheduling tasks within Cyber-Physical Production Systems. Additionally, this research includes a proof-of-concept and validation to assess the DT framework's ability to manage industrial complexities dynamically. A significant innovation introduced in this paper is the ET framework—a DT variant enhanced by FL-based decision modules developed through user interactions with the system. This approach aims to integrate a higher volume of data from PLCs, MES, and ERP systems while preserving the critical role of human DM expertise. This potentially creates a more efficient scheduling paradigm compared to traditional methods, as the DT serves as a dynamic reference model to detect disturbances and enrich scheduling decisions with extensive data integration.

The proposed ET framework, enhanced by integrating expert rule sets and alternatives proposed by DES models, presents an adaptable and user-friendly solution. This framework is designed to streamline the technological requirements for DT creation by minimizing the required software tools. Consequently, it offers an accessible solution for small and medium-sized enterprises seeking to adopt DT technologies.

Table 1
Specific literature review summary table (R: real, V: virtual, TCP/IP: Transmission Control Protocol/Internet Protocol, SCH: scheduling, RESCH: rescheduling, OPT: optimization, MAIN: maintenance, LAB: laboratory testbed, SIM: simulation, THE: theoretical example, TCs: test cases, RPSD: real production system data)

References	Detailed components	Communication	DES involvement	FL	Digital Twin utilization	Validation methodology
[30]	R/V	OPC-UA	yes	yes	SCH, RESCH	LAB
[29]	V	-	yes	no	SCH, RESCH	SIM
[21]	V	-	yes	no	OPT	SIM
[22]	R/V	OPC-UA	yes	no	DT creation, visualization	LAB
[31]	V	OPC-UA	yes	yes	reconfiguration	SIM
[23]	V	Kepware	yes	no	prediction	LAB
[37]	V	-	-	yes	OPT	THE
[32]	V	-		yes	changeability level determination	THE
[33]	V	-	-	yes	fault-tolerant production	TCs
[25]	V	-	-	no	SCH, RESCH	RPSD
[34]	V	OPC-UA	-	no	resource allocation	RPSD
[35]	V	-	-	yes	MAIN	TCs
[26]	R/V	OPC-UA	-	no	reactive action	LAB
[36]	R/V	OPC-UA	-	no	material handling, OPT, MAIN	LAB
[38]	R/V	Socket-based TCP/IP	yes	no	OPT	LAB
[13]	R/V	OPC-UA	yes	no	identification, tracking, monitoring	LAB
[28]	R/V	OPC-UA	yes	no	synchronization, anomaly detection	LAB

3. Methodology

Based on the literature review prepared and published in Section 2 and the authors' experience in industrial digitization, Section 3 introduces a novel framework. It delineates the architecture, operational mechanisms, and the framework's suggested software and hardware specifications.

3.1 Proposed Expert Twin Framework

The framework is engineered to enhance efficiency and productivity. Figure 1 presents a conceptual diagram of the proposed structure. Central to this framework is an innovative decision support module that integrates DES's optimization and scenario exploration features with FL. This integration is informed by experts familiar with the system under consideration, encapsulating their observations and insights. The DT maintains a real-time linkage with the actual system, enabling dynamic interaction via OPC-UA protocols between the physical and virtual environments. This interaction facilitates the real-time acquisition, preprocessing, and filtration of field data, capturing the primary characteristics or states of the devices.

Current literature highlights using computational technologies like FSs, which the DT employs to derive optimal decisions, actions, or recommendations to address uncertainties and non-linearities. These may include rescheduling or necessary interventions. Should an intervention be necessary, the decision-making module (DMM) conducts an optimization process to rearrange the production schedule. Utilizing the built-in genetic algorithm of the DES software and empirical analysis of experimental runs, this module estimates the optimal product sequence that either minimizes total production time or maximizes on-time deliveries. These objective functions are user-defined, and tailored specifically to the production system in question.

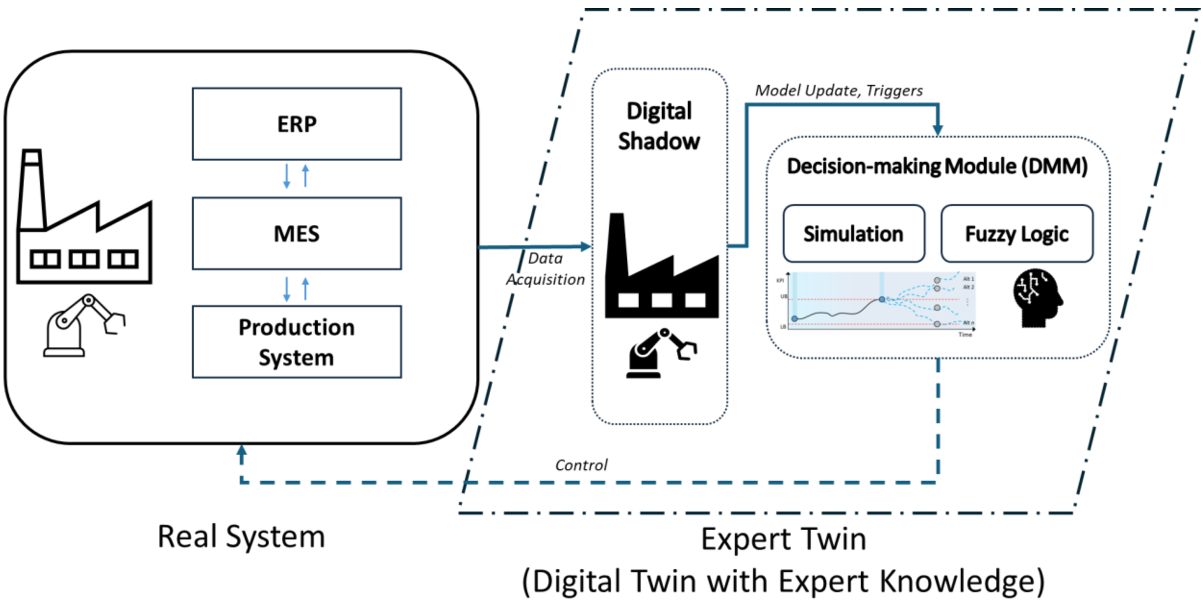

Fig. 1. The Expert Twin framework

3.2 Digital Shadow module

The proposed framework incorporates a DS model, essential for responding in real-time to alterations in the parameters and states of the physical system. The initial phase involves mapping the physical system within a DES environment, crafted to the requisite level of detail akin to conventional process simulation modeling. However, a key distinction lies in the fact that event triggers are derived directly from the physical system. Consequently, the PLC managing the physical system necessitates a direct and rapid communication link with the DES software, ideally without the intermediation of additional middleware or hardware. OPC-UA protocol offers a viable solution for M2M communication, supported by contemporary PLCs and compatible with DES software. Upon establishing this connection, sensor and actuator signals from the physical system are treated as events, enabling continuous remote monitoring and control and systematic data collection. Employing this methodology, the DS module alone can furnish actionable insights to facilitate optimization, though currently reliant on manual feedback.

Proposed Hardware and Software

- Siemens Tecnomatix Plant Simulation for developing the DS.
- PLCs equipped with OPC-UA capability, such as the Siemens S7-1200 and S7-1500 product families.

Required Competencies: Expertise in software environments and programming for both DES and PLC, alongside skills in OPC-UA information modeling.

3.3 Decision-making module

3.3.1 Simulation submodule

The architecture of the Simulation submodule is intricately linked to the DS module. When constructing the model, elements from the DS are integrated sequentially; however, the programming of operational methodologies differs significantly. In the DS module, operational logic is controlled by signals emitted from the PLC. Conversely, in the Simulation submodule, the programmer is tasked with crafting the logic to mirror the system under simulation with high fidelity. This requires accurate input data and resource data to operationalize the model. To illustrate, within the DS framework, a product remains stationary at a specific station until the PLC issues an end-of-process signal. In contrast, the Simulation model requires predefined knowledge about the duration of processes at each station. This essential data can be derived from the DS module, facilitating a more comprehensive representation within the simulation environment.

This component is integral to converting the DS into a DT, aligning with the Kitzinger approach, which posits that the DT should facilitate bidirectional automatic data exchange between the physical and cyber systems. The employed communication protocol enables reciprocal data transmission, a common feature in various frameworks. Nonetheless, the mere capability for two-way communication is inadequate; a systematic approach to DM and intervention coordination is essential.

3.3.2 Fuzzy logic submodule

This block is responsible for turning the DS into a DT; following the Kritzinger approach [39], a DT should be a bidirectional automatic data exchange between the physical and the cyber system. It is necessary to incorporate decision logic into the DT to support or fully automate decision processes. Among the various methodologies employed in DM, Fuzzy Inference Systems (FIS) are prominently featured in the literature and widely adopted in industrial applications due to their simplicity, efficacy, and intuitiveness [30]. FIS effectively models the non-linear relationships between inputs and outputs, facilitating robust and adaptable DM by applying fuzzy sets and rules. An FL module has been developed to recognize the challenges in the contemporary industrial digital landscape, where decision-critical information may not always be available with the requisite precision. The module should be constructed by experts with a good knowledge of the real system. The Sugeno-Fuzzy (SF) inference system is selected for its computational efficiency and effectiveness in handling optimization and adaptive challenges, making it particularly suitable for dynamic, nonlinear system control. In designing a Sugeno Fuzzy controller, a T-S Fuzzy model tailored to the nonlinear system is required. This system is characterized by blending fuzzy logic principles with systematic, mathematical methodologies to form a structured model capable of handling complex systems' inherent ambiguities and uncertainties. The formulation begins with defining the necessary fuzzy sets and their corresponding membership functions, categorizing the input variables into linguistic terms such as 'low', 'medium', and 'high'. Rules are then constructed, linking these fuzzy sets with their outcomes based on the logical operators AND, OR, and NOT. Constructing such a model is a fundamental and crucial step in this methodology. Generally, there are two prevalent strategies for developing fuzzy models:

1) Identification, or fuzzy modeling, utilizing input-output data.
2) Derivation based on the equations of the nonlinear system.

The final output of the system is calculated by a weighted average of each rule's output, where the weights are the truth values of the rule's premises, evaluated using the membership functions of the inputs. This aggregation of outputs provides a single crisp output that effectively captures the system's behavior under various input conditions. The deployment of such a fuzzy inference system within operational frameworks can dramatically enhance DM capabilities by providing a robust mechanism for processing a range of input uncertainties and converting them into actionable outcomes. This capability is integral to optimizing operational efficiency and responsiveness in real-time applications.

Mathematical formulation of the Takagi-Sugeno Fuzzy Inference System:

$IF\ x_1\ is\ A_1\ and\ x_2\ is\ A_2\ THEN\ y = f(x_1, x_2)$

$Where$ A and B are fuzzy sets and $y = f(x_1, x_2)$ $is\ a\ crsip\ function\ in\ the\ consequent$

i-th rule can be represented as follows:

$\boldsymbol{IF\ x_1\ is\ A_1^i\ AND\ x_2\ is\ A_2^i \dots\ x_n\ is\ A_n^i\ THEN\ y^i = a_0^i + a_1^i x_1 + \cdots + a_n^i x_n}$

$\boldsymbol{Where\ a_0, a_1, \dots a_n\ are\ the\ constants}$

weight of i-th rule can be determined as follows:

$$\boldsymbol{w^1 = \mu_{A_1}^i(x_1) \times \mu_{A_2}^i(x_2) \times \dots \times \mu_{A_n}^i(x_n)}$$

$$\boldsymbol{x^* = \frac{\sum_{i=1}^k w^i\ y^i}{\sum_{i=1}^k w^i}}$$

Where k indicates total number of rules

Proposed hardware and software:

- Siemens Tecnomatix Plant Simulation to create a production process simulation.
- Matlab Fuzzy Toolbox to create an SF system.

3.4 Overview of Framework Operation

The operational mechanism of the framework is structured as follows: The ERP system collaborates with the MES to compile the task list for the PLC of the manufacturing system. If historical data are accessible, the simulation module can be employed to formulate an optimized sequence plan prior to process initiation. Upon commencement of the process, the DS system monitors the physical system in real-time, logging each event systematically. It continually assesses the alignment between the preliminary plan and the actual status. Should discrepancies surpass predefined thresholds or an unforeseen event occur (e.g., raw material shortages, equipment failures), the DS issues a trigger signal to DMM. The FL submodule evaluates whether new optimization is warranted based on the current data to avoid unnecessary actions. If optimization is deemed necessary, the simulation submodule revises its operation using the log data collected by the DS, and the updated model then assesses potential enhancements to the plan for the remaining tasks. The FL submodule, guided by established rules, determines whether intervention is required. If an intervention is decided upon, it prompts a modification in the task list of the PLC that controls the actual system.

4. Results

4.1 Test manufacturing cell

To demonstrate and validate the efficiency of the proposed Expert Twin framework, a customized FESTO Modular Production System (MPS) has been utilized. This manufacturing cell, modern in terms of its components and reflective of contemporary industrial applications, serves as a testbed to exhibit the functionality and effectiveness of the newly developed system through a scaled-down industrial setup (Figure 2).

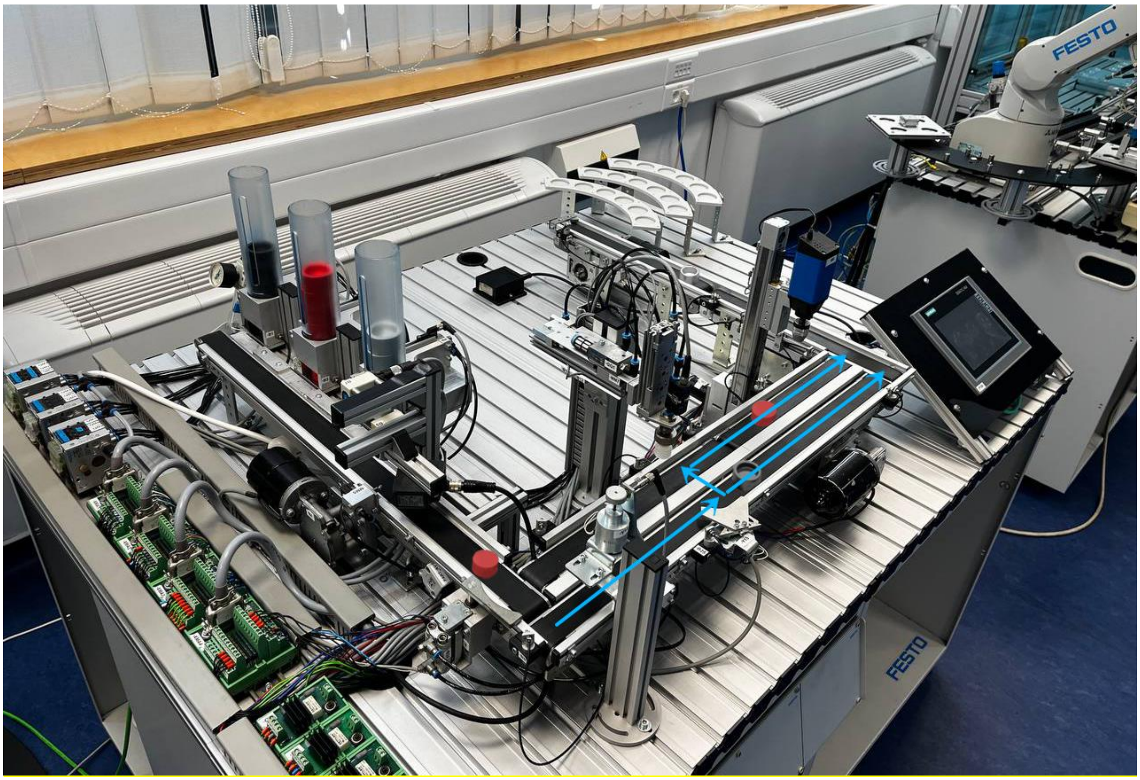

Fig. 2. Real System. Customized FESTO modular cell

The MPS processes cylindrical parts differentiated by three distinct colors. These parts are segregated into containers based on color; however, each container may contain both machined (hollow) and unmachined (solid) items, a distinction crucial to subsequent processing stages. Initial processing involves a sensor station that performs color verification and depth measurement, with these characteristics encoded onto an RFID tag attached to each part. Following the digital cataloging of these attributes, the required machining degree is assessed at a mechanical depth detection station. Based on these defined product characteristics, subsequent decisions regarding the routing of each part are made at the next station. Machined parts may proceed directly if the conveyor belt elements ahead are unoccupied; otherwise, they are held until the pathway is clear. Parts requiring additional machining are transferred by a manipulator equipped with a vacuum head gripper to another conveyor leading to the machining station. Post-machining, the parts retrace their path to the production line's end, where they are systematically placed in a storage area by a robotic arm.

In order to increase the complexity of the process shown, products of different colors are assigned varying processing times at each station. Additionally, the system can be configured to disable direct routes from parallel conveyors, necessitating the transfer of all products to the machining branch, even those not requiring further processing. In this case, products not needing to be machined are also placed at the machining station to continue without processing time.

4.2 DS and Simulation Model implementation

The authors' prior investigations [27,28] have already dealt in detail with the development of DS and DT solutions capable of replicating processes in manufacturing systems, which is summarized in the current article.

The initial development phase involved establishing a DS (Figure 3). This required setting up an automatic data linkage between the physical system and its digital counterpart. It is crucial to ensure the presence of a communication channel compatible with both the hardware and software components involved. As discussed earlier, this connectivity is achieved through the OPC-UA communication protocol, a standard that satisfies real-time communication requirements and is broadly supported across various IoT devices. This compatibility facilitates future integrations with additional devices, enhancing the collection of data and thus refining the virtual model of the real system. On the hardware side, a Siemens S7-1516P/N PLC is employed to manage the control functions within the production system. This PLC gathers comprehensive data from all sensors and actuators in the system, making this information accessible to connected clients through a structured OPC-UA information model, effectively functioning as a server. The software environment utilized is Siemens Tecnomatix Plant Simulation, which interacts with the PLC data, responding and transmitting information back to the PLC. This integration of a modern PLC with a contemporary event-driven simulation tool allows for creating a DS module without the need for additional software or hardware.

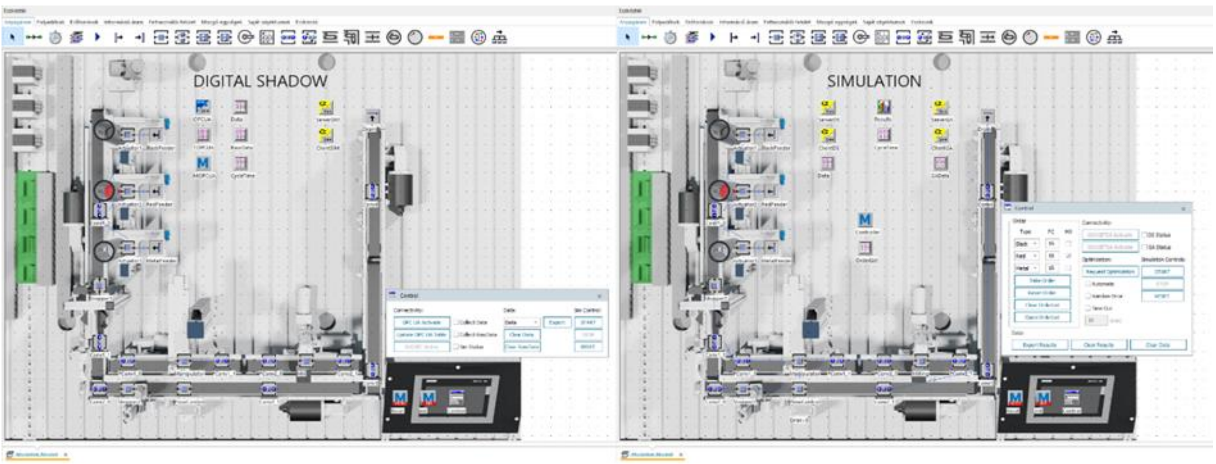

Fig. 3. Digital Shadow and Simulation model implemented in DES environment

4.3 Expert knowledge implementation

This work primarily aims to enhance the efficiency of automated decision support processes by integrating human expert knowledge. The method is demonstrated using a simplified approach due to the lower computational demands and the relatively uncomplicated nature of the test system compared to a full-scale industrial environment, which consequently restricts the scope for process improvement and intervention. It is essential to acknowledge that while the proposed framework is universally adaptable, the individual modules must be customized to the specific manufacturing context by experts familiar with the system. Additionally, the framework's performance should be continuously monitored and adjusted as necessary. Moreover, the framework can integrate not only one but several different fuzzy inference systems. Two levels of DM have been distinguished. The first one (DMM_I) takes two input parameters (Figure 4), and the second one (DMM_II) takes three input parameters into account to determine whether it is necessary to modify the current production schedule to minimize lead time. The parameters in each case are:

DMM_I:

- Expected downtime: within an industrial setting, it is a critical component of production management for maintenance and diagnostic personnel to estimate the anticipated downtime in the event of a potential equipment malfunction.
  Membership functions: short, medium, long.
- Percentage of remaining quantity: this metric denotes the proportion of the remaining volume to be processed on a specified resource, relative to the total batch size currently under production.
  Membership functions: few, moderate, many.

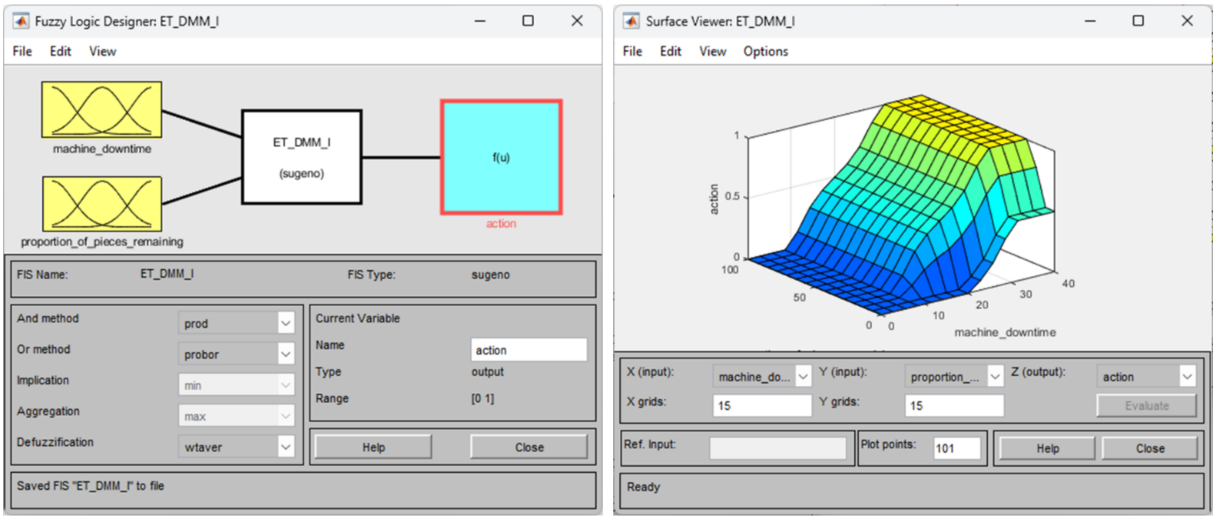

Fig. 4. A Fuzzy model applicable to the specified use case (DMM_I)

DMM_II:

- *f(u)*: outcome of the antecedent decision module (DMM_I). This parameter quantifies the urgency of intervention based on the primary criteria evaluated.
  Membership functions: low, medium, high.
- Achievable efficiency: this value indicates the achievable efficiency improvement of each re-planning option compared to the current plan under the changed circumstances. The simulation module searches for an optimal solution with updated values synchronized from DS.

Membership functions: low, medium, high.

- Level of schedule modification: in industrial contexts, maintaining schedule stability is paramount during revisions. This metric expresses the extent of adjustments associated with the rescheduling. From a DM perspective, this is significant as new optimizations may yield a schedule distinctly divergent from the original.
  Membership functions: low, medium, high.

Figure 5 presents a schematic representation of the expert twin DM algorithm, specifically tailored to the use case. This flowchart delineates the systematic progression of computational steps and decision nodes that constitute the algorithm. The algorithm encapsulates a series of logical assessments and data processing tasks that facilitate real-time DM based on the dynamic data received from the physical system it mirrors. The structured arrangement of these tasks within the flowchart allows an intuitive understanding of the DM process, highlighting how data inputs are transformed into actionable insights or operational adjustments.

4.4 Test scenario findings

Several tests were carried out on the system presented during the case study. These evaluations involved the application of the proposed Expert Twin (ET) methodology, whose outcomes were benchmarked against those derived from a reference solution employing predefined lower and upper intervention thresholds. In this comparative analysis, the deviations between the actual operational states and the theoretically designed states were scrutinized using the limiting value methodology. The findings from these experiments substantiated the efficacy of utilizing a DMM equipped with precisely calibrated parameters. It was demonstrated that this approach significantly curtails the frequency of non-essential rescheduling activities, typically of low utility. Consequently, this reduction in unnecessary adjustments leads to decreased time spent on machine changeovers and the reorganization of logistical processes, thereby enhancing the overall efficiency of the production line and reducing lead times.

Conversely, the method used for comparison purposes was observed to prompt re-optimization of the process in several instances. This frequently resulted in extended reallocation times and increased lead times, albeit maintaining lower idle times. This contrasts with the ET approach, where it was more commonly noted that the system experienced delays awaiting necessary resource adjustments. This comparative analysis highlights the ET methodology's distinct operational dynamics and potential efficiencies in streamlining production processes.

The ET significantly enhanced the utility of the production line, achieving an increase of up to 28%. Additionally, the frequency of rescheduling operations was effectively reduced by half. These findings are derived from data collected within the test environment; consequently, asserting that analogous substantial outcomes will be observed across all systems is not universally applicable. The replicability of these results is contingent upon the system's specific characteristics under examination, and the efficacy of the DMM and associated simulation models developed. Nevertheless, by leveraging a human knowledge base, there is a considerable probability that an effective automated decision support framework can be established that would be well-suited to various operational contexts. This solution also demonstrates a greater alignment with real-world industrial applications. Introducing a new schedule or deviations from the predefined plan can considerably elevate the risk of quality errors, often attributable to lapses in attention. Such circumstances necessitate stringent work management practices to ensure that these adjustments do not compromise the quality and integrity of the production process. Effective management and precise coordination are essential to mitigate these risks, emphasizing the critical nature of robust oversight in dynamic industrial settings.

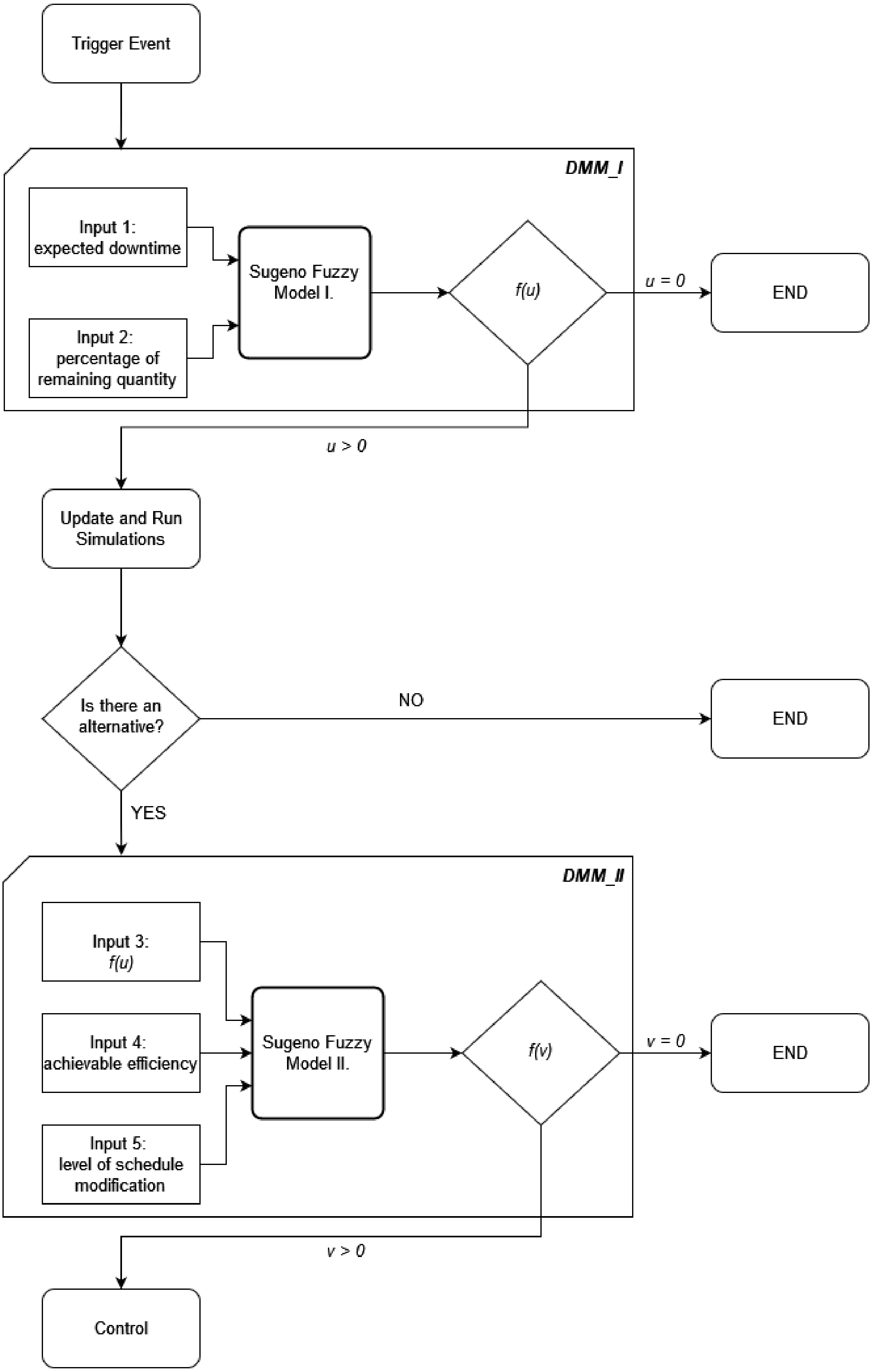

Fig 5. Decision-making flow chart to the specified use case

5. Conclusions

The research presented in this paper elaborates on the Expert Twin framework, an innovative DT system that integrates an FL-based DMM to enhance manufacturing processes. The framework is a significant advancement in the field of I4.0, facilitating real-time operational adjustments and decision support through seamless integration with CPS.

The ET framework has demonstrated considerable improvements in production efficiency and DM capabilities. In controlled testing environments, implementing the ET framework led to a 28% increase in production line utility and a 50% reduction in the necessity for rescheduling operations. These enhancements underscore the framework's potential to optimize manufacturing workflows significantly, thus reducing operational lead times and enhancing system responsiveness to unforeseen production variables. It is essential to recognize the limitations of these findings as they are derived from controlled test scenarios. The actual applicability and effectiveness of the ET framework in diverse manufacturing settings may vary based on specific system characteristics and the intricacies of the deployment environment. Therefore, while the initial results are promising, further real-world applications and extended validation studies are necessary to ascertain the framework's universal effectiveness and adaptability fully.

The integration of fuzzy logic within the DM processes of the ET framework highlights its capability to handle ambiguous and fluctuating manufacturing data effectively. This integration supports robust DM that accommodates the complexities and nonlinearities inherent in dynamic manufacturing environments. Future research should focus on enhancing the scalability of the ET framework to support its application across a broader range of industrial settings and complexities. Additionally, increasing the autonomy of the DM processes through more advanced artificial intelligence methodologies could further reduce the reliance on human intervention and streamline operations.

Overall, the Expert Twin framework represents a significant stride towards more intelligent, efficient, and adaptable manufacturing systems, aligning with the goals of I4.0 to integrate digital and physical processes seamlessly. As industries continue to evolve towards fully automated and smart manufacturing systems, the principles and technologies demonstrated in the ET framework will likely play a pivotal role in shaping future manufacturing paradigms.

List of abbreviations

CPPS	Cyber-Physical Production System
CPS	Cyber-Physical System
DES	Discrete Event Simulation
DM	DM
DMM	Decision-making Module
DS	Digital Shadow
DT	Digital Twin
ERP	Enterprise Resource Planning
ET	Expert Twin
FIS	Fuzzy Inference System
FL	Fuzzy Logic
FLAIS	FL-enabled Autonomous IoT Systems
FTA	Fault Tree Analyzer
I4.0	Industry 4.0

IoT	Internet of Things
JIS	Just in Sequence
JIT	Just in Time
LAB	Laboratory testbed
LT	Lead Time
M2M	Machine to Machine
MAIN	Maintenance
MES	Manufacturing Execution System
MPS	Modular Production System
NFC	Near Field Communication
OPC-UA	OPC-Unified Architecture
OPT	Optimization
PLC	Programmable Logic Controller
PS	Tecnomatix Plant Simulation
R	Real
RESCH	Rescheduling
RFID	Radio-frequency Identification
RPSD	Real production system data
SCH	Scheduling
SF	Sugeno-Fuzzy
SIM	Simulation
SMIs	Small and Medium Industries
SVM-ANFIS	Support Vector Machine-Adaptive Neuro-Fuzzy Inference System
TC	Test case
TCP/IP	Transmission Control Protocol/Internet Protocol
THE	Theoretical example
V	Virtual
ZDD	Zero-suppressed Decision Diagram

Author Contributions

Conceptualization, G.D.M. and S.F.; methodology, G.D.M. and S.F.; software, G.D.M.; validation, G.D.M.; formal analysis, G.D.M. and S.F.; investigation, G.D.M. and S.F.; resources, G.D.M. and S.F.; data curation, G.D.M.; writing—original draft preparation, G.D.M. and S.F.; writing—review and editing, G.D.M. and S.F.; visualization, G.D.M.; supervision, S.F.; project administration, G.D.M. and S.F.; funding acquisition, G.D.M. and S.F. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

The datasets generated or analyzed during this study are available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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