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A decision-making framework for dynamic scheduling of cyber-physical production systems based on digital twins

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ABSTRACT

Nowadays, one important challenge in cyber-physical production systems is updating dynamic production schedules through an automated decision-making performed while the production is running. The condition of the manufacturing equipment may in fact lead to schedule unfeasibility or inefficiency, thus requiring responsiveness to preserve productivity and reduce the operational costs. In order to address current limitations of traditional scheduling methods, this work proposes a new framework that exploits the aggregation of several digital twins, representing different physical assets and their autonomous decision-making, together with a global digital twin, in order to perform production scheduling optimization when it is needed. The decision-making process is supported on a fuzzy inference system using the state or conditions of different assets and the production rate of the whole system. The condition of the assets is predicted by the condition-based monitoring modules in the local digital twins of the workstations, whereas the production rate is evaluated and assured by the global digital twin of the shop floor. This paper presents a framework for decentralized and integrated decision-making for re-scheduling of a cyber-physical production system, and the validation and proof-of-concept of the proposed method in an Industry 4.0 pilot line of assembly process. The experimental results demonstrate that the proposed framework is capable to detect changes in the manufacturing process and to make appropriate decisions for re-scheduling the process.

1. Introduction

Currently, a fresh push towards smart manufacturing and cyber-physical production systems is given to automatically and dynamically update production by decision-making tools in runtime (Panetto, Iung, Ivanov, Weichhart & Wang, 2019). This is an open challenge and various approaches have been proposed in the past for the automated decision-making in this field, among which distributed and agent-based architectures are a rich research stream Chan & Chung (2013). Nowadays, the digitization and the Industry 4.0 enabling technologies may offer new possibilities in this realm (Frazzon, Agostino, Broda & Freitag, 2020).

Reprogramming is in fact necessary, in order to update a production schedule when a change in the state of the manufacturing system makes the current schedule unfeasible or inefficient (Ma, Yang, Liu & Wu, 2018). Therefore, rescheduling updates are performed in response to certain performance indicators, e.g. subsequent to some predictive maintenance activities leading to the prediction of the remaining useful life before the failure. Overall, the dynamic scheduling capability aims at increasing the productivity and reducing the operational costs of the manufacturing system.

There are many strategies to perform production rescheduling, especially if the new trend towards Industry 4.0 (I4.0), which brings Information and communications technology (ICT) to production systems, is considered. Industrial Internet of Things (IIoT) and Industrial Cyber-Physical Systems (ICPS) have led to achieve the next level in smart manufacturing (Iarovyi, Martinez Lastra, Haber & Del Toro, 2015). ICPS have become particularly relevant as the main enablers in bridging virtual and physical worlds, thanks to their computing and communication capabilities Wolf (2009) (Villalonga, Beruvides, Castano & Haber, 2020). An important ICPS-based technology that is fostering the digital transformation process is the Digital Twin (DT). In order to

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obtain a perfect emulation and mirroring of the operating conditions of the corresponding real systems, DT uses the best available representations, physical and virtual models (Rosen, Von Wichert, Lo & Bettenhausen, 2015)(Guerra, Quiza, Villalonga, Arenas & Castano, 2019), in order to support an enhanced decision-making. There is no unique definition of DT. DT can be considered as one or many simulation model (s) of a real system that is/are always connected with the physical counterpart (or is/are disconnected only temporarily for specific reasons). This connection enables to gather real-time data from the field, to perform simulations (e.g. scenario analyses or other types of analyses) and to send feedback to the physical world in order to modify the behavior of the real entity or component. Very often, the DT is connected to an intelligence layer that contains rules, optimization algorithms, and decision-making functionalities, in order to make decisions on how to act on the real system.

Looking at manufacturing operations management, Cyber-Physical Systems (CPS) are leading to an evolution towards future smart factories where decentralization and autonomy are two important characteristics (Napoleone, Macchi & Pozzetti, 2020). Some collaborative CPS (Ivanov & Sokolov, 2012; Nazarenko & Camarinha-Matos, 2017), specifically Cyber-Physical Production Systems (CPPS), behave as evolving entities with a high degree of autonomy to ensure the adaptive response to disturbances, while communicating and coordinating their actions by exchanging information in order to meet common organizational goals. A key change is driven by the development of advanced and distributed DT-based frameworks on the basis of engineering methods focused on condition-based monitoring (CM) strategies (Leitão, Colombo & Karnouskos, 2016).

Efficient and reliable decision-making procedures are indeed the bottleneck at machine/equipment level with two main needs: (i) highly accurate and (ii) high fidelity mirroring and efficient communication between physical and virtual spaces are required. Special relevance is given to emulate human-in-the-loop socio-cognitive skills (Haber-Haber, Haber, Schmittdiel & del Toro, 2007). Moreover, DTs are assuming a leading role for DT-based scheduling frameworks, both at global level to manage the production process in the factory, and at local level for generating simulations to address the CM of production equipment Barricelli, Casiraghi & Fogli (2019).

Nowadays, the availability of data from industrial equipment and the computing power open up the opportunity of designing and developing a new framework to carry out production scheduling tasks. This can be done by exploiting a new type of aggregation of multiple DTs representing different physical assets. Therefore, the main motivation of the present work is to better exploit DTs, data gathered from physical assets and decision-making to improve the scheduling process, thus optimize, and increase the productivity of manufacturing systems. This leads to consider new DT-based scheduling methods to reduce scheduling deviations, by updating resource parameters from interactive programming strategies(Fang et al., 2019). In addition, a DT model enhances the ability to digitally simulate how the production line will perform in the real world, contributing to decision-making when a rescheduling in the production system is needed on the basis of state-of-art frameworks (Zhang, Liu, Chen, Zhang & Leng, 2017). DTs for supporting dynamic and automated decision making also eliminate human errors in gathering data and can respond faster to the changes in a production system, thanks to the constant update with the field data (Bevilacqua et al., 2020; Borangiu et al., 2020). Furthermore, DTs can decentralize the decision-making activities and new modification are easier to be introduced into the system.

The literature is plenty of new methods to move towards DT-based scheduling frameworks that exploits CM strategies. On one hand, the use of architectures seamlessly integrating the production scheduling and CBM (Condition Based Maintenance) through a DT-based field synchronization is proposed by Negri et al. (2020); this leads to a scheduling optimization method (based on genetic algorithms) and a field-synchronized Equipment Health Indicator module, all together embedded into the DT-based simulation. A step ahead could be embedding DTs in local controllers, to make the role of predictive models for CBM easy, as well as to provide an efficient local decision-making to detect faults and assist the operators. Therefore, implementing distributed frameworks with embedded DTs in the local nodes while making decisions based on adaptive thresholds techniques and local simulations is a promising strategy that could be used in order to improve the manufacturing operations management and conduct more efficient scheduling tasks.

On the other hand, the use of distributed architectures in smart manufacturing contributes to enhance efficiency and reliability. In particular, it is worth remarking that scalability provides robustness against failures, facilitating reconfiguration actions without affecting the production. One strategy is to develop distributed frameworks based on DTs which, besides the robustness against failures, to enrich the knowledge about the manufacturing process because of the added value given by the simulations, close to the local process, and the generation of useful data. This information allows to take more efficient actions both globally (at factory level) and locally (at the level of workstations or single equipment pieces), finally improving the scheduling and the optimization tasks.

Potentialities of DTs can be better exploited in distributed frameworks. Nowadays, there are some important gaps and shortcomings. The lack of well-defined frameworks that combine DTs, the limitation of methods for aggregating DTs, the limited practical applications and the poor use of the data gathered from physical counterparts are some evident weaknesses. Overall, current limitations of DTs can be overcome by designing a distributed framework where different virtual-physical embedded nodes at the local and global levels cooperate for achieving common goals. The work reported in this paper proposes the design and implementation of a framework based on local and global DTs for smart decision-making in cyber-physical production system and then validate the technical viability and the possibility to use it real industrial setups by a proof-of-concept in an Industry 4.0 pilot line. The proposed approach is supported on DTs that simulate the performance of each device/machine of the production system as well as of the whole production system. Correspondingly, DTs are adopted at local (e.g., device/machine) and at global (e.g., production system or plant) levels, combined with local CM for rescheduling actions. This aims to improve efficiency by avoiding the decrease in production performances due to malfunctioning or components degradation.

In order to illustrate the proposed contribution, the paper is structured as follows. Section 2 presents a review of the state-of-the-art of related works about DT-based architectures and shows the main gaps and shortcomings. Section 3 describes the distributed DT-based framework and the decision-making algorithms. Section 4 presents the case study and framework proof-of-concept validation in a use case to show the validity of the proposed framework. The conclusions are provided in Section 5.

2. Related works

The definition and the concept of DT in smart manufacturing are not new and not unique in literature. The first definition of a DT was given by the NASA, stating that a DT is “an integrated multi-physics, multiscale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its flying twin” (Shafto et al., 2012). From this first description, the concept of DT evolved, and the scientific community provided several definitions, declined in different fields and applications. However, in literature the proper characteristics of a DT are common among the different descriptions given by the authors. Nowadays a DT is referred as a real-time simulation of a physical asset, capable to communicate to its physical “twin”, to elaborate data coming from it in a seamless way, to optimize its performance, to monitor and to predict its behavior (Fei Tao et al., 2018). Indeed, today the availability of data and information coming from industrial equipment is higher than in the past, and as many studies demonstrate, the intersection between optimization models and available information, has not been thoroughly explored yet (Cimino, Negri & Fumagalli, 2019). A DT has to be frequently updated or tuned, and any change in software or hardware in the physical counterpart has to be carefully implemented also in the DT (Borangiu et al., 2020). For this reason, a DT is an evolving virtual entity.

The use of DTs to improve the operational activities in a production system is worldwide addressed, and many applications have been already described and reported (Cimino et al., 2019). DTs have been exploited in real-time reading of machine states (Kritzinger, Karner, Traar, Henjes & Sihn, 2018), to address some production problems by interacting with the manufacturing execution system (MES) (Negri, Berardi, Fumagalli & Macchi, 2020), or by scheduling tasks on the basis of actual health state of the assets, thus providing a more robust solution (Negri et al., 2020).

Decision making algorithms for scheduling process in CPPS are focused on goals such as minimization of the makespan, the work in progress or the production costs (Hamid, Nasiri, Werner, Sheikhahmadi & Zhalechian, 2019). One challenge is to determine if the current decision-making performs well enough in complex systems. An improvement can be achieved by simulating the effects of decision-making in scheduling systems (Frantzén, Ng & Moore, 2011). An appropriate system can schedule under consideration of the current system state and the production goals. Instead of using one single priority rule focus on one production goal, other rules can be considered such as the state of the assets or the combination of different production goals. By introducing simulations, the impact of different rules on the system the can be compared Güçdemir & Selim (2018). Moreover, the use of artificial intelligence techniques such Fuzzy Logic (Han, Liu, Luo & Mao, 2020)(Dorfeshan, Tavakkoli-Moghaddam, Mousavi & Vahedi-Nouri, 2020) and machine learning (Poongothai, Kannan & Godhandaraman, 2021)(Feng, Li, Cen & Huang, 2003) can improve the decision-making process in presence of uncertainty.

This work contributes to this challenge by proposing a new framework to carry out production scheduling tasks exploiting a new aggregation in a framework with several DTs representing different physical assets. The focus of the scheduling process is on the decision-making framework based on the aggregated DTs and the corresponding data and information coming from them. For this reason, the literature review is centered on available architectures of DTs, to understand how information and data can be better exploited to improve schedules and thus optimize the productivity of the manufacturing system.

This work is the natural evolution and a next step in the research on dynamic production scheduling with distributed architectures, such as those based on multi-agent systems (Cavalieri, Garetti, Macchi & Taisch, 2000; Li, Xiao & Yang, 2019). With the advent of Industry 4.0, the use of CPS in manufacturing, the new levels of autonomy and smartness, naturally rejuvenated the interest to change the centralized scheduling methods into decentralized ones. Thus, dynamic decision-making and scheduling methods have to be re-designed in order to ensure flexibility and adaptation before disturbances in the production systems (Jiang, Jin, Mingcheng & Li, 2017). This is influencing on current studies for production scheduling optimization, putting the focus on the definition of new methods that more easily describe the complex modern CPS and change accordingly to their modification or breakdown, leading to research works on new dynamic scheduling algorithms that elaborate more robust and reliable solutions Long, Zheng & Gao (2017).

2.1. Literature review on digital twin-based architectures

The review of the state-of-the-art focused the attention on DTs explicitly considered in distributed architectures. In particular, the main priority is to study the published works where more than one DTs were built and merged or connected into a unique architecture or platform for complex production systems. Works considered relevant for this literature review are reported in Table 1. They were analysed based on six criteria, essential to understand the aggregation of DTs into a single architecture or platform. Columns in the Table 1 are devoted to each criterion:

- *Architectures*, in which the described DTs are interacting with each other;
- *Domain* refers to whether the DTs are built using a single software (single-domain scenario) or different DTs are built with different software tools (multi-domain scenario);
- *Machine to model (M2M) communication* deals with the IT part of the architecture, describing the way DTs are connected to their physical counterparts, the communication protocols and the connected communication problems;
- *Targets* considers the application fields for which the proposed frameworks are thought, namely the main objectives reachable by the adoption of the studied solutions;
- *Practical application* takes into account if a purely theoretical approach is addressed or a practical implementation of the DTs is present, either in a real or in a lab context;
- *Software* considers the software tools, when mentioned, used to develop the DTs; this aspect also helped the authors to understand which software fits the requirements of the application, according to its software characteristics;
- *Industry 4.0* alignment to identify if the reported work explicitly mentions the Industry 4.0 paradigm.

This review of a wide spectrum of architecture models reveals that most of them are hierarchical models (H.M.). Each level of the hierarchy has its own function and provides data or information to the level above. Moreover, the upper levels can send commands or information downstream the hierarchy to actuate decisions in a specific lower level. The arrangement in a hierarchy eventually expresses the relative importance of the decisions/gathered information: a higher level in the architecture corresponds to a higher priority of the decisions/information. Activity-Resource-Type-Instance architecture (ARTI), first proposed by Valckenaers (2019) is characterized by a local DT for each equipment piece and by the fact that the intelligence layer is separate from the DT simulation modeling (Borangiu et al., 2020); it has been also considered of interest for the relationship between the DT and the computational layer where data are processed and decisions are taken. The co-simulation framework is also quite common due to its ability to describe complex and heterogeneous systems and its flexibility (Stecken, Lenkenhoff & Kuhlenkötter, 2019). Co-simulation represents a complex and heterogeneous system implemented in a distributed way. Different simulation models are built to represent the entire system, but they can be used in a black-box way. This allows to de-couple the problems and provides highly flexible solutions. The simulation models, in fact, can be built with different software and run as standalone models (Stecken et al., 2019). From the literature review, other types of architecture emerged, however their implementations are at early stages of development and thus are not relevant yet.

The multi-domain scenario is adopted to describe complex systems while considering more disciplines in the DT simulation, e.g. thermodynamics, mechanical behavior, operations performance, etc., thus more requirements are needed to better describe or represent the complex system. On the contrary, when dealing with only one discipline, the reported works suggested specific architectures that are suitable for a single-domain scenario.

Machine-to-model communication was thoroughly considered to understand the current most used communication protocols in smart manufacturing. The Open Platform Communications Unified Architecture protocol(OPC-UA) (A. Redelinghuys, Basson & Kruger, 2019) and the cloud-based approach are the most widely adopted. The OPC UA protocol is well known in the industrial world as one of the standards on which Industry 4.0 is leveraging. The cloud-based communication

Table 1
Literature review summarizing table.

REF.	Architecture				Domain		M2M Communication					Targets	Practical application		Software	Industry 4.0
	H. M.	ARTI	Co sim	Other	Single	Multi	OPC UA	Cloud	TCP/ IP	Modbus TCP	Others		Industrial case	Lab case		
(A. Redelinghuys et al., 2019)	x						x					C				x
(A. J. H. Redelinghuys, Kruger & Basson, 2020)	x						x					C	x (cell)			x
(Fei Tao et al., 2019)	x										x	S				x
(Uhlemann et al., 2017)				x		X		x				C				x
(Gurjanov, Zakoldaev, Shukalov & Zharinov, 2019)				x							x					x
(Qi et al., 2018)	x					X		x								x
(Cardin et al., 2020)		x			x					x		M, CT		x	Rock-well Arena, Java	x
(Wang & Wang, 2018)				x		X		x				T		x		x
(Beregi et al., 2018)	x					X			x			E		x	Tech. Plant Simulation, AnyLogic	x
(Alam & Saddik, 2017)	x							x						x(s)	Java	x
(Bakliwal, Dhada, Palau, Parlikad & Lad, 2018)			x			x					x	M	x (fleet)		Python	x
(Ashtari Talkhestani et al.,)			x			x	x	x	x	x		M		x	Java	x
(Jung, Shah & Weyrich, 2018)			x			x	x					C(s)			Simulink, Modelica	x
(Stecken et al., 2019)	x		x			x					x	C(s)		x(s)	AutomationML	x
(Havard et al., 2019)			x			x					x	VR		x	Catia, Modelica	x
(Brandenbourger & Durand, 2018)	x				x		x							x		x
(Qamsane et al., 2019)				x		x	x	x				M		x(s)	Rockwell, AutoMod	x
(Catarci et al., 2019)		x				x					x	M		x(s)		x
(F Tao & Zhang, 2017)				x	x				x	x				x(s)	Catia, SolidWorks	x
(Fera et al., 2020)				x	x						x	VR		x	Tecnomatix Process Simulate	x
(Khan, Farnsworth, McWilliam & Erkoyuncu, 2020)				x		x					x					x
(Morel, Pereira & Nof, 2019)		x				x						CT				x

M2M: Machine To Model; C: conceptual contribution, M: monitoring, T: tracking, CT: control, E: error management, VR: virtual reality, S: simulation, (s): simulated application.

approach is not a protocol. However, it has been considered relevant for the analysis of the state-of-the-art, since many papers deal with DT developed in cloud ambient, thus often the issue related to their communication and interoperability is mentioned (Qi, Zhao, Liao & Tao, 2018). TCP/IP (Transmission Control Protocol and Internet Protocol) is a set of communication protocols widely used today in internet and similar networks of computers. It has often been mentioned when DTs were connected via Internet or the data sources were reachable mainly via network (Beregi, Szaller & Kádár, 2018). The last major communication method described several times among the papers is the Modbus/TCP. This is the most used protocol for communications with the programmable logic controllers (PLC).

Targets are namely the objectives for the architectures proposed in the papers. DTs can be used for many different purposes (monitoring the production, improving maintenance, making decision, etc.). The aim of this criterion is then to classify the studied papers according to their main purpose. It is possible to see that the main targets proposed in the analysed research works on DT-based architectures and platforms are: control, monitoring, error management and virtual reality. Control targets, using DTs, mainly deal with the online managing of a production system, by adopting decisions and changes in real-time. On the other hand, monitoring regards the tracking and the evaluation of KPIs (Key Performance Indicators) of a production system, or the state monitoring of the physical assets (e.g. health states, machine states, etc.). The last most common target is virtual reality, where the DT-based architectures is exploited to render the behavior and the state of a whole production system in real-time or to perform simulations for layout performance assessment (Havard, Jeanne, Lacomblez & Baudry, 2019).

The study of practical applications of the analysed DT-based architectures demonstrates a gap of this topic. Few practical implementations of the analysed DT-based architectures are in fact reported: most of them elaborate only theoretical solutions and approaches. In addition, simulations only validate most of the practical realizations, and therefore DTs are not really assessed in real scenarios with a physical counterpart. In Table 1 this is summarised as follows: lab cases and industrial cases are ticked if the architecture under analysis is contextualized within an industrial or academic laboratory or in a real production system, respectively. When the cells in the columns are empty, this means that the analysed architecture had no practical implementation and the contribution remained at a theoretical level.

The software aspect deals with the specific software tool used or suggested for developing the architecture proposed in each paper. This analysis intrinsically helps to understand the characteristics of each software. Indeed, the architecture's purpose deeply affects the selection of the software, since - as emerged from the literature review - some software tools are apt to address only some specific tasks, and others are more generic, thus more flexible but less focused on specific tasks.

As emerges clearly from the analysed papers in Table 1, Industry 4.0 is explicitly mentioned by all analysed research works, suggesting that the most recent works on DT-based architectures are developed and analysed in the context of Industry 4.0 research. This is not surprising because, as mentioned in the Introduction section, DT can be considered as hosted in the cyber aspect of CPS, and therefore together with CPS are among the main concepts related to the Industry 4.0 paradigm.

2.2. State-of-the-art: gaps and shortcomings

The review of the state-of-the-art shows that some key developments are still required to cover four identified scientific and technical gaps and to better support operations management of cyber-physical production processes. From this analysis emerges that Industry 4.0 paradigm and in particular the potential of the DTs can be better exploited when a well-defined framework for multiple DTs connected into a single architecture is available. This is not evident in architectures analysed so far, thus leading to a clear shortcoming in the aggregations of several DTs into a unique architecture to represent and improve smart manufacturing systems. It is a relevant gap, as ICPS equipped with DTs have proven to be an alternative approach to conduct optimization and monitoring tasks in a faster and efficient way Uhlemann, Lehmann & Steinhilper (2017).

The main gaps of the state-of-the-art are summarised as follows.

- (First gap) A well-defined framework that combines and links many DTs is not available, and this is the most evident gap. DTs for modeling different single physical assets at local level, linked into a single architecture that has also a representation of the whole production system at global level, are missing. Besides, there is the need of a method to describe a system of heterogeneous physical assets into a single-domain scenario, rather than each single asset into a multi-domain scenario (which is quite often reported in the literature review).
- (Second gap) The proposed methods of aggregation of DTs are only targeting already generated DTs. It results in poverty of studies related to "green-field" scenarios, where there is the need to describe a whole system from scratch.
- (Third gap) There are only few practical applications (either in laboratory or in industrial contexts), and very few models appropriately and strictly consider smart manufacturing systems. Besides theoretical studies, only single tasks done by DTs are reported, instead of heterogeneous tasks (Fei Tao, Qi, Wang & Nee, 2019) such as decision-making, problem resolution, optimization, health assessment, performance evaluations, etc. This is not fulfilling the expectations in Industry 4.0 paradigm with regard to the role of DTs.
- (Fourth gap) Current reported applications of DTs in state-of-art architectures make a poor usage of the data gathered from their physical counterparts. The reported studies propose solutions limited to data collection and visualization, i.e., structured and more elaborated data analysis and decision-making are not convincingly supported on the real time data. This does not take advantage of having a virtual representation, constantly updated with the last available information from the physical counterpart, which is the improvement of understanding and managing of the physical assets promised in the Industry 4.0 paradigm.

2.3. Objectives of the work

In order to address the main gaps found in the state-of-the-art review, the overarching goal of this paper is to design and implement a distributed DT-based framework to address smart decision-making for scheduling tasks in CPPS.

The framework is characterized by three fundamental elements: (i) DTs at different hierarchy levels, (ii) local CM and (iii) a global decision-making. The approach is centered on the local CM of different workstations and the production rate of the production system, in order to automatically perform the re-scheduling to improve the performance of the whole system. The local condition of the single workstations is inferred from the local CM that makes use of local DTs, whereas the production rate is evaluated and assured from the global DT of the whole system.

Industrial setups usually depict uncertainty and complexity. Nonlinearities, noise and uncertainty are still limiting the effectiveness and validity of first-principle and mathematical models based on differential equations. Alternative techniques are usually applied to obtain more reliable and accurate models. Machine learning-based strategies are becoming the main methods reported to develop models in industrial environments. Indeed, this is the main rationale for using machine learning to generate the local DTs and the CM. Likewise, autonomous decision-making in the industry should be intuitive, user-friendly and emulate operators' know-how and their socio-cognitive skills through verbalization. Therefore, the design of the smart decision-making system will be carried out using Fuzzy Logic-based inference systems. Another important aspect of the work reported in this paper is the aim of carrying proof-of-concept and validation to assess feasibility of the DT-based framework for decision-making to dynamically deal with uncertainty and complexity of industrial setups.

3. The proposed framework

The design and the implementation of a distributed framework based on DTs and CM facilitate decision-making at each level of the manufacturing system, with the ultimate goal of increasing efficiency of operations management. From single equipment to the overall shop floor management, the behaviors are emulated, and decisions are made according to the condition of different local assets and the global performance of the whole plant or floor shop. The final target is certainly reaching higher efficiency and productivity at a global factory level.

Fig. 1 illustrates the conceptual diagram of the proposed framework. The framework is centered on a novel decision-making to improve the global performance by using scheduling actions through the global DT, while exploiting the local condition-based monitoring to consider the currently running conditions of the physical assets, through the local DTs. The framework takes advantages of the potential of edge computing in local DTs. In each workstation of the shop floor is located a local node in charge of gathering, preprocessing and filtering data from the field in order to obtain, in real time, the main features/conditions of the assets. The use of edge computing in local nodes can improve the real-time response of the framework because these are in constant interaction with the dynamics of each of the assets of the shop floor.

Local nodes in fact consist of two main modules: one for the local DT and one for CM algorithm, respectively. The DTs at local workstations mirror and emulate the behavior of the workstations and the process, enabling simulations to detect and predict the current and future behavior of the asset. CM consists of a predictive model based on a machine learning strategy, to predict the state of the components that compose each of the assets. By combining both modules, the future state/condition of the system components or devices can be detected, enriching the global decision-making of the whole production system.

The global node is composed of three modules: (i) the global DT, (ii) the global decision-making and (iii) the scheduling optimization module. The global DT collects the information from local DTs. Simulations of Global DT are run with the collected data to predict the behavior of the production system; it is then possible to analyze future production and efficiency rates. The global DT is also fed with the production goals of the production system. which are typically an external input coming from the production management level (see in the Fig. 1 the box, called "Goals for the production system"). The global decision-making determines which is the best action to be performed to improve the performance of the whole CPPS. In order to deal with uncertainty and nonlinearities, the literature is plenty of soft-computing technologies such as Fuzzy and Neuro-Fuzzy Systems, that can be used by global DT and CM of each local workstation to make the best decision, action or recommendation, such as triggering the rescheduling action or simply informing the operator in the shop floor for minor adjustments. The module for scheduling optimization eventually performs an optimization process to reschedule the production system. It can use gradient-free population-based optimization algorithms to estimate the optimal sequence of products that minimizes the overall production makespan. The inputs are the jobs that have to be performed and the processing times of the worktations involved in the process. The algorithm then computes different possible schedules, which are later on evaluated by Discrete Event Simulation (DES) model of the production system. The best sequence, that accomplishes the stopping criterion, is the feedback given to the operator or to the manufacturing execution system.

It is important to remark that the proposed framework can be extended without losing generality to any CPPS with local and global DTs. This advantage of the framework is endorsed by a data exchange method, which is independent from the application case. The main features, specificities or peculiarities of the production system and its components are fully included into the global and local DT modules that are developed for the specific application. DTs must be updated or re-tuned along the time. If a component or sub-system represented by the DT in the virtual world is modified or changed, either in relation to software or, hardware, the DT must be updated. This is a crucial aspect to be considered when building a DT as well as the interoperability between DTs. Each local DT is independent from the others in the proposed framework, and thererfore it can be managed as a single entity of the framework without affecting the other entities.

3.1. Local digital twin

The design and implementation of a local DT for representing a local process is essential to guarantee a good performance of the proposed framework. A model that appropriately mirrors and emulated the physical counterpart is essential to detect deviations in KPIs of the local

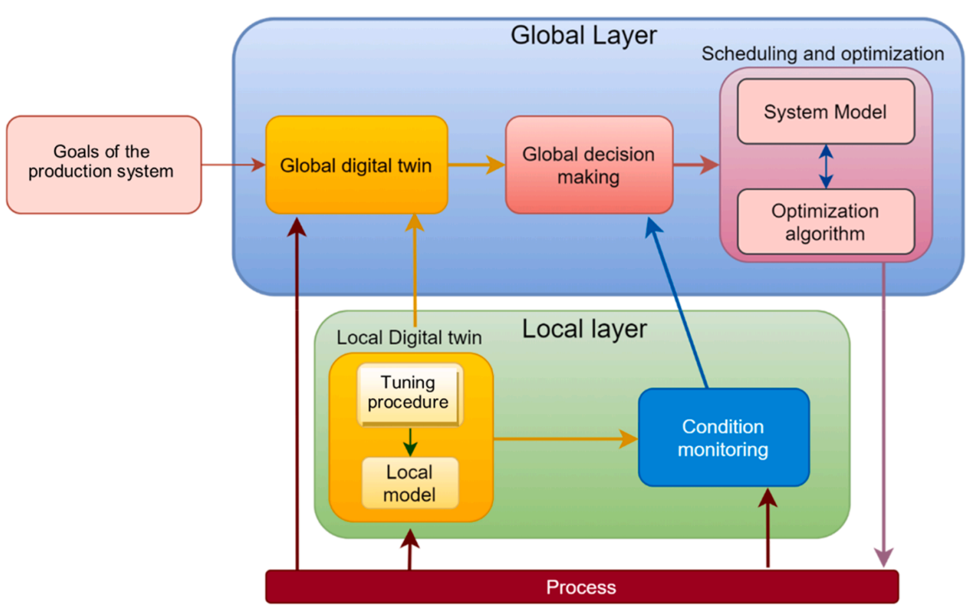


Fig. 1. Conceptual diagram of the proposed framework.

system and thus clearly contributes to improve the predictive maintenance and the decision-making procedures. modeling an industrial process is usually a complicated task. Due to the nonlinearities or in general uncertainties, it is not straightforward to obtain an accurate mathematical representation. Machine learning-based modeling techniques usually are alternative techniques due to their ability to represent some nonlinearities and to capture the main characteristics of the physical processes. Among dozens of available methods for modeling reported in the literature, the hybrid incremental model (HIM) that exploits the principle of incrementality was selected. The design and implementation of the HIM –based method is inspired by Pedrycz and Kwak (2007).

HIM approach has the advantage of using a general representation to capture the main characteristics of the physical process in addition to an incremental representation to catch nonlinearities. Overall, it is recommended to use generic models, such as linear or polynomial regressions, when there is no prior knowledge of the system to be modelled. In this study, the general representation is carried out by a polynomial of degree *m* fitted using the least squares algorithm. The output has the following expression:

$$\hat{y}_B(x_i) = f_B(x_i, O(x_i)) \quad (1)$$

where xi is the i th input point and O(xi) is the output value of the xi point.

Likewise, a wide range of techniques is also available for yielding the incremental part. In this study, Fuzzy k-Nearest Neighbours (F-kNN) is selected because of its simplicity from the computational viewpoint, ease of interpretation and good accuracy. F-kNN consists of averaging the value of the points closest to the objective point weighted by the similarity of each points. In order to calculate the proximity, the Euclidean norm, the most widely used approach, was applied.

Finally, the HIM-based approach combines the two above-mentioned representations (the physical representation and the incremental one). The tuning parameters of HIM are the degree of the polynomial (m), the neighborhood size (k), and the fuzzy strength (p). The training of the general representation consists in fitting the polynomial of degree m and the incremental training to populate the state space of F-kNN. The evaluation consists in calculating the output, at a point q, by adding the term from the incremental model to the output of the general representation, as follows:

$$\hat{y}(q) = \hat{y}_B(q) + \hat{l}(q) \quad (2)$$

where $\hat{y}_B(q)$is the general model output, $\hat{l}(q)$the term obtained by the incremental model and $\hat{y}(q)$ is the output value at q point.

Once the DT is obtained, it is continuously updated to keep the accuracy in the physical asset emulation and, for that purposes, it is continuously connected with the physical process. The tuning procedure is triggered when the accuracy of the DT decreases. Fig. 2 shows the local DT evaluation and updating diagram. The output, corresponding to an operation, is compared with the real values to calculate the fitting error. When the error exceeds a threshold, the model is re-trained through the tuning procedure supported on (Beruvides, Castaño, Haber, Quiza & Villalonga, 2017). The objective function is the minimization of the fitting error.

3.2. Condition based monitoring

The CM in the local workstation takes into consideration the signals obtained from sensors and the output from the local DT to determine the current state of the corresponding asset. Thus, the influence of degradation on the different components of the shop floor can be detected. Moreover, in combination with the DT, equipment degradation can also be predicted in advance. In this way, scheduling decisions can be made not only considering the production KPIs.

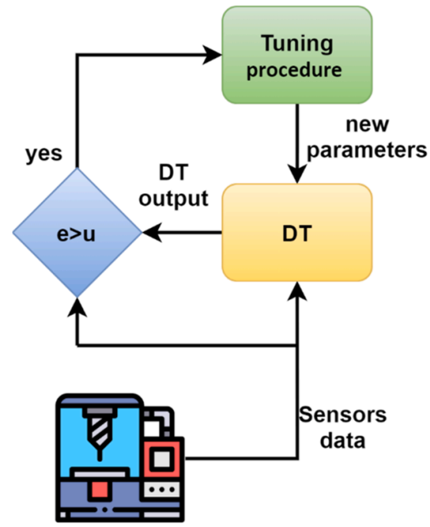


Fig. 2. Diagram of the local digital twin evaluation and updating mechanism.

Monitoring the state of the assets in a production system is a very important task. For example, an unexpected failure in one of the elements of a production system could cause the stop or decrease the production rate. Certainly, CM is a powerful tool in predictive maintenance because it makes it possible to more accurately schedule production and maintenance actions. In addition, CM contributes to minimize the risk of unexpected failures improving equipment reliability and operators' safety.

The CM system is composed of two main stages Jardine, Lin & Banjevic (2006): the data processing and the predictive model. The first stage carries out the features extraction of the signal obtained from the sensors. This stage allows detecting the main characteristics of the signals measured. Thereby noise is filtered obtaining more precise information to generate more accurate predictive models. Furthermore, the input data volume is reduced thus decreasing the training and evaluation computational cost of the models.

The predictive model is the most important element of the CM. It evaluates the current condition of the asset analyzing the signals obtained from the sensors. Due to the main characteristics of the industrial signals, the use of a machine learning strategy is proposed to generate the predictive models.

3.3. Global digital twin

Until now the local DTs were presented: they can run as stand-alone models of the single workstations and interact with the CM to predict the future state of the asset. Local DTs are then connected to a global DT, that is the DT of the whole production system.

The global DT interrogates the local DTs to acquire the required data and information. Obviously, the role of the global DT is to merge and to elaborate data and information coming from the local DTs in a coherent and efficient way, by only gathering those data and information that are necessary to the decision-making at this level with the required sampling frequency to meet specifications. This global DT does not interface directly with the physical world, instead it communicates with the local DTs that lay on the lower levels to get the information about the shop floor. It is worth to say that this type of DT can also be seen as a middle representation, this may happen in situations where the complexity of the production systems is higher such as in Cyber-Physical Systems of Systems; in this way, the structure, that here is presented as a double layer, could be expanded to have three or more layers of aggregation.

The functionality of the global DT is described as follows.

3- Firstly, it collects data and information from relevant variables in the lower-level DTs, to give a comprehensive view of the behavior and performance of a production system. The local DTs collect data from the field sensors and IIOT. In addition, they can combine information by elaborating those coming from the field using proper algorithms or models included inside the DT. The large amount of data that can be generated, for instance in a shop floor, is huge. This potential overflow has thus to be managed by the DT-based framework, by pre-processing and processing the proper data at each level of the production system. Thus, data must be filtered to get the right information, volume, sampling frequency, data already elaborated and aggregated, etc. For this reason, local DTs should share with the global DT only data and information that are useful to be replicated and simulated.

3- The global DT has the fundamental role to enable communication with all the underlying local DTs. This capability will allow the global DT to control and to manage the local DTs, which in turn support the actuation on their physical counterparts. The operating configuration must be correspondingly set.

3- The global DT also supports decisions to be sent to the lower level of the framework, for instance stopping a machine with deviated behavior (e.g., malfunctioning, failure, etc.) from the pre-defined one, according to the CM task run by the DT.

3- The global DT interacts with the production system management on the shop floor, therefore with the MES, or with the HMI (Human Machine Interface) to production operators. Indeed, at this point all decisions and actions will be the ones that have the most influence on the whole system. The global DT will host the computational procedures and interface with tools that elaborate and carry out decision-making, in order to enhance the performance of the production systems replicated in the virtual world. In this sense, it is work remarking that global decisions will affect the whole system rather than a single unit and can be sent to a single or multiple local DTs. These types of decisions are then considered more important, and they will prevail on the local decisions, since the global optimum overcomes the local ones. At the end, the communication with MES/HMI makes possible to leverage the information elaborated by the global DT, such as a rescheduled production plan or an alarm setting for the operators or plant workers in case of a failure on the system.

Another important aspect that characterizes the global DT is that users, such as operators or operation managers, mostly interact only at this level of the architecture. Thus, the inputs and the outputs of this level of the framework should be suitable for interactions with humans.

Fig. 3 shows the scheme of the DT-based framework (i.e., case of double layered architecture). It represents the logical connection of the global DT to various local DTs, linked to the single workstations as physical assets composing the production system. The optimization module is connected to the global DT that is composed of two other sub-modules, represented by discrete event simulation (DES) model of the production system and the scheduling optimization algorithm. This module performs the scheduling optimization triggered by the global decision-making and will be better described in Section 3.5.

3.4. Global decision-making

In this work, the main target of the decision-making process is to increase productivity of a production system. For the sake of computational efficiency, a simple approach is proposed using two key variables: the production rate (*PR*) and the currents state of each workstation ($ST_{1...M}$) where M is the total number of local workstations/assets. The production rate is obtained by running the global DT of the production system. The condition of workstations is also a very important aspect to be taken into account because a failure can slow down the production or lead to stop the whole production system. The condition of workstations is inferred from CM model embedded in local workstations.

Within the different approaches used for decision-making processes, fuzzy inference systems (FIS) are among the most reported in the literature Isermann (2005). FIS are a technology widely applied in industry since they are very simple, powerful and intuitive (Haber, Alique, Alique, Hernández & Uribe-Etxebarria, 2003)(Ramírez, Haber, Peña & Rodríguez, 2004). FIS have the potential to appropriately represent the non-linear relationship between input and output variables and to support the decision-making procedure in a robust and flexible way based on the fuzzy sets and the fuzzy rules (Caiado et al., 2021) Haber & Alique (2007).

Therefore, the selected inputs for the fuzzy inference system are the global production rate (*PR*) and the condition of the workstations of the production system ($ST_{1...M}$). Fuzzy membership functions are defined by Gaussian-type functions, shown in Fig. 4. The selection of the type of membership function is not straightforward due to the influence on the whole performance of the fuzzy inference system. The rationale for selecting Gaussian membership functions for the input is twofold. Firstly, this selection is supported on most contemporary studies reported in the literature. A recent study presents a comparison of fuzzy inference systems including Gaussian and linear membership functions for inputs and outputs, respectively. The study demonstrates that Sugeno FIS outperformed the Mamdani FIS for accurate results Tabbussum & Dar (2021). Secondly, both Gaussian and triangular membership functions have demonstrated to be closely performing well without remarkable differences. However, the continuity and concise notation of Gaussian-type functions pave the way of future works in

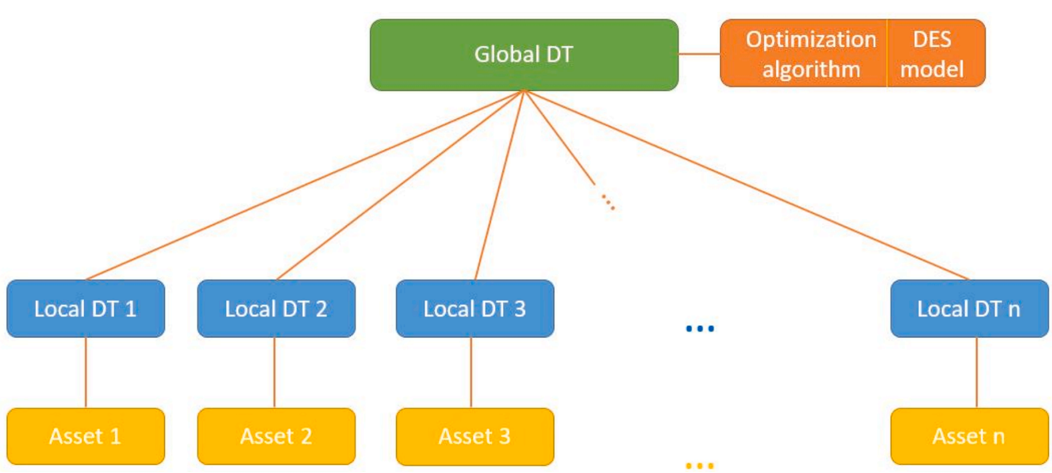


Fig. 3. Diagram of digital twins at local and global levels.

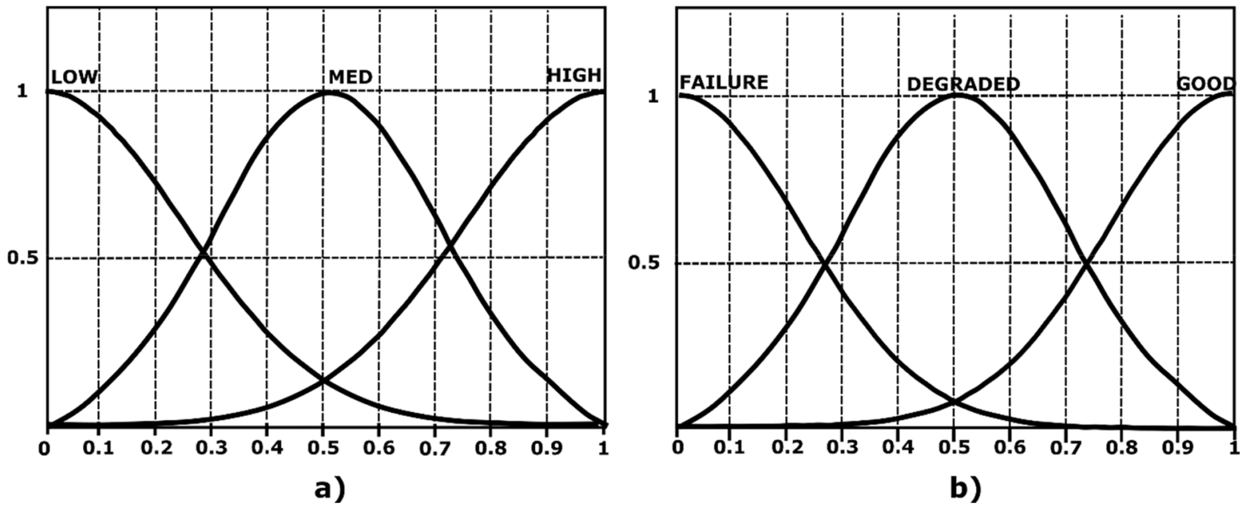


Fig 4. Inputs membership functions. a) Production rate (*PR*). b) Workstation condition (*ST*).

relation to optimization Tabbussum & Dar (2021) and hybridization with other techniques such as neuro-fuzzy evolving systems (Gajate, Haber, Vega & Alique, 2010).

The membership functions of the global production rate were labelled as **LOW, MED** and **HIGH** indicating the three possible states of the production. The membership functions of the workstation condition are **FAILURE, DEGRADED** and **GOOD.**

Takagi-Sugeno-Kang (TSK) is the choice of fuzzy system because it is considered more flexible and computationally efficient (La Fé-Perdomo, Beruvides, Quiza, Haber & Rivas, 2019). Moreover, the outputs in TSK provide a more explicit relationship with the inputs since a weighted sum of the data points is used in the defuzzification stage. The output is defined as singleton membership functions labelled: **NO_OPERATION (1), OPERATOR_ASSISTANCE (0.5)** and **SCHEDULING (0)**. The first

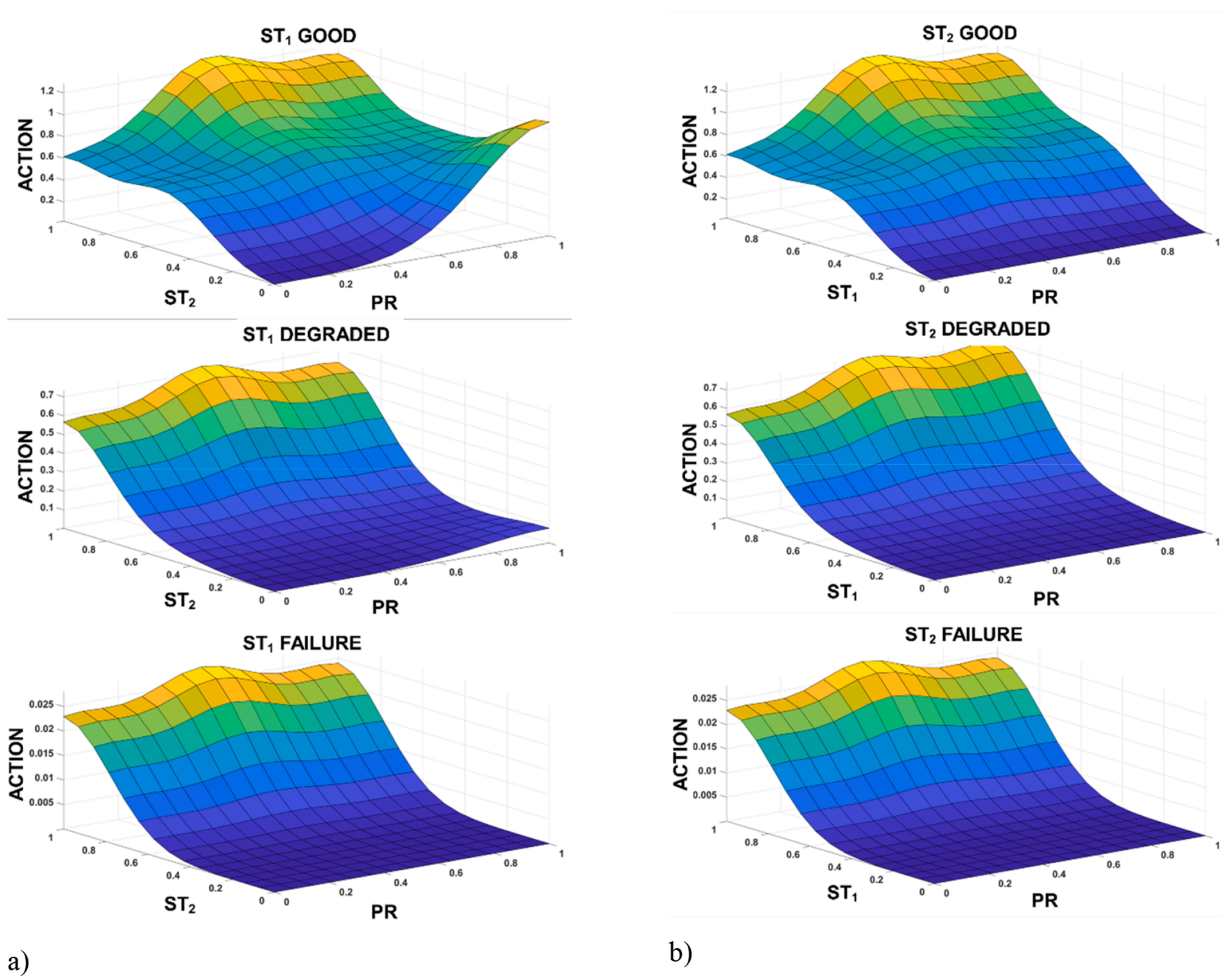


Fig. 5. Surfaces resulting from the fuzzy inference system, a) for each ST_1 condition, b) for each ST_2 condition.

membership function represents that no action is needed. The second one means that the system does not count with enough information to take an action so the operator attention is mandatory, therefore keeping the human in the loop. The last membership function represents the need of automatically triggering the scheduling procedure.

The fuzzy rules are defined establishing a direct relationship between the production rate and the workstations condition with the action needed to improve the system. A fragment of the pseudocode of the rules considering the monitoring of two workstations is shown in Pseudocode 1. In this case, the rule base is composed by 27 rules. The number of rules are set in two iterations. Firstly, rules are automatically generated on the basis of input and output variables and the number of membership functions. Secondly, the pruning of the rule base is done by combining the know-how of operators and technologists with a verbalization technique. "Sup-Product" is applied as compositional rule of inference. In Pseudocode 1, labels ST_1 and ST_2 correspond to the state of the workstations 1 and 2, respectively and PR is the production rate.

The representation of surfaces resulting from the FIS is not easy when there are more than two antecedents in the rules. For the sake of clarity and without losing generality, Fig. 5 shows the surfaces assuming that each condition (FAILURE, DEGRADED and GOOD) of the workstation ST_1 is constant (Fig. 5a) and vice versa for ST_2 (Fig. 5b).

3.5. Scheduling optimization

When a decrease in the production rate is detected, the decision-making module could trigger the scheduling process to solve the problems that is affecting the production system. The scheduling process has two main stages: (i) a population-based optimization algorithm and (ii) a simulation model. The simulation of the production system is used to replicate the sequence of operations, and their processing times, occurring during a production for each individual of the population. A population-based optimization algorithm is selected because it is appropriate to deal with noise and uncertainty. This strategy, based on generated populations with a large number of individuals, makes it possible to try different scenarios for optimization. These elements are representing the optimization module, already depicted in the diagram shown in Fig. 3, enabling global DT to perform the scheduling process described in this section.

The simulation model is a discrete-event simulation model synchronized according to the field conditions with the global DT model and then it is used to emulate various alternative scheduling sequences of the production system to support the scheduling optimization algorithm. More specifically, it is used to replicate the production in terms of processing times of each workstation. Thus, it is able to determine the makespan of a single product or an entire batch of products for each simulation run. The required simulation inputs are the processing times of each workstation of the production system and the list of jobs that must be produced. This list considers all the operations that each single product requires to be produced, and at the same time, it also considers the priority that each job might have. The DES model is also part of the DT-based framework. However, it must not be confused with the global DT module that monitors the operations of the production system through the connection with the local DTs and alerts on the global field conditions.

The scheme shown in Fig. 6 is applicable for any kind of population-based optimization algorithm (in the picture it is Opt. A). The objective function of the optimization algorithm is the minimization of the total makespan and it operates as follows:

1 It receives as inputs: the list of products (later called jobs) to be produced. Each job is identified with an ID number, a priority index (the higher the index the sooner the product must be produced) and its technological route.
2 The optimization algorithm will generate a first population of individuals, which are different scheduling alternatives. Each individual consists of a unique sequence of jobs which expresses the order in which the jobs are released into production.
3 The first population is then simulated in the simulation model. The single individual is given as input at the simulation model which will simulate the production. For each individual the optimization algorithm collects the production performance, namely the makespan. The processing times at this step are fixed and set by the simulation model.
4 The optimization algorithm selects the best individuals (i.e. the ones with the lowest makespan) and it generates a new population. Then the discrete simulation model simulates again this population to find the most performing individuals. This process is iterative, and it finishes once the stopping criterion is achieved, and the lowest makespan sequence will be the new production schedule of the whole system.

4. Case study on pilot assembly line

The case study aims at demonstrating the suitability of the proposed DT-based decision-making framework applied to a pilot assembly line at

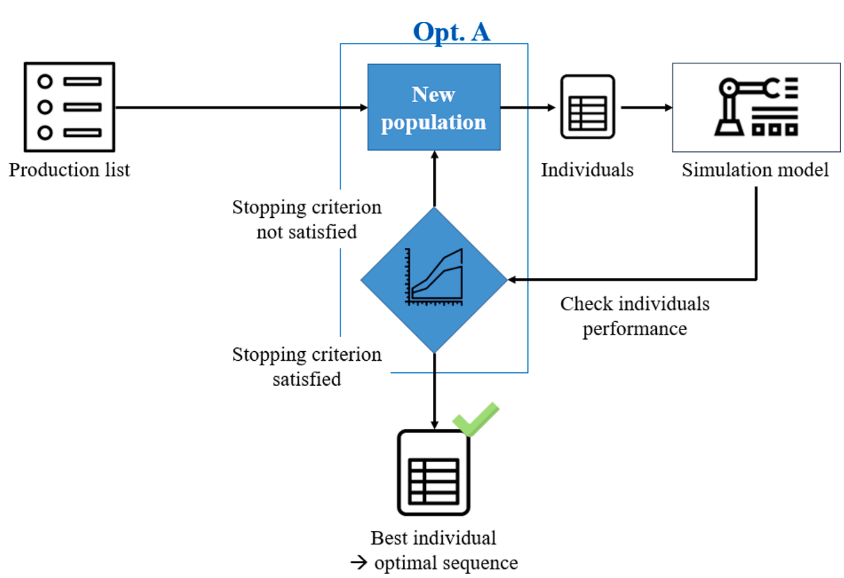


Fig. 6. Diagram of the scheduling optimization process.

the Industry 4.0 Laboratory of the School of Management of Politecnico di Milano. The assembly line is composed of an educational set of modular workstations provided by Festo, that can be arranged to form different combinations of assembly lines for research and educational purposes. All workstations are equipped with two PLC from Siemens (one for actuation control and sensor reading and the other for energy monitoring). Each workstation is also equipped with sensors for electrical energy and for pneumatic air consumptions. The line has an internal MES for production progress control and an energy management MES. Each PLC, both of the operational and energy PLC types, provides an OPC UA server publishing all the internal variables and sensors states of the workstation.

The pilot line, represented in Fig. 7a, is composed of seven workstations, each one dedicated to one or more tasks, to assemble a simplified mobile phone.

In Fig. 7b, the "Manual" workstation (1) is the starting point of the process, where the loading/unloading takes place. The "Front Cover" workstation (2) is in charge of the positioning of the front cover on the pallet. The "Drilling" workstation (3) is the workstation where cover drilling is performed. In the "Robot Assembly" workstation (4), the Printed Circuit Board (PCB) and the fuses are placed inside the front cover. The "Camera Inspection" workstation (5) controls the different components positioned in the inside of the cover. In the "Back Cover" workstation (6) the back cover is placed over the front cover. The "Press" workstation (7) presses the two covers to close the product. At the end, the piece returns to the initial workstation where it is unloaded by the operator. The position 8 represents a bridge to switch the production flow either to the robotic cell or to the camera workstation, depending on the assembly route of the current piece.

The pilot line has a pneumatic compressor, which supplies pressurized air to the seven workstations. Each workstation then operates the pneumatic actuators through the compressed air. The single workstation is also responsible for a section of the conveyor. In fact, despite there is only a single conveyor route on the line, the conveyor system is fragmented into eight modules, that allow to stop any of them when not needed, thus saving energy. Finally, considering the IIOT already available in the line, it is worth remarking that: i) the path of each product can be tracked using a RFID-tagged chip embedded on the pallet that carry the product, ii) the line is equipped with sensors for energy and condition monitoring; iii) all the elements in the local network interchange data via OPC UA protocol (i.e. MES, edge computers, sensors).

Data communications in the assembly line are carried out via OPC UA protocol to the MES of the line. Moreover, data are also stored in an online database, which is a MongoDB. This database stores and eventually provides data for further utilizations. The process of data sharing is automatic, and the frequency of acquisition is 1 Hz for all the data coming from the field. The only exception is the accelerometer sensor, which has a frequency of acquisition of 200 Hz.

Overall, the assembly line complexity and the variety of products that can be produced through different operations performed by the workstations provide it with the characteristics proper of a real "industrial like" system. Given this setting, the implementation of the framework was then performed by firstly developing the local nodes for two different workstations – the front cover workstation and the drilling workstation – whereas the global node was finally deployed in the computer managing the whole line. The results obtained so far (and presented in next sub-sections) allow validating the framework as an initial proof-of-concept.

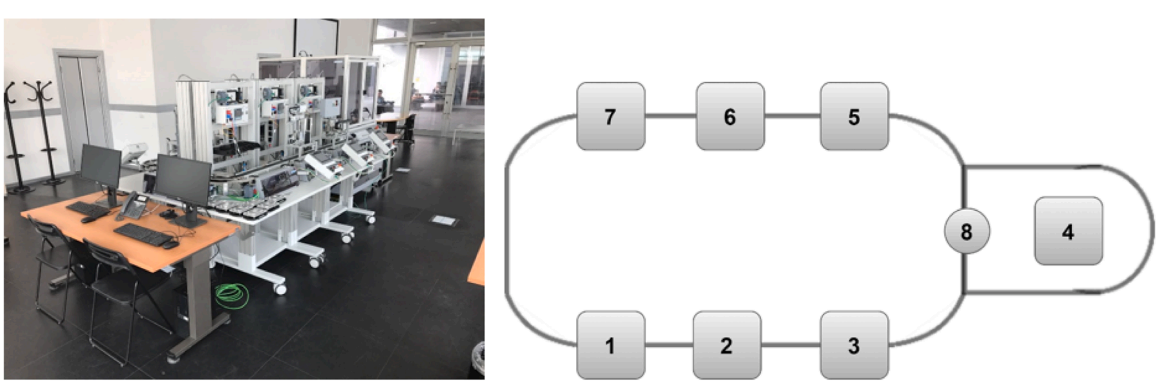
There are several gradient-free and bio-inspired optimization methods reported in the literature (Haber, Beruvides, Quiza & Hernandez, 2017). A full review of most emerging techniques goes beyond the scope of this paper. Genetic Algorithm (GA), is selected because it is considered the most promising optimization approach for dynamic scheduling, widely used simulations and DT modeling (Fumagalli, Polenghi, Negri & Roda, 2019; Negri et al., 2020). The most important parameters and their setting such as genetic operators (crossover and mutation), stopping criteria (maximum number of iterations; maximum number of iterations in which the makespan does not decrease), amond others are summarized in Table 2.

4.1. Results: local digital twin and condition-based monitoring

As a first step, the local DT and the CM models corresponding to each workstation were generated. The local DTs were trained with data acquired from the real operation of the whole pilot line. Table 3 shows the parametrization corresponding to each model. As described in Section 3.1, the tuning parameters are the degree of the polynomial (m), the neighborhood size (k), and the fuzzy strength (p). To analyze the quality of the local DT, three indexes were considered: root mean square error (RMSE), the mean absolute error (MAE) and the relative absolute error (RAE). Table 4 shows the models performance indicators, and Figs. 8 and 9 illustrate the behavior of the DT and the process signals.

Table 2
Parameters of the implemented GA.

Parameter	*Value*
No. of jobs scheduled	50
Population dimension	10
Mutation rate	0.02
No. of children for elitism operator	1
Maximum number of iterations	100
No. of iterations for stall criterion	20
No. of repetitions of each simulation	30
Weighing factor	0.5



a) b)

Fig. 7. a). Picture of the Industry 4.0 assembly line b) Scheme of the main assets.

Table 3
Digital twin initial parametrization.

	Front cover workstation		Drilling workstation	
	Pressure	Current	Pressure	Current
m	2	2	2	2
k	3	5	3	5
p	1.89	2.01	1.93	1.98

Table 4
Digital Twin performance indicators.

	Front cover workstation		Drilling workstation	
	Pressure	Current	Pressure	Current
RMSE	0.0430	0.0042	0.0318	0.0037
MAE	0.0335	0.0030	0.0252	0.0040
RAE	0.1621	0.138	0.146	0.1238

Pseudocode 1
Fuzzy rules.

if (*PR* **is** HIGH) and (ST_1 **is** FAILURE) **then** (ACTION **is** SCHEDULING)
if (*PR* **is** HIGH) and (ST_1 **are** DEGRADED) and (ST_2 **is** GOOD) **then** (ACTION **is** OPERATOR_ASSISTANCE)
if (*PR* **is** HIGH) and (ST_1 **is** DEGRADED) and (ST_2 **is** DEGRADED) **then** (ACTION **is** OPERATOR_ASSISTANCE)
if (*PR* **is** HIGH) and (ST_1 **is** GOOD) and (ST_2 **is** GOOD) **then** (ACTION **is** NO_OPERATION)
if (*PR* **is** MED) and (ST_1 **is** FAILURE) **then** (action **is** SCHEDULING)
if (*PR* **is** MED) and (ST_1 **is** DEGRADED) and (ST_2 **is** Good) **then** (ACTION **is** OPERATOR_ASSISTANCE)
if (*PR* **is** MED) and (ST_1 **is** DEGRADED) and (ST_2 **is** DEGRADED) **then** (ACTION **is** SCHEDULING)
if (*PR* **is** MED) and (ST_1 **is** GOOD) and (ST_2 **is** DEGRADED) **then** (ACTION is NO_OPERATION}
if (*PR* **is** LOW) and (ST_1 **is** FAILURE) **then** (ACTION **is** SCHEDULING)
if (*PR* **is** LOW) and (ST_1 **is** GOOD) and (ST_2 **is** GOOD) **then** (ACTION **is** OPERATOR_ASSISTANCE)
if (*PR* **is** LOW) and (ST_1 **are** GOOD) and (ST_2 **is** DEGRADED **then** (ACTION **is** OPERATOR_ASSISTANCE}
if (*PR* **is** LOW) and (ST_1 **is** DEGRADED) and (ST_2 **is** DEGRADED) **then** (ACTION **is** SCHEDULING)

In order to generate the CM models an experimental set-up was designed to emulate failures in the different workstations. In the front cover workstation, the monitoring of the pneumatic system was considered. In the drilling workstation, the pneumatic system and the drilling process were considered. In the pneumatic system, an exhaust valve was opened to drop the pressure and simulate a failure. In order to analyze the pressure signal, the standard deviation and the mean were chosen as pre-processing analyses. Predictive models were built using artificial neural networks, in particular the multilayer perceptron topology (MLP). This topology is used due to its suitability to emulate the nonlinear behavior of industrial systems (Alique, Haber, Haber, Ros & Gonzalez, 2000) because of good tradeoff between generalization capacity and computational cost. The model corresponding to the front cover workstation was configured with a hidden layer of 12 neurons, trained with 5000 epochs. The transfer function of the hidden layer was hyperbolic tangent, while the linear function was used for the output layer. The learning rate was 10^{-3} and the minimum gradient 10^{-7}. The MLP in the drilling workstation was configured with the same parameters but the hidden layer was populated with 15 neurons. Figs. 10 and 11 show the performance of the models in the validation process. The states of the workstation were defined as good (2), degraded (1) and failure (0).

The vibration signal from three accelerometers was also used to develop the CM of the drilling workstation. In order to emulate the degradation in the process, a shaker was applied to the drilling tool. The preprocessing of the vibration signal was carried out by wavelet transform, taking as the mother wavelet (db4) and $n = 1$, combined with the statistics, i.e. RMS and kurtosis of the obtained wavelet coefficients. The algorithm used for the predictive model was MLP with backpropagation with a hidden layer with 22 neurons, 5000 epochs for training, hyperbolic tangent hidden layer transfer function, linear output layer, output layer with one neuron, learning rate $\mu = 10^{-3}$ and minimum gradient of 10^{-7}. Fig. 12 depicts the behavior of the CM model for the vibration in the drilling workstation.

4.2. Results: global digital twin, decision-making and scheduling optimization

The proof-of-concept validation of the whole developed system is presented in this section. For the sake of clarity and in order to validate the framework an experimental set up was designed. The set up consists of five stages over time: 1- normal conditions, 2- Shaker turned on, simulating degradation in drilling workstation, 3-Normal conditions,4-Leak in pressure valve and 5- Failure in pressure. The main objective is to evaluate the decision-making capability of the system under different situations. Having generated the local DTs and CM procedures, the decision-making module was embedded into the global layer and connected to the global DT as it is shown in Fig. 1. The global layer is the higher level of the framework, from where the global DT has a complete overview of the system, thus overall optimization decisions can be made.

More specifically, different stages are so arranged, as follows: i) 20 operations in normal condition were initially run; ii) at operation 21 the

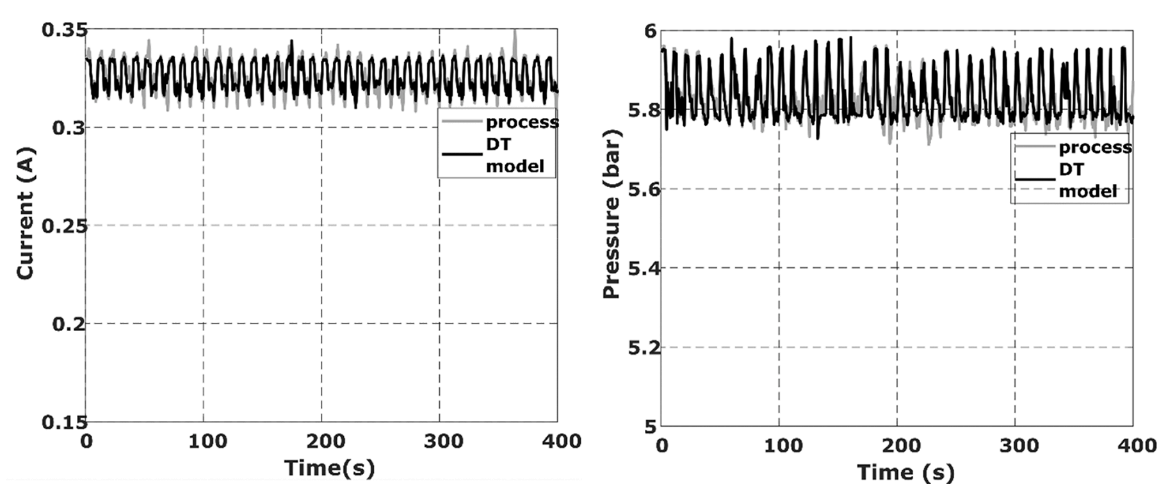


Fig. 8. Digital twin in the drilling workstation.

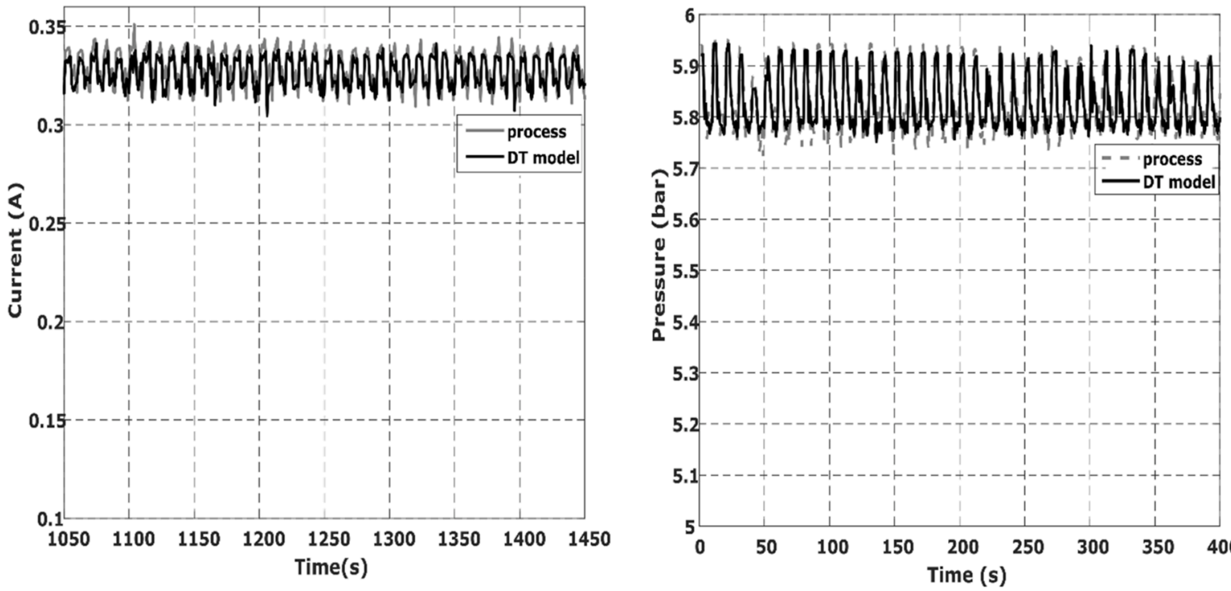


Fig. 9. Digital twin in the front cover workstation.

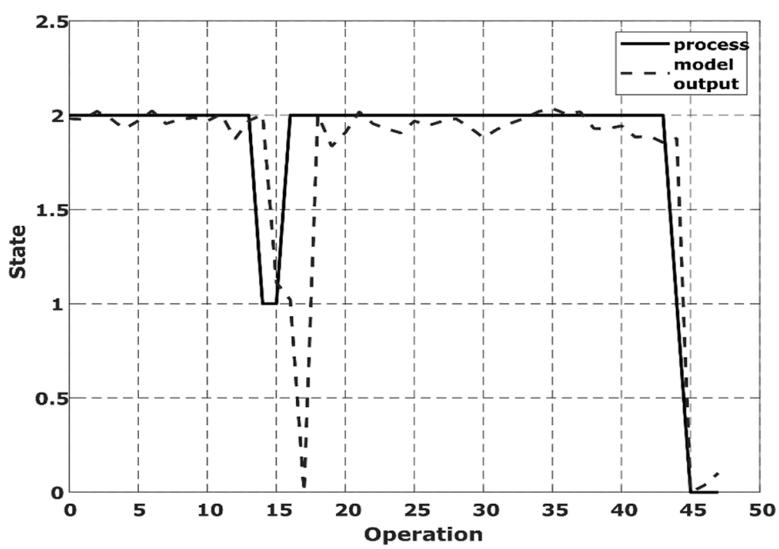


Fig. 10. Pressure condition-based monitoring of the drilling workstation.

shaker is turned on to simulate degradation in the drilling process; iii) in operation 26, the shaker is turned off and the production process comes back to normal conditions; iv) during the operation 31, an exhaust valve was opened in the front cover workstation to emulate a failure in the pressure system; v) in operation 43, a failure occurs in pressure in the front cover workstation.

In order to illustrate the performance of the framework, Fig. 13 shows the results of the global decision-making module. It is worth pointing out that the system correctly detects the failure in the front cover workstation, triggering the scheduling algorithm to avoid a decrease in production. The decision-making module, hosted into the global layer together with the global DT, triggers the optimization module for the rescheduling process, which will then start to elaborate the information gathered from the local DTs to compute the production schedule that minimizes the overall makespan. The global DT plays then a key role, merging the information gathered from the CM module of each local DT, elaborating a decision based on the embedded decision-making module, and finally activating the scheduling process through the optimization module.

According to the re-scheduling order sent by the global DT-supported decision-making module, the scheduling algorithm computes a new sequence of the remaining products that had to be produced. After nine generations, the GA found the best sequence and the stopping criterion was reached. The output is the sequence of products that minimizes the overall makespan. As already stated, this scheduling activity was triggered by the decision-making module, to consider what happened on the assembly line and to produce an updated schedule. Fig 14 shows the output of the scheduling algorithm, where the reaching of an optimal solution is clearly visible considering the trend of the solution found after each generation. The sequence provided as the ID of each product in the proper order, is expected to take around 3.43 min to be fully produced by the assembly line.

5. Conclusions

The work reported in this paper is fueled by the current research line aimed at designing and providing more autonomy, decentralization and more integrated decision-making functionalities on the basis of digital

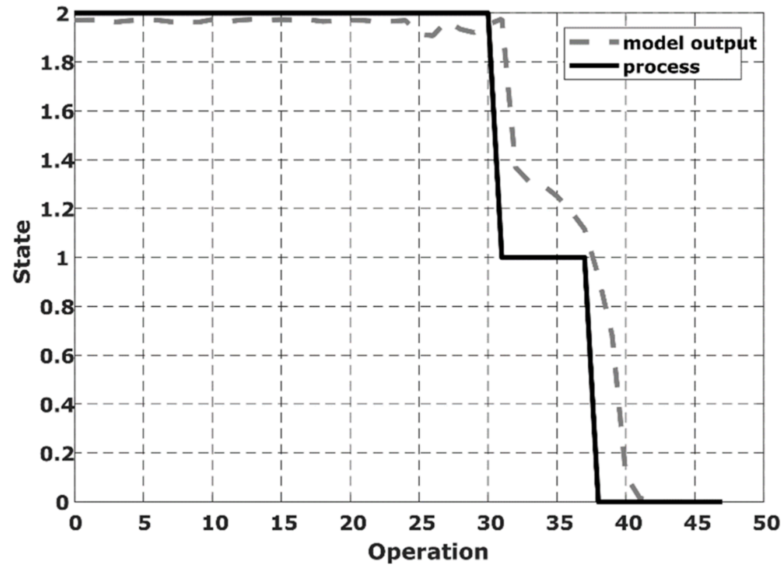


Fig. 11. Pressure condition-based monitoring of the front cover workstation.

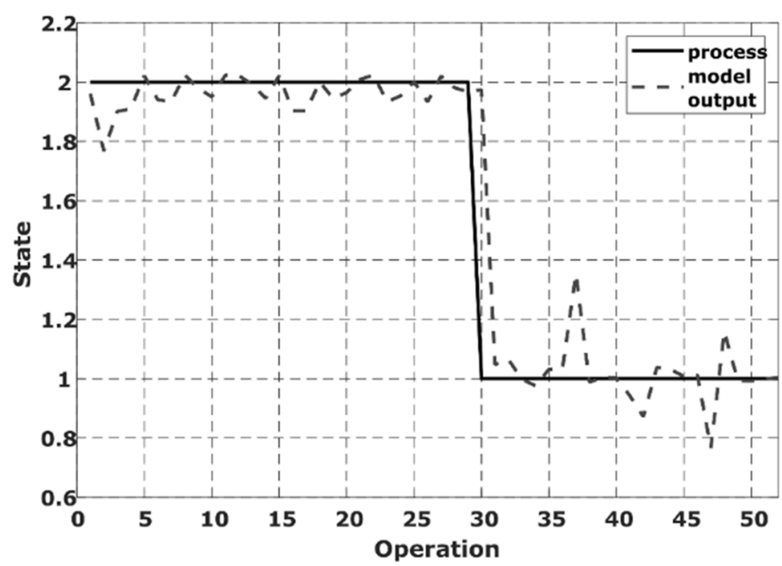


Fig. 12. Vibration condition-based monitoring of the drilling workstation.

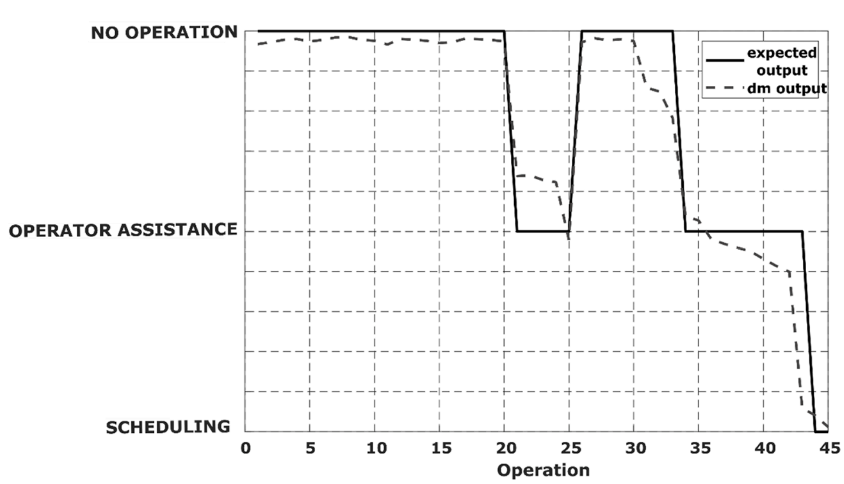


Fig. 13. Behavior of the global decision-making.

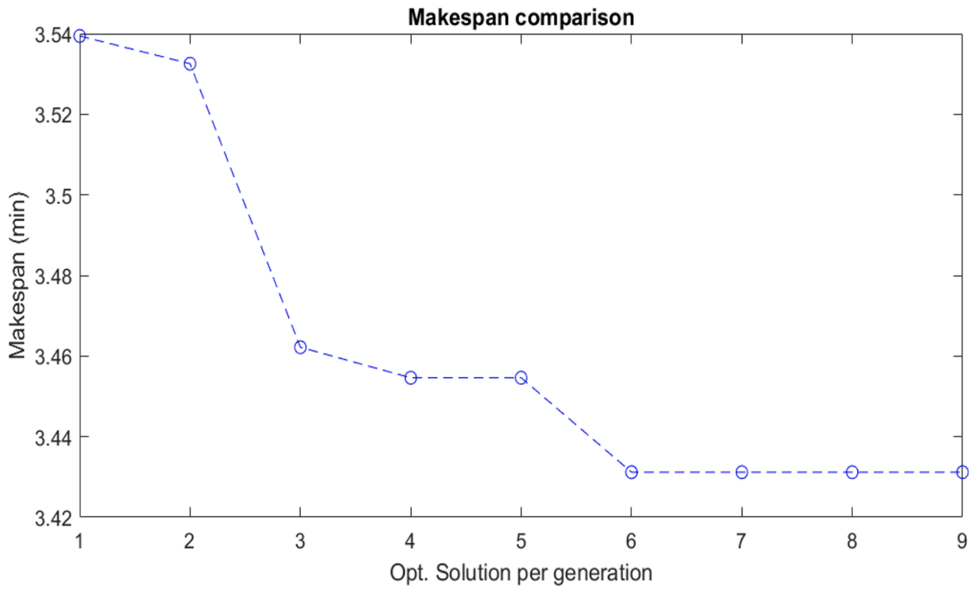


Fig. 14. Output of the optimization algorithm (genetic algorithm).

twin-based frameworks and architectures, with the final goal of achieving automated decision making in cyber-physical production processes. The presented proof-of-concept demonstrates that the proposed architecture for decision-making supported on local and global digital twins, and optimization is very promising to face challenges beyond re-scheduling of cyber-physical production processes. The proposed strategy outperforms available solutions in the market to address production scheduling in terms of automated decision-making and higher flexibility, taking into account that local and global digital twins can be also automatically updated.

From the viewpoint of cyber-physical production systems, digital twins has not only the role of accompanying the physical production systems in a mirroring simulation mode but has also the role of elaborating advanced data analytics to actively control and perform dynamic decision-making. The proposed framework combines a fuzzy inference system and a scheduling procedure, in an efficient decision-making strategy at the global level of the production system. Furthermore, the distributed framework exploits digital twins and condition monitoring for intelligent decision-making by enabling the use of local data to elaborate the required condition monitoring of cyber-physical production processes, which is a key aspect to for automatic dynamic scheduling and further steps towards self-reconfiguration.

The framework is defined as a generic digital twin-based layered architecture merging local digital twins with a single global digital twin, capable of representing, assessing, and managing the whole production system. The proposed architecture is fully independent of type of the cyber-physical production system, as it defines data flows whereas the digital twin modules at local and global levels are incorporating the whole specificity of production system. Moreover, all the bricks that constitute this structure, namely the single local digital twins, are also able to work as stand-alone modules for local decision-making support. The only hierarchical rule is that a global optimization overwrites local ones.

The experimental study corroborates how local digital twins and condition monitoring serve to predict the state of the components based on the information collected by sensors. Then, the global digital twin estimates the production rate based on the data collected from the shop floor. This information is processed in the decision-making stage to determine if re-scheduling of the whole system is required. The implemented modules are assessed and validated in an assembly pilot line, and the proposed approach serves to automatically detect changes in the manufacturing process and make appropriate decisions for re-scheduling accordingly.

This work contributes to the progress of the state-of-the-art filling some gaps identified in this study. Firstly, the proposed framework integrates local digital twins into a global one representation. Secondly, the design of layered digital twins contextually is deployed in experimental setup of a real cyber-physical production process. Moreover, the proposed distribute framework integrates both digital twins structures and real-time data gathering and analysis for an accurate dynamic decision-making. The main contribution is therefore the design and implementation of a framework that integrates local digital twins and global digital twin to deal with an automatic re-scheduling process for cyber-physical production processes.

The main limitations of the proposed framework are the computing constraints for re-scheduling which relies on the accuracy of the digital twins and the complexity of the production system in relation to the computing power nowadays available in cyber-physical production systems. Secondly, the complexity of data acquisition, gathering and processing grows with the size of cyber-physical production systems, especially when the framework is applied to real industrial environments.

Future works will be conducted to add more functionalities to the framework, to explore other modeling approaches and the decision-making strategies, and to extend the proposed strategy beyond the dynamic rescheduling. Moreover, further studies should be carried out to reduce the latency by developing more computational efficient machine learning algorithms and to improve the communication with the manufacturing execution systems. Another future work is the development of new monitoring method to detect any change both in productivity and ergonomics of operators in the workstations. This may lead to design local digital twins of a different nature, as they must be adapted to the human behaviors and tasks.

Declaration of Competing 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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