Local Decision Making based on Distributed Digital Twin Framework

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Abstract: In recent years, digitalization has taken an important role in the manufacturing industry. Digital twins (DT) are one of the key enabling technologies that are leading the digital transformation. Integrating DT with IoT and artificial intelligence enables the development of more accurate models to improve scheduling tasks, production performance indices, optimization and decision-making. This work proposes a distributed DT framework to improve decision making at local level in manufacturing processes. A decision-making module supported on an adaptive threshold procedure is designed and implemented. Finally, the proposed framework is evaluated on a pilot line, highlighting the behavior of the decision-making module for detecting possible faults, alerting the operator and notifying the manufacturing execution system to trigger actions of reconfiguration and scheduling.

Keywords: Digital Twin, distributed Digital Twin framework, MES, fault detection, local decision making.

1. INTRODUCTION

Nowadays, digitalization has taken an important role in the manufacturing industry. New paradigms such as the Internet of Things (IoT) and Cyber-Physical Systems (CPS) have contributed to achieving smart-factory solutions based on real-time communications, data exchange between all the production system elements, fault detection and prediction and knowledge-based decision making (Cattaneo et al. 2018). CPS bridge the gap between the virtual and physical worlds, thanks to their computing and communication capabilities (Wolf 2009; F. Castaño et al. 2019). In this sense the Digital Twin (DT) plays a very important role due to the ability to replicate an existing physical twin, by emulating the behaviour in the informational space and offering a connection between the physical system and virtual counterpart (Michael Grieves 2015). Moreover, it is persistent although the corresponding physical twin may not always be connected or online (Borangiu et al. 2020). Thus, it is possible to mirror in the virtual world what is happening in the physical world through synchronization of the simulation model parameters with the physical values in real time (Negri, Fumagalli, and Macchi 2017). By integrating DT with IoT and artificial intelligence (AI) it is possible to run, in the cyber space of CPS, living simulation models that continuously learn and update from their interaction with the physical world. Moreover, the DT has the potential to be the beating heart of certain types of decision making in manufacturing, when full implementation of DT allows a bi-directional communication (Kritzinger et al. 2018); this, in fact, enables the possibility both to monitor and control the production equipment, when properly connected to the control system (Cimino, Negri, and Fumagalli 2019).

The application of Manufacturing Execution Systems (MES) on shop floors is a popular solution to monitor and track the production progress and to orchestrate visualization, planning and control tasks in several industrial scenarios (Ramis Ferrer and Martinez Lastra 2018; Mohammed et al. 2017). MES provides many functionalities to the current industry (Arica and Powell 2017). Integrating DT models with MES may improve many of those functionalities, such as the execution of real-time monitoring, resources scheduling, management, maintenance and performance analysis on the shop floor. In particular, one of the most promising approaches to exploit the DT is to monitor specific sensor data to elaborate them in order to make predictions in the realms of safety, energy consumption and reliability of the production system (Negri, et al. 2019). In order to carry out this task, several approaches have been proposed based on statistical and machine learning models (Cattaneo and Macchi 2019; Beruvides et al. 2018). In order to yield better predictive models for condition-based monitoring, fault detection and predictive maintenance, DT play a fundamental role because through simulations it is possible to enrich the existing knowledge databases relevant for the prediction. Improved predictive models, then, provide capabilities to perform optimal decision making and reconfiguration actions in order to improve the shop floor production performances (Villalonga et al. 2018; La Fé-Perdomo et al. 2019).

The use of distributed architectures in manufacturing also allows an increase in efficiency and reliability (Ferrer et al. 2018; Iarovyi et al. 2015; Haber et al. 2015). Scalability provides robustness against failures, allowing reconfiguration actions without affecting the production. Besides, distributed frameworks based on DT allows to exploit the computational capabilities of CPS for local decisions, through the local DT-based monitoring (e.g. component wear monitoring). Only the locally generated data that are needed for a systemic decision making (e.g. scheduling or system optimization) are then passed on from the local DT (at workstations, single

equipment pieces) to the global DT level (at production system level) (Haber et al. 2017; Beruvides et al. 2017).

Embedding DT in local controllers offers other advantages when enriched with improved predictive models for condition-based maintenance, as well as with an efficient local decision making to detect faults and aid operators. Therefore, the design and deployment of a distributed DT framework with embedded DT in the local nodes, by using a decision-making procedure supported on adaptive thresholds techniques and local simulations is expected to improve the operation management and to carry out more efficient scheduling tasks. The following research presents a distributed DT framework for manufacturing processes to carry out condition monitoring and decision making at equipment level.

The paper is structured as follows. Section 2 presents the research design. The review of the state of the art of DT in manufacturing is presented in Section 3. Section 4 describes the proposed distributed DT framework and the decision-making algorithm. Following, section 5 introduces the case study and framework validation. Finally, the conclusions are presented in section 6.

2. RESEARCH DESIGN

This paper aims at proposing a framework for distributed decision making based on a DT simulation synchronized with the field. The role of local and global decision-making and the relative interaction with the DT of the production equipment, and of the production system as a whole, will be pointed out. The DT simulation is run on MatLab/Simulink (www.mathworks.org) following the simulation software selection methodology by (Fumagalli et al. 2019). The distributed framework is then validated in the Industry 4.0 LAB at the School of Management of Politecnico di Milano. The DT simulation model has been created starting from the work reported in the literature (Negri, et al. 2019).

3. RELATED WORKS

DTs are one of the key enabling technologies that are leading the digital transformation. They were not initially conceived in the manufacturing sector: the first DT were developed in the aerospace sector to replicate the crack and fatigue behavior of the air vehicles in order to improve their safety and maintenance policies (Shafto et al. 2012); in some cases the DT were used for the design and the system engineering of the air vehicles (Ríos et al. 2016). It is with this system thinking and lifecycle perspective that this concept has migrated also to the manufacturing sector, initially as a virtual replica of robot systems (Schluse and Rossmann 2016; Grinshpun et al. 2016) and later to improve the lifecycle of products and production systems starting from the design phase (Gabor et al. 2016; Guerra et al. 2019). This is to grant a higher reuse and sharing of information generated during a phase of the system lifecycle and valuable for another phase. Literature reports many examples of information continuity and data management along product lifecycle through DT (Rosen et al. 2015; Abramovici, Gobel, and Dang 2016). Powered by the IoT, CPS capabilities, fog and cloud computing and AI (F Castaño et al. 2018; Fernando Castaño et al. 2017), DT supports new intelligent services to connect and interact with physical objects. These capabilities allow to realise various functions, spanning from simple monitoring (Schroeder et al. 2016) to data elaboration to predict and optimize future asset behaviour (Gabor et al. 2016). Moreover, by connecting and synchronizing with the physical world, DT empowers real-time human-machine collaboration improving cognitive services, proactive guidance, etc. (Wang et al. 2019). It is this double nature of data modelling and elaboration that allows the decision making support for asset lifecycle management according to (Macchi et al. 2018).

Literature does not provide a unique vision of DT-based decision making. An interesting work by (Kritzinger et al. 2018) classifies the DT proposals in literature according to their communication properties for decision making. The three situations are: (i) "Digital Model", if the digital replica does not connect to the physical word but it is a separated modelling of the real system; (ii) "Digital Shadow", if the digital replica is synchronized by communicating and connecting physical and the digital worlds; (iii) "Digital Twin", if the communication is bidirectional, from the physical system to the digital world and vice versa. It is clear therefore that in order to have automated support of decision making is necessary to have a "Digital Twin" in this latter meaning, being able to communicate decisions and trigger actions to the control system of a production equipment.

On one side, it is clear why research on DT is investigating their role inside the changes in the control hierarchies brought forward by the digitalization: e.g. in view of the adaptations of the automation pyramid and, in particular, of the MES in CPS-based production systems (Cimino, Negri, and Fumagalli 2019). On the other side, other research works investigate which decisions are made in detail. In fact, DT may be digital replicas of a single equipment, of a single production process or of the overall production system and decisions may also involve only single equipment or processes or the whole production system. From this viewpoint, some works are focused on two strategies. Firstly, based on the fact that the decision supporting AI does not lay in the DT itself but is a connected layer that offers the rules and the capability to identify the best alternative (Raileanu et al. 2020; Cardin et al. 2020). Secondly, the possibility to distribute the decision making by triggering the DT of single equipment as modules of the overall production system digital replica (Valckenaers 2019). Different architectures to aggregate the DT modules of single equipment into a unique DT of the production system have been proposed on the basis of these two strategies (Redelinghuys, Kruger, and Basson 2020; Micheal Grieves and Vickers 2016).

Theoretical foundations of this work are inspired in the strategy considering that, through DT, it is possible to leverage local and global control capabilities (Borangiu et al. 2020). The former ones are related to decisions that are made following local parameters and impact on local actions. For example, health monitoring of a single equipment piece, following one or few parameters gathered through local sensors, and the decision to stop the machine or send an alert to the workstation by operator screen. The latter are related to decisions that are made following a number of information gattered from different system sources and impact on the system as a whole, such as multi-objective optimization or scheduling (Beruvides, Quiza, and Haber 2016).

4. DIGITAL TWIN-BASED DISTRIBUTED FRAMEWORK

The DT modelling can be classified into three main detail levels: (1) local, (2) system and (3) global, according to the system that it represents. At the local level, DT represent the dynamics of the equipment pieces that compose the different production systems. At system level, the interaction between the equipment pieces that make up a production line. Finally, at global they replicate the behaviour of the entire shop floor production. Depending on the DT level, different actions can be carried out aimed to optimise the production, perform predictive maintenance, scheduling, reconfiguration and, generally speaking, decision making to assist the operators, as shown in the Section 3.

Implementing distributed DT frameworks provides the ability to carry out actions at each level to increase management efficiency. This may hold true at all levels, from the single equipment pieces to the overall shop floor management: the behaviors are simulated and decisions can be made according to alternative scenarios trials and what-if analysis, reaching a higher efficiency not only at a global level but also at a local level. Figure 1 shows the proposed framework. It is centred on promoting local decision-making, as an example for improving maintenance actions on a single equipment, through the DT module. The framework implements the local and global levels.
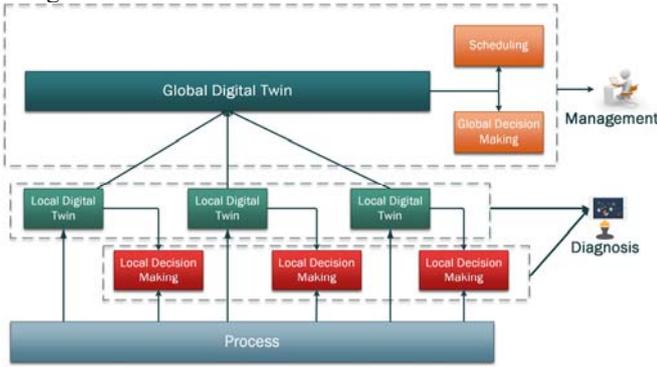

Fig. 1. Distributed Framework diagram.

Two main modules compose local nodes: the DT of manufacturing equipment and the decision-making procedure. Moreover, a predictive model based on machine learning algorithms is embedded in the local DT module. This model interacts with the DT and the process in order to detect and predict the current and future state of the asset, thus enabling to improve the decision making process. In particular, to implement condition-based maintenance with some predictive capabilities, different tools can be adopted, either based on statistical approaches, AI approaches or model-based approaches, in order to assist the operator in the fault detection, and also to predict the asset behavior up to the failure (Guillén et al. 2016; Jardine, Lin, and Banjevic 2006). Thus, the local DT, also enhanced with machine learning algorithms, may enable to support the development of the whole prognostics and health management (Guillén et al. 2016).

In the global node, a DT of the shop floor collects the information from local DTs, which include part of the sensors data and the relevant information of the local decision-making. It also interacts with the MES to get additional information to improve the accuracy of the digital replica in order to guarantee a better scheduling and global optimization. The scheduling and the global optimisation modules are responsible to carry out actions of reconfiguration and optimization based on the information collected from the global DT, the MES, the performance indices and other parameters and variables defined by the operators.

4.1 Local decision making

The decision making about the process condition or state is conducted by analyzing residuals (difference between the actual output and the output estimated by the model). Diagnosis techniques establish a threshold that determines the residuals limits, which correspond to normal operating conditions. The threshold value is decisive since an excessively low value would generate too many false alarms and high thresholds would increase the not detected existing faults probability. Setting the critical value of the residuals to identify a fault becomes a hard task. The threshold is set based on different statistical criteria (variance, standard deviation, mean), deterministic criteria (based on distance measurements in vector spaces) or using methods based on AI techniques (Zhang et al. 2019; Matía et al. 2019).

The evaluation of the residuals and the decision making about the condition or state of the process are two stages closely linked and essential for the proper functioning of the whole system. One of the simplest strategies is the method of the weighted sum of the square of the residuals (WSSR) (Hatami 2018). The WSSR method is based on the sequence of residuals (e_M):

$$e_M(t) = y(t) - \hat{y}(t) \tag{1}$$

where $y(t)$ is the output of the real process, and $\hat{y}(t)$ is the estimated output.

Under ideal operating conditions, the process is theoretically considered with white noise and zero mean with a covariance matrix $V_R(t)$. The deviation of a certain variable (η) is used to detect faults based on a threshold (ε), empirically calculated, and using a time window length [t-NT -1: t] (Eq. 2). A simple approach to establish threshold levels is to observe the residuals in the fault-free cases and set the appropriate level to obtain activation in the real cases.

$$\eta = \sum_{t-N_T-1}^{t} e_M^T(t) \cdot V_R(t) \cdot e_M(t) \begin{cases} > \varepsilon \rightarrow \text{failure} \\ \leq \varepsilon \rightarrow \text{no failure} \end{cases} \tag{2}$$

Improving the system fault detection robustness is necessary for the decision making stage. Most of these techniques are based on the use of an adaptive threshold in the decision making module. Different adaptive strategies can be used based on heuristic criteria or using exact mathematical functions (Beruvides et al. 2013). The direct relationships between the occurrence of failures and the infinite and Euclidean norms of the residuals vectors and their derivative can be established. Thus, the threshold value can be dynamically updated. In the local decision making, two main functions were considered by combining the influence of the residuals vector and its derivative on setting the adaptive threshold (Eq. 3-4). Thus, the information of the residuals vector and its derivative is used, not only to evaluate the

degree of process-model matching, but also to use the trend in the residuals vector to check the process state.

$$\varepsilon_1(t) = \frac{1}{|\mathbf{e}_M|_2 + |\dot{\mathbf{e}}_M|_2} \qquad (3)$$

$$\varepsilon_2(t) = \frac{1}{|\mathbf{e}_M|_\infty + |\dot{\mathbf{e}}_M|_\infty} \qquad (4)$$

where $|\cdot|_\infty$ and $|\cdot|_2$ are the infinite norm and the Euclidean norm respectively; $\mathbf{e}_M$ and $\dot{\mathbf{e}}_M$ are the residuals vector and its derivative in the window [t-NT –1, t].

5. CASE STUDY

The validation of the proposed framework was conducted on an assembly pilot line at the Industry 4.0 Laboratory at the School of Management of Politecnico di Milano. The system consists on a simplified mobile phone prototype assembly line. The route of each product can be tracked through a RFID-tagged chip embedded on the pallets that carry the product. The production line is fully equipped with sensors. The measured value from each sensor can be read via OPC UA protocol from all elements in the local network (i.e. MES, edges). The line is composed of seven workstations, each one dedicated to one or more assembly tasks.
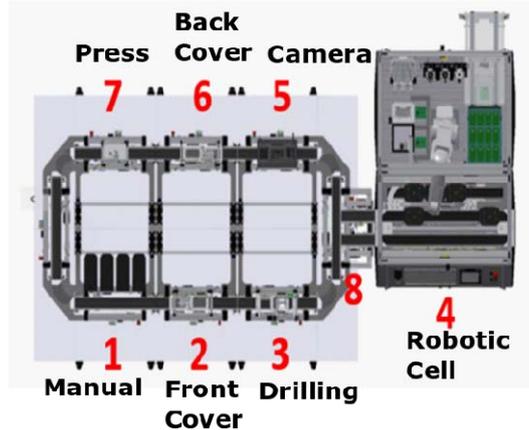

Fig. 2. Pilot line schema.

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

5.1 Results
In industrial production systems it is important to maintain the operational parameters into the established limits since failures cause unexpected stops in the production process or breakdowns in some of the main components. Sometimes failures are hard to detect just in time by the operators, and usually a complex analysis of the signals is needed. The proposed framework improves the decision making process in local stations. Through the DT simulations at local level and the signals acquired from the process, the decision making module either directly sends commands to the MES to solve automatically the issues or sends to the operator screens assists the information for an early stage fault detection resulting in a better maintenance scheduling and increasing the asset useful life. The validation of the framework was carried out through a real-time analysis of the pressure signal in the station 2. During the process, 41 operations were considered. In each operation, 10 samples of the pressure were measured, with a sampling frequency of 1 Hz, obtaining a total of 410 samples. A DT of the station 2 was developed in MatLab, and the decision making algorithms were embedded in the station 2 local edge.
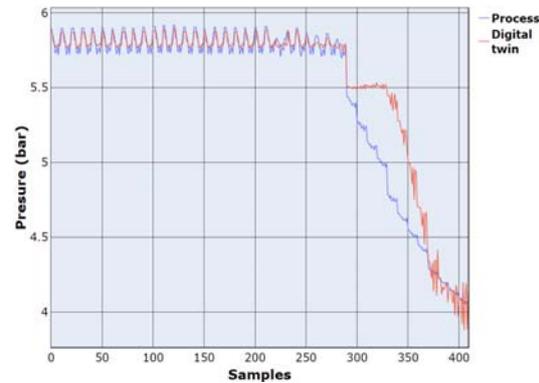

Fig. 3. Process signals and DT output.

In order to measure the system capability to identify the occurrence of anomalous situations and to trigger the decision making process, a leak was simulated by opening an exhaust valve while the operation 27 (samples from 270 to 280) was carried out. The valve opening was increasing gradually to exceed the process operational limits. The DT was able to reproduce the process behavior in normal conditions and even during the leak start stage, through the DT re-parametrization process. When the pressure presents a higher decrease rate, a deviation arises between the pressure signal from process and the output of the DT, the model parameters update process is not able to fallow the dynamics. Although as the trend of the leak stabilizes DT was able to follow the dynamics of the process. Figure 3 presents the pressure signal and the output from the DT simulation during the operations. Based on adaptive threshold algorithms, the residuals, obtained from process signals and the output of the DT, are analysed in a window of time. In the current process the number of samples within a window was set to 10 to cover an entire operation. Since the window covers an entire operation, the alarm value was set differently in each operation based on the value of the calculated threshold.

While the process is in normal conditions, the alarm value, calculated from the threshold, keeps in a narrow strip because the residuals trend was very similar in each operation. When the leak starts, the alarm is still set in normal state since the pressure signal still shows a normal tendency. In operation 28

(samples from 280 to 290) when the leak drops the pressure with an accelerated rate, the algorithm detects the change in the residuals and sets the system in alarm mode to alert the operator and triggers the global decision making. Figure 4 presents process pressure signal and the value of the alarm set in each operation. The change on the actual value trend of pressure causes a deviation in the residuals, which is detected by the system, allowing an early detection of abnormalities.

In general, the DT and the local decision making module provide the system with the capability to detect abnormal conditions in operation and either trigger actions on the MES or warn operators. Moreover, it also serves to notify the MES that the station is operating out of parameters and to trigger a general decision making process to reschedule the production line and maintain the target productivity.
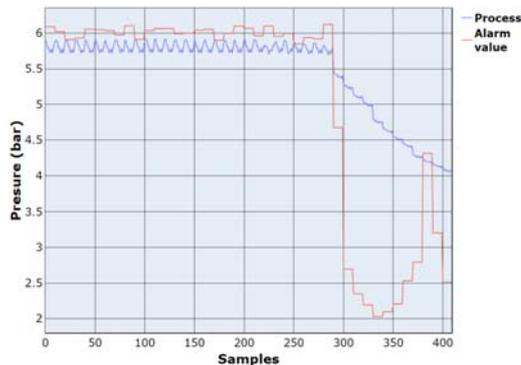

Fig. 4. Process signal and alarm value during the operations

6. CONCLUSIONS

This paper presents a distributed DT framework that enables a clear improvement in decision making about abnormal situations at local level. The framework is composed by several local DT, to simulate every equipment of a production line, and by a global DT that replicates overall system behaviours. Within this framework, the local decision making module was implemented using an adaptive threshold procedure. Finally, the framework is tested and validated on an Industry 4.0 pilot line. The decision making module was able to detect a possible fault in the pressure line through the analysis of the pressure signal of the real process and the outputs of the local DT. The implemented framework is able to alert the operator and to notify the MES about the occurrences of anomaly conditions in order to re-schedule and carry out corrective actions and to adapt the production schedule accordingly. The results contribute to research on DT by demonstrating their effectiveness in operations and asset management, pointing out the variant scenario of decision making, supported by synchronized simulation, data management and data conditioning to monitor, predict and optimize the behaviour of manufacturing systems. Future works will focus on exploring the industrial impact of the decision making support system and will expand the application areas to other operations such as quality control and safety issues.

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