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ONLINE VALIDATION OF SIMULATION-BASED DIGITAL TWINS EXPLOITING TIME SERIES ANALYSIS

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ABSTRACT

Recently, the development of new technologies within the Industry 4.0 revolution enabled to increase the digitization level of manufacturing plants. To benefit from the functionalities of digital twins, it is essential to guarantee a correct alignment between the physical system and the associated digital model along the whole system life cycle, and to assess the validity of the digital model online. Traditional validation techniques cannot be applied for such purpose because of the restrictive assumptions and the need of large amounts of data. This work proposes a novel online validation method to assess the correctness of Discrete Event Simulation models. Validation is done by treating shop-floor data as sequences, and measuring the similarity between the data streams from the physical system and its corresponding digital model. The proposed method has been tested via offline experiments and with an application within a digital twin architecture exploiting a lab-scale manufacturing system.

1 INTRODUCTION

In the recent years, the manufacturing field is evolving towards the concept of Industry 4.0 and smart manufacturing. The change is enabled by the development of new technologies such as Internet of Things, big data analytics, cloud computing and artificial intelligence. These technologies allow to integrate several software components within the plant information system to collect and analyse large amounts of data, as well as to reproduce and predict the behaviour of the factory. The digital twin (DT) is a growing technology able to improve the performance of a manufacturing system and support decision making. In the manufacturing field, the DT is defined as: *"a virtual representation of a production system that is able to run on different simulation disciplines that is characterized by the synchronization between the virtual and the real system [. . .]."* (Negri, Fumagalli, and Macchi 2017). The main components of a DT are the physical entity and the virtual entity. Within the scope of production planning and control, the virtual entity can be represented by a Discrete Event Simulation (DES) model. A bi-directional exchange of information and synchronisation between the physical and the virtual components are essential features of a DT. In addition, the DT capability of providing feedback actions to the physical system allows to improve promptness and efficiency of decision making. Indeed, short-term decision making requires a rapid detection of disruptions, and any delay in the implementation of corrective actions may cause a big impact on production, reflecting on economic losses for the company. To prevent this scenario, it is essential to have a model coherently representing a real system along its whole life-cycle, adapting to possible changes. As a consequence, to benefit from the DT functionalities, the correctness of the virtual component must be continuously checked.

Existing DT applications usually do not discuss how the validity of the digital model is assessed. Also, significant contributions on the digital model validation for short-term applications are scarce. Traditional validation techniques often rely on statistical methods which require large data sets, that may be available only for systems that never change, which is a quite unlikely scenario in industry. These requirement may affect the promptness with which disruptive events are detected: the most recent behaviour is averaged with historical data and potential deviations can be hidden. Moreover, since only one set of data can be acquired from the field, batching procedures have to be applied to avoid auto-correlation effects and satisfy the assumption of independence. However, batching leads to data averaging and the performance trend might be lost. As a consequence, it is difficult to detect changes that do not impact on the average behaviour of the system. Given these characteristics, we may conclude that traditional statistical approaches may not be suitable for real-time applications.

To overcome the aforementioned limitations, there is the need to study new approaches to validate DES models in real-time. This work aims to assess the validity of a DES model representing a generic manufacturing system. The goal is to apply a technique that can deal with a limited data set; in addition, it must be capable of analysing the evolution in time of the behaviour. Such an approach could allow the successful deployment of simulation-based DT in smart manufacturing systems. The digital model validity is assessed measuring the similarity between real system data and digital model data. Indeed, most data from a production system are collected with a regular cadence (e.g., production rate, quality inspections, physical measurements). For instance, Figure 3 shows the real-time collection of inter-departure times from a manual assembly station. These data are typically saved in the form of time-series and it is possible to treat them as sequences. Hence, we can measure the similarity level with digitally produced data by means of a sequence comparison technique.

The rest of the paper is organized as follows. The research gap on real-time validation is discussed in section 2. Section 3 outlines the DT framework used as reference in this work. The developed method to assess the correctness of a DES model in real-time is explained in section 4. Section 5 presents the preliminary experiments to test the proposed approach. A case study to assess the model validity of a lab-scale manufacturing system is reported in section 6. Finally, conclusions are drawn in section 7.

2 STATE OF THE ART

In this section, we outline significant contributions from the literature in support of this work. Section 2.1 lists contributions that defined the role and features of DTs in manufacturing. Section 2.2 summarizes the traditional methods for digital model validation, while section 2.3 focuses on recent contributions that aim at the real-time validation of DTs.

2.1 Digital Twins for Smart Manufacturing

In the most basic form, a DT is a virtual copy of a real system (Grieves and Vickers 2017). Since the DT is a recent concept, in the literature there are no globally recognized definitions, standard construction methods, and DT components. It is important to create a common understanding and align future developments in order to avoid confusion and provide more efficient applications (VanDerHorn and Mahadevan 2021). In order to better delineate the DT, Kritzinger et al. (2018) proposed a classification based on the integration level of data, namely the direction of automatic exchange of information between the physical entity and the virtual counterpart. The digital model (DM) is *"a digital representation of an existing or planned physical object that does not use any form of automated data exchange between the physical object and the digital object."* The digital shadow (DS) is *"a digital model with an automated one-way data flow from physical to virtual."* The digital twin (DT) is reached when *"data flows between an existing physical object and a digital object are fully integrated in both directions"*. Further, Tao et al. (2018) introduced the following DT characteristics: (1) *Real-time reflection*: the virtual space is capable of reflecting the real space with high level of fidelity and synchronization. (2) *Interaction and convergence*: data connection between various phases of the physical system, between physical space and virtual space, and connection between real-time data and historical data. (3) *Self-evolution*: the DT model is able to continuously adapt to the physical system. According to both Grieves and Vickers (2017) and Tao et al. (2018), the DT is characterized by three main parts: the physical object, the virtual object, and their connection. The three dimensions previously mentioned are then extended to five by Tao et al. (2019) by adding the services and the different sources of data.

Based on the existing literature, we may assert that the main feature of a DT for smart manufacturing is the capability to autonomously act on the physical system, thanks to the presence of a bi-directional flow of data. The near real-time synchronization between the physical system and the virtual counterpart is essential (Lugaresi and Matta 2018), and it can be achieved by means of sensors placed on the equipment capable of collecting useful data. Optimization algorithms are used to find the optimal solutions to be sent back to the physical system in terms of practical actions. In this way, the virtual system can also control the physical counterpart and support near real-time decision making. An additional important characteristic of the DT is the capability to dynamically update the digital model. As a result, it can adapt to any change occurring in the physical system.

2.2 Offline Validation of Discrete Event Simulation Models

Assessing the correctness of the digital model is a fundamental step during the development phase of a simulation model. Models are used to support decision making in the real world and it is important to assess the reliability of the obtained results. To achieve this, the concept of verification and validation (V&V) has been introduced. According to Sargent (2010), V&V of a simplified model development process includes four parts: (1) conceptual model validation, (2) computerized model verification, (3) operational validation, and (4) data validity. This work focuses on the operational validation procedure, which is defined as *"determining that the model's output behaviour has a satisfactory range of accuracy for the model's intended purpose over the domain of the model's intended applicability"* (Sargent 2010). It is important to underline that the model validity is always checked under specific experimental conditions and for specific purposes. Indeed, validation in absolute terms is highly costly and time consuming. Moreover, results of the validation process depend on the level of accuracy defined by the user (Sargent 2010). Balci (1994) proposed a taxonomy on more than seventy-five V&V testing techniques composed of four main categories, each counting a wide set of techniques, characterized by an increasing level of formality and complexity: (1) *informal techniques* are based on human reasoning and subjectivity; (2) *static techniques* are established on the model design and source code (i.e., no model execution is needed); (3) *dynamic techniques* are dependent on the model execution and comparison of the output behaviour; (4) *formal techniques* rely on a mathematical proof of correctness. As stated by Sargent (2013), model validation consists in comparing the output behaviour of the system with that of the simulation model, this approach is in accordance with the techniques identified in the dynamic category of the taxonomy proposed by Balci (1998). Results of the comparison determine the level of accuracy of the digital model.

According to the aforementioned authors, the most common approaches used for model validation are graphical comparison, confidence intervals, and hypothesis tests. With respect to DT applications, graphical comparison is characterized by subjective decisions leading to difficulties in evaluating results. On the other hand, confidence interval and hypothesis tests are based on statistical assumptions that are not always satisfied. In addition, the comparisons are based on the average behaviour of the system. Hence, traditional methodologies are not suitable for the purpose of this work.

2.3 Online Validation of Discrete Event Simulation Models

Recently, new studies about online validation have been published: the most relevant are reported in the following paragraphs. Marquardt et al. (2021) introduced the importance of online validation when dealing with a DT. In order to provide both strategic and operational decision support, it is fundamental for the digital model to be always updated with respect to the real system. In particular, the paper highlights the effects caused by a model not coherently representing reality, considering both inconsistencies of input

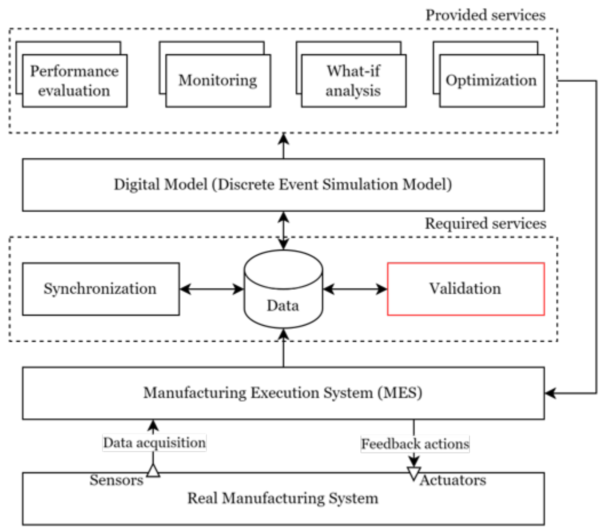


Figure 1: Digital twin framework used as reference in this work.

parameters and model assumptions. Although explaining the importance of having a model accurately representing the real world, the paper lacks a possible online validation approach. An attempt to tackle this issue has been proposed by Overbeck et al. (2021). The authors propose two indicators to detect deviations, the first is based on the relative variation of a specific Key Performance Indicator (KPI) within the end of the reference time, the second deals with the Normalized Root Mean Square Error (NRMSE) of the KPI, measured at specific points in time along the reference period. The latter contribution shows the growing interest in the topic, but still focuses on the average behaviour of real and digital systems. Lugaresi et al. (2019) presented a new method to perform online validation based on harmonic analysis. Compared to statistical techniques, this method is able to achieve reliable results even when applied to a relatively small dataset. The main idea behind this procedure is to consider KPI trends as signals. Using information about the power spectral density, it is possible to detect potential deviations between the model and the real system. Namely, the difference between the power spectral densities of the two outputs is used to define a measure called spectral indicator, that can be used to assess the level of consistency of the model. Morgan and Barton (2022) proposed a methodology to discriminate between two systems based on the Fourier transform of the output trajectory. The weighted average of the Fourier coefficient magnitudes is used to detect differences between the two systems under analysis. What differentiates the latter two approaches from other methodologies is the analysis of data in the frequency domain, that allows to take into account the temporal evolution of data, rather than comparing aggregated values such as the average.

To the best of the authors' knowledge, few solutions to the online validation problem for manufacturing systems are present in literature. This paper aims at developing a method to assess the short-term validity of a DES model using the Dynamic Time Warping algorithm. The goal is to apply the proposed method to compare real-time data sequences from the shop-floor with the data produced by its digital counterpart. The validation procedure must provide reliable results even when a small dataset is available, enabling a fast detection of disturbances.

3 DIGITAL TWIN FRAMEWORK

The high-level DT architecture used as reference for this work is illustrated in Figure 1. The architecture is consistent with the DT definitions and features discussed in section 2. The real manufacturing system represents the physical entity of interest (e.g., assembly production line, flexible manufacturing system, job shop), while the digital model is the associated DES model. By exploiting sensors embedded in the

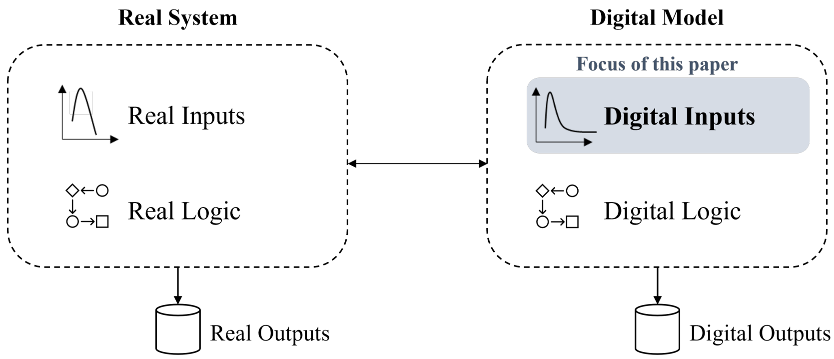


Figure 2: Simplified representation of the relationship between a real system and its digital model (adapted from Nelson et al. 2013).

system, the Manufacturing Execution System (MES) allows to collect and store shop-floor data in real-time (Negri et al. 2020). The digital model requires to be synchronized and validated in order to properly reproduce the dynamic behaviour of the system. Synchronization deals with the alignment between the real manufacturing system and the digital model (Lugaresi and Matta 2018), while validation ensures the model is correctly built. Once the digital model is synchronized and validated it can be used to provide services such as monitoring, performance evaluations, what-if analysis, and optimization. From evaluations and analysis, possible required feedback actions are executed on the real system by means of MES. These characteristics allow to achieve a bi-directional flow of information and implement feedback actions on the real system. In addition, the synchronization capability is consistent with the DT features found in literature. In this work, we focus on the essential role of the validation module. This component must ensure in real-time that the digital model is consistently representing the real manufacturing system.

4 REAL-TIME VALIDATION

This work proposes a method to support the validation of digital models of dynamic manufacturing systems. The goal is to develop a technique that can be used within a component of a DT framework and that can deal with real-time applications.

As introduced by Nelson (2013), a system is described by its logic and input. Based on this consideration, a validation procedure may be divided in two parts, one for each aspect. The logic validation of the model concerns the building of the model itself and its assumptions. The input validation ensures the correctness of the input data fed to the model. The uncoupling of logic and input validation is useful to identify a deviation and the corresponding solution. Differently, traditional validation instead is usually performed in one single phase. Hence, when a model is not valid, it is not possible to understand if the reason for its rejection is related to wrong logical assumptions or input data. A model is defined valid if both its logic and inputs properly represent the ones of the real system. In this work, we focus on the input validation.

4.1 Real-time Data from a Manufacturing System

In smart manufacturing systems, it is reasonable to assume that an adequate sensor network has been put in place, and data collection is possible within the same level of detail expected by the user. In this context, we may treat both real and digital data as sequences. A sequence is defined as a succession of values ordered by time. For instance, the left side of Figure 3 shows the extraction of the sequence of inter-departure times from an assembly station.

4.2 Validation Method

Dynamic time warping (DTW) is a time-series-analysis algorithm able to assess the alignment between two sequences and measure their distance. The procedure computes all possible alignments between each point of both sequences and then identifies, as the best alignment, the one that minimizes the distance. The measure is a cumulated distance since it represents the sum of the distances between all matching points in the path.

Let v_1 and v_2 represent the data sequences of a quantify of interest (i.e., inter-arrival times) of a digital and a real system, respectively. Further, let us accept the notation $v_{1[i]}$ to represent the i-th point of the sequence v_1, while $v_{1[i,j]}$ represents the portion of sequence going from the i-th point to the j-th point. Lastly, let l_1 and l_2 be the length of the sequences v_1 and v_2, respectively. The DTW-based validity index Θ is obtained by equation (1).

$$\Theta = 1 - \frac{dDTW(\bar{v}_1, \bar{v}_2)}{max(l_1, l_2)} \tag{1}$$

where

$$\bar{v}_1 = \frac{v_1}{max(max(v_1), max(v2))} \quad \textit{and} \quad \bar{v}_2 = \frac{v_2}{max(max(v_1), max(v2))}$$

and

$$dDTW(v_1, v_2) = \begin{cases} 0 \quad \text{if} \quad l_1 = 0 \quad \text{and} \quad l_2 = 0 \\ \infty \quad \text{if} \quad l_1 = 0 \quad \text{or} \quad l_2 = 0 \\ dDTW(v_{1,[1]}, v_{2[1]}) + \quad \min\{dDTW(v_1, v_{2[2,l_2]}), \\ \qquad dDTW(v_{1,[2,l_1]}, v_2), \qquad \text{else} \\ \qquad dDTW(v_{1,[2,l_1]}, v_{2,[2,l_2]})\}. \end{cases}$$

The validation procedure is conducted comparing a set of real and digital data to obtain the validity index in equation (1), which ranges between 0 and 1. The closer to 1, the more likely the digital model is valid with respect to the representation of the real system inputs.

In order to cope with the variability that is caused by the random number generator of a simulation model, digital data are obtained by means of a particular procedure named quasi Trace-Driven Simulation (qTDS), a technique in which the digital inputs are generated in correlation with the real system data without introducing randomness due to sampling (Lugaresi et al. 2019). It is possible to define an *acceptance threshold* α and consider the digital model valid if $\Theta > \alpha$. Acceptance thresholds must be defined in accordance to preliminary investigation and user requirements.

Figure 3 illustrates an example of the proposed procedure. The physical system is composed by a manual assembly station, the shop-floor data collection allows to store in the sequence v_2 the inter-departure time of parts leaving the system. The digital model representing the system is a discrete event simulation model of a G/G/1 queue, the digital inter-departure times obtained from simulation are stored in the sequence v_1. The two sequences are compared using the DTW-based validity index defined in equation (1), which is able to assess the correctness of the digital model. If the validity index is greater than the acceptance threshold set by the user, the model is considered a valid representation of reality and can be used for decision-making.

5 NUMERICAL EXPERIMENTS

An experimental campaign is conducted to understand the applicability of the proposed method to assess the validity of a digital model. The system used to conduct the experiments is a G/G/1 queue. The system is a single-station characterized by one server. It is assumed that the server is perfectly reliable and follows

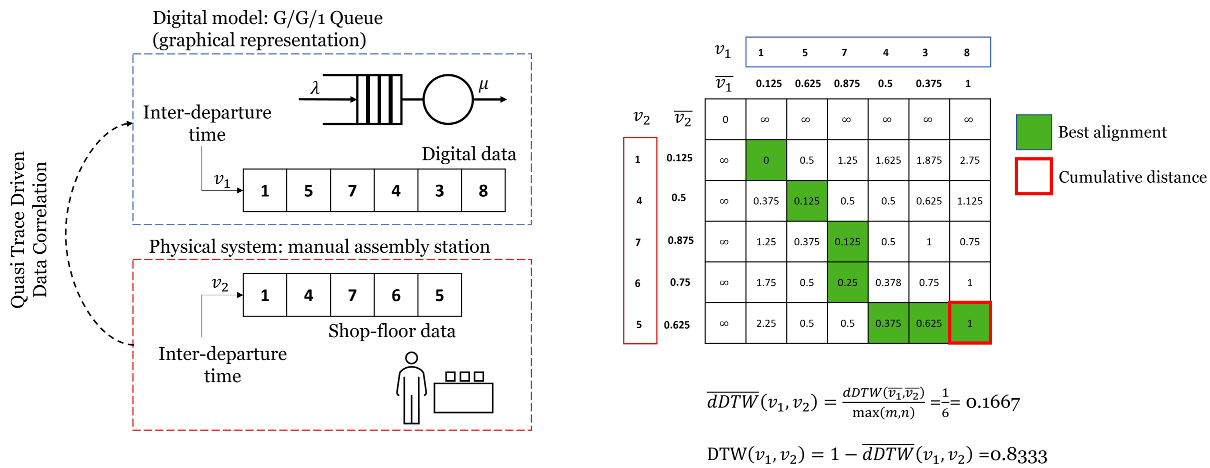


Figure 3: Example - Comparison of data sequences generated by a real system (i.e., manual assembly station) and its digital model (i.e., a discrete event simulation model of a G/G/1 queue).

a first-come-first-served dispatching policy, and that the queue capacity is infinite. The processing rate of the server μ follows a normal distribution with mean $4s$ and standard deviation equal to $\sigma = 1s$, while the arrival time λ follows an exponential distribution with mean $5.5s$. As a result, the utilization of the system is $\rho = 0.73$.

The DTW-based validation method has been applied in comparison with other techniques. Namely, the same setting has been done by using Edit distance, discrete Frechet distance, and Euclidean distance (Toohey and Duckham 2015). In all cases, the proposed method has proved to perform better that the alternative approaches. For brevity, the methods comparison is omitted in this work, the reader is invited to consult the related work for further information (Gangemi and Gazzoni 2022) .

A design of experiments concerning the input validation of the digital model has been done. The goal is to investigate the ability to detect changes in the input distribution parameters of the digital model. The system response of interest is identified as the value for which the similarity indicator reaches convergence and the associated time. The time is measured as the number of parts necessary to reach a stable indicator. It is assumed to have a perfect knowledge about the arrival time of parts in the system. Such simplification leads to focus on just one specific portion of the system, in this case the processing time distribution. The identified factors affecting the response are the mean $\bar{\mu}$ and standard deviation σ of the processing time distribution. $\bar{\mu}$ and σ are characterized by three levels each: the first level corresponds to the value of the real system, and two further levels represent deviations from the distribution parameters. Such deviations could represent an error in the model building, in parameter estimation, or a gradual misalignment along the life cycle of the system. Each configuration of factors is characterized by 10 independent replications. Hence, in total, 90 simulation experiments have been executed.

Real-time validation is conducted following the method described in section 4, using as reference the inter-departure time. Figure 4 illustrates the obtained DTW-based indicator associated to different input configurations. The indicator value has been extracted in correspondence to different number of parts produced n. Specifically, $n \in \{50, 100, 500, 1000, 2000, 4000, 6000, 8000, 10000\}$. For correct input distribution parameters (blue curve, i.e. $\bar{\mu} = 4$, $\sigma = 1$), the indicator converges to 1. As the input parameters deviate with respect to the reference values (orange and green curves), the indicator stabilizes at a lower level. This result shows the capability of DTW-based validation procedure to detect a difference between the model and system performance due to wrong input distribution parameters of the model.

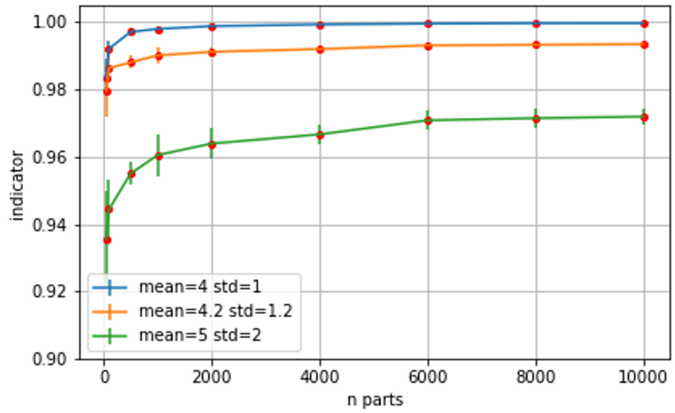


Figure 4: Numerical Experiments - Input validation results using Dynamic Time Warping (DTW), the vertical bars refer to a 95% confidence interval.

6 COMPONENT DEPLOYMENT AND CASE STUDY

In this section, the proposed method is integrated with a digital twin demonstrator. The aim of the demonstrator is to monitor, optimize and support decision making of a manufacturing system within a controlled environment (Lugaresi et al. 2021). This section gives an overview of the demonstrator, with a focus on the deployment of the validation component.

6.1 Physical System

The real system is a two-station closed loop lab-scale manufacturing system available in the Department of Mechanical Engineering of Politecnico di Milano. The system is illustrated in Figure 5. The system emulates a closed-loop production line. Wooden discs tagged by red plates represent pallets. A fixed number of pallets circulates in the system. It is assumed that unlimited parts to be processed are available and that the pallet loading and unloading phases are very short. Each station processes one pallet at the time. The pallet is held in the station for an amount of time that represents the physical operation (e.g., milling, engraving, welding). If a failure occurs, the pallet is held for an additional amount of time in the station. The conveyors bring pallets from one station to the other. They also operate as buffers: pallets may accumulate in front of a station to wait until it is available to process parts. Further, a station cannot download parts until the corresponding downstream buffer is full. The lab-scale system is built with LEGO MINDSTORMS[1] components (Lugaresi et al. 2019). Each station is composed by an EV3 brick, three optical sensors, a motor and a part entrance system. The EV3 is the controller of the station, and it interfaces with sensors and motors by means of a python code. The connection between all components is achieved by means of Secure Shell Host (SHH) protocol, and the system is controlled using messages exploiting the Message Queue Telemetry Transport (MQTT) protocol. Thanks to this architecture, it is possible to exchange information and implement actions on the system in real-time.

6.2 Validator Component within a Digital Twin Architecture

The demonstrator digital twin architecture is the implementation of the framework described in section 3, and it is achieved by means of six main components: the real system, a discrete event simulation model, a database, a controller, a validator component, and a real-time dashboard. The whole architecture has been developed in *python*.

The aim of the validator component is to use the method summarized in Section 4 to assess the validity of the digital model. The validation procedure is conducted in real-time. Indeed, subsets of data produced

[1]LEGO, LEGO MINDSTORMS, and EV3 are trademarks of the LEGO Group.

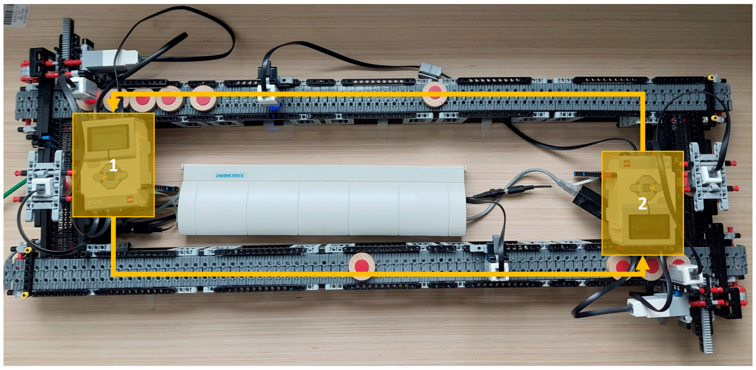


Figure 5: Two-station closed loop lab-scale manufacturing system used for the case study.

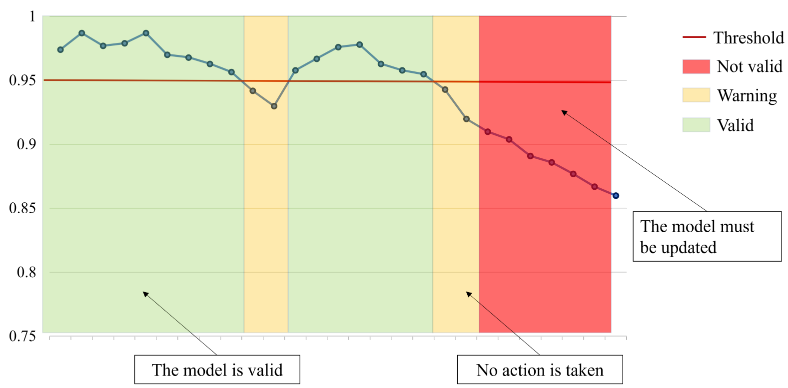


Figure 6: Example of validation indicator trend and DT response actions.

by the real system and by the discrete event simulation model are extracted from the database and compared while the system is working. The *system time*, defined as the time needed by a pallet to visit the entire system, is chosen as performance measure of interest and the acceptance threshold is set to $\alpha = 0.92$ based on previous analyses. To assess the validity of the model the indicator trend is monitored. The data used for the comparison are the ones characterizing the last 10 minutes of production in a rolling approach, and a new indicator is computed every minute using equation (1). This procedure allows to detect deviations rapidly and avoid possible erroneous alerts due to wrong data acquisition.

Once a Θ value is available, three possible outcomes can be defined: (1) *"valid"*, (2) *"warning"*, and (3) *"not valid"*. When the indicator is located above the acceptance threshold line (i.e. $\Theta > \alpha$), the model is *"valid"* and a correct monitoring is provided. To account for noise and wrong input data, when the indicator value lays below the threshold, a *"warning"* message is returned but no action is taken on the system. Instead, after three consecutive warnings, the *"not valid"* message is returned and the model is updated. An example of the indicator trend is represented in Figure 6.

6.3 Demonstration Setting

For this case study, the system represented in figure 5 is set with the following initial parameters. The stations are perfectly reliable, and can process one part at a time. The processing times on station 1 follow a triangular distribution with parameters $[3,8,5]$, while the processing times of station 2 follow a triangular distribution with parameters $[2,5,3]$. The stations follow a Blocking After Service (BAS) discipline, and the buffer capacity is 8 for both stations. The number of circulating pallets is equal to 12.

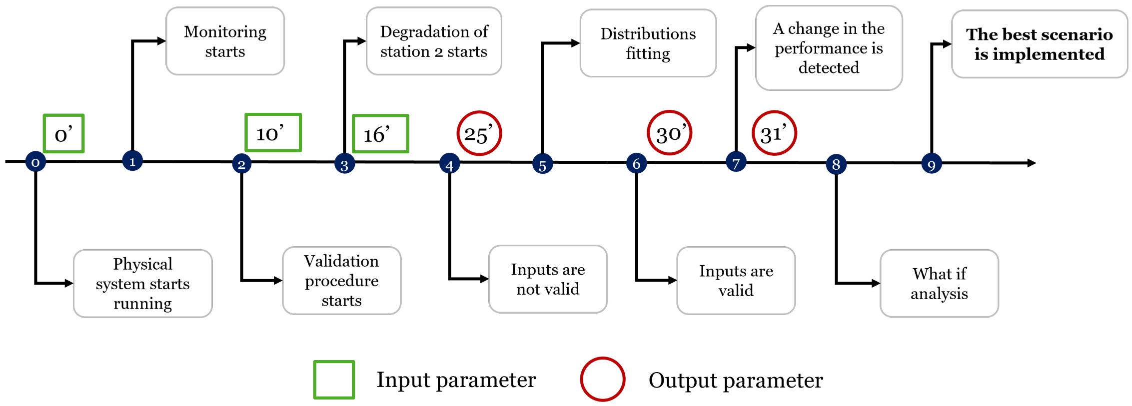
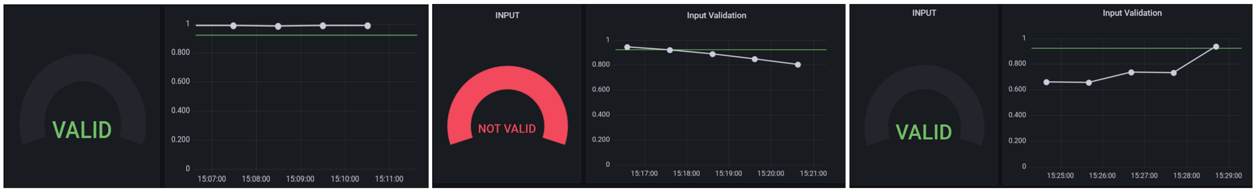


Figure 7: Temporal view of the case study.

The temporal schema of the case study is illustrated in Figure 7, while Figure 8 shows the Θ indicator values in three points of interest. The time values indicated by the squares are resulting from user decisions and they are input parameters of the demonstration, while the circled values cannot be known a-priori and they are obtained as output results. A detailed explanation of each step is reported.

- The physical system starts running. The second station is faster, hence the majority of pallets are located in the upstream buffer of station 1.
- The conceptual model is automatically generated using the event log stored in the database and it is converted into an executable model. Once the digital model is available, monitoring can start. For this demonstration *SimPy* is used to build a discrete event simulation model of the system.
- The validation procedure starts with the parameters initially set.
- As the system operates, station 2 undergoes degradation. The new processing time distribution of station 2 follows a triangular distribution with parameters $[9, 14, 11]$, while the distribution of station 1 remains unchanged. The input validation indicator gradually drops and a *"warning"* message is returned.
- At the third *"warning"* alert, the *"not valid"* message is returned, input validation detects a change in the input distributions.
- The processing times of both stations are fitted again to find the new distributions using the last ten minutes of acquired data.
- The input validation procedure is repeated until the new distributions are validated. The *"valid"* message is returned.
- The controller detects a change in the performance due to the degradation pattern of station 2 (notice that, differently from the initial condition, now the buffer of station 2 is full and station 1 is frequently blocked).
- A what-if analysis is conducted on two alternatives: (1) *"do-nothing"*, keep producing at a slower pace and repair the machine at the end of the shift; (2) *"react"*, stop the plant to allow repairing activities and then continue with the production pace before the slow-down.
- The second alternative is identified as the best scenario since it leads to a higher value of expected production at the end of the time horizon; the repairing actions are automatically implemented on the system. Once completed, the system returns operating at its original production pace.



a) b) c)

Figure 8: Temporal view of the validity indicator Θ in three points of interest in the case study: a) point 3, b) point 4; c) point 6.

6.4 Results

The goal of the case study is the maximization of production within the end of the shift. The DT demonstrator is able to identify the best alternative and automatically implement it on the system. A validator component has been developed and implemented in this case study. The validator component is essential to identify changes in the physical system that must be reflected in the digital model before using it for further evaluations. Validation is conducted online and with a relatively small dataset and the whole evolution in time of the DTW-based indicator is monitored rather than the single point value. The results proved that the proposed method is applicable in a realistic environment.

It is worth to notice that the choices of update frequency and data retention policy are strictly dependent on the production pace of the system under analysis and on how quickly the disruptions need to be identified. Indeed, as the dataset used to compute the indicator contains data acquired during the correct functioning of the system, some time is always required to detect the occurrence of a disruption.

7 CONCLUSIONS

This work proposes an innovative approach to deal with online validation of DES models. Thanks to the proposed method, it is possible to guarantee that a digital model is always updated in terms of inputs, enabling short-term decision making. The main advantages are the possibility to achieve reliable results even with a limited dataset and to take into account the specific behaviour rather than relying on aggregated measures such as the average performance. The results obtained by the case study demonstrated the applicability of the proposed approach within a DT architecture. Indeed, the case study proves that the proposed method is applicable also for a physical system in a realistic environment, where perfect modelling cannot be achieved. The validator is an essential component of the proposed DT architecture. It is fundamental to support a rapid detection of disruptions and to provide efficient decision making.

This work is still affected by several limitations. This approach is still not able to identify the specific cause for the anomaly behaviour of the model. Future works could be dedicated to develop procedures to automatically detect the reason for which the model is not valid. Also, a-priori analysis on the system is still required to properly identify the acceptance threshold. Future developments must investigate how to automatically identify the acceptance thresholds based on the system and on the accuracy level requested by the user. Also, further studies could be dedicated to detailed experimental campaigns and to define guidelines for the choice of the update frequency and the data retention policy has not been investigated.

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