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Digital Twins based on integrated models: Supporting joint decisions on maintenance and production planning

Chiara Cimino*, Laila El Warraqi*, Elisa Negri*

* *Department of Management, Economics and Industrial Engineering, Politecnico di Milano, Piazza Leonardo da Vinci, 32, 20133 – Milan – Italy (e-mail: chiara.cimino@polimi.it; laila.elwarraqi@polimi.it; elisa.negri@polimi.it)*

Abstract: Within Industry 4.0 (I4.0), technological advancement has brought manufacturing to the adoption of different Digital Twins (DTs) for the same physical system – or Physical Twin (PT) – in order to make different decisions. Nevertheless, independent decisions with DTs not integrated among each other and/or with their reference models can affect production efficiency. This paper focuses its attention on production planning control and maintenance and proposes an approach for models' integration that support those analyses in order to use them as the basis for the creation of a DT that can provide structured support through the whole system's lifecycle. With this aim, the paper proposes a model for DEVS simulation capable of integrating production planning with preventive and corrective maintenance to support joint decisions.

Keywords: production planning, maintenance, integration, manufacturing, industry 4.0, digital twin, DEVS simulation

1. INTRODUCTION AND MOTIVATIONS

Digital technology advancements in recent years have brought traditional manufacturing industries into shifting to smart factories. The demand for faster delivery times, more efficient and automated processes, higher quality and customised products drove companies to the industry 4.0 (I4.0) vision, which relies on the adoption of technologies such as the Internet of Things (IoT), big data, artificial intelligence and cloud computing (Zheng et al., 2021). In manufacturing environments, I4.0 allows preparing for a high degree of flexibility in various aspects, including (mass-) customized products, smart production processes, virtualization and transparency. Nevertheless, constructing such manufacturing systems is a complex effort comprising different tasks which involve different engineering disciplines (Novák et al., 2020). Indeed, I4.0 technologies significantly impact different analyses and their goals, such as production, planning and control (PPC) and its goals of high schedule reliability, short lead times, high-capacity utilization, and low inventory levels (Wiendahl & Breithaupt, 1999) and maintenance planning to preserve machine performances and save part of the total operation cost (Syan & Ramsoobag, 2019). It is well-known that production and maintenance planning are two critical interrelated tasks in manufacturing systems (An et al., 2023; Azimpoor et al., 2022). Failure and unplanned maintenance may cause machines to be unavailable (Annie Francie et al., 2014; Chen et al., 2020) and unavailability periods must be considered for the production planning outcome prediction. Therefore, considering production or maintenance planning independently will most likely lead to production inefficiency.

1.1 Digital Twin for production planning and maintenance

Considering the advancement of digital technologies, in the I4.0 context different tools can be used to support production. The Digital Twin (DT) is an emerging concept which goes hand in hand with the development of I4.0. Its usage enables the optimization of manufacturing scenarios, through advanced simulations of real industrial contexts. The usage of DTs, besides building digital representations of physical objects, can support different field data elaborations, both online and offline, and it can support decision-making during the lifecycle of a physical system. In particular, the DT in its online usage can be used for real-time monitoring and maintenance decisions, while offline can be used for the analysis of different design alternatives without requiring the connection to the physical system (Cimino et al., 2021). Given its relevant role in production systems, a DT should support the analysis of both maintenance and production planning, and in particular, it can be used to assess the synchronization between production planning and maintenance decisions as the two parts are strictly related in manufacturing contexts. Indeed, considering production and maintenance as separate problems affects the production efficiency: considering only the production planning means assuming that the system is continuously available, while evaluating maintenance singularly can be useful to avoid machine breakdown but could affect the expected production planning (Sortrakul et al., 2005). In this sense the DT could reveal many benefits, such as: a) integrated production control and maintenance planning analyses, b) improved production machine's reliability, c) assessment of the causes of maintenance, d) cost reduction through the minimisation of unplanned downtimes and the reduction of the needs for emergency repairs, to name a few. Nevertheless, assigning all those roles to a DT requires (i) a structured integration of the modelling approach used to describe a specific system, (ii) the possibility of collecting all the historical data of that system consistently with the said modelling approach and (iii) a systematic approach to update the system model accordingly to the acquired historical data.

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As depicted in Figure 1, suppose that a model – or a set of models – exists to describe a system during the design stage, when at most only prototypes of the system exist. When the physical counterpart is created – that will be herein called Physical Twin (PT) – a DT, or again a set of DTs can be created in order to connect the related PT and monitor the system. The system can be analysed and, in case the DT is consistent to the models used during the design, it will be possible to evaluate the performances of a system with respect to the expected ones. It can be noticed that being connected to its PT, a DT must be capable of keeping track of all the unplanned and unpredictable unavailability periods of a system, considering that those should be analysed consistently to the expected behaviour of the system. Hence, considering a simple example of simulation for production system's planning, suppose that predicted outcome of a system was already given by a certain number of pieces in output within determined statistics about both service times and maintenance times. When the PT exists, a DT should report that the system behaviour is "too distant" from the predicted one, and this should trigger the analysis of the system – through the use of another related DT, or set of DTs, consistent to the one that monitors the system – through the simulation of a series of what-if scenarios starting from the actual situation, in order to evaluate which scenario brings the system back to the expected outcome. Consequently, if a system changes during the system's lifecycle, and these changes affect also the what-if scenario, the model(s) used for the design should be updated to follow the real behaviour of the system.

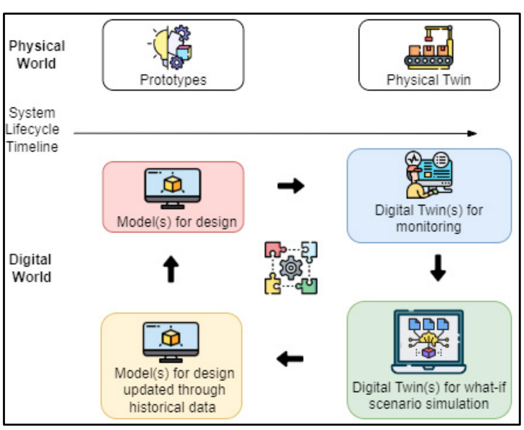

Figure 1. General scheme that follows a PT, its related models and DTs evolution and integration through the system's lifecycle.

1.2 Objective of the work

The aim of this paper is to explore the use of a model to integrate maintenance and production planning and see how this can be used to support joint decisions through the use of DTs based on these models for both monitoring and what-if scenario simulations. With this objective, after a brief introduction on the I4.0 technologies and on DT for production planning and maintenance which highlight the motivation of this work, the paper explores related works on production and maintenance in Section 2. Section 3 presents the proposed model, and finally, Section 4 provides a brief conclusion together with an outlook on future works.

2. RELATED WORK

2.1 The role of Digital Twins

Industry 4.0 allowed the introduction of the Cyber-Physical System (CPS) (Alam & El Saddik, 2017) that enables the integration between a physical system – hence, the so-called PT – and its digital counterpart, the digital twin (DT), hosted in the digital world of the CPS. This tool acts as a system's digital counterpart (at different levels of detail and for different purposes) relying on IoT, big data and cloud computing, with the aim of optimizing the system and facilitate decision-making at different phases of the lifecycle (Kritzinger et al., 2018; Negri et al., 2017). Both CPS and the DT benefited from the advances in new IT, causing them to emerge almost simultaneously: the CPS concept characterizes the architecture of the systems from a scientific point of view enabling the interconnection between the physical and virtual world; a DT lives in the digital world and it can be used as an industrial practice for many engineering applications with different viewpoints, depending on the different levels of detail required (Tao et al., 2019). DT in manufacturing has been designed to monitor the present in real-time, track information from the past, and support operational decision-making for the future. Liu et al. (2021) propose an analysis on the activities that could be improved through the application of a DT and revealed that some advantages can be seen in: a) Real-time monitoring: DT for real-time monitoring is not just a presentation of current data and status of physical object, but the high-fidelity model of DT also helps understanding the situation and make optimization decisions. b) Production control: since manufacturing systems need to perform prescheduled operations and react to disturbances continuously, by real-time data perception of dynamic environment and high accuracy model, DT implements timely smart control strategy in complex context, which caters to today's complex and demanding manufacturing system. c) Process evaluation and optimization: traditional process planning has become inefficient due to the increasing manufacturing complexity. DTs collect relevant data from the physical system (e.g., measured data, process planning data) and integrate these data with geometric model, mechanical model and material model. This allows a DT to interact with its manufacturing environment through interoperability interfaces, evaluating and optimizing the combination of process and parameters. e) Asset management: DT supports the asset-related decision-making process, including assets configuration, reconfiguration, planning, commissioning and condition monitoring. In literature, DT served to dynamically, realistically, and accurately mirror the working progress and status of manufacturing assets and manage the asset degradation. f) Production planning: DT allows a globally optimized production plan based on real-time status change.

2.2 Production planning and maintenance integration

In literature, different studies examine the integration between maintenance and production planning to reach different objectives. Hnaien et al. (2016) consider the production planning and preventive maintenance simultaneously through the scheduling on a single machine of a multi-product capacitated lot-sizing problem. The aim of this simulation is to minimize – using a linear mixed programming model – the sum of the total production and maintenance costs related to the inventory, backorder, production, set-up, preventive maintenance, and minimal repair under demand satisfaction and machine capacities constraints over the entire horizon. Alimian et al. (2019) consider the integration of production and maintenance planning in a multi-state system. In this case, production planning is considered for a multi-item capacitated lot sizing problem, while maintenance policy is considered to be corrective or preventive. A robust optimization method is used in modelling the integrated problem when the system faces demand fluctuations. Based on the demand, the model could allow to choose between imperfect (i.e., it allows to change the state of a component to "partially as good as new") or perfect preventive maintenance (i.e., to change the state of a component to "as good as new"). Alves & Ravetti (2020) integrate maintenance with lot-sizing and scheduling problems considering two parallel machines environment and a sequence of dependent setup times. The problem is solved hierarchically: first the preventive maintenance problem is solved, then the lot-sizing problem is considered. Based on the solution, simulations are performed to deal with corrective and predictive maintenances. Fakher et al. (2018) propose the integration of production, maintenance, and quality: experiments are performed to analyse the trade-offs between these three elements through the development of an integrated optimization model where the objective is to maximize the expected profit. Nourelfath et al. (2016) considers the integration of production, maintenance, and quality for an imperfect process in a multi-period multi-product capacitated lot-sizing context, in order to respond the objective of minimizing the total cost, while satisfying the demand for all products. The production system is modelled as an imperfect machine, whose status is either in-control or out-of-control. During each period, the machine is inspected, and imperfect preventive maintenance activities are performed. Yan et al. (2022) have considered a different approach through an optimisation method that simultaneously learn the possible selection of machines and operations in a job shop to achieve efficient real-time scheduling with preventive maintenance. To this aim the authors considered a double-layer Q-learning algorithm (DLQL) as a reinforcement learning-driven DT. Overall, literature demonstrates the relevance of production planning and maintenance integrated decisions. This denotes that predicting the production planning and its fluctuations, that depend on variable – or even unplanned – events, such as the maintenance ones, are one of the most important challenges that industries need to face.

2.3 The importance of supporting integrated decisions

Consider again a system during its lifecycle, as per Figure 1. When the physical system is not yet available, one can roughly predict the production rate and make a planning with respect to historical data or expected production times. However, when the physical system exists and starts working, various unplanned events can happen in real-time, so the predictions may deviate from the expected ones. Therefore, the model and the DTs derived from that model must be able to take these variations into account and assess how far the system is drifting from the predictions. In industrial contexts, unplanned events (e.g., machine failures, new job arrivals, order changes) could occur, leading to the re-evaluation of all the decision taken and to the consequent increase of the production planning complexity. Hence, predicting the behaviour of a system becomes more and more difficult when dealing with the conjunction of integrated analyses and unplanned events. The present model wants to study the occurrences of events that regard corrective and preventive maintenance within integrated production and maintenance planning analyses. Indeed, maintenance and production analyses may lead to conflicting decisions: a production manager could think that preventive maintenance actions use precious time that could be used for production, failing to recognize the importance of preventive maintenance to ensure higher productivity in the long term; on the contrary, not performing the recommended preventive maintenance actions on time could increase the failure rate of equipment, and this of course goes against the purpose of maintenance managers who want to reach the highest equipment availability. Moreover, corrective maintenance can happen with a certain variability and the maintenance manager must be sure to keep those events under control as much as possible through some scheduled maintenance interventions. To the best of the authors knowledge, as presented in literature, research on the usage of DTs in production system's lifecycle to support maintenance and production planning integrated decisions are still lacking. As shown, Yan et al. (2022) implement a DT with a different intention from what is the objective of the present paper, as it is used for reinforcement learning. Within the I4.0 context, DTs could help managers in optimizing decisions concerning maintenance and production. Nevertheless, those decisions must be consistent with all the others taken by other professionals' figures with the use of DT(s) that gives the correct overview of the system.

3. MODELLING PRODUCTION PLANNING AND MAINTENANCE

3.1 Modelling approach

Modelling production planning and maintenance in manufacturing environments is relevant as it can enable companies to improve related decisions. To simulate production planning, Discrete Event System (DEVS) can be used to replicate and improve production processes. DEVS is a modelling approach that replicates a system's operations as a sequence of discrete events in time. Its usage could be also relevant in simulating and analyzing possible what-if scenarios through the modelled system without needing to intervene on the real one, and this can support optimized decisions. In such simulation model, maintenance events can be introduced by considering parameters to describe machines unavailability. However, in order to be consistent with the real system, when modelling, it is relevant to distinguish between the different type of maintenance that could occur. Particularly, the simulation model has to include parameters on both preventive maintenance – which takes place after the machines work for a period of time which depends on their performances – and corrective maintenance – which takes place when machine breaks unexpectedly, therefore it is relevant to intervene in order to repair it.

3.2 Model implementation

The model development started from the choice of the environment, MATLAB/Simulink, for the creation of an effective example that could briefly show an application on the production planning field and make it immediate to extend the approach to other types of models in their respective fields. The model was developed from an existing example, also to show that our work itself wants to integrate as many analyses as possible and constructing different modelling to be used only separately– i.e., if the simulation environment cannot support a determined analysis. The reference model is the machine failure demo created in MATLAB/Simulink[1]. Indeed, this model describes a single station (and more generally the use of a service) that can transition between three different states (regular operation, planned maintenance and random failure) adding also the possibility of simulating the unavailability of the workers for all the working states. Nevertheless, the entire event generation only handles events of a periodic nature, even for random failures. Therefore, this paper wants to modify the model to add the possibility of simulating the system cyclically, as per Figure 1, always updating the model depending on the system behaviour. This will be useful to:

- simulate the system in the design phase.
- simulate the system in different what-if scenarios, with the possibility of insert single non-periodic faults.
- monitor and analyse the system with the addition of a DT integrated with the model.

As can be seen in Figure 2, the block structure has four distinct operating states for a machine. Three of them are the ones already present in the original schema: the *operationAction*, that identifies the normal operating state of the machine, in this state the system is working regularly; when a breakdown event happens, the system goes into the *breakdownAction* state when the machine requests a serviceman who performs the repair action; alternatively, if a maintenance intervention is scheduled, the machine enters the *maintenanceAction* state, requesting a serviceman who performs the service action. The fourth operating, the *UnplannedBreakdownAction* – the one in the red box in Figure 2 – has been added in the context of this work in order to take into account the type of events herein called "unplanned events".

The additional modelling allows to add to the simulation the occurrence of one or more sudden events at deterministic times. By means of an ad-hoc mask both periodic and unplanned events can be entered, also separately, in order to study the productivity of the individual machine if unplanned events occur, with the aim of discovering possible worst-case scenarios. For an easier visualisation of the considered events in simulation, a *state variable* has been added. When each event is generated, in the simulated model, the status variable indicates the state of the simulated PT. Specifically, the status can identify when the machine is in idle (status at 0), when the machine is working (status at 1), when the machine is not working for a breakdown event (in simulation identified by the status at 2 for the planned breakdown and by the status at 3 for the unplanned breakdown) or for a maintenance intervention (status at 4). The distinction between planned and unplanned breakdown is useful only for generating the events in simulation depending on how they are expected in a prevision (periodically or sporadically). Hence, from the simulation result viewpoint they are all unplanned breakdowns. Therefore, simulating the breakdown occurrences means to simulate a breakdown considering that the corrective maintenance will be associated to it, while simulating the maintenance intervention means that the intervention was planned by the preventive maintenance strategy.

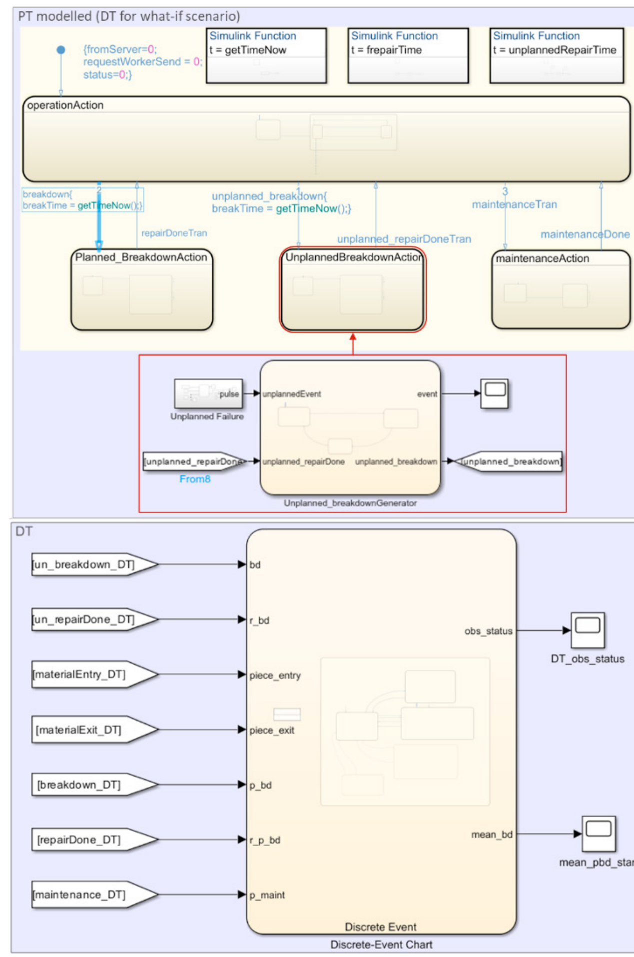

Figure 2. Simulink model of PT machine modelling with its DT.

3.3 DT implementation

A further addition to the above-mentioned model concerns the creation of a DT that is connected to the simulated PT. Indeed, MATLAB/Simulink modelling allows the construction of an additional model that observes all events occurring in the simulated system, as a DT would, records their occurrence and analyses the system accordingly. Given the expected state of the system in simulation, the real-time DT must be able to intercept the different events and analyse the situation in order to compare it with the expected prediction for the same system. This was reproduced in simulation with the creation of a DT that is able to record the model events and analyse them to reconstruct a so-called *observed status* that can reproduce the simulated one. The state machine is able to distinguish

[1] https://it.mathworks.com/help/simevents/ug/machine-failure-demo.html

between the events considered and to take into account important information about the system. It can observe the system and analyse the system behaviour. The one developed in Simulink, shown in Figure 2, monitors both the status and the breakdown occurrences. All the inputs to the machine are realized through SimEvent blocks that allow to duplicate the occurrence of an event in the PT and give it as an input to the DT, as will happen in a real-like system. Hence, the DT manages to record all the events that have occurred and to understand whether the periodicity of the faults is more or less frequent than the value expected by the reference model given by the PT. Obviously, this is all done with the aim of reproducing the observed status of a future PT system in real-time. Therefore, it is crucial that every event considered in the modelling part is recognised and labelled appropriately also in the real environment.

3.4 Lifecycle workflow application

In this article, for simplicity, an individual machine system is considered together with a simple example that follows the workflow of Figure 1, in order to show how simulating the unplanned events help during a system's lifecycle. Initially, when the system does not yet exist, one can assume a service time for a given machine and a theoretical planned maintenance, also determined by a history of machines similar to the one being considered. As a first hypothesis, considering the modelled system with the type of model introduced (without the proposed modifications), one can certainly estimate the expected production in the long term for the machine under consideration. When the machine starts working, if the machine's behaviour is similar to that expected, no issues will be considered. If, on the other hand, the machine's behaviour starts to deviate from what is expected, it should be possible to quantify how far it is deviating and how and when to intervene. For this reason, a DT can be helpful in noticing unexpected and sudden events, it takes them into account and categorise them in the correct way so that they can be evaluated and analysed accordingly. Consider a system

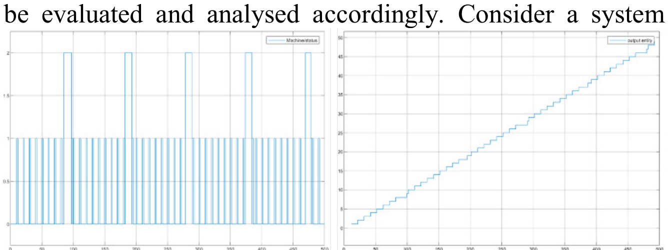

Figure 3. PT simulation of the expected production, machine status on the left, and entities in output on the right.

made by a single machine that works with a time service described by a normal distribution $N(2,2)$ hours, the mean time before failure (MTBF) is given by the distribution $N(85,2)$ hours (i.e. from historical information) and the mean time to repair (MTTR) by $N(10,4)$ hours. As simplifying hypothesis, it is considered that the fault comes from the same fault family, and it can be considered the same in terms of repairing time to be spent using the corrective maintenance procedure. The objective is to observe the system, to understand if preventive maintenance can improve the productivity of the process or is better to deal with the faults when they happen. Simulating this scenario for 500 hours, the resulting status can be observed in Figure 3 together with the expected production, at the end of the considered period, which is almost 50 pieces.

Using the unplanned event simulation, it is possible to simulate an alternative what-if scenario where a series of breakdowns – that do not have the expected rate of Figure 3 – happens. As shown in Figure 4, the DT observes the status of the system and calculates the rate of the breakdown through time: the observed status shows the correct event evolution (when the status is equal to 2, a breakout event is identified in the DT) and the mean time between breakout occurrences decreases below the expected average of 85 hours. As a consequence, the entities produced in the selected time period are almost 45.

Given this scenario, it is possible to evaluate if, for the specific system used, it is feasible to have the said decrease in terms of production. A possible solution would be to introduce a preventive maintenance. When it is introduced for the first time, one can simulate the system as per the expected conditions also including the maintenance intervention. Nevertheless, there are no historical information on the

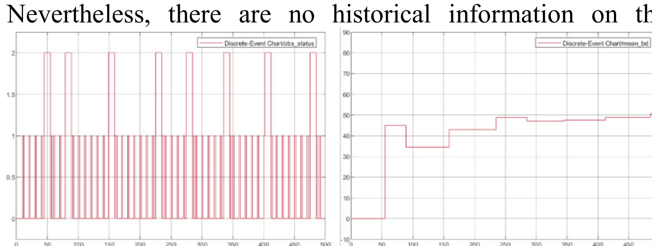

Figure 4. The DT monitoring of a PT what-if scenario simulation as would happen on a real machine, the observed machine status on the left, and the observed breakdown mean on the right.

breakdown rate variation when the maintenance is scheduled. Hence, again, the DT could help into observing the state of the machine, monitoring from the physical system the breakdown variation. If after a certain number of unplanned events, a preventive maintenance is scheduled, it is possible to monitor the system and check that indeed that decision has improved the occurrence of sporadic events for which corrective maintenance is needed. All the information provided by the DT increase the knowledge on the system and provide information to be used in future what-if analyses to be considered in the model. In this simulation-monitoring-model updating loop, simulation parameters for the what-if scenario can be changed or even added, but modelling and monitoring must always remain consistent between them in order to always identify performance trends.

4. CONCLUSIONS

This paper presented a model that allows to integrate production planning with preventive and corrective maintenance, that could serve as the basis for creating a DT to support joint decisions. To this end, by comparing both predictive maintenance and corrective maintenance, the DT - connected to its PT - allowed assessing some critical scenarios during machines breakdown to support the detection and correction of anomalies in production.

As the proposed solution provides only a PT, future works of investigation should apply this solution on a real production system in order to validate it. In this case, not only the models but also the data regarding the PT status must be organized for the what-if scenarios and related. One can opt for identifying the right architectural framework to describe all this

information following the ISO standards to evaluate their maturity level for this scope, i.e. RAMI 4.0, Asset Administration Shell (AAS) (Quadrini et al., 2023).
Additionally, different scenarios when an anomaly happens should be assessed, trying to make the starting conditions depending on the actual machine status. It will be relevant also to consider and assess the impact of each what-if analysis on the other level of details of a system, i.e. how a single machine what-if analysis would impact an entire line. Furthermore, the cyclical approach will need to be generalized to other levels of detail of a system. Indeed, having a reference model of a system with a DT integrated allows to improve the knowledge of the system, compare information accurately and update the model with new information to simulate what-if scenarios with increasing knowledge about the behaviour of the system.

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