Digital Twin for decision-support: An insight into the integration of simulation models into Digital Twin architecture

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Abstract The fourth industrial revolution aims to achieve greater flexibility and adaptability in manufacturing systems through the use of information and communication technologies. The Digital Twin technology has emerged as a promising solution to support human-centered decision-making in this context. Despite growing interest in this area, there is still a lack of applications that integrate decision-support functionality and emphasize the relationship between real-time Digital Twin models and what-if simulation models. Hence, this paper discusses the integration of simulation models into a Digital Twin architecture to assist operators in making appropriate decisions. A proof of concept is presented to demonstrate this approach's feasibility and open up perspectives for further research in this area.
Keywords: Digital Twin; simulation; integration; decision-support; reconfiguration; architecture

1 Introduction

Seen as an important pillar of the Industry 4.0 paradigm, the Digital Twin (DT) has gained a strong following in both the scientific and industrial communities during the last few decades [10]. As it has been expanding to new sectors and applications, the DT paradigm has known a plethora of definitions, which can demonstrate a lack of maturity on this subject [28]. Although there is no one-size-fits-all definition of DT, it can be thought of as one or more simulation models of a real system that are always connected to the physical counterpart or are only briefly connected, to achieve accurate emu-

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lation and mirroring the operational conditions of the real systems, employing the best available representations, phys-ical and virtual models, and decision-making tools [32]. According to NASA's literature, three key functions of the DT can be summarized [9]:

- Prediction is the conduct of research before the system runs.
- Monitoring and control of the system state while the system is running.
- Diagnosis is the investigation of unexpected problems that occur during the system's operation.

From a manufacturing perspective, the real-time connection allows for permanent updating, monitoring, optimizing, and enhancing industrial production system functions [7]. These systems are often characterized by a dynamic environment where different types of events can occur. Hence, the need for adaptation and reconfiguration is predominant. To this end, the DT can be a promising technology to support the decision-making process. For instance, DT may generate "what-if" scenarios based on the state of the real system and, if necessary, send feedback to the human operators to modify the system behavior [2]. This implies combining DT models known generally as emulation models with offline simulation models. Following that, ideas from Boschert and Rosen [12] and/or Schluse and Rossmann [27] can be adopted to choose an appropriate simulation model from a model data-base coupled with collected real-time data. Alternatively, automatic simulation model generation could be used by combining semantic data models and operational data from the real system [13]. Although the use of DT to steer decision-making provides advantages, there are limitations to its implementation. [30] assert that the primary obstacle is ensuring integration, communication, and synchronicity between the physical and virtual domains, which often necessitates a technological infrastructure comprising sensors, intelligent systems, databases, and other components.

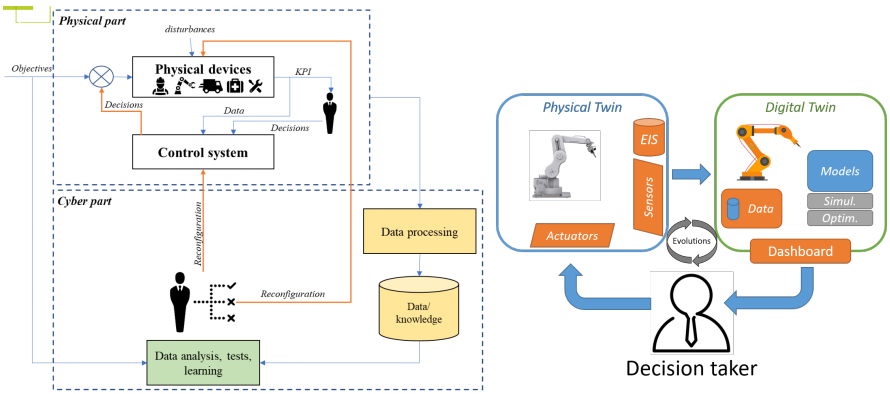
In this context, a major challenge is having a representation that is as close as possible to the real system by the simulation model to test different scenarios. This entails the integration of the relevant data in the simulation model to initialize it with the current state of the system but also provide enough information to estimate the future state of the system through the connection to the information system. While it is acknowledged that there are numerous additional challenges due to the complexity of decision-support systems, this research will solely concentrate on the challenge of integrating the simulation models into a DT architecture to test scenarios, focusing on the initialization mechanism of these models to best represent the real system.

The remainder of the paper is structured as follows: section 2 provides the state of the art, section 3 presents the methodology, and section 4 details the proof of concept. Finally, section 5 gives concluding remarks and perspectives.

2 State of the art

To achieve a holistic perspective about DT and decision-support, and contextualize the scope of this study, different existing DT architectures are examined in this section for starters. Among the most referenced architecture, one can find the Grieves architecture [11] based on 3-dimension architecture including the physical entity, the virtual model, and the connection between them. Tao et al. [31] proposed a five-dimensional DT architecture that contains, in addition to the three original components, the DT service and data exchange between entities. According to Kritzinger et al. [17], another perspective based on integration level allows for a thorough grasp of how a DT should be defined. However, this positioning is not consistent with our point of view on manufacturing systems, with a clear integration of the human in the decision loop.

In a domain close to the DT paradigm, a Cyber-Physical Production Systems (CPPS) have been introduced as connected systems enhancing the decision-making process in real-time. They are systems of systems of autonomous and co-operative elements connecting in situation-dependent ways, on and across all levels of production, from processes through machines up to production and logistics networks, enhancing decision-making processes in real-time, response to unforeseen conditions, and evolution over time [5]. From all existing CPPS architectures, the one from Cardin et al. [6] illustrates the positioning between the physical part and the cyber (i.e. digital) part, with a clear integration of the human in the decision loop for reconfiguration (Fig. 1a). In the same perspective, Bouleux et al. [3] give a clear definition of what the DT represents in manufacturing (Fig. 1b) by illustrating the connection between the physical system, so-called physical twin (PT) and the DT that can integrate virtual models, simulation, optimization, etc. where the human plays a central role in decision-making process.



(a) A CPPS architecture [6] (b) A DT simplified architecture [3]

Fig. 1: Comparison between two architectures

In this context, there has been a growing interest in the development of decision-support systems based on DTs in the manufacturing sector. The following is a selection of relevant literature on the subject at hand. One approach discussed in the literature is the use of a tier-based context model with a generic ontology and model, with a focus on external factors such as the case study presented in [24]. Another paper presents a simulation-based decision support tool that analyzes the activities occurring in distribution and production facilities by developing two simulation models [8]. Some papers propose the use of DTs to optimize production scheduling, rescheduling, and order management through the aggregation of several DTs representing different physical assets [18]. In [22], a DT architecture is used to schedule preventive maintenance interventions, exploiting real-time opportunities and periodically accessing an updated digital model of the shop floor. Other studies propose the integration of discrete event simulation and fore-casting methods for operational planning [25]. Decision-making based on the interlinkage of DTs is achieved through the semantic ontology model in [19]. An architecture combining a real-time DT of logistics systems with simulation logic is discussed starting with the current state in [16]. To better manage patient routes in Emergency Departments (EDs), an agent-based architecture of a DT is suggested in [20]. This DT is regularly synchronized with the IS of the physical system. A comprehensive overview of DTs in the manufacturing domain is proposed in [23] which defines a conceptual architecture that considers simulation capabilities to optimize production processes. Another study presents a systematic literature re-view of the use of simulation as a DT to support decision-making, highlighting various uncertainties and discussions around the simulation model [26]. While the use of simulation in DT is a relatively recent phenomenon in production processes [21, 14], other comparable approaches suggest that this concept has been investigated for several decades. For instance, Katz and Manivannan [15] and Cardin [4] proposed linking a simulation model to manufacturing equipment for monitoring purposes, an approach known as "Online Simulation". It is noted that the objectives of this method are similar to those employed in DT approaches, and similar designations have been used over the years to refer to this technique [26].

To conclude, it is observed from these papers that offline simulation models for decision-support are frequently employed to evaluate static and dynamic scenarios coupled with classic control approaches based on operational research and/or artificial intelligence for instance, or as a DT by often retrieving the necessary information for initializing the simulation model directly from the actual system. The Manufacturing Execution System (MES) as part of the information system (IS) can partially provide this information. This solution has several advantages. The collected data is reliable and represents the real state of the production system, The simulation initializes relatively quickly and it requires a minimal hardware architecture to be effective. However, a significant challenge arises because the MES only possesses partial

knowledge of the system's complete state at any given time. This limitation is due to the placement and characteristics of sensors and detectors within the production system, leading to uncertainties in the state information provided by the MES. Thus, the objective of this paper is to integrate the simulation models with real-time emulation models in the DT architecture for decision support. More precisely, the study will focus mainly on the link to initialize the simulation models based on the information captured from the emulation models and the information systems.

3 3 Integration of simulation into DT architecture

This section presents first the definition of system state and model state to lay the foundation, then the integration strategy is discussed and finally, the synchronization levels are detailed.

3.1 Real System vs. virtual model

To be able to save the current state of the physical system with the emulation model and push it to the simulation model, it is important to understand some sensitive notions such as the state of the system, the state of the model, and the model's properties. A definition of these notions is suggested as follows:

- **System state**: The state of a system can be defined as a set of data that is used to describe the system's behavior at a specific moment and estimate the future behavior.
- **Model properties**: Static properties of a model refer to the characteristics of the model that remain constant over time. These properties include features such as the position and speed of conveyors, the capacity of resources, and the number and types of entities involved in the process. On the other hand, the dynamic properties of a model are those that change over time. These properties include variables such as the quantity and type of products on the conveyor, the utilization of resources, and the status of entities as they move through the system.

In both emulation and simulation models, static properties remain constant, while dynamic properties are captured from the emulation model and sent to initialize the simulation model with the current state of the system. The emulation model can store this data as intermediate data models, which can be read by the simulation model to reconstruct the current state of the real system. The emulation model is designed to serve the simulation model for decision-making purposes, rather than fitting precisely to the real system for monitoring or anomaly detection purposes for instance. Therefore, the design of the emulation model is influenced by the simulation model since it is the one performing the decision-support task. Consequently, careful attention is given to capturing the necessary information that represents the

system state to be transferred and read by the simulation model during the design process. For this reason, it can be seen in Fig. 2 that the information flow comes from the top to the bottom represented in blue arrows: the operator requests the simulation, the simulation requests the emulation model to capture the current state; then the data flow represented in red arrow goes from the emulation to the simulation to deliver the necessary data. Fig. 2 will be further detailed in section 3.2.

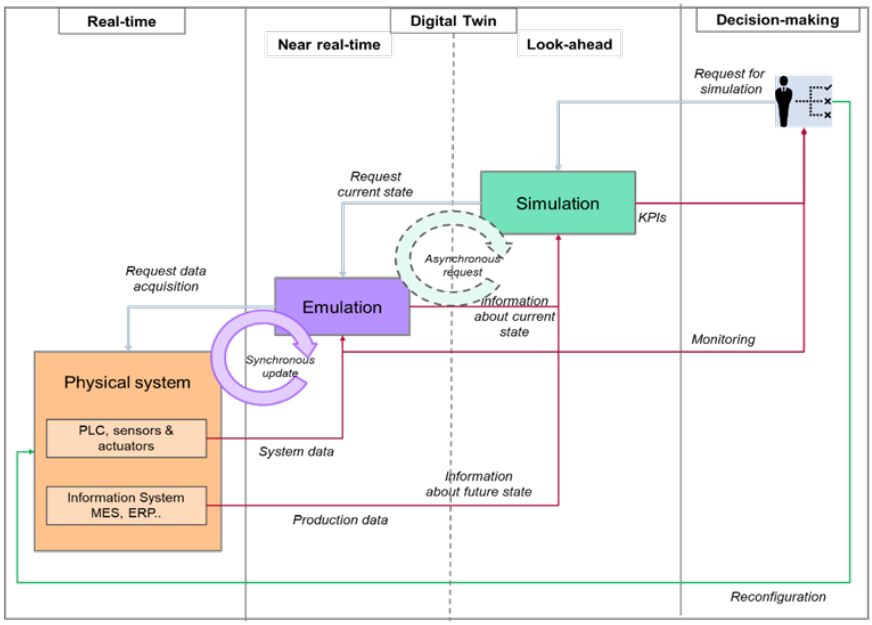


Fig. 2: Integration of simulation with DT real-time models

3.2 Integration strategy

It is important to initialize the simulation model to closely match the initial state of the real system. An alternative approach is to employ an emulation model that is connected to the actual system for continuous monitoring. This model maintains a constant and seamless connection with the system, enabling prompt adjustment and synchronization of its estimations as soon as new information becomes avail-able. This approach minimizes uncertainty in the data by ensuring a continuous stream of reliable data directly from the real system.

Real-time data captured from the actual system is used to feed the emulation model, which subsequently supplies data to the simulation model. The controllers of the real system provide sensory information in discrete forms,

typically represented as binary values (0s and 1s). Nevertheless, the emulation model can maintain continuous synchronization with the real system by utilizing the collected data to estimate nominal behavior. For example, when tracking the position of a pallet on a conveyor—a continuous data stream over time—the controllers report the pallet's position at each sensor point. This allows the emulation model to synchronize with the sensor data, bridging the gap between consecutive sensors. Even in instances where the real system does not provide information between two sensors, the emulation model estimates the behavior between them and synchronizes this estimation with each sensor input.

To minimize uncertainty and achieve a high level of resemblance between the simulation model and the real system, the emulation model conveys a continuous estimated value for the pallet's position on the conveyor. Consequently, the information required for initializing the simulation model may exceed that necessary for control purposes in this scenario.

The emulation model provides the current system state obtained from the controllers. Additionally, complementary data are required from the information system (MES, e.g.) to supply production data to the simulation model. This enables the simulation model to estimate the system's future state. Fig. 2 illustrates the integration of simulation models with Digital Twin (DT). The emulation models operate on a near-real-time horizon, maintaining continuous synchronization with the physical system. In contrast, the simulation model is triggered only upon operator demand, resulting in asynchronous requests

The simulation model's time horizon is referred to as "look-ahead," as it rapidly tests future scenarios. Further details regarding these two levels of synchronicity are provided in section 3.3. System data from sensors, actuators, or PLCs are consistently fed to the emulation model to maintain an up-to-date system state. Meanwhile, production data from the MES are directly supplied to the simulation model as needed. It's important to note that this process can vary depending on the application's purpose, although an attempt has been made to consider a generic scenario.

3.3 Synchronization levels

Tao et al. [29] highlight that a crucial component of applying DT is its capacity for coevolution and synchronization between the physical and virtual realms. DT facilitates more efficient decision-making in such scenarios and is envisioned to adapt to the physical system with each improvement step, leading to a mutually beneficial development of both environments.

Two levels of synchronization can be distinguished in Fig. 2: the first one is be-tween the physical system and the emulation model and will be referred to as a "**Synchronous update**". In a previous study, the synchronization mechanism be-tween the physical system and the DT emulation model has

been detailed and demonstrated in a case study by the authors [1]. This synchronization is done on events as follows: When an actual process occurs, it prompts the DT emulation model to generate an event. There are two scenarios: firstly, if the physical system lags behind the DT then the DT needs to wait for the physical system, and secondly, if the event occurs in the physical system before it is in the DT, then the DT should move forward to be aligned with the physical system. The second level of synchronization will be denominated as "**Asynchronous request**" and it represents the link between the emulation and simulation models. When triggered on demand, the synchronization is conducted by pushing all the current events happen-ing in the emulation model representing the current state of the physical system to the simulation model at once.

4 Proof of concept

For this work, a proof of concept is provided in this section to help the validation of the discussed integration.

4.1 Experimental setting

To demonstrate the suggested mechanism, a preliminary proof of concept has been carried out on a conveyor system that is responsible for transporting pallets. The conveyor system is equipped with two position sensors and RFID tag readers that can read the RFID tags on the pallets and is controlled by a PLC. The conveyor feeds two workstations; the operator would need to choose where to send the pal-lets depending on parameters like processing time. For the sake of this study, the physical system is represented by a model. We acknowledge that both the case study and the system used are straightforward. However, our objective is to im-plement the suggested technique, establish its viability, and illustrate its intricacy.

The emulation model is designed using the discrete simulation software Flexsim and connected to the real system via an OPC-UA server to collect data from sensors and RFIDs. Although we tend to believe that the two models are the same, this is not the case. As explained before in section 3.3, the static properties are the same; however, the dynamic properties are different. Additionally, the simulation time horizon is different between the two models. Whereas the emulation model acquires real-time data from the system and is synchronized each time it gets the data with the real system and represents only the current state of the system, the simulation model operates at a much higher speed. Fig. 3 illustrates the implementation framework that will be detailed next.

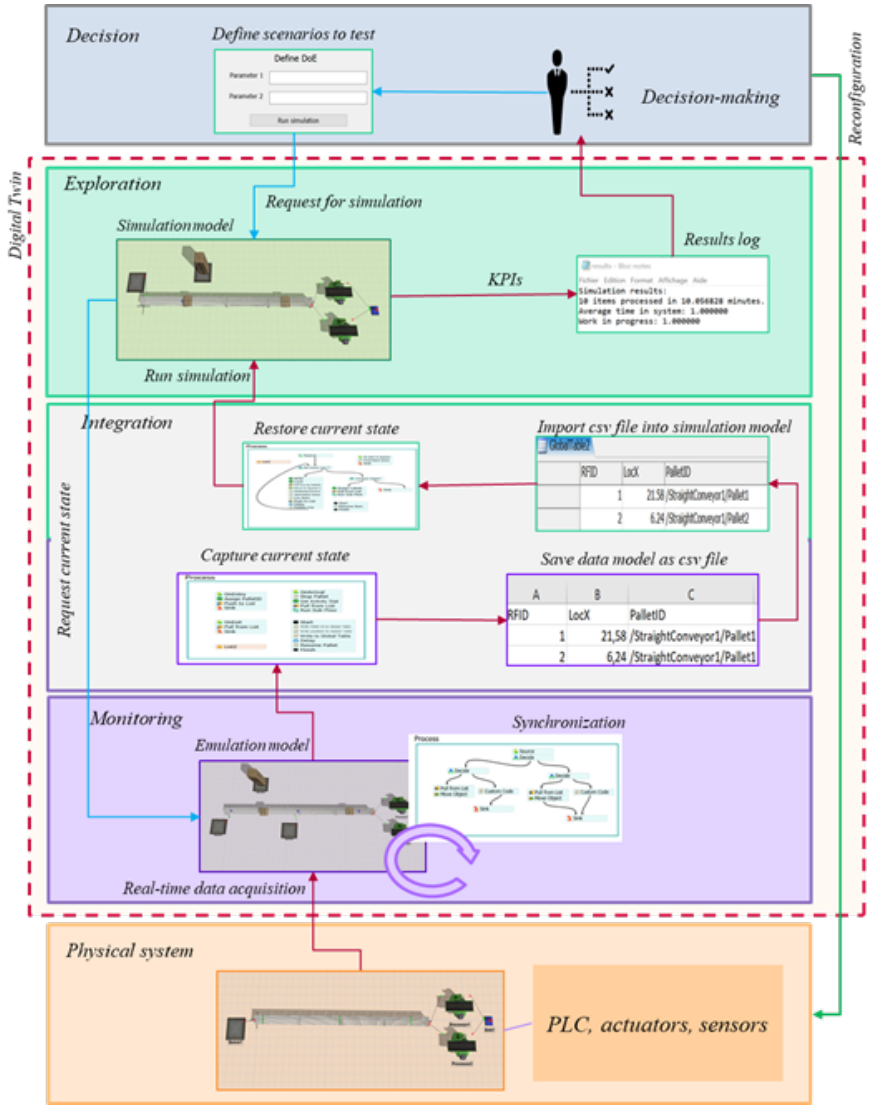


Fig. 3: Implementation framework

4.2 Implementation

Upon the occurrence of an external event, the operator may request a reconfiguration by defining the scenarios to be tested and sending a request to the simulation model. The simulation model requests the emulation model to deliver the necessary information. The emulation model is continuously updated and synchronized with the physical system. At this stage, the emu-

lation model records all current events and generates a table to capture the current state, which is subsequently saved as a CSV file for instance. In this example, the properties of interest include the pallet number, its position on the conveyor, and its ID, which is defined as its access path in the model.

The data file containing the current system state is imported into the simulation model, which restores the system to its previous state. The simulation is then executed for a defined period, during which performance metrics, such as average time in the process and work in progress, are measured and recorded. These metrics are presented to the operator as a log of results, and he can make appropriate decisions or request further testing of alternative scenarios if deemed necessary. The focus of this case study did not involve the integration of the MES due to its complexity. Fig. 3 illustrates the implementation framework with the detailed steps highlighting five layers namely (a) the physical system (physical device along with the sensors, actuators, and PLCs), (b) the monitoring made up from the real-time connected emulation model under Flexsim software along with the synchronization mechanism, (c) the initialization which represents the detailed link between the emulation and simulation models and is made up of the intermediate data model to capture the current state, (d) the exploration which represents the test of different scenarios under simulation models and finally, (e) the decision layer where the operator requests for reconfiguration or take the appropriate decisions.

5 Conclusion and perspectives

The current phase of Industry 4.0 envisions achieving greater flexibility and adaptability in manufacturing systems by progressively leveraging information and communication technologies. In this regard, the DT technology shows promise to support the human-centered decision-making process. Despite the growing interest of the scientific community in this field, there is still a dearth of applications that include decision-support functionality emphasizing the link between real-time models and what-if simulation models.

In this paper, we focused on integrating simulation models into a DT architecture to supplement real-time models and test what-if scenarios, thereby assisting operators in making appropriate decisions. We shed light on the relationship be-tween real-time and what-if simulation models by discussing various implications, such as possible integration strategies, synchronization levels, and system states. We proposed a small proof of concept to demonstrate these concepts. The paper presents new research opportunities. First, the case study can be expanded to a more complex case, such as an industrial production system, to aid operators in their daily decision-making. This will entail integrating more complex infrastructures, such as MES or ERP, to enhance the functionality of the simulation model. Future work could

also concentrate on proposing a decision-support-centered DT architecture by studying decision perimeters and frequencies.

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