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IFAC PapersOnLine 54-1 (2021) 886–893

Unifying Digital Twin Framework: Simulation-Based Proof-of-Concept

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Abstract: In recent years, the Digital Twin (DT) concept has surfaced in many areas and landed the approach in top strategic technology trends. However, there seems to be no unique understanding of the concept, and debates about what is a DT are leading to ambiguity on the concrete solution to be developed in a given situation. This paper introduces a unifying reference framework, to both serve as a conceptual basis that disambiguates the concept and a guide to derive custom solutions. It is a technology-agnostic three-layered model, which reconciles existing understandings of DT under a common umbrella. We also derive an operational architecture as a possible implementation of the framework, which we demonstrate on two use cases. The large adoption of such a framework will draw a clear line between what is a DT and what is not, while establishing a high-level standard model for DT engineering.

Keywords: Digital Twin, Simulation, Framework, Anylogic.

1. INTRODUCTION

Digitalization is gradually permeating all sectors of society, from industry to health, from education to urbanization, leading to engineering and development efforts towards the concept of "smart everything". Consequently, our realities are part of new types of system, where virtual technologies and data have a preponderant place. These systems are complex, and their management calls for model-based approaches. The Digital Twin (DT) concept is one of the main concepts associated to this trend. It promotes the idea of a model continuously synchronized with the system of interest, which is mobilized in different ways in place of the system, so as to firstly reflect any event or management initiative on this artefact, and to assess its consequences before transferring it to the system. This twin is the digital counterpart of the system, and is specific to the system; this differentiates it from a traditional model, which is rather representative of a family of similar systems and is not paired with any of them. The NASA is recognized as a pioneer in the systems pairing approach, in that it simulated from the ground situations occurring in its ships millions of kilometers from the command center, to indicate to astronauts how to intervene. However, if this pairing technique is famous for having brought the Apollo 13 crew safe and sound in 1970, it did not involve a digital model, but two physical twins (one in space, and the other on earth).

There is no unique understanding of the concept of digital twin, as evidenced by the use of the word in very diverse professional contexts and applications (Smith et al., 2011; Stackpole, 2015; Johnson, 2016; DHL, 2019), and the flowering of definitions in the available literature (Glaessgen & Stargel, 2012; Lee et al., 2013; Rosen et al., 2015; Grieves & Vickers, 2016; Bacchiega, 2017; Söderberg et al., 2017; Bolton et al., 2018; El Saddik, 2018; Tao et al., 2018). This results in debates about what a digital twin is, leading to ambiguity on the concept among stakeholders, and therefore on the solution to be developed in a given situation.

It is admitted that the term of Digital Twin has been coined in (Piascik et al., 2010), and equally recognized that its underlying principle (i.e., a digital informational construct about a physical system, created as an entity on its own and linked with the physical system in question) was anticipated in (Gelernter, 1991). In a series of works centered around Product Lifecycle Management (PLM), the model of a conceptual ideal has been introduced and referred to as Mirrored Spaces Model (Grieves, 2005), and then Information Mirroring Model (Grieves, 2006), and finally Digital Twin (Grieves, 2011). The concept has been defined as: "a set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level" (Grieves & Vickers, 2016). However, this data-centric view has turned towards behavioral aspects in (Glaessgen & Stargel, 2012), where a DT is defined as "an integrated multi-physics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin". From a simulation point of view, this represents a disruptive approach as experiments are driven from current information available from the system, instead of assumptions (Rosen, 2015; Grieves, 2017). That way, the DT not only serves representation purposes but is also applicable for making predictions about the expected system behavior (Boschert & Rosen, 2016; Schluse & Rossmann, 2016). Consequently, it is not only one complete model of the system it represents, but a set of integrated sub-models that reflect different features of the system (Negri et

10.1016/j.ifacol.2021.08.105

al., 2017). Other aspects emerged, such as the use of the DT for prognostics and diagnostics (Reifsnider & Majumdar, 2013), (Tao et al., 2017), and real-time optimization (Söderberg et al., 2017; Zhang et al., 2017).

Current DT applications span from Industry – such as automotive (Damjanovic-Behrendt, 2018; Tharma et al., 2018; Bottani et al., 2017), avionics (Tuegal et al., 2011; Rios et al., 2015; Li et al., 2017), aerospace (Glaessgen & Stargel, 2012), energy (Zhang et al., 2018), or manufacturing (Rosen, 2015; Uhlemann et al., 2017; Parrott & Warshaw, 2017; Schleich et al., 2017; Zhuang et al., 2018), etc., to Healthcare (Bramlet et al., 2016) and services (Bolton et al., 2018, Martinez et al., 2018). In Industry, DTs are used to drive predictive maintenance of equipment, to improve reliability and safety of assets, and to optimize the design of products and the operation of processes as well. In Healthcare, DTs carry the promises of designing personal tailor-made treatments for diseases, rather than basing the treatments on what is the best on average for a large group of patients. DT also support servitization by allowing companies to monitor their products when they are in the customer's hands.

Strong companies (such as General Electric, Siemens, Dassault, Microsoft, PTC, Akselos, etc.) started launching products that fulfil at least part of the characteristics that are associated with DTs, offering their own proprietary versions. In various contexts, DT are referred to as digital avatars (Rios et al., 2015), replicas (El Saddik, 2018), counterparts (Rios et al., 2015), mirrors (Boschert & Rosen, 2016; Park et al., 2019; Josifovska et al., 2019), clones (Ben Miled & French, 2017), doppelgangers (Bailenson & Segovia, 2010), etc. A unifying reference framework is needed, to both serve as a conceptual basis that disambiguates the concept and a guide to derive custom solutions. Motivated by this need, the paper introduces a candidate framework to achieve that aim.

We first discuss in Section 2 some works related to the provision of a generic approach to DT, both in terms of concepts, models and platforms. Then, we review in Section 3, each of the major DT viewpoints, which we use to elaborate a unifying framework. We illustrate in Section 4 how this framework offers a common umbrella to various use cases. In Section 5, we discuss the scope of our framework. A conclusion and future work are given in Section 6.

2. RELATED WORKS

Some notable efforts have been done in trying to capture the diversity of DT approaches. Some of them are surveys of the DT concepts in the literature, with in some cases an attempt to provide formal definitions or at least characterizations. Some other are reference models for DT in specific domains.

Negri et al. (2017) analyze the definitions of the DT concept in scientific literature, retracing it from the initial conceptualization to most recent interpretations in Industry 4.0 and smart manufacturing research. The authors also propose a definition of DT for Industry 4.0 manufacturing, in the context of the MAYA project, as a contribution to the research discussion about DT concept. Jones et al. (2020) provide a characterization of DT, identification of gaps in knowledge, and required areas of future research, based on a review and a thematic analysis of almost 100 publications on the topic. Monsone et al. (2019) present an overview of the role of DTs in transforming industrial ecosystems and discuss also the environmental impact. Kritzinger et al. (2018) provide a DT-related literature review with a categorization of contributions in terms of integration levels, focused areas, and technologies used.

Alam and Saddik (2017) present a digital twin architecture reference model for the cloud-based Cyber Physical Systems (C2PS), where they focus in identifying various degrees of basic and hybrid computation-interaction modes in this paradigm. They also define a smart interaction controller using a Bayesian belief network so that the C2PS dynamically considers current contexts. Talkhestani et al. (2019) highlight the added value of a DT in an intelligent automation system and discuss various existing DT definitions and architectures. They also propose an architecture for an Intelligent DT and its required components. Josifovska et al. (2019) perform a systematic DT-related literature review, and then specifies the main building blocks of a DT within a CPS in terms of structure and interrelations. The so-defined framework is expressed in an ontological way.

Our work is unique in that it proposes a framework that unifies existing DT viewpoints, as each of these viewpoints can be seen as a particular interpretation of the framework. We also provide a reference architecture that concretizes the framework in a technology-agnostic way, which we demonstrate on technology-specific use cases.

3. UNIFYING DIGITAL TWIN FRAMEWORK

The way the concept of DT is approached by different professional communities and how they define it is similar to the metaphor of a group of blind men who have never come across an elephant before and who learn and conceptualize what the elephant is like by touching it. Each blind man feels a different part of the elephant's body, but only one part. They then describe the elephant based on their limited experience and their descriptions of the elephant are different from each other. Similarly, when interacting with stakeholders in different communities, the use of the term Digital Twin constantly and immediately raises the question of its proper and formal definition. Nonetheless, the various DT viewpoints fall under one common umbrella, which we try to express here.

3.1. Invariant characteristic

The invariant characteristic that makes a numerical model a DT is that, as illustrated by Fig. 1, there is a synchronization between the world of interest (which is a real entity, whether a product, a process, or a system) with its cyber representation (which is an abstraction of some aspects of the world of interest), based on data tracked in the world of interest. At this point, we introduce a terminology:

Definition 1: A Twin of Interest (TOI) refers to a world of interest, seen from a system-theoretic perspective (i.e., a product system, a service system, or a process system). As the world of interest can even be a software (therefore an immaterial/virtual entity), the term TOI is preferred to terms such as "physical twin" or "real twin".

Definition 2: A Digital Twin (DT) refers to a virtual model synchronized with a TOI. As a model, it is a digital abstraction that may reflect one or multiple perspectives (static, dynamic, functional, etc.) of the TOI.

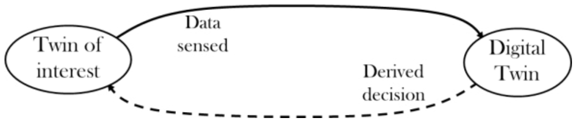

Fig. 1. DT principle.

The synchronization between the TOI and the DT is either clock-based (ranging from high frequency – real-time or near real-time synchronization, to low frequency – cyclic synchronization) or event-based (ranging from high predictability – conditional synchronization, to low predictability – on-demand synchronization). Fig. 2 shows the two dimensional nature of the TOI-DT synchronization. Highly predictable TOIs require low synchronization frequency as there is a high confidence in the faithfulness of the model. On contrary, unpredictable TOIs call for a high synchronization frequency, as the model would quickly deviate from reality in the absence of updating data.

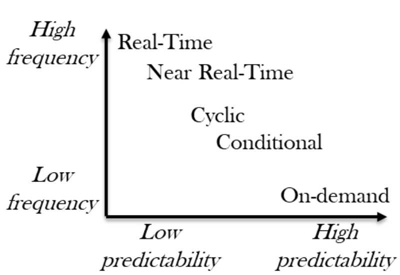

Fig. 2. Characteristics of twinning synchronization.

This invariant characteristic draws a line between what is a DT (that falls under the proposed framework), and what is not a DT, even if called as such by its stakeholders.

3.2. DT-aided versus DT-controlled viewpoint

The dotted line from DT to TOI in Fig. 1 is not necessarily a straight-forward feedback from the DT to the TOI. In other words, while there is a strict requirement for data to be sensed at the TOI side and sent to the DT without any other intermediary except the communication middleware, there might be a human third party to derive decision for the TOI from the information derived at the DT side. Therefore, as illustrated by Fig. 3, the twinning loop can either be closed (in which case, the DT not only monitors the TOI but also directly controls it) or open (in which case a third party makes and applies the control decision). The dotted line from DT to TOI in Fig. 1 is a generic representation for both cases.

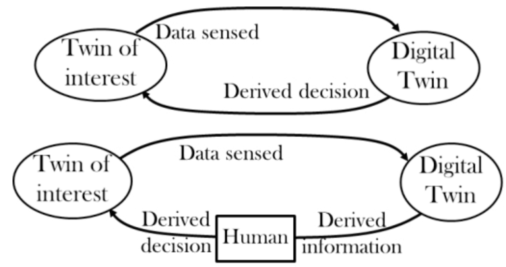

Fig. 3. Closed and open twinning loops.

DT-based predictive maintenance is mainly achieved in an open twinning loop. Consider for example the turbine of a power plant that comprises thousands of components, each of which is subject to failure based on metallurgy, load, environment, and other factors. As it is impossible to pinpoint the proper time to take the turbine offline for maintenance using traditional mean time between failure estimates, the plant operators have no choice but to schedule expensive and often unnecessary maintenance cycles based on historical operating experience and the knowledge of a few expert employees, to avoid exposing the plant to the risk of unscheduled outages. By building a DT for the turbine assembly, enriching it with situational data such as system load, ambient temperature, and air quality, and continuously analyzing it using advanced statistical tools, plant operators can bring the turbine down for maintenance predictively, eliminating the costs of unnecessary downtime and mitigating the risks of unplanned outages.

On contrary, DT-based automated control is achieved in a closed twinning loop. Considering the example of the power plant with multiple turbines under interest, the DT of each turbine can be leveraged in the whole supply chain of the plant, such that the behavior of the supply chain can dynamically be regulated based on energy consumption of the plant's customers (such that the turning on/off or thrust of one or more turbines once the energy consumption is below/above some threshold).

3.3. Role-based viewpoints

The two examples just discussed shows how the role envisioned for a DT can impact the understanding of the concept itself, from being a data-based mirror of a system of interest, to being an augmented replica able to take decision and act on the system. Different components are involved in the various viewpoints, as shown by Fig. 4.

The DT viewpoint at the top level of Fig. 4 is the one of a simulation model, that operates from synchronized data, as well as historical data. An example DT definition from that viewpoint, in the context of aerospace is the one reported in Section 1 by (Glaessgen & Stargel, 2012). The DT viewpoint at the middle level of Fig. 4 is "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 real system, thanks to sensed data and connected smart devices, mathematical models and real time data elaboration. The topical role within Industry 4.0 manufacturing systems is to exploit these features to forecast and optimize the behavior of the production system at each life cycle phase in real time." (Negri et al., 2017). The DT viewpoint at the bottom level of Fig. 4 is the one of generalized role towards prognostics and diagnostics activities (Reifsnider & Majumdar, 2013).

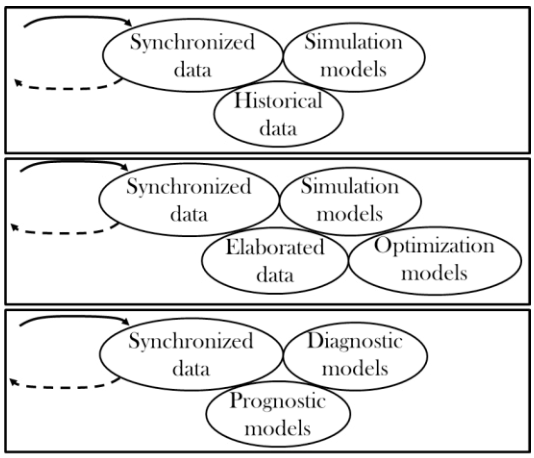

Fig. 4. Some major DT viewpoints.

Going through definitions available in the literature, we identify a modular structural pattern comprising synchronized data interfaced with one or several models that perform specific functionalities to achieve the role which the DT is meant for. Table 1 summarizes roles and functionalities from existing DT viewpoints. The five major roles are: visual interface, diagnosis interface, prognostic interface, optimization interface, and documentation interface.

In each of the role, DT can be used in open or closed loop for different goals, and therefore provide different functionalities:

- In visual monitoring, the DT is a replica based on current data sensed, which allow users visually monitoring the TOI indirectly and getting augmented insights that they would not be able to get directly from the TOI.
- In visual control, decisions are directly sent by the DT to the TOI, even if they are derived by a human operator. The DT serves as a proxy to the TOI.
- In data-based monitoring, not only current data sensed are used by the DT, but also historical data, therefore allowing to identify trends and peculiar situations. The DT serves as a dual of the historical life of the TOI.
- In automated control, the DT doesn't need a human operator to derive decisions to be sent to the TOI. As such, it is the exact cyber counterpart of the TOI.
- In simulation-based forecasting, the DT allows what-if scenarios be explored, through discrete/continuous/3D-motion simulations, to predict the future of the TOI from data sensed.
- In real-time simulation-based decision making, faster than real what-if explorations are performed in order to take the best control decision for the TOI.
- In exploration-based design, the what-if scenarios exploration is done to select the best configuration for the redesign of some of the TOI's components.
- In exploration-based decision making, the what-if scenarios exploration supports the decision making process that the DT uses to control the TOI.
- In data laking, the DT is the collection of all descriptions related to the TOI in all of its lifecycle phases (including from when the TOI is an idea to prototype and then to final entity).
- In information mining, the DT derives insights from the data lake to directly feed the TOI back, a general case where all the previously presented forms of DT-controlled TOI approaches (closed loop cases) can be combined.

Table 1. Role-driven DT functionalities

Role	*Open loop functionality*	*Closed loop functionality*
Visual interface	Visual monitoring	Visual control
Diagnosis interface	Data-based monitoring	Automated control
Prognostic interface	Simulation-based forecasting	Real-Time Simulation-based decision making
Optimization interface	Exploration-based design	Exploration-based decision making
Documentation interface	Data laking	Information mining

3.4. Common subsuming viewpoint

Fig. 5 shows a subsuming viewpoint to all existing viewpoints, based on a 3-layered framework:

- The data layer realizes the synchronization and data management of the DT. Functionalities here range from data exchange features (interoperability, integrity, etc.) to data cleaning, interpretation, preservation… Each DT solution populates this layer with technology-specific modules.
- The capability layer realizes the representations of the TOI, including data models (from diagrams to statistical representations), simulation models (whether continuous, discrete, hybrid, 3D-motion…), 3D models (highly faithful visual representations), decision models (e.g., game theory-

based, AI-based…), etc. We call them capability models, and they are obtained from data sensed and produced, as well as from experts' knowledge.

- The service layer realizes what the DT is meant for: control, diagnosis, prognosis (i.e., correlations from data and other knowledge), prediction….

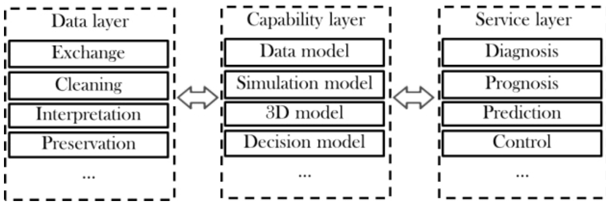

Fig. 5. Unifying framework for DT concept.

This framework reconciles various understanding of DT under a common umbrella. Some understandings make the focus on the high fidelity aspect of the DT, therefore putting emphasis on a 3D representation, with or without dynamic simulation capabilities. Such a high-fidelity 3D representation allows, for example in Architecture, to make the right choices upstream of construction and thus secure performance at each stage, from building design to execution. This specific view of DT falls under the framework proposed, as the capability layer is reduced in that case to a 3D model, and the service layer is reduced to Control. Similarly, a very different use case, such as the predictive maintenance of urban infrastructures in a smart city, instantiates the framework with a capability layer composed of a Data model (possibly augmented with a simulation model and any other useful model) and a service layer composed of diagnosis and prognosis (possibly augmented with prediction) services.

4. OPERATIONAL ARCHITECTURE

We propose here an operational architecture as a possible instantiation of our framework, and we use it to build the DT of an energy-efficient building, as well as the one of a smart manufacturing shop floor.

4.1. Operational Value Chain

The DT value chain, shown by Fig. 6, defines a system that achieves rationality to a human operator by:

(i) perceiving the real-world product/process/system which it is twinned with through some sensors, thus collecting data (via the data exchange interface), cleaning and interpreting them (via the data exchange interface), and storing them (in the data history lake);

(ii) transforming what is perceived into capability models, i.e., data model for diagnosis and prognosis, simulation model for prediction, 3D model for visualization and monitoring, and decision model that combines the previous models and uses rules to derive what the best action is; and then

(iii) acting accordingly either automatically, or by human initiative (via the decision interface), through some actuators, thus possibly modifying the real-world twin.

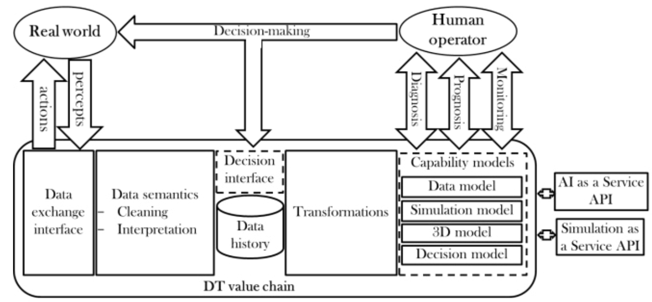

Fig. 6. Operational architecture for a DT value chain.

Application Programming Interfaces (APIs) that integrate existing Artificial Intelligence (AI) on-demand platforms at one hand, and multi-physics simulation tools at the other hand, provide the as-a-Service engines to execute the capability models. For simulation, we use Anylogic Cloud. For AI, we use the AI4EU platform (https://www.ai4eu.eu/).

In order to demonstrate this architecture, two cases of high socio-economic value are considered: (i) energy-efficient building, and (ii) smart manufacturing shop floor.

4.2. Energy monitoring in a smart building

The IMS building (a research lab) on the Talence campus of the University of Bordeaux is a fully Internet of Thing (IoT)-enabled 3-floors building. As part of the "Smart Campus" initiative, within the context of the CUBE2020 challenge (an annual buildings energy efficiency contest: https://www.cube2020.org/), this use case aims at building the digital twin of this building, in order to allow real-time visualization of energy consumption in the building (according to data sensed), as well as analytics-based diagnosis, and what-if simulation-based prediction. The solution presented by Fig. 7 provides a decision-support tool that can help the building users in their attempt to reduce their energy consumption.

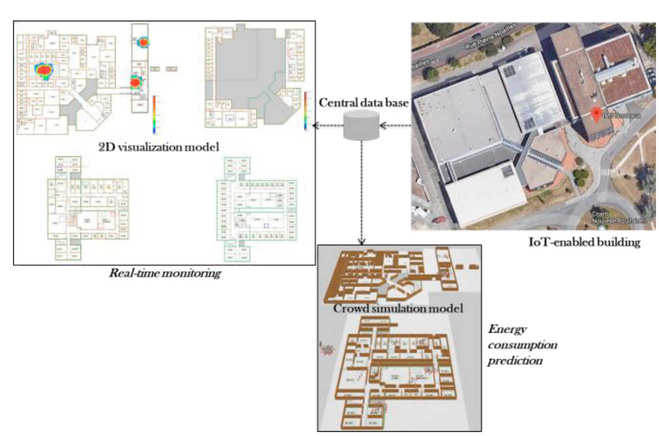

Fig. 7. DT for a smart building.

The IoT devices are sensors of six sorts: temperature, brightness, electric tension, humidity, movement, and energy consumption sensors. The measurements are sent into a central database, through a private and secured computer network. The data are available to the capability models of the DT value chain, which is composed of: (i) a 2D visualization model of each floor of the building; (ii) a simulation model of the daily crowding within the building that allow exploring what-if scenarios based on various profiles of the building users (researchers, students, visitors, etc.); and (iii) a data model displaying statistical information about the energy performances of the building.

4.3. Optimization in a smart manufacturing shop floor

In this use case, the real system is a simulated shop floor (available in the Anylogic library). The corresponding factory is composed of two Computer Numerical Control (CNC) machines. Raw materials are delivered to the factory in pallets by truck to the reception dock of the factory. Forklifts then allow palletized products to be stored in entry racks, then brought to treatment on one of the two CNC machines. Operators of the CNC machines return each finished product to a pallet. Forklifts transport these finished palletized products through outlet racks, then to the shipping dock where all of the production will be trucked to its destination (see the top level of Fig. 8 – Twin Of Interest).

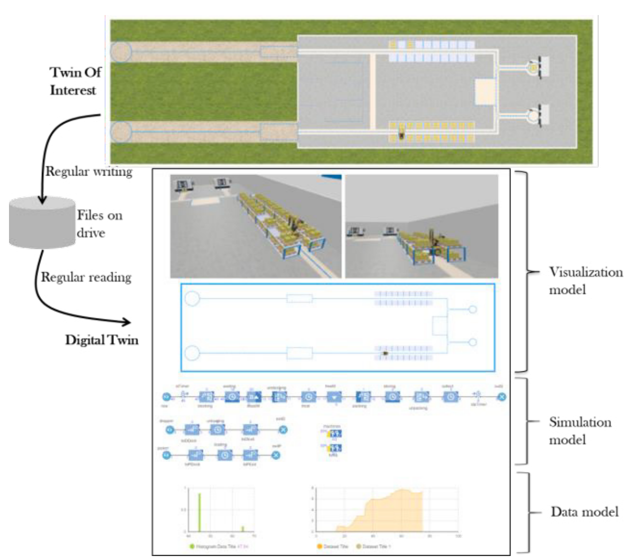

Fig. 8. DT for a smart manufacturing plant.

We improved that model by adding sensors to various components (forklifts, CNC machines, trucks). Each sensor is an Anylogic event, which regularly send data into a file (e.g., position sensors send coordinates of forklifts and trucks, while vibration sensors send operation speed of CNC machines, and failure sensors send operational status of forklifts and CNC machines). Files are shared between the simulated shop floor and the DT to be built, through a cloud-based drive, therefore implementing the data circuit through an existing IoT infrastructure. The capability models of the DT value chain are: (i) a 2D and two 3D visualization models of the shop floor; (ii) a process-based simulation model of the shop floor that allow exploring what-if scenarios, such as the shop floor performances with various number of operating components; and (iii) a data model displaying statistical information about the performances of the components. As the twinning loop is not closed, there is no decision model, and the human operator is in charge of making decision and acting directly on the simulated shop floor.

5. DISCUSSION

Grieves and Vickers (2006) introduced the terms Digital Twin Prototype (DTP), Digital Twin Instances (DTI), and Digital Twin Aggregate (DTA) to distinguish the different character and purpose of the DT as they defined it. The DTP is used in the design phase to represent design versions of the non-existing system with all variants, in order to check design alternatives and to test product functionalities against its requirements. The DTI are twinned, each with an individual entity of the system, thus emphasizing the importance of having information about that entity throughout its life. The DTA is the aggregation of all the DTIs, and it serves to correlate the behavior of these DTIs, as well as to convey what is learnt by a group of DTIs to the rest of the DTIs. Unfortunately, these terms don't contribute to a consensus on what constitutes a DT, even if coming from DT concept pioneers. Rather, it breaks the barrier that would differentiate a digital twin from any other types of computer model or simulation (a DTP is nothing else than a set of traditional simulation models, even if it can intentionally be built as a sort of first born in a dedicated pairing plan).

With the framework introduced, the following are to be ticked all by a candidate DT to be considered as a true digital twin (anyone not ticked makes the candidate not a DT from the point of view of our framework):

- A DT is a virtual model of a real thing, and is connected to the thing, updating itself in response to known changes to the thing's state, condition, or context. The model turns into a twin only when it is connected to its real counterpart. It ends being a twin at the real counterpart disposal, and turns to a digital documentation. Note that this disrupts with the original view from Grieves where the lifecycle of the twin continues beyond the one of its counterpart – calling it a twin at that stage is from our point of view a confusing abuse of language. It is equally noteworthy to relate to the burgeoning concept of Digital Shadow (Bauernhansl et al., 2018; Kritzinger et al., 2018), which in our framework corresponds to an open DT-TOI loop.

- A DT is uniquely associated with a specific instance of the thing. Such a uniqueness doesn't mean the DT contains a single model, as various representations of the same thing can simultaneously be considered. It means that the virtual model or the set of virtual models can't be the twin of several things (even if they are similar in structure and behavior).

- A DT provides value through functionalities and services (analysis, prediction, optimization, etc.), based on capability models (visualization, simulation, interpolation, correlation, etc.). Poor DTS are reduced to minimal capabilities and are mainly used as faithful data sources and coupled with external modules, which run decisions. On contrary, rich DTs host the intelligence in their capability models.

The proposed framework suggests a 3-layered structure that subsumes all the viewpoints found in the literature about DT. While these viewpoints look very different, they all fall under a common umbrella, which can be described as a compartmental value chain. Under this umbrella, what differentiates the various viewpoints is the way compartments of the value chain are populated with functional components. At the operational level, differences come from the technologies used to implement/integrate the compartments.

The framework proposes a reference model that allows to clearly state what is a DT and what is not. Its layered architecture also provides a modular conceptual basis that can guide in defining specific solutions in a very flexible way.

6. CONCLUSION

We propose in this work a framework to unify existing viewpoints on DT, as a way to disambiguate the concept while being inclusive of the various understandings available from the literature. The layered model of the framework serves as a high level guideline to approach digital twin engineering, in a way similar to how the Open Systems Interconnection (OSI) model defines a standard for computer networking. We also provide a reference architecture that technology-agnostically concretizes the framework, which we demonstrate on two technology-specific use cases.

A major issue that remains open as part of our on-going and future research efforts is the following: the development of the DT technology ranges from relatively simple collections of IoT data to complete multi-competences infrastructure, including connectivity to make data about a remote device available to the DT, fast computational techniques to simulate complex multi-physics, statistics and machine learning to gain insights from the data that are not readily obtained by physical modelling, and cyber security, to make the digital system safe. Without an open collaborative platform, the development and adoption of DTs may be restricted to an industrial oligopoly that can deploy an army of engineers to create custom digital twins for their exclusive experiments. Such an open platform can elaborate upon the foundations that have already be laid by projects like Ditto or iModel.js. We intend to achieve that goal, based on the framework proposed and the reference architecture derived from it.

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