Proceedings of the 2021 Winter Simulation Conference
S. Kim, B. Feng, K. Smith, S. Masoud, Z. Zheng, C. Szabo and M. Loper, eds.

USING SIMULATION AND DIGITAL TWINS TO INNOVATE: ARE WE GETTING SMARTER?

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ABSTRACT

Digital Twins have recently emerged as a major new area of innovation. Digital Twins are often found at the core of “smart” solutions that have also emerged as major areas of innovation. Modeling and Simulation (M&S) approaches create a model of a real-world system that is linked to data sources and is used to simulate and predict the behavior of its real-world counterpart. On the face of it Digital Twins and M&S appear to be similar, if not the same. Is this actually the case? Are the two fields really separate or is Digital Twin research re-inventing the “M&S wheel”? To investigate these relationships, in this panel we will explore some contemporary innovations with Digital Twins and discuss whether or not Digital Twins is a contemporary “refresh” or “rebranding” of M&S or if there are exciting new synergies.

1 INTRODUCTION

The concept of Digital Twins has created much interest and activity in academia, industry, and government. There are many “versions” of these ranging from what appears to be a conventional discrete-event simulation to complex ecosystems of technologies that attempt to control real-world systems. Digital Twins are also often found at the core of “smart” solutions. There continue to be many innovations. However, are these all really “Digital Twin” innovations or just new applications of Modeling and Simulation (M&S)? Following the discussions that started with the Winter Simulation Conference (WSC) 2019 Panel (Shao, et al. 2019), this panel considers what is actually a Digital Twin. Each of the following sections presents a

978-1-6654-3311-2/21/$31.00 ©2021 IEEE

unique perspective from a panelist, whose name is shown at the end of the section title in parentheses. Shao presents a standardization perspective. Lee, Jeon and Johansson then present three contemporary examples of Digital Twins. Lendermann then discusses these advances with respect to key aspects of research. Overall, this panel captures many aspects of Digital Twin innovations and shows that although M&S is a key part, there are many other components that need to be incorporated for an innovation to be considered a "real" Digital Twin. One could argue that with these, M&S is getting smarter!

2 DIGITAL TWINS FOR SMART MANUFACTURING: A STANDARDIZATION PERSPECTIVE (GUODONG SHAO)

2.1 Differences Between Simulation and Digital Twins

Simulations and digital twins both play important roles for digital transformation to achieve Smart Manufacturing. However, what are their roles? Are there any differences between simulations and digital twins?

Simulations are digital models that imitate the operations or processes within a manufacturing system. Simulations have been used for analyzing the performances of manufacturing systems and testing of new concepts for decades. There are many simulation tools available for these purposes, however, most of them only support standalone applications without direct connection to the real systems.

A digital twin is an integrated model that represents, connects, and synchronizes a part of or the whole physical manufacturing system or process, enabled by historical and real-time data from the physical system or process (Shao and Kibira 2018). The real-time data from the physical system and process are collected by using smart sensors and Internet of Things (IoT) devices. A digital twin may include various digital models such as simulation, data analytics, and optimization.

Simulations can help understand what may happen in the real world. Digital twins not only help understand what may happen, but also what is happening in the real world. While simulation can be an important and an integral part of digital twins, the purpose of a digital twin stretches beyond simulation. A digital twin covers not only digital models but also includes synchronization between the digital models and their physical counterparts. Therefore, implementing digital twins may involve not only modeling and simulation, but also the use of advanced technologies such as IoT, 5G, edge computing, and cloud computing.

Shao et al. (2019) discusses the differences between digital model, digital shadow, and digital twin based on the level of data integration between the digital and physical counterparts. In summary, most of the offline simulation models are classified as digital models, simulation models that use near real-time sensor data as inputs are digital shadows, and simulation models that use near real-time sensor data as inputs and also control the physical counterparts by updating control parameters are digital twins. A digital twin can be a simulation model or include a simulation model, but a simulation model may not necessarily be a digital twin. Multiple standalone simulations may be used within a digital twin to get different views. Therefore, simulation models with different focuses and various granularities can be regarded as building blocks for a digital twin.

From the lifecycle perspective, simulation normally focuses on a particular phase of a product lifecycle, e.g., the design phase, operation phase, or the maintenance phase. But a digital twin stays throughout the lifecycle to enable information continuity, better communication and documentation for the physical systems. For example, an offline simulation model of a computer numerical control (CNC) machine can be used to validate NC programs to avoid collisions, but a digital twin of a CNC machine may be used not only for NC program validation and update, but also for evaluation of the machine health by continuously monitoring and analyzing machine status and conditions such as machine energy consumption, temperature, pressure, volume, speed, vibrations, noise levels, and humidity using data collection standards or smart sensors. Decisions regarding machine scheduling and preventive maintenance can be made in a timely manner so that the problem can be resolved before it causes any major failure or damage.

There are still a lot of challenges for manufacturers, especially Small and Medium-sized Enterprises (SMEs) to effectively, efficiently, and correctly implement digital twin technologies for their operations. Relevant standards and technologies need to be developed to help address these challenges. Standards include concepts and terminologies, guidelines, and frameworks for digital twin development. Technologies involve those for data collection, data processing, data security, data communication, data synchronization, data analytics, model generation, and model verification and validation.

2.2 Current standardization efforts related to digital twin

Since digital twins are still in their early stage, there are fewer standards specifically developed for digital twins. However, existing standards for data collection, data security, information modeling, simulation, visualization, and networking can be used to support the development of digital twin applications.

Recently, an International Organization for Standardization (ISO)/Draft International Standard (DIS), ISO 23247, Digital Twin Manufacturing Framework, has been developed to provide a generic development framework that can be instantiated for case-specific implementations of digital twins in manufacturing. The standard has four parts: (1) Overview and general principles, (2) Reference architecture, (3) Digital representation, and (4) Information exchange. These four parts provide guidelines and procedures for analyzing digital twin requirements for an Observable Manufacturing Element (OME), promoting common terminology usage, instantiating a generic reference architecture, supporting information modeling of OMEs, and synchronizing a digital twin with its OME (ISO 2020a). The standard also provides examples of data collection, modeling and simulation, communication, integration using existing relevant standards. Figure 1 shows the functional view of the framework reference architecture.

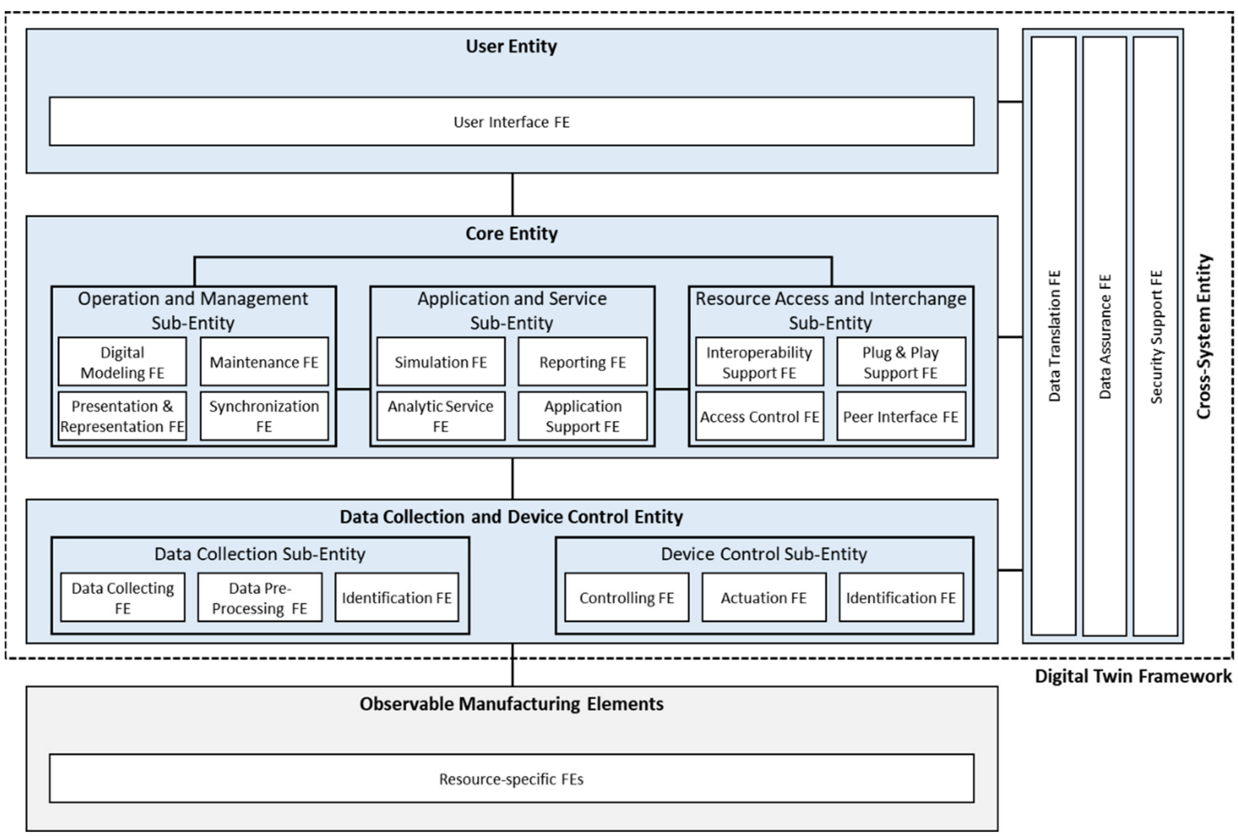

Figure 1: Functional view of the digital twin framework for manufacturing (ISO 2020b).

This framework reference architecture consists of possible functional entities in each domain entity, i.e., User Entity, Core Entity, and Data Collection and Device Control Entity. Each functional entity (FE) performs specific tasks. For example, as one of the functional entities within the Application and Service sub-entity in the Core Entity, the Simulation FE is responsible for simulating the OME according to the scope, objectives, and context of the application. Implementations of the framework do not necessarily need to implement all the functional entities, only those that are relevant to the use case need to be selected and implemented. Therefore, it is possible that a digital twin may not even have the simulation functionality. The methods and tools selected to model a digital twin depend on the purpose of the digital twin (Shao and Helu 2020).

Other than ISO 23247, NIST researchers currently also participate in the development and testing of relevant ISO/IEC JTC1 digital twin standards such as the definitions of digital twin concept and terminology and the digital twin user case templates.

3 SIMULATION AUGMENTED DIGITAL TWIN FOR DECISION MAKING IN COMPLEX SYSTEMS (LOO HAY LEE)

In line with its objective to move Singapore to be a smart nation, the government puts together the industry transformation maps, and encourages the industry to explore new and innovative concepts when developing their next generation systems. One of them is the next generation container port system, and the other the next generation warehouse system. Singapore plans to consolidate all the container port operations and build a mega port with a capacity of 65 million Twenty Foot Equivalent Units (TEUs), innovative concepts such as polders and above ground structure approaches are explored for use. As there is a shortage of land and labor, the government encourages the industry to adopt automation and analytics. Given the emphasis on automation and analytics, it is important to provide guidance to the industry on the types of automation technologies to be used in order to achieve the highest effectiveness. Automation and analytics need innovative and robust concepts (e.g., Internet of Things (IoT), simulation-based analytics, Artificial Intelligence.). In this case, digital twins are developed to help to design the systems and evaluate and optimize the system's operations in a real-time setting where crucial decisions are being made. Digital twins function as a "crystal ball" of the systems simulated. Various "what-if" scenarios relating to the future can then be explored. To fulfill the full potential of digital twins and to achieve the purpose of digital twin in helping to design an innovative system and an online Just-In-Time (JIT) analysis, there is a need to develop a new digital twin concept.

3.1 A Digital Twin for Next Generation Port and Logistics in Singapore

For this new Digital Twin to realize a detailed JIT analysis online, we have proposed a digital twin framework emphasizing four dimensions. As shown in Figure 2, these four dimensions are fundamentally essential.

1. Visibility, so that all analysis is intuitive and readily accessible by human management system online. This includes a user-friendly interface that can define the analysis problem and present the analysis results efficiently. It enables an efficient collaboration between real and virtual systems.
2. Analyzability, so that the detailed dynamics of the real system can be analyzed to support decision making. The analysis tool should be flexible enough to enable both long term and short term, micro and macro analysis with a flexible decision window.
3. Granularity, so that the framework in digital twin is flexible enough to assemble model at different fidelity level to suit analysis tasks.
4. Connectivity, so that the digital twin can maintain a valid replication of the current real system and any suggested action by analysis can be implemented automatically in a real system.

3.2 Research Challenges in Digital Twin Embedded Simulation Analytics

Among these four dimensions of Digital Twins, we face new optimization challenges in Analyzability and Granularity. On one hand, conditioned on a given dataset, how to use existing data to provide higher quality data-driven analysis becomes the first issue. On the other hand, due to the massive scale and high stochasticity of systems, the real historical data collected may not be sufficient for analysis. Thus, an augmentation of simulation to acquire knowledge in "what-if" situations becomes important. However, since time is scarce online, to provide a JIT analysis, the simulation needs to be flexible with different fidelity and time cost to suit the requested problem. How to effectively allocate simulation budget in multiple level of granularity becomes the second issue.

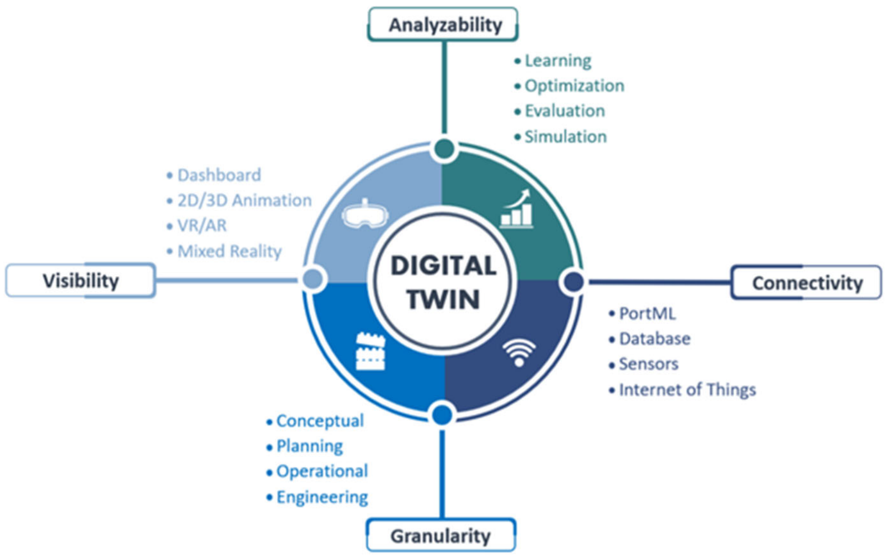

Figure 2: A framework for a four-dimensional digital twin (Li 2020).

To systematically solve issues of data-driven analysis and multi-fidelity budget allocation, we propose the framework of "Simulation Analytics" that enables online decision support by realizing active learning augmented by modularized multi-fidelity simulation. The fundamental logic (shown in Figure 3) is to pre-execute high-fidelity yet time-consuming simulation offline, then learn from simulated observations to support online optimization. On one hand, the accumulated data acquired in both simulation and the real system is used to train and synthesize a model that can be implemented online so that when a real scenario is realized, we will have sufficient analysis power online to deliver the conditional analysis in time. On the other hand, offline learning actively drives a modularized multi-fidelity simulator to simulate outcomes in critical scenarios. The simulator is modularized so that a model that simulates the whole system can be disassembled and reassemble when needed and each sub-module can be treated as an independent simulator and be trained. The simulator is multi-fidelity so that for each module, multiple models with different "resolutions" of the simulation are available to make a trade-off between the quality and responsiveness of the simulation. The simulated data together with real data can be applied to improve the fidelity of each module thus improve the synthesized model online. In a nutshell, we simulate into the future, module by module in a suitable fidelity, and use that simulated information to synthesize a model to fast deliver a present policy that can lead us to the optimal future.

The key to the solution is successful active learning using simulation in parallel to the real system. To effectively support such active learning, a modularized multi-fidelity simulation framework is essential, and to realize this framework, we highlight five important research directions:

1) How to specify fidelity of a model?
2) How to make a trade-off between fidelity and responsiveness of a model?
3) How to actively conduct more simulation experiment?
4) How to continuously run a multi-fidelity simulator in parallel to the real system?
5) How to establish a database dedicated to this multi-fidelity simulator?

These research topics can help to realize the dream of digital twins being the crystal ball for us to glance through the future so that we can help the system to evolve to be a better system and maintain being efficient and robust as possible

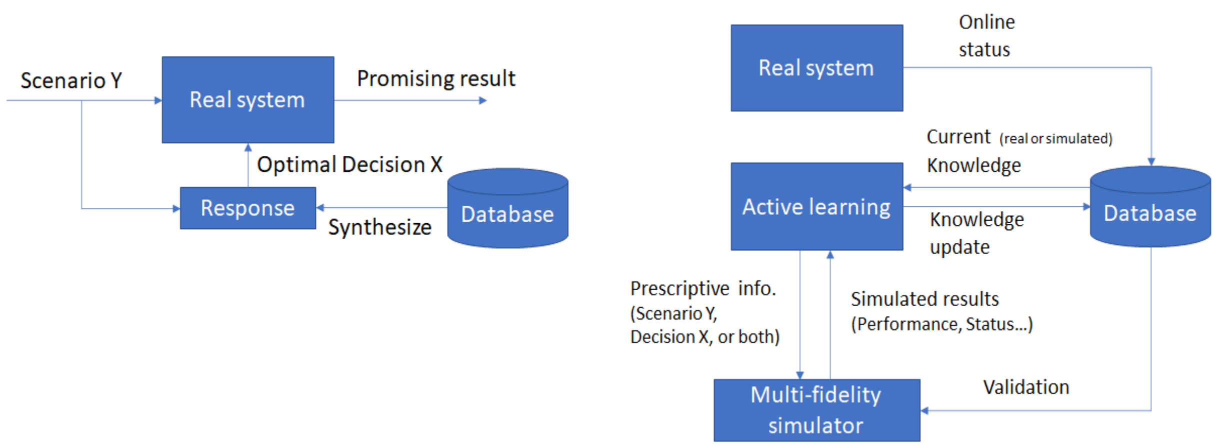

Figure 3: Framework of simulation analytics: Left, online part: decision-making support by synthesizing response online using both real and simulated data; Right, offline part: active learning augmented by a modularized multi-fidelity simulation model.

4 CLOSED LOOP DIGITAL TWIN (CLDT) FOR SMART FACTORY (SUMIN JEON)

Digital twins refer to a comprehensive physical and functional description together with all available operational data of a component, product or system, which includes more or less all information which could be useful in all lifecycle phases (Boschert and Rosen 2018). To realize entire product lifecycle digital twins, Siemens defines three categories of digital twins approached as: product, production, and performance.

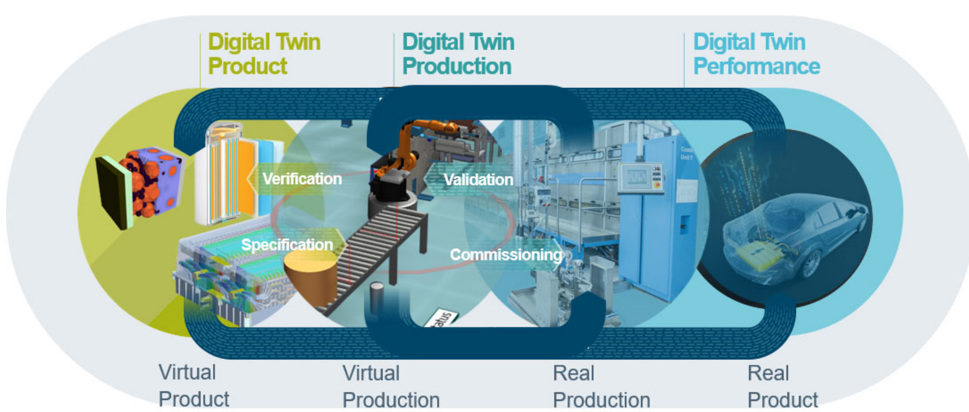

Figure 4: Siemens digital twin solution suite.

A product digital twin includes all design elements of a product to create a virtual product by using computer aided design and engineering. The product design, design validation, and testing are performed virtually. After validation of product design, product specification information will be sent to a production line for manufacturing the final product. A production digital twin solution enables to inform an accurate description of manufacturing process flow and production status. The value of the digital twin is to virtually simulate, validate, and optimize from product design to production manufacturing for end-product. A performance digital twin is a virtual representation of a product or production system, connected with corresponding assets using IoT data coming from sensors and programmable logic controllers (PLCs). This enables the closed loop data flow to realize a fully digitalized factory model. The IoT data needs data repository to record all events signals at real production system to push back to virtual production line to analyze real time information for preventive maintenance in facility planning or production planning. In order to derive solution for those real system issues, simulation-based solution approach is necessary to evaluate production optimization without disturbing real operation. This simulation based solution approach has been studied many researchers as a standalone virtual modeling approach. A proposed digital twin approach allows evaluation of a virtual model with real system data and enables the interpretation of operational situations rather than just detecting them. The main concept of Closed Loop Digital Twin (CLDT) is to enable the communication between a real-world asset and virtual model of that asset to solve real world problems efficiently as a practical solution. A starting point of digital twin solution approach is to create a virtual simulation model. The communication between the virtual simulation model and the real-world model is performed through an IoT to support agile decision making in smart factory.

4.1 Digital Twin Example: CLDT for Smart Factories

A framework of CLDT is shown as Figure 5. An objective of CLDT is to support smart decision-making process and to facilitate intelligent factory automation through simulation. Closed loop data flow presents how production digital twin process data flows using cloud base IoT platform. A technical function of CLDT is summarized as below.

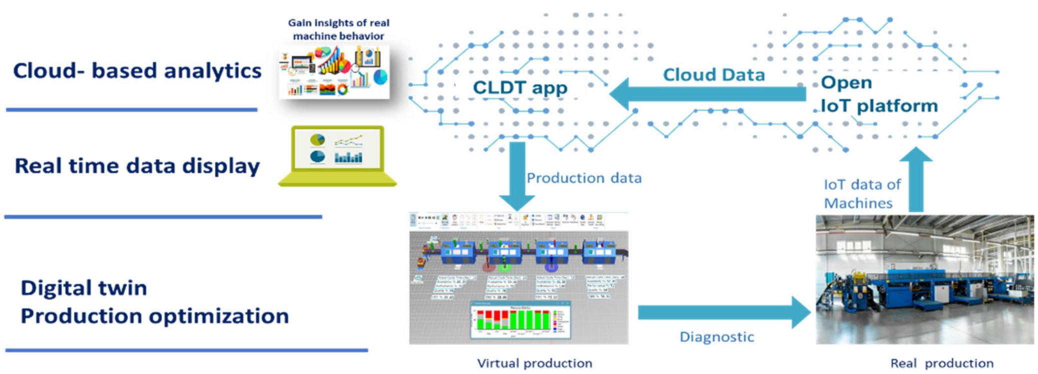

Figure 5: A framework of the closed loop digital twin.

In the production digital twin, data interaction can be seen between real production and virtual production. In real production, all equipment is connected to each other and the information system through sensors. The input/output sensors are connected to the PLC to communicate between real production and virtual production simulation. The simulation model can use real-time data to perform simulation implementation to display the actual state of the real production. By using cloud base IoT in production digital twin, data driven simulation is also able to validate data analytics. Before applying the CLDT in smart factory, some challenges (accuracy of data analytic, agile data interface, robust digital twin interaction) should be overcome. Expectations of the successful CLDT application in smart factory can be highlighted as four points: 1. Real time-based machine to simulation communication, 2. Near-real time diagnostics of production system, 3. Simulation based production optimization, 4. Real production data driven simulation.

4.2 Summary

A discrete event-based simulation for CLDT is suitable to describe the varying state of material flow or jobs in manufacturing with sequence of event simulation time. If we consider different fidelity simulations such as process models in the digital twin, it is important to design levels of process model fidelity using dynamic performance data for CLDT. As a result, the digital model comes to life and starts exhibiting real-asset behavior and hence transforms into a CLDT. The CLDT would become the innovation backbone of the product lifecycle which connects various teams and organizations across the value chain to enable faster decision making and stronger collaboration. It also allows optimization of assets, resources, workflows, and processes to prevent costly downtime and faster response to market conditions and needs.

5 DIGITAL TWIN AT STENA INNOVATION INDUSTRY LAB (BJORN JOHANSSON)

Stena industry innovation lab (SII-Lab) in Gothenburg is a research laboratory for sustainable production and Industry 4.0 hosted by Chalmers University of Technology. The SII-Lab serves as an open access innovation arena for experiments conducted by industry/institutes and academia collaboratively. The drone factory inside SII-lab is a so-called Simulated Work Environment (SWE), a real factory built for both research and training on Industry 4.0 applications. The drone factory exists as a real production environment, as well as a digital twin. The drone factory consists of four different areas; training of operators, internal logistics of components, final assembly of the drone, and quality control. The central part of Figure 6 is visualizing the control, and the drone produced is shown in the lower left. In addition, there are also several software systems that are used for order management, planning, instructions, and design. Since all events and actions are digitally actuated and monitored, it consists a direct possibility for connecting a digital twin to the physical production system in several aspects.

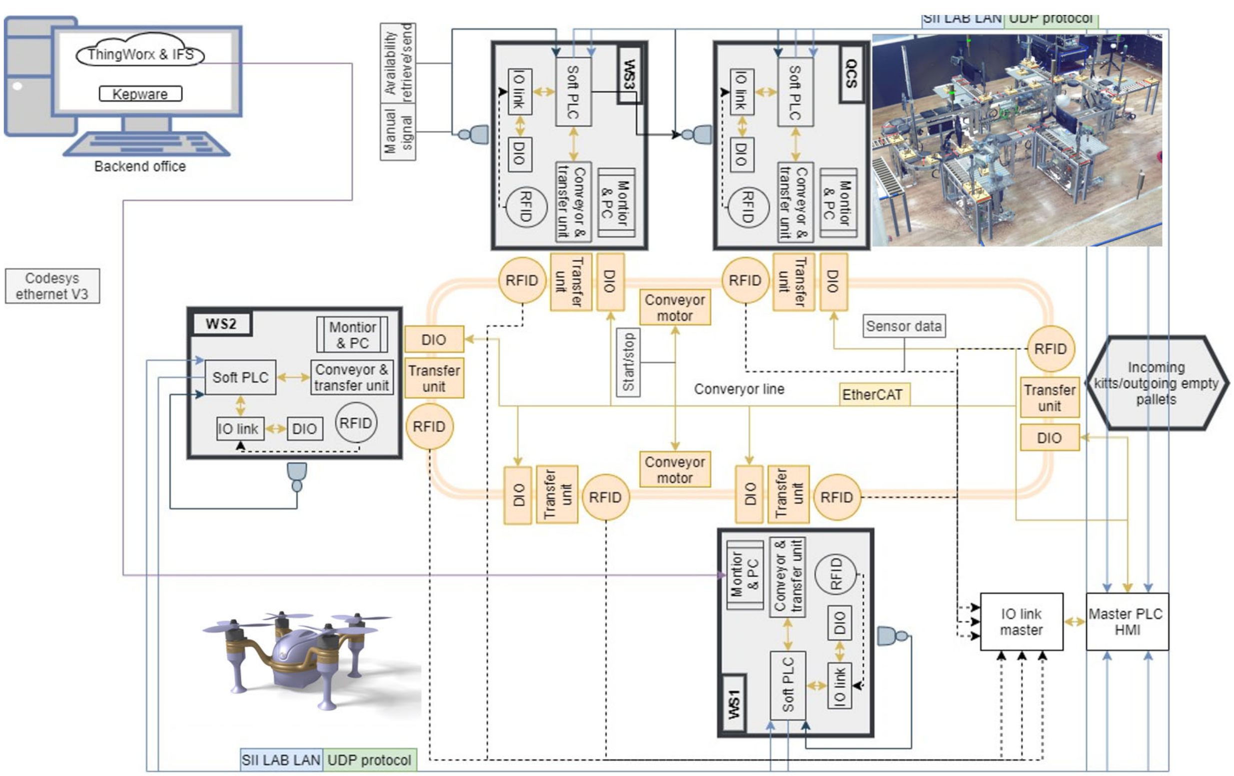

Figure 6: Drone factory simulated work environment.

Figure 6 and its data connectivity is connected to a discrete event simulation model with point cloud data of the facility as a baseline for communicating to the user where events and triggers are actuated and monitored, see upper right for a snapshot of the point cloud DES model.

5.1 Research themes and challenge under investigation

Two of the main research themes investigated in the digital twin concept at SII-Lab are:

1. What is the benefit for industry provided by digital twins and how can it aid to create more sustainable manufacturing?
2. What is a suitable way to connect the simulation model to reality when utilizing digital twins for performance and sustainability improvements?

The following Key Performance Indicators (KPIs) are currently in process of being connected to monitor the real production of drones as well as to the discrete event simulation model triggered by physical events. The KPIs are added into the digital twin in the simulation model step by step for the particular scenarios, e.g., energy monitoring, waste monitoring, and OEE monitoring.

The main challenge is to enable tacking of products in-between sensors and then link the position to the discrete event simulation model, since the model is lacking data in-between the sensors. One option investigated is to introduce 3D trackers and trace the products. Another solution which is investigated is to attach a physical position tracker to the carriers or product and use a tracking system with positioning through the 5G network which is installed in SII-Lab.

Since facts based decision relies on KPIs, the SII-Lab with the digital twin is investigating how sustainability KPIs, listed under the research themes, can be collected and used to support stakeholders such as operators, maintenance engineer, logistics, and decision makers. These aspects are a bit tricky, monitoring energy, measuring waste, and utilizing Life Cycle Assessment (LCA) databases to find suitable data on emission will not be perfect but gives a ballpark number. In addition, how should these sustainability KPIs from the real drone production be influenced by findings from the digital twin?

6 DIGITAL TWIN FOR SMART MANUFACTURING (PETER LENDERMANN)

6.1 Digital Twin versus Simulation

Digital Twins have become a key enabler of a campaign called Industry 4.0 with the objective to speed up digitalization in production and logistics. As such, the potential of the Digital Twin concept for the enhancement and continuous re-optimization of manufacturing and logistics operations has generally been recognized and accepted not only by industry but also by academia. In this setting, a Digital Twin is termed as an integrated computer model that represents, connects, and synchronizes a part of or the whole physical manufacturing system or process, enabled by historical and real-time data from the physical system (Shao and Kibira 2018).

As opposed to a Digital Twin, as stated by Shao in this paper, a “Simulation Model” is a “digital model that imitates the operations or processes within a manufacturing system”. Such simulation models “have been used for analyzing the performances of manufacturing systems and testing of new concepts for decades”. The objective is typically to make sure that certain decisions can be made in a timely manner so that problems can be resolved before they cause any major failure, damage or system performance loss, no matter whether they are longer-term decisions such as tool purchases or short-term decisions such as Preventive Maintenance timing or even production control parameters.

Out of the above-mentioned three attributes of a Digital Twin, the most important one is “represent”, i.e., the capability to portray the behavior of the system. The other two attributes “connect” and “synchronize” are not a purpose of a Digital Twin per se, rather they are means to better enable “represent”, in particular to increase the degree of automation for extracting and analyzing the data required for the simulation model (which is possible nowadays through connection with corresponding assets using IoT data coming from PLCs and IoT devices such as sensors) in order to be able to

(1) Detect and consider even recent changes/trends in the underlying behavioral patterns in the real system to improve the quality of the simulation model (i.e., the quality of "represent"),
(2) Make the Digital Twin also applicable for operational decision-making purposes such as described for example in Scholl et al. (2012).

So with regard to the title of this panel discussion, we are not really getting smarter through the Digital Twin but rather faster and more agile. But no matter whether a "Digital Twin" or a "Simulation Model" is to be used for an analysis, in both cases we are talking about experimentation with the underlying computer model (in a more or less automated manner) before implementing in the physical system decision variable settings derived through the analysis.

As also stated by Shao, "simulations can help understand what *may* happen in the real world". That indeed is the main purpose of a simulation model. But a Digital Twin is not able to help understand what *is* happening in the real world". Like a simulation model, it can only help understand what *has* already happened in the real world. And the purpose is to be able to translate this "what has happened in the world" into a model that can be used to understand what in future may happen in the real world.

As such no fundamental difference between Digital Twin and Simulation Model can be discerned. Rather, "Digital Twin" appears to be a new term for something that has been around for a long time.

6.2 Digital Twin versus Data Analytics and Optimization

As also stated by Shao in this paper, a "Digital Twin may include various digital models such as simulation, data analytics and optimization". However, are data analytics and optimization really part of a Digital Twin? Are they not rather methodologies to identify better (decision variable) settings in a Digital Twin with the objective to eventually enhance the performance of the physical system with regard to a desired objective? Optimization would and should be part of the Digital Twin only if in the real system the optimization is carried out in the same way as in the Digital Twin, for example through a scheduling procedure. But if this is not the case then why should it be considered part of the Digital Twin?

6.3 Digital Twin to replicate system behavior versus Digital Twin to describe a system

As opposed to Shao, Jeon favors a definition of "Digital Twin as a "comprehensive physical and functional description together with all available operational data of a component, product or system, which includes more or less all information which could be useful in all lifecycle phases" according to Boschert and Rosen (2018). From my point of view, however, a description (of a component, product or system) is not sufficient: As mentioned above the actual behavior of the Digital Twin must also be "the same" (or at least very similar) as compared to the physical system, otherwise why would it be a Digital Twin? As such, a Digital Twin without a validated simulation model as a core is hard to imagine.

6.4 Fundamental Challenges with regard to Digital Twins

Simulation is an important enabler for creating a Digital Twin of a manufacturing and/or logistics system. However, a Digital Twin will never be able to be an "identical virtual duplication of a physical entity or an entire system" as stated by Shao, main reason being that the behavior of basically all manufacturing and logistics systems also involves human considerations and decision-making which inherently cannot be portrayed a computer simulation model. As such, the Digital Twin concept appears to be more applicable for highly automated systems with little human involvement. In D-SIMLAB Technologies, the concept of Digital Twin is therefore pursued mainly for semiconductor manufacturing, in particular highly automated wafer fabs.

An important question to be addressed through a Digital Twin could be, for example whether certain scheduling parameters can be enhanced and better parameter value be identified consistently. However, in a cleaning area of a large 300 mm fab comprising more than 100 wet benches, furnaces and metrology tools, for example, commercially available scheduling tools typically run at a frequency of once every 10 minutes, whereby the scheduling procedure runs most of this time and the remaining time is needed for data input and output. This basically means that the scheduler runs almost continuously and hence also the Digital Twin, i.e., the simulation model of the cleaning area (in which the scheduler would have to run equally frequently) will inherently not be able to run faster than real-time. Optimization of scheduling parameters, in the sense of what are the best parameter values under which circumstances, will therefore be possible only retrospectively by comparing the (simulated) performance associated with different scheduler settings for different historical down or lot arrival patterns. Because of these challenges not only dispatch rules or scheduling procedures but also other characteristics such as tool behavior, sampling policies, or Automated Material Handling Systems can never be modelled to the lowest level of detail. As such, a Digital Twin is always a simplified twin of the physical system and therefore always needs to be validated with regard to a specific purpose before it can be used for any kind of strategic, tactical or operational decision making in manufacturing. As such, a "Digital Twin" can never be more than a (significantly) simplified twin, or rather – because of the common data sources that both the physical and the digital system are connected to – a "Conjoint Simplified Digital Twin". In the light of the above, the proposed "Simulation Analytics" framework as described by Lee in this paper including the five associated research directions appear to makes sense to me because it is based on pre-execution of high-fidelity offline simulations (where time consumption is of less concern) and it allows accumulation of sufficient data which can be used to train and synthesize a decision-support solution that can be used online. Each instance of a Digital Twin a specific purpose is essential and needs to be clear. As such, creating a Digital Twin first, as described by Johannsson in this paper, and only then researching the benefit for industry provided by a Digital Twin appears to be rather challenging.

7 CONCLUSIONS

This panel has considered many aspects of Digital Twin innovation. We hope this will inspire researchers in the creation of new innovations in this area.

DISCLAIMER

This paper presents unique perspectives from different panelists. The panelists may not necessarily agree with each other on some of the arguments, the intention of the panel is not to unify researchers' thinking, but to help researchers in the simulation community have a better understanding of the concept, definition, challenges, and modeling requirements of digital twins and inspire innovations. Certain commercial software systems are identified in this paper to facilitate understanding. This does not imply that these software systems are necessarily the best available for the purpose. No approval or endorsement of any commercial product by NIST is intended or implied.

ACKNOWLEDGEMENTS

The research was supported by the NIST Model-Based Enterprise (MBE) program, the TWINGOALS project (grant number 20019) funded by EIT Manufacturing, and Chalmers AoA Production.

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