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DIGITAL TWIN FOR SMART MANUFACTURING: THE SIMULATION ASPECT

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ABSTRACT

The purpose of this panel is to discuss the state of the art in digital twin for manufacturing research and practice from the perspective of the simulation community. The panelists come from the US, Europe, and Asia representing academia, industry, and government. This paper begins with a short introduction to digital twins and then each panelist provides preliminary thoughts on concept, definitions, challenges, implementations, relevant standard activities, and future directions. Two panelists also report their digital twin projects and lessons learned. The panelists may have different viewpoints and may not totally agree with each other on some of the arguments, but the intention of the panel is not to unify researchers' thinking, but to list the research questions, initiate a deeper discussion, and try to help researchers in the simulation community with their future study topics on digital twins for manufacturing.

1 INTRODUCTION

Recent technology advancement of smart sensors, Internet of Things (IoT), cloud computing, Artificial Intelligence (AI), Cyber-Physical Systems (CPS), and modeling and simulation make it possible to realize the "digital twin" of a manufacturing product, system, and process (Bolton 2016). These technologies enable better real-time data collection, computation, communication, integration, modeling, simulation, optimization, and control that are required by digital twins. "Digital Twin" has become an important component in programs and initiatives related to Smart Manufacturing, Digital Manufacturing, Advanced

Manufacturing, and Industry 4.0 globally. It is a "hot" topic among researchers, educators, software vendors, and practitioners in these fields, as one panelist indicates that searches of the key word "digital twin" has been growing rapidly since 2016. On Gartner's 2017 Hype Cycles of Emerging Technologies, digital twin is listed with a time to acceptance of (five to ten) years, i.e., one-half of companies, by 2022, will be using digital twins to achieve more efficient system performance analysis and improved productivity (Panetta 2017). The International Data Corporation (IDC) forecasts that companies investing in digital twins will see improvements of 30% in cycle times of their critical processes in the next five years.

However, manufacturers are not implementing or embracing digital twins as rapidly and efficiently as expected. This may be because digital twins are still in their infancy stage, and there is a lot of confusion about what they actually are, what they should include, and where to start to implement them. The lack of consensus among researchers and practitioners in different communities and different industrial sectors also hinders the acceptance of digital twins by manufacturers. Many companies, especially small- and medium-sized enterprises (SMEs), do not have the expertise and resources required to study and understand the digital twin concept, definitions, and associated challenges; and then effectively implement the digital twin concept for their products and manufacturing operations. They typically have neither sufficient information on the required technologies and standards, nor systematic procedures guiding the implementation of a digital twin. In the simulation community, we thought that we knew digital twins better because we have been performing modeling and simulation for a few decades. However, with the opportunities of new technologies and data and the challenges and requirements of new data-driven and real-time modeling, we, as a community, should equip and update ourselves for this new era of modeling and simulation.

The goal of this panel is to start a discussion regarding the state of the art in digital twins for manufacturing research and development from the perspective of the simulation community. The panelists come from the US (Guodong Shao and Sanjay Jain), Europe (Christoph Laroque and Oliver Rose), and Asia (Loo Hay Lee and Peter Lendermann). Among them are four researchers from academia (Sanjay Jain, Christoph Laroque, Oliver Rose, and Loo Hay Lee), one panelist from the US government (Guodong Shao), and one panelist from a software vendor (Peter Lendermann). Each panelist has provided preliminary thoughts on concept, definitions, challenges, implementations, and future directions. Two panelists also report on their digital twin projects and lessons learned. The panelists may have different viewpoints and may not totally agree with each other on some of the arguments, but the intention of the panel is not to unify researchers' thinking, but to identify research questions, initiate a deeper discussion, and try to help researchers in the simulation community for their future study topics on digital twin for manufacturing.

The remainder of this paper contains the list of panelists' statements, which represent their personal thoughts, their research findings, and their implementation results of digital twins.

2 PANELIST STATEMENTS

This section provides initial thoughts of each panelist on the simulation aspect of Digital Twin for Smart Manufacturing.

2.1 Digital Twin for Smart Manufacturing: Impact on the Simulation Community and Relevant Standards (Guodong Shao)

2.1.1 What is a digital twin?

The digital twin concept was originated by Grieves in 2002 to create a digital informational construct of a physical system as an entity on its own. This digital information would be a "twin" of the information that was embedded within the physical system and be linked with that physical system through the entire lifecycle of the system (Grieves and Vickers 2017). The digital twin concept allows manufacturers to create models of their production systems and processes using real-time data collected from smart sensors and used for near-real-time analysis and control. The digital twin and the physical system are connected through

IoT or smart sensors and actuators. Synchronization between the digital twin and its physical twin, either online or offline, ensures that the production systems are constantly optimized as the digital twin receives real-time performance information from the physical system.

Currently, there are multiple different definitions of the digital twin out there (Ahuett-Garza and Kurfess 2018; Coronado et al. 2018; Garetti et al. 2012; GE 2018; Haag and Anderl 2018; Hughes 2018; Negri et al. 2017; Siemens 2018; Tao et al. 2017). Many of the definitions imply that a digital twin is an identical virtual duplication of a physical entity or an entire system. However, from my perspective, there may be multiple digital twins each representing different focus, aspect, or view of the system, i.e., each digital twin application should have its own focus. A digital twin is context-dependent and could be a partial representation of a physical system, it may consist of only relevant data and models that are specifically designed for their intended purpose (Boschert and Rosen 2018; Shao and Kibira 2018).

2.1.2 What are the relationships between digital twins and simulation models?

Many people may think that simulation models are digital twins. The fact is that a digital twin can be a simulation model, but a simulation model may not necessarily be a digital twin. Digital models used in simulations often have the same type of sensor information and controls of a digital twin, but the information may be generated and manipulated within the simulation. The simulation may replicate what could happen in the real world, but not necessarily what is currently happening (Wong 2018). Kritzinger et al. (2018) propose a classification of digital models into three subcategories based on their level of data integration between the physical and digital counterparts: (1) Digital model: a digital representation of an existing or planned physical object without any form of automated data exchange between the physical and digital objects. Most of the current offline simulation models are this kind of digital model; (2) Digital shadow: a digital model with an automated one-way data flow between the physical and digital objects, e.g., a simulation model using real-time sensor data as inputs (Yang et al. 2017); (3) Digital twin: a digital model with bi-directional data flow between the physical and digital objects, e.g., a simulation model that uses real-time sensor data as inputs and updates some of the parameters of a manufacturing process or equipment.

2.1.3 Typical digital twin applications for smart manufacturing

Digital twins can be used to ensure information continuity throughout the entire product/system lifecycle; perform real-time monitoring, predict system behavior, provide production control and optimization; view, analyze, and control the state of products or processes; enable preventive maintenance, and realize virtual commissioning. The applications of the digital twin concept help reduce resource downtime, improve product throughput and quality, reduce manufacturing costs, and ensure operation safety. Advanced digital twins may update products in the field and provide service to end-user customer (Hughes 2018).

2.1.4 What are the research directions to promote digital twin applications in the simulation community?

Digital twins are gaining more attention but are still in their early stage. There are a lot of challenges that need to be overcome before manufactures can effectively, economically, and correctly implement digital twin technologies. Manufacturers, especially SMEs, need help interpreting the concepts, relevant standards and technology implementations. In the simulation community, we need to help solve issues related to data management including data collection, data processing, and data analytics; real-time model synchronization that guarantees the digital twin reflects the current status of its physical twin; model generation that includes automatic data driven model creation and standard-based model generation; and model verification, validation, uncertainty quantification (VVUQ) (Shao and Kibira 2018; Lugaresi and Matta 2018).

2.1.5 Current relevant standardization efforts

Useful standards for digital twin implementation include guidelines for consistently performing credible digital twin modeling and specifications that define the information models and data formats to enable the interoperability of data and models within digital twins. NIST researchers currently participating in the development and testing of multiple such standards. Two of them are listed below:

- ISO 23247 - Digital Twin Manufacturing Framework: is intended to provide a generic manufacturing digital twin development framework that can be instantiated for case-specific digital twin implementation. The standard will have four parts: (1) Overview and general principles, (2) Reference architecture, (3) Digital representation of physical manufacturing elements, and (4) Information exchange. The completed framework standard will provide guidelines, methods, and approaches for the development and implementation of manufacturing digital twins. It will also help facilitate the composability of models and interoperability among modules, provide examples of data collection, modeling and simulation, communication, integration, and applications of relevant standards. The framework will also enable the generation and management of common data and model components that most digital twins need to have to facilitate the reuse of these components. For example, a simulation components library or model template may be useful for composing and reusing components for future models. This standard is currently work-in-progress.
- The American Society of Mechanical Engineers (ASME) Verification and Validation (V&V) standards committee is developing best practices, general guidance, and a common language for verification, validation, and uncertainty quantification for computational modeling and simulation in advanced manufacturing. The guidelines for incorporating VVUQ for data-driven models and throughout model lifecycle are especially applicable to digital twin development. It will allow better traceability, improved verification and validation capability, and better model credibility.

2.2 From Virtual Factory to Digital Twin? (Sanjay Jain)

The panel members' inputs present a range of overlapping perspectives on digital twins in the context of manufacturing. All the perspectives appear to agree on some major aspects. All of us consider digital twins to have simulation models as the key platform and include interfaces to the real system and to analytics applications as part of the concept. Some of us include a few analytics capabilities as part of the digital twin. Some of us explicitly identify the capability to vary level of details and supporting the lifecycle of the manufacturing system. With that overall agreement, the views appear to diverge a bit as we get into some details.

The challenge appears to be in achieving an alignment in our understanding at the deeper level. Considering that all the panel members are long time participants of Winter Simulation Conference (WSC), a practitioner or even a researcher from outside the community may expect us to be quite well aligned. The differences in our perspectives underline the need to work towards a common understanding. If we, being a part of the same community over a long period, differ on the details, it is not surprising that a whole range of diverse viewpoints are found in the larger community of manufacturing practitioners and researchers.

Interestingly the challenge of developing a common understanding of the digital twin concept is rather similar to the challenge with the virtual factory concept. Based on Google Scholar searches the earliest mention of virtual factory appears to be by Fisher (1986) as below:

"*Perhaps the most important benefit that can be derived from the development of an intelligent factory design agent is the ability to create an electronic model of the factory for subsequent use by other KSs (knowledge-based systems) and problem solvers. This virtual factory would benefit, for example, redesign of a factory when a change in product line occurs because only change related information would need to be collected due to the a priori existence of a factory model.*"

It can be seen that this original idea of virtual factory as an "electronic model" of the real factory that can be updated is quite similar to at least some definitions of digital twins. This is indeed why the challenge of definition of virtual factory has been referred to rather than any of other multitude of concepts that suffer from overuse with varying definitions. We submit that the digital twin in the context of manufacturing is almost the same concept as virtual factory, at least with the definition that we are using now and that is somewhat enhanced version of original idea described in Jain (1995).

Virtual factory was conceptualized as going beyond the simulation of only the material flow and immediately associated resources and activities. The three major enhancements proposed were in taking an integrated view of multiple relevant aspects of the factory, developing the virtual factory in parallel with the development of a real factory through its life cycle, and simulating and analyzing at different resolution levels. The concept was more recently enhanced in Jain and Shao (2014) to include open standard based interfaces with data sources and with analytics capabilities and is shown in Figure 1.

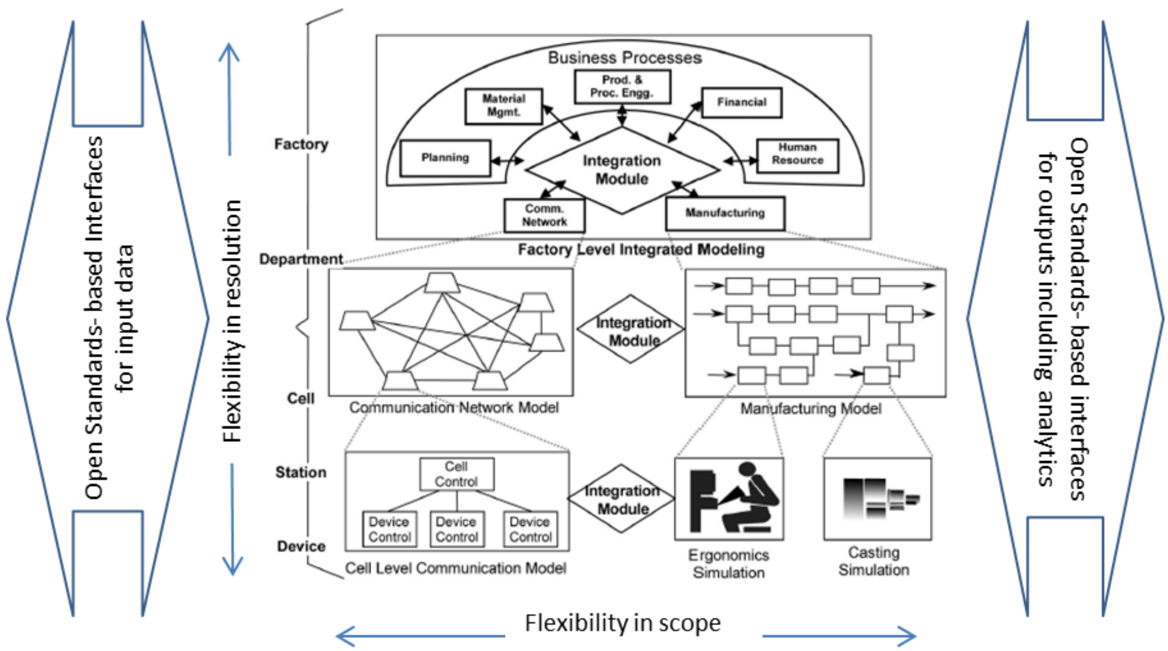

Figure 1: Virtual factory concept (adapted from Jain and Shao (2014)).

It should be apparent that the virtual factory concept largely overlaps with the digital twin concept applied to manufacturing. Digital twin is clearly a more generic concept as it can be applied to other environments such as a port and it appears to be used frequently for products. One would need to use an additional specifier such as the factory's digital twin. Some authors appear to use digital factory largely in the sense of factory's digital twins. It will be beneficial to all to agree on the terminology to avoid potential miscommunications between the providers and users of such capabilities.

It would help define not only one phrase representing the envisaged virtual factory or factory's digital twin capability, but also successively larger subsets that provide a path to start small and build a factory's true digital twin. The coining of digital model, shadow, and twin mentioned elsewhere in this paper is in the right direction and so is the idea of the increasing capabilities defined on four dimensions but perhaps a more comprehensive maturity model approach and/or additional dimensions are needed. Such a set would need to be developed via an international multi-party effort for wider acceptance. The development of the comprehensive model will help with better communication and allow practitioners and researchers to focus on advancing towards smart manufacturing without being lost in definitions.

The multi-resolution capability for the concept in Figure 1 will likely require multiple simulation paradigms for implementation including continuous simulation at for modeling individual manufacturing processes, discrete event simulation for modeling factory flow, and system dynamics for modeling interactions of business processes. Jain et al. (2015) present a virtual factory prototype that employs continuous simulation for modeling the turning process dynamics and kinematics, agent-based modeling for machine level model, and discrete event simulation for job shop level model. While the use of multiple paradigms provides the capability for analysis appropriate to level of detail, it does increase the expertise requirement for the modelers and analysts to carry out the task.

There are multiple challenges beyond definitions of the concept and the high expertise requirement for multiple resolution modeling that are facing manufacturers, particularly SMEs, interested in implementing their factory's digital twins. These include the effort and expertise required to collect and set up data for simulation, build the interfaces, analyze the outputs, and provide timely input to the decision makers. Technology advancements in multiple fields are helping address the challenges. Jain, Narayanan, and Lee (2019) propose a standards-based infrastructure to move towards addressing the challenges.

2.3 The Digital Twin for Simulation in Operations – Something new beyond marketing? (Christoph Laroque)

Data-driven Decision Support such as Simulation, Advanced Data Analytics, and AI are changing how modern manufacturing processes are planned and executed. Within the vision of Industry 4.0 and Cyber-Physical Production Systems, complex problems due to planning, scheduling and control of production, and logistic processes are derived by data-driven decisions in the nearer future. Thus, new processes and interoperable systems must be designed, and existing ones have to be improved, since Industry 4.0 has placed extremely high expectations on production systems to have substantial increase in productivity, resource efficiency, and level of automation. The deliverance of these expectations lies in the ability of manufacturing companies to accurately predict and plan their activities on the machine, the plant, as well as at the supply-chain-level.

Discrete event simulation (DES) is very suitable to model the reality in a manufacturing system with high fidelity. Such models are easy to parameterize and they are able to consider several influences including stochastic behavior. However, simulation models are challenged when it comes to operational decision support in manufacturing as well as logistics. The simulation models are very complex and need huge amount of production data and up to hours for the execution of simulation experiments. A better approach is to integrate the methods and algorithms from (big) data analytics and AI during the implementation of the "digital production twin" for different purposes, e.g., Predictive Maintenance or Workforce Scheduling. The digital twin represents the behavior of the corresponding real object or process and is compared with it at (mostly regular) defined points in time. A large amount of data can be used, the data is generated when implementing the Industry 4.0 concepts during operation as so-called "digital shadows."

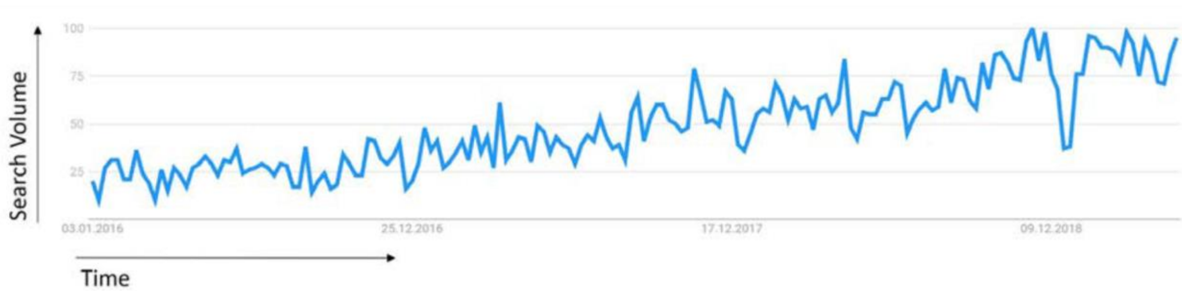

Figure 2: Worldwide searches for the term "Digital Twin" (Source: Google Trends).

One might say, that the concepts behind the innovative term "digital twin" might be old and known, which seems to be reasonably true from the perspective of a simulation expert. However, with the growing importance of searches for the term from all over the world (Figure 2 indicates that searches grow by 400% in the last two years) and within the technological roadmap of the larger consultancies, the "digital twin"' might lead to a higher visibility in top-management and at the decision-makers desk (at least this panelist thinks so).

But also, from a technological perspective, it might be reasonable to think about innovative combinations of the existing data-driven methods for decision making or decision support with DES, specifically material flow simulation, in order to implement more applications of simulation in daily manufacturing operations to achieve better planning, scheduling, and control results. Especially, approaches from data analytics that perform pre-simulation data aggregation, selection, and analysis might lead to performing successful applications in the manufacturing practice.

2.4 Building Toward the Digital Twin for the Smart System (Loo Hay Lee)

A digital twin is the manifestation of the physical system in the digital world that can be used for various purposes. It can provide an environment for monitoring, testing, planning, and decision-making without real physical or time constraints. Besides the spatial representation of its physical counterpart, digital twin also needs to include simulation model and analytic methodologies.

The desired capability for the digital twin includes four dimensions as illustrated in Figure 3. Namely, the **Connectivity** that indicates the level of communication with its physical counterpart; the **Visibility** that indicates the ease of perception for human beings; the **Granularity** that indicates the detail level of the model, which can help us to look into the future scenarios in different fidelities; and the **Analyzability** that indicates how it can be used to assist for decision making (e.g., simulation optimization that can help us to find the best decision for the future; an analytics tool that can help us to learn based on the future simulated optimized data).

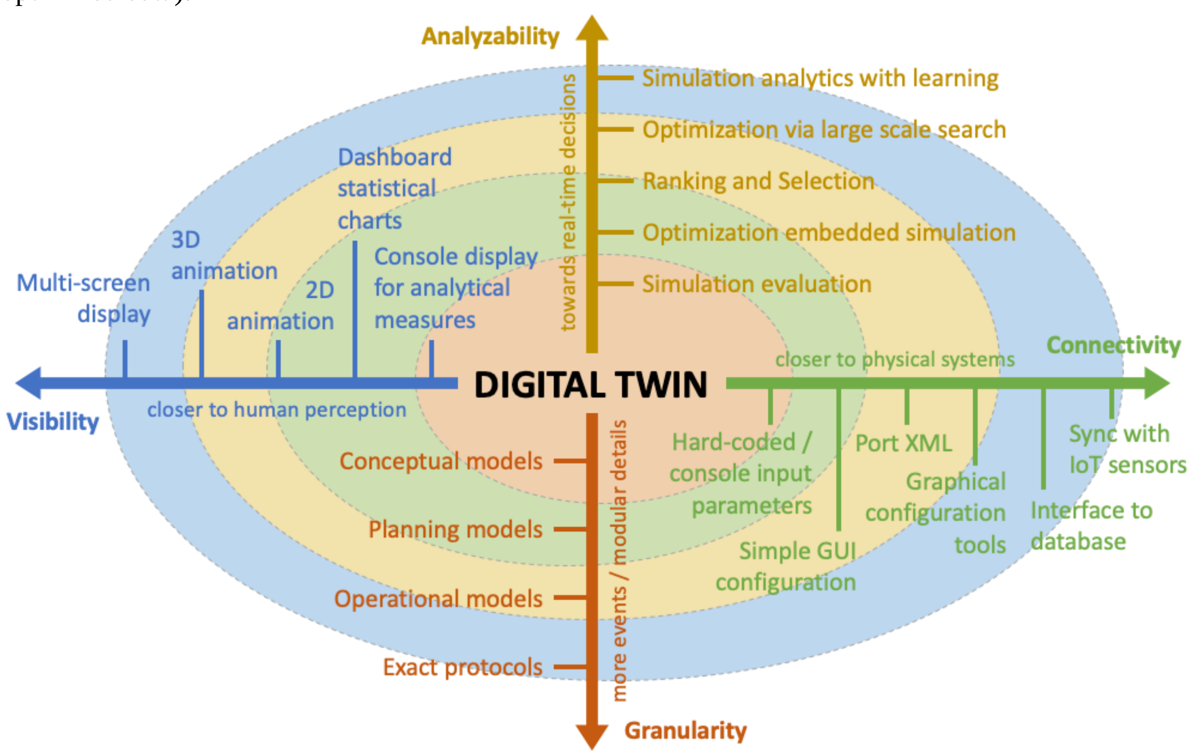

Figure 3: The four dimensions of desired capability for digital twin.

We have developed an O²DES (object-oriented discrete-event simulation) framework as shown in Figure 4 (Zhou et al. 2017). With a rigorously defined Trinary modeling paradigm, the O²DES framework allows developers and researchers to implement algorithmic tools to perform various types of analysis including (1) simulation to handle discrete event model, (2) optimization in simulation that can help to model the operation decision, (3) simulation in optimization (SimOpt approach) that can help to find the best decision under each scenario (Xu et al. 2015; Xu et al. 2016), as well as (4) learning based decision-making, i.e., simulation analytics that can learn the optimal decision function based on future optimized data. We have used this framework to develop digital twin for container terminal (Li et al. 2017; Zhou et al. 2018), aircraft spare part management (Li et al. 2015), warehouse (Pedrielli et al. 2016), and wafer fab plant.

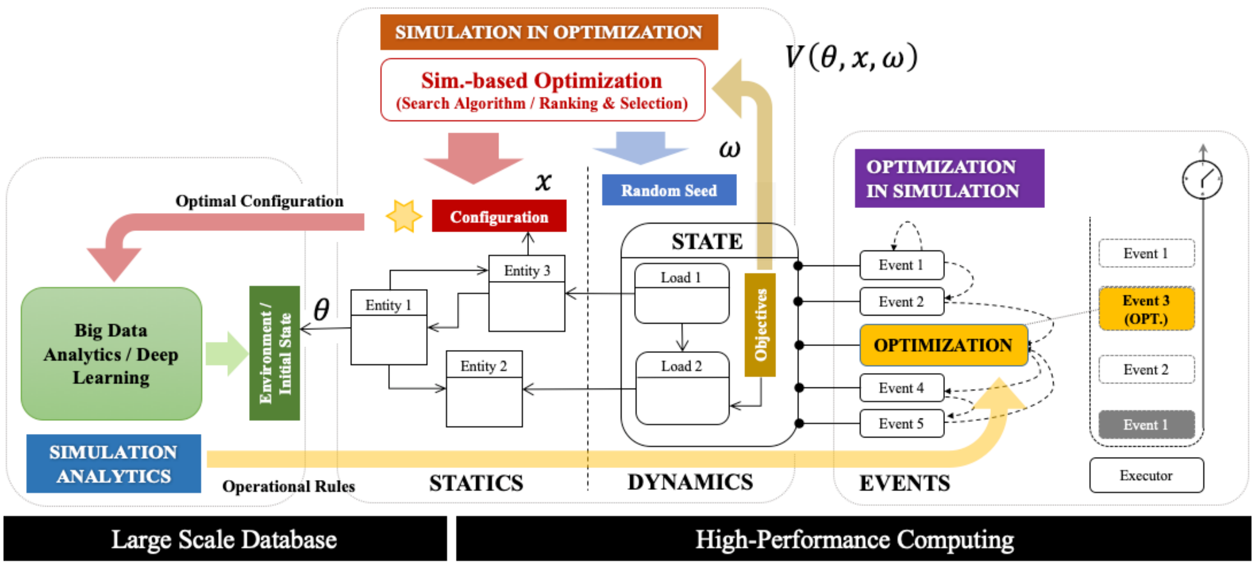

Figure 4: The illustration of O²DES framework with trinary modeling paradigm.

Digital twins are not only the crystal ball to look into future but also the doctors that help provide solution for the future. Digital twins can enable us to actively learn from future, so that we are more prepared for the future, and aim to learn for success.

2.5 Challenges with regard to the Usefulness of Digital Twins (Peter Lendermann)

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 academia but also by industry as it is an important backbone of the Industry 4.0 paradigm.

As mentioned by several co-panelists, 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 applicable mainly for highly automated systems with little human involvement.

In D-SIMLAB Technologies, the concept of digital twin is currently pursued mainly for semiconductor manufacturing, in particular highly automated 300 mm wafer fabs.

An additional complication in such a manufacturing environment, however, is the high degree of randomness on the production floor, caused by process steps such as quality measurement that, dependent on their outcome, may or may not result in re-work. As such, meaningful deterministic forecasts are only possible for very short time horizons in the order of a few hours at maximum.

Such deterministic forecasts are also the basis for complicated scheduling procedures that nowadays are used to optimize the material flow performance at critical equipment groups in wafer fabs. How this typically looks like in a wafer fab in terms of system architecture is outlined in the upper half of Figure 5.

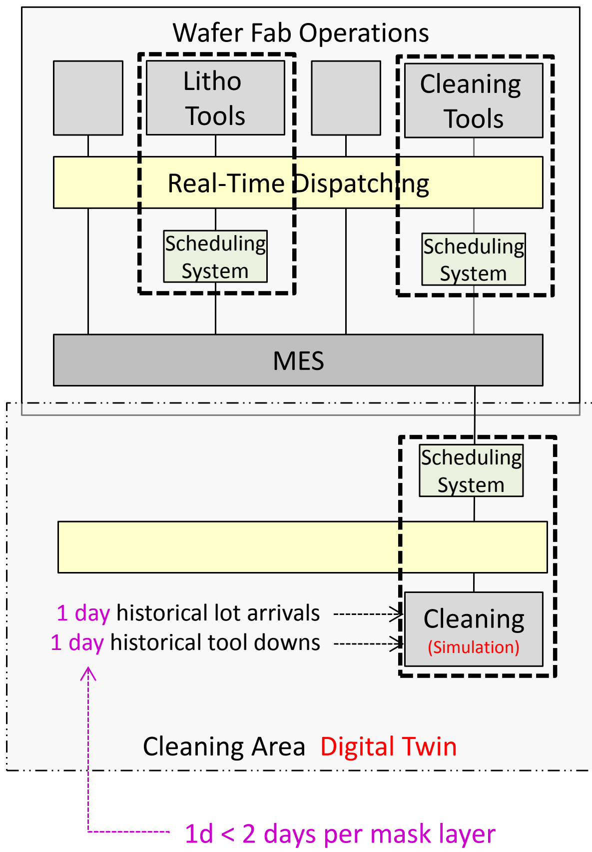

Figure 5: Simplified system architecture for material flow management in a wafer fab (upper half) and Digital Twin representing the cleaning area (lower half).

An important question to be addressed through a digital twin could be, for example whether certain scheduling parameters can be enhanced and better parameter values can 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 min, 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.

As indicated in Figure 6, parallel execution of different scenarios will be required, otherwise a meaningful analysis of scheduling parameters will not be possible. Also, multiple instances of the Scheduling solution will be required, basically equivalent to the number of instances that would be required to compare different scenarios on a cloud infrastructure, posing challenges to the licensing models currently practiced by commercial vendors of scheduling solutions.

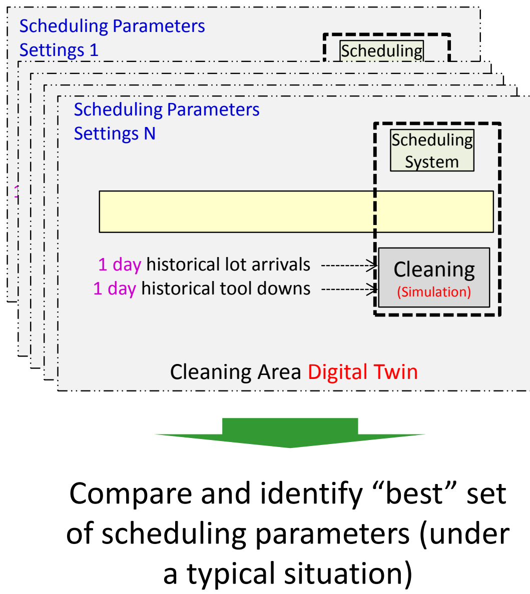

Figure 6: Comparison of different Digital Twin settings on a parallel (Cloud) computing infrastructure.

2.6 Some Simple Thoughts beyond the Industry 4.0 Hype (Oliver Rose)

The term "Digital Twin" was coined as a part of the huge marketing campaign called Industrie/Industry 4.0 to speed up digitalization in production and logistics. Computer simulation models of production and logistics models are in use since the 50s of the last century. A computer model is a digital twin per se. What is more important is the question of what will be achieved with a newly invented digital twin that could not be achieved with computer simulation of manufacturing systems before. In my opinion, the goals are the same, the concepts and methods are the same, and eventually the problems are the same. For high-fidelity trustworthy models we needed and need appropriate data sources that still do not exist in almost all industries, even in high-tech cutting-edge manufacturing facilities, after decades of trying to achieve digital factories, smart factories, and the like. The only difference compared to the approaches of the past is that our computer equipment that is used to analyze the data, build models, and run simulations became much more capable over the years: it is considerably faster and has more memory. This means that we can have more model details, more simulation runs, and improved methods for analyzing data and building models such as machine learning. But this is just an evolution of the same old concept and nothing that is fundamentally new.

3 SUMMARY

In this panel paper, the panelists' statements are meant to aid researchers and manufacturers to have a better understanding of the concept, definition, challenges, and modeling requirements of digital twins. Two panelists also provided implementation examples to explain the digital twin concept and reported lessons learned. The panelists' statements represent their preliminary thoughts. The panelists may have different viewpoints, but all these viewpoints are worthwhile for further investigation and research.

This panel initiated a discussion on the topic of digital twin for smart manufacturing in the simulation community. The implementations of the digital twin concept have been initiated and better received in the design community for monitoring and improving product design (e.g., jet engine or turbines) and performance throughout the product lifecycle (Grieves 2014). It is mainly because of the characteristics of the problems and the relevant technological advances, i.e., the existence of the formal models of the products (e.g., CAD models) and the capabilities of integrating the system representation models with the system analysis models. These factors facilitate the successful implementation of digital twins for products.

The implementation of the digital twin concept in manufacturing has seen multiple approaches used with varying success as clear from the preceding statements of the panel members. The manufacturing community does not have the benefit of widely accepted formal models of the factory configuration or factory control, though there have been some efforts in this direction. The Core Manufacturing Simulation Data (CMSD) standard (Riddick and Lee 2010) developed under the auspices of Simulation Interoperability Standards Organization (SISO) has been used by multiple researchers in the US and Europe for representing factory configuration data with associated simulation data, such as statistical distributions for processing times. Lin and McGinnis (2017) show the feasibility of developing standard reference models for semantics and syntax of semiconductor manufacturing system models. Continued progress of such efforts will facilitate a more common approach for digital twins in manufacturing.

In the WSC community, most of the manufacturing applications are DES models of the manufacturing systems, processes, and supply chains. Some work does use multiple paradigms as pointed out by one of the panelists. Digital twins of manufacturing systems are anticipated to continue to largely use DES models. The simulation community is invited to help the move towards digital twins of manufacturing systems with efforts in the following tentative areas that are likely to get updated during the panel discussion at the conference:

- Agree on a definition of digital twins in manufacturing perhaps with an associated maturity model that allows clear identification of their capabilities at each stage.
- Agree on standard representations for configurations at each level of manufacturing hierarchy (e.g., machine, cell, line, factory, supply chain). The standards may vary for different manufacturing sectors.
- Develop and agree on standard representation of manufacturing control systems at different hierarchical levels. Again, the standards may vary for different manufacturing sectors.
- Enhance the capabilities of real-time model generation and its validation.
- Develop interfaces for model synchronization with its real manufacturing system counterpart.
- Develop standards for interfaces between models with different simulation paradigms.
- Integrate the digital twins with data analytics applications.
- Integrate digital twins' visualization capabilities (e.g., virtual reality(VR), augmented reality (AR), or mixed reality (MR)) if needed.
- Develop standard infrastructure for digital twins for manufacturing in particular for their implementations by small and medium enterprises.

DISCLAIMER

No approval or endorsement of any commercial product by NIST is intended or implied. Certain commercial software systems are identified in this paper to facilitate understanding. Such identification does not imply that these software systems are necessarily the best available for the purpose.

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