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MAINTENANCE AND OPERATIONS OF MANUFACTURING DIGITAL TWINS

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ABSTRACT

Digital twins have become an important element in smart manufacturing. As any other product, digital twins also have a lifecycle, starting from specifying the requirements of the digital twins until their decommissioning. As part of the Manufacturing and Industry 4.0 track of the Winter Simulation Conference (WSC), the purpose of this panel is to discuss the state of the art in digital twins with a special emphasis on the operations and maintenance of manufacturing digital twins during their lifecycles. The panelists come from academia, industry, and government with experience in the digital-twin landscape of the manufacturing industry in the United States, Europe, and Asia. This paper provides a collection of the statements from each panelist with the objective of initiating a deeper discussion during the panel session and inspiring researchers in the simulation community with their perspectives on the use of digital twins for smart manufacturing.

1 INTRODUCTION

According to the definition in ISO 23247, a digital twin in manufacturing is a “fit for purpose digital representation of an observable manufacturing element with synchronization between the element and its digital representation” (ISO 2020). Observable Manufacturing Elements (OMEs) include any physical artifacts (e.g., products, processes, systems, equipment, and materials) in a manufacturing environment. A

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digital twin can persist throughout the lifecycle of an OME to enable information continuity and leverage data from various stages of the OME lifecycle. In addition to the lifecycle of the OME it represents, the digital twin itself also has a lifecycle (from requirements to decommissioning). The digital twin must be maintained and managed to ensure it stays valid and makes the right decisions throughout the digital-twin lifecycle. Figure 1 shows a high-level lifecycle diagram of a digital twin.

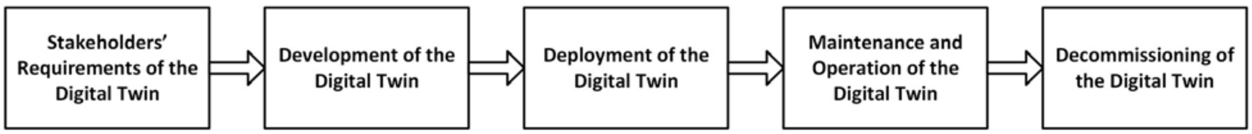

Figure 1: A high-level lifecycle of a digital twin

The purpose of the panel is to discuss the state of the art in digital twin research and practice in the manufacturing sector, and to reflect on the challenges and opportunities in various lifecycle stages of digital twins. A particular focus will be on the maintenance and operations of manufacturing digital twins to ensure the digital twin is capable of continuing to deliver trusted analysis and decisions throughout its entire lifecycle. Some specifics topics for the panel discussion include:

- What makes digital twins in manufacturing different than digital twins in other sectors?
- What are the key factors in manufacturing that can make a digital twin implementation a success or a failure?
- What are the sources of uncertainty in creating and operating a manufacturing digital twin? How to identify, quantify, and eliminate this uncertainty?
- What are the factors that determine the remaining useful lifetime of a manufacturing digital twin?
- What are the components of a manufacturing digital twin that require maintenance?
- How to identify effective and efficient maintenance policies and how to implement them?
- How to quantify the total cost of ownership of a digital twin from a manufacturer perspective?
- How to simultaneously manage the digital twins developed for different OMEs? Can we have these digital twins learn from each other?
- What can be gained by collaborations with technology providers and other digital-twin users?

2 PANELIST STATEMENTS

This section provides the initial thoughts of each panelist on manufacturing digital twins as an input to the panel discussion.

2.1 Introduction to Manufacturing Digital Twins (Boon Ping Gan)

A manufacturing digital twin comprises of a data query engine that extracts data from production databases that are required to build a simulation model, a data correction engine that makes data corrections with defined rule sets, a historical data analyzer that generates statistical distributions required for the simulation model, a simulation model that describes the production line, a forecast quality monitor engine that continuously monitor the quality of the simulation model for model maintenance, and a discrete event simulation engine. A manufacturing digital twin with defined components was built for many wafer fabrication plants. Some examples can be found in Scholl et al. (2012), Mosinski et al. (2017), and Seidel et al. (2017). The following steps were taken to construct the manufacturing digital twins with the components shown in Figure 2: (i) select a simulation engine, (ii) determine the modeling fidelity for each modeling element, (iii) locate data required for the modeling needs (including historical data for stochastic events modeling), (iv) identify potential data gaps for automatic correction, and (v) defines the KPIs of interest for the manufacturing digital twin use case.

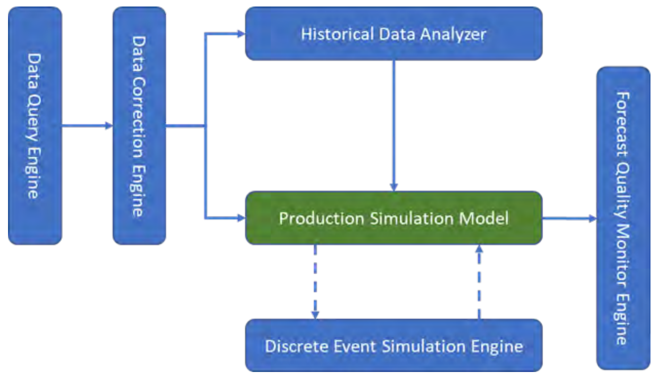

Figure 2: A manufacturing digital twin component

2.1.1 Building a manufacturing digital twin

The first step to build a manufacturing digital twin is to obtain a simulation model engine that possesses the ability to describe the manufacturing line with the right level of fidelity. A general purpose commercial off-the-shelf simulation engine would be the first option. But these engines lack industry-specific vertical modeling features and require modelers to spend a lot of effort to construct the basic modeling element and logic. An alternative option will be to deploy a domain-specific simulation engine where most of the industry-specific modeling features are already available. But these engines could lack the customization flexibility for very specific company-centric modeling features.

The second and third steps of building the manufacturing digital twin go together. The decision on model fidelity is governed by data availability, model feature availability, and customizability of the simulation engine. This is the most challenging aspect of building a manufacturing digital twin, to obtain complete, consistent, and correct data to drive the simulation model. The challenge arises because the dataset is typically maintained by engineers and subject to individual engineer interpretation of what the data really mean. For example, when an equipment throughput data is provided by an engineer, the value could be peak throughput of the equipment, or it could also be an average throughput of the equipment over a time period. Which data is required by the simulation model to reflect the true capability of the equipment must thus be carefully analyzed and understood. In addition, some stochastic modeling elements, such as equipment down time, require large amount of historical data to drive the generation of statistical distribution. The challenge of filtering away outliers and making the right data categorization will be crucial.

Once a manufacturing digital twin is built and in operation, it is then crucial to maintain the accuracy of the model. A forecast quality engine holds the responsibility of measuring the forecast gap between the simulation and reality. It regularly provides a forecast quality report at different modeling levels and ensures that users are alerted to any deviation that would trigger model maintenance exercise.

2.1.2 Maintaining a manufacturing digital twin

The manufacturing digital twin components illustrated in Figure 2 require continuous maintenance to ensure the relevance of the manufacturing digital twin. The most challenging aspect of the maintenance is the data feeding the manufacturing digital twin. Typically, the data feed to the manufacturing digital twin is refreshed regularly to ensure the data captures the production's current behavior. But often, these data are shared among different production applications and the semantics of the data might be altered over time, and eventually lead to gaps in the intended versus actual use of the data. This problem could be eliminated by creating an additional control layer where data could only be refreshed when it is approved by a modeler or user. But this significantly adds to the responsibility of the modeler (or user) and is typically deemed impractical in a very large manufacturing company.

Maintenance of the modeling logic is also essential to ensure the relevance of the manufacturing digital twin. As the production line evolves with added capacity, new product introduction and productivity improvement projects, there is a need to adapt the modeling logic to reflect the operational practices. These maintenance activities are only possible if the team responsible for the manufacturing digital twin maintains a close daily working relationship with the production team. Any information on operational changes must be conveyed and understood by the manufacturing digital twin team to make assessment on the need to make modifications to the modeling logic.

Often, there will still be an element of change that slips through and resulting in the inaccuracy of forecast provided by the manufacturing digital twin. Typically, such gaps grow slowly day by day and might not be visible right away. Continuous forecast quality monitoring for different modeling elements is thus crucial to ensure such gaps are detected early and corrective action can be taken. One example is that equipment group throughput is improved by some percentage points due to a productivity improvement project and it is not reflected in the throughput data. Though the system's throughput has improved, the impact on the global production output will not be visible right away but only after some days or weeks. With a forecast quality monitor at equipment group level, this gap could be detected early, and action could be taken to maintain the accuracy of the manufacturing digital twin.

One question remains. Is there a lifetime for such a manufacturing digital twin? We would argue that the manufacturing digital twin is good for continuous operational usage if it is continuously maintained for the lifetime of the production line. Some example use cases of such manufacturing digital twins are: (i) daily production output forecast for preemptive actions for recovery, (ii) preventive maintenance scheduling taking into action of workload at an equipment group, (iii) visibility into productivity project prioritization in relation to return-on-investment, (iv) alternative operation policy evaluations and refinement before implementation, (v) prescriptive analytics training.

2.2 Lifecycle of Manufacturing Digital Twins (Guodong Shao)

2.2.1 Verification and Validation of Digital Twins in Manufacturing

A digital twin in operation does not necessarily mean that it will provide trusted analysis and decisions. Because during the digital-twin lifecycle, errors and uncertainties may be introduced into various digital twin components. Verification, Validation, and Uncertainty Quantification (VVUQ) of the digital twin model and supporting data must be performed (Shao, Hightower, and Schindel 2023). Verification ensures that the digital twin is built right (i.e., no implementation errors), validation ensures that the digital twin is the one that stakeholders asked for (i.e., it satisfies the stakeholders' requirements), and uncertainty quantification deals with uncertainties that may be introduced during the lifecycle of the digital twin.

Verification and validation (V&V) of digital twins require a rigorous and systematic approach, involving both technical expertise and domain knowledge. Various existing V&V techniques can be applied. Important steps include to include are:

- Establish clear and consistent requirements: Define the requirements for the digital twin with stakeholders, the requirements should specify what aspects of the OME that the digital twin needs to focus on and what performance criteria it must meet.
- Build and verify the digital twin: Select appropriate software and hardware tools, this may involve developing models and algorithms to simulate the OME, as well as integrating sensors and other data sources to provide real-time data inputs. The completed digital twin and its components need to be verified.
- Test the digital twin: Test the digital twin using a variety of scenarios, both realistic and extreme. This may involve comparing the outputs of the digital twin to real-world data from the OME to ensure that the digital twin is accurately representing various aspects of the OME.

- Validate the digital twin: Validate the digital twin by comparing its outputs to those of the OME over an extended period of time. This may involve conducting experiments and collecting data to compare with the digital twin's outputs. Stakeholders' requirements need to be checked to ensure they are all satisfied.
- Maintain the digital twin: Once the digital twin is validated, it is important to continue to maintain and update it throughout the lifecycle of the OME since there will be changes. This may involve updating the software and algorithms used to model the system, as well as integrating new data sources, sensors, and uncertainties to ensure that the digital twin continues to accurately represent the OME.

2.2.2 Sources of Uncertainties for Creating and Operating a Digital Twin in Manufacturing

Creating and maintaining an accurate and reliable digital twin requires careful handling of the sources of uncertainty, as well as robust data collection, modeling, and implementation processes. Several sources of uncertainty that can arise when building a digital twin include:

- Incomplete data: Digital twins rely on data collected from sensors and Internet of Things (IoT) devices. Incomplete or missing data can result in an inaccurate representation of the OME. For example, a malfunctioned sensor can produce data with error and introduce uncertainties.
- Data quality: The accuracy and reliability of the data used to create a digital twin are crucial. Poor data quality can lead to inaccurate predictions and simulations. Data errors can be introduced during any related stages such as data collection (e.g., faulty sensors), data processing, data storage, data transmission, and data analytics.
- Digital twin model accuracy: The accuracy of the models used to create the digital twin is critical. If the models are not sufficiently accurate, the digital twin will not accurately represent the OME. These models might be over simplified, which would miss some critical relevant aspects in the model. Oftentimes, coding errors will result in wrong models of the digital twin and lead to computational errors.
- Variability: OMEs can vary over time due to changes in operating conditions, environmental factors, and other variables. Accounting for variability is essential for an accurate digital twin.
- Computational limitations: Creating and executing a digital twin may require significant computational resources. Computational limitations can result in reduced model complexity or simulation accuracy.
- Human error: Human error during the data collection, modeling, or implementation stages can introduce uncertainties into the digital twin. Human error can also occur when interpreting the digital twin results.
- Maintenance and updating: Failure to maintain and update the digital twin can lead to inaccurate predictions and simulations as the OME evolves over time.

2.2.3 Consideration of Maintenance and Operation for Digital Twins in Manufacturing

Maintaining a digital twin involves ongoing monitoring, updating, and improvement to ensure that it remains an accurate representation of the OME it models. Here are some key steps in digital twin maintenance:

- Monitoring and data collection: Continuously monitor the performance and behavior of the OME and collect relevant data from sensors, IoT devices, and through standard protocols. This data can be used to compare with the digital twin's outputs and identify any discrepancies or anomalies.
- Calibrating the data sources: Regular data validation and cleansing should be performed to ensure that the digital twin remains up-to-date and reflects changes of the OME. Regularly calibrate the sensors and other data sources to ensure that they are providing accurate and reliable data. This

may involve conducting regular maintenance and testing of the sensors and devices and adjusting the calibration as necessary to ensure that the data is accurate.

- Managing and analyzing data: Continuously manage and analyze the data collected from the OME and the digital twin. This may involve using data analytics tools to identify patterns or trends in the data, as well as using machine learning algorithms to improve the accuracy and performance of the digital twin.
- Calibrating and updating the digital twin: As the OME changes, update the digital twin's models, algorithms, and data inputs to ensure that it accurately reflects the current state of the OME. This may involve adding or removing sensors or IoT devices, updating software or hardware components, or adjusting the models and algorithms used to simulate the OME.
- Ensuring security: Ensure that the digital twin and its associated data are secure and protected from cyber threats or other security risks. This may involve implementing appropriate security protocols, such as encryption, authentication, and access controls, as well as conducting regular security audits and vulnerability assessments.
- Ensuring interoperability of the digital twin with other systems: Manufacturing digital twins are often integrated with other systems, such as manufacturing execution systems (MES), enterprise resource planning (ERP) systems, and statistical process control (SPC) systems. The digital twin should be designed to work seamlessly with these systems to ensure that data flows smoothly and that the digital twin remains accurate and up to date.

The operation of a manufacturing digital twin requires specialized skills and knowledge. Staff who are responsible for operating the digital twin should receive appropriate training to ensure that they can use it effectively. Manufacturing digital twins also require regular software updates, bug fixes, and performance optimizations. When analysis is performed and discrepancy is noted between the physical twin and the digital twin, a human developer may need to decide what the cause are and how to fix the problem. Since digital twins are the digital representations of the OMEs for analysis and decision making, they need to stay verified and validated throughout their life cycles for the purpose of use. This will facilitate the adoption of the digital twin and its acceptance as an accurate, valuable, and trusted technology (Eriksson 2020).

2.3 Building and Operating the "Best" Digital Twin (Alp Akcay)

The European manufacturing industry is at the center of a transformation driven by digitalization and the ambition to achieve climate neutrality (Made in Europe 2021). In this transformation, the adoption of digital twins can be seen as a milestone for supporting better decisions on factory floor tasks such as job scheduling, workforce planning, equipment maintenance, and material handling.

The ability to simulate a manufacturing system in an accurate and efficient way is a key driving force of manufacturing digital twins. The "manufacturing system" is a broad term that can be defined differently in different applications in the manufacturing industry, while the principles to build an accurate and efficient simulation model remain more or less the same. Two of these principles are (1) the use of real-life data to calibrate the simulation input models and (2) the ability to build efficient simulation models in the face of ever increasing complexity of manufacturing systems and abundance of data. In the remainder of this section, these two principles will be discussed, followed by their application in a real-world use case at a global semiconductor manufacturer headquartered in the Netherlands.

2.3.1 Data-driven Simulation Input Modeling

Every simulation requires an input model that represents the objects to generate future scenarios during the simulation execution. The effective use of real-life data to obtain the "right" input model is a challenging task, considering its impact on the validity of the simulation. The input model can be estimated from data, but then the estimation errors influence the decisions obtained from the simulation models, as illustrated, for example, in an inventory-control context by Akcay and Corlu (2017) for a single product and Akcay and Biller (2018) for multiple products with correlated demand. Corlu et al. (2020) provide an overview of the literature that explicitly considers input-model uncertainty in simulation output data analysis.

It is known that changing environmental and operational characteristics in a factory can make some historical data "too old" to use for input modeling. With the increasing role of digital twins and their use for data-driven decision-making in manufacturing, the effect of decisions on the data collected during the operations of a simulation model (and later used for simulation re-calibration) must be carefully investigated. Just like an autonomous vehicle detects the real-time road traffic around it, the realization of an autonomous factory requires automatically detecting changes in a production environment (e.g., shifts in order patterns, system interventions, and deviations from plans) from real-time data and re-calibrating the simulation input models accordingly. The resulting self-calibrating simulation models will be instrumental for manufacturers to assess alternative production policies accurately by requiring little human intervention for the maintenance and upgrading of manufacturing digital twins.

2.3.2 Complex-system Simulations: Need for Efficiency

A discrete-event simulation may include many details of a factory to reflect the factory dynamics accurately. Despite the advances in computing technologies, detailed simulation models can be computationally expensive, making the wider adoption of digital twins difficult especially for real-time decision-making applications (Adan et al. 2022). Therefore, it is critical to achieve the most appropriate trade-off between the efficiency and the accuracy of a simulation model. The definition of "the most appropriate" depends on the specific application at hand.

There are various ways to create efficient simulation models. For example, Adan et al. (2018) develop a fluid simulation model that approximates the discrete flow of products through an assembly line (serial machines with buffers in between) similar to a continuous fluid flow. There are also more general approaches. For example, the simulation metamodels are obtained by executing detailed simulation models to approximate a response surface representing the relationship between simulation design parameters and output. Subsequently, the best-fit response surface can be used as a surrogate of a computationally expensive detailed simulation model. Another way to simplify a detailed simulation model is by aggregating the non-bottleneck workstations. The idea here is to build a detailed simulation model to determine the performance of bottleneck (i.e., critical capacity) resources while approximating the rest with simpler models. Similarly, the Effective Processing Time (EPT) modeling, a concept introduced by Hopp and Spearman (2011) in their classical book "Factory Physics," is based on the idea of aggregating all of the time a production job sees (i.e., raw process time, setup time, handling time, and outages) and simulating this aggregated time as so-called EPT. Figure 3 illustrates the realization of the EPT values for five subsequently started production jobs.

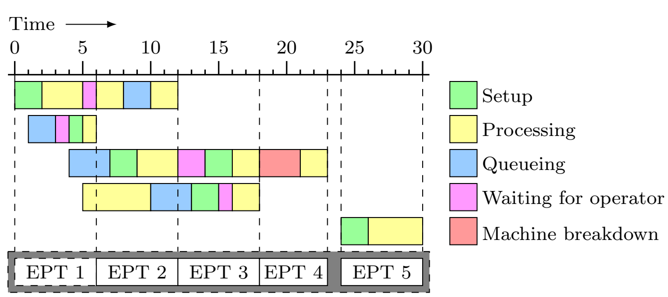

Figure 3: EPT realizations of five jobs (Deenen et al. 2022)

An EPT-driven aggregate simulation model is based on the idea of modeling an area of interest (e.g., the ion-implantation area in a wafer fab) as a single server with an infinite buffer, where the server handles departures according to the best-fit EPT distribution and the queue handles the arrivals according to an overtaking distribution that determines how many jobs that a new job overtakes in the queue. The EPT and overtaking distributions can be made dependent on the work-in-progress (WIP) level, or other factors (e.g., the type of layer to be processed on a wafer). Note that it is possible to obtain these two distributions by only using the arrival and departure data collected in the area being modeled. In many manufacturing systems, this data is readily available in a manufacturing execution system (MES).

2.3.3 Application: Aggregate Simulation Modeling of a Semiconductor Wafer Fab

In order to ensure a smooth operation of a wafer fab, it is essential to have good estimates of production cycle times and WIP levels in various areas of the fab. Deenen et al. (2023) has developed an EPT-driven aggregate simulation model for this purpose by using real-life wafer-fab data. First, an aggregate model is built for individual areas (e.g., implant, wet etch work, and sputtering) to predict the mean and variance of WIP levels and cycle times in the corresponding work areas. For example, Figure 4 illustrates that normalized WIP levels can be estimated accurately. Similar promising results have been obtained for cycle-time predictions. Furthermore, the aggregate models built for individual work areas are connected to create a network of aggregate models to model the entire fab efficiently.

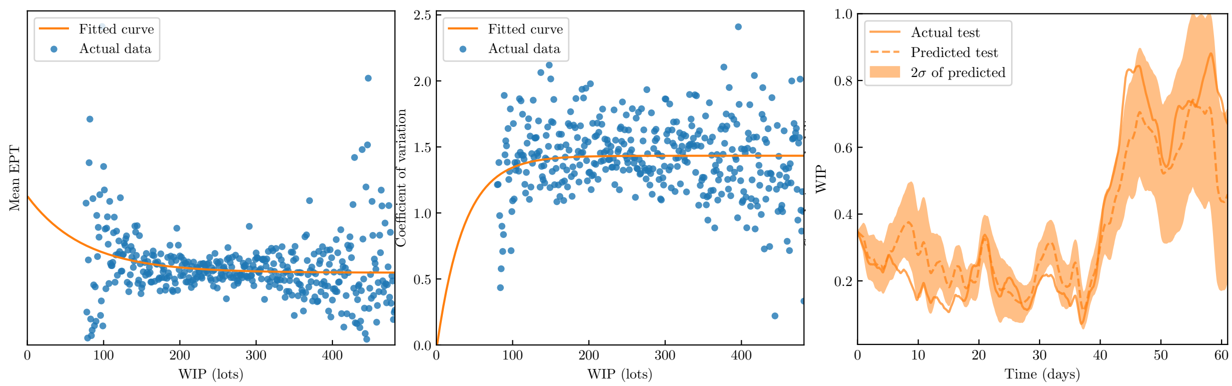

Figure 4: Measured and fitted mean EPT (left), coefficient of variability of EPT (middle), and measured and predicted normalized WIP levels of the test period (left) (Deenen et al. 2022)

It turns out the classical factory physics terminology "effective processing time modeling" can be a promising building block for creating efficient digital twins that require little maintenance and are capable of delivering accurate performance estimates for an entire manufacturing system by only using arrival and departure data in distinct work areas.

2.4 Digital Twins: Smart Manufacturing's DNA for a bright future (Stephan Biller)

In a recent blog (Biller 2023), I wrote about the significant impact of Smart Manufacturing on the future of U.S. Manufacturing and what Purdue is doing to help with that endeavor. The statement here is largely based on that blog.

Smart manufacturing uses and integrates digital software tools and data throughout the product lifecycle and in a smart plant, every resource is digitalized. That means not only every operation, every cell, and every line that is contributing to production, but also every forklift, all maintenance operations, inventory count on the line, and even the inventory that is still on the road and will arrive at the plant in a few hours is digitally tracked and optimized.

In a smart manufacturing plant, we always have perfect visibility into the current state of the plant (are we ahead of plan or behind? what machines are up or down? etc.). We have AI tools that will allow us to predict when things will deviate from the optimal stage. We have decision support systems that will guide us to make the best possible decision for the six key performance indicators (KPIs) — throughput, quality, cost, on-time delivery, sustainability, and (the latest addition) resiliency. These KPIs are interdependent, so it is crucial that all data and tools are integrated, enabling us to see the impact of any decision on all six KPIs simultaneously.

Smart manufacturing consists of five connected major elements:

- *Virtual manufacturing*. This is where we take a digital representation of a product (a "product digital twin") as input and simulate its launch in a virtual factory to optimize manufacturing processes and systems ("process digital twins"), so we can find and solve problems beforehand in both product performance and process hiccups.
- *Optimization of factories and supply chains in real time on the factory floor*. We feed plant-floor data into process digital twins roughly every second, from controls, robots, sensors, cameras, and IT systems — or even from technicians, supervisors, or plant managers — and then use AI and analytics to optimize the factory's KPIs.
- *Predictive maintenance*. When customers are using the product, sensors on the product predict when it will have to be maintained and what maintenance will have to be performed. Sensor data and decision support software helps direct the products into the most appropriate service shop. You might have seen this when your car continuously tells you its remaining oil life, which is based on sensoric and driving data.
- *Real-time optimized service shops*. In the service shops, we optimize for throughput, quality, cost, and on-time delivery, again by modifying the digital twin of the real product.
- *Digital thread*. Smart manufacturing requires seamless data connectivity — a "digital thread" from virtual manufacturing through factory and supply chain, to usage, to service shop, back to product design "closing the loop." We analyze data and optimize all along this digital thread to continuously improve product and manufacturing.

We are still in the early stages of the smart manufacturing revolution, and hurdles remain. Some 98 percent of all manufacturers are Small and Medium Manufacturers (SMMs), with fewer than 500 employees. A lot of them lack the people and resources to implement smart manufacturing. And even if they solve the resource problem, they often still do not know where to start. We talk a lot about resilient supply chains these days, especially after the COVID-19 pandemic. But resilient supply chains require digitalization and transparency for the entire supply chain — not just for the large manufacturers.

We are launching three major initiatives at Purdue to advance smart manufacturing:

- We are creating a new Purdue Manufacturing Gateway initiative to unify manufacturing programs across campus including the Colleges of Engineering, Business, Agriculture, Science, and Polytechnic.
- We will help create the manufacturing innovation ecosystem for SMMs in the US, engage with students and the National Institute of Standards and Technology (NIST) Manufacturing Extension Partnership in pilot implementations, and explore new not-for-profit business models to scale innovations for SMMs (and large manufacturers).
- We will create educational offerings in the Mitchell E. Daniels, Jr. School of Business to make it the best business school for digital-industrial technology on the planet and we will create and enhance offerings in engineering and the Purdue Polytechnic Institute to enable the workforce to design, engineer, and operate smart manufacturing tools.

2.5 Manufacturing Digital Twins: Challenges for adoption and future research directions (Christoph Laroque)

Digital twins have been discussed in the last few years and summarize various solutions and applications in the area of operational decision support, in which an analytical model, often also a simulation model of some kind, is technically linked with the digital shadow of a real factory plant (digital shadow here means a more or less complete and structured data model of the factory). Applications are mostly in the area of tactical decision support in various application areas of production planning and control. Even though the topic is still gaining importance in the field of research, concrete practical applications in the real environment of manufacturing companies are still relatively rare today. If and where they exist, such systems are more likely to be in use by large companies at a significant expense. In addition to the limited number of practical applications, the scientific discussion still lacks a more general definition today – a fact that has, however, already been recognized by various bodies. For example, the German Association of Engineering has set up a guideline committee to work on such standardization topics (VDI 5000 - work in progress).

In the context of the implementation of concrete manufacturing digital twins, numerous questions arise during modeling and implementation in the real environment that could and, in my view, should also be researched and investigated more closely by the scientific community in the coming years. In addition to questions of a more empirical nature, such as why implementation lags so far behind the scientific discussion, there are also questions that call for technical concepts to address today's known problems in modeling, operating and maintaining the applications themselves. Before this section turns more to the scientific issues, a short note on the empirical investigation might be allowed.

Within the framework of the Saxon transfer project DataLab WestSax, it was possible to realize practical implementation projects with numerous companies that are dedicated to the digital transformation of medium-sized production companies, and in particular to data-based value creation. Over the past months, the following observations could be made in the "real-life experiments," which may also allow indications of the low prevalence of digital twins in such an environment:

- The respective companies in the majority do not have a clear data strategy today and thus the very availability of a structured and holistic digital shadow as a basic prerequisite for the implementation of analytical approaches based on it is not given.
- Although small and medium enterprises have increasingly recognized the concrete need for the digital transformation of their business and decision-making processes, company executives are usually unable to achieve a holistic top-down strategy for concrete measures and their technical implementation on their own.
- Within the companies themselves, employees with advanced IT skills are growing up; however, concrete expertise in innovative approaches to data-driven methods such as Big Data, AI, and/or simulation-based solutions is rarely available. Ultimately, so many ideas fail in advance due to internal company capacities and skills.

With regard to the operation and up-to-dateness of existing manufacturing digital twins, questions arise in practical application above all with regard to the design of interfaces for data exchange between the digital shadow (data lake, data warehouse, data fabric, etc.) and the simulation model that are as smooth and performant as possible in both directions, i.e., to overcome performance problems both in the initialization of the simulation model with current factory data and in the storage of large data volumes from simulation.

With respect to the simulation model itself, there is the question of the technical, and especially organizational processes, for updating the modeling of the digital twin per se against the background of an increasingly dynamically changing system structure of the underlying factory. In addition, the parameterization of the individual model modules must ideally be automated and continuously updated based on historical data (drifting parameterization). If this process of continuously adapting the simulation model and its parameters were to be performed using a semi-automatic term, the ongoing validation of this model with the real factory model would still remain as an operational challenge. In addition to the usual key figure systems for the performance of the factory itself, qualitative and quantitative validation of the simulation model and the simulation models would have to be carried out concurrently. This in turn leads to a considerably larger volume of simulation experiments, which even today have a significant time consumption even on powerful computer systems.

As a final indication of possible research directions in relation to the manufacturing digital twins, their future extension to supplementary and alternative KPIs for the performance evaluation of factories should be considered. In addition to classic performance metrics such as Overall Equipment Effectiveness (OEE), WIP and/or delivery performance of the simulated overall system, there are also increasing operational questions regarding optimal insertion times for orders, so that delivery dates promised in advance can also be met with a high degree of probability. Last but not least, in addition to purely economic measures of performance evaluation, ecological evaluations will increasingly become the focus of attention, and the manufacturing digital twins available today will gradually evolve into "green" digital twins (BeverGreen 2023). The first research projects are already underway.

3 CONCLUSION

This paper provides the statements of five panelists for a panel session on the maintenance and operations of manufacturing digital twins. The statements, which have been collected before the panel session, are meant to serve as a starting point for a deeper discussion. A formal description of manufacturing digital twins has been provided, followed by personal views and past experiences of the panelists on the key activities regarding building, operating and maintaining manufacturing digital twins. The intention of the panel is not to come up with a unified framework for the maintenance and operations of manufacturing digital twins, but to pose relevant research findings and challenges in the area of manufacturing digital twins and inspire researchers in the simulation community to create new innovations on this topic.

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