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SHAPING TOMORROW'S FACTORIES: A PANEL ON SIMULATION-DRIVEN MANUFACTURING

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ABSTRACT

Simulation has been an indispensable tool for the design, analysis, and control of manufacturing systems for decades. With new digital twinning technologies and artificial intelligence capabilities appearing in a fast pace, will simulation – as we know today – retain its prominent role in the manufacturing industry of the future? What are the current and projected trends in manufacturing industry that will make simulation even more relevant? How will simulation evolve to address the needs of next-generation factories? Motivated by these initial questions, the Manufacturing and Industry 4.0 track of 2025 Winter Simulation Conference (WSC) brings together a panel of experts to discuss the future of simulation in manufacturing.

1 INTRODUCTION

Simulation, as a key tool within operations research and industrial engineering, is widely used to support better decision-making at the strategic, tactical, and operational levels. In factories and manufacturing networks, it helps improve productivity, reduce costs and waste, and enhance product quality. The Manufacturing & Industry 4.0 track at the Winter Simulation Conference (WSC) has served as a vital platform for researchers and simulation practitioners to share their work toward these goals.

In recent years, there has been a notable increase in contributions to this track on digital twins, AI in simulation, and data-driven modeling techniques, reflecting the community's commitment to pushing the boundaries of simulation technology in manufacturing applications. In this panel paper, we aim to reflect on these recent trends and look forward to both short- and long-term changes we expect for simulation landscape in manufacturing industry.

2 SIMULATION FOR MANUFACTURING

2.1 Manufacturing Applications in Winter Simulation Conference

To get a snapshot of recent trends of simulation applications in manufacturing, we look back at papers published over the past 10 years in the Manufacturing & Industry 4.0 track (known as the Manufacturing Applications track until 2023) at WSC. In the ten-year period from 2015 to 2024, a total of 194 proceedings papers have been published in the Manufacturing & Industry 4.0 track of WSC. We analyze the titles and abstracts of these articles to provide a picture of the state-of-the-art manufacturing applications in the WSC community and also to see how our field has evolved in the recent past.

We begin our analysis by searching if any specific manufacturing sector has been studied more often than others. It turns out that a large majority of the studies (152 out of 194) can be classified as cross-

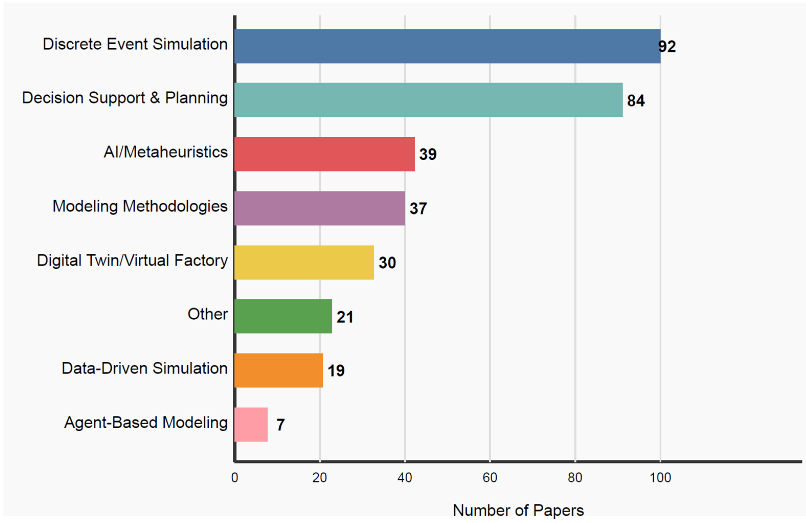

Figure 1: Selected categories in the last 10 years.

industry since their focus is not limited to any specific sector and they are broadly applicable in a general manufacturing context. By counting the number of abstracts containing a specific industry sector, we identify the most common sectors as semiconductor manufacturing (11), automotive (10), warehousing (8), aerospace (3), wood processing (3), biomanufacturing (3), and poultry processing (3). The significant number of abstracts categorized as cross-industry shows the strong emphasis on fundamental research in simulation techniques and their general applications in the Manufacturing & Industry 4.0 track.

As a framework for grouping the papers based on their similarity, we identify a set of categories as shown in Table 1 and come up with related keywords. If one of the keywords is present in the title or abstract of a paper, we counted that paper in the corresponding category (it is possible for a paper to belong to multiple categories). If the title or abstract of a paper does not contain any of the specified keywords, it is marked as “Other”. Figure 1 shows the results, summarizing the most popular topics that have appeared in the last 10 years.

Category	**Keywords**
Data-Driven Simulation	data analytics, machine learning, neural network, deep learning, data mining, predictive modeling, big data, analytics, data-centric
Digital Twin/Virtual Factory	digital twin, cyber-physical, virtual factory, IoT, virtual twin, digital replica, smart factory
AI/Metaheuristics	artificial intelligence, simulation-based optimization, reinforcement learning, genetic algorithm, simulated annealing, metaheuristic, evolutionary
Agent-Based Modeling	agent-based, agents, decentralized, multi-agent simulation
Discrete Event Simulation	discrete event, DES, queuing, event-driven
Modeling Methodologies & Frameworks	modeling, model development, verification, validation, uncertainty quantification
Decision Support & Planning Applications	decision support, decision support system, planning, scheduling

Table 1: Categories and the corresponding keywords used in abstract classification.

Finally, we focus on the first and the last three years in our sample and create a word cloud to visualize the most frequent terms in the titles of the papers. We remove the words that do not immediately hint any information (words such as "using", “approach", “problem") as well as the words “manufacturing” and “simulation” as they are too dominant in both data sets. Figure 2 presents the results and a visual summary of key topics and themes on which researchers focused during these years. An immediate observation from

Figure 2 is the emergence of digital twins as the leading theme. The most recent panel in the Manufacturing & Industry 4.0 track (Akcay et al. 2023) has also focused on the lifecycle aspects of digital twins in manufacturing, and particularly on their operations and maintenance. Furthermore, (deep) reinforcement learning appears as a more specialized term as an alternative term for optimization. The past two years have seen an intense focus on artificial intelligence, with generative AI emerging as a particularly transformative area of innovation and research, with implications for manufacturing simulation yet to be seen.

Figure 2: Word clouds created from the titles of the papers in the Manufacturing & Industry 4.0 track.

2.2 Looking Ahead: Simulation in the Factory of the Future

The purpose of our panel is to discuss the future of simulation research and practice in manufacturing and to reflect on the challenges and opportunities. Section 3 includes statements from the panelists prepared before the panel session scheduled for the Winter Simulation Conference in 2025. These statements will explore the future of simulation in the manufacturing industry, focusing on challenges, opportunities, and the influence of new technologies. We hope that our perspectives will shed light on what we can do as a community to help the factories of the future achieve their goals.

3 PANEL PERSPECTIVES

3.1 Transforming Manufacturing and Simulation: Today and Future (Akcay)

Simulation has been a valuable tool for decades, with numerous applications that have created real business value. From optimizing production schedules to testing layout designs and evaluating logistics strategies, simulation has helped industrial engineers make better decisions in complex systems.

But today, we are witnessing a disruptive shift in the broader business analytics space, driven by artificial intelligence (AI)—particularly the rapid rise of generative AI and large language models. These tools are beginning to transform how businesses operate, offering new ways to automate workflows, generate insights, and support decision-making. In this fast-evolving landscape, a critical question emerges: Where does simulation stand in this disruption? Is simulation visible - or in danger of being overlooked - in the rapidly changing AI trends and tools?

I will start with a brief reflection on the evolution of the manufacturing industry and the forces shaping its future. Then, I offer a perspective on how simulation must evolve to stay relevant and valuable.

3.1.1 The Future of Manufacturing: An Industrial Engineering Perspective

The future will undoubtedly bring shifts in how we design, operate, and scale manufacturing systems. For example, microfactories—compact, modular, and highly automated facilities—are poised to play a key role in this future. Enabled by cyber-physical systems, additive manufacturing, and cloud-connected automation, microfactories will support localized production, faster responsiveness, and scalable customization. At the

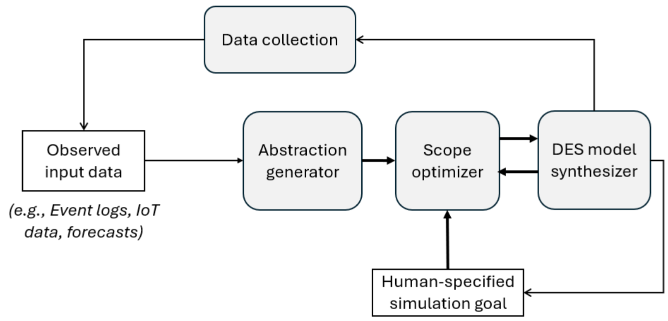

Figure 3: Simulation modeling with self-scoping.

same time, the increasing digitalization to make systems connected brings new challenges. Cybersecurity is more than a compliance issue. As machines, products, and processes become interconnected via Internet of Things (IoT) platforms, protecting manufacturing systems from data theft, tampering, and operational disruption will require resilient architectures, active monitoring, and simulation-optimization methodologies that allow collaborative decision making across the supply chain. On the other end of the spectrum, giga-factories—-large-scale, high-throughput manufacturing facilities such as those for batteries, semiconductors, or electric vehicles– will increasingly require automated decision-making tools for energy and resource optimization as well as the coordination of manufacturing with inbound and outbound logistics.

Sustainability will continue to shape manufacturing priorities as companies respond to their customers' environmental concerns, energy efficiency regulations, and circular economy principles. Manufacturers will need tools that support lifecycle assessments, closed-loop supply chains, and waste-aware decision-making at both strategic and operational levels. As advances in AI enable human-level exception handling on the factory floor, human-machine collaboration in manufacturing will evolve into hybrid autonomy, where simulation-based scenario analysis and optimization tools can play a key role in dynamically updating the decision-making responsibilities of humans on the factory floor.

3.1.2 The Future of Simulation in Manufacturing: Vision and Imperatives

To meet the demands of future manufacturing systems, simulation itself must undergo a deep transformation. Traditional approaches—while still valuable—are often static, manual, and isolated to serve as the backbone of tomorrow's decision-making. Future-ready simulation tools must be:

- *Self-scoping*: Able to determine automatically what level of abstraction or detail is required, depending on the question being asked and the data available. The aggregation and model abstraction has been a fundamental research topic in simulation modeling methodology, with recent applications in semiconductor manufacturing (Deenen et al. 2024) and supply chains (Rosman et al. 2024). However, state-of-the-art in real-world applications still take scoping decisions for simulation models (e.g., what is included in the simulation model and what is excluded) as a manual task, which requires a lot of human effort during the entire lifecycle of the simulation model. Figure 3 illustrates a discrete-event simulation (DES) modeling architecture as the backbone of self-scoping simulation models that can balance model realism and usability, aligning the model's fidelity with its intended decision-support purpose in a dynamically changing uncertain environment.
- *Self-calibrating*: Continuously updated based on live data streams (e.g., IoT, enterprise resource planning, and manufacturing execution systems) to reflect the current state of the system. This capability is closely linked to model calibration, often referred to as input-model uncertainty in simulation community (Corlu et al. 2020). Simulation models must be aware of the external and internal factors that influence the input data used for their calibration. To support autonomous manufacturing, these

models must adapt dynamically—without human modeling intervention. Achieving this capability would mark a significant milestone in manufacturing planning and control for autonomous factories.

- *Interoperable*: Interoperability is essential for the future of simulation in manufacturing because it enables seamless integration across heterogeneous systems, platforms, and data sources—from shop-floor sensors to enterprise-level planning tools. This connectivity allows simulation models to be automatically updated, validated, and deployed in real-time environments, supporting agile decision-making. As manufacturing systems become increasingly distributed and data-driven, interoperability ensures that digital twins and simulation tools can scale and adapt without costly custom integration. While previous work has integrated optimization algorithms for specific applications—such as the digital platform for manufacturing intralogistics agents in Singh et al. (2024)—similar efforts are needed to ensure seamless communication across networks of simulation models.

Addressing these requirements would lead to simulation models that automate the scope-definition process, leveraging event logs and production data to dynamically abstract the system and learn what to model in detail. This addresses a long-standing challenge of using simulation in industrial settings, and the "art" of model building becomes more algorithmic, repeatable, and data-driven.

3.2 Simulation-in-the-Loop for Operational Decision Support (Laroque)

Tomorrow's production will need to be even more resilient, flexible and dynamic than today's. Product and production complexity will continue to increase, and in addition to traditional performance metrics such as capacity utilization and output, other optimization criteria such as energy and consumption of new and recycled raw materials and/or the resulting CO2 footprint of production will play a significant role.

The traditional simulation study will increasingly have to take into account such characteristics and objectives, in addition to logistical performance indicators and a business evaluation, but this will also make tactical and operational planning and control of production more challenging. This is a great opportunity to further develop the operational use of simulation-based decision support systems in the environment of today's emerging digital production twins.

Factory simulation is already being used in individual applications in industry to support operational decision-making. In most cases, however, the commissioning, maintenance and servicing of these digital twins still involves a great deal of manual effort, meaning that their use is still limited due to economic criteria. At least in principle, however, a simulation-based solution would of course be able to map various forms of dynamic factory behavior, reflect them in the decision-making processes and thus provide higher-quality support for operational planning and control. In the future, in addition to the expansion of modeling and evaluation criteria, the infrastructures for digital twins and their maintenance and servicing must also be further developed. The new approaches from the field of artificial intelligence can do useful work here by automatically detecting anomalies and system drifts and, as far as possible, automatically using these findings for the modeling, validation, and verification of the models.

In the next generation of decision support systems, simulation can therefore be integrated as a complex evaluation function of a dynamic system behavior as a central building block to promote good decisions, be it in the form of concrete evaluation of possible action scenarios and/or as a generator of a synthetic database for complex systems for which an insufficient amount of data is still available today, for example to realize other ambitious solution approaches using machine learning methods. The distributed execution of large simulation experiments already allows the generation of large amounts of data as a basis for learning processes; with the constantly growing performance of computer technology and corresponding IT infrastructures, this approach is also becoming economically attractive and offers smaller and medium-sized companies in particular further opportunities to build simulation-in-the-loop operational decision support in addition to the new planning and redesign of the system.

3.3 The Role of Digital Engineering and Simulation in Future Manufacturing (Rencher)

The forward-looking capability of the aerospace defense industry is based on the following premises. First, the digital threading of product lifecycle data throughout the aerospace and defense ecosystem. The current technical and digital solution has amassed a crippling stranglehold on future investment dollars intended to retain a profitable commercial aviation industry and a capable aerospace ad defense supply chain system. The current definition and utilization of digital thread reinforces and sustains a legacy perspective and strategy by allowing for the persistence of legacy monolithic software solutions and data storages strategies. A comprehensive service based digital thread system is needed to systematically disintermediate legacy systems and data stores into modularized function-based software services that utilize logically defined data stores that are aligned to purpose built value streams. Second, the digital twin will become the de facto methodology to design, engineer and manufacture through simulating and analyzing the product lifecycle of manufacturing and assembly processes. This will require an aggressive transformation of legacy manufacturing and assembly methodology and capability to become a fully digital ecosystem. Third, Digital Engineering becomes the integrating strategy and methodology to align model-based engineering, software engineering, digital twin and digital thread capabilities into a cohesive industry strategy adopted by the US industrial base. Lastly, we need to pay attention to global initiatives outside the United States. For example, The European Union and individual European governments are investing, promoting and demonstrating the GAIA-X Product Digital Passport, enabling an integrated transparent digital supply chain capabilities

3.3.1 Digital Twins Opportunity Vectors

Figure 4 represents digital twin opportunity vectors. Each vector along the left Y axis and Lower X axis represent areas of both opportunity and constraints. Each vectors' ability to enable innovation has unique value and constraint challenges. This diagram represents a sample of technological, organizational and industry vectors. Understanding the interaction or interoperability of these vectors defines the opportunity of success and understanding of how quickly innovation may occur. In this example, for PLM Digital Transformation to be realized, there are several correlating vector transformations that need to occur. The timing of vector progress is relative and needs to occur within a window of opportunity. Addressing the question of how digital twin technology will transform traditional simulation methods is a function of validating the opportunity vectors, understanding velocity of change within the vector and the constraints that must be addressed to enable the intended outcome. There is sufficient emergent technology to establish first generation digital twin simulation that would prove to make a significant impact. The noted constraints will be insufficiently mature standards and minimal industry collaboration to facilitate the need for collaborative investment. This points to the requirement to revisit industry leadership. Additionally, the slowly evolving digital ecosystem will minimize the adoption and collaborative use of emergent simulation technology across the major manufactures and tier-1 suppliers.

3.3.2 Digital Engineering

The incorporation and use of digital engineering formulates and establishes the digital engineering ecosystem. This digital engineering ecosystem is defined as an "ecosystem that may include, but is not limited to, government-to-government, contractor-to-government, and contractor-to-supplier digital collaboration. Contrary to today's vertical and hierarchical organizations, these collaborative digital environments are key to involving all stakeholders in developing models, executing simulations, and performing analysis and optimization for the digital models or digital twins.

The characteristics of digital engineering include the computerization of the analog form. In addition, the digitalized artifact must be in a standard form and annotated with necessary metadata to enable machines of different types to access and automatically utilize the digital artifact. Digitalization is at the core of digital engineering. The immediate targets of digital systems engineering are the digitalization of engineering

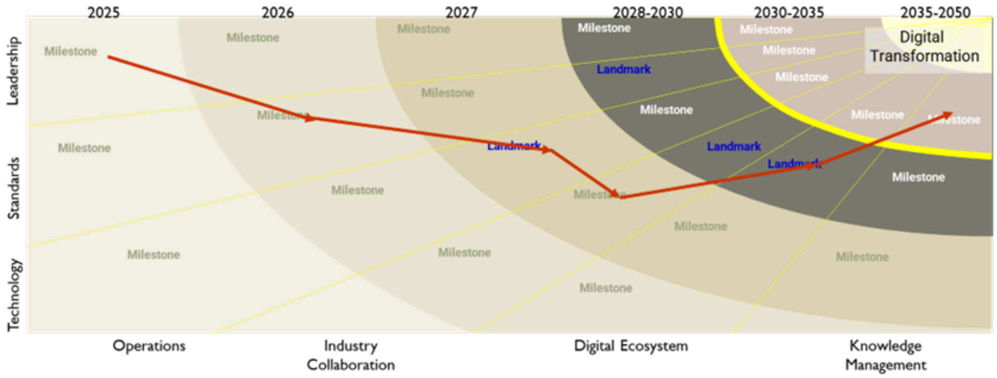

Figure 4: Digital twins opportunity vectors.

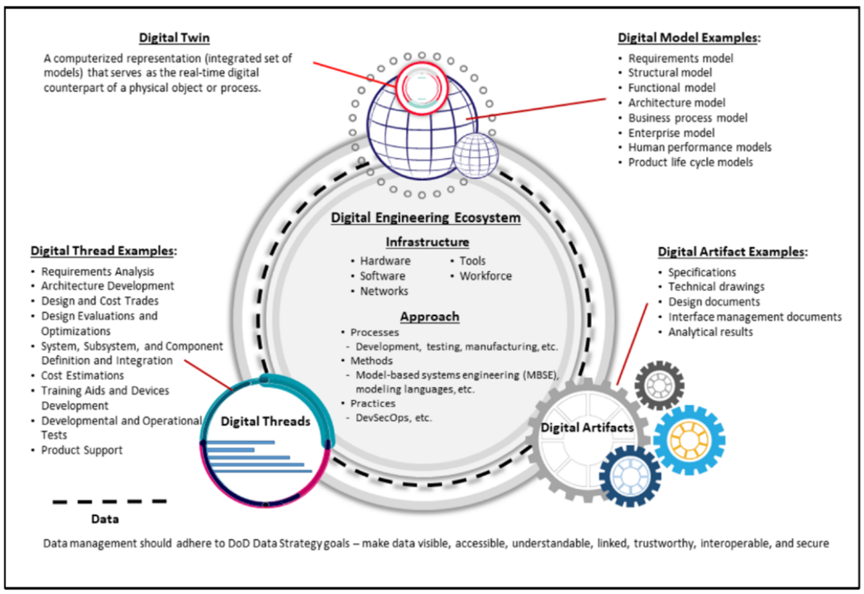

Figure 5: Digital Engineering Framework (U.S. Department of Defense 2023).

artifacts, information and model sharing, and the associated matters of artificial intelligence, digital trust, big data, automatic machine processing, and machine learning.

3.3.3 Workforce Development for Digital Engineering

A knowledgeable workforce is essential for the realization of digital engineering. The knowledge and skills required for digital engineering practice are beyond those of the traditional engineering workforce and beyond traditional engineering education and training programs. Multi-skilled product lifecycle teams will foster and improve collaboration between business users (focus on value creation), information technologists (focus on the technology resiliency, knowledge, and maturity), and data managers (data architects, data analysts, data custodians, etc.).

The digital twin introduces the need for new engineering skill types. The designing and engineering of a product and the designing and engineering of a digital twin of a product follow a similar methodology. However, new tools, methods and technology will be utilized to define, represent and simulate the digital twin of the physical object. Similarly, the definition, curation and management of the digital thread and the data used to define and operationalize the digital twin will require existing tools to evolve to support the increasingly complex data structures. This will require digital twin design, integration and simulation engineers. The organizational structure of these new skill types may include subject matter experts from traditional engineering and information technology organizations.

3.4 The Enabling Role of Standards in Next-Generation Simulations (Shao)

3.4.1 How Can Standards Help Digital Twin Technology Transform Traditional Simulation Methods in Manufacturing?

Digital twin technology is revolutionizing traditional simulation methods in manufacturing by providing real-time, dynamic, and more accurate representations of manufacturing systems and processes. However, barriers, including high implementation costs, lack of expertise, data integration and interoperability issues, cybersecurity and data privacy risks, and scalability limitations, hinder widespread adoption of the technology in manufacturing. Standardization is critical to overcoming these challenges, making digital twins more reliable and practical for manufacturing applications. This, in turn, enhances operational efficiency, reduces costs, and improves sustainability, reliability, and security in smart manufacturing. Below are a few examples of such aspects and relevant standards.

- Ensuring interoperability across systems and platforms: Traditional simulations are often built on proprietary models that lack compatibility across different tools and platforms. Standards can help address these issues by (1) defining common data formats (e.g., IEEE P2806 (IEEE 2019), OPC UA (OPC Foundation 2017), IEEE 1516 HLA (IEEE Computer Society 2010)) for digital twins, (2) enabling integration of sensor data, simulation models, and enterprise systems (e.g., product lifecycle management (PLM), enterprise resource planning (ERP) and manufacturing execution systems (MES)), and (3) supporting cross-platform collaboration among manufacturers, suppliers, and regulators.
- Enhancing real-time data integration and validation: Traditional simulation methods rely on static or historical data, leading to discrepancies with real-world conditions. Standards can help address these issues by (1) defining protocols for real-time data acquisition from Internet of Things (IoT) devices, (2) ensuring data integrity, accuracy, and synchronization between the physical and digital twins; and (3) supporting edge computing and cloud-based analytics for minimize the delays. For example, ISO 23247 (ISO 2021a) defines an architecture for digital twins in manufacturing, guiding synchronized data flow between machines and their virtual models. Standards such as MTConnect (MTConnect Institute 2022), OPC UA, and ISO 10303 (STEP) (ISO 2021c) ensure consistent data representation. These standards enable digital twins to continuously update with real-time sensor data, improving simulation accuracy and reducing latency.
- Security and trust for digital twins: Digital twins handle sensitive operational data, and traditional simulation often lacks robust security measures, making models vulnerable to cyber threats. Standards can help address these issues by (1) applying Zero Trust Architecture (Rose, Borchert, Mitchell, and Connelly 2020) to digital twin ecosystems, (2) implementing secure identity and access management (IAM) for digital twin interactions, and (3) ensuring data provenance and tamper resistance using blockchain. For example: the NIST's Cybersecurity Framework (CSF) (NIST 2024b) and ISO/IEC 27001 (ISO 2022) provide security guidelines for digital twin implementations, ensuring secure data exchange, access control, and resilience against cyberattacks in industrial environments.
- Standardized verification and validation (V&V) of digital twin models: Traditional simulations may lack standard verification methods, leading to unreliable results. ASME Verification, Validation, and Uncertainty Quantification (VVUQ) standards committee has developed a set of V&V standards that can be leveraged for validating digital twin predictions, helping ensure digital twin models accurately represent physical systems and maintain predictive reliability.

3.4.2 How Do Standards Support Emerging Technologies for Future Manufacturing Simulations?

Several emerging trends in simulation are set to redefine future manufacturing strategies. These innovations are driven by advancements in AI, computing power, and data analytics. The simulation trends will converge, leading to autonomous, AI-driven smart factories that continuously optimize production in real time by leveraging AI-driven digital twins, quantum computing, advanced robotics, and decentralized smart factories. Standards will be critical enablers for these technologies to work together to achieve interoperability, security, reliability, and scalability.

- AI-driven autonomous digital twins: Self-learning AI-driven digital twins will continuously optimize simulations in real time; simulations will not only perform predictions; they will also self-correct and take autonomous actions; AI will help generate new factory layouts, optimize supply chains, and suggest material alternatives. For example, if a factory model detects supply chain disruptions, it should automatically reconfigure production plans accordingly. AI-driven digital twins must communicate across systems, ensuring model accuracy, interoperability, and security. Relevant standards and generic frameworks include ISO 23247 (ISO 2021a; ISO 2021b), NIST AI Risk Management Framework (NIST 2024a), IEEE P2806 (IEEE 2019), and ASME VVUQ standards.
- Quantum computing for ultra-high-speed simulations: Traditional simulations in manufacturing, such as real-time control systems, may be computationally expensive. Quantum computing can solve certain types of complex problems exponentially faster, especially those involving combinatorial optimization (e.g., scheduling, routing), multi-variable simulation (e.g., energy use, waste reduction, cost minimization), quantum-level material behavior, and real-time decision-making under uncertainty. Relevant standardization efforts might include developing benchmarking tools for quantum-enhanced manufacturing simulations, creating standardized quantum-classical workflows for industrial use, establishing interoperability protocols between quantum solvers and digital twins, and evaluating trust and validation models for quantum-accelerated decision-making. Standards such as IEEE P7130 (IEEE 2021), ISO/IEC 4879 (ISO/IEC 2024), and NIST Quantum Algorithm Standards will help ensure consistency and security in quantum-based simulations in manufacturing.
- Extended reality (AR/VR/MR) and haptic feedback for real-time simulation: human users will be able to walk inside a digital twin factory using VR/XR before it's built, real-time haptic feedback will allow engineers to touch and feel a virtual product before manufacturing, and digital twins will simulate entire factory environments, including worker movements and robotic collaboration. To accomplish these, standardized rendering, physics models, and safety protocols are essential. Relevant standards include ISO/IEC 18520 (ISO/IEC 2019), IEEE P2048, and XR Accessibility User Requirements (W3C 2021). These will help enable realistic, secure, and interoperable XR-based manufacturing simulations.
- Swarm robotics and decentralized smart factories: Autonomous robotic swarms will simulate self-organizing production, factories will adjust without human intervention, edge computing, and blockchain-based supply chain simulations will enable trustless collaboration between suppliers from different geographical locations, and manufacturing won't be limited to a single location, hyperconnected global production networks will shift resources dynamically. Decentralized manufacturing relies on autonomous, self-organizing systems, standardized data exchanges and security protocols are essential. Relevant standards include ISO 23704 (ISO 2022), IEEE P7002 (IEEE 2022), ISO/TC 307: Blockchain and Distributed Ledger Technologies (ISO/TC 2016), and OPC-UA and MQTT: Communication protocols for IoT-driven manufacturing (ISO/IEC 2016). These will enable secure, standardized data exchange between factories, robots, and supply chains.
- Bio-manufacturing and sustainable simulation: Simulations will design biomaterials that self-assemble or degrade after use, zero-waste manufacturing will be simulated at the molecular level before production, and AI simulations will ensure full lifecycle sustainability, tracking manufacturing efficiency. Biomaterials, lifecycle simulations, and zero-waste production require standardized

sustainability metrics. Relevant standards and committees include ISO 14040: Life Cycle Assessment for Sustainable Manufacturing (ISO 2006), ISO 50001: Energy Management for Smart Factories (ISO 2018), and ASTM E60: Sustainability Standards for Industrial Production.

3.5 Knowing What We Know and What We Don't (Uzsoy)

3.5.1 Setting the Stage

In order to usefully discuss the implications of digital twins for manufacturing systems, we need to agree on what exactly is meant by the term. I will follow the recent study by the U. S. National Academies of Science, Engineering and Medicine (National Academies of Science and Medicine 2024), taking the position that a digital twin, to be called such, must involve bidirectional communication of information between the physical system and the simulation model. The timing of the information flow between physical and simulation levels, as well as the nature of the simulation model, may vary, but the bidirectional information flow between the physical system and simulation are, in my opinion, what distinguishes a digital twin from a simulation model. The scientific community is ill-served by conventional simulation models claiming to be digital twins; whatever their particular nature (discrete-event simulation, finite-element or computational fluid dynamics models, predictive machine learning model etc.), the strengths and limitations of conventional simulation models are well-understood, while the development and deployment of digital twins as defined above raises interesting and important questions that need to be addressed.

I will focus on discrete-event simulation models as the simulation layer of a digital twin, as I believe these are most relevant to the design and control of manufacturing systems. I also distinguish between simulation for system design, and simulation for system control. When using simulation models for system design, a great deal more time is available to run models and analyze results, whereas when a simulation model is part of a control system the simulation model must be capable of producing results and communicating the resulting information to the physical layer in "real time". The definition of "real time" will depend on the frequency of significant events on the shop floor that require some form of control action, such as the start and completion of processing tasks, the detection of a quality excursion on some critical parameter at a particular process, or the arrival of an urgent job.

The most interesting potential of digital twins for manufacturing systems is enabling the more widespread use of simulation for control, as opposed to system or policy design. Hence the most important contributions of digital twins to simulation methodology will lie in addressing the problems raised by this use case. Two of these are tight time constraints on model execution and issues related to model verification, validation and uncertainty quantification.

3.5.2 Time Constraints on Model Execution

Simulation models for large manufacturing systems generally require substantial computation time to run, especially since multiple replications are required to obtain valid statistical estimates of performance measures. Data-driven surrogate models can, in principle, be trained and deployed in inference mode to replace a time-consuming simulation model, allowing predictions of system state and performance to be made extremely rapidly. It is interesting to note, in passing, that most applications of data-driven methods to engineering problems are used in this manner, to speed up a time-consuming step of an engineering workflow, very seldom leading to a new workflow.

There are a number of challenges that need to be addressed here. The first of these is the need for large volumes of training data that must be obtained from a validated simulation model. Assuming such a simulation model is available - a strong assumption in itself - the amount of training data needed to develop a reliable surrogate model of a large, complex manufacturing system may be very large, and the task of quantifying the uncertainty associated with its predictions is challenging. It should give us all pause to consider that for many AI-based surrogate models such as deep neural networks we currently do not know how to perform the equivalent of a power analysis in conventional statistics - how large a sample of training data is needed to achieve a desired level of statistical precision in the prediction. This is troubling enough for prediction of means, but even more so when we wish to predict extreme events, for example the failure of a piece of equipment. Use of industrial data collected in the field can also be problematic since many manufacturing systems are operated in a relatively restricted set of regimes, limiting the ability of surrogate models using this data to accurately capture situations not represented in the training data.

The underlying physical system the digital twin seeks to represent is usually evolving over time. This requires that the digital twin be capable of detecting the change and updating itself in near to real time requiring, in turn, updates to the surrogate model if one is being used. While there is an extensive literature on anomaly detection in manufacturing systems that is closely related to the issues of uncertainty quantification, how to perform the updates to both simulation and surrogate models remains a complex question. If the extent of the updates is limited to updating model parameters, the situation may be more manageable. However, if structural changes to the models are required that must be verified and validated, how to perform these updates so they can be implemented and yield useful information before the system changes again brings many open questions.

3.5.3 The Crucial Technology: Verification, Validation and Uncertainty Quantification

Anyone who has made the attempt will acknowledge the enormous effort involved in building a simulation model of a large, complex manufacturing system. Anecdotally, the time required to develop a working simulation of a large semiconductor wafer fab with a dedicated team is usually of the order of at least a year; the resulting model then usually requires 1-2 full-time engineers to run and maintain it. Verification of such a complex model is a major undertaking. Validation requires a clear understanding of what the model will be used for, i.e., what level of accuracy in its predictions of system states and performance measures is sufficient, in addition to extensive data from the physical system against which the simulation model can be validated. In the current state of the art we have considerable insight into how to perform these tasks for a simulation model of a static system whose design and parameters are not changing over time. However, the need to detect changes in the physical system, update the simulation model in a timely manner and implement and validate the updates in near real time raises a host of interesting research questions that are actively being studied in various engineering disciplines, computer science, mathematics and statistics, but do not yet provide clearcut methods for the digital twin context. The very substantial investment of resources needed to build a validated digital twin is likely to create pressures to make it serve multiple purposes, each of which may impose different requirements for validation and uncertainty quantification. The temptation to use a digital twin for purposes outside its verified and validated capabilities ought to be resisted as far as possible, especially when the results will be used for decisions that may have significant consequences if mistaken.

3.5.4 Roles for Large Language Models

A persistent trend in simulation tools since I first started using them more than 40 years ago (SLAM, on a Control Data mainframe in my undergraduate simulation course at Bogazici University in Spring 1983!) has been the ever-increasing ease of use of such tools. Graphical user interfaces, ever-increasing computing power and excellent software engineering have placed these tools in the hands of more users than one would have thought possible. Many firms whose simulation capabilities began with a dedicated engineer and their workstation now have individual line units building their own simulation models to study problems of local interest to them. AI tools like large language models (LLMs) can further assist users in structuring their code and their analysis, both on the input and the output side. In terms of input analysis, LLMs can help users to select and apply relevant data analysis tools, while at the output side they can help structure analysis of results and suggest appropriate analyses as well as possible interpretations of results. Similar output analysis assistants would also be extremely valuable for conventional optimization models such as large, complex linear or integer programs. The training data for such AI-driven assistants, however, poses a major bottleneck for their development. In the current state of the art, we do not have rigorous, reliable methods for determining how much additional training data is needed to reliably customize a large language model to a specific application domain. This is a fundamental problem of transfer learning which is an active area of research. It may well be the case that any individual user may simply not have access to enough data to train such a model to reliable performance. This suggests multiple users pooling their training data, which has proven to be difficult to achieve, especially in the manufacturing domain where confidentiality concerns predominate, rightly or wrongly. The tools of privacy-preserving computation and federated learning are relevant here, but remain an active and evolving area of research.

3.5.5 Barriers and Skills

The principal barrier to the deployment of simulation in manufacturing systems is the large investment of resources, including skilled personnel, ongoing data collection and computing, required to develop and maintain simulation models in the face of changes in the manufacturing system being modelled and the evolving needs of the firm. The advent of digital twins extends the scope of these needs to include sensors, real-time data transmission and processing, and communication from the simulation model back to the physical system. Given the broad set of skills and resources required, the incorporation of a digital twin of a large manufacturing system into manufacturing control is currently within reach of large firms with deep pockets. How to make these tools available to smaller manufacturing entities remains an open question, as is the case with other tools such as data-driven models and conventional optimization.

At the risk of some exaggeration, I believe that the steadily improving quality of simulation software and available training resources has brought us to the point where coding a simulation model of a relatively simple manufacturing system is within reach of any engineer with coding experience who is willing to invest a modest amount of time in learning the software tools. Engineers with the necessary skills in data science and statistics to perform the necessary input and output analysis are in short supply. Again anecdotally, many university courses as well as industrial training resources focus on the use of specific software tools, providing limited exposure to the underlying statistical concepts that need to inform the use of the tools. In the digital twin context, the difficulties associated with real-time model verification and updating are not well understood even in the relevant research communities, and it will take some considerable time for even a working understanding of these topics to develop. While devoting resources to addressing these fundamental questions, manufacturing personnel involved in developing and using digital twins should at the very least be aware of where the potential difficulties lie, and what the consequences of those difficulties might be for their system if not properly addressed.

3.6 Advancing Manufacturing with Simulation: Lessons from Industry Practice (Valkhoff)

In an era defined by rapid technological advancement and shifting global demands, the manufacturing industry stands at a pivotal crossroads. Traditional production methods are no longer sufficient to meet the growing need for flexibility, efficiency, and sustainability. Next-generation simulation-driven manufacturing offers a transformative approach, leveraging digital models, data analytics, and predictive tools to design, test, and optimize processes prior to physical implementation.

3.6.1 Challenges in Manufacturing

The manufacturing sector is under increasing pressure to adapt to rapid change, facing a convergence of challenges that include rising demand for mass customization, shorter product life cycles, global supply chain volatility, and heightened sustainability expectations. At the same time, legacy infrastructure, workforce shortages, and growing cybersecurity risks further complicate operational continuity and innovation. In this complex environment, simulation and digital twin technologies play a pivotal role in enabling manufacturers to remain agile and competitive. By creating virtual replicas of physical systems and processes, digital twins allow real-time monitoring, predictive maintenance, and continuous optimization, reducing downtime and increasing resilience. Simulation tools empower engineers to test and refine production strategies virtually, improving decision-making while minimizing risk and cost. Together, these technologies form the backbone of a smarter, more adaptive manufacturing ecosystem—one that can respond dynamically to both market demands and internal constraints.

3.6.2 Digital Twins

Looking ahead, the convergence of simulation with digital twin technologies marks a transformative evolution in the manufacturing domain. In manufacturing contexts, digital twins can represent individual machines, entire production lines, or complete factories, providing unprecedented visibility into operations and enabling data-driven decision-making. Where traditional simulation provides powerful insights into what might happen, digital twins go further—synchronizing real-time data from physical assets with virtual models to enable continuous learning, adaptation, and optimization. By embedding simulation capabilities within digital twin frameworks, we enable predictive, closed-loop systems that can autonomously assess performance, detect anomalies, and recommend improvements. This fusion of virtual experimentation and live operational feedback opens new frontiers in smart manufacturing—where factories are no longer just reactive systems, but intelligent ecosystems capable of anticipating change and evolving in step with it.

A challenge of using digital twins for manufacturing is the real-time data exchange that is needed. Manufacturing environments use a wide array of machines, sensors, control systems (PLCs), and software (ERP, MES, SCADA). These systems often use different protocols, data formats, and interfaces, making seamless integration highly complex. Incomplete, noisy, or misaligned data leads to inaccurate digital twins. Real-time systems need robust mechanisms for cleaning, validating, and synchronizing data streams.

3.6.3 AI and Simulation

The rapid development in AI, combined with simulation and digital twins, also creates new possibilities in manufacturing. AI can continuously analyze simulation outputs and operational data from the digital twin, automatically suggesting or implementing process improvements in real time.

An example where simulation and AI go hand in hand is reinforcement learning, where AI agents learn by interacting with an environment and receiving feedback, particularly benefits from simulation. In production scheduling, for instance, initial AI-generated plans might be far from optimal. Allowing AI systems to learn through trial and error in real production settings would be prohibitively expensive and disruptive. Instead, simulated production environments enable AI systems to explore various scheduling strategies, learn from mistakes, and optimize their approaches without affecting real operations. AI can experience thousands of production days in simulation before being deployed to make actual decisions.

Another example of simulation and AI is where AI agents can simulate decentralized manufacturing systems (e.g., AGVs, collaborative robots) using agent-based modeling. Simulated factory floors and warehouse environments allow developers to test navigation algorithms, obstacle avoidance systems, and traffic management protocols across countless scenarios. These simulations enable comprehensive testing of the AI decision-making processes in different applications, from material transport to inventory management, ensuring reliable and safe operation in real environments.

3.6.4 Advancing Simulation Capabilities

One of the critical challenges facing simulation today is the limited use of modern multi-core computing capabilities in many simulation engines. Parallel simulation will reduce the execution time and increase the simulation scalability. Moreover, the rapid advancement of artificial intelligence is redefining expectations. To fully leverage the potential of AI in manufacturing, simulation platforms must enable seamless, real-time data exchange with machine learning models. The use of digital twins also requires real time data exchange with the machines, sensors and control systems of a manufacturing system. To support this, InControl has developed the Enterprise Resource Simulator platform (ERS). As manufacturing systems evolve in complexity, interconnectedness, and intelligence, the tools we use to design, optimize, and control them must evolve as well. Simulation and digital twins, once used primarily for offline planning, are now becoming central to real-time decision-making and adaptive system behavior. The emergence of platforms like ERS signals a pivotal shift—where high-performance, multi-formalism, and AI-integrated simulation becomes a foundation for truly smart manufacturing. The future of manufacturing will not be shaped solely on the shop floor, but within intelligent, virtual environments where ideas can be tested, systems can learn, and transformation can be scaled.

4 CONCLUSION

This panel brought together diverse perspectives on the evolving role of simulation in manufacturing. While traditional simulation has long served as a cornerstone for decision support, the panelists emphasized that its future lies in tighter integration with AI, digital twins, and real-time data. Key imperatives include achieving self-adaptive, interoperable, and secure simulation models that support both strategic planning and operational control. The rise of digital engineering, the need for standards, and the demands of next-generation manufacturing highlight that simulation must evolve into a dynamic, scalable, and collaborative capability. Moving forward, continued convergence of academic research, industry practice, and standardization efforts will be essential to shaping the factories of tomorrow.

DISCLAIMER

Certain commercial products and 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. No approval or endorsement of any commercial product by NIST is intended or implied.

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