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SIMULATION IN SEMICONDUCTOR MANUFACTURING BETWEEN 2000 AND 2050 - LESSONS LEARNED AND FUTURE EXPECTATIONS

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ABSTRACT

This is a panel paper which discusses the use of discrete-event simulation to address problems in semiconductor manufacturing. We have gathered a group of expert semiconductor researchers and practitioners from around the world who (often successfully) applied discrete-event simulation to semiconductor-related problems in the past. The paper collects their answers to an initial set of questions. These serve to not only showcase the current state-of-the-art of discrete-event simulation (DES) in semiconductor manufacturing but also provide insights into where the field is heading and the impact it will have on our world by 2050 in the semiconductor manufacturing domain.

1 INTRODUCTION

Semiconductor manufacturing deals with producing integrated circuits (ICs), chips, on wafers, discs made from silicon or gallium arsenide. The production takes place in semiconductor supply chains. Among the different nodes of these chains there are semiconductor wafer fabrication facilities, called wafer fabs, where the ICs are built up layer-by-layer (Mönch *et al.* 2013). The sheer size and complexity of these supply chains, the pervasive presence of different kinds of uncertainties, and the rapid pace of change suggest that simple, intuitive, manual techniques are unlikely to perform well (Chien *et al.* 2011). Because of the fierce competition among semiconductor companies, model-based decision making has became more and more important. DES is notably successful among the different methods and techniques from Industrial Engineering (IE), Computer Science (CS), and Operations Research (OR).

Using simulation in semiconductor manufacturing was the object of intensive scientific discussions (cf. Fowler *et al*. 1998; Fowler and Rose 2004; Fowler *et al.* 2015 amongst others). At the same time, new requirements arise for simulation-based decision making that can be addressed by new soft- and hardware capabilities. This panel that will explore some of the most pressing and exciting questions related to the past and the future of simulation, mainly based on the DES paradigm, in semiconductor manufacturing.

We have structured the paper around a set of questions on these topics. Each of the panelists provides his answers in turn. The panelists' initials are used to identify who has written each response. The paper finishes with a brief conclusion that aims to bring together the key points raised by the panelists.

2 QUESTIONS REGARDING THE PAST

2.1 What are the main development directions of discrete-event simulation in semiconductor manufacturing in the last 25 years from your point of view

a) technology-wise

b) application-wise?

JF: DES has become a very important tool for semiconductor manufacturing companies over the last 25 years. In 2000, DES was not widely used on a day to day basis by most major semiconductor companies. If DES was used at all, it was generally used offline to evaluate potential long-term changes in the way the manufacturing system (wafer fab or assembly, test, and packaging facility) or complex equipment (cluster tool) operated, e.g. evaluating which dispatching rules should be used to schedule the factory (Akcali et al. 2000) or assessing the design of a cluster tool (Poolsup and Deshpande 2000). These days DES is much more widely used and considers decisions that are closer to real-time, e.g. what should be the production schedule be for the next four hours (Deenan et al. 2022) and/or determining how to reduce the probability of violating a time constraint (May et al. 2024). In addition, much of the data needed to run the factory DES model is automatically pulled from various information systems, e.g. Manufacturing Execution System (MES).

YJJ: From my perspective, the development of DES in semiconductor manufacturing over the past quarter-century has advanced in the following key directions:

1. Advancements in DES Application and Computational Capabilities: There has been significant progress in the scalability, speed, and fidelity of DES tools. This includes improvements in modeling large and complex semiconductor fabs, enabling more detailed simulations with reduced computational time through parallel processing and optimized algorithms.
2. Integration of Process Simulation and Material Handling Systems: A key development has been the integration of process-level simulation with material handling simulations, particularly automated material handling systems (AMHS) such as overhead hoist transportation (OHT) and stockers. This integration enables a holistic analysis of both production workflows and intralogistics, providing more accurate performance assessments and optimization strategies.
3. Integration of DES into Fab Design and Operational Planning: The role of DES has evolved from a purely analytical tool to an integral part of fab design and operational strategy. Simulation is now commonly used in the early design phase to validate layout configurations, tool allocations, and capacity planning, thus enabling more efficient and cost-effective fab planning.
4. Simulation-Based Decision Support in Fab Operations: DES has increasingly been applied to real-time and near-real-time decision-making in semiconductor operations. It supports scenario analysis, predictive maintenance, and dynamic scheduling, contributing to more agile and informed operational strategies in highly volatile manufacturing environments.

These developments collectively reflect the transition of DES from a reactive analysis tool to a proactive, strategic instrument embedded across the semiconductor manufacturing lifecycle.

AK: Over the last 25 years, DES has evolved significantly from being merely a simulation of the realistic system over time, to being a powerful tool for multiple uses. First, the simulation application itself has evolved from being a general-purpose simulation to becoming a more interactive platform, such as web-based, cloud-based, Simulation as a Service (SaaS) or even a simulation embedded in other platforms, such as integrated with artificial intelligence (AI) and Machine Learning (ML). Second, dedicated DES packages have emerged over time, which has made the simulation task easier for specific industries. A classic example of this is Autosched AP©, which has been broadly used in the semiconductor industry thanks to the ease of simulating complex semiconductor equipment such as wet stations or cluster tools.

Application-wise, simulation has expanded from being primarily used for industrial settings such as semiconductor production lines, or AMHS to being used extensively for supply-chain modeling, capital and productivity improvements, cost reduction of energy and utilities (e.g. consumption dedications or equipment bagging opportunities), or even yield improvement. Furthermore, it has become a tool not just for strategic long-term analysis of existing and changing operational settings but also for short-term tactical planning (weekly or shiftly) and real-time decision making and execution (allocation, routing, dispatching). More recently, it has been used successfully as a testbed for practitioners (see Kopp et al. 2020), to test a new type of restrictions which have emerged in advanced semiconductor manufacturing such as lithography dedications (lot-to-lens) or critical queue time (CQT) limitations.

PL: When I started to deal with the application of DES for decision-making for capacity planning and work in process (WIP) flow optimization in semiconductor manufacturing in 2000 (which happens to be exactly 25 years ago), simulation analysis was typically carried out by releasing a fixed high-volume, low mix of production lots at a constant release rate into an empty wafer fab, waiting for a warm-up period to be completed, and then drawing conclusions from observing KPIs during steady-state fab operations. The corresponding simulation model would have been created manually by manipulating and consolidating a variety of input data from multiple sources. Obviously, the applicability of this kind of simulation was limited because of many simplifications in the model that had to be made and also because already at that time there was never such a thing as steady state in wafer fab operations. Moreover, computing power was expensive, and parallel running of replications (not to mention different decision variable settings) was not established. Because of these shortcomings, the use of simulation for capacity planning and WIP flow optimization in semiconductor manufacturing, at least for commercial, real-world applications, was considered dead around 2010 by many semiconductor manufacturers. The subsequent turnaround was then enabled through achievements as follows:

- Ability to portray the non-steady-state nature of fab operations. Statistical confidence can be achieved through sufficient number of replications (rather than by running a steady-state simulation long enough),
- Ability to run simulations on a parallel computing infrastructure and make simulation analysis faster by orders of magnitude,
- Ability to connect and synchronize simulation models with production systems to develop simulation models into real digital twins, by automating peripheral processes for model generation and model maintenance and making simulation applicable for tactical and even operational use cases. Users were now able to use solutions to carry out meaningful analysis fast, instead of spending most of their time on data crunching and achieving reasonable model quality.

LM: My first project as an assistant professor exactly 25 years ago involved creating a simulation model of an existing Application Specific Integrated Circuit (ASIC) fab to propose and test improvements in the photolithography (Mönch et al. 2001). At this time, building a simulation model from scratch using data from a MES was time-consuming and error-prone, any necessary customization of popular commercial DES tools for wafer fab modeling such as Tyecin Systems' ManSim/X, AutoSimulations' AutoSched, Systems Modeling's wafer fabrication template, or Chance Industrial Solution's Delphi (Factory Explorer) (see Mason et al. 1996) was a challenging exercise, often requiring to code various user exits. After the model was ready to apply it, it took a fairly long time to perform the simulation runs. An important application of simulation at this time was dynamic capacity planning making static calculations based on spreadsheets obsolete. Over the years, the number of available simulation tools for wafer fab simulation has become smaller, however, today’s tools are more open allowing to integrate, for instance, software for mathematical programming, metaheuristics for simulation-based optimization, or ML libraries. Moreover, they are much faster than the ones 25 years ago. This results in the possibility to use simulation for much more decision-making tasks on the wafer fab level, but also on the entire semiconductor supply chain level in semiconductor companies. Academics use DES intensively to test their algorithms in a risk-free simulation environment (Ziarnetzky et al. 2020; Herding et al. 2022). This also allows for testing complicated integrated solutions for master planning, demand fulfillment, and production planning (Herding and Mönch 2024). Testbeds for modern wafer fabs of realistic size including the major process restrictions are now available (Kopp et al. 2020).

OR: From a technological point of view, due to advances in computing power and memory sizes, bigger and more detailed factory models could be run in minutes. In addition, real-time data input from shop-floor sensors lead to the implementation of digital shadows or even digital twins of the manufacturing facilities. From an application point of view, simulation is an integral part of all production planning and control activities of the fabs.

GS: More computational power is available. Therefore, it is easier to run parallel simulations even of fab size simulation models. Basic data needed for simulation runs is nowadays often stored in databases and can be accessed easily. Because more and more fabs are fully automated the basic data availability and accuracy improves implicitly. New application software is available, often with convenient interface options and plug and play modules. Longer existing software improved over time, getting more features. Additional software for data manipulation, preparation, and visualization is available.

CY: Over the past 25 years, DES in semiconductor manufacturing has undergone significant technological advancements. A notable progression has been the integration of DES with alternative modeling frameworks, such as agent-based and system dynamics approaches, enabling more comprehensive and multi-faceted analysis (Werling et al. 2020). Combining DES with optimization methodologies, including linear programming, branch & bound, and metaheuristics, has substantially enhanced its decision-making efficacy. These enhancements have fortified the alignment between global and local scheduling decisions within fabrication facilities (Bureau et al. 2007). The models have evolved in complexity, tackling recipe-level, chamber-level, and re-entrant flow issues (Yugma et al. 2007). Advancements in high-performance computing have enabled larger, more scalable simulations, while the advent of digital twins has enhanced real-time data integration, permitting dynamic updates and predictive control (Khemiri et al. 2021). Concurrently, visualization and usability have significantly enhanced, making DES tools more accessible and understandable for engineers and decision-makers.

From an application perspective, DES has expanded its function across various aspects of semiconductor manufacturing. It continues to be a crucial tool for production planning and scheduling (Fowler et al. 2015). Capacity planning and the management of automated transportation systems are essential, allowing organizations to assess the effects of new equipment or layout modifications (Aresi et al. 2019). Simulation facilitates equipment availability assessments, predictive maintenance, and operational inquiries, in addition to balancing WIP across stages to mitigate variability and enhance flow control (Barhebwa-Mushamuka et al. 2019). In the field of metrology and quality control, simulation has been employed to enhance sampling policies and inspection strategies (Dauzère-Pérès et al. 2010). A developing field of application is sustainability, in which DES assists in assessing the energy consumption and environmental impact of manufacturing processes (Khemiri et al. 2021).

2.2 What are the major successes from your point of view?

JF: Perhaps the most important success is that upper management now sees the value of using DES to support factory level decision making. Many semiconductor companies now have established simulation teams that maintain the models and perform analyses on demand. As mentioned above in response to the earlier question, having much of the data being automatically pulled from other systems, allows the simulation team to spend more time doing analysis.

YJJ: One of the most significant successes from my perspective has been the institutionalization of DES as a core part of the decision-making culture in both fab design and operations. Over the past two decades, the semiconductor industry has moved beyond using DES merely as a technical tool. It is now deeply embedded in strategic planning processes—ranging from capacity sizing and layout optimization during fab design to scenario-based operational decision-making for dynamic scheduling, bottleneck management, and throughput optimization during live production. This cultural shift—adopting simulation not only for validation but also for proactive, data-driven decision support—has enhanced the agility, reliability, and economic efficiency of fab development and operations.

AK: One of the recent major successes is the ability to leverage simulation for synthetic data feeds into an ML algorithm e.g., a scheduling optimizer or semiconductor equipment fault detection. Simulation can significantly enhance real data for learning acceleration in such cases. A good example is provided in Kalir et al. (2023) where a complex cluster tool fails unpredictably and real data of several years may not be enough for learning if a failure occurs every few weeks. A couple more successes of simulation are:

1. the ability to integrate simulation with optimization, e.g., for capital optimization: Since equipment capital expenditure is the biggest component of wafer cost in semiconductor manufacturing, the need to optimize capital for desired volume and product mix is critical. Over the years, several papers have shown that with an iterative simulation over a changing number of tool-types, an optimal setting for tools and capital can be derived.
2. the ability to model transient states of semiconductor manufacturing: Unlike typical manufacturing environments which perform at relatively steady-state of high utilization and high-volume production, semiconductor manufacturing is often at a non-steady-state due to ramp or de-ramp, fluctuating market demands (volume changes), product mix changes, and technology changes (de-ramping one process and ramping another process). Thus, for semiconductor manufacturing, it is essential to be able to model transient states and make decisions based on transient system behavior.

PL: In D-SIMLAB Technologies we have been addressing these challenges and essentially managed to bring simulation into wafer fabs from 2010 onwards as an essential tool for constrained capacity planning and enabling use cases where the interdependencies between capacity and cycle time are of relevance, to the extent that it was possible to turn factors such as preventive maintenance timings, which previously had to be considered as constraints, into decision variables. Throughout the years, this was also showcased at the Winter Simulation Conference through numerous joint presentations with semiconductor manufacturers such as Infineon, Bosch, GlobalFoundries, and Seagate, as described for example by Scholl et al. (2012), Mosinski et al. (2017), Ab Rahim et al. (2022), and Surman et al. (2024).

LM: Over the last two decades, DES has become more accepted as a decision support tool applied in wafer fabs. Many semiconductor companies have now simulation teams on place. First steps are made to apply simulation even on the supply chain level. Expectations in digital twins for semiconductor manufacturing (da Silva 2024) continue to promote the use of DES methods. While performing the integrated simulations for the production planning approach proposed by Hung and Leachman (1996) requires several days, today hundreds of simulation runs are possible within an acceptable amount of computing time (Sekiya and Mönch 2025). Due to reference simulation models for wafer fabs and semiconductor supply chains (Ewen et al. 2017; Kopp et al. 2020) DES is a necessary prerequisite to validate results of academics and make results comparable.

OR: The major success is, as stated above, that simulation is now a well-accepted tool in decision-support or even decision-making.

GS: The accuracy and the acceptance of simulation results increased due to continuous improvement of simulation models and basic data quality.

CY: The notable accomplishments of DES in semiconductor manufacturing over the last 25 years are apparent in its transformative impact on decision-making, productivity, and system understanding within this complex and capital-intensive sector (Fowler et al. 2015). The extensive implementation of DES as a strategic decision-support instrument signifies a notable achievement. This has enabled semiconductor manufacturers to make informed decisions about FAB design, capacity planning, and tool investments, thereby reducing the risk and cost linked to infrastructure development (Fowler and Rose 2004). Simulation has been crucial in minimizing cycle time and managing WIP, thereby enabling the equilibrium of throughput and lead time in intricate, stochastic settings (Barhebwa-Mushamuka et al. 2019). The effective incorporation of DES into operational systems, particularly in conjunction with MES and predictive maintenance platforms, is noteworthy. This has enabled more agile and data-informed factory operations, employing simulation models for offline scenario testing and near real-time digital twin applications (Khemiri et al. 2021). Moreover, DES has been instrumental in training and knowledge dissemination, especially during intricate ramp-up periods or the deployment of new technologies. The visualization and experimentation with diverse operating conditions in a risk-free environment have fostered the cultivation of a more simulation-proficient workforce (Werling et al. 2020).

2.3 Are there areas/applications where discrete-event simulation does not work well?

JF: While DES can be used to solve many problems, there are some cases where DES may not be as efficient as another technique. For example, there are situations where deterministic optimization or stochastic programming could provide an optimal solution with less computational effort.

YJJ: One key area where DES has not worked well is in the integration of simulation practices across the full lifecycle of a semiconductor fab. Throughout the fab lifecycle ranging from early-stage conceptual design to operational execution—different DES tools and models are often employed in isolation:

- During the early fab design stage, simplified or trivial simulations are used primarily for high-level capacity planning.
- In the detailed design phase, advanced simulation tools such as AutoMod are used to validate layout, equipment configurations, and material handling flow.
- At the fab integration stage, more sophisticated emulator-based simulators are introduced to ensure system-level compatibility and control logic testing.
- During the operational stage, companies often rely on custom, in-house DES models for performance monitoring, scheduling, and optimization.
- Each stage typically involves different modeling assumptions, simulation architectures, and software platforms, which leads to substantial inefficiencies—such as duplication of modeling effort, lack of data continuity, and difficulty in transferring knowledge or results across teams and phases.

This fragmented approach prevents the realization of a unified, end-to-end digital thread and undermines the potential of simulation to serve as a consistent decision-support tool throughout the fab lifecycle.

AK: DES is limited in its prediction of system behavior when the variability is large and accumulates over time, while the planning horizon is significant relative to the time window of the variability accumulation. As an example, it does not work well in predicting the semiconductor production line behavior over a few production shifts. In fact, by the end of the first production shift, i.e., after 8-12 hours, it is already off significantly since the cumulative variability across the production line of unscheduled downtimes has likely completely altered the original prediction for the state of the line. It is for this reason that when simulation is used for real-time tactical decisions, it is done for a relatively short-time horizon such as 2-4 hours ahead, and then reset and re-executed or sometimes, re-executed every small-time window of 15-30 minutes, to ensure it is always up to date with the current state of the real production line. The simulation is also limited and does not work well for equipment failures such as wafer breaks or parametric out of control. Since these events occur at a low frequency and are highly dependent on multiple conditions which are not merely statistical but are primarily physical and mechanical, it is almost impossible for the simulation to be able to mimic these events accurately. Recently, with the progress made in ML, it has become possible to integrate ML with DES such that these events can be modeled with a higher success rate and accuracy.

PL: DES faces challenges

- in wafer fabs with low degree of automation because human decision-making is often difficult to portray, especially if there are no clear dispatch rules that are either not documented or not enforced,
- in wafer fabs with high degree of automation because scheduling procedures need to be simplified in the simulation because otherwise simulations would slow down too much to real time (or even slower than real time) which would make them inapplicable for many use cases.

For this reason, a simulation-enabled digital twin will always have to be validated with regard to a specific application purpose or use case. However, since DES is the only techniques that is able to portray causalities with regard to capacity and WIP flow related issues, it will continue to be the principal technique for the associated application use cases.

LM: Simulating wafer fabs with many complicated cluster tools is still challenging since modeling the internal behavior of cluster tools is not well supported by existing simulation engines. Approximations are required that must be validated. Detailed DES models of entire semiconductor supply chains containing dozens of front-end and backend facilities are too large to be supported by commercial simulation engines. Although there are reduced DES models in use which represent only the behavior of bottleneck tools in a detailed manner (Ewen et al. 2017), constructing such models is still done in an ad-hoc manner, without much scientific foundation. DES models for integrated lot processing and transport operations are still complicated to build and to perform since often different simulation tools are involved (Drießel and Mönch 2012). Often only the AMHS is modeled in detail and the lot processing part is simplified or vice versa.

OR: As soon as the appropriate fab data is available, simulation works quite well. There are still fabs, however, where this is not the case and, as a consequence, simulation does not work well.

GS: It is still very challenging to forecast on lot level and for low volume products. To reach a good forecast quality for a small production line with many single tools is typically hard.

CY: DES is not always effective in semiconductor manufacturing, despite its advantages. One of its main drawbacks is its unsuitability for real-time control or extremely quick decision-making, as DES models often incur high computational overheads and cannot deliver the instantaneous responses required for dynamic dispatching or low-level tool control in fast-changing environments (Fowler et al. 2015). Furthermore, DES may not be practical for very large-scale or long-horizon systems, such as multi-year strategic plans or global supply chain operations. In such cases, more aggregated or continuous modeling approaches like system dynamics or mathematical optimization can offer better insight and computational efficiency (Chien et al. 2011). DES is also limited when it comes to capturing organizational dynamics, human behavior, or ill-structured decision-making processes. Because it is fundamentally quantitative and rule-based, DES struggles to model qualitative aspects such as decision-making under pressure, resistance to change, or team interaction dynamics areas better suited to behavioral modeling or agent-based frameworks. Likewise, DES is not ideal for continuous processes such as chemical reactions, fluid flows, or thermal transfer phenomena. These are better handled using hybrid models or differential equation-based simulations (Fowler and Rose 2004). Another limitation is the heavy dependency on detailed and accurate data; when system data is sparse, noisy, or poorly documented, DES model calibration and validation become very difficult (Barhebwa-Mushamuka et al. 2021). Lastly, DES can be misused by being applied to overly simple problems where spreadsheet calculations or analytical formulas would suffice, thus adding complexity without providing added value (Fowler et al. 1998).

3 QUESTIONS REGARDING THE FUTURE

3.1 What are the main innovations of discrete-event simulation in semiconductor manufacturing for the next 25 years that you expect

a) technology-wise

b) application-wise?

JF: I think AI is one area of technology-wise innovation in DES over the next 25 years. AI tools and techniques will be used in many different aspects of DES including model development, model parameter updating, and model validation. There are three main areas of application-wise innovation in DES over the next 25 years. First, there will be much more effort put into modeling and simulating the entire semiconductor supply chain instead of just at the factory level. This will include the development and significant implementation of federated models where each company in the supply chain will have a DES model of their operations that will communicate with models of the other actors in the supply chain. Second, DES will be combined with other modeling paradigms and computational techniques to address a wider range of semiconductor problems, e.g. using systems dynamics to model demand and DES to mimic the operations needed to meet the demand. Finally, true digital twins of semiconductor factories and supply chains will allow real-time decisions to improve overall performance.

YJJ: Looking ahead, I anticipate several transformative innovations in how DES will evolve and be applied in semiconductor manufacturing:

1. Integration of Physical Simulation and DES: The convergence of DES with physical-level simulations (e.g., kinematic or physics-based models) will enable more comprehensive and accurate modeling of both system-level behavior and real-world constraints. This fusion will be critical in applications such as complex AMHS or next-generation robot-assisted operations.
2. Emergence of Physical AI in DES Environments: The concept of Physical AI—where AI agents interact within simulated physical environments—will become central to DES innovation. By embedding intelligent decision-making agents into simulation frameworks, fabs can test and validate autonomous control strategies in safe, virtual environments before physical deployment.
3. AI-driven Operational Optimization: DES will increasingly serve as a training and validation ground for AI-based operational algorithms, especially reinforcement learning (RL) and transfer learning. These methods require high-fidelity simulated environments to learn from, and DES—when integrated with physical dynamics—can offer a scalable platform for training robust AI agents that generalize across varying production scenarios.
4. Unified Simulation Frameworks for Smart Fabs: Future smart fabs will require a tightly coupled simulation framework where DES and physical AI models operate in tandem. This integration will support real-time digital twin applications, dynamic scheduling, fault recovery, and adaptive routing in increasingly heterogeneous and automated environments.

Together, these innovations will shift DES from a primarily planning-oriented tool to a core enabler of autonomous, adaptive, and intelligent fab operations.

AK: Over the next 25 years, DES is going to be used extensively with AI and ML models and applications, such that it would enhance these models and accelerate the learning process from real data, by generating synthetic data from the real data, to improve accuracy and enable dynamic self-tuning of these models. Another area with huge potential for the coming years where DES will play a significant role is digital twin. A digital twin is a virtual representation of an object or system designed to accurately reflect all aspects of the physical object, i.e., its fingerprint, structure, behavior, processes, etc. Digital twins in the semiconductor industry are not yet developed, and they only begin to emerge for specific tools in semiconductor manufacturing, such as lithography or a dry etch tool. However, in the future, digital twins would represent the whole fab (clean room, sub-fab, utilities, pipe routes, AMHS) throughout the life cycle of the fab, from the early construction phase and through its many transitions of ramps and de-ramps of new and old technologies. DES would be essential in developing such capabilities, particularly around behavior and processes, such as the ability to perform engineering experiments with digital twins as if it were in the real fab world. In the longer term, simulations may be integrated with quantum computing for modeling extremely complex systems with exponentially intensive number of system states and behaviors.

Application-wise, simulation software will become much more accessible to the public and unskilled practitioners in the semiconductor industry, transitioning to be a "Low-Code/No-Code" simulation. This will allow other semiconductor domain experts (not just IE simulation specialists), such as process and equipment engineers or safety and environmental engineers, or even shop-floor technicians, to build and run models using intuitive (e.g., drag-and-drop) interfaces.

PL: In the next 25 years, innovations will comprise the following:

- Enhanced surrogate models for to portray equipment behavior, AMHS and maybe even scheduling procedures in order to be able to further speed up simulation runs without having to compromise fidelity.
- Automation of not just model verification but even model validation.
- Enhancements in simulation-based optimization through AI-enabled agents which "know" what parameter should be adjusted under which circumstance (and possibly at what time) to increase capacity, reduce cycle time, or enhance other KPIs. Simulation techniques will still be required to verify that such enhanced settings would actually result in such enhanced performance.

LM: For the next 25 years, I expect the following innovations for DES in semiconductor manufacturing:

1. There will be open source DES tools for wafer fabs. Such tools together with High Performance Computing (HPC) clusters will allow to conduct many simulation experiments in parallel.
2. Online simulation efforts will be better supported by Internet of Things (IoT) platforms which make it easier to determine correct initial states.
3. Through digital twin technologies, DES models will be embedded in various planning and production control systems.
4. DES will be used for making decisions on the operational, tactical, and strategic level. Simulation-based optimization will be much more important than today to solve hard decision-making problems in semiconductor supply chains. In addition to demand and process uncertainty, other sources of uncertainty, for instance wind or sun, will be incorporated into decision-making activities.
5. More hybrid models will be used for decision making, for instance, combinations of mathematical programming and simulation where simulation is used to provide information to model workload-dependent lead times. ML techniques will be used to compute metamodels that replace certain parts of time-consuming DES models. DES will be even more hybridized with other simulation paradigms.

OR: Technology-wise, we will become closer and closer to real-time digital shadows or twins, and we will be able to integrate this technology into the complete supply chain. Application-wise, due to the improved technology, we will see better predictions for the behavior of the whole supply chain, and an improved decision-making process.

GS: Basic data availability and accuracy will further improve due to ongoing fab automation. Simulation results will be used for AI training. Simulation will be used for online decision support.

CY: The primary technology advancements in DES will center around real-time data streams and extensive integration with AI. Intelligent DES models will increasingly combine AI with OR methods, taking into account structural and problem-specific characteristics rather than relying solely on brute-force learning approaches (Khemiri et al. 2021). Enabled by Industrial IoT and MES, these models will evolve into self-adaptive digital twins, continuously updated by real-time production data—especially when patterns or anomalies are detected (Fowler et al. 2015). Another significant innovation will be the development of intelligent simulation agents, transforming DES from a purely descriptive tool into a prescriptive and autonomous decision-making system. These agents will support the construction and real-time refinement of optimal control policies, leveraging explainable AI and reinforcement learning techniques to guide dynamic adjustments in the production system. In order to help manufacturers adapt to abrupt changes in demand, regulation, or sourcing constraints, simulation will play an important role in building resilient, adaptable, and regionalized supply networks, particularly as geopolitical risks and global supply chain disruptions become more frequent (Chien et al. 2011). In terms of operations, DES will be central to closed-loop production systems, supporting smart lot release policies, adaptive scheduling, and real-time maintenance reconfiguration (Barhebwa-Mushamuka et al. 2019). Additionally, virtual prototyping of production flows enabled through DES can drastically reduce time-to-market, making simulation a critical tool during the product development and ramp-up phases (Khemiri et al. 2021). Finally, by enabling the simulation of complex or risky scenarios that are difficult to test in live environments, DES is expected to serve as a training and certification platform for both AI models and human operators. This will enhance production readiness and reduce the cost and risk of experimentation (Werling et al. 2020).

3.2 How will these innovations revolutionize the industry?

JF: These innovations will revolutionize the industry by both allowing better decisions to be made to semiconductor problems and by reducing the time and cost to provide these decisions.

YJJ: The integration of DES with physical simulation and AI will fundamentally transform the way semiconductor fabs are designed and operated. Most notably, these innovations will enable seamless collaboration between AI systems and human experts throughout both the fab design and operational phases. By combining high-fidelity simulation environments with intelligent agents, engineers will be able to co-design systems alongside AI, leveraging machine-driven optimization while maintaining human oversight and domain expertise. In fab operations, AI-trained models—developed through simulation—will support real-time decision-making, adapt to dynamic conditions, and manage increasingly complex production environments. This human-AI collaboration will lead to smarter, faster, and more resilient fabs, ultimately improving throughput, efficiency, and responsiveness across the entire semiconductor value chain. In essence, these innovations will not merely automate existing processes—they will redefine the operational paradigm of semiconductor manufacturing through intelligent co-optimization of resources, layouts, and workflows.

AK: Today's semiconductor industry is extremely capital-intensive with machinery and equipment costing up to $300M for a single lithography EUV tool, while the tools themselves, on the other hand, do not perform with high availability and predictability, and are not effectively utilized. This is a major concern of the semiconductor industry: the cost to build fabs increase exponentially every tech node while the productivity and performance of the equipment and utilities hardly improves linearly. However, this trend is going to change with the innovations described earlier. Similar to the revolution that other industries, such as the automotive industry, experienced in the 20th century, the semiconductor industry will experience such a revolution in the next 25-50 years where the cost to build fabs will converge while the productivity and performance of the equipment will experience a sharp uptick. Tools will no longer run with 70-80% availability and poor predictability owing to significant unscheduled downtimes. Tools will no longer perform at inefficient run-rates owing to process variations and/or processing inefficiencies (such as internal transfer delays or wafer-attached setups). Such inefficiencies will be completely resolved with the introduction of new and advanced AI/ML models integrated with simulations within a fully functional digital twin platform for a fab, all running as agents to detect and correct any anomaly or inefficiency in real-time.

PL: The above innovations will further reduce the deployment cycles for simulation-based decision support solutions, widen the range of use cases, and eventually be a critical enabler of the lights-out fab.

LM: On the one hand, the expected innovations described above will allow for better simulation-based planning and control decisions within semiconductor supply chains. On the other hand, it will be easier for academics to use DES to conduct relevant and rigor research useful for the semiconductor community.

OR: Better predictions lead to less consumed resources and better reaction to market volatilities which are typical for the semiconductor industry. Companies which are capable of implementing these new technologies will be able to better cope with complex economic situations than their competitors.

GS: Simulation will be an integral part of decision making within semiconductor manufacturing. Decisions like e.g. which maintenance task will be done first, lot dispatching, batching strategies, fab loading will be supported by simulation. This will improve overall fab performance.

CY: These new developments in DES have the potential to significantly transform the semiconductor industry by changing the way factories operate, how decisions are made, and how risks are managed across the value chain. First, the integration of AI into simulation models and the rise of self-adaptive digital twins will enable real-time, data-driven decision making with unprecedented speed and precision (Khemiri et al. 2021). Instead of relying on static rules or historical averages, factories will be able to continuously simulate hundreds of evolving scenarios in the background, dynamically adjusting lot release policies, tool scheduling, and maintenance strategies—even in complex, re-entrant, and highly variable environments (Barhebwa-Mushamuka et al. 2019). This advancement will boost responsiveness, throughput, and cycle time control. As DES grows more intelligent and autonomous, engineers will be freed from routine model maintenance and can focus more on strategic problem-solving.

At the strategic level, DES will empower semiconductor firms to build robust and sustainable operations, allowing accurate modeling of trade-offs involving sustainability, supply chain disruptions, and capital investment decisions (Chien et al. 2011). DES is poised to become a core instrument for enterprise-wide planning, able to simulate the global ripple effects of shifts in market demand, policy, or technology (Fowler et al. 2015). Moreover, as simulation tools become more accessible thanks to natural language interfaces and no-code development platforms DES will expand its reach beyond technical experts. It will enable cross-functional teams to engage with simulation for decision making and innovation, ultimately driving faster collaboration and broader adoption across the organization.

3.3 What role will simulation play in shaping the education and training of future generations of scientists, engineers, and decision-makers?

JF: Simulation can be used to familiarize people with a specific domain and the potential impact of decisions made in that domain. The classic example of this is the computer game Sim City which was originally developed as a tool to help city managers/officials to understand the complexities of a modern city and the challenges faced by those people. The semiconductor industry is complex and a "game" that facilitates learning about the semiconductor ecosystem will allow participants to be better equipped to tackle industry challenges.

YJJ: Simulation will play a pivotal role in shaping the education and training of future professionals in the semiconductor industry by enabling immersive, data-driven, and AI-integrated learning environments. Key developments include:

1. Virtual Environment-Based Training: Simulation platforms will serve as realistic, risk-free environments where students and professionals can experiment with complex fab systems, explore various "what-if" scenarios, and gain hands-on experience without the constraints of physical facilities. This approach will significantly enhance conceptual understanding, operational intuition, and systems-level thinking.
2. AI-enabled Education for Fab Design and Operations: Integrating simulation with AI will empower learners to interact with AI-driven tools that can propose design alternatives, optimize operational strategies, and adapt to feedback. This type of intelligent educational support system will train future

engineers and decision-makers not only to understand manufacturing systems, but also to collaborate with AI in optimizing them.

Overall, simulation will evolve from a passive teaching aid to an active, interactive educational platform, cultivating a new generation of professionals equipped with both theoretical knowledge and practical skills in digital manufacturing, intelligent automation, and decision science.

AK: DES will play a central role in preparing the next generation of problem-solvers — giving them the tools to visualize, test, and optimize complex systems in a risk-free, interactive, and engaging way. While today's simulation software tools still largely require expert skills, this will be eliminated in the future, and the simulation will become a powerful tool that does not require expertise. It will be operated using interactive and intuitive interfaces accompanied by 3D visualization capabilities and supported by additional capabilities such as live demos of 'what-if' experiments, enhancing engineering insights for design and execution of semiconductor manufacturing operations. In terms of decision making, this will be a consistent gradual process of transitioning from manual decision making to smart real-time event driven and fully automated decision making, via ML models with reinforcement learning (RL), supervised and corrected in the early phase, and gradually becoming superior and independent over time.

PL: The increasing usage of simulation for decision-making will help scientists, engineers, and decision-makers better understand not just what happens in the fab, but also why it happened and what are the associated implications, and what could possibly be done to address it and do better in the future.

Rather than just to be used for training of future generations of scientists, engineers and decision makers, high-fidelity simulation models will also be an important training ground for AI agents which, because this cannot be done in the real factory, can experiment with decisions and their resulting impact that have not appeared in historical data, allowing to significantly supplement training data sets to enable "learning from the future", even though it is only a simulated future.

LM: I expect that DES will also be used in the future to train engineers that are responsible for planning and control in semiconductor supply chains. DES will serve a risk-free laboratory environment. Moreover, I believe that DES will be used to emulate the base system and process of semiconductor supply chains. This will help to support the commissioning of large-scale planning and control systems in a fully automated situation (cf. Herding and Mönch 2022 for some initial steps towards a cloud-based cyber infrastructure). Ontologies will play an important role to automate the generation of the planning and corresponding simulation models (cf. Herding et al. 2025 for some initial steps towards this direction). As in the past, DES will continue to be important for illustrating the dynamics and stochasticity of production systems to students at universities.

OR: Simulation models were, are, and will be the sole modeling technology among all OR tools with the smallest math footprint. In addition, they lead to white-box models which can be understood, discussed, and validated by very heterogeneous groups of people. Due to these characteristics, it will stay the number one analysis tool for complex systems (such as semiconductor fabs) of future generations of scientists, engineers, and decision-makers.

GS: Simulation will be used to strengthen and prove concepts out of Factory Physics. Simulation will be used to illustrate the impact of different decision-making strategies in semiconductor manufacturing.

CY: Future generations of scientists, engineers, and decision-makers will receive education and training increasingly through simulation, especially in high-tech, complex sectors like semiconductor manufacturing. As manufacturing systems increasingly adopt automation, networking, and data-centric approaches, the capacity to model, simulate, and analyze complex systems will become as vital as programming or data analysis (Fowler et al. 2015). Simulation offers a dynamic, immersive, and secure educational environment for students to engage with authentic production scenarios—eliminating the risks and expenses linked to actual manufacturing. Through DES, learners can analyze the effects of decisions on critical performance metrics, including cycle time, utilization, bottlenecks, and throughput. This promotes the cultivation of systems thinking, an essential competency for comprehending the interrelations among machines, processes, resources, and policies (Werling et al. 2020). Secondly, educational curricula will progressively incorporate training on designing intelligent systems, validating simulation-based algorithms, and interpreting outputs for decision-support applications. This trend is propelled by the emergence of digital twins and AI-enhanced simulation environments (Khemiri et al. 2021). Moreover, simulation is important in interdisciplinary education, connecting fields such as data science, OR, engineering, and management. Simulation-based tools will be utilized in lifelong learning initiatives, including operator training, skill certification, and AI model testing in regulated virtual environments (Fowler and Rose 2004). In summary, simulation will function as both a professional field and an educational tool, fostering a new generation adept at constructing, optimizing, and overseeing the complex systems that will characterize the future industry.

4 CONCLUSIONS

Our group of expert semiconductor researchers and practitioners from around the world dealing with DES in their daily work provided their insights on the past and future of DES applications in the semiconductor manufacturing domain. This included their own experiences in applying DES and identifying some research direction and additional problems in the future that could benefit from the use of DES. They also discussed situation where the applicability of DES was limited in the past. A period of 50 years was considered, 25 years in the past, and 25 years into the future.

The discussion in this paper revealed that DES is notably successful among the different methods and techniques from IE, CS, and OR. It is expected by the panelists that AI, ML, and IoT will expand and broaden the possible application areas and the general applicability of DES in semiconductor supply chains. One important future area is the usage of DES principles in digital twins for semiconductor supply chains.

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