Proceedings of the 11th North American International Conference on Industrial Engineering and Operations Management, Milwaukee, Wisconsin, USA, June 9-11, 2026

Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/NA11.20260183
Published: June 9, 2026

Simulation as a Strategic Decision-Support Tool: A Review of Current Practices and Future Directions

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Abstract

Simulation modeling has become a cornerstone of decision support in complex industrial systems, offering a robust analytical foundation for evaluating alternative strategies, improving performance, and managing uncertainty without disrupting real-world operations. Over the past two decades, discrete-event simulation (DES) and its hybrid variants have played a central role in supporting operational planning, production scheduling, resource allocation, and logistics optimization. As manufacturing systems evolve toward Industry 4.0 paradigms—characterized by cyber-physical integration, real-time data exchange, and autonomous decision-making- the role of simulation is expanding rapidly. However, despite significant technological progress, the field remains fragmented, with many implementations confined to tactical decision contexts and limited in their adaptability to real-time, multi-objective, or strategic challenges. This review aims to synthesize the state of the art in simulation-based decision-support for industrial systems by classifying the current body of literature based on simulation type, application domain, decision level, and tool integration; identifying methodological innovations; highlighting key research gaps; and proposing a forward-looking research agenda to guide future scholarship and practice.

Keywords
Simulation modeling, Discrete-event simulation, Digital twin, Industry 4.0, Decision support.

1. Introduction
Simulation has become an indispensable decision-support mechanism across manufacturing, logistics, and supply chain operations. As global competition intensifies and production environments become increasingly dynamic, organizations face heightened pressures to make rapid, data-driven, and risk-informed decisions. Traditional planning methods, often deterministic, spreadsheet-based, and reliant on static assumptions, struggle to capture the complexity, uncertainty, and interdependencies that characterize modern industrial systems. In contrast, simulation provides a flexible, robust analytical foundation that enables decision-makers to explore system behavior, evaluate "what-if" scenarios, and anticipate the consequences of alternative strategies without disrupting live operations.

Over the past three decades, discrete-event simulation (DES) has emerged as the dominant modeling paradigm for representing queuing systems, material flows, bottlenecks, and resource interactions. DES has proven particularly effective for tactical and operational planning decisions such as shift scheduling, layout optimization, capacity allocation, and bottleneck detection. In parallel, the simulation landscape has evolved considerably. Researchers increasingly adopt hybrid simulation approaches, combining DES with Agent-Based Modeling (ABM), System Dynamics (SD), meta-modeling techniques, and, more recently, reinforcement learning (RL).

Simulation has also become a core enabler of Industry 4.0. The emergence of digital twins, IoT-enabled sensing, data-driven predictive models, and cloud-based simulation platforms has expanded the role of simulation from offline analysis to real-time operational decision support. Despite these advances, the current body of knowledge remains fragmented and reveals several important limitations. Most existing studies are highly application-specific and lack generalizable frameworks or standardized methodologies for broader use. SMEs—despite representing the majority of global manufacturing—remain underrepresented in simulation research, mainly due to resource and skill barriers. Given the rapid acceleration of digital transformation and the growing demand for flexible, resilient, and sustainable operations, a comprehensive review of simulation as a decision-support tool is both timely and essential.

1.1 Objectives

The primary objective of this review is to critically evaluate how simulation modeling has been used to support operational and strategic decision-making in industrial systems, with particular emphasis on: discrete-event simulation (DES), hybrid simulation (DES with ABM, SD, or optimization), simulation-driven layout and capacity planning, integration of simulation with AI and digital twins, and simulation applications for continuous improvement and resilience. This review limits its scope to simulation studies that provide decision-support capabilities, whether through performance prediction, scenario evaluation, resource optimization, or policy testing.

2. Literature Review

Simulation has long served as a core analytical tool for modeling and evaluating complex manufacturing and supply chain systems. Within this domain, the literature reveals several dominant trends that characterize how simulation is applied as a decision-support mechanism. This review categorizes existing work into five main thematic areas.

2.1 Discrete-Event Simulation in Production and Capacity Planning

The most widely adopted simulation approach in industrial systems is DES, which models the flow of entities through queues, resources, and process stages. A substantial body of literature demonstrates DES's utility in modeling production lines, capacity constraints, machine availability, and process variability. For instance, studies have shown how DES can validate production plans, identify bottlenecks, and assess the impact of material variability on yield and inventory. Other works have applied DES in sector-specific contexts: optimizing door manufacturing shifts (Chronis et al. 2021), evaluating bottlenecks in container terminals (Rusca et al. 2018), and improving throughput in textile production (Silva et al. 2021). These case-based applications consistently demonstrate that DES enables practitioners to evaluate "what-if" scenarios, improve layout configurations, and reduce idle times, but are often limited to narrow operational scopes.

2.2 Hybrid Simulation for Complex and Stochastic Systems

While DES is effective for process-level modeling, it lacks the ability to capture feedback, adaptation, or emergent behavior. To address this, several researchers have explored hybrid simulation approaches that combine DES with other methods, such as Agent-Based Modeling (ABM), System Dynamics (SD), and analytical optimization. The review by Brailsford et al. (2019) further confirms the growing prevalence of hybrid approaches, citing the increasing use of DES–SD and DES–ABM models in operational research. These hybrid models expand simulation beyond system throughput to include adaptability, coordination, and long-term system evolution, though methodological complexity and validation challenges remain a concern.

2.3 Simulation for Layout, Flow, and Bottleneck Optimization

A recurring theme in the literature is the use of simulation for layout design and material flow optimization. Multiple studies have used tools such as Tecnomatix Plant Simulation, Arena, and Witness to model production layouts and test alternative configurations. Other research illustrates how combining Lean tools (e.g., VSM, Kaizen) with DES can inform layout changes, process redesign, and labor allocation.

2.4 Simulation Integrated with Optimization, AI, and Decision Analytics
The literature increasingly incorporates optimization techniques and artificial intelligence into simulation workflows to enhance decision quality and reduce the burden of scenario testing. More advanced integrations involve reinforcement learning (RL) and deep Q-networks to autonomously learn and refine scheduling decisions (Behrendt et al. 2020). The DMPG framework (Seipolt et al. 2024) pushes this integration further by enabling digital twin-reinforcement learning co-simulation, demonstrating strong potential for real-time decision-making.

2.5 Simulation in Real-Time and Digital Twin Environments
Recent contributions emphasize the shift from offline simulation to real-time, in situ simulation environments enabled by digital twins, IoT integration, and semantic modeling. In the Virtual Factory for In Situ Simulation (Terkaj et al. 2015), an ontology-based model is synchronized with live shop floor data to support short-term production and maintenance planning. The Digital Twin for Operational Efficiency (Fantozzi et al. 2025) uses simulation and machine learning to detect bottlenecks and test predictive maintenance strategies, achieving close alignment between simulated and real operational data.

3. Methodology
This review adopts a structured, thematic approach to synthesize the literature on simulation as a decision-support tool across production, operations, and supply chain contexts.

3.1 Thematic Classification Framework
The selected articles were categorized based on a five-dimensional framework, reflecting the evolving application and methodological depth of simulation in decision support: Simulation Type (Discrete-event, agent-based, system dynamics, hybrid), Application Domain (Production planning, layout design, supply chain, maintenance, scheduling), Integration with Other Tools (Optimization, AI/ML, VSM, digital twins), Decision Level (Operational, tactical, or strategic), and Real-Time/Static Use (Offline planning or real-time/live simulation).

3.2 Qualitative Analysis
Each article was analyzed for problem definition, methodology, validation approach, outcomes, and stated limitations. These factors were cross-compared to synthesize trends, identify methodological innovations, and highlight limitations across the body of literature.

3.3 Limitations
While this review is based on a comprehensive, thematically rich dataset, it is limited to studies captured in the original summarization matrix. Future expansions could involve a systematic literature review (SLR) using PRISMA guidelines, the inclusion of grey literature, and broader bibliometric analysis to enhance representativeness and generalizability.

4. Data Collection
4.1 Literature Identification Process
The reviewed studies were drawn from a curated summarization matrix of 82 peer-reviewed articles spanning academic journals, conference proceedings, and application-focused case studies. The original matrix was compiled using structured searches from reputable scholarly databases, including Scopus, Web of Science, ScienceDirect, IEEE Xplore, and SpringerLink.

4.2 Inclusion Criteria
To ensure focus and consistency, only studies meeting the following inclusion criteria were retained for this review: The study must explicitly use simulation modeling as a core methodology; it must be used to support operational or strategic decision-making; the application must involve industrial systems; studies must report quantitative outcomes or validation; and only English-language, peer-reviewed articles or case studies were considered. A total of more than thirty simulation-focused articles met these criteria.

Table 1: Studies classification of simulation-focused classified by simulation type, application domain, decision level, tool integration, and real-time use

Article ID	Simulation Type	Application Domain	Decision Level	Integrated with Other Tools	Real-Time or Offline
Article #1	Hybrid Simulation (Analytical + DES)	Production Planning (Garment/E-commerce)	Tactical	Yes	Offline
Article #2	Discrete-Event Simulation	Capacity Planning (Automotive Supplier)	Tactical	No	Offline
Article #3	Hierarchical Distributed Simulation	Distributed Assembly (Aerospace)	Strategic	Yes	Offline
Article #4	Stochastic Programming + Monte Carlo	Sawmill Yield Planning	Tactical	No	Offline
Article #6	LP + Simulation + Interactive Procedure	Aggregate Production Planning	Tactical	No	Offline
Article #10	VSM + DES	Production Scenario Investment Decision	Tactical	No	Offline
Article #12	Hybrid Simulation + Meta-Modeling	Paint Shop Optimization	Tactical	Yes	Offline
Article #13	DES (Tecnomatix)	Nail Production Logistics	Operational	No	Offline
Article #14	DES + VR (Review Study)	Industry 4.0 / Smart Factory Planning	Strategic	Yes	Real-Time Potential
Article #15	DES (Tecnomatix)	Bottleneck Analysis (Sanitary Sector)	Operational	No	Offline
Article #18	VSM + Simulation (ProModel)	Automotive Assembly Lean Transformation	Tactical	No	Offline
Article #21	Hybrid BPS (ABM + DES)	Sustainable PSS Design	Strategic	No	Offline
Article #27	Agent-Based Petri Net	Mine Production Target Feasibility	Operational	No	Offline
Article #30	DES + GA Optimization	Precast Component Scheduling	Tactical	Yes	Offline
Article #35	DES (Arena)	Container Terminal Performance	Operational	No	Offline
Article #36	Model-Linking Automation Framework	Production System Co-Simulation	Strategic	Yes	Offline
Article #37	Review (Hybrid Simulation)	Simulation Methodology	Strategic	Yes	Offline
Article #38	DES (Arena)	Spare Parts with AM vs. Warehousing	Strategic	No	Offline
Article #40	DES (Witness)	Assembly Line Layout Design	Operational	No	Offline
Article #42	DES + Deep Q-Network	Real-Time FJSP Scheduling	Operational	Yes	Real-Time
Article #47	DES (AnyLogic)	Door Manufacturing Shift Planning	Tactical	No	Offline
Article #48	DES (Arena)	Textile Material Flow Optimization	Operational	No	Offline
Article #54	DES (Arena)	Eyeglasses Production Scheduling	Operational	No	Offline
Article #58	Automated DT + Simulation	Production Layout Modeling	Operational	Yes	Real-Time Potential
Article #63	Custom Simulation + Line Balancing	Apparel Assembly Line	Operational	No	Offline
Article #67	DES + Reinforcement Learning	Production Scheduling Framework	Operational	Yes	Real-Time

Article #72	Digital Twin (Tecnomatix)	Production Line Bottleneck & OEE	Tactical	Yes	Real-Time
Article #9	Ontology-Based DES	Virtual Factory for Maintenance Planning	Operational	Yes	Real-Time

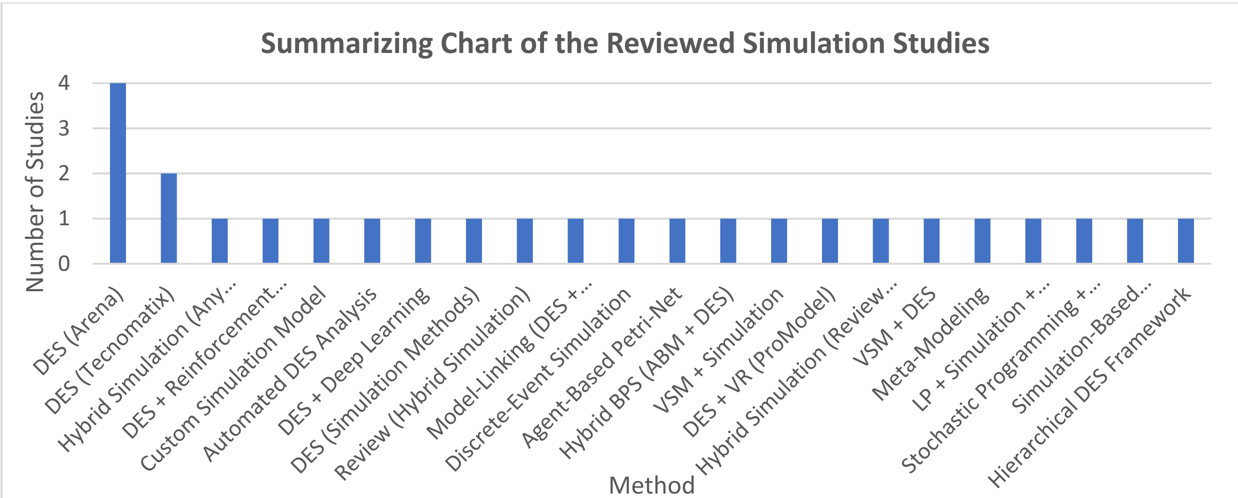

Figure 1: Shows the dominance of discrete-event and hybrid simulation methods.

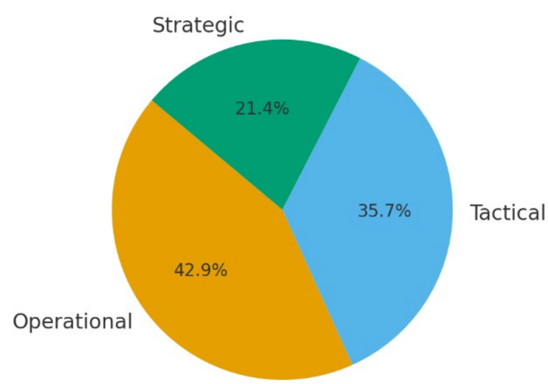

Figure 2: Most studies support operational and tactical decisions, with fewer targeting strategic decisions.

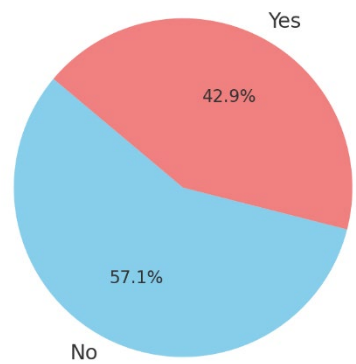

Figure 3: Nearly half of the studies integrate simulation with AI, optimization, or digital tools.

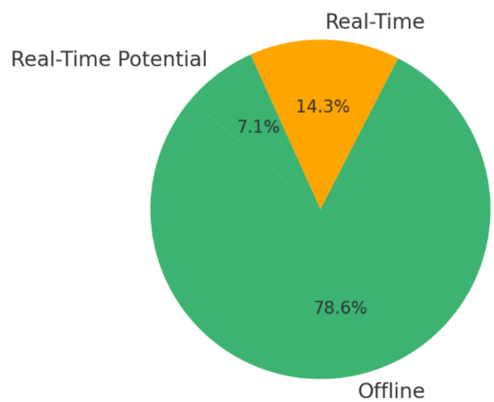

Figure 4: The majority of simulations are still offline; real-time or digital-twin integration remains emerging.

Table 2: This is the citation-mapping table, showing each reviewed article's ID, shortened title, simulation type, application domain, and decision level.

Article ID	Short Title	Simulation Type	Application Domain	Decision Level
Article #1	Hybrid for E-Com Planning	Hybrid Simulation (Analytical + DES)	Production Planning (Garment/E-commerce)	Tactical
Article #2	DES in Auto Supplier	Discrete-Event Simulation	Capacity Planning (Automotive Supplier)	Tactical
Article #3	Distributed Assembly Sim	Hierarchical Distributed Simulation	Distributed Assembly (Aerospace)	Strategic
Article #4	Stochastic Yield Planning	Stochastic Programming + Monte Carlo	Sawmill Yield Planning	Tactical
Article #6	Interactive APP Model	LP + Simulation + Interactive Procedure	Aggregate Production Planning	Tactical
Article #10	VSM + DES for Investment	VSM + DES	Production Scenario Investment Decision	Tactical
Article #12	Hybrid Paint Shop Model	Hybrid Simulation + Meta-Modeling	Paint Shop Optimization	Tactical
Article #13	DES for Logistics Flow	DES (Tecnomatix)	Nail Production Logistics	Operational

Article #14	DES + VR Smart Factory	DES + VR (Review Study)	Industry 4.0 / Smart Factory Planning	Strategic
Article #15	Tecnomatix Bottleneck ID	DES (Tecnomatix)	Bottleneck Analysis (Sanitary Sector)	Operational
Article #18	VSM Lean Auto Assembly	VSM + Simulation (ProModel)	Automotive Assembly Lean Transformation	Tactical
Article #21	Hybrid for PSS Design	Hybrid BPS (ABM + DES)	Sustainable PSS Design	Strategic
Article #27	Mine Planning (ABPN)	Agent-Based Petri Net	Mine Production Target Feasibility	Operational
Article #30	GA-DES for Precast	DES + GA Optimization	Precast Component Scheduling	Tactical
Article #35	Container Terminal DES	DES (Arena)	Container Terminal Performance	Operational
Article #36	Automated Model Linking	Model-Linking Automation Framework	Production System Co-Simulation	Strategic
Article #37	Hybrid Sim Review	Review (Hybrid Simulation)	Simulation Methodology	Strategic
Article #38	DES for Spare Parts	DES (Arena)	Spare Parts with AM vs. Warehousing	Strategic
Article #40	Layout Optimization DES	DES (Witness)	Assembly Line Layout Design	Operational
Article #42	RL-DES Job Shop	DES + Deep Q-Network	Real-Time FJSP Scheduling	Operational
Article #47	Shift Planning (Doors)	DES (AnyLogic)	Door Manufacturing Shift Planning	Tactical
Article #48	Textile Flow Optimization	DES (Arena)	Textile Material Flow Optimization	Operational
Article #54	Eyeglass Scheduling	DES (Arena)	Eyeglasses Production Scheduling	Operational
Article #58	Auto DT Layout Creation	Automated DT + Simulation	Production Layout Modeling	Operational
Article #63	Apparel Line Balancing	Custom Simulation + Line Balancing	Apparel Assembly Line	Operational
Article #67	DMPG RL Framework	DES + Reinforcement Learning	Production Scheduling Framework	Operational
Article #72	DT for OEE Optimization	Digital Twin (Tecnomatix)	Production Line Bottleneck & OEE	Tactical
Article #9	Virtual Factory DES	Ontology-Based DES	Virtual Factory for Maintenance Planning	Operational

5. Results and Discussion

While the literature demonstrates a wide range of simulation applications for supporting decision-making, several critical gaps persist. Most simulation studies are still used for periodic planning rather than continuous, in situ decision-making. The opportunity exists to develop scalable frameworks for real-time, data-driven simulation that enable dynamic re-planning.

Current models often neglect the need to balance multiple conflicting performance indicators, demonstrating a lack of structured methodology for combining modeling paradigms. Furthermore, a significant portion of the global manufacturing ecosystem remains excluded from the benefits of simulation due to cost, complexity, and capability barriers. AI use in simulation is nascent and often disconnected from real-time operations or management dashboards. Collectively, these gaps reveal that while simulation has matured as a tactical decision-support tool, it has yet to fulfill its full potential as a strategic, intelligent, and inclusive platform.

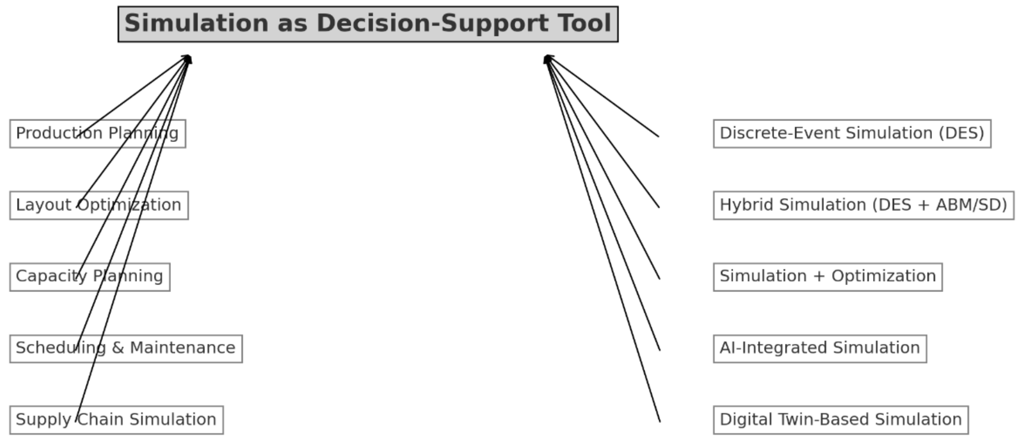

Figure 5: Visual conceptual framework illustrating.

6. **Conclusion**

The modern STEM landscape calls for an unprecedented level of agility. This research reveals the severe "Category Mismatch" between academic syllabi and job market requirements, confirming that the true premium in the entry-level job market lies in immediate technical application and dynamic communication. The primary objectives of this research—to systematically quantify this skill gap through a comparative content analysis and establish the foundational framework for an automated 9-layer Curriculum Intelligence Platform—have been successfully met. A unique research contribution of this work is the proven Keyword Grouping framework that definitively uncovers this "Category Mismatch" between theoretical academic instruction and practical workforce demands. By moving our proven framework into the scalable Curriculum Intelligence Platform, we provide higher education institutions with an intelligent, data-driven system that explicitly explains how and why education must evolve based on real-time labor market intelligence, guaranteeing that future graduates are completely equipped for the 21st-century workforce.

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Biographies

Sana Bhimani is a graduate of SAU and currently works at SAUTech as an instructor for Data Science and Administrative Specialist III. Her academic and professional focus centers on Data Science, STEM, and workforce readiness. Her academic and professional focus centers on Data Science, STEM education, and workforce readiness. Dedicated to bridging the gap between academic preparation and industry demands, she has successfully completed a previous research project in collaboration with Dr. Hayder Zhgair titled "Simulation as a Strategic Decision-Support Tool: A Review of Current Practices and Future Directions." Currently, she is partnering with Dr. Zhgair and Seema Powar on an ongoing study to systematically quantify and evaluate the specific misalignment between higher education STEM syllabi and entry-level workforce expectations. Through her instruction and collaborative research across both SAUTech and SAU, she aims to provide higher education institutions with actionable, data-driven frameworks to effectively integrate market-driven tools into theoretical curricula.

Dr. Hayder Zghair is an Assistant Professor of Industrial Engineering and the Director of Industrial Engineering Development at Southern Arkansas University (SAU). He earned his Ph.D. and M.S. in Manufacturing Systems Engineering from Lawrence Technological University, alongside a B.S. and M.S. in Industrial and Production Engineering from the University of Technology. Before joining SAU, he served as an Assistant Teaching Professor at Pennsylvania State University and a lecturer at Kettering University. Dr. Zghair's research encompasses Flexible-Automated Manufacturing, Robotics, Sustainability Engineering, Analytical Modeling, Simulation, Optimization, and Industry 4.0/5.0 technologies like AI and IIoT. Currently, he is collaborating with Sana Bhimani and Seema Powar to investigate the STEM skills gap and to develop analytical frameworks to align academic curricula with entry-level workforce demands. An active leader in the engineering community, he serves on the Board of Directors for the ASEE Environmental Engineering Division and is an Affiliate Researcher at the Penn State Institute of Energy and the Environment. He holds professional memberships in ASEE, INFORMS, SAE, and IEOM, and actively mentors students as the faculty advisor for the SAE, SAU Baja, and IEOM student chapters at SAU.