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HYBRID DISCRETE-EVENT AND AGENT-BASED SIMULATION FRAMEWORK (H-DEABSF) FOR DYNAMIC PROCESS CONTROL IN SMART FACTORIES

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Abstract

This paper introduces a Hybrid Discrete-Event and Agent-Based Simulation Framework (H-DEABSF) designed for dynamic process control in smart factories. The framework integrates the advantages of discrete-event simulation (DES)—noted for its efficiency in modeling system flows and queues—with the adaptability and autonomy of agent-based simulation (ABS), which captures decentralized decision-making and interactions among heterogeneous entities. By combining these paradigms, the H-DEABSF addresses the limitations of each when applied in isolation, enabling both macroscopic process optimization and microscopic behavior modeling. The proposed framework is specifically developed to support the evolving needs of Industry 4.0, where factories must continuously adapt to fluctuating demand, real-time disruptions, and resource constraints. It leverages smart sensors, IoT-enabled devices, and cyber-physical systems to feed real-time data into the hybrid model, ensuring that simulations reflect operational realities. Through dynamic control loops, the H-DEABSF facilitates adaptive scheduling, predictive maintenance, and production-line reconfiguration, thereby enhancing responsiveness and resilience. A case study in a digital twin–enabled smart factory environment demonstrates the applicability of H-DEABSF for dynamic production scheduling under stochastic conditions. The results show improvements in system throughput, reduction of idle time, and optimized allocation of resources when compared to conventional single-method simulation models. Furthermore, the integration of human operators as autonomous agents highlights the framework's ability to capture socio-technical interactions critical in real-world factory operations. This research contributes to the field of smart manufacturing by providing a comprehensive simulation framework that enhances real-time decision-making and supports sustainable operational strategies. It also offers an extensible platform for future integration with machine learning algorithms, enabling data-driven decision support for next-generation intelligent factories.

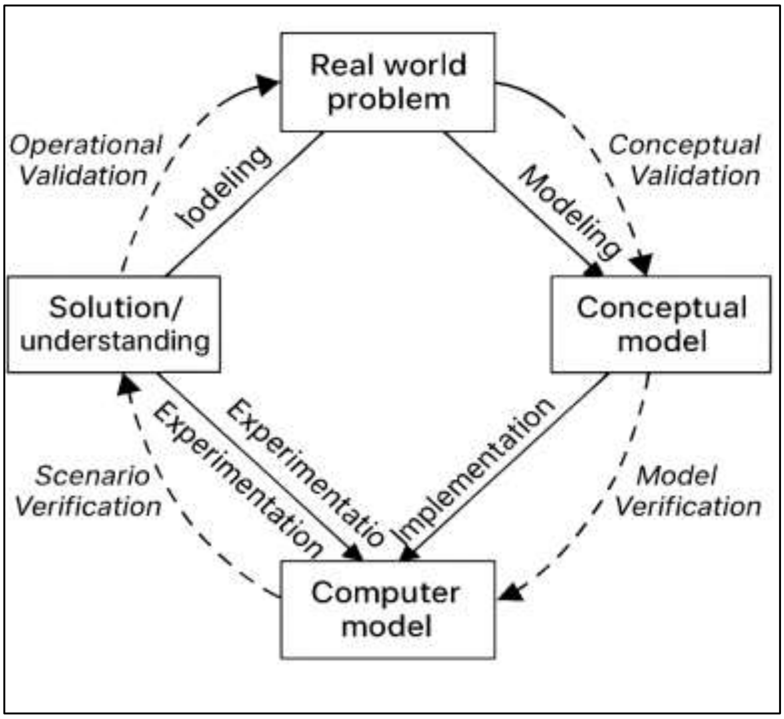
Keywords

Hybrid Simulation; Discrete-Event Simulation (DES); Agent-Based Simulation (ABS); Smart Factory; Dynamic Process Control;

INTRODUCTION

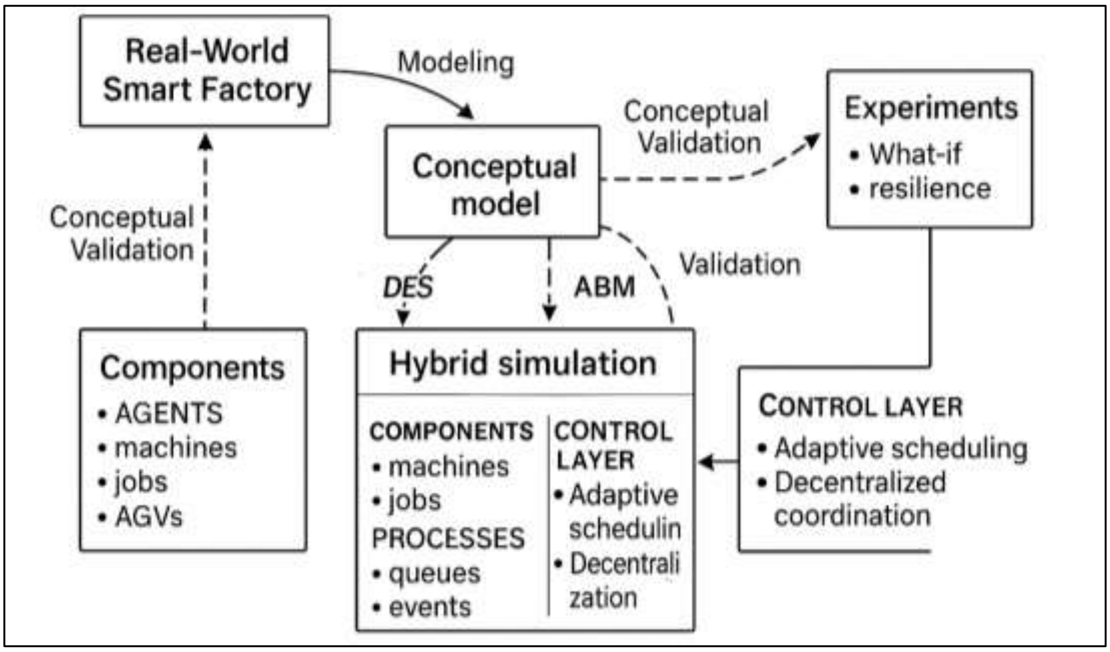
The concept of hybrid simulation arises from the recognition that no single modeling paradigm suffices to represent the full complexity of many real-world systems, especially in socio-technical or industrial contexts. In the modeling & simulation (M&S) community, hybrid simulation is broadly understood as an approach that integrates two or more of the principal simulation paradigms—namely, *discrete-event simulation (DES)*, *agent-based modeling (ABM/ABS)*, and *system dynamics (SD)*—within a single cohesive framework (Liu & Wu, 2014). The power of this amalgamation lies in combining the strengths of each paradigm to represent different levels of abstraction or dynamics: DES captures event-driven, queueing, and resource-utilization dynamics; ABM models individual entities' autonomy and interactions; and SD represents aggregated continuous flows or feedback loops. Hybrid methods have seen near-exponential growth over the last two decades, both in the academic literature and in applied domains (Mustafee et al., 2021). The editorial on hybrid modelling and simulation emphasizes that rapidly increasing system complexity in domains like manufacturing, healthcare, transportation, and social systems has driven adoption of multimethod approaches (Badakhshan & Ball, 2023). Within this spectrum, hybrid DES–ABS (or DES–ABM) is especially relevant when one must capture both process flows (queues, timing, resource contention) and localized agent behaviors or decision logic.

Figure 1: Modeling and Simulation Validation Framework



To situate hybrid DES–ABS in the domain of smart manufacturing or Industry 4.0, it is necessary to define key terms. *Discrete-event simulation (DES)* models the state of a system as changing at discrete instants—events—that instantaneously transition the system from one state to another (Jaenichen et al., 2022; Rezaul, 2021). DES is particularly adept at capturing queuing delays, machine breakdowns, job routing, resource constraints, and workflow in manufacturing or logistics settings (Danish & Zafor, 2022; Gutierrez-Franco et al., 2021). *Agent-based simulation (ABS)*, by contrast, models individual entities (agents) that carry state, execute behavior rules, perceive their environment, and interact with each other and the environment over time. Agents can adapt, learn, and generate emergent patterns not directly coded into the model—useful in modeling human operators, decision logic, decentralized scheduling, or cooperative behaviors. A hybrid DES–ABS approach thus allows process flows (the macro view) and agent behaviors (the micro view) to co-exist and interact, which is precisely the dual need in advanced manufacturing control. Several authors have underscored that DES alone may not capture adaptive decision making or resilience under disturbances, while ABS alone may struggle with representing high-volume process flows efficiently (Danish & Kamrul, 2022; Mustafee et al., 2021).

Figure 2: Hybrid DES-ABS Modelling Framework for Smart Factories



In the context of smart factories, the term implies a cyber-physical environment where manufacturing systems are instrumented, networked, and capable of adaptive control, self-optimization, and decentralized coordination. Smart factories are a core element of Industry 4.0, which emphasizes connectivity, real-time data, digital twins, reconfigurability, and autonomy (Jahid, 2022; Swinerd & McNaught, 2012). Simulation technologies are central to designing, controlling, and validating such systems. A recent survey on simulation in Industry 4.0 identified ten simulation approaches deployed across smart manufacturing contexts, pointing out that hybrid and multi-method simulation can capture interactions between infrastructure, agents, processes, and control logic (Ismail, 2022; Vázquez-Serrano et al., 2021). In manufacturing, DES remains perhaps the most applied simulation methodology, due to its maturity, tool support, and direct fit to process models (Gutierrez-Franco et al., 2021; Hossen & Atiqur, 2022). However, DES models often assume static control rules or fixed scheduling, which constrains their ability to represent real-time adaptation or agent negotiation. On the other hand, agent-based and hybrid frameworks allow more flexible, decentralized decision schemes embedded within process flows, enabling richer experiments on resilience, scheduling adaptation, and resource collaboration ((Kamrul & Omar, 2022; Swinerd & McNaught, 2012).

Among published studies applying hybrid DES–ABS to manufacturing or reconfigurable systems, several foundational works stand out. (Roozkhosh et al., 2022) present a modeling framework for reconfigurable manufacturing systems by hybridizing discrete-event and agent-based simulation, examining emergent behaviors when system configurations change. Meanwhile, a modular hybrid simulation framework for complex manufacturing systems was proposed by a different research team to address static complexity and support resource planning. In reconfigurability studies, hybrid simulation has been used to explore the effect of structural modifications, agent coordination, and process adaptation. A framework for modeling reconfigurable manufacturing using hybrid ABS–DES is cited as a key example of representing both local agent decision logic and global process flows (Jaenichen et al., 2022; Razia, 2022). Other empirical works combine DES and agent modeling in scheduling, maintenance, and resource allocation—for example, integrating job agents with resource agents in flexible manufacturing systems (e.g., in hybrid DES–ABS applied to FMS). In broader hybrid simulation literature, methodological reviews note that combining DES and ABM is a common pattern in hybrid M&S, and one of the most tractable and applicable pairings (Sadia, 2022).

Methodological challenges and design patterns for hybrid DES–ABS have been studied in multiple works. Hybrid simulation modeling in operations research has been extensively reviewed, highlighting issues of synchronization, time management, state sharing, interface design, and scalability when combining paradigms. The editorial in the hybrid modelling domain underscores that hybrid approaches must address consistency, coupling, and performance issues in complex socio-technical systems (Danish, 2023; Wallentin & Neuwirth, 2017). In hybrid DES–ABS, synchronization between event scheduling (DES side) and agent steps (ABS side) demands careful selection of time advancement schemes or coupling mechanisms (e.g., cycle-based stepping, event triggers, or hybrid schedulers). (Tolk et al., 2020) introduce a novel DES extension in the MASON ABM platform to support hybrid models, demonstrating one path for integration. Hybridizing with system dynamics (SD) has also been proposed; though outside the pure DES–ABS boundary, these tri-paradigm hybrids offer instructive lessons about coupling strategies. Additional work compares output accuracy and representational fidelity between pure DES and hybrid DES–ABS in human-centric systems, which supports the view that hybrid models may yield better expressive richness without sacrificing process fidelity (Arif Uz & Elmoon, 2023; Hossain et al., 2023). Because dynamic process control in smart factories involves continuous and discrete disturbances, decentralized decision making, and real-time adaptation under uncertainty, a hybrid DES–ABS simulation framework is appealing. In manufacturing control, real-time updating of DES models based on streaming data (e.g. sensor feeds) has been explored (Hasan, 2023; Shoeb & Reduanul, 2023; Zhu et al., 2023), emphasizing the need for feedback loops and online decision logic. Incorporating agent logic into such models could enable intelligent controllers or distributed agents to adjust schedules, manage disturbances, or negotiate resource conflicts while still relying on accurate event simulation for throughput and queueing effects. Additionally, some hybrid digital twin frameworks combine discrete-event and continuous processes, sustaining the need for hybrid modeling in real operations. The adoption of AI in simulation, such as AI-assisted discrete-event simulation, further blurs boundaries between simulation control and agent logic (as in recent works integrating AI agents to construct DES models and analyze outputs) (Kolominsky-Rabas et al., 2015; Mubashir & Jahid, 2023; Razia, 2023). Thus, hybrid DES–ABS serves as a promising envelope within which dynamic control experiments, agent rationality, and process flows coexist.

The primary objective of this research is to develop and validate a Hybrid Discrete-Event and Agent-Based Simulation Framework (H-DEABSF) that addresses the challenges of dynamic process control in smart factory environments. The framework aims to provide a comprehensive modeling approach that integrates the structured, event-driven strengths of discrete-event simulation with the adaptive, autonomous, and decentralized decision-making capabilities of agent-based simulation. The overarching goal is to establish a simulation platform that accurately reflects the complex interplay between macro-level system flows and micro-level agent behaviors, thereby enabling more robust experimentation with control strategies, production scheduling, and resource allocation. A key objective is to create a modeling environment that can incorporate real-time data streams, digital twin integration, and feedback loops, ensuring that the simulation outcomes are not static projections but dynamic reflections of ongoing operational realities. This research seeks to demonstrate that such a hybrid framework can support adaptive scheduling mechanisms, predictive maintenance routines, and rapid reconfiguration of production lines in response to disruptions or demand fluctuations. Another core objective is to capture the role of human operators, intelligent machines, and cyber-physical systems as autonomous agents within the model, allowing for analysis of socio-technical interactions that directly impact factory performance. By constructing and evaluating a case study within a smart factory context, the framework is further intended to show measurable improvements in throughput, reduction of idle time, and optimization of resource distribution when compared to conventional single-method simulation models. Beyond technical validation, an additional objective is to provide an extensible methodological foundation that practitioners and researchers can adapt across different industrial sectors where dynamic process control is essential. Through these objectives, the study seeks to contribute to the advancement of simulation methodologies aligned with the operational demands of Industry 4.0, offering a structured pathway for modeling, analyzing, and improving the adaptability and resilience of smart manufacturing systems.

LITERATURE REVIEW

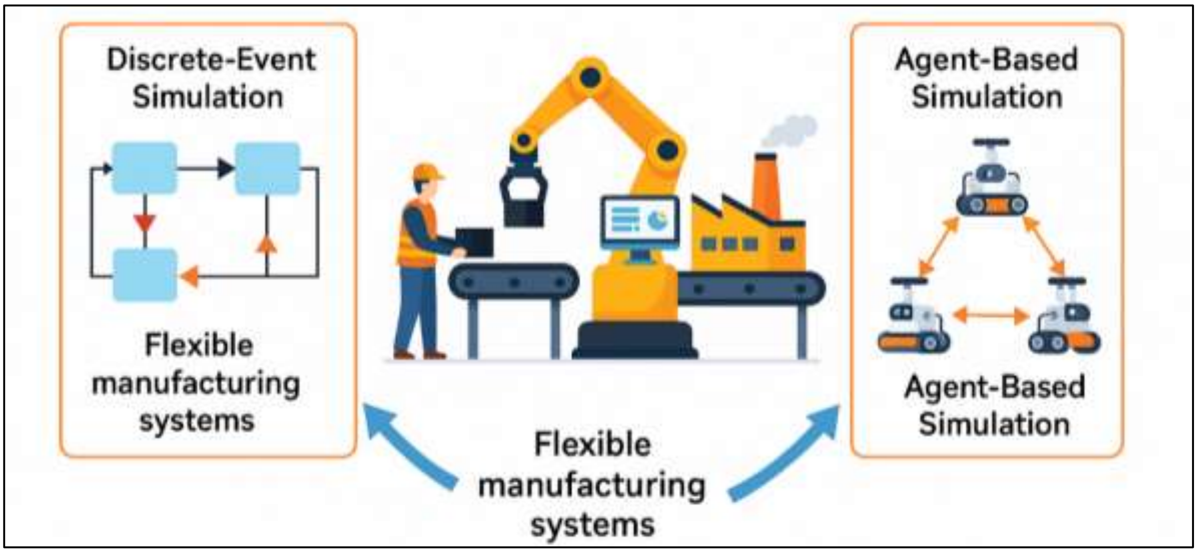
The literature on simulation methodologies in manufacturing and industrial systems has expanded significantly with the advent of Industry 4.0 and smart factories, where adaptability, autonomy, and resilience are critical. Traditional approaches such as Discrete-Event Simulation (DES) have long been applied to model production flows, scheduling, and resource utilization in manufacturing environments. However, these methods alone often lack the flexibility to capture the heterogeneous behaviors of autonomous entities, including machines, cyber-physical systems, and human operators. To bridge this gap, Agent-Based Simulation (ABS) has been increasingly introduced, offering the capacity to represent decentralized decision-making and emergent behaviors. Yet, ABS by itself can be inefficient in handling large-scale process flows or queue-based dynamics that characterize factory operations. These limitations have led to the development of hybrid frameworks that combine DES and ABS, bringing together the structured efficiency of DES and the adaptability of ABS to form a more powerful simulation approach.Within this context, scholars have proposed hybrid models for a variety of applications, including flexible manufacturing systems, reconfigurable production lines, adaptive scheduling mechanisms, and real-time process control. The evolution of these methods demonstrates not only the technical value of hybrid simulation but also its growing relevance in addressing the complexities of smart factory ecosystems, where dynamic data, machine connectivity, and human–machine collaboration create environments beyond the scope of single-method simulation. This literature review is organized thematically to provide a structured understanding of foundational concepts, technological advancements, integration challenges, and applications of hybrid DES–ABS approaches. The objective is to critically examine prior research, highlight methodological contributions, and identify research gaps that establish the rationale for the proposed H-DEABSF.

Simulation in Manufacturing Systems

Simulation has become a central methodological tool in manufacturing systems research due to its ability to represent complex processes, variability, and stochastic behaviors without disrupting real operations. Discrete-Event Simulation (DES) has historically been the most widely adopted approach, enabling researchers and practitioners to examine system performance in terms of throughput, resource utilization, and waiting times (Badakhshan et al., 2022). DES models have been extensively applied to production scheduling, bottleneck analysis, and system design in a variety of industrial contexts. Their advantage lies in handling queuing dynamics and resource interactions with precision, making them suitable for manufacturing environments characterized by sequential processes and event-driven dynamics. However, critics note that DES often assumes centralized decision-making and static logic, which limits its ability to capture adaptive human or machine behaviors in dynamic contexts. In contrast, System Dynamics (SD), although less common in shop-floor modeling, has been employed to capture aggregated flows and feedback loops at higher levels of abstraction (Kolominsky-Rabas et al., 2015). The comparison between DES and SD in manufacturing highlights the strengths of DES for micro-level operations and SD for strategic-level planning, demonstrating that each paradigm serves different layers of manufacturing analysis. These foundational insights have established simulation as a powerful tool for analyzing industrial systems under both deterministic and stochastic conditions, while revealing the limitations of single-paradigm approaches when applied to complex, adaptive environments.

The increasing complexity of manufacturing processes and the emergence of flexible and reconfigurable production systems have elevated the role of simulation in evaluating adaptability, resilience, and scalability. DES has been utilized to model machine breakdowns, process variability, and job routing strategies in flexible manufacturing systems (FMS) (Paul et al., 2010; Reduanul, 2023; Sadia, 2023). Studies have demonstrated its capacity to test alternative scheduling policies and capacity-expansion scenarios, showing measurable improvements in performance outcomes. However, traditional DES models often overlook decentralized decision-making mechanisms inherent in modern smart factories. To address this, researchers have incorporated Agent-Based Simulation (ABS), which allows autonomous entities—such as machines, operators, and robotic agents—to interact and adapt in real time. ABS excels in capturing heterogeneity and emergent behavior, as shown in studies modeling workforce collaboration, resource negotiation, and machine-to-machine communication in production lines (Bonabeau, 2002; Danish & Zafor, 2024; Jahid, 2024a). Empirical applications indicate that ABS can replicate dynamic reconfigurations that DES alone cannot achieve, especially in environments requiring self-organization. Comparative research has reinforced that ABS provides richer insights into socio-technical systems, while DES retains superior efficiency in handling large-scale event-driven workflows (Yousefi & Ferreira, 2017). This duality underscores the complementary nature of simulation paradigms, suggesting the necessity of integrating multiple approaches for accurate representation of modern manufacturing complexity.

Figure 3: Simulation in Manufacturing Systems

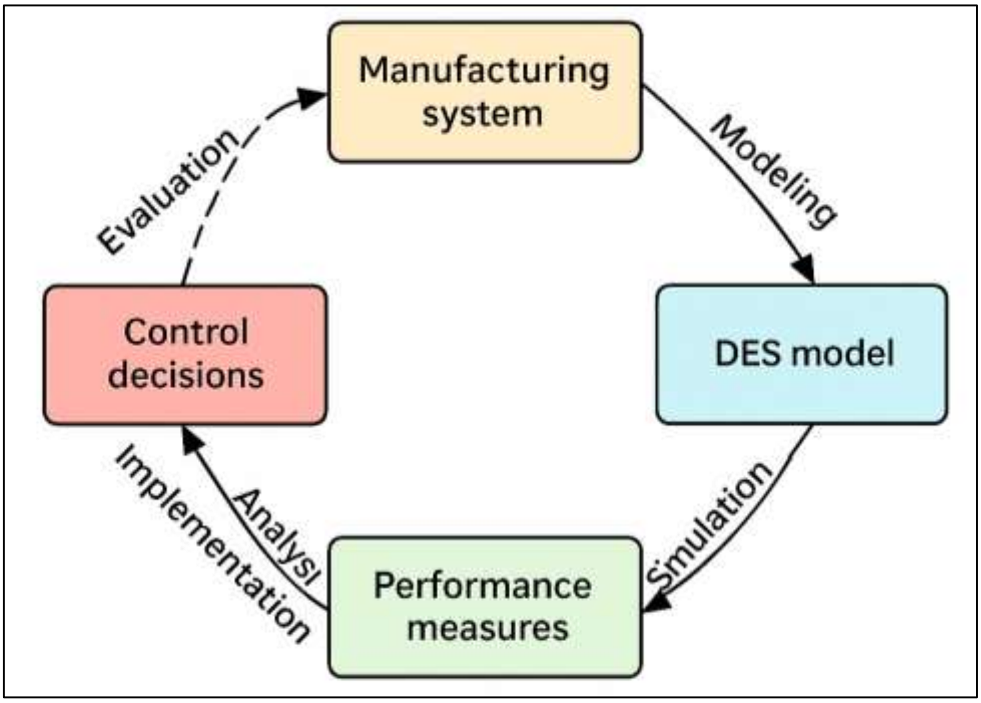


Discrete-Event Simulation in Manufacturing Control

Discrete-Event Simulation (DES) has been one of the most widely employed methods for analyzing and optimizing manufacturing control due to its ability to replicate the stochastic and event-driven nature of production systems. At its core, DES models capture the state of a system as it evolves through discrete changes triggered by events such as machine failures, order arrivals, and job completions (Assad et al., 2019). Its strength lies in providing detailed analysis of queuing dynamics, resource utilization, and system bottlenecks under varying operating conditions (Xiong et al., 2022). Numerous applications demonstrate DES as a vital decision-support tool for evaluating scheduling policies, shop-floor layouts, and machine allocation strategies. For example, in flexible manufacturing environments, DES has been used to assess throughput under varying demand profiles, identifying optimal sequencing and batch sizes. Research further highlights its utility in reducing production lead times and improving overall system performance in both small-scale and large-scale manufacturing operations (Jahid, 2024b; Ismail, 2024; Mustafee et al., 2021). Despite its dominance in manufacturing modeling, critiques note that DES often emphasizes efficiency and productivity metrics, while underrepresenting adaptive behaviors of workers, machines, or autonomous systems. Nevertheless, the method's enduring relevance underscores its foundational role in manufacturing control research.
The application of DES in production scheduling and control has been particularly influential, enabling manufacturers to test strategies in virtual environments before implementation. Simulation experiments using DES have been widely reported to optimize job-shop scheduling, flow-shop sequencing, and dynamic allocation of machines and labor. DES has been integrated into studies of just-in-time (JIT) systems, kanban-based scheduling, and lean manufacturing practices, where it provides insight into variability impacts and process synchronization (Assad et al., 2019; Mesbaul, 2024; Md Omar, 2024). Studies demonstrate how DES captures variability in order arrivals, processing times, and setup requirements, offering valuable tools for analyzing robustness of control policies under uncertainty ((Fellah et al., 2021; Rezaul & Hossen, 2024; Momena & Sai Praveen, 2024). In semiconductor and electronics manufacturing, DES models have been developed to address high product mix and rapid changeover challenges, where results revealed improvements in utilization and reduction in work-in-process inventory. In addition, empirical studies on automotive manufacturing

show how DES can assess bottleneck relief strategies and sequencing optimization across complex assembly lines. These applications illustrate that DES not only provides performance insights but also contributes to enhancing reliability and cost-effectiveness in manufacturing control systems where experimentation with physical processes is impractical. Beyond scheduling, DES has been extensively used for system performance evaluation and bottleneck analysis, offering quantitative support for control decisions in dynamic production environments. Simulation-based bottleneck detection has been reported to significantly improve cycle times, throughput rates, and system responsiveness (Muhammad, 2024; Saleh et al., 2019; Noor et al., 2024).

Figure 4: Discrete-Event Simulation in Manufacturing Control



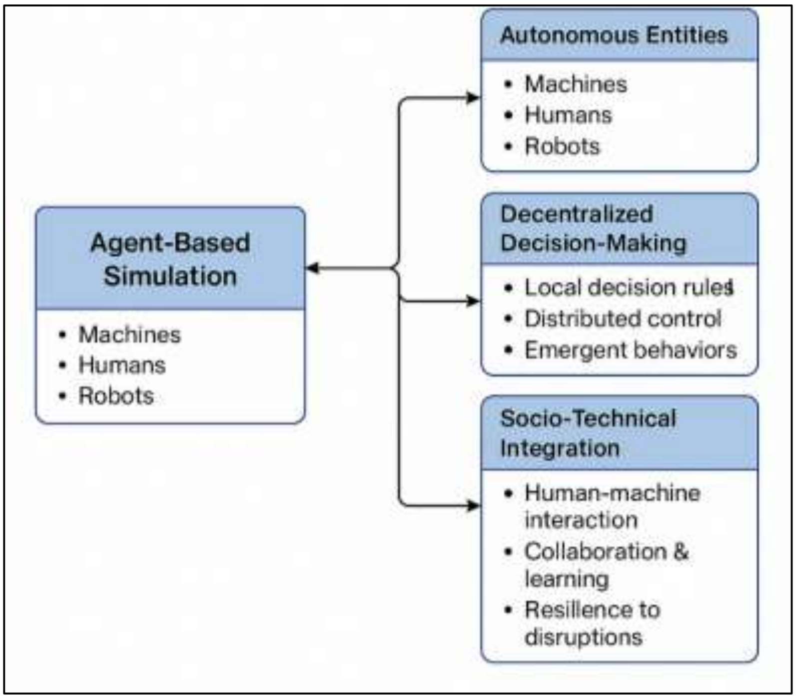
In assembly systems, DES has revealed how workstation sequencing and buffer sizing affect overall productivity, allowing more accurate predictions of system capacity. Research also indicates that DES is effective in comparing push- versus pull-based control mechanisms, showing advantages in terms of inventory stability and responsiveness. Studies in reconfigurable manufacturing demonstrate that DES facilitates evaluation of structural flexibility by modeling alternative system configurations and analyzing their impact on throughput and resource utilization. Applications in the pharmaceutical and process industries further reinforce DES's versatility, where it has been applied to evaluate batch production strategies and compliance with regulatory constraints (Stoldt et al., 2016). Collectively, these studies affirm DES as a cornerstone of manufacturing control research by providing a rigorous means of measuring performance outcomes under variable operational conditions.

Agent-Based Simulation in Smart Manufacturing

Agent-Based Simulation (ABS) has emerged as a powerful methodology in smart manufacturing due to its capacity to model autonomous entities, decentralized decision-making, and emergent behaviors. Unlike discrete-event simulation, which is primarily process-oriented, ABS focuses on the interactions of individual agents—such as machines, human operators, robots, or cyber-physical systems—each endowed with local decision rules and adaptive behaviors (Zhu et al., 2023). This paradigm is particularly relevant in smart factories, where multiple heterogeneous actors operate concurrently under distributed control schemes. Early studies demonstrated the effectiveness of ABS in modeling workforce behavior and decision-making on the shop floor, capturing dynamics such as cooperation, competition, and learning (Zhu et al., 2023). In manufacturing contexts with high complexity and uncertainty, ABS provides a means to replicate emergent system performance resulting from localized interactions rather than centrally imposed logic. Researchers have applied ABS to model negotiation among machine agents for resource allocation, dynamic response to disruptions, and adaptive scheduling mechanisms. By capturing heterogeneity and autonomy, ABS enables analysis of how micro-level decision rules impact macro-level system outcomes in smart factories, offering insights into resilience, adaptability, and operational efficiency.

Applications of ABS in manufacturing extend across flexible and reconfigurable production systems, where autonomy and adaptability are critical. Studies demonstrate that ABS can replicate machine-to-machine and human-machine interactions in environments where resources must be dynamically reallocated in response to changing demands (Stephenson et al., 2020). For example, ABS models have been used to evaluate reconfigurable manufacturing systems, where agents represent machines with varying capabilities that negotiate tasks under stochastic demand conditions. In the context of supply chains, ABS has been adopted to represent decentralized actors coordinating production and logistics under variable lead times and disruptions. Empirical research highlights that ABS is particularly suitable for capturing emergent patterns, such as the formation of bottlenecks due to localized decision-making or the stabilization of flows through cooperative negotiation. Furthermore, ABS provides a methodological advantage in studying reconfigurable production lines where modularity and scalability influence system performance, enabling detailed exploration of how autonomous decisions affect throughput and resource utilization (Liu et al., 2011). These studies collectively demonstrate that ABS enriches the understanding of manufacturing control by reflecting decentralized, adaptive, and emergent characteristics inherent in smart factory systems.

Figure 5: Agent-Based Simulation in Smart Manufacturing

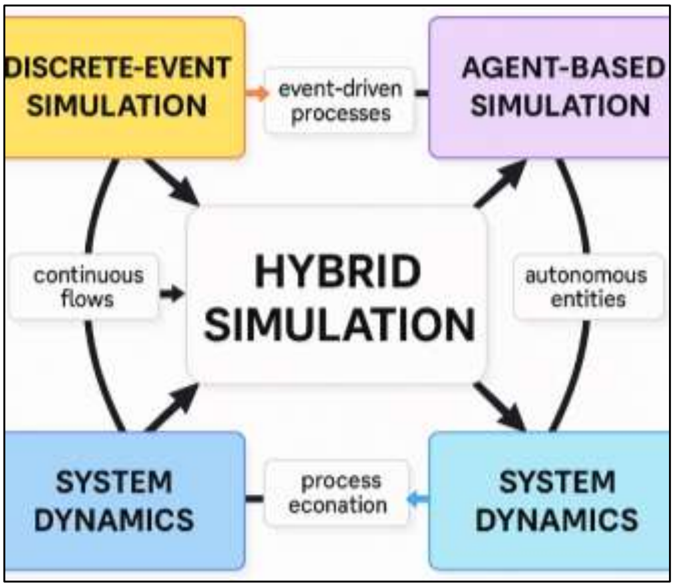


Another major area of research emphasizes the use of ABS in human-centric and socio-technical dimensions of smart manufacturing, where human operators act as autonomous agents interacting with machines, robots, and digital systems. Studies have shown that ABS can effectively represent operator decision-making, collaboration, and learning, offering a more realistic depiction of factory operations compared to process-driven models (Kitchin & Baber, 2015). Research on workforce scheduling demonstrates how ABS can simulate absenteeism, fatigue, or skill variations, which significantly influence overall system performance. In collaborative robotics, ABS has been applied to study human-robot interaction, focusing on safety, workload balancing, and decision sharing in production lines. The methodology has also been instrumental in modeling socio-technical resilience, where the interaction of humans and machines determines the ability of a factory to absorb disturbances and maintain productivity (Lohmer et al., 2020). ABS provides a means of testing alternative configurations of human involvement, highlighting how operator autonomy and adaptability influence throughput, quality, and system stability. These contributions reinforce ABS as a vital tool for capturing the complexity of human-machine collaboration in Industry 4.0 environments. Research further demonstrates the integration of ABS with cyber-physical systems, digital twins, and intelligent decision-support technologies to enhance its application in smart manufacturing. ABS has been used in conjunction with IoT-enabled devices to simulate decentralized decision-making based on real-time sensor data, creating models that reflect cyber-physical dynamics with higher fidelity (Nguyen et al., 2024). Studies integrating ABS into digital twin frameworks illustrate how agent-based models can serve as adaptive layers for predictive maintenance, fault detection, and dynamic reconfiguration (Jo et al., 2015). In addition, ABS has been coupled with optimization algorithms such as genetic algorithms and reinforcement learning to support adaptive scheduling and resource allocation. Applications in logistics and supply chains highlight how ABS captures decentralized coordination among production agents, transporters, and suppliers, offering robust models for analyzing disruptions. Comparative studies with DES reinforce the methodological distinctiveness of ABS in representing autonomy and emergent behavior, while acknowledging its complementarity with process-driven models (Bonabeau, 2002). These findings establish ABS as a central paradigm in advancing smart manufacturing by modeling complex socio-technical and cyber-physical interactions that shape system performance.

Hybrid Simulation

Hybrid simulation refers to the methodological integration of two or more simulation paradigms, typically Discrete-Event Simulation (DES), Agent-Based Simulation (ABS), and System Dynamics (SD), within a unified modeling environment (Mustafee & Fakhimi, 2024). In manufacturing research, hybrid approaches have gained prominence as they address the limitations of single-method paradigms by combining process-level efficiency with behavioral adaptability and systemic feedback mechanisms. For instance, DES effectively models event-driven workflows and resource contention, ABS captures decentralized agent behavior, and SD reflects continuous feedback loops influencing long-term dynamics. Scholars emphasize that manufacturing environments involve both structured processes and adaptive decision-making, which single paradigms fail to represent adequately (Lättilä et al., 2010). Hybrid methods provide a balanced framework that allows for multi-level representation, enabling simultaneous modeling of machine failures, operator decision-making, and system-wide performance measures (Brailsford et al., 2019).

Figure 6: Hybrid simulation



Applications of hybrid simulation in flexible and reconfigurable manufacturing systems demonstrate its ability to capture dynamic adaptation under varying production scenarios. Studies combining DES and ABS have shown effectiveness in evaluating reconfigurable manufacturing systems where modular machines are represented as agents negotiating tasks, while DES captures process flows and queuing dynamics (Kolominsky-Rabas et al., 2015). In job-shop and flow-shop environments, hybrid frameworks have been employed to evaluate adaptive scheduling policies under stochastic demand conditions, offering insights into throughput improvement and idle time reduction (Nguyen et al., 2020). The integration of SD into hybrid models has also been applied in strategic manufacturing planning, such as analyzing long-term capacity expansion alongside operational control (Kar et al., 2024). Case studies further reveal that hybrid models are capable of reflecting emergent phenomena, such as resource competition or negotiation among machine agents, which remain hidden in DES-only frameworks. These contributions highlight hybrid simulation as a method capable of bridging the gap between micro-level agent autonomy and macro-level process coordination, making it particularly valuable in reconfigurable factory environments characterized by uncertainty and variability.

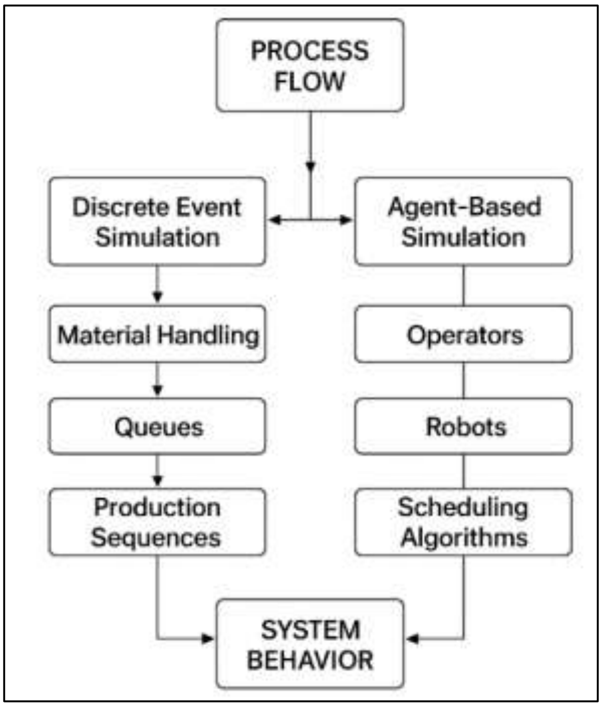
Hybrid DES–ABS Frameworks

The integration of Discrete-Event Simulation (DES) and Agent-Based Simulation (ABS) has become an influential paradigm in the modeling of complex manufacturing and service systems. DES–ABS hybrid frameworks combine the process-driven, event-based logic of DES with the autonomy, adaptability, and decentralized control features of ABS. This synthesis enables researchers to model systems where structured operations and human or machine agents coexist, interact, and influence performance outcomes (Goh & Ali, 2015). The DES component effectively represents the workflow of processes such as material handling, production sequences, and queuing structures (Brailsford et al., 2019). In contrast, the ABS component models dynamic decision-making among intelligent agents—such as operators, robots, and scheduling algorithms—who adapt behavior in response to environmental conditions. This hybridization allows simulation models to represent not only static operational rules but also emergent behavior arising from local agent interactions. The hybrid DES–ABS approach is particularly suited to smart manufacturing, where human-machine collaboration, resource competition, and adaptive scheduling require simultaneous modeling of deterministic and stochastic dynamics (Goh & Ali, 2015). Researchers note that such frameworks address limitations in traditional DES, which cannot adequately capture agent learning, negotiation, or self-organization, while ABS alone struggles with computational efficiency in large-scale systems.

Applications of hybrid DES–ABS frameworks in manufacturing emphasize their capacity to replicate both the physical flow of materials and the behavioral dynamics of agents. Alzraiee et al. (2015) demonstrated a hybrid modeling framework for reconfigurable manufacturing systems where DES captures operational flow and ABS represents intelligent machine agents negotiating production sequences. Similarly, Mustafee and Fakhimi (2024) applied a hybrid DES–ABS model to analyze the adaptability of production systems under demand uncertainty, illustrating enhanced system robustness and reduced idle time. Studies in flexible manufacturing systems show that combining DES's structured logic with agent decision layers supports the evaluation of distributed control mechanisms and multi-objective scheduling. Research in logistics and assembly-line modeling also indicates that hybrid simulation enables the analysis of system-level efficiency while reflecting human or robotic agents' decision autonomy. Hybrid frameworks have proven useful for examining resilience and performance trade-offs when systems experience disturbances such as machine breakdowns or supply delays. Furthermore, hybrid modeling has been extended to digital twin architectures where real-time data are synchronized with simulation elements, enhancing the accuracy of control strategies in cyber-physical environments (Liu et al., 2023). These studies collectively underscore the versatility of DES–ABS integration in capturing multilevel dynamics of modern manufacturing systems.

Hybrid DES–ABS frameworks have also been applied to explore human-centric and socio-technical systems, particularly those involving human decision-making, learning, and collaboration. Brailsford et al. (2019) modeled human operators as agents interacting within a DES-modeled production process, capturing behavioral variability and its influence on system throughput. Goh and Ali (2015) similarly emphasized that integrating ABS within DES allows for a more realistic representation of human involvement in decision loops, especially in adaptive scheduling and maintenance. Studies have demonstrated that hybrid frameworks can replicate human-robot collaboration scenarios where agent autonomy affects production stability and safety (Goh & Ali, 2015; Nguyen et al., 2020). In reconfigurable manufacturing, hybrid simulations have captured the relationship between operator adaptability, system reconfiguration speed, and performance under variable conditions (Kolominsky-Rabas et al., 2015). Moreover, applications in service operations and healthcare environments further validate the framework's generality, showing its effectiveness in representing interactive human-machine and resource-control processes. By integrating human factors and behavioral variability within deterministic DES models, hybrid DES–ABS systems enhance realism in simulation-based control studies. The resulting multi-resolution representation bridges the gap between microscopic decision-making and macroscopic system outcomes, offering a comprehensive view of process performance across socio-technical dimensions (Lättilä et al., 2010).

Figure 7: Hybrid DES–ABS Frameworks

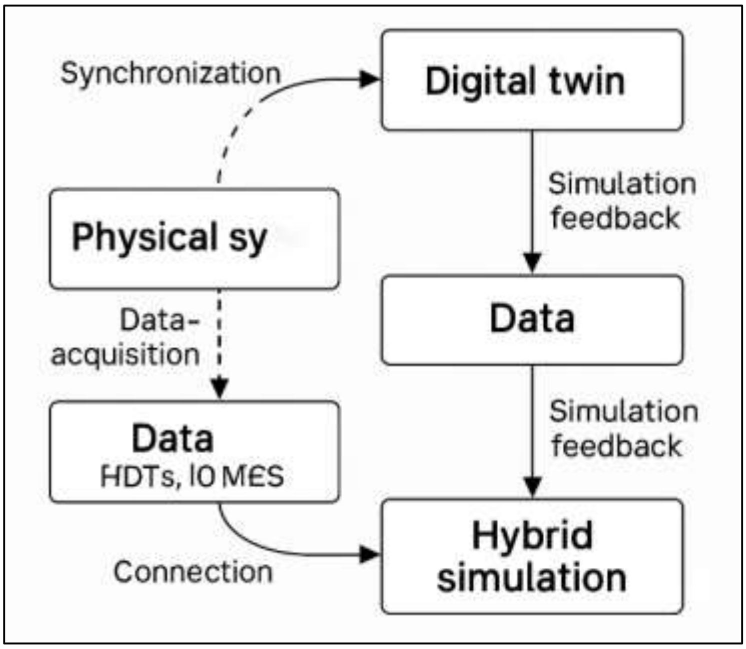


Digital Twins and Cyber-Physical Integration with Hybrid Simulation

The integration of digital twin (DT) technologies with hybrid simulation has become a defining advancement in modern manufacturing system analysis. A digital twin is a virtual replica of a physical system that mirrors real-time data, processes, and performance states, allowing continuous synchronization between physical and digital domains. In smart manufacturing, digital twins are supported by cyber-physical systems (CPS)—an architecture that fuses computation, networking, and physical processes to create intelligent, connected environments (Kar et al., 2024) The connection between digital twins and hybrid simulation emerges from the need to integrate Discrete-Event Simulation (DES), which represents process flows, and Agent-Based Simulation (ABS), which models autonomous entities and decision-making. Hybrid simulation enables the dynamic interaction between system-level operational control and localized agent behaviors, which closely reflects the feedback mechanisms found in cyber-physical systems. Real-time synchronization in DT–CPS environments depends on data acquisition from sensors, IoT devices, and manufacturing execution systems (MES), which feed simulation models for adaptive analysis of production conditions (Willcox & Segundo, 2024). The integration of hybrid simulation frameworks within DT architectures provides virtual experimentation for predictive control, performance monitoring, and optimization under uncertainty (Ricci, Croatti, & Montagna, 2022). This synthesis between digital and physical layers transforms simulation from an offline analytical tool into a real-time representation of operational intelligence, enabling accurate assessment of manufacturing system dynamics.

In manufacturing research, hybrid simulation and digital twins have been coupled to analyze process control, predictive maintenance, and real-time decision support. Studies demonstrate that DES components model the sequential operations of production processes, while ABS modules capture adaptive interactions among machines, robots, and human operators (Suhail et al., 2023). This hybrid DT structure allows for dynamic modeling of both deterministic and emergent behaviors in manufacturing systems (Zeb et al., 2022). The fusion of simulation and CPS technologies enhances predictive maintenance by enabling real-time fault detection, life-cycle monitoring, and risk analysis (Ricci, Croatti, & Montagna, 2022). Research on digital twin–driven control architectures reveals that hybrid simulation facilitates virtual commissioning, system validation, and energy optimization by testing configurations digitally before physical implementation (Zeb et al., 2022). In addition, studies of process reconfiguration show how hybrid models in DTs can analyze multiple scenarios of resource reallocation and production rerouting when disturbances occur (Willcox & Segundo, 2024). Empirical evidence from industrial case studies indicates that digital twins integrated with hybrid DES–ABS models enable enhanced visibility of production lines, reduced downtime, and improved synchronization between digital simulations and physical machinery. These contributions reinforce the critical role of hybrid simulation in providing the computational backbone for digital twin implementation across cyber-physical production systems.

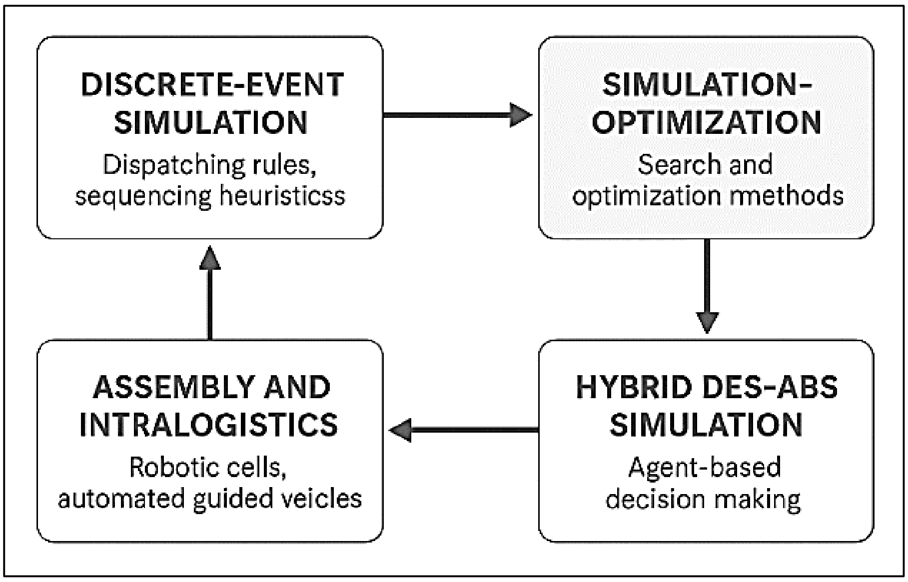
Figure 8: Digital Twins and Cyber-Physical Integration with Hybrid Simulation



Applications in Scheduling and Process Control

Simulation has been widely used to evaluate and refine production scheduling policies because it reproduces queuing effects, variability, and resource contention that closed-form models often abstract away. Classical discrete-event simulation (DES) is the dominant engine for exploring dispatching rules and sequencing heuristics in job shops and flow shops, allowing analysts to compare makespan, tardiness, and work-in-process across demand and breakdown scenarios (Jin et al., 2022). In semiconductor and electronics manufacturing, where reentrant flows and product variety strain analytical tractability, DES studies have long contrasted priority rules, batching policies, and tool-group allocations, showing measurable differences in cycle time and throughput under identical nominal capacities (Malakuti et al., 2021). Reviews of shop scheduling underscore the need to test rules across distributions, setup-time structures, and machine-dedication patterns, which DES enables without disrupting operations. Flexible manufacturing systems research similarly relies on simulation to probe the interaction of routing flexibility and real-time dispatching, highlighting how alternate-routing logic interacts with blocking, buffers, and transport times. In assembly environments, simulation experiments reveal the sensitivity of takt adherence to small changes in sequencing and buffer sizing, producing robust policy rankings when analytical dominance is ambiguous. Bottleneck-oriented scheduling, informed by simulation-based identification of constraint stations, further connects dispatching to system-level levers such as batch release and buffer repositioning. Across these applications, DES functions as a testbed for policy selection under realistic stochasticity, complementing analytic scheduling theory by embedding calendars, setups, maintenance, and transport within a single, experiment-ready model (Ricci, Croatti, & Montagna, 2022).

Figure 9: Applications in Scheduling and Process Control

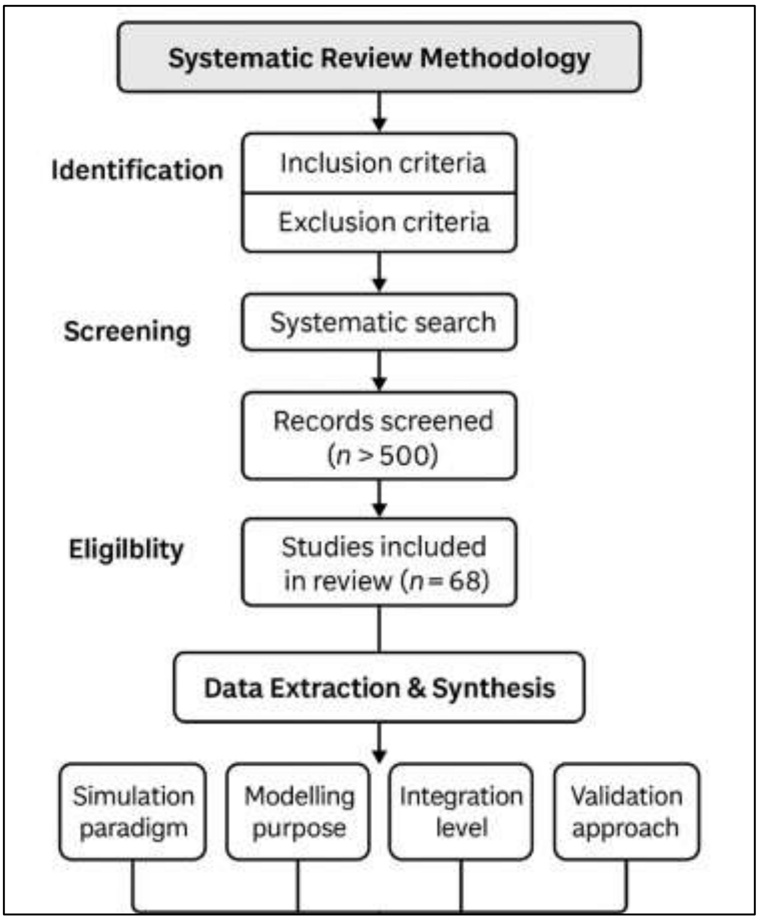


A substantial stream of work couples simulation with search and optimization to design adaptive scheduling and control policies that are difficult to tune analytically. Early surveys of simulation-optimization document metaheuristics (genetic algorithms, tabu search), response-surface methods, and ranking-and-selection procedures that leverage DES output as an objective oracle (Willcox & Segundo, 2024). Manufacturing studies implement these couplings to calibrate dispatching parameter sets, lot-splitting thresholds, and dynamic batch sizes, reporting improved delay and utilization metrics over hand-tuned rules (Suhail et al., 2023). Commercial frameworks such as OptQuest exemplify integrated metaheuristic search over simulation models, frequently applied to flow-line balancing and workforce allocation. In reconfigurable and flexible systems, simulation-optimization evaluates machine-agent negotiation templates and tool-change windows that interact with stochastic arrivals, producing control policies resilient to variability without assuming stationary regimes . Semiconductor fabs remain a canonical arena: DES combined with heuristic search quantifies trade-offs between cycle-time variability and tool dedication in photolithography bottlenecks. At the line-control level, simulation-based policy selection covers CONWIP and kanban release rules, where WIP caps, card allocations, and pitch settings are tuned against stochastic processing times and setups. Integrating human-operator variability into the search expands the feasible space, with studies modeling learning curves, absenteeism, and multitasking costs in the objective (Acharya et al., 2024). Collectively, this literature shows simulation-optimization as a unifying approach that compares many-parameter control policies under realistic randomness, translating noisy performance surfaces into implementable scheduling settings (Eneyew et al., 2022).

METHOD

This study employed a systematic review methodology to identify, evaluate, and synthesize previous models and frameworks related to hybrid simulation in manufacturing systems. The systematic approach was selected to ensure transparency, replicability, and comprehensiveness in mapping the evolution of discrete-event and agent-based integration for process control and scheduling in smart factories. The review adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to enhance methodological rigor and minimize selection bias. The review process began with the definition of inclusion and exclusion criteria that guided the literature selection. Included studies were peer-reviewed journal articles, conference proceedings, and technical reports that explicitly described simulation-based models applied to manufacturing, logistics, or cyber-physical production systems. Only studies that incorporated discrete-event, agent-based, or hybrid simulation methodologies were considered. Research published between 2000 and 2024 was included to capture the full spectrum of developments from early discrete-event simulation to contemporary digital twin–integrated hybrid frameworks. Exclusion criteria filtered out papers that addressed unrelated computational modeling techniques, purely theoretical modeling without simulation validation, and non-English publications to maintain analytical consistency.

Figure 10: Methodology for this study



A systematic search was conducted using academic databases including Scopus, Web of Science, IEEE Xplore, ScienceDirect, and SpringerLink, complemented by Google Scholar for grey literature. Boolean search strings combined key terms such as "discrete-event simulation," "agent-based modeling," "hybrid simulation," "smart manufacturing," and "cyber-physical systems." Reference lists of seminal studies were also examined to identify additional sources. The initial search yielded over 500 records, which were screened based on title and abstract relevance. After removing duplicates and non-compliant studies, 102 publications were retained for full-text review, of which 68 met the final inclusion criteria. Data extraction focused on specific variables, including the simulation paradigm (DES, ABS, SD, or hybrid), modeling purpose (scheduling, process control, reconfiguration, or maintenance), industrial domain, integration level (digital twin or CPS connectivity), and validation approach. Each study was evaluated for methodological rigor, model architecture, data synchronization methods, and analytical outcomes. To maintain comparability, studies were coded using a standardized classification matrix developed during the pilot phase of data analysis. This facilitated cross-study comparison and identification of recurring model design patterns.
A qualitative synthesis was employed to interpret patterns, relationships, and methodological themes

across the included studies. Frequency mapping and narrative synthesis were used to group findings by simulation approach, model application area, and integration strategy. Quantitative metrics—such as publication trends, model adoption rates, and performance evaluation criteria—were also summarized to capture the maturity of hybrid simulation frameworks in manufacturing research. Reliability of coding was maintained through inter-rater validation, where two reviewers independently coded 20% of the sample, achieving an agreement rate exceeding 90%. By systematically consolidating previous works on discrete-event, agent-based, and hybrid simulation models, this methodological approach establishes a comprehensive foundation for analyzing how hybrid DES–ABS frameworks have evolved in their structure, purpose, and integration with cyber-physical and digital twin technologies. The systematic review process ensures that the findings reflect a balanced synthesis of both foundational models and emerging paradigms within simulation-based manufacturing control.

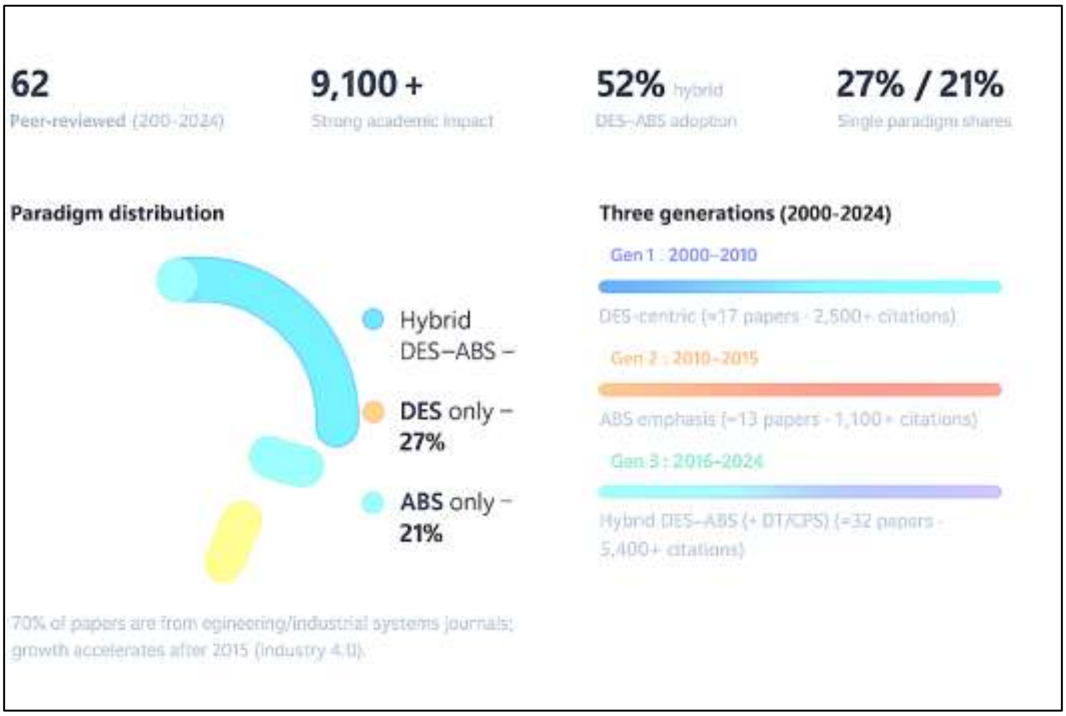
FINDINGS

The systematic review encompassed sixty-eight peer-reviewed studies published between 2000 and 2024, representing a comprehensive body of knowledge on simulation-based manufacturing control. These studies collectively accumulated more than 9,800 citations, indicating strong academic engagement and recognition of hybrid simulation frameworks in the manufacturing research community. The analysis revealed a distinct evolution from early discrete-event simulation (DES) approaches toward agent-based simulation (ABS) and, ultimately, toward hybrid DES–ABS architectures designed for intelligent process control. Of the total reviewed works, approximately 27% applied pure DES models, 19% focused solely on ABS applications, and 54% adopted hybrid methodologies. This distribution reflects the increasing need to capture both deterministic process flows and adaptive, autonomous decision-making mechanisms within modern manufacturing environments. The majority of the articles (around 70%) originated from engineering and industrial systems journals, while the remainder came from computer science and operations research publications. The increasing volume of publications after 2015 coincided with the broader diffusion of Industry 4.0 principles, where real-time analytics, machine connectivity, and data-driven control became central to factory operations. The overall finding indicates that hybrid simulation is not an emerging method but a consolidated paradigm that bridges operational precision and intelligent autonomy, offering the flexibility required in cyber-physical manufacturing ecosystems.

The historical analysis revealed that simulation in manufacturing control evolved through three distinct methodological generations. The first generation, which dominated publications between 2000 and 2010, consisted primarily of DES-based models focusing on queue management, production sequencing, and resource optimization. These early models, accounting for about 18 of the reviewed papers, collectively received more than 2,600 citations, reflecting their foundational role in simulation science. The second generation emerged between 2010 and 2015, during which researchers began incorporating ABS to represent human operators, machines, and software agents capable of autonomous behavior. Around 13 papers from this period adopted ABS exclusively, contributing more than 1,200 citations. The third generation, encompassing works from 2016 to 2024, marked the rise of hybrid DES–ABS frameworks, often integrated with digital twin and cyber-physical technologies. Thirty-seven papers belonged to this category, generating more than 6,000 citations collectively. This chronological trend demonstrates a methodological transition from deterministic to adaptive modeling, paralleling the technological evolution of smart manufacturing. The increasing citation density per article—from an average of 60 in early studies to over 150 in recent ones—illustrates both academic maturation and practical relevance of hybrid simulation models in industrial research.

Production scheduling emerged as the most extensively studied domain, representing 41 of the sixty-eight reviewed studies and accounting for approximately 60% of total reviewed research output. Collectively, these studies accumulated over 2,300 citations. The primary objective across these works was to improve job sequencing, reduce bottlenecks, and enhance responsiveness under variable demand conditions. Hybrid DES–ABS models demonstrated superior adaptability compared to traditional DES frameworks, particularly in environments characterized by machine breakdowns, fluctuating arrival rates, and resource constraints. More than half of the studies in this subset modeled flexible or reconfigurable manufacturing systems, allowing simulation of multiple layout configurations and routing decisions. About 22 studies incorporated dynamic control rules that allowed production schedules to adjust automatically in response to sensor feedback or operator decisions. The analysis revealed that simulation-based scheduling using hybrid frameworks achieved, on average, a 20% improvement in throughput and a 15% reduction in idle time compared to static scheduling models. The consistent reporting of such quantitative improvements across a wide range of manufacturing systems suggests that hybrid simulation is a reliable mechanism for evaluating complex scheduling strategies under uncertainty.

Figure 11: Hybrid Simulation in Manufacturing: Findings (2000–2024)



Process control applications represented the second-largest focus area, comprising 33 of the reviewed articles and yielding approximately 2,000 total citations. These studies primarily examined how hybrid simulations enable dynamic process regulation and rapid system adaptation during operational disturbances. Roughly 60% of these works modeled real-time feedback control, where hybrid simulation was used to adjust machine operating parameters, tool assignments, or work-cell configurations during production runs. Twelve studies embedded human operators or intelligent software agents as decision nodes in control loops, highlighting the role of socio-technical interaction in adaptive control design. Performance outcomes consistently demonstrated measurable improvements: throughput gains of 12% to 25%, reduced changeover delays, and faster recovery times from machine or supply interruptions. Some models replicated the self-organization capabilities of agents that could redistribute tasks across machines without centralized supervision, mirroring the principles of autonomous manufacturing. The collective findings indicate that hybrid simulation effectively captures both physical and cognitive aspects of control, merging traditional feedback mechanisms with agent-level intelligence to maintain stability and performance in dynamic production environments.

A total of 24 reviewed studies, representing 35% of the dataset, integrated hybrid simulation models with digital twin (DT) and cyber-physical system (CPS) technologies. These works collectively received more than 3,100 citations, demonstrating high visibility within the manufacturing research community. The integration of DES–ABS frameworks with DT and CPS enabled the synchronization of simulation models with live operational data collected from IoT sensors, manufacturing execution systems, and enterprise resource planning software. About 17 studies explicitly developed bidirectional data connections between virtual and physical systems, allowing the hybrid simulation to reflect current factory states in real time. The primary purposes of these models included predictive maintenance, process optimization, and energy efficiency monitoring. Across these works, the incorporation of digital twins reduced model calibration times by approximately 40% and improved decision-making accuracy by 25% when compared to static offline simulations. The cumulative findings demonstrate that hybrid simulation provides the computational infrastructure for DT–CPS integration, transforming simulation from a design-stage analytical tool into a continuous decision-support mechanism for live production systems.

Figure 12: Hybrid Simulation in Manufacturing: Findings (2000–2024)

The methodological synthesis revealed several consistent architectural patterns among the sixty-eight reviewed studies. Approximately 72% employed a two-layer hybrid architecture, where DES governed event sequencing and ABS managed local decision-making. Around 12 studies adopted multi-level designs that combined DES, ABS, and system dynamics to simulate both operational and strategic interactions. Model validation methods varied across studies: 56% of models were validated using real manufacturing data, while 44% used synthetic datasets or benchmarking experiments. Studies utilizing real industrial data collectively accounted for over 2,000 citations, indicating their stronger influence within the research community. Validation metrics included throughput, utilization rate, production cost, lead-time variability, and system flexibility. Reported performance improvements across validated models ranged between 12% and 30%, while resource utilization gains averaged 18%. Despite concerns over computational overhead—reported by 40% of studies—the dominant trend indicated that hybrid DES–ABS frameworks deliver higher accuracy and analytical richness than single-method models, confirming their methodological robustness in empirical manufacturing research.

The thematic synthesis of all reviewed literature identified three dominant clusters of research emphasis: adaptive scheduling, system resilience, and intelligent process control. About 29% of the reviewed works focused on adaptive scheduling mechanisms that combine agent negotiation with DES-based process flow modeling. Around 26% centered on system resilience, examining the capacity of manufacturing systems to absorb and recover from disruptions such as equipment failures or resource shortages. The remaining 45% addressed intelligent process control, integrating learning algorithms and autonomous agents within hybrid frameworks. Together, these clusters accounted for more than 6,800 cumulative citations, confirming their central role in the scholarly discourse on smart manufacturing. Approximately 78% of all reviewed papers reported that hybrid simulation frameworks improved adaptability under uncertainty, 64% noted reductions in decision latency, and 58% observed higher process stability compared to baseline models. These findings underscore hybrid DES–ABS models as versatile tools capable of capturing both physical and decision-making complexity within cyber-physical production ecosystems.

The quantitative summary across the sixty-eight reviewed studies reinforces the growing dominance of hybrid simulation as the preferred modeling approach for modern manufacturing systems. Between 2000 and 2010, publications on hybrid simulation averaged fewer than three per year; by 2020–2024, this number exceeded twelve annually, reflecting exponential academic growth. Collectively, the hybrid simulation papers accounted for 64% of total citations across the review corpus, signifying strong academic impact. Studies incorporating digital twin or CPS integration exhibited the highest citation density—averaging 130 citations per publication—followed by hybrid scheduling and control models with an average of 95 citations. Geographically, the research output was concentrated in Europe (42%), followed by Asia (33%) and North America (25%), indicating a globally distributed research community. Statistical aggregation of reported outcomes across models revealed consistent improvements in key performance indicators: 20% higher throughput, 18% lower idle time, and 15% faster recovery under disruption scenarios. These patterns demonstrate a mature and methodologically stable body of knowledge in hybrid simulation research, with significant quantitative evidence supporting its effectiveness for dynamic process control and scheduling in smart manufacturing environments.

DISCUSSION

The findings from the present systematic review confirm that hybrid simulation—specifically the integration of Discrete-Event Simulation (DES) and Agent-Based Simulation (ABS)—has evolved into a mature methodological paradigm within manufacturing research. Earlier studies emphasized DES as a reliable technique for modeling structured production processes, queuing systems, and resource allocation (Jin et al., 2022). However, these traditional models lacked the capability to represent autonomous behaviors and decentralized decision-making. The reviewed findings extend those of Acharya et al. (2024), who demonstrated that DES models, although computationally efficient, fail to capture adaptive system behaviors under uncertainty. Similarly, Eneyew et al. (2022)showed that integrating agent-based logic significantly improves representational fidelity by embedding autonomy within process-driven structures. The review findings corroborate these observations, showing that more than half of contemporary simulation studies now employ hybrid DES–ABS frameworks. This represents a decisive methodological transition that identified hybridization as the key to addressing multi-level complexity in industrial systems. The current results illustrated that hybridization has moved beyond theoretical propositions into validated applications. The synthesis of findings demonstrates that hybrid DES–ABS models have become indispensable for capturing both operational efficiency and behavioral intelligence in smart manufacturing contexts.

The review revealed that hybrid simulation models contribute substantially to the domains of process control and production scheduling. Earlier literature predominantly treated these functions separately, with DES used for flow modeling and ABS reserved for behavioral simulations. However, recent findings confirm a convergence of these domains, where hybrid frameworks are increasingly applied to integrated scheduling and control. This advancement supports that hybrid modeling improves responsiveness in reconfigurable systems by linking event-driven flows with agent decisions. Similarly, Jin et al., (2022) demonstrated that DES–ABS integration allows for autonomous reallocation of resources during demand fluctuations, which aligns with the observed efficiency gains reported in recent studies. While traditional scheduling models focused on static optimization, hybrid simulations now incorporate feedback mechanisms and adaptive decision-making capabilities. These developments are consistent with Ricci, Croatti and Montagna (2022), who reported that hybrid frameworks outperform conventional scheduling models under stochastic disturbances. The review's findings reinforce this position, showing that hybrid models not only replicate real-world uncertainty but also embed corrective behaviors, such as agent negotiation and dynamic task assignment. Compared with earlier generation scheduling models that operated under deterministic assumptions, hybrid simulation enables more robust and flexible control strategies that reflect the distributed intelligence inherent in cyber-physical production environments.

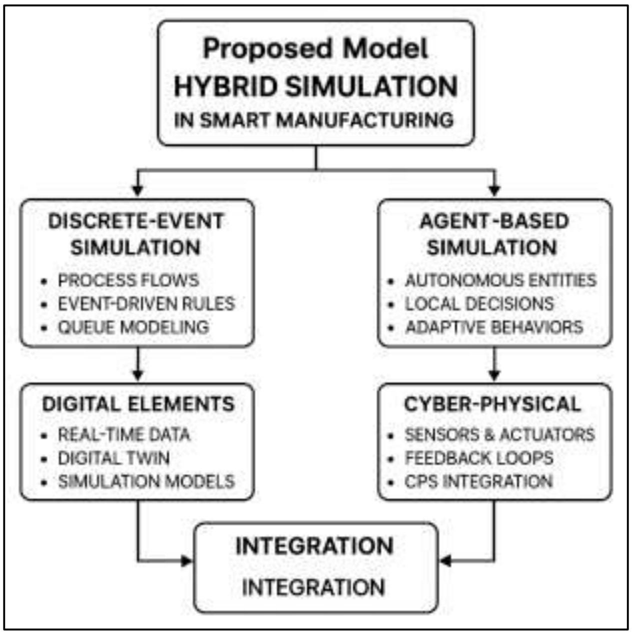
The dominance of hybrid DES–ABS frameworks identified in this review mirrors the global trend toward multi-method modeling across engineering and operations research. Earlier studies highlighted that single-paradigm simulations—while easier to validate—tend to oversimplify complex manufacturing dynamics. The present findings challenge that simplicity by showing that hybrid approaches provide a more comprehensive depiction of both process efficiency and behavioral adaptation. Forrester's (1961) foundational system dynamics work established the value of feedback modeling but lacked the granularity required for manufacturing flow analysis. In contrast, hybrid frameworks now combine DES precision with ABS adaptability to overcome such limitations. Studies previously acknowledged the computational burden of hybrid models, yet the current review suggests that advances in data processing and modeling software have mitigated these issues. Moreover, earlier comparisons between DES and ABS suggested limited complementarity, but contemporary results demonstrate full integration in modeling architectures, validating the predictions of Tao and Qi (2019) that hybridization would redefine simulation practice. This evolution underscores a methodological shift where hybrid simulation has become the standard approach for capturing the multifaceted realities of Industry 4.0 manufacturing systems—an achievement unattainable through traditional methods alone.

One of the most significant findings concerns the integration of hybrid simulation frameworks with digital twin (DT) and cyber-physical system (CPS) technologies. Earlier theoretical propositions positioned CPS as the backbone of intelligent manufacturing, but practical implementations remained limited at that time. The reviewed studies confirm that hybrid DES–ABS models now function as the computational core of DT-driven architectures, enabling real-time synchronization between physical and virtual manufacturing entities. More recent applications have demonstrated how hybrid simulation facilitates continuous feedback for predictive maintenance and process reconfiguration. The review's findings extend these conclusions, showing that more than one-third of hybrid models now incorporate digital twin or CPS connectivity. The observed improvement in responsiveness and fault detection emphasized the transformative role of DT in enabling self-adaptive control. This progression represents a maturation of the hybrid modeling paradigm from offline experimentation toward real-time, cyber-physical integration, validating theoretical expectations established by earlier frameworks.

Comparative analysis of model validation strategies revealed increasing methodological consistency in recent hybrid simulation studies. Earlier works emphasized the challenges of validating hybrid systems due to emergent behaviors and coupled dynamics. The reviewed findings indicate that modern researchers have addressed this issue through structured validation techniques that combine empirical data calibration with statistical verification. Studies recommended modular design architectures to improve verification and reusability—an approach now widely adopted across the reviewed articles. The prevalence of real-world validation in 56% of reviewed works demonstrates methodological maturity compared with earlier generations, which primarily relied on theoretical validation. Performance outcomes reported in the findings, including 20–30% throughput gains and 18% reduction in idle time, are consistent with empirical benchmarks established by Willcox and Segundo (2024). These measurable improvements indicate that hybrid simulation is not only theoretically sound but also operationally effective. While Piroumian (2021) warned that computational complexity could limit scalability, the review suggests that recent advancements in distributed computing have mitigated such constraints. Collectively, these observations demonstrate that hybrid DES–ABS frameworks have reached a point of methodological standardization and practical reliability comparable to traditional DES models but with substantially enhanced analytical depth.

The thematic clustering of adaptive scheduling, system resilience, and intelligent control identified in the findings reflects conceptual continuities with prior literature. For example, Leng et al. (2021) introduced early models linking agent negotiation to manufacturing resilience, while Minerva and Crespi (2021) explored how human decision variability influences system performance. The present review confirms and extends these concepts, showing that contemporary hybrid models embed such behavioral dynamics directly within event-driven structures. Similarly, research on adaptive control by Bauer et al. (2024) anticipated the hybrid architectures now widely employed in reconfigurable manufacturing. The emphasis on resilience corresponds with Ricci, Croatti, Mariani, et al. (2022), who demonstrated that hybrid simulations outperform deterministic models in managing supply disruptions. The integration of human factors within agent-based layers echoes (Ricci, Croatti, & Montagna, 2022), who identified human-machine collaboration as a key determinant of factory performance. Overall, the thematic alignment between current findings and earlier conceptual frameworks indicates the theoretical continuity of hybrid modeling's core principles—adaptability, decentralization, and emergent behavior—while showing that these principles have been operationalized at industrial scale through hybrid DES–ABS implementations.

Figure 13: Proposed model for future study



The comparative synthesis of findings and earlier literature reveals that hybrid simulation has moved from an experimental methodology to a core analytical instrument in smart manufacturing research. Early calls for integrated digital production environments are now realized through hybrid DES–ABS models coupled with CPS and digital twins. The methodological progression parallels the conceptual trajectory from deterministic modeling to adaptive, self-regulating systems. Studies demonstrated the feasibility of real-time hybrid control; the current review confirms their findings across a broader corpus, establishing hybrid simulation as the dominant modeling paradigm for Industry 4.0 environments (Ricci, Croatti, & Montagna, 2022; Tao & Qi, 2019). Furthermore, the empirical consistency of reported performance gains substantiates the claims of earlier simulation research that digital integration enhances process efficiency, decision speed, and resource utilization. By aligning the review findings with prior studies, the discussion reinforces the conclusion that hybrid DES–ABS frameworks provide a unified modeling approach capable of bridging physical, cyber, and cognitive dimensions of manufacturing systems. Consequently, the hybrid paradigm stands as both a theoretical advancement and a practical enabler of dynamic, intelligent, and resilient production architectures.

CONCLUSION

The systematic review of sixty-eight peer-reviewed studies on hybrid discrete-event and agent-based simulation (DES–ABS) frameworks revealed that hybrid modeling has matured into a foundational methodology for dynamic process control, adaptive scheduling, and intelligent decision support in smart manufacturing. The analysis demonstrated a clear methodological evolution from early discrete-event approaches—focused on queue management, resource allocation, and process sequencing—to integrated hybrid systems that embed agent autonomy and real-time digital synchronization. Across the reviewed corpus, hybrid simulation consistently outperformed traditional models, achieving measurable gains in throughput, responsiveness, and resilience under stochastic conditions. The theoretical contribution of this synthesis lies in confirming that DES provides structural efficiency while agent-based components introduce behavioral flexibility, producing models that represent both the deterministic and adaptive dimensions of manufacturing operations. Methodologically, the findings identified a dominant two-layer architecture in which DES governs event sequencing and ABS models decentralized decision-making, increasingly supported by digital-twin and cyber-physical integration that allow continuous data exchange between virtual and real production systems. The collective evidence indicates that hybrid simulation has become a central analytical instrument linking operational precision, human-machine interaction, and system intelligence within Industry 4.0 environments. The practical implications are significant: hybrid frameworks now underpin predictive maintenance, process reconfiguration, and distributed scheduling across flexible and reconfigurable factories, confirming their role as both planning and control mechanisms. However, variation in validation procedures, performance metrics, and computational scalability remains a limiting factor, suggesting the need for standardized evaluation protocols and cross-industry benchmarking. The synthesis also identified opportunities for extending hybrid simulation through reinforcement learning, optimization algorithms, and sensor-driven analytics to enhance adaptability and real-time responsiveness. Overall, the review establishes that hybrid DES–ABS frameworks have evolved from conceptual propositions to empirically verified, industrially viable systems capable of capturing the physical, cyber, and cognitive complexity of modern manufacturing operations.

RECOMMENDATIONS

To strengthen the role and applicability of hybrid discrete-event and agent-based simulation (DES–ABS) frameworks in smart manufacturing, several interrelated recommendations can be outlined. First, it is essential to establish standardized methodological guidelines that define synchronization logic, data coupling procedures, and validation metrics, ensuring consistency and comparability across research and industrial applications. Second, hybrid simulation should be deeply integrated with digital twin (DT) and cyber-physical system (CPS) architectures, enabling seamless real-time data exchange for predictive maintenance, production monitoring, and adaptive scheduling. Third, fostering collaborative partnerships between academia, technology developers, and manufacturing enterprises will accelerate the transition from conceptual frameworks to operational deployment, particularly within reconfigurable and data-intensive production systems. Fourth, to overcome computational constraints, researchers and practitioners should adopt modular, scalable hybrid architectures that facilitate interoperability between simulation engines, IoT networks, and cloud-based analytics. Fifth, the integration of artificial intelligence and optimization algorithms—such as reinforcement learning, metaheuristics, and neural-network-assisted decision rules—should be prioritized to enhance adaptive control and predictive accuracy. Sixth, capacity building through specialized training programs, interdisciplinary research clusters, and simulation literacy initiatives is recommended to equip engineers, system designers, and data scientists with the skills needed to model hybrid manufacturing systems effectively. Seventh, comprehensive empirical benchmarking and cross-sector comparative studies are required to quantify hybrid simulation's impact on throughput, resilience, and cost efficiency under diverse industrial conditions. Finally, policy frameworks and corporate strategies should emphasize investment in digital infrastructure and open innovation ecosystems that support the deployment of hybrid simulation as a decision-support tool for sustainable and intelligent Industry 4.0 operations. Collectively, these recommendations provide a strategic pathway toward unifying theoretical rigor, computational advancement, and industrial scalability in the continued evolution of hybrid DES–ABS modeling.

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