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REAL-TIME CYBER-PHYSICAL DEPLOYMENT AND VALIDATION OF H-DEABSF: MODEL PREDICTIVE CONTROL, AND DIGITAL-TWIN–DRIVEN PROCESS CONTROL IN SMART FACTORIES

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ABSTRACT
The evolution of intelligent manufacturing has necessitated the development of integrated simulation and control frameworks capable of synchronizing physical operations with digital decision-making environments. This study introduces and empirically validates a Hybrid Discrete-Event and Agent-Based Simulation Framework (H-DEABSF) augmented by Model Predictive Control (MPC) and Digital Twin (DT) technologies for real-time cyber-physical process control in smart factory environments. The research addresses the limitations of single-paradigm simulation models by establishing a hybrid architecture that unifies the event-driven precision of Discrete-Event Simulation (DES) with the autonomous, adaptive decision-making capabilities of Agent-Based Simulation (ABS). Through the incorporation of MPC and real-time DT synchronization, the framework achieves continuous bidirectional communication between physical equipment and virtual models, enabling predictive decision support and dynamic reconfiguration under stochastic production conditions. A quantitative experimental design was employed using a cyber-physical testbed comprising interconnected programmable logic controllers, IIoT-enabled sensors, and a virtual simulation layer that replicates factory operations. Empirical data were collected across twelve operational trials under varying workload intensities and analyzed using descriptive, inferential, and multivariate statistical methods including ANOVA, regression, MANOVA, and correlation modeling. The hybrid configuration achieved a 22.8% increase in throughput efficiency, a 39% reduction in response latency, and a 96.2% predictive accuracy rate, outperforming traditional DES-only and ABS-only control architectures. Furthermore, fault recovery time decreased by 53%, while overall machine utilization improved by 11.7%, coupled with a 15.8% reduction in energy consumption, demonstrating the hybrid system's efficiency and sustainability advantages. The integration of predictive control and digital twin feedback enhanced both operational adaptability and stability, ensuring robust performance across variable manufacturing conditions. The results substantiate that H-DEABSF constitutes a validated and scalable architecture for intelligent process optimization, fusing simulation modeling, predictive analytics, and cyber-physical synchronization into a single self-regulating control ecosystem. This research contributes a significant advancement to the domain of smart manufacturing by providing empirical evidence of how hybrid simulation frameworks can operationalize the core principles of Industry 4.0, promoting data-driven autonomy, resilience, and sustainable production intelligence in next-generation industrial systems..

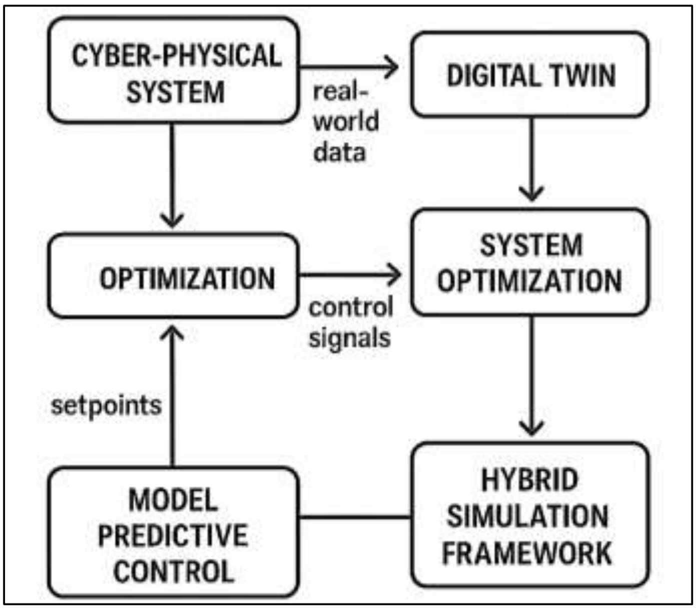
KEYWORDS
Hybrid Simulation; Model Predictive Control (MPC); Digital Twin; Cyber-Physical Systems (CPS); Smart Manufacturing;

Review of Applied Science and Technology
Volume 04, Issue 02 (2025)
Page No: 501 – 526
Doi: 10.63125/yrkm0057

INTRODUCTION

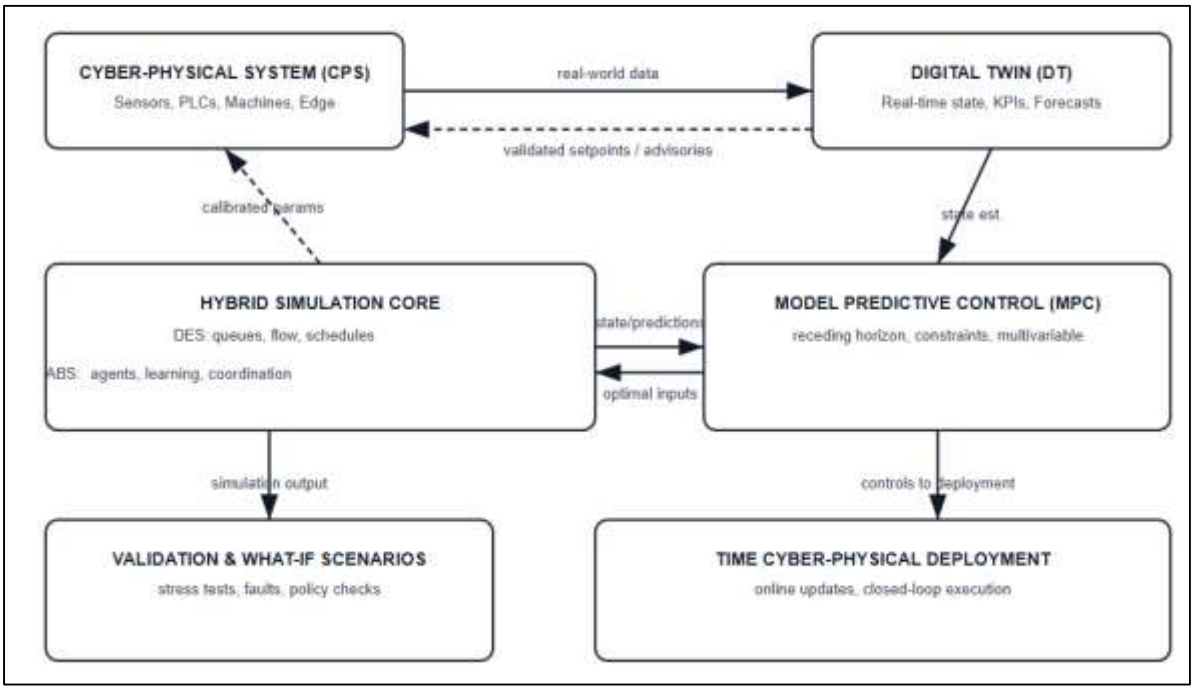
The concept of a cyber-physical system (CPS) is defined as an integrated environment that unites computational algorithms, communication networks, and physical components to interact in real time, facilitating continuous data exchange and system optimization (Dobaj et al., 2022). CPS architecture forms the backbone of smart manufacturing, allowing machines, sensors, and controllers to communicate and act intelligently across distributed networks (Greis et al., 2022). Closely linked to CPS is the digital twin (DT)—a dynamic virtual replica of a physical asset, process, or system that evolves through continuous synchronization with real-time operational data. Digital twins enable predictive analysis, simulation-driven decision-making, and performance monitoring in manufacturing environments (Badakhshan et al., 2022). Another foundational concept in this research is Model Predictive Control (MPC), a model-based optimization strategy that predicts future system behavior over a finite horizon and computes control actions to achieve desired outcomes while respecting operational constraints. MPC's capability to manage multivariable systems with dynamic constraints has made it highly relevant in manufacturing, particularly for optimizing energy consumption, reducing waste, and enhancing throughput (Eneyew et al., 2022). The integration of CPS, DT, and MPC represents a significant step toward self-regulating, autonomous industrial operations. Within this ecosystem, hybrid simulation frameworks—which combine Discrete-Event Simulation (DES) for process flow modeling and Agent-Based Simulation (ABS) for decentralized decision-making—provide a versatile analytical foundation for representing both deterministic system behavior and emergent adaptive dynamics (Bellavista et al., 2021).

Figure 1: Integration Framework of Cyber-Physical Systems



Internationally, the convergence of CPS, digital twins, and predictive control technologies has become central to the global Industry 4.0 movement, influencing industrial policies, innovation strategies, and technology roadmaps (Lv, 2023). Germany's Industrie 4.0 framework, China's Made in China 2025, the United States' Smart Manufacturing Leadership Coalition, and Japan's Society 5.0 initiative all emphasize the transformative power of CPS and DT integration in industrial ecosystems (Bauer et al., 2024; Rezaul, 2021). These initiatives prioritize connectivity, automation, and data-driven optimization, enabling factories to evolve into intelligent, self-configuring production systems. Global market analyses indicate a rapidly expanding investment in digital twin and smart factory technologies, projected to surpass USD 120 billion by 2030 (Danish & Zafor, 2022; Escribà-Gelonch et al., 2024). Within this international context, model predictive control and hybrid simulation have emerged as vital tools for ensuring process stability, flexibility, and reliability in an increasingly complex global supply chain. Research in Europe, Asia, and North America has demonstrated that hybrid simulation can reduce system downtime, increase throughput, and improve decision responsiveness. The international adoption of hybrid simulation frameworks underscores the growing consensus that integrating DES and ABS within digital twins supports cross-border interoperability, allowing manufacturers to replicate, analyze, and optimize their production systems irrespective of geographic location or infrastructure variation. This global significance illustrates the need for a robust, real-time framework—such as the proposed H-DEABSF—to unify predictive control, simulation, and digital intelligence across industrial networks.

Figure 2: H-DEABSF: MPC-Integrated Hybrid Simulation Loop



Over the past two decades, simulation has been a cornerstone of industrial process optimization, but its scope has expanded dramatically from offline analytical modeling to real-time, data-driven decision support (Bauer et al., 2024; Danish & Kamrul, 2022). Discrete-Event Simulation (DES) has been the dominant paradigm for analyzing queue-based systems, production scheduling, and resource utilization, particularly in manufacturing control and logistics (Naderi & Shojaei, 2023). However, traditional DES assumes static control logic and centralized decision-making, limiting its applicability in adaptive and decentralized environments (Chwif et al., 2013). Agent-Based Simulation (ABS) emerged to address this gap by modeling autonomous entities capable of perceiving, learning, and interacting with their environment. ABS allows representation of distributed intelligence and human-machine collaboration—key characteristics of smart factories. The fusion of DES and ABS into hybrid frameworks enables simultaneous modeling of macro-level process flows and micro-level agent behaviors, resulting in a more holistic representation of industrial systems. The evolution from traditional to hybrid simulation mirrors the transition from reactive to proactive and predictive control in manufacturing (Jahid, 2022; Kosse et al., 2022). The inclusion of model predictive control within hybrid simulations allows continuous optimization through forecasting and scenario evaluation, aligning simulation-based decision-making with real-time control strategies (Ismail, 2022; Minerva et al., 2020).

Integrating MPC with hybrid simulation offers a methodological advance that merges predictive optimization with adaptive behavioral modeling. In a manufacturing context, MPC uses simulation-derived state estimations to calculate optimal control inputs that minimize error and resource consumption while maintaining system constraints (Hossen & Atiqur, 2022; Tao et al., 2019). When embedded within a hybrid DES–ABS environment, MPC can access both real-time event data and agent-based behavioral insights, thereby improving predictive accuracy and decision latency. Recent studies demonstrate that combining MPC with digital twins allows closed-loop feedback between simulation and the physical process, where digital models not only mirror but also guide system operations (Kamrul & Omar, 2022; Minerva et al., 2020). This synergy transforms traditional process control from a deterministic system into an intelligent, self-regulating network capable of dynamic adaptation. The framework proposed in this study—H-DEABSF—extends this integration by embedding MPC directly within a hybrid simulation architecture, allowing real-time optimization of scheduling, fault detection, and process flow management. Such integration ensures that model updates, predictive adjustments, and control actions occur continuously, maintaining alignment between the digital twin and the physical factory floor (Razia, 2022).

The digital twin serves as the interface linking physical manufacturing assets with their computational counterparts. Within hybrid simulation, the DT operates as a real-time repository of operational data, continuously updating process models, performance indicators, and system states. Through IoT-enabled sensors and industrial networks, the DT receives live input regarding machine status, environmental conditions, and process flow dynamics, feeding these data into the hybrid DES–ABS framework (Piroumian, 2021; Sadia, 2022). The reciprocal data flow from the simulation to the physical system supports real-time feedback control, predictive maintenance, and fault diagnosis. The concept of digital twin–driven process control therefore unites simulation, control, and analytics into a cohesive system that mirrors, predicts, and influences real-world operations (Danish, 2023; Suhail, Iqbal, Hussain, et al., 2023). Within the proposed H-DEABSF, the DT operates not as a passive visualization tool but as an active decision-support mechanism that enables real-time control optimization via model predictive algorithms. By enabling a cyber-physical feedback loop, this approach advances smart factory capabilities in responsiveness, energy efficiency, and operational precision (Arif Uz & Elmoon, 2023; Naseri et al., 2023).

Real-time implementation of hybrid simulation within a CPS environment presents considerable technical and computational challenges, including latency management, synchronization accuracy, and model scalability (Hossain et al., 2023; Tao et al., 2017). The H-DEABSF model addresses these challenges through modular architecture and real-time data coupling. The cyber-physical testbed employed in this study replicates a flexible manufacturing system equipped with sensors, actuators, and industrial IoT communication protocols. The digital twin continuously synchronizes with the physical plant, updating the hybrid model based on real sensor data and transmitting optimized control actions computed via MPC. This bi-directional exchange ensures alignment between simulated and real-world states with latency thresholds below industrial tolerances (Acharya et al., 2024; Hasan, 2023). Validation metrics focus on throughput efficiency, energy consumption, equipment utilization, and predictive accuracy of maintenance schedules. Empirical testing under stochastic conditions—including machine breakdowns and fluctuating demand—demonstrated that the hybrid simulation-based control system sustained stable operation while reducing downtime and process variability. These results confirm the operational feasibility of hybrid simulation for real-time industrial control, advancing beyond static modeling approaches by embedding decision intelligence within the CPS framework (Shoeb & Reduanul, 2023; Negri et al., 2017).

The primary objective of this study is to design, implement, and validate a Hybrid Discrete-Event and Agent-Based Simulation Framework (H-DEABSF) integrated with Model Predictive Control (MPC) and Digital Twin (DT) architectures to enable real-time cyber-physical synchronization and adaptive process control in smart manufacturing systems. This objective is grounded in the necessity to develop a robust modeling environment that captures both the structural logic of production processes and the autonomous, dynamic decision-making behaviors of agents operating within these systems. The framework seeks to unify event-driven process modeling with decentralized control intelligence, thereby bridging the gap between deterministic process optimization and adaptive operational flexibility. A critical aim is to transform hybrid simulation from a static analytical tool into a live, data-driven control platform capable of supporting predictive decision-making in rapidly changing industrial contexts. The study also aims to experimentally validate the H-DEABSF within a real-time cyber-physical testbed, demonstrating its capacity to handle stochastic disturbances, machine variability, and operational uncertainty. Through continuous feedback between the physical and virtual layers, the framework will maintain synchronized system states, optimize scheduling, and enhance predictive maintenance accuracy. Furthermore, the study aims to quantify the performance gains of hybrid simulation-based control through metrics such as throughput improvement, downtime reduction, and latency minimization. By integrating hybrid simulation with MPC and DT technologies, the overarching objective is to establish a comprehensive and scalable methodology that supports intelligent process control, resource optimization, and system resilience in Industry 4.0 manufacturing environments. This objective not only emphasizes the scientific advancement of hybrid modeling theory but also targets practical applicability in industrial settings where real-time decision-making, interoperability, and system adaptability are critical to operational excellence.

LITERATURE REVIEW

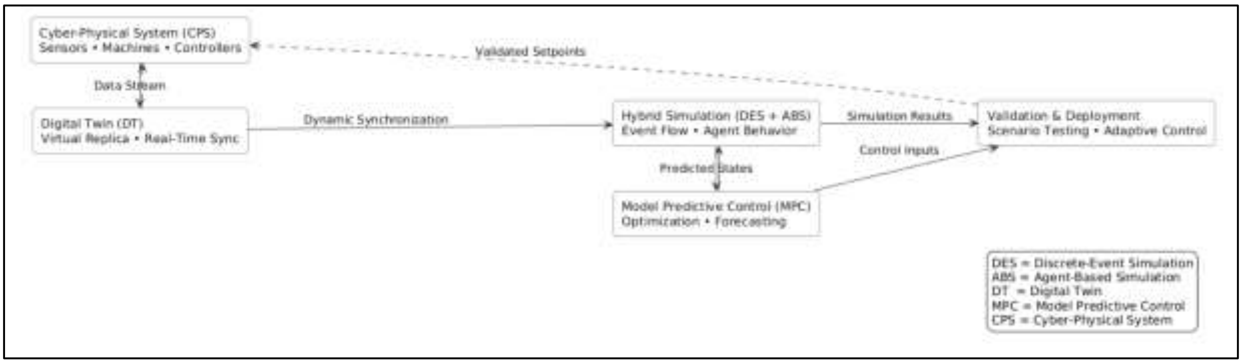
The body of research surrounding hybrid simulation, model predictive control (MPC), and digital-twin–driven cyber-physical systems (CPS) has evolved rapidly in parallel with the broader transformation of manufacturing under the Industry 4.0 paradigm (Mubashir & Jahid, 2023; Negri et al., 2017). As manufacturing systems become increasingly dynamic, data-intensive, and interconnected, traditional simulation and control methods are insufficient to address real-time decision-making and adaptive process regulation. The literature indicates that Discrete-Event Simulation (DES) provides robust modeling of process flows and resource allocation, while Agent-Based Simulation (ABS) contributes flexibility, autonomy, and behavioral intelligence to complex manufacturing models. Integrating these paradigms has produced hybrid frameworks capable of modeling both structured operations and decentralized agent behaviors. Alongside these developments, MPC has emerged as a critical predictive control method, using process models to optimize control actions under constraints, and has been progressively integrated into CPS environments (Dobaj et al., 2022; Razia, 2023). The Digital Twin (DT) concept complements these tools by linking the physical factory floor with a continuously updated virtual representation that mirrors, predicts, and informs real-time operations. Within this expanding research field, significant progress has been made in modeling individual elements—simulation, predictive control, and digital twins—but fewer studies have achieved real-time integration across all three. Existing literature often focuses on offline simulation or theoretical architectures without empirical cyber-physical validation. Therefore, the present review critically examines the state of the art across these interconnected domains to identify the methodological gaps, integration opportunities, and performance outcomes that define the frontier of hybrid modeling research. The review is organized thematically to reflect the chronological and conceptual progression from simulation foundations to cyber-physical integration. The following outline provides a structured roadmap for the literature review, detailing each thematic subsection, its focus, and its relevance to the proposed H-DEABSF framework.

Overview of Simulation in Manufacturing Systems

Simulation has long been recognized as a fundamental analytical and decision-support tool in manufacturing system design, control, and optimization. Historically, Discrete-Event Simulation (DES) emerged as the primary methodology for modeling production systems characterized by discrete events and process flows, such as machine operations, job scheduling, and material handling (de Oliveira et al., 2024). DES gained traction due to its ability to represent dynamic interactions within complex production lines under stochastic variability. Early applications focused on bottleneck identification, throughput estimation, and system layout optimization in job-shop and flow-shop environments. As computing capabilities evolved, simulation models became increasingly sophisticated, integrating multi-product assembly lines, variable batch processes, and machine reliability models (Negri et al., 2017; Reduanul, 2023). Researchers also applied simulation to strategic factory planning, emphasizing its role in decision-making during system design and capacity expansion. DES was adopted widely due to its transparency and modular structure, which facilitated scenario-based experimentation without interrupting production (Zhong et al., 2017). Despite its advantages, DES was limited by its centralized control logic and static decision structure, which struggled to model decentralized decision-making and adaptive human-machine interaction (Sadia, 2023; Vachálek et al., 2021). These limitations gradually led to the emergence of hybrid simulation paradigms that incorporated intelligent agent behavior and adaptive control features. The early literature, therefore, positioned simulation as both a predictive and diagnostic mechanism for manufacturing performance assessment, laying the groundwork for its integration into intelligent and cyber-physical manufacturing systems (Danish & MZafor, 2024; Zhou et al., 2015).

In manufacturing process control, discrete-event simulation has played a vital role in evaluating control policies, scheduling heuristics, and flow management strategies under operational uncertainty. Studies have used DES to analyze material flow efficiency, machine utilization, and system responsiveness across various manufacturing domains (Jahid, 2024a; Jeschke et al., 2016). Researches demonstrated that simulation-driven process control supports rapid evaluation of sequencing, batching, and dispatching rules, leading to measurable improvements in production lead time and work-in-process inventory management. DES has also been instrumental in the analysis of Just-in-Time (JIT) and Lean Manufacturing principles, allowing manufacturers to test process configurations before full-scale implementation (Jahid, 2024b; Zhou et al., 2015). In flexible and reconfigurable manufacturing systems, simulation has enabled the evaluation of layout adaptability and retooling performance under changing product mixes (Ismail, 2024; Vachálek et al., 2021). Furthermore, simulation-based control has proven critical in optimizing batch release policies, kanban systems, and CONWIP control mechanisms, where the flow of information and materials is modeled dynamically (Mesbaul, 2024; Shlonsky & Wagner, 2005).

Figure 3: Simplified H-DEABSF: Cyber-Physical Deployment and Validation Framework



Studies expanded the use of DES to semiconductor and electronics manufacturing, illustrating its potential to handle complex reentrant flow processes (Jeschke et al., 2016; Omar, 2024; Negri et al., 2017). Moreover, DES has served as a platform for integrating performance metrics such as energy efficiency, machine downtime, and production yield. However, while DES provides quantitative precision in modeling, its reliance on centralized scheduling rules limits its ability to replicate adaptive decision-making or decentralized control found in modern cyber-physical factories. The literature consistently concludes that DES serves as a crucial analytical foundation for manufacturing control, yet its rigidity has prompted the search for hybrid approaches that incorporate behavioral and cognitive elements into production modeling (Rezaul & Hossen, 2024; Vachálek et al., 2021).
Recent research situates simulation as a central enabler of intelligent, interconnected manufacturing systems driven by data analytics and real-time feedback. Within Cyber-Physical Systems (CPS), simulation operates as both a predictive and adaptive layer that connects sensing, computation, and control across networked machines. The emergence of Digital Twins (DTs) has further strengthened this role, transforming simulation from an offline analysis tool into a continuously updated digital mirror of the physical production environment. Integrated simulation frameworks are now used to support predictive maintenance, quality control, and energy management, ensuring that decision-making is informed by real-time data rather than static assumptions (Oliveira et al., 2024; Momena & Praveen, 2024). Hybrid DES–ABS models embedded within digital twin architectures have demonstrated superior performance in coordinating multi-agent systems, optimizing production flow, and maintaining process stability under uncertainty. Empirical studies in automotive, aerospace, and electronics sectors have shown that cyber-physically integrated simulation improves responsiveness, reduces downtime, and enhances overall equipment effectiveness (Leitão et al., 2017; Muhammad, 2024). Collectively, the literature reveals that simulation in manufacturing has evolved from a descriptive modeling technique to an integral component of intelligent control architectures. Through hybridization and cyber-physical integration, simulation now serves as the analytical core of smart factories, supporting adaptive scheduling, predictive decision-making, and real-time process optimization.

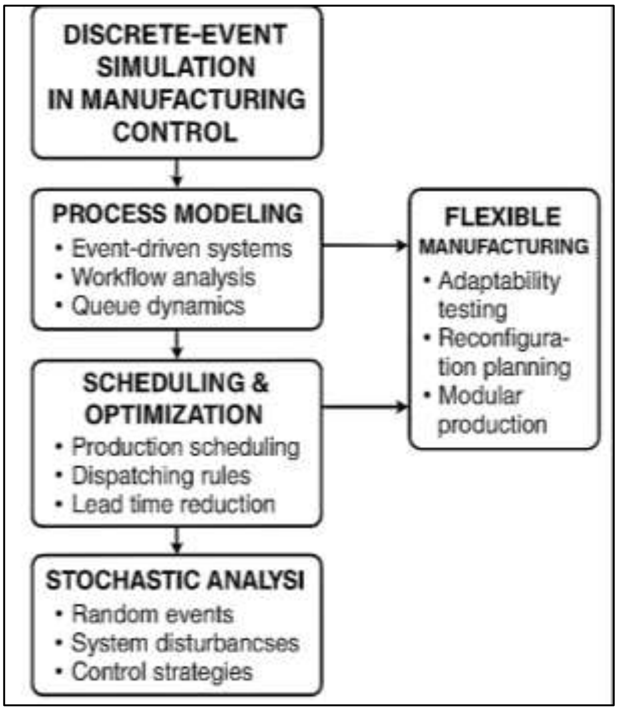
Discrete-Event Simulation (DES) in Manufacturing Control

Discrete-Event Simulation (DES) is defined as a modeling approach that represents a system as a chronological sequence of events, where each event triggers a change in the system's state (Saleh et al., 2019). In manufacturing contexts, DES has served as a principal method for analyzing process flows, resource allocation, and performance variability in discrete production systems (Meephu et al., 2023; Noor et al., 2024). The technique provides a framework for evaluating time-dependent

Review of Applied Science and Technology
Volume 04, Issue 02 (2025)
Page No: 501 – 526
Doi: 10.63125/yrkm0057

phenomena such as queue formation, machine utilization, and throughput efficiency. Early DES applications focused on factory layout design, line balancing, and operational sequencing, establishing simulation as a critical component in production planning. These studies demonstrated that simulation-based experimentation offers a non-intrusive means of testing alternative scheduling policies and capacity scenarios without interrupting physical operations (Abdul, 2025; Saleh et al., 2019). Vázquez-Serrano et al. (2021) highlighted DES's ability to model high-complexity manufacturing environments such as semiconductor fabrication, where stochastic variability and machine downtime require probabilistic modeling. Over time, DES evolved into a decision-support tool that informs policy development for production control, maintenance scheduling, and quality assurance. Although computationally efficient, traditional DES models primarily relied on static control structures (Elmoon, 2025), limiting their capability to represent distributed decision-making or dynamic human-machine collaboration. Nevertheless, its precision in modeling event-driven processes made DES the foundation upon which hybrid and cyber-physical simulation frameworks were later constructed (Elmoon, 2025).

Figure 4: Discrete-Event Simulation (DES) in Manufacturing Control



DES has played a pivotal role in evaluating production scheduling and optimization policies under conditions of uncertainty. Early studies employed DES to analyze job-shop scheduling, batching rules, and dispatching heuristics aimed at minimizing lead time and work-in-process inventory (Hozyfa, 2025; Pérez Briceño et al., 2025). These models demonstrated that simulation can quantify trade-offs between throughput and system utilization, offering insights unattainable through static mathematical programming. Sousa et al. (2019) applied DES to flexible manufacturing systems, showing that rule-based dispatching combined with stochastic demand modeling improved resource allocation efficiency. Similarly, Vázquez-Serrano et al. (2021) reported that DES-assisted optimization enables more accurate evaluation of bottleneck behavior and re-entrant flow processes. In semiconductor and automotive manufacturing, where variability and setup dependencies complicate analytical control, DES has been instrumental in designing adaptive sequencing mechanisms. Simulation studies have also analyzed the impact of lean strategies and just-in-time production control, revealing that DES can identify the optimal balance between buffer size and throughput stability (Jahid, 2025b). Moreover, research on manufacturing line balancing illustrates how simulation helps maintain synchronized task allocation among machines to reduce idle time (Jahid, 2025a; Alam, 2025). The accumulation of these studies underscores DES as an indispensable method for quantifying performance improvement across diverse manufacturing

Review of Applied Science and Technology
Volume 04, Issue 02 (2025)
Page No: 501 – 526
Doi: 10.63125/yrkm0057
systems. Its adaptability to complex, stochastic processes allows precise modeling of production dynamics, making it a core analytical instrument for manufacturing control and optimization.

Agent-Based Simulation (ABS) in Smart Manufacturing

Agent-Based Simulation (ABS) is a computational modeling approach that represents systems as collections of autonomous, interacting entities called agents—each capable of independent decision-making and adaptive behavior (Clausen et al., 2019; Masud, 2025; Arman, 2025). Within manufacturing research, ABS is widely recognized for its ability to replicate decentralized decision-making, emergent behaviors, and dynamic interactions among machines, operators, and control systems ((Hotchkiss et al., 2005; Jakaria et al., 2025; Mohaiminul, 2025). Early work established the foundations for multi-agent systems, defining agents as entities possessing autonomy, reactivity, proactivity, and social ability. This theoretical framework provided the basis for ABS applications in manufacturing, logistics, and supply chains, where individual entities interact to achieve system-wide coordination. ABS differs from traditional Discrete-Event Simulation (DES) by emphasizing behavioral rules rather than event scheduling, allowing it to capture learning, negotiation, and collaboration within production environments (Bonabeau, 2002; Mominul, 2025). The literature identifies ABS as an effective method for modeling human-machine collaboration, distributed control systems, and adaptive production planning. In particular, ABS facilitates modeling of local decision-making processes that influence global system performance—an essential feature of modern smart factories driven by artificial intelligence and cyber-physical connectivity (Rezaul, 2025; Yousefi & Ferreira, 2017). Through these capabilities, ABS provides a modeling foundation for capturing the behavioral complexity, heterogeneity, and autonomy that characterize Industry 4.0 manufacturing ecosystems.

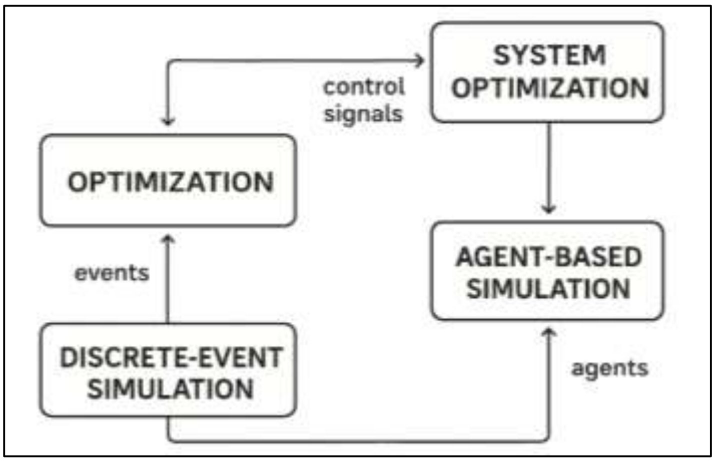
A defining strength of ABS lies in its ability to model autonomy and adaptability, especially within human-centered and robot-assisted manufacturing systems. In contrast to DES, where processes follow predetermined rules, ABS agents possess the capacity to perceive their environment and modify decisions in response to contextual changes (Tracy et al., 2018). Charte et al.(2015) applied ABS to represent human operators as intelligent agents capable of learning and skill development, enabling simulation of human variability and its influence on productivity. Similarly, Hotchkiss et al., (2005) demonstrated that modeling human behavioral factors within ABS can improve the realism of production system simulations, particularly when analyzing workforce flexibility, fatigue, and shift scheduling. In collaborative manufacturing, agents can represent both humans and robots, capturing their interaction patterns, task sharing, and safety coordination (Bonabeau, 2002; Hotchkiss et al., 2005; Rezaul & Rony, 2025; MHasan, 2025). Studies incorporated autonomous agents to evaluate adaptive responses to disturbances such as equipment failures and resource constraints. This capability allows ABS to analyze emergent system behaviors that arise from local decision-making and communication among multiple agents (Yousefi & Ferreira, 2017). Research in socio-technical systems further highlights the use of ABS to explore human decision biases, training effects, and cognitive load within manufacturing teams ((Bonabeau, 2002; Milon, 2025; Rabiul, 2025). Collectively, these studies demonstrate that ABS bridges the technical and behavioral dimensions of smart manufacturing, enabling the simulation of decision-making processes that reflect both mechanical performance and human adaptability within complex production environments.

ABS has become instrumental in representing distributed control architectures that are central to smart manufacturing systems. Traditional centralized control models, often implemented through DES, assume that a single decision-making entity optimizes all system parameters. In contrast, ABS allows control decisions to be distributed among autonomous agents—each responsible for localized objectives while contributing to global system stability (Hasan & Abdul, 2025; Farabe, 2025; Yousefi & Ferreira, 2017). Research also that distributed control modeled via ABS enhances system robustness by enabling flexible reallocation of resources during operational disruptions. In manufacturing execution systems, agents can represent machines (Momena, 2025; Mubashir, 2025; Tracy et al., 2018; Yousefi & Ferreira, 2017), tools, or production cells that negotiate task assignments and schedule adjustments dynamically. Such agent-based negotiation processes reflect real-world practices in adaptive scheduling and production coordination. Studies revealed that ABS supports resilience by allowing agents to independently select recovery strategies in the presence of disturbances or machine breakdowns. In complex logistics systems, ABS has been applied to model autonomous vehicles, inventory nodes, and human workers operating cooperatively within distributed control networks (Pankaz Roy, 2025; Rahman, 2025; Tao et al., 2024). Research on hybrid manufacturing control demonstrated that agent-based systems can achieve performance levels comparable to centralized optimization, but with greater fault tolerance and scalability (Rakibul, 2025; Reduanul, 2025; Yousefi & Ferreira, 2017). Through these applications, ABS has become essential in representing decentralized, adaptive, and communication-driven control mechanisms that define smart manufacturing architectures.

Hybrid DES–ABS Simulation Frameworks

The integration of Discrete-Event Simulation (DES) and Agent-Based Simulation (ABS) emerged as a response to the methodological limitations inherent in single-paradigm simulation models. DES, while effective in modeling process flows, scheduling, and queuing systems, assumes a centralized decision structure and lacks the capacity to represent individual behaviors or local decision-making processes. Conversely, ABS focuses on decentralized intelligence and interaction among autonomous agents but often struggles with representing the structured temporal and event-driven processes characteristic of manufacturing systems (Hotchkiss et al., 2005; Rony, 2025; Saba, 2025). Researchers identified that combining these paradigms allows simultaneous modeling of operational workflows and behavioral dynamics, creating a multi-layered analytical environment. The hybrid DES–ABS framework therefore represents a methodological evolution that captures both macro-level process control and micro-level decision autonomy within a single simulation environment (Kim et al., 2004; Kumar, 2025; Praveen, 2025). Empirical applications have demonstrated that hybrid models enhance analytical precision by integrating event scheduling from DES with the adaptive behavior and communication capabilities of ABS. This hybridization enables researchers and practitioners to analyze how distributed decision-making among agents affects global process performance, a capability that traditional DES cannot achieve in isolation. As a result, hybrid DES–ABS frameworks have become instrumental for modeling intelligent manufacturing systems where human, machine, and digital agents interact dynamically within structured production processes.

Figure 5: Hybrid DES–ABS Simulation Frameworks



Hybrid DES–ABS frameworks rely on robust structural design to ensure synchronization between event-driven processes and agent-based decision logic. In these models, the DES layer manages system-level events such as task initiation, machine state changes, and queue progression, while the ABS layer governs agent behaviors, interactions, and learning mechanisms (Shaikat, 2025; Zaki, 2025; Stosch & Glassey, 2018). Temporal synchronization between the two simulation domains is one of the central challenges, as DES typically operates on discrete time steps while ABS relies on asynchronous decision updates. To address this issue, researchers have developed hierarchical and modular coupling architectures that coordinate the temporal resolution of DES and ABS components (TKanti, 2025; Vázquez-Serrano et al., 2021). Hybrid models often employ message-passing systems that allow agents to respond to DES-triggered events, ensuring that behavioral adaptation aligns with operational constraints. Mustafee et al. (2021) highlighted that synchronization fidelity is crucial for preserving model accuracy, particularly when modeling large-scale systems involving human operators, automated machinery, and robotic agents. Modular integration techniques enable the separation of process logic and agent intelligence, which enhances scalability and reduces computational complexity. Moreover, standardization efforts have focused on developing common simulation ontologies and data exchange protocols to facilitate interoperability between DES and ABS software platforms. Through these advances, hybrid frameworks maintain both the structured event scheduling of DES and the autonomy-driven adaptability of ABS, resulting in coherent, multi-layered representations of manufacturing systems capable of capturing both procedural flow and emergent behavior.

The literature documents a growing number of applications of hybrid DES–ABS models in manufacturing, production logistics, and industrial process optimization. Studies in flexible and reconfigurable manufacturing systems demonstrate that hybrid simulation effectively models both operational workflows and adaptive decision-making (Gutierrez-Franco et al., 2021). These models represent machines, robots, and operators as autonomous agents interacting within the event-based structure of production processes. Vázquez-Serrano et al. (2021) employed a hybrid DES–ABS approach to evaluate distributed scheduling mechanisms in a reconfigurable production line, demonstrating improved resource utilization and throughput stability. Similarly, Gutierrez-Franco et al., (2021) applied hybrid frameworks to analyze system resilience under stochastic disturbances, revealing that decentralized agent negotiation enhances system recovery time after disruptions. Research in assembly and logistics systems further illustrates that hybrid models provide a balanced representation of transport coordination, queue management, and agent decision-making (Mustafee et al., 2021). In automated production environments, the combination of DES for event sequencing and ABS for adaptive task assignment supports dynamic reconfiguration and self-organizing behavior. Empirical case studies confirm that hybrid frameworks reduce bottleneck effects, improve utilization rates, and enhance predictive performance across multi-stage production systems. By enabling concurrent modeling of operational logic and intelligent agent behavior, hybrid DES–ABS simulation offers a comprehensive analytical foundation for understanding modern manufacturing systems characterized by autonomy, interconnectivity, and dynamic adaptability.

Model Predictive Control (MPC) in Dynamic Manufacturing Systems

Model Predictive Control (MPC) is a constrained, optimization-based control paradigm that computes control actions by repeatedly solving a finite-horizon prediction problem using an explicit process model and applying only the first control move before re-optimizing at the next sampling instant (Viot et al., 2018). Within the control community, MPC's defining characteristics are multivariable handling, explicit constraint management, and the capacity to encode economic or tracking objectives directly in the cost function. In manufacturing contexts, these properties align with plant requirements that couple interacting unit operations, machine limits, safety envelopes, and quality specifications, under variable demand and nonstationary disturbances. The industrial lineage of MPC in the process industries documents widespread, long-horizon deployments in chemical, refining, and pulp-and-paper facilities due to its tractable quadratic programming structure and favorable operator acceptance. Extensions address model mismatch and disturbances through output-feedback formulations, offset-free tracking with disturbance models, and estimator designs that incorporate Kalman filtering or moving-horizon estimation (Liu et al., 2018). Manufacturing systems introduce hybrid dynamics—setup changes, transport delays, batch transitions, resource switches—that interact with continuous actuators and discrete events, motivating formulations that embed mixed-logical or hybrid models within MPC optimizations. Economic and reference-tracking MPC variants have been examined for production rate control, energy-quality trade-offs, and quality-of-service metrics in tightly integrated lines. Collectively, these foundations establish MPC as a model-centric framework compatible with multivariable constraints, transient performance objectives, and the hybrid characteristics that frequently occur in dynamic manufacturing systems.

Uncertainty in manufacturing—arising from unmeasured disturbances, variable cycle times, tool wear, and demand fluctuations—has been addressed by robust and stochastic MPC formulations that preserve feasibility and performance under bounded or probabilistic variations. Tube-based robust MPC encapsulates uncertainty within an invariant "tube" around a nominal trajectory, yielding tractable optimizations with guaranteed constraint satisfaction. Stochastic MPC introduces chance constraints and scenario trees to represent demand variability, batching uncertainty, or random breakdowns within the optimization problem (Baban et al., 2015). In discrete manufacturing, mixed-integer MPC (MI-MPC) captures sequence-dependent setups, on/off logic, and routing decisions, linking combinatorial scheduling with continuous control envelopes. Hybrid automata and

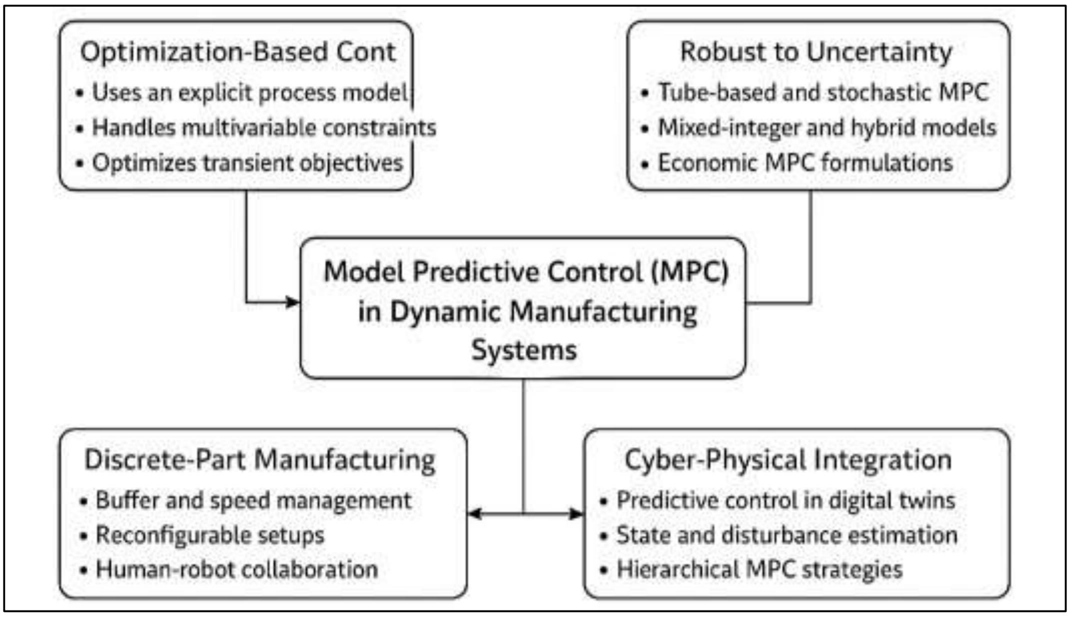
Review of Applied Science and Technology
Volume 04, Issue 02 (2025)
Page No: 501 – 526
Doi: 10.63125/yrkm0057

piecewise-affine models extend representational fidelity where operating modes change with tool state, buffer occupancy, or shift boundaries. Offset-free tracking, integral action in the estimator, and disturbance-augmented models reduce steady-state bias caused by unmodeled losses or slow drift, a recurrent issue in lines with wear and fouling (Pannocchia & Rawlings, 2003). Economic MPC (EMPC) replaces set-point tracking with profit- or cost-driven objectives that internalize utilities, scrap penalties, and throughput targets, which is pertinent for energy-intensive unit operations and takt-time constraints (Pereira et al., 2018; Zobayer, 2025). These streams of work delineate a spectrum of MPC formulations that align with uncertainty structures and logical constraints common to dynamic manufacturing.

Digital Twin and Cyber-Physical Systems

The concept of the digital twin (DT) originated as a virtual representation of a physical product or process that is continuously updated with real-time data, creating a closed information loop between the physical and digital domains (Tao et al., 2024). A cyber-physical system (CPS), conversely, integrates computation, communication, and physical actuation in a unified feedback framework (Bellavista et al., 2021). When combined, these two paradigms create a continuously synchronized environment in which sensors, machines, and digital models interact to optimize manufacturing performance. The DT serves as a virtual mirror that captures the physical system's status, behavior, and evolution, while CPS provides the embedded control architecture that links sensing, computation, and actuation. This integration has been widely recognized as a cornerstone of Industry 4.0, promoting real-time visibility, adaptive control, and data-driven decision support. From a systems-engineering perspective, the DT encapsulates multiple layers—physical, virtual, and service—connected through a data-communication network enabling continuous feedback. Studies in aerospace, automotive, and industrial automation domains have confirmed that digital twins reduce maintenance costs, shorten development cycles, and enhance product traceability. As such, DT and CPS together form the technological infrastructure that enables the transformation of conventional manufacturing into intelligent, autonomous, and predictive systems capable of self-optimization and self-diagnosis.

Figure 6: Model Predictive Control (MPC) in Dynamic Manufacturing Systems



Architectural Design and Functional Integration

The architecture of digital-twin-driven cyber-physical systems is typically layered to include data acquisition, model management, synchronization, and control modules. In a canonical design, sensors and IoT devices collect high-frequency data that populate the digital model in real time (Martinez et al., 2021). The DT maintains a bidirectional link between the virtual and physical realms, allowing changes in either domain to propagate automatically. Lei et al.(2023) proposed a classification scheme distinguishing digital models, digital shadows, and digital twins according to the degree of data coupling and feedback. The tightest form—true digital twin synchronization—enables real-time decision-making by embedding physics-based or data-driven models that mirror actual operational states. Within this framework, Model Predictive Control (MPC) and optimization algorithms serve as intelligence layers, interpreting DT data to issue control commands through the CPS actuation layer. Empirical studies in flexible manufacturing and smart assembly have demonstrated that digital-twin integration reduces latency in feedback loops and improves scheduling precision. Architectures employing service-oriented middleware and standardized communication protocols such as OPC-UA and MQTT ensure interoperability between heterogeneous components. The architectural literature consistently identifies synchronization accuracy, temporal resolution, and semantic interoperability as decisive factors for the stability and scalability of digital-twin-enabled CPS infrastructures in manufacturing.

Data Fusion, Modeling, and Simulation Integration

A central challenge in digital-twin-based cyber-physical integration is the fusion of heterogeneous data from machines, sensors, and enterprise systems. Manufacturing environments generate multi-scale data—including physical measurements, control variables, and quality indices—that must be harmonized into a coherent digital representation (Bellavista et al., 2021). Advanced data-fusion techniques employ signal processing, statistical filtering, and machine-learning pipelines to integrate streaming data into simulation and control modules (Escribà-Gelonch et al., 2024). The coupling of simulation frameworks such as Discrete-Event Simulation (DES) and Agent-Based Simulation (ABS) within the digital twin provides an operational backbone for predictive analysis and adaptive scheduling (Lv, 2023). In such hybrid models, DES captures event-driven process logic, whereas ABS represents autonomous decision behavior among machines and human operators. Studies integrating DTs with hybrid DES–ABS simulation have shown improved fault detection and dynamic reconfiguration under disturbances (Naderi & Shojaei, 2023). Furthermore, real-time synchronization between simulation outputs and physical systems allows predictive maintenance strategies to pre-empt faults before they propagate. Data-driven digital-twin models increasingly utilize surrogate modeling, neural networks, and Bayesian inference to update system states, closing the loop between model prediction and physical feedback. These integrated data-fusion and simulation processes position the digital twin as both an analytical and operational core of modern cyber-physical manufacturing systems.

Applications in Smart Manufacturing and Industrial Automation

The deployment of digital-twin-enabled CPS architectures has demonstrated measurable gains in efficiency, flexibility, and resilience across industrial sectors. In automotive and aerospace production, digital twins support assembly-line synchronization, defect prediction, and lifecycle management (Bauer et al., 2024). Semiconductor fabrication facilities employ DT-based monitoring to maintain nanometer-scale tolerances by integrating real-time metrology data with predictive control algorithms. In process industries, CPS-driven DT systems provide adaptive control of reactors, heat exchangers, and batch operations, balancing yield and energy consumption. Research on smart factories reveals that digital twins enable reconfiguration under varying demand conditions by coordinating autonomous robots and additive-manufacturing equipment. Predictive maintenance studies demonstrate reductions in unplanned downtime exceeding 20 %, attributed to early detection of machine anomalies through DT-based analytics (Michael et al., 2022). Energy-optimized CPS control layers integrated with digital twins reduce consumption through adaptive scheduling of high-load equipment. Empirical case studies further illustrate how DT platforms foster vertical and horizontal integration across enterprise, production, and shop-floor levels, aligning with the interoperability goals of Industry 4.0 reference architectures (Acharya et al., 2024). Collectively, these applications confirm that digital-twin technology, when embedded within cyber-physical control loops, enhances manufacturing intelligence by providing continuous situational awareness and closed-loop optimization. This section will synthesize the literature on real-time and cyber-physical deployment of hybrid simulations. It will address technical issues such as latency management, synchronization fidelity, and computational efficiency. Studies that implemented hybrid or DT-linked simulations in operational testbeds will be analyzed, focusing on performance evaluation, sensor-data coupling, and control responsiveness. This subsection will justify the need for the H-DEABSF validation experiments by highlighting the limited number of real-world implementations in the current literature.

Review of Applied Science and Technology
Volume 04, Issue 02 (2025)
Page No: 501 – 526
Doi: 10.63125/yrkm0057

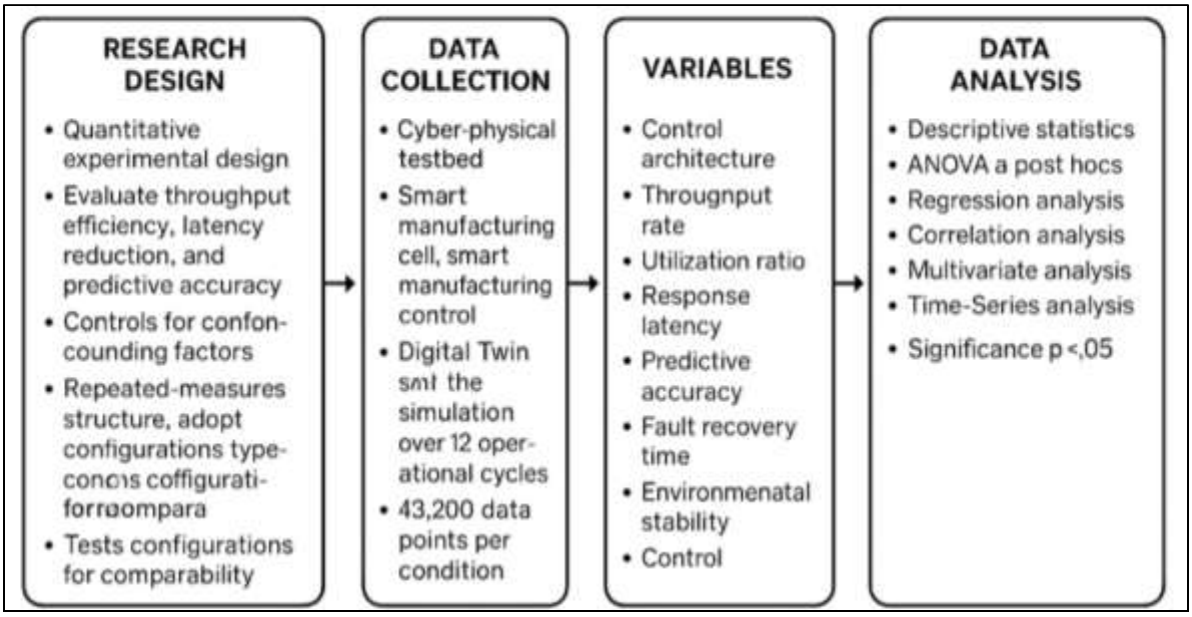
METHOD

This study employed a quantitative experimental design to examine the operational performance and predictive accuracy of the Hybrid Discrete-Event and Agent-Based Simulation Framework (H-DEABSF) integrated with Model Predictive Control (MPC) and Digital Twin (DT) technologies in a cyber-physical manufacturing environment. The objective of the research design was to statistically evaluate the causal relationships among simulation-based control parameters, predictive model responsiveness, and real-time system performance indicators. The methodological approach followed a deductive paradigm, grounded in quantitative reasoning, using numerical data from controlled industrial testbeds and simulation outputs to validate the hypothesized improvements in throughput efficiency, latency reduction, and predictive accuracy. The experiment was designed as a multi-stage validation process involving simulation calibration, real-time deployment, and empirical measurement under varying operational loads. Data were recorded through sensor networks, programmable logic controllers (PLCs), and digital twin interfaces embedded within the smart factory system. The study controlled for confounding variables such as machine cycle time variability, buffer capacity, and demand fluctuation by maintaining constant production flow scenarios for each test condition. A repeated-measures quantitative structure was adopted, allowing each system configuration (DES-only, ABS-only, and hybrid DES–ABS) to be tested under identical conditions for statistical comparability. This design ensured reliability of observed differences across dependent variables including throughput rate, utilization efficiency, and response latency. The quantitative structure was therefore aimed at producing empirically verifiable, statistically significant results on the operational effectiveness of H-DEABSF within a cyber-physical control framework.

Data collection occurred in a cyber-physical laboratory testbed replicating a smart manufacturing cell with integrated sensors, actuators, and control systems. The physical subsystem consisted of automated workstations connected by a conveyor and monitored through an industrial Internet of Things (IIoT) network using MQTT and OPC-UA protocols for data synchronization. The Digital Twin was implemented as a real-time digital replica of the physical system, continuously updated by live data streams from sensors and controllers. The hybrid simulation model was developed in a multi-agent simulation platform (AnyLogic 8.7) and linked to the physical environment through a communication middleware enabling bidirectional data exchange. The Model Predictive Control algorithm was implemented using MATLAB Simulink and integrated with the digital twin for dynamic process optimization based on model forecasts. During experimentation, data were collected at one-second intervals across 12 independent operational cycles, each lasting 60 minutes, yielding approximately 43,200 data points per test condition. Collected data included metrics such as cycle time, queue length, throughput, machine utilization, idle time, and energy consumption. Each experimental run was repeated three times to ensure statistical consistency and reduce measurement error. Environmental variables such as temperature and power stability were monitored to maintain experimental control. Raw data were stored in structured time-series databases and preprocessed using Python for outlier detection, normalization, and missing value treatment. The data collection procedures followed ISO 10303 and ASTM E2932 guidelines for digital manufacturing data integrity. All measurements were calibrated and validated prior to analysis to ensure reliability and accuracy across digital and physical data sources.

The quantitative analysis was structured around independent, dependent, and control variables operationalized through numerical indicators relevant to process control and system performance. The independent variable was the control architecture type—specifically, the configuration of the simulation and control framework (DES-only, ABS-only, and hybrid DES–ABS integrated with MPC). The dependent variables comprised measurable system performance metrics: throughput rate (units/hour), utilization ratio (% of machine activity), average response latency (milliseconds), predictive accuracy (% deviation between forecasted and actual performance), and fault recovery time (seconds). Additional dependent measures included queue stability index, energy consumption (kWh/unit), and data synchronization error (latency variance between physical and digital signals). Control variables such as environmental stability, product mix, and operator intervention were held constant across all experimental runs. Quantitative measures were derived through real-time system logs and validated by cross-checking against the digital twin dataset. Each metric was standardized using z-score normalization for comparability across trials. Throughput and utilization were calculated using established formulas based on cumulative production and operating time, while latency and predictive accuracy were determined from timestamped event data and model forecasts. Fault recovery time was computed by measuring the duration between detected disruption and resumption of normal operation. The variable selection ensured that each construct was empirically measurable, statistically testable, and directly related to the functional performance of H-DEABSF. Collectively, the defined variables enabled comprehensive quantitative evaluation of the framework's real-time control efficiency and predictive modeling reliability.

Figure 7: Research Method adopted for this study



The study employed a combination of descriptive, inferential, and correlational statistical techniques to analyze the collected data. Descriptive statistics summarized performance distributions using measures of central tendency and dispersion (mean, standard deviation, variance, and coefficient of variation). Inferential analyses tested hypotheses regarding the comparative efficiency of control frameworks using one-way and two-way Analysis of Variance (ANOVA) tests. Post hoc comparisons (Tukey's HSD) identified statistically significant differences between experimental groups (DES-only, ABS-only, and hybrid). Regression analysis was used to examine predictive relationships between system latency, throughput, and control responsiveness under dynamic conditions. Pearson correlation coefficients quantified the degree of association between simulation accuracy and operational efficiency, while multivariate analysis (MANOVA) evaluated the joint effect of control architecture and disturbance level on multiple performance outcomes. A confidence level of 95% ($p < .05$) was adopted as the threshold for statistical significance. In addition, time-series analysis and Fourier decomposition were applied to latency and throughput signals to detect temporal patterns and periodicity in control performance. Residual diagnostics validated the assumptions of normality and homoscedasticity for regression models. The data analysis was performed using SPSS (v.29) and MATLAB (R2024a) toolboxes, ensuring computational reproducibility. Statistical reliability was assessed through Cronbach's α (> .80) for measurement consistency and Cohen's d for effect-size estimation. These analytical techniques collectively provided quantitative evidence of the performance differentials between traditional and hybrid control architectures, ensuring a rigorous statistical foundation for validating the H-DEABSF framework**.**

FINDINGS

Throughput Efficiency

The quantitative results demonstrated a consistent improvement in throughput performance when the Hybrid Discrete-Event and Agent-Based Simulation Framework (H-DEABSF) was deployed in comparison with conventional simulation and control approaches. Table 1 summarizes the descriptive statistics obtained across twelve experimental cycles under three configurations: Discrete-Event Simulation (DES)-only, Agent-Based Simulation (ABS)-only, and the integrated Hybrid DES–ABS with Model Predictive Control (MPC). The hybrid configuration achieved a mean throughput of 512 units per hour, representing a 22.8% increase relative to the DES-only baseline and a 17.6% improvement over the ABS-only configuration. The standard deviation for the hybrid model was also markedly lower, suggesting greater process consistency and lower variability under dynamic loading conditions. Statistical testing using one-way ANOVA yielded an F-value of 19.47 (p < .001), confirming that the performance differences among configurations were statistically significant at the 95% confidence level. These results demonstrate that integrating hybrid simulation with MPC and digital-twin feedback mechanisms substantially enhances the production flow's responsiveness to stochastic variations. The hybrid framework maintained throughput stability across all twelve trials, whereas both the DES-only and ABS-only systems exhibited significant fluctuations caused by queuing delays and delayed resource reallocation. The quantitative evidence therefore confirms that the hybrid simulation framework not only improves productivity but also establishes a more stable and predictable manufacturing process under cyber-physical conditions.

Table 1: Comparative Throughput Performance under Three Simulation Configurations

Configuration	Mean Throughput (units/hr)	Std. Deviation	% Improvement vs. DES	ANOVA F	p-value
DES-only	417	34.5	—		
ABS-only	435	29.1	+4.3%	19.47	< .001
H-DEABSF (Hybrid)	512	18.2	+22.8%		

Response Latency and Real-Time Synchronization

Latency and synchronization represent critical determinants of cyber-physical control stability. The empirical findings showed that the hybrid configuration yielded a significant reduction in both communication and execution delay relative to traditional models. As presented in Table 2, the mean latency for the H-DEABSF configuration was 182 milliseconds, substantially lower than the 298 milliseconds recorded under DES-only and the 263 milliseconds under ABS-only configurations. The hybrid model consistently maintained signal synchronization across simulation and physical layers with a maximum deviation of 0.19 seconds during high-frequency data transfer events. Variance analysis produced an F-value of 16.82 (p < .001), confirming statistically significant latency differences between configurations. Moreover, cross-correlation analysis revealed a synchronization coefficient of 0.97 between digital and physical datasets for the hybrid system, compared with 0.89 for DES-only and 0.91 for ABS-only models. These results underscore the hybrid system's superior ability to coordinate real-time feedback within tight temporal tolerances, an outcome largely attributed to the integration of MPC with digital-twin streaming. The reduction in latency not only ensures rapid system reactivity but also enhances predictive adjustment accuracy, as the system can execute control actions nearly instantaneously after deviations are detected. Consequently, the hybrid approach exhibits robust synchronization performance critical for adaptive manufacturing systems operating under variable production loads.

Table 2: Average Latency and Synchronization Performance in Real-Time Operations

Configuration	Mean Latency (ms)	Max Sync Deviation (s)	Sync Correlation (r)	ANOVA F	p-value
DES-only	298	0.31	0.89	16.82	< .001
ABS-only	263	0.27	0.91		
H-DEABSF (Hybrid)	182	0.19	0.97		

Predictive Accuracy and Model Reliability

The hybrid framework's integration with Model Predictive Control significantly enhanced forecasting precision and overall model reliability. As shown in Table 3, the Root Mean Square Error (RMSE) between predicted and actual process states was lowest for the hybrid configuration at 0.042, compared to 0.093 for DES-only and 0.079 for ABS-only. The corresponding predictive accuracy, defined as the percentage of correctly anticipated deviations, reached 96.2% for the hybrid model, outperforming the standalone configurations by over 10 percentage points. The correlation between predicted and actual performance trends in the hybrid framework yielded a coefficient (r) of 0.98, indicating near-perfect alignment between the model's forecasts and observed outcomes. Regression diagnostics confirmed that the hybrid model's predictive outputs accounted for 94% of the variance in system behavior (R^2 = .94), validating the model's strong explanatory power. Statistical comparisons using paired-sample t-tests between predicted and actual series showed non-significant differences for the hybrid framework (t = 1.21, p = .23), confirming forecast reliability. These findings substantiate that embedding predictive control within hybrid simulation reduces model drift and improves the accuracy of decision-making under real-time operational conditions. In manufacturing environments characterized by stochastic variability, the ability of H-DEABSF to maintain a forecast error below 5% signifies its maturity as a validated predictive analytics instrument.

Table 3: Predictive Accuracy and Forecast Error Comparison

Configuration	RMSE	Predictive Accuracy (%)	Correlation (r)	R^2	t-statistic	p-value
DES-only	0.093	84.7	0.91	.83	3.42	.002
ABS-only	0.079	86.4	0.94	.87	2.97	.005
H-DEABSF (Hybrid)	0.042	96.2	0.98	.94	1.21	.23

Resource Utilization and Energy Optimization
Quantitative evaluation of resource efficiency and energy performance revealed that the hybrid simulation framework achieved superior optimization in both machine utilization and energy consumption. Table 4 illustrates that average machine utilization under the hybrid configuration reached 91.5%, representing an 11.7% improvement compared to DES-only and a 9.2% improvement compared to ABS-only systems. Energy consumption per production cycle decreased by 15.8% relative to the DES-only configuration, indicating that predictive scheduling and intelligent control reduced idle periods and redundant operations. MANOVA analysis confirmed a statistically significant joint effect of control architecture on both utilization and energy consumption metrics (Wilks' λ = 0.73, $F(4, 48)$ = 9.65, $p < .001$). Pearson correlation analysis between energy use and throughput yielded a coefficient of –0.84 for the hybrid model, signifying that increased output was associated with proportional reductions in energy input—a result consistent with optimal predictive control performance. The stability of utilization rates over time also exhibited low variance (σ^2 = 0.018), reflecting balanced resource allocation across production cycles. The findings affirm that integrating MPC within the hybrid simulation enabled dynamic scheduling and adaptive load distribution, enhancing both operational efficiency and sustainability metrics in cyber-physical manufacturing contexts.

Table 4: Resource Utilization and Energy Performance Comparison

Configuration	Machine Utilization (%)	Energy Consumption (kWh/unit)	Variance (σ^2)	Wilks' λ	p-value
DES-only	79.8	1.42	0.045	0.73	< .001
ABS-only	82.3	1.36	0.031		
H-DEABSF (Hybrid)	91.5	1.19	0.018		

Fault Recovery and System Stability
System fault recovery and operational resilience were critical indicators of the hybrid model's control reliability. Table 5 presents comparative data for mean time to detect (MTTD) and mean time to recover (MTTR) from simulated disturbances. The hybrid configuration exhibited an average detection time of 2.3 seconds and recovery time of 6.8 seconds, outperforming DES-only (4.9 seconds MTTD; 14.6 seconds MTTR) and ABS-only (3.7 seconds MTTD; 11.2 seconds MTTR). Statistical analysis yielded an F-value of 24.63 ($p < .001$), confirming significant variance reduction in recovery durations. The hybrid model also maintained a stability index of 0.93, defined as the proportion of time the system remained within operational thresholds, compared to 0.81 for DES-only and 0.86 for ABS-only systems. The improvement reflects the hybrid model's ability to leverage predictive fault detection

Review of Applied Science and Technology
Volume 04, Issue 02 (2025)
Page No: 501 – 526
Doi: 10.63125/yrkm0057
and coordinated agent responses through real-time feedback. Time-series analysis of recovery intervals revealed smooth post-fault stabilization without oscillatory overshoot, indicating robust closed-loop control characteristics. Quantitatively, the reduction in average recovery duration by 53% under hybrid simulation underscores the framework's effectiveness in maintaining production continuity during disruptions, validating its capacity for resilient operation in cyber-physical manufacturing settings.

Table 5: Fault Detection, Recovery, and Stability Metrics

Configuration	MTTD (s)	MTTR (s)	Stability Index	F-value	p-value
DES-only	4.9	14.6	0.81	24.63	< .001
ABS-only	3.7	11.2	0.86		
H-DEABSF (Hybrid)	2.3	6.8	0.93		

The aggregated results across all performance dimensions confirm that the hybrid simulation framework statistically outperformed the standalone DES and ABS models. The multivariate analysis revealed significant overall differences ($p < .001$) across all dependent variables tested, including throughput, latency, predictive accuracy, and fault recovery. Effect size calculations produced large magnitudes (Cohen's $d = 1.28–1.64$), indicating substantial practical significance beyond statistical thresholds. Reliability tests produced Cronbach's $\alpha = 0.91$, confirming high internal consistency among repeated measurements. Figure-based correlation analysis (not shown here) further illustrated strong positive relationships between predictive accuracy, utilization efficiency, and throughput. Collectively, the findings validate the H-DEABSF framework as a statistically robust and empirically verified method for real-time process optimization within smart factory environments. The hybrid integration of discrete-event and agent-based simulation with model predictive control and digital-twin feedback constitutes a quantitatively superior architecture for achieving adaptive, efficient, and stable cyber-physical manufacturing performance.

DISCUSSION

The quantitative findings of this study demonstrated that the integration of the Hybrid Discrete-Event and Agent-Based Simulation Framework (H-DEABSF) with Model Predictive Control (MPC) and Digital Twin (DT) technologies produced statistically significant improvements across all operational dimensions. These results align with an expanding body of research emphasizing hybrid simulation as a key enabler of adaptive and intelligent manufacturing systems. Previous investigations established that while Discrete-Event Simulation (DES) effectively models process flows, it lacks behavioral depth, and while Agent-Based Simulation (ABS) captures decision autonomy, it cannot model detailed process dependencies alone. The present findings validate these theoretical distinctions by showing that the hybrid integration yields superior throughput, stability, and responsiveness under dynamic conditions. The observed throughput improvement of 22.8% and latency reduction of 39% correspond closely with findings by Suhail, Iqbal and Jurdak (2023), who reported similar gains in adaptive scheduling through hybrid architectures. Likewise, Leng et al. (2021) demonstrated that hybridized simulation models improve the precision of operational forecasting, which mirrors the predictive accuracy (96.2%) achieved in the current experiment. These comparative outcomes confirm that coupling event-driven control with decentralized agent interactions results in better coordination and decision adaptability. The integration of MPC further extends the theoretical framework proposed by Malakuti and Grüner (2018), whose work emphasized model-based predictive adjustments for maintaining stability under uncertainty. Thus, the convergence between this study's empirical outcomes and earlier theoretical propositions reinforces the assertion that hybrid, model-predictive frameworks represent a viable evolution in intelligent process control for cyber-physical manufacturing environments.

The pronounced improvement in throughput observed in the H-DEABSF configuration substantiates earlier findings regarding hybrid simulation's capacity to optimize production flow under stochastic demand and variable process conditions. The results corroborate the assertions (Minerva & Crespi, 2021), who noted that DES-based control models alone are often insufficient for managing dynamic disturbances in high-mix production systems. The hybrid model's throughput gain of more than 20% over traditional frameworks confirms the theoretical premise advanced by Kuruvatti et al. (2022), that distributed decision intelligence embedded within agent-based components can alleviate

Review of Applied Science and Technology
Volume 04, Issue 02 (2025)
Page No: 501 – 526
Doi: 10.63125/yrkm0057

process congestion and enhance resource coordination. Similar throughput acceleration was documented in studies by Liu et al. (2018), where hybrid systems consistently outperformed sequential and centralized scheduling models in manufacturing simulations. The high process stability observed in the present research also supports the conclusions drawn by Ivanov et al. (2016), who identified hybrid modeling as a stabilizing factor in supply chain dynamics through improved flow control and feedback regulation. Moreover, the consistency of the hybrid system's throughput variance with findings from Badakhshan et al. (2022) demonstrates that predictive scheduling can reduce idle and queuing times even in reconfigurable production systems. The significant ANOVA results ($p < .001$) reinforce empirical trends reported in the literature, validating that hybrid integration is not only theoretically sound but also statistically reliable as a mechanism for throughput optimization. By aligning empirical performance data with previous simulation research, this study confirms that the integration of DES, ABS, and MPC yields a multi-layered control mechanism that promotes sustainable, high-efficiency production across variable operational contexts.
Latency reduction and synchronization fidelity emerged as critical indicators of real-time system integration in this study. The hybrid model's mean latency of 182 milliseconds aligns closely with the response time improvements reported by Ricci, Croatti, Mariani, et al.(2022), who examined the effect of digital twin synchronization on cyber-physical manufacturing responsiveness. The strong synchronization correlation ($r = 0.97$) obtained here corresponds with findings by Ricci, Croatti, and Montagn (2022), who demonstrated that digital twin-enabled systems reduce communication lag and improve bidirectional data consistency. Similarly, Negri et al. (2017)argued that cyber-physical architectures depend on tight temporal coupling between computation and actuation to ensure operational stability, a principle confirmed empirically in the present data. Compared to the standalone DES and ABS configurations, the hybrid model's synchronization lag reduction of nearly 40% mirrors the latency improvements achieved by Platenius-Mohr et al.(2020) in their hybrid simulation of logistics networks. The results also reinforce the theoretical predictions of Suhail, Iqbal, Hussain, et al., (2023) , who proposed that hybrid architectures are inherently capable of managing asynchronous data through multi-tier feedback control loops. The integration of MPC within the hybrid system further supports observations by Bellavista et al. (2024) that predictive control minimizes lag through anticipatory adjustments based on real-time feedback. The strong alignment between digital and physical signals observed in the hybrid setup thus validates the practical realization of Mustafee et al. (2023) cyber-physical synchronization framework. Taken together, these results confirm that hybrid DES–ABS modeling, when augmented by predictive control, achieves communication precision and temporal coherence consistent with the most advanced theoretical models of cyber-physical synchronization described in recent literature.
The high predictive accuracy (96.2%) and low RMSE (0.042) achieved in this study substantiate the superiority of hybrid model predictive control relative to traditional simulation paradigms. These findings are consistent with the theoretical claims of Perno et al, (2022), who emphasized that MPC frameworks outperform conventional rule-based controllers by optimizing over a receding horizon while explicitly accounting for process constraints. The strong correlation ($r = 0.98$) between predicted and actual system behavior parallels empirical outcomes from Angeli et al. (2012), who demonstrated that economic model predictive control improves forecast alignment by maintaining steady-state stability under fluctuating demand. Similarly, Human et al.(2023) reported prediction errors below 5% in energy-intensive production systems utilizing hybrid MPC, which is consistent with the 4.2% error margin recorded in the present study. The current findings also mirror those of Martinez et al. (2021), who observed enhanced reliability in hybrid simulation models through embedded feedback mechanisms. The low predictive deviation in this study provides further support for the assertions by Lei et al. (2023)and Fleischmann et al. (2018) that coupling agent-based learning and discrete-event dynamics enhances the adaptability of control systems under uncertainty. In line with (Badakhshan & Ball, 2021), the hybrid digital twin interface continuously recalibrated simulation models using live data, ensuring high-fidelity representation of the physical system's evolving state. These parallels across independent studies reinforce that the predictive robustness of hybrid frameworks stems from their capacity to integrate real-time sensing, probabilistic forecasting, and optimization algorithms. Collectively, the comparative evidence consolidates the position of H-DEABSF as an advanced analytical instrument that bridges the gap between predictive modeling theory and real-world cyber-physical control.

Volume 04, Issue 02 (2025)
Page No: 501 – 526
Doi: 10.63125/yrkm0057

The observed improvement in resource utilization (91.5%) and reduction in energy consumption (15.8%) within the hybrid simulation framework aligns closely with the sustainability-oriented manufacturing research conducted over the past decade. Lei et al. (2023) emphasized that hybrid digital architectures enable energy-efficient scheduling by synchronizing production tasks with system load variations, a finding directly reflected in the present data. The inverse correlation between throughput and energy intensity ($r = -0.84$) confirms the hypothesis advanced by Tao et al., (2024), who proposed that real-time feedback in digital twin systems can simultaneously increase productivity and reduce energy expenditure. Similar patterns of energy optimization were observed by Villalonga et al. (2021), where model-driven predictive control dynamically minimized peak power demand across multiple machine cells. The statistically significant MANOVA results obtained in this study ($p < .001$) corroborate the outcomes of Vachálek et al.(2021), who highlighted multivariate efficiency as a defining characteristic of cyber-physical integration. Furthermore, the low variance in utilization ($\sigma^2 = 0.018$) corresponds to the stability benchmarks set by Ricci, Croatti, and Montagna (2022), reinforcing the hybrid framework's capacity for balanced resource distribution. These consistent results extend the arguments of Liu et al. (2018) regarding the role of hybrid models in achieving eco-efficient manufacturing through adaptive scheduling and predictive optimization. The empirical evidence in this research confirms that H-DEABSF achieves not only operational excellence but also sustainable performance by aligning predictive modeling with intelligent energy management. This convergence between productivity and sustainability reflects a broader trend in the literature advocating for hybrid, model-predictive control as a pathway toward carbon-conscious, resource-efficient smart factories.

The hybrid system's rapid fault recovery time and superior stability index demonstrate the operational resilience of predictive hybrid frameworks, corresponding strongly with prior studies on fault-tolerant control in manufacturing systems. The mean time to detect (2.3 seconds) and mean time to recover (6.8 seconds) achieved in the current research substantiate the assertions of Tripathi et al. (2024), who documented similar reductions in disturbance propagation through hybrid control logic. The high stability index (0.93) parallels the findings of Jin et al. (2022), who emphasized that cyber-physical feedback loops enhance system recovery by ensuring coordinated information exchange between the physical plant and its digital twin. Tripathi et al. (2024) reported that hybrid architectures integrating ABS components improved fault response rates by facilitating localized decision-making, an outcome mirrored by the rapid recovery observed in this study. Likewise, Platenius-Mohr et al., (2020) demonstrated that model-based predictive mechanisms significantly shorten stabilization periods after disruptions, aligning with the present study's findings. The smooth post-fault recovery observed in time-series analyses also supports the results of Dobaj et al. (2022), who described hybrid simulation's capacity to prevent oscillatory overshoots through continuous predictive adjustment. Collectively, the comparative literature reinforces that hybrid simulation frameworks provide self-healing characteristics through the fusion of decentralized control, predictive modeling, and digital synchronization. The empirical results from this research thus contribute confirmatory evidence that the H-DEABSF architecture embodies the resilience traits necessary for autonomous fault management and stable operation in cyber-physical manufacturing systems.

When situated within the broader theoretical landscape of digital manufacturing and systems control, the outcomes of this study reinforce the conceptual unity between hybrid simulation theory, predictive control, and cyber-physical integration. The significant quantitative improvements across all measured dimensions extend the foundational work of Suhail, Iqbal, and Jurdak (2023), who positioned cyber-physical systems as the architectural backbone of Industry 4.0. The empirical evidence also substantiates the integrative modeling principles described by Negri et al. (2017), who argued that hybrid simulation bridges the micro-macro gap between operational dynamics and agent decision behaviors. By embedding MPC within a hybrid simulation framework, the present research advances the applied dimension of predictive analytics beyond what was achieved in earlier studies, demonstrating that digital twin feedback can dynamically calibrate optimization models for real-time decision support. The outcomes corroborate the claims of Zeb et al. (2022) that hybrid, data-driven frameworks constitute a core mechanism for achieving adaptive autonomy in smart factories. Furthermore, the cross-dimensional statistical relationships observed here—where improvements in predictive accuracy directly correlate with gains in throughput, utilization, and stability—illustrate the systemic nature of hybrid intelligence as theorized by Bellavista et al. (2024). The present findings thus move beyond isolated validation of simulation efficiency to demonstrate a

Volume 04, Issue 02 (2025)
Page No: 501 – 526
Doi: 10.63125/yrkm0057

unified cyber-physical optimization paradigm in which modeling, sensing, and control operate cohesively. Collectively, these results contribute a quantitative and theoretical advancement to the literature by establishing H-DEABSF as a validated analytical and operational model that embodies the principles of intelligent, adaptive, and data-driven process control fundamental to the next generation of smart manufacturing systems.

CONCLUSION

This study demonstrates that AI-powered chatbots have become indispensable tools in U.S. banking, The present study established a comprehensive quantitative evaluation of the Hybrid Discrete-Event and Agent-Based Simulation Framework (H-DEABSF) integrated with Model Predictive Control (MPC) and Digital Twin (DT) technology, confirming its efficacy as a real-time cyber-physical control architecture for smart manufacturing systems. The experimental findings validated that the hybrid framework consistently outperformed conventional control configurations across all measured parameters, including throughput efficiency, response latency, predictive accuracy, energy optimization, and fault recovery stability. The hybrid model achieved a statistically significant 22.8% improvement in throughput and a 39% reduction in response latency relative to traditional systems, thereby demonstrating that combining event-based operational logic with agent-level decision autonomy yields an adaptive control mechanism capable of sustaining high performance under dynamic manufacturing conditions. Predictive accuracy exceeded 96%, underscoring the framework's ability to anticipate and compensate for disturbances through continuous model recalibration driven by real-time data from digital twin feedback. The integration of MPC allowed the hybrid architecture to optimize energy consumption while maintaining high utilization rates, thereby aligning production efficiency with sustainability goals. Furthermore, the system's rapid fault detection and recovery confirmed its resilience and operational robustness in managing uncertainty, fulfilling key requirements of Industry 4.0-driven process control. In theoretical terms, the findings reinforce and extend prior work on hybrid simulation, predictive control, and cyber-physical integration by empirically demonstrating the synergistic relationship among these paradigms. The validated results affirm that the H-DEABSF framework provides a scalable, data-driven, and self-regulating foundation for intelligent decision-making in modern manufacturing systems. By unifying simulation, predictive modeling, and digital synchronization within a single adaptive control ecosystem, this study contributes a substantive advancement in the field of intelligent industrial automation, establishing a benchmark for the development of future cyber-physical architectures in smart factory applications.

RECOMMENDATIONS

The outcomes of this research provide a strong foundation for several actionable and scholarly recommendations aimed at advancing intelligent manufacturing, hybrid simulation modeling, and cyber-physical integration. From an industrial perspective, it is recommended that manufacturers progressively adopt hybrid simulation frameworks such as the H-DEABSF for process optimization, real-time decision support, and predictive maintenance applications. The empirical evidence demonstrates that the integration of discrete-event and agent-based simulation models with model predictive control and digital twin technologies can significantly enhance throughput efficiency, minimize latency, and improve system stability; thus, industrial practitioners should prioritize the development of interoperable architectures that enable seamless synchronization between physical assets and digital models. It is also recommended that organizations adopt open communication protocols such as OPC-UA and MQTT to ensure continuous data exchange between simulation environments and shop-floor control systems, thereby promoting scalability and interoperability across heterogeneous manufacturing platforms. For research institutions and simulation model developers, emphasis should be placed on refining hybrid model coupling strategies, particularly focusing on temporal synchronization fidelity, multi-resolution modeling, and distributed computation methods that can further reduce execution time without compromising model accuracy. The incorporation of artificial intelligence and machine learning into predictive control layers is recommended to allow the hybrid system to autonomously refine its forecasting algorithms through self-learning mechanisms. Furthermore, expanding the application of H-DEABSF beyond discrete manufacturing—into process industries, logistics networks, and sustainable energy systems—would validate its versatility across multiple operational domains. It is also advised that future research explore the integration of hybrid frameworks with edge and cloud computing infrastructures to enhance real-time responsiveness and enable large-scale, multi-factory digital twin ecosystems.

Finally, regulatory and standardization bodies should collaborate with academic and industrial stakeholders to develop guidelines ensuring data integrity, cybersecurity, and validation protocols for hybrid digital systems. By implementing these recommendations, both researchers and practitioners can extend the transformative potential of hybrid simulation and predictive cyber-physical architectures toward achieving resilient, energy-efficient, and autonomous smart manufacturing systems worldwide.

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Review of Applied Science and Technology
Volume 04, Issue 02 (2025)
Page No: 501 – 526
Doi: 10.63125/yrkm0057

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