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Hybrid Machine Learning Optimization for Production Scheduling and Resource Allocation in Smart Manufacturing Systems: A Review

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Abstract

Efficient resource allocation and production scheduling directly dictate manufacturing productivity, cost efficiency, and energy utilization. However, intensifying sustainability mandates, operational uncertainty, and demand volatility have exposed the limits of traditional, deterministic optimization methods. Consequently, contemporary research has pivoted toward integrating mathematical programming with Machine Learning (ML) to enhance decision-making under uncertainty. This review synthesizes literature from 2020 to 2026 across standalone classical optimization, ML approaches, and hybrid ML-optimization frameworks, critically evaluating their performance outcomes, architectural trends, and robustness across diverse manufacturing systems. The findings indicate that while mathematical models ensure solution transparency and strict constraint enforcement, ML components maximize adaptability to dynamic conditions and demand forecasting precision. While hybrid frameworks generally yield superior makespan reduction and schedule robustness, their efficacy is bounded by distinct computational latency and data-density trade-offs. Additionally, multi-tiered sensitivity and scenario analyses are established as vital diagnostics for validating model stability against stochastic shopfloor noise and macro-systemic shocks. Despite these analytical advances, significant deployment barriers persist regarding computational complexity, interpretability, real-time scalability, and data quality. To bridge these gaps, this review maps emerging frontiers in Industry 5.0 human-centric optimization, reinforcement learning, and digital twins, providing a structured foundation for deploying resilient, scalable, and sustainable production planning systems.

Keywords: resource allocation, machine learning, mathematical models, hybrid optimization models, sensitivity analysis.

List of Abbreviations

Abbreviation	Full form
ACO	Ant Colony Optimization
A-GRU	Autoencoder-Gated Recurrent Unit
DDMRP	Demand-Driven Material Requirements Planning
DNNs	Deep Neural Networks
DT	Decision Tree

ESG	Environmental, Social, and Governance
ESRS	European Sustainability Reporting Standards
FEA	Finite Element Analysis
FFF	Fused Filament Fabricated
FSQCA	Fuzzy-Set Qualitative Comparative Analysis
GA	Genetic Algorithms
IoT	Internet of Things
LP	Linear Programming
LLMs	Large Language Models
MAPE	Mean Average Percentage Error
MCDNF	Multi-Channel Data Fusion Network
MILP	Mixed-Integer Linear Programming
MIP	Mixed-Integer Programming
ML	Machine Learning
MSE	Mean Square Error
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RF	Random Forest
RL	Reinforcement Learning
RNNs	Recurrent Neural Networks
RSM	Response Surface Methodology
SDG	Sustainable Development Goal
SMEs	Small and Medium Enterprises
XGBoost	Extreme Gradient Boosting

Introduction

Production scheduling and resource allocation are core decision-making problems in manufacturing systems (Palominos et al., 2026). They directly affect productivity, cost efficiency, energy use, and customer satisfaction (Wikarek & Sitek, 2025). In demand-driven industries such as food and beverage manufacturing, effective coordination of machines, labour, materials, and energy is essential for operational competitiveness and sustainability (Alemão et al., 2021). Consequently, leading manufacturing economies increasingly rely on data-driven planning and optimization frameworks to enhance responsiveness and reduce inefficiencies (Jaskó & Ruppert, 2025).

The economic relevance of intelligent production planning is evident in the global beverage industry. The United States, the world's largest beverage market, generates approximately US$457.5 billion in revenue, supported by advanced scheduling systems and digitally optimized supply chains (Cognitive Market Research, 2026). In Africa, South Africa leads the beverage sector with a market value of about US$19.8 billion, outperforming Nigeria largely due to the adoption of smart manufacturing and integrated production planning practices (Mordor Intelligence, n.d.). In contrast, Nigerian beverage manufacturers continue to face persistent challenges. The challenges include limited automation, high energy costs, unstable power supply, import dependency, financial constraints, and infrastructural and regulatory (Jaskó & Ruppert, 2025). These collectively result in production bottlenecks, poor schedule adherence, and underutilized capacity (Chinedu et al., 2025).

Traditional approaches to resource allocation and production scheduling such as classical mathematical programming and rule-based heuristics models, offer theoretical optimality and transparency but rely on static demand inputs and simplified assumptions (Gorchakov et al., 2024; Semenov et al., 2025. These methods struggle to cope with real-world manufacturing environments characterized by demand volatility, supply uncertainty and machine disruptions (Ostojić et al., 2025). Similarly, conventional statistical forecasting techniques often fail to capture nonlinear and seasonal demand patterns typical of fast-moving consumer goods, leading to excess inventory or stockouts (Maragkos & Refanidis, 2025).

Recent advances in ML have improved demand forecasting accuracy by capturing complex, nonlinear relationships in historical production and sales data (Razzaq & Shah, 2025). However, ML models lack the ability to enforce operational constraints required for feasible production schedules (Barbierato & Gatti, 2024). Conversely, mathematical optimization models such as Mixed-Integer Linear Programming (MILP) explicitly handle constraints but are highly sensitive to forecast accuracy and scalability limitations (Vicente, 2025). As a result, hybrid of ML and optimization frameworks have emerged as a promising solution, it incorporates data-driven forecasting with constraint related scheduling (Campos Diocaretz et al., 2025).

Despite expanding smart manufacturing literature, existing surveys exhibit two critical limitations. First, they evaluate predictive ML models and prescriptive optimization frame-

works in isolation, failing to map the structural failure modes of combined hybrid topologies. Second, current reviews rely on general descriptions, neglecting the multi-tiered nature of manufacturing uncertainty and localized computational-material boundaries. This review addresses these gaps through a multi-tiered, analytical synthesis of literature from 2020 to 2026. The unique contributions of this study are fourfold:

i. Architectural topology mapping, thereby defining specific boundaries where hybrid networks underperform standalone models due to computational latency, data scarcity, or convergence bottlenecks.
ii. Three-layer taxonomy categorizing uncertainty into process, shopfloor, and macro-systemic domains to map robust modelling approaches directly to distinct disturbances for multi-tiered uncertainty classification.
iii. Empirical process-level validation where current research that involved integrated multi-dimensional statistical validation paradigms, including Taylor diagrams, residual tracking, and Finite Element Analysis (FEA) to bridge macro-scheduling logic with component-level physical constraints.
iv. Translating theoretical algorithms into decision-ready strategies that align computational resilience and human-centric scheduling for actionable industry 5.0 pathways with Sustainable Development Goal (SDG) 9 (Edbais & Hossain, 2025).

Methodology of the Study

Review Design and Protocol

This study adopts the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework to ensure transparency, reproducibility, and methodological rigor in synthesizing literature on ML, mathematical optimization, and hybrid frameworks for production scheduling and resource allocation (Page et al., 2021). In the PRISMA framework, "N" denotes the number of records (articles) identified, screened, assessed for eligibility, or included at each stage of the review process. A meta-analysis was not conducted due to methodological heterogeneity across studies such as varying algorithms, datasets, performance metrics, and industrial contexts. Instead, the study emphasizes structured qualitative synthesis, methodological classification, and comparative performance evaluation. The review focused on literature published between 2020 and 2026 to capture contemporary advancements in hybrid ML and optimization integration within smart manufacturing systems. Table 1 highlighted the comparison between the previous and this review the, while Figure 1 presents the PRISMA flow diagram summarizing this selection process.

Table 1: Comparison of the Present Review with Existing Surveys

Author & Year	Review Period	Focuses on Hybrid Coupling?	Evaluates Robustness/Sensitivity?	Explores Industry 5.0 / SDGs?
Survey A (2023)	2015–2022	Partially	No	No
Survey B (2024)	2018–2023	Yes	No	No
This Work (2026)	2020–2026	Explicitly	Yes (Robustness/Sensitivity)	Yes (SDGs)

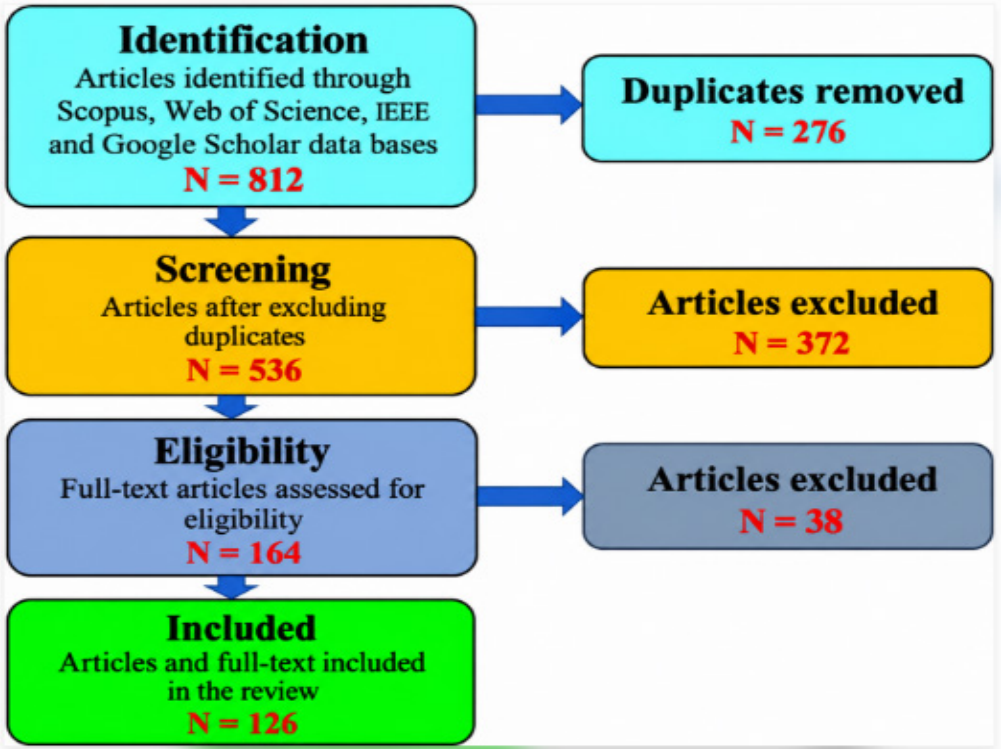


Figure 1: PRISMA Flowchart Diagram of the Study.

As presented in Figure 1, the selection process followed four stages in accordance with the PRISMA framework.

Identification: A total of N = 812 records were identified through database searching (Scopus, Web of Science, IEEE Xplore, SpringerLink, ScienceDirect, and Google Scholar). After removing duplicate records (N = 276), N = 536 unique records remained for screening.

Screening: The titles and abstracts of the N = 536 records were screened for relevance. At this stage, N = 372 records were excluded for not meeting the inclusion criteria, such as studies outside the manufacturing domain, purely theoretical algorithm development without industrial application, or unrelated optimization problems. This resulted in N = 164 articles proceeding to full-text assessment.

Eligibility: Full-text assessment was conducted on N = 164 articles to evaluate methodological rigor, industrial relevance, and applicability to production scheduling and resource allocation. Following detailed evaluation, N = 38 articles were excluded due to insufficient methodological transparency, lack of hybrid ML–optimization integration, or limited practical relevance.

Included: Overall, a final dataset of N = 126 studies was included in the qualitative synthesis and structured review.

Search Strategy and Data Sources

A structured literature search was conducted across Web of Science, Scopus, IEEE Xplore, SpringerLink, ScienceDirect, and Google Scholar. This is to ensure comprehensive coverage of high-quality peer-reviewed research. Search strings combined core terms related to resource allocation, production scheduling, ML forecasting, mathematical optimization, and hybrid decision-support systems. Boolean operators were applied to refine the search, and backward reference screening was used to identify highly and influential cited studies. Only English-language journal articles, authoritative reviews, and conference papers were considered.

Study Selection, Data Handling, and Review Scope

The followed a three-stage screening process which includes; title screening, abstract evaluation, and full-text assessment. Included studies were required to address production scheduling or resource allocation, employ ML, optimization, or hybrid methods, and demonstrate applicability to manufacturing systems. Excluded studies includes study that focused only on non-industrial domains, theoretical algorithm development, or lacked sufficient methodological detail. Extracted data included performance metrics, forecasting techniques, optimization models, problem formulation, and application context. The review scope focused on comparative synthesis and methodological insight, rather than numerical replication. Particular emphasis is placed on hybrid ML and optimization frameworks, reflecting their growing relevance for intelligent and data-driven production planning in modern manufacturing environments.

Findings

Production Scheduling and Resource Allocation in Manufacturing

Production scheduling and resource allocation are fundamental decision-making functions in manufacturing (Singh et al., 2026). It concerned with assigning limited resources such as machines, labour, materials, and energy to competing production tasks over time to meet demand efficiently (Arif et al., 2025). Classical scheduling problems, including flow shop, job shop, and batch scheduling, operates under constraints related to workforce availability, delivery deadlines, production capacity, and inventory levels, often assumes deterministic demand (Sitahong et al., 2025; Denizhan et al., 2026). Production performance is commonly evaluated using metrics such as production cost, machine utilization, makespan and service level (Lewicki et al., 2025). Resource allocation decisions further influence system efficiency by determining how scarce resources are distributed time and across products (Tussupova & Murzabekov, 2025). While classical methods provide a transparent and structured foundation for production planning, their solution and assumptions approach limit adaptability in dynamic environments (Modrak & Soltysova, 2025).

The following section reviews related studies to trace the evolution of resource allocation and scheduling methods highlighting how traditional approaches have shaped modern intelligent manufacturing systems. Ngwu et al. (2025) provided a comprehensive review of Reinforcement Learning (RL) approaches for dynamic job shop scheduling, demonstrating that RL-based methods significantly outperform classical heuristics in highly volatile environments characterized by frequent machine breakdowns and stochastic job arrivals. However, the review also revealed that RL models underperform in data-scarce environments and small-scale production systems, where training instability and high computational requirements limit practical deployment. While makespan and throughput improvements were consistently reported, model interpretability and reward design sensitivity remain critical weaknesses, particularly in regulated or safety-critical industries where explainability is required.

Pratama (2026), further examined ML-driven scheduling models, including Q-Learning, Deep Q-Networks, and Proximal Policy Optimization, emphasizing their ability to adapt to uncertainty and demand variability. The study confirmed that deep reinforcement learning models outperform deterministic optimization when real-time decision updates are necessary. However, performance degradation was observed when system states expanded significantly (large combinatorial spaces), leading to scalability challenges and convergence instability. The findings suggest that ML-based approaches are most effective in dynamic, high-variability production systems but may be inefficient for stable, repetitive manufacturing environments where deterministic optimization provides faster and more transparent solutions.

Akhavan et al. (2025) addressed production scheduling within cloud manufacturing systems using multi-objective optimization for resource sharing across distributed facilities. The model effectively balanced logistics costs, carbon emissions, and operational constraints under multi-product scenarios. Figure 2 presented the True Pareto front of optimization trials.

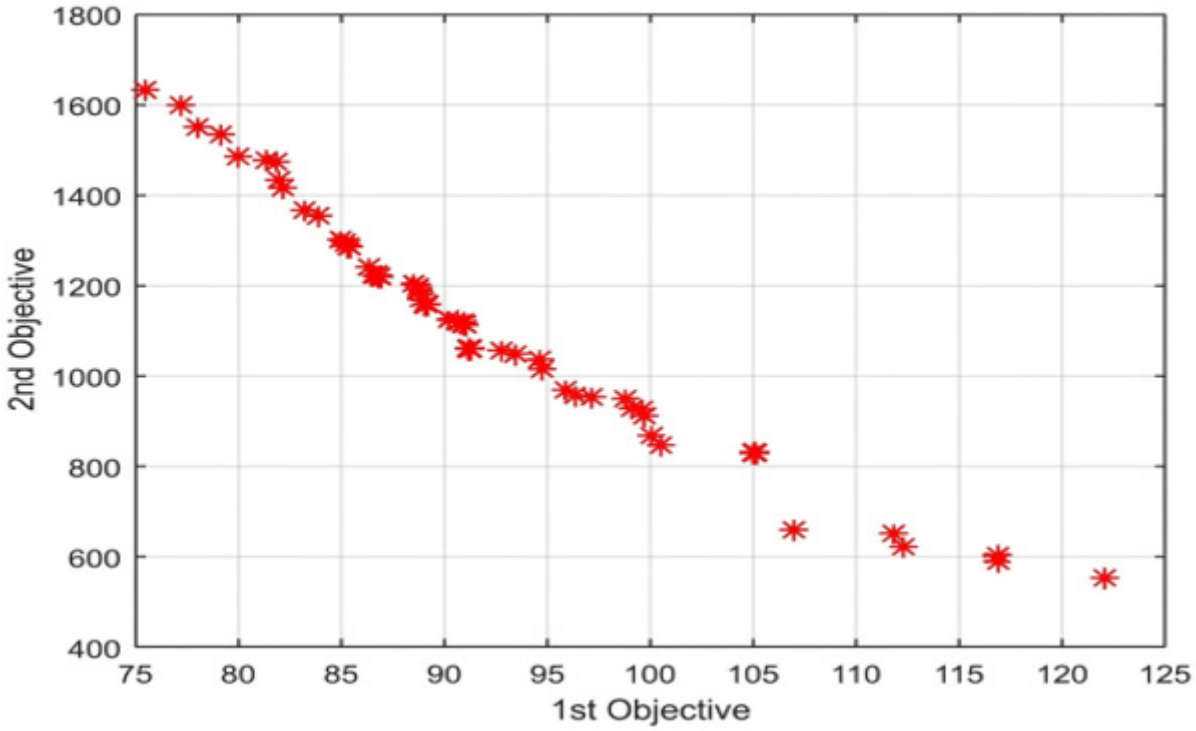


Figure 2: True Pareto front of 63 trials. Source: (Akhavan et al., 2025)

Nonetheless, the study demonstrated that classical optimization struggles when demand uncertainty and real-time disturbances increase, as static Pareto-optimal solutions require frequent re-computation. This highlights a structural limitation of deterministic multi-objective frameworks in volatile supply chain networks, reinforcing the need for predictive or hybrid augmentation.

Morariu et al. (2020) advanced the discussion by integrating ML and big data analytics within a cloud manufacturing architecture. Their hybrid architecture enabled predictive maintenance and adaptive resource reassignment using real-time shop-floor data. Despite improved responsiveness and energy-aware scheduling, the framework exhibited high infrastructure dependency, requiring advanced digital integration and large-scale data acquisition systems. This limits applicability in Small and Medium Enterprises (SMEs) or developing industrial contexts where digital maturity remains low. Additionally, model retraining requirements introduce latency risks in time-sensitive production systems.

Shaikat et al. (2025) examined production scheduling in Industry 4.0 settings where classical job-shop, flow-shop, and batch scheduling methods faced limitations under dynamic resource constraints. The study proposed a hybrid reinforcement learning a genetic algorithm framework, to manage machine availability, workforce limits, energy use, and demand variability. The approach improved production efficiency to 39% and raises resource utilization to about 91%, while reducing machine downtime to 34%. Scheduling reliability was enhanced, achieving around 94% deadline adherence across dynamic scenarios. The results illustrate the transition from static heuristic scheduling toward adaptive, learning-based resource allocation in smart manufacturing environments. However, hybrid models may underperform when data quality is poor, computational infrastructure is limited, or real-time retraining is infeasible.

The reviewed studies show that classical production scheduling and resource allocation methods established essential frameworks for managing cost, makespan, and resource utilization in manufacturing systems (Ciepliński et al., 2022). However, their reliance on fixed assumptions and static constraints limits their effectiveness in increasingly dynamic and data-rich production environments (Covei, 2025; Zhao et al., 2025). Recent developments have progressively extended these foundations by incorporating adaptive decision rules, real-time data, and system-wide optimization perspectives (Dan et al., 2025). Despite this evolution, many scheduling challenges remain fundamentally structured around

mathematical formulations of constraints, objectives, and system interactions (Makhoabenyane et al., 2025). Consequently, the next section examines mathematical modelling approaches that formalize these relationships and provide the analytical backbone for both traditional and emerging intelligent manufacturing solutions.

Mathematical Modelling Approaches

This technique forms the analytical foundation for formalizing production scheduling and resource allocation problems by expressing system objectives and constraints as optimization formulations (Kantaros et al., 2025). Such models capture relationships between costs, makespan, utilization, and limited resources, enabling structured solution development beyond heuristic rules (Phan et al., 2025). This type of model ranges from MILP and multi-objective optimization to hierarchical and hybrid formulations that accommodate dynamic demand, resource scarcity, and sustainability criteria (Essabar & Touil, 2025; Mohamed Alshabibi et al., 2025). These approaches offer rigorous frameworks for both classical deterministic problems, data-driven, and intelligent scheduling paradigms (Tsai & Wu, 2025). It bridges theoretical constructs with practical solution strategies (Cerda-Flores et al., 2022). The following selected papers exemplify current advances in mathematical modelling that align with evolving manufacturing scheduling and allocation research.

Mathematical programming models serve as the foundational baseline for constraint handling and solution transparency in smart manufacturing scheduling, yet their operational efficiency is heavily bounded by the specific architectural configuration and industrial environment. Hierarchical and multi-level optimization structures, such as the decomposition MILP framework proposed by Wang et al. (2025), demonstrate strong utility in high-mix, resource-constrained environments like medical device manufacturing by simultaneously balancing demand feasibility, asset allocation, and sustainability objectives. As shown in Figure 3, on the compared schedules from the proposed approach to those from the original method, the applied model improved the system.

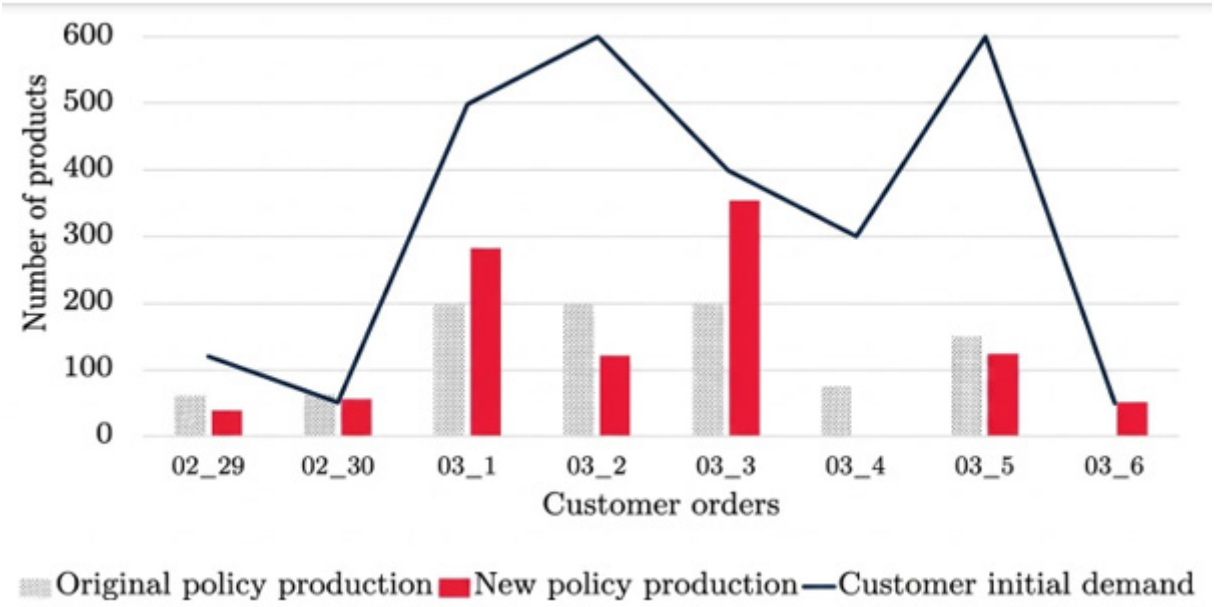


Figure 3: The Comparison Trend of the New and Previous System. Source: (Wang et al., 2025)

However, while such multi-level decompositions improve resource utilization and minimize idle times without escalating labour costs, they scale poorly under high-frequency demand volatility; the structural complexity drastically amplifies the computational burden, rendering them less effective for real-time, dynamic shopfloor modifications. To bypass these scalability barriers in large-scale, multi-objective environments such as foundries, hybrid quantum-classical architectures can be deployed.

As demonstrated by Sawamura et al. (2025), integrating quantum annealing algorithms with localized MILP task-scheduling modules yields significant reductions in computation time and superior solution quality compared to monolithic Liner programming (LP) or MILP formulations. Nevertheless, the industrial applicability of this hybrid framework undercurrent manufacturing conditions remains severely bottlenecked, as it underperforms or fails completely in facilities lacking immediate access to specialized quantum hardware solvers, reinforcing the continued reliance on classical, easily integrated MILP setups.

Beyond hardware limitations, the operational agility of mathematical models is frequently constrained by the manual overhead required to translate physical factory environments into rigid optimization code. Knowledge-augmented frameworks mitigate this by utilizing local Large Language Models (LLMs) to automatically extract spatiotemporal

constraints and generate MILP code with high accuracy, establishing a highly scalable and privacy-compliant paradigm for complex multi-robot task allocations in aerospace manufacturing (Peng et al., 2025). Yet, this approach reveals a critical operational vulnerability: it underperforms significantly in non-standardized or highly customized production environments, where a lack of high-quality, structured domain knowledge results in erroneous constraint extraction or suboptimal code generation.

This structural dependence highlights why classical mathematical programming remains localized to rigid, well-defined boundaries. When the operational objective shifts from discrete task scheduling to macro-level automation growth and trend forecasting, regression-based polynomial mathematical models implemented in environments like MATLAB offer high predictive precision (R2 = 0.965) (Grešová & Svetlík, 2021). However, these regression models fundamentally underperform on the active shopfloor because they lack explicit constraint-handling mechanisms, and higher-order iterations (such as degree-8 polynomials) introduce severe overfitting risks and exponential computational demands when fed fluctuating, real-time industrial data streams. Consequently, while alternative mathematical and regression structures offer localized advantages in hardware acceleration or data extraction, classical MILP frameworks maintain industrial dominance precisely because they offer an optimal, resilient compromise between mathematical solvability, strict constraint enforcement, and algorithmic transparency under disruptive operational conditions.

The findings showed that these models remain dominant in industry due to their strong constraint-handling capability and guaranteed optimality under deterministic assumptions (Ahmed et al., 2024). Also, their scalability challenges, computational burden, and reliance on accurate demand inputs limit performance in highly dynamic environments (Kantor et al., 2020). Most studies therefore simplify uncertainty rather than modelling it explicitly (Al-Hotmani et al., 2020). These limitations directly motivate the transition to data-driven demand forecasting, where ML methods learn demand variability to enhance downstream scheduling decisions (Popescu, 2025). Next section reviewed advanced impact made in manufacturing systems using ML models.

ML Models for Demand Forecasting in Manufacturing

This approach has become central to demand forecasting in manufacturing by overcoming limitations of traditional statistical methods and improving predictive accuracy under dynamic market conditions (Alfayoumi et al., 2025). ML models such as tree-based algorithms, Recurrent Neural Networks (RNNs), and deep learning architectures capture nonlinear patterns, seasonal trends, and multivariate influences that classical forecasts often miss (Razzaq & Shah, 2025). Their integration into production planning enhances inventory optimization, lead-time prediction, and real-time responsiveness, supporting more agile and efficient manufacturing operations (Hijry, 2026). The following current studies discussed advances in ML models in production systems.

ML architectures have become integral to predictive quality monitoring and operational forecasting in smart manufacturing, with their success heavily contingent on data density, noise levels, and the structural complexity of the industrial application. In localized, rule-driven environments like quality tool selection and machining stability assessment, tree-based classifiers exhibit exceptional reliability. As demonstrated by Starzyńska & Rojek (2026), Decision Tree (DT) classifiers outperform neural networks by achieving a classification accuracy of 96.75% versus 94.87% as presented in Figure 4.

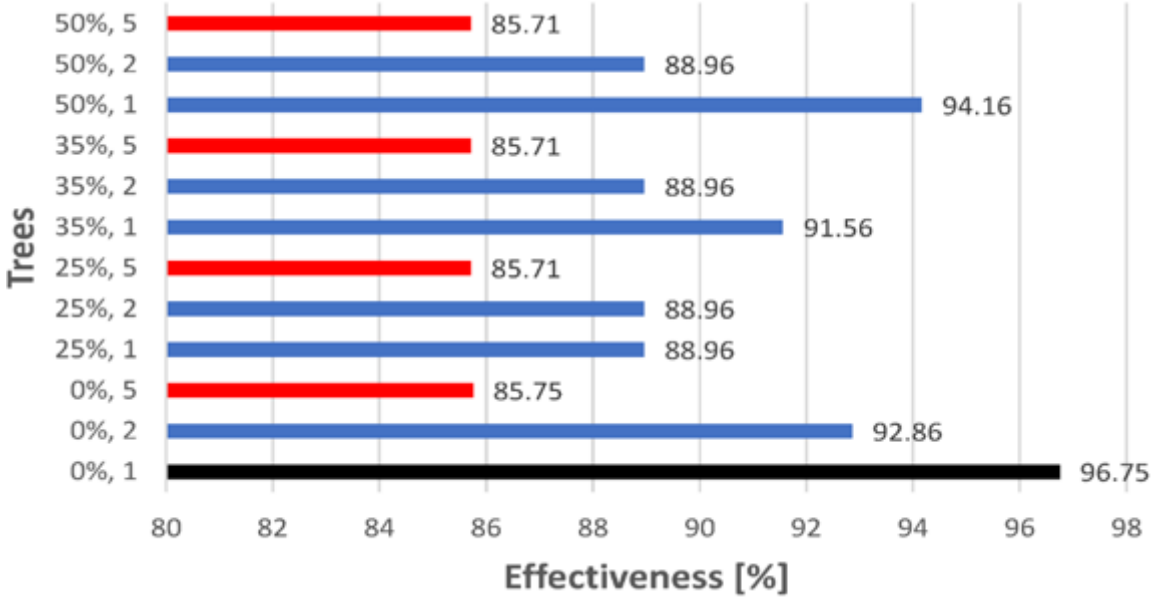


Figure 4: Effectiveness of the Tree-Based Model in the System. Source (Starzyńska & Rojek, 2026).

This performance edge is further amplified under optimal structural configurations (e.g., a restricted leaf size of three), where DT models can achieve near-zero error rates and up to 100% accuracy in pattern recognition on control charts (Rojek et al., 2024). The operational superiority of these basic tree structures over complex deep learning or traditional statistical time-series charts in Quality 4.0 systems stems from their low data requirements and inherent mathematical transparency, which provides the explicit, rule-based interpretation required for operator trust. However, these localized classifiers expose a significant operational vulnerability: they lack intrinsic dynamic adaptability, meaning they underperform or fail when confronted with shifting batch characteristics unless a resource-intensive programmatic retraining loop is explicitly instituted.

The structural stability of tree-based frameworks degrades significantly when the operational domain shifts from stable, batch-processed sensor data to highly volatile, noisy, high-frequency data streams. This performance boundary is sharply illustrated by Deep et al. (2025), where RF ensembles achieved strong in-sample training metrics (R2 = 0.749 – 0.812) but completely collapsed to a negative R2 during out-of-sample testing in high-frequency environments. In such scenarios, tree-based models overfit by relying heavily on raw, unrefined features (accounting for over 60% of feature importance) while failing to extract meaningful signals from classical technical indicators like RSI or Bollinger Bands. This reveals that standalone ML models underperform simple benchmarks (such as a baseline buy-and-hold strategy yielding losses of -2.4% to -3.9% when deployed for direct target prediction in hyper-dynamic environments, proving more viable as risk-control filtering mechanisms rather than primary predictive engines.

Conversely, when high-frequency noise is minimized and the data structure contains complex, non-linear relationships with high class imbalance, advanced ensemble variants demonstrate robust resilience. Comparative evaluations across multi-equipment manufacturing datasets indicate that RF ensembles can maintain a balanced precision and recall to secure an overall predictive maintenance classification accuracy of 99.5% (Yang & Wang, 2025). The algorithm maintains structural stability under complex sensor patterns due to hyperparameter tuning and targeted feature screening, though it remains localized by underperforming when transferred across heterogeneous equipment without cross-validation protocols. To resolve these cross-system complexities and mitigate the risks of high false-negatives in green supply chains, tree ensembles must be coupled with configurational logic. Integrating Fuzzy-Set Qualitative Comparative Analysis (FSQCA) with XGBoost structures drives a 66% improvement in recall, a threefold increase in high-risk sample capture, and a 150% boost in positive detections compared to standalone linear or basic ML variations (Wu et al., 2025). This hybrid integration minimizes the critical operational risk of false negatives, mirroring the data efficiency found in structural cost estimation. As shown in Figure 5, gradient-boosted ensembles like XGBoost maintain a superior predictive accuracy (R2 = 0.96) over Deep Neural Networks (DNNs, R2 0.91) and standalone Random Forest (RF = R2 0.80) when handling mixed attributes under constrained sample sizes (Alshboul et al., 2022).

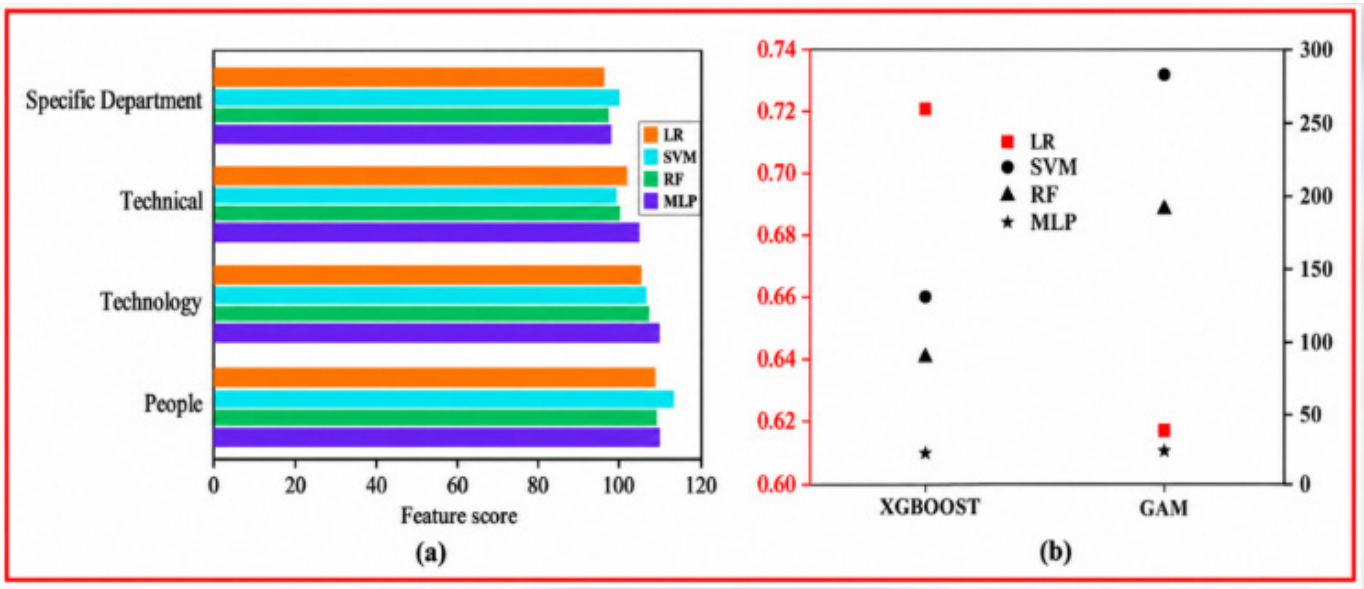


Figure 5: Important Features (a) and Evaluation metric comparison (b) outcomes of the study. Source (Alshboul et al., 2022)

Consequently, the empirical consensus indicates that while tree-based ML methods are computationally efficient and robust against class imbalances, they underperform significantly in unmapped, high-frequency noisy streams, necessitating structural coupling with configuration logic or hybrid optimization frameworks to ensure multi-path operational resilience.

The reviewed studies highlighted that ML models significantly outperform classical time-series methods in capturing nonlinear demand patterns under uncertainty (Hall & Rasheed, 2025). Tree related ensembles and DL models consistently deliver superior forecasting accuracy, while explainability remains a key industrial requirement (Lin et al., 2025). However, accurate forecasts alone do not guarantee operational gains unless translated into production decisions. This gap motivates the integration of ML-driven demand predictions with optimization models for scheduling and resource allocation. Accordingly, the next section examined hybrid ML optimization techniques that embed forecasts into MILP and decision-support systems for manufacturing.

Hybrid ML Optimization Frameworks

This optimization frameworks bridge the gap between accurate prediction and actionable decision-making in manufacturing systems (Bernárdez et al., 2025). By embedding ML-based demand and process forecasts into MILP and scheduling models, these frameworks enable adaptive, data-driven production planning (Wang et al., 2025). They move beyond static rule-based and heuristic methods, offering scalable solutions validated through real manufacturing and process industry case studies (Nacar et al., 2025). The following current studies presents advances in the application of hybrid techniques (ML and mathematical models) in manufacturing optimization.

The architectural integration of ML with mathematical programming or metaheuristic optimization defines the technological frontier of agile production scheduling. However, the operational efficacy of these hybrid frameworks is strictly bounded by their integration topology, computational complexity, and the nature of the data pipeline. Sequential "forecast-then-optimize" architectures rely on high-fidelity predictive components to map environmental variables before executing optimization loops. In hyper-dynamic or event-driven demand environments, advanced architectures like the Multi-Channel Data Fusion Network (MCDFN) proposed by Jahin et al. (2025) excel by integrating heterogeneous data streams to achieve low error rates of Mean Square Error (MSE) of 23.57 and Mean Average Percentage Error (MAPE) of 20.16 % as shown in Figure 6 on the evaluation performance of the applied models. Yet, the critical operational bottleneck of such deep-learning-driven predictive components is their high computational overhead and massive data requirements.

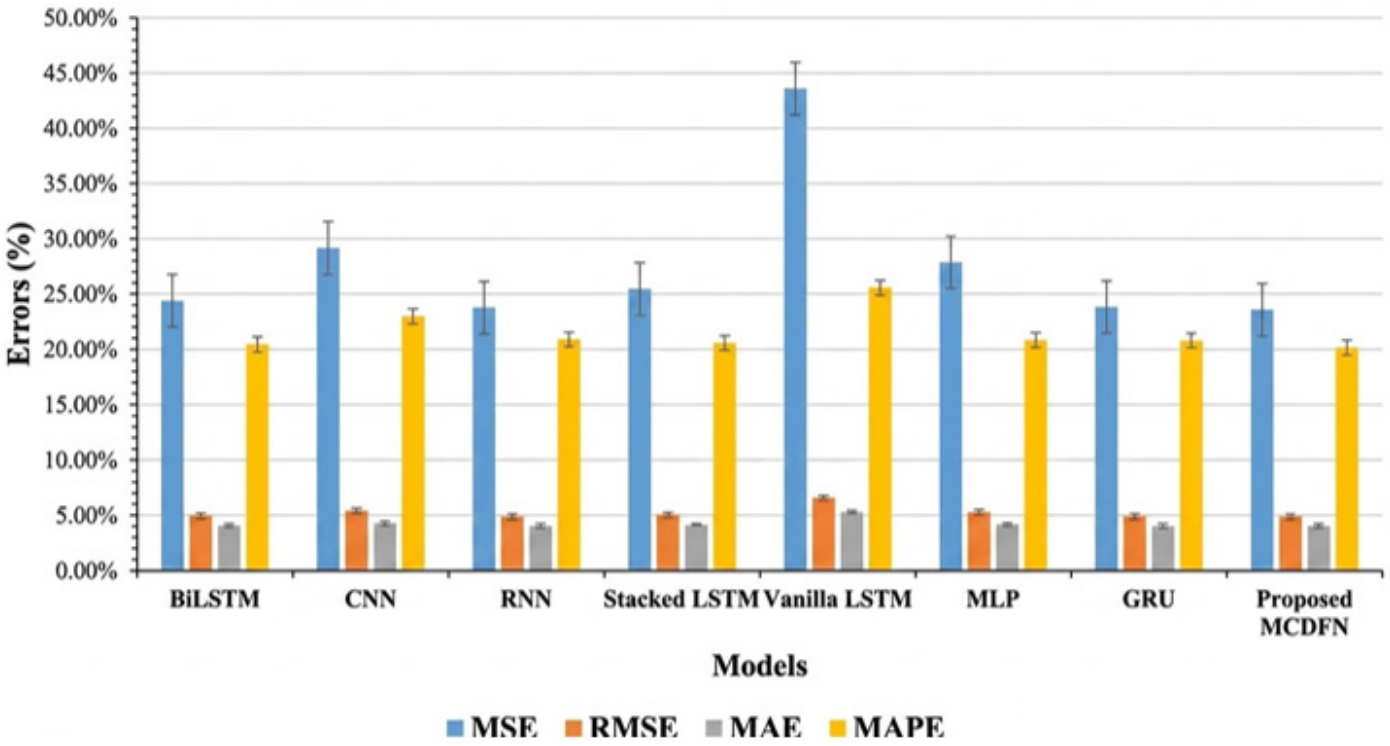


Figure 6: Performance Analysis Outcome of the Applied Models. Source: (Jahin et al., 2025)

These frameworks frequently underperform or fail in SMEs with sparse data histories, where simpler, tree-based ensembles or baseline statistical models prove more robust and cost-effective due to lower deployment barriers. Furthermore, when these predictive frameworks are applied to long-horizon, end-of-life spare-part planning across vast product portfolios (e. 1,709 automotive components), standalone ML models like RF require stabilization through decay-function blending ($\alpha = 0.2 - 0.4$) to avoid structural forecast drifting over extended lifecycles (Nathan et al., 2026). Figure 7 illustrated the forecasted annual demand trajectories representative of the spare parts. Without this manual engineering intervention, hybrid inventory-optimization models fail due to compounding downstream errors, proving that the stability of the optimization layer is entirely hostage to the generalization capacity of the preceding ML model.

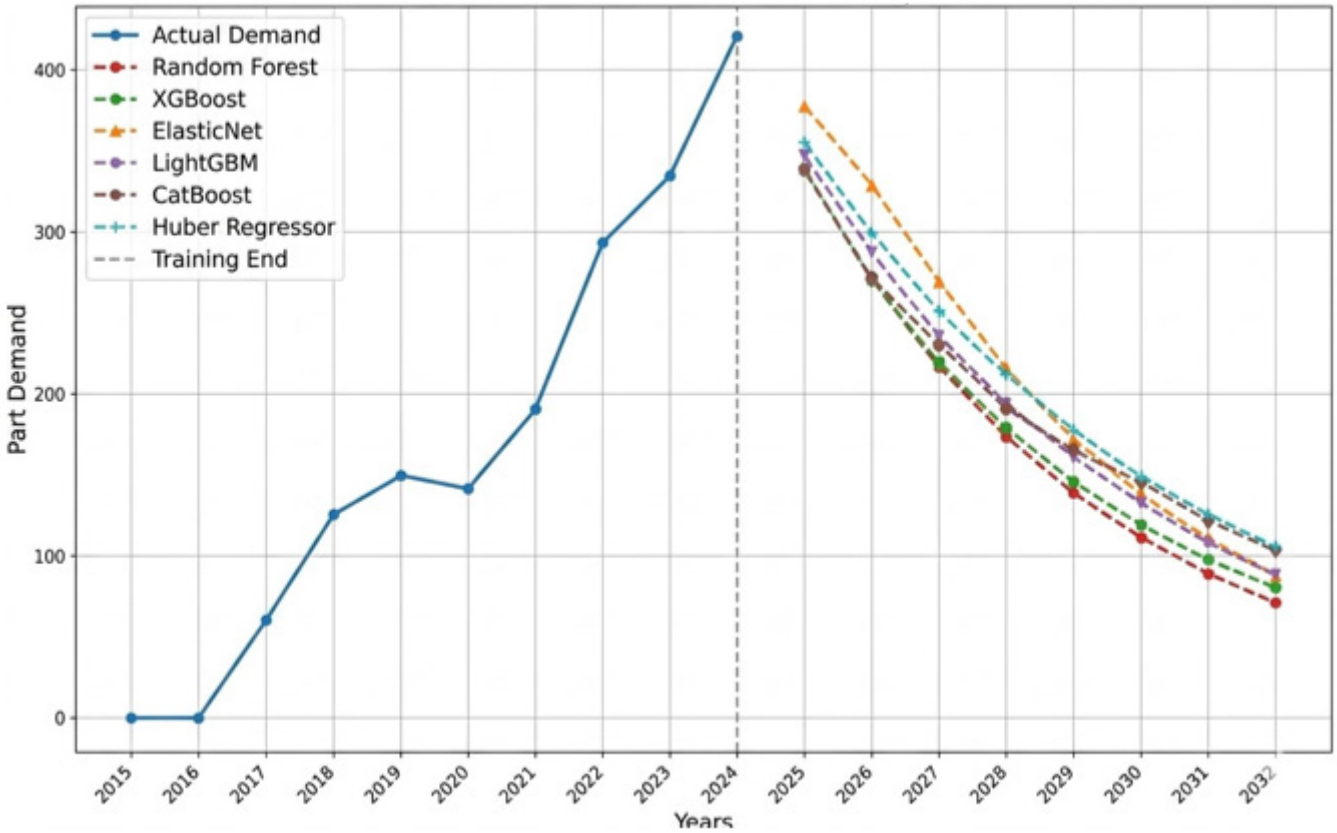


Figure 7: Combined historical and 8-year forecasted demand using multiple ML model (2015–2032). Source: (Nathan et al., 2026)

When predictive models are embedded directly into active control loops, the coupling mechanism must resolve real-time stochastic disruptions like machine breakdowns. Marzia et al. (2025) addressed this by mining real-time dispatching rules via ML to predict setup priorities within flexible job shops, feeding these dynamic inputs into a downstream heuristic scheduling framework to achieve a 42.6% reduction in makespan and a 35% boost in schedule robustness. The model achieved 92% prediction accuracy on unseen cases and generated rescheduling decisions within seconds, demonstrating clear forecast optimize design patterns as shown in Figure 8.

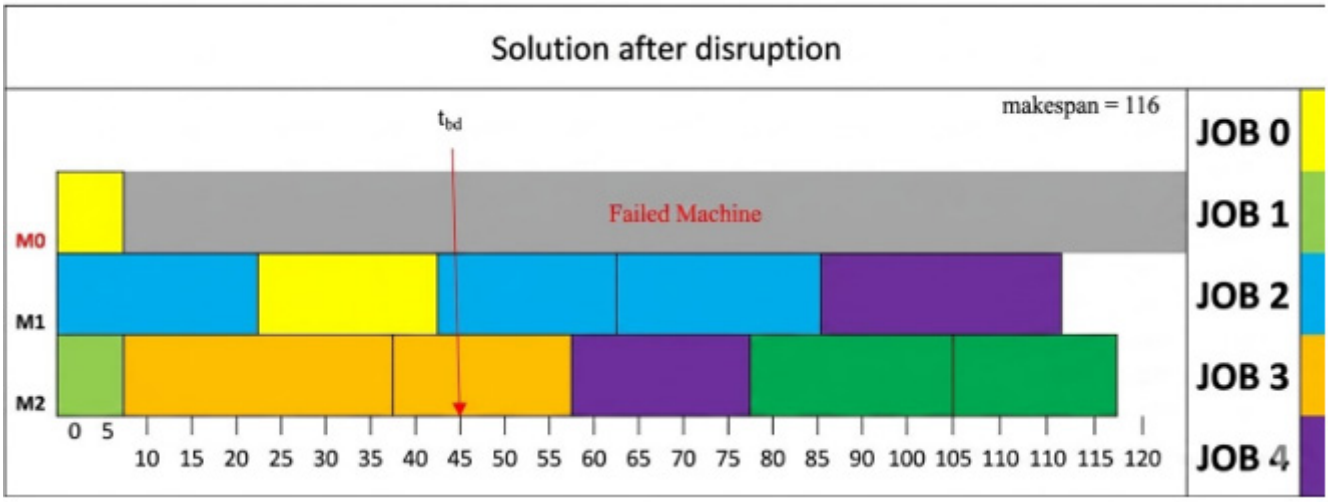


Figure 8: The improved rescheduling solution. Source: (Marzia et al., 2025)

Similarly, coupling ML demand forecasting with Mixed-Integer Programming (MIP) and Genetic Algorithms (GA) allows for adaptive structural reconfigurations in complex inventory control systems (Saaad et al., 2025). By utilizing GA specifically to determine optimal buffer positions within a Demand-Driven Material Requirements Planning (DDMRP) network, unsatisfied demand can be drastically mitigated across variable plant setups.

Despite these performance gains, a critical comparison of these approaches reveals that hybrid metaheuristics such as GA combined with Ant Colony Optimization (GA-ACO) and multi-layered MILP-GA workflows underperform significantly under extreme scaling or real-time execution constraints (De Giovanni et al., 2025). As systems transition toward highly responsive Industry 4.0 and human-centered Industry 5.0 digital twins, the non-deterministic nature of metaheuristics can cause execution time spikes during proactive bottleneck detection. If a major disruption occurs simultaneously across multiple production lines, the optimization layer may fail to converge on a near-optimal solution within the narrow decision window required for on-line rescheduling. Consequently, while hybrid models consistently outperform standalone mathematical models in handled uncertainty, they introduce a distinct risk of computational latency and structural opacity, underperforming in high-throughput environments unless bounded by local heuristic shortcuts or simplified decomposition rules.

Across the reviewed architectures, the operational superiority of hybrid optimization frameworks over standalone heuristic or rule-based methods depends entirely on their underlying structural coupling mechanisms (Kho et al., 2025). Rather than merely executing sequential, unlinked operations, these frameworks establish an integrated topology where ML functions as a dynamic, feed-forward predictive layer that reconfigures the constraint spaces and boundary parameters of the mathematical optimization models in real time (Aljohani, 2023). By converting multi-channel forecasts, dynamic demand streams, or mined setup priorities directly into automated buffer configurations and predictive constraints, the hybrid framework immunizes rigid solvers against stochastic shopfloor disruptions. This structural interdependence yields significant industrial performance gains such as reduced makespan, lower inventory risk, and enhanced schedule robustness by using data-driven intelligence to adaptively guide exact optimization algorithms (Douaioui et al., 2024). What ultimately distinguishes these hybrid approaches is this mathematical capability to manage non-linear, time-dependent parameter variations before they cause optimization infeasibility (Bi et al., 2021). This deep coupling underscores the necessity of analyzing how these integrated pipelines perform under localized parameter perturbations, directly motivating the subsequent section on sensitivity and scenario analysis for model robustness.

Sensitivity and Scenario Analysis for Model Robustness

Assessing sensitivity and robustness is critical to ensure that advanced scheduling and optimization models maintain performance under parameter uncertainty, demand volatility, and real world disturbances (Shao et al., 2025). Sensitivity testing reveals how variations in inputs and assumptions influence outputs, guiding risk aware decision support (Wang & Solomatine, 2019). Robust models adapt to fluctuations in demand, machine availability, and external disruptions, making them more reliable for practical manufacturing deployment. The following are the current studies that applied sensitivity and scenario analysis for enhanced model implementation and decision making in production and service rendering systems.

Quantifying model robustness through sensitivity and scenario analysis is the definitive prerequisite for translating theoretical smart manufacturing frameworks into resilient,

deployable industrial systems. However, the critical evaluation of these analytical approaches reveals that their mathematical efficacy depends entirely on the operational layer at which uncertainty is modelled. At the operational and component layer, sensitivity analysis maps physical parameter deviations to prevent localized structural failures. As demonstrated by Staffa et al. (2025), evaluating additively manufactured embedded sensors under combined thermal and dynamic loading through frequency response functions ensures predictable piezoresistive behaviour with zero resonance frequency detection errors under uncertainty. As shown in Figure 9, the result showed a parabolic resistance temperature relationship and a stable linear piezoresistive response within each temperature range, confirming predictable sensor behaviour under uncertainty.

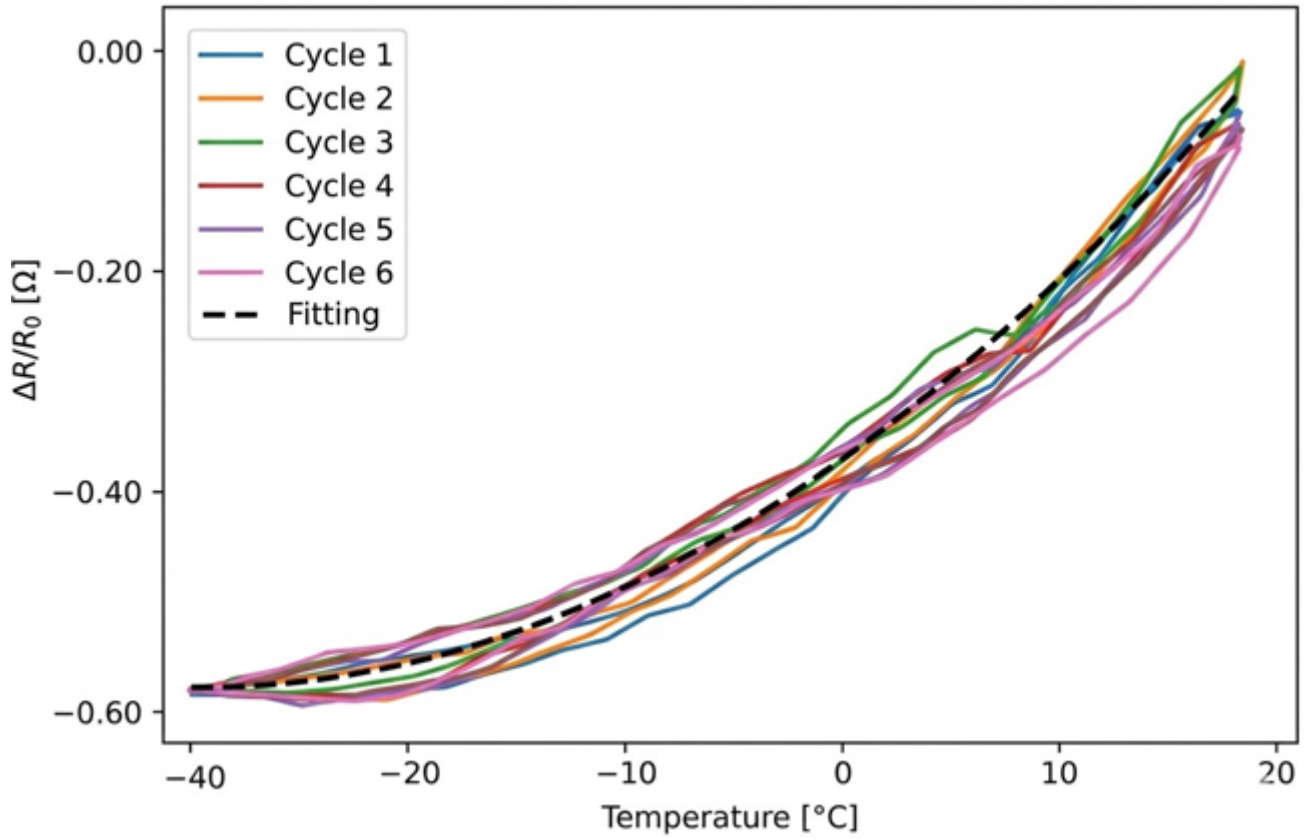


Figure 9: Parabolic Sensory Trend of the Temperature Analysis. Source: (Staffa et al., 2025)

While this component-level validation ensures physical asset integrity, standalone empirical models at this layer underperform in active scheduling architectures because they ignore system-level queues, processing bottlenecks, and inventory delays. To capture these multi-variable network behaviours, system-level discrete-event simulations and regression meta-models must be utilized. Grznár et al. (2024) applied linear and non-linear regression techniques alongside global screening to isolate a critical subset of dominant input variables such as work-in-process and production lead times out of numerous fluctuating parameters. By visualizing these impacts via tornado charts, system-level sensitivity analysis guides robust decision-making.

Nevertheless, a prominent structural vulnerability of these system-level simulation models is their frequent underperformance when handling the stochastic variability of human behaviour. De Felice et al. (2022) addressed this by employing "what-if" scenario testing to map human-machine interaction parameters, proving that human-centered process redesign can cut line blocking rates from a range of 55 – 58% down to 23 – 28% while scaling throughput from 130 to 220 units. This critical insight underscores that deterministic scheduling optimizations fail if they rely solely on automation variables while neglecting human-induced process noise.

When scheduling systems expand to include supply chain networks, model stability faces long-horizon risks from external corporate governance and macro-economic shocks. At this macro-systemic layer, multi-criteria frameworks must evaluate qualitative structural shifts, such as perturbations in Environmental, Social, and Governance (ESG) weights under European Sustainability Reporting Standards (ESRS) (De Felice et al., 2025). While automated weighting handles subjective bias to limit Sustainability Index fluctuations to a marginal ΔSI (shifted SI) = ±0.07 under a ±10% weight shift, these multi-criteria optimization models fail to

maintain predictive validity when macro-disruptions cause structural breaks in historic data streams. This vulnerability is validated by Hu & Jia (2025), whose robustness testing of intelligent manufacturing using national time-series data yielded high positive correlation factors ($\beta \approx 0.76 - 1.50$), but exposed that systemic benefits collapse rapidly under external macroeconomic shocks such as trade frictions or global pandemics compared to baseline technological capacities.

At the component and process validation layer, simple statistical performance metrics often mask underlying localized variance. To address this, recent advancements utilize multi-dimensional statistical validation frameworks to map predictive behaviour under highly dynamic thermal-material interactions. Der (2025) and Der et al. (2025) systematically evaluated the robustness of multiple ML architectures ranging from baseline linear models to complex deep recurrent structures, when mapping the non-linear dependencies of carbon dioxide laser cutting parameters on Fused Filament Fabricated (FFF) engineering-grade thermoplastics. By subjecting architectures like Extreme Gradient Boosting (XGBoost), RF, and hybrid autoencoder systems to variance screening across varying plate thicknesses, laser powers, and cutting speeds, these studies moved past selective optimization profiles to establish generalized performance envelopes. While standard error matrices present aggregated accuracy, they fail to reveal how models track standard deviation and correlation simultaneously across distinct target conditions. This structural insight is achieved via Taylor diagrammatic analysis, which maps correlation coefficients (r) against standard deviations (σ) to expose architecture-specific underperformance under varying physical constraints as shown in Figure 10.

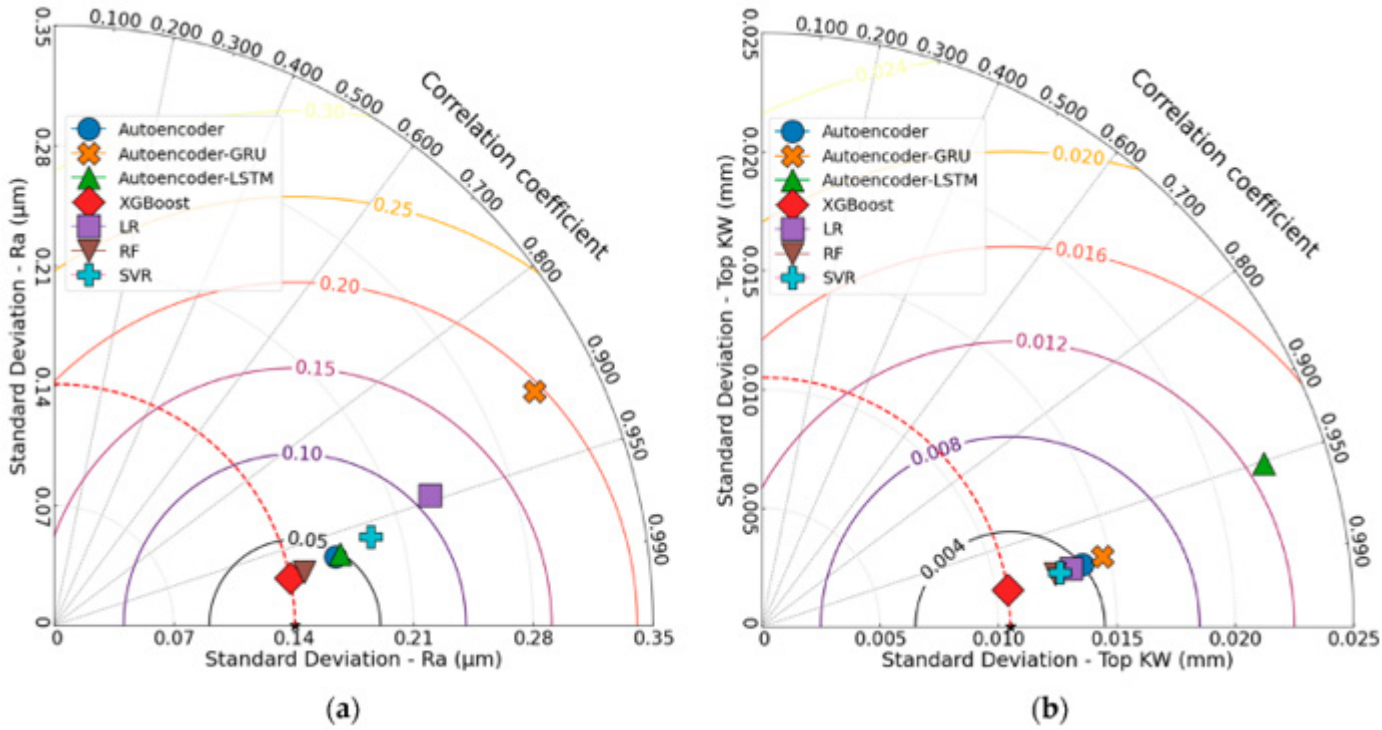


Figure 10: Taylor diagrammatic validation of multi-output machine learning architectures across FFF-manufactured polymer laser-cutting responses: (a) Surface Roughness (Ra), (b) Top Kerf Width (Top KW), (c) Bottom Kerf Width (Bottom KW), and (d) Bottom Heat-Affected Zone (Bottom HAZ) (Der, 2025).

As graphically established in the Taylor diagram framework in Figure 10, the predictive resilience of ML architectures is not monolithic; it varies drastically depending on the specific physics of the spatial target being modelled. When mapping surface roughness (Ra), tree-based ensembles like XGBoost display superior robustness ($r = 0.9804$, $\sigma = 0.1408$) alongside RF ($r = 0.9778$, $\sigma = 0.1495$), whereas hybrid configurations such as the Autoencoder-Gated Recurrent Unit (A-GRU) underperform significantly ($r = 0.8995$, $\sigma = 0.3120$) due to an architectural inability to capture localized variance in material thickness dependencies.

Critically, when the target transitions to fluid-thermal boundaries like the bottom exit kerf width (Bottom KW), the autoencoder structure exhibits a severe localized failure mode ($r = 0.9476$, $\sigma = 0.0248$). This underperformance proves that complex deep learning frameworks can experience severe predictive drift when encountering the chaotic melt-blown physics of exit-side polymer ablation, while simpler, non-parametric tree ensembles maintain stable tracking.

Similarly, when evaluating alternative thermoplastic matrices like carbon fibre reinforced polymers or polyethylene terephthalate glycol, MLP and RF, they demonstrate varying sensitivity to thermal distortion, proving that model validation must be explicitly tied to specific material properties to prevent real-time quality control failures (Wang et al., 2022).

This reliance on multi-tiered sensitivity screening highlights an inherent trade-off in hybrid process optimization: while advanced statistical and ML frameworks can map non-linear behaviours without the heavy computational burden of physical testing, their real-world stability is entirely hostage to the quality of the training data distribution. To circumvent this, advanced hybrid optimization workflows couple metaheuristics and Response Surface Methodology (RSM), directly with computational mechanics, such as FEA, as shown in Figure 11, to synthesize predictive training fields for heavy machining conditions (Der et al., 2025).

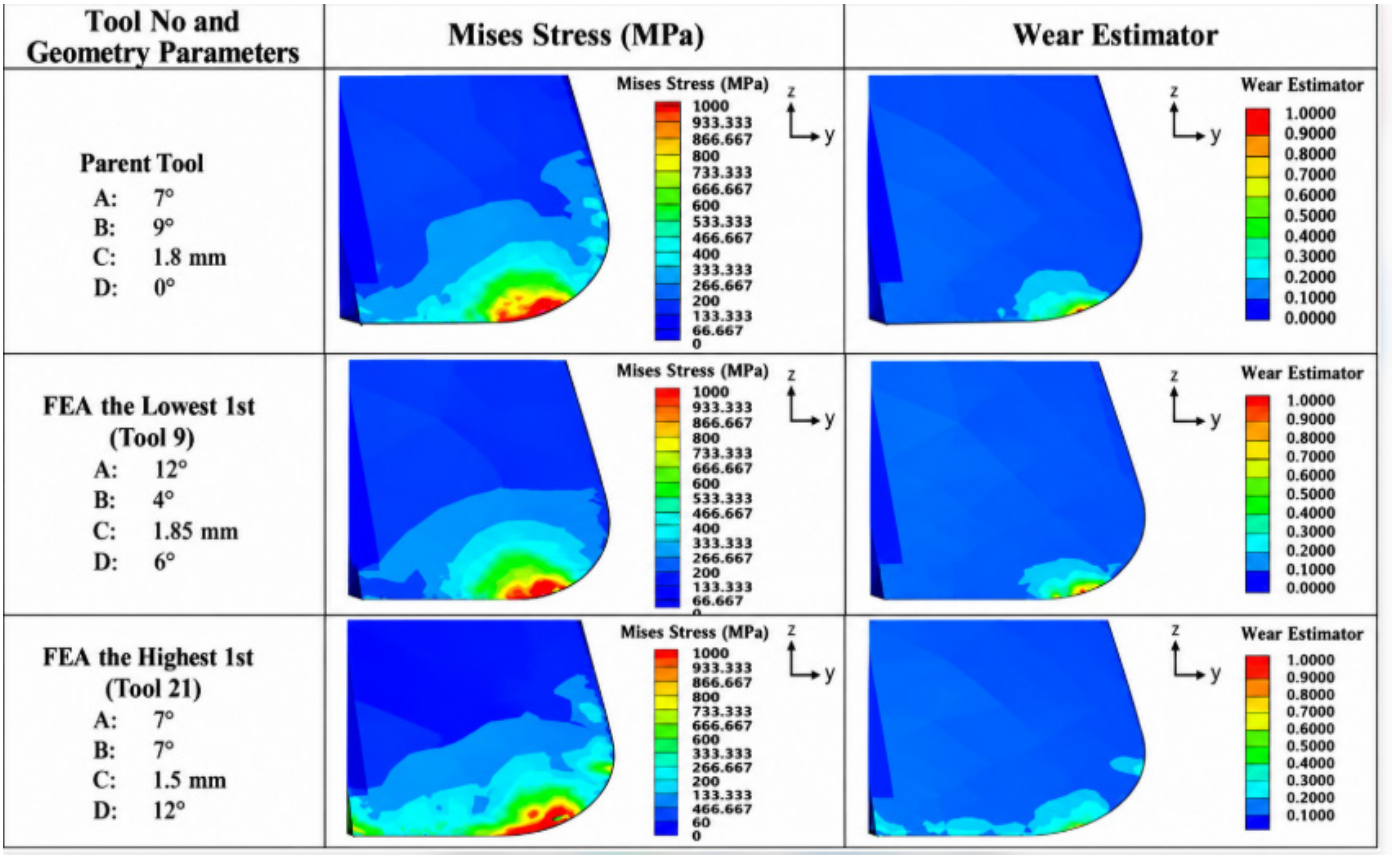


Figure 11: Comparative multi-axis field analysis of Von Mises stress distributions and structural tool wear metrics generated via computational FEA for end mill geometry optimization (Der et al., 2025).

However, evaluating these coupled mechanics-optimization workflows reveals a critical industrial boundary condition, which is the idealization bias of numerical simulations. The idealized FEA layers assume structural continuity and predict that a robust tool wedge with a low relief angle improves structural integrity. In physical industrial operation, however, this optimized geometry fails. Parasitic frictional forces, flank-workpiece rubbing, and localized thermal accumulation outweigh the simulated structural advantage. This breakdown demonstrates that hybrid framework optimization models underperform when their underlying simulation layers ignore real-world stochastic variables like dynamic friction and structural chatter.

Consequently, a comparative assessment reveals a clear hierarchy of structural boundaries: component-layer sensitivity analysis fails to capture manufacturing flow mechanics; system-layer discrete simulations underperform under unmapped human operational variability; and macro-layer scenario frameworks lack the granular agility needed for real-time shopfloor adaptations. Transforming scheduling models from rigid, deterministic tools into decision-ready smart manufacturing architectures requires multi-layered, scenario-aware engineering that bounds localized mathematical optimization within a broader, multi-tiered framework of empirical sensitivity testing (Şirin et al., 2026; Tarantola et al., 2024; Aung et al., 2026). This led to the next review section, where such robust models are examined in case-based and real industrial applications and implementations.

Industrial Applications and Case Studies

This section demonstrates how robust ML-based and analytical optimization models perform in real manufacturing environments characterized by extreme scale, tight operational constraints, and volatile uncertainty. Rather than presenting these architectures as isolated theoretical constructs, a cross-industry synthesis reveals that the choice and deployment efficacy of specific optimization topologies are fundamentally dictated by the physical nature of the industrial sector.

As summarized in Table 2, a clear operational divide exists between continuous and batch process industries with high-variety discrete manufacturing sectors. In continuous process industries such as breweries, chemical plants, pharmaceutical manufacturing, and steel processing, the primary modelling barriers are non-linear process dynamics, strict safety regulations, and raw material chemical variability (Wang & Solomatine, 2019; Hu & Jia, 2025; Aung et al., 2026). In these domains, standalone ML models underperform if used in isolation because they lack the capacity to guarantee hard physical and chemical conservation constraints. Consequently, these industries rely on tightly coupled hybrid frameworks such as integrating empirical ML layers with MILP or multi-axis FEA to ensure that real-time optimization updates remain within safe, compliant operational boundaries (Vicente, 2025; Der et al., 2025).

Conversely, discrete manufacturing environments including automotive assembly, electronics components, textiles, and Fast-Moving Consumer Goods (FMCG) are governed by combinatorial complexity, rapid demand shifts, and intense scheduling instability caused by short product lifecycles (Cognitive Market Research, 2026; Shao et al., 2025). For these sectors, the optimization focusses on shifts away from chemical and thermal constraints toward minimizing makespan, eliminating assembly bottlenecks, and managing complex routing queues. Here, tree-based ensembles such as XGBoost, RF and deep reinforcement learning networks demonstrate maximum utility due to their capacity to process massive streams of transactional shopfloor data and generate near-instantaneous heuristic scheduling updates under high volatility (Razzaq & Shah, 2025; Cerda-Flores et al., 2022).

Furthermore, resource-constrained environments like discrete manufacturing SMEs face a completely distinct bottleneck: severe data scarcity and low organizational readiness (Pratama, 2026; Mohamed Alshabibi et al., 2025). While capital-intensive automotive or semiconductor plants leverage continuous data streams via advanced digital twins to run scenario analyses, SMEs must deploy low-parameter, non-parametric ML models that provide stable decision-support metrics without requiring heavy computational infrastructure or massive historic training datasets (Makhoabenyane et al., 2025; Nathan et al., 2026). This comparative analysis underscores that there is no universal modelling framework; instead, industrial deployment requires balancing model complexity against sector-specific data densities and physical constraint rigidities.

Table 2: Industrial Applications of the Highlighted Techniques

S/N	Industry Type	Primary Operational Disruptions & Constraints	Implemented Modelling & Optimization Framework	Achieved Systemic Outcomes & Performance Gains	Ref(s)
1	Food & Beverage	Thermal inefficiencies, perishable inventory, demand volatility.	Integrated ML forecasting and analytical optimization pipelines.	Drastic waste reduction, minimized perishability metrics, optimized energy loads.	(Wang et al., 2026; Cabrera et al., 2025)
2	Breweries	Biochemical raw material variability, batch-to-batch inconsistency.	Sensitivity analysis paired with empirical process models.	Improved raw material utilization, stabilized chemical output parameters.	(Nosratabadi et al., 2021; Li et al., 2025)
3	FMCG Manufacturing	Ultra-short product lifecycles, high product variety, planning drift.	ML-integrated dynamic scheduling architectures.	Enhanced delivery service levels, robust cost control, rapid agility.	(Zapryanova et al., 2025; Paull et al., 2025)
4	Chemical Process	Non-linear process safety limits, volatile dynamic chemical constraints.	ML-assisted empirical optimization models.	Superior process robustness, higher yield metrics, minimized energy usage.	(Tarallo et al., 2019; Kamińska et al., 2024)

5	Pharmaceutical	Strict regulatory compliance, demand shocks, batch tracking risks.	Hybrid ML and MILP.	Maximized supply chain reliability, optimal batch sizing, guaranteed compliance.	(Trinh et al., 2021; Fourkiotis & Tsadiras, 2024)
6	Automotive	Combinatorial assembly sequencing, severe component supply blockages.	Analytical data forecasting and algorithmic bottleneck screening.	Eradicated assembly blockages, maximized asset throughput rates.	(Oliva, 2025; Xiang et al., 2025))
7	Cement & Building	Resource scarcity, highly unstable supply logistics for raw components.	Mathematical programming linked with ML screening.	Enhanced production consistency, robust raw material blending.	(Ranabhatt et al., 2025; Ekpechi et al., 2025)
8	Steel Processing	High furnace scheduling instability, variable thermal raw inputs.	Predictive ML models tied to structural process control.	Lowered cost predictability risks, uniform production consistency.	(Fan et al., 2025; Antosz et al., 2024)
9	Electronics	Aggressive product defect risks, hyper-rapid demand shifts.	Adaptive AI-driven scheduling and real-time vision analytics.	Drastic reduction in product defect rates, elevated operational resilience.	(Carlsson & Samuelsson, 2023; Amato et al., 2025)
10	Textile & Apparel	Highly seasonal customer shifts, fast-fashion inventory overproduction.	ML frameworks coupled with multivariate statistical modelling.	Enhanced supply chain agility, minimized structural overproduction losses.	(Ndukwe et al., 2023; Wang et al., 2022)
11	Energy Distribution	Epileptic power grid distribution profiles, sudden source shortages.	Advanced metaheuristic mathematical optimization.	Optimized sustainability metrics, elevated macroeconomic grid resilience.	(Malashin et al., 2025; Maity et al., 2025)
12	Discrete SMEs	Pervasive data scarcity, low capital infrastructure, high volatility.	Low-parameter ML models and robust decision support indices.	Stabilized operational planning baselines despite restricted data profiles.	(Ekpechi et al., 2025; Urban et al., 2024)

The reviewed industrial case studies demonstrated that data-driven optimization and modelling impacted tangible gains in decision accuracy, efficiency and cost reduction across manufacturing systems. The highlighted real-world implementations confirmed that hybrid frameworks outperform rule-based practices particularly operational disruptions, under demand uncertainty and process variability (Jahin et al., 2025). However, the studies revealed recurring challenges related to organizational readiness, data quality, scalability and system integration. These practical insights highlighted the gap between methodological potential and industrial deployment. However, the next section presented the key challenges limiting the applicability and enhancement of manufacturing industries. Also, the phase outlined future research directions required to achieve scalable, robust and intelligent manufacturing systems.

Key Challenges and Future Research Directions

Despite significant advancements in standalone ML, mathematical modelling, and their respective hybrid configurations, distinct structural bottlenecks continue to impede their widespread industrial adoption and operational reliability. The reviewed literature reveals a persistent performance gap between algorithmic execution in idealized, controlled settings and empirical robustness when subjected to real-world operational disruptions. By extracting and synthesizing the specific systemic vulnerabilities identified across the reviewed frameworks, this section establishes a direct link between documented modelling failures and the advanced research paths required to transition intelligent decision-support architectures into viable, industry-grade solutions.

Uncertainty Handling, Data Quality, and Structural Volatility

A critical limitation across the reviewed literature is the pervasive reliance on high-frequency, pristine datasets, which contrasts sharply with the sensor noise, data dropouts, and historical data scarcity typical of actual shopfloors (Mohammed et al., 2026). When these data imperfections propagate through tightly coupled optimization pipelines, they introduce significant prediction drifting. As demonstrated

in recent multi-output polymer cutting validations, even advanced deep learning hybrids like Autoencoder Long Short-Term Memory (ALSTM) networks experience severe localized variance and tracking errors when mapping unstable physical boundaries like bottom exit kerfs due to unmapped process fluctuations (Podobnikar, 2025). To mitigate this propagation of error, future research must shift away from deterministic assumptions toward uncertainty-aware learning frameworks. Prioritizing probabilistic modelling, robust data governance protocols, and confidence-aware predictive horizons will be vital to ensure model stability under high material and parameter variability (Peixoto et al., 2025; Novoa-Muñoz & Lagos-Álvarez, 2026).

Decision Timeliness and Algorithmic Computational Complexity

The architectural integration of predictive ML with exact mathematical optimization introduces a severe, unaddressed trade-off between optimization depth and computational runtime (Boulealam et al., 2025). While complex deep recurrent ensembles, multi-axis FEA fields, and high-dimensional MILP models yield unmatched schedule optimization and structural precision, their massive computational overhead causes them to struggle under the tight, near-instantaneous decision windows required for online factory corrections (Moussaoui et al., 2025). This operational bottleneck exposes a glaring gap in the literature regarding lightweight, decentralized, or surrogate-assisted optimization approaches. Future research trajectories must prioritize the development of parallelized decomposition techniques and low-parameter metaheuristics that dramatically compress execution latency while preserving global solution quality for real-time manufacturing adjustments (Spyrou et al., 2025).

Model Interpretability, Spatial Heteroscedasticity, and Managerial Trust

While high-capacity black-box models including multi-layer perceptron, deep autoencoders, and dense tree-based ensembles consistently dominate predictive accuracy metrics throughout the reviewed studies, their lack of structural transparency remains a severe barrier to industrial acceptance (Pereira et al., 2025). This interpretability deficit obscures how a model dynamically recalculates its optimization landscape when transitioning between diverse target metrics, which severely compromises regulatory compliance and managerial confidence during edge-case anomalies (Arévalo-Cordovilla & Peña, 2025). Furthermore, existing literature rarely links raw algorithmic outputs to clear, actionable domain insights. Bridging this trust gap requires the targeted integration of explainable AI frameworks, causal reasoning layers, and sensitivity-driven explanation models capable of translating intricate mathematical weights into intuitive, human-verifiable operational directives (Adesina & Obokoh, 2025).

Real-Time Industrial Deployment, Scale Boundaries, and Standardization

A systemic vulnerability in current smart manufacturing research is that the vast majority of developed frameworks are validated exclusively via offline simulations, highly restricted benchmark datasets, or isolated single-plant scenarios (Marín Díaz, 2025). Consequently, these models remain largely untested against the compounding scalability demands of multi-site production systems, which require continuous, dynamic adaptation to simultaneous machine breakages, supply chain frictions, and sudden demand shocks (Cerqueus & Delorme, 2023). The absence of standardized deployment blueprints represents a definitive operational bottleneck. To bridge this gap, future research must prioritize the development of rolling-horizon optimization routines, interoperable cloud-edge execution topologies, and continuous online learning pipelines validated through rigorous, multi-facility industrial case studies (Nnabude et al., 2026).

Industry 5.0, Autonomous Digital Twins, and Multi-Objective Sustainability

Emerging research frontiers are steadily moving toward closed-loop digital twins that natively fuse real-time Internet of Things (IoT) telemetry with predictive ML forecasts and prescriptive mathematical solvers (Kubiak et al., 2022). Although hybrid reinforcement learning models offer an adaptive path for automated shopfloor scheduling, their industrial deployment is strictly constrained by a current lack of formal stability bounds and operational safety guarantees (Khan et al., 2025). Crucially, multi-objective sustainability metrics such as direct carbon emission tracking, localized energy-consumption limits, and material waste minimization remain weakly integrated into core scheduling logic, often treated as secondary constraints rather than primary objectives. Future frameworks must natively align multi-criteria sustainability indices with autonomous AI decision-making and human-centric optimization to fulfill the Industry 5.0 vision of ethical, resilient, and environmentally responsible manufacturing networks (Alginahi et al., 2025).

Furthermore, a promising frontier for next-generation Industry 5.0 systems lies in bridging the current gap between macro-level factory scheduling models and localized, micro-level execution layers. Specifically, future frameworks should investigate the algorithmic coupling of plant-wide resource allocation with computational assembly sequence generation, stable subassembly identification, and tool-integrated human-robot collaborative task planning to achieve seamless, real-time synchronization between factory-floor robotics and enterprise planning engines.

Conclusion

This study highlights a definitive paradigm shift in production scheduling and resource allocation away from purely deterministic optimization toward integrated, data-driven hybrid decision-support frameworks. While mathematical

programming remains vital for structural constraint enforcement and solution transparency, standalone ML models offer the dynamic adaptability required to handle stochastic demand fluctuations. The empirical consensus indicates that while hybrid ML-optimization frameworks generally yield superior performance metrics regarding makespan reduction and asset utilization, their success is not monolithic; they face clear operational trade-offs, underperforming standalone methods in scenarios governed by severe data scarcity or hyper-dynamic real-time execution windows where computational latency becomes prohibitive. Furthermore, sensitivity and scenario analyses have emerged as indispensable diagnostic tools for mapping model boundaries under parameter perturbations and macro-systemic shocks. Real-world industrial case studies confirm tangible resilience gains, yet barriers regarding data quality, algorithmic interpretability, and cross-equipment scalability persist. Future research must bridge these computational complexities by embedding human-centric principles and sustainability metrics aligned with the industry 5.0 mandate, establishing scalable, robust planning systems capable of weathering realistic operational disruptions.

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All authors participated in the study

Consent for publication
All authors consent for the manuscript to be published.

Availability of data and material/ Data availability
Not applicable.

Code availability
Not applicable.

Authors' contributions
This work was carried out in collaboration between all authors. Author RMO, OOO and DAE did the Conceptualization and Methodology. BEO, RMO and OCN wrote the protocol, and wrote the first draft of the manuscript. Author VUC, DAE and OOO managed the literature searches. All authors read and approved the final manuscript.

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