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DECISION INTELLIGENCE SYSTEMS FOR AUTONOMOUS PRODUCTION PLANNING AND CONTROL

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Abstract
This review examines decision intelligence systems for autonomous production planning and control in Industry 4.0 manufacturing. It addresses the limits of conventional production planning and control systems, which depend on deterministic models, historical data, human expertise, and a two-tier structure of schedule generation and execution control. Such systems perform poorly when demand variability, resource constraints, machine workload changes, material shortages, and quality disruptions make released schedules suboptimal. The review synthesizes evidence from multi-agent systems, holonic manufacturing, cyber-physical production systems, digital twins, machine learning, reinforcement learning, data-driven scheduling, and prescriptive analytics. It shows how decision intelligence links data acquisition, analytics, optimization, and execution through a closed-loop sense-decide-act structure. The framework rests on four core components: data acquisition and management, analytical models, decision algorithms, and execution mechanisms. It evaluates five operational domains: dynamic scheduling, inventory and supply chain coordination, resource allocation, predictive maintenance, and resilient production control. Numerical evidence strengthens the review. Digital twin literature shows 38% use simulation models to represent physical systems and predict future states, while 29% integrate optimization into simulation models. A validated multi-agent logistics case reported savings of 2.6 million pallet-days per year through better use of terminal free time. The review also identifies six unresolved barriers: data quality and integration, model interpretability, scalability, real-time implementation, human-system interaction, and lack of standard frameworks. Future systems should combine explainable AI, edge-cloud computing, digital twin-based optimization, hybrid control, and standardized evaluation protocols to achieve adaptive, scalable, and trusted autonomous production control.

1. Introduction

1.1. Background and Context

Production planning and control (PPC) forms the backbone of manufacturing operations. It governs scheduling, resource allocation, inventory management, and workflow coordination across the shop floor (Herrmann et al., 2022; Okpala et al., 2025). Traditional PPC systems rely on deterministic models, historical data, and human expertise to generate plans and schedules (Igbokwe et al., 2025; Rolón & Martínez, 2012). These conventional systems typically follow a two-tier hierarchy comprising monolithic schedule generation at the upper layer and execution control at the lower layer (Rolón & Martínez, 2012). While effective in stable environments, such rigid and centralized architectures struggle to respond to dynamic changes and unforeseen events (Nwamekwe et al., 2025; Rolón & Martínez, 2012). The shift toward Industry 4.0 has introduced cyber-physical production systems that integrate physical and decision-making aspects of manufacturing, enabling decentralization and autonomy (Rossit et al., 2019; Herrmann et al., 2022). Decision intelligence systems represent a new paradigm that fuses data analytics, artificial intelligence, and optimization to support autonomous decision-making (Herrmann et al., 2022; Rossit et al., 2019). These systems combine descriptive, predictive, and prescriptive analytics to generate actionable insights with minimal human intervention (Yang et al., 2022; Khadiri et al., 2023). Multi-agent systems and holonic manufacturing paradigms bring modularity, decentralization, and scalability to distributed manufacturing control (Nwamekwe et al., 2025; Okpala et al., 2024; Pulikottil et al., 2021).

1.2. Problem Framing

Modern production environments face demand variability, resource constraints, and complex interdependencies that conventional PPC systems handle poorly (Okeagu et al., 2024; Chidiebube et al., 2025). Centralized planning and scheduling systems are vulnerable to abrupt changes because schedules become ineffective shortly after release to the shop floor (Rolón & Martínez, 2012; Igbokwe et al., 2025a). Without considering real-time machine workloads and shop floor dynamics, process plans often become suboptimal or invalid at execution time (Igbokwe et al., 2025a). Conventional rigid control architectures fail to respond efficiently to disturbances, and the gap between planning and execution widens under uncertainty (Nwamekwe et al., 2025a; Ismayyir et al., 2024). Autonomous production systems require decision frameworks that learn from data, adapt to changing conditions, and optimize performance continuously (Rossit et al., 2019; Herrmann et al., 2022). Real-time data from sensors and cyber-physical systems now enable scheduling decisions ahead of time, on the basis of richer information (Rossit et al., 2019; Khadiri et al., 2023). Dynamic scheduling, agent-based architectures, and digital twin models address parts of this need, but full integration of these technologies remains a challenge (Khadiri et al., 2023; Pulikottil et al., 2021; Ismayyir et al., 2024).

1.3. Objective of the Review

This review synthesizes research on decision intelligence systems for autonomous production planning and control. It examines system architectures, modelling frameworks, and application strategies drawn from multi-agent systems, holonic manufacturing, cyber-physical production systems, and data-driven scheduling approaches. It also identifies challenges related to scalability, interpretability, real-time implementation, and the weak industrial adoption of distributed intelligent control. The review traces how complementary technologies from digital twins to reinforcement learning converge to enable autonomous and adaptive PPC. By mapping current advances against established PPC models and Industry 4.0 requirements, this work highlights both researched areas and gaps that demand further investigation.

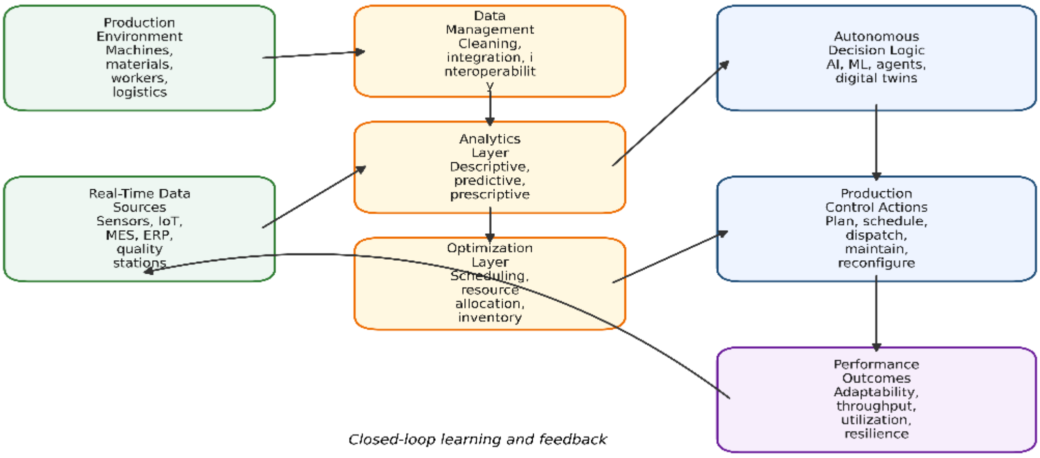


Figure 1. Conceptual Framework for Decision Intelligence Systems in Autonomous Production Planning and Control

Figure 1 presents a closed-loop architecture linking production environment, real-time data acquisition, analytics, optimization, and autonomous control. Data from sensors and enterprise systems flows into analytical and optimization layers, where AI-driven decision logic generates production actions. Feedback from performance outcomes re-enters the system, enabling continuous learning and adaptation. This structure aligns with the manuscript's emphasis on integrating descriptive, predictive, and prescriptive analytics into a unified decision loop that responds to dynamic shop-floor conditions.

2. Conceptual Foundations of Decision Intelligence in Manufacturing

2.1. Definition of Decision Intelligence Systems

Decision intelligence systems integrate data, models, and algorithms to support and automate decision-making in complex operational settings. In manufacturing, these systems draw on distributed artificial intelligence techniques to coordinate autonomous entities across the production process (Nwamekwe et al., 2025a). They combine domain knowledge with analytical models to generate actionable insights and execute decisions at speed. Leitão et al. (2016) describe how multi-agent systems empower cyber-physical systems with intelligence, modularity, flexibility, and adaptation, forming a foundation for decision intelligence in industrial contexts. Vater et al. (2019) frame decision intelligence around the progression from descriptive to prescriptive analytics, where the system determines a sequence of decisions to obtain a desired result and answers the question of what actions achieve a specific goal. The integration of real-time data, learning algorithms, and optimization models distinguishes decision intelligence systems from conventional decision support tools, which typically require significant human interpretation before action (Estrada-Jimenez et al., 2023). In essence, decision intelligence systems close the loop between sensing, reasoning, and acting within production environments.

2.2. Components of Decision Intelligence

A decision intelligence system in manufacturing rests on four interrelated components: data acquisition and management, analytical models, decision algorithms, and execution mechanisms. Data acquisition relies on sensor networks and IoT infrastructure embedded in cyber-physical production systems, which collect real-time information from machines, products, and logistics flows (Matenga & Mpofu, 2025; Zeid et al., 2019). Analytical models process this data to represent system states, predict future conditions, and evaluate alternative courses of action. Adi et al. (2020) describe how IoT-generated data feeds machine learning pipelines for predictive and adaptive analytics, enabling systems to learn from evolving data streams. Decision algorithms, including agent-based negotiation protocols and optimization heuristics, select appropriate actions based on model outputs (Nwamekwe et al., 2025b; Pulikottil et al., 2021). Execution mechanisms translate decisions into physical actions through automated controllers, robotic systems, or reconfigurable manufacturing modules (Emeka et al., 2025). The coordination of these components requires standardized communication architectures. Beregi et al. (2021) demonstrate how Manufacturing Execution Systems serve as interoperability enablers among autonomous and distributed cyber-physical production system entities, linking data flows to execution on the shop floor.

2.3. Autonomous Production Systems

Autonomous production systems operate with minimal human intervention by using real-time data and adaptive algorithms to make and execute decisions. Vitalis et al. (2024) define autonomy in assembly systems through the clustering of subsystems and modules, each receiving a degree of autonomy and controlling themselves in a decentralized way. This decentralization enables rapid adaptation to changing product variety and demand volume. Estrada-Jimenez et al. (2023) characterize autonomous manufacturing through self-organizing elements capable of self-management and self-decision-making under a context-aware and intelligent infrastructure. Mo et al. (2022) formalize autonomy in manufacturing through a five-level model, ranging from no autonomy to a fully autonomous factory where the system is self-adaptable to uncertain or unforeseen inputs through advanced self-learning. Multi-agent systems provide a natural implementation paradigm for such autonomy. Each intelligent agent represents the capabilities and goals of a manufacturing processing unit, and agents collectively work toward overall system goals (Mo et al., 2022; Pulikottil et al., 2021). Nwamekwe et al. (2025g) notes the advantages of modularity, decentralization, scalability, and reusability that agent-based and holonic paradigms bring to autonomous manufacturing control. The shift from automated to autonomous production demands not only sensing and actuation but also reasoning, learning, and cooperative decision-making among distributed system elements (Leitão et al., 2016; Sanderson et al., 2018).

2.4. Decision-Making Paradigms

Decision intelligence systems incorporate three complementary analytical paradigms: descriptive, predictive, and prescriptive analytics. Descriptive analytics processes historical and real-time data to characterize the current state of the production system, identifying patterns and anomalies in machine performance, throughput, and quality (Yang et al., 2022; Zeid et al., 2019). Predictive analytics uses statistical models and machine learning to forecast future outcomes such as equipment failures, demand fluctuations, or bottleneck formation. Adi et al. (2020) explain how predictive models in IoT environments adjust their outputs when new input data arrives, enabling adaptive, real-time stream data processing. Prescriptive analytics goes further by recommending or automating optimal decisions. Vater et al. (2019) define prescriptive analytics as ensuring an adaptive, autonomous, time-based and optimal decision that recommends the best approach to achieve specific key performance indicators. Zeid et al. (2019) identify prescriptive operations through data analytics as a defining characteristic of cyber-physical production systems. The progression from descriptive to prescriptive analytics represents increasing levels of decision automation. In practice, these paradigms operate concurrently within a decision intelligence architecture, where descriptive outputs feed predictive models, and predictive forecasts inform prescriptive optimization (Vater et al., 2019; Adi et al., 2020).

2.5. Performance Metrics for Decision Intelligence Systems

Evaluating decision intelligence systems requires metrics that capture both decision quality and system behaviour. Decision accuracy measures how closely system outputs align with optimal or near-optimal solutions, a concern raised by Nwamekwe et al. (2025g) in discussing the trade-off between optimality in hierarchical control and reactivity in heterarchical control. Response time reflects the speed at which the system detects changes and generates appropriate decisions. Rossit et al. (2019) emphasize the importance of real-time data access in smart manufacturing, where scheduling decisions must be made ahead of time based on richer information from cyber-physical systems. Resource utilization tracks how effectively machines, materials, and labour are allocated across production tasks, a primary objective in both agent-based scheduling and distributed planning approaches (Pulikottil et al., 2021; Yang et al., 2022). System adaptability gauges the capacity to reconfigure and maintain performance under disturbances. Mo et al. (2022) associate adaptability with maturity levels in their autonomy model, where higher autonomy levels correspond to greater self-adaptation to uncertain inputs. Estrada-Jimenez et al. (2023) add that self-organizing manufacturing systems must demonstrate responsiveness, reconfigurability, and resilience as core performance attributes. Taken together, these metrics provide a multi-dimensional evaluation framework for assessing decision intelligence systems in autonomous production environments.

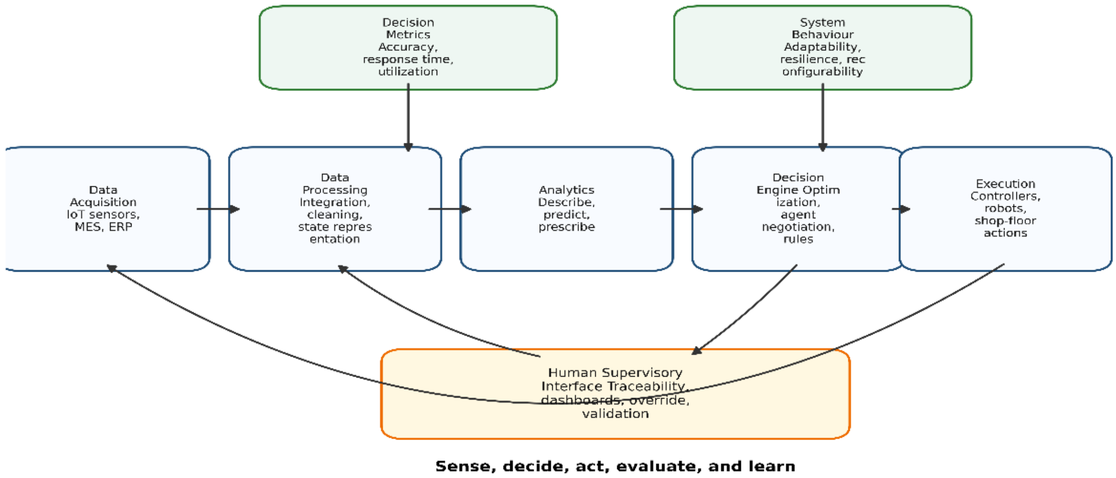


Figure 2. Decision Intelligence Framework Integrating Data, Analytics, and Autonomous Decision-Making

In figure 2, the framework depicts a sequential yet iterative pipeline from data acquisition to execution, supported by performance metrics and human supervisory control. Decision accuracy, response time, and resource utilization guide system evaluation, while adaptability and resilience define system behaviour. The inclusion of a supervisory interface reflects the manuscript's position that human oversight remains essential for trust and validation, especially where autonomous decisions affect safety and operational constraints.

3. System Architectures and Modelling Frameworks

3.1. Data Infrastructure and Integration

Decision intelligence systems for autonomous production planning and control depend on robust data infrastructure that integrates information from multiple sources. Shopfloor sensors, enterprise resource planning systems, and external data streams all feed into the decision-making pipeline (Herrmann et al., 2022; Okpala et al., 2025). In cyber-physical production systems, IoT-enabled devices generate continuous streams of operational data from machines, conveyors, and quality inspection stations (Igbokwe et al., 2025; Rolón & Martínez, 2012). Matenga and Mpofu (2025) identify a key challenge in planning autonomous IoT systems: integrating and managing data from multiple sources, which come in various formats and are generated at different scales using different platforms. Beregi et al. (2021) address this integration problem through standardized service models based on OPC UA and MQTT protocols, enabling interoperability among autonomous and distributed cyber-physical production system entities. Yang et al. (2022) stress the importance of interoperability at different levels of the manufacturing ecosystem, from shop-floor devices and control systems to cloud-based platforms. Without unified data management, systematic vulnerabilities emerge across enterprise information systems (Nwamekwe et al., 2025b). Effective data infrastructure therefore requires both vertical integration across hierarchical levels and horizontal integration across distributed production resources (Herrmann et al., 2022; Khadiri et al., 2023).

3.2. Analytical and Predictive Models

Predictive models form a core layer of decision intelligence architectures by forecasting demand, production performance, and resource availability. These models support proactive decision-making rather than reactive responses to disruptions (Okpala et al., 2024; Pulikottil et al., 2021). Yang et al. (2007) identify predictive production planning as one of four major research themes in smart factory operations, confirming its centrality to intelligent manufacturing. Chidiebube et al., 2025) describe how machine learning pipelines in IoT environments process streaming data to generate predictions that adjust outcomes when new input data arrives. In agent-based manufacturing systems, predictive models inform individual agents about expected machine workloads and potential bottlenecks, allowing them to negotiate schedules before conflicts arise (Ismayyir et al., 2024; Nwamekwe et al., 2025d). Rossit et al. (2019) propose a data-driven scheduling architecture in which the system accesses real-time data so scheduling decisions are made ahead of time, on the basis of richer information than traditional methods allow. Leitão et al. (2016) argue that even when working with deterministic plans in uncertain environments, the need for change should be anticipated as early as possible through predictive simulation techniques. The accuracy of these models depends on data quality, feature selection, and the representativeness of training data relative to actual operating conditions (Chidiebube et al., 2025a).

3.3. Optimization and Prescriptive Models

Optimization algorithms generate decisions that satisfy system constraints while maximizing or minimizing defined objectives such as throughput, cost, or lead time. Prescriptive analytics extends predictive models by recommending specific actions to achieve target outcomes (Vater et al., 2019; Estrada-Jimenez et al., 2023). Vater et al. (2019) define prescriptive analytics in manufacturing as ensuring an adaptive, autonomous, time-based and optimal decision that recommends the best approach to achieve specific key performance indicators. Ismayyir et al. (2024) frame manufacturing scheduling as an optimization process by which limited manufacturing resources are allocated over time among parallel and sequential activities. Agent-based optimization approaches distribute this problem across multiple autonomous agents, each solving local subproblems while coordinating with others through negotiation protocols (Nwamekwe et al., 2025c; Matenga & Mpofu, 2025). Nwamekwe et al. (2025h) discusses the trade-off between global optimality, typically achieved through centralized hierarchical control, and responsiveness, achieved through decentralized heterarchical control. Hybrid architectures attempt to balance these competing demands. Zeid et al. (2019) describe switching mechanisms that dynamically flip between hierarchical predictive scheduling and heterarchical reactive execution to maximize the benefits of both approaches. Adi et al. (2020) report that 29% of digital twin studies incorporate optimization into simulation models, transforming predictive digital twins into prescriptive decision tools.

3.4. AI and Machine Learning Integration

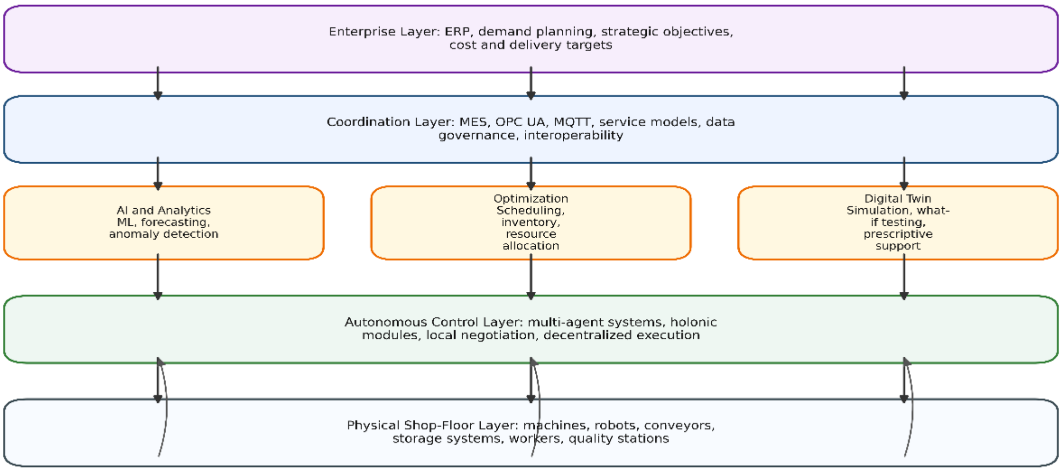
Machine learning models enable adaptive decision-making and continuous improvement within production planning and control systems. These models learn from historical and real-time data to refine scheduling rules, quality predictions, and resource allocation strategies (Chidiebube et al., 2025a; Pulikottil et al., 2021). Pulikottil et al., 2021) show that deep learning-assisted smart process planning facilitates continuous monitoring of smart shop floors and supports autonomous identification of and reaction to variable and unplanned situations. Reinforcement learning represents a growing area of interest. Matenga and Mpofu (2025) survey complementary technologies in multi-agent manufacturing and identify reinforcement learning as a mechanism for agents to improve their decision policies through interaction with the production environment. Vitalis et al. (2024) describe how software agents empowered with learning capabilities achieve complexity management, intelligence, and adaptation in industrial cyber-physical systems. Beregi et al. (2021) associate higher levels of manufacturing autonomy with advanced self-learning, where the system becomes self-adaptable to uncertain or unforeseen inputs. A persistent challenge is the interpretability of learned models. Mo et al. (2022) note that many self-organizing manufacturing approaches remain at the conceptual or experimental stage, partly because the decision logic of complex AI models is difficult for operators and managers to trust and validate in safety-critical production settings.

3.5. Real-Time Decision Engines

Decision engines process incoming data and execute decisions within the time constraints of production operations. Real-time responsiveness distinguishes autonomous systems from traditional batch-oriented planning tools (Okpala et al., 2024a; Herrmann et al., 2022). Sanderson et al. (2018) describe manufacturing execution systems that perform reactive control by filling in missing details, providing alternatives for unfeasible assignments, and handling auxiliary tasks based on shop-floor information and real-time control. Yang et al. (2022) propose a supervised and distributed holonic architecture (SUDIHA) that combines global supervision with dynamic local control, enabling real-time scheduling responses to random disruptions such as failures, raw material shortages, and quality defects. The architecture of real-time decision engines typically follows a sense-decide-act loop. Sensors detect the current state, analytical models evaluate options, and actuators or controllers implement the selected action (Okeagu et al., 2024; Igbokwe et al., 2025b). Pulikottil et al. (2021) confirm that artificial intelligence data-driven IoT systems necessitate high-performance operations and adjustable production systems through flexible and real-time scheduling. The latency requirements vary by application. Safety-critical decisions demand millisecond responses, while scheduling adjustments tolerate seconds or minutes (Nwamekwe et al., 2025d). Designing decision engines that meet these heterogeneous timing requirements across a production facility remains an active area of research (Matenga & Mpofu, 2025; Mo et al., 2022).

3.6. Integration with Digital Twins

Digital twins provide virtual environments for simulation, monitoring, and optimization of production decisions before and during execution. A digital twin creates a virtual replica of the physical production system that synchronizes with real-time data, enabling continuous analysis and what-if scenario testing (Yang et al., 2022; Liu & Tarelnyk, 2024). Yang et al. (2022) demonstrate how digital twin configurations for each holon in a distributed architecture enable intelligent and real-time data-driven operation control. Adi et al. (2020) report that simulation modelling is the inseparable element of digital twins, with 38% of reviewed studies developing simulation models to represent physical twins and predict future system states. Park et al. (2025) identify digital twins as a promising technology for enabling smart production and making better decisions based on data from simulations that aid decision-making in production design, planning, and maintenance. The integration of digital twins with optimization and data analytics transforms them from passive monitoring tools into active prescriptive instruments (Adi et al., 2020). Turgay and Akar (2023) propose a digital twin design and simulation model for reconfigurable manufacturing systems, showing how virtual representations support the deployment of different production configurations in response to changing market conditions. Challenges persist in maintaining model fidelity, managing computational costs, and handling the complexity of modelling low-frequency events and emergent phenomena in production systems (Park et al., 2025; Adi et al., 2020).



Vertical integration connects strategic planning to shop-floor execution, while feedback supports continuous adaptation.

Figure 3. Architecture of Decision Intelligence System for Autonomous Production Planning and Control

Figure 3 structures the system into hierarchical layers: enterprise, coordination, intelligence, autonomous control, and physical execution. Vertical integration ensures alignment between strategic planning and shop-floor actions, while feedback loops support real-time adaptation. The architecture captures the manuscript's core argument that hybrid systems combining centralized planning with decentralized agent-based control provide a balanced solution to the trade-off between global optimality and local responsiveness.

4. Applications in Production Planning and Control

4.1. Dynamic Production Scheduling

Decision intelligence systems adjust production schedules in real time based on current system conditions, responding to disruptions and changing priorities as they occur. Traditional scheduling methods rely on pieces of information directly related to schedule performance, such as processing times and delivery dates, and assume the production system is operating normally (Herrmann et al., 2022). When disruptions arise, conventional approaches focus on corrective operations like rescheduling after machine breakdowns (Herrmann et al., 2022). Autonomous control takes a different approach. Okpala et al. (2025a) describe autonomous control methods that enable situation-dependent decision-making at the system element level, where individual production orders or resources make local scheduling decisions based on real-time information. Igbokwe and Nwamekwe (2025) present an agent-based approach using extensive-form games to adapt energy-optimized production schedules, where a scheduler agent and energy agents respond to changing energy prices and unforeseen production events. Rolón & Martínez (2012) emphasize the gap between scheduling theory and practice, arguing that the ideal planning and control system should combine local autonomous decisions globally aligned with higher planning levels. Nwamekwe et al. (2025h) further investigate coupling strategies that combine central planning with autonomous control, balancing the logistic efficiency of autonomous methods against the planning accuracy of centralized schedules. The simulation results from their job shop study show that the appropriate coupling strategy depends on the level of dynamic influences in the production environment (Nwamekwe et al., 2025c).

4.2. Inventory and Supply Chain Management

Decision intelligence systems optimize inventory levels and coordinate supply chain activities by processing distributed information across multiple tiers of the production network. In multi-tier manufacturing environments, scheduling and resource allocation are critical components of operations management, yet systematic vulnerabilities emerge due to a lack of unified and synchronized data management systems across enterprises (Rossit et al., 2019). Yang et al. (2022)

propose a digital-twin-based implementation framework for production service systems that enables online collaborative operation and autonomous decision-making control of production logistics under high dynamic interference. Their framework supports real-time dynamic capture, operational precision mapping, and iterative decision optimization for synchronized production and logistics (Yang et al., 2022). Khadiri et al. (2023) demonstrate how multi-agent systems coordinate logistics processes, reporting savings of 2.6 million pallet-days per year in warehouse operations through better utilization of free times at container terminals in a validated real-world case. Onyeka and Emeka (2025) characterize self-organizing logistics in transportation through autonomous decision-making and decentralized control structures, which reduce the complexity of decision-making and require less computational effort. Their framework positions different approaches along axes of autonomy and cooperativity (Okpala et al., 2024a). Pulikottil et al. (2021) show how autonomously controlled intralogistics systems respond to transport orders through decentralized bidding among available transport systems, including automated guided vehicles and collaborative tugger trains, with decisions made locally regarding lead-time and schedule adherence.

4.3. Resource Allocation and Utilization

Decision intelligence improves the allocation of machines, labour, and materials by distributing decision authority to the entities closest to the operational context. Onyeka et al. (2024) describe how agent-based systems address resource allocation in reconfigurable enterprises, where each entity in charge of specific planning decisions makes its own decision autonomously while global planning decisions are achieved through coordination and negotiation. Ezeanyim et al. (2025) explain how autonomous assembly systems cluster into subsystems and modules, each receiving a degree of autonomy to control resource usage in a decentralized way. This approach achieves high, consistent resource utilization even in dynamic environments (Chidiebube et al., 2025b). Ismayyir et al. (2024) present a cost-based model for integrating maintenance strategies into autonomous production control, arguing that adaptive and decentralized production control reduces planning efforts and enables shorter reaction times. Nwamekwe et al. (2025i) note that autonomous systems shift the role of the production planner from active decision-maker to supervisor and maintainer of the system, which changes how resource allocation decisions are structured and communicated. Leitão et al., (2016) confirm that cyber-physical production systems redesign decision-making processes across manufacturing environments, including dynamic, distributed, and inverse scheduling, to optimize resource allocation through real-time sensor networks and deep learning-assisted process planning.

4.4. Predictive Maintenance Integration

Maintenance decisions integrated into production planning improve equipment availability and reduce unplanned downtime. Ismayyir et al., (2024) identify the absence of maintenance factors in autonomous production control models as a source of inefficiency and low acceptance among manufacturing enterprises. Their conceptual cost-based model integrates different maintenance strategies, including condition-based and predictive approaches, into autonomous production control using a market-based mechanism (Ismayyir et al., 2024). The model provides relevant decision aspects and a cost function so that maintenance actions compete with production orders for available resources and time slots (Ismayyir et al., 2024). Leitão et al., (2016) describe how deployment of artificial intelligence-based decision-making algorithms and real-time sensor networks enables condition-based maintenance through massive volumes of data gathered on equipment and processed through product decision-making information systems. Yang et al., (2022) show how digital twin frameworks support maintenance integration by providing virtual simulation environments where the impact of maintenance scheduling on production logistics is evaluated before execution. Ezeanyim et al. (2025) argue that future production planning and control systems must turn to closed-loop controllers that continuously adapt the manufacturing system toward the required state and functionality, which includes accounting for equipment degradation and maintenance needs in scheduling decisions.

4.5. Resilient and Adaptive Production Systems

Decision intelligence systems enable production systems to adapt to disruptions and maintain performance under uncertainty. Schukraft et al. (Okpala et al., 2025a) demonstrate the applicability and suitability of autonomous control in complex and dynamic production and transportation environments, where methods evaluate performance under varying levels of dynamic influences.

Schuhmacher and Hummel (Pulikottil et al., 2021) show that purely deterministic planning does not provide optimal solutions in turbulent systems and results in lower overall system performance, while autonomous control increases flexibility and robustness through decentralized information processing and execution. Igbokwe and Nwamekwe (2025) address resilience through agent-based adaptation of production schedules, where game-theoretic mechanisms allow the system to respond to unforeseen events and changing energy prices without centralized replanning. Rolón & Martínez, (2012) argue that as complexity in production networks grows and responsiveness must increase, the need for autonomous decision-making becomes stronger, though the ideal system combines local autonomous decisions with global planning alignment. Yang et al., (2022) verify the effectiveness of their digital-twin-based framework in enabling adaptive decision-making and control of production logistics to cope with high dynamic interference, reporting improvements in visualization, decision-making, and cost for the manufacturing enterprise studied. The common thread across these approaches is the shift from rigid, predetermined plans to flexible, data-informed decision structures that absorb and respond to variability at the point of occurrence (Okpala et al., 2025; Chidiebube et al., 2025b; Ismayyir et al., 2024).

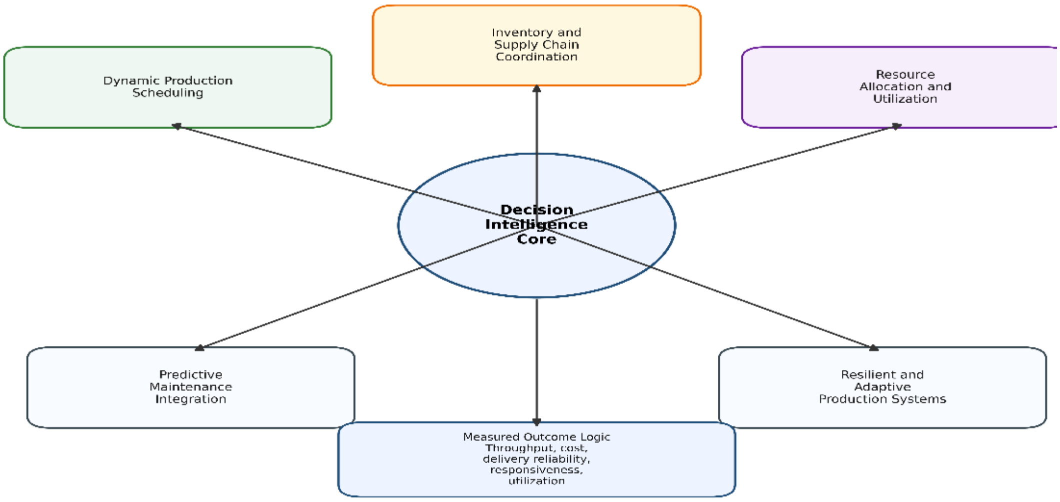


Figure 4. Application Domains of Decision Intelligence Systems in Autonomous Production Planning and Control

Figure 4 positions decision intelligence as a central capability applied across five domains: scheduling, inventory and supply chain coordination, resource allocation, predictive maintenance, and system resilience. Each domain reflects a critical operational function where real-time data and autonomous decision-making improve performance. The figure reinforces the manuscript's evidence that distributed intelligence enhances responsiveness and efficiency across interconnected production activities.

5. Key Challenges and Research Gaps

5.1. Data Quality and Integration Issues

Reliable decision-making in autonomous production systems depends on high-quality data drawn from heterogeneous sources across the manufacturing enterprise. Herrmann et al., (2022) identify a key challenge in integrating and managing data from multiple sources, which come in various formats and are generated at different scales using different platforms. This problem intensifies in multi-tier production environments where enterprise information systems lack unified and synchronized data management (Herrmann et al., 2022). Okpala et al. (2025a) stress that interoperability remains a fundamental challenge at different levels of the manufacturing ecosystem, from shop-floor devices and control systems to cloud-based platforms. The scope of this challenge ranges from communication protocols and logical semantics to architectural differences between machines and software packages (Okpala et al., 2025a). Igbokwe and Nwamekwe (2025) point out that varying IoT infrastructures, including cloud, edge, and fog configurations, along with limitations of application layer protocols in transmitting and receiving messages, create barriers for intelligent IoT applications. These barriers prevent current intelligent applications from adaptively learning from other IoT applications (Igbokwe et al., 2025b). Rolón and Martínez (2012) address part of this problem through standardized service models using OPC UA and MQTT protocols, but acknowledge that achieving reliable interoperability among autonomous and distributed cyber-physical production system entities requires sustained effort in model standardization and data governance.

5.2. Model Complexity and Interpretability

Complex models used in decision intelligence systems are often difficult to interpret and validate, which limits their adoption in production environments. Estrada-Jimenez et al. Nwamekwe et al. (2025e) report that most self-organizing manufacturing approaches remain at the conceptual or experimental stage, partly because the decision logic embedded in complex AI models is difficult for operators and managers to trust. Rossit et al. (2019) argue that the incomprehensiveness of decision models and related decision support tools causes inefficiency in production planning and leads to low acceptance among manufacturing enterprises. When the underlying reasoning of a model is opaque, production planners struggle to verify whether the system's recommendations align with operational constraints and safety requirements (Rossit et al., 2019). Yang et al., (2022) discusses the trade-off between optimality and reactivity in distributed manufacturing control, noting that heterarchical systems, while responsive, produce decisions whose global consequences are hard to predict or explain. Khadiri et al. (2023) observe that deep learning-assisted smart process planning and artificial intelligence-based decision-making algorithms are understood to a limited extent in the current literature, particularly regarding the underlying mechanisms between cyber-physical production networks and product decision-making information systems. This gap between model sophistication and human comprehension remains a barrier to industrial deployment.

5.3. Scalability and Computational Requirements

Large-scale production systems require efficient algorithms that maintain performance as the number of decision variables, agents, and data streams grows. Onyeka et al. (2024) characterize manufacturing scheduling as an optimization process involving limited resources allocated over time among parallel and sequential activities, a problem whose computational complexity increases rapidly with system size. Yang et al., (2022) identifies scalability as one of the advantages of multi-agent and holonic manufacturing paradigms, yet notes that weak industrial adoption persists partly because scaling laboratory prototypes to full factory environments introduces unforeseen coordination overhead. Pulikottil et al., (2021) survey multi-agent manufacturing approaches and confirm that scalability remains an open challenge, particularly when complementary technologies such as reinforcement learning and digital twins add computational layers to the decision architecture. Onyeka et al. (2024) argue that decentralized control structures reduce the complexity of decision-making and require less computational effort compared to centralized optimization, making them faster and reducing the risk that changes during decision-making render the solution invalid. Ezeanyim et al. (2025a) observe that as complexity in production networks and products grows, the ideal system should combine local autonomous decisions globally aligned with higher planning levels, but achieving this balance at scale remains an unresolved design problem.

5.4. Real-Time Implementation Constraints

Low-latency decision-making is critical for autonomous production systems that must respond to disruptions as they occur on the shop floor. Ismayyir et al. (2024) propose a data-driven scheduling architecture where the system accesses real-time data so decisions are made ahead of time, but acknowledge that the technical infrastructure for continuous data access and processing at production speed is demanding. Nwamekwe et al. (2025i) describe a supervised and distributed holonic architecture for dynamic scheduling that handles random disruptions such as failures, raw material shortages, and quality defects in real time, yet the computational cost of maintaining synchronized digital twin models alongside physical operations adds latency. Leitão et al. (2016) demonstrate that purely deterministic planning does not provide optimal solutions in turbulent systems, and autonomous control based on decentralized information processing and execution at the system element level offers a path forward, though real-time coordination among multiple autonomous entities introduces communication delays. Khadiri et al. (2023) confirm that artificial intelligence data-driven IoT systems necessitate high-performance operations and adjustable production systems through flexible and real-time scheduling. The gap between theoretical real-time capability and practical deployment in noisy, high-throughput factory settings remains significant (Yang et al., 2022; Pulikottil et al., 2021).

5.5. Human-System Interaction

Operators and production planners must understand and trust autonomous systems for successful deployment. Vater et al., (2019) examine how autonomous production control shifts the role of the production planner from active decision-maker to supervisor and maintainer of the system. This role change creates acceptance challenges because planners lose direct control over decisions, they remain accountable for (Vater et al., 2019). Rossit et al. (2019) emphasize that ensuring a high level of acceptance among operational planning staff requires underlying models to comprehensively account for relevant factors of the production system and make robust decisions. Estrada-Jimenez et al. (2023) argue that autonomous processes should support human capabilities such as knowledge, experience, and creativity rather than replace human activities. Nwamekwe et al. (2025f) note that self-organizing manufacturing solutions must address the human factor, as operators need clear interfaces and explanations to maintain situational awareness when the system acts autonomously. Matenga & Mpofu (2025) show that in logistics applications, the visualization of agent-based decision-making through dashboards helps users understand and monitor autonomous control actions. The design of effective human-system interaction remains an active research area, particularly regarding how to present complex multi-agent decisions in forms that support rapid human comprehension and intervention when needed (Vater et al., 2019; Nwamekwe et al., 2025f).

5.6. Lack of Standardized Frameworks

No unified approach exists for designing, implementing, and evaluating decision intelligence systems in autonomous production planning and control. Yang et al., (2022) discusses the diversity of multi-agent and holonic manufacturing architectures in the literature and identifies the absence of common standards as a factor contributing to weak industrial adoption. Rolón & Martínez (2012) propose a methodology for universally modelling, digitalizing, and integrating services offered by isolated work cells into a single standardized production system, but acknowledge this addresses only the execution layer. Nwamekwe et al. (2025) conduct a systematic review of self-organization in smart manufacturing and find that works are developed under different application scenarios using different methodologies, making comparison and replication difficult. Pulikottil et al., (2021) survey multi-agent manufacturing frameworks and report a fragmented field where each research group develops its own architecture with limited interoperability across implementations. Ezeanyim et al. (2025a) confirm the gap between scheduling theory and practice, noting that many proposed decisions support systems lack the standardization needed for deployment in actual manufacturing environments. Zeid et al. (2019) attempt to address this gap by proposing a five-level autonomy model with associated maturity levels for features, but the model has yet to achieve broad adoption. The absence of standardized benchmarks, reference architectures, and evaluation protocols slows progress toward industrial-scale decision intelligence systems (Yang et al., 2022; Nwamekwe et al., 2025f; Pulikottil et al., 2021).

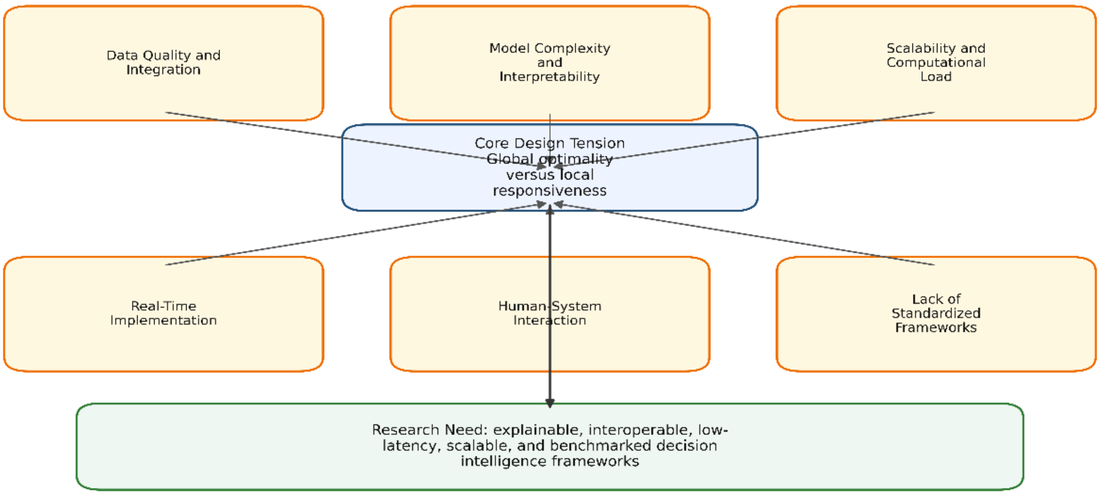


Figure 5. Challenges and Trade-offs in Decision Intelligence Systems for Autonomous Production Control

Figure 5 identifies six key challenges and links them to a central design tension between global optimality and local responsiveness. Data integration, model interpretability, scalability, real-time execution, human interaction, and lack of standardization constrain system performance and adoption. The diagram highlights the need for balanced system design, where improvements in one dimension do not degrade performance in another, consistent with the manuscript's analysis of unresolved research gaps.

6. Future Directions and Conclusion

6.1. AI-Driven Autonomous Decision Systems

Artificial intelligence should move decision intelligence systems from assisted planning to autonomous, closed-loop production control. The manuscript shows this direction through machine learning, reinforcement learning, agent-based negotiation, predictive scheduling, and prescriptive analytics. These tools support the full decision chain: sensing, reasoning, optimization, and execution. Future research should strengthen AI models that learn from real-time shop-floor data and translate predictions into production actions. This is important because conventional schedules lose value when machine workloads, demand patterns, material availability, or quality states change after release. AI-driven systems should therefore predict disruptions early, select feasible alternatives, and coordinate local decisions across machines, products, and logistics units. The strongest future pathway lies in explainable autonomous decision systems. The manuscript identifies interpretability as a major adoption barrier because operators and planners need to understand why a system selected a schedule, delayed a job, reassigned a resource, or triggered maintenance. Future AI systems should therefore combine predictive accuracy with traceable decision logic, clear dashboards, and human-supervised override functions. This will improve trust and reduce the gap between intelligent control research and industrial deployment.

6.2. Integration with Edge and Cloud Computing

Future decision intelligence systems should integrate edge and cloud computing to balance response speed, data capacity, and system scalability. The manuscript shows that real-time decision engines need different timing levels. Safety-critical decisions require millisecond responses, while scheduling changes tolerate seconds or minutes. This timing difference makes hybrid computing necessary. Edge computing should handle time-sensitive shop-floor tasks such as sensor filtering, anomaly detection, machine status monitoring, and local dispatching. Cloud platforms should support heavier tasks such as long-horizon optimization, historical learning, enterprise-wide planning, and cross-site performance analysis. This structure reduces latency at the machine level while retaining the analytical strength of cloud infrastructure. The manuscript also identifies data integration as a central challenge because production data comes from multiple sources, formats, scales, and platforms. Hybrid edge-cloud architectures should therefore include standard communication protocols, strong data governance, and synchronized interfaces across sensors, MES, ERP, digital twins, and autonomous agents. OPC UA and MQTT-based service models provide a useful foundation for this integration.

6.3. Digital Twin-Based Decision Optimization

Digital twins should become the main experimental layer for autonomous production decision-making. The manuscript shows that digital twins create virtual replicas of physical production systems and synchronize them with real-time data. This allows production planners and autonomous agents to test decisions before execution. The numerical evidence in the manuscript supports this direction. Simulation modelling appears in 38% of reviewed digital twin studies, while 29% of digital twin studies incorporate optimization into simulation models. These figures show that digital twins already support prediction and prescriptive decision-making, but the optimization layer remains underdeveloped. Future work should therefore focus on digital twins that evaluate scheduling, maintenance, inventory, and logistics decisions before physical implementation. This will reduce trial-and-error decisions on the shop floor. It will also support what-if analysis under machine breakdowns, raw material shortages, energy price changes, quality defects, and demand volatility. Digital twin-based decision optimization should also address model fidelity and computational burden. A twin that fails to represent real production dynamics will produce weak recommendations. A twin that consumes too much computing time will fail in real-time control. Future systems should therefore balance accuracy, speed, and usability.

6.4. Scalable and Adaptive Frameworks

Future decision intelligence frameworks should scale across different production environments without losing reliability. The manuscript identifies scalability as a major research gap, especially when multi-agent systems, reinforcement learning, real-time IoT data, and digital twins operate together. The strongest framework should combine centralized planning with decentralized execution. Centralized layers should preserve global production objectives such as throughput, delivery performance, cost, and resource balance. Decentralized agents should respond locally to disruptions at machines, cells, storage areas, and transport systems. This hybrid structure addresses the trade-off between global optimality and local responsiveness. The manuscript also shows that adaptive systems work better in dynamic environments because purely deterministic planning performs poorly under turbulence. Future frameworks should therefore support reconfiguration across production types, including job shop, flow shop, smart shopfloor, logistics-intensive production, and reconfigurable manufacturing systems. The logistics example in the manuscript gives a strong practical signal. A validated multi-agent logistics case reported savings of 2.6 million pallet-days per year through improved use of free time at container terminals. This value shows that autonomous coordination has measurable operational value when data, agents, and decision rules work together.

6.5. Concluding Insight

Decision intelligence systems provide a strong framework for autonomous production planning and control because they connect data acquisition, analytics, optimization, and execution in one decision loop. The manuscript shows that these systems respond to the limits of conventional PPC, especially rigid scheduling, delayed reaction to disturbances, weak integration between planning and execution, and limited use of real-time shop-floor data. The review also shows that autonomous production requires more than automation. It requires systems that sense production states, predict future conditions, recommend actions, execute decisions, and learn from outcomes. Multi-agent systems, cyber-physical production systems, digital twins, reinforcement learning, predictive analytics, and prescriptive optimization all support this shift. Future research should focus on five priorities: explainable AI, edge-cloud integration, digital twin-based optimization, scalable hybrid control, and standardized evaluation frameworks. These areas directly address the manuscript's main gaps, namely data integration, model complexity, computational requirements, real-time implementation, human-system interaction, and lack of standardization. Decision intelligence will shape the next stage of production planning and control when it becomes accurate, interpretable, scalable, and fast enough for industrial conditions. Its value lies in adaptive decisions that protect throughput, reduce disruption losses, improve resource use, and keep production systems aligned with changing operational realities.

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