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Cognitive Intelligent Decision-Making for Digital Transformation of Reconfigurable Production Systems

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Abstract

The digital transformation of manufacturing has accelerated the adoption of reconfigurable production systems (RPS). RPS promise modularity, scalability and agility in response to increasing product variety and market volatility. To fully realize these benefits, it is essential to align high-level planning with real-time shop floor execution through intelligent coordination across system layers. This paper proposes a cognitive-intelligent decision-making framework to support data-driven planning, scheduling and execution in an RPS environment. The framework aligns digital infrastructure with decision intelligence by integrating knowledge graph-based product-process modeling, blockchain-enabled information services and adaptive scheduling algorithms. It further incorporates sociotechnical system modeling to model and analyze human behavior dynamics on the shop floor. Core research topics include variety management via extended GBOMO, trusted information sharing through a blockchain-IaaS system, manufacturing load balancing using data-driven and game-theoretical approaches, and supervision–compliance synergy modeling with fuzzy game-theoretic approach. These research topics establish a coherent architecture for resilient, reconfigurable, and human-centric manufacturing decision support.

Keywords
Cognitive intelligence, Reconfigurable production systems, Sociotechnical systems, Production plan and control

1. Introduction

Volatile markets, shorter product lifecycles, and mass customization are pushing manufacturers toward agile, digitally enabled systems (ElMaragh 2009). Industry 4.0 advances—such as IIoT, big data, AI, cyber-physical systems, and digital twins—enable smarter, reconfigurable production with enhanced flexibility and decision-making (Jiao et al., 2021). Digital transformation embeds these technologies across business processes, shifting the focus from data collection to intelligent analytics (Song 2025), though progress is slowed by gaps in strategy, skills, and infrastructure. Cyber-physical systems (CPS) integrate machine connectivity and real-time optimization, while humans remain essential, driving research into cognitive manufacturing that supports shared perception and reasoning (Wu et al. 2013). Reconfigurable Manufacturing Systems (RMS) extend Flexible Manufacturing Systems (FMS) with modular design, and Reconfigurable Production Systems (RPS) build on this by adding planning and control layers. Most plants mix digital and legacy lines, requiring cohesive data-driven frameworks for predictive, adaptive decision-making (Borangiu et al. 2020).

To empower the digital transformation, the present study advances a cognitive-intelligent decision-making framework that closes the strategy–execution gap in the digital transformation of Reconfigurable Production Systems (dRPS). Section 2 surveys relevant literature, while Section 3 outlines the overarching research framework. Sections 4–7 detail each fundamental issue alongside its corresponding research tasks and solutions, and Section 8 closes the paper with concluding remarks.

2. Emerging Trends and Industrial Consensus

2.1 Paradigm Shifts in Manufacturing Systems

Manufacturing has progressed from dedicated, mechanically isolated lines to digitally networked, cyber-physical ecosystems. Early Dedicated Manufacturing Systems (DMS) delivered high-volume output for a single product (Mehrabi et al., 2000). FMS then introduced numerically controlled machines and data networks, enabling family-level product variety and quicker changeovers (Koren 2007). Digital control served a dual role—as the central coordinator and as a conduit for machine-to-information-system integration (Kostal & Velisek 2011). Building on FMS, RMS added modularity, scalability, integrability, convertibility, customization and diagnosability, allowing rapid physical or software reconfiguration in response to demand swings (Bortolini et al. 2018). To address this complexity, we extend the concept to the RPS, a paradigm that incorporates system-level planning, logistics and decision support in addition to machine-level agility. Implementing RPS remains difficult because structured methods for embedding reconfigurability during system design are scarce (Rösiö & Säfsten 2013). Effective solutions must blend digital twins, computer-integrated manufacturing and real-time tracking so that new product requirements can be simulated, evaluated and deployed swiftly.

2.2 Real-time Data-driven Decision-making in Production Planning

Order acceptance and task scheduling (OATS) has long been a core theme in production-and-operations management. Guerrero (1988) identified four foundational elements which are capacity constraints, order prioritization, scheduling integration and feedback loops. These elements set the stage for optimization models that marry shop-floor data with order decisions. Subsequent Order Acceptance and Scheduling (OAS) studies progressed from static, single-machine settings to multi-objective, constraint-rich environments: branch-and-bound and heuristic methods, genetic algorithms, tabu search, machine-availability considerations (Zhong et al. 2014) and sequence-dependent setups. Extensions include demand-uncertainty planning, hyper-heuristic, and GA hybrids (Nguyen et al. 2016).

As manufacturing migrates toward RPS, decision complexity widens from isolated OAS to Manufacturing Load Balancing (MLB). This dynamic allocation of work across heterogeneous resources. Prior load-balancing research spans semiconductor fabs, fuzzy-logic tool balancing, cloud-manufacturing GA schedulers and IoT-enabled shop-floor coordination. Unlike traditional OAS, MLB must continuously redistribute tasks among lines and machines with different digitalization levels, integrating real-time state changes and system heterogeneity.IoT, smart sensors and edge/cloud analytics now make such responsiveness feasible. Real-time data streams power predictive maintenance, energy optimization, quality control and adaptive scheduling (Tao et al. 2018). Key research topics include system integration, simulation, AR visualization, big-data analytics and cyber-security (Bousdekis et al. 2021). Practical implementations employ simulation-based optimization, Petri-net-driven assembly orchestration (Qian et al. 2020), discrete-event MPC for WIP optimization and max-plus/graph-based model-predictive scheduling.

In an RPS context, such techniques must converge into a unified decision architecture capable of harmonizing streams from legacy equipment, advanced robotics and AI analytics. Only by fusing these heterogeneous data sources can RPS proactively reconfigure resources, allocate tasks and balance workload realizing a system-level intelligence that surpasses earlier manufacturing paradigms.

2.3 Industrial Knowledge Graphs and Large Languages Models in Production and Manufacturing

Knowledge graphs (KGs) evolved from early semantic networks and linked-data concepts that captured entities and their relationships (Schank 1972). Google's 2012 release popularized the term as a structured web of entities for better information retrieval, and KGs are now widely defined as "graph-based representations of data designed to accumulate and convey real-world knowledge" (Hogan et al.2021). Because their explicit structure supports reasoning, integration and simulation of human thought, KGs are viewed as building blocks for cognitive intelligence.

Manufacturing plants naturally exhibit graph-like interdependencies among machines, materials, processes and people. Traditional expert systems relied on manual encoding, whereas KGs improve scalability and heterogeneous data integration (Sarazin et al.2021). Studies show they can unify standards, machine data, safety knowledge and material-selection rules (Ma et al. 2021). Industrial adopters such as Siemens embed KGs in digital twins, risk assessment and service operations, while research prototypes connect Industry 4.0 data hubs, IIoT services and dynamic resource allocation. In the RPS, KGs must link diverse shop-floor streams—legacy equipment logs, sensor feeds, maintenance records—to deliver context-aware guidance for operators, technicians and engineers. This human-centric, multi-level decision supports distinguish RPS graphs from earlier automation-only frameworks.

Large Language Models (LLMs) such as GPT-4 add a complementary, implicit layer of knowledge. Although powerful, LLMs face hallucination, domain gaps and opacity (Sun et al. 2023). Coupling them with KGs mitigates these issues: LLMs can extract entities and relations from unstructured text, enrich graph embeddings, refine graph topology and act as conversational interfaces that return traceable, KG-grounded answers. Chain-of-thought prompting further exposes the reasoning path, enhancing interpretability (Pan et al.2024).

3. Holistic Research Framework of dRPS

RPS can achieve its promised agility only when improvements in digital infrastructure are tightly coupled with advances in cognition-enabled decision support across the full temporal hierarchy of factory operations. Digital-transformation research secures the data foundation—collecting, contextualizing and validating artefacts—whereas cognitive-intelligent decision-making converts that data into adaptive, value-optimizing actions. Mapping the two domains onto the canonical planning, scheduling and execution stages ensures that each layer of the production stack receives the type of information it needs at the cadence it can exploit: long-horizon variant rules must be set before finite-capacity scheduling, and real-time behavioral feedback must reach the shop floor within seconds. By explicitly aligning digital-transformation topics with data-centric tasks and cognitive topics with decision-centric tasks, the framework guarantees coherent, closed-loop control without duplicating effort or leaving gaps between strategic intent and operational reality.

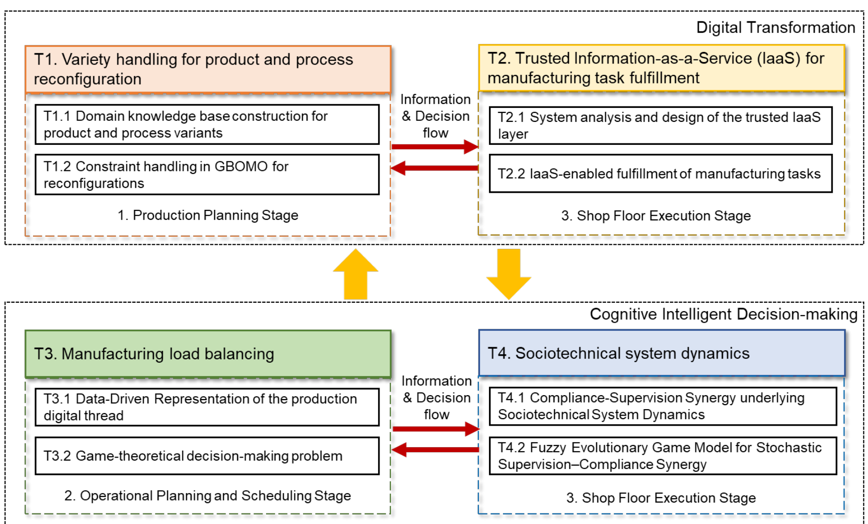

Figure 1. A holistic framework for cognitive intelligent decision-making for digital transformation of RPS

As shown in figure 1, the digital transformation domain meets two essential needs. In the production planning stage, the production system must compile a complete catalogue of valid product process combinations and store the related feasibility rules in a generic bill of materials and operations (GBOMO). This structured variant library anchors the entire framework, because without it neither the scheduler nor the shop floor can know whether a proposed reconfiguration is feasible. In the execution stage, the plant requires a secure, high-speed data channel that records every machine action—operation starts, parameter adjustments, quality results—and publishes these events as semantically labeled services. Delivering trusted, real time shop floor information to the upper layers is critical for accurate load balancing and for the behavioral models that track operator machine interactions.

Within the cognitive intelligent decision-making domain, the two topics occupy distinct stages of the production hierarchy. Manufacturing load balancing, positioned in the scheduling stage, tackles the chronic mismatch between a changing mix of orders and the uneven capacities of reconfigurable resources. As product variants shift, bottlenecks move and idle time grows; without a systematic way to redistribute work, throughput drops and due dates slip. A formal load balancing model converts real time capacity data into task assignments that keep resources evenly used while respecting economic targets and variant specific rules. Sociotechnical system dynamics, situated in the execution stage, confronts the human side of the same challenge. Even the best schedule falters if operators and engineers react unpredictably to workload changes or new machine settings. Variations in supervision, compliance, and knowledge sharing can ripple through the line, magnifying delays or quality losses.

3.1 Variety Handling for Product and Process Reconfiguration

Variety handling for product and process reconfiguration—forms the planning backbone of an RPS by cataloguing every feasible combination of parts, routings and machine capabilities. An industrial knowledge graph is used to build this domain knowledge base because its semantic structure can merge engineering drawings, ERP master data, and machine-capability tables into a single, queryable network; this unification lets planners run graph reasoning to discover equivalent materials, alternative operations or missing capability links in seconds. Encoding the resulting information and its feasibility rules in a generic bill of materials and operations (GBOMO) gives the plant an authoritative source for rapid product-and-process variety management, preventing infeasible orders from entering the schedule and supplying optimization algorithms with trustworthy constraints. The approach is significant because it turns what has traditionally been a manual, error-prone variant-review process into an automated service that shortens quotation lead time, improves first-time-right planning and supports mass customization at scale. Key research challenges include automatically extracting variant knowledge from heterogeneous sources, keeping the graph representation lightweight enough for real-time reasoning, and modelling constraints that range from simple compatibility checks to capacity-driven expressions; overcoming these issues is essential to maintain both the expressiveness and the computational efficiency of the GBOMO framework.

3.2 Trusted Information-as-a-Service for Manufacturing Task Fulfillment

Trusted Information-as-a-Service (IaaS) for manufacturing task fulfillment, introduces a modular data layer that captures shop floor events and republishes them as verified information services. Its first subtopic, System analysis and design of the trusted IaaS layer, specifies the architectural requirements—millisecond latency, tamper evidence, and semantic consistency—and develops a permissioned blockchain gateway that time stamps every machine action and exposes the results through uniform application interfaces. The second subtopic, IaaS enabled fulfillment of manufacturing tasks, shows how these services feed schedulers, digital twins, and human machine interfaces so that tasks can be dispatched, monitored, and corrected with full data provenance. Such trusted, real-time visibility is essential for agile reconfiguration; without it, capacity models drift, and optimization loses credibility. Major research challenges include choosing a consensus protocol that balances throughput with auditability, limiting ledger overhead on resource-constrained edge devices, and unifying heterogeneous machine vocabularies into a semantic model that higher layers can query without bespoke parsers.

3.3 Manufacturing Load Balancing and Planning

Manufacturing load balancing deals with the scheduling-stage task of assigning a continually changing order mix to production lines that differ in speed, change-over effort, and degradation. The first sub-topic develops a data-driven production digital thread that can represent each line's behaviors and predict job finish times under current queues and setup conditions; without accurate, real-time predictions, any attempt to balance loads risks creating hidden bottlenecks or missed due dates. The second sub-topic frames the inevitable trade-offs among throughput, lateness penalties, and line utilization as a game-theoretical decision-making problem, providing a structured way to weigh system-wide objectives against individual line constraints. Key challenges include modelling heterogeneous equipment in a unified representation, keeping finish-time forecasts current as shop-floor states evolve by the minute, defining pay-off structures that truly capture economic and operational priorities, and computing scheduling decisions quickly enough to remain relevant in a rolling-horizon environment.

3.4 Sociotechnical System Dynamics for Human Centric Manufacturing

Sociotechnical system dynamics examines how human behaviors, and technical processes interact on the shop floor and, ultimately, influence production performance. The first sub-topic, compliance–supervision synergy underlying sociotechnical system dynamics, seeks to explain how operators' willingness to follow standard procedures co-evolves with engineers' monitoring intensity, creating feedback loops that can either stabilize or destabilize output. The second sub-topic, a fuzzy evolutionary game model for stochastic supervision–compliance synergy, provides a formal lens for capturing how these interactions drift over time in the presence of perception gaps, learning effects and random disturbances. Understanding this layer is critical because even a well-balanced schedule can unravel when compliance drops or supervision becomes inconsistent, leading to hidden bottlenecks and quality escapes. Key challenges include observing human decisions without disrupting workflows, quantifying subjective factors such as perceived workload or risk, representing uncertainty in pay-offs and transition probabilities, and linking behavioral insights back to higher-level scheduling and planning decisions quickly enough to prevent performance degradation.

4. Knowledge Graph-based and LLM-enabled Product and Process Information Modelling for High-Variety Production

4.1 LLM-Based Knowledge-Graph Construction for Knowledge Modelling

The Generic Bill of Materials and Operations (GBOMO), introduced by Jiao et al. (2000), serves as a foundational framework for managing product variety by decoupling product structures (items), manufacturing steps (operations), and production assets (resources) into distinct entities with standardized attributes. This separation enables cross-functional analysis of cost, cycle time, and energy consumption across product families. However, while GBOMO captures high-level process sequences (e.g., Housing A undergoes Press Fit and Laser Mark), it omits granular control-layer specifications, such as programmable logic controller (PLC) routines governing press depth or robotic task scripts defining laser focus parameters. In RPS, such omissions hinder validation of whether new product variants can be executed by existing automation systems without reprogramming.

To address this limitation, a knowledge graph (KG) architecture is proposed to augment GBOMO. Unlike traditional hierarchical bill-of-materials structures, a KG represents entities and relationships as a unified network, enabling bidirectional links between GBOMO's high-level nodes (e.g., Laser_Mark_Operation) and control-layer artifacts (e.g., Robot_Task scripts, PLC_Block logic, sensor calibration thresholds, or maintenance logs). Prior research demonstrates KGs' utility in bridging design and process data for root-cause analysis; this work extends the capability to integrate real-time control logic and automation constraints.

Figure 2 outlines the implementation workflow. First, heterogeneous data sources—controller programs, equipment manuals, and production logs—are normalized into structured formats. A large language model (LLM), guided by domain-specific prompts, extracts key entities (part IDs, toolpaths, sensor tolerances) and semantic relationships (e.g., PLC_Routine_12 sets parameters for Press_Fit_Operation). A post-processing pipeline consolidates synonyms, standardizes units (e.g., converting psi to bar), and annotates provenance metadata. The refined data is mapped to an extended GBOMO schema in Neo4j, introducing control-layer node classes such as PLC_Block, Robot_Task, and Sensor_Limit. To enable hybrid querying (exact graph traversals + vector similarity searches), node embeddings are generated via graph neural networks and stored as attributes. This layered KG transforms GBOMO from a static product-process map into an adaptive decision-support system, explicitly associating product configurations with the control logic required to manufacture them.

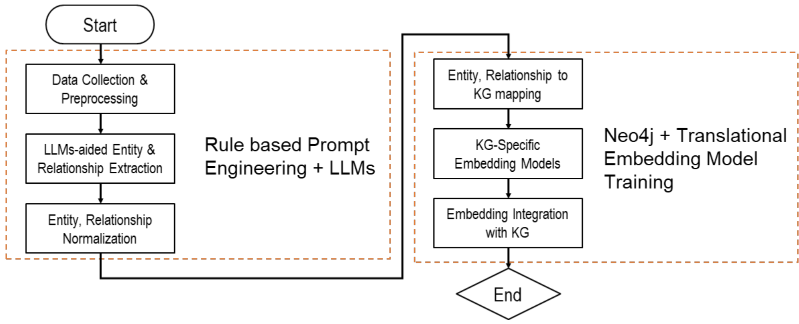

Figure 2. A basic procedures of LLM-based knowledge graph construction

4.2 LLM-Based Knowledge-Graph Construction for Knowledge Modelling

After the extended GBOMO knowledge graph has been populated with products, operations, resources, and control artefacts, it must yield the rules that determine whether a proposed product–process combination is feasible and on which equipment it can run. These rules—covering material-routing matches, operation sequences, capacity limits, quality checks, and regulatory requirements—transform a static variant list into a decision framework suitable for quoting, finite-capacity scheduling, and real-time rescheduling. Because manual rule writing cannot keep pace with continuous product and code updates, rule creation is automated.

The solution adapts the GraphRAG retrieval-and-generation pattern while enforcing GBOMO's hierarchy and parameter-inheritance logic. When a planner evaluates a parent item, an embedding query retrieves a focused sub-graph containing the parent's family-level parameters, associated child items and operations, relevant controller settings, and historical production data. This context is supplied to a large language model through a prompt requesting a single IF–THEN rule that links the parent to an admissible child or operation and respects inherited parameters. An example output might read:

"IF Base.Material = Aluminium THEN Press_Fit.Operation AND PLC_Routine = Depth_5 mm"

A two-stage validation then converts the candidate clause into a robust constraint. First, a normalization layer maps abbreviations to canonical labels and ensures that family-level constraints propagate to child operations. Second, the rule is expressed as a SHACL shape and tested against both the live graph and historical order data; only rules that create no conflicts and cover all required cases are accepted. Approved rules are stored in the graph as ":Constraint" nodes, complete with version, confidence score, and provenance. Conflict-resolution logic blocks any rule that contradicts a higher-level family rule until it is reviewed.

By aligning rule generation with GBOMO's product-family structure, enforcing parameter inheritance, and explicitly linking limits to control parameters, the approach keeps the constraint set consistent from the product family down to the line of code.

5. A Blockchain-Enabled IaaS System for RPS

5.1 System Architecture of Blockchain-Enabled IaaS Fulfillment System

Blockchain offers a tamper-evident ledger and smart contracts that synchronize shop-floor events without third-party oversight, boosting trust and automation (Crosby et al. 2016). Yet block size and network bandwidth can limit throughput, and heavy traffic adds latency (Mending et al. 2018). Equally challenging is linking cyber-physical-system data to an Information-as-a-Service layer so machine states and control rules flow in real time. The proposed solution meets both needs by structuring the IaaS architecture into information-sharing, virtual, and infrastructure spaces.

The left side of figure 3 depicts the information-sharing layer, where production lines, work cells, material-handling systems, and the central production-control unit exchange data. A permissioned blockchain captures three kinds of transactions: "*Cell_Info*", which holds the cell ID, equipment type, and a hash-based identity for access control; "*MaterialMove_Info*", which traces pallets or totes by logging departure point, destination, current location, and time stamps; and "*Process_Info*", which records operation details such as part number, quantity completed, start time, and end time. Blocks are sealed under a Proof-of-Authority consensus, forming an immutable chain whose raw data are continuously parsed into a structured database for fast queries. This mirrored store lets line supervisors check both upstream and downstream status in real time, while the production-control system enjoys full visibility for system-wide coordination and optimization.

In the middle of figure 3, The virtual space acts as the coordination hub between the blockchain-based information layer and the sensor-rich infrastructure of a reconfigurable production system. Here, plant-level applications—ERP for order promising, SCADA for machine data collection, and digital-twin analytics—share a common data pool that contains process plans, equipment capabilities, schedule targets, process data, and configuration changelog.Right side of figure 3 details the infrastructure layer where sensors on machine tools, robots, conveyors and AGVs capture temperatures, positions, cycle counts and inventory levels. IoT gateways write this data to local databases, then forward summaries to the information-sharing layer. Operators use local dashboards for immediate feedback, while the production-control unit aggregates the data to fine-tune schedules and trigger line reconfiguration when bottlenecks emerge.

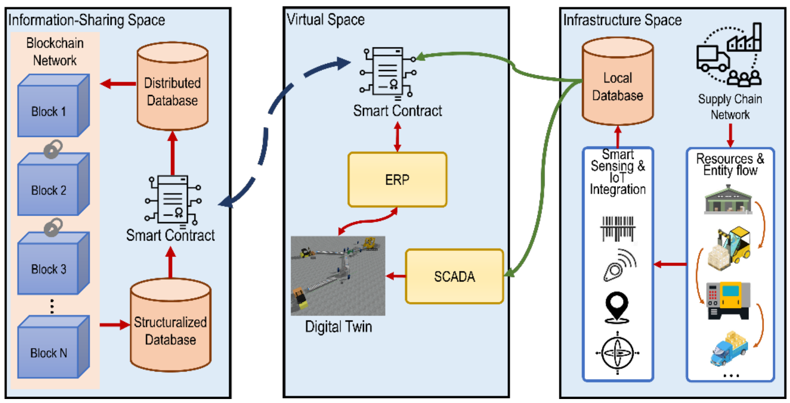

Figure 3. System architecture of the proposed IaaS fulfillment system

5.2 Mechanism of the blockchain-enabled IaaS fulfillment system

Building on the system architecture, a software solution is proposed for Information-as-a-Service fulfilment on a reconfigurable production shop floor. The solution combines a permissioned blockchain and an Interplanetary File System (IPFS) layer so that line controllers, work-cell PLCs, and material-handling units can upload, access and share production data with traceable integrity. As shown in figure 4, a browser-based interface connects these shop-floor entities to both the blockchain network and the IPFS store, while smart contracts and application programming interfaces (APIs) coordinate data flow and enforce shop rules.

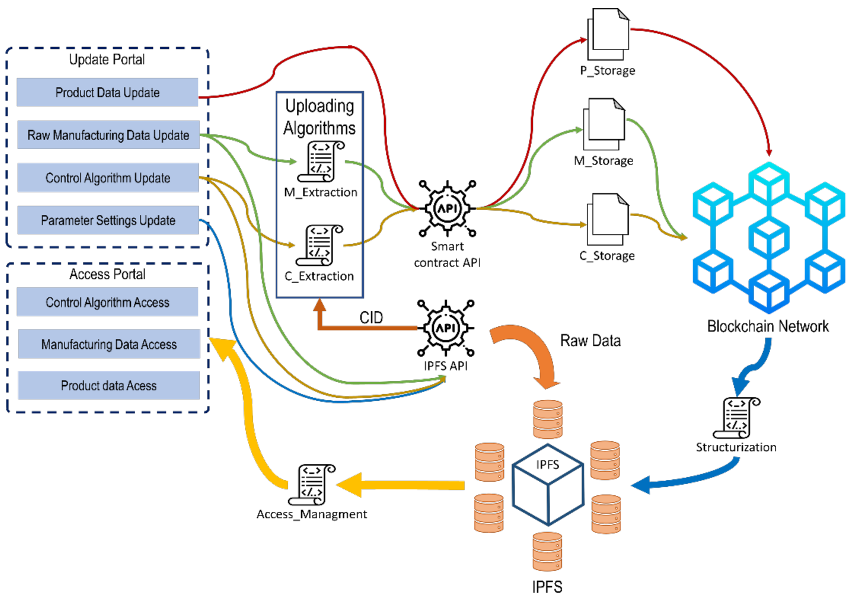

Figure 4. Blockchain-enabled information sharing mechanism of the IaaS fulfillment system

The blockchain network functions as an auditable event ledger. Each block contains a header—previous-block hash, timestamp, nonce and Merkle root—and a body of encrypted transactions. Blocks are chained in sequence, beginning with a genesis block, and transaction hashes allow any event to be traced. Proof-of-Authority consensus is adopted because the nodes—production-control servers, cell controllers and AGV managers—operate within a trusted plant network; this choice delivers high throughput without the heavy computation of Proof-of-Work. Smart contracts deployed on the chain codify machine capabilities, quality limits and routing permissions. Once a contract is triggered, it executes autonomously across all nodes, ensuring that every pallet move or tool change follows the same rule set.

Large sensor files, part programs and quality images are stored off-chain in IPFS to avoid overloading the ledger. IPFS identifies each file with a content identifier (CID), a short cryptographic hash that never changes unless the file changes. If a robot program is revised, the new version receives a new CID while the old one remains accessible, giving the plant a built-in version trail. The blockchain stores only the CID, the file owner and a timestamp, keeping the on-chain payload small yet fully traceable.

6. Real-Time Data-Driven Manufacturing Load Balancing and Planning

6.1 Manufacturing Load Planning Mechanism Modelling

Figures 2 uses the IDEF0 notation to show the proposed real-time, data-driven load-balancing mechanism for dRPS. The top-level activity, A0 mLBP, continually revises the schedule whenever new shop-floor information arrives. Three data streams drive the revision: disruptive events such as machine breakdowns or operator absences (I1), the current schedule that may need adjustment (I2), and incoming order details—quantities, due dates and customer priorities (I3). Four control sets shape every decision. Order-priority rules (C1) guarantee that urgent jobs are never deferred; strategic objectives (C2) translate business goals into optimization weights; internal shop constraints (C3) capture machine health, operator skills and line capacity; and external constraints (C4) cover regulations, energy limits and supply-chain links.

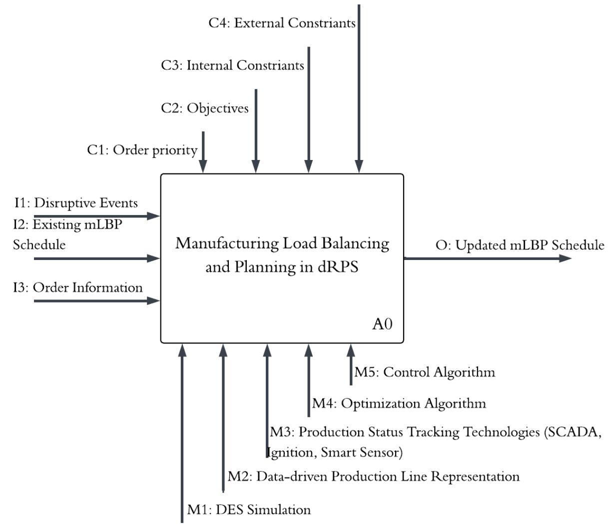

Figure 5. Holistic view of manufacturing load balancing mechanism in dRPS

Five mechanism blocks enable the loop. Discrete-event simulation (M1) predicts completion times for highly digital lines, while max-plus algebra models (M2) estimate throughput on legacy lines with sparse data. Real-time status tracking from SCADA and IoT sensors (M3) keeps both models current. A nested genetic algorithm (M4) solves the bilevel optimization, balancing strategic and operational goals, and a rule-based controller (M5) applies the new schedule and handles disruptions as they occur. The result is an updated mLBP schedule (O) that reflects the latest plant state and satisfies both tactical targets and long-term objectives.

6.2 Max-Plus Modelling of Production Lines

In dRPS, achieving effective manufacturing load balancing depends on accurate prediction of task completion times, especially across production lines with different levels of digital maturity. Conventional lines—characterized by limited sensors, no digital twins, and fixed buffer capacities propose a modeling challenge due to restricted data availability and lack of real-time feedback. To address this, max-plus algebra offers a simple yet powerful approach for modeling discrete event systems where job flows and process synchronization drive performance.

Max-plus algebra models the timing of events using maximization and addition operations, making it well-suited for representing serial production systems with deterministic workflows. It captures the timing relationships between process steps, enabling planners to estimate job finish times without requiring detailed control-level data. This is particularly useful in traditional lines where operations follow strict sequences and system flexibility is limited. Within dRPS, max-plus modeling enables low-digitalization lines to be integrated into system-wide load balancing strategies. It supports reconfiguration analysis and schedule forecasting, providing reliable input to higher-level planning and optimization tools. While it does not enable real-time control like digital twins, max-plus models contribute predictive insights essential for distributing tasks among heterogeneous resources. By bridging the digital gap in legacy lines, max-plus modeling enhances the responsiveness and efficiency of the overall system. It allows dRPS to maintain coordinated operations across advanced and conventional lines, improving adaptability and throughput while minimizing disruption during reconfiguration.

6.3 Leader-follower Hierarchical Decision-making Problem in RPS

In reconfigurable production systems (RPS), manufacturing load balancing requires multi-objective optimization that reflects both strategic goals and operational constraints. To address the inherent hierarchy between production planning and execution, a leader-follower decision-making mechanism is introduced, separating high-level task selection from low-level job scheduling. At the leader level, the goal is to maximize total revenue by determining whether rejectable task loads should be accepted for each production line. Strategic decisions consider revenues from completed tasks, penalties for lateness, and priority levels of tasks. These accepted tasks are passed to the follower level, where detailed scheduling decisions are made to minimize engineering costs and machine degradation. Operational costs are calculated based on job-level task durations, resource usage, and machine wear, reflecting workload intensity and system fatigue.

This two-level framework ensures alignment between business priorities and shop-floor feasibility. It avoids the need to merge conflicting objectives into a single weighted function by keeping each decision layer focused on its native metrics. Feedback from the follower level—such as job completion times—is sent back to the leader level for refined revenue estimation, enabling adaptive planning. Assumptions include one product type per task, fixed changeover times, and the requirement that accepted jobs must be processed consecutively on the same line. Figure 6 shows the system architecture, while constraints ensure consistency and feasibility across decision levels. This hierarchical model supports responsive, scalable planning for real-time order fulfillment in RPS environments.

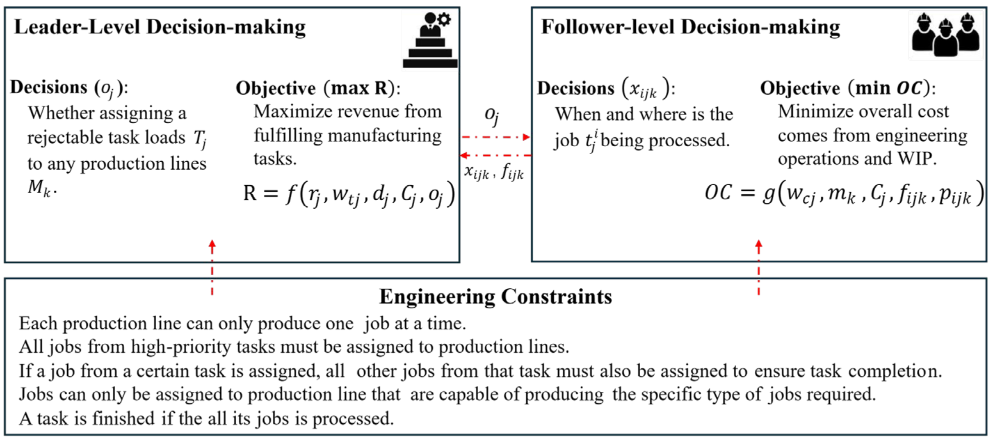

Figure 6. Leader-Follower Hierarchical Decision-Making Mechanism

7. Modeling and Analysis of Sociotechnical System Dynamics

7.1 Compliance-Supervision Synergy underlying Sociotechnical System Dynamics

In modern manufacturing environments, particularly in high-mix assembly settings such as electronics for the automotive industry, compliance with standardized operating procedures (SOPs) is crucial but often strained by production pressures and increasing product complexity. Operators may skip or shorten tasks like quality checks to boost throughput, while engineers must weigh the cost of increased supervision against the risk of quality lapses. This creates a dynamic where decisions on the shop floor are shaped by the strategic interactions between human agents and technical systems, rather than by individual behavior alone. At the core of this dynamic lies a synergy between operator compliance and engineering supervision. Operators balance the benefit of deviating from SOPs with the perceived risk of being caught, which is shaped by the level of active oversight. Conversely, engineers must decide whether to invest time and resources in supervision or trust that operators will self-regulate, with both choices influencing system performance metrics like defect rates, downtime, and rework.

Five key interactions define this sociotechnical system. Among operators, peer influence affects collective tolerance for deviation, amplifying or damping individual decisions. Among engineers, collaboration governs how supervision efforts are distributed and how anomalies are addressed. Operator–machine interactions involve trade-offs between routine execution and shortcutting tasks for efficiency, while engineer–machine interactions involve preventive maintenance and corrective responses to detected deviations. Lastly, cross-population dependencies link the two groups: increased supervision discourages deviation, while higher compliance reduces engineers' need for intervention. These interactions create nonlinear feedback loops that shape overall system behavior. As operator and engineer decisions co-evolve, the balance between compliance and supervision continuously shifts, reinforcing the importance of modeling this synergy to improve system resilience and performance.

7.2 Modeling and Analysis of Supervision–Compliance Synergy

Figure 7 presents the conceptual model used to analyze supervision–compliance synergy (SCS) in manufacturing systems. The structure is organized into two main layers: modeling and analysis. On the left, the modeling layer introduces two core approaches. The Evolutionary Game Model comprises two configurations: a two-player single-machine model, which captures local operator–engineer interactions, and a multi-machine extension that introduces behavioral spillovers across machines, reflecting the interdependencies common in real-world shop floors.

To further capture the subjective and uncertain nature of human decision-making, the Fuzzy Evolutionary Game Model expands this deterministic base. In the fuzzy payoff modeling phase, crisp values in the payoff matrix are replaced with triangular fuzzy numbers to represent perceptual ambiguity—such as how operators interpret risk or engineers evaluate supervision cost. These fuzzy payoffs feed into a Fuzzy Moran Process, which simulates how strategies evolve over time under uncertainty. Transition probabilities between behaviors—like compliance or deviation—are computed using fuzzy fitness values, modeling how populations adapt to shifting conditions. The framework concludes with simulation and optimization stages: deterministic parameter tuning aligns baseline models with observations, and fuzzy simulations explore long-term equilibrium behaviors.

The right side of Figure 7 shows the SCS Analysis layer, which transforms these models into actionable insights. Equilibrium analysis uses replicator dynamics to explore stable behavior patterns, identifying conditions under which consistent supervision–compliance synergy can emerge. Building on these results, adaptive calibration modules allow managers to fine-tune incentives, penalties, and supervision levels in real time. Finally, stochastic validation applies the Fuzzy Moran Process to test strategy robustness against real-world variability, making the framework a practical tool for supporting resilient, human-centric manufacturing operations.

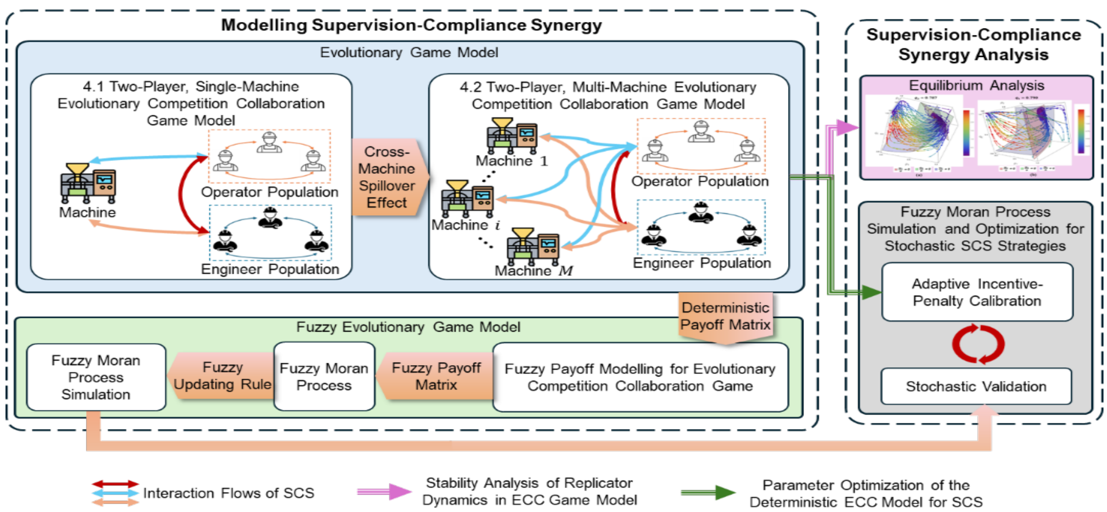

Figure 7. A conceptual model for SCS analysis

8. Conclusions

The need for adaptive, resilient manufacturing systems is growing as industries face shrinking product lifecycles, high customization demand, and volatile market conditions. Reconfigurable Production Systems (RPS) offer a compelling solution by allowing hardware and software configurations to be rapidly altered. However, fully realizing their potential depends on more than reconfigurable machines—it requires digital transformation to ensure data availability and integrity, and cognitive decision-making capabilities to act on that data in real time. This paper addresses this dual challenge by framing it as a coordinated effort across planning, scheduling, and execution layers, aligning system flexibility with decision intelligence.

To tackle these challenges, a cognitive-intelligent decision-making framework is proposed that integrates four fundamental research directions. First, knowledge graph-based modeling enhances GBOMO by encoding variant-specific logic down to the control level. Second, a blockchain-enabled IaaS architecture ensures trusted, real-time visibility of shop-floor events for digital twins, optimization engines, and human interfaces. Third, manufacturing load balancing is addressed through a data-driven, game-theoretical mechanism that dynamically assigns tasks under capacity and operational constraints. Fourth, supervision–compliance synergy is modeled using fuzzy evolutionary game theory to capture human decision dynamics on the shop floor. Together, these solutions form a closed-loop control system capable of supporting agile, scalable production. Future work will validate the proposed components through industrial testbeds and focus on scaling the framework to support decentralized decision-making and human–AI collaboration across globally distributed RPS networks.

References

Bharadwaj, A., Sawy, O. a. E., Pavlou, P. A., & Venkatraman, N. , Digital Business Strategy: Toward a next generation of insights. MIS Quarterly, 37(2), 471–482,2013.

Björkdahl, J. , Strategies for digitalization in manufacturing firms. California Management Review, 62(4), 17–36,2020. https://doi.org/10.1177/0008125620920349

Bortolini, M., Galizia, F. G., & Mora, C. , Reconfigurable manufacturing systems: Literature review and research trend. Journal of Manufacturing Systems, 49, 93–106,2018. https://doi.org/10.1016/j.jmsy.2018.09.005

Bousdekis, A., Lepenioti, K., Apostolou, D., & Mentzas, G. , A review of Data-Driven Decision-Making Methods for Industry 4.0 maintenance Applications. Electronics, 10(7), 828,2021.

Choi, B. K., & Kim, B. H. , MES (manufacturing execution system) architecture for FMS compatible to ERP (enterprise planning system). International Journal of Computer Integrated Manufacturing, 15(3), 274–284,2002.

Daneels, A. , What is SCADA. Prepared For, 339–343,1999. http://epaper.kek.jp/ica99/papers/mc1i01.pdf

ElMaraghy, H. A., "Changeable and reconfigurable manufacturing systems," Springer Series in Advanced Manufacturing, pp. 1–20, 2009.

Guerrero, H. H. , How to more effectively accept and refuse orders. Production and Inventory Management Journal : The Journal of the American Production and Inventory Control Society, Inc., 29(4), 59–63,1988.

Hogan, A., Blomqvist, E., Cochez, M., D'amato, C., Melo, G. D., Gutierrez, C., Kirrane, S., Gayo, J. E. L., Navigli, R., Neumaier, S., Ngomo, A.-C. N., Polleres, A., Rashid, S. M., Rula, A., Schmelzeisen, L., Sequeda, J., Staab, S., & Zimmermann, A. , Knowledge Graphs. ACM Computing Surveys, 54(4), 1–37,2022.

Jiao, R., Commuri, S., Panchal, J., Milisavljevic-Syed, J., Allen, J. K., Mistree, F., & Schaefer, D. (2021). Design engineering in the age of industry 4.0. Journal of Mechanical Design, 143(7). https://doi.org/10.1115/1.4051041

Koren, Y. , General RMS Characteristics. Comparison with Dedicated and Flexible Systems. In Springer eBooks (pp. 27–45),2007. https://doi.org/10.1007/3-540-29397-3_3

Kostal, P., & Velisek, K. , Flexible manufacturing system. World Academy of Science, Engineering and Technology, 77, 825-829,2011.

Ma, K., Ilievski, F., Francis, J., Bisk, Y., Nyberg, E., & Oltramari, A. , Knowledge-driven Data Construction for Zero-shot Evaluation in Commonsense Question Answering. Proceedings of the AAAI Conference on Artificial Intelligence, 35(15), 13507–13515,2021. https://doi.org/10.1609/aaai.v35i15.17593

Mehrabi, M. G., Ulsoy, A. G., & Koren, Y. (2000b). Reconfigurable manufacturing systems: Key to future manufacturing. Journal of Intelligent Manufacturing, 11(4), 403–419,2000b. https://doi.org/10.1023/a:1008930403506

Nguyen, S. , A learning and optimizing system for order acceptance and scheduling. the International Journal of Advanced Manufacturing Technology/International Journal, Advanced Manufacturing Technology, 86(5–8),2016,

Pan, Z., Luo, H., Li, M., & Liu, H. , Chain-of-Action: Faithful and Multimodal Question Answering through Large Language Models. arXiv (Cornell University),2024. https://doi.org/10.48550/arxiv.2403.17359

Qian, C., Zhang, Y., Jiang, C., Pan, S., & Rong, Y. , A real-time data-driven collaborative mechanism in fixed-position assembly systems for smart manufacturing. Robotics and Computer-Integrated Manufacturing, 61, 101841,2020.

Rösiö, C., & Säfsten, K. ,Reconfigurable production system design – theoretical and practical challenges. Journal of Manufacturing Technology Management, 24(7), 998–1018,2013. https://doi.org/10.1108/jmtm-02-2012-0021

SAP Software Solutions | Business Applications and Technology. (n.d.). SAP. https://www.sap.com/index.html

Sarazin, A., Bascans, J., Sciau, J.-B., Song, J., Supiot, B., Montarnal, A., Lorca, X., & Truptil, S. ,,2023 Expert system dedicated to condition-based maintenance based on a knowledge graph approach: Application to an aeronautic system. Expert Systems with Applications, 186, 115767,2021. https://doi.org/10.1016/j.eswa.2021.115767

Schank, R. C. , Conceptual dependency: A theory of natural language understanding. Cognitive Psychology, 3(4), 552–631,1972. https://doi.org/10.1016/0010-0285(72)90022-9

Song, M., Gong, X., Jiao, R. J., & Moore, R. (2025). A blockchain-enabled information as a service (IaaS) system for crowdsourced manufacturing: A crowdsourcing case study of tank trailer manufacturing. Journal of Industrial Information Integration, 45, 100844. https://doi.org/10.1016/j.jii.2025.100844

Sun, K., Xu, Y. E., Zha, H., Liu, Y., & Dong, X. L. , Head-to-Tail: How Knowledgeable are Large Language Models (LLM)? A.K.A. Will LLMs Replace Knowledge Graphs? arXiv (Cornell University),2023. https://doi.org/10.48550/arxiv.2308.10168

Tao, F., Zhang, H., Liu, A., & Nee, A. Y. C. , Digital twin in industry: State-of-the-Art. IEEE Transactions on Industrial Informatics, 15(4), 2405–2415,2019. https://doi.org/10.1109/tii.2018.2873186

Tseng, M. M., Jiao, J., and Merchant, M. E. Design for mass customization. CIRP Annals, 45(1), 153–156, 1996.

Wu, D., Greer, M. J., Rosen, D. W., & Schaefer, D. , Cloud manufacturing: Strategic vision and state-of-the-art. Journal of Manufacturing Systems, 32(4), 564–579,2013. https://doi.org/10.1016/j.jmsy.2013.04.008

Yadav, G., & Paul, K. , Architecture and security of SCADA systems: A review. International Journal of Critical Infrastructure Protection, 34, 100433,2021. https://doi.org/10.1016/j.ijcip.2021.100433

Zhong, X., Ou, J., & Wang, G. Order acceptance and scheduling with machine availability constraints. European Journal of Operational Research, 232(3), 435–441,2014. https://doi.org/10.1016/j.ejor.2013.07.032

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