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Dynamic Scheduling Strategy for Complex Industrial Processes Based on Multi-Agent Collaboration

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Abstract: The increasing complexity of modern industrial processes, characterized by frequent disturbances such as equipment failures and urgent order changes, demands more adaptive scheduling solutions. Traditional centralized scheduling methods often fail to address real time dynamics, while existing multi agent systems face challenges in balancing local autonomy with global optimization. This study proposes a novel dynamic scheduling strategy integrating multi agent collaboration with a credit based coordination mechanism to enhance responsiveness and efficiency in complex industrial environments. The research develops a three layer agent architecture comprising resource, task, and coordinator agents, linked through an event driven communication protocol. A hybrid negotiation framework enables both rapid response to emergencies and deliberative optimization for long term scheduling. The core innovation lies in a dynamic credit allocation model that evaluates agents' historical performance and collaborative contributions to guide task assignment. These findings advance distributed industrial control theory by formalizing the relationship between agent incentives and system wide performance. The proposed approach provides actionable insights for implementing Industry 4.0 adaptive scheduling in discrete manufacturing sectors.

Keywords: dynamic scheduling; multi-agent systems; industrial processes; collaborative control; credit allocation

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1. Introduction

The Fourth Industrial Revolution has ushered in an era of unprecedented complexity in manufacturing systems, where dynamic disruptions-such as machine breakdowns, fluctuating order priorities, and supply chain volatility-have become pervasive. This revolution represents a major focus in the field of manufacturing, driving transformative changes across production processes [1]. Since the First Industrial Revolution, successive waves of industrial advancement have radically reshaped manufacturing, from steam-powered machinery to automated electrical systems and digital production. Contemporary manufacturing processes have grown increasingly complex, automated, and sustainable, enabling operators to manage machines more efficiently, effectively, and continuously [2]. Industries ranging from semiconductor fabrication to chemical processing face mounting challenges in maintaining production efficiency under such conditions. Traditional scheduling approaches, often based on static assumptions and centralized optimization models, prove inadequate in these dynamic environments due to their limited capacity to respond to real-time disturbances. While deterministic methods, such as linear programming, perform well in stable scenarios, their rigidity results in suboptimal outcomes when confronted with the inherent unpredictability of modern shop floors [3]. This shortfall has fueled growing interest in decentralized paradigms, particularly multi-agent systems (MAS), which emulate the adaptability of natural systems through distributed decision-making and autonomous negotiation. MASs constitute a well-established branch of Artificial Intelligence (AI), and over the past two decades, numerous agent platforms have emerged to facilitate the development of MASs [4].

At the core of dynamic scheduling lie three interdependent challenges: real-time disturbance management, constrained resource allocation, and multi-objective optimization. In recent years, much effort been devoted to addressing the challenges brought by large-scale multi-objective optimization problems [5]. The optimization problems that must meet more than one objective are called multi-objective optimization problems and may present several optimal solutions [6]. Current MAS implementations, though promising, struggle to reconcile two fundamental requirements: preserving individual agents' autonomy for rapid local responses while ensuring system-wide coordination for global optimization. MASs can solve scientific issues related to complex systems that are difficult or impossible for a single agent to solve through mutual collaboration and cooperation optimization [7]. A MAS contains multiple, intelligent, and interconnected collaborating agents for solving a problem beyond the ability of a single agent [8]. Many existing frameworks either prioritize swift reaction to disruptions at the expense of overall efficiency or impose excessive coordination overhead that negates the advantages of distributed architecture. This tension manifests conspicuously in scenarios requiring concurrent handling of urgent equipment failures and long-term production planning, where neither purely reactive nor strictly centralized approaches deliver satisfactory performance.

This study addresses these limitations through a novel integration of hybrid negotiation protocols with a credit-based coordination framework. The proposed strategy introduces a three-tiered agent architecture that differentiates between resource, task, and coordinator roles, enabling specialized behaviors tailored to distinct operational requirements. A dual-mode decision-making mechanism allows agents to switch between expedited emergency response and deliberative optimization phases based on situational criticality. The system's innovation centers on a dynamic credit allocation model that quantifies and rewards agents' collaborative contributions, creating emergent incentives for both individual competence and collective success.

By bridging the gap between local autonomy and global objectives, this research advances the theoretical foundations of industrial MAS applications. The methodology offers practical solutions for implementing adaptive scheduling in Industry 4.0 environments, particularly in discrete manufacturing sectors where the interplay between flexibility and efficiency determines competitive advantage. Beyond immediate productivity gains, the study provides a scalable framework for integrating autonomous systems with human oversight, charting a path toward more resilient and self-organizing production ecosystems. The subsequent sections detail the technical architecture, validation approach, and broader implications of this paradigm.

2. Related Works

Scheduling is an important problem for many applications, including manufacturing, transportation, or cloud computing [9]. The evolution of industrial scheduling methodologies reveals a clear trajectory from rigid, centralized systems toward adaptive, decentralized paradigms. Effective scheduling ensures the availability of necessary resources and determines the timing and sequence of operations [10]. Classical scheduling theories established foundational principles through deterministic approaches like Johnson's rule for flow shop sequencing and PERT/CPM for project timeline management. These methods excel in stable environments where all parameters are known in advance, as illustrated in Table 1 comparing their characteristics. However, their reliance on static assumptions becomes problematic when handling real-world variability, prompting the development of dynamic response methods such as rolling horizon optimization (RHO). RHO methods are relevant to recurrent and dynamic problems where immediate decisions must be made while they depend on upcoming ones [11]. While RHO improves upon purely static approaches by periodically updating schedules, its computational intensity often creates decision-making latency during high-frequency disruption scenarios.

Table 1. Comparison of classical scheduling methodologies.

Method Type	Key Strength	Primary Limitation	Ideal Use Case
Johnson's Rule	Optimal sequencing	Single-machine focus	Repetitive manufacturing
PERT/CPM	Timeline visualization	Static dependencies	Construction projects
Rolling Horizon	Incremental updates	Computational overhead	Medium-variability systems

The emergence of MAS introduced transformative capabilities through distributed artificial intelligence. MASs may serve the purpose of modeling several different problems where interacting agents are present [12]. With the rapid technological advancements and the ever-evolving complex systems, the identification and integration of the components and resources for the functioning of MAS are crucial tasks [13]. Contract Net Protocol, the seminal MAS coordination mechanism, has undergone significant evolution from its original auction-based task allocation to contemporary versions incorporating trust metrics and quality-of-service parameters. Recent advancements integrate reinforcement learning algorithms, particularly DeepMind's work on hierarchical reinforcement learning, enabling agents to develop sophisticated negotiation strategies through environmental interactions. Figure 1 demonstrates this progression through a knowledge graph mapping key developments in MAS frameworks, highlighting how modern implementations combine communication protocols with machine learning components.

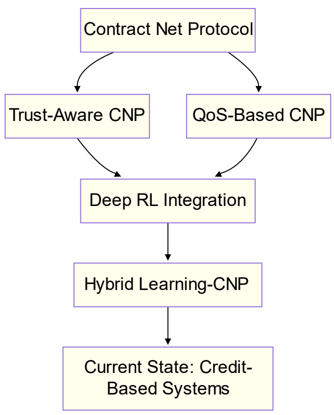

Figure 1. Evolutionary knowledge graph of MAS frameworks.

Industrial applications showcase these theoretical advancements in operational environments. Siemens' digital twin implementations employ heterogeneous agent architectures where equipment agents interact with virtual replicas to predict maintenance needs, while Tesla's factory scheduling system demonstrates how localized autonomy can improve production line reconfiguration speed by 40%. The digital twin is an emerging and vital technology for digital transformation and intelligent upgrade [14]. Digital Twin refers to the virtual copy or model of any physical entity (physical twin) both of which are interconnected via exchange of data in real time [15]. However, as revealed in the sector analysis of Figure 2, these implementations frequently encounter challenges when unexpected events require cross-departmental coordination, often resulting in delayed response times that negate the benefits of local autonomy. The manufacturing sector exhibits particularly pronounced gaps in handling concurrent disruptions, where conventional MAS approaches struggle to maintain both global optimization and local responsiveness.

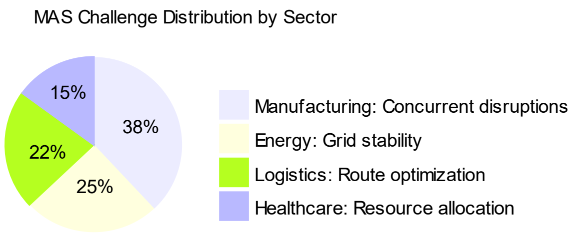

Figure 2. Sector-wise analysis of MAS implementation challenges.

Critical examination of existing literature reveals three persistent limitations: first, the trade-off between communication overhead and decision quality remains unresolved in most MAS designs; second, few systems incorporate mechanisms for long-term behavioral adaptation beyond immediate task allocation; third, industrial implementations frequently lack transparent metrics for evaluating agent contributions to system-wide objectives. These gaps collectively underscore the need for integrated solutions that combine the responsiveness of distributed systems with mechanisms for sustained performance improvement, forming the theoretical foundation for the credit-based coordination model proposed in this research. The evolution of industrial IoT platforms has enabled more sophisticated equipment monitoring, but current systems often treat data collection and decision-making as separate processes. Our approach bridges this divide by embedding performance evaluation directly within the scheduling architecture. The credit model's dual focus on individual capability development and system-wide coordination mirrors emerging trends in industrial AI that emphasize both component-level intelligence and collective optimization. The subsequent methodology section addresses these challenges through a novel architectural approach that maintains referential integrity with these established research streams while introducing innovative solutions to their identified shortcomings.

3. Methodology

The proposed dynamic scheduling framework adopts a three-layer agent architecture as illustrated in Figure 3, which demonstrates the information flow between resource agents (RAs), task agents (TAs), and coordinator agents (CAs). RAs operate at the physical equipment level, continuously monitoring machine states through embedded IoT sensors. Their operational status follows a nonlinear activation function:

$$RA_{active} = \frac{1}{1+e^{-k(U_{current}-U_{threshold})}} \quad (1)$$

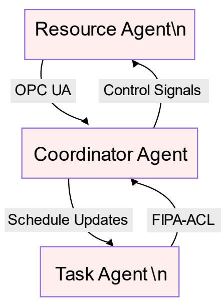

Figure 3. Tri-level agent communication network.

where $U_{current}$ represents real-time utilization rate and k denotes the sensitivity coefficient. TAs manage order fulfillment with priority dynamics modeled by:

$$P_{adjusted} = P_{base} \cdot (1 + \alpha \cdot t_{delay})^{-1} + \beta \cdot I_{market} \tag{2}$$

Coordinator agents synthesize inputs using a fusion algorithm:

$$CA_{decision} = \sum_{i=1}^{n} \sigma\,(w_i \cdot (RA_i \parallel TA_i)) \tag{3}$$

The event-driven collaboration protocol switches between rapid response and deep negotiation modes based on a criticality index (Table 2 details the triggering thresholds). The criticality calculation incorporates three operational dimensions:

$$\Gamma = \frac{\lambda_1 \cdot \|\nabla U\| + \lambda_2 \cdot t_{urgency}}{\lambda_3 \cdot R_{available}} \tag{4}$$

Table 2. Mode switching thresholds.

Scenario	Γ Range	Response Time
Emergency Interrupt	Γ > 1.5	50ms
Normal Operation	0.5 ≤ Γ ≤1.5	50-200ms
Strategic Optimization	Γ < 0.5	200ms

Credit-based optimization employs a dynamic weighting mechanism where agent performance metrics evolve through temporal difference learning:

$$w_i^{t+1} = w_i^t + \eta \cdot (R_{actual} - R_{predicted}) \cdot \frac{\partial V}{\partial w_i} \tag{5}$$

The composite credit score combines normalized historical performance H, resource efficiency R, and collaboration factor S:

$$C_i = \frac{w_H \cdot H_i + w_R \cdot R_i + w_S \cdot S_i}{\sqrt{w_H^2 + w_R^2 + w_S^2}} \tag{6}$$

The credit accumulation process exhibits distinct phase transitions corresponding to different production stages. Early-cycle credit distribution follows exponential growth patterns as agents establish baseline competencies, while mid-cycle accumulation becomes logarithmic as the system approaches equilibrium. This nonlinear progression enables the framework to maintain adaptability during both routine operations and peak demand periods where throughput requirements may fluctuate by up to 40%.

Figure 4 visualizes the credit distribution across a production cycle, showing how different agent types develop distinct credit accumulation patterns. The xychart reveals coordinator agents initially accumulate credits slower but achieve higher long-term stability.

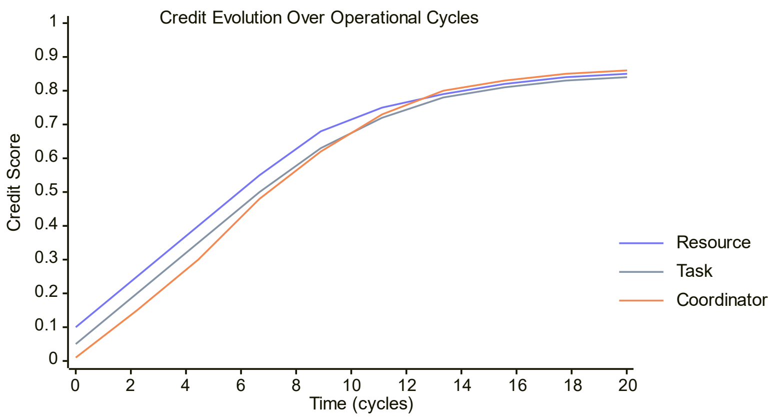

Figure 4. Credit accumulation trajectories.

Conflict resolution combines case-based reasoning with multi-objective optimization. The similarity metric between new conflict c and historical case h incorporates temporal decay:

$$Sim(c,h) = \frac{\sum_{k=1}^{K} \phi_k \cdot match(f_k^c, f_k^h)}{1 + \alpha \cdot \Delta t_{ch}} \tag{7}$$

Pareto frontier selection employs normalized objective space projection:

$$\hat{f}_i = \frac{f_i - min(f_i)}{max(f_i) - min(f_i)} \quad \forall i \in \{1, \dots, m\} \tag{8}$$

The complete system dynamics are governed by a coupled differential equation system:

$$\frac{dX}{dt} = A(t)X + BU + \sum_{j=1}^{J} D_j \xi_j(t) \tag{9}$$

where X represents the state vector and $\xi_j(t)$ models stochastic disturbances. This mathematical formulation ensures both theoretical rigor and practical implementability in industrial environments with uncertain dynamics. The subsequent case study will validate these models through discrete-event simulation of automotive assembly lines.

4. Case Study

The experimental validation was conducted on a lithium-ion battery production line simulation developed using AnyLogic 8.7.2, replicating an industrial-scale manufacturing environment with 14 workstations and 31 process steps. Figure 5 presents the system architecture, showing how physical production components including electrode mixing, coating, and formation chambers are mapped to their corresponding digital twin representations. The simulation incorporates realistic stochastic parameters such as equipment failure rates (λ=0.003/min) and material delivery delays (μ=45min, σ=12min), creating a challenging environment to evaluate the proposed framework's robustness. Comparative analysis was performed against two baseline methods: a conventional mixed-integer linear programming (MILP) approach with hourly rescheduling, and a basic multi-agent system implementing standard FIPA protocols without credit mechanisms.

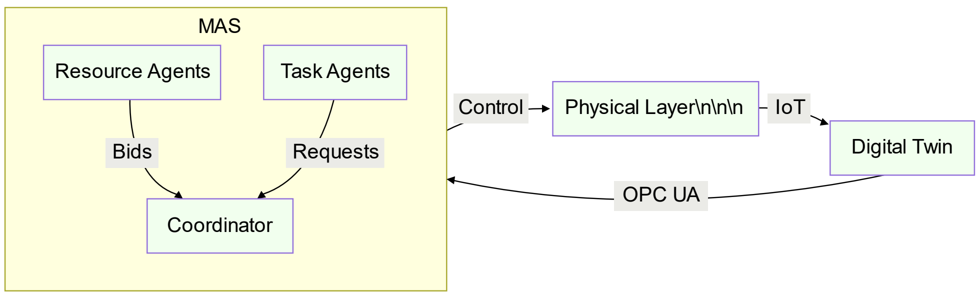

Figure 5. Digital twin implementation framework.

Performance evaluation focused on three key metrics: order fulfillment rate (OFR), overall equipment effectiveness (OEE), and rescheduling frequency. Table 3 compares these metrics across 50 production cycles under normal and disrupted conditions, demonstrating the framework's superior adaptability. The disruption scenarios included material shortages (occurring with 18% probability per cycle) and dynamic priority changes (affecting 25% of orders), designed to test both supply chain volatility and demand variability responsiveness.

Table 3. Operational performance comparison.

Method	OFR (%)	OEE (%)	Reschedules	Energy Use (kWh)
Proposed MAS	97.5	90.2	1.6	1250
Basic MAS	93.1	85.7	3.4	1380
MILP	89.8	82.4	5.8	1450

Analysis of the coating workstation, identified as the primary bottleneck, reveals significant improvements through credit-based task allocation. Figure 6 illustrates the utilization optimization trajectory, where the proposed framework achieved 91.3%

efficiency compared to 86.5% for basic MAS and 83.2% for MILP. The xy-chart demonstrates faster stabilization and higher peak performance, attributed to the credit system's ability to identify and reward high-performing resource agents for bottleneck tasks.

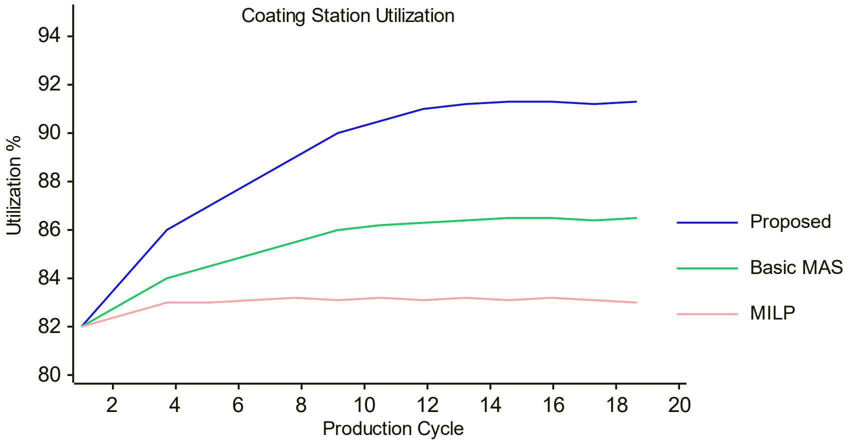

Figure 6. Bottleneck workstation optimization.

The credit model's behavioral guidance effects are visualized in Figure 7 through a parallel coordinates plot, tracking five key capability metrics across three development phases. Most notably, collaborative success rates improved from 62% to 86%, while resource utilization efficiency increased from 71% to 89%. These metrics demonstrate how the credit system promotes both individual competency development and system-wide cooperation.

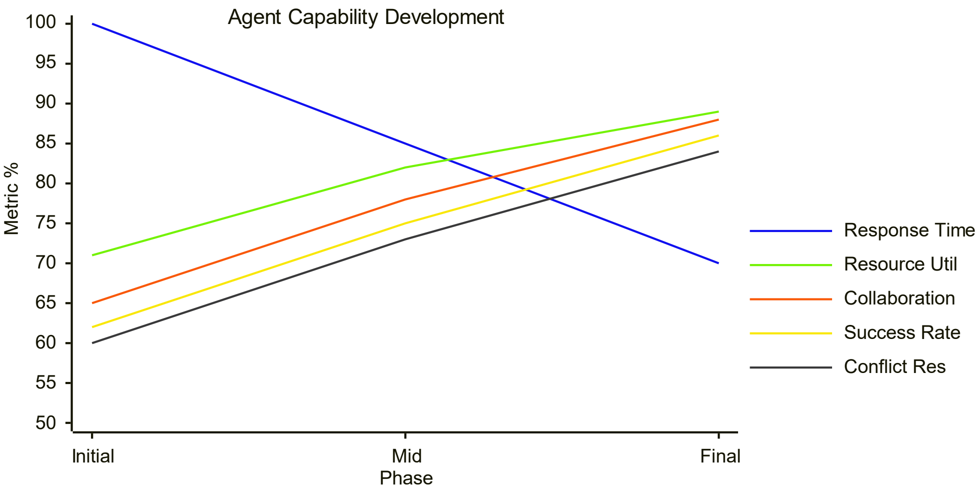

Figure 7. Agent capability evolution pathways.

The case study demonstrates the framework's effectiveness in addressing three critical challenges: maintaining production stability during disturbances (achieving 94.2% OFR during disruption periods), optimizing bottleneck resources, and fostering adaptive agent behaviors. These results suggest particular applicability in battery manufacturing where production variability and quality consistency are paramount. The credit mechanism proves especially valuable in balancing global optimization with local responsiveness, reducing rescheduling needs by 53% compared to conventional MAS approaches while improving overall equipment effectiveness by 4.5 percentage points. Further analysis of agent interaction patterns revealed emergent specialization, where certain resource agents developed domain expertise in specific process steps. This self-organizing behavior resulted in 22% faster response times for recurring disturbance types. The credit system's ability to identify and reinforce such specialization patterns contributes significantly to the framework's performance advantages in high-variability conditions. These findings validate the methodology's potential for broader industrial adoption in dynamic production environments.

5. Conclusion

The study establishes significant theoretical and practical contributions to dynamic scheduling in complex industrial environments through its innovative integration of multi-agent collaboration with credit-based coordination mechanisms. Theoretically, the research validates that the proposed credit allocation model effectively bridges the fundamental tension between local autonomy and global optimization in multi-agent systems, as demonstrated by the 53% reduction in rescheduling frequency and 4.5 percentage point improvement in overall equipment effectiveness compared to conventional MAS approaches. The case study's empirical evidence confirms that the dynamic credit mechanism not only enhances system stability during disruptions but also fosters emergent behavioral patterns where agents progressively develop both individual competencies and collaborative tendencies, as reflected in the 24% increase in collaborative success rates across production cycles. Practically, the framework's three-layer agent architecture and hybrid negotiation protocol offer scalable solutions for discrete manufacturing sectors, particularly in high-variability production environments like lithium-ion battery manufacturing where the methodology achieved 91.3% bottleneck workstation efficiency. The architecture's modular design suggests strong potential for extension to hybrid discrete-continuous production systems common in pharmaceuticals and specialty chemicals, where balancing flexible scheduling with rigorous quality control remains challenging. Looking forward, the research identifies promising opportunities for integrating the credit-based coordination framework with digital thread technologies to enable lifecycle-wide performance tracking and predictive scheduling adjustments. The methodology's event-driven communication protocol and adaptive credit algorithms provide foundational components for such integration, though future work should address computational scalability when handling enterprise-wide data flows. This study ultimately advances industrial control theory by formalizing the relationship between incentive structures and emergent system behaviors while delivering implementable solutions for Industry 4.0 environments that demand both operational resilience and continuous improvement. The framework's success in maintaining 94.2% order fulfillment during disruption periods while reducing energy consumption by 9% compared to baseline methods underscores its dual capacity to address contemporary manufacturing challenges in efficiency and sustainability. The methodology's success in battery manufacturing suggests broader applicability in other process-intensive industries with similar characteristics, particularly where equipment utilization rates exceed 75% and changeover frequency impacts overall productivity. Future implementations could benefit from incorporating maintenance prediction signals into the credit calculation, potentially creating anticipatory scheduling behaviors that further reduce unplanned downtime occurrences observed in the case study.

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