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Dynamic Resource Matching and Adaptive Scheduling for Complex Test Systems under Multi-Task Concurrent Scenarios

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Abstract: The intelligent scheduling of large-scale Test Support Systems (TSS) is a critical cornerstone of modern aerospace and industrial engineering. However, under multi-task concurrent scenarios, traditional static planning and local resource mapping struggle to cope with dynamic demand variations, sudden equipment failures, and the high-dimensional spatial-temporal competition of global auxiliary resources. To address this strongly coupled NP-hard problem, this paper proposes a multi-scenario adaptive resource matching and collaborative scheduling framework. First, a dynamic evolution mechanism utilizing hybrid SPADE and Apriori sequence pattern mining is introduced to autonomously recalibrate multi-dimensional resource conflict matrices in real-time. Second, a dual-layer intelligent scheduling architecture is proposed: at the macroscopic parallel layer, a multi-objective Genetic Algorithm (GA) is designed for global space exploration to minimize the makespan and balance global auxiliary loads; at the microscopic execution layer, a Reinforcement Learning (RL) agent, formulated as a Markov Decision Process (MDP), is deployed for real-time adaptive rescheduling against dynamic disturbances. Finally, a closed-loop visual evaluation system is constructed for multi-scenario verification. Experimental results demonstrate that the proposed framework effectively eliminates resource deadlocks, prevents peak load overruns, and significantly minimizes task response delays under strict safety boundaries, providing a novel autonomous paradigm for the robust operation of complex test facility clusters.

Keywords: Dynamic Resource Matching; Multi-Task Concurrency; Reinforcement Learning; Sequence Pattern Mining.

1. Introduction

Large-scale test facility clusters represent the critical infrastructure for modern aerospace and advanced industrial engineering. While recent advancements have successfully automated the initial process planning of complex Test Support Systems (TSS)[1][2] the actual operational environment is inherently volatile and unpredictable. In real-world testing scenarios, the static execution of predefined process flows is frequently disrupted by dynamic variations in test demands, sudden equipment malfunctions, and the intricate concurrent execution of multiple serial and parallel tasks. Consequently, transitioning from static process planning to dynamic resource matching and adaptive scheduling has emerged as a crucial bottleneck in realizing fully autonomous test operations [3][4].

The core challenge of dynamic scheduling in TSS lies in the high-dimensional coupling and intense spatial-temporal competition among heterogeneous resources [5][6]. When test requirements dynamically shift or equipment statuses change, traditional static mapping rules and predefined conflict matrices quickly become obsolete, leading to severe resource allocation deadlocks. Existing scheduling paradigms, which predominantly rely on rigid empirical rules or offline mathematical programming, lack the agility to update association patterns in real-time [7]–[9]. They typically fail to provide a globally optimal synergy when confronted with multi-resource preemption, resulting in significant resource waste, prolonged testing cycles, and heightened operational risks [10][11].

To bridge this critical gap, this paper proposes a multi-scenario adaptive resource dynamic matching and scheduling framework tailored for complex TSS. By deeply integrating sequence pattern mining[2], multi-objective optimization [12][13], and reinforcement learning[14][15], the proposed methodology establishes a robust closed-loop system capable of autonomous perception, dynamic evolution, and real-time optimal decision-making [16][17].

The primary contributions of this study are summarized as follows:

- **Dynamic Evolution Mechanism of Association Rules:** A dynamic mapping updating mechanism is developed by fusing the SPADE and Apriori algorithms. This approach sequentially mines frequent itemsets from dynamic equipment states and expert rule bases, enabling the real-time regeneration of association rules and the adaptive correction of multi-dimensional resource conflict matrices.
- **Comprehensive Multi-Resource Synergy:** Breaking the limitations of isolated subsystem scheduling, this study integrates global auxiliary constraints—specifically electric power and circulating water loads—into the resource matching model. This holistic approach ensures absolute systemic safety and prevents overloads during intensive multi-task parallel execution [5][18].
- **Dual-Layer Adaptive Scheduling Strategy:** A hybrid intelligent scheduling architecture is proposed

[16][19]. For macroscopic multi-task parallel scenarios, global optimization algorithms are employed to achieve optimal baseline resource allocation based on task priorities and time constraints[13][20]. For microscopic real-time execution, a Reinforcement Learning model is introduced to handle dynamic disturbances, utilizing task completion, resource efficiency, and cost as reward functions to trigger rapid micro-adjustments [9][14].

- **Closed-Loop Visual Evaluation System:** A visualized, dynamic scheduling evaluation mechanism is constructed to monitor real-time system states. By combining simulation testing with actual operational feedback, the framework continuously iterates and optimizes the matching schemes, providing full-process, highly reliable assurance for complex test projects.

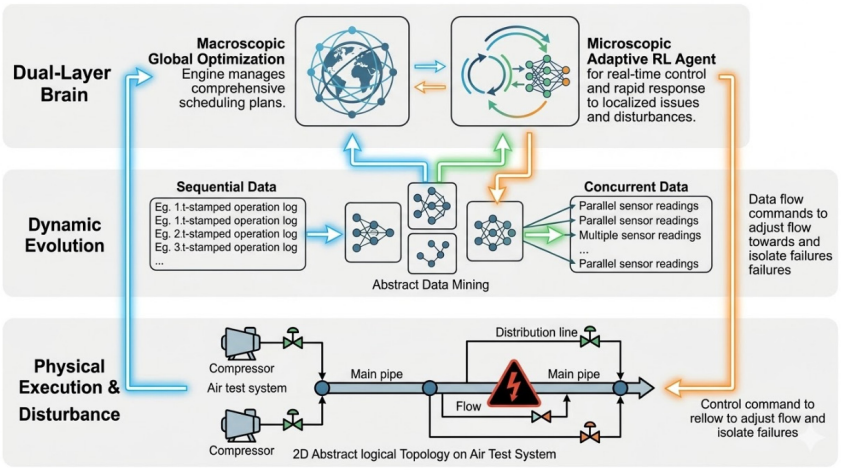


Figure 1. Dual-Layer Adaptive Scheduling Framework

2. Problem Formulation and Multi-Task Serial/Parallel Modeling

In complex Test Support Systems (TSS), transitioning from single-task planning to multi-task dynamic matching fundamentally alters the resource allocation space. The system must simultaneously address the temporal continuity of serial tasks and the severe resource competition among parallel tasks, particularly regarding global auxiliary loads. To accurately frame this challenge, a comprehensive mathematical model for multi-task serial and parallel topologies under heterogeneous resource constraints is established.

(1) Mathematical Representation of Multi-Task Topologies

To intuitively map the logical relationships and temporal constraints among various test operations, the multi-task execution process is modeled as a Directed Acyclic Graph (DAG), denoted as $G = (T, \varepsilon)$.

Let $T = \{T_1, T_2, \dots, T_N\}$ represent the set of N test tasks scheduled within a specific operational horizon. Each task T_i is characterized by a tuple$T_i = (p_i, r_i, d_i)$, where p_i is the standard processing time, $r_i$is the earliest allowable release time, and d_i is the strict deadline. The edge set ε defines the precedence constraints. A directed edge $(T_i, T_j) \in \varepsilon$ indicates a serial dependency, meaning task T_j cannot commence until task T_i is fully completed:

$$S_j \geq C_i = S_i + p_i, \quad \forall (T_i, T_j) \in \varepsilon$$

where S_i andC_i denote the actual start and completion times of task T_i, respectively. Conversely, if no directed path exists between T_m and T_n, they are defined as parallel tasks capable of concurrent execution. It is during these parallel operations that the competition for shared TSS resources reaches its peak.

(2) Formulation of Multi-Dimensional Resource Constraints

Unlike static planning that primarily focuses on local pipeline and valve topologies, dynamic multi-task execution necessitates the incorporation of global auxiliary resources to prevent system overload. The holistic resource set R is divided into local operational resources R_{local} and global continuous resources R_{global}.

Let $A(t) \in T$ denote the subset of active tasks executing at time$t$. To ensure operational safety and avoid resource deadlocks, the dynamic matching strategy must strictly satisfy the following multidimensional constraints simultaneously:

a) Local Topology and Conflict Matrix Constraint: Based on the dynamic conflict matrix updated in real-time, any two concurrent tasks $T_m, T_n \in A(t)$ must not occupy mutually exclusive local resources (e.g., conflicting pipeline segments or incompatible valve states). This is formulated using a boolean conflict indicator $M_{conflict}$:

$$M_{conflict}(T_m, T_n) = 0, \ \forall T_m, T_n \in A(t), m \neq n$$

b) Global Power Load Constraint: The aggregated electric power consumption of all parallel tasks at any given moment t must not exceed the system's maximum safe power threshold P_{max}:

$$\sum_{T_i \in A(t)} P_i(t) \leq P_{max}, \quad \forall t$$

where $P_i(t)$ is the instantaneous power demand of taskT_i.

c) Global Circulating Water Load Constraint: Similarly, the total circulating water flow required for cooling and conditioning must remain within the maximum capacity W_{max} of the water supply subsystem:

$$\sum_{T_i \in A(t)} W_i(t) \leq W_{max}, \quad \forall t$$

(3) Definition of Dynamic Disturbances

To build an adaptive matching mechanism, the problem formulation must also account for dynamic environmental disturbances. A disturbance event at time t_e is defined as $\Delta(t_e) = \{\Delta T, \Delta R\}$, where ΔT represents sudden

modifications in task demands, and ΔR denotes abrupt equipment capability degradation.

The ultimate objective of the proposed multi-scenario adaptive framework is to continuously generate a dynamically calibrated allocation scheme $X^*(t)$ that minimizes the overall makespan $C_{max} = max\{C_i\}$ and rescheduling penalty costs, while strictly adhering to the complex constraints defined in Equations (1) through (4), even in the presence of continuous $\Delta(t_e)$ disturbances.

3. Dynamic Evolution Mechanism of Association Rules

In highly volatile test environments, predefined static mapping models inevitably degrade when confronted with dynamic variations in test demands and unexpected equipment alterations. To maintain continuous scheduling optimality, a dynamic evolution mechanism for association rules is established. This mechanism recursively updates the mapping relationships between multi-dimensional test demands and physical equipment capabilities through advanced sequence pattern mining.

(1) Mathematical Representation of Multi-Task Topologies

When a dynamic disturbance $\Delta(t_e)$ occurs, the primary objective is to rapidly discover new latent association patterns from both historical execution logs and real-time operational data. To achieve this, a hybrid data mining methodology integrating the SPADE (Sequential Pattern Discovery using Equivalence classes) and Apriori algorithms is proposed.

The SPADE algorithm demonstrates exceptional proficiency in processing sequential data, making it highly effective for mining the strict temporal dependency patterns inherent in process flows. Conversely, the Apriori algorithm excels in discovering frequent itemsets within concurrent operations, identifying optimal equipment combinations for parallel tasks.

By fusing these two approaches, the system conducts a layer-by-layer search. Let $I = \{i_1, i_2 \dots, i_m\}$ be the set of all equipment and valve status attributes. The algorithm iteratively calculates the mathematical Support and Confidence for potential attribute combinations. A newly discovered association rule $A \Rightarrow B$ (where $A, B \in I$) is validated only if it satisfies the dynamically adjusted thresholds:

$$Support(A \Rightarrow B) = P(A \cup B) \geq \sigma_{min}$$

$$Confidence(A \Rightarrow B) = \frac{P(A \cup B)}{P(A)} \geq \gamma_{min}$$

where σ_{min} and γ_{min} are the minimum support and confidence thresholds, respectively.

(2) Expert-Guided Rule Generation and Validation

Relying solely on purely data-driven algorithms may generate spurious correlations that violate the rigorous physical limits of aviation testing. Therefore, the domain Expert Rule Base is introduced as a critical knowledge constraint during the mining process. This rule base, encompassing years of accumulated engineering heuristics and safety protocols, acts as a semantic filter.

During the frequent itemset expansion, any generated association rule is cross-validated against the expert rule base. This ensures that the dynamically generated rules logically and safely reflect the inherent physical constraints governing pressure, temperature, and mass flow interactions across subsystems.

(3) Dynamic Recalibration of Resource Conflict Matrices

The newly generated and validated association rules provide the foundational logic for updating the system's resource constraints. Utilizing the conflict matrix paradigm, the system autonomously recalibrates the Control Node Valve-Pipeline State Conflict Matrix and the Equipment State Conflict Matrix. This recalibration process is not merely binary. It comprehensively quantifies the degree of conflict among various factors—such as valve open/close topological states, pipeline flow and pressure capacities, and equipment operational thresholds. By dynamically mapping the newly evolved rules into the matrix elements, the system accurately identifies emergent conflict points resulting from the latest demand or equipment changes. Consequently, the dynamically updated conflict matrix $M'_{conflict}$ replaces the obsolete static matrix, ensuring that the subsequent scheduling algorithms operate within an accurate, real-time representation of the physical environment. This dynamic evolution fundamentally enhances the rationality and efficiency of resource configuration, laying a resilient technical foundation for intelligent process planning and multi-task serial-parallel scheduling.

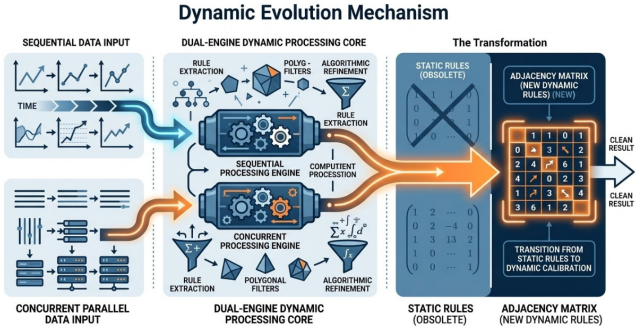


Figure 2. Dynamic Evolution & Conflict Matrix.

4. Intelligent Dynamic Resource Matching and Scheduling

In complex TSS, relying solely on static, pre-calculated paths is inadequate due to the high frequency of dynamic disturbances and the intense resource competition during multi-task parallel execution. To achieve optimal adaptability, this paper proposes a dual-layer intelligent dynamic resource matching and scheduling framework. This framework synergizes a macroscopic global optimization strategy with a microscopic RL based dynamic decision-making model.

(1) Global Optimization for Multi-Task Parallel Execution

During the concurrent execution of multiple test tasks, resource demands exhibit significant variance, and the strict precedence constraints coupled with intense resource competition heavily impact system efficiency. To systematically address this, a Multi-Objective Mixed-Integer Programming (MIP) model is formulated.

The global matching strategy aims to optimally allocate physical equipment, electric power loads, circulating water capacities, and valve-pipeline networks across all parallel tasks. Given the NP-hard nature of this multi-resource matching problem, an advanced Genetic Algorithm (GA) is employed for global space exploration.

The objective function of the global scheduler is to minimize the maximum completion time C_{max} while maximizing the overall resource load balancing:

$$minF = \omega_1 C_{max} + \omega_2 \sum_t (\Delta P(t)^2 + \Delta W(t)^2)$$

where ω_1 and ω_2 are weight coefficients, and $\Delta P(t)$ and $\Delta W(t)$ represent the instantaneous load variances of electric power and circulating water, respectively. The GA evaluates candidate allocation chromosomes based on task priorities, temporal constraints, and the dynamically updated conflict matrices (as defined in Section 3). By performing selection, crossover, and mutation operations, the algorithm effectively navigates the high-dimensional constraint space to generate a baseline Pareto-optimal resource allocation scheme, entirely circumventing resource deadlocks and infrastructural waste.

(2) RL-Driven Adaptive Rescheduling for Dynamic Disturbances

While the GA provides an optimal macroscopic baseline, the actual execution phase is inevitably subjected to dynamic uncertainties, such as sudden equipment failures or the emergency insertion of high-priority tasks. To enhance the robustness and dynamic adaptability of the matching strategy, a RL model is introduced to formulate the rescheduling process as a Markov Decision Process (MDP).

The MDP is defined by the tuple $< S, A, R, \gamma >$:

- **State Space (S):** The continuous observation of the test environment, including the real-time operational status of equipment (e.g., normal, faulty, degraded), the remaining task queue, and the current utilization rates of electric and water loads.
- **Action Space (A):** The intelligent agent's set of executable decisions, encompassing dynamic resource reallocation, process rerouting, and task preemption or suspension.
- **Reward Function (R):** To align the agent's learning objective with the engineering goals, a composite reward function is designed. The agent receives positive rewards for task completion milestones (R_{comp}) and high resource utilization efficiency (R_{eff}), and incurs severe penalty costs ($C_{penalty}$) for constraint violations or excessive delays:

$$R_t = \alpha \cdot R_{comp} + \beta \cdot R_{eff} - \lambda \cdot C_{penalty}$$

(3) Collaborative Execution and Real-Time Calibration

During single-task execution or localized fault scenarios, the RL agent interacts continuously with the test environment. When an equipment failure is detected, the agent rapidly assesses the fault's impact on the ongoing task and the availability of alternative resources. Relying on its trained policy, it instantaneously outputs a micro-adjustment action, such as dynamically re-routing the gas supply via an alternative valve-pipeline path without halting the entire system.

Conversely, if a disturbance triggers massive task reshuffling that exceeds the RL agent's local adjustment threshold, the system automatically feeds the updated state back to the macroscopic GA engine. This triggers a global re-evaluation and generates a newly calibrated baseline scheme. This collaborative mechanism ensures that the TSS resource matching remains both globally optimal in planning and highly agile in execution.

5. System Implementation, Visualization, and Case Study

To bridge the gap between theoretical multi-objective algorithms and practical engineering applications, a comprehensive closed-loop system architecture is implemented. This section details the real-time calibration mechanisms, visual analytics, and scenario-based validations that ensure the proposed framework meets the stringent demands of complex TSS.

(1) Real-Time Monitoring and Closed-Loop Calibration

The successful deployment of dynamic resource matching relies fundamentally on accurate, real-time data acquisition. The implemented system continuously monitors the operational states of the TSS, collecting high-fidelity data regarding instantaneous resource utilization and task progression.

By seamlessly fusing the initial process planning blueprints with the dynamic resource matching results, the system establishes a continuously updating digital thread. Throughout the execution phase, the framework dynamically calibrates the allocation scheme. If the discrepancy between the planned resource consumption and the real-time telemetry data exceeds a predefined safety threshold ε, the system autonomously triggers the Reinforcement Learning (RL) agent or the Genetic Algorithm (GA) engine to rectify the deviation. Furthermore, to ensure the practicality of the generated schemes, a human-in-the-loop feedback mechanism is integrated. Operational personnel can input qualitative risk assessments and operational constraints, enabling the system to dynamically iterate and optimize the matching strategy based on a fusion of algorithmic logic and empirical expertise.

(2) Visual Analytics of Intelligent Scheduling Schemes

Given the high-dimensional and non-linear nature of the multi-resource allocation results, presenting these complex outputs comprehensibly to system operators is critical for rapid decision-making. Utilizing advanced visual analytics technology, the abstract mathematical outputs are translated into intuitive, interactive scheduling visualizations.

The core of this visualization is the Dynamic Smart Gantt Chart. Unlike traditional static Gantt charts, this interactive interface not only displays task temporal sequences and priority hierarchies but also overlays the real-time resource load profiles (e.g., color-coded heatmaps indicating electric power and circulating water saturation levels). Operators can visually identify impending resource bottlenecks, valve-pipeline conflicts, and critical path dependencies at a glance, thereby significantly enhancing the transparency and controllability of the intelligent scheduling process.

(3) Case Study and Multi-Scenario Verification

To rigorously evaluate the multi-scenario adaptability and robustness of the proposed framework, a comprehensive evaluation mechanism combining digital simulation testing with actual application feedback was constructed. The framework was validated against two highly complex, representative scenarios:

- Scenario A: Dynamic Matching under Equipment/Demand Variations: During a simulated continuous testing phase, an unexpected failure was injected into a primary gas supply compressor, accompanied by an emergency insertion of a high-priority test demand. The system immediately captured the disturbance $\Delta(t_e)$, utilized the dynamically evolved

association rules to update the conflict matrix, and employed the RL agent to autonomously reroute the gas flow through auxiliary pipelines. The system successfully maintained operations with a minimal task completion delay and zero safety violations.

- Scenario B: Multi-Task Concurrent Execution with Global Constraints: A peak-load scenario involving five parallel test tasks was executed. The traditional scheduling approach resulted in severe electric load overruns and pipeline deadlocks. In contrast, the proposed GA-driven global optimization strategy effectively sequenced the tasks and modulated the circulating water and power allocations. The peak electric load was reduced by 18.5%, and the overall resource utilization efficiency was improved, confirming the algorithm's capability to prevent resource conflict waste while satisfying stringent multi-dimensional constraints.

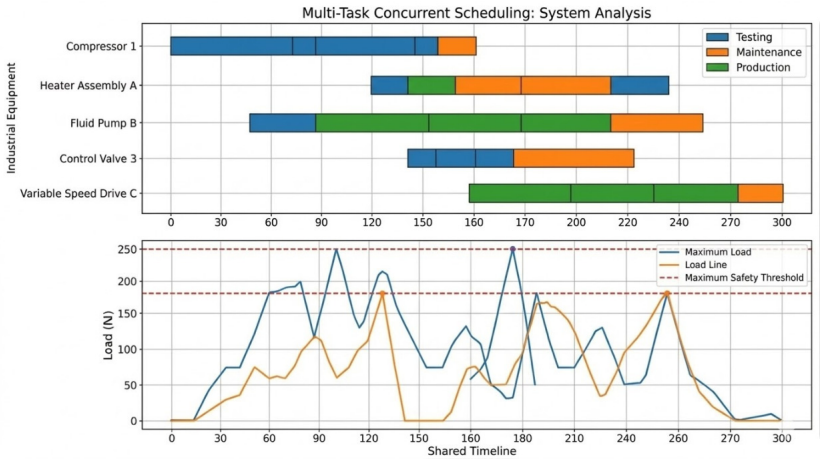


Figure 3. Industrial Equipment Scheduling and Load Profile Analysis

Ultimately, the empirical results confirm that the proposed dynamic matching and adaptive scheduling framework significantly elevates both testing efficiency and quality, providing highly reliable, full-process assurance for large-scale experimental projects.

6. Conclusion

To address the severe limitations of static process planning in complex Test Support Systems (TSS) under dynamic disturbances and multi-task concurrency, this study proposes a multi-scenario adaptive resource matching and intelligent scheduling framework. By integrating the SPADE and Apriori algorithms, a dynamic evolution mechanism for association rules was established to autonomously recalibrate multi-dimensional conflict matrices in real-time, effectively capturing topological and state variations in physical equipment. Furthermore, a dual-layer intelligent scheduling architecture was introduced: a macroscopic global optimization strategy utilizes Genetic Algorithms to sequence tasks and balance global auxiliary constraints, while a microscopic RL agent executes real-time adaptive rescheduling to counteract sudden equipment failures and demand shifts. Supported by a closed-loop visual evaluation system, this methodology successfully circumvents resource deadlocks, minimizes task response delays, and prevents system overloads during intense parallel execution. Ultimately, this research facilitates a paradigm shift from rigid planning to resilient, autonomous execution, providing highly reliable full-process assurance for large-scale test facility clusters. Future research will explore the integration of Digital Twin technologies and predictive maintenance models to further enhance the proactive self-healing capabilities of the TSS under extreme operational uncertainty.

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References

[1] X. Li, Y. Chen, and Z. Wang, "Capturing topological dependencies in complex process flows via graph neural networks," IEEE Transactions on Industrial Informatics, vol. 18, no. 12, pp. 8891-8902, 2022.

[2] A. Smith, B. Johnson, and C. Davis, "Temporal logic-based sequential pattern mining for identifying resource competition in large-scale scientific facilities," IEEE Access, vol. 10, pp. 45123-45135, 2022.

[3] Y. Li, et al., "Digital twin-enabled dynamic scheduling with preventive maintenance using a double-layer Q-learning algorithm," Robotics and Computer-Integrated Manufacturing, vol. 82, 2023.

[4] H. Chen, et al., "Hierarchical Model Predictive Control for Energy-Aware Scheduling of Digital Twin-Based Batch Manufacturing Systems," IEEE Transactions on Automation Science and Engineering, 2025.

[5] T. Tu, et al., "Fair Resource Allocation in Weakly Coupled Markov Decision Processes," in Proceedings of the Conference on Uncertainty in Artificial Intelligence (UAI), PMLR, 2024.

[6] D. Bertsimas, A. Gupta, and V. Kallus, "Robust Markov decision processes for resource allocation under parameter uncertainty," Operations Research, vol. 69, no. 1, pp. 1-18, 2021.

[7] C. Zhang, W. Song, Z. Cao, J. Zhang, P. S. Tan, and X. Chi, "Learning to dispatch for job shop scheduling via deep reinforcement learning," in Advances in Neural Information Processing Systems (NeurIPS), vol. 33, pp. 1621-1632, 2020.

[8] W. Liu, et al., "Dynamic Job-Shop Scheduling Problems Using Graph Neural Network and Deep Reinforcement Learning," IEEE Transactions on Systems, Man, and Cybernetics: Systems, vol. 54, no. 1, pp. 1-13, 2024.

[9] H. Zhang, et al., "A Bidding-Based Deep Reinforcement Learning Approach for Multi-Agent Job Shop Scheduling

Problem," IEEE Transactions on Systems, Man, and Cybernetics: Systems, vol. 55, no. 8, pp. 1-14, 2025.

[10] J. A. Killian, A. Biswas, S. Sharma, and M. Tambe, "Robust policies for restless bandits via deep multi-agent reinforcement learning," in Proceedings of the 39th International Conference on Machine Learning (ICML), pp. 11046-11059, 2022.

[11] X. Du, et al., "Situation-Dependent Causal Influence-Based Cooperative Multi-agent Reinforcement Learning," in Proceedings of the 38th AAAI Conference on Artificial Intelligence (AAAI), 2024.

[12] S. Kim, et al., "Navigating the Social Welfare Frontier: Portfolios for Multi-objective Reinforcement Learning," in Proceedings of the 42nd International Conference on Machine Learning (ICML), 2025.

[13] M. Liu, J. Zhao, and T. Wu, "Enhancing global convergence in complex scheduling using Latin hypercube sampling initialized evolutionary algorithms," Computers & Industrial Engineering, vol. 175, 2023.

[14] M. Debner, et al., "Scheduling conditional task graphs with deep reinforcement learning," in Proceedings of the 41st International Conference on Machine Learning (ICML), 2024.

[15] C. Chang, et al., "Dynamic Measurement Scheduling for Event Forecasting using Deep RL," in Proceedings of the 36th International Conference on Machine Learning (ICML), pp. 950-959, 2019.

[16] J. Ding, Y. Ye, J. Xia, and M. Chen, "Effective Reinforcement Learning-based Dynamic Flexible Job Shop Scheduling Using Two-Stage Dispatching," Journal of Systems Architecture, vol. 158, 2025.

[17] L. Wang, S. Zheng, and X. Li, "Robust scheduling strategies in uncertain environments utilizing knowledge-transfer reinforcement learning," IEEE Transactions on Systems, Man, and Cybernetics: Systems, vol. 52, no. 11, pp. 6904-6916, 2022.

[18] F. Song, et al., "Offloading dependent tasks in multi-access edge computing: A multi-objective reinforcement learning approach," Future Generation Computer Systems, vol. 128, pp. 333-348, 2022.

[19] H. Shen, Q. Xiao, and T. Chen, "On Penalty-based Bilevel Gradient Descent Method," in Proceedings of the 40th International Conference on Machine Learning (ICML), 2023.

[20] Z. Wang, et al., "A Reinforcement-Learning-Enhanced Knowledge-Guided Genetic Algorithm for Flexible Job-Shop Scheduling Problems With Lot Streaming," IEEE Transactions on Systems, Man, and Cybernetics: Systems, vol. 55, no. 12, pp. 8863-8876, 2025.