A Dynamic Graph Model-Based Method for Special Equipment Resource Scheduling

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Abstract. As a critical component for ensuring safety in major events, special equipment resource scheduling faces challenges like dynamic status changes, environmental disturbances, and multi-entity collaboration, making traditional static methods insufficient for real-time response. This paper proposes a dynamic graph model-based method, constructing a multi-layer directed weighted graph with task, environment, and resource nodes to characterize their couplings. An adaptive weight update mechanism optimizes paths in real time by integrating risk levels, environmental intensities, and resource availability. A multi-objective model with response time, utilization, and risk is built, solved by particle swarm optimization. Experiments in dynamic scenarios show 12%-17% higher resource matching rates and 13%-20% shorter durations than traditional methods, offering a scalable framework for safe scheduling.

Keywords: Special equipment; Graph model; Resource scheduling; PSO.

1. Introduction

Over the past two decades, special equipment inventory has correlated positively with GDP growth, contributing 2%-3% directly and 64.13% along the industrial chain during the "13th Five-Year Plan," highlighting its economic role. However, safety incidents, like 90 nationwide in 2023 causing 128 fatalities, have raised concerns[1,2]. In major events, regional scheduling is vital, yet high-frequency, multi-region equipment like elevators challenges static methods. Dynamic internal changes, external disturbances, and resource constraints demand real-time response, while multi-entity collaboration requires global modeling. Thus, intelligent dynamic scheduling and risk control are critical for major event safety.

Existing resource scheduling research mainly relies on linear programming, heuristic algorithms, and static graph models. García-Nieves proposed a flexible linear programming model for construction scheduling, integrating sub-activity associations and multi-team collaboration to handle complex constraints [3]. Aceituno used integer linear programming (ILP) for multi-core systems, reducing interference by 83.47% and improving schedulability [4]. Liu developed an adaptive ant colony algorithm for cloud computing to enhance convergence and load balance [5]. Zhao proposed a particle swarm-based CAP algorithm for random demand scheduling [6]. Cai integrated reinforcement learning and graph neural networks for resource-constrained scheduling under disruptions [7]. Jiang formalized cross-vertex critical section scheduling to improve system analysis [8]. However, these methods have limitations in dynamic scenarios: static models with fixed topologies fail to describe real-time correlations, heterogeneous multi-dimensional data lacks a unified framework with dynamic weights, and cross-departmental collaboration leads to local-optimal priorities, weakening global optimization and resilience.

To address this, we present a dynamic directed weighted graph model for special equipment scheduling, constructing a multi-layer structure with nodes for equipment, tasks, environments, and resources, and directed edges for dependencies. Real-time data adjusts edge weights and node states for multi-objective optimization. Key innovations include a unified multi-dimensional graph framework integrating equipment attributes, geographic distribution, hazards, and environmental parameters via spatio-temporal analysis, and an adaptive weight update mechanism optimizing paths with evolving risks, resource availability, and environmental disturbances. Validated in dynamic and static scenarios, the method outperforms traditional approaches in resource matching and response speed, offering a scalable framework for major event safety.

2. Dynamic graph model and scheduling algorithm

2.1 Construction of the multi-dimensional dynamic graph model

As an important tool for modeling complex systems, the graph model can intuitively describe the dependency relationships and dynamic interaction mechanisms among multiple factors through the topological structure of nodes and edges. In the field of resource scheduling, graph models are often used to model problems such as task allocation, path planning, and risk propagation, with advantages including: (1) supporting the unified representation of heterogeneous data, such as equipment status, environmental parameters, and resource constraints; (2) dynamically responding to real-time changes through weight adjustment and structural evolution; (3) providing a computable mathematical framework for global optimization. However, traditional graph models mostly rely on static network assumptions and are difficult to characterize the dynamic characteristics of special equipment scheduling scenarios, such as sudden changes in equipment status, frequent environmental disturbances, and multi-entity collaboration. Therefore, addressing the dynamic coupling characteristics of task requirements, environmental disturbances, and resource constraints in special equipment resource scheduling, this paper constructs a multi-layer dynamic directed weighted graph model:

$$G(t) = (V(t), E(t), W(t)) \tag{1}$$

where t is a time variable representing the dynamic evolution characteristics of the model with changes in equipment status, environmental disturbances, and task requirements. The specific definitions are elaborated from three dimensions: nodes, edges, and weights:

Node Set V：Includes three types of entity nodes:

Edge Set E: Defines the dependency relationships and resource flow paths between nodes:

Weight Set W: Dynamically adjusts edge weights to reflect real-time priorities:

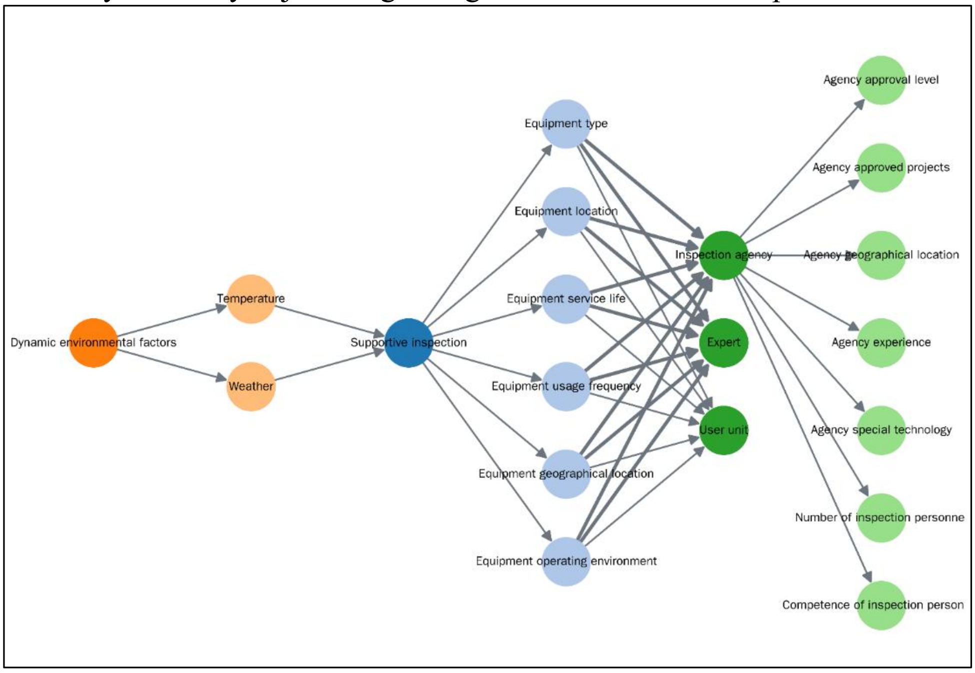

Fig. 1 Example of Graph Model in Preparation Phase

As shown in Figure 1, a graph model of the preparation phase is drawn using partial activity data, which includes dynamic environment nodes, resource nodes, and task nodes.ADAPTIVE WEIGHT UPDATE MECHANISM

To address dynamic multi-constraint scenarios, a weight adjustment algorithm based on priority propagation is proposed. The weight update formula is as follows:

$$w_{ij}^{t} = \alpha \cdot w_{ij}^{t-1} + \beta \cdot \Delta S_{ij}^{t} + \gamma \cdot \sum_{k \in N(i)} \frac{w_{ik}^{t-1}}{|N(i)|} \tag{2}$$

Where， ΔS_{ij}^{t} is the difference in the state changes between nodes i and j at time t(such as stage transition, resource scheduling delay), N(i)is the set of neighbor nodes of node i, and α , β , and γ are decay factors. The weight update trigger conditions include:

Stage Transition: For example, the change from the preparation stage to the pre-fight stage causes a change in ΔS_{ij}^{t};

Environmental Disturbance Events: Extreme weather warnings trigger the reallocation of Wed ；

Resource Constraint Changes: For example, obstacles in maintenance personnel scheduling require the re-planning of Wtr.

3. Simulation experiments and result analysis

3.1 Experimental design

①Dataset:

Equipment Data: Includes inspection records of 1000 hazard elevators, boilers, and pressure vessels, with fields such as equipment type, service life, usage frequency, failure times, and geographic location (Jiading District), etc.

Task Data: 500 inspection tasks in activity scenarios, each task associated with equipment number, task type, average inspection duration, task start/end time, etc.

Resource Data: Data of 200 inspectors from 50 inspection agencies, recording capability types, certification levels, professional titles, participation times in major event safety, daily working hours, etc.

②Scenario description:

Scenario 1: Simulate a large international event based on task and resource datasets, including 50 pieces of special equipment, including elevators, boilers, pressure vessels, and pressure pipelines; 20 inspectors of various special equipment are required to carry out protective inspections on these equipment within 72 hours.

Scenario 2: The basic situation is the same as Scenario 1, but extreme weather disturbances are added, increasing the difficulty of equipment inspection, and still requiring protective inspections on these equipment within 72 hours.

3.1.1 Selection of evaluation indicators

Task Completion Rate (TCR): The task completion rate refers to the proportion of the number of tasks completed to the total number of tasks to be completed.

Total Task Duration (TTD): The time consumed to complete all tasks.

Resource Matching Rate (RMR): The number of tasks where the difficulty level of equipment inspection matches the capability level of inspectors divided by the total number of completed tasks.

3.2 Experimental results

① Scenario 1:

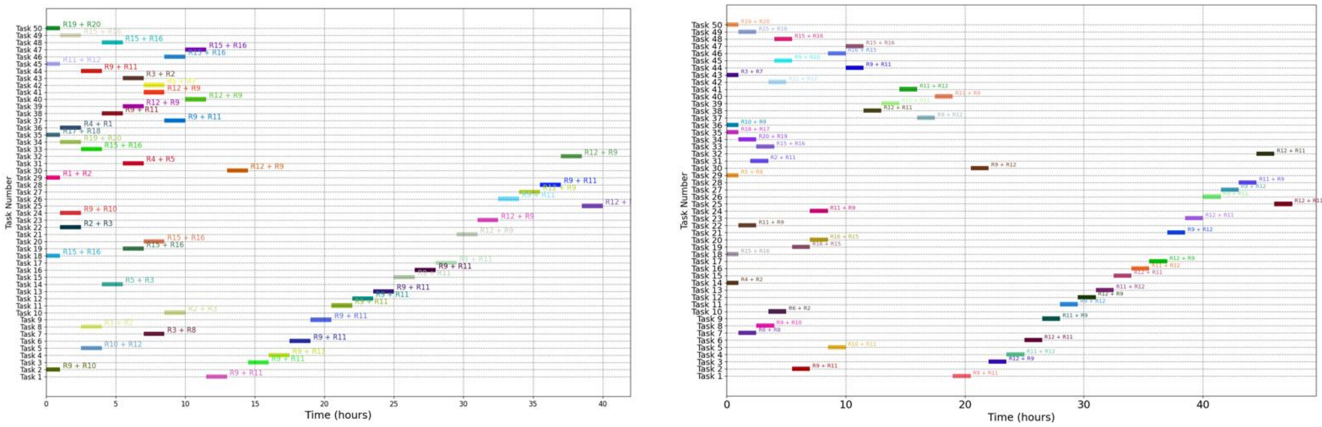

Figure. 2 Gantt Chart for Scheduling via Graph-PSO and Graph-ACO

As shown in Fig. 2, the PSO algorithm effectively balances resource load by preferentially matching low-capability personnel to low-complexity tasks (such as Task 35 executed by R19+R20), reducing the redundant use of high-capability personnel, with tight task time intervals and control of travel time costs at a low level; The task scheduling of the ACO algorithm has a certain degree of resource concentration (such as R11+R12 continuously executing Tasks 4, 5, 6), leading to an increase in travel time, with a total duration of 46 hours. Although the task completion rate meets the standard, the duration is longer; The FIFO algorithm's sequential task allocation results in some high-capability personnel (such as R15+R16) undertaking too many low-complexity tasks (such as Tasks 18-21), causing unbalanced resource utilization and uneven task time distribution. The final total duration is 43.5 hours, but the resource matching rate is low.

② Scenario 2:

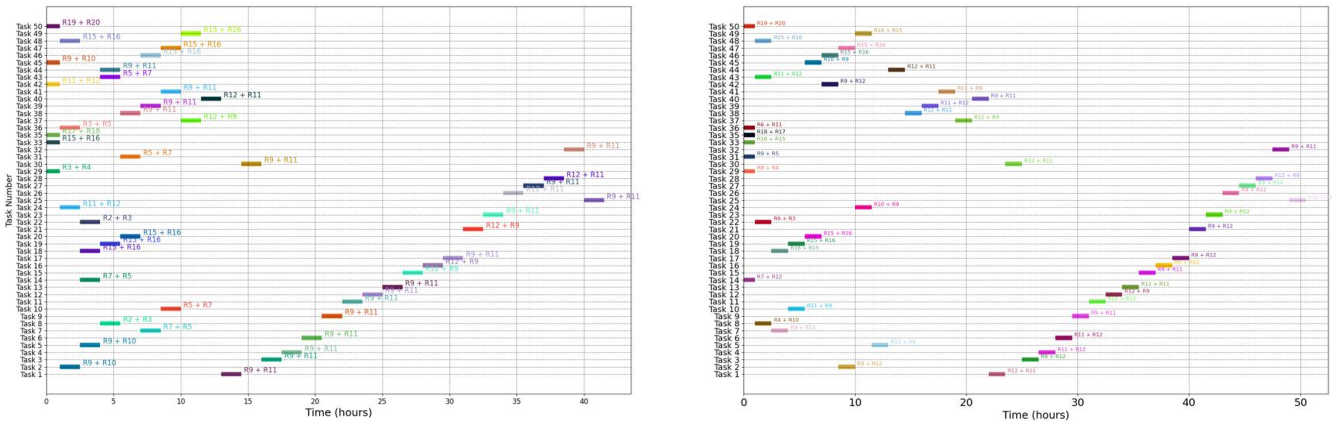

Figure. 3 Gantt Chart for Scheduling via Graph-PSO

As shown in Fig. 3, the PSO algorithm preferentially schedules high-capability personnel to tasks with temporarily increased complexity under extreme weather, while avoiding continuous operation of a single personnel, reflecting the rapid response capability of the adaptive weight mechanism to environmental disturbances; The ACO algorithm has more task time overlaps and resource conflicts in Scenario 2, leading to a significant increase in travel time, with a total duration of 47.5 hours, indicating insufficient global optimization capability under dynamic constraints; Due to the lack of a dynamic adjustment mechanism, the FIFO algorithm has some tasks delayed or retried due to personnel capability mismatches, with the resource matching rate dropping to 71.64%, further verifying the limitations of static scheduling methods in complex scenarios.

Table 1 summarizes the quantitative results of both scenarios, merging the original two tables for unified analysis. In Scenario 1, all algorithms achieve 100% task completion, but Graph-PSO outperforms others with a 75% resource matching rate and 40 hours total duration, representing an 8.05% improvement in speed over FIFO and a 7.1% higher matching rate than Graph-ACO. Under Scenario 2, task completion rates slightly drop to 98% due to environmental disturbances, but

Graph-PSO still leads with an 83.67% matching rate and 41.5 hours duration, effectively mitigating resource allocation pressure through dynamic weight adjustment.

Table 1. Performance Comparison of Different Algorithms in Dynamic and Static Scenarios

Algorithm	Scenario1			Scenario2		
	TCR	RMR	TTD(h)	TCR	RMR	TTD(h)
G-PSO	100%	75%	40	98%	83.67%	41.5
G-ACO	100%	70%	46	98%	81.63%	47.5
FIFO	100%	66%	43.5	98%	71.64%	45

The results highlight the superiority of the dynamic graph model combined with PSO in handling both static and dynamic scheduling challenges, showcasing enhanced resource matching accuracy and shorter completion times, especially under environmental disturbances. The adaptive weight update mechanism proves critical for real-time optimization, validating the proposed method's effectiveness in complex scenarios.

4. Conclusion

By integrating dynamic graph models with adaptive algorithms, this study provides a full-chain solution for resource scheduling of special equipment, characterized by "data-driven, model-optimized, and real-time responsive" capabilities. This solution holds significant theoretical and practical value for enhancing the safety assurance of major urban events. Future research will focus on improving adaptability to complex scenarios, optimizing algorithm efficiency, and facilitating engineering implementation, with the aim of promoting the in-depth application of intelligent scheduling technologies in the safety management of special equipment.

5. Acknowledgements

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