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Multi-Objective Collaborative Optimization of Power Equipment Selection and Maintenance Path Considering Risk Priority and Spatiotemporal Penalties

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Abstract: Aiming at the maintenance scheduling problem of power equipment such as Ring Main Units (RMUs) in distribution systems, this paper constructs a priority-based maintenance optimization model. The model integrates real-time risk indicators, historical maintenance records, and sudden extreme risk factors, determines equipment priority through a hierarchical scoring mechanism, and introduces soft time constraints on travel and maintenance time. Built in the form of a single-layer mixed-integer programming (MIP), the model's objective function includes dual penalty terms for overtime and underload. The scheduling adaptability and response capability of the model in basic scenarios, updated history, and sudden risk situations are verified through three-stage simulation experiments.

Keywords: Vehicle Routing Problem (VRP); Ring Main Unit (RMU); Multi-objective optimization; Risk-aware scheduling

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1. Introduction

In recent years, the maintenance of power equipment such as Ring Main Units (RMUs) and switchgear in distribution networks has become increasingly dependent on condition-based monitoring systems. Under the constraints of limited time and resources, how to scientifically select maintenance objects and plan efficient on-site maintenance paths is a key challenge for power equipment management. Common maintenance strategies mainly include breakdown maintenance and preventive maintenance [1]. Preventive maintenance has a significant effect on reducing system operation and maintenance costs. Condition-Based Maintenance (CBM) has become one of the most advantageous solutions due to its high efficiency.

The optimization of maintenance paths in CBM is essentially a Vehicle Routing Problem (VRP), whose goal is to minimize the total travel time or cost of visiting multiple locations. Cui et al. proposed a hybrid heuristic algorithm to solve the VRP, distinguishing between priority and non-priority customers, which ensures that priority nodes receive timely services. Hou et al. set task priorities during scheduling, effectively improving the traffic efficiency of key vehicles. Dukkanci et al. incorporated economic, environmental, and social welfare into the objective function, establishing a triple-objective model with multi-priority. The above studies have explored node selection and priority control strategies in VRP by introducing weight coefficients and setting hard constraints. The VRP with Time Windows (VRPTW) requires vehicles to visit customers within predefined time intervals. For example, Lai et al. adopted hard time window constraints, specifying that vehicles can only arrive within fixed times. Taş et al. explicitly and simultaneously incorporated early and delay costs, reflecting customer dissatisfaction on both sides of the time window. In the study of Li et al., services outside the predefined time window are allowed, and delays trigger penalty costs directly included in the objective function [2].

To address the above issues, this paper proposes a priority-based equipment selection mechanism combining real-time monitoring information and historical maintenance data; constructs a dual-penalty objective function including overtime and underload penalty terms; integrates maintenance task selection and path optimization into a single MIP optimization framework; and verifies the effectiveness of the model through simulation experiments under various equipment configurations.

2. Model construction

Taking the Ring Main Unit (RMU) as an example, this section elaborates on the construction process of the objective function. The objective function integrates risk coefficients and maintenance frequencies derived from modern RMU feedback detection data, and incorporates soft constraints related to working hours. In addition, the basic constraints of the vehicle routing problem will be introduced.

2.1. Selection and priority calculation of power equipment to be maintained

This section proposes an RMU risk assessment parameter, taking detection frequency as a supplementary factor to construct a comprehensive maintenance priority index. Current and temperature signals are first processed to extract intermediate indicators, including the cumulative duration of over-limit current fluctuation T_r, cumulative duration of overload T_h, maximum recorded temperature T_{max}, and the installation correctness judgment index S. The overall risk level of each RMU is calculated through a weighted summation R. The final maintenance priority score P is determined by comprehensively considering the risk level R and detection frequency C. To evaluate current deviation behaviors that may indicate short-term fluctuations or long-term overload, a relative deviation measure is defined based on IEC 61000-3-7 and IEC 60038 standards:

$$r(t) = \left| \frac{I(t) - I_N}{I_N} \right| \tag{1}$$

where I_N is the rated current, and $I(t)$ represents the instantaneous current at time t. A current deviation fluctuation threshold r_0 is set; when $r(t)>r_0$, the power equipment is regarded as having a significant deviation. Another higher threshold h_0 is set to identify continuous overcurrent states. Within a monitoring cycle of n consecutive days, two cumulative time indicators are defined: T_r is the total cumulative duration satisfying $r(t)>r_0$, and T_h is the total cumulative duration satisfying $r(t)>h_0$. T_{max} is the maximum recorded temperature during the monitoring cycle, capturing potential overheating conditions. A binary variable $S \in \{0,1\}$ is introduced; when $S=1$, it indicates that the RMU is incorrectly installed.

Let set I = {1, 2, ..., n} be the set of all monitored RMUs. Normalize the priority detection indicators of each monitored RMU:

$$\widehat{T_{ri}} = \frac{T_{ri}}{\max_{j\in I} T_{rj}} \tag{2}$$

$$\widehat{T_{hi}} = \frac{T_{hi}}{\max_{j\in I} T_{hj}} \tag{3}$$

$$\widehat{T_{maxi}} = \frac{T_{maxi}}{\max_{j\in I} T_{maxj}} \tag{4}$$

Based on this, the risk coefficient R_i of RMU(i) is defined as the weighted sum of each normalized indicator:

$$R_i = \beta_1 \widehat{T_{ri}} + \beta_2 \widehat{T_{hi}} + \beta_3 \widehat{T_{maxi}} + \beta_4 S_i \tag{5}$$

where the weight coefficients $\beta_1, \beta_2, \beta_3, \beta_4 \geq 0$ can be preset or obtained through learning, reflecting the relative importance of each risk dimension. The detection frequency variable C_i tends to assign higher priority to RMUs with fewer detections. A binary emergency risk judgment index $E_i \in \{0,1\}$ is added; when $E_i = 1$, it indicates that the RMU has abnormal behavior. The calculation formula for the RMU maintenance priority score is as follows:

$$P_i = \gamma_1 R_i + \frac{\gamma_2}{C_i + 1} + \gamma_3 \cdot E_i \tag{6}$$

where the weight coefficients $\gamma_1, \gamma_2, \gamma_3 \geq 0$ correspond to the contribution degrees of long-term risk level, detection frequency, and emergency risk status, respectively.

2.2. Maintenance path optimization model

The core goal of the maintenance path optimization model is to optimize daily operation and maintenance efficiency. The model introduces a virtual node 0 representing the detection center, and defines the complete set of nodes as $V = \{0\} \cup I$. The optimized path must start and end at node 0, forming a closed loop. Based on the above goals, the following objective function is established:

$$\max \sum_{i\in I} P_i \cdot x_i - \lambda_o \cdot \max\left(0, T - T_{\text{std}}\right) - \lambda_u \cdot \max\left(0, T_{\text{std}} - T\right) \tag{7}$$

where x_i is a binary decision variable indicating whether node i is selected into the daily maintenance plan (1 if selected, 0 otherwise); λ_o is the unit penalty weight T_{std} when the total working hours exceed the standard working hours; λ_u is the unit penalty weight when the total working hours do not reach the standard working hours. The actual total working hours consist of path travel time and node service time, whose expression is:

$$T = \sum_{(i,j)\in V\times V} d_{ij} \cdot t_{ij} + \sum_{i\in I} s \cdot x_i \tag{8}$$

where d_{ij} represents the travel time required to move from node i to node j ; t_{ij} is a binary decision variable indicating whether the optimized path directly connects node i and node j (1 if connected, 0 otherwise); the constant s represents the fixed service time required to perform maintenance operations on a single RMU.

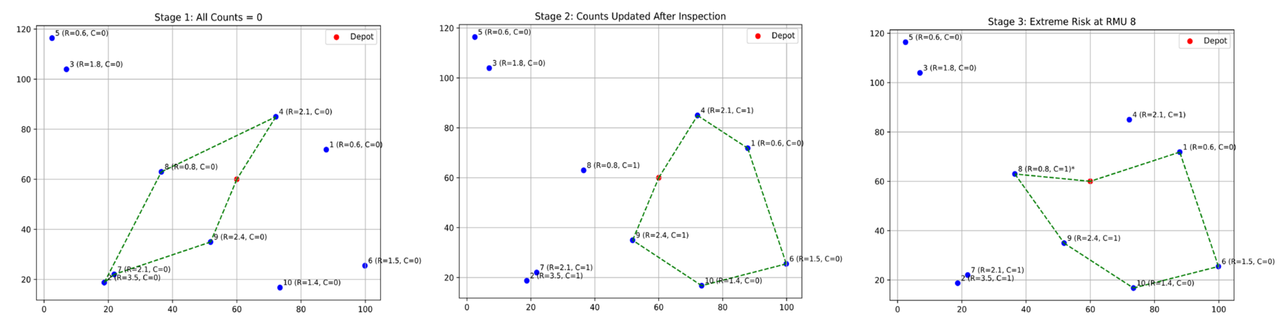
3. Simulation experiments

3.1. Simulation experiment design

The simulation experiment assumes that the travel time between any two points is linearly positively correlated with their Euclidean distance, and the detection time of a single RMU is fixed and uniform. Set N= 10 RMUs randomly distributed in a preset 60×60 area, with the detection center fixed at the coordinate center (30, 30); the detection time of a single RMU $s = 60$ minutes; the upper limit of standard daily working hours $T_{\text{std}} = 480$ minutes; the equipment risk score R_i is generated using a truncated normal distribution with a mean of 2 and a standard deviation of 1; the initial RMU maintenance count C_i = 0; the priority weights adopt default values $\gamma_1 = 1, \gamma_2 = 100, \gamma_3 = 1000$; the objective function penalty coefficients are set to \ $\lambda_o = 5, \lambda_u = 1$. All $C_i = 0$ and there is no emergency risk state ($E_i = 0$), generating each equipment risk score. Incrementally update the maintenance count of the RMUs selected in the first stage ($C_i \leftarrow C_i + 1$), and maintain the state of other equipment unchanged. Randomly select one equipment with $C_i = 1$ to mark the emergency state ($E_i = 1$), evaluating the model's forced response capability to sudden high-risk equipment [3].

3.2. Simulation result analysis

Adjust the parameter combination of priority score and time penalty weight to achieve differentiated maintenance strategies. Taking the default parameter configuration as an example (**Figure 1**):

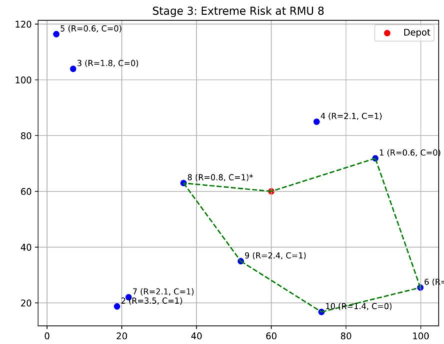


a) Path Selection Scheme Stage 1   b) Path Selection Scheme Stage 2   c) Path Selection Scheme Stage 3

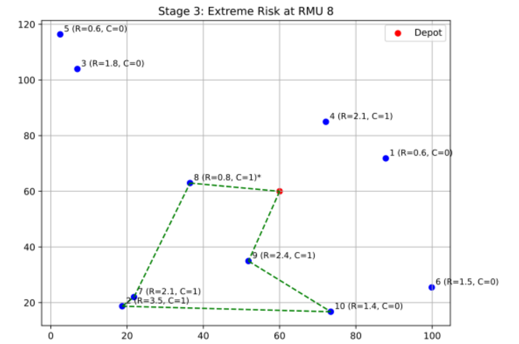
Figure 1. Path selection results considering time constraints and equipment priority

Figure 1 a) shows that when all RMU detection counts are initially zero, and there is no emergency risk, the model mainly selects nodes based on risk scores, with a total time consumption of 480.87 minutes, exceeding the standard working hours of 480 minutes by 0.87 minutes. **Figure 1** b) displays that after updating the maintenance count of the RMUs inspected in the first stage to 1, the model significantly shifts to equipment with low detection frequency, with a total time consumption of 478.60 minutes, close to full-load working hour utilization. **Figure 1** c) simulates a sudden emergency risk of RMU No. 8; the model forcibly includes it in the path regardless of its recent inspection record. This adjustment increases the total time consumption to 489.89 minutes, indicating that the model can accept moderate overtime to respond to emergency risks.

Figure 2 further reveals the influence mechanism of priority weights. When the detection frequency weight is reduced from 100 in **Figure 2** a) to 5 in **Figure 2** b), the path selection scheme tends to select high-risk equipment rather than equipment with low detection frequency.



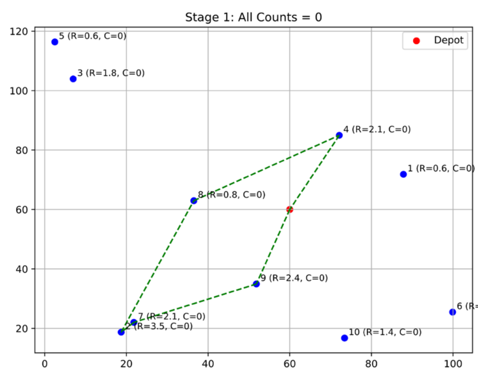
a) Path Selection Scheme with Higher Maintenance Frequency Weight



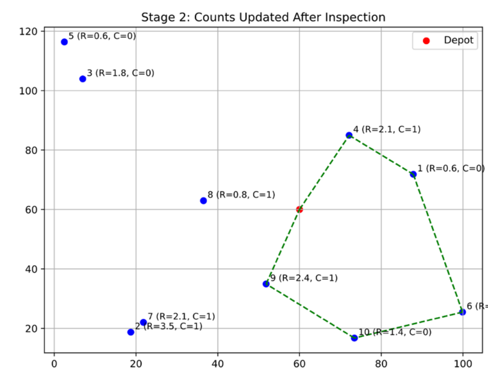
b) Path Selection Scheme with Higher Equipment Risk Score Weight

Figure 2. Comparison of path selection schemes under different priority weights

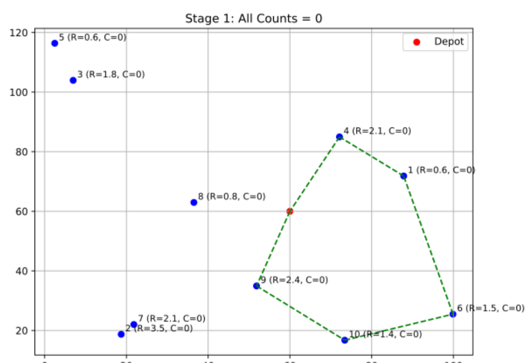
Figure 3 verifies the regulatory effect of time penalty weights. The comparison between **Figure 3** a) and **Figure 3** b) shows that enhancing the underload penalty of working hours can prompt the model to select more equipment in the second stage; **Figure 3** c) and **Figure 3** d) confirm that increasing the overtime penalty can effectively suppress the overtime phenomenon of paths in the first stage.



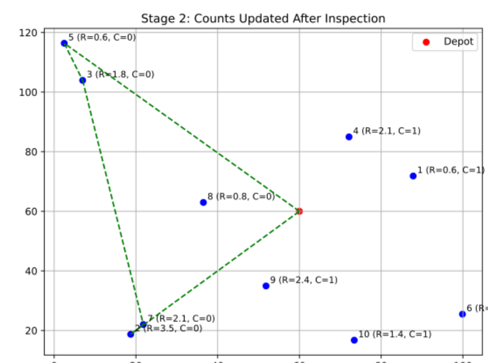
a) Path Selection Scheme Stage 1 (Low Underload Penalty)



b) Path Selection Scheme Stage 2 (Low Underload Penalty)



c) Path Selection Scheme Stage 1 (High Overtime Penalty)



d) Path Selection Scheme Stage 2 (High Overtime Penalty)

Figure 3. Comparison of path selection schemes under different time penalty weights

The experimental results fully verify that the model has the ability to dynamically adjust maintenance plans based on equipment historical detection records and real-time status (**Tables 1** and **2**). When equipment detection records are updated or sudden risk states occur, the model can actively reconstruct the detection path; the design of overtime and underload penalty parameters coordinates the balance between maximizing detection value and working hour utilization, ensuring that operation and maintenance decisions are both risk-sensitive and executable.

Table 1. Experimental results

Maintenance Strategy	Experimental Stage	Maintenance Path	Actual Total Working Hours
Default Strategy	Stage 1	[9, 7, 2, 8, 4]	480.87 min
	Stage 2	[4, 1, 6, 10, 9]	478.60 min
	Stage 3	[8, 9, 10, 6, 1]	489.89 min
Risk-Priority Strategy	Stage 1	[9, 7, 2, 8, 4]	480.87 min
	Stage 2	[4, 1, 6, 10, 9]	478.60 min
	Stage 3	[9, 10, 2, 7, 8]	481.04 min
Overtime Penalty-Priority Strategy	Stage 1	[4, 1, 6, 10, 9]	478.60 min
	Stage 2	[2, 7, 3, 5]	479.96 min

Table 2. Weight selection

Maintenance Strategy	Weights
Default Strategy	$\gamma_1 = 1, \gamma_2 = 100, \gamma_3 = 1000$, $\lambda_o = 5, \lambda_u = 1$
Risk-Priority Strategy	$\gamma_1 = 1, \gamma_2 = 5, \gamma_3 = 1000$, $\lambda_o = 5, \lambda_u = 1$
Overtime Penalty-Priority Strategy	$\gamma_1 = 1, \gamma_2 = 100, \gamma_3 = 1000$, $\lambda_o = 5, \lambda_u = 0.1$

4. Conclusion

Aiming at the inspection and scheduling problem of electrical equipment such as power RMUs under real constraints and intelligent monitoring conditions, this paper constructs a variant model of vehicle path planning integrating multi-dimensional decision-making factors. The model integrates three key parameters—real-time state risk of equipment, historical detection frequency, and sudden emergency risk—through a unified framework, realizing the systematic evaluation of maintenance priority.

A hierarchical priority decision-making mechanism is proposed: first respond to emergency risk equipment, then prioritize scheduling equipment with low detection frequency, and finally sort according to regular risk scores. Mathematical modeling is realized through weight constraints, and a penalty mechanism is introduced to handle travel and detection time constraints, maintaining decision flexibility while ensuring scheduling feasibility. This framework provides an extensible decision-making tool for smart grid equipment maintenance.

Disclosure statement

The authors declare no conflict of interest.

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