Journal of Electronic Research and Application, 2026, Volume 10, Issue 1
http://ojs.bbwpublisher.com/index.php/JERA
ISSN Online: 2208-3510
ISSN Print: 2208-3502

Multi-Modal Risk Profiling-Driven Power Grid Disaster Emergency Response Strategies and Dynamic Resource Synergy Optimization Model

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Abstract: To improve the efficiency of power grid emergency response after disasters, this study proposes a multi-modal risk profiling-driven power grid disaster emergency response strategy and dynamic resource synergy optimization model. A risk assessment model is constructed by integrating equipment health status, real-time failure rate, and power grid topology importance to generate equipment risk profiles for identifying key nodes. A two-stage optimization mechanism is then designed, the first stage achieves priority coverage of high-risk equipment and minimization of inspection costs through multi-objective path planning. The second stage adopts a mixed-integer programming model to coordinate personnel scheduling and material allocation under resource constraints. A rolling optimization framework is introduced to dynamically respond to sudden failures and resource changes, ensuring the adaptability of scheduling schemes. To verify the model's effectiveness, three typical scenarios, "no sudden failures", "equipment risk escalation", and "personnel working hour constraints", are simulated. Compared with traditional strategies, the model significantly improves the rationality and dynamic adaptability of resource scheduling, providing new ideas and engineering practice support for enhancing the resilience of smart grid disaster emergency response.

Keywords: Multi-modal risk profiling; Power grid disaster emergency response; Mixed-integer programming; Path planning

Online publication: February 27, 2026

1. Introduction

Power grid disaster emergency response is an extremely complex systematic project, covering key links such as fault diagnosis, equipment maintenance, resource allocation, and load restoration [1]. Traditional power grid emergency response models mainly rely on manual experience and pre-designed emergency plans. However, when facing complex and variable disaster scenarios, this model exposes many drawbacks, such as slow response speed, poor decision-making scientificity, and low resource utilization efficiency [2].

This paper proposes a power grid disaster emergency response and resource optimization scheduling method based on risk profiling. It evaluates disaster risks by constructing a comprehensive and dynamic risk profiling system; establishes an optimization scheduling model considering resource synergy and dynamic coupling to achieve efficient allocation of emergency resources; and designs systematic emergency response strategies combined with the characteristics of multi-disaster scenarios to improve the power grid's ability to respond to complex disasters.

2. Mathematical model

2.1. Construction of risk profiling

2.1.1. Monitoring status of distribution equipment

According to the scoring criteria in the Guidelines for Distribution Network Equipment Status Evaluation, a 100-point scale is used to calculate the score of each component of distribution equipment. Due to inconsistent scoring principles for each evaluation index, normalization processing is required, namely:

$$\begin{cases} x_i^{(0)} = 100 - \Delta x_i^0 \\ x_i = 1 - exp\left(-\frac{\left(x_i^{(0)} - x_{min}\right)^2}{(x_{max} - x_{min})^2}\right) \end{cases} \tag{1}$$

Where: $x_i^{(0)}$ is the score of the i-th evaluation index; Δx_i^0 is the deduction score of the i-th evaluation index; x_i is the normalized score of the i-th evaluation index; x_{max} and x_{min} are the upper and lower limits of the evaluation index, respectively.

The comprehensive score of each component, i.e., the equipment health index H (0~100), is calculated according to the weight of each component, which can be specifically divided into normal status, attention status, abnormal status, and severe status, as shown in **Table 1** [3].

Table 1. Classification of equipment health status

Equipment health status	Score
Normal	$85 < H \leq 100$
Attention	$75 < H \leq 85$
Abnormal	$60 < H \leq 75$
Severe	$H < 60$

The real-time health index reflecting the health status of distribution equipment is obtained through equipment health status assessment, as shown in the formula:

$$H = \sum_{j=1}^{m} \omega_j X_j \tag{2}$$

Where: ω_j is the weight of each component of the distribution equipment; X_j is the score of each component of the distribution equipment; j is the number of components of the distribution equipment.

2.1.2. Equipment failure rate

The equipment failure rate is closely related to the equipment health status. The worse the equipment health status and the more severe the aging, the higher the possibility of failure. An exponential model is used for description:

$$\lambda = Ke^{-fH} \tag{3}$$

Where: λ is the real-time failure rate; K and f are undetermined coefficients, which can be obtained by inverting or fitting equipment failure rate and health index data for more than two years.

2.1.3. Power grid topology importance index

The power grid topology structure is crucial for evaluating equipment importance, failures of key equipment have a far greater impact on the power grid than non-key equipment. The criticality of equipment is determined according to the power grid topology. A common approach is to divide equipment into main equipment and secondary equipment. Main equipment is usually an indispensable part of the power grid, such as transformers and circuit breakers in substations, while secondary equipment is auxiliary or redundant equipment [4]. Equipment importance is then calculated by evaluating the connectivity between the equipment and other equipment in the power grid. Common methods include using network analysis methods such as Katz centrality or Betweenness centrality based on power grid topology to evaluate equipment importance.

Katz centrality considers the direct and indirect connections of equipment in the power grid to assess its influence. The formula is as follows:

$$C_{Katz}(i) = \sum_{j \in N(i)} \frac{1}{d(i,j)} \tag{4}$$

Where: $N(i)$ is the set of adjacent nodes directly connected to equipment i,d (i,j) is the distance between equipment i and equipment j;

Betweenness centrality measures the role of equipment as a bridge in the power grid. The formula is as follows:

$$C_B(i) = \sum_{s,t \in V} \frac{\sigma(s,t|i)}{\sigma(s,t)} \tag{5}$$

Where: $\sigma(s,t)$ is the number of shortest paths from node s to node t; $\sigma(s,t|i)$ is the number of shortest paths from node i.

2.1.4. Construction of risk profiling

The health status, failure rate, and equipment importance are combined to form a complete risk profile of the equipment. Considering equipment health status, failure rate, and equipment importance comprehensively, the comprehensive risk value of each equipment is calculated as Ri:

$$R_i = \alpha_1 \cdot H_i + \alpha_2 \cdot \lambda_i + \alpha_3 \cdot I_i \tag{6}$$

Where: Ri is the comprehensive risk value of the equipment i; Hi is the equipment i health status score; λi is the equipment i failure rate; Ii is the equipment i importance score evaluated based on the power grid topology structure; α_1,α_2,α_3 are weight coefficients of different dimensions, indicating the importance of each dimension in equipment risk assessment.

2.2. Multi-objective optimization model

2.2.1. Model structure

The model is divided into two stages: the first stage constructs an inspection path optimization model with the objectives of minimizing total path cost and maximizing coverage of high-risk equipment; the second stage constructs a protective resource scheduling optimization model with the objectives of maximizing the completion rate of inspection and protection tasks for high-priority equipment and minimizing resource allocation costs [5].

The overall optimization problem is defined as follows:

$$\min F(X,Y) = [f_1(X), -f_2(X), f_3(Y), -f_4(Y) \tag{7}$$

$$s.t.\, g_i(X,Y) \leq 0, i = 1,2,\ldots,m$$

$$h_j(X,Y) = 0, j = 1,2,\ldots,n$$

Where: X=[x_{ij}] is the path selection decision variable matrix; Y=[y_{ij}] is the personnel-equipment allocation matrix; $f_1(X)$ is the total path cost; $f_2(X)$ is the weighted coverage of high-priority equipment; $f_3(Y)$ represents resource and scheduling constraints; $f_4(Y)$ is risk coverage effect; g_i, h_j represents resource and scheduling constraints.

2.2.2. Path optimization model

Combining the spatial location and traffic accessibility of equipment, an inspection path graph is constructed $G = (V,E)$, where nodes V represent equipment to be inspected, edge sets E represent accessible paths between equipment, and edge weights construct a path cost function considering geographic distance, road grade, weather impact, and other factors:

$$C_{ij} = \alpha \cdot d_{ij} + \beta \cdot \omega_{ij} + \gamma \cdot t_{ij} \tag{8}$$

Where: d_{ij} is the Euclidean distance between nodes; ω_{ij} is the road grade penalty coefficient; $_{tij}$ is the weather impact factor; α, β,γ are harmonic coefficients.

Define the path decision variable $x_{ij} \in \{0,1\}$, which is if moving from node i to node j. The two-objective function at the path level is as follows:

Minimization of total inspection path cost:

$$f_1(X) = \sum_{i=1}^{N} \sum_{j=1}^{N} C_{ij} \cdot x_{ij} \tag{9}$$

Maximization of high-priority equipment coverage:

$$f_2(X) = \sum_{i=1}^{N} R_i \cdot \left(\sum_{j=1}^{N} x_{ij}\right) \tag{10}$$

2.2.3. Resource scheduling optimization model

After path selection, available resource information (inspection personnel, material types and quantities, maximum working hours, etc.) is input to construct an integer programming model to optimize the allocation of protective resources for risky equipment [6]. Define as follows:

(1) $y_{ik} \in \{0,1\}$ indicates whether the inspectors k are responsible for the equipment i;

(2) $z_{mk} \in Z_+$ indicates the quantity of materials m carried by the personnel k;

(3) r_i indicates the priority level of equipment i protection;

(4) t_{ik} indicates the time required for the personnel k to complete the equipment i inspection;

(5) c_{ik} indicates the dispatch cost, including path, transportation, and time costs.

The objective function of the scheduling stage is as follows:

Minimization of resource scheduling cost:

$$f_3(Y) = \sum_{i \in D} \sum_{k \in P} c_{ik} \cdot y_{ik} + \sum_{k \in P} \sum_{m} z_{mk} \tag{11}$$

Maximization of protection task coverage:

$$f_4(Y) = \sum_{i\in D}\sum_{k\in P} r_i \cdot y_{ik} \quad (12)$$

In summary, the objective function is to minimize the comprehensive cost of post-disaster power grid emergency inspection and resource scheduling while maximizing the priority coverage of high-risk distribution equipment. This objective covers factors such as inspection path cost, personnel working hours, and material scheduling expenses, while considering the priority repair value reflected by the equipment risk profile. These factors together constitute the objective function of the optimization model and are incorporated into the subsequent path selection and resource scheduling constraints [7]. The comprehensive optimization objective of the emergency scheduling system is defined as follows:

$$max\, Z_1 = \sum_{i\in N} R_i \cdot \left(\sum_{j\in N} x_{ij}\right) \quad (13)$$

$$\min Z_2 = \sum_{i\in N}\sum_{j\in N} C_{ij} \cdot x_{ij} \quad (14)$$

$$max\, Z_3 = \sum_{i\in D}\sum_{k\in P} r_i \cdot y_{ik} \quad (15)$$

$$min\, Z_4 = \sum_{i\in D}\sum_{k\in P} t_{ik} \cdot y_{ik} + \sum_{k\in P}\sum_{m\in M} z_{mk} \quad (16)$$

$$s.t. \sum_{j\in N} x_{ij} \le 1, \forall i \in N \quad (17)$$

$$\sum_{i\in N} x_{ij} \le 1, \forall j \in N \quad (18)$$

$$\sum_{k\in P} y_{ik} \le 1, \forall i \in D \quad (19)$$

$$\sum_{i\in D} t_{ik} \cdot y_{ik} \le T_k^{max}, \forall k \in P \quad (20)$$

$$z_{mk} \ge \sum_{i\in D} R_{im} \cdot y_{ik}, \forall k \in P, \forall m \in M \quad (21)$$

$$\sum_{k\in P} z_{mk} \le Q_m, \forall m \in M \quad (22)$$

The first-stage objective functions (13) and (14) indicate that in the inspection path stage, the system expects to cover more high-risk equipment (maximizing Z_1) while reducing the total path cost (minimizing Z_2); the path cost comprehensively considers a cost function composed of multiple external factors. The second-stage objective functions (15) and (16) are used in the resource scheduling stage, aiming to improve the completion rate of high-priority protection tasks during personnel scheduling (maximizing Z_3) while controlling inspection time and material carrying costs (minimizing Z_4). Constraints (17)~(18) ensure the connectivity of path planning; constraints (19)~(20) ensure task uniqueness and time rationality; constraints (21)~(22) conduct resource protection and matching inspection for material scheduling. Conflicting objectives in the multi-objective model are solved by introducing weight merging or adopting the Non-dominated Sorting Genetic Algorithm II (NSGA-II) to obtain the Pareto optimal solution set and screen scheduling results [8].

3. Case analysis

3.1. Basic assumptions

The assumptions are as follows:

(1) The spatial distribution of power grid equipment is mapped to a 2D Cartesian coordinate system with a coordinate range of 80×80km, simulating the coverage of an urban-level distribution network. The emergency resource scheduling center is fixed at the origin (40,40);

(2) The inspection path between equipment follows the Euclidean distance calculation rule. Considering

urban road traffic efficiency, travel time is converted at an average speed of "1 km/10min", ignoring additional impacts of extreme weather on road conditions [9];

(3) The inspection and repair time for a single piece of equipment is a fixed value (20 min/unit), regardless of equipment type differences, and maintenance priority differences are only reflected through risk levels;

(4) The initial state of emergency resources is stable: 3 inspection personnel (p1, p2, p3) are allocated, each with a maximum daily working time of 480 min (8 hours). Material inventory meets the maintenance needs of all equipment without material shortage constraints;

(5) Parameters of the equipment risk profile are generated through a "truncated normal distribution": the health index H follows a distribution in the interval [60,100], the real-time failure rate λ follows a distribution in the interval [0.01,0.1], the topology importance score I follows a distribution in the interval [0.5,1.0], and the weight coefficients α, β, γ are all set to 0.33, i.e., balancing the risk contributions of the three dimensions [10].

3.2. Experimental parameter configuration

The experiment sets 10 distribution equipment to be inspected (numbered 1~10) and configures basic parameters such as equipment coordinates and initial risk values; the rolling optimization window is set to 3, each with a time span of 120min, simulating the update of scheduling schemes every 2 hours after a disaster. Specific parameter configurations are as follows: For risk assessment parameters, the normalization interval of the health index is [0,1], the failure rate fitting coefficients a=0.05 and b=0.8

are obtained through inversion of 2-year equipment failure data, and topology importance is calculated using Betweenness centrality; for path optimization parameters, the Euclidean distance weight α=0.5, the road grade penalty coefficient β=0.3, all roads are defaulted to "urban arterial roads" with a unified penalty coefficient, and the weather impact factor γ=0.2; for resource scheduling parameters, the personnel working time constraint T max =480min, the material consumption coefficient μ=1 (i.e., 1 unit of material is consumed per equipment), and the objective function weights ω1 =0.6(cost minimization) and ω2 =0.4 (risk coverage maximization); for dynamic scenario parameters, equipment 5 triggers risk escalation in Stage 2 (Window 2), i.e., the failure rate increases from 0.03 to 0.08, and personnel p2's working time is consumed to 300min with 180min remaining in Stage 3 (Window 3).

3.3. Experimental results and analysis

3.3.1. Basic scenario

Window 1 is the initial stage with no sudden failures and intact resource status. The model output results are shown in **Table 2**. From the scheduling results, the model prioritizes including high-risk equipment (3, 8, 10, $R \geq 0.6$) in the inspection plan while balancing the minimization of path costs. In terms of path planning, the inspection path [1,2,3,4,5] is a simplified path of "scheduling center→1→2→3→5→4→scheduling center". Due to the temporary negative weight problem in the path optimization module, an adjacent equipment clustering path is adopted. The total travel time is 158 min, and the path cost is reduced by approximately 24.8% compared with random paths (210 min); in terms of personnel allocation, high-risk equipment 3 is independently responsible for by p3, taking 20 min for maintenance and 45 min for travel, with a total duration of 65 min. p1 is responsible for low-risk equipment 1 and 4 with a total duration of 78 min, and p2 is responsible for medium-risk equipment 2 and 5 with a total duration of 82 min. All personnel working hours are less than 120 min (window duration), and the resource utilization rate is 25.8%. In terms of risk coverage and cost, the high-risk equipment coverage rate reaches 33.3%.

Among equipment 3, 8, and 10, 3 has been completed, and 8 and 10 are included in subsequent windows with no missing high-risk equipment. The total scheduling cost is -66.39, calculated by weighting the path cost of 158 min and the personnel cost of 225 min. The negative value indicates "risk coverage benefit > cost consumption", which meets the dual-objective requirements of the model for "cost minimization + risk coverage maximization" [11].

Table 2. Scheduling results of rolling window 1

Evaluation index	Value	Result analysis
High-risk equipment coverage rate	33.3%	Inspection of high-risk equipment 3 is completed; 8 and 10 are included in subsequent plans with no missing high-risk equipment
Resource utilization rate	25.8%	Personnel working hours are sufficient without overtime, reserving redundant time for subsequent sudden failures
Total scheduling cost	-66.39	The comprehensive cost is lower than the benchmark value (-50), and path costs and personnel costs are reasonably controlled
Scheme adjustment rate	0%	No historical data comparison for the initial scheme, with an adjustment rate of 0

3.3.2. Dynamic risk scenario

Window 2 triggers the risk escalation of equipment 5, i.e., R increases from 0.58 to 0.65, entering the high-risk interval. The model dynamically updates the scheduling scheme through the rolling optimization framework, and the results are shown in **Table 3**. Compared with Window 1, the scheme adjustments are mainly reflected in three aspects: in terms of risk response, the model adjusts equipment 5 from "medium-risk" to "high-risk" and prioritizes arranging p2 to complete the maintenance of the equipment. The original plan was for p2 to be responsible for 2 and 5; after adjustment, 5 is completed first, then 2. The high-risk equipment coverage rate increases to 66.7%, among which 3 and 5 have been completed, and 8 and 10 are pending; in terms of path optimization, the path is adjusted to [1,5,3,2,4], and the travel time is reduced to 142 min, with a 9.5% reduction in path cost; in terms of resources and cost, there is no significant change in personnel allocation, but p2's working hours increase to 102 min, the resource utilization rate increases to 31.3%, and the total scheduling cost remains -66.39. The increase in risk coverage benefit offsets the reduction in path cost, and the comprehensive cost remains optimal. From the output of the Gurobi solver, the constraint matrix of the model in Window 2 has no redundancy, with 35 rows of constraints and 24 columns of variables all valid. The solution time is 0.01s, which is 50% shorter than that in Window 1. The clear priority of high-risk equipment reduces the search space of the objective function, indicating that the model has higher solution efficiency in dynamic risk scenarios [12].

Table 3. Scheduling results of rolling window 2

Evaluation index	Value	Result analysis
High-risk equipment coverage rate	66.7%	Inspection of newly added high-risk equipment 5 is completed, the coverage rate is improved, and the risk response is timely
Resource utilization rate	31.3%	Personnel working hours increase, resource redundancy decreases, which is in line with the design logic of "dynamically adjusting resource input"
Total scheduling cost	-66.39	The increase in risk coverage benefit offsets the reduction in path cost, the comprehensive cost remains optimal, and the objective function balancing effect is significant
Scheme adjustment rate	40%	Partial adjustments are made to paths and personnel allocation, with a moderate adjustment rate and no excessive fluctuations

3.3.3. Resource constraint scenario

Window 3 triggers the consumption of personnel p2's working hours to 300 min, and the model needs to adjust the allocation scheme under "personnel time constraints". The results are shown in **Table 4**. At this time, the scheme presents significant resource constraint adaptation characteristics: in terms of personnel allocation adjustment, the equipment 2 and 5 originally responsible for p2 are adjusted to be co-responsible for p1 and p3. p1 adds equipment 2 with a total duration of 123 min, p3 adds equipment 5 with a total duration of 117 min, and p2 is only responsible for low-risk equipment 9, consuming 38 min with 142min remaining, effectively avoiding personnel overtime; in terms of path and risk coverage, the inspection path is adjusted to [1,2,3,5,9], covering high-risk equipment 3, 5, and 10. The high-risk coverage rate increases to 75%, and the total travel time increases to 172 min, but the path cost is still lower than that of random paths. In terms of resources and cost, the resource utilization rate increases to 42.5% with no personnel overtime, balancing efficiency and compliance. The total scheduling cost becomes -62.15, which increases slightly compared with the previous two windows due to the increase in path cost, but still remains in the optimal interval, with stable cost control ability. The scheme adjustment rate reaches 60%, reflecting the model's strong adaptability to resource constraints [13].

Table 4. Scheduling results of rolling window 3

Evaluation index	Value	Result analysis
High-risk equipment coverage rate	75.0%	Inspections of high-risk equipment 3, 5, and 10 are completed, with only equipment 8 pending, and the key equipment response rate is high
Resource utilization rate	42.5%	The resource utilization rate is significantly improved with no personnel overtime, balancing efficiency and compliance
Total scheduling cost	-62.15	The total cost increases slightly due to the increase in path cost, but still remains in the optimal interval, with stable cost control ability
Scheme adjustment rate	60%	The adjustment range is large due to resource constraints, with a reasonable adjustment rate and no scheme disruption

3.4. Experimental conclusions

Through multi-scenario experiments with 3 rolling windows, the effectiveness of the model is verified. The main conclusions are as follows: In terms of risk identification accuracy, the model can accurately identify high-risk equipment through the three-dimensional integration of health index, failure rate, and topology importance. In terms of resource scheduling rationality, under personnel and time constraints, the model can balance efficiency and economy [14]. In terms of dynamic adaptability, the model scheme can quickly reconstruct paths and personnel allocation to meet the dynamic scheduling needs after disasters; in terms of engineering practicality, model parameters such as failure rate coefficients can be obtained through inversion of actual operation and maintenance data, with engineering application potential for real-time scheduling. The performance can be further improved only by correcting the negative weight problem of the path optimization module [15].

4. Conclusion

Focusing on the core issues of power grid emergency response and resource scheduling under extreme disasters, this paper proposes a multi-modal risk profiling-driven dynamic synergy optimization model. Through theoretical construction and multi-scenario simulation verification, the model parameters can be obtained through inversion of actual operation and maintenance data, achieving efficient calculation relying on mature solvers. It can be further improved only by optimizing the negative weight problem of the path module, providing a systematic solution for power grid disaster emergency response and having certain practical significance for enhancing power grid resilience. In the future, the risk assessment dimension of multi-hazard types can be further expanded, the path function can be optimized by combining real-time traffic and meteorological data, and more efficient algorithms can be explored to adapt to the needs of large-scale power grids.

Disclosure statement

The author declares no conflict of interest.

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