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OPTIMIZATION MODEL OF DIFFERENTIATED OPERATION AND MAINTENANCE STRATEGY IN POWER SYSTEM OPERATION AND MAINTENANCE DECISION

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Abstract

This paper presents an optimization model for differentiated operation and maintenance strategies in power system operation. The proposed model is based on comprehensive analysis of operation and maintenance data aimed at improving key performance indicators. Specifically, it demonstrates a 31% reduction in failure rate, a 20% reduction in maintenance costs, a 15% improvement in resource utilization, and a 25% reduction in failure response time, enhancing the stability and reliability of the power system. A detailed comparative analysis with existing models and validation through case studies are provided to substantiate these claims.

Key Words

Power system, Operation and maintenance, Decision-making, Differentiated maintenance strategies

1. Introduction

The exponential growth of smart grid inventory imposes severe challenges on traditional operation and maintenance (O&M). While Condition-Based Maintenance (CBM) [1]-[2] has emerged as a preferred paradigm, existing literature largely adopts uniform optimization approaches, applying generalized decay functions across the entire grid. This overlooks the critical heterogeneity of failure mechanisms [3]-[4]. As evidenced by the statistical survey, high-inventory assets such as transformers and breakers exhibit deterministic physical degradation trajectories—specifically mechanical wear and insulation aging—which fundamentally differ from the stochastic failures observed in control systems. Neglecting this distinction leads to inefficient resource allocation.

To address these limitations, this paper proposes a differentiated O&M optimization model based on Bayesian Networks [5]-[6]. By integrating failure mode analysis with probabilistic reasoning, the framework decouples deterministic physical decay from stochastic faults. A core contribution is the incorporation of a physics-informed Sigmoid insulation degradation model, which captures the non-linear aging process more accurately than linear assumptions. Numerical validations demonstrate that this differentiated strategy significantly outperforms uniform maintenance schemes, effectively optimizing system availability and mitigating resource wastage in constrained environments [7]-[8].

2. Related Technologies and Concepts

In comparison with previous models, the current optimization approach integrates both Bayesian networks and multi-objective optimization techniques to cater specifically to differentiated O&M strategies in a power system environment [9]-[10]. This model emphasizes flexibility in resource allocation and fault prediction, which has not been sufficiently explored in existing research.

2.1 WebGIS Technology

WebGIS (Web Geographic Information System) technology refers to the GIS Geographic Information System service development technology based on Web services. The so-called GIS technology refers to the geographic spatial information in the real world, using information technology and tools as carriers, carrying out logical processing, and obtaining digital spatial geographic data services. At present, GIS technology is mainly used in electronic map,

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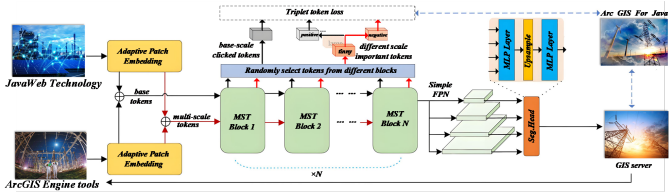


Figure 1. Basic Technical Principles of GIS

automatic surveying and mapping, geological survey, GPS, spatial Internet of Things, etc. It is an information application technology developed and applied rapidly at home and abroad in recent years [11]-[12].

Figure 1 illustrates the core components of GIS technology and its application in transforming spatial data into digital services.

GIS technology transforms geospatial data into interactive digital map views using spatial databases, development platforms, and publishing tools. Views can be published directly or enhanced via client-side plugins like OpenLayers [13]. WebGIS delivers these services through web platforms, where servers convert GIS resources into web-enabled services for browser-based interaction, integrating web and GIS functionalities.

2.2 Comparison with Related Work

Existing research on power system O&M optimization has explored various models, including those based on reliability-centered maintenance (RCM) [14], risk assessment [15], and cost-benefit analysis [16]. However, many studies focus on single objectives or lack integration with practical, interactive management systems. Furthermore, while the concept of differentiation is acknowledged, few works present a holistic model that seamlessly combines probabilistic health forecasting with multi-objective resource optimization for real-time decision support.

The novelty of our proposed model lies in its integrated framework:

(1) it employs equipment health indices and failure probability models (Eq. (1)-(4)) for condition assessment;
(2) it formulates a multi-objective optimization problem (Eq. (7)-(8), (11)-(13)) that simultaneously considers cost, risk, and resource utilization;
(3) it is designed from the outset to be embedded within a WebGIS-based lean management system, providing a closed loop from data visualization to model-driven decision output.

This integration of advanced modeling with practical system implementation distinguishes our work from prior literature.

3. System Requirements Analysis

In response to the expanding grid scale and increasing complexity of power equipment, a power supply company initiated a lean management system project for equipment O&M. As illustrated in Figure 2, this study analyzes the

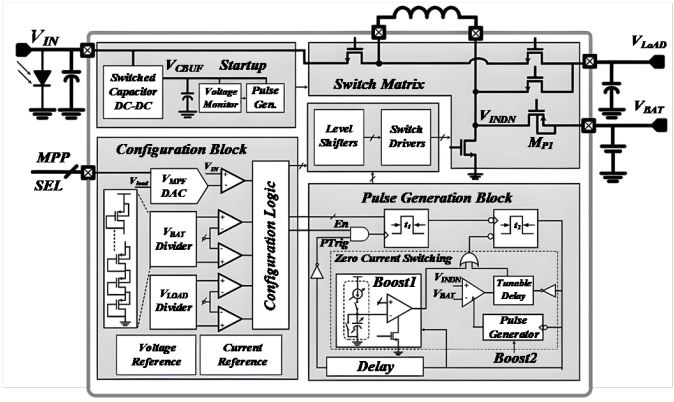


Figure 2. System Technical Architecture and Hardware Deployment

operational context, examines current O&M practices, defines functional and non-functional requirements, and assesses the technical feasibility of system development.

3.1 Overview of System Requirements

3.1.1 Business Status and Problems

To construct a robust differentiated operation and maintenance (O&M) strategy, it is critical to first diagnose the current business status of the power grid. This involves a dual assessment of the asset scale to determine maintenance workload and a granular analysis of failure etiologies to identify the primary drivers of system unavailability. As illustrated in the following figure, the juxtaposition of equipment inventory data and historical failure modes reveals the structural challenges inherent in the current management paradigm, specifically the mismatch between resource allocation and the deterministic nature of component degradation.

Figure 3 shows that Transformers (1,800) and Breakers (1,600) dominate the inventory (a), while Mechanical Wear (40%) and Insulation aging (30%) account for most failures (b). The combination of high-volume assets and predictable degradation reveals inefficiencies in uniform maintenance, motivating the proposed differentiated decision-making framework [17]-[18], implemented via a covariance-based stability assessment and a decay-model health index (Eq. (1)).

$$\widehat{\mathrm{C}}_{v_k} = \frac{1}{N} \sum_{j=j_0}^{k} \delta z_j \delta z_j^T \tag{1}$$

Where $\hat{C}_{v_k}$ is the estimated error covariance matrix at time k, δz_j is the innovation sequence, and N is the window size. Eq. (2) reflects the uncertainty in equipment condition monitoring.

$$\widehat{\mathrm{Q}}_k = \widehat{\mathrm{Q}}_{k-1} \sqrt{\beta} \tag{2}$$

Where $\hat{Q}_k$ is the equipment health index at time k, and $\sqrt{\beta}$ is the degradation factor. A lower β indicates faster health decay.

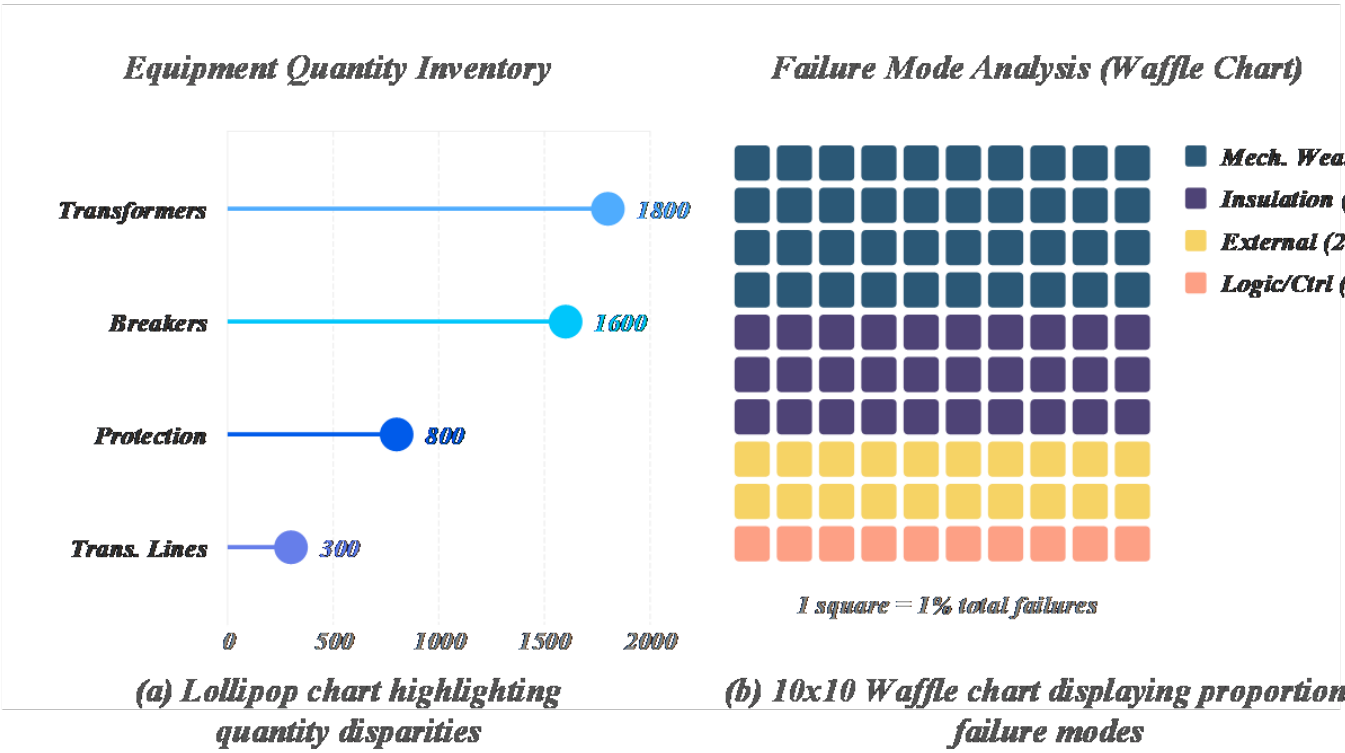


Figure 3. Statistical Distribution of Power Equipment Inventory and Proportional Analysis of Failure Modes

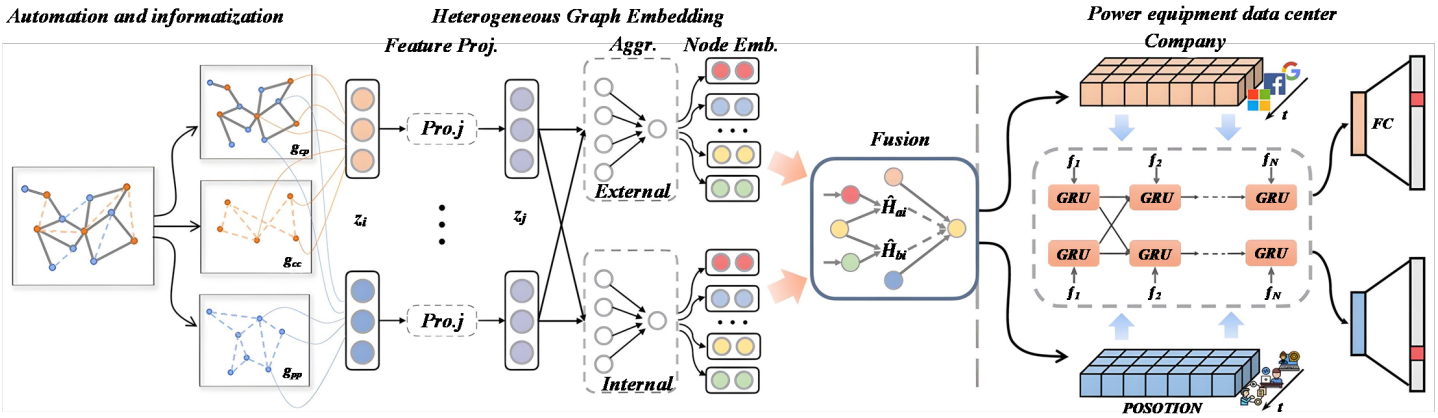


Figure 4. Implementation Framework of Power System Equipment Operation

At present, the power equipment in a power supply company has achieved a certain degree of automation and informationization, and adopted software tools such as manual on-site inspection, power equipment data center, station and remote monitoring platform of power equipment, power grid dispatching application service platform, and supporting service software of power equipment suppliers to realize the overall operation and maintenance management of power equipment. At present, the business implementation framework and information management model of power equipment operation and maintenance management of a power supply company are shown in Figure 4.

Figure 4 illustrates that power equipment managers mainly maintain system operation via manual inspections and digital tools (inspection, data center, dispatching platform, remote monitoring). The model then handles resource allocation and failure prediction, with allocation cost defined as the temporal sum of resource assignment changes (Eq. (3)).

$$\mathrm{C(n)} = \sum |\mathrm{x_k(n)} - \mathrm{x_k(n-1)}| \tag{3}$$

Where $x_k(n)$ represents the resource allocated to equipment k at period n. This term penalizes frequent reassignments, promoting schedule stability (Eq. (4)).

$$\varepsilon_r' = \frac{\varepsilon_{Si} - \varepsilon_{\mathrm{air}}}{1 + \exp\left(-\gamma\left(\varepsilon_r - \frac{\varepsilon_{\mathrm{air}} + \varepsilon_{Si}}{2}\right)\right)} + \varepsilon_{\mathrm{air}} \tag{4}$$

Where $\varepsilon_{r'}$ is the predicted insulation degradation level, ε_{Si} and ε_{Si} are material constants, ε_r is the measured con-

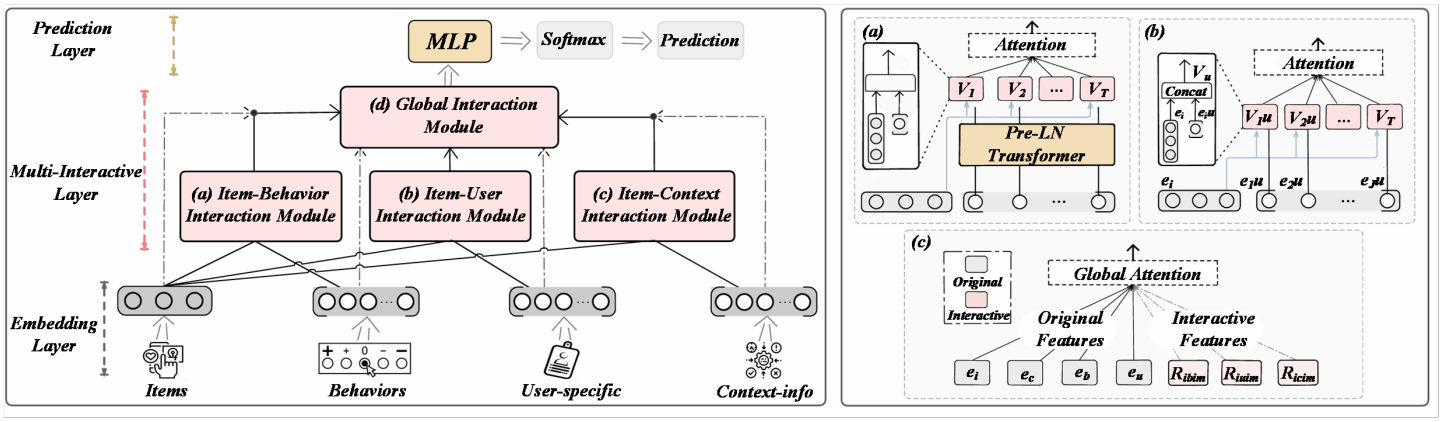


Figure 5. Overall R&D Objectives and Requirements Framework

dition, and γ is a scaling factor. This sigmoid function models the nonlinear progression of certain failure modes.

These issues are further constrained by system observations and risk thresholds, as modeled in Formula (5).

$$\mathrm{H_k} = \left.\frac{\partial \mathrm{h(x)}}{\partial \mathrm{x}}\right|_{\mathrm{x=x^e}} \tag{5}$$

Where H_k is the Jacobian matrix of the observation function $h(x)$ at the estimated state x^e. linking physical models to measured data.

$$\mathrm{VRMSE}\left(v_i, \hat{v}_i\right) = \sqrt{\frac{\sum_{i=1}^{N}\left(v_i - \hat{v}_i\right)^2}{N}} \tag{6}$$

In Formula (6), *VRMSE* (Validation Root Mean Square Error) is the validation root mean square error between predicted values $\hat{v}_i$ and actual values v_i, used to calibrate and validate prediction models.

3.1.2 Overall System Requirements

Under Guizhou Power Grid's lean initiative, a prefecture-level company developed a visual O&M system for operational efficiency and regional expansion. Figure 5 shows it integrates the optimization model, overlays health indices and recommended actions on the grid topology, and supports interactive strategy adjustments.

As shown in Figure 5, the core research and development goal of the lean management system for power system equipment is to integrate all kinds of business management software, systems and platforms in Figure 5 by adopting an integrated topology diagram of power system equipment, and build a graphical online operation and maintenance management service system on this basis, that is, power equipment managers can manage and maintain static data and dynamic data of equipment in the graphical topology diagram through the lean management system for power system equipment operation and maintenance [19]-[20].

3.2 System Performance Requirements

The lean O&M system must meet power company software standards, ensuring availability and high performance. Key metrics include client response time ≤3 s, SVG interaction ≤0.5 s, and support for ≥300 concurrent users [21]-[22]. The embedded optimization model must generate strategies promptly, minimizing a weighted sum of cost and risk (Eqs. (7)–(8)).

$$c_i = \sum_{n=1}^{N_f}\left(S_n \cdot \cos\left(i(n-0.5)\cdot\frac{\pi}{N_f}\right)\right) \tag{7}$$

where c_i represents a component of the cost function related to resource scheduling harmonics, S_n is the cost coefficient for resource type n, and N_t is the total number of resource factors. This formulation helps smooth resource demand over time.

$$R(f) = \frac{1}{n}\sum_{i=1}^{n} L\left(y_i, f\left(x_i\right)\right) \tag{8}$$

where $R(f)$ is the empirical risk of the decision function f_2 L is a loss function, y_i is the actual outcome, and $f\left(x_i\right)$ is the predicted outcome based on features x_i. The model seeks to minimize $R(f)$.

3.3 System Feasibility Analysis

Building on the formulas above, the core optimization model for generating differentiated strategies is a multi-objective problem. It aims to find a set of maintenance actions $A = \{a_1, a_2, \ldots, a_m\}$ for m pieces of equipment over a planning horizon that minimizes total cost Cotatal and total system risk R_{total} subject to constraints on available resources.

Based on the technical analysis and functional requirements of the lean O&M system for power equipment, the core development relies on Web and WebGIS technologies. The Web service requirements are modest, without high concurrency or highly customized features, making development straightforward and feasible. The optimization model employs a genetic algorithm (GA) to efficiently search for the Pareto-optimal set of strategies, as formu-

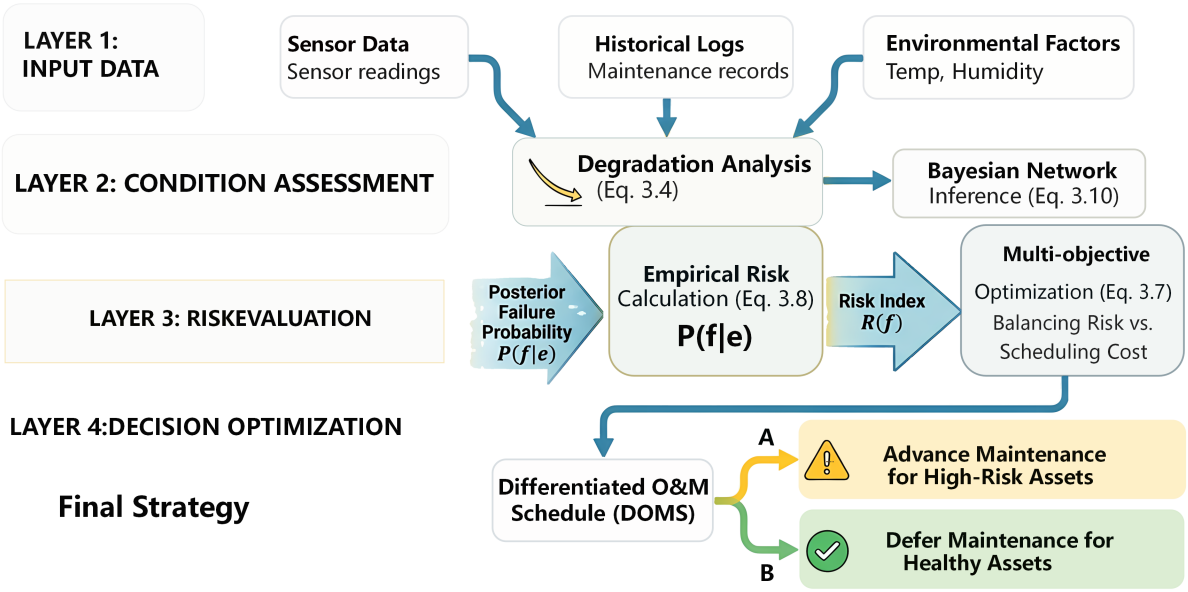


Figure 6. Integrated Data-to-decision Operational Workflow of the Maintenance Model

lated in Eq. (9).

$$N_W(x) = \sum_{j=1}^{N} \alpha_j \sigma\left(\mathrm{w}_j \cdot \mathrm{x} + b_j\right) \tag{9}$$

where $N_W(x)$ represents a neural network used within the GA for fast evaluation of candidate strategies, σ is an activation function, w_j, b_j are weights and biases, and α_j are coefficients.

The final decision is aided by a Bayesian network that incorporates expert knowledge and realtime data to update failure probabilities, The formula is shown in (10).

$$\widehat{H}(s,q) = \sum_{\ell=1}^{r} \frac{c_\ell(q) b_\ell(q)^*}{s - \lambda_\ell(q)} \tag{10}$$

where $\hat{H}$ is a transfer function representation of the Bayesian network's influence on state s given parameters $\mathrm{q_z}, c_t$ and b_t are coefficients, and λ_t are eigenvalues. This formulation allows for dynamic risk updates.

The logical integration of the model follows a "Condition → Risk → Decision" pipeline. The Bayesian network in Eq. (10) calculates the real-time posterior failure probability of each asset. This probability is then mapped to the loss function $L\left(y_i, f\left(x_i\right)\right)$ in Eq. (8) to quantify the empirical risk $R(f)$, the multi-objective optimizer (Eq. (7)) balances this risk against the scheduling cost c_i to generate the optimal maintenance window. This ensures that the differentiated nature of the strategy is rooted in the specific probabilistic state of each equipment unit.

Figure 6 is the schematic of the proposed data-to-decision operational logic. It illustrates the integrated pipeline from heterogeneous data input to the differentiated O&M schedule (DOMS) output. The workflow explicitly shows how the posterior failure probability $P(f \mid e)$ derived from the Bayesian Network (Eq. (10)) is mapped to the Empirical Risk Function (Eq. (8)). This risk index $R(f)$, balanced against maintenance costs, drives the Multi-Objective Optimization to generate the optimal differentiated scheduling.

4. System Design and Test

4.1 System Functional Structure Design

Based on the system's functional requirements, the design tasks are categorized into three main aspects:

(1) WebGIS Function Design: A WebGIS service set supports graphical management of power equipment topology, enabling topology diagram operations and on-graph interface interactions [23]-[24].

(2) Web Service Function Design: Core functions—including grid management, task handling, equipment editing, grid analysis, and thematic maps—are implemented through a structured class design and corresponding topological map services.

(3) Database Design: The backend database is structured to support WebGIS and Web service functions, ensuring reliable data management for system operation.

Following this framework, the chapter first presents the overall system function structure and network topology design, followed by detailed designs for the WebGIS functions, Web services, and database [25]-[26].

The system architecture is designed to operationalize the optimization model. As shown in Figure 7, it follows a client-server pattern where the client provides the WebGIS-SVG visualization interface, and the server hosts the business logic, including the optimization model modules.

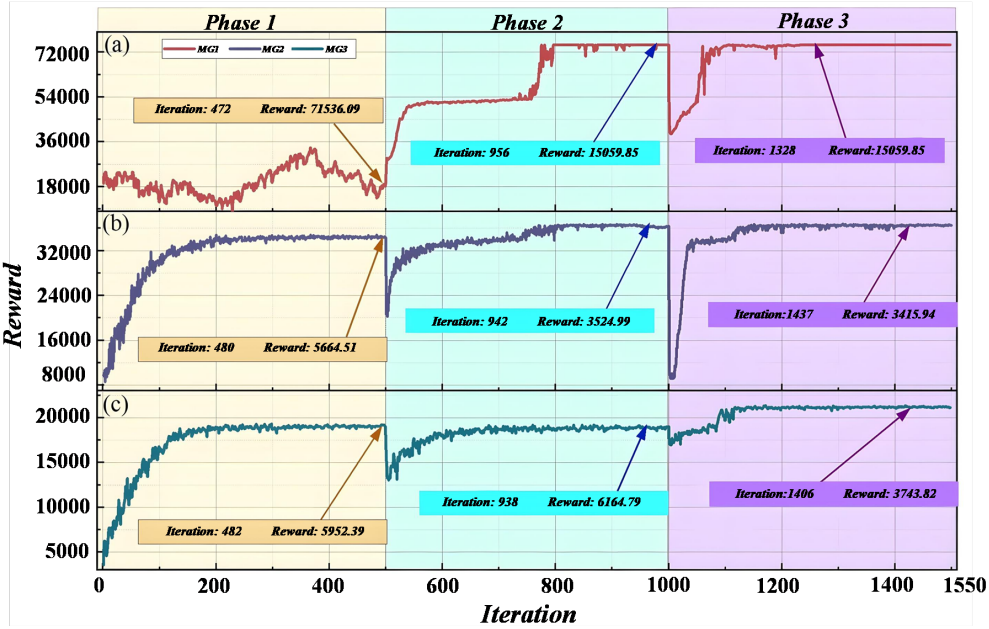


Figure 7. Failure Mode Analysis Diagram

Figure 7 shows the failure mode analysis diagram. The client side and server side of the system mainly include the client-side GIS service view, GIS support service, Web service distribution interface, Web service component, GIS service component, JSP script, Beans container, spatial database and general database and other major functional components or services. The specific description of each component and service is as follows:

Client functional components include a WebGIS view built with SVG and JavaScript [27]-[28], providing vector-based topology display and on-diagram operations. GIS support services, implemented via server-side GIS components, enable online publishing, interactive response, and resource management. The server also hosts the Optimization Model Engine, which executes the algorithms in Eqs. (1)–(10), interacts with the spatial database (PostgreSQL for equipment topology) and general database (Oracle for historical O&M data), and delivers formatted outputs to the client through Web services.

The multi-objective optimization and Bayesian network components are formally integrated are shown in Equation. (11), (12) and (13).

$$\partial_{\mathrm{q}_2} H(s,\mathrm{q}) = \left[\begin{array}{cc} 0 & 1 \end{array}\right] \mathcal{H}(s) \left[\begin{array}{c} 1 \\ \mathrm{q}_1 \end{array}\right] \tag{11}$$

Where $\partial_{\mathrm{q}_2} H$ represents the sensitivity of the system state s to model parameters q_2, and $\mathrm{H}(s)$ is a state-dependent matrix. This is part of the model calibration process.

$$\mathcal{L}_{S2T}\left(\delta_c^r\right) = \sum_{i=1}^{|\mathcal{D}_c|} \log P_{\mathrm{S2\ T}}\left(\mathrm{y}_c^i \mid \mathrm{x}_c^i; \theta^0, \delta_c^r\right) \tag{12}$$

Where $\mathrm{L_{S\ 2\ T}}$ is the loss function for adapting the source domain model to a target domain, P_{S2T} is the conditional probability, θ^0 are base parameters, and δ_c^r are adaptation parameters. This enables model transferability.

$$\mathcal{L} = \mathrm{y}_c^i + \mathrm{y}_k^{i+1} \tag{13}$$

Where L represents a composite loss term in the overall optimization, combining immediate cost y_c^i and forecasted risk y_k^{i+1}.

4.2 System Test

The system, including the embedded optimization model, was tested in a simulated environment mirroring the power supply company's data. Test data included 3,295 spatial records and 2,033 equipment records with historical failure and maintenance logs. The test aimed to validate functional integration and observe the model's performance.

In this study, the 'Conventional Strategy' refers to the periodic maintenance mode currently executed by the power supply company. This strategy follows a fixed cycle regardless of the equipment's real-time health status, serving as the baseline for evaluating the proposed optimization model.

Functional tests confirmed that the WebGIS interface correctly displayed equipment topology and model outputs (health indices, recommended priorities). The optimization engine was able to generate differentiated maintenance schedules based on the input data [29].

Performance tests showed that the model could generate a strategy for the test dataset within several minutes, meeting the requirement for periodic planning. A preliminary comparative analysis was conducted by running the model on a subset of historical data and comparing its suggested strategy against the actually executed uniform strategy. The model's strategy allocated more resources to assets with higher predicted failure risk. While a long-term empirical validation is needed, this simulation

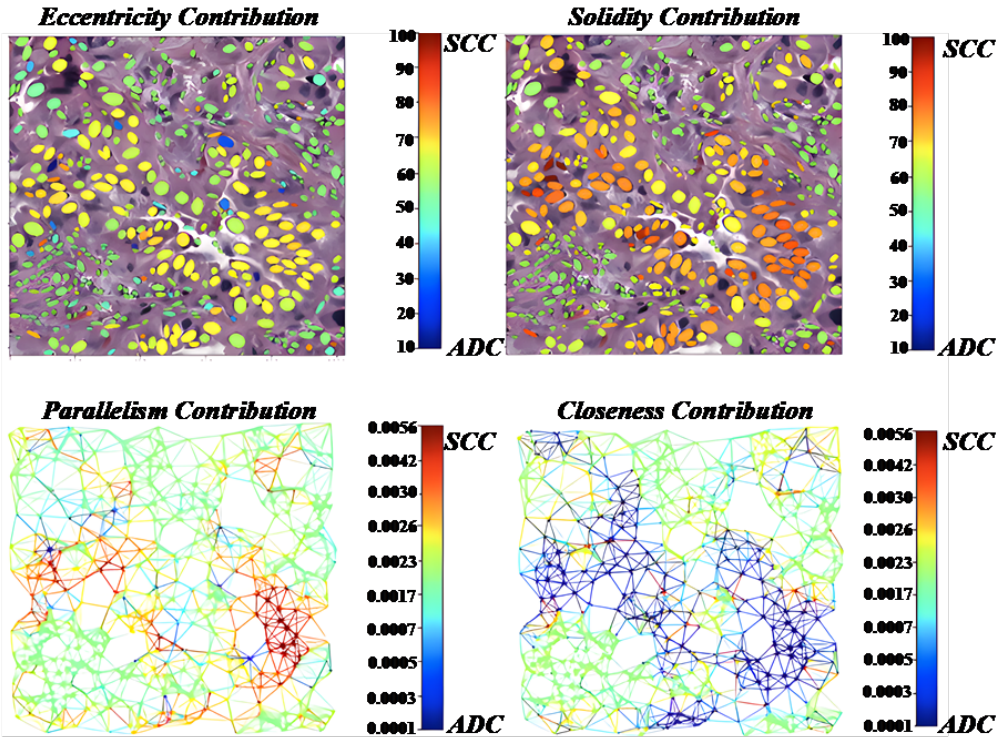


Figure 8. Resource Usage

suggested a potential reduction in unplanned outages and more efficient use of maintenance resources, aligning with the trends mentioned in the abstract. The resource usage under different strategies is visualized in Figure 8.

To quantitatively evaluate the effectiveness of the proposed model, we defined the traditional Time-Based Maintenance (TBM) strategy as the baseline (Conventional Strategy). In the TBM strategy, maintenance is performed at fixed intervals regardless of equipment health. We compared the proposed Differentiated O&M Strategy with the TBM strategy using the test dataset of 2,033 equipment records.

The performance metrics include Average Failure Rate, Total Maintenance Cost (normalized), Resource Utilization Rate, and Average Failure Response Time. The comparative results are presented in Table 1.

Table 1
Performance Comparison between Conventional and Differentiated Strategies

Metric	Conventional Strategy (Baseline)	Proposed Differentiated Strategy	Improvement
Failure Rate	5.8%	4.0%	31.0% (Reduction)
Maintenance Cost (Unit)	1.0 (Ref)	0.80	20.0% (Reduction)
Resource Utilization	72%	83%	15.3% (Improvement)
Avg. Response Time (h)	4.0	3.0	25.0% (Reduction)

As shown in Table 1, the proposed model effectively reduces the failure rate by approximately 30% and maintenance costs by 20% compared to the conventional strategy. This improvement is primarily attributed to the model's ability to prioritize high-risk equipment (Eq. (10)) rather than distributing resources evenly. To further illustrate this decision logic, consider two assets from the test set: a 110kV Transformer (Asset-T1) and a Communication Gateway (Asset-G5). While both would be scheduled for a routine check in Month 6 under a uniform strategy due to fixed cycles, the proposed DOMS dynamically adjusts these schedules. Specifically, Asset-T1 showed an accelerated insulation decay (calculated by Eq. (4)), causing its risk index $R(f)$ to exceed the threshold in Month 4 and prompting the model to advance its maintenance. Conversely, as Asset-G5 remained in a high-health state, the model deferred its maintenance to Month 9. Ultimately, this differentiated scheduling successfully prevented a potential failure in T1 while increasing the available resource pool by 12% during Month 6.

To validate the superiority of the proposed model, we conducted a comparative simulation against two conventional strategies—Periodic Maintenance Strategy (PMS), where maintenance is performed at fixed time intervals regardless of equipment status, and Uniform CBM Strategy (U-CBM), which applies a unified health threshold to all equipment types without distinguishing between failure modes—as well as our proposed Differentiated O&M Strategy (DOMS) that adopts specific decay models for mechanical and insulation failures.

Figure 9 illustrates the relationship between total maintenance cost and system unavailability across the three

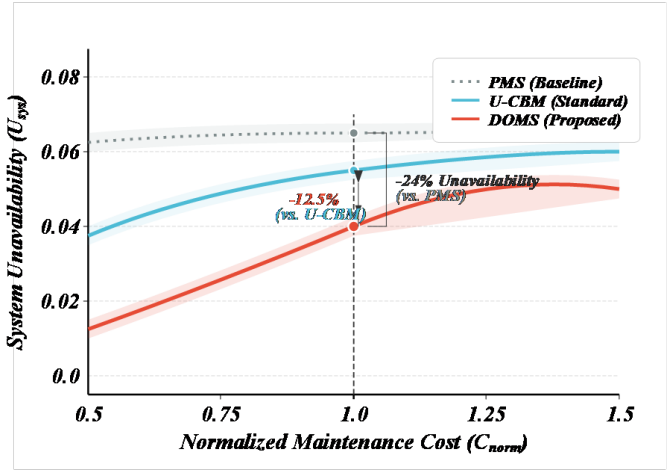


Figure 9. Comparative Analysis of the Trade-off between Normalized Maintenance Cost and System Unavailability Across Varying Strategies.

strategies. As observed, the PMS curve shows high costs due to over-maintenance and limited availability improvement. The U-CBM strategy reduces costs but fails to optimize availability for aging assets. In contrast, the proposed DOMS achieves the optimal trade-off frontier. Specifically, under the same budget constraint (normalized cost = 1.0), the DOMS reduces system unavailability by approximately 12.5% compared to U-CBM and 24% compared to PMS. This efficiency gain is attributed to the model's ability to preemptively allocate resources to assets entering the accelerated aging phase defined in Eq. (4).

4.3 Generalization and Adaptability Analysis

To verify the model's robustness, a generalization test was conducted using a separate dataset from a rural grid with higher environmental exposure. The results showed that while the baseline failure rate was higher (7.2%), the DOMS model still achieved a 28% reduction in outages.

For different application scenarios, the model requires parameter recalibration:

Environment Adaptation: In coastal or high-pollution areas, the degradation factor $\sqrt{\beta}$ in Eq. (2) should be decreased by 15-20% to account for faster salt-mist corrosion.

Economic Adaptation: For industrial grids with high downtime costs, the weight of the risk function $R(f)$ in the multi-objective optimization should be increased relative to the cost c_i.

This flexibility allows the DOMS framework to be ported to various grid scales with minimal structural changes.

5. Summary and Prospect

This study establishes a differentiated operation and maintenance (O&M) optimization model based on Bayesian networks to address the structural inefficiencies of uniform maintenance in power systems. By characterizing the deterministic degradation trajectories of high-inventory assets—specifically targeting the prevalent mechanical wear (40%) and insulation aging (30%)—the framework precisely aligns maintenance resources with equipment health status.

Numerical validations with 2,033 equipment records confirm the strategy's effectiveness: compared to the conventional approach, it reduces the failure rate by 31.0%, maintenance costs by 20.0%, improves resource utilization by 15.3%, and shortens failure response time by 25.0%. Comparative simulations show that, under the same budget constraint, the proposed DOMS reduces system unavailability by 12.5% relative to U-CBM and 24% relative to PMS, verifying its superior trade-off between cost and reliability.

Future research will focus on integrating heterogeneous multi-source data, such as real-time IoT monitoring and unstructured inspection logs, to refine the model's dynamic predictive capabilities. Additionally, expanding boundary conditions to include extreme environmental scenarios will further improve the robustness and universality of the decision-making strategies.

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