

Power Grid Repair Time Prediction and Scheduling Using GA-BP for Emergency Power Supply Operations

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Abstract: Accurate prediction of power grid repair time and efficient allocation of resources are critical to improving the response capability of emergency power supply operations and infrastructure resilience under extreme events. However, current methods still show clear limitations in prediction accuracy, scheduling efficiency, and the coordination between these two aspects. This manuscript presents a prediction and scheduling strategy for emergency power supply scenarios. It develops a repair-time prediction method by combining a Genetic Algorithm (GA) with a Backpropagation (BP) neural network, and constructs a coordinated scheduling model using Improved Ant Colony Optimization (ACO). Experimental results show that the prediction method achieves a coefficient of determination of 0.958 for the repair time task, with a Mean Absolute Error of only 0.181 h. The prediction accuracy is higher than that of the comparison models. In addition, the scheduling model restores the load in 5.98 h under severe fault conditions. The average repair radius stays within 8.46 km, the resource use rate reaches 76.39%, and the load loss is more than 41.43% lower than that of the comparison models. These results show that the method proposed in this manuscript provides stable prediction performance and effective scheduling ability in emergency power supply operations. It offers a reliable technical path for an intelligent emergency command system and helps improve response speed and resource utilization efficiency in complex power grid environments.

Keywords: Genetic algorithm–backpropagation (GA-BP); power grid repair; time prediction; resource scheduling; improved Ant Colony Optimization (ACO); infrastructure resilience; emergency management.

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1. Introduction

1.1. Background

The frequent occurrence of extreme weather events has severely tested the resilience of power grid infrastructure. How to achieve rapid response, precise decision-making, and efficient scheduling after a fault has become a core issue in power grid emergency management. As new power system construction advances, the structure of distribution networks has become increasingly complex, and the large-scale integration of distributed energy resources has profoundly changed system operating characteristics (Wang et al., 2024). Meanwhile, the frequency of extreme weather events has significantly increased the risk of grid failures, with fault patterns increasingly characterized by large-scale, cascading, and compound failures (Atrigna et al., 2023). In this context, the emergency power supply command system, as the core hub for fault

handling, urgently needs to break through traditional repair decision-making modes that rely on manual experience and rule-based reasoning, and address issues such as delayed response and low resource allocation efficiency in complex fault scenarios (Qiu et al., 2023). Accurate prediction of grid repair time is a key component of emergency management for intelligent decision-making. However, repair time is influenced by multidimensional features such as fault type, equipment status, and environmental factors, with complex nonlinear relationships, making it difficult for managers to make scientific resource allocation decisions within the golden window of emergency response. Backpropagation (BP) neural networks, with their powerful nonlinear mapping capabilities, can effectively establish correlation models between multidimensional features and repair duration (Tanhaeean et al., 2023). Genetic Algorithm (GA), with its excellent global optimization capability, can significantly overcome the limitation of BP networks' tendency to converge to local optima (Sohail, 2023). By combining the advantages of both, more accurate and stable repair-time predictions can be provided to support emergency power supply command decision-making, laying a solid foundation for subsequent resource scheduling.

1.2. Related Works

To enhance the intelligent decision-making capabilities of emergency power supply operations, the academic community has conducted extensive research on grid repair time prediction, resource scheduling optimization, and system coordination. In grid repair time prediction, Jamal and Hasan (2023) constructed a generalized accelerated failure time model, introducing spatial correlation into restoration time prediction for the first time, improving model fit by 12% and revealing the significant impact of socioeconomic factors on restoration time. Pang et al. (2023) formulated repair crew scheduling as an event-driven model and proposed a dynamic restoration strategy for active distribution networks. This strategy optimizes power supply restoration through coordinated repair crew scheduling and cold load pickup under frequency constraints, and introduces a model predictive control method to estimate and convexify stochastic repair time. Numerical simulation results on an actual 136-bus distribution network validated the approach's effectiveness. In the field of repair scheduling and restoration strategies, Wang et al. (2023) proposed a hierarchical multi-agent reinforcement learning method that enabled collaborative decision-making among mobile power sources and repair crews in power-transportation-coupled networks. Zhao et al. (2024) further considered the coordinated optimization of new charging and battery-swapping stations, repair teams, and network reconfiguration, adopting a two-stage stochastic programming framework and introducing Copula theory and conditional value-at-risk measures to enhance the system's ability to handle uncertainty in renewable energy. In multi-system coordinated optimization, Li et al. (2023) proposed a method for coordinating emergency response in transportation-distribution networks. Through deep integration of dynamic transportation network models and multi-period distribution network models, and employing adaptive piecewise linearization techniques, the method achieved coordinated scheduling of resources across both systems under disaster conditions. BP neural networks, as feedforward neural networks with powerful nonlinear fitting capabilities, have been successfully applied to prediction tasks across multiple domains. For example, Dai (2023) validated the effectiveness of BP in foreign trade forecasting by constructing multi-factor and single-factor export prediction models, achieving over 30% higher prediction accuracy than traditional methods. Wibawa et al. (2023) innovatively introduced mean smoothing optimization techniques for predicting electronic journal visitor volume, reducing the mean square error of the BP model to 0.00129 with a learning rate of 0.4 and a 1-2-1 network structure, thereby providing a new technical pathway for prediction for time series prediction. Sharma and Jain (2023) proposed a two-step prediction mechanism that combines BP and radial basis function neural networks, effectively improving power load forecasting performance by introducing stacked noise to enhance data variability. GA, as an effective optimization tool, also plays a key role in optimizing neural network structures and tuning parameters. For instance, the hybrid model combining GA and a grey model, developed by Sapnken (2023), achieved an ultra-low mean absolute percentage error of 0.02% in petroleum product consumption forecasting, demonstrating the powerful capability of genetic algorithms for parameter optimization. Jhong et al. (2024) used GA to optimize Long Short-Term Memory (LSTM) hyperparameters, improving the Nash-Sutcliffe efficiency coefficient to 0.917-0.931 in flood forecasting tasks, demonstrating the strong potential of combining genetic algorithms with deep learning models.

1.3. Purpose and Innovation

Although existing research on grid repair time prediction and scheduling has made progress, problems such as insufficient prediction accuracy, low scheduling efficiency, and weak coordination between prediction and scheduling still persist. Therefore, from the perspective of emergency management and decision support, this study introduces a GA-optimized BP neural network. With its strong nonlinear mapping ability and global optimization characteristics, a power grid repair time prediction algorithm for emergency power supply scenarios is designed to provide a reliable decision-making basis for managers. To achieve coordination between prediction and resource scheduling, this study introduces Ant Colony Optimization (ACO), utilizing its positive feedback mechanism and multi-objective optimization capability. This approach constructs a complete repair scheduling model to coordinate repair resources. The model forms a closed management decision loop from accurate prediction to efficient scheduling, thereby improving the scientific validity and execution efficiency of emergency command. The main innovations of this study lie in two aspects. First, improvements at the algorithm level are introduced. Dynamic pheromone updates, multi-objective weight-adaptive adjustments, and other mechanisms are introduced to optimize the ant colony algorithm, thereby improving the solution efficiency and dynamic adaptability of the scheduling model. Second, an innovation in the coordination mechanism is presented. A two-way coordination mechanism between prediction and scheduling is constructed. By integrating prediction results into real-time scheduling decisions and feeding scheduling execution data back to optimize the prediction model, a complete decision-making closed loop from repair time prediction to resource allocation is formed, providing a new decision paradigm for power grid emergency management.

1.4. Theoretical Contribution

This study contributes to infrastructure operations management and emergency decision-support theory by providing an integrated framework that connects repair-time prediction to emergency scheduling. The proposed framework establishes a new coordination mechanism between prediction and scheduling, which transcends simple algorithmic coupling by enabling bidirectional interaction: prediction results inform dynamic scheduling decisions, while scheduling execution data are fed back to refine prediction models. This mechanism supports more reliable and robust emergency resource allocation decisions for power grid systems under extreme events, offering an actionable decision-support paradigm for infrastructure emergency management.

2. Construction of Power Grid Repair Prediction and Scheduling Models

2.1. Design of the GA-BP Power Grid Repair Time Prediction Method

Existing methods for predicting power grid repair time struggle to accurately capture the complex nonlinear relationship between fault features and repair duration, which limits prediction accuracy. The backpropagation neural network, a typical multilayer feedforward network, automatically adjusts network weights and thresholds based on input data, thereby precisely approximating complex nonlinear relationships (Shen, 2023). Therefore, this study introduces a single-layer BP neural network to predict power grid repair time. The BP topology and information flow are shown in Fig. 1.

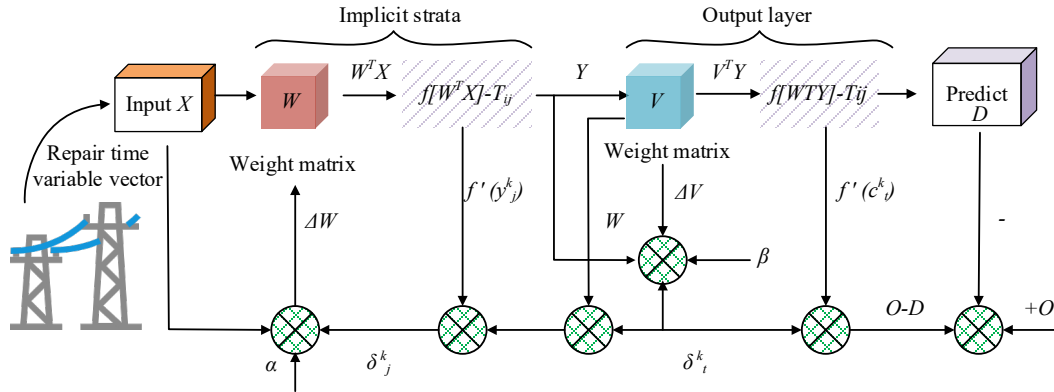


Fig. 1. Structure of the BP neural network for emergency power supply operations

As shown in Fig. 1, the single-hidden-layer BP structure for repair time prediction consists of forward propagation and error backpropagation. The input data undergoes a linear transformation by the first weight matrix and an activation function, producing the hidden layer output. This output then passes through the second weight matrix and the output layer activation function to generate the predicted repair time. The transformation from the input layer to the hidden layer is shown in Eq. (1).

$$\begin{cases} b_j^k = \sum_{i=1}^n \omega_{ij} x_i^k + t_j \\ y_j^k = f_1(b_j^k) \\ f_1(x) = \frac{1 - e^{-x}}{1 + e^{-x}} \end{cases} \quad (1)$$

In Eq. (1), y_j^k is the output, $f_1(x)$ is the activation function, b_j^k is the input to the hidden layer, ω_{ij} and t_j represent the hidden layer weights and thresholds, and x_i^k is the initial input. The transformation from hidden layer to output layer is shown in Eq. (2).

$$\begin{cases} f_2(x) = x \\ c_t^k = \sum_{j=1}^l v_{jt} y_j^k + s_t \\ d_t^k = f_2(c_t^k) \end{cases} \quad (2)$$

In Eq. (2), d_t^k denotes the output of the output layer, $f_2(x)$ is the activation function, c_t^k is the input to the output layer, and v_{jt} and s_t are its weights and thresholds. During the backpropagation phase, the network compares the predicted value with the actual repair time using mean square error as the objective function, expressed in Eq. (3).

$$\begin{cases} E = o_t^k - d_t^k \\ E_{rme} = \frac{1}{2} \sum_{t=1}^m (o_t^k - d_t^k)^2 \end{cases} \quad (3)$$

In Eq. (3), E_{rme} is the mean square error, and d_t^k and o_t^k are the predicted and expected outputs, respectively. According to the gradient descent rule, the error propagates backward to adjust the weights and thresholds layer by layer to minimize E_{rme} , as shown in Eq. (4).

$$\begin{cases} v_{jt}^k = v_{jt}^k + \Delta v_{jt} \\ \Delta v_{jt} = -\beta \frac{\partial E}{\partial v_{jt}} \\ \Delta s_t = \beta \delta_t^k \end{cases} \quad (4)$$

In Eq. (4), Δv_{jt} and Δs_t are the adjustments of output layer weights and thresholds, β is the learning rate, and δ_t^k is the error adjustment. The hidden layer weights and thresholds are updated similarly, with error signals backpropagated from the output layer. By iteratively performing forward and backward processes, the BP network parameters gradually optimize. The repair time prediction process based on BP neural network is shown in Fig. 2.

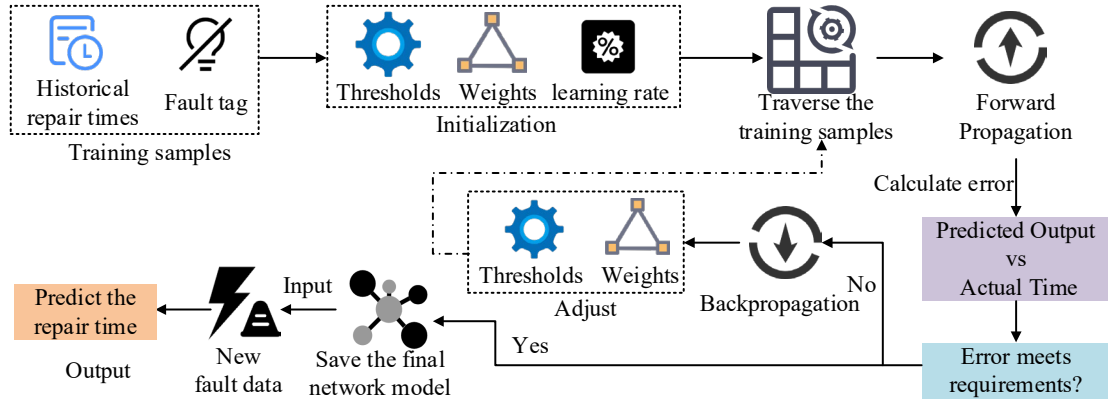


Fig. 2. Flowchart of power grid repair time prediction using BP neural network

As shown in Fig. 2, the BP-based prediction process begins with data preparation and network initialization. Its core step is iterative training, in which forward propagation computes predicted values. If the error does not meet the standard, backpropagation adjusts network parameters. This cycle continues until the model converges, after which the model is used to predict repair time for new faults. However, BP performance depends heavily on initial network parameters and can easily fall into local optima (Sabharwal and Gupta, 2024). GA simulates natural evolution and efficiently searches the solution space (Alexi et al., 2024). Therefore, this study introduces GA to optimize the initial weights and thresholds of the BP network, thereby constructing the GA-BP power grid repair time prediction algorithm. The algorithm's fitness depends on the network's training prediction accuracy, as defined in Eq. (5).

$$F_m = \frac{1}{\frac{1}{2} \sum_{m=1}^N (y_m - z_m)^2} \quad (5)$$

In Eq. (5), y_m is the actual output, z_m is the predicted output, and f_i represents the fitness of individual i . The evolution probability of an individual is obtained in Eq. (6).

$$P_i = f_i / \sum_{i=1}^N f_i, i = 1, 2, \dots, N \quad (6)$$

In Eq. (6), P_i denotes the probability of selecting individual i during GA population construction. The mutation probability for an individual is given by Eq. (7).

$$P_m = \begin{cases} P_{m \max} - \frac{(P_{m \max} - P_{m \min})(f_{\max} - f)}{(f_{\max} - f_{avg})}, & f \geq f_{avg} \\ P_{m \max}, & f < f_{avg} \end{cases} \quad (7)$$

In Eq. (7), f_{avg} is the average fitness of individuals, f is the fitness after mutation, $P_{m \max}$ is the maximum mutation probability, and $P_{m \min}$ is the minimum mutation probability. Similarly, the crossover probability for individuals is given by Eq. (8).

$$P_c = \begin{cases} P_{c \max} - \frac{(P_{c \max} - P_{c \min})(f_{\max} - f')}{(f_{\max} - f_{avg})}, & f' \geq f_{avg} \\ P_{c \max}, & f' < f_{avg} \end{cases} \quad (8)$$

In Eq. (8), f' represents the fitness for crossover. Through iterative selection, crossover, and mutation in a GA, an optimized set of initial BP parameters is obtained. Assigning these parameters to BP weights and thresholds significantly improves convergence speed and prediction accuracy. The GA-BP repair time prediction process is shown in Fig. 3.

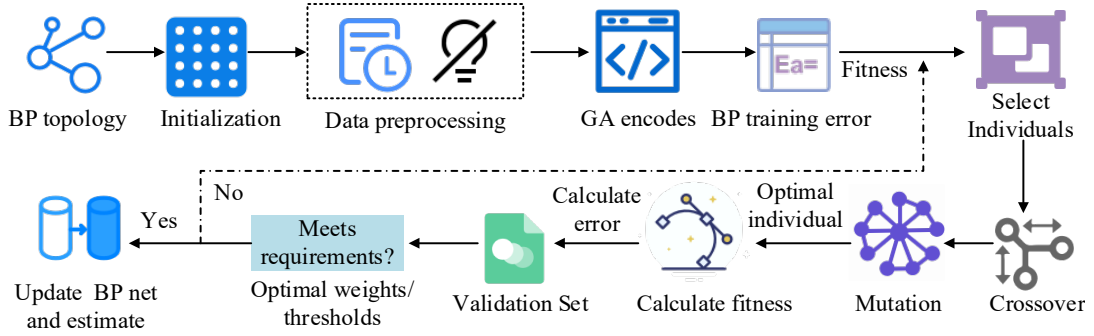


Fig. 3. Flowchart of GA-BP grid repair time prediction

As shown in Fig. 3, the GA-BP repair time prediction adopts a two-stage optimization strategy. First, fault data and historical repair times are preprocessed. GA encodes and optimizes BP initial weights and thresholds, using network training error as the fitness criterion. During iteration, selection, crossover, and mutation evolve the population while retaining optimal parameters. Once convergence conditions are met, the optimized weights and thresholds are assigned to BP, and the prediction results are output by simulating repair data.

2.2. Construction of the GA-BP-IACO Scheduling Model

After accurately predicting power grid fault repair time using GA-BP, efficiently scheduling personnel, vehicles, and equipment based on the prediction becomes key to improving the efficiency of emergency power supply. Repair resource scheduling is a complex multi-objective combinatorial optimization problem that seeks optimal solutions subject to time, cost, and path-efficiency constraints (Chen et al., 2023). To reduce solution complexity, this study first applies a clustering method to partition fault points. The fault clustering principle is shown in Fig. 4.

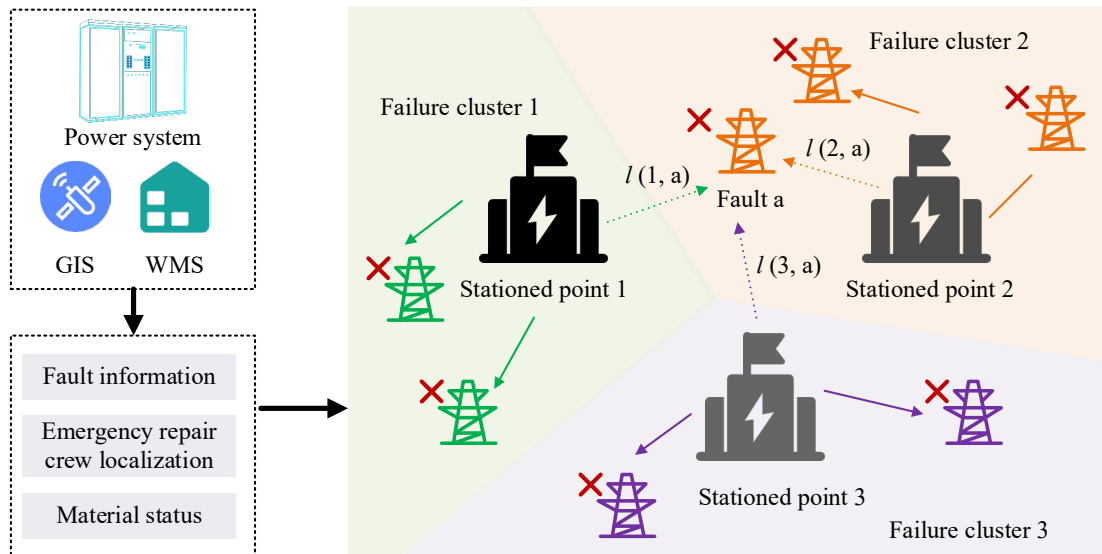


Fig. 4. Fault clustering based on power supply command system

As shown in Fig. 4, a represents a fault, and l denotes its distance to the repair point. The cluster allocation of faults is expressed in Eq. (9).

$$g_{m,a} = \begin{cases} 1, & \text{Fault } a \text{ belongs to fault cluster } m \\ 0, & \text{Others} \end{cases} \quad (9)$$

In Eq. (9), m is the fault cluster. The clustering decision considers distance, material supply and demand, and real-time traffic. Its objective function is shown in Eq. (10).

$$\min_g \sum_m \sum_a l(rst_m, a) g_{m,a} \varpi_{m,a} \quad (10)$$

In Eq. (10), rst_m is the repair team station, and $\varpi_{m,a}$ is the traffic condition coefficient between m and a . The constraints of Eq. (10) are expressed in Eq. (11).

$$\begin{cases} \sum_m g_{m,a} = 1, \forall a \\ R_m^A \geq \sum_a R_a^N g_{m,a}, \forall m \\ g_{m,a} \in \{0,1\}, \forall m, a \end{cases} \quad (11)$$

In Eq. (11), R_a^N denotes the materials required for repair a , and R_m^A represents the available materials at the repair team station. After completing fault clustering, to achieve a closed loop from accurate prediction to efficient execution, a multi-objective scheduling model is constructed for each subregion, with a focus on maximizing load restoration and minimizing repair time. The objective function is shown in Eq. (12).

$$\max_{Z,L} (\varepsilon_1 \sum_t \sum_i \gamma_{i,t} d_i (\alpha_{1,i} \exp(\alpha_{2,i} \tau_i) + \alpha_{3,i}) p_{i,t}^D - \varepsilon_2 \sum_t \sum_i \beta_{a,t}) \quad (12)$$

In Eq. (12), Z represents the system operational variables, and L denotes repair scheduling variables. ε_1 and ε_2 are the optimization weights for load restoration and repair time. $\gamma_{i,t}$ indicates the power supply status of node i at time t ; if supply is restored, $\gamma_{i,t}=1$, otherwise $\gamma_{i,t}=0$. The restoration value i is characterized by the basic influence coefficient d_i , fitting coefficients $\alpha_{1,i}$, $\alpha_{2,i}$, $\alpha_{3,i}$, and damage degree index τ_i . $p_{i,t}^D$ represents active power demand, and fault recovery sequence is marked by $\beta_{a,t}$; if a fault is cleared at t , $\beta_{a,t}=1$, otherwise $\beta_{a,t}=0$. For solving the objective model, traditional scheduling methods often struggle with dynamic traffic conditions and complex real-world constraints. ACO simulates ants communicating via pheromones to find the shortest path. Its positive feedback mechanism offers a new approach for addressing such complex optimization problems (Poudel and Bhandari, 2023). However, standard ACO applied to real repair scheduling may fall into local optima and show poor adaptability in dynamic environments. Therefore, this study implements multiple improvements and designs an Improved ACO (IACO) to optimize the scheduling model. The process is shown in Fig. 5.

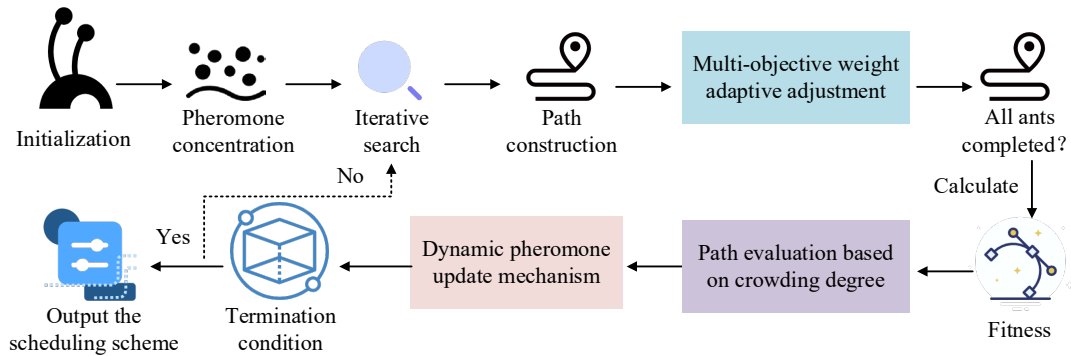


Fig. 5. Scheduling method based on IACO

As shown in Fig. 5, IACO embeds multi-objective selection and real-time adjustment mechanisms in path construction and introduces congestion evaluation and dynamic pheromone strategies in evaluation and update. This creates an efficient optimization loop that addresses local optima and limited dynamic adaptability in traditional scheduling. The dynamic pheromone update mechanism is expressed in Eq. (13).

$$\tau_{ij}(t+1) = (1-\rho) \tau_{ij}(t) + \rho \tau_{ij}^k \exp\left(-\frac{d_{ij}}{d_{\max}}\right) \quad (13)$$

In Eq. (13), ρ is the pheromone evaporation coefficient, d_{ij} and $d_{\max}$ represent path distance and maximum path distance, $\tau_{ij}(t)$ is the pheromone concentration on path (i, j) at time t , and $\Delta\tau_{ij}^k$ is the pheromone increment released by ant k . After introducing a multi-objective, weight-adaptive adjustment mechanism, the path selection probability is calculated as in Eq. (14).

$$P_{ij}^k = \frac{[\tau_{ij}(t)]^\alpha [\eta_{ij}(t)]^\beta [\omega_{ij}(t)]^\gamma}{\sum_{s \in allowed_k} [\tau_{is}(t)]^\alpha [\eta_{is}(t)]^\beta [\omega_{is}(t)]^\gamma} \quad (14)$$

In Eq. (14), $\omega_{ij}(t)$ is the dynamic weight factor, $allowed_k$ denotes the set of nodes allowed to be visited, $\eta_{ij}(t)$ is the heuristic information, and α, β, γ are importance coefficients. Considering multi-objective trade-offs in repair scheduling, a congestion-based path evaluation function is introduced to achieve uniform distribution and effective selection of non-dominated solutions, as shown in Eq. (15).

$$F(path) = \lambda_1 \frac{L}{L_{\max}} + \lambda_2 \frac{T}{T_{\max}} + \lambda_3 \frac{C}{C_{\max}} + \lambda_4 \frac{J}{J_{\max}} \quad (15)$$

In Eq. (15), λ represents the weight coefficient of each indicator, T is travel time, J is traffic congestion, L is path length, and C is the scheduling cost. To handle dynamic traffic environments, a real-time path adjustment mechanism is introduced in Eq. (16).

$$T_{ij}(t) = T_{ij}^0 [1 + \mu \sin(\frac{2\pi t}{24}) + \sigma R(t)] \quad (16)$$

In Eq. (16), μ is a time-varying coefficient, $R(t)$ is a random number in $[-1, 1]$, T_{ij}^0 is the baseline travel time of path (i, j) , and σ is the random disturbance intensity. IACO effectively solves the complex optimization problem of scheduling power supply repair resources, enabling fast, economical, and efficient assignment of repair forces. Therefore, based on the emergency power supply system, fault clustering and GA-BP repair time prediction, combined with IACO optimization, a GA-BP-IACO scheduling model is constructed. Its overall architecture is shown in Fig. 6.

As shown in Fig. 6, the GA-BP-IACO model integrates multi-source data from warehouse management and distribution automation systems. In the data fusion layer, work orders, spatial distances, repair duration, and resource inventory are integrated and preprocessed. The command system then executes a three-level intelligent decision process: fault clustering, GA-BP repair time prediction, and IACO resource scheduling optimization. This forms a complete operational loop from multi-source data perception and intelligent analysis to decision-making and precise command execution, enabling rapid response and efficient allocation of power repair resources.

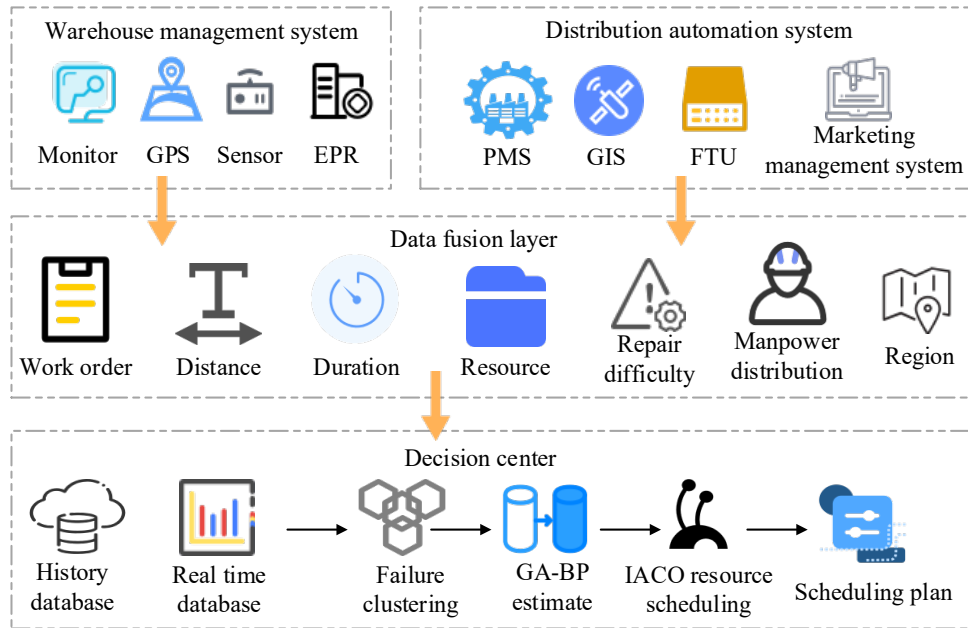


Fig. 6. GA-BP-IACO decision-support framework for emergency power supply

3. GA-BP-IACO Prediction and Scheduling Performance

3.1. Verification of GA-BP Prediction Performance

To verify the predictive performance of GA-BP for grid repair duration, this study constructed a test set using actual fault repair work order data from a provincial power grid in 2024. The dataset covered typical fault types, including transformer overload, line short circuit, switch failure, and insulator breakdown, containing complete fault characteristics, environmental parameters, and actual repair duration records. The experiment was conducted on a hardware environment equipped with an Intel Core i7-12700H processor, an NVIDIA GeForce RTX 3060 graphics card, and 32 GB of DDR4 memory, using MATLAB R2023a to implement the algorithm and perform performance testing. To verify the prediction accuracy and operational efficiency of GA-BP, this study selected the Coefficient of Determination (R^2) to measure goodness of fit and model training time to evaluate computational efficiency. Meanwhile, the study assessed the convergence performance of the Mean Squared Error (MSE) between predicted and actual repair durations and selected the Particle Swarm Optimization-Long Short-Term Memory (PSO-LSTM) and Grey Wolf Optimizer-Support Vector Regression (GWO-SVR) algorithms for comparison. The results are shown in Fig. 7.

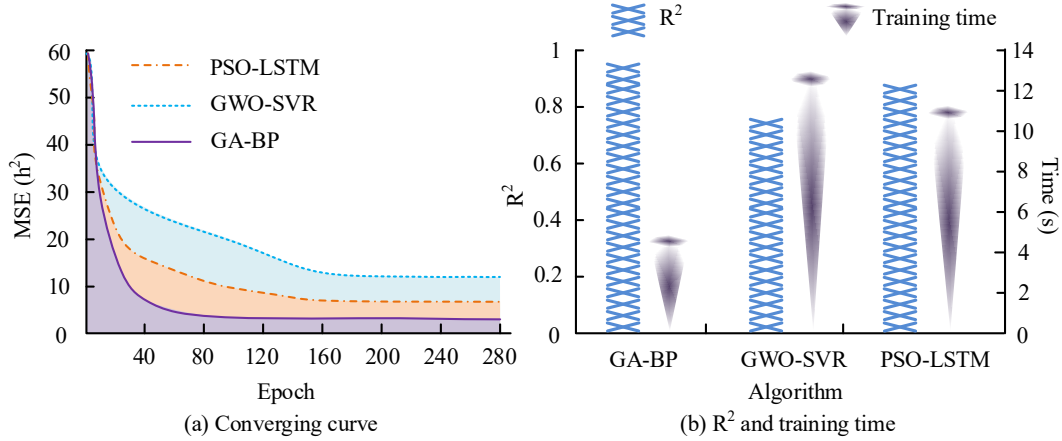


Fig. 7. Comprehensive evaluation of algorithm training

As shown in Fig. 7(a), GA-BP successfully converged to $2.83 h^2$ at the 105th iteration, with both convergence speed and accuracy significantly superior to the comparison models. PSO-LSTM required 160 iterations to reach $8.14 h^2$, whereas GWO-SVR required 175 iterations to reach $11.84 h^2$, indicating that the GA-BP model exhibited better stability and optimization efficiency during training. Fig. 7(b) shows that GA-BP had a runtime of 4.36 s during testing, with R^2 reaching 0.958, achieving the best overall performance. In comparison, PSO-LSTM had a runtime of 11.06s and an R^2 of 0.891, while GWO-SVR had a runtime of 12.22s and an R^2 of 0.782, indicating that GA-BP could achieve higher prediction accuracy under limited computational resources. To evaluate the prediction accuracy of GA-BP on specific samples, this study further analyzed prediction errors based on 30 actual work order samples. These samples are typical, representative fault records that cover various fault types and weather conditions. Since the samples have complete features and high quality, the sample size will not significantly affect the stability and reliability of the prediction results. The results are shown in Fig. 8.

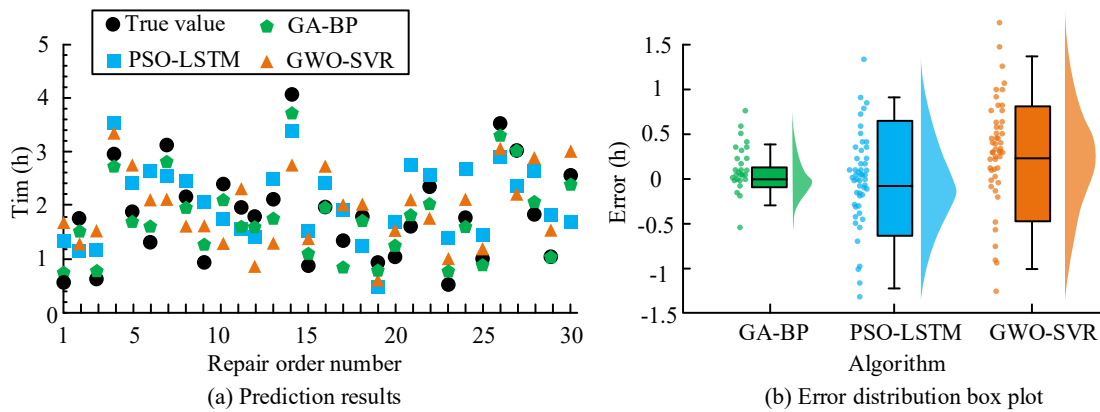


Fig. 8. Prediction results and error distribution

Fig. 8(a) shows that the predicted values of GA-BP were closest to the actual repair duration, with most sample deviations kept within $0.035 h$, and the fitting effect was significantly better than those of PSO-LSTM and GWO-SVR. From the error distribution in Fig. 8(b), the median error of GA-BP was $0.002 h$ with no obvious outliers, and the interquartile range was only $0.124 h$, showing that overall errors were concentrated with small fluctuations. In contrast, the median errors of PSO-LSTM and GWO-SVR were $-0.152 h$ and $0.246 h$, respectively, with interquartile ranges reaching $0.622 h$ and $0.805 h$, reflecting the instability of their prediction deviations. This demonstrates that the GA-BP model combined high accuracy with high stability in specific work order predictions. To verify its adaptability across multiple scenarios, this study analyzed the relative errors between predicted and actual repair durations for different fault types and

assessed the impact of weather conditions on prediction performance. The results are shown in Fig. 9.

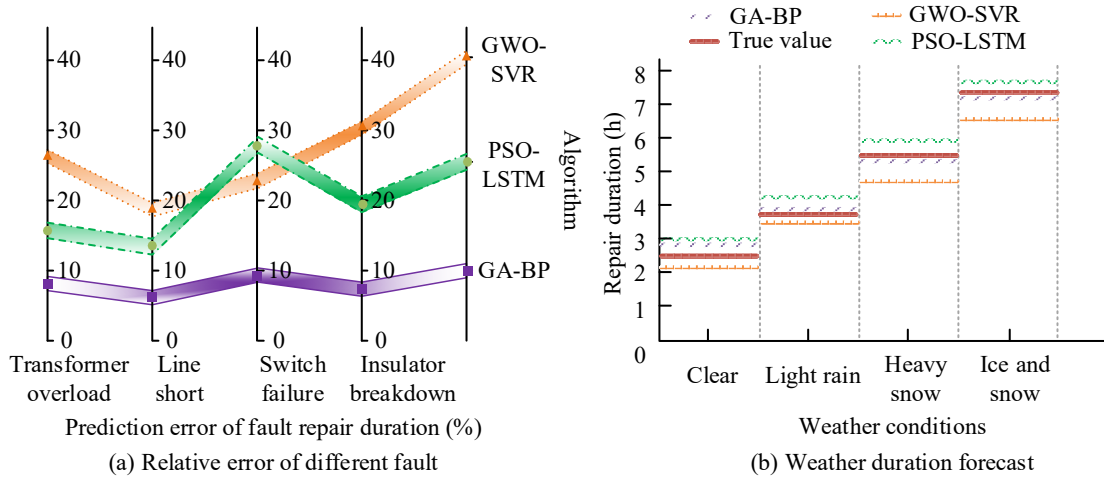


Fig. 9. Prediction results of repair time under multiple scenarios

As shown in Fig. 9(a), for repair duration prediction across different faults, GA-BP achieved higher prediction accuracy than the comparison algorithms. Its prediction errors for transformer faults, line short circuits, switch failures, and insulator breakdowns were 8.02%, 6.21%, 9.04%, and 7.16%, respectively, which were significantly lower than those of PSO-LSTM and GWO-SVR. In the switch-failure scenario, the prediction error of GA-BP was reduced by 19.35% compared with PSO-LSTM, demonstrating its ability to capture complex fault patterns. Fig. 9(b) shows that under four weather conditions of clear, light rain, heavy rain, and ice/snow, the predicted values of GA-BP were 2.58 h, 3.97 h, 5.42 h, and 7.11 h, respectively, highly consistent with actual repair times, with an average absolute error of only 0.181 h. In contrast, the average deviations of PSO-LSTM and GWO-SVR reached 0.332 h and 0.520 h, respectively. This indicates that GA-BP maintained reliable predictive performance across different environmental conditions, providing an accurate basis for decision-making in repair resource allocation.

3.2. Verification of GA-BP-IACO Actual Scheduling Performance

To systematically evaluate the effectiveness of the scheduling model, this study set the grid baseline power supply load at 47 MW and divided fault scenarios into three levels: mild, moderate, and severe. Mild faults affected no more than one distribution unit, involved two or fewer fault points, and required coordination of one repair team and one material vehicle for local faults. Moderate faults affected more than one distribution area, had 3-5 fault points, and required coordination of two repair teams and multiple vehicle types for regional faults. Severe faults involving main lines or key nodes, with more than five fault points, required multi-round, multi-type coordination and network reconfiguration for systemic faults. On this basis, this study compared the load restoration progress of the GA-BP-IACO model with that of the Sparrow Search Algorithm-Support Vector Regression (SSA-SVR) and Whale Optimization Algorithm-Deep Q-Network (WOA-DQN) models under different fault severity levels. The results are shown in Fig. 10.

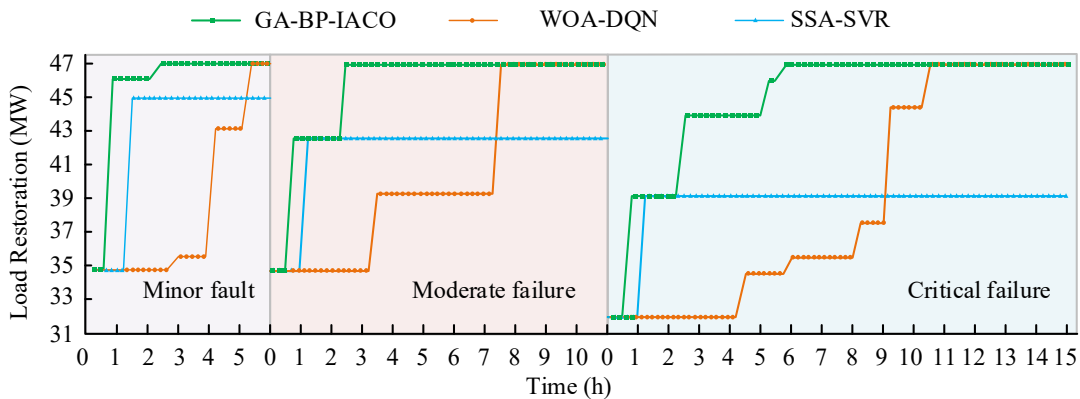


Fig. 10. Fault severity-load recovery curves

As shown in Fig. 10, in the mild fault scenario, GA-BP-IACO required only 2.55 h to achieve complete load restoration, representing a 50.09% improvement in restoration speed over WOA-DQN. By contrast, the SSA-SVR model did not achieve complete restoration. As fault severity increased, the performance differences among models became more pronounced. In the severe-fault scenario, the SSA-SVR model restored only 39.02 MW, corresponding to an 83.02% restoration rate. Although WOA-DQN achieved complete restoration, the process exhibited pronounced fluctuations and took up to 10.58 h. In contrast, GA-BP-IACO demonstrated excellent stability and efficiency, restoring 82.97% of the load within 2.59 h after fault occurrence and completing full restoration within 5.98 h. To accurately evaluate the scheduling

model's resource allocation effectiveness, this study constructed a resource combination comprising two repair teams, A and B, a material vehicle X, and a crane Y. The repair teams were responsible for on-site fault handling; vehicle X transported routine spare parts; and crane Y undertook large equipment replacement tasks. Based on this resource configuration, the time-series changes in load restoration ratio and resource utilization rate for each scheduling model over 24 h are shown in Fig. 11.

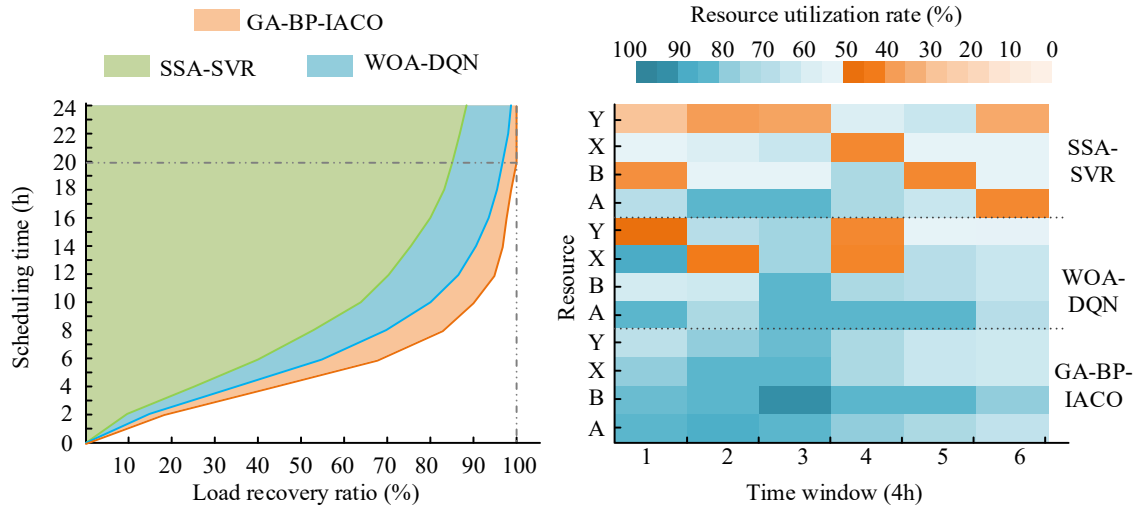


Fig. 11. Comparison of scheduling efficiency and resource utilization

As shown in Fig. 11(a), the restoration rate of the GA-BP-IACO model was significantly higher than that of the comparison models, achieving 100% load restoration in only 20 h, reflecting the model's efficient coordination and rapid response capability in deploying repair resources. In contrast, SSA-SVR achieved only an 89.45% restoration rate within 24 h, while the final restoration rate of WOA-DQN was 98.95%. In Fig. 11(b), window 1 started at 0:00, window 6 ended at 24:00, with each time window being 4 h. It can be observed that GA-BP-IACO maintained high resource utilization levels across all periods, with an average utilization rate of 76.39%, and could still maintain above 62.39% during the evening peak period of 20:00-24:00. In contrast, the average utilization rates of SSA-SVR and WOA-DQN were 51.30% and 63.75%, respectively. This shows that GA-BP-IACO had significant advantages in improving load restoration efficiency and comprehensive resource utilization. To comprehensively evaluate the models' overall performance in fault repair, this study compared indicators such as power-outage load loss, average repair radius, and model computation time. The results are shown in Table 1.

Table 1. Comprehensive performance evaluation of scheduling models

Indicator	Fault level	GA-BP-IACO	SSA-SVR	WOA-DQN
Power outage load loss (MWh)	Mild fault	6.85	18.24	12.59
	Moderate fault	35.17	82.41	56.93
	Severe fault	98.62	235.74	168.35
Average repair radius (km)	Mild fault	3.25	5.67	4.32
	Moderate fault	5.83	8.94	7.15
	Severe fault	8.46	12.75	10.28
Model calculation time (s)	Mild fault	4.36	12.75	8.92
	Moderate fault	6.83	18.42	12.67
	Severe fault	9.25	24.86	16.35

As shown in Table 1, the GA-BP-IACO model demonstrated significant advantages across all performance indicators. In terms of power supply reliability, the total power outage load loss caused by this model in the severe fault scenario was 98.62 MWh, representing reductions of 58.16% and 41.43% compared to the SSA-SVR and WOA-DQN models, respectively. In terms of repair efficiency, the average repair radius of GA-BP-IACO under severe faults was 8.46 km, which was 4.29 km and 1.82 km shorter than those of SSA-SVR and WOA-DQN, respectively, indicating more rational task allocation and more efficient spatial scheduling. In terms of computational efficiency, the solution time of this model under severe faults was 9.25s, achieving computational speeds that were 2.69 times those of SSA-SVR and 1.77 times those of WOA-DQN. Therefore, GA-BP-IACO exhibited superiority in power supply reliability, repair efficiency, and computational efficiency, providing effective technical support for grid emergency repair decision-making. This means that the proposed model can effectively shorten power outage time, reduce load loss, improve resource utilization efficiency,

and significantly enhance power grid reliability and infrastructure resilience. The above performance improvement can be directly translated into practical scheduling decisions. Compared with the traditional experience-dependent repair mode, the proposed method can prioritize fault nodes with large impact scope and high importance based on accurate predictions, and dynamically optimize the allocation of repair teams and the dispatch sequence of resources to form a more reasonable restoration sequence. Managers can directly determine repair priorities, crew allocation and restoration sequences based on the model output, thereby enabling the transition from experience-driven to data-driven decision-making.

4. Conclusion

To address the problems of insufficient prediction accuracy, low resource allocation efficiency, and weak dynamic response capability in current grid repair scheduling, this study integrated the GA algorithm with BP neural networks and proposed a GA-BP repair duration prediction algorithm for emergency power supply operation systems. In combination with an improved ACO algorithm, the study developed a GA-BP-IACO collaborative scheduling model. Experimental results showed that GA-BP achieved an R^2 of 0.958 in repair time prediction tasks, with a median prediction error of 0.002 h and an average absolute error of 0.181 h, demonstrating significantly superior predictive accuracy compared with the comparison algorithms. In terms of scheduling performance, GA-BP-IACO controlled the average repair radius within 8.46 km, with an average resource utilization rate of 76.39%. Under severe faults, this model required only 5.98 h to achieve complete load restoration, with a total load loss of 98.62 MWh, representing a reduction of 41.43% or more compared to other models. These results indicate that the proposed method is highly reliable in real-world grid repair environments, provides systematic decision support for power grid emergency management, and promotes the transformation of repair work from experience-driven to data-driven, intelligent decision-making.

From a management and policy perspective, this study can provide practical support for formulating critical infrastructure resilience policies, improving power system emergency preparedness standards, optimizing disaster response governance frameworks, and upgrading smart grid resilience regulation. By constructing an integrated closed-loop decision-making process for prediction and scheduling, managers can shift from a traditional experience-based repair decision-making model to one that determines repair priorities, optimizes repair team layouts and dynamically adjusts resource dispatch sequences and restoration paths based on accurate predictions. This transforms emergency response from experience-driven to data-driven and significantly improves the standardization and intelligence level of power grid emergency management under extreme events. However, the study has not been sufficiently verified in cross-regional joint scheduling and extreme disaster scenarios. Future work can further test the system's adaptability in new power systems and multi-integrated load environments.

Author Contributions

Jian Li contributes to conceptualization, methodology and manuscript editing. Xuefang Dong contributes to methodology, analysis and manuscript editing. Dan Shao contributes to software, validation and analysis. Shuang Gu contributes to the investigation, data collection and draft preparation. Haipeng Zhang contributes to the investigation and data collection. Gang Meng contributes to conceptualization and manuscript editing. Yanmei Li contributes to visualization. All authors have read and agreed with the manuscript before its submission and publication.

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References

- Alexi, A., Lazebnik, T., and Shami, L. (2024). Microfounded tax revenue forecast model with heterogeneous population and genetic algorithm approach. *Computational Economics*, 63(5), 1705-1734.
- Atrigna, M., Buonanno, A., Carli, R., Cavone, G., Scarabaggio, P., Valenti, M., and Dotoli, M. (2023). A machine learning approach to fault prediction of power distribution grids under heatwaves. *IEEE Transactions on Industry Applications*, 59(4), 4835-4845.
- Chen, Y., Zhang, N., Yan, J., Zhu, G., and Min, G. (2023). Optimization of maintenance personnel dispatching strategy in smart grid. *World Wide Web*, 26(1), 139-162.
- Dai, C. (2023). A method of forecasting trade export volume based on back-propagation neural network. *Neural Computing and Applications*, 35(12), 8775-8784.
- Jamal, T. B. and Hasan, S. (2023). A generalized accelerated failure time model to predict restoration time from power outages. *International Journal of Disaster Risk Science*, 14(6), 995-1010.
- Jhong, Y. D., Chen, C. S., Jhong, B. C., Tsai, C. H., and Yang, S. Y. (2024). Optimization of LSTM parameters for flash flood forecasting using genetic algorithm. *Water Resources Management*, 38(3), 1141-1164.
- Li, J., Xu, X., Yan, Z., Wang, H., Shahidepour, M., and Chen, Y. (2023). Coordinated optimization of emergency response resources in transportation-power distribution networks under extreme events. *IEEE Transactions on Smart Grid*, 14(6), 4607-4620.

- Pang, K., Wang, C., Hatziaargyriou, N. D., and Wen, F. (2023). Dynamic restoration of active distribution networks by coordinated repair crew dispatch and cold load pickup. *IEEE Transactions on Power Systems*, 39(2), 4699-4713.
- Poudel, Y. K. and Bhandari, P. (2023). Control of the BLDC Motor Using Ant Colony Optimization Algorithm for Tuning PID Parameters. *Archives of Advanced Engineering Science*, 2(2), 108-113.
- Qiu, F., Zhang, Y., Yao, R., and Du, P. (2023). Power system restoration with renewable participation. *IEEE Transactions on Sustainable Energy*, 14(2), 1112-1121.
- Sabharwal, T. and Gupta, R. (2024). Human face identification after plastic surgery using SURF, Multi-KNN and BPNN techniques *Complex & Intelligent Systems*, 10(3), 4457-4472.
- Sapnken, F. E. (2023). A new hybrid multivariate grey model based on genetic algorithms optimization and its application in forecasting oil products demand. *Grey Systems: Theory and Application*, 13(2), 406-420.
- Sharma, A. and Jain, S. K. (2023). A novel two-stage framework for mid-term electric load forecasting. *IEEE Transactions on Industrial Informatics*, 20(1), 247-255.
- Shen, H. (2023). Assessment of financial risk pre-alarm mechanism based on financial ecosystem using BPNN and genetic algorithm. *Soft Computing*, 27(24), 19265-19279.
- Sohail, A. (2023). Genetic algorithms in the fields of artificial intelligence and data sciences. *Annals of Data Science*, 10(4), 1007-1018.
- Tanhaeean, M., Ghaderi, S. F., and Sheikhalishahi, M. (2023). Optimization of backpropagation neural network models for reliability forecasting using the boxing match algorithm: electro-mechanical case. *Journal of Computational Design and Engineering*, 10(2), 918-933.
- Wang, X., Li, S., and Iqbal, M. (2024). Live power generation predictions via AI-driven resilient systems in smart microgrids. *IEEE Transactions on Consumer Electronics*, 70(1), 3875-3884.
- Wang, Y., Qiu, D., Teng, F., and Strbac, G. (2023). Towards microgrid resilience enhancement via mobile power sources and repair crews: A multi-agent reinforcement learning approach. *IEEE Transactions on Power Systems*, 39(1), 1329-1345.
- Wibawa, A. P., Utama, A. B. P., Lestari, W., Saputra, I. T., Izdihar, Z. N., Pujianto, U., and Nafalski, A. (2023). Mean-Median Smoothing Backpropagation Neural Network to Forecast Unique Visitors Time Series of Electronic Journal. *Journal of Applied Data Sciences*, 4(3), 163-174.
- Zhao, X., Xu, Q., and Yang, Y. (2024). Service restoration of distribution system considering novel battery charging and swapping station, repair crews, and network reconfigurations. *Journal of Modern Power Systems and Clean Energy*, 12(6), 1905-1917.



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