



ARTICLE

An Upgrade Strategy for Active Distribution Networks Considering Probabilistic Power Flow

Xiaotong Li^{1,2}, Mingquan Qiu², Wenjun Zhang², Pengfei Li², Chong Liu², Chong Yang², Han Xiao², Feng Hu², Binghui Liu^{1,*} and He Wang¹

¹Key Laboratory of Modern Power System Simulation and Control & Renewable Energy Technology, Ministry of Education (Northeast Electric Power University), Jilin, China

²State Grid Beijing Electric Power Company, Beijing, China

*Corresponding Author: Binghui Liu. Email: 2202400393@needu.edu.cn

Received: 08 August 2025; Accepted: 29 September 2025; Published: 12 July 2026

ABSTRACT: To address the operational uncertainties and power quality challenges brought by high-penetration distributed energy integration into distribution networks, this paper proposes a precision renovation optimization method for active distribution networks (ADNs) that considers probabilistic power flow. First, based on probabilistic power flow analysis, a comprehensive power quality evaluation index system is constructed to accurately quantify the impact of uncertainties caused by photovoltaic fluctuations on distribution network power quality under high-penetration distributed photovoltaic (PV) scenarios. On this basis, a precision renovation optimization model is established with the goals of minimizing renovation cost, maximizing renewable energy hosting capacity, and optimizing the comprehensive power quality index, thereby achieving coordinated optimization of economic and operational performance. To address the challenges of solving this high-dimensional, mixed-variable, and strongly constrained model, an Adaptive and Feedback-enhanced Multi-strategy Particle Swarm Optimization (AFM-PSO) algorithm is proposed. This algorithm incorporates structured particle encoding, a dynamic information entropy feedback mechanism, and a local perturbation strategy, significantly improving search efficiency and convergence accuracy, making it suitable for rapidly solving complex distribution system renovation problems. Finally, the effectiveness of the proposed model and algorithm is verified using an IEEE 33-node distribution system with high-penetration PV integration as a simulation platform. The results demonstrate that the proposed method significantly enhances system voltage stability and renewable energy hosting capacity while controlling renovation costs, validating its superiority in achieving refined renovation and efficient operation of distribution networks.

KEYWORDS: Active distribution networks; distribution network upgrade; probabilistic power flow; power quality evaluation index; multi-strategy particle swarm algorithm

1 Introduction

With the continuous advancement of China's dual-carbon goals and the construction of new power systems, the penetration rate of renewable energy in the grid has been gradually increasing [1–3]. For distribution transformer areas with high-proportion distributed generations (DGs) integration, the intermittency and volatility of renewable energy output combined with aging grid equipment may lead to power quality issues such as reverse power flow and voltage limit violations [4,5]. Therefore, to accommodate high-penetration distributed generation, it is imperative to promote the upgrade and upgrading of traditional

distribution networks, improve power quality, and facilitate the high-quality development of modernized distribution system.

Currently, scholars worldwide have conducted extensive research on the upgrade of ADNs, primarily focusing on network reconfiguration and feeder-area upgrade [6]. Reference [7] proposed a rapid network reconfiguration strategy based on case-based reasoning (CBR) and the HATSGA hybrid algorithm, constructing a CBR-SGRec framework that accelerates decision-making through historical case retrieval, enabling large-scale distribution network topology optimization while reducing computation time and enhancing self-healing capability. Reference [8] adopted a hybrid approach combining genetic algorithms and linear programming to develop an optimization model aimed at maximizing distributed photovoltaic (PV) hosting capacity, mitigating voltage rise and network loss issues through dynamic network topology adjustment. Reference [9] integrated the grey wolf optimizer (GWO) with power flow calculation methods to optimize DGs-integrated feeder reconfiguration, achieving reduced power losses and improved voltage profile. Reference [10] employed a modified binary particle swarm optimization (BPSO) algorithm to aggregate diverse load types through feeder reconfiguration, enhancing feeder load factor while reducing power supply costs. Reference [11] utilized the ant lion optimizer (ALO) to simulate hunting mechanisms for optimizing distribution network switch states while maintaining radial structure, thereby minimizing network losses and improving voltage distribution. Reference [12] developed a reinforcement learning method based on deep deterministic policy gradient (DDPG), proposing a safe action correction framework to satisfy line flow constraints, enabling rapid and secure load transfer and distribution network reconfiguration. Reference [13] introduced an improved particle swarm clustering algorithm that integrates distributed energy resources and energy storage systems (ESS), constructing an intelligent reconfiguration optimization model for DGs and ESS integrated distribution networks with objectives including non-distributed energy sources, energy losses, and voltage stability. Reference [14] proposed a dynamic simulated annealing particle swarm algorithm that treats network loss and voltage deviation as objective functions, constructing a multi-objective optimization model for DG-integrated distribution network reconfiguration by incorporating Pareto principles and fuzzy membership functions. These studies have achieved notable results in multi-timescale coordinated planning for distribution network renovation and consideration of multiple uncertainty factors. However, most of these works primarily focus on economic objectives while neglecting grid operational characteristics, making it difficult to meet the requirements of high-precision modeling and refined decision-making for precision distribution network renovation.

Regarding feeder-area upgrade, Reference [15] established an economically and reliability-balanced distribution network upgrade model using improved minimum spanning tree (MST) and NSGA-II algorithms to optimize network framework and switch configuration. Reference [16] applied the CYMDIST-Reliability Assessment Module software to evaluate distribution system reliability based on minimum cut-set and failure mode and effects analysis (FMEA) techniques, analyzing performance differences among urban, industrial, and rural feeders to provide reliability-based indicators for line upgrade. Reference [17] investigated a regional distribution network to analyze reactive power variation trends under different cable structures and DGs penetration levels, developing a reactive power demand analysis model that considers both feeder upgrade and distributed generation. Reference [18] implemented a backpropagation (BP) neural network to explore correlations between upgrade measures and loss-of-load indicators, constructing a data-driven investment decision model to optimize distribution network upgrade strategies. In the field of feeder renovation, the aforementioned literature has established a multi-dimensional research foundation. Nevertheless, these studies exhibit significant limitations in terms of closed-loop validation for precision renovation. Most renovation schemes focus on static optimization at the planning stage and lack a dynamic performance

evaluation system for post-renovation distribution networks, resulting in an inability to comprehensively determine whether the renovations genuinely enhance overall grid performance.

As evidenced by the aforementioned research, precision upgrade methodologies for ADNs have achieved notable progress; however, the following critical challenges persist:

- (1) There is an inherent conflict between the stochastic output of probabilistic power flow and existing deterministic power quality index systems, making it difficult to accurately evaluate the true power quality status under high-penetration distributed photovoltaic integration. To address this, this study innovatively establishes a comprehensive power quality evaluation index system compatible with probabilistic outputs, which can quantitatively assess power quality levels under different probabilistic scenarios, thereby bridging the gap between stochastic and deterministic evaluations.
- (2) Most existing renovation models focus on the macro-planning level with insufficient accuracy, failing to support the practical requirements of “precision renovation.” To overcome this limitation, this paper proposes a refined renovation optimization model that accounts for source-load multiple uncertainties. This model deeply integrates probabilistic power flow calculations with renovation decision-making, significantly enhancing the targeting and effectiveness of renovation plans.
- (3) Solving the precision renovation model involves a large number of discrete variables and high model complexity, posing serious challenges to the global optimization capability and efficiency of the solution algorithm. Therefore, this study designs and employs an improved AFM-PSO algorithm for solution.

In response to the above issues, the main innovations of this paper are as follows:

- (1) Construction of a comprehensive power quality evaluation index system for active distribution networks based on probabilistic power flow calculations. This system utilizes the probability distribution characteristics of power flow to compute evaluation indicators, enabling precise quantification of the impact of uncertainties from high-penetration distributed photovoltaic integration on power quality, thereby improving the accuracy and reliability of evaluation results.
- (2) Development of a precision renovation model for active distribution networks that comprehensively considers renovation cost, hosting capacity, and power quality. The order relationship analysis method is adopted to determine the weight coefficients of each objective, achieving strict cost control and effective management of power quality issues such as voltage fluctuations, thus enhancing the overall benefits and decision-making rationality of renovation plans.
- (3) An Adaptive and Feedback-enhanced Multi-strategy Particle Swarm Optimization (AFM-PSO) algorithm is proposed to achieve rapid solving of the distribution network renovation model. Through its customized encoding and dynamic feedback strategies, it effectively addresses premature convergence and low convergence efficiency in the model solving process, thereby enhancing both the optimization efficiency and the quality of the final solution for precision renovation decision-making in distribution networks.

The subsequent sections of this paper are structured as follows: [Section 2](#) develops a Monte Carlo simulation-based probabilistic power flow calculation method that accounts for stochastic source-load uncertainties, and formulates a comprehensive power quality assessment index for ADNs using probabilistic power flow results. [Section 3](#) constructs a precision reformation optimization model for ADNs derived from the established power quality indices. [Section 4](#) proposes an enhanced particle swarm optimization algorithm for efficient solving of the ADNs precision reformation model. [Section 5](#) validates the precision reformation model's accuracy and computational efficacy through the IEEE 33-node benchmark distribution system, analyzing reformation outcomes through case studies.

2 Operational Evaluation Index for ADNs Considering Probabilistic Power Flow

With the widespread integration of high-penetration DGs into distribution networks, the strong randomness and volatility of its output pose unprecedented uncertainty challenges to system operation. Based on probabilistic power flow calculation results, this paper proposes a comprehensive power quality evaluation index for ADNs with high-penetration distributed PV integration, providing effective support for precision upgrade.

2.1 Probabilistic Power Flow Calculation Accounting for Source-Load Uncertainty

Following high-penetration PV integration into distribution networks, numerous uncertain factors emerge in the system. Deterministic power flow calculation cannot account for the volatility of PV generation and random loads [19]. Power system probabilistic power flow calculation, based on given probability models of power sources and loads, solves for numerical characteristics of power flow variables such as cumulative distribution functions and mean values, thereby effectively quantifying the impact of these fluctuations on the system [20]. This paper establishes probability models for PV output and loads, generates n sets of uncertainty samples using Monte Carlo simulation, performs deterministic power flow calculations for each sample set, and finally obtains numerical characteristics of probabilistic power flow through statistical analysis, including cumulative distribution functions and mean values.

(1) PV generation probability model

The solar irradiance probability distribution is known to follow a Beta distribution [21]. As the output power of PV plants is closely related to solar irradiance, it also follows a Beta distribution, expressed as:

$$f(P_M) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} \cdot \left(\frac{P_M}{P_{Mmax}}\right)^{\alpha-1} \cdot \left(1 - \frac{P_M}{P_{Mmax}}\right)^{\beta-1} \quad (1)$$

where P_M and P_{Mmax} represent the actual PV output and maximum PV output during this period, α and β denote the shape parameters of the Beta distribution, and Γ represents the Gamma function. The shape parameters of the Beta distribution can be derived from the mean (μ) and variance (σ^2) of solar irradiance during this period, with the relationships shown in Eqs. (2) and (3):

$$\alpha = \mu \cdot \left[\frac{\mu \cdot (1 - \mu)}{\sigma^2} - 1 \right] \quad (2)$$

$$\beta = (1 - \mu) \cdot \left[\frac{\mu \cdot (1 - \mu)}{\sigma^2} - 1 \right] \quad (3)$$

As the Beta distribution inherently captures the stochastic characteristics of irradiance within a bounded interval, its shape parameters α and β can be calibrated based on historical irradiance data under different weather conditions (e.g., sunny, cloudy, overcast, etc.). Thus, the model implicitly incorporates the influence of diverse weather scenarios through probability distributions, effectively reflecting the uncertainty of PV output under varying weather conditions.

(2) Load probability model

Most current probabilistic power flow calculations treat loads as continuous probability models, using normal distribution to approximate their probability distribution [22]. Let μ_P , σ_P , μ_Q , and σ_Q represent the expected values and standard deviations of active power and reactive power in historical load data, respectively. Their probability density functions are shown in Eqs. (4) and (5):

$$f(P) = \frac{1}{\sqrt{2\pi}\sigma_P} \exp\left(-\frac{(P - \mu_P)^2}{2\sigma_P^2}\right) \quad (4)$$

$$f(Q) = \frac{1}{\sqrt{2\pi}\sigma_Q} \exp\left(-\frac{(Q - \mu_Q)^2}{2\sigma_Q^2}\right) \quad (5)$$

The key parameters, including the shape parameters of the Beta distribution and the mean and variance of the normal distribution, are derived from actual historical operational data provided by a regional grid company in China. These data, after statistical processing and validation, accurately reflect the local solar irradiance variation characteristics and load fluctuation patterns.

(3) Probabilistic power flow calculation based on Monte Carlo simulation

Probabilistic power flow is an extension of deterministic power flow into the domain of uncertainty. Its core concept involves replacing the input variables in deterministic power flow—originally fixed values—with random variables following specific probability distributions, and then solving for the probability distribution of state variables using probabilistic methods. Deterministic power flow calculation serves as the foundation and kernel of probabilistic power flow. Regardless of the probabilistic power flow algorithm employed, each computation for a specific scenario is essentially a deterministic power flow calculation. Probabilistic power flow can thus be understood as a statistical generalization of numerous deterministic power flow calculations.

Deterministic power flow is typically computed using the Newton-Raphson method. Its corresponding mathematical model in the rectangular coordinate system [23] can be expressed as:

$$P_i = U_i \sum_{j=1}^n U_j (G_{ij} \cos \delta_{ij} + B_{ij} \sin \delta_{ij}) \quad (6)$$

$$Q_i = U_i \sum_{j=1}^n U_j (G_{ij} \sin \delta_{ij} - B_{ij} \cos \delta_{ij}) \quad (7)$$

$$P_{ij} = -G_{ij} U_i^2 + U_i U_j (G_{ij} \cos \delta_{ij} + B_{ij} \sin \delta_{ij}) \quad (8)$$

$$Q_{ij} = B_{ij} U_i^2 - b_{ij0} U_i^2 + U_i U_j (G_{ij} \sin \delta_{ij} - B_{ij} \cos \delta_{ij}) \quad (9)$$

where P_i and Q_i represent the active and reactive power injected into the network at node i , P_{ij} and Q_{ij} denote the active and reactive power flow on line ij , U_i and U_j indicate the voltage magnitudes at nodes i and j , δ_{ij} stands for the phase angle difference between voltages at nodes i and j , G_{ij} and B_{ij} correspond to the real and imaginary parts of the admittance matrix Y_{ij} , and b_{ij0} represents the susceptance near node i on line ij .

The Monte Carlo simulation method serves for stochastic simulation in probabilistic power flow calculation, generating n sets of random numbers based on the probability models of PV and load as input variables for deterministic power flow. Through massive sampling, the Monte Carlo method approximates the true distribution with high computational accuracy.

The probabilistic power flow calculation procedure based on Monte Carlo simulation are as following:

Step 1: Input deterministic data including network topology, node parameters, and line parameters of the ADNs, along with the number of Monte Carlo simulations n .

Step 2: Generate one set of corresponding PV output and load random samples based on the probability models of PV and load.

Step 3: Use the obtained samples as input variables for deterministic power flow. Perform deterministic power flow calculation using the Newton-Raphson method based on power flow Eqs. (6)–(9), and save the power flow results.

Step 4: Repeat Steps 2 and 3 until completing n independent Monte Carlo simulations of probabilistic power flow calculation.

Step 5: Statistically analyze the results of n deterministic power flow calculations to obtain the mean values of node voltage $\bar{U}_i$ and branch power flow $\bar{I}_j$, along with their standard deviations and cumulative distribution functions $F(U_i)$ and $F(I_j)$.

Through the aforementioned Monte Carlo probabilistic power flow calculations, the probability distributions and numerical characteristics of key power flow variables in the system were obtained. These results provide the foundation for accurate calculation of subsequent power quality indicators, thereby effectively quantifying the impact of photovoltaic volatility-induced power flow uncertainty on system operation.

2.2 Comprehensive Power Quality Evaluation Indices for ADNs Considering Probabilistic Power Flow

This paper establishes a comprehensive power quality evaluation index for ADNs. Based on power flow results from probabilistic power flow calculations, it quantifies violation risks and power quality issues caused by distributed PV integration, accurately identifies weak areas in ADNs under high PV penetration, and provides basis for precision upgrade.

- (1) Voltage deviation index [24]

$$U_{DI,i}(t) = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (\bar{U}_i(t) - U_N)^2} \quad (10)$$

where $U_{DI,i}(t)$ represents the voltage deviation at node i at time t , $\bar{U}_i(t)$ denotes the mean voltage at node i at time t , U_N indicates the nominal voltage, and N is the total number of system nodes. The magnitude of the voltage deviation index reflects the concentration or dispersion of bus voltage distribution in the power grid. A smaller voltage deviation index indicates more concentrated bus voltage distribution and better power quality.

- (2) Voltage compliance rate [25]

$$U_{QR,i}(t) = \left(1 - \frac{t_{U,\text{super,max}} + t_{U,\text{low,min}}}{t_{\text{total}}}\right) \times 100\% \quad (11)$$

where $U_{QR,i}(t)$ represents the voltage qualification rate at node i at time t ; $t_{U,\text{super,max}}$ denotes the number of over-voltage occurrences; $t_{U,\text{low,min}}$ indicates the number of under-voltage occurrences; t_{total} is the total number of Monte Carlo samples. The allowable range for voltage deviation: $\pm 5\% U_N$.

- (3) Maximum voltage offset ratio [24]

$$U_{DR,i}(t) = \max \left(\frac{|\Delta U_k(t)|}{U_N} \right) \times 100\% \quad (12)$$

where $U_{FR,i}(t)$ represents the maximum voltage deviation rate at node i at time t , and $\Delta U_j(t)$ denotes the difference between the actual voltage and nominal voltage for the k -th sample at time t .

(4) Average voltage fluctuation rate [26]

$$U_{FR,i}(t) = \frac{\sqrt{\frac{1}{n_{i,t}} \sum_{j=1}^{n_{i,t}} (U_k(t) - U_N)^2}}{U_N} \times 100\% \quad (13)$$

where $U_{FR,i}(t)$ represents the average voltage fluctuation rate at node i at time t , and $n_{i,t}$ denotes the total number of samples at node i at time t .

(5) Node voltage violation risk index [27]

(1) Node voltage violation probability

$$\begin{cases} P_{VUP}(U_i(t)) = P_t(U_i(t) > U_{\max}) = 1 - F_t(U_{\max}) \\ P_{VLP}(U_i(t)) = P_t(U_i(t) < U_{\min}) = F_t(U_{\min}) \end{cases} \quad (14)$$

where $P_{VUP}(U_i(t))$ represents the probability of voltage exceeding the upper limit at node i at time t , $P_{VLP}(U_i(t))$ indicates the probability of voltage falling below the lower limit at node i at time t , $U_{\max}$ and $U_{\min}$ represent the upper and lower limits of allowable voltage deviation (1.05 and 0.95 U_N , respectively), and $F_t(U_i)$ denotes the cumulative distribution function of voltage at node i at time t .

(2) Node voltage violation severity

The voltage violation severity at node i at time t is:

$$S_{VLP}(U_i(t)) = \begin{cases} \frac{U_{\min} - U_o(t)}{U_{\min}}, & U_i(t) < U_{\min} \\ 0, & U_i(t) \geq U_{\min} \end{cases} \quad (15)$$

$$S_{VUP}(U_i(t)) = \begin{cases} \frac{U_o(t) - U_{\max}}{U_{\max}}, & U_i(t) > U_{\max} \\ 0, & U_i(t) \leq U_{\max} \end{cases} \quad (16)$$

where $S_{VLP}(U_i(t))$ represents the upper-limit violation severity at node i at time t , $S_{VUP}(U_i(t))$ denotes the lower-limit violation severity at node i at time t , and $U_o(t)$ indicates the average voltage value at node i at time t .

(3) Voltage violation risk index

The voltage violation risk index at node i at time t is:

$$R_i(t) = \max(P_{VUP}(U_i(t))S_{VUP}(U_i(t)), P_{VLP}(U_i(t))S_{VLP}(U_i(t))) \quad (17)$$

(6) Comprehensive power quality evaluation index

The normalized sequential weighting method is employed to weight and integrate the aforementioned five conventional power quality evaluation indicators into a comprehensive evaluation index. The procedure is as follows:

(1) The min-max normalization method [28] is used to eliminate dimensional differences among indicators. The calculation formula is: the benefit index

$$x'_{ij} = \begin{cases} \frac{x_{ij} - x_{j,\min}}{x_{j,\max} - x_{j,\min}}, & x_{ij} \in \{U_{DI,i}(t), U_{DR,i}(t), U_{FR,i}(t), R_i(t)\}, \text{ the cost index} \\ \frac{x_{j,\max} - x_{ij}}{x_{j,\max} - x_{j,\min}}, & x_{ij} \in \{U_{QR,i}(t)\}, \text{ the benefit index} \end{cases} \quad (18)$$

- (2) The order relation analysis method is applied to determine the weights of each power quality index. The specific steps are as following:

Step 1: Experts rank all power quality indices in descending order of importance.

Step 2: The relative importance between each pair of indicators is systematically compared to determine their corresponding scaling factors t_i [29].

Step 3: After determining the scaling factors in the previous step, calculate other element values based on the transitivity of importance and establish the following judgment matrix R :

$$R = \begin{bmatrix} 1 & t_1 & t_1 t_2 & \cdots & \prod_{i=1}^{m-1} t_i \\ \frac{1}{t_1} & 1 & t_2 & \cdots & \prod_{i=2}^{m-1} t_i \\ 1/t_1 t_2 & 1/t_2 & 1 & \cdots & \prod_{i=3}^{m-1} t_i \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1/\prod_{i=1}^{m-1} t_i & 1/\prod_{i=2}^{m-1} t_i & 1/\prod_{i=3}^{m-1} t_i & \cdots & 1 \end{bmatrix} \quad (19)$$

in matrix R , m represents the number of indicators to be evaluated, and element r_{ij} denotes the scale value when comparing the i -th indicator with the j -th indicator.

Step 4: Calculate the weight coefficients of each indicator from matrix R using the following formula:

$$\alpha_i = \sqrt[m]{\prod_{j=1}^m r_{ij}} / \sum_{i=1}^m \sqrt[m]{\prod_{j=1}^m r_{ij}} \quad (20)$$

where w_i is the weight of the i -th indicator, and $\prod_{j=1}^m r_{ij}$ is the product of all elements in the i -th row of matrix R .

- (3) Based on the weight coefficients obtained through order relation analysis, perform weighted integration of the five normalized sub-indicators to calculate the comprehensive power quality evaluation index for node i at time t :

$$S_i^{\text{PQ}}(t) = w_1 U_{DI,i}(t) + w_2 U_{QR,i}(t) + w_3 U_{DR,i}(t) + w_4 U_{FR,i}(t) + w_5 R_i(t) \quad (21)$$

where w_1, w_2, w_3, w_4 and w_5 represent the weight coefficients of the corresponding indicators.

3 Precision Upgrade Model for ADNs

To address practical issues in active distribution network upgrade including high upgrade costs, suboptimal power quality, and insufficient precision in traditional upgrade methods, this paper establishes a precision upgrade model for ADNs. The model comprehensively considers upgrade costs, accommodation rate, and optimizing power quality evaluation indices as its objectives.

3.1 Objective Function of Upgrade Model

The objective function for the precision upgrade of ADNs consists of three components: upgrade cost, accommodation rate, and power quality evaluation indices. These three objective functions are combined through linear weighting, with the expression of the objective function as following:

$$\min F = v_1 f_1 + v_2 f_2 + v_3 f_3 \quad (22)$$

where v_1, v_2 and v_3 represent the weights of sub-objectives; f_1, f_2 and f_3 denote upgrade cost, accommodation rate, and power quality evaluation indices, respectively.

(1) Upgrade cost

$$f_1 = \sum_{a=1}^{A_{ref}} x_a c_{ref,a} l_a + \sum_{b=1}^{B_{ref}} x_b c_{ref,b} \quad (23)$$

where f_1 includes line investment cost and tie-switch investment cost; x_a and x_b are binary variables (1 when selected, 0 otherwise); $c_{ref,a}$ indicates the unit upgrade cost of line a ; l_a represents the length of renovated line a ; $c_{ref,b}$ denotes the unit upgrade cost of planned tie-switch b .

(2) Accommodation rate

$$f_2 = \left[\frac{\sum_{t=1}^{24} (P_{SC}(t) + P_{bat}(t)) \Delta t}{\sum_{t=1}^{24} P_{PV}(t) \Delta t} \right] \times 100\% \quad (24)$$

$$P_{SC}(t) = \min \{P_{PV}(t) + P_{WT}(t), P_{out}(t)\} \quad (25)$$

where $P_{SC}(t)$ indicates the renewable energy output consumed by loads in real-time; $P_{bat}(t)$ represents the charging/discharging power of energy storage during period t ($P_{bat}(t) > 0$ when charging); $P_{out}(t)$ shows the real-time load power after electricity price optimization; $P_{PV}(t)$ denotes the day-ahead forecasted PV output.

(3) Power quality evaluation index

$$f_3 = w_1 U_{DI,i}(t) + w_2 U_{QR,i}(t) + w_3 U_{DR,i}(t) + w_4 U_{FR,i}(t) + w_5 R_i(t) \quad (26)$$

3.2 Restrictive Constraints of Upgrade Model

(1) Network topology constraints

(1) Maximum allowable line modernization constraints

$$A_{ref} \leq A_{ref}^{\max} \quad (27)$$

where A_{ref} represents the actual number of renovated lines, and $A_{ref}^{\max}$ denotes the maximum number of lines proposed for upgrade.

(2) Tie-switch installation quantity constraints

$$B_{ref} \leq B_{ref}^{\max} \quad (28)$$

where B_{ref} indicates the actual number of renovated tie switches, and $B_{ref}^{\max}$ represents the maximum number of tie switches proposed for upgrade.

(3) Radial structure constraint

$$T \in T_{rad} \quad (29)$$

where T denotes the system structure, and T_{rad} represents the set of radial system structures.

(2) Operational constraints

(1) Node voltage constraint

$$U_i^{\min} \leq U_i \leq U_i^{\max} \quad (30)$$

where $U_i^{\min}$ and $U_i^{\max}$ represent the minimum and maximum voltage values at node i , respectively.

(2) Power balance constraint

$$\begin{cases} P_i = U_i \sum_{j=1}^N U_j (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}) \\ Q_i = U_i \sum_{j=1}^N U_j (G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij}) \end{cases} \quad (31)$$

where G_{ij} , B_{ij} , N , and θ_{ij} denote the conductance, susceptance, total number of nodes, and phase angle difference between nodes i and j of branch ij , respectively; U_i and U_j represent the voltages at nodes i and j ; P_i and Q_i indicate the active and reactive power at node i .

4 Solution of Precision Upgrade Model for ADNs Based on Improved PSO

Given the challenges faced by traditional methods in efficiently solving multi-objective hybrid models, this paper proposes the AFM-PSO algorithm to optimize the distribution network upgrade model considering probabilistic power flow, thereby enhancing solution accuracy and convergence speed.

4.1 AFM-PSO Algorithm

To enhance solution performance for strongly-constrained hybrid variable problems, this paper proposes the AFM-PSO algorithm. The algorithm effectively improves search capability and convergence speed through dynamic information entropy adjustment, particle structure mapping, local perturbation, and coordinated feedback mechanism between upper and lower layers.

The AFM-PSO algorithm implements an adaptive search and feedback linkage optimization mechanism through nine key steps. The algorithm implementation procedures are as following:

(1) Initialize algorithm parameters

Before optimization begins, set the basic control parameters including: population size $N_{\text{ps}} = 50$, current iteration count $t = 1$, maximum iterations $T_{\text{max}} = 500$, initial inertia weight $\omega_{\text{init}} = 0.9$, minimum/maximum weights $\omega_{\text{min}} = 0.4$, $\omega_{\text{max}} = 0.9$, learning factors $c_1 = 1.5$, $c_2 = 1.7$, stagnation perturbation threshold $T_{\text{stagnant}} = 30$, structural entropy range thresholds $\epsilon_1 = 0.05$, $\epsilon_2 = 0.15$.

(2) Construct unified structured particle encoding

To accommodate various discrete and continuous variables in distribution network upgrade problems (line selection, switch status, etc.), this paper designs a unified particle encoding structure using Boolean and binary variable combinations to represent line upgrade status and switch operation states, thereby adapting to mixed-variable space and improving algorithm feasibility and adaptability. The particle structure is defined as:

$$X_i = [x_i^{\text{line-status}}, x_i^{\text{line-type}}, x_i^{\text{line-length}}, x_i^{\text{switch-status}}] \quad (32)$$

where $x_i^{\text{line-status}}$ is a Boolean variable indicating whether the corresponding branch is to be renovated, $x_i^{\text{line-type}}$ is an integer variable representing the selected line type, $x_i^{\text{line-length}}$ is a continuous variable

indicating the actual line length in km, $x_i^{switch-status}$ is a binary variable representing the installation and switching status of the tie switch ('1' denotes installed status, '0' indicates non-operational state).

- (3) Embed power flow model and establish bi-level cooperative fitness function

Based on each particle's encoding results, construct corresponding distribution network topology and invoke the probabilistic power flow analysis module to evaluate key indicators including node voltage and voltage deviation. Then perform fitness evaluation using the multi-objective comprehensive function, achieving closed-loop feedback between upper-level optimization and lower-level simulation.

- (4) Update individual and global optimal solutions

Traverse current population to compare each particle's current fitness $f(X_i^{(t)})$ with historical optimum $f(p_i)$, if superior to historical record, update individual best position $p_i = X_i^{(t)}$, if $f(p_i) < f(g)$, update global best particle to $g = p_i$.

- (5) To quantify the diversity of the population during the search process, a structural entropy metric is introduced. This metric serves to objectively evaluate the population state and provides a basis for subsequent adaptive adjustments, with the goal of reducing performance fluctuations caused by random initialization:

$$H(t) = - \sum_{j=1}^K \frac{n_j}{N_{pso}} \log \left(\frac{n_j}{N_{pso}} \right) \quad (33)$$

where K is the number of particle feature partitions, n_j is the number of particles in the j -th category, N_{pso} is the population size.

Set the entropy variation $\Delta H = H(t) - H(t-1)$ to determine the current evolutionary state: If $|\Delta H| > \delta$, it is judged as "convergence phase" to enhance convergence; If $0 < |\Delta H| < \delta$, it is "diversity phase" to promote exploration; If $|\Delta H| = 1$, it is "stagnation phase" to trigger the perturbation mechanism.

- (6) To enhance the behavioral consistency of the algorithm across different independent runs, it is necessary to adopt the most suitable parameters according to the current search phase. Specifically, based on the entropy feedback state, the core search parameters—namely the inertia weight and learning factors—are dynamically adjusted to achieve a transition from extensive exploration to refined tuning:

$$\begin{aligned} \omega(t) &= \omega(t-1) + \alpha \cdot \Delta H(t) \\ c_1(t) &= c_1(t-1) + \beta \cdot \Delta H(t) \\ c_2(t) &= c_2(t-1) - \beta \cdot \Delta H(t) \end{aligned} \quad (34)$$

where α, β are adjustment coefficients used to perceive evolutionary trends and adjust search strategies. The updated parameters directly affect particle velocity and position updates, controlling search direction and range.

- (7) Perform position and velocity updates

$$v_i^{(t)} = \omega v_i^{(t-1)} + c_1 r_1 (p_{Best_i} - x_i) + c_2 r_2 (g_{Best} - x_i) \quad (35)$$

$$x_i^{(t)} = x_i^{(t-1)} + v_i^{(t)} \quad (36)$$

where p_{Best_i} represents the particle's historical optimal position, g_{Best} denotes the current global optimal particle position; r_1, r_2 are uniform random numbers.

The updated particles undergo variable type conversion and boundary checking through a type mapper and feasibility correction module to ensure legal positions, type matching, and constraint satisfaction:

$$x_i^{(t)} \leftarrow M\left(P\left(x_i^{(t)}\right)\right) \quad (37)$$

where $P(\cdot)$ indicates a variable boundary correction function that projects out-of-bound variables back into the defined domain, $M(\cdot)$ represents a variable type mapping function that converts integer and Boolean variables in particles into feasible variables satisfying constraints.

- (8) To avoid premature convergence to local optima and enhance the robustness of the solution, thereby reducing result variability across multiple runs, a perturbation triggering mechanism is constructed based on information entropy and stagnation generation count. Unlike random mutation, this perturbation is conditional and deterministic—it is activated only when the algorithm confirms a stagnant state, with its perturbation probability defined as:

$$P_{\text{mut}} = \eta \cdot \left(1 - \frac{H(t)}{H_{\text{max}}}\right) \cdot \frac{g_i}{N_{\text{pso}}} \quad (38)$$

where $H(t)$ is the current structural entropy value, H_{max} represents the entropy upper limit during algorithm initialization, $\eta = 0.5$ is the global perturbation sensitivity coefficient; g_i indicates the position of the i -th particle's historical optimal solution in the global ranking, N_{pso} is the population size.

To simplify triggering criteria, introduce a perturbation threshold $\theta = 0.3$, if $P_{\text{mut}} > \theta$, execute the following perturbation:

$$x_i^{\text{new}} = x_i + N(0, \sigma^2) \quad (39)$$

where $N(0, \sigma^2)$ represents a normally distributed perturbation term with zero mean and variance σ^2 , σ controls perturbation amplitude, dynamically adjusted with iterations, which can be set as:

$$\sigma(t) = \sigma_{\text{max}} \cdot \left(1 - \frac{t}{T_{\text{max}}}\right) \quad (40)$$

- (9) Terminate iteration and output optimal particle
When any termination condition is met (including reaching maximum iterations, or global optimal solution showing no significant improvement over consecutive generations with structural entropy convergence), the algorithm terminates. The final output is the current global optimal particle, whose encoding represents decision information including distribution line upgrade status, tie-switch states, type selection, and capacity configuration.

The specific flowchart is shown in [Fig. 1](#):

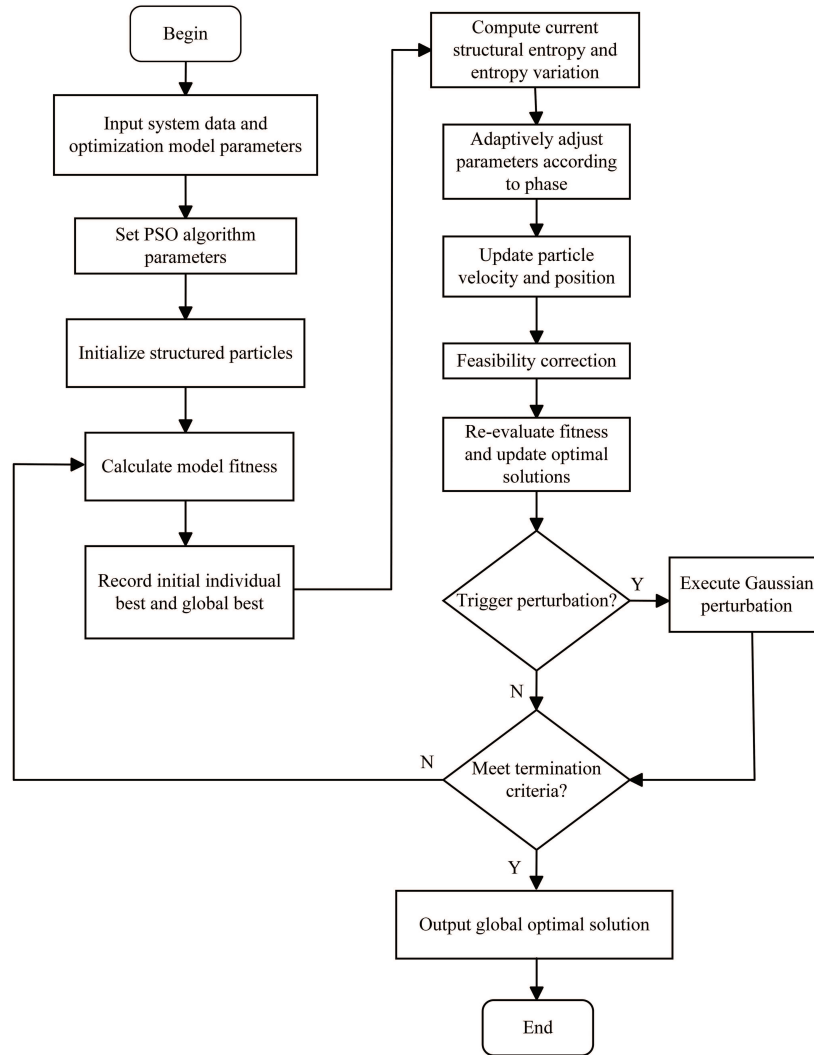


Figure 1: AFM-PSO algorithm implementation flowchart.

4.2 Overall Implementation Process of Precision Upgrade for ADNs.

To achieve optimal upgrading of the existing distribution network structure, the AFM-PSO algorithm constructed in Section 4.1 is embedded into the solution process for the precision upgrade of ADNs. The steps are as following:

- (1) Input node loads (P_i , Q_i), branch parameters (resistance R_{ij} reactance X_{ij}), voltage limit constraints ($U_i^{\min}$, $U_i^{\max}$), optional line types with their unit costs, and set optimization weight coefficients (w_1 , w_2 , w_3) along with AFM-PSO algorithm control parameters.
- (2) Calculate node voltage deviation, maximum deviation rate, average voltage fluctuation rate, voltage violation probability and risk index. Combine these weighted indicators to compute a scoring function.
- (3) Encode optimization variables including line selection x_{line} , line type selection x_{type} , line length x_{length} , and tie-switch configuration x_{switch} to form the search space, then initialize particle swarm positions and velocities.
- (4) Normalize the evaluation indicators, accommodation rate, and upgrade cost, then construct a comprehensive fitness function based on the weights.

- (5) Using the fitness function values, dynamically update particle positions with the AFM-PSO algorithm for global search, while checking convergence conditions.
- (6) After algorithm convergence, output the optimal upgrade scheme corresponding to the global best particle, including line upgrade types and switch configurations.

The specific flowchart is shown in Fig. 2:

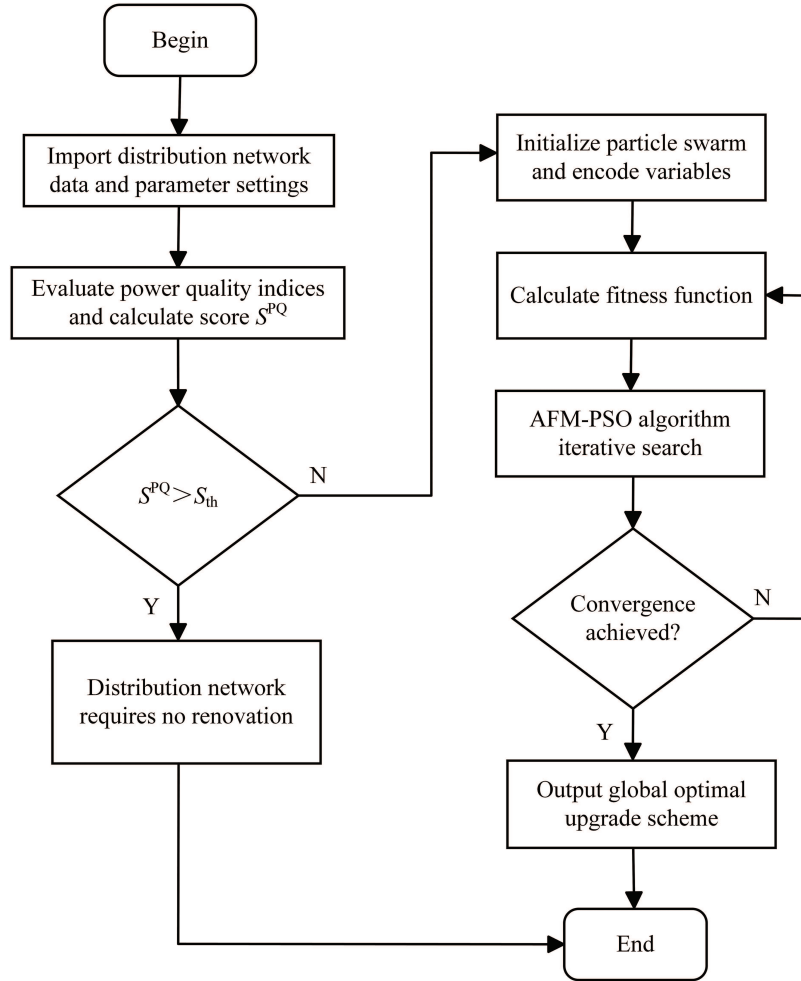


Figure 2: Overall implementation flowchart of precision upgrade for ADNs.

5 Simulation Experiments and Performance Analysis

5.1 Simulation Environment Configuration

The reliability assessment of the proposed ADNs precision reformation model employs the IEEE 33 node benchmark system under typical daily operating conditions (Fig. 3). This radial test network features a 12.66 kV base voltage with node voltage bounds of 0.95–1.05 per unit and 10 MVA base power. System loading comprises 3715 kW active power and 2300 kVar reactive power demand. External grid interconnection occurs through root node 1. PV units are located at nodes 28–33 with 0.4 MW per node, and ESS units are installed at nodes 17 and 20 with 0.05 MWh per node. The basic data of the IEEE 33 node distribution network refers to [30]. Parameters of optional lines for upgrade and tie switches are provided in Appendix A Tables A1 and A2.

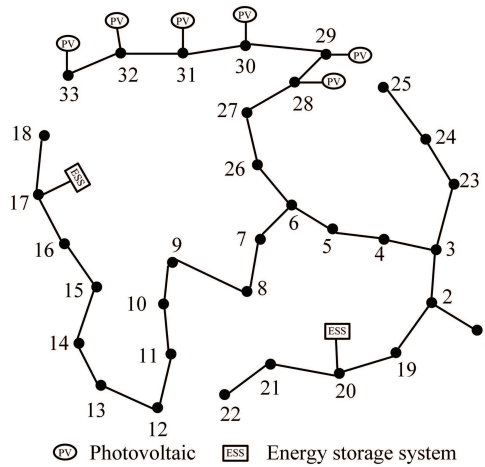


Figure 3: IEEE 33-node distribution system.

5.2 Verification of Precision Upgrade for Distribution Areas

To validate the effectiveness of the proposed model and algorithm, simulation tests were conducted on the IEEE 33-node distribution system. The simulation yielded the following upgrade scheme: installation of 3 new branches, upgrading of 8 existing lines, and deployment of 6 additional tie switches. Detailed upgrade results are presented in [Table 1](#) (added branches), [Table 2](#) (line upgrades), and [Table 3](#) (added tie switches), respectively.

Table 1: Precision upgrade results for active distribution network (Added Branches).

Branch number	Line	Length (km)	Line type
Branch 33	L ₂₁₋₈	5.5	JKLYJ-120
Branch 34	L ₁₂₋₂₂	15.4	JKLYJ-120
Branch 35	L ₂₅₋₂₉	13.6	JKLYJ-120

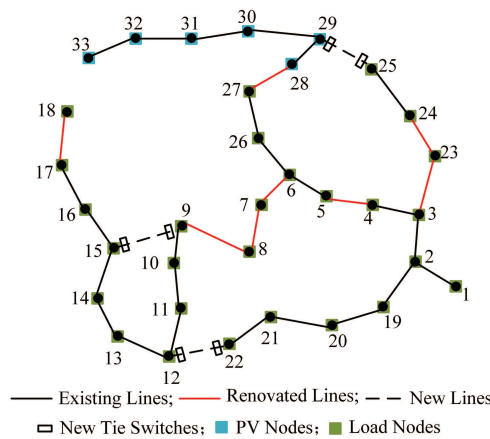
Table 2: Precision upgrade results for active distribution network (Line Upgrades).

Branch number	Line	Length (km)	Line type
Branch 4	L ₄₋₅	2.1	JKLYJ-300
Branch 6	L ₆₋₇	1.4	JKLYJ-300
Branch 7	L ₇₋₈	1.3	JKLYJ-300
Branch 8	L ₈₋₉	1.5	JKLYJ-300
Branch 17	L ₁₇₋₁₈	3.2	JKLYJ-300
Branch 22	L ₃₋₂₃	1.2	JKLYJ-300
Branch 23	L ₂₃₋₂₄	1.2	JKLYJ-300
Branch 27	L ₂₇₋₂₈	1.7	JKLYJ-300

Table 3: Precision upgrade results for distribution network (Added Tie Switches).

Installation node	Model	Cost (¥)
8	ZW32-12F/630	8000
12	ZW32-12F/630	8000
21	ZW32-12F/630	8000
22	ZW32-12F/630	8000
25	ZW32-12F/630	8000
29	ZW32-12F/630	8000

Fig. 4 shows the network topology of the distribution network after precision upgrade. The upgrade replaced outdated lines with new conductors (JKLYJ series) featuring lower losses and higher current carrying capacity, significantly optimizing power transmission efficiency. New lines were added to expand network coverage, making power supply layout more rational. Additionally, all new feeders strictly followed the “two-segment two-tie” connection mode for switch configuration, establishing a flexible and reliable network topology.

**Figure 4:** Network architecture of upgrade distribution network.

The simulation results present the hourly node voltage distribution of the IEEE 33-node system before and after upgrade, as shown in Figs. 5 and 6.

The comparative analysis of Figs. 5 and 6 demonstrates that the proposed precision renovation strategy significantly improves voltage quality in the distribution network. Prior to renovation, the system voltage distribution exhibited considerable dispersion and large fluctuations, with some node voltages dropping to 0.93 p.u.—approaching the lower limit of normal operating voltage—indicating the presence of low-voltage issues and the vulnerability of traditional distribution network structures under source-load multiple uncertainties. After renovation, the voltage distribution becomes noticeably more concentrated and stable, with the vast majority of node voltages maintained above 0.98 p.u., confirming the significant effectiveness of the proposed optimization method in enhancing voltage stability.

This result validates the effectiveness of the renovation model constructed in this study in coordinating distributed energy resources, loads, and network renovation strategies. Through precise renovation measures, the system’s adaptability to high penetration of renewable energy integration has been enhanced.

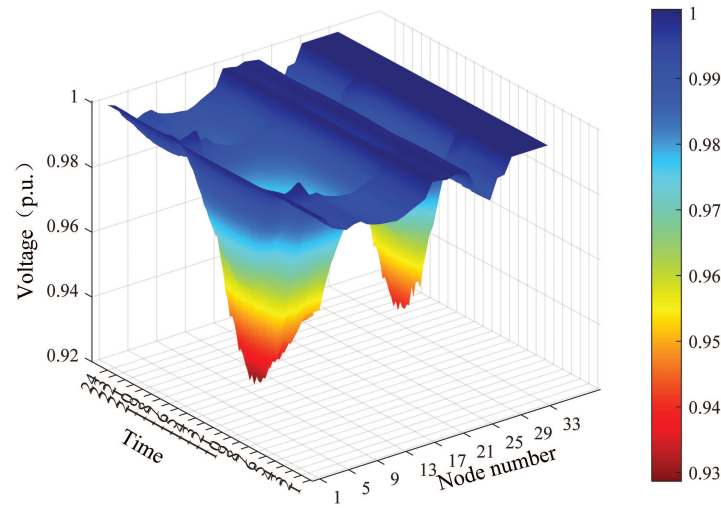


Figure 5: Node voltage curves before upgrade.

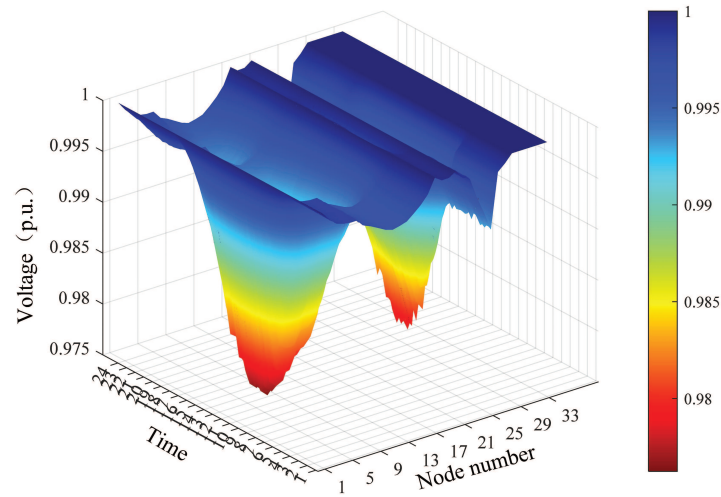


Figure 6: Node voltage curves after upgrade.

5.3 Comparative Analysis of Power Quality Evaluation Indicators Before and After Upgrade

Following the evaluation method described in [Section 2.2](#), comparative analyses of power quality evaluation indicators before and after upgrade were conducted. The comparison results of power quality evaluation indicators and power quality before vs. after upgrade are shown in [Figs. 7 and 8](#).

According to the comparative results of power quality evaluation indicators shown in [Fig. 7](#), the overall performance of the distribution network significantly improved after precision upgrade. The maximum voltage deviation (U_{DI}) decreased by 63.3% ([Fig. 7a](#)), the average voltage fluctuation rate (U_{FR}) reduced by 62.5% ([Fig. 7b](#)), and the average voltage violation probability (P_{VP}) dropped to 0 ([Fig. 7c](#)) compared to pre-upgrade values. These results demonstrate that the upgrade effectively reduced voltage fluctuations, improved voltage stability, and completely eliminated voltage violations. The comprehensive power quality score (S^{PQ}) increased from 0.743 before upgrade to 0.884 after upgrade ([Fig. 7d](#)), representing a 19% improvement that exceeded the threshold score of 0.75, indicating no further upgrade is required. These improvements

primarily resulted from optimized network topology through rational line layout adjustments and switch configurations, which enhanced the network's flexibility, adaptability and stability.

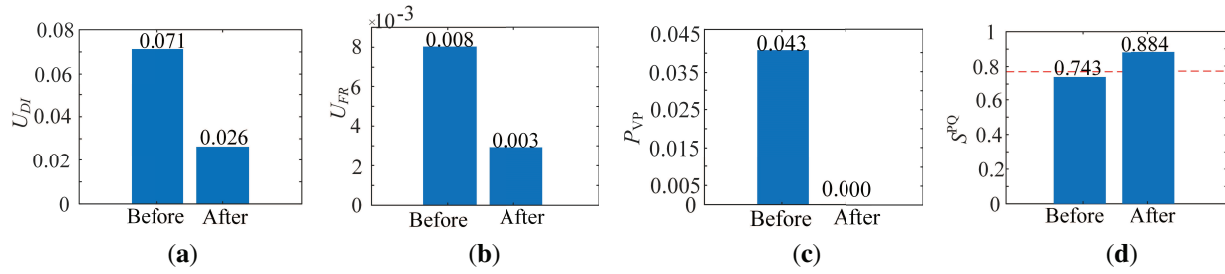


Figure 7: Comparison of power quality evaluation indicators before and after upgrade (a) Maximum voltage deviation (b) Average fluctuation rate (c) Average violation probability (d) Comprehensive score.

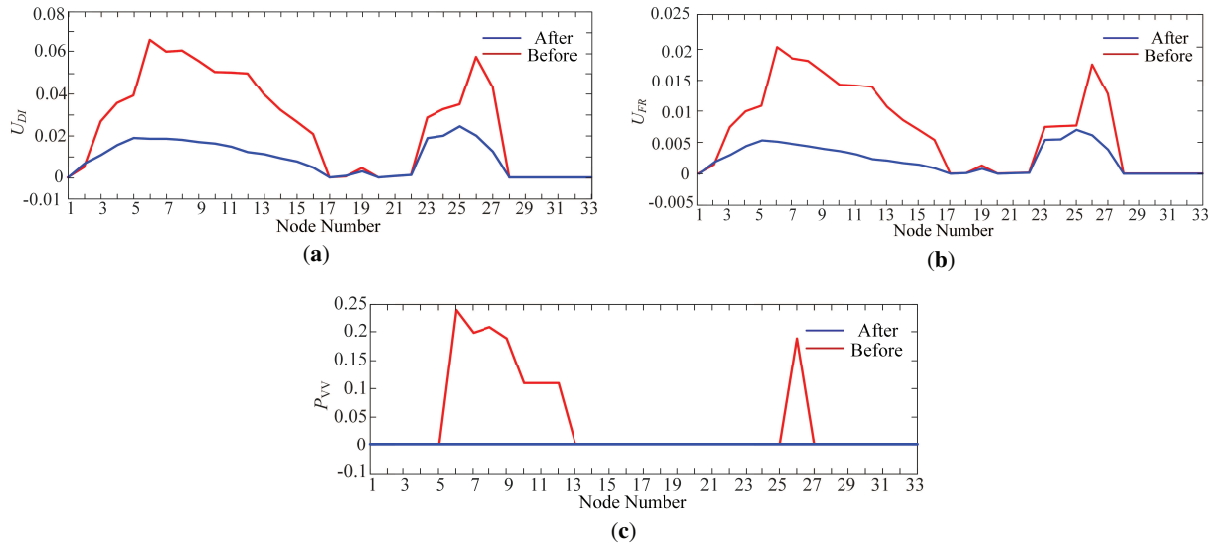


Figure 8: Power quality comparison before and after upgrade (a) Maximum node voltage deviation (b) Node voltage fluctuation rate (c) Node voltage violation probability.

Through comparative analysis of power quality before and after upgrade in Fig. 8, the following conclusions can be drawn: The renovated distribution network shows significant improvement in voltage deviation and voltage fluctuation. Specifically, as shown in Fig. 8a, the voltage deviation (U_{DI}) curve after upgrade becomes smoother, with its maximum voltage deviation average decreasing by 64.1% compared to pre-upgrade, significantly enhancing voltage stability. Fig. 8b demonstrates the voltage fluctuation rate (U_{FR}) after upgrade, with its average value reduced by 65.1% from pre-upgrade levels, effectively decreasing voltage volatility and thereby improving power quality. Furthermore, Fig. 8c shows the average voltage violation probability (P_{VV}) after upgrade decreased by 100%, indicating the upgrade measures completely eliminated voltage violation events and significantly improved distribution network reliability. In summary, the proposed upgrade method achieved remarkable results in reducing voltage deviation, decreasing voltage fluctuation, and lowering voltage violation probability, effectively enhancing the overall power quality of the distribution network.

5.4 Comparative Analysis of Different Optimization Algorithms

To evaluate the performance of the proposed AFM-PSO algorithm, it is compared with genetic algorithm (GA) [31], traditional PSO [32], and sparrow search algorithm (SSA) [33]. The accurate renovation model established in this study is a multi-objective optimization problem. For ease of solution, the weighted sum method is adopted to convert it into a single-objective problem. The four algorithms are applied to solve the accurate renovation model of the distribution network, and the variations in the fitness values of the comprehensive objective and each sub-objective during the iterative process are shown in Fig. 9.

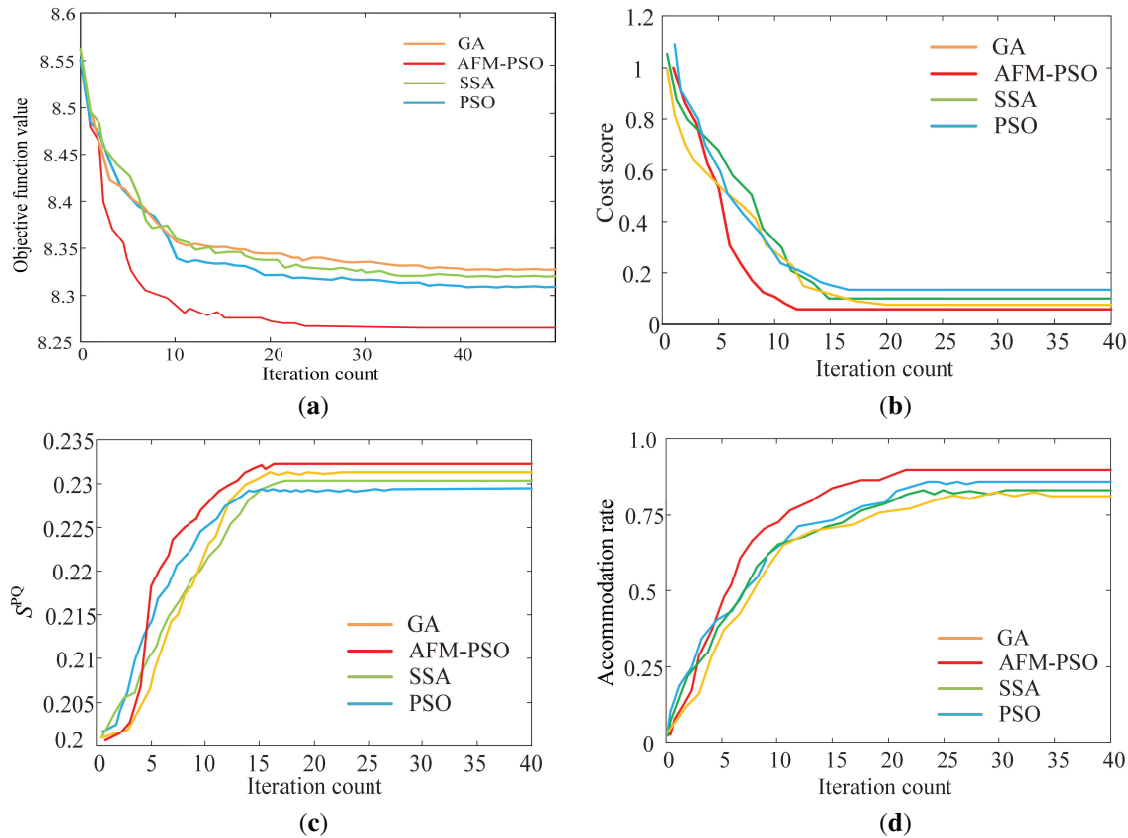


Figure 9: Convergence curves of different algorithms (a) Convergence curve of the comprehensive objective (b) Convergence curve of sub-objective 1 (c) Convergence curve of sub-objective 2 (d) Convergence curve of sub-objective 3.

The comparative analysis of experimental results in a–d of Fig. 9 shows that, compared with traditional PSO, GA and SSA, the AFM-PSO algorithm converges to a smaller objective function value, indicating its solution is closer to the theoretical optimum with higher solving accuracy. Additionally, the AFM-PSO algorithm demonstrates superior convergence performance during iterative optimization, requiring only about 25 iterations to precisely locate the optimal value (Fig. 9d), significantly reducing computation time. This efficient optimization capability effectively overcomes the bottlenecks of low efficiency and long computation time existing in traditional algorithms when handling complex optimization problems, substantially improving solving efficiency. It provides more efficient and reliable algorithmic support for solving complex engineering optimization problems such as precision upgrade of distribution networks.

5.5 Economic Comparative Analysis of Distribution Network Upgrade

To evaluate the economic efficiency of different upgrade approaches, three distinct methods were implemented:

Case 1: The cost-minimization approach for distribution network upgrade (method from reference [34]);

Case 2: The proposed upgrade method in this work;

Case 3: The balanced approach considering both cost minimization and feeder loading rate optimization (method from reference [35]).

The distribution network upgrade results under different case scenarios are presented in Table 4.

Table 4: Upgrade results under different cases.

Cases	Upgraded lines (count)	Added lines (count)	Total cost (¥)	S^{PQ}
Case 1	8	0	267,112.60	0.793
Case 2	8	3	347,857.59	0.884
Case 3	11	0	410,681.81	0.827

Table 4 demonstrates that while Case 1 achieves the lowest upgrade cost, its power quality index ($S^{PQ} = 0.793$) shows significant inferiority, indicating excessive compromise on grid performance for cost minimization that raises concerns about long-term economic viability. Case 3 attains feeder loading balance at the highest upgrade cost, yet its power quality score ($S^{PQ} = 0.827$) remains lower than the proposed solution due to inefficient cost-benefit ratio resulting from comprehensive line replacement. The proposed method (Case 2) reduces costs by 18.1% compared to Case 3 while improving the power quality score by 11.5% relative to Case 1. The key advantage lies in its hybrid “critical line upgrades + new line additions” strategy, which avoids both the performance limitations of Case 1 and the overinvestment issues of Case 3, achieving optimal power quality at moderate cost. This approach fully demonstrates the superiority of our method in balancing economic efficiency and power quality, proving its optimal cost-performance ratio and comprehensive benefits.

5.6 Actual Case Analysis

To validate the effectiveness and practicality of the proposed method in real-world complex scenarios, an actual distribution network in a certain area of Beijing was selected for case study. The topology of this distribution network is shown in Appendix B Fig. A1. It consists of 83 load nodes and 214 feeders, with high penetration of distributed photovoltaics introducing significant uncertainties, providing a highly challenging platform to verify the engineering value of the proposed method.

After applying the precision renovation optimization method proposed in this paper, the resulting renovation plan is presented in Tables 5 and 6. A comparison of key power quality evaluation indicators before and after the renovation is shown in Fig. 10.

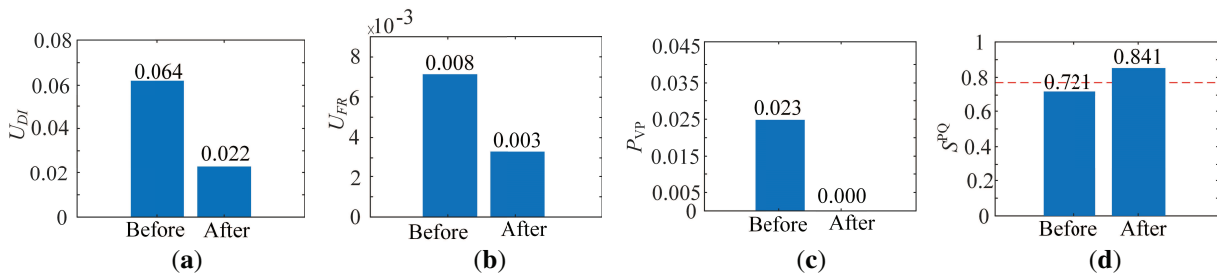
As shown in Fig. 10, the maximum voltage deviation, average voltage fluctuation rate, and average voltage violation probability were significantly reduced by 65.7% (Fig. 10a), 62.5% (Fig. 10b), and 100% (Fig. 10c), respectively. This indicates that the system has become more stable in responding to photovoltaic output fluctuations and load variations. Additionally, the comprehensive renovation score (Fig. 10d) increased by 14.3% compared to the pre-renovation level.

Table 5: Precision renovation results (Newly Added Branches).

Start substation	End Substation	Line type	Length (km)
32	57	LJ-150	1.127
19	60	LJ-150	0.742
11	30	LJ-150	1.376
42	47	LJ-150	2.919
40	41	LJ-150	0.143

Table 6: Precision renovation results (Line Upgrades).

Start substation	End substation	Original type	Upgraded type	Length (km)
6	7	JKLYJ-10-150	JKLYJ-10-240	0.321

**Figure 10:** Comparison of power quality evaluation indicators before and after upgrade (a) Maximum voltage deviation (b) Average fluctuation rate (c) Average violation probability (d) Comprehensive score.

These results demonstrate that the proposed method effectively addresses the challenges of precision renovation in large scale, highly complex practical distribution networks. The solution not only accurately identifies weak points in the network but also significantly enhances the system's hosting capacity for distributed energy resources and operational reliability through limited and cost-effective renovation measures. This indicates that the study is not merely theoretical but provides a decision-making tool and solution with direct application value for meeting the practical upgrade and renovation needs of distribution networks under the "Dual Carbon" goals.

6 Conclusion

To address power quality issues arising from high-penetration distributed PV integration and overcome the limitations of conventional extensive upgrade methods, this paper proposes an upgrade strategy for ADNs considering probabilistic power flow. The principal findings are as following:

- (1) A multi-dimensional comprehensive evaluation index system for power quality has been constructed, enabling systematic assessment of the overall effectiveness of renovation schemes. Simulation results show that this index system can effectively reflect improvements in power supply reliability and power quality after distribution network renovation. This index system provides grid planning departments with a quantitative evaluation tool, helping them scientifically select the solution with the optimal comprehensive benefits from multiple renovation options, thereby avoiding inefficient investment decisions caused by reliance on empirical judgments.

- (2) The proposed optimization method significantly enhances the distribution network's hosting capacity for high penetration of renewable energy, effectively suppresses voltage fluctuations, and improves power quality, providing a practical solution for the secure and stable operation of distribution networks under high penetration of distributed energy resources. This method can be directly applied to urban distribution network upgrade projects, especially in areas with high photovoltaic coverage and significant load fluctuations. Through targeted investment and renovation, it effectively prevents voltage violations and enhances the grid's capacity to integrate green energy.
- (3) The AFM-PSO algorithm is proposed to solve the optimization model. Simulation experiments demonstrate that this algorithm exhibits excellent convergence performance and global optimization capability. Under the same sample size, its optimization efficiency is significantly superior to genetic algorithm, sparrow search algorithm, and traditional particle swarm optimization. The high efficiency of this algorithm makes it suitable for real-time optimization calculations in large-scale distribution networks. It can be embedded into smart decision support systems for power grids, providing operators with a fast and reliable tool for solving renovation schemes, thereby improving the decision-making efficiency of grid planning.

Acknowledgement: This paper is supported by the Science and Technology Project of State Grid Beijing Electric Power Corporation (Research and Application of Precision Upgrade Methods for Active Distribution Networks Based on the Unified Grid Mapping Framework, B70208240006).

Funding Statement: The authors received no specific funding for this study.

Author Contributions: The authors confirm contribution to the paper as follows: study conception and design: Xiaotong Li, Mingquan Qiu, Wenjun Zhang, Pengfei Li, Chong Liu, Chong Yang; data collection: Pengfei Li, Han Xiao, Chong Yang, Feng Hu, Mingquan Qiu; analysis and interpretation of results: Xiaotong Li, Han Xiao, Binghui Liu, Feng Hu, He Wang; draft manuscript preparation: He Wang, Binghui Liu, Chong Liu, Wenjun Zhang. All authors reviewed and approved the final version of the manuscript.

Availability of Data and Materials: The authors confirm that the data supporting the findings of this study are available within the article. The additional data that support the findings of this study are available on request from the corresponding author, upon reasonable request.

Ethics Approval: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1: Optional line parameters.

Model specification	Unit length resistance (R/km)	Reactance (X/km)	Current carrying capacity (A)	Cost (¥/km)
JKLYJ-120	0.253	0.125	320	16,000
JKLYJ-150	0.206	0.078	366	17,000
JKLYJ-185	0.164	0.062	423	17,000
JKLYJ-240	0.125	0.044	503	18,000
JKLYJ-300	0.100	0.038	583	24,000

Table A2: Optional tie switch parameters.

Model specification	Rated voltage (kV)	Rated current (A)	Mechanical life (times)	Cost (¥)
ZW32-12F/630	12.66	630	20,000	8000
ZW20-12FG/630	12.66	630	20,000	10,000
FZW28F-12/630-20	12.66	630	20,000	12,000

Appendix B

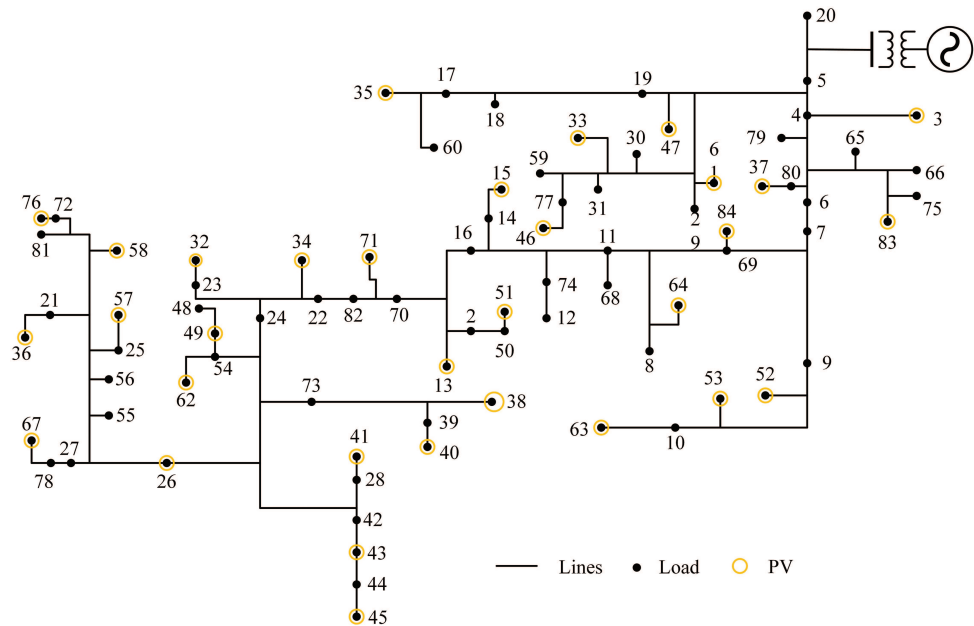


Figure A1: Topology of a regional distribution network in Beijing.

References

1. Wang J, Sun K, Wu H, Zhu J, Xing Y, Li Y. Hybrid connected unified power quality conditioner integrating distributed generation with reduced power capacity and enhanced conversion efficiency. *IEEE Trans Ind Electron.* 2021;68(12):12340–52. doi:10.1109/TIE.2020.3040687.
2. Wang X, Zhang Z, Bian G, Liu C. Analysis of renewable energy absorption and economic feasibility in multi-energy complementary systems under spot market conditions. *Energy Eng.* 2025;122(2):577–619. doi:10.32604/ee.2024.056748.
3. Ma H, Xiang Y, Sun W, Dai J, Zhang S, Liu Y, et al. Optimal peer-to-peer energy transaction of distributed prosumers in high-penetrated renewable distribution systems. *IEEE Trans Ind Applicat.* 2024;60(3):4622–32. doi:10.1109/tia.2024.3357790.
4. Yu Q, Chen X, Li X, Zhou C, Li Z. Using grey target theory for power quality evaluation based on power quality monitoring data. *Energy Eng.* 2022;119(1):359–69. doi:10.32604/ee.2022.015397.
5. Liang C, Teng Z, Li J, Yao W, Wang L, He Q, et al. Improved S-transform for time-frequency analysis for power quality disturbances. *IEEE Trans Power Deliv.* 2022;37(4):2942–52. doi:10.1109/tpwrd.2021.3119918.
6. Yang B, Zhang R, Zhang J, Cheng X, Li J, Zhou Y, et al. A critical review of active distribution network reconfiguration: concepts, development, and perspectives. *Energy Eng.* 2024;121(12):3487–547. doi:10.32604/ee.2024.054662.

7. Calhau FG, Martins JSB. A electric network reconfiguration strategy with case-based reasoning for the smart grid. In: 2019 8th Brazilian Conference on Intelligent Systems (BRACIS); 2019 Oct 15–18; Salvador, Brazil. p. 633–8. doi:10.1109/bracis.2019.00116.
8. Jing Z, Chai L, Hu S, Jin X, Jiang R, Tang W. Active network reconfiguration strategy for a distributed smart grid for the enhancement of its distributed PV accommodation capacity. In: 2024 9th Asia Conference on Power and Electrical Engineering (ACPEE); 2024 Apr 11–13; Shanghai, China. p. 140–4. doi:10.1109/ACPEE60788.2024.10532493.
9. Drus SMFS, Saad NM, Abas MF, Ab-Ghani S, Jaalam N, Ali A. Distribution feeder reconfiguration with distributed generation using backward/forward sweep power flow—grey wolf optimizer. In: 2023 19th IEEE International Colloquium on Signal Processing & Its Applications (CSPA); 2023 Mar 3–4; Kedah, Malaysia. p. 213–8. doi:10.1109/CSPA57446.2023.10087738.
10. Jnawali RP, Thapa KB, Karki NR. Load factor improvement of distribution feeders by feeder reconfiguration using modified BPSO considering losses. In: 2021 International Conference on Sustainable Energy and Future Electric Transportation (SEFET); 2021 Jan 21–23; Hyderabad, India. p. 1–5. doi:10.1109/sefet48154.2021.9375637.
11. Zainal MI, Yasin ZM, Zakaria Z. Network reconfiguration for loss minimization and voltage profile improvement using ant lion optimizer. In: 2017 IEEE Conference on Systems, Process and Control (ICSPC); 2017 Dec 15–17; Meleka, Malaysia. p. 162–7. doi:10.1109/SPC.2017.8313040.
12. Zhou F, Li L, Jia T, Yin Y, Shi A, Xu S. Intelligent power grid load transferring based on safe action-correction reinforcement learning. *Energy Eng.* 2024;121(6):1697–711. doi:10.32604/ee.2024.047680.
13. Lei G, Xu C. Optimal intelligent reconfiguration of distribution network in the presence of distributed generation and storage system. *Energy Eng.* 2022;119(5):2005–29. doi:10.32604/ee.2022.021154.
14. Tao C, Yang S, Li T. Application of DSAPSO algorithm in distribution network reconfiguration with distributed generation. *Energy Eng.* 2024;121(1):187–201. doi:10.32604/ee.2023.042421.
15. Du W, Lu M, Li D. Distribution network planning with comprehensive economy and reliability. *IOP Conf Ser Mater Sci Eng.* 2019;486(1):012016. doi:10.1088/1757-899x/486/1/012016.
16. Sekhar PC, Deshpande RA, Sankar V. Evaluation and improvement of reliability indices of electrical power distribution system. In: 2016 National Power Systems Conference (NPSC); 2016 Dec 19–21; Bhubaneswar, India. p. 1–6. doi:10.1109/NPSC.2016.7858838.
17. Baghban-Novin S, Mahzouni-Sani M, Hamidi A, Golshannavaz S, Nazarpour D, Siano P. Investigating the impacts of feeder reforming and distributed generation on reactive power demand of distribution networks. *Sustain Energy Grids Netw.* 2020;22:100350. doi:10.1016/j.segan.2020.100350.
18. Xiong J, Liu Z, Xiang Y, Chai Y, Liu J, Liu Y. An investment decision model of distribution network planning based on correlation mining of reconstruction measures and loss load index. *IOP Conf Ser Mater Sci Eng.* 2018;428:012011. doi:10.1088/1757-899x/428/1/012011.
19. Aien M, Fotuhi-Firuzabad M, Aminifar F. Probabilistic load flow in correlated uncertain environment using unscented transformation. *IEEE Trans Power Syst.* 2012;27(4):2233–41. doi:10.1109/TPWRS.2012.2191804.
20. Li Y, Wan C, Chen D, Song Y. Nonparametric probabilistic optimal power flow. *IEEE Trans Power Syst.* 2022;37(4):2758–70. doi:10.1109/TPWRS.2021.3124579.
21. Hung DQ, Mithulananthan N, Lee KY. Determining PV penetration for distribution systems with time-varying load models. *IEEE Trans Power Syst.* 2014;29(6):3048–57. doi:10.1109/TPWRS.2014.2314133.
22. Zhang P, Zhang H, Li Y, Chen W, Zhang X, Li H. Probabilistic power flow calculation based on improved LHS semi-invariant method. *Acta Energaie Solaris Sin.* 2021;42(1):14–20. (In Chinese).
23. Li J, Zhang B, Liu Y. Data mining in nonlinear probabilistic load flow based on Monte Carlo simulation. In: 2009 First International Conference on Information Science and Engineering; 2009 Dec 26–28; Nanjing, China. p. 833–6. doi:10.1109/ICISE.2009.448.
24. Shi S, Liu Y, Wang Q, Cen B. Economic indicator-based power quality assessment of distribution network incorporating electric vehicle stations. In: 2024 14th International Conference on Power and Energy Systems (ICPES); 2024 Dec 13–16; Chengdu, China. p. 408–13. doi:10.1109/ICPES63746.2024.10856647.

25. Yin J, Du X, Yuan H, Ji M, Yang X, Tian S, et al. TOPSIS power quality comprehensive assessment based on a combination weighting method. In: 2021 IEEE 5th Conference on Energy Internet and Energy System Integration (EI2); 2021 Oct 22–24; Taiyuan, China. p. 1303–7. doi:10.1109/EI252483.2021.9713201.
26. Guan J, Jia H, Zhao Y, Wei C, Xu X, Yang Z. Research on power quality assessment method of new distribution system considering uncertainty. In: 2024 7th International Conference on Energy, Electrical and Power Engineering (CEEPE); 2024 Apr 26–28; Yangzhou, China. p. 1603–7. doi:10.1109/CEEPE62022.2024.10586290.
27. Wei X. Comprehensive risk assessment method for distribution network dispatching considering equipment risk. In: 2021 3rd Asia Energy and Electrical Engineering Symposium (AEEES); 2021 Mar 26–29; Chengdu, China. p. 459–64. doi:10.1109/AEEES51875.2021.9403041.
28. Romanov NO, Skvortsova DA, Filin NA, Shvaiko BA, Kuznetsov AA. Studying data normalization methods in the sustainable development indicators analysis. In: 2025 7th International Youth Conference on Radio Electronics, Electrical and Power Engineering (REEPE); 2025 Apr 8–10; Moscow, Russia. p. 1–4. doi:10.1109/REEPE63962.2025.10970921.
29. Wang J, Pang W, Wang L, Pang X, Yokoyama R. Synthetic evaluation of steady-state power quality based on combination weighting and principal component projection method. CSEE J Power Energy Syst. 2017;3(2):160–6. doi:10.17775/CSEEJPES.2017.0020.
30. Shang L, Wei B, Wang W, Xiong X, Ci H, Li J, et al. Dynamic configuration planning method for energy storage in ADNs. Power Syst Prot Control. 2020;48(17):84–92. (In Chinese).
31. Liu C, Xu J, Wang Z, Wei S, Qian J, Xu D, et al. Research on dynamic reconfiguration method of new distribution system network to enhance new energy carrying capacity. In: 2025 4th International Conference on Smart Grid and Green Energy (ICSGGE); 2025 Feb 28–Mar 2; Sydney, Australia. p. 272–7. doi:10.1109/ICSGGE64667.2025.10984655.
32. Su Y, Zhu Q, Tian Y, Dai R, Lv Z, Zhang M. Distribution network reconfiguration based on hybrid particle swarm optimization and grey wolf optimization. In: 2023 IEEE 7th Conference on Energy Internet and Energy System Integration (EI2); 2023 Dec 15–18; Hangzhou, China. p. 718–23. doi:10.1109/EI259745.2023.10512561.
33. Chen Q, Wang W, Wang H. Bi-level optimal operation strategy for distribution networks with distributed energy resources. Acta Energetica Sin. 2022;43(10):507–17. (In Chinese).
34. Sun Q, Wang Q, Yang L, Zhang Y, Pan W. Distribution network modernization method for distributed PV integration. Proc CSU-EPSA. 2014;26(5):60–5. (In Chinese).
35. Zhang Z, Tang W, Li Z, Zhang L, Zhang X. Feeder line upgrade considering PV hosting capacity and spatiotemporal multi-level power balance. Power Syst Technol. 2025 2025;8:3156–66, 10036–9. (In Chinese).