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Bi-Objective Optimization of Distribution Network Reliability Enhancement Using Quantitative Decomposition

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Received: 25 September 2025; Accepted: 24 November 2025; Published: 12 July 2026

ABSTRACT: Ensuring reliability in distribution networks is essential under increasing operational and economic constraints. Traditional planning models rely on power flow calculations, leading to high computational costs and poor scalability. This study proposes a quantitative decomposition framework that establishes a direct linkage among reliability improvement measures, reliability parameters, and reliability indices, enabling fast and analytical reliability evaluation without power flow analysis. A bi-objective optimization model is developed to minimize both reliability indices (SAIDI) and investment costs, solved using Pareto-based multi-objective PSO combined with the TOPSIS method. Case studies on a 519-node distribution network demonstrate that the proposed approach achieves significant reliability improvement with superior computational efficiency, offering a practical and scalable tool for reliability-oriented distribution planning.

KEYWORDS: Distribution network; reliability improvement measures; quantitative analysis; optimization decision

1 Introduction

The modernization of distribution networks has introduced significant challenges in maintaining reliable electricity supply under increasingly complex operating environments and constrained investment budgets. The rapid growth of electrification in transportation and industry, along with the widespread integration of distributed energy resources (DERs), energy storage systems (ESS), and flexible loads, has fundamentally increased the operational coupling and uncertainty in distribution systems [1–3]. At the same time, aging infrastructure and the rising frequency of severe weather events continue to expose networks to higher failure risks, resulting in prolonged outages, increased interruption costs, and heightened regulatory pressure [4]. Ensuring reliable operation has therefore become a strategic requirement that demands an effective balance between engineering performance, economic feasibility, and regulatory compliance.

Traditional reliability indices such as SAIDI and SAIFI are widely used to quantify system performance; however, these indicators offer limited guidance on which specific measures should be implemented, where they should be located, and to what extent they should be deployed to achieve cost-effective reliability



improvements [5]. The challenge is amplified when multiple reinforcement measures—such as feeder automation, conductor replacement, switching operations, and tie-line construction—interact nonlinearly with power network topology and operational characteristics. This motivates the development of analytical tools capable of establishing a clear and quantitative mapping from reliability enhancement measures to parameter changes and ultimately to system-level indices.

A substantial body of research has investigated reliability evaluation and planning approaches. Earlier works predominately relied on probabilistic and Monte Carlo simulation-based techniques [6], which produce accurate indices but become computationally prohibitive for large-scale systems or iterative planning studies. To mitigate this, analytical and surrogate-based reliability evaluation models have been proposed. Zhao et al. developed a dimensional-decomposition-based method using Chebyshev metamodels to accelerate reliability assessment [7], while Ling et al. introduced sensitivity-aided surrogate modeling to improve the computational efficiency of reliability-based design optimization [8]. In parallel, several predictive asset-management frameworks have been proposed to incorporate reliability into long-term infrastructure planning, particularly in cable, transformer, and aging-aware asset management [9–11].

Complementary studies explore reinforcement and operational strategies for improving reliability. Krstivojević and Stojković Terzić presented a Monte Carlo-driven multi-objective investment planning model to identify cost-effective reliability enhancement portfolios [12]. Other works have incorporated DERs, ESS, and network expansion into reliability-oriented frameworks under stochastic or risk-based formulations [13–15]. Switching and reconfiguration strategies also play a crucial role: classical feeder reconfiguration techniques emphasize minimizing ENS, SAIDI, and SAIFI through optimal switch placement [16,17], while emerging metaheuristic and deep reinforcement learning approaches enable improved scalability and adaptability in real-time reliability optimization [18,19]. A recent comprehensive review summarized these developments and highlighted the need for more transparent, scalable, and analytically grounded reliability planning approaches in future active distribution networks [20].

Despite these advancements, significant gaps remain. Most existing methods still depend heavily on repeated power-flow calculations and simulation loops, resulting in substantial computational burden and limited scalability for large distribution systems. More importantly, few studies have provided an explicit, analytically transparent mapping that connects reliability enhancement measures → reliability parameters (e.g., failure rates, repair times, affected load) → system-level reliability indices (e.g., SAIDI, SAIFI) within a unified optimization framework. This lack of quantifiable linkage reduces interpretability and complicates practical deployment. Additionally, the combined effects of heterogeneous reinforcement strategies—automation, reconfiguration, equipment replacement, and sectionalizing—are rarely represented through a unified decomposition structure.

To address these challenges, this study proposes a quantitative decomposition-based bi-objective optimization framework for enhancing reliability in large-scale distribution networks. The main contributions are as follows:

A quantitative decomposition model is developed to establish explicit analytical relationships linking enhancement measures, reliability parameters, and reliability indices, enabling power-flow-free reliability evaluation.

A bi-objective optimization model is formulated to jointly minimize SAIDI and investment cost, providing a systematic means for utilities to explore cost-reliability trade-offs.

A Pareto-based multi-objective particle swarm optimization algorithm, combined with TOPSIS, is applied to identify non-dominated investment portfolios. Case studies on a 519-node practical distribution system demonstrate that the proposed framework achieves substantial reliability improvement while significantly reducing computational time compared with traditional power-flow-based methods.

The remainder of this paper is structured as follows: [Section 2](#) introduces the quantitative relationships between reliability measures and reliability parameters. [Section 3](#) presents the optimization model based on the proposed decomposition framework. [Section 4](#) describes the Pareto-based multi-objective particle swarm optimization algorithm. [Section 5](#) provides the case study, followed by the results and discussions in [Section 6](#). Finally, [Section 7](#) concludes the paper and outlines future research directions.

2 Quantitative Relationship between Reliability Improvement Measures and Reliability Parameters Based on Association Rules

2.1 Analysis of Reliability Indices and Related Parameters

Internationally, commonly used reliability indices for distribution networks include the System Average Interruption Frequency Index (SAIFI), the System Average Interruption Duration Index (SAIDI), and the System Average Availability Index (ASAI), among others. In China, the commonly used indicator is the ASAI index (also known as the RS-3 index), which does not account for electricity supply curtailments and is used to measure the reliability level of a specific region. Since U_{SAIDI} is linearly related to I_{ASAI} ($I_{ASAI} = 1 - U_{SAIDI}/8760$) [10], the difference in outage duration can be directly observed, making this index particularly useful in the analysis conducted in this paper. Other indices can be analyzed similarly.

Reliability indices during the calculation process can be decomposed into three categories: interruption frequency, interruption duration, and interruption coverage. Taking U_{SAIDI} as an example, a reliability parameter matrix $\mathbf{B} = [\lambda_a, \lambda_p, t_d, t_s, t_g, t_r, t_p, \varphi, m]^T$ is constructed, where the specific definitions and calculation methods for these parameters are listed in [Table 1](#).

Table 1: Meaning of reliability parameters

Type	Parameter	Meaning
Frequency parameter	λ_a (failures/year)	Failure rate, a weighted average encompassing conductors, cables, switching devices, transformers, and other critical equipment
	λ_p (failures/year)	Planned outage rate, $\lambda_p = \frac{\text{The number of customers affected by planned outages}}{\text{Number of customers} \times \text{Total outage time}}$
Time parameter	t_d (h)	Fault location time
	t_s (h)	System power transfer operation time
	t_g (h)	Fault isolation time
	t_r (h)	Fault recovery time
	t_p (h)	Planned power outage time
Range parameter	φ (p.u.)	Line transfer rate, $\varphi = P_s/P_a$, where P_s denotes the transferable capacity of the feeder, and P_a represents the total capacity of the feeder.
	m	Number of line segments, for overhead lines, it is defined as “the number of sectionalizing switches plus one”; for cable lines, it is defined as “the number of ring main units (or switching stations) plus one.”

Reliability parameters are related to distribution network construction, management, operation, maintenance, and the different reliability improvement measures and can be obtained through statistical data analysis.

For the failure rate λ_a of a distribution line, the following formula can be used to calculate it:

$$\lambda_{a,i} = \frac{\sum_{l=1}^{N_{p,i}} \lambda_{i,l}}{N_{p,i}} = \sum_{x \in \{Br, L, S, Tr, Fu\}} \lambda_{x,i} N_{x,i} \lambda_{Tr,i} \quad (1)$$

$$\lambda_a = \frac{\sum \lambda_{a,i} N_{e,i}}{\sum N_{e,i}} \quad (2)$$

where $\lambda_{a,i}$ is the failure rate of line i ; $\lambda_{i,l}$ is the average annual failure rate of load point l on line i ; $N_{p,i}$ is the number of load points (distribution transformers) on line i ; $\lambda_{x,i}$ is the failure rate of type x equipment on line i , where x can be Br (circuit breaker), L (conductor), S (isolating switch), Tr (transformer), Fu (fuse); $N_{x,i}$ is the quantity of type x equipment on line i (for conductors, this is the length of the line); $N_{e,i}$ is the number of users connected to line i .

2.2 Quantitative Relationship between Reliability Parameters and Reliability Indexes

Based on the type of interruption, the outages affecting distribution network reliability can be classified into fault outages and planned outages. For interruptions caused by higher-level network factors, the outage time U_i for line i is defined by Eq. (3):

$$U_i = \lambda_{a,i} r_{a,i} + \lambda_{p,i} r_{p,i} \quad (3)$$

where $\lambda_{p,i}$ is the fault outage rate of line; $r_{p,i}$ is the average planned outage time of line. Since planned outages mainly depend on management policies and maintenance effectiveness, we can use t_p to replace $r_{p,i}$. The term $r_{a,i}$ includes t_d , t_g , t_s , t_r . Different switching operations for equipment also impact these factors. Therefore, based on the property of the recovery process, users connected to lines can be classified into three categories.

In the example of the line shown in Fig. 1, if a fault occurs on the conductor at segment P of the line, with isolating switches A and B being the closest sectionalizing devices at distances P from the fault, the following applies:

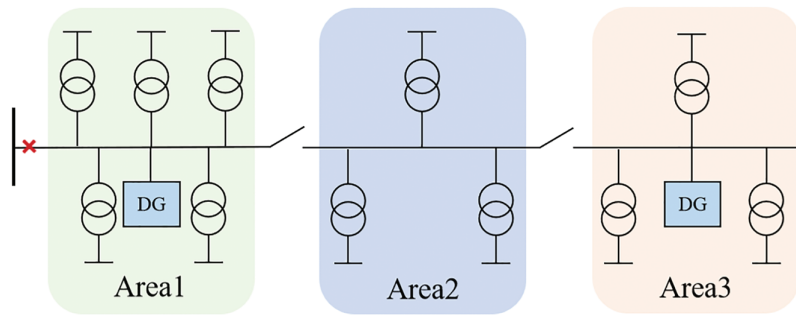


Figure 1: Schematic diagram of different types of areas under fault conditions

1. For users in Area 1, located upstream of the fault, the fault is isolated by opening switch A before it propagates to the fault point. The original line can continue to supply power, and this area is referred to as the upstream fault Area.
2. For users in Area 3, located downstream of the fault, the fault is isolated by opening switch B. If Area 2 can transfer load via connected lines, power can be restored to Area 3, which is referred to as the downstream fault Area.

3. For users in Area 2, which is directly adjacent to the fault, these users must wait for repairs to complete before power can be restored. If the connected line transfer capacity is insufficient, this area is referred to as the fault region.

Due to the different load locations, the outage durations and impacts on reliability vary. Under the assumption that the failure rates across the distribution network are uniform, the users in these three Areas can be represented by $\beta_1, \beta_2, \beta_3$, and the outage times for these Areas are denoted by t_1, t_2, t_3 . The effective average outage time for users in the fault Area can be represented by Eq. (4):

$$r_{a,i} = \beta t^T \quad (4)$$

where $\beta = [\beta_1, \beta_2, \beta_3]$ represents the proportion of users in each Area, $t = [t_1, t_2, t_3]$ represents the outage times for each Area.

For the elements of β and t , the following calculations can be used:

$$\begin{cases} \beta_1 = \frac{m-1}{2m} \\ \beta_2 = \frac{\varphi(m \pm 1)}{2m} \\ \beta_3 = 1 - \beta_1 - \beta_2 \end{cases} \quad (5)$$

$$\begin{cases} t_1 = t_d + t_g \\ t_2 = t_d + t_g + t_s \\ t_3 = t_d + t_g + t_r \end{cases} \quad (6)$$

The overall reliability improvement effect for any given line can be represented by:

$$U_i = \lambda_{a,i} (\beta t^T) + \lambda_{p,i} t_p \quad (7)$$

For the common reliability index U_{SAIDI} , it is calculated as:

$$U_{SAIDI} = \frac{\sum U_i N_{e,i}}{\sum N_{e,i}} \quad (8)$$

The general form of this relationship can be expressed as:

$$U_{SAIDI} = g(B) \quad (9)$$

where $g(\cdot)$ represents a function of the matrix B_0 , composed of reliability parameters and indices. The method described has broad applicability and can be used to calculate other reliability indices in a similar fashion.

2.3 Quantitative Relationship between Reliability Improvement Measures and Reliability Parameters

The reliability level of a power distribution network is fundamentally determined by three critical dimensions: the frequency of equipment outages, the duration of each outage event, and the scope of affected customers during outages as shown in Fig. 2. Consequently, all reliability enhancement measures for distribution networks must generate impacts on one or more of these three dimensions to effectively improve overall system reliability. This multidimensional framework underscores the comprehensive nature of distribution network reliability as an integrated reflection of operational failure characteristics and their social-economic consequences.

A typical relationship between reliability improvement measures and parameters is shown in Fig. 3.

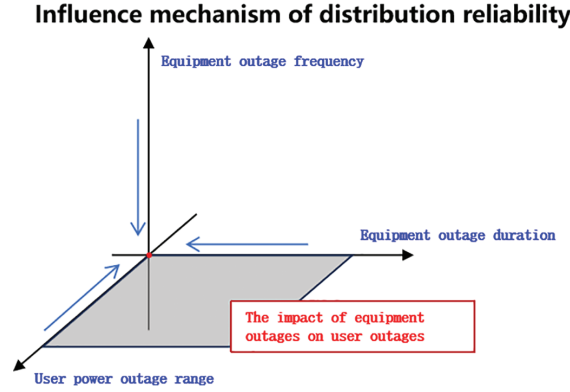


Figure 2: Reliability measures and corresponding reliability parameters

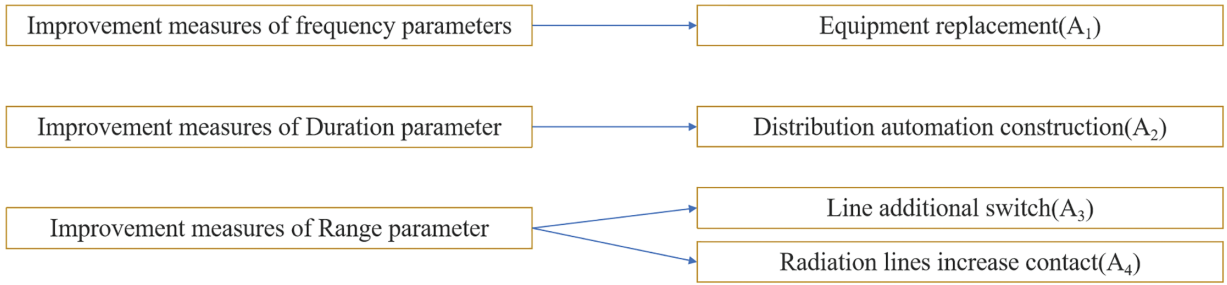


Figure 3: Reliability measures and corresponding reliability parameters

The functional form of equipment replacement A_1 is expressed as follows:

$$\mathbf{x}_{Er} = (x_{Er1}, x_{Er2}, \dots, x_{Ern}) \quad (10)$$

$$C_{Er} = \sum_{i=1}^n c_{Er} x_{Eri} \quad (11)$$

where x_{Ern} denotes the replacement status of the n -th equipment, where 0 indicates no replacement and 1 indicates replacement. C_{Er} represents the unit cost of equipment replacement.

The functional form of distribution automation construction A_2 is expressed as follows:

$$\mathbf{x}_{Dac} = (x_{Dac1}, x_{Dac2}, \dots, x_{Dacm}) \quad (12)$$

$$C_{Dac} = \sum_{i=1}^m c_{Dac} (x_{Daci}) \quad (13)$$

where x_{Dacm} represents the automation construction status of the m -th line, 0 indicates no construction, and 1, 2, and 3 represent three different levels of construction plans, respectively. $C_{Dac}()$ denotes the cost of distribution network automation construction, which is expressed as follows:

$$C_{Dac}(x) = \begin{cases} 0, & x = 0 \\ c_{Dac1}, & x = 1 \\ c_{Dac2}, & x = 2 \\ c_{Dac3}, & x = 3 \end{cases} \quad (14)$$

The functional form of line additional switch A_3 and radiation lines increase contact A_4 is expressed as follows:

$$\mathbf{x}_{Las} = (x_{Las1}, x_{Las2}, \dots, x_{Lasj}) \quad (15)$$

$$\mathbf{x}_{Riic} = (x_{Riic1}, x_{Riic2}, \dots, x_{Riicl}) \quad (16)$$

$$C_{Las} = \sum_{i=1}^j c_{Las} x_{Lasj} \quad (17)$$

$$C_{Riic} = \sum_{i=1}^l c_{Riic} x_{Riicl} \quad (18)$$

where x_{Lasj} denotes the number of switches added to the j -th line, and x_{Riicl} represents the interconnection bus addition status for the l -th line. C_{Las} and C_{Riic} represent the unit costs of adding switches and interconnection buses, respectively.

Through quantitative analysis, the impact of reliability improvement measures on various parameters can be determined. Each reliability improvement measure may affect one or more parameters. How the relationship between the change in reliability parameters and the improvement measures is expressed through formulas is one of the most critical aspects. For any given reliability improvement measure, a corresponding general matrix $\mathbf{R}$ is constructed to represent the relationship between matrix $\mathbf{B}$ and the measure, as shown in Eq. (19):

$$\mathbf{R}_k = [\Delta\lambda_a, \Delta\lambda_p, \Delta t_d, \Delta t_g, \Delta t_s, \Delta t_r, \Delta t_p, \Delta\varphi, \Delta m]^T \quad k = 1, 2, \dots, K \quad (19)$$

where K is the number of reliability improvement measures. $\mathbf{R}_k$ represents the reliability parameter change matrix caused by the k -th reliability improvement measure A_k .

Using the updated matrix $\mathbf{B}_k$, the reliability index after the measure can be calculated using Eq. (20). Taking outage duration as an example, the reduction in $\Delta U_{SAIDI,k}$ due to reliability improvement measures is:

$$\Delta U_{SAIDI,k} = |U_{SAIDI,k} - U_{SAIDI,0}| \quad (20)$$

3 Optimization Model of Distribution Network Improvement Based on Quantitative Decomposition

3.1 Optimization Model

The traditional optimization models for distribution network improvement generally aim to maximize the investment benefits of the distribution network. These models are subject to constraints such as the project library of improvement measures, investment budget, power flow constraints, and safety constraints. However, solving power flow and safety constraints and embedding iterative reliability calculations incur high computational costs. To address these challenges, this paper proposes a quantitative relationship model between reliability improvement measures and reliability parameters based on association rules, as below:

$$\begin{aligned} & \min F(\mathbf{x}_{Er}, \mathbf{x}_{Dac}, \mathbf{x}_{Las}, \mathbf{x}_{Riic}) \\ \text{s.t.} \quad & C_{Er} + C_{Dac} + C_{Las} + C_{Riic} \leq C_{\max} \end{aligned} \quad (21)$$

(4)–(20)

where F is a bi-objective function, $C_{\max}$ is the maximum investment cost, (4)–(20) refer to the simplified forms of Eqs. (4)–(20) presented above.

3.2 Objective Function

Firstly, to represent the degree of improvement in power system reliability achieved by enhancement measures, this paper uses SAIDI (System Average Interruption Duration Index) as the metric to describe the improvement in system reliability, which can be expressed as:

$$\min E(\mathbf{x}_{Er}, \mathbf{x}_{Dac}, \mathbf{x}_{Las}, \mathbf{x}_{Riic}) = -\Delta U_{SAIDI,k} \quad (22)$$

Secondly, due to the limitations of construction funding, from the perspective of the power grid, minimizing investment costs is preferred when the degree of reliability improvement is the same. Therefore, it is necessary to describe the investment cost as an objective function, which can be expressed as:

$$\min C(\mathbf{x}_{Er}, \mathbf{x}_{Dac}, \mathbf{x}_{Las}, \mathbf{x}_{Riic}) = \sum_{i=1}^n C(\mathbf{x}_{Er}, \mathbf{x}_{Dac}, \mathbf{x}_{Las}, \mathbf{x}_{Riic}) \quad (23)$$

Thus, the multi-objective problem can be reformulated as follows:

$$\begin{aligned} & \min [E(\mathbf{v}); C(\mathbf{v})] \\ \text{s.t.} \quad & C_{Er} + C_{Dac} + C_{Las} + C_{Riic} \leq C_{\max} \end{aligned} \quad (24)$$

(4)–(20)

which synthetically considers reliability improvement and investment cost, and thus becomes the main objective pursued by the present study.

4 Multi-Objective Particle Swarm Optimization Based on Pareto Optimization

The particle swarm optimization (PSO) algorithm is characterized by its simplicity, high search efficiency, and strong generalizability. It demonstrates significant advantages in solving multi-variable, nonlinear, discontinuous, and non-differentiable problems.

The objective function in this study optimizes two evaluation metrics as a global goal, where the objectives exhibit mutually constraining relationships. Since the Pareto optimal solution set is a set of non-dominated solutions, the Pareto dominance theory is incorporated into the multi-objective particle swarm optimization algorithm.

4.1 Pareto Front

The Pareto optimization theory is actually to solve the mapping from the decision variable space R^m to the target space R^k , which can be summarized as:

S is the feasible solution region containing m -dimensional decision variables, $t_n \in S \subset R^m$, let $t_n^1, t_n^2 \in S \subset R^m$, if and only if $\forall k \in \{1, 2, \dots, K\}$, $f_k(t_n^1) \leq f_k(t_n^2) \wedge \exists k \in \{1, 2, \dots, K\}$ such $f_k(t_n^1) < f_k(t_n^2)$, the solution t_n^1 is said to be not inferior to the (dominant) solution t_n^2 , denoted as $t_n^1 \prec t_n^2$.

If $t^* \in S$, there is no more superior solution in S , it is the Pareto optimal solution of the feasible solution set.

The set is the Pareto optimal solution set:

$$S^* = \left\{ t_n \in S \mid \neg \exists t_{n'}' \in S, \forall t_{n'}' < t_n \right\} \quad (25)$$

The region formed by the objective function values corresponding to all Pareto optimal solutions is Pareto Front.

4.2 Particle Swarm Optimization Algorithm

In the PSO algorithm, a massless particle j can be characterized by its position vector x_j and velocity vector m_j . Here, $x_j = [x_{j,1}, x_{j,2}, \dots, x_{j,D}]^T \in R^D$, $m_j = [m_{j,1}, m_{j,2}, \dots, m_{j,D}]^T \in R^D$, $i = 1, 2, \dots, N$, N represents the number of particles in the population, and D denotes the number of decision variables. During the evolutionary process, each particle in the population updates its velocity and position according to Eq. (26):

$$\begin{cases} m_j(t+1) = \omega m_j(t) + c_1 r_1 (\mathbf{pBest}_j - x_j(t)) + c_2 r_2 (\mathbf{gBest} - x_j(t)) \\ x_j(t+1) = x_j(t) + m_j(t+1) \end{cases} \quad (26)$$

where t denotes the iteration number, $\omega \geq 0$ represents the inertia weight coefficient, and $c_1, c_2 \geq 0$ represents the acceleration coefficient. r_1 and r_2 are uniformly distributed random numbers in the range $[0, 1]$, $\mathbf{pBest}_j$ representing the individual optimal solution of the j -th instance. $\mathbf{gBest}$ represents the global optimal solution of the entire population.

The first term in the velocity update equation represents (26) inertia—the particle's tendency to maintain its current motion. The second term reflects self-cognition from historical experience, while the third term represents social interaction within the swarm.

4.3 Particle Swarm Optimization Algorithm Based on Pareto Optimization

The Pareto-optimized particle swarm algorithm employs Pareto dominance relationships and Euclidean distance to establish particle elimination criteria, ultimately obtaining the non-dominated solution set for the multi-objective problem. The detailed algorithm and selection strategy are illustrated in Fig. 4.

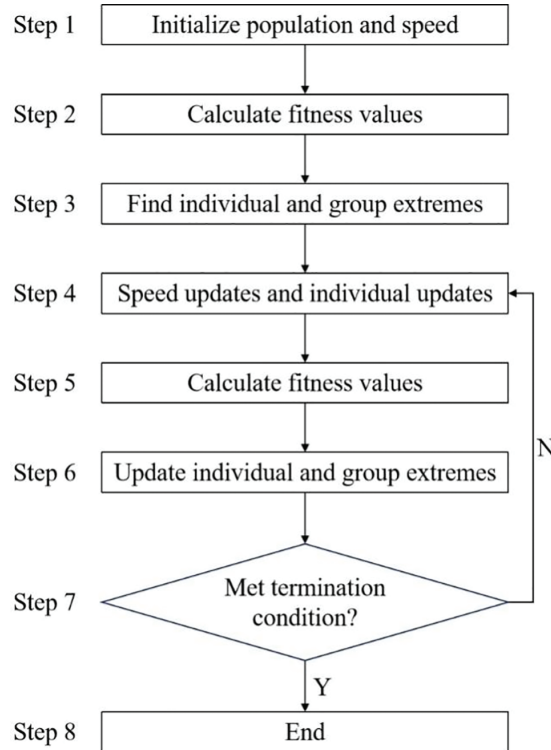


Figure 4: Algorithm flow chart

Step 1: Set the iteration counter $t = 1$ and initialize the parameters of the particle swarm optimization algorithm, including acceleration constants, maximum particle velocity, inertia weights, and other variables such as particle positions (improvement measure vectors) and particle velocities.

Step 2: Calculate the particle fitness using Eqs. (25) and (26).

Step 3: In the first iteration, the individual historical best position pp is the current position of each particle. The fitness function values are compared pairwise in sequence to determine the Pareto dominance relationship among the particles, generating a set of Pareto fronts ranked incrementally from 1. The first front (rank 1) is the Pareto optimal front in the current iteration. Among the particles in the first front, the Euclidean distances of their positions are compared, and the particle with the largest Euclidean distance is considered superior. The signal timing corresponding to this particle is selected as the global best position in this iteration, and the particle's current position is set as its individual historical best position pp .

Step 4: Increment the iteration counter $t = t + 1$. Update the weights and use the dynamic position and velocity update expressions based on the individual best positions and the global best position to update the particle's position and velocity.

Step 5: Recalculate the fitness of each particle using Eqs. (25) and (26).

Step 6: Based on the new particle positions, compare each particle's current position with its individual historical best position pp . If the new particle position dominates pp in terms of the Pareto dominance relationship, update pp with the new position; otherwise, no update is made. Then, sort the new particle positions according to the Pareto dominance relationship, generating Pareto fronts ranked in ascending order starting from 1. Particles with smaller rank values dominate those with larger values. The first front (rank 1) is the Pareto optimal front for the current iteration. Among the particles in the first front, the Euclidean distances of their positions are compared, and the particle with the largest Euclidean distance is considered superior. The signal timing corresponding to this particle is selected as the global best position. If the fitness function value of the current global best position dominates the previous global best position, update global best position. Combine the current global best position with the global best positions from all previous iterations to form a new non-dominated solution set, eliminating any dominated particles.

Step 7: Repeat Steps 4 to 7 until the pre-specified number of iterations or accuracy requirements are met. The final non-dominated solution set for the bi-objective problem is obtained.

Step 8: Terminate the algorithm. Using the TOPSIS method, randomly select one particle from the non-dominated solution set. Output the enhancement measure vector and the corresponding evaluation metrics (fitness function values) for the selected particle.

5 Case Study

5.1 Simulation Settings

This study conducts simulation validation based on an actual urban distribution network in China. The test system comprises 519 nodes and 518 feeder segments. Given the substantial system scale, a simplified network structure is adopted for analysis—the entire system is partitioned into 9 supply zones (denoted as Q1 through Q9), as showed in Fig. 5. The simulations were conducted using custom programs developed in MATLAB 2020b, running on a computer equipped with an Intel(R) Core (TM) i7-14650HX CPU. The cost parameters for various retrofit measures presented in Table 2 are empirical values, derived from engineering practice and historical project data.

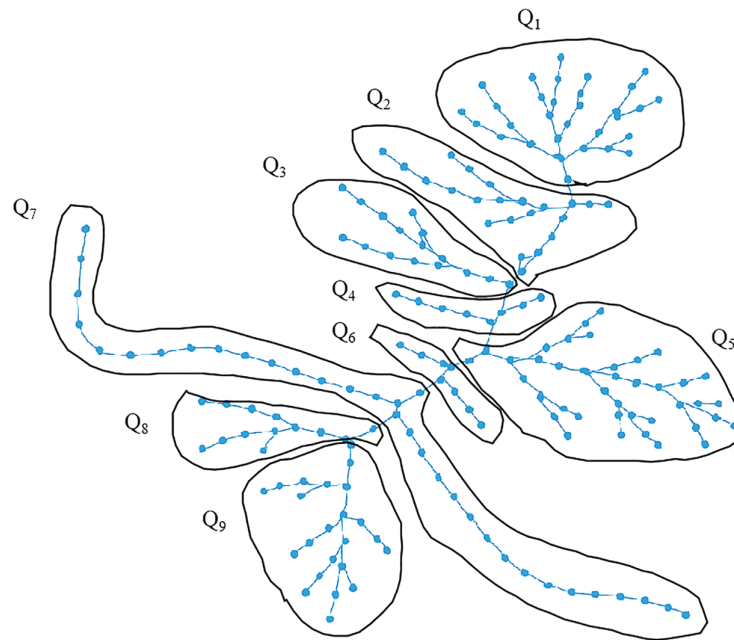


Figure 5: The structure of 519-node distribution system

Table 2: The cost parameters

Parameter	Value (¥)	Parameter	Value (¥)
c_{Er}	2500	c_{Dac3}	12,000
c_{Dac1}	4500	c_{Las}	2000
c_{Dac2}	7000	c_{Riic}	8000

5.2 Simulation Results and Analysis

According to the proposed investment planning model based on quantized decomposition for reliability enhancement, the case study will implement four reinforcement measures illustrated in Fig. 3 to upgrade the distribution network system across nine distinct zones (Q1–Q9) with differentiated reliability requirements. The Pareto frontier of simulation results is presented in Fig. 6, where solution M (285, 9.9256) has been selected using the TOPSIS method.

The optimal investment plans for each zone are listed in Table 3, while Table 4 compares the reliability indices before and after system upgrades. The optimal investment schemes for each zone are presented in Table 3, while Table 4 compares the reliability indices before and after system upgrades. Fig. 4 also includes results from a traditional power-flow-based method for direct comparison with the proposed approach. In areas with lower reliability demands, such as Q3 and Q7, the desired service reliability can be achieved primarily through fundamental infrastructure improvements and the deployment of distribution automation. Conversely, high-demand regions like Q4 and Q9 require additional actions, including tie-line construction and installation of transfer switches, combined with infrastructure modernization and automation enhancements.

It should be noted that this study employs SAIDI as a representative reliability metric for analysis, with corresponding results obtained. The proposed methodology can be similarly extended to evaluate other reliability indices (e.g., SAIFI, MAIFI, or EDNS) using analogous analytical procedures.

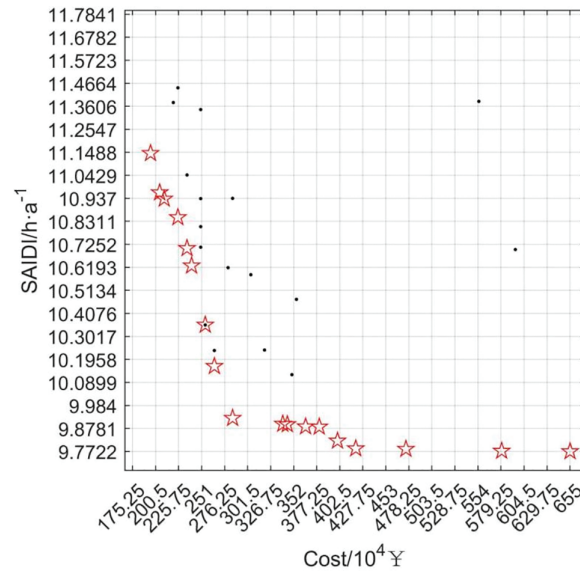


Figure 6: The pareto front of optimization model

Table 3: Optimal investment schemes of nine areas in distribution network

Improvement measures	Investment cost/10 ⁴ ¥								
	Q ₁	Q ₂	Q ₃	Q ₄	Q ₅	Q ₆	Q ₇	Q ₈	Q ₉
x_{Er}	14.25	13.25	13.5	8.25	14.5	10.25	13.75	9.5	11
x_{Dac}	6.85	7.1	6.3	6.2	5.4	6.7	5.7	7.15	7.15
x_{Las}	6.6	5.4	5.2	6.8	6.2	4.2	6.2	7.2	6.4
x_{Riic}	7.2	8	6.4	5.6	6.4	7.2	8.8	8	6.4

Table 4: Reliability index results before and after reconstruction

Region	SAIDI/(h·a ⁻¹)		
	Before	After	
		This paper	Traditional method
Q ₁	4.8169	1.3436	2.1687
Q ₂	5.5893	1.0248	3.6257
Q ₃	5.9348	1.2893	2.3541
Q ₄	3.2836	0.8924	1.5796
Q ₅	5.1943	1.3679	2.6871
Q ₆	2.8536	0.5139	1.2658
Q ₇	5.6391	1.3694	2.5879
Q ₈	4.5813	1.0368	2.9856
Q ₉	2.6891	0.5825	1.6743

6 Results & Discussions

6.1 Simulation Results and Analysis

Fig. 6 illustrates the Pareto front obtained by the proposed quantitative decomposition-based bi-objective optimization model. Each point represents a feasible investment scheme characterized by a pair of objective values: total investment cost and the corresponding SAIDI index. The Pareto frontier demonstrates a clear inverse relationship between investment and reliability improvement, indicating that significant reliability gains can be achieved with moderate capital expenditure before diminishing returns appear. The smooth, well-distributed frontier also suggests the stability of the proposed optimization algorithm, with no apparent clustering or oscillation, confirming its capability to effectively explore the entire solution space.

The solution selected through the TOPSIS method (denoted as solution M) achieves a SAIDI value of $9.9256 \text{ h}\cdot\text{a}^{-1}$ at a total investment of 2.85 million CNY. Compared to other non-dominated solutions, this configuration offers the most balanced trade-off between cost efficiency and reliability enhancement, aligning with practical decision-making needs of utilities under constrained budgets.

6.2 Regional Reliability Enhancement

The optimization results reveal distinct investment and reliability characteristics across the nine planning zones (Q1–Q9). As summarized in Tables 3 and 4, regions with relatively low baseline reliability—such as Q2, Q3, and Q7—benefit most from basic infrastructure reinforcement (e.g., conductor replacement and distribution automation). These measures substantially reduce outage duration while maintaining cost-effectiveness. In contrast, zones Q4 and Q9 with higher reliability requirements demand comprehensive strategies, including tie-line installation, additional switches, and automation upgrades to achieve further reliability gains.

Across the entire system, the proposed approach reduces the average SAIDI from 4.95 to $1.16 \text{ h}\cdot\text{a}^{-1}$ —representing a 76.6% improvement compared with the pre-upgrade condition. When compared to traditional power-flow-based planning, the new model achieves comparable or superior reliability outcomes with over 40% less computational effort, demonstrating its analytical efficiency.

6.3 Sensitivity and Methodological Insights

To assess the stability of the optimization process, additional runs were conducted with randomized initial populations. The resulting Pareto fronts exhibited negligible variation (<2% in SAIDI difference at equivalent investment levels), validating the repeatability of the MOPSO–TOPSIS framework.

The comparative analysis also confirms that introducing quantitative decomposition effectively substitutes iterative power-flow calculations with analytical reliability evaluation, thereby significantly reducing computation time while maintaining consistency with conventional reliability indices. This result highlights the framework's potential for scalable application in large-scale distribution networks, where computational burden has traditionally hindered comprehensive planning.

7 Conclusion

This study presents a quantitative decomposition-based bi-objective optimization framework for enhancing reliability in distribution networks. By formulating an explicit analytical mapping from reliability improvement measures to reliability parameters and subsequently to reliability indices, the proposed approach enables fast, transparent, and simulation-free reliability evaluation. This establishes a methodological advancement beyond conventional power-flow-dependent reliability assessment.

The case study on a 519-node practical distribution system quantitatively verifies the effectiveness of the proposed framework. The system-wide SAIDI is reduced from 4.95 to 1.16 h·a⁻¹, corresponding to a 76.6% reduction in outage duration, while requiring an investment of only 2.85 million CNY. Compared with traditional power-flow-based planning models, the proposed method achieves comparable or superior reliability improvements with over 40% reduction in computational effort, demonstrating its superior scalability and applicability to large-scale networks. Moreover, the Pareto-front analysis indicates that approximately 70% of the attainable reliability gains can be achieved with moderate capital input, providing actionable insights for distribution utilities facing budgetary constraints.

Overall, the proposed framework offers a mathematically rigorous and computationally efficient solution for reliability-oriented distribution planning. Its quantitative decomposition mechanism, combined with the Pareto-based multi-objective PSO and TOPSIS decision strategy, provides a scientifically grounded decision-support tool capable of balancing economic investment and reliability performance. Future extensions will incorporate uncertainties such as renewable generation variability, load stochasticity, and equipment degradation to further enhance the robustness and generalizability of the model.

Acknowledgement: Not applicable.

Funding Statement: This paper is supported by the Science and Technology Project of Southern Power Grid Guangxi Power Grid Co., Ltd. (GXKJXM2022157).

Author Contributions: The authors confirm contribution to the paper as follows: conceptualization: Chenying Yi and Yangjun Zhou; methodology: Yuanchao Zhou; software: Juntao Pan; validation: Yangjun Zhou, Yuanchao Zhou and Bin Feng; formal analysis: Wei Zhang; investigation: Hongwen Wu; resources: Weixiang Huang; data curation: Yangjun Zhou; writing—original draft preparation: Chenying Yi, Wei Zhang, Like Gao and Hongwen Wu; writing—review and editing: Yangjun Zhou, Yuanchao Zhou, Ke Zhou, Weixiang Huang, Juntao Pan, Shan Li and Bin Feng; supervision: Shan Li; project administration: Ke Zhou; funding acquisition: Like Gao. All authors reviewed the results and approved the final version of the manuscript.

Availability of Data and Materials: The data that support the findings of this study are available from the Corresponding Author, Yuanchao Zhou, upon reasonable request.

Ethics Approval: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest to report regarding the present study.

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