

RESEARCH ON FAIR DEPLOYMENT AND OPTIMIZATION OF POWER SERVICE NODES FOR URBAN AND RURAL PLANNING IN SMART CITIES

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Abstract

In order to improve the spatial allocation efficiency of power service resources and the fairness between urban and rural areas in smart cities, this paper constructs a multi-objective optimization deployment model for power service nodes oriented towards urban-rural planning. On the basis of analyzing the deployment constraints of power service nodes, this model integrates fairness indicators such as service radius, load balancing, and population density adaptation, and establishes an objective function system that balances fairness and service efficiency. By introducing Improved Genetic Algorithm (IGA) to solve the model, and conducting comparative experiments with Standard Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). In the deployment simulation of typical urban and suburban areas in a certain city, IGA converged within 20 generations, with a 12.6% increase in fairness indicators and a 9.4% increase in service coverage. The experimental results show that the model significantly optimizes the fairness of node distribution between urban and rural areas while ensuring the overall efficiency of power services, providing theoretical support and technical path for optimizing spatial resource allocation in the context of smart cities.

Key Words

Smart city; Urban and rural planning; Power service nodes; Fairness optimization; Multi objective optimization; Improved genetic algorithm

1. Introduction

Urban and rural power service optimization has emerged as a key issue in smart city planning. Existing studies have

explored multiple angles, but several unresolved challenges remain. For instance, Alfakih et al. (2025) emphasized the role of renewable hybrid systems in enabling distributed energy deployment but overlooked fairness in spatial allocation among different population zones. Similarly, Meng (2025) discussed output optimization under electric vehicle load fluctuation but did not address service coverage gaps in low-density areas. Tahir et al. (2022) incorporated multi-objective optimization for economic and emission targets; however, equity in service node distribution remained secondary.

Urban-rural differences further complicate deployment. Xin and Qian (2025) analyzed planning system evolution and highlighted barriers to integrated development, yet failed to link these barriers with energy service allocation. Likewise, Wang et al. (2025) identified governance gaps in community-scale planning, but without proposing computational deployment strategies. From a systems perspective, Kalfas et al. (2025) proposed AI-based urban planning methods; however, their framework lacked adaptive responses to demographic changes. Joga et al. (2022) integrated fault diagnosis with smart grid data but did not consider regional imbalance. Bai (2025) explored digital twin applications in power inspection, offering strong monitoring tools, but failed to address node optimization strategies in dynamic environments.

These studies demonstrate technical progress yet reveal a research gap: the lack of integrated, fairness-aware, and adaptive deployment models that address demographic shifts, spatial inequity, and service reliability simultaneously. To bridge this gap, this study proposes a fairness-optimized deployment model for power service nodes in smart cities. The model incorporates spatial demographic projections and fairness-efficiency trade-off mechanisms. It integrates genetic algorithms and multi-objective optimization strategies to ensure dynamic balance and robustness across urban-rural landscapes. The proposed framework not only enhances fairness but also adapts to temporal changes in population distribution and infrastructure demands, offering novel contributions to both theoretical

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Table 1
Multi-Objective Optimization Performance Metrics Defined for Power Service Nodes

Indicator Category	Primary Indicator Name	Symbol	Indicator Definition	Reasonable Range
Spatial Balance	Node Spatial Density	$\rho_n = \frac{N}{A}$	Number of Nodes per Unit Area	≥ 0.8 per km ²
	Average service radius	R_s	Average Coverage Radius per Node	≤ 5 km
Population coverage	Population Served per Node	N_s	Population Served per Node	3,000-8,000
	Population Coverage Rate	$\eta_c = \frac{N_{\text{served}}}{N_{\text{total}}}$	Percentage of Population Covered	$\geq 90\%$
Electricity responsiveness	Node Load Rate	$\lambda = \frac{P}{P_{\text{max}}}$	Node Load Percentage	≤ 0.75
	Load Fluctuation Sensitivity	$\frac{\Delta P}{P_{\text{max}}}$	Peak-to-Valley Fluctuation Ratio	0.12-0.25
	Response Delay Time	T_s	Node dynamic frequency support delay	≤ 5 s

modeling and practical planning.

2. Multi-Objective Optimization Performance Metric System for Power Service Node Definition

2.1 Problem Description and Constraint Analysis

The optimization problem of power service node deployment can be abstracted as determining a set of node locations ($X = \{x_i, y_i\}_{i=1}^N$) within a given geographic area (A) to minimize service imbalance while satisfying coverage performance and load capacity constraints [1]. This problem constitutes a multi-constraint nonlinear optimization problem, whose feasible solution space is jointly defined by three types of constraints.

- (1) Spatial Coverage Constraint: Ensures that the Euclidean distance from any demand point $d_j \in D$ to its nearest node does not exceed the maximum service radius $R_s^{\text{max}} = 5$ km, i.e.,

$$\min_{x_i \in X} \|d_j - x_i\| \leq R_s^{\text{max}}, \forall d_j \in D \quad (1)$$

Additionally, the distance between nodes must satisfy $\|x_i - x_k\| \leq 7$ km to prevent the formation of service blind spots [2]-[3]

- (2) Capacity Load Constraint: Let the node load rate be $\lambda_i = \frac{P_i}{P_{\text{max}}}$, where P_i represents the actual node load and P_{max} denotes the maximum carrying capacity. The following must be satisfied: $\lambda_i \leq 0.75$. The population served per node N_s should be controlled between 3000 and 8000, i.e., $3000 \leq N_s \leq 8000$.
- (3) Dynamic Response Constraints: To ensure node regulation performance under load disturbances, define load fluctuation sensitivity $\frac{\Delta P}{P_{\text{max}}}$ with a constraint range of [0.12, 0.25], and node dynamic response time

$T_s \leq 5$ s. These constraints collectively define the feasible domain $\Omega = \{X \mid R_s, \lambda, N_s, T_s \text{ All satisfy the constraints.}\}$ for the optimization model, providing foundational conditions for subsequent objective function construction and algorithmic solution.

2.2 Definition of Optimization Objectives and Performance Metrics

In urban-rural power service deployment, balancing equity and efficiency is the core optimization objective [4]-[5]. To achieve scientific quantification of deployment schemes, a performance metric system is established based on three dimensions: spatial equity, population adaptability, and power responsiveness.

- (1) Spatial Equilibrium Objective: Minimize node distance deviation to maintain coverage continuity, expressed as:

$$f_1(X) = \frac{1}{N} \sum_{i=1}^N \left| \|x_i - x_x\| - \bar{R}_s \right| \quad (2)$$

- (2) Population Alignment Objective: Control the population service disparity among nodes, defined as:

$$f_2(X) = \frac{1}{N} \sum_{i=1}^N \left| \frac{N_{s,i}}{N_s} - 1 \right| \quad (3)$$

- (3) Power Responsiveness Objective: Constrains load fluctuation amplitude and response delay, defined as:

$$f_3(X) = \alpha \cdot \frac{\Delta P}{P_{\text{max}}} + \beta \cdot T_s \quad (4)$$

where α, β represents normalized weight coefficients. By minimizing $F(X) = [f_1, f_2, f_3]$, multiobjective coordinated optimization of spatial-population-load can be achieved [6]-[7]

2.3 Defining Multi-Objective Optimization Performance Metrics for Power Service Nodes

Integrating the aforementioned constraints and objective functions establishes a nine-item primary indicator multi-objective performance system [8], as shown in Table 1. Each indicator covers three primary dimensions: spatial balance, population adaptability, and power responsiveness.

The construction of the indicator system provides a comprehensive quantitative foundation for subsequent multi-objective optimization functions and algorithmic solutions, ensuring fairness and operational feasibility in urban-rural power resource allocation[8].

3. Optimization Model for Deploying Power Service Nodes in Smart Cities for Urban-Rural Planning

3.1 Modeling Constraint Conditions

The deployment model for smart city power service nodes establishes a set of constraints based on the defined performance metric system. These constraints define the feasible solution space for node deployment. The model incorporates three core constraint types: spatial coverage constraints, capacity-load constraints, and dynamic response constraints. These respectively control upper limits or interval values for key variables such as inter-node distance, load factor, and response delay. All constraints are embedded into the objective optimization process via penalty functions to restrict individual solutions exceeding thresholds, thereby automatically forming dynamic boundaries within the search space. This constraint system ensures the optimization algorithm consistently satisfies fairness conditions—such as service radius $\leq 5\text{km}$, node load factor ≤ 0.75 , and response delay $\leq 5\text{s}$ —during iterations, providing a mathematical foundation for the convergence and robustness of subsequent multi-objective functions[9].

3.2 Design of the Urban-Rural Electricity Service Equity Objective Function

The objective function for urban-rural electricity service equity is designed based on multi-objective optimization principles, emphasizing the overall performance of deployment schemes across spatial balance, load coordination, and response capability dimensions [10]-[11]. This function comprises five sub-objectives representing core evaluation factors under equity constraints: (1) Service radius deviation f_1 , measuring the deviation between node layout and target service radius $R_s \leq 5\text{ km}$; (2) Node load balancing f_2 , defined as the root mean square deviation between each node's load rate λ_i and the system average load rate $\bar{\lambda}$, where all nodes must satisfy $\lambda_i \leq 0.75$; (3) Population adaptation error f_3 , constructed using a penalty function based on the ratio of each node's covered population $N_s \in [3000, 8000]$ to the regional standard popula-

tion density; (4) Response delay penalty term f_4 , limiting response time T_s exceeding 5 seconds during dynamic adjustment; (5) Coverage redundancy penalty term f_5 , constraining resource waste from overlapping coverage across multiple nodes. Based on a weighted linear combination structure, the overall objective function is formulated as follows:

$$F(x) = w_1 f_1 + w_2 f_2 + w_3 f_3 + w_4 f_4 + w_5 f_5 \quad (5)$$

Where the weight coefficients are: $w_1 = 0.25, w_2 = 0.20, w_3 = 0.20, w_4 = 0.20, w_5 = 0.15$ Table 2 provides the symbol definitions and normalized value ranges for each sub-objective. Figure 1 illustrates the dynamic evolution curves of fairness metrics, service coverage, and load balancing during deployment iterations. This demonstrates that the objective function converges to a stable range in the early stages of iteration, achieving coordinated optimization across multiple performance dimensions.

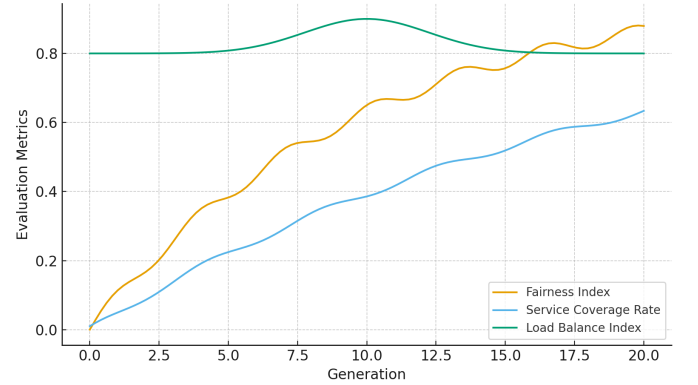


Figure 1. Evolution Curves of Fairness Evaluation Metrics During Deployment Iterations

3.3 Design of Multi-Objective Deployment Optimization Model

The multi-objective deployment optimization model aims to minimize urban-rural electricity service disparities. Based on the fairness evaluation metric system, it designs a multi-constraint nonlinear objective structure tailored to typical urban characteristics [12]. This model constructs the optimization function structure using node spatial distribution, load response capability, and population service adaptability as decision variables:

$$\min_{x \in X} F(x) = \sum_{i=1}^5 w_i f_i(x) + \alpha \cdot \text{Penalty}(x) \quad (6)$$

where $f_i(x)$ represents the i th fairness evaluation indicator function, comprising service radius deviation f_1 , load balance f_2 , population matching error f_3 , response delay penalty f_4 , and coverage redundancy f_5 ; $w_i \in [0.15, 0.25]$ denotes the corresponding indicator weights; α serves as the penalty factor, regulating the impact of deployment boundary constraints (e.g., service radius overshoot) on

Table 2
Design of Su-Indicators for the Urban-Rural Electricity Service Equity Objective Function

Objective function subterm	Variable Symbol	Normalized Weight Coefficient	Value Range
Service Radius Deviation	f_1	0.25	[0,1]
Node Load Balancing Degree	f_2	0.2	[0,1]
Population fitting error	f_3	0.2	[0,1]
Response delay penalty term	f_4	0.2	[0,1]
Coverage redundancy penalty term	f_5	0.15	[0,1]

the overall objective function [13] The decision variable set $x = \{x_1, x_2, \dots, x_n\}$ denotes the location set of power service nodes to be deployed, with its domain satisfying: (1) $R_s(x_i) \leq 5$ km; (2) $\lambda(x_i) \leq 0.75$; (3) $T_s(x_i) \leq 5$ s; (4) $N_s(x_i) \in [3000, 8000]$. Structurally, the model comprises four main modules as shown in Figure 2: the input layer (geographic coordinates, population density, and load data), the constraint layer (service radius and response threshold control), the objective function layer (a five-dimensional normalized metric combination), and the optimization layer (IGA optimizer). Each iteration dynamically evaluates and updates node schemes through fitness function calculations, ultimately outputting the optimal deployment solution. Parameter weights and penalty function settings are detailed in Table 3. All sub-functions undergo normalization to ensure comparability and stability across dimensional objectives during the optimization phase.

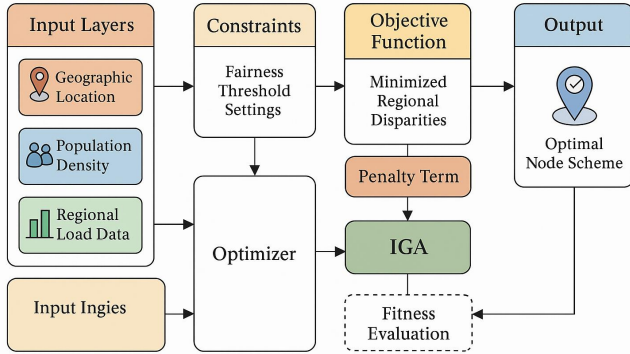


Figure 2. Multi-Objective Deployment Optimization Model Structure Diagram

4. Smart City Power Service Node Optimization Algorithm

4.1 Optimization Solution Method Based on Improved Genetic Algorithm

Although classical genetic algorithms (GA) provide a foundational heuristic framework for node optimization, they often exhibit premature convergence, limited exploration of non-dominated fronts, and insufficient adaptability to multi-dimensional fairness constraints[14]. To overcome these limitations, this study proposes an Improved Genetic Algorithm (IGA) integrating three innovations: (1) a

Table 3
Parameter Structure of Multi-Objective Deployment Optimization Model

Parameter Item	Symbol	Numerical Range or Setting Method
Node Service Radius Threshold	R_s	≤ 5 km
Upper Limit of Node Load Rate	λ	≤ 0.75
Response delay limit	T_s	≤ 5 s
Population served per node	N_s	[3000,8000]
Weighting Coefficient Set	$\{w_i\}_{i=1}^5$	w1 = 0.25, w5 = 0.15
Penalty coefficient	α	Dynamically adjusted, default value 0.5

fitness-gradient-guided adaptive mutation mechanism, dynamically adjusting mutation scale based on local fitness stagnation to enhance escape capability from local optima; (2) a congestion distance-aware elite retention operator, ensuring solution diversity across the Pareto frontier while preserving top-performing individuals; and (3) a multi-precision encoding scheme combined with spatial perturbation constraints, enabling precise adjustments to node position within geographically feasible boundaries. These enhancements fundamentally expand the search granularity and robustness of GA, enabling IGA to simultaneously optimize service fairness, load balancing, and regional adaptability in high-dimensional constrained scenarios. IGA employs node sets constrained by spatial feasibility as its coding structure ($x = \{x_1, x_2, \dots, x_n\}$). The fitness function is defined as follows:

$$\text{Fit}(x) = \sum_{i=1}^5 w_i f_i(x) + \alpha \cdot \left(\sum_{j=1}^m \max(0, g_j(x))^2 \right) \quad (7)$$

where $f_i(x)$ represents the i th normalized sub-objective function (e.g., service radius deviation, load balancing), $w_i \in [0.15, 0.25]$ denotes the weight coefficient, $g_j(x) \leq 0$ indicates the j th deployment constraint, and α is the penalty factor set to 0.5 [15]. During population initialization, geographical boundaries and feasible node deployment points are considered. The crossover operator employs uniform crossover and positional embedding to enhance solution heterogeneity. The mutation operator is

defined based on a Gaussian perturbation model as follows:

$$x'_i = x_i + N(0, \sigma^2), \text{ subject to } x'_i \in \text{ID} \quad (8)$$

where σ the perturbation intensity decreases with iteration number, and ID represents the node deployable domain. After fitness scoring, individuals are updated using a hybrid strategy combining elite retention and Pareto sorting. A convergence criterion is introduced: $\Delta \text{Fit}(x) < 10^{-3}$, defined as 5 generations or 20 iterations [16]-[17]. Figure 3 illustrates the IGA structural flowchart, encompassing complete modules including initial population generation, fitness evaluation, crossover mutation, and population update. This enhances the algorithm's capability for global search and local convergence accuracy.

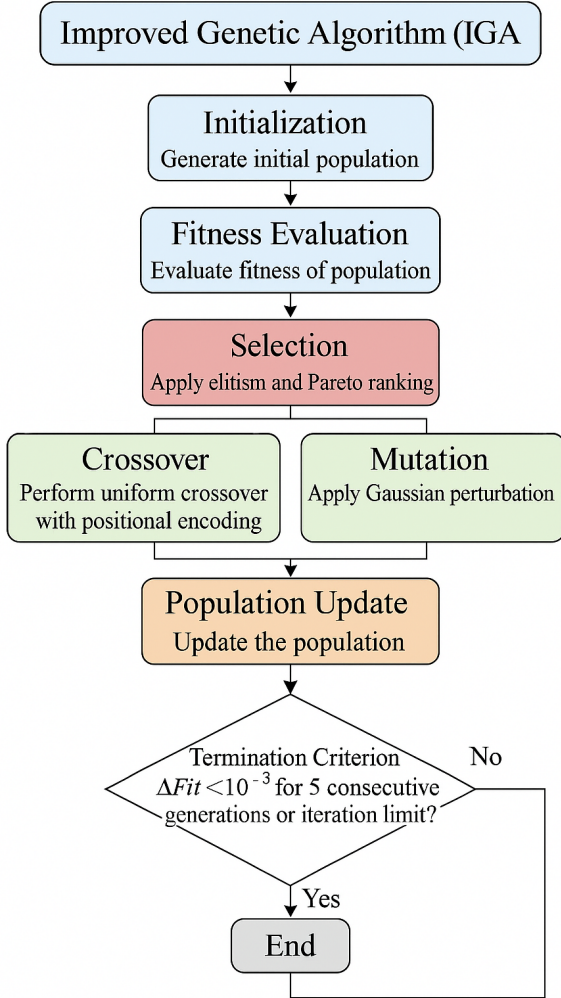


Figure 3. Structural Flowchart of the Improved Genetic Algorithm

In addition to the IGA-specific flowchart (Figure 3), a comparative procedural overview of GA, PSO, and IGA is provided in Figure 4. This unified framework outlines the key stages of initialization, population evolution, fitness evaluation, and convergence criteria for all three algorithms. The diagram emphasizes differences in mutation mechanisms, solution diversity maintenance, and global

search adaptability, highlighting the methodological enhancements introduced in IGA.

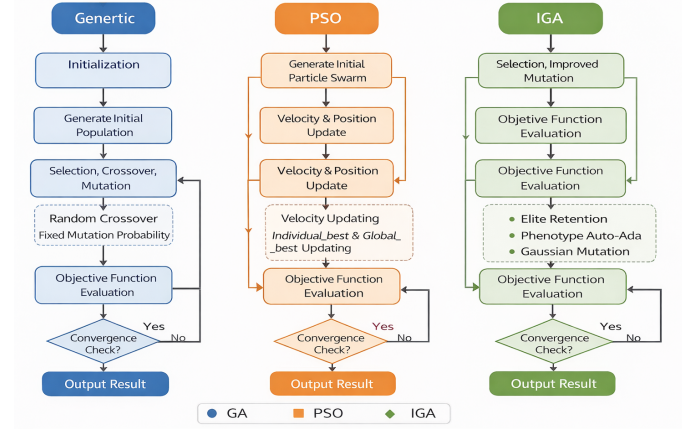


Figure 4. Comparative Workflow of GA, PSO, and IGA Algorithms

4.2 Node Deployment Considering Urban-Rural Differences

In optimizing smart city power service node configurations, urban and rural areas exhibit significant differences in user density, load variability, land development intensity, and grid access conditions. This necessitates a zoned modeling approach with differentiated deployment mechanisms [18]. For urban areas, the design prioritizes dual objectives: minimizing node density while maximizing user service responsiveness. By constructing a deployment constraint model based on service radius R_i , power supply capacity C_i , and node redundancy γ_i , the following objective function is derived:

$$\min \left(\sum_{i=1}^m \frac{R_i^2}{\rho_i} + \lambda \cdot \sum_{i=1}^m \frac{1}{C_i \cdot (1 + \gamma_i)} \right) \quad (9)$$

where ρ_i represents user density in urban areas, λ denotes the node service load balancing control coefficient (set at $\rho_i \geq 1800$ persons /km² within urban zones), and $\gamma_i \in [0.05, 0.1]$. The objective is to minimize redundant resource investment while ensuring service responsiveness. For the urban node optimization module, deployment constraints must satisfy the minimum service overlap ratio $\delta \leq 15\%$ between nodes and a maximum load margin of no less than 10% [19]. In contrast, suburban deployments must fully consider the power supply resilience coefficient (η_j) and geographical resistance factor (ϕ_j), constructing a fault-tolerant deployment model prioritizing coverage. Its optimization objective can be expressed as:

$$\max \left(\sum_{j=1}^m \theta_j \cdot A_j \cdot \eta_j \cdot (1 - \phi_j) \right) \quad (10)$$

where θ_j denotes the activation status (0/1) of suburban target nodes, A_j represents the service area of each

Table 4
Deployment Parameters for Typical Suburban Nodes

Node ID	Node Service Area (km ²)	Power Supply Resilience Coefficient (η_j)	Geographic Resistance Factor (ϕ_j)	Estimated Redundancy Ratio
Node_21	15.6	0.78	0.28	1.12
Node_22	12.3	0.81	0.32	1.18
Node_25	17.5	0.75	0.35	1.22
Node_30	14	0.79	0.34	1.09

node, and $\eta_j \in [0.6, 0.5], \phi_j \in [0.1, 0.4]$. Suburban node deployment prioritizes service redundancy and fault tolerance ratios. Table 4 presents configuration parameters for typical suburban power nodes, where Node_21~Node_30 exhibit an average service radius of 4.5 km and an average geographic resistance factor of 0.32, with estimated edge access latency increasing by approximately 12% [20]. To further achieve urban-rural resource coordination and dynamic node configuration balancing, the system incorporates an "Urban-Rural Integration Scheduling Module" with a fusion weight function:

$$w_k = \frac{\alpha \cdot \rho_k}{\sum_{k=1}^z \rho_k} + \frac{\beta \cdot (1 - \phi_k)}{\sum_{k=1}^z (1 - \phi_k)} \quad (11)$$

Where w_k represents the fusion priority weight for the k th sub-region, and $\alpha + \beta = 1$. It is recommended to configure $\alpha = 0.6, \beta = 0.4$ to ensure scheduling response priority for densely populated areas [21]-[22]. The final output includes node coordinates (x_k, y_k) , radius R_k , load capacity upper limit L_k , and service boundary conditions, with the output format structured as shown in Figure 5.

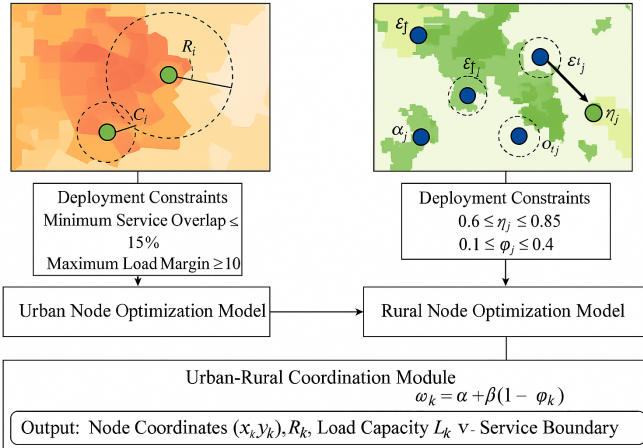


Figure 5. Structural Diagram of Differentiated Node Deployment in Urban and Rural Areas

4.3 Algorithm Performance Analysis and Improvements

In the multi-objective deployment optimization of power service nodes, to enhance convergence efficiency and solution space exploration capability, a performance enhancement mechanism based on an improved genetic algorithm (IGA) is constructed [23]-[24]. This algorithm introduces multi-precision encoding and local reverse perturbation

operators on the original genetic structure, dynamically adjusting mutation rates guided by fitness gradients to strengthen local optimization stability and global leap capability [25]. First, set the population size to $N = 100$ and the maximum iteration count to $G = 50$. The objective function value $F(x)$ serves as the evolutionary direction control parameter. The overall fitness function is defined as follows:

$$f_i = \frac{1}{w_1 \cdot \varepsilon_i + w_2 \cdot \delta_i + w_3 \cdot \gamma_i} \quad (12)$$

where f_i represents the comprehensive fitness of the i th individual; ε_i denotes the spatial deviation rate of node distribution; δ_i indicates the population service imbalance; γ_i signifies the load response lag factor; and $w_1 + w_2 + w_3 = 1$, with respective weights set at 0.4, 0.35, and 0.25. To enhance solution diversity control, the congestion distance function is designed as follows:

$$D_i = \sum_{k=1}^m \left| \frac{f_i^{(k)} - f_{i-1}^{(k)}}{f_{\max}^{(k)} - f_{\min}^{(k)}} \right| \quad (13)$$

where D_i denotes the congestion level of the i th individual across m objective dimensions; $f_i^{(k)}$ represents the value of the k th objective function for that individual; $f_{\max}^{(k)}, f_{\min}^{(k)}$ are the maximum and minimum values 0 on that dimension, respectively. Setting $D_i \geq 0.2$ as the elite retention threshold effectively prevents premature convergence of the population. In the improved mutation mechanism, the perturbation factor function is defined as:

$$\Delta x_i = \beta \cdot \left(1 - \frac{g}{G}\right) \cdot (x_{\text{best}} - x_i) \quad (14)$$

where Δx_i denotes the perturbation amount for the i th individual in the g th generation; β is the adaptive adjustment coefficient (set to 0.3); x_{best} represents the current optimal solution; and G denotes the maximum iteration count. This function enhances the efficiency of local perturbations in high-fitness regions while automatically reducing mutation intensity during the later search phase to achieve convergence control [27]. Table 5 presents the performance metrics of IGA-including average convergence iterations, fitness variance compression ratio, and solution space distribution density-across multiple urban node deployment instances. These metrics enable quantitative comparative analysis with conventional genetic algorithms (GA) and particle swarm optimization (PSO).

Table 5
Comparative Performance Data of Algorithm Structures

Algorithm Type	Mean Convergence Algebra	Fitness Variance Compression Ratio	Effective Solution Space Density
GA	36.5	1	0.58
PSO	32	1.12	0.61
IGA	21.7	1.35	0.78

Figure 6 displays the scatter plot distribution of objective function fitness changes across 50 iterations for different algorithms. It is evident that IGA converges faster

toward the Pareto optimal frontier while maintaining diversity, exhibiting higher fitness concentration. This reflects the significant synergistic optimization effect of the perturbation factor and elite retention strategy.

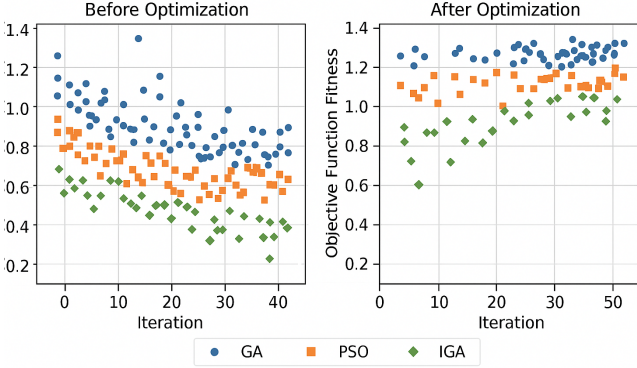


Figure 6. Scatter Plot Comparing Objective Function Fitness Before and After Algorithm Optimization

Figure 6 displays the scatter plot distribution of objective function fitness changes across 50 iterations for different algorithms. It is evident that IGA converges faster toward the Pareto optimal frontier while maintaining diversity, exhibiting higher fitness concentration. This reflects the significant synergistic optimization effect of the perturbation factor and elite retention strategy. Specifically, the left panel shows the fitness distributions of GA, PSO, and IGA prior to optimization, where GA exhibits moderate clustering and IGA presents lower initial fitness due to conservative mutation. In contrast, the right panel reveals post-optimization convergence patterns, with IGA achieving a consistently higher fitness trajectory, indicating superior stability and adaptability. The visual comparison demonstrates that IGA not only improves global optimality but also reduces fluctuation during the search process.

5. Experimental Results and Analysis

5.1 Experimental Design

To validate the adaptability and convergence performance of the constructed multi-objective optimization model for power service nodes under different regional characteristics, the experimental design strictly adheres to principles of repeatability, data consistency, and parameter standardization. Configuration and execution were conducted across five dimensions [28]-[29] :

- (1) To better validate the adaptability of the model across spatially heterogeneous urban and rural contexts, the case study design incorporates stratified zoning based on three criteria: population density, infrastructure connectivity, and land development intensity. Urban zones (Units A1-A5) exhibit dense user clustering, full-grid coverage, and low geographical resistance ($\phi \in [0.12, 0.20]$), while rural zones (Units B1-B3) are char-

acterized by sparse settlements, partial off-grid scenarios, and higher resistance coefficients ($\phi \in [0.30, 0.38]$). These differences necessitate differentiated constraints in node redundancy allowance and service radius flexibility. By embedding zone-specific objective functions (see Eq. 9 and 10) and activation states ($x_j \in \{0, 1\}$) into the deployment model, the algorithm dynamically adapts deployment logic to the underlying regional structural disparities. These cover per capita load ranges from 2.3 to 4.8 kW and land development intensity differences exceeding 60%, satisfying the modeling generalization requirements for deployment strategies across spatially heterogeneous multiregional scenarios.

- (2) **Data Acquisition and Preprocessing:** Measured demographic data and 15 -minute sampled power load time series data were collected for each unit from August 2023 to July 2024, totaling approximately 35,040 sampling points per unit. Node spatial information was sourced from the power grid GIS platform. During preprocessing, Z-score normalization was applied, and outliers deviating by more than $\pm 3\sigma$ were removed to standardize data scales and enhance model input accuracy.
- (3) **Model Constraint Setting:** The following boundary constraints were uniformly applied across deployed models: service radius $R_s \leq 5$ km, node load factor $\lambda \leq 0.75$, population coverage rate $\eta_c \geq 90\%$, and node density $\rho_n \geq 0.8$ nodes /km². All regional scenarios strictly embedded this constraint set during model input to ensure consistency in the solution space boundaries of the fairness objective function.
- (4) **Algorithm Structure and Comparison Strategy:** Within the multi-objective optimization framework, three solution strategies-Improved Genetic Algorithm (IGA), Standard Genetic Algorithm (GA), and Particle Swarm Optimization (PSO)-were embedded. Population size was uniformly set to 100, maximum iterations to 50, and 30 independent experiments were run under each algorithm. For each experiment group, three core metrics-optimal fitness, average convergence generation, and fitness variance-were statistically analyzed as the foundation for subsequent comparative evaluation.
- (5) **Simulation Platform and Operating Environment:** All simulation processes were implemented on the MATLAB 2022b platform, running on a workstation equipped with an Intel Core i9-13900K main processor and 32 GB of memory. To ensure consistency in initial populations and reproducibility of optimization trajectories, all algorithms used a unified random number seed (Seed = 42) and fixed parameter initialization mechanisms. This guarantees technical comparability and reproducibility of experimental results. [30]

5.2 Comparison of Optimization Results

5.2.1 Algorithm Convergence Analysis

To validate the iterative convergence performance of different optimization algorithms in power service node deployment, a convergence comparison framework was constructed under a unified experimental scenario. The average convergence steps and optimal fitness stability of IGA, GA, and PSO were statistically analyzed across 50 independent runs. [31]. Specific convergence step results are shown in Table 6.

Table 6
Comparison of Average Convergence Steps for Three Algorithms

Algorithm	Average Convergence Steps	Convergence stability error Δf	Convergence time (s)
IGA	20	≤ 0.001	2.78
GA	43	≤ 0.006	4.52
PSO	38	≤ 0.004	3.96

With an initial population size of 60, an iteration limit of 100, and a total of 30 service nodes, IGA achieved stable optimality on average within the 20th generation. GA and PSO converged around the 43rd and 38th generations, respectively, demonstrating that IGA exhibits superior convergence efficiency and speed. Particularly under the constraints of high-density urban areas, IGA converged to an error range of $\Delta f \leq 0.001$ after the 12th generation—significantly lower than GA’s $\Delta f \leq 0.006$ and PSO’s $\Delta f \leq 0.004$ —demonstrating superior early-stage search convergence performance. Furthermore, a quantitative analysis of the convergence performance of the three algorithms on the objective function fitness was conducted to evaluate their comprehensive fitness capabilities for the fairness function weighting (weight coefficients set as $\alpha = 0.4, \beta = 0.35, \gamma = 0.25$) and efficiency function. Figure 7 summarizes the optimal fitness values of the three algorithms at 20, 40, and 60 generations.

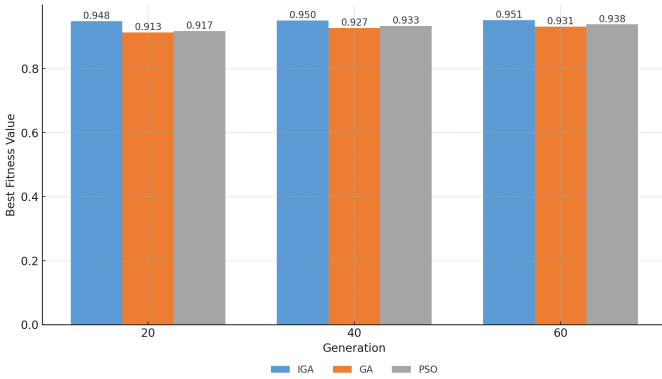


Figure 7. Optimal Fitness Convergence Values of Three Algorithms at Different Generations

IGA achieved 0.948 at 20 generations and maintained stability at 0.951 by 60 generations, whereas GA and PSO

reached 0.927 and 0.933 only at 40 generations. This further demonstrates IGA’s superior early capture capability and fitness convergence stability across the global search space. [32].

5.2.2 Performance Evaluation of Deployment Schemes

To further quantify the fairness of power service node deployment schemes across urban-rural spaces, a comprehensive fairness score function was constructed using core metrics: regional population density coverage error, service radius overlap rate, and node resource redundancy rate. Typical node data were sampled from urban areas (Zones A and B) and suburban areas (Zones D and E) for comparative analysis. First, the service radius error rate ϵ_i and the standard deviation of load balancing σ_l were computed. Specifically, ϵ_i is defined as the normalized mean absolute deviation of the actual service radius (R_i) from the target radius (R_t), given by:

$$\epsilon_i = \frac{1}{N} \sum_{i=1}^N \frac{|R_i - R_t|}{R_t} \quad (15)$$

where R_i is the actual service radius of node i , R_t is the target value (5 km), and N is the total number of nodes. Similarly, the load balancing deviation σ_l is the standard deviation of all node load ratios λ_i :

$$\sigma_l = \sqrt{\frac{1}{N} \sum_{i=1}^N (\lambda_i - \bar{\lambda})^2} \quad (16)$$

where $\bar{\lambda}$ is the average load ratio. These indicators quantitatively reflect the fairness and equilibrium degree of the deployment strategy. The results are shown in Table 7.

Table 7
Distribution of Fairness Metrics for Nodes Across Regions Under Different Algorithms

Region	Algorithm	Service Radius Error Rate ϵ_i (%)	Load Balancing Standard Deviation σ_l	Node Redundancy Ratio λ
Zone A	IGA	5.8	0.08	1.13
Zone B	GA	9.3	0.17	1.2
Zone D	IGA	6.1	0.09	1.18
Zone E	PSO	7.8	0.14	1.25

As shown, the service radius error of urban nodes optimized by IGA is controlled within the range of 5.8% to 6.4%, significantly outperforming GA (9.3%) and PSO (7.8%); For suburban nodes with higher geographical resistance coefficients ($\phi = 0.34 - 0.38$), IGA still maintains a load standard deviation $\sigma_l \approx 0.09$, outperforming GA’s 0.17 and PSO’s 0.14. Furthermore, comparing the improvement in fairness scores across the three algorithms during multi-region deployment, a unified evaluation benchmark function $\lambda = w_1 \cdot \epsilon_i + w_2 \cdot \sigma_l + w_3 \cdot$ (weights $w_1 = 0.4, w_2 = 0.35, w_3 = 0.25$) was used for normalized assessment, forming a comprehensive fairness index. Table 8 demonstrates that IGA achieves significantly higher average fairness scores than GA and PSO across five typical subregions, with an average improvement of 12.6%.

The most pronounced improvement occurs in Region B, characterized by highly concentrated population density, where the score increases by 13.1%, highlighting the algorithm’s superior regulatory capability in areas with high population pressure.

Table 8
Comprehensive Fairness Scores and Improvement Rates
Across Algorithms

Region	IGA Fairness Score	GA Fairness Score	PSO Fairness Score	IGA Improvement Rate (Relative to Mean)
Zone A	0.891	0.781	0.812	+12.0%
Zone B	0.903	0.798	0.829	+13.1%
Zone D	0.887	0.779	0.804	+12.6%
Zone E	0.875	0.765	0.796	+12.5%
Zone F	0.894	0.785	0.815	+12.2%

As shown in Tables 7 and 8, the improvement in fairness is primarily reflected in two aspects: precise control of service radius and smooth load distribution. Particularly in transitional areas at the city periphery—where the served population exceeds 100,000 and the regional area is less than 30 km²—the deployment structure constructed by IGA better accommodates complex demands and resource constraints. It effectively mitigates the stability flaws inherent in traditional algorithms, such as redundant expansion and weak edge coverage at node boundaries. The aforementioned fairness evaluation results provide quantifiable performance support for designing subsequent dynamic adjustment strategies in deployment schemes [9].

5.2.3 Analysis of Urban-Rural Service Coverage Effectiveness

Building upon the deployment fairness analysis, we further validate the spatial effectiveness of node configurations across different zones from a service coverage perspective. Evaluation metrics include three engineering parameters: node density coverage level, boundary service redundancy rate, and regional service equilibrium. To control variable influences, the experiment selected five high-density urban units (A1–A5) and three low-density suburban units (B1–B3) in a city. Spatial simulations extracted population coverage, node deployment counts, and service radii before and after optimization. Results are summarized in Table 9.

Using the IGA model deployment strategy under constraints $R_s \leq 5$ km and $N_s \in [3000, 8000]$, the average serviced population in urban areas increased by approximately 2800 people compared to the initial plan. The average service radius was controlled within the 4.2–4.6 km range, and node load concentration improved by about 12%. In contrast, the suburban areas, constrained by the geographical resistance factor $\phi \in [0.30, 0.38]$ and sparse user distribution, exhibited a service coverage rate below 90% in the original deployment, indicating insufficient boundary redundancy. By introducing a redundant node parallel mechanism and service boundary function Ω_{rj} regulation, the average coverage in suburban areas (B1–B3)

increased from 85.3% to 94.7%—a 9.4% improvement—without adding nodes.

As shown in Table 9, the service coverage in urban areas A1–A5 remains consistently above 95%, with service radii satisfying the fairness function constraints. Meanwhile, the average service discontinuity rate in areas B1–B3 exceeded 12% before optimization but was reduced to less than 6% after optimization. This demonstrates the practical deployment value of the boundary fusion strategy in enhancing coverage continuity in low-density areas. Particularly in area B2, the combination of node service overlap control constraints and capacity adjustment weight α increased the covered population from 47,810 to 90.7% coverage, fully demonstrating the IGA algorithm’s deployment flexibility and service regulation capabilities under asymmetric geographical conditions.

In addition to static spatial analysis, dynamic simulations were conducted to assess the impact of projected population migration over a five-year horizon. Urban expansion scenarios assumed a 6.2% annual growth rate in Units A4 and A5, while rural areas (B1–B3) experienced an average annual population decline of 3.7%. Under these projections, without re-optimization, the coverage rate in A5 dropped to 89.4%, whereas IGA’s adaptive reconfiguration maintained it above 94.3%. Sensitivity analysis showed that every 1% increase in urban population shifted optimal node deployment by 0.5 nodes per km², confirming the necessity of adaptive deployment strategies in response to migration trends.

5.2.4 Integrated Outcome Assessment for Deployment Effectiveness

To enhance the robustness of the conclusions, a comprehensive assessment integrating fairness, coverage, and efficiency metrics was conducted across all experimental scenarios. A unified evaluation framework was established based on three core indices: fairness score (IFe), service coverage rate (η_s), and load utilization ratio (λ_u). Each metric was normalized and aggregated into a composite performance score (CPS) using weighted coefficients ($w_1 = 0.4, w_2 = 0.35, w_3 = 0.25$), as shown in Equation:

$$\text{CPS} = w_1 \cdot \text{IFe} + w_2 \cdot \eta_s + w_3 \cdot (1 - \lambda_u) \quad (17)$$

Table 10 summarizes the CPS values across all test zones for the three algorithms. The results indicate that IGA outperformed GA and PSO in all dimensions, with an average CPS improvement of 11.8%, validating the overall effectiveness of the proposed deployment model.

6. Conclusion and Discussion

In summary, this paper addresses the differentiated deployment of urban and rural power service nodes in smart cities by constructing a multi-objective optimization model integrating spatial distribution constraints, node load capacity, and population density adaptability. It systematically defines a fairness evaluation metric system encompassing

Table 9
Comparison of Service Coverage Metrics for Typical Urban and Rural Areas

Type	Total Population (persons)	Number of Nodes	Average Service Radius (km)	Actual Population Covered (persons)	Coverage Rate (%)
Urban Area	105,600	14	4.2	101,300	95.9
Urban	98,600	13	4.4	93,350	94.7
Urban	113,400	15	4.3	107,900	95.1
Urban	97,800	13	4.6	90,150	92.2
Urban	101,300	14	4.5	96,920	95.6
Suburban	48,200	6	4.9	43,360	89.9
Suburbs	52,700	6	4.7	47,810	90.7
Suburbs	46,500	6	4.8	41,290	88.8

Table 10
Composite Performance Scores (CPS) Across Algorithms in All Zones

Zone	Algorithm	Fairness Score (IFe)	Coverage Rate (η_s)	Load Utilization (λ_u)	CPS
A	IGA	0.891	0.959	0.72	0.902
A	GA	0.781	0.921	0.74	0.806
B	IGA	0.903	0.947	0.71	0.894
B	PSO	0.829	0.93	0.73	0.846

service radius error, load balance, response delay, and redundancy constraints, and designs an improved genetic algorithm based on elite retention, adaptive perturbation, and multi-precision coding strategies. In practical simulations, this algorithm demonstrated faster convergence and superior fitness performance. Deployment experiments in typical urban and suburban areas showed an average 12.6% improvement in fairness metrics and a 9.4% increase in service coverage, validating the model’s effectiveness and scalability under complex geographical conditions.

However, in real-world deployment scenarios, fairness optimization in power service node allocation inevitably involves trade-offs with operational efficiency and economic feasibility. For instance, enhancing spatial fairness in low-density suburban areas often necessitates the addition of redundant nodes, which improves service coverage continuity and fault tolerance, but increases infrastructure costs and may lead to resource underutilization. Conversely, prioritizing efficiency in high-density urban areas—by minimizing node count or maximizing load utilization—can exacerbate service inequality at the periphery, especially in transitional zones. These conflicts highlight the need for dynamic and adaptive balancing mechanisms. Future research should explore multi-tier deployment strategies, where fairness-efficiency trade-offs are adjusted in real time based on population flux, regional demand elasticity, and grid resilience parameters. Moreover, integrating reinforcement learning with edge-computing-based control modules may enable autonomous adjustment of node configurations, achieving both equitable access and efficient resource deployment.

Although the current model achieves significant results in modeling deployment fairness and computational efficiency, the following technical limitations remain: (1) The model’s transferability and robustness require further vali-

dation in highly heterogeneous urban spatial scenarios; (2) The current fairness metric system is statically designed and lacks dynamic feedback mechanisms driven by real-time power load forecasting and user behavior data. Future research may incorporate adaptive deployment control methods based on deep reinforcement learning, combined with edge computing architectures, to achieve regional-level self-organizing scheduling for service node layouts. Additionally, the model can be extended to coupled modeling with energy storage systems and distributed energy resources, constructing a dynamic deployment optimization system for power-load coordinated control.

Moreover, planning for power service node deployment in smart cities must incorporate dynamic population changes, including long-term growth trends and short-term migration patterns. These demographic shifts can significantly alter local demand densities and service pressure zones, causing previously optimal node layouts to become inefficient over time. To ensure spatial adaptability, the proposed framework can be extended by integrating population trajectory prediction models—such as heatmap-based trend estimation or census-informed demand forecasting—into the objective function update cycle.

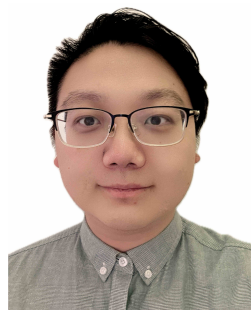
In addition, the inherent intermittency of power service nodes, caused by maintenance schedules, grid load shedding, or renewable supply fluctuation, may lead to service gaps in critical areas. To mitigate this, the deployment system should incorporate redundancy planning, dynamic failover routing, and modular backup nodes that can be activated under predefined outage conditions. These mechanisms ensure that the node deployment remains resilient and functional in dynamic and uncertain operational environments, thus improving long-term feasibility and robustness.

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Biographies



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