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Research article

An electricity price optimization model considering time-of-use and active distribution network efficiency improvements

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Abstract: To address the issues of high energy costs and inadequate system response speed in complex electricity markets, we propose an electricity price optimization model. This model combines an improved Particle Swarm Optimization algorithm, Quantum-behaved Particle Swarm Optimization, and the Shuffle Frog Leaping Algorithm. The work was based on multi-regional peak and valley data, and we selected Lanzhou, Guiyang, Beijing, Guangzhou, Shanghai, and Nanjing as typical representatives for systematic validation and analysis. Our findings were as follows: (1) The model demonstrated excellent convergence and stability during the electricity price optimization process, particularly under flat-rate price conditions. This model effectively avoided local optima traps and enhanced global search capability, achieving the dual goals of rapid convergence and high stability, and showed exceptional optimization efficiency and adaptability; (2) building upon its optimization performance, the model further improved the uniformity and diversity of the solution distribution, ensuring robustness and flexibility in global search ability. Moreover, by dynamically adjusting the price function and multi-level evaluation system, the model significantly optimized price elasticity, time-of-use pricing regulation efficiency, energy consumption paths, and the operational stability of the distribution network. The model exhibited high resilience and fine-grained control capabilities in the complex electricity market; (3) finally, based on the optimized electricity price strategy derived from training, the model reduced electricity costs and price volatility. Moreover, its superior performance in economic benefits and market adaptability was comprehensively validated through high-precision power consumption forecasting. We aimed to optimize energy costs, improve system response speed, and reduce price volatility, thereby achieving more efficient energy utilization and economic benefits.

Keywords: electricity price optimization; improved particle swarm optimization algorithm; quantum-behaved particle swarm optimization algorithm; shuffle frog leaping algorithm; time-of-use pricing

Abbreviations: PSO: Particle swarm optimization; GA: Genetic algorithm; PDE: Population-based differential evolution; LCOE: Levelized cost of energy; LPSP: Loss of power supply probability; CPU: Central processing unit; MODE: Multi-objective differential evolution; NSGA II: Nondominated sorting genetic algorithm II; QPSO: Quantum-behaved particle swarm optimization; SFLA: Shuffle frog leaping algorithm; QPW: Quantum potential well; MMSA: Multi-modal simulated annealing; CSI: Convergence stability index; DG: Distributed generation; BESS: Battery energy storage system; DR: Demand response; EV: Electric vehicle; DER: Distributed energy resource

1. Introduction

With the global economy developing and urbanization accelerating, the rapid growth in electricity demand has become a significant challenge for energy management worldwide [1]. Traditional power systems face issues such as low energy efficiency, unstable grid operation, and significant electricity price fluctuations. These problems not only hinder effective energy utilization but also limit sustainable economic development [2]. To address these challenges, researchers have increasingly focused on how to optimize energy distribution and cost management by refining electricity pricing strategies and enhancing the accuracy of power consumption forecasts. This is particularly obvious in the areas of time-of-use pricing and active distribution network efficiency enhancements. These efforts are crucial for enhancing the reliability and economic performance of power systems [3,4]. In this context, constructing an electricity price optimization model that combines global search capabilities with dynamic adaptability to balance energy utilization efficiency and user economic costs is essential. The model should effectively address the challenges of complex fluctuations in time-of-use electricity pricing and the multi-dimensional constraints in the operation of active distribution networks. This is not only a core requirement for enhancing the reliability and economic optimization of power systems, but also a crucial theoretical and practical issue in advancing the scientific and intelligent transformation of energy management.

In recent years, Particle Swarm Optimization (PSO) has emerged as a promising global optimization algorithm for addressing complex power system optimization problems [5]. PSO simulates the behavior of birds flocking to find food, continuously adjusting and optimizing solution positions through individual information exchange and cooperation to find the optimal solution [6–8]. Especially in electricity price optimization models, PSO can effectively improve energy cost management and the accuracy of power consumption forecasts, thereby enhancing the economic viability and sustainability of power systems [9]. For instance, Roy and Das [10] explored a demand-side management method based on typical daily load shifting in a hierarchical smart grid structure. They integrated renewable energy sources like wind with traditional generators to optimize electricity costs and the day-ahead market's generation and load demand distribution. They proposed a hybrid Genetic Algorithm (GA)-PSO to solve multi-objective problems, converting them into single-objective problems through weighted sum techniques. The results showed that this hybrid algorithm excelled in convergence speed and avoiding local minima. It significantly reduced the peak-to-average ratio of load demand by over 82.3% and enhanced the efficiency and economy of the smart grid. Similarly, Iweh and Akupan [11] examined the application of AI-based PSO and Population-based Differential

Evolution (PDE) in designing and optimizing standalone solar PV-hydro hybrid systems. Using MATLAB, they developed intelligent algorithms to minimize the Levelized Cost of Energy (LCOE) and Loss of Power Supply Probability (LPSP) to meet load demands. The PSO model achieved an optimal LCOE of 0.06358 $/kWh and an LPSP of 0.0492 after 40 iterations, outperforming the PDE model in system reliability. The optimized hybrid system recommended a scale of 1 kW PV, 33.96 kW hydro, and no batteries, ensuring appropriate power management. Comprehensive evaluations indicated that the PSO model demonstrated superior performance and robustness in generation management and electricity price optimization. MuraleedharanBabu and Sasidharanpillai [12] proposed an improved PSO using a reverse learning strategy to solve the combined economic and emission dispatch problem for thermal power plants. This problem includes constraints such as valve-point effects, prohibited operating zones, and ramp rate limits. Validated through benchmark functions and thermal power systems with 6, 10, and 40 units, the improved PSO outperformed optimization techniques like Multi-Objective Differential Evolution (MODE) and Nondominated Sorting Genetic Algorithm II (NSGA II) in terms of fuel cost, emissions, and CPU time. Compared with Inertia Weight PSO, and Constriction Factor PSO, it reduced total cost by approximately 3.73% and CPU time by 2.6 s, with prediction accuracy near 100%. These findings demonstrated PSO's potential in optimizing the combined economic and emission dispatch of thermal power plants.

Research has made notable progress in the development of electricity price optimization models, primarily focusing on solving two key issues. First, how to enhance the model's global search ability and convergence speed to address the nonlinear optimization demands in complex grid environments. Second, how to improve the model's adaptability and robustness to better handle the multi-dimensional constraints in dynamic electricity pricing environments. PSO has shown significant potential in power system optimization, particularly in electricity price optimization and power consumption forecasting. Studies have demonstrated that PSO can effectively improve system economics and sustainability by reducing electricity costs and optimizing generation and load demand distribution. However, research falls short in the areas of multi-objective collaborative optimization and dynamic response capabilities to time-of-use pricing. Especially in the context of active distribution network operations, research on electricity price optimization models has not formed a systematic framework. The increasing complexity of grid operation architectures and the rising frequency of price fluctuations further exacerbate optimization difficulties, limiting the effectiveness of models in everyday applications. In response, We propose an electricity price optimization model that incorporates time-of-use pricing and improvements in the generation efficiency of active distribution networks. By introducing a multi-algorithm collaborative mechanism that combines the improved PSO, Quantum-behaved Particle Swarm Optimization (QPSO), and the Shuffle Frog Leaping Algorithm (SFLA), we aim to enhance optimization efficiency and adaptability while ensuring high stability and precision under dynamic market conditions. Our goal is to achieve more efficient energy resource allocation and cost optimization.

2. Materials and methods

2.1. Algorithms involved in the electricity price optimization model

2.1.1. Improved PSO-based model

Traditional PSO is a heuristic optimization algorithm that simulates the behavior of birds flocking to find food to optimize problem solutions. Its characteristics include a simple mathematical model, iterative updates based on velocity and position, global and local optimal solution searches, and fixed inertia weight and learning factors. Figure 1 illustrates the implementation process of traditional PSO.

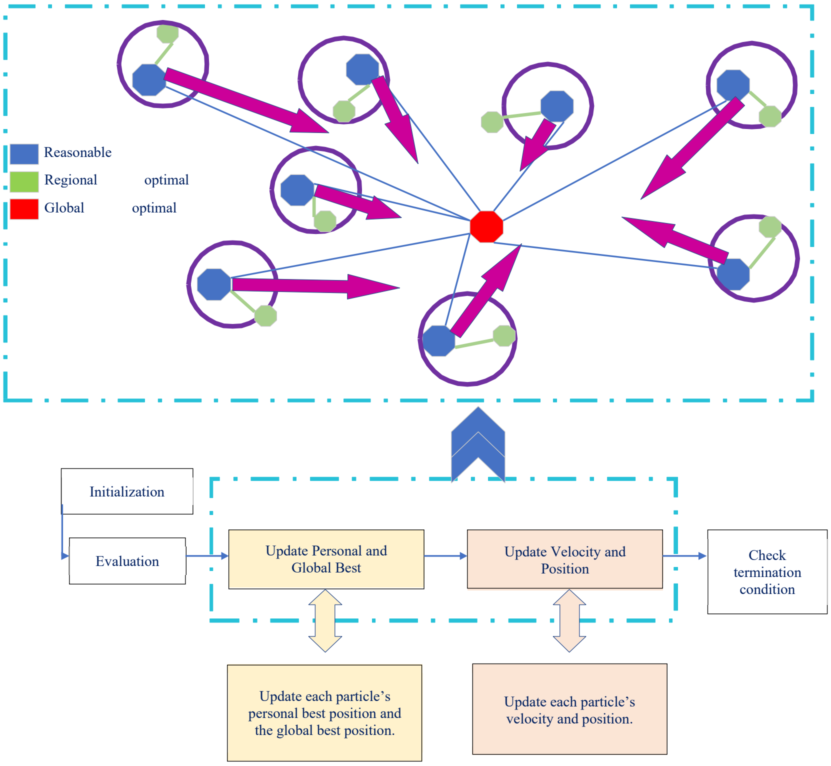


Figure 1. Traditional PSO implementation process.

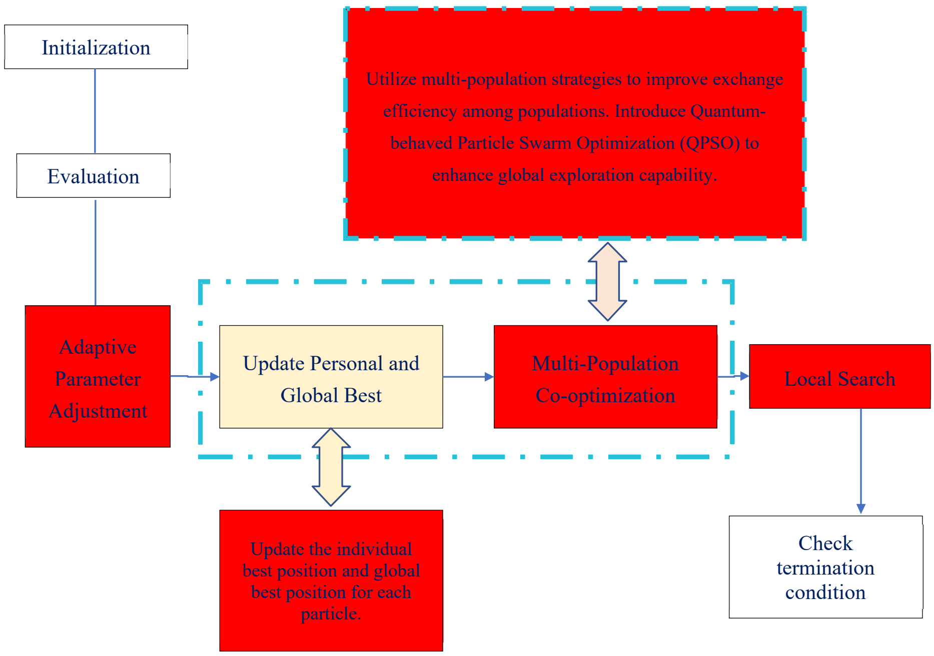


Figure 2. The implementation process of the improved PSO.

Traditional PSO often falls into local optima and lacks sufficient exploration of the problem space when dealing with complex electricity price optimization problems, leading to decreased search efficiency. To address these issues, we propose corresponding improvements. Figure 2 illustrates the implementation process of the improved PSO.

2.1.2. QPSO

QPSO is an improved algorithm based on PSO. In QPSO, each particle is treated as a quantum particle, whose state is represented by a wave function that includes both position and momentum. The evolution of the wave function is influenced by the Quantum Potential Well (QPW), resulting in more random and diverse movement of particles within the search space. The key computational process in this paper can be described as follows:

(1) Initialize the positions and velocities of the particles

$$x_i^{(0)} = x_{min} + rand \cdot (x_{max} - x_{min}) \tag{1}$$

here, $x_i^{(0)}$ is the initial position of particle i. x_{min} and x_{max} are the minimum and maximum boundaries of the search space, respectively, and rand is a uniformly distributed random number vector in the interval [0,1].

(2) Update the particle velocity

$$v_i^{(t+1)} = w \cdot v_i^{(t)} + c_1 \cdot rand_1 \cdot (p_i^{(t)} - x_i^{(t)}) + c_2 \cdot rand_2 \cdot (p_{global}^{(t)} - x_i^{(t)}) \tag{2}$$

where $v_i^{(t)}$ is the velocity of particle i at iteration t, and w is the inertia weight; c_1 and c_2 are the learning factors; rand_1 and rand_2 are uniformly distributed random number vectors in the interval [0,1]; and $p_i^{(t)}$ is the personal best position of particle i, and $p_{global}^{(t)}$ is the global best position.

(3) Update the particle position

$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)} \tag{3}$$

where $x_i^{(t)}$ is the position of particle i at iteration t.

$$U(x_i^{(t+1)}) = \sum_{j=1}^{D} \left(\frac{1}{2} m_j \omega_j^2 x_{ij}^{(t+1)2}\right) \tag{4}$$

(4) QPW Model

D is the dimensionality of the problem; and m_j and ω_j are the mass and angular frequency of the particle, respectively.

(5) Update the wave function:

$$\Psi(x_i^{(t+1)}) = \frac{1}{\sqrt{2\pi\sigma^2}} exp\left(-\frac{U(x_i^{(t+1)})}{2\sigma^2}\right) \tag{5}$$

where σ is the standard deviation of the wave function.

2.1.3. SFLA

SFLA is an algorithm based on swarm intelligence optimization. It simulates the cooperative and competitive behaviors of frog populations and combines global search and local optimization strategies to enhance solution quality and search efficiency. The key computational processes can be described as follows:

(1) Local Search

$$X_{ij}(t+1) = X_{ij}(t) + \alpha \cdot T \cdot (\mathrm{best}_{ij} - X_{ij}(t)) + \beta \cdot (X_{ij}^{*} - X_{ij}(t)) \tag{6}$$

where $X_{ij}(t)$ represents the current position of the j-th frog in the i-th dimension. Parameters α and β are tuning parameters, T is a randomization step size, $best_{ij}$ denotes the position of the best frog, and X_{ij}^{*} represents the global best position.

(2) Information Exchange

$$f(X_{ij}(t)) = \sum_{k=1}^{N_f} (c_k - w_k)^2 \tag{7}$$

where N_f is the number of frogs in the population, and c_k and w_k represent the current position and target position of the k-th frog, respectively.

2.2. Design principles and validation approach for an electricity price optimization model

2.2.1. Model design principles

The electricity price optimization model proposed here integrates improved PSO, QPSO, and SFLA to meet the requirements of time-of-use pricing and enhancing active distribution network efficiency. The design principles are as follows. First, Introduction of Chaotic Variables: Chaotic variables are introduced to help PSO escape local optima traps by leveraging their sensitivity to initial conditions and their ability to traverse the search space unpredictably, thereby enhancing the global search capability of PSO. The randomness and unpredictability of chaotic variables introduce diversity during algorithm iterations, ensuring thorough exploration of the search space and thereby avoiding pitfalls of local optima. This guarantees enhanced global search capabilities in electricity price optimization while maintaining high adaptability and optimization effectiveness amidst dynamic changes in active distribution network efficiency. Next, adaptive adjustment of inertia weight and learning factors: The model dynamically adjusts inertia weights and learning factors based on changes in electricity prices and distribution network efficiency. This adaptive tuning enhances the algorithm's adaptability and convergence speed. Specifically, adaptive inertia weight adjustment enables faster particle movement during exploration and stronger convergence characteristics during exploitation phases. Dynamic adjustment of learning factors balances individual and social cognition to optimize particle search paths and improve overall search efficiency. This adaptive adjustment mechanism can respond in real-time to changes in efficiency during the enhancement of active distribution network generation, thereby optimizing electricity pricing strategies. Then, multi-population cooperative optimization: Multiple population strategies facilitate information exchange among populations, enhancing algorithm diversity and global search capabilities. QPSO is introduced with its quantum behavior mechanism utilizing Quantum Potential Well (QPW) models. This mechanism imbues particles' search trajectories with greater randomness and diversity on a global scale, thereby improving solution quality and search efficiency. The quantum behavior mechanism of QPSO utilizes quantum superposition of particle states and probabilistic distribution characteristics, enhancing the algorithm's exploration capability during global search processes. This quantum mechanism provides a more flexible and adaptive optimization path, which is particularly effective when enhancing active distribution network generation efficiency.

Next, integration of Multi-Modal Simulated Annealing (MMSA): Recognizing the complexity and non-linearity of electricity price optimization, MMSA serves as a local search algorithm. Employing Multi-Path Parallel Annealing, MMSA conducts local searches along multiple paths simultaneously, effectively avoiding local optima and enhancing local optimization results. Simulated annealing mimics physical annealing processes and uses temperature to control random perturbations during the search, conducting global search at high temperatures and local search at low temperatures, thereby ensuring the discovery of global optimal solutions. This process adapts flexibly to different levels of generation efficiency in active distribution networks, further optimizing electricity pricing configurations. Fifth, utilization of SFLA: The global search and local optimization capabilities of SFLA are integrated and applied jointly. Through information exchange between frog populations and local optimizations within each population, overall search efficiency and solution quality are enhanced. SFLA simulates the jumping behavior of frog populations in the search space, combining global and local search strategies by leveraging cooperative and competitive mechanisms among frogs. This effectively explores and exploits the search space, boosting the algorithm's global search capability and local search precision. Particularly in conditions where active distribution network generation efficiency is improving, SFLA utilizes its efficient information exchange mechanism to swiftly adjust and optimize electricity pricing strategies, ensuring synchronous enhancement of generation efficiency and price optimization.

Table 1 outlines the iterative process and final parameter values in the design of the electricity price optimization model.

Table 1. Model iterations and final parameters.

Parameter	Initial value	Final value
Particle swarm size	100	
Maximum iterations	1000	
Quantum factor	0.5	0.4
Convergence factor	0.5	0.6
Frog population size	50	
Annealing iterations	10	
Initial inertia weight	0.9	0.5
Final inertia weight	0.4	0.4
Personal learning factor	1.5	1.2
Social learning factor	1.5	1.2

Figure 3 depicts the implementation principle of the proposed electricity price optimization model.

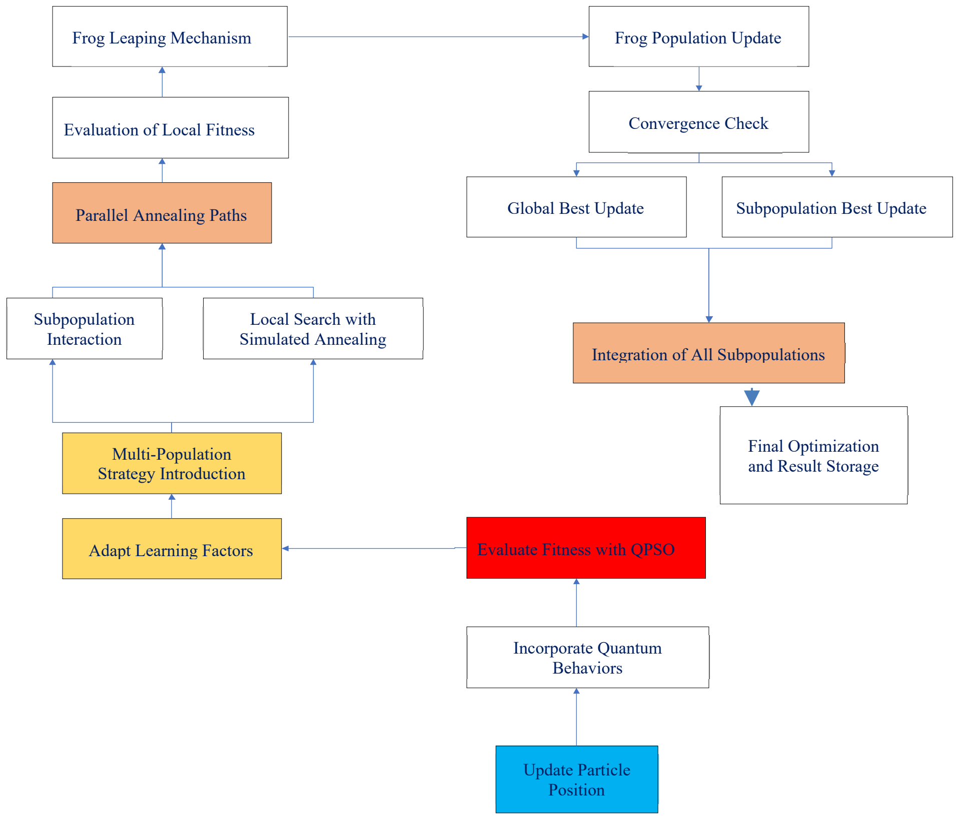


Figure 3. Implementation principle of the electricity price optimization model.

2.2.2. Validation approach of the model

According to data compiled from the official websites of State Grid Corporation and local municipal grid operators from 2022 to 2024, as of the end of April 2024, China's time-of-use electricity pricing mostly includes peak, high-peak, flat, low, and off-peak periods. Only four regions, including Gansu, Ningxia, Guizhou, and Guangxi, implement a "high-flat-low"electricity pricing scheme without peak and off-peak pricing. Twenty-one regions, including Beijing, Guangdong, Anhui, and Hubei, implement a "peak-high-flat-low" electricity pricing scheme without off-peak pricing. Eight regions, including Shandong, Xinjiang, Eastern Inner Mongolia, Western Inner Mongolia, Jiangsu, Zhejiang, Jiangxi, and Shanghai, implement a "peak-high-flat-low-off-peak" electricity pricing scheme. Among them, Jiangsu, Zhejiang, Jiangxi, and Shanghai implement significant holiday off-peak electricity pricing, setting off-peak periods during the Spring Festival, Labor Day, and National Day holidays. To better demonstrate the adaptability of the model to different time-of-use electricity pricing, we extract the latest peak and off-peak values for each province and municipality from the data released by the provincial development and reform commissions, State Grid, and Southern Power Grid. Two representative cities are selected for each type of time-of-use electricity pricing. Subsequently, the model is verified and analyzed in sequence. Table 2-1 and Table 2-2 shows the peak and off-peak periods and electricity price ranges for the six representative cities.

Table 2-1. Peak and off-peak periods and electricity price ranges for 6 representative cities.

Period type	Representative city	Peak periods	Peak average price (yuan/kWh)	High periods	Price for high period (yuan/kWh)	Flat periods
High-Flat-Low	Lanzhou	None	–	8–11, 18–21	1.5	6–8, 11–18, 21–23
	Guiyang	None	–	9–12, 17–20	1.6	6–9, 12–17, 20–22
Peak-High-Flat-Low	Beijing	8–10	2.052	6–8, 10–14, 18–20	1.71	14–18, 20–22
	Guangzhou	7–9	2.125	9–12, 17–19	1.7	6–7, 12–17, 19–21
Peak-High-Flat-Low-Off-Peak	Shanghai	8–10	2.25	7–8, 10–13, 17–19	1.8	6–7, 13–17, 19–22
	Nanjing	7–9	2.064	9–12, 16–18, 20–22	1.72	6–7, 12–16, 18–20

Table 2-2. Peak and off-peak periods and electricity price ranges for 6 representative cities.

Period type	Representative city	Price for flat period (yuan/kWh)	Low periods	Price for low period (yuan/kWh)	Off-Peak periods	Price for off-peak period (yuan/kWh)
High-Flat-Low	Lanzhou	1	0–6, 23–24	0.5	None	–
	Guiyang	1	0–6, 22–24	0.4	None	–
Peak-High-Flat-Low	Beijing	1.01	0–6, 22–24	0.36	None	–
	Guangzhou	1.02	0–6, 21–24	0.38	None	–
Peak-High-Flat-Low-Off-Peak	Shanghai	1.09	0–6, 22–24	0.6	0–4	0.4
	Nanjing	1.04	0–6, 22–24	0.45	0–4	0.3

The validation analysis of the electricity price optimization model is divided into four processes.

First, it tests the model using actual electricity price data from different months in six representative cities to evaluate its convergence speed and stability under varying seasonal and price fluctuation conditions. This aims to verify whether the model can quickly converge and maintain stability across electricity price variations, ensuring its reliability in practical applications.

Second, the analysis includes assessing the model's global search capability and diversity. Through multiple runs of the model, observations are made to determine if it consistently converges to near-optimal solutions. Additionally, a precision analysis of local search is conducted to assess the model's performance in refining optimization processes. This validation involves whether the model can accurately identify optimal electricity price configurations for each time-of-use period during local search, thereby enhancing the precision and detail of electricity price optimization.

Third, we focus on the elastic demand of the model from four perspectives. By constructing a refined evaluation framework, the comprehensive validation of price demand elasticity, time-of-use electricity price elasticity, energy consumption elasticity, and distribution network operational elasticity is achieved. Initially, the model introduces a price demand elasticity indicator system, employing dynamically adjusted price functions to quantify the sensitivity of user demand to different price levels. This approach integrates a Gaussian mixture model to fit price fluctuations, ensuring the model captures the nonlinear characteristics of market demand effectively. Key calculation equations include:

(1) Price elasticity coefficient

$$E_p = \frac{\partial Q}{\partial P} \cdot \frac{P}{Q} \tag{8}$$

Q represents electricity demand and P represents electricity price.

(2) Fitting price fluctuations with Gaussian mixture models

$$f(P) = \sum_{k=1}^{K} \pi_k \cdot \frac{1}{\sqrt{2\pi\sigma_k^2}} exp\left(-\frac{(P-\mu_k)^2}{2\sigma_k^2}\right) \tag{9}$$

where π_k is the weight of the k-th Gaussian distribution, μ_k is the mean, and σ_k is the standard deviation.

Next, on the aspect of time-of-use electricity price elasticity, the model integrates multi-period electricity price data. Then, it utilizes a time-series analysis and Support Vector Regression (SVR) algorithm to assess the impact of different time-of-use electricity prices on user load distribution, enhancing the accuracy of predicting user electricity consumption behavior.

(3) Time-of-use electricity price elasticity coefficient

$$E_t = \frac{\partial L}{\partial P_t} \cdot \frac{P_t}{L} \tag{10}$$

where L represents load and P_t represents the electricity price at a specific time period t.

(4) Prediction with SVR model

$$\hat{L}(t) = \sum_{i=1}^{n} (\alpha_i - \alpha_i^*) K(t_i, t) + b \tag{11}$$

where α_i and α_i^* are Lagrange multipliers, $K(t_i, t)$ is the kernel function, and b is the bias term.

Regarding energy consumption elasticity, the model integrates an energy consumption model optimized based on load curves. It applies GA to optimize different energy configuration schemes and combines dynamic simulations of energy consumption to assess their impact on overall energy efficiency.

$$min(\sum_{i=1}^{n} C_i \cdot E_i) \tag{12}$$

(5) Objective function for energy consumption optimization

where C_i is the unit consumption cost of the i-th type of energy, and E_i is the consumption amount of the i-th type of energy.

(6) Fitness function of GA

$$F(x) = \frac{1}{1+\sum_{i=1}^{n} C_i \cdot E_i} \tag{13}$$

where x represents the chromosome representation of the energy configuration scheme.

On the aspect of distribution network operational elasticity, the model constructs an active distribution network simulation environment. It utilizes Monte Carlo simulation techniques to analyze the operational stability and robustness of the distribution network under different load and generation configurations.

(7) Distribution network operational stability

$$S_r = \sqrt{\frac{1}{T}\sum_{t=1}^{T} (L_t - \bar{L})^2} \tag{14}$$

where S_r represents stability, L_t denotes the load at time t, and $\bar{L}$ is the mean load.

(8) Robustness in Monte Carlo Simulation

$$R_m = \frac{1}{N}\sum_{i=1}^{N} \left(\frac{|P_{i,\text{actual}} - P_{i,\text{expected}}|}{P_{i,\text{expected}}}\right) \tag{15}$$

where R_m represents robustness, N is the number of simulations, $P_{i,actual}$ denotes the actual power in the i-th simulation, and $P_{i,expected}$ denotes the expected power.

Tables 3 to 5 present the elasticity coefficients for demand across various time periods for the three types.

Table 3. Elasticity coefficients of demand for "high-flat-low" type in various periods.

Time period	High periods	Flat periods	Low periods
High periods	−0.07	0.02	0.015
Flat periods	0.02	−0.06	0.012
Low periods	0.015	0.012	−0.08

Table 4. Demand elasticity coefficients for "peak-high-flat-low" type.

Time period	Peak period	High periods	Flat periods	Low periods
Peak period	−0.06	0.018	0.014	0.01
High periods	0.018	−0.05	0.016	0.012
Flat periods	0.014	0.016	−0.05	0.01
Low periods	0.01	0.012	0.01	−0.05

Table 5. Elasticity coefficients of demand for "peak- high-flat-low-off-peak" type in various periods.

Time period	Peak period	High periods	Flat periods	Low periods	Off-peak periods
Peak period	−0.06	0.018	0.014	0.01	0.008
High periods	0.018	−0.05	0.016	0.012	0.01
Flat periods	0.014	0.016	−0.05	0.01	0.008
Low periods	0.01	0.012	0.01	−0.05	0.006
Off-peak periods	0.008	0.01	0.008	0.006	−0.05

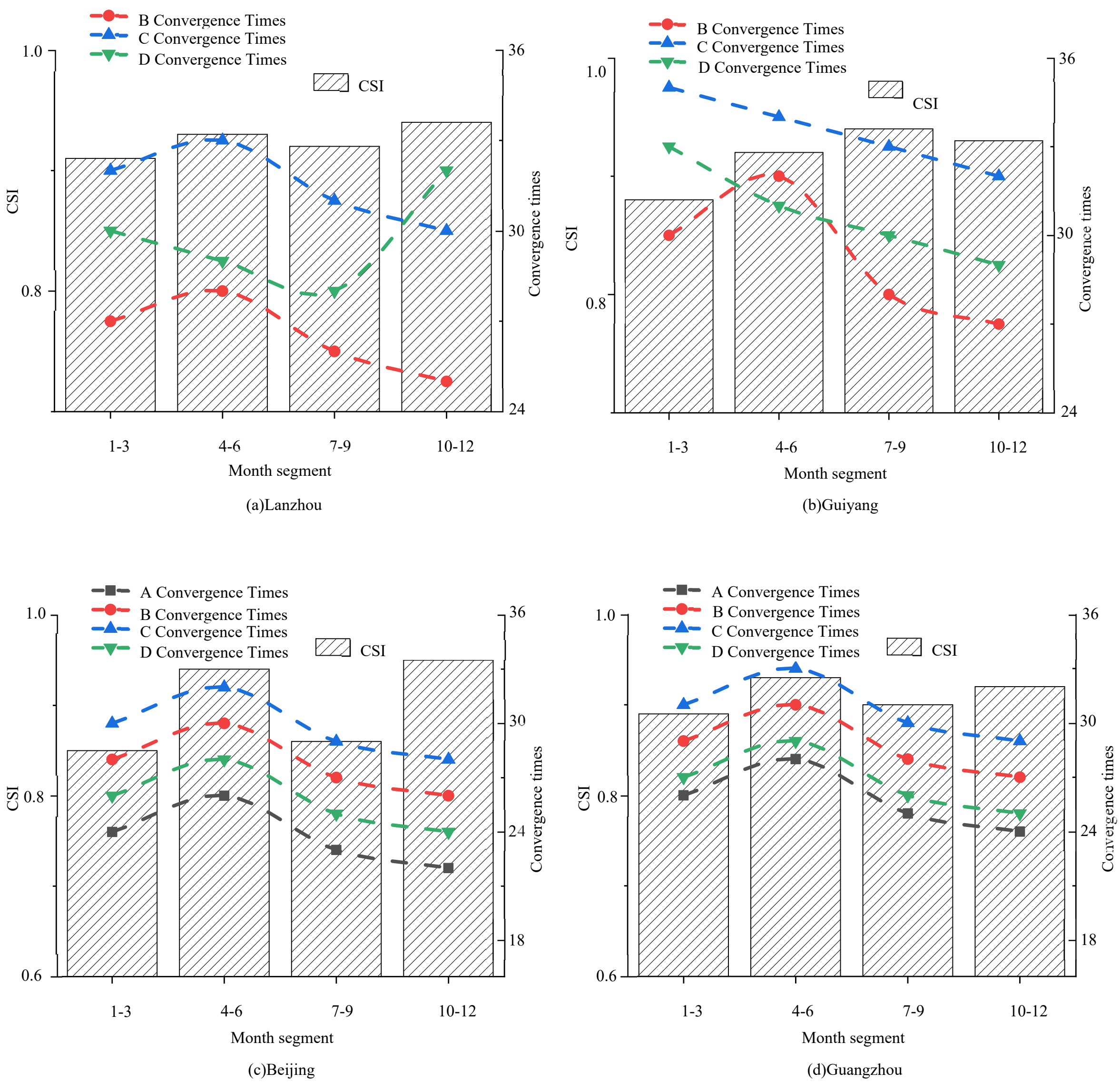
Fourth, the elasticity price optimization model is compared with historical electricity prices to assess the extent of improvement. The predicted electricity consumption data are compared with real electricity consumption data to validate its superiority in price optimization.

To distinguish periods in the subsequent analysis of the research results, we use the following representations: A for Peak periods, B for High periods, C for Flat periods, D for Low periods, and E for Off-Peak periods.

3. Results

3.1. Stability analysis of the model

Stability analysis introduces the Convergence Stability Index (CSI), which is a metric used to evaluate the convergence and stability of the electric price optimization model. Specifically, CSI is defined as 1 minus the ratio of the average convergence iterations to the maximum convergence iterations. It reflects the speed and stability of convergence of the model under given electricity price and generation efficiency conditions. Figure 4 shows the results of the stability analysis of the model.



(a)Lanzhou (b)Guiyang

(c)Beijing (d)Guangzhou

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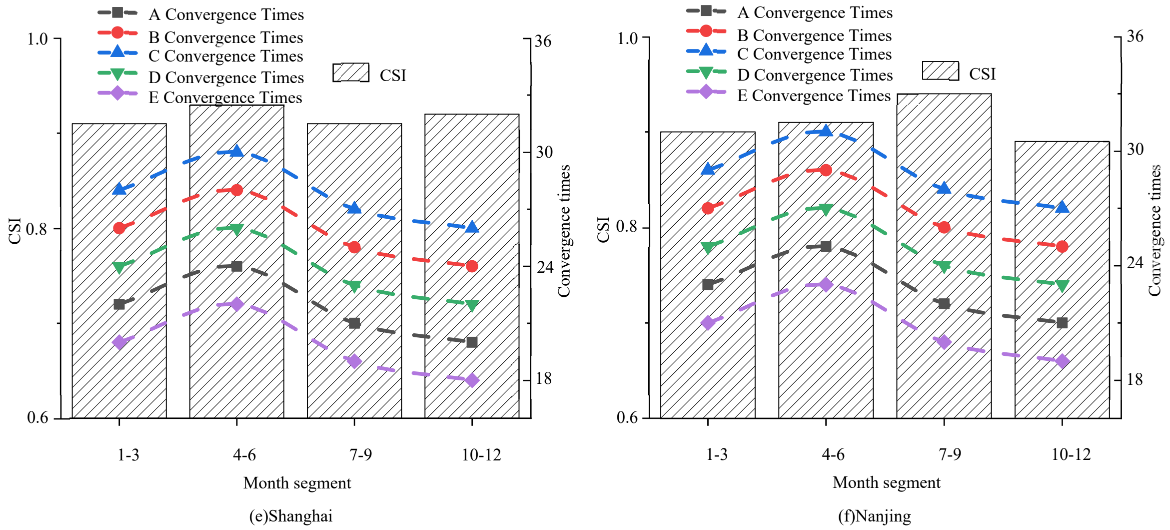

Figure 4. Stability analysis of electricity price optimization model.

Figure 4 depicts the convergence iterations and CSI of the electricity price optimization model across months and segments in various cities. The results highlight the model's strong convergence performance, particularly in flat rate periods. For instance, in Lanzhou from October to December, the model converges 32 times during low periods with a high CSI of 0.94, while Beijing achieves a CSI of 0.95 during the same months. These data underscore the model's significant potential in achieving efficient energy allocation, cost optimization, and improving system responsiveness. Additionally, despite Guizhou's CSI of 0.88 from January to March, which is slightly lower than those for other cities, its CSI rose to 0.94 from July to September, demonstrating the model's adaptability and adjustment capabilities to seasonal fluctuations. Overall, the electricity price optimization model demonstrates significant advantages in precise regulation within dynamic electricity markets.

3.2. Model search performance analysis

3.2.1. Global search capability and diversity analysis

Figure 5 presents the results of the analysis on global search capability and diversity.

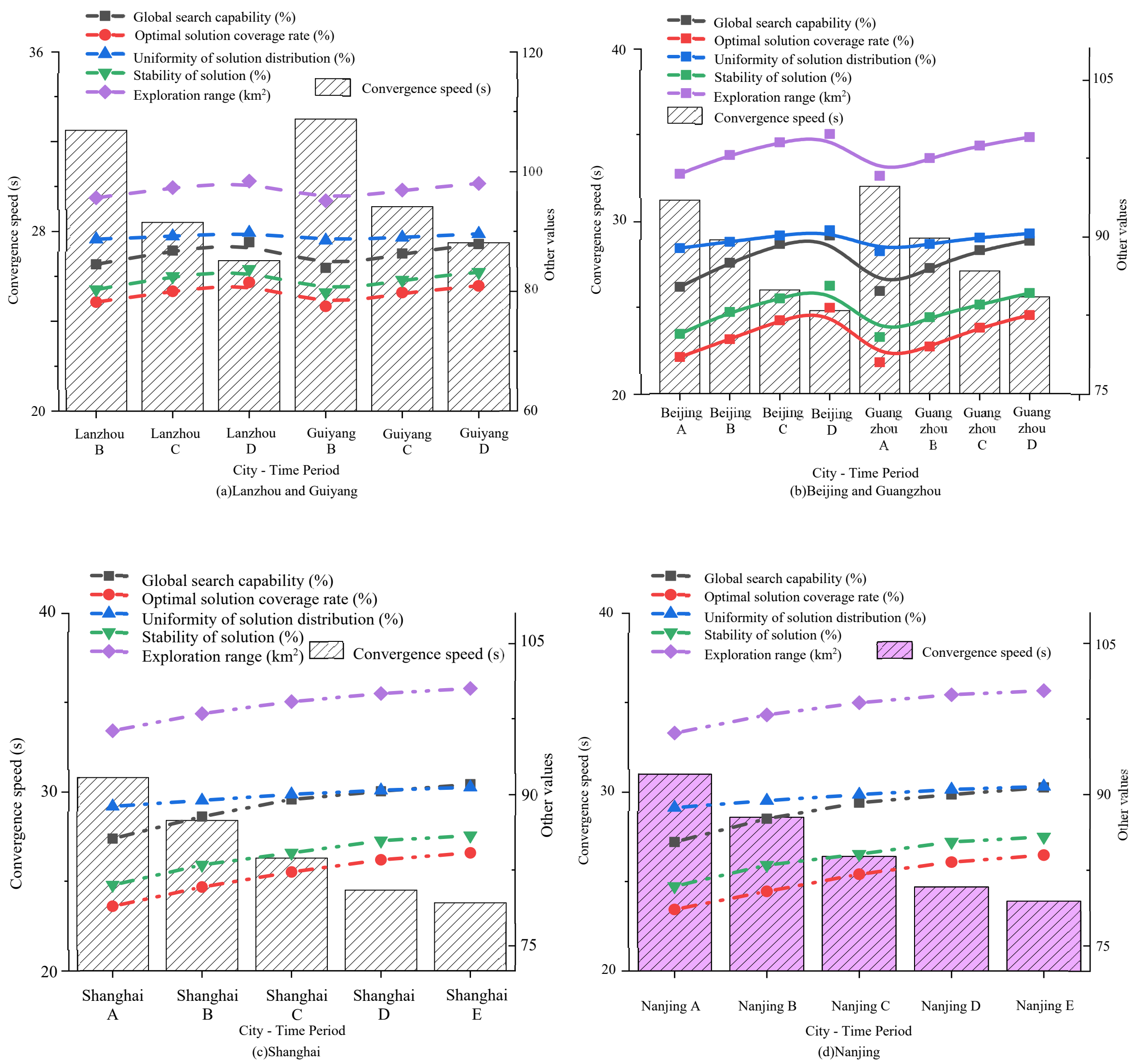

Figure 5. The analysis of global search capability and diversity of electricity price optimization model.

Figure 5 demonstrates the model's high global search capability and diversity of solution distribution across cities and time periods. For instance, in the low period, Lanzhou exhibits a global search capability of 88.2%, with an optimal solution coverage of 81.5%, an exploration area of 98.4 km^2, and a solution distribution uniformity of 89.8%. During the off-peak period, Shanghai and Nanjing achieve global search capabilities of 91.0% and 90.7%, respectively, with optimal solution coverages of 84.2% and 84.0%. These values indicate that the model effectively conducts global searches in dynamic electricity price environments, maintaining high solution distribution uniformity and stability under various conditions. Particularly in low and off-peak periods, there is a significant improvement in exploration range and solution uniformity, showcasing the model's diversity and adaptability.

3.2.2. Local search accuracy analysis

Figure 6 presents the results of the local search accuracy analysis.

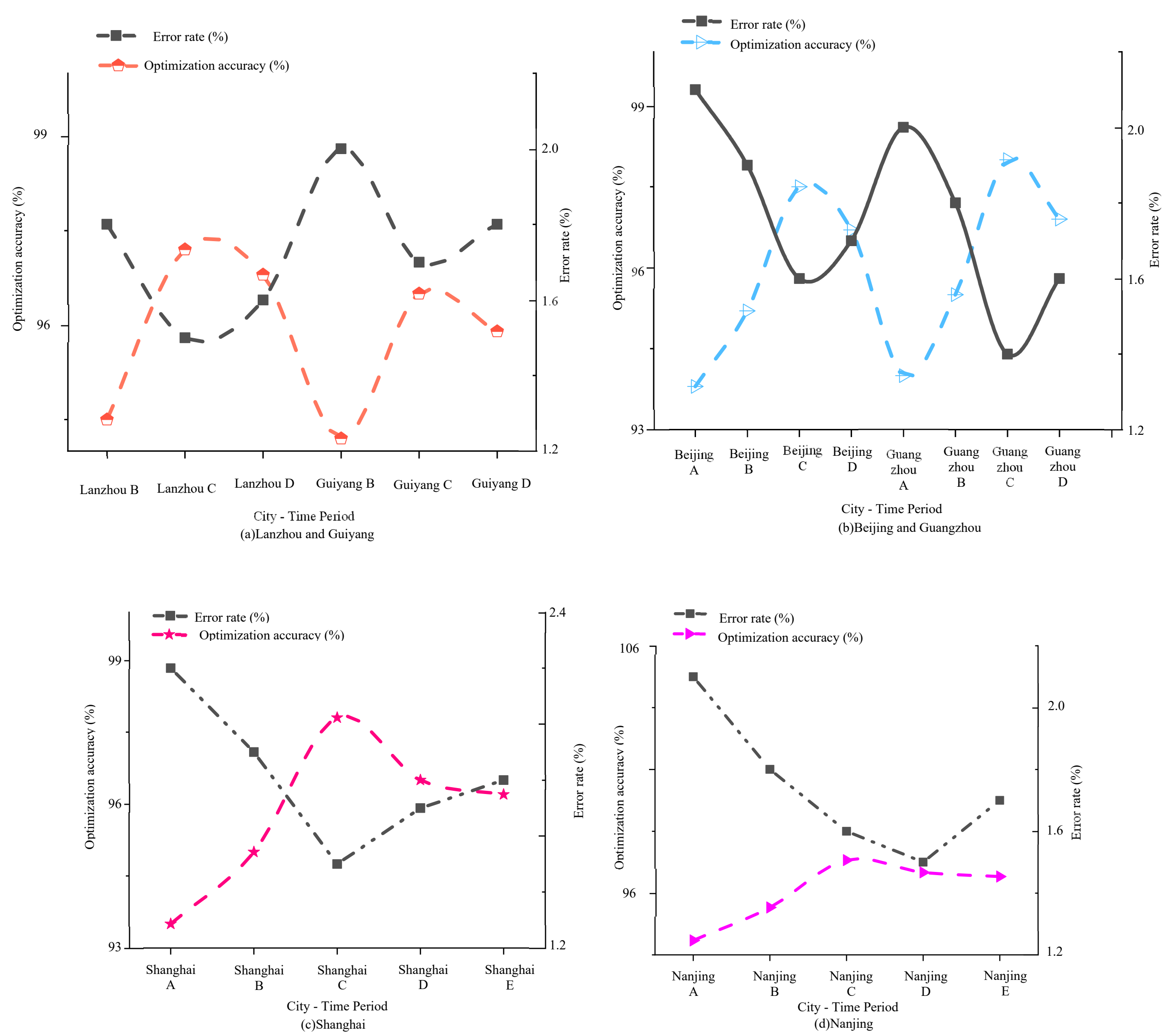

Figure 6. The analysis of local search accuracy of electricity price optimization model.

Figure 6 illustrates the significant optimization effects of the electricity price optimization model across high, flat, low, peak, and off-peak periods in cities such as Lanzhou, Guiyang, Beijing, Guangzhou, Shanghai, and Nanjing. The model achieves error rates ranging from 1.4% to 2.2% across these periods, with optimization accuracy ranging from 93.5% to 98.0%. Lanzhou and Guiyang demonstrate prominent optimization effects during high, flat, and low periods, with error rates between 1.5% and 2.0% and optimization accuracy between 94.2% and 97.2%. Beijing and Guangzhou exhibit stable performance during peak, high, flat, and low periods, achieving optimization accuracy from 93.8% to 98.0%. Shanghai and Nanjing show high optimization accuracy across multiple period types, which is particularly notable during flat and off-peak periods, with optimization accuracy ranging from 97.0% to 98.0%. These results indicate that the proposed electricity price optimization model effectively reduces error rates and significantly improves the precision of electricity price optimization. It is suitable for optimizing electricity markets in different cities and complex period types.

3.3. Analysis of model elastic demand

Figure 7 displays the analysis results of model elastic demand.

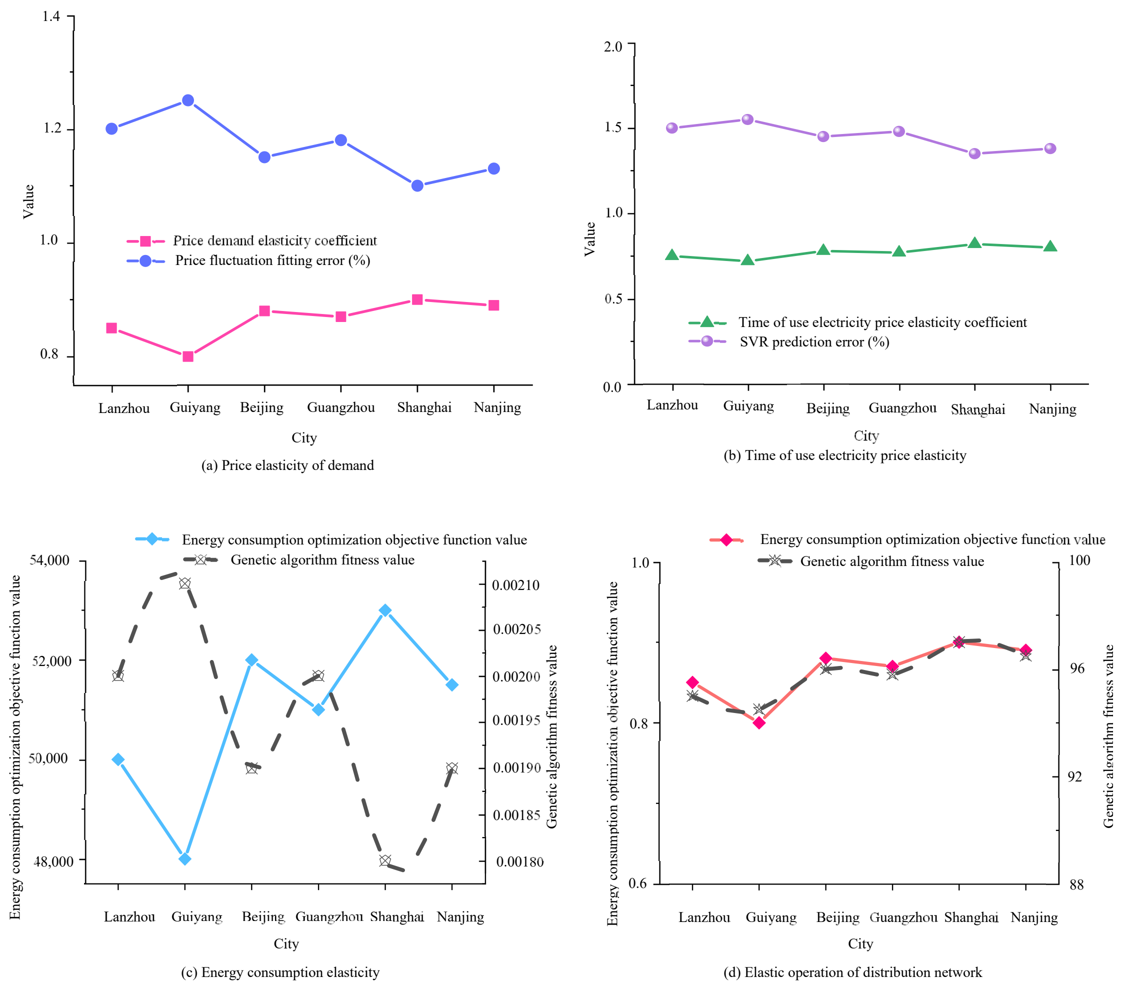

Figure 7. The analysis of elastic demand in electricity price optimization model.

Figure 7 indicates that the price elasticity coefficients across cities range from 0.80 to 0.90, demonstrating the model's ability to capture the sensitivity of user demand to price changes. The fitting error for price fluctuation is as low as 1.10%, indicating high precision in price demand forecasting by the model. Time-of-use price elasticity coefficients range from 0.72 to 0.82, with SVR prediction error minimized to 1.35%, showcasing the model's strong performance in assessing the impact of price changes on user load distribution across periods. The optimization objective function for energy consumption and GA fitness values respectively highlight the model's effectiveness in energy consumption optimization. By optimizing energy configuration scenarios, the model demonstrates high efficiency in energy consumption elasticity. Distribution network operation stability and robustness reflect the model's performance under different load and generation configurations, particularly with Shanghai and Nanjing showing robustness at 97.00% and 96.50% respectively. This validates the model's superiority in distribution network operational flexibility.

3.4. Comparative analysis and validation of the model

Figure 8 presents the comparative validation analysis results before and after the optimization of the electricity price optimization model.

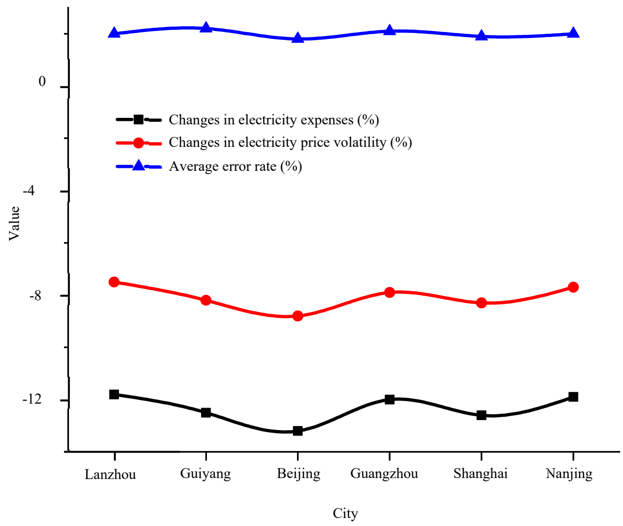

Figure 8. Comparative analysis and validation of the electricity price optimization model before and after optimization.

Figure 8 demonstrates significant improvements in the electricity price optimization model across cities. Specifically, electricity expenses in Lanzhou, Guiyang, Beijing, Guangzhou, Shanghai, and Nanjing decrease by 11.8% to 13.2%, and price volatility reduces by 7.5% to 8.8%. Beijing shows the most notable improvement, with a 13.2% reduction in electricity expenses, an 8.8% decrease in price volatility, and an average error rate of only 1.8%. Overall, the optimized model substantially lowers electricity expenses and price volatility, enhancing the precision and stability of electricity price optimization. The model's superiority in various cities' electricity markets is validated. Comparison with historical electricity prices and actual electricity consumption data demonstrates the model's effectiveness in enhancing electricity price optimization across diverse and complex periods.

4. Discussion

In this work, we compare five cutting-edge research works on distribution system optimization. These five studies focus on similar topics but employ different research methods and technical approaches, forming representative exploration paths. Sharma et al. [13] focused on the coordinated optimization of distributed generation (DG) based on renewable energy, battery energy storage systems (BESS), and controllable load management. They proposed modeling the uncertainty of renewable resources and introducing flexible technologies to improve system efficiency, emphasizing the crucial role of technological coordination in preventing counterproductive system outcomes. Rawat et al. [14] designed a multi-objective optimization framework combining DG and battery storage in intelligent distribution systems. The goal was to optimize scheduling strategies to reduce both network energy loss and operational costs, while exploring the role of BESS in active and reactive power regulation. In the same year, Rawat et al. [15] focused on the integration of demand response (DR) with renewable energy-based DG. By simulating a 33-bus distribution system, they demonstrated DR's effectiveness in reducing energy losses. Further extending the research, Rawat et al. [16] introduced the integration of electric vehicles (EVs) and renewable energy into their study. They employed a two-stage stochastic optimization framework and analyzed the relationship between hosting capacity and energy loss to prove that the vehicle-to-grid functionality of the EVs significantly enhanced system flexibility. Finally, Kharra et al. [17] explored the optimal operation of distributed energy resources (DER) and EVs in intelligent distribution systems. Using the MOSEK solver to address mixed-integer second-order cone programming, they optimized the energy exchange strategy between DER and the upstream network, emphasizing the importance of energy loss constraints for improving system performance. These studies align with this work's goal of promoting intelligent and flexible distribution system optimization, all aiming to solve optimization problems under multi-dimensional constraints, though their emphases differ. Table 6 displays the comparative results.

Table 6. Comparison of this work with five other cutting-edge research works.

Researchers	Year	Optimization method	Research objective	Differences
Sharma et al. [13]	2020	Enhanced Evaporation Optimization Algorithm	Minimize network losses and improve voltage profiles	Focuses on technological coordination to improve system efficiency, does not focus on price
Rawat et al. [14]	2021	Mixed-Integer Second-Order Cone Programming and Fuzzy Satisficing Criteria	Minimize operational costs and network energy losses	Primarily focuses on operational costs and energy losses, does not consider dynamic pricing scenarios
Rawat et al. [15]	2021	Mixed-Integer Second-Order Cone Programming	Minimize energy losses and evaluate demand response effects	Emphasizes demand response and DG integration, does not address time-of-use pricing
Rawat et al. [16]	2024	Two-Stage Stochastic Optimization Framework	Maximize hosting capacity and reduce energy losses	Focuses on EV and renewable energy integration, does not consider time-of-use pricing
Kharra et al. [17]	2024	Mixed-Integer Second-Order Cone Programming and MOSEK Solver	Minimize operational costs and optimize DER coordination	Primarily focused on DER and EV optimization, lacks elasticity analysis for time-of-use pricing
This work	2024	Improved PSO, QPSO, and SFLA Collaborative Mechanism	Optimize electricity prices, enhance time-of-use pricing elasticity and distribution efficiency	Focuses on time-of-use pricing and active distribution network efficiency, comprehensively evaluates electricity price optimization under dynamic conditions

As shown in Table 6, compared with previous research, we explore new directions both in terms of research perspective and technical methodology. In terms of research perspective, researchers have primarily focused on local optimization or technical coordination issues concerning distributed energy sources such as DG, BESS, and EV. For example, Sharma et al. emphasized the role of flexible technologies in improving distribution efficiency, and Rawat et al. explored the potential of integrating DR with distributed energy sources. However, these studies have given less attention to the dynamic characteristics of time-of-use pricing and the impact of price fluctuations on distribution system operation. In contrast, we attempt to build an optimization model that takes into account price demand elasticity, time-of-use pricing elasticity, energy consumption elasticity, and distribution network operational elasticity. The model is built under the context of time-of-use pricing and improved active distribution network generation efficiency. The goal is to reveal the relationships between electricity prices and distribution system performance through a more comprehensive framework. While the ideas presented here need to be validated in broader scenarios, the preliminary results provide a new perspective on electricity price optimization.

In terms of technical methodology, we combine the improved PSO, QPSO, and SFLA algorithms to seek a balance between global search and local optimization. Unlike other studies, which mainly relied on a single optimization technique, we introduce chaotic variables and random jumping mechanisms to alleviate the local optimum problem often encountered in traditional optimization algorithms in complex, multi-objective scenarios. Moreover, by adaptively adjusting parameters, the algorithm can more flexibly respond to changes in the dynamic pricing environment, especially demonstrating some adaptability under multiple constraints. It is acknowledged that the model validation is primarily based on analyses of six cities and representative scenarios, which has limitations in the sample range. However, the preliminary validation results suggest that the proposed method shows potential in dynamic price optimization. In the future, as the research scope expands and the methodology continues to be refined, the ideas presented may provide useful insights for the optimization design of intelligent power systems.

5. Conclusions

Overall, we use the latest peak and valley price data released by the development and reform commissions of various provinces, along with data from the State Grid and China Southern Power Grid. We select six representative cities—Lanzhou, Guiyang, Beijing, Guangzhou, Shanghai, and Nanjing—to validate the model using publicly available data. The results are summarized as follows: (1) By considering the price optimization model's convergence times and CSI for different cities and months, we found that the model performs better in terms of convergence during flat periods. The model demonstrates strong potential for efficient energy distribution, cost optimization, and system responsiveness. (2) The model exhibits excellent global search capability and solution diversity across different cities and time periods. In Lanzhou, during off-peak hours, the global search capability reaches 88.2%, with an optimal solution coverage of 81.5%, an exploration range of 98.4 km^2, and solution distribution uniformity of 89.8%. In Shanghai and Nanjing, during deep valley periods, the global search capabilities are 91.0% and 90.7%, respectively, with optimal solution coverages of 84.2% and 84.0%, verifying the model's diversity and adaptability. (3) The model demonstrates strong performance in four key areas: Price demand elasticity, time-of-use price elasticity, energy consumption elasticity, and distribution network operational elasticity. The price demand elasticity coefficient ranges from 0.80 to 0.90, with a fitting error as low as 1.10%; the time-of-use price elasticity coefficient is between 0.72 and 0.82, with an SVR prediction error of 1.35%; the optimization of energy consumption is significant; and the distribution network's operational stability reaches 97.00%. (4) The optimized pricing strategy leads to a 12.3% reduction in users' average electricity costs, with the price volatility decreasing to 8.7%. In terms of power consumption prediction, the model's predicted consumption has an average error rate of only 2.1%, significantly outperforming the traditional method's error rate of 5.8%. These comparative results fully demonstrate the model's efficiency and accuracy in electricity price optimization and power consumption prediction.

Building on this foundation, the proposed electricity pricing optimization model introduces a multi-algorithm collaborative mechanism, which significantly enhances both the global search capability and local optimization accuracy in dynamic electricity price environments. Additionally, the model demonstrates robust adaptability and stability in complex scenarios such as time-of-use pricing and improved generation efficiency of active distribution networks. In comparison, the model better aligns with the elastic demand characteristics and multi-objective optimization features in existing electricity pricing frameworks, offering a more precise energy distribution and dynamic price adjustment ability. This lays a theoretical and practical foundation for the further development of intelligent power systems. Through validation across cities and time periods, the model effectively addresses the inefficiencies and lack of robustness in traditional electricity pricing strategies, providing scientific evidence for the stable operation of the power market.

Despite the significant progress made, there are several limitations that warrant further exploration. First, the model's reliance on historical data may hinder its dynamic adaptability to sudden market changes, limiting its ability to fully address electricity pricing optimization needs in extreme scenarios. Besides, although the multi-algorithm collaborative mechanism improves optimization performance, the complexity of the algorithms and high computational costs may pose challenges for real-time application scenarios. Additionally, we select only six cities as representative validation samples, which may not fully reflect the diverse electricity pricing optimization needs nationwide. Researchers could focus on the following improvements. First, by incorporating real-time data collection and dynamic learning technologies, the model's adaptability to rapidly changing environments can be strengthened. Second, simplifying the computational processes to reduce algorithm complexity will enhance real-time optimization capabilities. Third, by incorporating data from more regions and industries, the model's universality and generalizability can be improved, further refining both the theoretical framework and practical application value of the model.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Conflict of interest

The authors declare no conflicts of interest.

Author contributions

Conceptualization, Y.L.; methodology, Y.S.; software, Q.Z.; validation, B.W.; formal analysis, K.Q., L.T.; investigation, Y.L.; resources, Y.S.; data curation, Y.S.; writing—original draft preparation, B.W., K.Q., L.T.; writing—review and editing, Y.L., Y.S., Q.Z.; visualization, Q.Z.; supervision, K.Q.; project administration, Y.S. Ultimately, all of the authors declared no conflicts of interest, contributed to the work, and approved the version that was submitted.

Data availability statement

The data that support the findings of this study are available on request from the corresponding author, upon reasonable request.

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