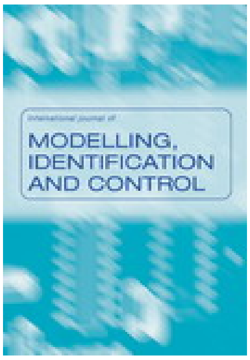

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An intelligent distribution network source grid load storage optimisation scheduling based on improved ant lion algorithm

Guangyong Zheng*, Junjie Zhang, Weiquan Ye,
Jin Yi and Lianghao Huang

Jiangmen Power Supply Bureau,
Guangdong Power Grid Co., Ltd.,
Jiangmen, 529000, China
Email: zgy_1300@163.com
Email: 670723291@qq.com
Email: weiqye@163.com
Email: 29543711@qq.com
Email: 8975936@qq.com
*Corresponding author

Hui Jiang

Product Department,
Dongfang Electronics Corporation,
Yantai, 264000, China
Email: 43553470@qq.com

Abstract: To enhance the stability of the distribution network's load and minimise its loss rate, an optimised scheduling approach for intelligent distribution network source load storage is introduced, leveraging an improved ant lion algorithm. Firstly, mathematical modelling is conducted on the diversified energy supply capacity within the intelligent distribution network, and a charging and discharging model is designed for the energy storage device. Secondly, a comprehensive optimisation scheduling system is established with the goal of reducing costs and minimising pollutant gas emissions, and multiple constraint factors are carefully planned. Finally, by improving the ant lion algorithm, a balance between global search and local optimisation is achieved. The results of the experiments demonstrate that the proposed technique closely approximates the actual load in terms of overall load correspondence within the distribution network, with the power grid experiencing a consistent loss rate of approximately 3% across all periods.

Keywords: intelligent distribution network; improve the ant lion algorithm; source network load storage; optimise scheduling.

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Biographical notes: Guangyong Zheng graduated from the School of Automation at South China University of Technology, and he received his Master's in Pattern Recognition and Intelligent Systems. He works at Jiangmen Power Supply Bureau of Guangdong Power Grid Co., Ltd. as a senior engineer. His research interests include optimising power control strategies for smart grids, power control models and algorithms based on artificial intelligence, and intelligent monitoring of power systems.

Junjie Zhang graduated from the School of Electrical Engineering of South China University of Technology and he received his Bachelor's in Electrical Engineering and Automation. He works at Jiangmen Power Supply Bureau of Guangdong Power Grid Co., Ltd. as a senior engineer. His main research directions include intelligent monitoring and operation control of power systems, secondary remote operation technology based on artificial intelligence and operation analysis research of relay protection in power systems.

Weiquan Ye received his Masters of Engineering in Control Theory and Control Engineering in 2016 from the School of Automation at South China University of Technology. Currently, he is a Senior Operator at the Electric Power Dispatching and Control Center of Jiangmen Power Supply

Bureau, Guangdong Power Grid. His research interests include optimising power control strategies for smart grids, developing power control models and algorithms based on artificial intelligence, intelligent monitoring and control of power systems, as well as cybersecurity in the context of power systems and smart grids.

Jin Yi graduated from the School of Electrical Engineering and Automation at Huazhong University of Science and Technology. He received his Master's in Electrical Engineering from the School of Electrical Engineering of South China University of Technology. He works at Jiangmen Power Supply Bureau of Guangdong Power Grid Co., Ltd. as a senior engineer. His research interests include power grid control system, dispatching automation, remote operation and maintenance of distribution terminal and distributed energy resources construction.

Lianghao Huang graduated from the School of Computer Science and Technology at Guangdong University of Technology with a Master's in Engineering. He works at Jiangmen Power Supply Bureau of Guangdong Power Grid Co., Ltd. as a senior engineer with main research interests in information technology, internet of things, network security of power monitoring systems, automation of power grid dispatching, and substation automation.

Hui Jiang graduated from the Shandong Radio and Television University with a major in Computer Science. He works as the Regional Manager of State Grid Corporation of China in the Product Department of the Technical Center of Dongfang Electronics Co., Ltd., mainly researching project management of smart grid dispatch systems, intelligent monitoring and operation control of power systems, distribution terminal and distributed energy resources construction.

1 Introduction

With the accelerated transformation of energy structure and continuous growth of power demand, smart distribution networks as core hubs of energy internet face unprecedented challenges and opportunities (Qi et al., 2023). In response to large-scale access of distributed energy, increased load volatility and rapid development of energy storage technology, traditional distribution networks have exposed problems such as insufficient scheduling flexibility and low energy efficiency, making it difficult to meet new power system requirements for safe, reliable, green and efficient operation (Zhu et al., 2023). Research on optimal scheduling of source-network-load-storage in intelligent distribution networks has been conducted. Through deep integration of intelligent algorithms and advanced communication technologies, efficient coordination and precise control of source, network, load and storage are achieved, becoming key pathways to improve distribution network operation efficiency, promote renewable energy consumption, and enhance system resilience (Sheikh et al., 2022; Man et al., 2022). This research holds far-reaching significance for promoting energy production and consumption revolution and building clean, low-carbon, safe and efficient energy systems, while providing important technical support for addressing global climate change and achieving 'double carbon' goals. The urgency lies in responding quickly to energy transformation needs, ensuring safe and stable power system operation, and promoting sustainable economic and social development (Suo and Liu, 2022; Liu et al., 2022).

Chai et al. (2024) proposed an optimal source-network-load-storage scheduling method based on Fisher time division, establishing an integrated 'energy-network-load-storage' optimisation framework across time series and analysing the Fisher optimal time division strategy using source-load power interval data. The study developed three optimisation models: a day-ahead scheduling optimisation model, a real-time dynamic adjustment optimisation model, and a local autonomous control optimisation model, which collectively address operation strategies for discrete grid equipment, demand response loads, photovoltaic power generation systems and their energy storage devices. However, Fisher's time division strategy demonstrates limited flexibility when handling special scenarios or emergencies, as the predetermined time division scheme cannot be readily adjusted to accommodate sudden power demand surges. Wang et al. (2024) proposed a source-network-load-storage optimisation scheduling method based on new energy-load similarity, establishing adjustable load response targets according to new energy and load (NRE-LD) fitness. By defining a correlation coefficient, the study developed an NRE-LD compatibility evaluation index that accurately quantifies the matching degree between load and new energy generation, incorporating this index into a two-stage optimal scheduling framework for integrated source-load-storage systems. The first-stage model maximises the unplanned offline loss correlation coefficient (NRE-LD) to determine schedulable load response power across different time windows, achieving optimal grid load configuration. The second-stage model minimises wind/solar curtailment rates and peak-shaving operational costs while improving energy efficiency through thermal power unit output and energy storage system optimisation. However, determining schedulable load response targets solely based on NRE-LD consistency proves overly simplistic and may yield suboptimal scheduling outcomes. Shi et al. (2023) proposed a load storage coordination scheduling method for source networks based on an improved clustering algorithm. It optimises the node weight of rival competitive learning (RPCL) algorithm using sample density and introduces an enhanced RPCL clustering algorithm. By analysing node relationships in the network, the algorithm employs the improved RPCL clustering method to evaluate effectiveness, particularly for clean energy internet reliability assessment. A source network load storage collaborative scheduling model is constructed and solved using a modified particle swarm optimisation algorithm with shrinkage factor to determine the optimal scheduling strategy. In practical source network load storage systems, data may exhibit localised concentration or dispersion, potentially causing sample density evaluation deviations and negatively impacting node weight optimisation.

To address the shortcomings of current methodologies, this study introduces an optimised source-network-load-storage scheduling approach for intelligent distribution networks based on an enhanced ant lion algorithm.

2 Modelling of power generation output for multiple types of power sources

The core objective of multi-type power generation output modelling involves accurately characterising stochastic features of photovoltaic, wind power and energy storage systems to provide theoretical foundations for optimal operation of smart distribution networks. The photovoltaic generation model utilises beta distribution for solar radiation, while the wind power output model incorporates Weibull distribution for wind speed. The energy storage system dynamically represents charge-discharge processes through state-of-charge parameters. This modelling approach effectively quantifies renewable energy volatility and employs probability distribution functions to assess generation uncertainty, thereby enhancing grid adaptability to intermittent power. By integrating spatiotemporal complementary characteristics of diverse power sources, the model optimises system dispatch strategies to improve grid stability and economic efficiency, delivering crucial technical support for high-penetration renewable energy integration.

2.1 Model for photovoltaic electricity production output

The photovoltaic power generation output model development under the intelligent distribution network framework can be expressed as follows:

$$Q_{PV} = LM\theta \tag{1}$$

where Q_{PV} stands for the photovoltaic power generation, L denotes the solar radiation intensity, M indicates the illuminated area, and θ symbolises the power generation of the photovoltaic unit.

The probability density expression of Q_{PV} is:

$$f_{PV}\left(Q_{PV}\right) = \frac{1}{Q_{PV}^{\max}} \frac{\daleth(a+b)}{\daleth(a)\daleth(b)} \left(\frac{Q_{PV}}{Q_{PV}^{\max}}\right)^{a-1} \left(1 - \frac{Q_{PV}}{Q_{PV}^{\max}}\right)^{b-1} \tag{2}$$

where a and b represent shape parameters, $\daleth(.)$ represents the beta distribution function, and $Q_{PV}^{\max}$ represents the maximum output of photovoltaic power generation (Singh et al., 2023).

According to formula (2), calculate $f_{PV}(Q_{PV})$ and construct the cumulative distribution function expression for photovoltaic power generation output:

$$F_{PV}\left(Q_{PV}\right) = \int_0^{Q_{PV}} f_{PV}(x)dx \tag{3}$$

2.2 Wind power output model

Taking into account the direct influence of wind speed, formulate an expression for the output of wind turbines:

$$Q_W(v) = \begin{cases} 0, & v < v_c, v > v_f \\ Q_r \dfrac{v - v_c}{v_r - v_c}, & v_c \le v \le v_r \\ Q_r, & v_r \le v \le v_f \end{cases} \tag{4}$$

where Q_r denotes the maximum power value attainable by the wind turbine. v_c and v_f signify the wind speeds at which the wind turbine commences and ceases its operation respectively. v_r represents the standard operating wind speed of the wind turbine, and v stands for the actual wind speed, as referenced in (Singh et al., 2023).

Wind strength exhibits significant uncertainty. Based on the Weibull distribution model, wind speed probability distribution characteristics can be established:

$$f_v(V) = \left(\frac{\vartheta}{\varphi}\right)\left(\frac{V}{\varphi}\right)^{\vartheta-1} \tag{5}$$

where φ is the scale parameter, ϑ is the shape parameter, V is the probability density function expression of wind speed v (Zhao et al., 2021).

According to formulas (4) and (5), a probability density function for the output of wind turbines can be constructed:

$$f_W\left(Q_W\right) = \begin{cases} \beta\left[1 - e^{-(V_c/\varphi)^{\vartheta}} + e^{-(V_f/\varphi)^{\vartheta}}\right], & Q_W = 0 \\ \beta\left(\dfrac{k}{\varphi}\right)\left(\dfrac{\gamma}{\varphi}\right)^{\vartheta-1} e^{-(\gamma/\varphi)^{\vartheta}}, & 0 < Q_W < Q_r \\ \beta\left[e^{-(V_c/\varphi)^{\vartheta}} - e^{-(V_f/\varphi)^{\vartheta}}\right], & Q_W = Q_r \end{cases} \tag{6}$$

$$\beta = \frac{V_r - V_C}{Q_r} \tag{7}$$

Therefore, a cumulative distribution function of wind turbine output can be constructed:

$$F_W\left(Q_W\right) = 1 - e^{-\left[\left(V_c + \beta Q_W/\varphi\right)\right]^{\vartheta}} \tag{8}$$

2.3 Energy storage device's charging and discharging profile

The nuclear power status and assembled energy storage system's charge-discharge capacity are represented as follows:

$$SOC_t = SOC_{t-1} + c_f \lambda \frac{r_k^i \Delta t \kappa}{S_{\max}} \tag{9}$$

where SOC_{t-1} stands for the state of charge at time $t-1$, c_f is used to denote the capacity coefficient, λ symbolises the variable activation parameter, r_k^i indicates the charging power, Δt represents the time variation, κ is the symbol for the charging and discharging efficiency, $S_{\max}$ designates the maximum energy storage capacity of the energy storage device.

3 Optimisation scheduling model for load storage in distribution network source network

The distribution network serves as the power system's critical link by delivering high-voltage transmission network power to end users, with operational efficiency directly determining power supply reliability and economic performance. Mathematical modelling transforms optimal scheduling of load and storage in the source network into a multi-objective optimisation problem that minimises economic costs and pollution emissions while coordinating thermal power, photovoltaic, wind power and energy storage systems. Key constraints encompass power balance, generation output limits, energy storage charge-discharge capacity and load reduction ranges to ensure system safety and stability. This optimisation requires balancing generation costs, environmental benefits and supply-demand matching. Intelligent algorithms determine optimal scheduling strategies that satisfy technical constraints to achieve efficient and low-carbon distribution network operation.

3.1 Objective function construction

Following modelling and analysis of multiple power sources' generation output, the power distribution network's optimal scheduling objective function is constructed to minimise costs and pollutant emissions. Cost minimisation alleviates user financial burdens and improves distribution network operational efficiency, particularly crucial given energy price volatility and resource scarcity. Emission reduction fulfils environmental protection requirements and mitigates climate change impacts. Multi-objective optimisation enables comprehensive distribution network performance enhancement, ensuring efficient resource allocation and environmental sustainability while maintaining power supply-demand balance (Rahman et al., 2022).

The minimum cost objective function is:

$$\begin{aligned} \min F_1 = \min\Big[& \sum\nolimits_m \left(C_F^m + C_F^{m,0}\right) G_F^m \\ & + \sum\nolimits_u \left(C_X^u + C_X^{u,0}\right) G_X^u + \sum\nolimits_g C_{PV}^g G_{PV}^g \\ & + \sum\nolimits_f C_W^f G_W^f + C_d(i,t) + C_R(i,t) \Big] \end{aligned} \tag{10}$$

where C_F^m and $C_F^{m,0}$ signify the expenses associated with thermal power generation and operation respectively, with G_F^m denoting the thermal power unit's capacity. C_X^u and $C_X^{u,0}$, on the other hand, represent the costs of generating and operating the standby unit, respectively, with G_X^u indicating its power output. C_{PV}^g and C_W^f are the costs of generating photovoltaic and wind power, respectively, corresponding to G_{PV}^g and G_W^f, which designate their respective power generations. $C_d(i, t)$ is the cost associated with load control, while $C_R(i, t)$ signifies the expense of load dispatch.

The objective function expression for minimising pollutant gas emissions is:

$$\min F_2 = \min \sum\nolimits_{m,u} \left[\left(G_F^m + G_X^u\right)\left(e_{CS} + e_{CY} + e_{CN}\right) \right] \tag{11}$$

where e_{CS}, e_{CY}, and e_{CN} stand for the emission coefficients of sulphur dioxide, particulate matter, and nitrogen oxides, correspondingly.

3.2 Constraint conditions

3.2.1 Conditions for maintaining power equilibrium

The representation of the constraint for maintaining power balance is outlined below:

$$\begin{aligned} & \sum\nolimits_m Q_F^m + \sum\nolimits_m Q_X^u + \sum\nolimits_m Q_{PV}^g + \sum\nolimits_f Q_W^f \\ & + \sum\nolimits_i r_k^i - Q_{LOSS} = D_{toal} - Q_d(i,t) \end{aligned} \tag{12}$$

where Q_F^m, Q_X^u, Q_{PV}^g and Q_W^f signify the power outputs of thermal power units, reserve units, photovoltaic systems, and wind turbines respectively. r_k^i represents the energy storage equipment's load, Q_{LOSS} denotes the power loss in the distribution network, D_{toal} symbolises the total load demand of the distribution network, and $Q_d(i, t)$ stands for the quantity of load reduction.

3.2.2 Constraint on electricity production output

The formulation outlining the limitation on electricity production output is provided below:

$$\begin{aligned} & Q_F^{\min} \le Q_F^m \le Q_F^{\max} \\ & Q_{PV}^{\min} \le Q_{PV}^g \le Q_{PV}^{\max} \\ & Q_{PV}^{\min} \le Q_{PV}^f \le Q_{PV}^{\max} \\ & Q_X^{\min} \le Q_X^{uu} \le Q_X^{\max} \end{aligned} \tag{13}$$

The output power of various generators must be maintained within their rated capacity range, neither exceeding nor falling below the set minimum limit. The constraint expression is as follows:

$$-\rho_{F,d}\Delta t \leq \Delta Q_{F,t} \leq \rho_{F,u}\Delta t \tag{14}$$

$$-\rho_{X,d}\Delta t \leq \Delta Q_{X,t} \leq \rho_{X,u}\Delta t \tag{15}$$

where $\Delta Q_{F,t}$ signifies the output variation of thermal power units, while $\Delta Q_{X,t}$ represents the same for standby units. $\rho_{F,u}$ and $\rho_{F,d}$ denote the maximum upward and downward ramp rates for thermal power units, respectively. Conversely, $\rho_{X,u}$ and $\rho_{X,d}$ signify the peak ascending and descending adjustment rates for standby units (Nazemi et al., 2021).

3.2.3 Energy storage output and capacity constraints

The expression for energy storage output and capacity constraints is:

$$\begin{aligned} &R_{\min}^{i} \leq r_k^i \leq R_{\max}^{i} \\ &SOC_{\min} \leq SOC_t \leq SOC_{\max} \\ &r_{k,t}^{i} t \leq \left(SOC_{t-1} - SOC_{\min}\right) S_{\max} \\ &r_{k,t}^{i} t_{i,t} \leq \left(1 - SOC_{t-1}\right) S_{\max} \end{aligned} \tag{16}$$

where $R_{\max}^{i}$ designates the peak power rating of the energy storage device, and $SOC_{\min}$ indicates its lowest storage level.

3.2.4 User load reduction amount

The constraint expression for reducing user load is:

$$D_{\min}^{i} \leq d_k^i \leq D_{\max}^{i} \tag{17}$$

where $D_{\min}^{i}$ denotes the minimum value of load reduction for users, while $D_{\max}^{i}$ indicates the maximum value of load reduction for users.

4 Optimisation scheduling of source network load storage based on improved ant lion algorithm

The improvement of ant lion algorithm focuses on optimising the search boundary adjustment mechanism and elite guidance strategy to balance global exploration and local development capabilities. By designing a smoothly increasing boundary adjustment coefficient, the jumping contraction of search is avoided and the solution space is fully traversed. The dynamic weight coefficient is introduced to adjust the roulette selection mechanism, which strengthens global search at the initial stage and focuses on fine mining guided by elite ant lions at the later stage. Regarding the problem of premature convergence caused by declining population diversity, a premature judgment criterion based on fitness variance and individual spacing is proposed. When local optimal stagnation is detected, the normal Cauchy hybrid mutation strategy is used to disturb ant lion positions, while evolution direction is maintained through the multi-candidate solution selection mechanism. The key improvement process includes continuous updating of boundary coefficient, dynamic weight position migration, premature detection and hybrid mutation operation, ultimately enhancing the solution quality and convergence speed for optimal scheduling of load storage in source networks.

The ant lion algorithm's foundational design requires ants to probe around traps while progressively narrowing the search perimeter toward optimal solutions. Erratic boundary adjustment coefficients may cause ants to overlook areas, potentially missing global optima. Incorporating a smoothly increasing boundary adjustment coefficient during iteration enhances traversal capability, ensures comprehensive solution space exploration, and accelerates convergence. The boundary exploration update strategy for ants is specifically defined as follows:

$$\begin{cases} c^t = c^t / I \\ d^t = d^t / I \\ I = \dfrac{\gamma}{T} \cdot \sinh\left(\lambda \cdot \dfrac{t}{T}\right) \end{cases} \tag{18}$$

where γ and λ represent the contraction factor and scaling factor of the boundary, respectively.

In the elite stage, ants imitate action patterns of ant lions and elite ant lions based on the roulette wheel mechanism to adjust their position. The probability calculation formula for an ant lion being selected through the roulette wheel mechanism is:

$$p\left(Antlion_j^t\right) = \frac{f\left(Antlion_j^t\right)}{\sum_{i=1}^{N} fit\left(x_i\right)} \tag{19}$$

where $fit(x_i)$ represents the fitness function.

Given that elite ant lions exhibit the highest fitness scores, their likelihood of being selected as ant lion candidates in the roulette wheel segment significantly increases according to formula (19). This tendency causes ants to focus predominantly on elite ant lions and weakens the algorithm's overall search performance. The relevant expression follows:

$$Ant_j^t = \frac{\left(R_A^t = R_E^t\right) + R_E^t}{2} = R_E^t \tag{20}$$

To tackle the aforementioned challenges, the ant position update equation is augmented with dynamic weight coefficients that vary according to the iteration count, yielding:

$$\begin{cases} Ant_j^t = \dfrac{k_1 R_A^t + k_2 R_E^t}{2} \\ k_1 = 1 - \dfrac{t^3}{T^3} \\ k_2 = \dfrac{t^3}{T^3} \end{cases} \tag{21}$$

In formula (21), the weight coefficient k_1 assigned to the ant lion R_A^t through the roulette wheel selection process plays a pivotal role during the initial stages of the algorithm, encouraging the ant colony to conduct a thorough exploration of promising regions within the search space. As the iteration progresses to later stages, the weight coefficient of elite ant lions near the optimal solution gradually increases, guiding the ant colony to perform fine-grained mining around the optimal solution, thereby optimising the algorithm's balance between global search and local optimisation (Ali-Dahmane et al., 2023).

As search boundaries tighten and leading ant lions' guidance concentrates the population, diversity decreases, making the algorithm prone to premature convergence and suboptimal solutions. To enable escape from local optima, the proposed enhanced approach integrates early convergence detection with dynamic mixed mutation. The measure for the overall fitness dispersion in Generation t is defined as:

$$\alpha^t = \sum_{i=1}^{N} \left(\frac{fit^t(x_i) - fit_{mean}^t}{f_\alpha'} \right) \tag{22}$$

where N represents the population size, $fit^t(x_i)$ represents the fitness of t iterations, f_{mean}^t represents the average fitness, f_α' represents the calibration factor, and its expression is:

$$f_\alpha' = \begin{cases} \max\left|fit^t(x_i) - f_{mean}^t\right|, & \max\left|fit^t(x_i) - f_{mean}^t\right| > 1 \\ 1, & other \end{cases} \tag{23}$$

The distance between individuals in the population is:

$$D^t = \frac{1}{N \cdot L} \cdot \sum_{i=1}^{N} \sqrt{\sum_{d=1}^{n} \left(x_{id}^t - x_{mean}^t \right)^2} \tag{24}$$

where L denotes the largest diagonal extent of the exploration area, while n signifies the number of dimensions being searched, x_{id}^t represents the individual's position in the d dimension at t iterations, and x_{mean}^t represents the average position.

In the case of complete population aggregation, the values of α^t and D^t will return to zero, which may indicate the achievement of global optimum or the stagnation of local optimum. To clearly distinguish between these two states, it is defined that the algorithm is considered to converge prematurely when $\alpha^t < \beta$ and $D^t < \sigma$. When confronted with the issue of algorithms getting stuck in local minima, a dynamic adjustment approach that integrates normal and Cauchy distributions is utilised to mutate the position $Antlion_j^t$ of ant lions. The mathematical formulation for this is given below:

$$\begin{cases} Antlion_j^{t+1} = \{1 + \eta[w_1 \cdot K(0,1) + w_2 \cdot N(0,1)]\} \cdot Antlion_j^t \\ w_1 = 2 - 1.9\dfrac{t^3}{T^3} \\ w_2 = \dfrac{t^3}{T^3} \end{cases} \tag{25}$$

where $Antlion_j^{t+1}$ represents the position of the ant lion under $t + 1$ iteration, η represents the adjustment parameter, and $K(0, 1)$ and $N(0, 1)$ represent the variation factors that follow Cauchy distribution and normal distribution, respectively.

To ensure the mutation operation guides new solutions toward better regions, M current ant lion positions are replicated for mutation in each operation round to generate candidate solutions. From $M + 1$ candidate solutions, the optimal one is selected as the next iteration's starting point. This process continues until reaching the preset maximum iteration count, when the optimal solution for the distribution network's source-network-load-storage optimisation scheduling objective function is output.

5 Test experiment

5.1 Testing environment and data

Taking a North China smart grid as an example, this region demonstrates remarkable achievements in renewable energy utilisation. The grid-connected wind power capacity reaches 920 MW, indicating strong wind generation capability. Simultaneously, grid-connected photovoltaic capacity reaches 450 MW, supplying clean solar power. Over 24 hours, specific data including average solar radiation intensity and its fluctuation range are available in Table 1, providing critical references for grid operation and energy dispatch.

Table 1 Mean and standard deviation of 24-hour solar radiation illuminance

Time slot	*Mean value/($W \cdot m^{-2}$)*	*Standard deviation*
5	13	0.043
6	84	0.101
7	125	0.131
8	275	0.148
9	377	0.161
10	421	0.192
11	548	0.217
12	661	0.256
13	655	0.249
14	538	0.202
15	404	0.189
16	348	0.154
17	224	0.139
18	111	0.118
19	72	0.062

In the field of wind power generation, various wind speed parameters have clear specifications. The cut-in wind speed is 3.3 m/s, indicating the wind turbine begins generating electricity at this value. The standard operating wind speed is 10 m/s, representing the optimal wind speed for efficient turbine operation. The cut-out wind speed reaches 15 m/s, where the turbine stops operating for safety when wind speed exceeds this threshold. Using cumulative probability distribution function analysis, Figure 1 illustrates the relationship between per-megawatt output power of photovoltaic and wind power generation and their cumulative probability distributions during a representative scheduling cycle.

The energy storage devices mainly comprise lithium-ion battery boxes and lead-acid battery boxes, with detailed parameters of both types presented in Table 2.

Figure 1 Wind and photovoltaic treatment and cumulative distribution map

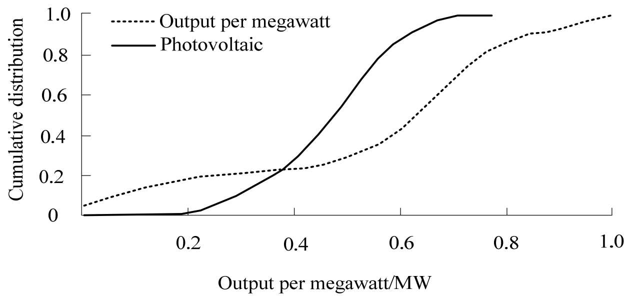


Table 2 Energy storage equipment data

Parameter	*Lithium battery container*	*Lead acid battery container*
Rated power/MW	0.5	1
Rated capacity/kW·h	800	500
Power change rate	From 0 to 0.5 MW within 10ms	From 0 to 1 MW within 20 ms
Charge and discharge efficiency/%	90	95
Number of cycles/time	1,700	3,000
Maximum energy storage capacity	0.15	0.1

Table 2 data review indicates both battery types can achieve full capacity from zero output within 20 milliseconds, ensuring smooth and reliable power system operation through this rapid response capability.

5.2 *Test plan and indicators*

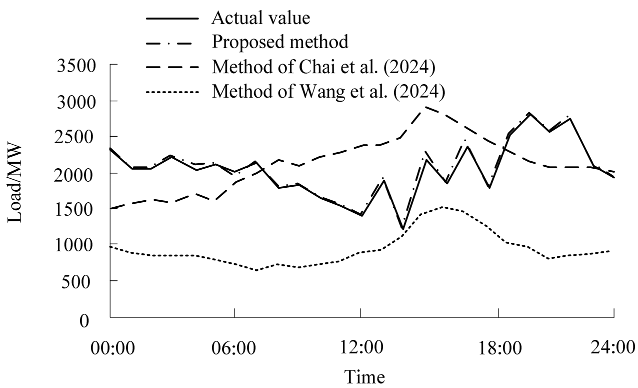
Using the total load of the intelligent distribution network and the grid loss rate as benchmarks, this technique is compared with the methods detailed in Chai et al. (2024) and Wang et al. (2024).

- Total load of distribution network: the distribution network's total load represents the aggregate electricity demand during a specific period. This value's fluctuation significantly impacts grid operation. Insufficient load may compromise power supply redundancy, affecting grid stability and user electricity consumption. Excessive load creates substantial operational pressure on the grid, increasing energy losses, reducing utilisation efficiency, and potentially endangering grid safety.
- Power grid loss rate: the power grid loss rate serves as a crucial indicator for evaluating grid operation efficiency, reflecting energy loss levels during transmission and distribution. High loss rates indicate not only energy waste but also increased operational costs and compromised supply reliability. Implementing scientific optimisation strategies, including rational generation scheduling, grid structure optimisation, and equipment efficiency improvements, can effectively reduce grid losses, enhance overall energy utilisation efficiency, and promote sustainable development in the power industry.

5.3 *Analysis of test results*

Distribution network load testing accurately measures power demand under various operating conditions, providing critical data for scheduling strategy optimisation. Real-time load trend monitoring and analysis facilitate improved coordination among generation, grid, load, and storage components, thereby enhancing system flexibility and responsiveness. Figure 2 presents the distribution network's total load results under three scheduling methods.

Figure 2 Total load of distribution network



The data curve in Figure 2 demonstrates significant fluctuation in the smart distribution network's total load during the 24-hour experimental period. Peak loads occurred between 9–11 am and 6–8 pm, while the lowest values appeared between 3–5 am. This pattern reflects both modern power grid load dynamics and periodic variations in user electricity consumption behaviour. Comparative experimental results indicate that traditional economic dispatch methods from Chai et al. (2024) and heuristic optimisation algorithms from Wang et al. (2024) exhibit significant deviations from actual demand loads, reaching a maximum of 15%. These deviations become particularly pronounced during rapid load transition periods, revealing traditional methods' limitations in tracking dynamic load changes. In contrast, application of the improved ant lion optimisation algorithm to coordinated source-grid-load-storage scheduling produces scheduling curves nearly identical to actual load curves, maintaining tracking errors below 2%. This performance persists during challenging periods including evening photovoltaic output drops and nighttime wind power fluctuations. The results validate the proposed method's superior load tracking capability while demonstrating its comprehensive optimisation of distributed generation, energy storage systems, and controllable loads, offering a reliable technical solution for smart grid precision scheduling.

Power grid loss rate assessment directly measures energy dissipation during optimisation and scheduling processes, serving as a fundamental indicator for evaluating grid operational and energy utilisation efficiency. Analysis of these rates provides critical insights into grid configuration, scheduling methodology, and equipment performance impacts on energy losses, forming the basis for scheduling strategy optimisation. Table 3 presents the power grid loss rate evaluation results using three methods.

Table 3 Test results of power grid loss rate

Period of time/h	*Power grid loss rate/%*		
	Proposed method	*Chai et al. (2024) method*	*Wang et al. (2024) method*
2	3.02	6.98	6.95
4	3.10	6.92	6.97
6	3.05	7.01	6.99
8	3.08	6.96	7.02
10	3.01	6.94	6.98
12	3.04	7.00	6.96
14	3.07	6.97	7.01
16	3.03	6.99	6.97
18	3.06	6.95	7.00
20	3.09	6.98	6.99
22	3.02	7.02	6.96
24	3.05	6.97	7.01

Through in-depth analysis of the power grid loss rate test results in Table 3, the optimisation scheduling method demonstrates significant technical advantages in reducing power grid losses. Specific data shows that during different testing periods of 24 hours, the power grid loss rate remained stable in the lower level range of 2.8%–3.2%, with fluctuations not exceeding 0.4 percentage points, demonstrating excellent stability. In contrast, the average loss rate of the classical linear programming method used in Chai et al. (2024) reached 6.9%, and the loss rate climbed to 7.5% during peak load periods. Although the intelligent optimisation algorithm in Wang et al. (2024) is slightly better than the former, its average loss rate remains as high as 6.3%. Further analysis shows that the significant loss reduction is due to an improved ant lion algorithm that integrates dynamic boundary adjustment mechanism, mixed mutation strategy, and adaptive adjustment, significantly improving the accuracy and energy efficiency of source network load storage coordination scheduling.

6 Conclusions

A distinctive strategy is introduced in this exploration, grounded in a sophisticated ant lion algorithm specifically tailored for optimising the scheduling of sources, networks, loads, and storage within intelligent distribution systems. The formulated comprehensive optimisation scheduling framework incorporates precise representations of power outputs from renewable sources like solar and wind, along with detailed operational characteristics of energy storage equipment. This framework pursues dual objectives: minimising operational costs and emissions of harmful gases while enforcing a meticulous set of constraints to ensure scheduling practicality and efficacy. Experimental evaluations demonstrate the method's exceptional proficiency in aligning with total load demands of the distribution network, showcasing high consistency with actual load profiles. Additionally, remarkable reductions in power grid losses have been achieved, with consistently low loss rates maintained across all timeframes. The research offers fresh insights and methodologies for enhancing intelligent distribution network scheduling while laying a strong foundation for fostering sustainable development and optimising energy utilisation.

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Declarations

All authors declare that they have no conflicts of interest.

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