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Research Article

Multi objective building energy efficiency optimization scheduling by integrating multi objective grey wolf optimizer and long short term memory network

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Abstract. Building energy consumption accounts for a large proportion of the overall energy use in society, and energy-saving optimization scheduling is currently a research hotspot. However, traditional scheduling methods often struggle to achieve an effective balance between multiple objectives such as energy conservation, economy, and indoor comfort. To construct an energy-saving scheduling model that can consider multiple objectives, this paper puts forward a building energy scheduling model based on a Multi-Objective Grey Wolf Optimizer, taking total energy consumption, operating cost, and indoor comfort deviation as the optimization objectives. The model introduces a set of multi-energy collaborative constraints involving wind energy, photovoltaic systems, energy storage, and combined cooling, heating, and power systems. To improve algorithm performance, we innovatively integrated particle swarm optimization and simulated annealing to enhance the model's global search and local optimization capabilities, and introduced residual long short-term memory networks to improve load forecasting accuracy. Experimental results show that compared to similar models, the proposed algorithm improves the energy-saving rate by 13.3% in a typical household scenario. Its response time is 12 s, memory usage is 89 MB, and convergence speed is 42.86% faster than the slowest comparable model. The Multi-Objective Grey Wolf Optimizer effectively coordinates the multi-objective needs of building energy systems. It significantly improves energy savings and economic performance while ensuring indoor comfort. This algorithm provides strong support for intelligent building energy scheduling and offers practical value for promoting the carbon neutrality goals in the building sector.

Keywords: Multi-objective grey wolf optimizer; Particle swarm optimization; Residual network; Building energy efficiency; Simulated annealing

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1. Introduction

With the global energy crisis and the advancement of carbon neutrality goals, optimizing energy use in buildings has become a core issue for sustainable development. Building energy-efficient scheduling dynamically adjusts air conditioning, lighting, energy storage, and renewable energy systems to reduce energy consumption while maintaining indoor comfort (Zhu *et al.*,2022). It is a key technological path toward low-carbon buildings. As building energy systems become increasingly complex, traditional rule-based scheduling or single-objective optimization methods can no longer meet the multi-dimensional demands of energy use, cost, and comfort. Efficient multi-objective optimization methods are urgently needed (Mou *et al.*,2022). At present, many related studies apply intelligent optimization algorithms to solve scheduling problems. For example, Genetic Algorithms and Particle Swarm Optimization (PSO) are widely used in load distribution but tend to fall into local optima. Simulated Annealing (SA) has a strong global search ability but suffers from slow convergence (Shekhar *et al.*,2023). The Multi-Objective Grey Wolf Optimizer (MOGWO), a newly developed intelligent algorithm, shows strong adaptability in handling multi-constraint and nonlinear problems and has been preliminarily applied in microgrid scheduling (Zhao *et al.*,2022). However, current MOGWO applications in building scenarios still face significant limitations. These include a lack of solution diversity, poor adaptability to the dynamic and multi-objective nature of building loads, weak handling of high-dimensional constraints, a tendency to generate infeasible solutions, and difficulty balancing convergence speed with solution accuracy. These issues make it hard to meet the needs of real-time scheduling (Zhao *et al.*,2023; Phong *et al.*,2022). In order to overcome these challenges, this study innovatively proposed an improved MOGWO for building energy-saving scheduling. By introducing PSO and SA to help MOGWO perform global search and escape from local optimality, and integrating the Residual Network-Long Short-Term Memory (ResNet-LSTM) network optimized by Cosine Annealing (CA) to make up for the defects of spatiotemporal feature extraction, finally constructed a building energy scheduling model that takes into account the lowest energy consumption, optimal cost and comfort guarantee. It is expected that it can provide theoretical and technical support for the efficient operation of complex building energy systems.

The innovation of this study lies in integrating PSO and SA into MOGWO, constructing a hybrid optimization mechanism, and proposing a ResNet LSTM optimized based on CA mechanism,

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which enhances the ability to extract and predict the spatiotemporal characteristics of building energy consumption. The main contribution of this study is the organic integration of improved optimization algorithms with load forecasting models, achieving full process optimization from data input to scheduling strategy generation. By introducing multi energy device constraints and dynamic load characteristics, the feasibility and practicality of the model in actual building environments have been improved.

2. Related works

MOGWO was developed based on the Grey Wolf Optimizer (GWO) and has been widely applied in various fields. Many researchers have conducted relevant studies on this algorithm. For example, Torabi A *et al.* (2024) proposed a method to link MOGWO with an integrated modeling framework to address the complex interactions between surface water and groundwater in dynamic studies. They identified optimal allocation parameters by minimizing groundwater extraction at the end of the operation period. Chen L *et al.*, (2024) inspired by the effectiveness of mathematical models in describing biological phenomena, introduced MOGWO to determine the optimal concentration of cancer cells during treatment. They formulated a drug delivery strategy by simultaneously minimizing cancer cell concentration and medication dosage. Bai Y *et al.* (2025) focused on the challenge of a single pursuer being unable to intercept an evader when the pursuer had limited maneuverability. They proposed an improved MOGWO to find the optimal game point. By describing the relative motion equations between the pursuer and the evader, they designed a constrained multi-objective function and developed an optimal strategy for the differential game. Goyal K K *et al.* (2022) aimed to overcome the lack of empirical models for every response in alloy processing. They proposed using an enhanced MOGWO to obtain a Pareto front across conflicting process responses. A Levy flight algorithm was introduced to improve the efficiency of MOGWO. Kumar A *et al.* (2024) addressed the difficulty in identifying optimal process parameters due to changes in processing conditions. They used an artificial neural network-based MOGWO to search for optimal parameter settings. By minimizing both pulsed and non-pulsed parameter corner errors, they achieved improved machining outcomes.

Building energy scheduling plays a critical role under the current energy crisis and increasingly strict environmental regulations. Many researchers have explored this topic in depth. Tang H and Wang S (2022) addressed the limited flexibility of aggregated buildings in electricity market bidding. They proposed a multi-level optimized scheduling strategy and developed a model-based quantification method aimed at increasing flexibility profits and minimizing the complexity of optimization. Li Z *et al.* (2022) focused on the suboptimal performance of distributed energy management in office buildings. They proposed an Active Distribution Network (ADN) energy management method for aggregated office buildings. By incorporating detailed building thermodynamics and occupants' movement patterns, they built an ADN optimization model. Zheng W *et al.* (2023) tackled the problem of traditional Integrated Energy Systems (IES) being unable to function due to the uncertain nature of hydrogen injection and gas transport properties. They proposed an HCNG-permeated IES scheduling method. A mass flow model considering variable blending ratios and initial flow directions was established to describe the hydrogen injection process. Sun Y (2025) aimed to improve voltage stability in energy scheduling and proposed a demand-side scheduling method that prioritizes energy-efficient buildings. By analyzing the load stacking behavior of energy-efficient buildings, an energy scheduling priority index was created, and the scheduling function was solved accordingly. Zhang B *et al.* (2024) highlighted the importance of integrated energy systems in achieving carbon peaking and neutrality goals. To manage electricity-heat-gas-cooling systems, they devised a two-stage robust optimization approach. A combined cooling, heating, and power model was built based on power-to-gas and carbon capture technologies. The robust two-stage model for IES scheduling enabled effective absorption of renewable energy and reduced the total system cost. Nath A D *et al.* (2025) investigated the performance of phase change material integrated cross laminated wood wall systems in 17 climate zones in the United States to address the lack of consensus on the optimal placement of phase change materials within wall components. They used EnergyPlus simulation to analyze five wall configurations. The results showed that the phase change material integrated cross laminated wood wall system achieved a cooling energy saving of up to 72.48%. Devianto D *et al.* (2025) investigated the management of carbon dioxide emissions and used Bayesian vector autoregression models to address the complexity of multiple interactions. The results indicate that the BVAR model demonstrates a considerable level of predictive accuracy. Kamaruddin M *et al.* (2025) addressed the issue of traditional methods being unable to capture the complexity of design and climate conditions by using parameterized energy modeling methods, and analyzed the impact of design parameters on building energy intensity. The simulation results indicate that building orientations of 140°, 90°, 135°, and 270° tend to generate higher energy intensity values.

In summary, existing research has made progress in the field of building energy scheduling. However, many optimization strategies still face difficulties in balancing multiple objectives, and the algorithms often lack generalizability and robustness. To tackle these problems, this paper proposes a building energy-efficient scheduling model based on MOGWO. By introducing PSO and CA to improve global search capability, and integrating a cosine-annealed ResNet-LSTM to extract spatiotemporal features from energy data, the proposed model aims to meet the multi-objective optimization needs of building energy systems. Compared with existing research, the outstanding advantage of this study lies in proposing a building energy-saving scheduling model that integrates multi energy collaborative constraints and improved multi-objective optimization algorithms, effectively balancing multiple conflicting objectives such as energy consumption, cost, and comfort, filling the research gap in multi-objective collaboration and real-time scheduling capabilities of existing methods in complex building energy systems.

3. Building energy-efficient scheduling model based on MOGWO

3.1 Design of MOGWO algorithm enhanced by PSO and SA

Building energy-efficient scheduling optimization dynamically manages energy systems, device operations, and load distribution. It meets constraints such as comfort and device safety while achieving multiple goals, including energy reduction, cost savings, and carbon emission control (Huang *et al.*,2025). MOGWO is an ideal tool for this task due to its ability to handle multiple objectives, perform global search, and provide efficient solutions (Liu *et al.*,2024). MOGWO inherits the

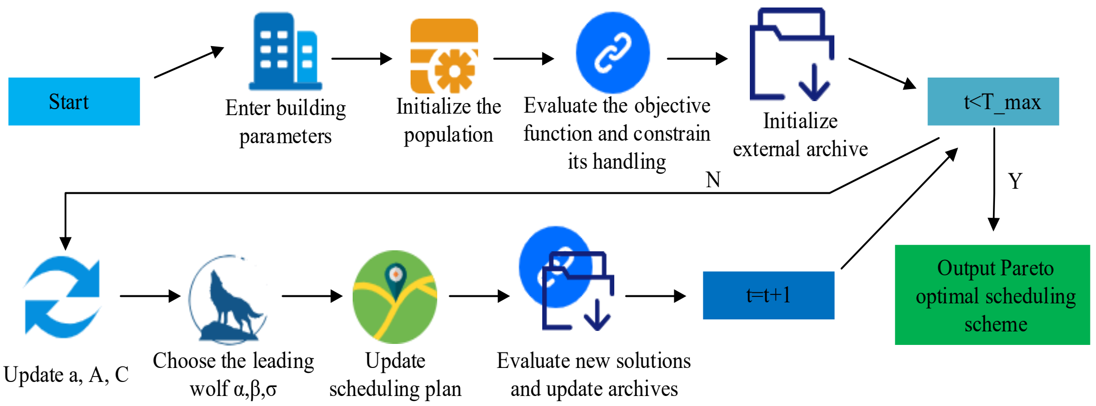


Fig 1 Schematic diagram of MOGWO's operation process (Icon source from: https://www.iconfont.cn/)

core parameters of GWO to balance global exploration and local exploitation (Heidari *et al.*,2023). The operational process of MOGWO in building energy scheduling optimization is shown in Figure 1.

As shown in Figure 1, the algorithm first collects basic data such as building energy device characteristics and environmental conditions. It then generates a grey wolf population representing potential scheduling schemes and initializes an external archive to store the Pareto optimal solutions found during iteration. Based on multi-objective functions such as energy efficiency and economy, and considering energy supply and demand as well as device operation constraints, the algorithm evaluates each scheme. The leader wolf guides the update of scheduling solutions, iterating until a preset threshold is reached and outputting the optimal energy-efficient scheduling plan for the building (Du *et al.*,2025). The convergence factor a of MOGWO is defined in Equation (1).

$$a = 2 - t \times \frac{2}{T_{max}} \tag{1}$$

In Equation (1), t is the current iteration number. The coefficient vector is calculated as shown in Equation (2).

$$\begin{cases} A = 2a \cdot r_1 - a \\ C = 2 \cdot r_2 \end{cases} \tag{2}$$

In Equation (2), A determines the direction and step size of position updates, and C simulates the random movement of prey. r_1 and r_2 are random vectors. In MOGWO, the position of each grey wolf is updated based on the best three wolves in the population by simulating the hunting behavior of wolves. MOGWO tackled multi-objective problems by incorporating Pareto dominance and maintaining an external archive to identify and retain non-dominated solutions (Navin Dhinnesh *et al.*,2024). For two solutions x and y, if x dominates y, denoted as $x \prec y$, the dominance condition must satisfy Equation (3) (Singh *et al.*,2023).

$$\begin{cases} \forall i \in \{1,2,\cdots,m\}, f_i(x) \le f_i(y) \\ \exists j \in \{1,2,\cdots,m\}, f_i(x) < f_i(y) \end{cases} \tag{3}$$

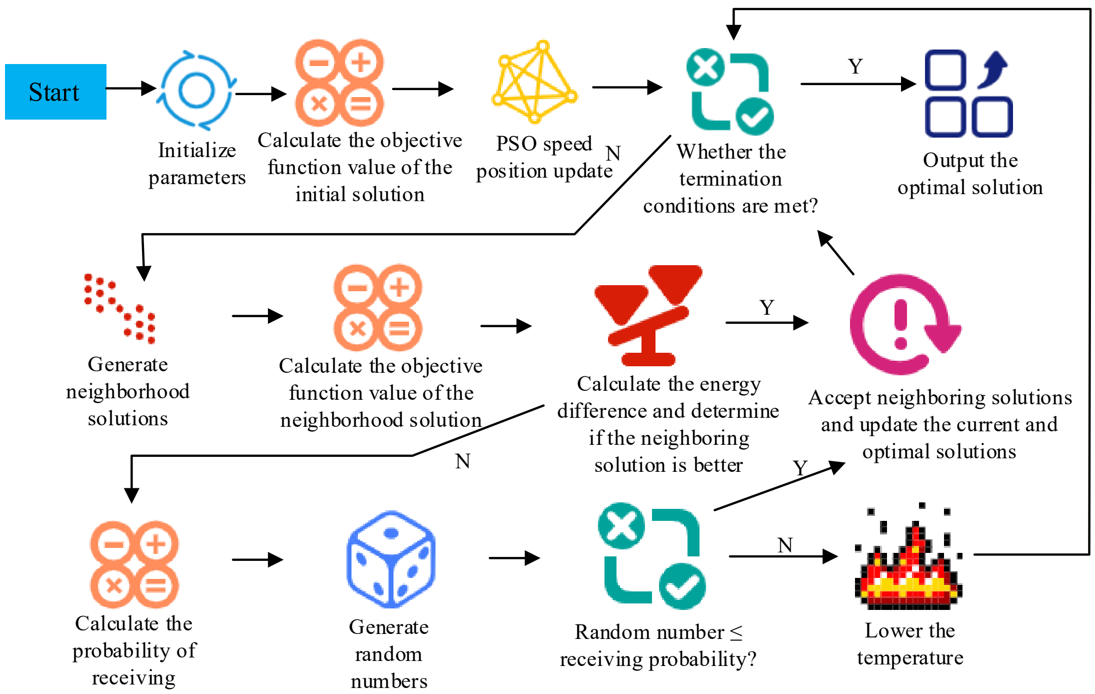


Fig 2 Structure diagram of PSO-SA (Icon source from: https://www.iconfont.cn/)

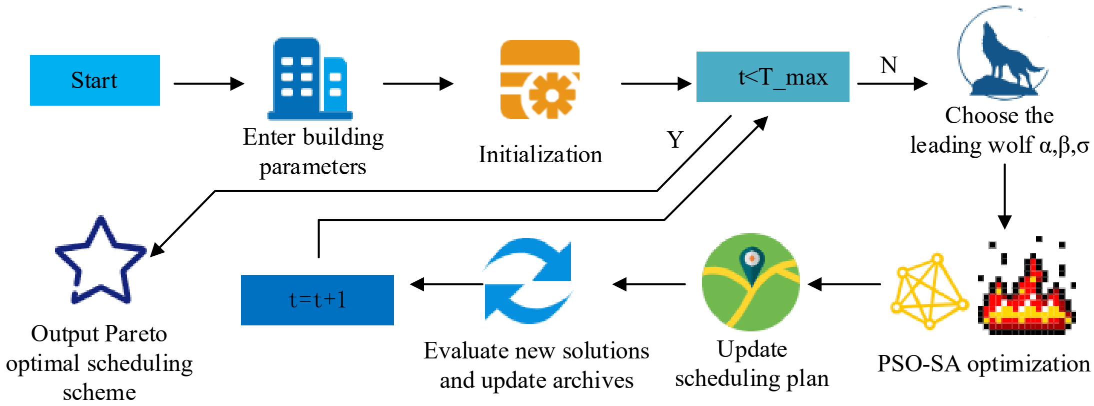


Fig 3 PSO-SA-MOGWO operation flow chart (Icon source from: https://www.iconfont.cn/)

In Equation (3), m is the number of objective functions, and $f_i(x)$ is the fitness value of solution x in the i -th objective. A non-dominated solution is one that is not dominated by any other solution (Hosseini *et al.*,2024). When the external archive contains more solutions than its defined threshold, the algorithm filters out redundant solutions using grid density to maintain diversity. The grid density is calculated by Equation (4) (Li *et al.*,2025).

$$Density(x) = \sum_{y \in Archive, y \neq x} exp(-\lambda \cdot d(x,y)) \qquad (4)$$

In Equation (4), $d(x,y)$ is the Euclidean distance, and λ is a tuning parameter. Although MOGWO demonstrates strong capabilities in multi-objective optimization for building energy scheduling, it has limitations such as insufficient solution diversity and difficulty balancing convergence speed and accuracy. SA algorithm, with its global optimization ability based on a probability acceptance criterion, can effectively address these issues (Poursaeid *et al.*,2025). When combined, MOGWO retains its multi-objective coordination capability, while SA enhances global search and helps avoid local optima. However, SA often suffers from slow convergence and sensitivity to parameter settings (Kosanoglu *et al.*,2024). Therefore, this study uses PSO to enhance SA. PSO provides global guidance for SA's neighborhood search by updating particle velocity and position, helping overcome the inefficiency of SA's random walk. The structure of PSO-SA is shown in Figure 2.

As shown in Figure 2, the algorithm first initializes parameters, including core algorithm settings and variables to be optimized in building energy scheduling. According to optimization rules, PSO adjusts device operation parameters through the utilization of personal and global best locations (Demir *et al.*,2023). The algorithm checks whether the termination condition is met. If not, SA performs local fine-tuning to generate neighborhood solutions. If the new solution has lower energy consumption, it is directly accepted. If not, the SA acceptance mechanism is used. This mechanism permits the acceptance of inferior solutions at higher temperatures while enforcing stricter selection criteria at lower temperatures, thereby facilitating the escape from local optima. The algorithm continuously updates the global best solution and finally outputs the optimal scheduling plan. SA simulates the physical annealing process, where high temperatures enable random search and low temperatures lead to convergence (Sylejmani *et al.*,2023). By introducing the Metropolis criterion, the global search capability is enhanced. The Metropolis criterion allows acceptance of solutions with worse objective values under a certain probability, as shown in Equation (5).

$$P = \begin{cases} 1 & \triangle f < 0 \\ exp\left(-\frac{\triangle f}{T}\right) & \triangle f \geq 0 \end{cases} \qquad (5)$$

In Equation (5), P is the chance of accepting a newly generated solution, $\triangle f$ is the difference in objective value. To replicate the temperature decline characteristic of physical annealing, SA adjusts the temperature using a cooling schedule, as defined in Equation (6).

$$T_{k+1} = \alpha \times T_k \qquad (6)$$

In Equation (6), T_k is the temperature at the k -th iteration, and α is the cooling rate. The core of the PSO enhancement lies in the velocity update, calculated by Equation (7).

$$v_{i,d}(t+1) = \omega \cdot v_{i,d}(t) + c_1 r_1 [p_{i,d}(t) - x_{i,d}(t)] + c_2 r_2 [p_{g,d}(t) - x_{i,d}(t)] \qquad (7)$$

In Equation (7), $v_{i,d}(t)$ is the velocity of particle i in the t -th generation and d -th dimension, $x_{i,d}(t)$ is the position. $p_{i,d}(t)$ is the historical best position of particle i, and $p_{g,d}(t)$ is the global best position. ω is the inertia weight. c_1 and c_2 are acceleration constants. The particle position update is defined in Equation (8).

$$x_{i,d}(t+1) = x_{i,d}(t) + v_{i,d}(t+1) \quad (8)$$

Based on the above, the complete flowchart of PSO-SA-MOGWO is shown in Figure 3.

As shown in Figure 3, the algorithm first inputs building parameters, including basic information, energy consumption targets, and comfort requirements. It then initializes algorithm parameters and controls the number of iterations by checking whether the maximum iteration count is reached. MOGWO performs multi-objective optimization guided by the leader wolf to update positions. PSO and SA carry out global exploration and local refinement respectively. The scheduling method is then updated, and the new solution is evaluated using objective functions. If it is better, the archive is updated and the algorithm proceeds to the next iteration. This process gradually approaches the optimal solution. Once the maximum number of iterations is completed, the algorithm outputs the Pareto optimal scheduling scheme. In the modeling process of this study, several key assumptions were set based on typical scenarios: (1) to control algorithm complexity for implementation and comparison, the research assumes that the core parameters of PSO, SA, and MOGWO remain stable or change according to preset rules during the optimization process. (2) To simplify the model construction and facilitate

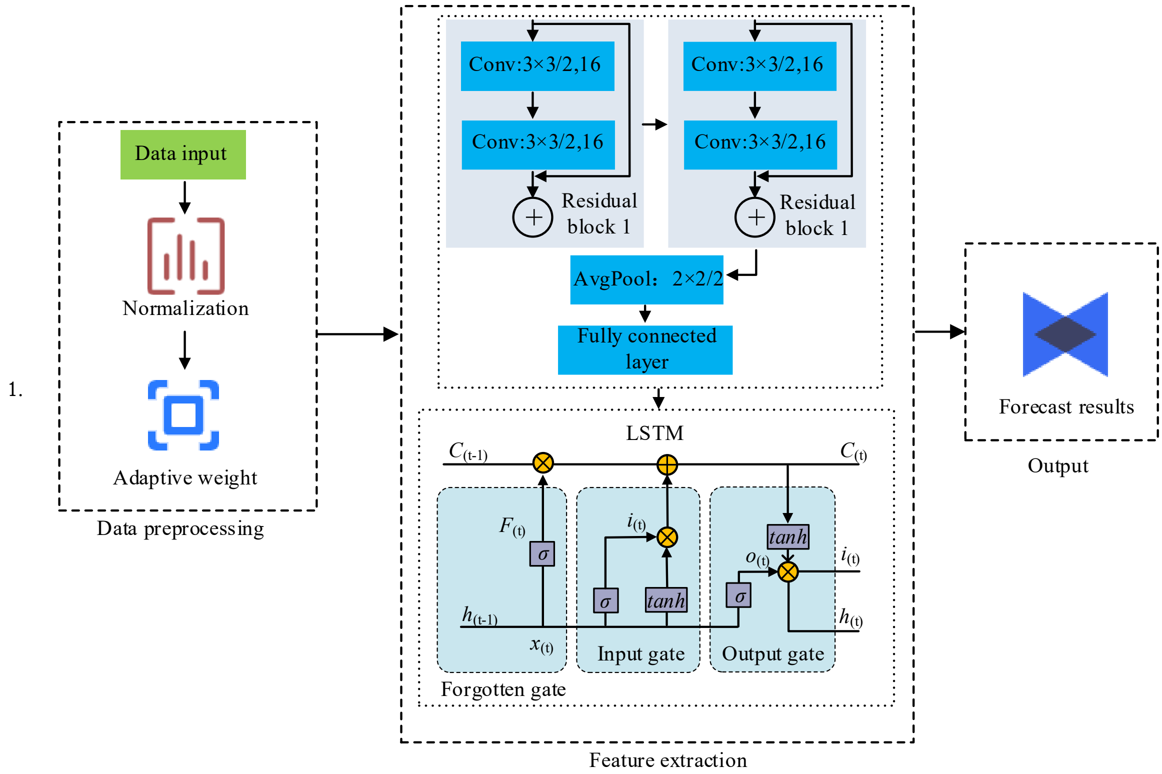


Fig 4 ResNet-LSTM structure diagram (Icon source from: https://www.iconfont.cn/)

quick solving, the model assumes that the efficiency of the energy conversion equipment is constant and ignores its start stop loss and ramp up constraints. (3) Assuming that the input building load, meteorological, and energy price data is complete and accurate.

3.2 The optimization model combining CA-ResNet-LSTM and improved MOGWO

Although the PSO-SA-MOGWO hybrid algorithm finds optimal scheduling schemes under complex constraints, it increases computational cost and algorithmic complexity, and it requires high-quality input data. To address these challenges, this study introduces ResNet-LSTM to enhance the model by extracting spatiotemporal features from energy consumption data, providing accurate prediction and intelligent decision support for energy-efficient scheduling (Lee *et al.*,2024). The workflow of ResNet-LSTM is shown in Figure 4.

In Figure 4, ResNet-LSTM first preprocesses the input data. It takes energy consumption monitoring data from different building zones at different times and applies normalization (Banerjee *et al.*,2024). Then it assigns adaptive weights to the data, emphasizing important information and weakening secondary information. After that, feature extraction is performed. The residual and LSTM modules improve the model's capability to extract features from data and capture energy consumption patterns across different time intervals. ResNet addresses the vanishing gradient issue in deep networks by incorporating residual blocks. Its core equation is shown in Equation (9) (Yu *et al.*,2024).

$$y = F(x, \{W_i\}) + x \tag{9}$$

In Equation (9), x and y represent the input and output features, and $F(x, \{W_i\})$ is the residual function. The forget gate of LSTM is defined in Equation (10) (Usman *et al.*,2023).

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{10}$$

In Equation (10), σ is the Sigmoid function, which compresses values into the $[0,1]$ interval. W_f is the weight matrix of the forget gate. $[h_{t-1}, x_t]$ represents the combination of the previous hidden state and the current input. b_f is the bias term of the forget gate. The input gate controls which information from the current input x_t is added to the cell state. The equation is shown in Equation (11).

$$\begin{cases} i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \\ \tilde{C}_t = tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \end{cases} \tag{11}$$

In Equation (11), W_i and W_c are the weight matrices of the input gate and the candidate cell state. b_i and b_c are their corresponding biases. $tanh$ is the hyperbolic tangent activation function with a range of $(-1,1)$. The cell state is updated according to Equation (12).

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \tag{12}$$

In Equation (12), $\odot$ indicates element-wise multiplication. The output gate determines which information in the cell state C_t is used to generate the current hidden state h_t. The equation is shown in Equation (13).

$$\begin{cases} o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \\ \quad h_t = o_t \, tanh(C_t) \end{cases} \tag{13}$$

In Equation (13), W_o is the weight matrix of the output gate, and b_o is the bias term. Although ResNet-LSTM effectively handles spatiotemporal data in building energy systems, it suffers from low training efficiency, local optima, and unstable gradients

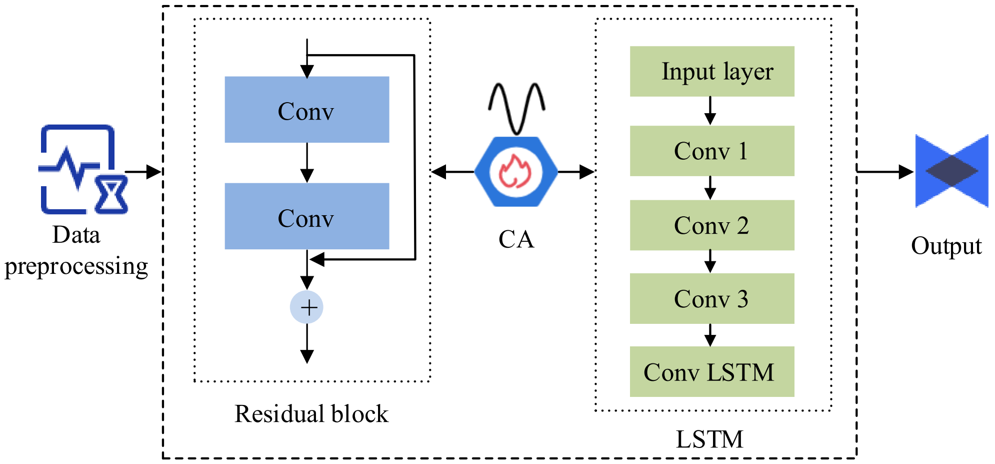


Fig 5 Schematic diagram of the operation process of CA-ResNet-LSTM (Icon source from: https://www.iconfont.cn/)

(Huang *et al.*,2024). To overcome these problems, this study applies CA to optimize the model. The CA-ResNet-LSTM workflow is shown in Figure 5.

As shown in Figure 5, after preprocessing, the algorithm extracts spatiotemporal features from the data. After each iteration, it calculates a new learning rate using the cosine function to coordinate the optimization of ResNet convolution layers and LSTM gate parameters. It then performs periodic restarts to help the model escape local optima. In the early stage, cosine annealing helps LSTM quickly capture energy consumption patterns across day and night. In the later stage, it supports ResNet in adjusting spatial weights across different zones. The final output provides reliable energy predictions for scheduling. The core idea of CA is to simulate the periodic decay of the cosine function to dynamically adjust the learning rate (Zhou *et al.*,2023). This method addresses the drawbacks of traditional learning rate decay, such as slow convergence and local optima. The key equation is shown in Equation (14).

$$\eta_t = \eta\frac{1}{2}\left(\eta min_{max}\left(1+cos\left(\frac{T_{current}}{T_{max}}()\right)()\right)\right)_{min} \quad (14)$$

In Equation (14), η_t is the learning rate at step t $T_{current}$ is the current training step, and T_{max} is the total number of steps in one cycle. To further enhance performance, a restart mechanism is often introduced. After completing one cycle T, the learning rate is reset to η_{max}, and a new decay cycle begins. The restart rule is shown in Equation (15).

$$\eta_t = \eta\frac{1}{2}\left(\eta min_{max}\left(1+cos\left(\frac{t-T_k}{T_{k+1}-T_k}\cdot\pi\right)\right)\right)_{min} \quad (15)$$

In Equation (15), T_k is the iteration number of the k -th restart. The restart mechanism facilitates the algorithm's ability to escape from local optima. The overall flowchart of the building energy-efficient scheduling model based on improved MOGWO and CA-ResNet-LSTM is shown in Figure 6.

As shown in Figure 6, the proposed model, named PSO-SA-IMOGWO, combines CA-ResNet-LSTM and PSO-SA-MOGWO for building energy-efficient scheduling. Firstly, input historical energy consumption, meteorological conditions, and time characteristics, and use the CA ResNet LSTM model for future load forecasting of buildings. The ResNet module is responsible for extracting spatial features of energy consumption data, LSTM is responsible for capturing temporal dependencies, and the CA mechanism is responsible for dynamically adjusting the learning rate to accelerate convergence and avoid local optima. Subsequently, the PSO-SA-MOGWO multi-objective optimization scheduling model takes total energy consumption, operating costs, and comfort deviation as objective functions, and introduces multi energy device constraints. In each iteration, MOGWO performs the dominant search, PSO updates the scheduling scheme based on individual and global optima, SA accepts neighboring solutions using Metropolis criteria to enhance local escape, and maintains solution set diversity using non dominated sorting and grid density. Finally, based on the prediction results of CA ResNet

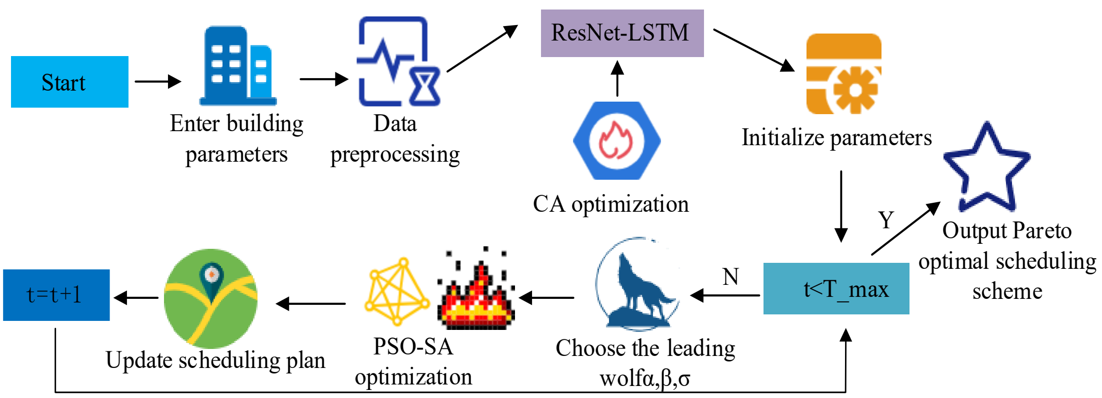


Fig 6 The operation process of the proposed building energy-saving optimization scheduling model (Icon source from: https://www.iconfont.cn/)

LSTM, dynamically adjust the scheduling strategies of renewable energy and energy storage systems, and ultimately output the Pareto optimal solution.

The experimental dataset includes the Honda Research Institute's European Intelligent Building Energy Dataset and the Pecan Street Dataset. Among them, the Honda Research Institute's European Intelligent Building Energy Dataset was collected from 2018 to 2020, covering data from 72 electricity meters, 9 heat meters, and meteorological stations, including operation records of multi energy equipment such as photovoltaics, gas-fired cogeneration, and central cooling systems. The Pecan Street dataset contains electricity consumption, solar power generation, outdoor temperature, and time of use electricity price data for American households from 2017 to 2021. The data is automatically collected through smart meters and sensors, and after cleaning, normalization, and missing value interpolation, it is constructed into standardized time-series samples. Divide the dataset into training set, testing set, and validation set in a ratio of 7:2:1.

4. Result

4.1 Validation of the PSO-SA-MOGWO algorithm

To verify the superiority of the PSO-SA-MOGWO algorithm for building energy-efficient scheduling, this study compared it with three other algorithms: Sparrow Search Algorithm–Genetic Algorithm (SSA-GA), Improved Satin Bowerbird Optimizer–Radial Basis Function (ISBO-RBF), and Non-dominated Sorting Genetic Algorithm II–Differential Evolution (NSGA-II-DE). The experimental environment used Windows 10 with a Linux 5.15.133 kernel, the deep learning framework was PyTorch, the optimizer was Adam, and the programming language was Python 3.10.12. The hardware configuration included an NVIDIA RTX 3080 GPU and 10 GB of memory. The experimental datasets included the Honda Research Institute Europe smart building energy dataset and the Pecan Street dataset. According to the standard strategy, the acceleration constant of PSO was set to 2.0, the initial temperature of SA was set to 1000, the convergence factor was set to 2 → 0, the maximum number of iterations was set to 1000, the epoch was set to 500, the batch_size was set to 64, the initial learning rate was set to 0.01, and the Adam optimizer was used. To evaluate the impact of key parameters on model performance, this study also designed parameter sensitivity experiments for the system. On the Pecan Street dataset, the control variable method was used to test five core parameters: PSO inertia weight, SA cooling rate, and MOGWO population size. Select 3 different values for each parameter within a reasonable range, and fix the other parameters as benchmark values (inertia weight of 0.9 → 0.4, cooling rate of 0.95, population size of 50). The evaluation indicators include energy-saving rate, convergence time, and absolute error. The results of parameter sensitivity analysis are shown in Table 1.

From Table 1, it can be seen that using a linear decreasing strategy of 0.9→0.4 for the inertia weight of PSO yields the best results. This may be because a higher initial inertia weight helps with global exploration, while a later decrease is beneficial for local fine search, in line with the design principles of dynamic balance search strategy (Choudhary *et al.*,2023). In contrast, if the inertia weight is too high (1.2→0.6), although it maintains strong exploration ability, the convergence time is significantly prolonged, indicating that parameter settings need to strike a balance between exploration and development. When the cooling rate of SA is 0.95, the optimal balance between solution mass and computational efficiency is achieved. A MOGWO population size of 50 is optimal for performance. A population size that is too small (N=30) can lead to insufficient diversity and decreased performance, while a population size that is too large (N=70) can result in doubled computational costs. To evaluate the practical performance of the PSO-SA-MOGWO, the study compared its processing time, memory usage, and energy consumption reduction rate with those of SSA-GA, ISBO-RBF, and NSGA-II-DE. All comparison algorithms are based on fair comparison of the same dataset partition and random seeds. The results are shown in Table 2.

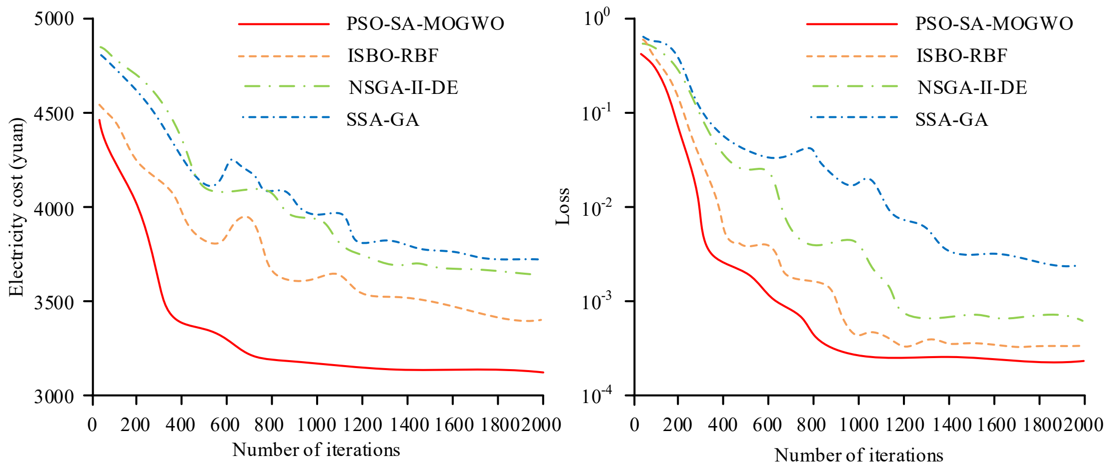
Table 1
Parameter sensitivity analysis results

Parameter	Value retrieval	Energy saving rate/%	Convergence time/s	Absolute error
Inertial weight	0.6→0.2	11.82	14.06	0.32
	0.9→0.4	13.31	11.98	0.28
	1.2→0.6	12.09	15.88	0.35
Cooling rate	0.90	12.24	10.14	0.31
	0.95	13.31	12.20	0.28
	0.98	13.08	18.11	0.29
Population size	30	12.04	8.04	0.33
	50	13.31	12.23	0.28
	70	13.37	20.86	0.27

As shown in Table 2, in the Honda dataset, the PSO-SA-MOGWO algorithm had the shortest computation time of 13 min, used 673 MB of memory, and achieved a 24.7% reduction in energy consumption. In contrast, the SSA-GA took 12 min longer, used 574 MB more memory, and only reduced energy consumption by 15.6%. In the Pecan Street dataset, PSO-SA-MOGWO completed processing in 12 s, used 89 MB of memory, and achieved a 13.3% reduction in energy consumption. ISBO-RBF also achieved a reduction rate above 10% but required 15 s and 114 MB of memory. The results indicate that the PSO-SA-MOGWO algorithm has good real-time processing potential while maintaining high optimization accuracy, which may be attributed to the collaborative mechanism of PSO's global guidance and SA's local optimization, effectively avoiding the problem of traditional multi-objective algorithms easily falling into local optima (Wei *et al.*, 2025). To further demonstrate the advantages of PSO-SA-MOGWO, all four algorithms were trained on the Pecan Street dataset to compare convergence and scheduling performance. The results are shown in Figure 7.

Table 2
Performance comparison of four algorithms in different datasets

Dataset	Algorithm	Processing time	Usage memory (MB)	Energy consumption reduction rate (%)
Honda	PSO-SA-MOGWO	13 min	673	24.7
	SSA-GA	25 min	1247	15.6
	ISBO-RBF	19 min	952	20.1
	NSGA-Ⅱ-DE	18 min	1032	18.3
Pecan Street	PSO-SA-MOGWO	12 s	89	13.3
	SSA-GA	12 s	103	7.6
	ISBO-RBF	15 s	114	10.4
	NSGA-Ⅱ-DE	14 s	107	9.7



(a) The electricity cost after four algorithm iterations (b) Loss function curves of four algorithms

Fig 7 Comparison of algorithm convergence and optimization scheduling capabilities

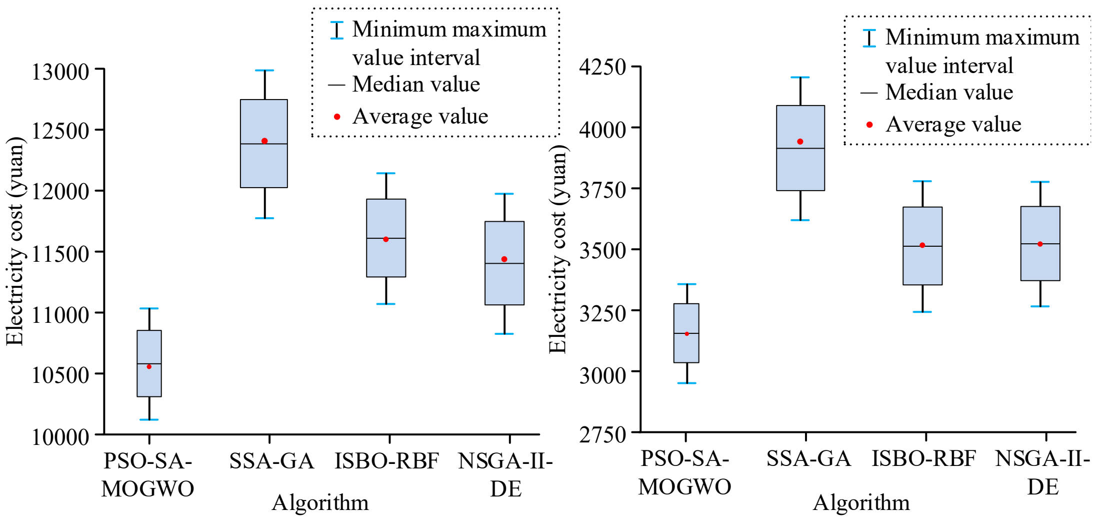
As shown in Figure 7, the PSO-SA-MOGWO algorithm stabilized after 800 iterations, with electricity cost maintained at 3150 yuan and loss values ranging between 10^{-4} and 10^{-3}. Its convergence speed was 42.86% faster than the slowest SSA-GA. The ISBO-RBF algorithm reached 3500 yuan after 1200 iterations. Other algorithms had slower loss function declines and still performed worse than PSO-SA-MOGWO after 1000 iterations, mainly due to their tendency to fall into local optima. Overall, PSO-SA-MOGWO demonstrated faster convergence and lower electricity cost, which may be attributed to the combination of PSO's group collaboration mechanism and SA's annealing acceptance strategy, helping the algorithm to jump out of local optima in the early stages and accelerate its approach to the Pareto front (Rafay *et al.*, 2025). To evaluate the robustness of the PSO-SA-MOGWO algorithm, robustness tests were conducted in comparison with the other algorithms. The results are shown in Figure 8.

In Figure 8, the PSO-SA-MOGWO achieved the lowest electricity cost in both datasets. In the Honda dataset, it maintained an average electricity cost of 10,500 yuan. The box plot was narrow and the whiskers were short, indicating high result stability and strong robustness. The SSA-GA performed the worst, with higher electricity cost and longer whiskers, indicating greater result fluctuation and weak robustness. ISBO-RBF and NSGA-II-DE showed similar, moderate performance. In conclusion, PSO-SA-MOGWO achieved both low energy consumption and strong robustness, making it the best among the four algorithms.

4.2 Evaluation of the improved scheduling model for building energy efficiency

After verifying the superior performance of the PSO-SA-MOGWO algorithm, the study further evaluated the practical application of the PSO-SA-IMOGWO model for building energy-efficient scheduling. The PSO-SA-IMOGWO model was compared with the ISBO-RBF, NSGA-II-DE, and SSA-GA models. The Honda dataset was used, the experimental environment remained unchanged, and the scheduling results are shown in Figure 9.

In Figure 9, the PSO-SA-IMOGWO model achieved the highest usage of photovoltaic and wind power during daytime hours, maximizing the use of renewable energy and reducing



(a) Comparison of robustness of four algorithms in Honda box plot (b) Comparison of robustness of four algorithms in Pecan Street box plot

Fig 8 Robustness comparison of four algorithms

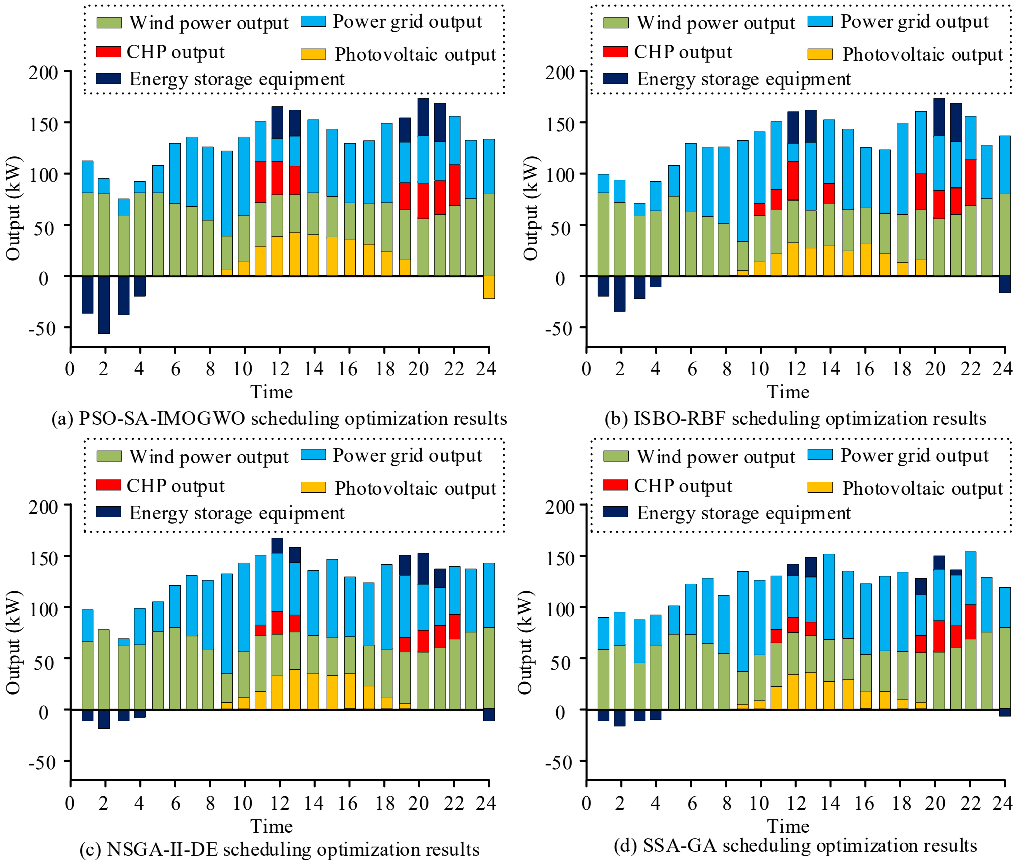


Fig 9 Comparison of scheduling optimization

dependence on traditional sources. Energy storage was concentrated between 22:00 and 4:00, and released during daytime low-demand periods. In contrast, the SSA-GA model had a lower proportion of photovoltaic and wind power, indicating a more conservative renewable energy scheduling strategy. The NSGA-II-DE model showed large fluctuations in energy storage charging and discharging, reflecting poor

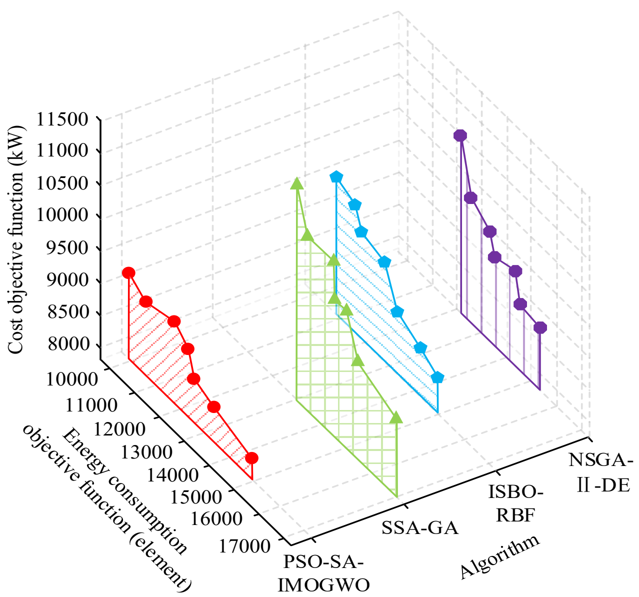
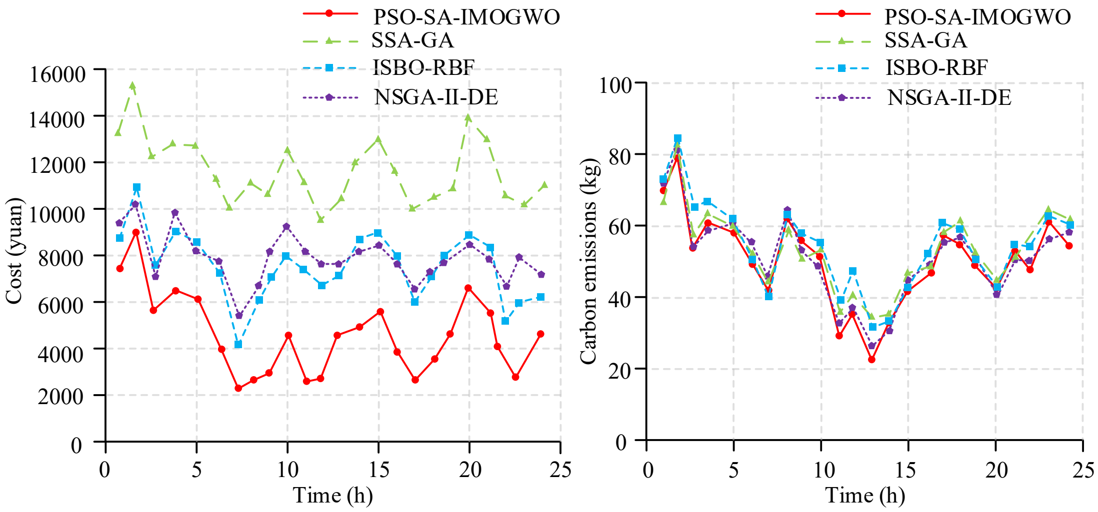


Fig 10 Comparison of results under dual-objective optimization objectives

scheduling stability. In summary, the PSO-SA-IMOGWO model more efficiently coordinated multi-energy complementarity, achieving better carbon reduction and energy savings. To evaluate the performance of PSO-SA-IMOGWO in multi-objective optimization, the four models were tested for their ability to balance energy consumption and cost. The results are shown in Figure 10.

In Figure 10, the PSO-SA-IMOGWO model achieved the best balance between energy consumption and cost. Its overall curve was closest to the coordinate origin. When the energy consumption target was 10,500 yuan, the cost was 9500 yuan. When the energy consumption target increased to 15,000 yuan, the cost decreased to 8100 yuan. In contrast, SSA-GA and NSGA-II-DE had more scattered distributions, and showed cases where energy consumption was reduced but cost increased. The PSO-SA-IMOGWO model performed better in building multi-objective energy-efficient scheduling because MOGWO effectively balanced objectives such as energy consumption, cost, and comfort. In conclusion, PSO-SA-IMOGWO simultaneously reduced energy use and controlled cost, demonstrating excellent performance. To further evaluate the dynamic scheduling ability of the PSO-SA-IMOGWO model, the study conducted low-carbon and economic cost tests in comparison with the other models. The results are shown in Figure 11.

As shown in Figure 11, within the 24-hour period, the PSO-SA-IMOGWO model consistently achieved the lowest minimum cost at each time point and maintained relatively low carbon emissions. When the minimum carbon emission was 21 kg, the minimum cost was 4500 yuan. The ISBO-RBF and NSGA-II-DE models had higher minimum costs over long periods, and their curves were more scattered. The SSA-GA model showed the



(a) Minimum cost comparison chart under different scheduling models
(b) Minimum carbon emissions comparison under different scheduling models

Fig 11 Comparison of minimum cost and carbon emissions

highest minimum cost and did not perform well in reducing carbon emissions. In summary, the PSO-SA-IMOGWO model successfully balanced the economic and low-carbon requirements of building energy scheduling.

5. Discussion

This study study proposes an efficient scheduling method based on MOGWO and establishes a multi-objective optimization model considering building energy consumption, indoor comfort, and operational cost. This model integrated a building load forecasting module and equipment constraints. The MOGWO algorithm was improved by introducing PSO and SA, which enhanced convergence speed and solution diversity in multi-objective spaces. In addition, a CA-optimized ResNet-LSTM was used to support building load prediction, enabling multi-objective optimization for energy saving. The results showed that PSO-SA-MOGWO improved convergence speed by 42.86% compared with SSA-GA, produced more evenly distributed solutions, and required only 89 MB of memory. For large buildings, the memory usage was 673 MB. In the Pecan Street dataset, the response time was only 12 s. In addition, on the larger Honda dataset, the memory usage is 673 MB, still maintaining high computational efficiency. Compared with existing research, this study has shown significant progress in method fusion and actual scheduling effectiveness. For example, the multi-level optimization strategy proposed by Tang *et al.* (2022) has a high complexity and does not deeply integrate the prediction module. Zhang et al. (2024) designed a two-stage robust optimization model for managing an electricity-heat-gas-cooling system, which effectively enhanced the renewable energy consumption capacity. However, its solution process typically involves a heavy computational burden. Li et al. (2022) constructed an active distribution network energy management model based on detailed building thermodynamics and human activity patterns, but did not conduct in-depth optimization in terms of algorithm convergence speed and computational resource efficiency. The PSO-SA-MOGWO model proposed in this study achieves finer flexibility scheduling while maintaining lower complexity through algorithm mixing and prediction scheduling closed loop. The quality flow model established by Zheng *et al.* (2023) has limitations in handling multi-objective collaboration and dynamic adaptability. In contrast, this study introduces CA ResNet LSTM for load and renewable energy output prediction and combines multi-objective optimization to dynamically adjust scheduling strategies, enhancing the adaptability to energy randomness and achieving a better balance between economic and low-carbon goals.

The theoretical contribution of this study is mainly reflected in the proposal of a multi algorithm collaborative hybrid optimization architecture and a prediction scheduling integrated modeling framework, which effectively solves the problems of multi-objective conflicts and dynamic system adaptability, providing theoretical support for dynamic scheduling. Through algorithm innovation and model integration, this study provides a new methodology for the transformation from single objective optimization to multi-objective collaborative scheduling in the field of building energy dispatch, promoting the development of intelligent building energy management theory. The proposed PSO-SA-IMOGWO model has broad application prospects in fields such as intelligent building energy management and regional multi energy collaborative scheduling. In practical applications, the model can be embedded in building energy management systems or regional energy coordination platforms, but parameter calibration needs to be carried out based on specific building types, equipment characteristics, and local energy policies, and interface integration with existing monitoring and control systems needs to be considered. In addition, the model is sensitive to the quality of input data, and corresponding data cleaning and anomaly detection modules need to be equipped in actual deployment.

6. Conclusion

Overall, the proposed PSO-SA-IMOGWO model effectively coordinates multiple objectives such as economic cost and energy efficiency, and has significant advantages in energy-saving effect, response speed, and computational efficiency, providing a reliable technical foundation for real-time energy scheduling in intelligent buildings. However, the adaptability of the model under extreme weather conditions is still insufficient, and the handling of the randomness of renewable energy is relatively simplified. Therefore, future work should introduce robust optimization mechanisms to further enhance the stability of the model in extreme scenarios, and combine stochastic programming theory to improve the modeling of wind and solar power output uncertainty.

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