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Energy-Saving Optimization Methods for Central Air-Conditioning Systems Based on a Combined Long Short-Term Memory Neural Network and Cuckoo Search Algorithm

Tiezhu Sun^{1,*}, Pengfei Lai¹, Guangyu Tian¹, Linnan Lei¹, Zhihua Wang², Suoying He³ and Muzaffar Ali⁴

¹School of Urban Planning and Municipal Engineering, Xi'an Polytechnic University, Xi'an, China

²School of Human Settlements and Civil Engineering, Xi'an Jiaotong University, Xi'an, China

³School of Nuclear Science, Energy and Power Engineering, Shandong University, Jinan, China

⁴Energy Engineering Department, University of Engineering and Technology, Taxila, Pakistan

*Corresponding Author: Tiezhu Sun. Email: suntiezhu@xpu.edu.cn

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ABSTRACT: This study presents an integrated optimization framework that combines long short-term memory (LSTM) load forecasting with hybrid optimization to improve the energy efficiency of central air-conditioning cooling-source systems. Grey-box energy consumption models are first established for chillers, pumps, and cooling towers based on their underlying operating mechanisms, with model parameters identified using the least-squares method. An LSTM model is subsequently trained using 96 days of hourly operational data to predict the short-term cooling load, achieving a root mean square error of 9.7 kW. The predicted cooling load is then used to constrain the system-level optimization. The chiller part-load ratio is determined using a maximum-coefficient-of-performance lookup-table approach, while the chilled-water flow rate, cooling-water flow rate, and cooling-tower airflow rate are optimized using the Cuckoo Search algorithm to minimize total system energy consumption. Application to a typical operating day at a pharmaceutical manufacturing facility demonstrates that the optimized strategy reduces the energy consumption of the chillers, pumps, and cooling-tower fans by 9.4%, 10.6%, and approximately 20%, respectively, resulting in an overall system energy saving of nearly 10%.

KEYWORDS: Central air-conditioning system; long short-term memory network; cuckoo search algorithm; energy-saving optimization; load forecasting

1 Introduction

Amid persistently escalating global energy demand and increasingly severe climate change, energy consumption in the building sector has become a core concern of the international academic community and policymakers. According to statistics from the International Energy Agency, energy used in building operations accounts for approximately 30% of total global final energy consumption, concurrently building operations are responsible for nearly 40% of energy-related CO₂ emissions [1]. Within the composition of building energy consumption, heating, ventilation, and air conditioning systems represent the largest energy end-use, with their share reaching 40%–60% of total building energy consumption in large commercial buildings [2]; the situation is equally pronounced in industrial plants [3]. As the core energy-consuming unit that ensures indoor thermal comfort and process environment stability, the operational efficiency

of central air-conditioning systems directly determines the overall energy consumption level and carbon emission intensity of a building [4].

A central air-conditioning system is intrinsically a typical complex thermodynamic system characterized by nonlinearity, strong multivariable coupling, and large time delays; its dynamic operating characteristics are jointly influenced by multiple intertwined factors, including time-varying disturbances in building loads, fluctuations in outdoor weather parameters, equipment performance degradation, and coupling effects of control strategies [5]. Traditional control strategies mostly rely on fixed setpoints or simple feedback regulation, lacking the capability for adaptive perception of global system states and predictive optimization, and thus fail to capture dynamic variations in loads and environmental conditions [5]. As a result, equipment operates outside high-efficiency regions for prolonged periods, causing the system's overall coefficient of performance (COP) and seasonal energy efficiency ratio to be significantly lower than design values [6]. Therefore, conducting in-depth research on energy-saving optimal control of central air-conditioning systems is of pressing theoretical necessity and significant engineering practical value for enhancing building energy efficiency, reducing operational carbon emissions, and supporting global carbon neutrality goals [7].

In the regulation and operational management of central air-conditioning systems, data-driven methods have been widely applied to load forecasting and unit loading optimization. The long short-term memory (LSTM) neural network, by virtue of its advantages in processing time-series data, can effectively capture the long-range dependencies and nonlinear characteristics of air-conditioning loads and has been extensively used in load forecasting tasks. Kondath et al. [8] proposed a deep-learning-based day-ahead cooling load forecasting method; by analyzing the cross-correlations between outdoor meteorological parameters such as temperature, humidity, and wind speed and building cooling loads, they confirmed that temperature-related parameters exert a dominant effect on the load, while wind speed and other parameters also exhibit significant periodic correlations. Asamoah et al. [9] compared the performance of neural networks and random forest in building heating and cooling load prediction, and the results demonstrated that neural networks achieve superior accuracy and fitting performance when processing multidimensional complex data. Irshad et al. [10] employed a data-driven method to forecast short-term heating and cooling loads based on diverse building characteristic data, confirming the method's high accuracy and low mean absolute error. Geng Yang et al. [11] introduced an error compensation model into an LSTM-GRU hybrid network for cooling and heating load prediction in integrated energy systems, achieving higher accuracy than other machine learning methods and meeting engineering requirements. Despite these advances, existing load forecasting studies are mostly concentrated on specific building types under particular climatic conditions, and their generalization capability across different building types and climate zones still needs to be sufficiently validated.

In the pursuit of dynamic optimization and closed-loop regulation, advanced modeling and control strategies have been extensively investigated for air-conditioning systems beyond conventional load forecasting. Kang et al. [12] developed a demand response framework through indoor temperature setpoint adjustments, demonstrating that approximately 40% of the rated cooling load can be shed during peak events while achieving notable energy savings, thereby confirming the practical value of predictive control. At the equipment level, Arahal et al. [13] integrated the transient start-stop dynamics of chillers into the optimization problem and employed a simultaneous perturbation stochastic approximation method, achieving substantial reductions in system energy consumption. To address the issue of data scarcity, subsequent studies [2] embedded physical prior knowledge by constructing neural networks with monotonic constraints, and the proposed approach was successfully validated in data center cooling plants, showing

improved generalization under limited training samples. In terms of system-level optimization, model predictive control has been introduced and benchmarked against conventional PID and linear quadratic regulation, with results confirming its enhanced setpoint tracking and disturbance rejection performance [14]. Further advances have combined MPC with collaborative neurodynamic optimization to handle mixed-integer programming problems involving binary and continuous variables, and this integrated strategy has demonstrated superior energy performance across multiple chiller configurations [15]. Moreover, a hierarchical hybrid MPC scheme tailored for subway station cooling plants [16] and a distributed chiller loading strategy based on neurodynamic optimization [17] have been proposed to address heterogeneous unit coordination. Nevertheless, these advanced control approaches generally rely on high-fidelity system models and substantial computational overhead, and their reported performances are predominantly based on steady-state simulations or single-site case studies. Consequently, achieving deep coupling and closed-loop implementation of high-precision models with adaptive predictive controllers in real-world building systems remains a critical bottleneck, which precisely motivates the present research.

Despite significant progress, three progressive gaps remain. First, system-level energy consumption modeling is absent: existing studies analyze individual equipment without integrating chillers, pumps, and cooling towers into a unified coupling framework. Second, LSTM-based load forecasting models suffer from predicting without decision-making—typically trained offline with fixed weights, they struggle with data distribution shifts due to equipment degradation or extreme weather, limiting real-time applicability. Third, optimization algorithms and forecasting models are disconnected: prior work either develops forecasting models without embedding them into optimization, or designs optimizers based on simplified or static load assumptions, resulting in no bidirectional data interaction between prediction and decision. To bridge these gaps, the cuckoo search algorithm, with its strong global optimization capability, is introduced to precisely convert LSTM forecasts into executable optimal control commands, thus simultaneously fulfilling prediction and optimization requirements.

In summary, this paper takes the central air-conditioning cooling source system of a pharmaceutical production base as the research object, focusing on the chilled water system (including chillers, chilled water pumps, cooling water pumps, and cooling towers). First, energy consumption models for each component are established based on equipment mechanisms, and the model parameters are identified using the least squares method. Second, an LSTM-based cooling load forecasting model is constructed to enable high-precision short-term forecasting of future loads. Then, the cuckoo search algorithm is introduced to perform global cooperative optimization of system operating parameters. The results show that this optimization method can significantly improve system energy efficiency, achieving a total energy consumption reduction of approximately 10%. This study validates the feasibility and effectiveness of the proposed “prediction–optimization” closed-loop strategy in actual complex systems, laying a theoretical foundation and providing methodological support for the intelligent regulation and energy-saving operation of air-conditioning systems.

2 Problem Description

The central air-conditioning system is extremely complex, characterized by nonlinearity, multiple variables, and significant time delays, and primarily consists of the chilled water system, the cooling water system, and the variable air volume system [18]. This paper focuses on the chilled water system as the research object. As shown in Fig. 1, the system is mainly composed of chillers, chilled water pumps, cooling water pumps, and cooling towers, which work cooperatively to accomplish heat transfer and dissipation [19,20].

The core operating principle of the conventional central air-conditioning cooling source system lies in the coordination between the chilled water system and the cooling water system, with the chiller serving as the medium to complete heat transfer and ultimate dissipation [21]. The chilled water cycle begins at the chiller evaporator, where low-temperature chilled water is delivered to various heat exchange terminals in the building. Through sensible heat exchange with indoor air via cooling coils, the chilled water absorbs heat, and its temperature rises before returning to the evaporator. Inside the evaporator, the low-temperature, low-pressure liquid refrigerant evaporates, absorbing the heat carried back by the chilled water and recooling it to the designed supply water temperature. This process continuously provides cooling capacity to the building.

The cooling side is an open-loop circulation system, with cooling water as the working medium, responsible for dissipating the condensation heat generated by the chiller to the atmosphere. High-temperature cooling water exiting the condenser is sent to the open cooling tower, where it flows through the fill packing and undergoes counterflow or crossflow heat and moisture exchange with outdoor air. A portion of the water evaporates, carrying away substantial latent heat [22], thereby transferring heat from the cooling water to the air. After its temperature decreases, the water falls into the collection basin and is then pumped back to the condenser [23].

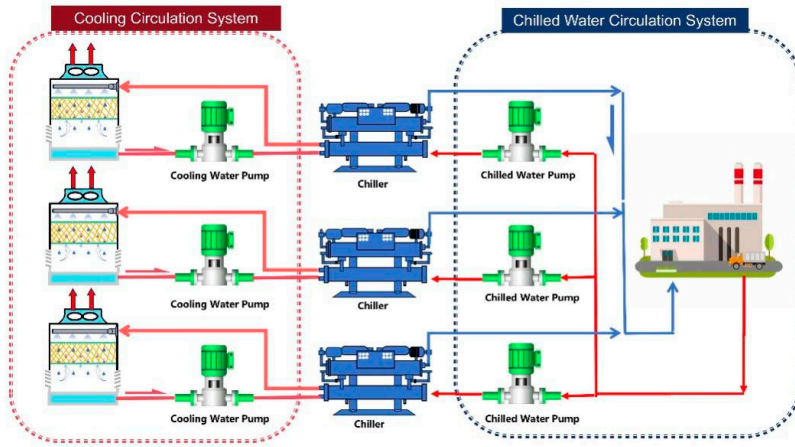


Figure 1: Schematic diagram of the central air-conditioning water system.

In this process, the main energy-consuming components are the chiller, cooling tower, cooling water pump, and chilled water pump [24]. Therefore, it is necessary to establish energy consumption models for each, as described below.

$$P_{ch} = a_0 + a_1(T_{cws} - T_{chws}) + a_2(T_{cws} - T_{chws})^2 + a_3Q_e + a_4Q_e^2 + a_5Q_e(T_{cws} - T_{chws}) \quad (1)$$

$$P_{chp} = f_1 + f_2G_{chp} + f_3G_{chp}^2 \quad (2)$$

$$P_{cp} = g_1 + g_2G_{cp} + g_3G_{cp}^2 \quad (3)$$

$$G_{cp} = \frac{3600Q_{con}}{\rho_w c \Delta T_{cw}} \quad (4)$$

$$P_{fan} = d_0 + d_1 \cdot PLR + d_2 \cdot PLR^2 + d_3 \cdot PLR^3 \quad (5)$$

where P_{ch} is the chiller power consumption kW, T_{cws} is the cooling water inlet temperature °C, T_{chws} is the chilled water supply temperature °C; Q_e is the chiller cooling load (kW); and $a_0, a_1, a_2, a_3, a_4, a_5$ are model parameters. P_{chp} is the chilled water pump power consumption (kW); G_{chp} is the chilled water flow rate (m³/h); and f_1, f_2, f_3 are model parameters. P_{cp} is the cooling water pump power consumption (kW); G_{cp} is the cooling water flow rate (m³/h); c is the specific heat capacity of water (kJ/(kg·K)); ρ_w is the density of water (kg/m³); Q_{con} is the condensation heat (kW); ΔT_{cw} is the cooling water temperature difference; and g_1, g_2, g_3 are model parameters. P_{fan} is the cooling tower fan power consumption (kW); PLR is the part-load ratio of the fan; and d_0, d_1, d_2, d_3 are model parameters (Table 1).

Table 1: Identified model parameters for cooling source equipment.

Equipment	Parameters	Values	R ²
Chiller	$a_0, a_1, a_2, a_3, a_4, a_5$	6.3609, 4.24496, -0.18695, -0.06207, 0.00001, 0.00918	0.92769
Chilled water pump	f_1, f_2, f_3	4.76812, -0.02575, 0.0002387	0.95695
Cooling water pump	g_1, g_2, g_3	16.0723, -0.0524, 0.0001843	0.94024
Cooling tower fan	d_0, d_1, d_2, d_3	-33.15615, 58.33788, -11.30292, 0.5943	0.95205

The adequacy of the equipment energy models was evaluated using the coefficient of determination (R²) after least-squares identification. The chiller, chilled-water pump, cooling-water pump, and cooling-tower models obtained R² values of 0.92769, 0.95695, 0.94024, and 0.95205, respectively, indicating that the fitted models meet the accuracy requirements for subsequent optimization.

To ensure the physical consistency of the optimization model, the energy balance and hydraulic-thermal coupling relationships among the components must be satisfied. The specific equality constraints are formulated as follows:

Cooling Load Balance Constraint: The cooling capacity provided by the chillers must satisfy the building cooling load demand predicted by the LSTM model. **Condenser Heat Rejection Constraint:** The heat rejected by the cooling tower must equal the sum of the chiller's cooling capacity and the compressor power consumption [25] **Cooling Tower Thermal Coupling Constraint:** The cooling water inlet temperature is coupled with the outdoor wet-bulb temperature and the fan performance [26]. This is governed by the heat transfer equation of the cooling water side [27]:

$$Q_e = \frac{c \cdot \rho_w \cdot G_{chp} \cdot (T_{chw,r} - T_{chws})}{3600} \quad (6)$$

$$Q_{con} = Q_e + P_{ch} = \frac{c \cdot \rho_w \cdot G_{cp} \cdot (T_{cw,out} - T_{cws})}{3600} \quad (7)$$

$$T_{cws} = T_{wb} + \frac{T_{cw,out} - T_{wb}}{\exp(K \cdot G_{air}(t)^n / G_{cp})} \quad (8)$$

where Q_e is the predicted cooling load at time c and ρ_w are the specific heat capacity and density of water, respectively; G_{chp} is the chilled water flow rate; $T_{chw,r}$, and T_{chws} are the return and supply temperatures of the chilled water, respectively. Q_{con} is the condenser heat load; P_{ch} is the power consumption of the chiller;

G_{cp} is the cooling water flow rate; $T_{cw,out}$ and T_{cws} are the outlet and inlet temperatures of the cooling water, respectively. where T_{wb} is the outdoor wet-bulb temperature; G_{air} is the cooling tower air flow rate; K and n are characteristic coefficients of the cooling tower determined by regression.

The process of adjusting the operation of the central air-conditioning (CAC) system according to the cooling load demand is essentially a process of searching for the optimal solution through an optimization algorithm. By adjusting the operating parameter values of the CAC system, the optimization algorithm minimizes the energy consumption of different equipment in the system [28]. Its core is to solve the extreme value of a nonlinear multivariate function under a set of equality and inequality constraints. Specifically, it aims to find the minimum total energy consumption of the CAC system under the corresponding constraints [29].

Therefore, the objective function and constraints are as follows:

$$\begin{cases} \min P_{total} = \min(P_{chiller} + P_{chp} + P_{cp} + P_{fan}) \\ Q_{e,min} \leq Q_e \leq Q_{e,max} \\ T_{cwi,min} \leq T_{cwi} \leq T_{cwi,max} \\ G_{chp,min} \leq G_{chp} \leq G_{chp,max} \\ G_{cp,min} \leq G_{cp} \leq G_{cp,max} \\ G_{fan,min} \leq G_{fan} \leq G_{fan,max} \end{cases} \quad (9)$$

where $\min P_{total}$ is the minimum total energy consumption of the central air-conditioning cooling source system; $P_{chiller}$ is the chiller power consumption; P_{chp} is the chilled water pump power consumption; P_{cp} is the cooling water pump power consumption; P_{fan} is the cooling tower fan power consumption; Q_e is the chiller cooling capacity; T_{cwi} is the cooling water inlet temperature; subscripts min and max denote the minimum and maximum allowable values, respectively; G_{chp} is the chilled water flow rate (m^3/h); G_{cp} is the cooling water flow rate (m^3/h); and G_{fan} is the cooling tower fan airflow rate (m^3/h).

3 Optimization Method

3.1 Data Foundation and Sample Construction

The data used in this study originate from the actual operational monitoring of the central air-conditioning cooling source system at a pharmaceutical production base. A continuous 96-day period of hourly load values after June 15th was selected as the initial total sample, i.e., hourly load data from June 15th to September 18th. Within the sample period, as temperature and humidity rose from June to July, the load gradually increased and reached its annual peak from late July to August. From the perspective of diurnal variation, the load curve exhibits significant day–night peaks and valleys, forming a daily load peak in the afternoon due to the full operation of production equipment and rising outdoor temperatures, while maintaining a relatively low base load at night. The variation of the air-conditioning load during the sample period is shown in Fig. 2a.

For the division of model input and output data, a sliding window method is adopted to construct input-output samples, where each sample uses 7 consecutive days of historical hourly load data as input to predict the 24-h hourly cooling load of the next day. To preserve the temporal causality of time-series prediction, a temporal split strategy is applied to divide the 96-day dataset: the first 80% of the continuous sample period is used as the training set for model training and parameter updating, while the last 20% of the continuous period serves as the test set to evaluate the generalization performance and prediction accuracy of the model. The temporal order of all samples is strictly preserved throughout the division

process to ensure no future information is introduced into the training phase. The division method is illustrated in Fig. 2b:

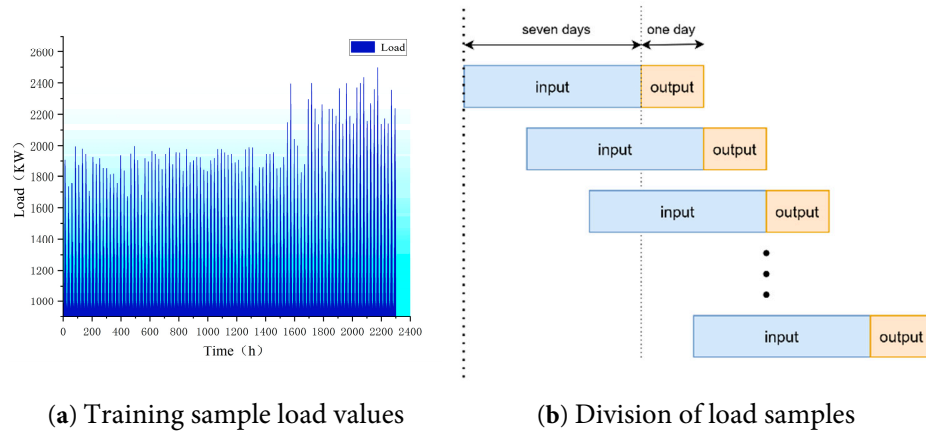


Figure 2: Training samples and partitioning method of load data (a,b).

3.2 Collaborative Optimization Framework of LSTM and CS Algorithm

The energy-saving optimization process proposed in this paper is illustrated in Fig. 3. Based on historical operation data, unknown parameters are identified using the parameter identification method. Subsequently, an energy-saving optimization model for the central air-conditioning (CAC) water supply system is established, and the operational constraints of each equipment in the CAC system are analyzed. The load prediction results are taken as one of the constraint conditions, and the air-conditioning operating parameters are adjusted in advance according to future cooling load demands to meet cold source supply requirements while achieving optimal energy-saving effects. By optimizing the system operating parameters, the cuckoo search optimization algorithm is finally applied to the actual air-conditioning system.

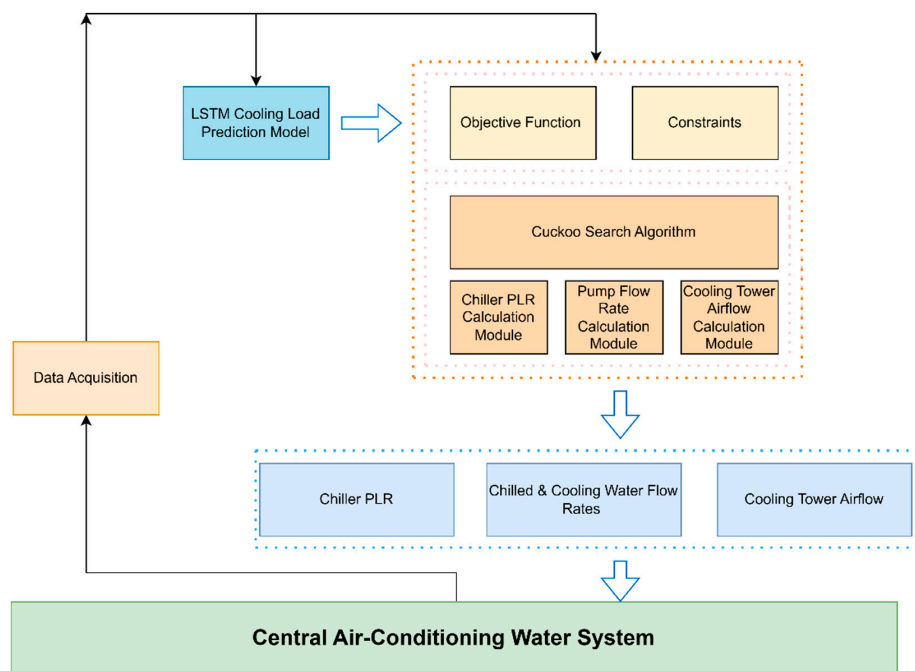


Figure 3: Framework of the energy-saving method for central air-conditioning water systems.

3.3 Coupling of LSTM Prediction and Cuckoo Search Algorithm

The LSTM network, owing to its unique gating mechanism (forget gate, input gate, output gate), can effectively capture the long-term dependencies and nonlinear characteristics inherent in air-conditioning load sequences [30]. The model constructed in this study adopts a sequential LSTM structure and is implemented using the Keras framework. The network consists of two LSTM layers, with 50 neurons in each layer. The first LSTM layer is configured with `return_sequences = True` to output the complete time series for processing by the second layer; the second LSTM layer outputs the hidden state of the last time step by default. Finally, the predicted value is generated through a fully connected layer. During model compilation, the mean squared error (MSE) is selected as the loss function, and the Adam optimizer is adopted to balance training efficiency and convergence stability. During the training process, the total samples are divided into a training set and a test set in an 8:2 ratio, the batch size is set to 16, and the number of training epochs is set to 10.

After completing the data sample division, the LSTM model was used to predict the load for 15 consecutive days. The results show that although the measured load data exhibited large fluctuations during the observation period, the calculated root mean square error (RMSE) was only 9.7 kW, indicating a small absolute deviation between predicted and actual values. Furthermore, the error did not increase with the magnitude of the load value. The experimental results are presented in Fig. 4, demonstrating that the model possesses excellent overall adaptability.

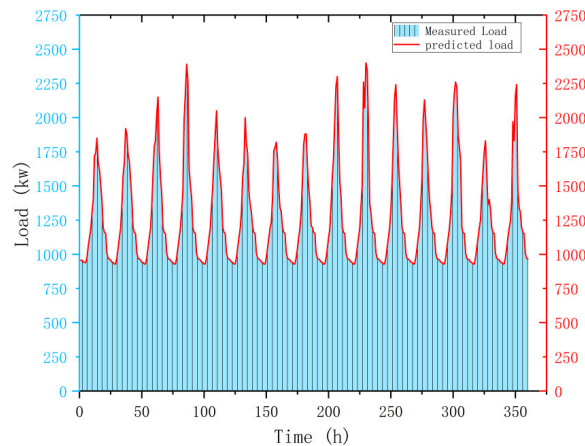


Figure 4: Comparative analysis of prediction results.

After obtaining reliable load prediction values, it is necessary to select appropriate optimization variables. The selection of optimization variables follows three principles: first, they have a significant impact on the operational energy efficiency of the cold source system; second, they are easily adjustable in actual system operation; third, they are relatively independent and conducive to solving the objective function. Based on these principles, this study selects the chilled water flow rate, cooling water flow rate, cooling tower fan airflow rate, and chiller part load ratio (PLR) as the optimization variables. Among them, the outdoor wet-bulb temperature and cooling load are uncontrollable environmental parameters and are treated as known variables, while PLR, pump flow rates, and fan airflow rates are actively adjustable parameters. Finally, these optimization variables are input into the cuckoo search algorithm.

Considering that the above optimization variables exhibit fundamental differences in their physical characteristics and mathematical forms, this study divides them into two categories and adopts distinct optimization strategies for each. The optimization of the chiller PLR relies on the discrete performance

Table 2 provided by the equipment manufacturer. The optimal operating point can be directly identified through a look-up process without the need for stochastic searching, and the look-up method guarantees that the result is the physically optimal solution for the given operating conditions. In contrast, the chilled water flow rate, cooling water flow rate, and cooling tower fan airflow are continuous variables with nonlinear relationships to their respective energy consumption, making them well-suited for global optimization using metaheuristic algorithms. This classification approach leverages the deterministic nature of chiller performance data while exploiting the advantages of intelligent algorithms in handling continuous nonlinear problems.

The chiller part-load ratio (PLR) is treated as a rule-based variable. It is not directly updated by the Cuckoo Search (CS) algorithm; instead, it is determined by querying the maximum coefficient of performance (COP) operating point from the performance map (Table 2) based on the current load demand and cooling water inlet temperature. The chilled water flow rate, cooling water flow rate, and cooling tower fan airflow are selected as continuous optimization variables for the CS algorithm. During the iterative optimization process, for each candidate solution generated by the CS algorithm, the chiller PLR is synchronously updated via the look-up table to calculate the corresponding total system power. This hybrid strategy accommodates both the discrete nature of chiller performance characteristics and the continuous nature of the water-side variables, ensuring optimization accuracy while improving computational efficiency. Finally, the above optimization variables are input into the Cuckoo Search algorithm for optimal solution search.

The cuckoo search algorithm is a metaheuristic optimization algorithm based on Lévy flight [31]. It achieves efficient optimization by simulating the brood parasitism behavior of cuckoos and combining the Lévy flight mechanism [32]. Its specific flow chart is presented as shown in Fig. 5:

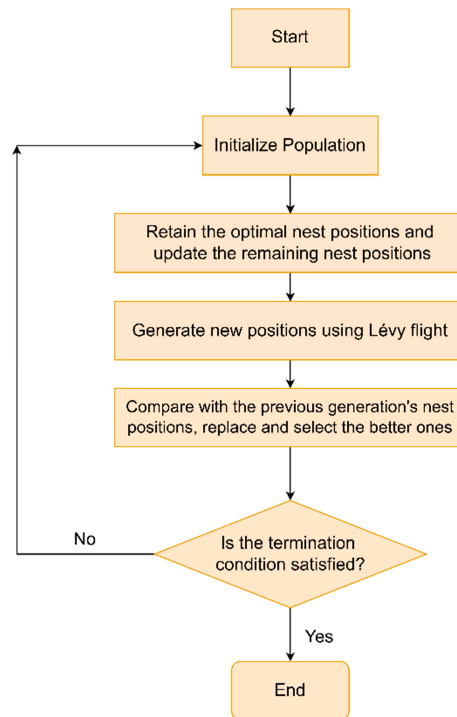


Figure 5: Flowchart of the cuckoo search algorithm.

The implementation of this algorithm in this study is described as follows (taking pump optimization as an example):

Step 1. Initialize parameters. Randomly generate n initial solutions within the allowable flow rate range $[G_{min}, G_{max}]$ of chilled water pumps or cooling water pumps, where each solution represents a possible flow rate value G .

Step 2. Calculate the fitness of each solution according to the objective function, the power consumption function $P_{chp}(G)$ of chilled water pumps or $P_{cp}(G)$ of cooling water pumps, with the goal of minimizing power consumption.

Step 3. Randomly select a nest and generate a new solution using a Lévy flight with step lengths generated by the Mantegna algorithm, ensuring that it does not exceed the flow rate boundaries. If the fitness of the new solution is better than that of the original solution, replace the original solution. Randomly eliminate some nests with probability p_a and regenerate new solutions in the solution space to maintain population diversity.

Step 4. After reaching the maximum number of iterations, select the solution with the optimal fitness as the optimal flow rate G and its corresponding minimum power consumption P_{min} .

Step 5. The parameter settings are as follows: population size $n = 20$, maximum number of iterations = 100, elimination probability $P_a = 0.25$, and step size factor = 0.5.

In addition, the specific optimization logic for each device is as follows:

Chiller: As shown in Fig. 6a, the cooling water inlet temperature is monitored in real time, and the corresponding row in the performance data table is located according to this temperature. Subsequently, within that temperature row, the COP values at load ratios ranging from 50% to 100% are compared sequentially, and the load ratio with the highest COP is taken as the theoretical optimal setting. Verification and adjustment are then conducted in conjunction with the actual terminal cooling load demand: if the cooling capacity corresponding to the theoretical optimal load ratio is sufficient to meet the demand, that load ratio is directly adopted; if the cooling capacity is insufficient, the load ratio is appropriately increased until the demand is satisfied, up to 100%; if the cooling capacity is excessive, the load ratio is moderately reduced, provided it is not lower than 50%, so as to approach the high-efficiency point as closely as possible. This process ensures that, while guaranteeing the cooling demand, the chiller always operates in the high-efficiency region through temperature–load matching. Table 2 presents the performance parameters of the chiller.

Table 2: Chiller performance parameters.

Inlet Temperature (°C)	Chiller COP at Percent Load					
	100%	90%	80%	70%	60%	50%
30	6.235	6.214	6.121	5.859	5.546	5.168
29	6.482	6.510	6.471	6.221	5.922	5.54
28	6.746	6.831	6.818	6.678	6.339	5.951
27	7.033	7.159	7.183	7.134	6.776	6.404
26	7.326	7.497	7.577	7.579	7.258	6.843
25	7.640	7.837	7.990	8.043	7.834	7.321
24	7.951	8.198	8.405	8.521	8.399	7.965
23	8.276	8.580	8.834	9.021	8.998	8.614
22	8.612	8.985	9.292	9.544	9.582	9.289
21	8.974	9.421	9.774	10.071	10.169	10.072
20	9.375	9.856	10.293	10.648	10.801	10.841
19	9.759	10.325	10.819	11.270	11.497	11.545

Chilled water pump: As shown in Fig. 6b, the feasible flow rate region is first calculated based on the predicted cooling load and the design temperature difference between the chilled water supply and

return. With the objective of minimizing the power consumption of the chilled water pump, the Cuckoo Search (CS) algorithm is employed to perform global optimization within this feasible region, thereby determining the optimal flow rate. Finally, negative feedback fine-tuning is conducted according to the actual temperature difference between the chilled water supply and return to ensure that the terminal cooling demand is satisfied.

Cooling water pump: As shown in Fig. 6c, the lower flow limit is determined by the condensing load and the temperature difference between the cooling tower inlet and outlet water, while the upper flow limit is set according to the pipeline characteristics; together, these define the optimal flow rate range for the cooling water. With the goal of minimizing the power consumption of the cooling water pump, the CS algorithm is used to solve for the optimal flow rate. Additionally, a feedback mechanism based on the cooling water temperature difference is introduced to ensure that the cooling system meets the heat dissipation requirements while operating in a high-efficiency state.

Cooling tower fan. As shown in Fig. 6d, an overall energy consumption model of the cooling system consisting of the chiller and the cooling tower fan is constructed to balance the fan energy consumption against the chiller energy consumption. By incorporating real-time outdoor meteorological parameters, the theoretical lower limit of the cooling water temperature is determined. The CS algorithm is then applied to solve for the optimal fan load ratio that minimizes the total energy consumption of the cooling system, thereby achieving coordinated optimization between the fan and the chiller.

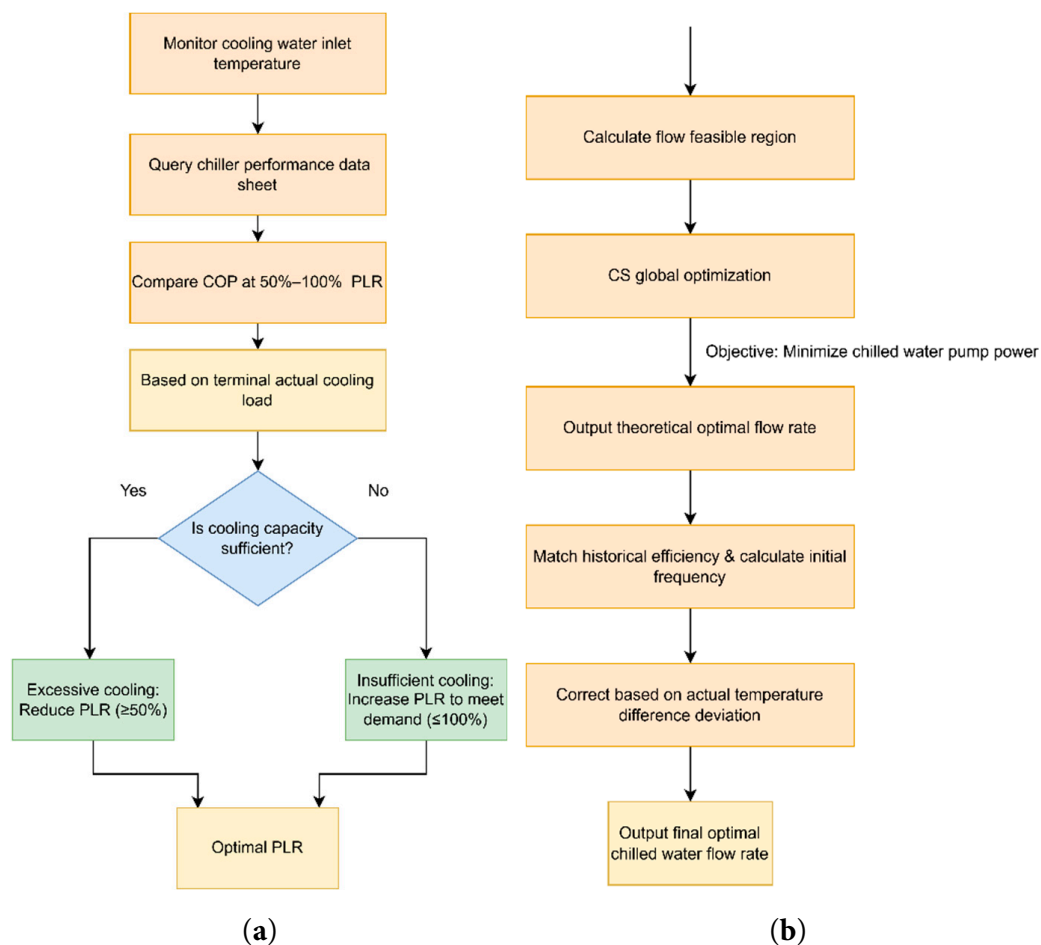


Figure 6: Cont.

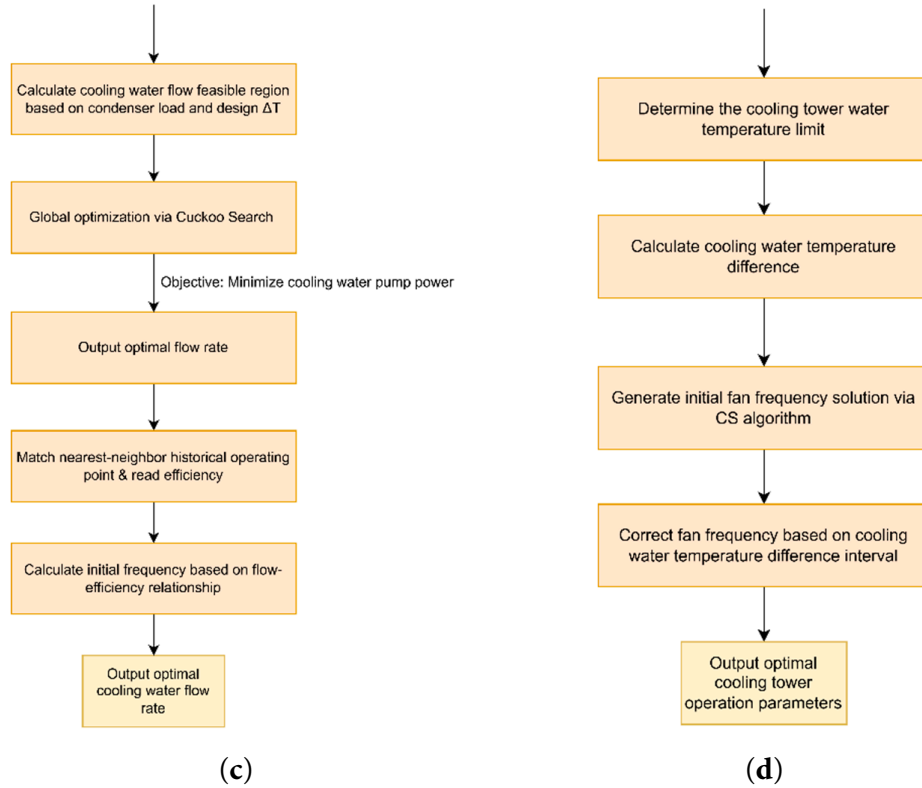


Figure 6: Optimization flowchart of each sub-component of the central air-conditioning system. (a). Chiller power calculation module. (b). Chilled water pump calculation module. (c). Cooling water pump calculation module. (d). Cooling tower calculation module.

3.4 Analysis of Optimization Results

This study is conducted at a pharmaceutical manufacturing base in Sichuan Province, China, where a central air-conditioning system provides year-round cooling for the entire production workshop. The equipment operates from 9:00 to 17:00 daily, and the total required cooling capacity of the cooling system is 4287 kW. The cooling load input values for the building are predicted by the LSTM model presented in the previous section.

Based on the established cold source system model, the proposed global optimization method is applied to a selected typical day whose cooling load and meteorological conditions are summarized in Table 3. The baseline for comparison is the conventional constant-flow constant-frequency strategy—chilled/cooling water pumps and cooling tower fans operate at fixed rated conditions, while the chiller passively adjusts its PLR to meet terminal demand. All optimization results are compared against this baseline under identical boundary conditions to ensure fair and reliable energy-saving evaluation.

Table 3: Typical daily operating conditions.

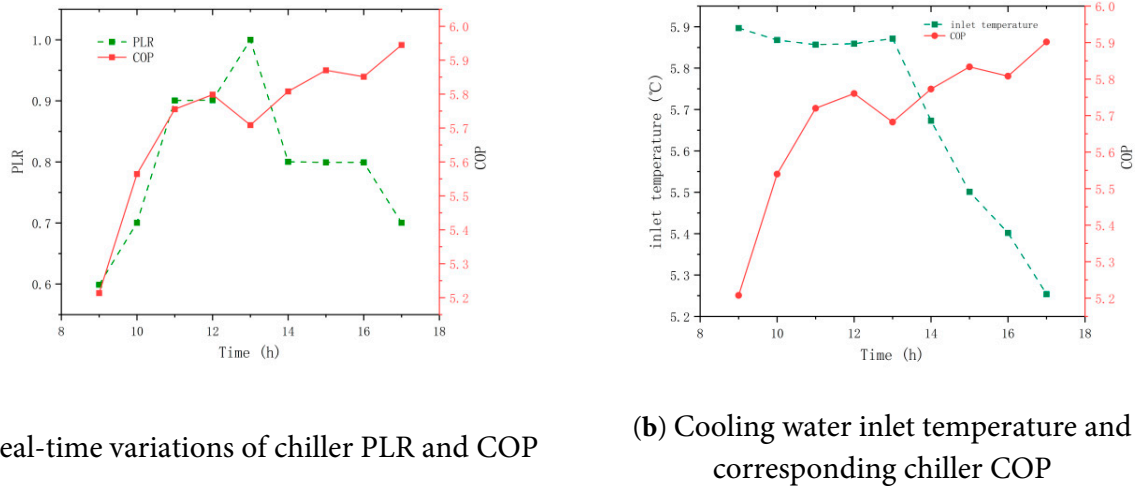
Time	Temperature (°C)	Relative Humidity (%)	Cooling Load (kW)
9:00	31.1	69.3	1285.0
10:00	31.9	67.0	1379.0
11:00	32.8	61.8	1727.0
12:00	32.6	64.9	1756.0
13:00	33.2	59.8	1857.0

Table 3: *Cont.*

Time	Temperature (°C)	Relative Humidity (%)	Cooling Load (kW)
14:00	34.3	49.7	1683.0
15:00	35.0	49.1	1616.0
16:00	35.4	44.2	1511.0
17:00	33.8	44.8	1391.0

3.4.1 Analysis of Chiller Optimization Results

The analysis of chiller optimization results focuses on the coupling relationship between the chiller part load ratio (PLR), cooling water inlet temperature and real-time operating conditions. By dynamically optimizing the chiller PLR, the operational energy efficiency is enhanced under the premise of ensuring cooling supply-demand balance, maintaining the chiller consistently within the high-efficiency operating range and thereby avoiding inefficient operation. The detailed analysis results are presented in Fig. 7.

**Figure 7:** Real-time variation of chiller PLR and COP (a,b).

As shown in Fig. 7a during the morning load rising phase, the PLR adjusts in tandem with the cooling load demand, and the chiller coefficient of performance (COP) remains within the conventional high-efficiency range. In contrast, during the afternoon load declining phase, although the PLR stabilizes in the range of 0.7–0.8, the COP shows a continuous upward trend and reaches the daily maximum value of 5.9 at 17:00. This phenomenon can be attributed to the fact that during the same period, despite the relatively high outdoor dry-bulb temperature, the cooling water inlet temperature decreases continuously from 29.5°C to 24.8°C due to the significant drop in relative humidity. For centrifugal chillers, the condensation temperature is the critical factor affecting the compression work. A 1°C reduction in cooling water inlet temperature leads to an approximately synchronous decrease in condensation temperature, which significantly reduces the compression ratio and power consumption of the chiller. Under the condition of providing the same cooling capacity, the reduction in power consumption directly results in an increase in chiller coefficient of performance (COP).

Therefore, the continuous improvement of chiller COP in the afternoon is not primarily driven by PLR adjustment, but by the reduction in outdoor relative humidity, which enhances the cooling performance of the cooling tower and leads to a substantial decrease in cooling water inlet temperature. This also

validates the principle of coordinated control between cooling towers and chillers in the central air-conditioning system.

As shown in Fig. 8, the dynamic optimization strategy demonstrates significant energy-saving performance in chiller operation. Throughout the entire daily operation period, the optimized chiller power consumption is systematically reduced compared with the pre-optimization condition. The total cumulative energy consumption from 09:00 to 17:00 decreases from 2046.3 kWh to 1854.3 kWh, achieving an overall energy-saving rate of 9.4%. Particularly at 13:00 during the peak load period, even though the cooling load reaches the maximum value of 1857 kW, the optimized power consumption is still reduced by 25.1 kW (a reduction of approximately 10%). With the decrease in outdoor relative humidity and continuous reduction in cooling water temperature in the afternoon, the power-saving effect is further enhanced while the system maintains the high-efficiency PLR range of 0.7–0.8. For example, at 15:00 under a cooling load of 1616 kW, a power saving of 22.6 kW is achieved, and the energy-saving rate remains at around 9.5%.

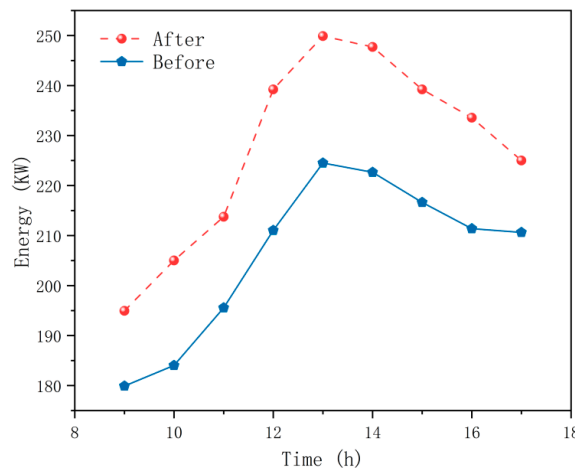


Figure 8: Chiller power consumption before and after optimization.

It is worth noting that even as the cooling load gradually decreases in the afternoon, the power consumption maintains a stable downward trend, and the energy-saving magnitude does not diminish with the reduction in load. This is because the optimization strategy coordinates the lower cooling water temperature with the appropriate PLR. The above analysis fully demonstrates that by comprehensively adjusting the part load ratio and coupling with cooling-side operating conditions, this dynamic optimization strategy not only improves the operational efficiency (COP) of the chiller, but also directly achieves substantial energy-saving effects. This validates the feasibility of the proposed optimization strategy for realizing efficient operation of chillers.

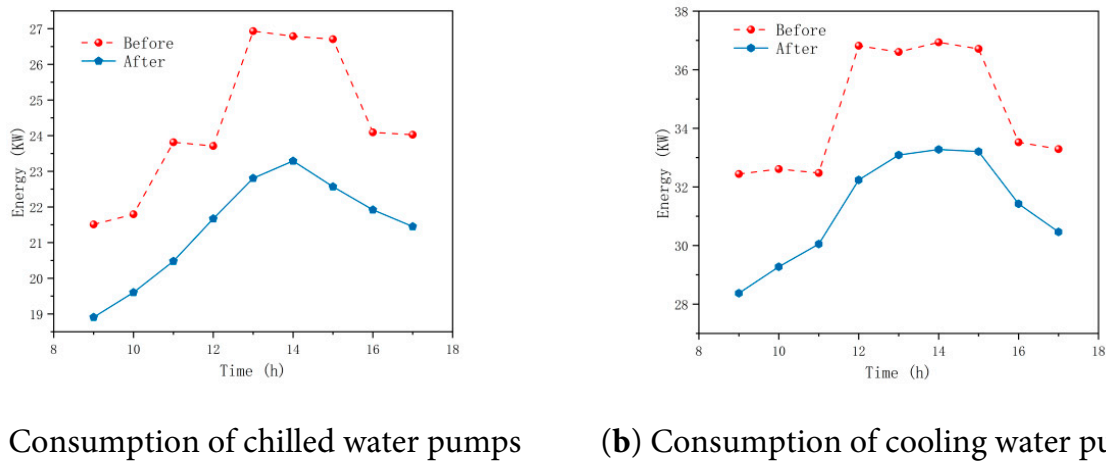
3.4.2 Analysis of Pump Operation Optimization

Fig. 9 presents the hourly energy consumption comparison of water pumps before and after optimization on the typical day.

As shown in Fig. 9a, the optimized variable-frequency control strategy realizes real-time linkage between the chilled water pump flow rate and the terminal cooling load: when the terminal cooling load rises from 1285 kW to 1857 kW (a load increase of 44.5%), the operating power consumption of the optimized chilled water pump increases correspondingly from 18.9 kW to 22.8 kW, representing an power consumption increase of only 20.6%, which is far lower than the load increase. Moreover, over the entire load variation

range, the power consumption of the optimized pump is consistently and significantly lower than that under the same operating conditions before optimization.

As shown in Fig. 9b, during the midday high-temperature and high-humidity period (13:00, outdoor dry-bulb temperature 33.2°C, relative humidity 59.8%), the high wet-bulb temperature limits the cooling tower's evaporative capacity, keeping the cooling water inlet temperature at about 29.5°C; the optimized cooling water pump then operates at 33.1 kW, 3.5 kW lower than before optimization (a saving of 9.6%). In the afternoon, the relative humidity drops below 45%, enhancing evaporative heat rejection and lowering the cooling water inlet temperature to 24.8°C. Consequently, the required cooling water flow rate decreases from 421.15 m³/h to 246.78 m³/h, a reduction of more than 41%. However, the pump power decreases only from 33.1 kW to 30.5 kW (about 8%). This asymmetric trend is consistent with the identified quadratic pump model (Table 1), where the large constant term ($g_1 = 16.0723$ kW) represents fixed losses independent of flow. Thus, reducing flow mainly decreases the hydraulic power component, while fixed losses remain, limiting the total power saving. This mechanism explains why the pump power reduction is much smaller than the flow reduction, while the optimization still achieves meaningful savings compared with constant-flow operation.



(a) Consumption of chilled water pumps

(b) Consumption of cooling water pumps

Figure 9: Power consumption of chilled water and cooling water pumps (a,b).

3.4.3 Analysis of Cooling Tower Optimization Results

Fig. 10 presents the hourly energy consumption comparison of cooling towers before and after optimization on the typical day.

As can be seen from Fig. 10, the power consumption of the cooling tower is generally reduced throughout the entire daily operation period after optimization, decreasing from 16.8–17.5 kW before optimization to 13.3–14.5 kW, with an average reduction of approximately 20%. This demonstrates the effectiveness of dynamic regulation.

This energy saving is mainly achieved through fine-grained control of fan air volume. During the high-temperature and high-humidity periods in the morning and noon, the fans operate at high frequency to cope with the high wet-bulb temperature and maintain the cooling water temperature at approximately 29.5°C resulting in relatively high energy consumption. In the afternoon, as the outdoor relative humidity drops significantly from about 60% to below 45%, the evaporative cooling efficiency increases. On the premise of ensuring that the cooling water temperature can steadily decrease to 24.8°C the system actively reduces the fan air volume to approximately 286,000 m³/h. Since the energy consumption of a fan is

approximately proportional to the cube of its rotational speed, a moderate reduction in air volume leads to a significant decrease in fan energy consumption when the outdoor wet-bulb temperature is low.

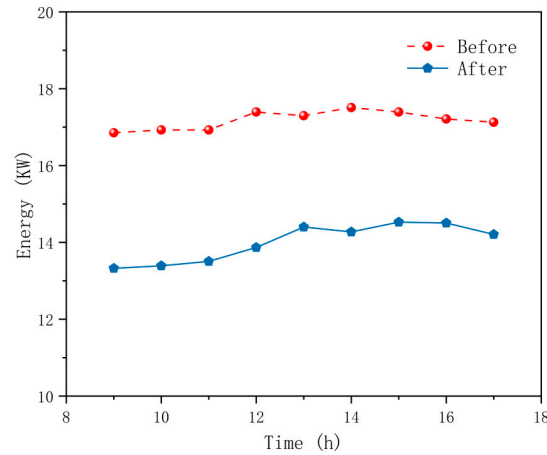


Figure 10: Cooling towers before and after optimization.

Therefore, the energy-saving optimization of the cooling tower is not simply frequency reduction. Instead, based on the real-time perception of outdoor wet-bulb temperature and system cooling demand, it dynamically adjusts the air volume to meet the condensation temperature requirements of the chiller while maximizing the utilization of favorable meteorological conditions to reduce its own energy consumption.

3.4.4 Analysis of Global Operation Optimization

The global optimization of the central air-conditioning system achieves a significant reduction in the comprehensive energy consumption of the system through the systematic coordinated regulation of the operating states of chillers, water pumps and cooling towers. The comparison before and after optimization is presented in Fig. 11.

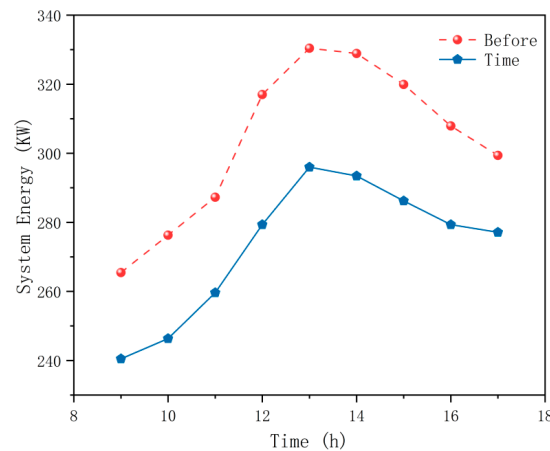


Figure 11: System consumption before and after optimization.

Based on the calculation and analysis of operational data, the total power consumption of the system shows a systematic reduction throughout the entire day after optimization. Particularly at 13:00 during the peak load period, the total power consumption decreases from approximately 330.5 kW to about 295.9 kW,

with a remarkable instantaneous power-saving effect. From the perspective of the cumulative daily effect, the total daily operational energy consumption decreased from 2732.5 kWh to 2457.1 kWh. From the perspective of the daily cumulative effect, the total energy consumption reduction after optimization reaches approximately 10%. This achievement is not a simple superposition of the independent energy-saving effects of each equipment, but originates from the synergistic gain among system components.

This saving, however, is not a mere arithmetic sum of individual equipment improvements; it originates from a thermodynamic synergy rooted in the cascade of exergy destructions. By coordinating the chiller's condensing temperature, pump flow rates, and tower airflow, the optimization minimizes the total irreversibility across the refrigeration cycle, heat rejection, and fluid transport. The physical coupling is manifested in a positive feedback loop: lower tower fan speed (when ambient humidity permits) reduces auxiliary consumption while maintaining or even lowering the cooling water inlet temperature T_{cws} ; the reduced T_{cws} lowers compressor pressure ratio and chiller power; the decreased compressor work in turn lessens condenser heat load, allowing further reduction in cooling water flow. This chain reaction transforms an initial meteorological advantage (low wet-bulb temperature) into multiplicative energy benefits, rather than additive ones.

Specifically, the optimization strategy simultaneously determines the high-efficiency operating range of chillers, the adaptive flow rate of water pumps and the optimal air volume of cooling towers according to dynamic loads and real-time meteorological parameters, keeping the cold source side and the distribution side in a coordinated and efficient state at all times. For example, when the outdoor humidity decreases in the afternoon, the system simultaneously achieves cooling tower air volume reduction, cooling water temperature drop, chiller efficiency improvement and cooling water pump flow reduction. This series of chain reactions reflects the coupled energy-saving mechanism of "cooling side condition improvement—host efficiency enhancement—distribution energy consumption reduction". Therefore, the global optimization successfully transforms the energy-saving potential of each link into an overall and stable energy consumption reduction of the system, verifying the feasibility of the proposed optimization strategy for improving the energy efficiency of cold source systems.

To further contextualize the energy-saving performance of the proposed method, a quantitative comparison with recent representative studies is conducted, as summarized in Table 4.

Table 4: Comparison of energy-saving performance with recent representative studies.

Reference	System/Method	Optimization Method	Energy Saving	Validation
Cen et al. [29]	Central A/C system	Multi-strategy improved sparrow search	4.85%–13.26%	Field measurement
Chen et al. [15]	Multi-chiller plant	Hybrid MPC + Neurodynamic optimization	13.20%	Simulation
Yin et al. [16]	Subway station chiller plant	Hierarchical MPC + Hybrid arithmetic optimization	15.73%	TRNSYS
This study	Pharmaceutical plant	LSTM forecasting + Hybrid CS	~10.0%	Mechanism-model

The energy-saving performance of the proposed method is contextualized against recent state-of-the-art studies in Table 4. Reported savings in the literature span approximately 4.85% to 17.50%, varying with building type, system scale, baseline control strategy, and climatic conditions. The total energy

saving of approximately 10.0% achieved in this pharmaceutical plant case falls well within this range and is comparable to the 13.20% reported for a multi-chiller plant and the 15.73% for a subway station, despite the more intricate and fluctuating load profiles characteristic of industrial production environments. This comparison substantiates that the proposed framework, integrating LSTM-based forecasting with a hybrid cuckoo search optimization, attains competitive energy-saving performance while preserving robust engineering practicability in real-world industrial settings.

4 Conclusions and Future Work

This paper addresses the problem of high operational energy consumption caused by the nonlinearity, multivariable coupling and large time-delay characteristics of central air-conditioning systems. A global energy-saving optimization method integrating long short-term memory (LSTM) neural network load prediction and cuckoo search (CS) algorithm parameter optimization is constructed, and verified in the central air-conditioning cold source system of an actual pharmaceutical manufacturing base. The following conclusions are drawn:

- (1) Based on the equipment operation mechanism, this paper establishes energy consumption models for chillers, chilled water pumps, cooling water pumps and cooling towers, and accurately identifies the model parameters using the least squares method. Taking the minimum total system energy consumption as the optimization objective, the chilled water flow rate, cooling water flow rate, cooling tower fan air volume and chiller PLR are selected as the core optimization variables. A complete global optimization mathematical model of the central air-conditioning cold source system under multiple constraints is established, which lays a theoretical foundation for the coordinated optimization of system operating parameters.
- (2) An LSTM-based cooling load prediction model was developed and trained and validated using 96 days of hourly operational data. The model achieves high-precision short-term load forecasting, with an RMSE between the predicted and measured values of only 9.7 kW, thereby providing a reliable input constraint for proactive optimal regulation.
- (3) In the optimization, a hybrid strategy was adopted: the chiller PLR was determined via a maximum COP look-up table, while the chilled water flow rate, cooling water flow rate, and cooling tower fan airflow were optimized as continuous variables by the Cuckoo Search (CS) algorithm to minimize total system energy consumption. This strategy achieved significant savings: chiller energy use dropped by 9.4%, average pump energy by 10.6%, and cooling tower fan energy by approximately 20%. Cumulatively, the daily total system energy consumption fell from 2732.5 kWh to 2457.1 kWh, an overall saving of nearly 10%.

In summary, the central air-conditioning energy-saving optimization method proposed in this paper, which integrates LSTM-based load forecasting with the cuckoo search algorithm, is capable of achieving intelligent coordinated regulation of system operating parameters while satisfying cooling demand. It exhibits strong engineering applicability and promising potential for wider application, thus providing a theoretical foundation and methodological support for intelligent energy-efficient operation of building central air-conditioning systems.

However, this study still has several limitations that need to be addressed. First, the generalization capability is limited. The validation was conducted only on the industrial cold source system of a pharmaceutical base, where the load characteristics and equipment configurations differ from those of public and commercial buildings; the adaptability of the method to other building types remains to be verified. Second,

regarding the operating conditions, the training and validation data cover only summer cooling conditions, without considering transition seasons and winter conditions. Moreover, the effects of long-term equipment performance degradation and scaling on model accuracy were not taken into account. Third, the validation period needs to be extended. This study only carried out typical-day validation, lacking long-term full-year operational verification, and the optimization performance under extreme meteorological conditions requires further evaluation.

Future research can be pursued in several directions. First, the generalizability and adaptive capability of the prediction and optimization models can be further improved by incorporating more influencing factors such as detailed meteorological data, actual building occupancy, and building load characteristics, and by introducing an online learning mechanism to enable the model to dynamically adapt to changes in building usage patterns and equipment performance degradation. Second, the optimization framework can be extended to multi-objective and higher-dimensional problems, comprehensively considering multiple indicators such as thermal comfort, equipment service life, operating cost, and demand response speed, thereby establishing a multi-objective optimization model and seeking more efficient solution strategies at the algorithm level to address more complex practical engineering constraints. Finally, promoting the in-depth transformation of research outcomes into practical applications is essential. Subsequent work can focus on developing lightweight intelligent control modules embedded with advanced algorithms, integrating them with existing building automation systems, and verifying their reliability and economic viability under full operating conditions and throughout the entire life cycle through long-term actual deployment and performance tracking.

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