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Research Article

Building energy management model integrating rule-based control algorithm and genetic algorithm

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Abstract. Energy is a crucial material foundation for the development of human society. Building energy consumption accounts for a significant proportion of global energy consumption. Optimizing building energy management is of great significance for achieving sustainable development. A building energy management model that integrates rule-based control algorithm and genetic algorithm is proposed, aiming to optimize building energy utilization and reduce operating costs. Mathematical models for different devices in the building energy system are established, and the rule-based control algorithm is used to provide system decision support. Then, the genetic algorithm is integrated to address the complexity and uncertainty of energy optimization problems. The comparative test results showed that the proposed fusion algorithm had higher fitness values and faster convergence speed. The root mean square errors of the algorithm in the training and testing sets were 43.6544 and 43.6844, with the lowest error and highest accuracy among the four algorithms. The simulation experiment results showed that the building energy management model integrating rule-based control algorithm and genetic algorithm had energy expenditures of 788.3 yuan and 967.6 yuan for two types of buildings, respectively. Taking Building 1 as an example, compared with Supervisory Control and Data Acquisition (SCADA), Beetle Antennae Search and Particle Swarm Optimization (BAS-PSO) algorithm, and Long Short-Term Memory-Convolutional Neural Network (LSTM-CNN) algorithm, the proposed model reduced the cost of energy consumption optimization by 39.30%, 28.32%, and 20.20%, respectively. Overall, the proposed building energy management model effectively reduces operating costs, utilizes building energy, and contributes to daily building energy management and decision support.

Keywords: Rule-based control algorithm; Genetic algorithm; Building energy management; Sustainable development; Energy consumption

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1. Introduction

With the continuous increase of global energy consumption and the increasingly severe environmental problems, intelligent technology has gradually made building energy management systems an effective means of optimizing energy utilization efficiency and reducing operating costs (Wu *et al*., 2023). Due to the complexity of the internal and external environment of buildings, traditional energy management methods are difficult to adapt to changing energy demands and supply conditions. Building energy management systems can optimize energy use, reduce resource waste, and achieve cost savings and environmental benefits (Ruiz *et al*., 2021). However, due to the complexity and dynamism of building systems, traditional energy management methods often struggle to meet the growing demand for energy optimization. The Rule-Based Control (RBC) algorithm has been widely used in building energy management due to its simple and intuitive characteristics (Feng *et al*., 2023; Romero *et al*., 2021). It can make quick decisions based on preset rules, but its performance may be limited when facing highly uncertain and nonlinear problems. As a heuristic search algorithm, Genetic Algorithm (GA) has shown great potential in solving complex optimization problems with the global optimization ability and adaptability (Garud *et al*., 2021; Mishra & Jatti, 2024).

Many experts have carried out research on this topic. Vašak *et al.* designed a modular building energy management strategy based on three-level hierarchical model. The building area, central air conditioning, and microgrid subsystems were independently controlled and integrated to form a layered coordinated control structure. This strategy provided important demand response services for buildings and maintained the independence of different building subsystems. Compared with RBC, the proposed method reduced overall building operating costs by 9%-12%, and reduced coordinated operations by 15%-24% (Vašak *et al*., 2021). Gao *et al.* believed that reducing building energy consumption was key to achieve future climate and energy goals. Therefore, a learning and iterative Internet of Things (IoT) system was proposed to achieve the zero energy consumption of the boundary element method for interconnected buildings. The research first shared operational data in the IoT system, and then used an aggregator to collect historical data for model training, developing optimization iterative algorithms. Finally, simulation experiments were conducted to validate the proposed IoT system based on learning and iteration (Gao *et al*., 2022). Shi and Cui proposed a point-to-point energy sharing model for adjacent energy

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buildings to promote sustainable energy development. Energy buildings with controllable loads and renewable equipment were analyzed. Under the constraint of energy balance, the total energy cost was minimized using the distributed algorithm. The simulation experiment results showed that the model improved energy efficiency and economic benefits (Shi & Cui, 2022). Giahchy *et al.* also believed that energy management systems were key to sustainable development. To this end, a quantitative and qualitative analysis based on amulti-criteria decision-making was conducted, and a mixed multi-objective mathematical decision-making method was designed. The study selected optimal options for all building shell components to optimize costs and energy. The research results indicated that the model saved approximately 16% of energy during the lifespan of the building (Giahchy *et al.*, 2023).

The RBC algorithm is a control strategy that uses predefined rules to guide the decision-making process, which is widely used in fields such as automation control systems, artificial intelligence, expert systems, etc (Maier *et al.*, 2024). Yuan *et al.* designed a model free control strategy for optimizing air conditioning operation systems by combining reinforcement learning methods with RBC algorithms. The RBC and proportional integral derivative were used as control strategies. The case study validated the optimization performance of the controller. The results indicated that the reinforcement learning controller performed the best in non-comfort time and energy cost in air conditioning systems (Yuan *et al.*, 2021). Begam *et al.* designed an RBC controller that combined adaptive neural fuzzy and hybrid energy storage systems to adjust the power flow of electric vehicle propulsion. The performance analysis of the RBC controller was conducted under three load conditions. The performance tracking was performed using battery currents greater than or equal to 90%. The proposed RBC controller reduced the non-linearity generated by the hybrid energy storage system, with good smooth tracking performance (Begam *et al.*, 2023). Due to the lack of a clear objective function in the RBC algorithm, it is mainly suitable for situations with a single control objective and cannot balance multiple control objectives well. GA is a gradient free heuristic search technique, demonstrating strong problem-solving ability, and also effectively avoiding the risk of getting stuck in local optima (Yuan *et al.*, 2022). Elghamrawy and Hassanien proposed a optimized strategy to design fuzzy systems, combining GA and Grey Wolf Optimization (GWO). This algorithm used genetic crossover and mutation operators to accelerate the exploration process, overcoming the premature convergence and poor solution utilization of GWO. Compared with existing optimization algorithms, the designed method had higher accuracy in Root Mean Square Error (RSME) and computation time (Elghamrawy & Hassanien, 2022). Hamdia *et al.* developed a GA-based integer optimization method for deep neural networks and adaptive neural fuzzy inference systems to overcome the design challenges of machine learning models. The selected variables were hidden layers, neurons, and activation functions to minimize the mean square error between the prediction and the target output for optimization. The results indicated that the algorithm improved the prediction accuracy of deep neural network models, while significantly reducing the number of generations in GA (Hamdia *et al.*, 2021).

In summary, many scholars have conducted research on the combination of zero energy building energy management with different methods. However, at present, building energy modeling and control systems are separated, making it difficult to implement real-time control management models. Based on this background, this study innovatively combines the building model and control system into a highly adaptable unified architecture. Depending on the fast response of RBC algorithm and the superior global search ability of GA in multi-objective optimization problems, a RBC-GA that can control algorithm efficiency is proposed to achieve more efficient and intelligent energy management. This study aims to optimize building energy utilization efficiency, reduce operating costs, and offer enhanced decision support for building energy management.

This study proposes multiple innovative points. Firstly, this study combines RBC with GA for the first time to solve multi-objective optimization and uncertainty problems. Secondly, this article constructs a unified model architecture that organically integrates the building model with the control system. By directly integrating the building energy consumption model with the control system, this study greatly improves computational efficiency and enhances the real-time control capability of the system, making it possible to optimize energy consumption in complex and changing building environments. Finally, the uncertainty problem of the system is addressed and a more efficient control strategy is achieved through multi-objective optimization methods. By combining GA and RBC, the system can flexibly adjust the control scheme when facing multiple uncertain factors, ensuring efficient balance between multiple objectives. Through these innovations, this study effectively fills the gap in the current field of building energy management, providing reference for the design of future intelligent building energy management systems.

2. Method

The study first introduces the main components of building energy systems and establishes mathematical models for different devices to complete the mathematical model construction. The control performance of RBC algorithm and the global optimization of GA are combined to manage and

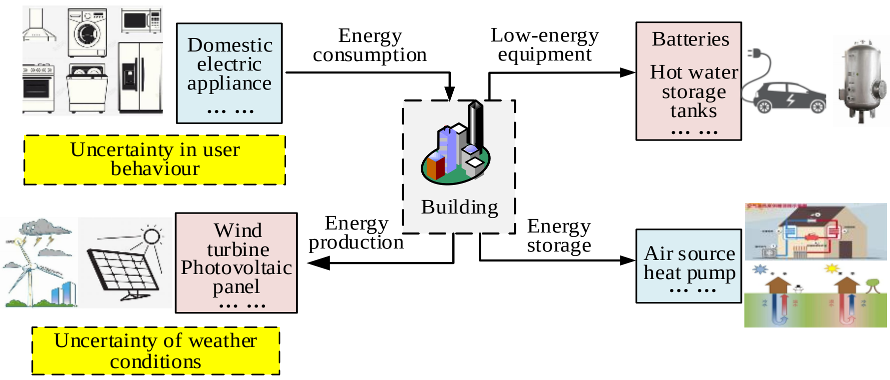


Fig.1 Schematic diagram of building energy system

control the building energy model, in order to optimize the building energy utilization efficiency and reduce costs.

2.1 Mathematical model construction of building energy system

According to different functions, buildings can be divided into different categories such as residential, industrial, and commercial. Each type of building requires energy services such as electricity, heating, cooling, and hot water supply, which are all met by the internal energy supply system of the building. The energy supply system also constitutes the main part of building energy consumption, as shown in Figure 1 (Jayashankara *et al.*, 2023).

In Figure 1, building energy consumption is affected by multiple factors, including climate, user habits, and equipment performance (Lv *et al.*, 2022). The research mainly focuses on constructing mathematical models of building energy systems for production capacity, energy storage, heating and cooling, and transportation equipment. The production capacity equipment covers renewable energy technologies such as solar panels, which convert solar energy into electrical energy. The study assumes that the solar panel operates in an ideal state, ignoring the influence of changes in the angle of the sun. Assuming that all radiated energy is completely absorbed, the power generation efficiency can be linearly described by equation (1) (Li., 2024).

$$P_{PV} = \eta_{PV} A_{PV} G[1 - 0.005(T_{amb} - 25)] \tag{1}$$

In equation (1), P_{PV} represents the power from the solar panel. η_{PV} represents the photoelectric conversion rate. A_{PV} represents the solar panel area. G represents the intensity of light radiation. T_{amb} represents the ambient temperature. The secondary production capacity model is shown in equation (2).

$$\begin{cases} P_{PV} = \frac{G}{1000}(1 + \alpha_{cur}\nabla T)(1 + \alpha_{vol}\nabla T)P_{PV,r} \\ \nabla T = T_{cell} - 25 \end{cases} \tag{2}$$

In equation (2), α_{cur} represents the thermal sensitivity of the solar panel to generate current. α_{vol} represents the thermal sensitivity of the solar panel to generate voltage. T_{cell} signifies the temperature of the solar panel. $P_{PV,r}$ signifies the power generation under experimental conditions. Except for converting solar energy into electricity, wind energy, as a common renewable energy source, also has important utilization value (Akporhonor *et al.*, 2024). Wind turbines can convert wind energy into electrical energy through their unique design, providing another efficient way to obtain clean energy. The production capacity model is shown in equation (3) (Emeksiz, 2022).

$$P_{WT} = \begin{cases} 0 & \upsilon_f \le \upsilon_{wind} or \upsilon_{wind} \le \upsilon_c \\ \frac{\upsilon_{wind}^3 - \upsilon_c^3}{\upsilon_r^3 - \upsilon_c^3} P_{WT,r} & \upsilon_c < \upsilon_{wind} < \upsilon_r \\ P_{WT,r} & \upsilon_r \le \upsilon_{wind} \le \upsilon_f \end{cases} \tag{3}$$

In equation (3), $P_{WT,r}$ signifies the rated power of wind power generation. υ_{wind} signifies the outdoor wind speed. υ_r signifies the rated wind speed. υ_c signifies the cut-in wind speed. υ_f signifies the cut-out wind speed. After changing the input parameters, the second model for wind power generation is shown in equation (4).

$$P_{WT} = \begin{cases} 0 & \upsilon_f \le \upsilon_{wind} or \upsilon_{wind} \le \upsilon_c \\ \frac{1}{2}\rho_{air}\pi R_{WT}^2 \upsilon_{wind}^3 C_{WT} & \upsilon_c < \upsilon_{wind} < \upsilon_r \\ P_{WT,r} & \upsilon_r \le \upsilon_{wind} \le \upsilon_f \end{cases} \tag{4}$$

In equation (4), ρ_{air} stands for the air density. π is pi. R_{WT} represents the blade radius. C_{WT} stands for the dynamic coefficient. Energy storage devices include electric and thermal storage devices, with electric storage devices being batteries (Lu *et al.*, 2023). Buildings equipped with battery systems can store energy when electricity demand is low and release energy during peak hours to alleviate grid pressure and achieve demand side management. Battery simulation includes both linear and nonlinear models. Considering that linear models accurately reflect the battery state and have better computational efficiency than nonlinear models, the study adopts linear models for analysis, as shown in equation (5) (Shakeri Kebria *et al.*, 2024).

$$\begin{cases} 0 \le \dot{Q}_{ch} \le \dot{Q}_{ch}^{\max}, 0 \le \dot{Q}_{dis} \le \dot{Q}_{dis}^{\max} \\ \dot{Q}_{ch}\dot{Q}_{dis} = 0 \\ \dot{S} = -\eta_{loss} S + \eta_{ch}\dot{Q}_{ch} - \eta_{dis}\dot{Q}_{dis} \\ S_{\min} \le S \le S_{\max} \end{cases} \tag{5}$$

In equation (5), $\dot{Q}_{ch}$ and $\dot{Q}_{dis}$ represent the charging and discharging speeds of the battery. $\dot{Q}_{ch}^{max}$ and $\dot{Q}_{dis}^{max}$ represent the maximum power of battery charging and discharging. η_{loss} represents the energy loss coefficient. η_{ch} and η_{dis} represent the efficiency of battery charging and discharging, respectively. Usually, $\eta_{ch} < 1 < \eta_{dis}$. S is the battery storage state. S_{max} and S_{min} represent the limits of the storage state. In addition to electricity, thermal energy is also an important form of energy for buildings, playing a crucial role in various aspects such as

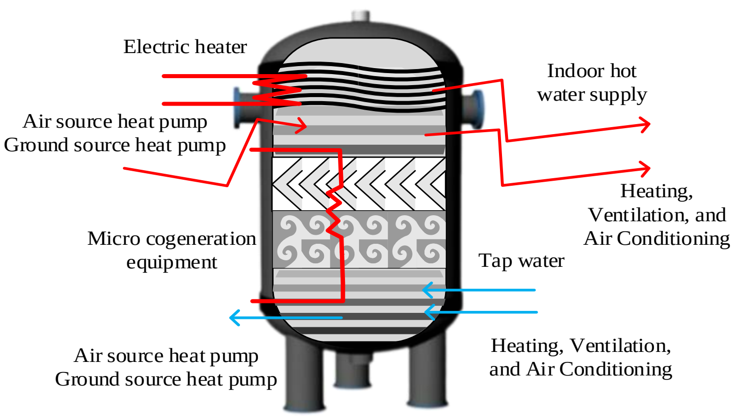


Fig.2 Hot water storage tank model

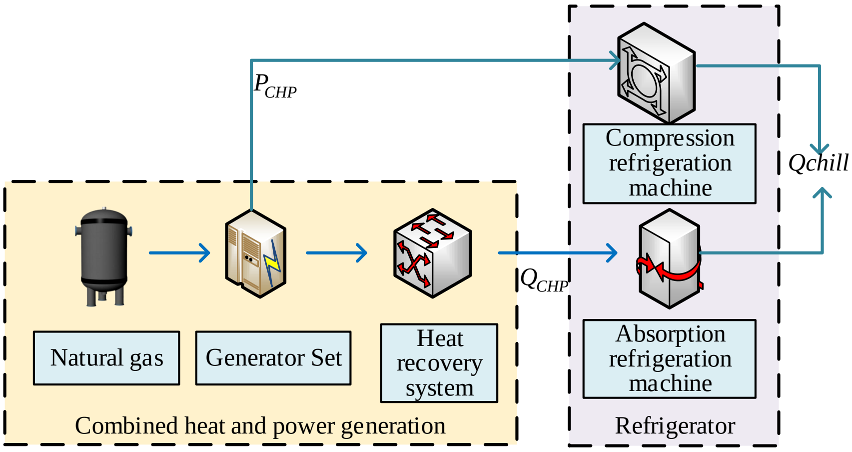


Fig.3 Structure of combined cooling, heating and power equipment

heating, cooling, and hot water supply. Hot water storage tank is an efficient thermal storage device (Handy & Coughlin, 2024). The research mainly explores the layered hot water storage tank model, as shown in Figure 2 (Huang *et al.*, 2021).

Figure 2 displays a layered hot water storage tank model consisting of 5 nodes, with each node representing an independent layer. The variation of inter-layer thermal energy is influenced by factors such as equipment heating, water flow transfer, and inner wall heat exchange (Guo *et al.*, 2022). Based on the principle of energy conservation, a mathematical model applicable to building water circulation systems is constructed, and heating and cooling equipment are evaluated. Unlike electric heaters, air source heat pumps use electricity to drive compression and condensation processes, elevating low thermal energy to high thermal energy. The performance coefficient of the air source heat pump is modeled and approximated as a linear function of T_{amb}, as displayed in equation (6) (Maleki Dastjerdi *et al.*, 2023).

$$COP_{ASHP} = 6.1189 + 0.676T_{amb} - 0.0632T_{ASHP,in} \tag{6}$$

In equation (6), COP_{ASHP} represents the performance coefficient of the air source heat pump. $T_{ASHP,in}$ represents the inlet water temperature. The heat generation power of the air heat source pump is shown in equation (7).

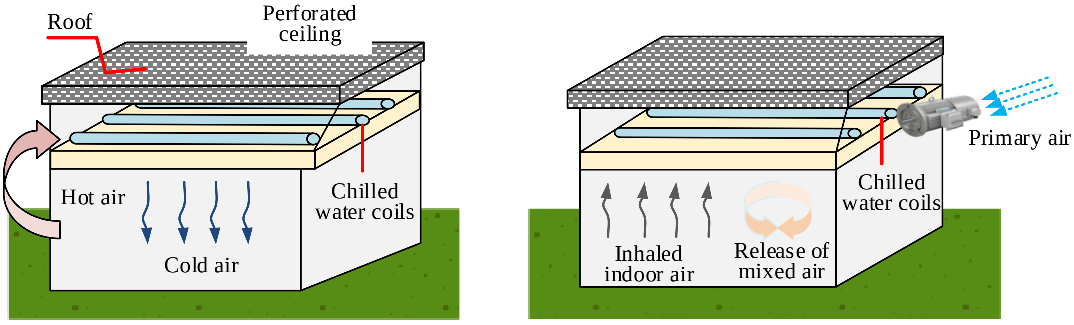
$$Q_{ASHP} = COP_{ASHP}W_{ASHP} = \dot{m}_{ASHP}C_w(T_{ASHP,out} - T_{ASHP,in}) \tag{7}$$

In equation (7), Q_{ASHP} represents the heat generation power of the air heat source pump. W_{ASHP} represents the electrical power of the air heat source pump compressor. $T_{ASHP,out}$ is the outlet water temperature. $\dot{m}_{ASHP}$ refers to the flow rate of water in the device. C_w refers to the specific heat capacity of water. The structure of the combined cooling, heating and power equipment is shown in Figure 3 (Atiz *et al.*, 2022).

In Figure 3, the system integrates cogeneration and refrigeration technology, using the electricity and waste heat generated during the power generation process to drive the refrigeration mechanism for cooling. The heat generated while using natural gas and other fuels for power generation is reused through a heat recovery process (Si *et al.*, 2023). The system uses water as the medium to regulate indoor temperature through the flow of water. The water heating system, as the main way of heat transfer in buildings, provides heating through cooling devices. Assuming that the energy equipment inside the building is directly connected, ignoring the influence of auxiliary components such as water pumps, the heating power of the water heating system is shown in equation (8) (Bayendang *et al.*, 2023).

$$\begin{cases} Q_{HR} = K_{HR}(T_{HR,w} - T_{zone}) \\ M_{HR,w}C_wT_{HR,w} = \dot{m}_{HR}A_{HR}C_wT_{HR,in} - \dot{m}_{HR}A_{HR}C_wT_{HR,out} - Q_{HR} \end{cases} \tag{8}$$

In equation (8), Q_{HR} represents the heating power of the water heating system. K_{HR} represents the heat transfer coefficient between the hot water and indoor temperature difference in the plumbing system. $M_{HR,w}$ represents the quality of hot water inside the device. $T_{HR,in}$ and $T_{HR,out}$ respectively represent the inlet and outlet water temperatures of the water heating system. $T_{HR,w}$ stands for the mean temperature of the hot water inside the device. T_{zone} and A_{HR} represent the surface area of the radiator and equipment, respectively. $\dot{m}_{HR}$



(a) Schematic diagram of passive cooling beam (b) Schematic diagram of active cooling beam

Fig.4 Working principles of passive and active cooling beams

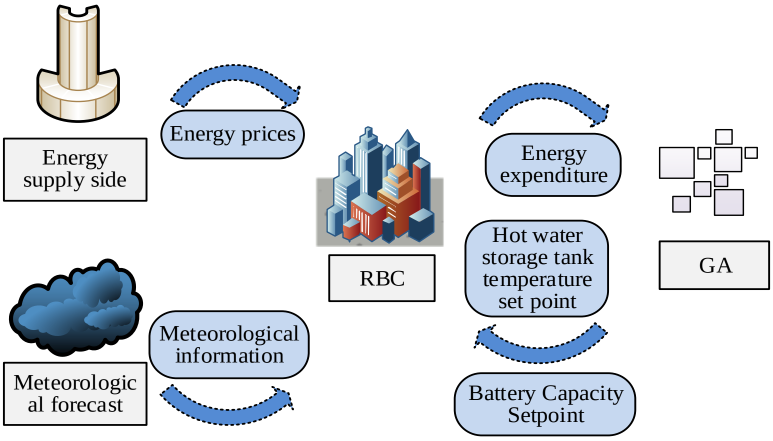


Fig.5 Schematic diagram of RBC-GA

represents the internal water flow rate of the device. In refrigeration systems, the cold beam system is widely used in air conditioning systems of various buildings and transportation vehicles, divided into passive and active types. The working principle is shown in Figure 4 (Mao *et al.*, 2024).

Figure 4 (a) displays the working principle of a passive cooling beam system. The passive cooling beam system transfers cold energy through heat exchange between internal cold water pipes and indoor warm air. After the temperature drops, the warm air rises to the cold beam due to the decrease in density. After coming into contact with the cold water pipeline, the temperature decreases. Subsequently, the cold air sinks back indoors due to the increase in density. Figure 4 (b) displays the active cooling beam system. The active cooling beam system uses forced convection to introduce indoor air through equipment, allowing it to exchange heat with the cold water pipeline and transfer cold energy.

2.2 Building energy management system based on RBC-GA

To improve building energy efficiency and achieve specific management goals, an energy system control strategy combining RBC and GA is proposed based on a mathematical model that integrates building modeling and control processes. This strategy utilizes the RBC algorithm to intelligently regulate the internal temperature setting of buildings and the start stop of energy equipment. Meanwhile, the GA is applied to accurately set the temperature of hot water storage tanks and the proportion of battery energy storage (Ren *et al.*, 2022). To improve computational efficiency while ensuring optimization results, the RBC-GA hybrid algorithm is adopted in the study, which separately processes the multi-dimensional control variables that are interrelated in the system. The algorithm flow is detailed in Figure 5.

In Figure 5, the building model integrates price data from the energy supply side, climate parameters, and target settings of hot water storage tanks and battery energy storage set by GA. The model utilizes the RBC algorithm to intelligently manage the energy system of buildings, predict and report daily energy costs (Darshi *et al.*, 2023). The GA is used to further optimize the data and determine the ideal temperature of the hot water storage tank and the optimal configuration of battery energy storage. When setting the indoor temperature, the RBC algorithm assumes that there is continuous human activity inside the building. The temperature setting during the heating season is shown in equation (9) (Gan *et al.*, 2023).

$$T_{zone}^{set,h}(t) = \begin{cases} 26 & p_{buy}(t) < p_1 \\ 24 & p_1 \le p_{buy}(t) < p_2 \\ 20 & p_{buy}(t) \ge p_2 \\ 18 & other \end{cases} \tag{9}$$

In equation (9), $T_{zone}^{set,h}$ represents the temperature set point during the building heating season. t refers to time. pbuy represents the price of energy on the supply side. p_2 and p_1 respectively represent the limits of energy prices. The temperature set point for the cooling season is shown in equation (10) (Shayan *et al.*, 2023).

$$T_{zone}^{set,c}(t) = \begin{cases} 26 & p_{buy}(t) < p_1 \\ 24 & p_1 \le p_{buy}(t) < p_2 \\ 22 & p_{buy}(t) \ge p_2 \\ 20 & other \end{cases} \tag{10}$$

In equation (10), $T_{zone}^{set,c}$ represents the temperature set point during the cooling season. During the transitional season, if the indoor temperature is not below 18°C or exceeds 26°C, heating or cooling equipment is usually not turned on, and the Heating, Ventilation, and Air Conditioning system remains turned off. The control rules for the air conditioning system switch are shown in equation (11) (Guo *et al.*, 2023).

$$S_{HVAC}(t) = \begin{cases} 1 & T_{zone}(t) \le T_{zone}^{set}(t) - 0.5 \\ 0 & T_{zone}(t) > T_{zone}^{set}(t) - 0.5 \\ S_{HVAC}(t-1) & other \end{cases} \tag{11}$$

In equation (11), $S_{HVAC}(t)$ represents the variable of system operating status. When $S_{HVAC}(t)$ is 1, it indicates that the system is in an open state. When $S_{HVAC}(t)$ is 0, the system shuts down. To ensure that the energy storage device can respond promptly to the needs of the air conditioning system, GA is used to set a fixed temperature for the hot water storage tank. The operating status of the device is shown in equation (12).

$$S_{heater}(t) = \begin{cases} 1 & T_{\text{tank}}(t) \le T_{\text{tank}}^{set}(t) - 1 \\ 0 & T_{\text{tank}}(t) > T_{\text{tank}}^{set}(t) + 1 \\ S_{heater}(t-1) & other \end{cases} \tag{12}$$

In equation (12), S_{heater} is the binary variable for the operation of the thermal storage device, and T_{tank} represents its internal temperature. In addition to thermal storage equipment, GA also precisely sets the proportion of battery energy storage in buildings. The adjustment mechanism of battery energy storage capacity is shown in equation (13).

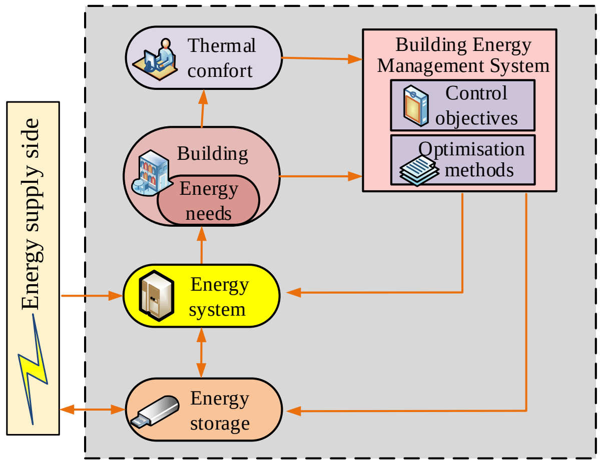


Fig.6 Architecture of building energy management model

$$S(t+1)=\begin{cases}S_{full}S_{set}(t)\\ S(t)+sign[S_{full}S_{set}-S(t)]\dot{Q}_{ch/dis}\end{cases} \tag{13}$$

In equation (13), S represents the proportion of the battery capacity. S_{full} stands for the capacity of the battery at full load. S_{set} represents the setting state of the battery capacity ratio. Within the allowable range of battery charging and discharging c apacity, the system adjusts the battery's charging and discharging status to achieve the set capacity target (Zhao *et al.*, 2 022). The battery control logic is crucial for the storage, use, or trading of renewable energy. The core principle is to first ensure that the charging and discharging needs of the battery are met, and then sell or supplement the insufficient power supply with the remaining electricity. The final architecture of the RBC-GA-based management model is displayed in Figure 6.

In Figure 6, the system utilizes advanced control optimization algorithms to collect thermal comfort and energy consumption data within the building, and completes control tasks through intelligent adjustment of energy and energy storage devices. Control parameters include energy flow, temperature setting, and continuous adjustment variables.

3 Results and discussion

On the basis of establishing a building energy system model, the proposed RBC-GA is compared with Supervisory Control and Data Acquisition (SCADA), Beetle Antennae Search and Particle Swarm Optimization (BAS-PSO), and Long Short-Term Memory-Convolutional Neural Network (LSTM-CNN) algorithm to verify the superiority of RBC-GA. Finally, four methods are used to validate the actual application effects.

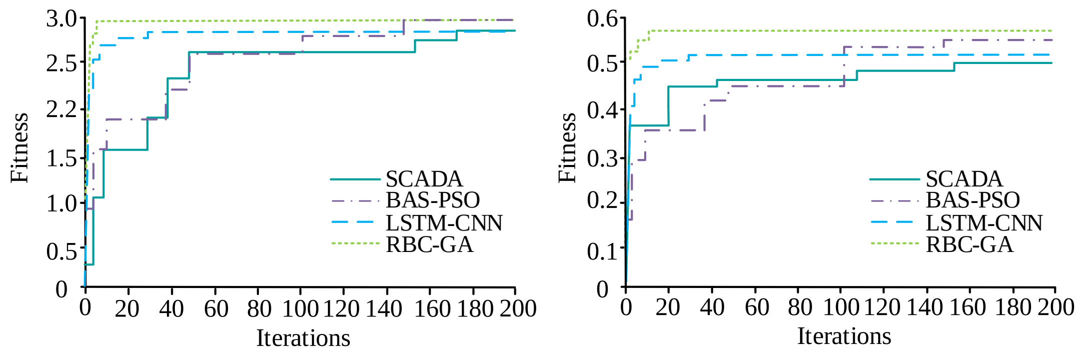
3.1 RBC-GA performance testing

To verify whether the RBC-GA has good performance, a computer using Windows 10 operating system and Intel (R) Core (TM) i5-9400F CPU is adopted. Energy NLP is used as the dataset, dividing into training and testing sets in a 7:3 ratio. The experimental parameters are set to 200 iterations. The convergence performance on the two sets is shown in Figure 7.

Figure 7 (a) shows the fitness convergence curves of RBC-GA, SCADA (Fazlollahtabar, 2022), BAS-PSO (Zhang & Zhang, 2022), and LSTM-CNN (Liu *et al.*, 2024) in the training set. Overall, the fitness convergence curves showed an increasing trend. RBC-GA and BAS-PSO had the highest fitness values, followed by the LSTM-CNN model, and the SCADA model had the lowest fitness. In terms of convergence speed, although the maximum fitness values of RBC-GA and BAS-PSO were the same, RBC-GA reached its optimal fitness value before the 20th iteration and gradually stabilized. Figure 7 (b) displays the fitness convergence results of four algorithms in the testing set. RBC-GA had the highest fitness value and the fastest convergence speed. Therefore, the RBC-GA model has a faster convergence speed and a higher fitness value, indicating that RBC-GA has a significant advantage in optimization speed and better optimization performance. The Precision-Recall (PR) of different algorithms is displayed in Figure 8.

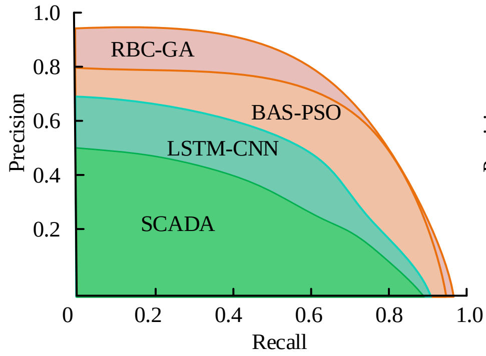
Figure 8 shows the recall curves of RBC-GA, SCADA, BAS-PSO, and LSTM-CNN in the training and testing sets, respectively. A large area enclosed by curves and coordinate axes demonstrates better performance. Figure 8 (a) displays the PR curves of the four methods in the training set. RBC-GA had the largest curve area, followed by BAS-PSO and LSTM-CNN, while SCADA had the smallest area. Figure 8 (b) displays the recall results of the four methods in the testing set. The area of RBC-GA was once again larger than the other three models. Overall, RBC-GA has the best performance, with good precision and recall. The RSME, Mean Absolute Percentage Error (MAPE), and coefficient of determination R^2 are displayed in Table 1.

In Table 1, the RMSE of RBC-GA was 43.6544 and 43.6844 in the two datasets, which were 3.6% and 7.0% lower than SCADA, respectively. RBC-GA had the smallest and highest prediction accuracy among the four algorithms. RBC-GA had R^2 of 0.9886 and 0.9981, respectively. In the test results, it was closest to 1, with the highest model fitness, significantly better than the other three models. RBC-GA model had lower MAPE values in both datasets, demonstrating good stability. This indicates that the RBC-GA can provide more reliable prediction results and higher accuracy.

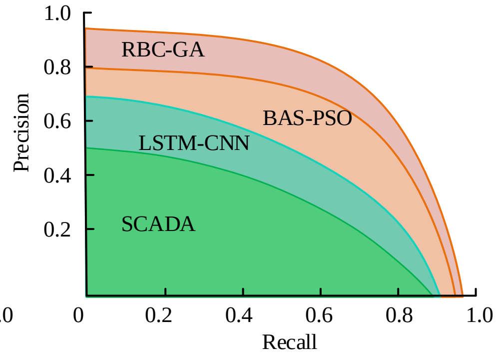


(a) Training set (b) Testing set

Fig.7 Convergence performance of four algorithms on datasets



(a) Training set



(b) Testing set

Fig.8 Recall results of different algorithms

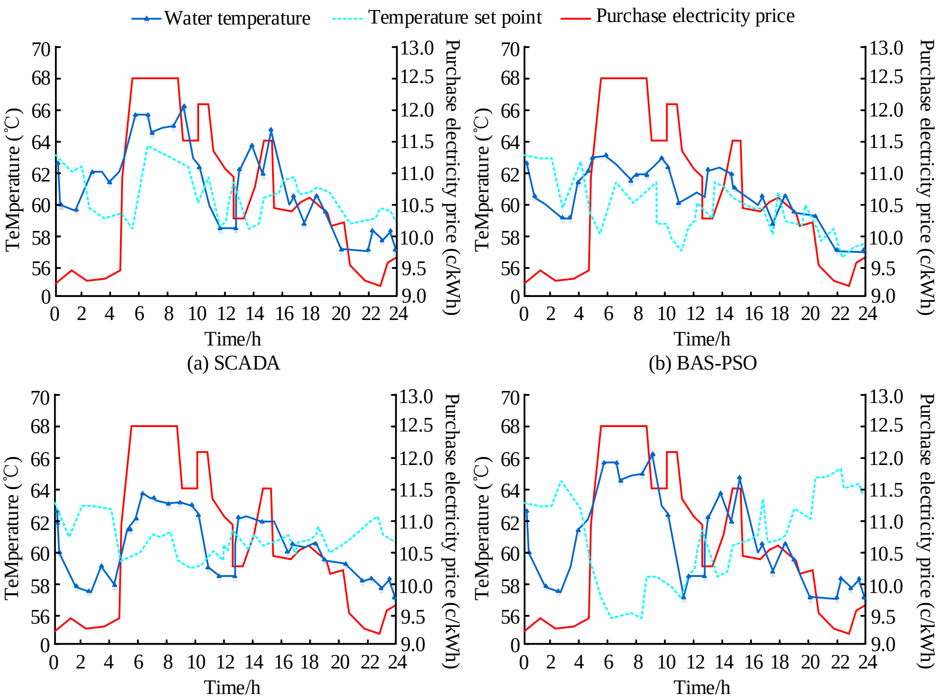
Table 1
Comparison of errors among various algorithms

Algorithm	Data set	RMSE	MAPE	R^2
SCADA	Training set	45.2678	8.6451	0.9722
	Testing set	46.9685	8.6854	0.9675
LSTM-CNN	Training set	46.1325	8.5432	0.9721
	Testing set	45.9846	7.6146	0.9715
BAS-PSO	Training set	44.6516	7.3542	0.9776
	Testing set	45.6544	6.9841	0.9821
RBC-GA	Training set	43.6544	6.3135	0.9886
	Testing set	43.6844	6.1332	0.9981

3.2 The effect of building energy management model based on RBC-GA

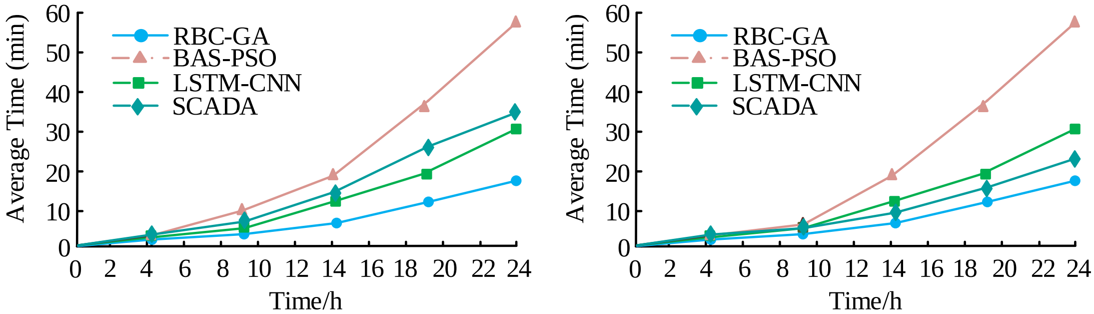
To analyze the application effect of the building energy management model based on RBC-GA, the MATLAB simulation platform is used to compare the actual application effect of building energy management models based on four different algorithms. The ideal temperature setting results of different management models for hot water storage tanks within 24 hours are shown in Figure 9.

In Figure 9, (a), (b), (c), and (d) show the results of SCADA, BAS-PSO, LSTM-CNN, and RBC-GA building energy management models for the temperature changes of hot water storage tanks within 24 hours. When setting the temperature point with the same purchase price, the SCADA and BAS-PSO algorithms in Figure 9 (a) and Figure 9 (b) mainly set it based on



(a) SCADA
(b) BAS-PSO
(c) LSTM-CNN
(d) RBC-GA

Fig.9 Temperature setting result of building hot water storage tank



(a) Building No.1 (b) Building No.2

Fig.10 Actual operating time of building energy management model

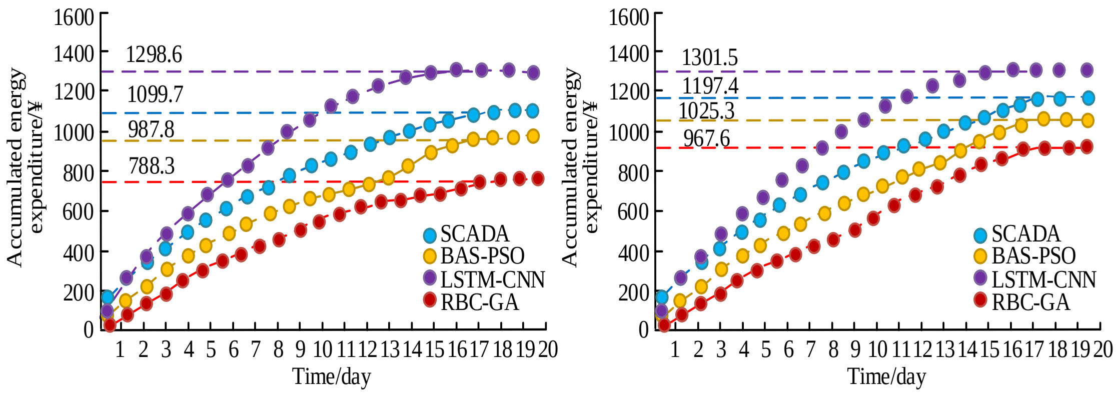
the peak electricity consumption period, without considering changes in electricity prices. In Figure 9 (c), the LSTM-CNN model did not consider the fluctuation of electricity prices when setting temperature points, and continued to purchase electricity even when electricity prices rose, resulting in unnecessary expenses. In Figure 9 (d), the RBC-GA building energy management model selected a time period with low electricity prices to purchase and store electricity for use in high electricity prices or insufficient local power supply when setting the temperature point. To verify the practical application effect of the RBC-GA integrated building energy management model, a residential building with an older structure and poor airtightness is selected as the first building model, and a residential building with advanced building equipment and better airtightness is selected as the second building model. The average running time of building energy management models with different algorithms for 24 hours is shown in Figure 10.

Figures 10 (a) and (b) respectively show the actual running time of different algorithms in two building models. During the 24-hour running process, the overall average running time of the four models also increased with the increase of running time. The average running time of RBC-GA was always lower than the other three models. This model has faster speed and can meet the requirements of real-time control. Compared with existing research, the building ener gy management strategy based on three-level hierarchical model predictive control proposed by Vašak *et al.* (2021) not only focuses on multi-objective optimization of energy, but also emphasizes the system's ability to respond quickly to changes in energy demand. The cumulative energy expenditure of the building energy management model based on four algorithms within 20 days is shown in Figure 11.

Figures 11 (a) and 11 (b) show the cumulative energy expenditure changes of different models in Building 1 and Building 2 within 20 days. In Building 1, the cumulative energy expenditure of building energy management models based on SCADA, BAS-PSO, LSTM-CNN, and RBC-GA within 20 days was 1298.6 yuan, 1099.7 yuan, 987.8 yuan, and 788.3 yuan, respectively. The cumulative energy expenditures in Building 2 were 1301.5 yuan, 1197.4 yuan, 1025.3 yuan, and 967.6 yuan, respectively. In the two types of buildings, the building energy management model based on RBC-GA has the lowest cost consumption. According to the comparative experimental results, this algorithm can effectively control and efficiently utilize building energy to save expenses. Compared with existing research, Shi *et al.* (2022) mainly focused on improving energy efficiency and economic benefits in the research of energy sharing models. This study further expanded its application in complex building systems and performed well in improving management efficiency.

4 Conclusion

A building energy management model based on RBC-GA was proposed to response the energy optimization of building energy management systems. The digital model of the energy system was established and connected to the control system, combing RBC and GA to manage and control the operation of various devices. The proposed model effectively solved multi-objective optimization problems due to its powerful global search and optimization capabilities, but the computing speed and real-time response ability of GA are still challenges. Based on the fast response advantage of RBC and GA optimization, multi-objective problems in energy management were



(a) Building No.1 (b) Building No.2

Fig.11 Cumulative building energy expenditure results of different models effectively controlled under high complexity conditions. The results indicated that the maximum fitness value of RBC-GA was significantly higher than the other three algorithms. It converged and stabilized before the 20th iteration. In the simulation experiment, the RBC-GA model considered the real-time changes in the purchase price when setting the temperature point for the hot water storage tank in the building energy management model. RBC-GA prioritized purchasing more electricity for storage when prices were low, and replenishing electricity when electricity prices rose or power supply was insufficient. During operation, the RBC-GA building energy management model had the shortest average running time, which achieved real-time control. Finally, from the cumulative energy expenditure of different models within 20 days, the results showed that the building energy management model based on RBC-GA had energy expenditures of 788.3 yuan and 967.6 yuan in Building 1 and Building 2, respectively. Compared with other models, this model achieves the minimum energy expenditure, indicating that it can efficiently manage and save building energy, thereby effectively reducing operating costs. Although the model can efficiently utilize resources, further improvement is necessary for its security.

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