

# Predictive Control of an Intelligent Energy-saving Operation System Based on Deep Learning

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An intelligent energy-saving operation system is a high-tech product specifically designed to transform the air conditioning systems, motor systems, and lighting systems, to reduce energy consumption. The concentration of equipment distribution within these systems leads to a strong coupling relationship between them. By conducting an overall energy efficiency prediction, the intelligent energy-saving operation system can fully explore its energy-saving potential. The existing research methods for the online control process of intelligent energy-saving operation systems are not accurate enough to predict energy-saving operations when numerous devices are involved. Consequently, this article focuses on studying the predictive control of an intelligent energy-saving operation system using deep learning techniques. The Generalized Regression Neural Network (GRNN) network is selected to describe the energy consumption of the system. The Beetle Antennae search algorithm is then employed to iteratively optimize the smoothing factor of the model, eliminating the need to rely on experiential parameter determination and enhancing the predictive performance of the model. For the predictive control of the intelligent energy-saving operation system, the optimized GRNN network model serves as the prediction model. The primary control objective is to minimize energy consumption while maintaining a unified carrying capacity, thus achieving intelligent energy-saving effects. Experimental results validate the effectiveness of the model.

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Computing methodologies → Artificial intelligence → Control methods → Computational control theory

*Keywords:* deep learning, intelligent energy-saving operation system, predictive control, optimized Generalized Regression Neural Network (optimized GRNN), improved Beetle Antennae Search Algorithm (improved BAS algorithm)

## 1. Introduction

Energy-saving is an important strategy for countries all over the world to achieve sustainable development. [1–7]. With the development of information technology, energy-saving, and consumption-reducing technologies have evolved from informatization to intelligence. An intelligent energy-saving operation system is a high-tech product tailored for the energy-saving and consumption-reducing transformations across various sectors, including air-conditioning system encompassing heating, ventilation, and central air conditioning; motor systems subject to frequent load changes and substantial grid voltage fluctuations; and lighting system spanning building lighting and high-pole street lamp lighting [8–15].

These systems possess centralized equipment distribution, resulting in a strong coupling relationship between them. The on-line control under actual operating conditions is complex and the response is slow [16–19]. At the same time, given the high energy consumption density of the aforementioned systems, the overall energy efficiency prediction of the intelligent energy-saving operation system can be used to save energy at the overall level of the system and fully explore its energy-saving potential [20–24]. Therefore, it is of practical value to establish an energy efficiency prediction model for intelligent energy-saving operation systems and explore an energy-saving predictive control

method for intelligent energy-saving operation systems suitable for online applications.

With the rapid construction of China's 5G low-carbon power grid, the landscape of distribution networks, including renewable energy, has witnessed a transformation compared to the traditional passive distribution network. Liang *et al.* [25] propose a hierarchical and partitioned energy Internet loss reduction method. This model incorporates the losses of the communication network into the category of power grid energy-saving, reducing distribution network losses. By employing optimization algorithms, the model searches for the optimal solution, enabling the attainment of an optimal network configuration, reducing network loss, and offering valuable insights for the development of the 5G low-carbon power grid.

The existing residential energy management system faces challenges when dealing with the calculation of multi-source energy management due to its linear management strategy based on single data. To address this, Li *et al.* [26] propose a multi-source distributed energy real-time management system for energy-saving in an intelligent community. This system employs the DES or CCHP framework based on distributed multi-source energy management. Through the establishment of a distributed hardware platform, different types of energy data are integrated and optimized using a multi-source management strategy. Simulation results show that the proposed energy management system has better management efficiency, delivers optimal energy-saving effect, and demonstrates better real-time performance.

Modern greenhouses require certain equipment to achieve the expected ambient temperature in a short time and save energy at the same time. To realize greenhouse temperature management and energy-saving through intelligent control, Fei *et al.* [27] first establish a greenhouse mechanism model and study the controller design of a greenhouse in Yiyang city. Then, the accuracy of the model is verified by experimental data. Based on the verified model, two intelligent control techniques, active disturbance rejection control, and fuzzy active disturbance rejection controller, are proposed. To control the temperature of the greenhouse and save energy, this model also adopts methods of adjusting the opening of a skylight and hot air conditioning.

Ishankhodjayev *et al.* [28] discuss the development of algorithms for optimizing energy-saving management processes in intelligent energy systems. They explore the main problems in the operation of enterprise energy-saving management process and provide methods and algorithms to solve these problems. The authors propose an improved algorithm for optimizing the energy-saving management process of intelligent energy systems, which includes solving the problems of reasonable regulation of fuel and energy consumption, optimal planning, operation accounting, control, and management decision-making, *etc.*

Based on the existing research status, scholars at home and abroad have conducted relevant studies on the online control process of intelligent energy-saving operation systems. However, there is a lack of optimal design for control architecture and control parameters, and the prediction accuracy of the system's energy-saving operations falls short when dealing with numerous devices. Therefore, this article studies the predictive control of an intelligent energy-saving operation system based on deep learning.

In the second chapter, the energy consumption of the intelligent energy-saving operation system is described using the GRNN network. The Beetle Antennae search algorithm is used to iteratively optimize the smoothing factor of the model, which avoids the uncertainty associated with determining the parameter values based solely on experience and improves the predictive performance of the model. In the third chapter, the optimized GRNN network model, described in the previous section, is used as the prediction model for predictive control in the intelligent energy-saving operation system. The primary control objective is to minimize energy consumption while maintaining a unified carrying capacity, thereby achieving intelligent energy-saving effects. Experimental results verify the effectiveness of the model.

## 2. Construction of Prediction Model Based on Optimized Generalized Regression Neural Network

The accuracy of the prediction model plays a crucial role in predicting and controlling intelligent energy-saving operation systems. The GRNN is

an effective prediction model established based on neural networks with a kernel function that can fit model representation functions by training on a large amount of real-world data. This fitting process yields results that closely align with real-world situations and can be used for high-accuracy prediction and control in intelligent energy-saving operating systems.

The accuracy of data fitting in GRNN is determined by its features. GRNN is composed of Radial Basis Function (RBF) neurons that can effectively adapt to the input space, enabling the network to learn and fit complex nonlinear data distributions. Moreover, the training process of GRNN is faster and more straightforward than many other neural networks, as it only requires setting a single parameter during training: the smoothing factor. The selection of this factor influences the degree of model fitting. A too-small smoothing factor may lead to overfitting the model to the training data, while a too-large one may cause underfitting. Therefore, a proper factor value should be selected to ensure that the GRNN achieves excellent accuracy in data fitting.

Consequently, in this paper, the GRNN network is selected to describe the energy consumption of intelligent energy-saving operation systems. The Beetle Antennae search algorithm is used to optimize the smoothing factor of the model

iteratively, which avoids the uncertainty of determining the parameter values based on experience and improves the predictive performance of the model.

Figure 1 shows the basic architecture of the GRNN network. The neuron structure of GRNN is divided into four layers: input layer, mode layer, summation layer, and output layer. To construct the neural network model of an intelligent energy-saving operation system, the input is determined as the power and carrying capacity of such intelligent energy-saving operation system:

$$A = [T(p), P(p)](p = 1, 2, \dots, 24) \quad (1)$$

The number of sample data of power and carrying capacity of the intelligent energy-saving operation system for model learning is equal to the number of neurons in the mode layer of the GRNN network, and there is a one-to-one corresponding relationship. Assuming that the input variable of the GRNN network is represented by  $A$ , the learning sample corresponding to the  $i$ -th neuron is represented by  $A_i$ , and the smoothing factor of the GRNN network is represented by  $\varepsilon$ , the following formula gives the expression of neuron transfer function:

$$t_i = \exp \left[ -\frac{(A - A_i)^T (A - A_i)}{2\varepsilon^2} \right]. \quad (2)$$

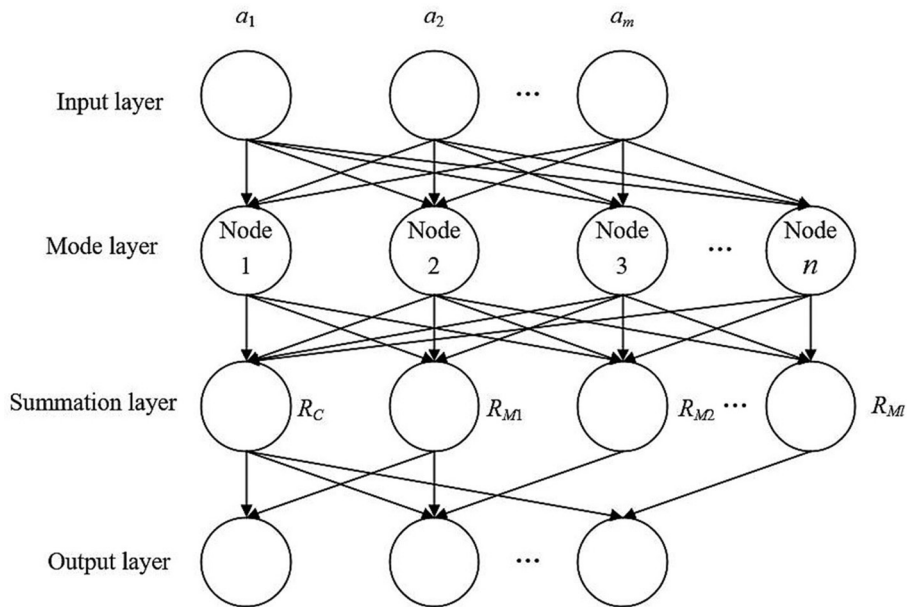


Figure 1. Basic architecture of the GRNN network.

The summation layer of the GRNN network uses two types of neurons to perform arithmetic summation and weighted summation of neuron output in the mode layer. Assuming that the arithmetic summation result is represented by  $R_C$  and the weighted summation result is represented by  $R_{Mj}$ , the corresponding transfer function expression is given by the following formula:

$$R_C = \sum_{i=1}^m T_i \quad (3)$$

$$R_{Mj} = \sum_{i=1}^m b_{ij} T_i, \quad j = 1, 2, \dots, l. \quad (4)$$

The dimension of the output vector of the model learning sample is equal to the number of neurons in the output layer of the GRNN network. The output of each neuron in the output layer can be obtained by dividing the output of the summation layer, which corresponds to the  $j$ -th element of the prediction result  $B(A)$ :

$$b_j = \frac{R_{Mj}}{R_C}, \quad j = 1, 2, \dots, l \quad (5)$$

$$B = [b_1, b_2, \dots, b_{24}]^P \quad (6)$$

In GRNN, the smoothing factor is a key parameter affecting the learning ability and generalization performance of the network. The selection of the smoothing factor can affect the shape of the transfer function, thereby affecting the connection weights between network neurons. If a too-small value is selected for the smoothing factor, the model may overfit the training data; but if a too-large value is selected, the model may underfit. In this study, the BAS algorithm is adopted to perform iterative optimization on the smoothing factor of the model. BAS is an adaptive optimization algorithm that simulates the tactile search mechanism of beetles to conduct global search efficiently in the parameter space and find the optimal solution.

Figure 2 shows the optimization model flow. The foraging process of the Beetle Antennae search algorithm is the process of global optimization. The following formula gives the position expression of the Beetle Antennae search algorithm in  $m$ -dimensional space:

$$A(a_1, a_2, \dots, a_m) \quad (7)$$

It is assumed that the distance between the centroid and tentacles of the Beetle is expressed by  $k$ , and the random unit vector is expressed by  $c^*$ . The following formula gives the position calculation formula of the left and right antennae of Beetle Antennae:

$$\begin{cases} A_s = A + k * c^* \\ A_k = A + k * c^* \end{cases} \quad (8)$$

Normalization of the unit vector is calculated as follows:

$$c^* = \frac{\text{rands}(C, k)}{\|\text{rands}(C, k)\|} \quad (9)$$

Assuming that the number of iterations is represented by  $p$ , the objective function is represented by the function  $g$ , the step size at the  $p$ -th exploration is represented by  $\zeta$ , and the sign function is represented by the  $sign$  function. Because the two antennae of a Beetle obtain the objective function information of the two positions respectively, it is necessary to select the two positions corresponding to the two antennae based on the following formula to determine the forward direction:

$$A_{p+1} = A_p + \zeta_p * c^* * sign[g(a_s) - g(a_k)] \quad (10)$$

$$sign(a) = \begin{cases} 1, & a > 0 \\ 0, & a = 0 \\ -1, & a < 0 \end{cases} \quad (11)$$

In the iterative process of the algorithm, the step size is continuously attenuated. Assuming that the attenuation coefficient of each iteration step is represented by  $\varphi$ , it can be set based on the following formula:

$$\zeta_{p+1} = \zeta_p * \varphi \quad (12)$$

To avoid the convergence of the Beetle Antennae search algorithm to the local optimum and enhance the global optimization ability of the algorithm, this paper introduces the nonlinear control parameter coordination algorithm and Levy flight strategy into the algorithm to improve the algorithm. Figure 3 shows the improved algorithm flow of the Beetle Antennae search algorithm. Because the optimization ability of the Beetle Antennae search algorithm is determined

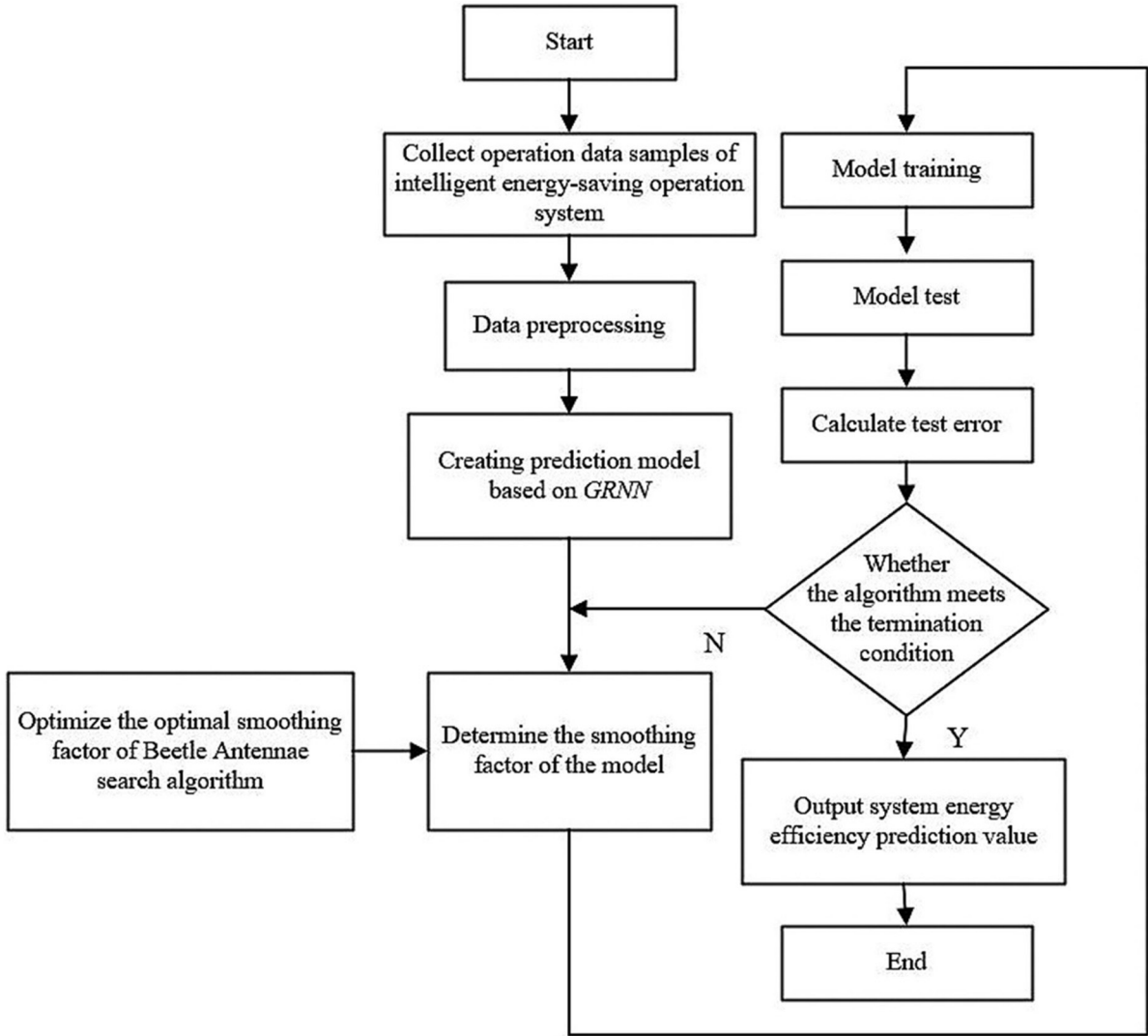


Figure 2. Optimization model flow.

by the position of each iterative update, this article uses dynamic adaptive weight  $\theta$  to adjust the update of position coordinates. Assuming that the initial and final values of the control parameters are represented by  $\theta_{imi}$  and  $\theta_{gim}$ , respectively, the current number of iterations is represented by  $p$ , and the maximum number of iterations is represented by  $P_{max}$ , then:

$$\theta(p) = \theta_{imi} - (\theta_{imi} - \theta_{gim}) \times \left( \frac{p}{P_{max}} \right)^2. \quad (13)$$

Substituting  $\theta$  into Formula 10 updates the position function as follows:

$$A_{p+1} = A_p + \theta \zeta_p * c^* * \text{sign}[g(A_s) - g(A_k)]. \quad (14)$$

In order to ensure comprehensive search ability, two termination conditions are set to indicate that the algorithm has completed the optimization. The first condition sets the desired accuracy level for the optimization value, while the second condition sets a fixed number of iterations. When solving the practical problems of optimal control of intelligent energy-saving operation systems, there is a degree of uncertainty regarding the accuracy requirements for the algorithm's optimization. If the precision requirement of the optimization value and the termination condition of fixed iteration times are not set, the algorithm will not stop the iterative process in a timely manner and deliver a solution that meets the desired criteria.

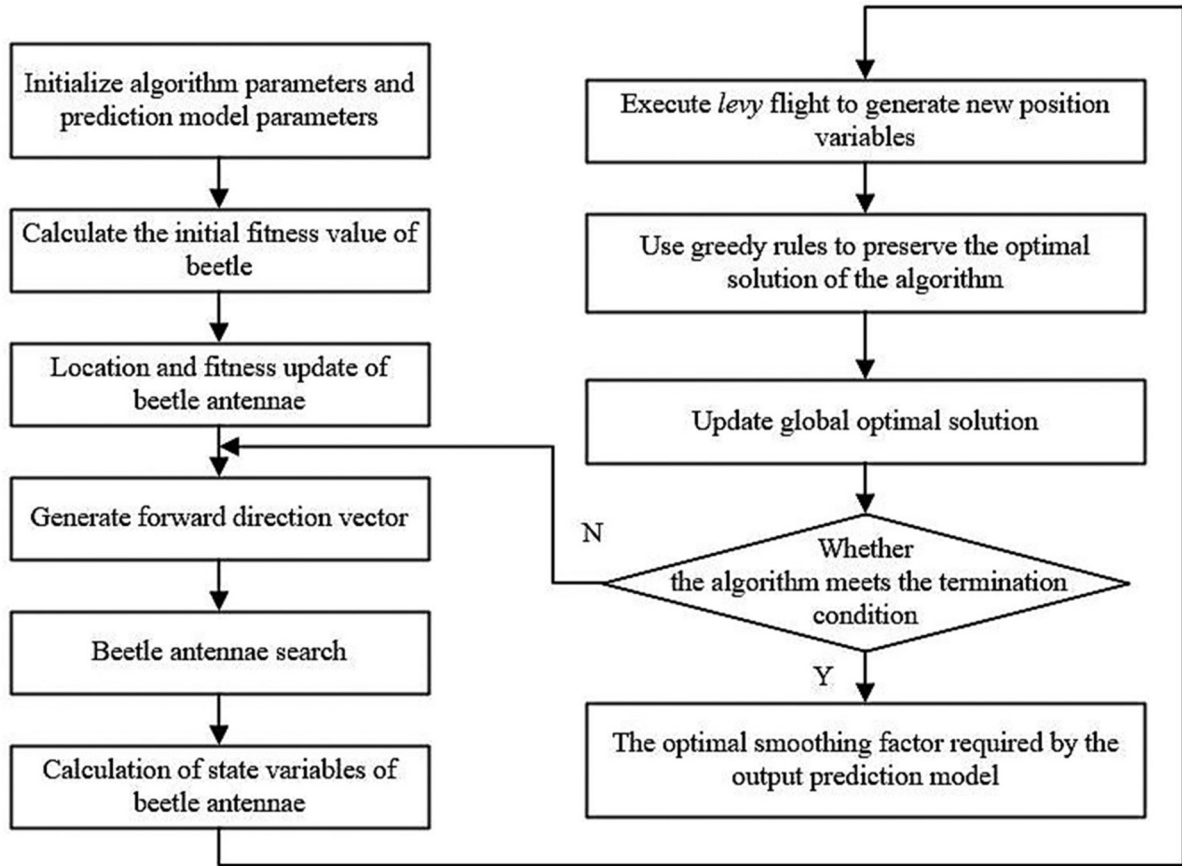


Figure 3. Improved algorithm flow of the Beetle Antennae search algorithm.

To ensure that the algorithm terminates when the prediction accuracy or iteration times reach the maximum, and at the same time improve the global optimization ability, the Levy flight strategy is adopted to enhance the algorithm's global optimization capability. Assuming that the global optimal solution obtained by the current iterative operation is represented by  $A_{best}$ , Levy random path is represented by  $GD(\gamma)$ , point-to-point multiplication is represented by  $\otimes$ , and the initial search step size is represented by  $x$ , the following formula gives the update formula of Levy flight position:

$$A_{p+1} = A_p + (A_{best} - A_p) \cdot (\beta \otimes GD(\gamma)) \quad (15)$$

In the iterative process, the algorithm does not choose the global optimal solution, but the optimal solution obtained by the current iteration. Therefore, this article introduces a greedy

mechanism to judge whether to retain the optimal solution obtained by the current iteration in the new position of Beetle Antennae. The following formula gives a new position expression for the generation of Beetle Antennae:

$$a_i(p) = \begin{cases} a_i(p), & fit(a'_i(p)) < fit(a_i(p)) \\ a'_i(p), & fit(a'_i(p)) > fit(a_i(p)) \end{cases} \quad (16)$$

That is, if the new position generated by the iteration is better than the position obtained by the previous iteration, the position is updated. If it is not as good as the position obtained in the previous iteration, the current position remains unchanged. To ensure that the constructed model has a good training effect, it is necessary to cross-validate it, and the validation method steps are given in Figure 4.

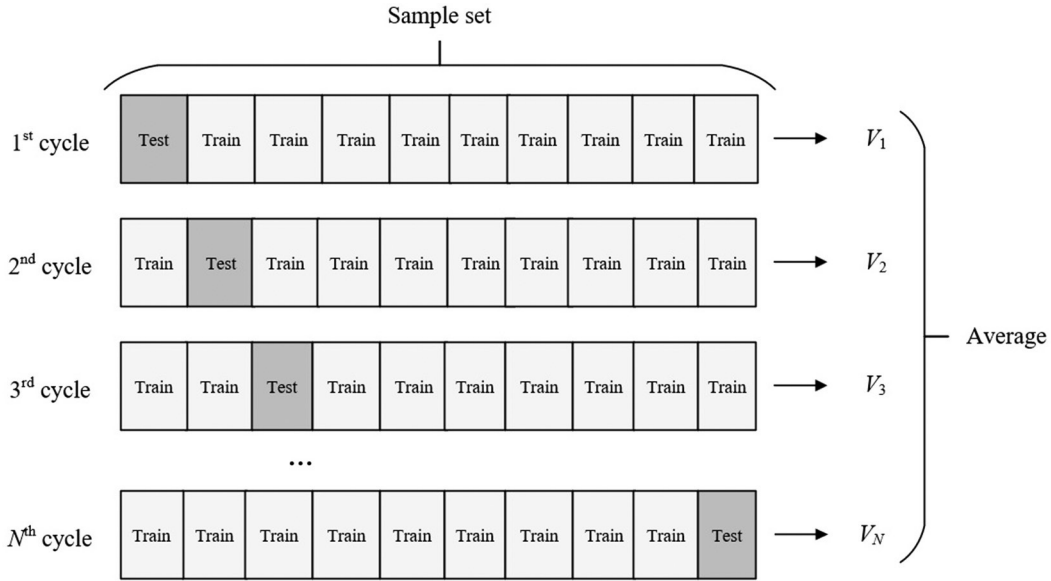


Figure 4. Steps of cross validation method.

### 3. Optimal Control Strategy of Intelligent Energy-Saving Operation System

In the context of predictive control of intelligent energy-saving operation systems, the previously optimized GRNN network model is taken as the prediction model for predictive control. The primary objective is to minimize the energy consumption while maintaining a unified carrying capacity. This approach enables the system to achieve intelligent energy-saving effects. The predictive control principle of the system is illustrated in Figure 5.

Assuming that the reference value is represented by  $q_T(l + i)$ , the output of predictive control is represented by  $b(l)$ , the energy efficiency of the intelligent energy-saving operation system is taken as the output, the predictive output value is represented by  $b_{TN}(l + i)$ , and the disturbance during fieldwork is represented by  $c(l)$ . To verify the effectiveness of the proposed optimization algorithm, the daily power consumption is taken as the optimization indicator, the optimization objective function is constructed, and its minimum value is obtained. Figure 6

shows the predictive control structure of the optimized model.

It is assumed that the total power consumption of the daily intelligent energy-saving operation system is expressed by the objective function  $J$ , the power of the system equipment in the  $i$ -th hour is expressed by  $T_i$ , and the time-sharing electricity cost in the  $i$ -th hour is expressed by  $N_i$ . The optimal energy efficiency of the intelligent energy-saving operation system obtained by the prediction model corresponds to the lowest power consumed by the system equipment. Combined with the time-sharing electricity cost of the system equipment during operation, the optimization objective function of daily power consumption is given by the following formula:

$$J = \sum_{i=1}^{24} T_i N_i \tag{17}$$

Constraints are usually determined based on the actual operating parameters of an intelligent energy-saving operation system. These limitations are associated with the system's model structure. For example, if the instantaneous change rate of the motor's running speed in the motor system is too high, it can potentially result in structural damage to the equipment.

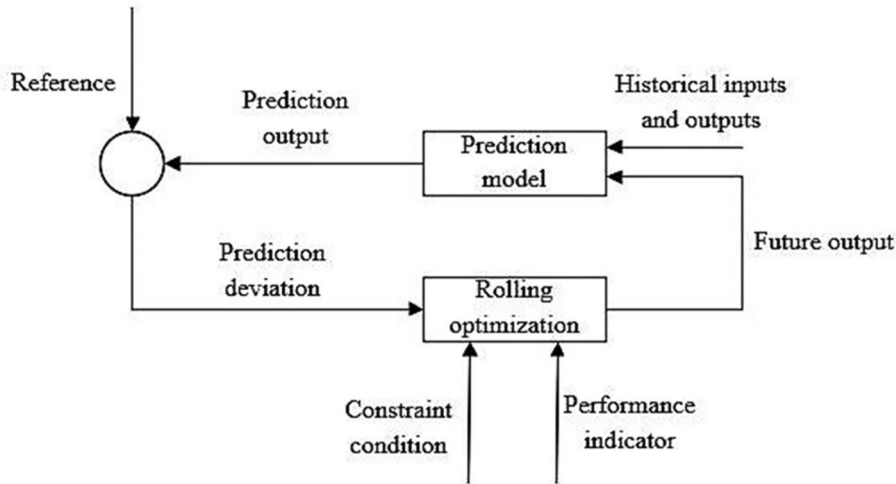


Figure 5. Predictive control principle for an intelligent energy-saving operation system.

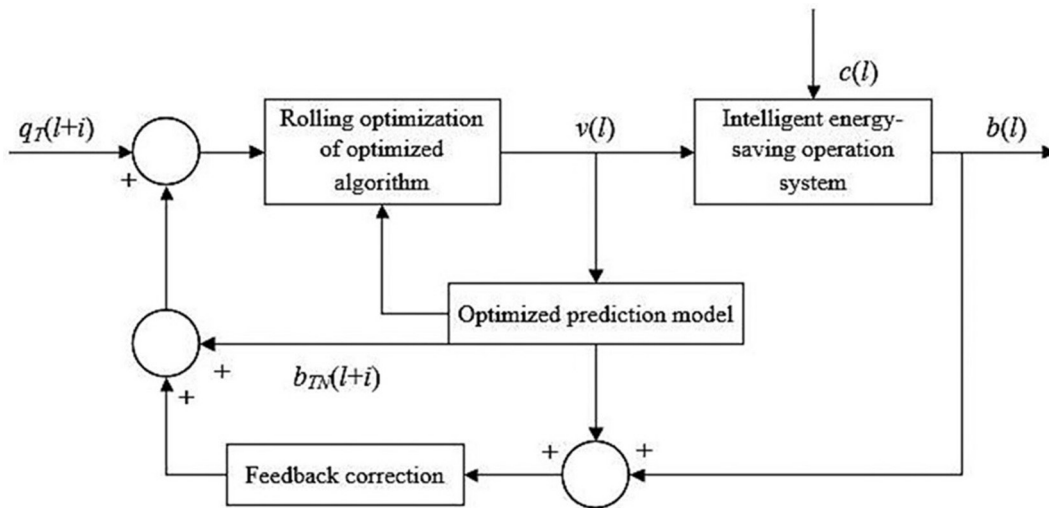


Figure 6. Predictive control structure of the optimized model.

To address these limitations, corresponding thresholds can be established for making judgments, and such threshold-based judgment can significantly improve computational efficiency. Initially, the threshold values of each parameter should be determined based on the system's requirements and equipment performance. For instance, the threshold for the instantaneous change rate of the motor's operating speed could be a fixed value, with any values exceeding this threshold considered too large. Simultaneously, the system needs to monitor the values of various parameters in real time. Once a parameter exceeds its threshold, immediate action must

be taken. The system should be able to respond promptly, such as adjusting the motor's operating speed or stopping it altogether to prevent equipment damage.

By implementing threshold settings, the complexity of the system can be reduced to a certain extent. Consequently, certain less significant parameters can be disregarded during calculation, leading to improved computation efficiency. The threshold-based judgment serves a dual purpose: protecting system equipment from damages caused by sudden parameter changes and increasing computation efficiency to ensure stable and highly efficient system operation.



Due to the size of the system carrying demand being limited by the actual carrying capacity of the system, and assuming that the total carrying demand of the system at the  $i$ -th hour is expressed by  $C_i$ , the new carrying demand of the system at the  $i$ -th hour is expressed by  $D_i$ , and the carrying capacity of the system at the  $i$ -th hour is expressed by  $P_i$ , then:

$$C_{i+1} = C_i + D_i - P_i \quad (18)$$

To ensure the effective operation of the intelligent energy-saving operation system, the system carrying demand  $C_i$  is constrained. If  $C_i$  is too high, the system will be excessively idle when the electricity cost is at its peak; if  $C_i$  is too low, the total carrying demand of the system cannot be met when the electricity cost is at a low point, which seriously affects the operation efficiency of the intelligent energy-saving operation system. To address this issue, it is common practice to reserve a certain margin for processing the system's carrying demand, and hence the upper and lower limits of the carrying demand of the system should not be directly based on the actual carrying capacity of the system. Assuming that the energy efficiency of system equipment at the  $i$ -th hour is represented by  $U_i$  and the power of the intelligent energy-saving operation system is represented by  $T$ , the following formula gives the constraint expression:

$$\begin{aligned} 0.2 < V < 3 \\ |U_i + 1 - U_i| &\leq 2 \\ 0 < T < 160 \\ 0 < P_i < 700 \\ 200 < C_i < 1000 \end{aligned} \quad (19)$$

Let the reference trajectory value and predictive output value be represented by  $q_T(d+c)$  and  $b_{TN}(1+i)$ , respectively. The control increment is denoted as  $\Delta v(1+j-1)$ . Non-negative weight coefficients,  $w$  and  $s$ , are used to suppress tracking error and control variable increment, respectively. The predictive time domain and control time domain are represented by  $t$  and  $n$ . The following formula gives the expression of the model predictive control objective function  $SU(l)$ :

$$\begin{aligned} SU(l) = \sum_{i=1}^t w_i [q_T(l+i) - b_{TN}(l+i)]^2 + \\ \sum_{j=1}^n s_j [\Delta v(l+j-1)]^2 \end{aligned} \quad (20)$$

From the above formula, it can be seen that the objective function is divided into two parts: the reference tracking error and the control variable increment.

In order to ensure the robustness of the proposed predictive control algorithm for intelligent energy-saving operation system, it is required that the curve of the expected output system energy efficiency sequence reaching the system target set value should be smooth. Assuming that the softening factor is expressed by  $\gamma$ , satisfying  $0 < \gamma < 1$ , the reference input is expressed by  $q_s$ , and the predicted output is expressed by  $b_{TN}$ , the following formula gives the expression of the expected output sequence:

$$q_T(1+i) = \gamma^i b_{TN}(1+i-1) + (1-\gamma^i)q_s \quad (21)$$

#### 4. Experimental Results and Analysis

The convergence curve of the improved Beetle Antennae search algorithm is illustrated in Figure 7. The graph demonstrates that the convergence accuracy of the improved Beetle Antennae search algorithm is higher than that of the traditional Beetle Antennae search algorithm, and the convergence speed is obviously better than that of the traditional Beetle Antennae search algorithm. The improved Beetle Antennae search algorithm only reaches the convergence state after about three iterations, while the traditional Beetle Antennae search algorithm needs more than 40-50 iterations before gradually reaching the convergence state.

The optimized prediction model is trained and fitted, and the fitting curves and errors obtained are compared with the corresponding fitting curves of the traditional GRNN model and the optimized GRNN model with the traditional Beetle Antennae search algorithm. The fitting curve and error curve of the model serve as indicators of the prediction accuracy to a certain extent. A fitting curve that closely resembles the real curve corresponds to a smaller fitting

error, indicating a higher prediction accuracy of the constructed model. Additionally, the iterative convergence curve reflects the execution speed of the GRNN model optimized by the improved Beetle Antennae search algorithm. A lower maximum iteration count in the convergence state signifies a faster calculation speed of the model is.

Figures 8 and Figure 9 show that the fitting performance of a traditional GRNN model is poor with a large fitting error, which is mainly

due to the inaccurate setting of super parameters. Compared with this model, the training error of the GRNN model optimized by the traditional Beetle Antennae search algorithm is slightly larger. The model with a dynamic adaptive weight and Levy flight strategy keeps the fitting error in the range of  $[-0.1, +0.1]$ . This error range is smaller than the error range of the GRNN model optimized by the traditional Beetle Antennae search algorithm, which spans  $[-0.5, +0.5]$ , and its training prediction value is

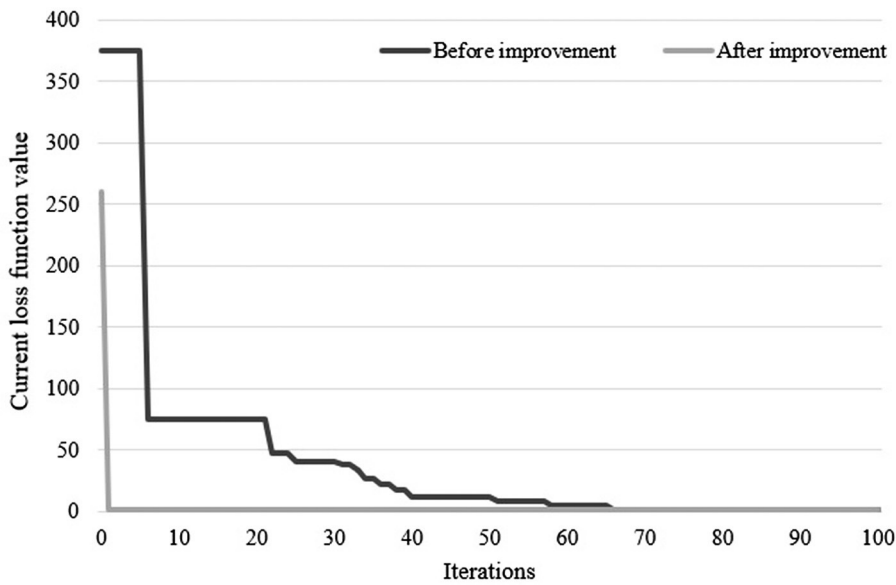


Figure 7. Convergence curve of the improved Beetle Antennae search algorithm.

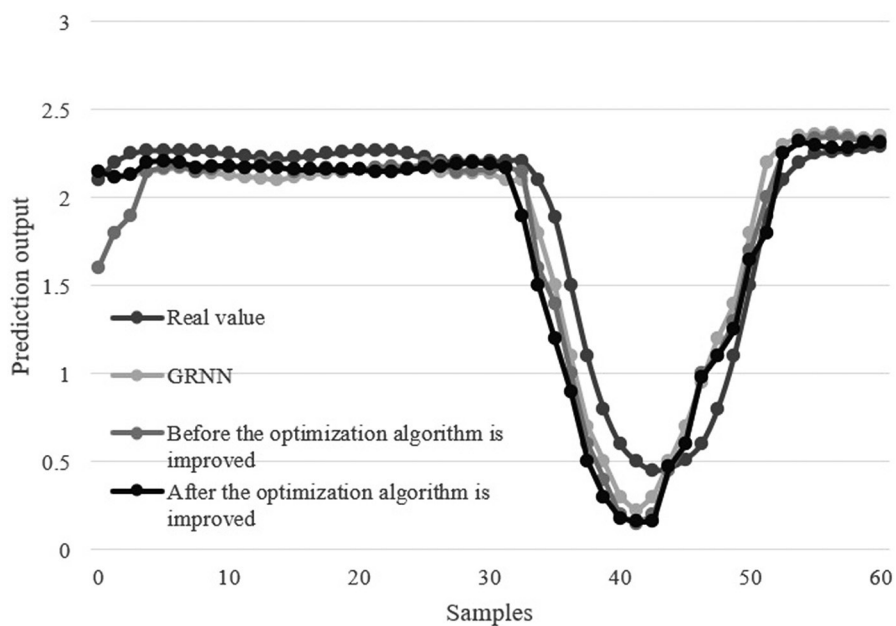


Figure 8. Comparison of training fitting of different models.

consistent with the real value. This shows that the model can improve the accuracy and stability of energy efficiency prediction of an intelligent energy-saving operation system.

According to the operation data from the intelligent energy-saving operation system collected on site, the energy efficiency and system car-

rying demands of the intelligent energy-saving operation system under the dynamic matrix control method, PID + BP neural network method and the control scheme proposed in this article are calculated and simulated, respectively. The simulation results are given in Figure 10 and Figure 11.

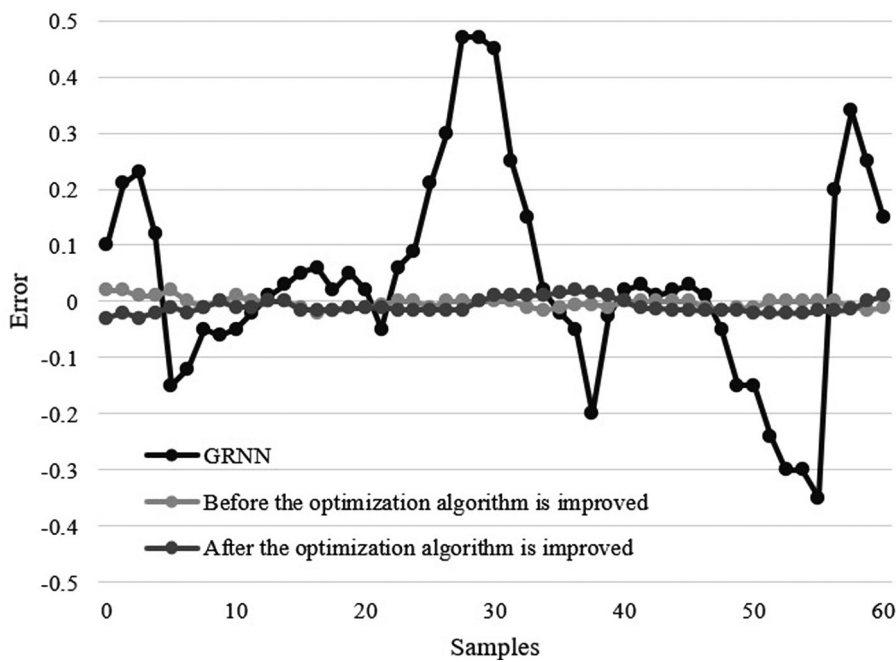


Figure 9. Training error of different models.

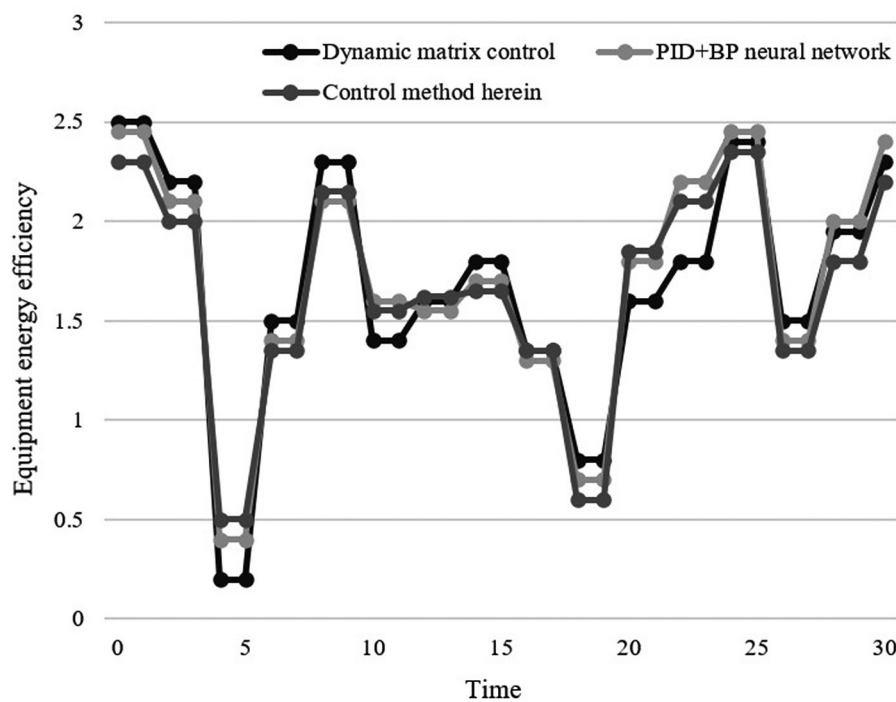


Figure 10. Comparison of energy efficiency of equipment using different methods in intelligent energy-saving operation system.

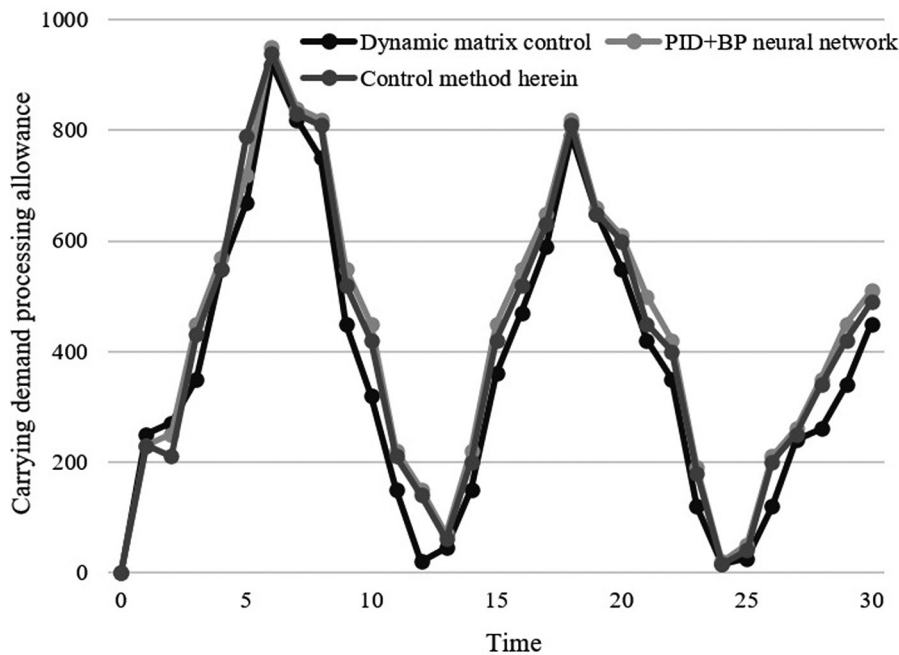


Figure 11. Comparison of carrying demands of intelligent energy-saving operation system.

As can be seen from Figure 10 and Figure 11, during the period when the time-sharing electricity cost is in the trough period, the system equipment runs more efficiently and the unprocessed amount of the system carrying demand is reduced. During the period when the time-sharing electricity cost is in the peak period, the energy efficiency of system equipment decreases, leading to an accumulation of the unprocessed system carrying demand. This paper focuses on an energy-saving strategy that involves transferring the load from the peak period of electricity cost to the low period of electricity cost, resulting in reduced power consumption by system equipment, thus reducing the overall expenditure on electricity cost. Compared with the dynamic matrix control method and the PID + BP neural network method, the proposed control method exhibits a smoother change in the energy efficiency of the system equipment.

The comparison of the system equipment in terms of running energy consumption and electricity cost under dynamic matrix control method, PID + BP neural network method and control method proposed in this paper is shown in Table 1 and Table 2.

As shown in Table 1, the performance of dynamic matrix control in the trough, average, peak, and daily energy consumption is 1280.1,

1921.1, 641.2, and 3841.1, respectively, with an energy saving rate of 3.5%. Under these conditions, the performance of the PID+BP method is 1262.7, 1827, 510.4, and 3597.2, respectively, with an energy-saving rate of 6.5%. The performance of the proposed method is 1208.5, 1759.6, 425.2, and 33.92, with an energy-saving rate of 11.85%. These results clearly demonstrate that the proposed method has a lower energy consumption and a higher energy-saving rate than the other two methods under all conditions, indicating that the proposed optimized method has achieved a better effect in energy-saving operations.

The results in Table 2 show the calculated values of the total electricity cost and the rate of electricity cost reduction for each method during different electricity charge periods (trough, average, peak). The electricity cost of dynamic matrix control in trough, average, and peak periods is 310.2, 1634.3, and 658.2, respectively; the total electricity cost is 2602.3, and the rate of electricity cost reduction is 4.17%. Meanwhile, the PID+BP method achieves values of 306.5, 1556.6, and 523.1, respectively, with a total electricity cost of 2385.4 and an electricity cost reduction rate of 6.5%. The results for the proposed method are 293.2, 1497.7, and 436.2, respectively, with a total electricity cost of

Table 1. Comparison of daily system energy consumption / kW h.

Optimization method	Trough energy consumption	Normal energy consumption	Peak energy consumption	Daily energy consumption	Energy saving rate
Dynamic matrix control	1280.1	1921.1	641.2	3841.1	3.5%
<i>PID + BP</i>	1262.7	1827	510.4	3597.2	6.5%
The method	1208.5	1759.6	425.2	33.92	11.85%

Table 2. Daily system electricity cost comparison/Yuan.

Optimization method	Trough	Normal	Peak	Total	Reduction rate of electricity cost
Dynamic matrix control	310.2	1634.3	658.2	2602.3	4.17%
<i>PID+BP</i>	306.5	1556.6	523.1	2385.4	6.5%
The method	293.2	1497.7	436.2	2224.6	11.85%

2224.6 and an electricity cost reduction rate of 11.85%. As can be seen from these results, the proposed optimized method has a lower electricity cost than the other two methods, and its electricity cost reduction rate is higher, indicating that the proposed method is more effective in reducing electricity costs.

#### 4. Conclusion

This article studies the predictive control of an intelligent energy-saving operation system based on deep learning techniques. The energy consumption of an intelligent energy-saving operation system is modelled using the GRNN network. The Beetle Antennae search algorithm is then used to iteratively optimize the smoothing factor of the model. The iterative optimization process eliminates the uncertainty associated with determining the parameter values based on experience and improves the predictive performance of the model. The optimized GRNN network model serves as the prediction model for the predictive control of an intelligent energy-saving operation system. The lowest energy consumption under the condition of unified carrying capacity is taken as the control target, with the aim to achieve the intelligent energy-saving effect.

Experimental results verify the effectiveness of the improvement of the traditional Beetle Antennae search algorithm. The optimized prediction model is trained and fitted, and the fitting curves and errors obtained are compared with the corresponding fitting curves of the traditional GRNN model and the optimized GRNN model with the traditional Beetle Antennae search algorithm. The findings verify that this model can improve the accuracy and stability of energy efficiency prediction of an intelligent energy-saving operation system as evidenced by the convergence curve presented.

Simulation and calculation are conducted for the dynamic matrix control method, PID + BP neural network method, and the control scheme proposed in this article, taking into account energy efficiency of the intelligent energy-saving operation system and system carrying demands. The simulation results show that the proposed control method ensures a smoother transition in the system equipment's operating energy efficiency. Finally, the comparison of operation energy consumption and electricity cost under different control methods demonstrates that the proposed control method achieves lower energy consumption and greater cost savings in electricity usage.

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