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Research article

Application of machine learning and its improvement technology in modeling of total energy consumption of air conditioning water system

Qixin Zhu[1,2,*], Mengyuan Liu[3], Hongli Liu[1] and Yonghong Zhu[4]

[1] School of Mechanical Engineering, Suzhou University of Science and Technology, No. 55 Changjiang Road, Suzhou 215009, China
[2] Jiangsu Province Key Laboratory of Intelligent Building Energy Efficiency, Suzhou University of Science and Technology, No. 1 Kerui Road, Suzhou 215009, China
[3] School of Environmental Science and Engineering, Suzhou University of Science and Technology, No. 1 Kerui Road, Suzhou 215009, China
[4] School of Mechanical Engineering, School of Mechanical and Electronic Engineering, Jingdezhen Ceramic Institute, No. 27 Taoyang south Road, Jingdezhen 333001, China

* **Correspondence:** Email: bob21cn@163.com; Tel: +(0512)68321761.

Abstract: Accurate energy consumption model is the basis of energy saving optimal control of air conditioning system. The existing energy consumption model of air conditioning water system mainly focuses on a certain equipment or a part of the cycle. However, the coupling between water system equipment will affect the setting of optimal energy consumption of equipment. It is necessary to establish the energy consumption model of water system as a whole. However, air conditioning water system is a highly nonlinear complex system, and its precise physical model is difficult to establish. The main goal of this paper is to develop an accurate machine learning modeling and optimization technique to predict the total energy consumption of air conditioning water system by using the actual operation data collected. The main contributions of this work are as follows: (1) Three commonly used machine learning techniques, artificial neural network (ANN), support vector machine (SVM) and classification regression tree (CART), are used to build prediction models of air conditioning water system energy consumption. The results show that all the three models have fast training speed, but the ANN model has better performance in cross-validation. (2) The improved differential evolution algorithm was used to optimize the parameters (initial weights and thresholds) of the ANN, which solved the problem that the ANN is easy to fall into the local optimal solution. The simulation results show that the root mean square error (RMSE) of the improved model decreases by 20.5%, the mean absolute error (MAE) decreases by 30.2%, and the coefficient of determination (R^2) increases from 0.9227 to 0.9512. (3) Sensitivity analysis of the established optimization model shows that chilled water flow, chilled water outlet temperature and air conditioning load are the main factors affecting the total energy consumption.

Keywords: machine learning; data-driven model; artificial neural network; support vector machine; improved differential evolution algorithm

1. Introduction

With the acceleration of economic globalization, energy has occupied an increasingly important strategic position in the development of the national economy. At the same time, energy issues have also become a focal issue. In 2017, about 38 quadrillion British thermal units of the total U.S. energy consumption was consumed by the residential and commercial sectors, according to the U.S. Energy Information Administration. Where it was found that in 2012, the space heating consumes most of the overall energy use in commercial buildings [1]. Among them, water system energy consumption accounted for 70% of air conditioning system energy consumption, or even more [2]. The optimal control of energy saving of air conditioning water system is of great significance to energy saving and emission reduction.

Modeling is an important means and premise to study the system. The choice of model directly affects the feasibility of the analysis and execution of the system. In the early stage of the research on energy-saving control of air conditioning, less attention was paid to the equipment model, and the research of the model was not comprehensive enough. Therefore, the error between theoretical research and actual optimization was large, and the energy-saving effect was not obvious. With the development of modern control technology, researchers begin to pay attention to the establishment of mathematical models for equipment and system, parameter identification and regression analysis, which improve the stability and accuracy of the optimal control system [3–6].

The mechanism models of most components of the air conditioning water system have been introduced in some literature, such as pump fan model [7,8], cooling tower model [9], cooling coil model [10], etc. Theoretically, the model based on physical properties has higher accuracy. However, air conditioning water system is a highly nonlinear complex system, which makes it difficult to establish an accurate mathematical model from the perspective of mechanism.

The development of modern control technology makes it easier to collect the operation data of air conditioning system, and the accuracy of data-driven model is gradually improved. Data-driven models based on real data proved to be useful tools for understanding the performance of HVAC systems and related subsystems. Chang [11] selected four parameters of chilled water inlet and outlet temperature and cooling water inlet and outlet temperature, and established a chiller energy consumption prediction model through back propagation neural network. Lee et al. [12] obtained 1000 sets of chiller data from manufacturer samples and field measurements, and used these data to study and evaluate six empirical models of chillers. It is found that the multivariate polynomial regression model has good simulation effects for different types of units. Xi et al. [13] adopted support vector regression algorithm to establish a central air conditioning system model with fan speed and chilled water valve as inputs and indoor temperature and relative humidity as outputs. Yang et al. [14]

compared support vector machines and regression trees. The chiller energy consumption was estimated using historical chiller energy consumption records, architectural characteristics, chilled water temperature, variables related to the ice storage tank, and local meteorological data. The mean absolute error and mean absolute percentage error of SVM estimation results were 1.4 kw and 3% respectively. Mean absolute error was 1.36 kw and mean absolute percentage error was 3%. Rand et al. [15] compared the models of water system components (cooling coils, fans and compressors) established by artificial neural network, support vector machine and Bootstrap polymerization based on the collected data. The results show that the three models have similar R^2, but the ANN training time is significantly less than the other methods.

Based on the above literature, it can be seen that the current optimized energy-saving model for the whole air conditioning water system is not mature enough. Most research is still focused on single devices or partial cycles. The coupling between devices will affect the judgment of the parameters of each device in the lowest total energy consumption state. Therefore, this study proposes to use machine learning technology to establish an energy consumption prediction model based on the whole air conditioning water system.

Machine learning techniques can be well applied to nonlinear system modeling. However, the accuracy and stability of most machine learning models depend on model parameter Settings. To find the most suitable model parameters and establish a stable and reliable model, optimization algorithms are often used to optimize model parameters. Particle swarm optimization (PSO) algorithm and genetic algorithm (GA) are the two most commonly used optimization algorithms. Literatures [16–18] combines genetic algorithm with artificial neural network, and uses GA algorithm to optimize the weights and thresholds of artificial neural network. The combination of these two algorithms achieves the complementarity of their respective advantages and has achieved good results. Literatures [19–21] use particle swarm optimization algorithm for the learning and training of neural network, which makes it easier for the algorithm to find the global optimal solution and has better convergence. Literature [22] uses PSO algorithm to optimize the two parameters c and g of support vector regression machine, and the optimized model also achieves better performance. However, the convergence speed of genetic algorithm is slow and the stability of particle swarm optimization is not good. Differential evolution (DE) algorithm was proposed by Store and Price in 1997 [23], which is also a heuristic parallel search algorithm based on groups. Differential evolution algorithm has been proved to have faster convergence rate and better stability [24]. The main research contents are shown in Figure 1, as follows:

(1) Based on the actual operation data of system parameters collected, we analyzed the energy consumption regression model of air conditioning water system from the overall perspective and respectively established three commonly used machine learning technologies (ANN, SVM, CART). With MAE, RMSE and R^2 as evaluation indexes, the optimal water system energy consumption model was selected by cross validation method. Finally, it is found that the three models have relatively fast training speed, but the ANN model has smaller error and higher fitting degree.

(2) To solve the problem that the artificial neural network can easily fall into the local optimal solution, we use an improved differential evolution algorithm to optimize the initial weights and thresholds of the artificial neural network. The performance of the artificial neural network model with random initial weights and thresholds, the artificial neural network model optimized by basic differential evolution and the artificial neural network model optimized by improved differential evolution in water system energy consumption prediction is compared, and the accuracy of the

improved model is improved.

(3) We conduct parameter sensitivity analysis for the established optimization model. And found that the three parameters that have the greatest influence on the total energy consumption of air conditioning water system are chilled water inlet temperature, chilled water flow and air conditioning load. This guides us to take the optimal control of these parameters as the focus of research on energy-saving optimization of air conditioning systems.

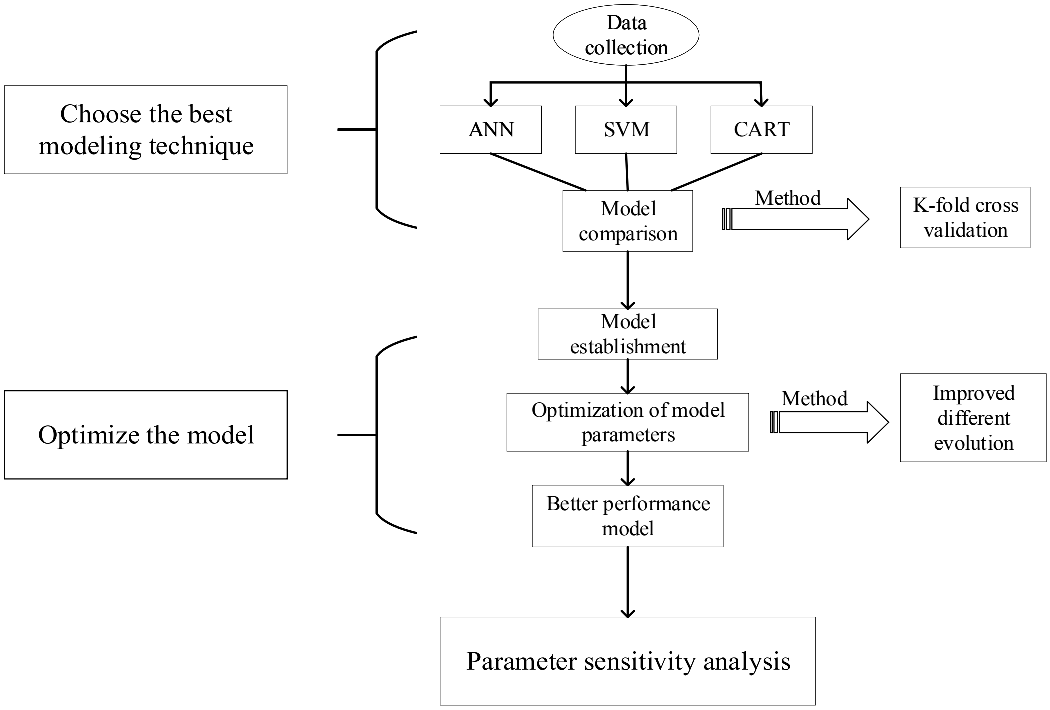

Figure 1. A schematic diagram of the research content.

2. Data collection

Figure 2 shows the flow chart of the air conditioning water system. It can be seen that the main energy consumption equipment in the air conditioning water system includes refrigeration unit, chilled water pump, cooling water pump and cooling tower fan. The prediction model of total energy consumption of air conditioning water system established in this paper does not consider the energy consumption of cooling tower fan (there is not enough data collected to represent it). Therefore, the total energy consumption of the air conditioning water system (P_{total}) mentioned in this article is the sum of the energy consumption of the chilled water pump ($P_{ch,p}$), the cooling water pump ($P_{c,p}$), and the refrigeration unit ($P_{chiller}$). That is:

$$P_{total} = P_{chiller} + P_{c,p} + P_{ch,p} \quad (1)$$

According to literature [25], there are seven factors that affect the total energy consumption: air conditioning load (Q), chilled water inlet temperature ($t_{ch,i}$), chilled water return temperature ($t_{ch,o}$), chilled water flow (G_{ch}), cooling water inlet temperature ($t_{c,i}$), cooling water return temperature ($t_{c,o}$) and cooling water flow (G_c). That is:

$$P_{total} = f(Q, t_{ch,i}, t_{ch,o}, G_{ch}, t_{c,i}, t_{c,o}, G_c) \quad (2)$$

We collected 1050 groups of actual operation data of ground source heat pump air conditioning water system in a university in Suzhou. Table 1 lists the values for this set of datas.

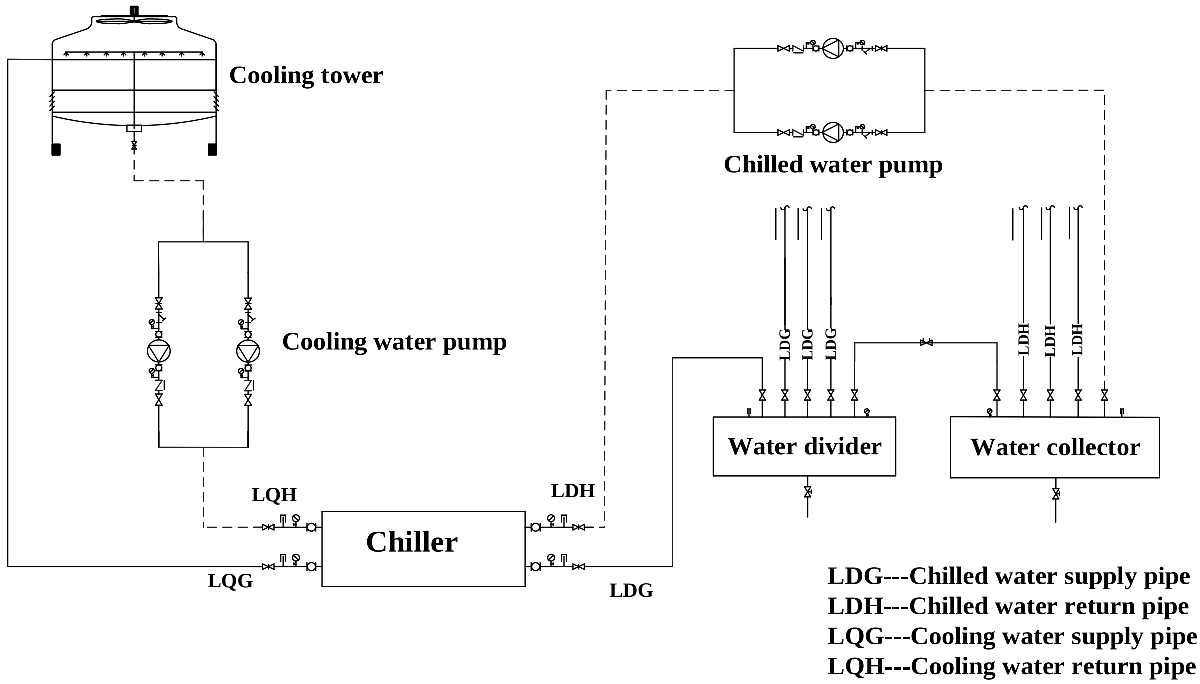

Figure 2. Flow chart of air conditioning water system.

Table 1. The values of the collected data.

Value	Q (kw)	Chilled water			Cooling water			P_{total} (kw)
		$t_{ch,i}$ (℃)	$t_{ch,o}$ (℃)	G_{ch} (m^3/h)	$t_{c,i}$ (℃)	$t_{c,o}$ (℃)	G_c (m^3/h)	
mean	93.2	11.7	14.3	30.6	30.8	32.3	45.3	13.4
max	197.9	14.8	18.4	34.0	32.6	34.8	47.4	26.8
min	17.5	9.4	12.3	29.3	24.5	25.6	5.4	4.2
dev.st	±24.5	±1.3	±1.1	±1.1	±1.9	±2.0	±1.3	±3.0

The value range of each parameter is different. When these parameters are used for model selection and verification, *mapminmax* function of MATLAB is used for normalization. Normalize all parameters to numbers between the interval [−1,1]. The specific calculation process is shown in Eq (3).

$$y = \frac{(y_{max}-y_{min})\times(x-x_{min})}{x_{max}-x_{min}} + y_{min} \tag{3}$$

In the above formula, x is the parameter value before normalization, and y is the value after normalization. In this case, $y_{max} = 1$ and $y_{min} = -1$, x_{max} and x_{min} are the maximum and minimum values of each parameter.

3. Model evaluation

3.1. Model evaluation index

To check the fit between the model and the data, statistical indicators are often used to test and validate the model performance. Both IPMVP (International Performance Measurement and Verification Protocol) and ASHRAE Guideline 14 indicate that determination coefficient (R^2) is the most important criterion by which a model's validity and usefulness should be assessed [26]. In addition, root mean square error (RMSE) and mean absolute error (MAE) are the most common error metrics. The calculation formulas for these parameters are as follows:

$$R^2 = 1 - \frac{\Sigma(y-y_i)^2}{\Sigma(y-y_0)^2} \tag{4}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{m}} \Sigma\,(\mathrm{y}-\mathrm{y_i})^2} \tag{5}$$

$$\mathrm{MAE} = \frac{1}{\mathrm{m}} \Sigma|\mathrm{y}-\mathrm{y_i}| \tag{6}$$

In the above formula, y is the true value of the sample, y_i is the predicted value of the sample, and y_0 is the average value of the sample, m is the number of samples.

R^2 tells us how good the model fits the data. Generally speaking, $R^2 \in [0,1]$, and the larger the determination coefficient is, the better the model is [27]. The smaller the error parameters (RMSE and MAE) are, the higher accuracy the model has.

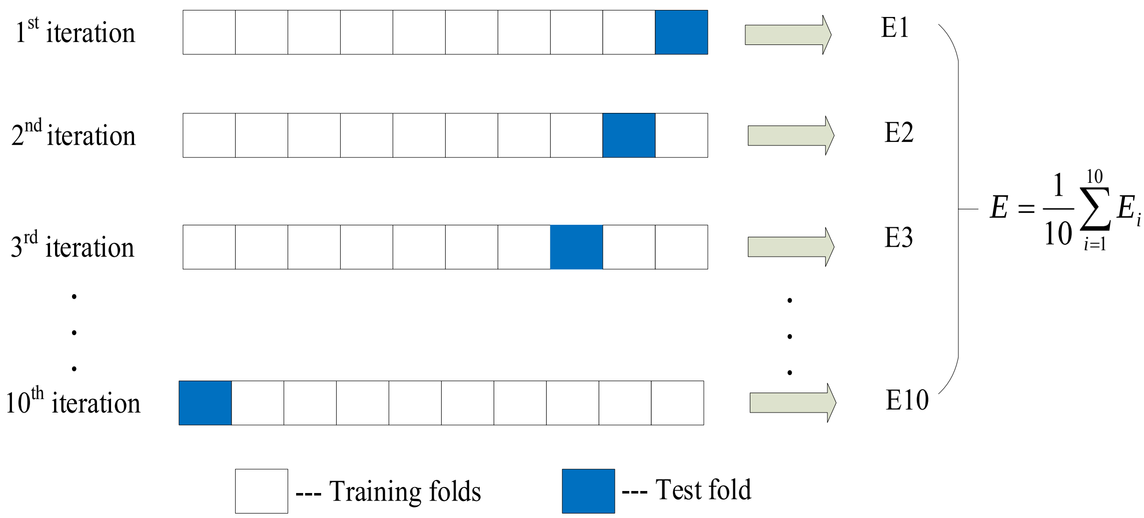

Figure 3. Ten-fold cross validation process.

3.2. K-fold cross validation

K-fold cross validation is a method to test the validity of a model. Figure 3 is a schematic diagram of ten-fold cross validation. The brief process of k-fold is as follows:

(1) Randomly divide the entire data set into *k* groups (*k* generally takes 10).

(2) Each time the model is trained with *k*-1 sets of data, and the remaining set of data is used for testing.

(3) Record the deviation of each prediction.

(4) Repeat this process *k* times until all data have been tested.

(5) Record the average of *k* deviations as a standard to measure the performance of the model.

4. Materials and methods

Three most commonly used machine learning technologies, ANN, SVM and CART, are used for energy consumption prediction modeling of air conditioning water system in this study. The same input and output data are used for training and testing, and the performance indicators of the three models are compared to select the most suitable model for this study. Parameters of the three models are set as follows:

(1) ANN: In the three-layer BP neural network, the number of input neurons is 7, the number of output neurons is 1, and the number of hidden layer neurons is 15. The initial weights and thresholds of the neural network are randomly set.

(2) SVM: The radial basis function (RBF) is used as the kernel function, and the penalty coefficient *c* and the kernel parameter *gamma* are set to default values.

(3) CART: The mean square error (MSE) of parent node and leaf node was taken as the standard of feature selection and the index of quality of regression tree.

Ten-fold cross validation was performed on these three models respectively. Figure 4 shows the performance of each model in these ten times of verification.

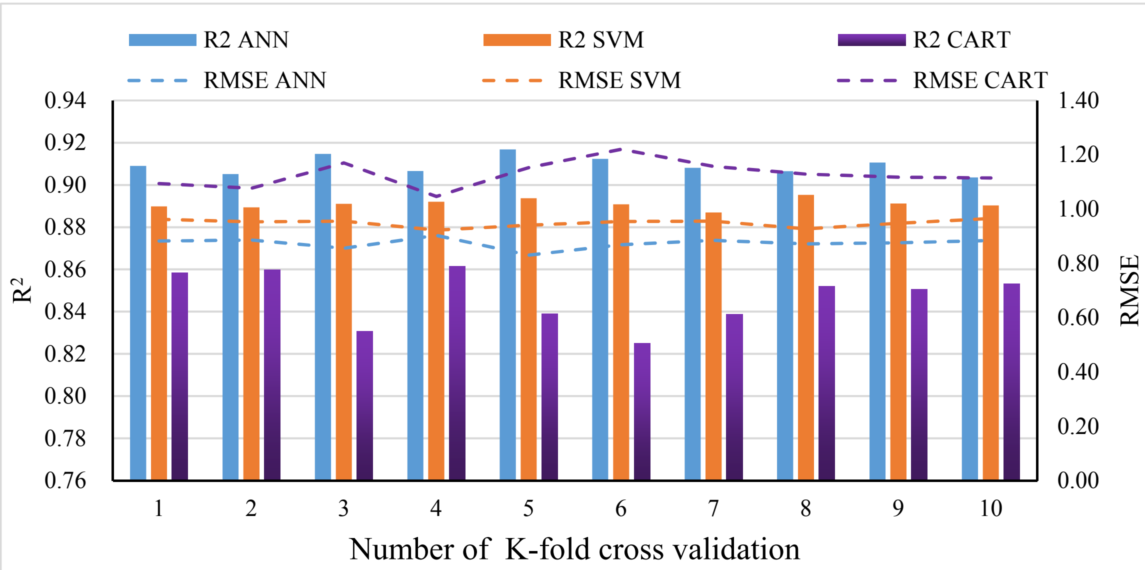

Figure 4. Evaluation index values of ten cross validation for the three models.

At the same time, 80% of all data (1050 groups) is randomly assigned as the training set and 20% as the testing set. Compare the model performance of the three models in the same training set and validation set, and the results are shown in Table 2.

Table 2. Performance of three models on the same training set and testing set.

Technique	R^2	MAE	RMSE	t (s)
ANN	0.9108	0.4787	0.8888	0.40
SVM	0.8922	0.5237	0.9773	0.07
CART	0.8433	0.4652	1.1481	0.25

From the above chart, we can see that the artificial neural network has achieved the best results in data modeling. In ten times of ten-fold cross validation, ANN has the smallest RMSE, followed by SVM, and CART has the worst performance. The R^2-value of the ANN model is basically around 0.91, the value of SVM is around 0.88, and the value of CART is only 0.85. Similarly, statistical validation using the same data set and validation set showed that ANN had the highest R^2-value and the smallest RMSE, and MAE was relatively small. Although ANN spent a longer training time, it was generally acceptable. Therefore, we choose ANN as the energy consumption modeling technology of air conditioning water system.

5. Optimization algorithm

In practical application, artificial neural network has some disadvantages such as easy convergence to local minimum value and slow convergence speed. One of the main reasons for these problems is the unreasonable selection of initial weight and threshold parameters. Therefore, this study uses the improved differential evolution algorithm to optimize the initial weights and thresholds of the neural network, so as to help the neural network jump out of the local optimal solution and improve the accuracy of the neural network model. The model optimization process is shown in Figure 5.

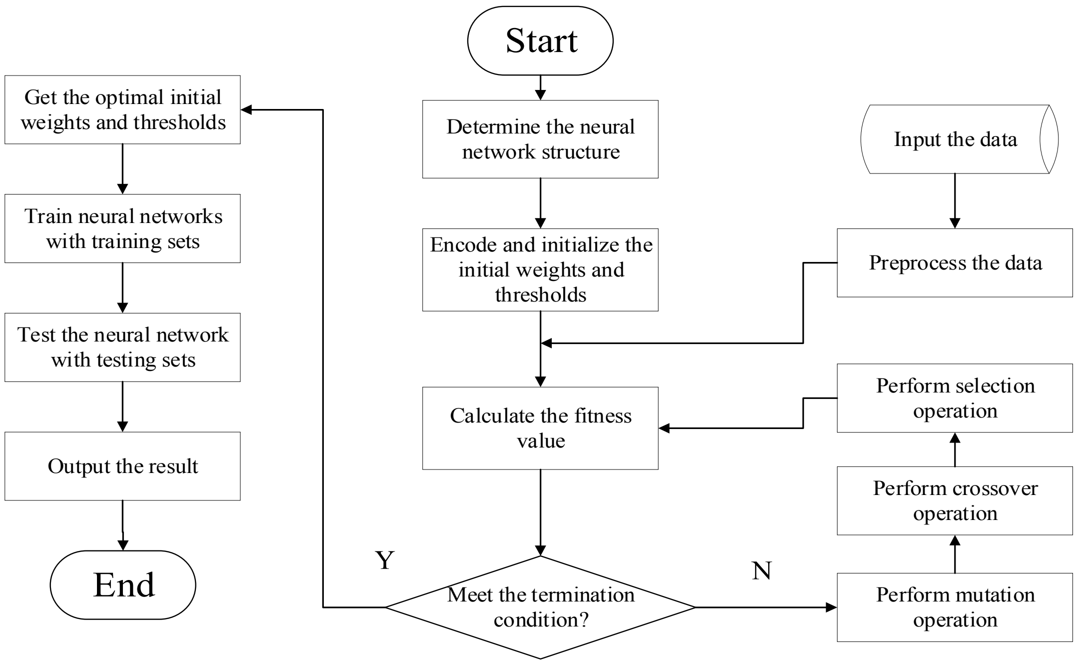

Figure 5. Flow chart of artificial neural network optimization by differential evolution algorithm.

5.1. Basic differential evolution algorithm

The working steps of differential evolution algorithm are basically consistent with other evolutionary algorithms. It mainly includes mutation operation, crossover operation and selection operation.

(1) Initial population. Randomly generated initial population according to the Eq (7), in which the $\{X_{i,j} \mid X_{min} < X_{i,j} < X_{max}, i = 1, 2,...,NP; j = 1, 2,...,D\}$, X_{max} and X_{min} represent the upper and lower bounds of the value range respectively, *rand* (0,1) represents random numbers evenly distributed in the interval (0,1), *NP* represents population size, *D* represents individual dimension, and *G* represents the number of evolutionary iteration.

$$X_{i,j,g} = X_{min} + rand(0,1) * (X_{max} - X_{min}) \tag{7}$$

(2) Mutation operation. The DE algorithm relies on difference strategy to achieve individual variation. The common difference strategy "*DE*/*rand*/1" is shown in Eq (8): firstly, two different individual vectors are randomly selected in the population to obtain the difference between the two vectors, then the variation factor F is used to scale the difference vector, and finally the individual vector to be mutated is combined with it. Where, $i \neq r1 \neq r2 \neq r3$, and F is the variation factor.

$$V_{i,g} = X_{r1,g} + F * (X_{r2,g} - X_{r3,g}) \tag{8}$$

(3) Crossover operation. Perform the crossover operation as shown in Eq (9) between the initial individual X_i and the mutant individual V_i to get the new individual U_i, and ensure that at least one value in the U_i comes from V_i. Where, *CR* is the crossover probability, and j_{rand} is the random integer in [1,2... *D*].

$$U_{i,j,g} = \begin{cases} V_{i,j,g} & if \ \ rand(0,1) \leq CR \ \ or \ \ j = j_{rand} \\ X_{i,j,g} & otherwise \end{cases} \tag{9}$$

(4) Selection operation. The DE algorithm uses the greedy algorithm to select the individuals to enter the next step. The specific selection method is shown in Eq (10), where f is the fitness function.

$$X_{i,g+1} = \begin{cases} U_{i,g} & if \ \ f(U_{i,g}) \ \leq f(X_{i,g}) \\ X_{i,g} & otherwise \end{cases} \tag{10}$$

5.2. Improved differential evolution algorithm

Basic differential evolution has problems of premature convergence and search stagnation. To improve the performance of optimization algorithm, an adaptive differential evolution algorithm with external archiving (JADE) was proposed. On the one hand, this adaptive algorithm uses historical success data to guide the direction of operation and accelerate the speed of convergence. On the other hand, it introduces failed individuals with a certain probability to increase the diversity of the population, which can effectively avoid the problems of premature convergence and search stagnation in the basic differential evolution algorithm. The improvement of differential evolution algorithm mainly includes two operations, namely archiving operation and parameter adaptive operation [28].

(1) Archiving operation

The file set is initialized as an empty set, and then the inferior individuals that fail after each generation selection operation of the differential evolution algorithm are archived. The method of JADE to generate mutant individuals is shown in Eq (11), where p is the preset excellence rate. For example, if $p = 0.1$, the best individuals, will be selected from the top 10% of the population to form $X_{best,g}^p$ to participate in the mutation. If P represents the current population set and A represents the archived inferior solution set, then $X_{best,g}^p$, $X_{i,g}$ and $X_{r1,g}$ are randomly selected from P and $X_{r2,g}$ are randomly selected from $P \cup A$.

$$V_{i,g} = X_{i,g} + F_i * (X_{best,g}^p - X_{i,g}) \ + F_i * (X_{r1,g} - X_{r2,g}) \tag{11}$$

In the Eq (11), the first difference vector represents that individuals in the group learn from the top several optimal solutions, that is, greedy strategy, which can accelerate convergence. The latter difference vector ($X_{r1,g}$ - $X_{r2,g}$) represents that some individuals are selected from the external archive. The external archive is not similar to the group at this moment, so the diversity of the group is expanded here to avoid falling into local optimum.

In addition, the size of the population will seriously affect the convergence speed of the algorithm. To improve the convergence speed of the algorithm, the adaptive differential evolution algorithm used in this paper adopts a dynamic population reduction strategy. The strategy stipulates that there are at most NP elements in the set of inferior solutions. When the number of elements is greater than NP, the extra individuals are randomly removed.

(2) Parameter adaptive operation

The adaptive parameters of the differential evolution algorithm are crossover probability CR and variation factor F.

In JADE, CR is generated by a normal distribution with a mean of uCR and a standard deviation of 0.1, that is $CR_i = randni(uCR, 0.1)$. The initial uCR is 0.5, and it is updated according to Eq (12) after each generation.

$$uCR = (1 - c) * uCR + c * mean_A(S_{CR}) \tag{12}$$

Among them, the value range of uCR is [0,1], and S_{CR} is the set of CR_i of successful individuals in each generation, $mean_A(\cdot)$ is the arithmetic mean value, and c is the weight value, which is generally set at 0.05.

Based on the principle that better control parameter values are more likely to produce better individuals, the crossover probability of success needs to be recorded and used to guide the generation of new CR_i.

F is produced by a cauchy distribution with a mean of uF and a standard deviation of 0.1, that is $F_i = randci(uCR, 0.1)$. The initial uF is 0.5, and it is updated according to Eq (13) after each generation,

$$uF = (1 - c) * uF + c * mean_L(S_F) \tag{13}$$

and the F_i will be truncated to be 1 if $F_i \geq 1$ or regenerated if $F_i \leq 0$. Among them, S_F is the set of F_i of successful individuals in each generation, $mean_L(\cdot)$ is the Lehmer mean value, and the calculation method is shown in Eq (14), c is the weight value, which is generally set at 0.05.

$$mean_L(S_F) \ = \frac{\Sigma_{F \in S_F} \ F^2}{\Sigma_{F \in S_F} \ F} \tag{14}$$

6. Results

6.1. Optimization model evaluation

The collected data were randomly divided into training sets (80%) and testing sets (20%). The artificial neural network (ANN) model, differential evolution optimized artificial neural network (DE-ANN) model and improved differential evolution optimized artificial neural network (JADE-ANN) model are simulated and tested with the same training set and testing set. Figure 7 and Figure 8 respectively reflect the output and output error of the three models on the test set.

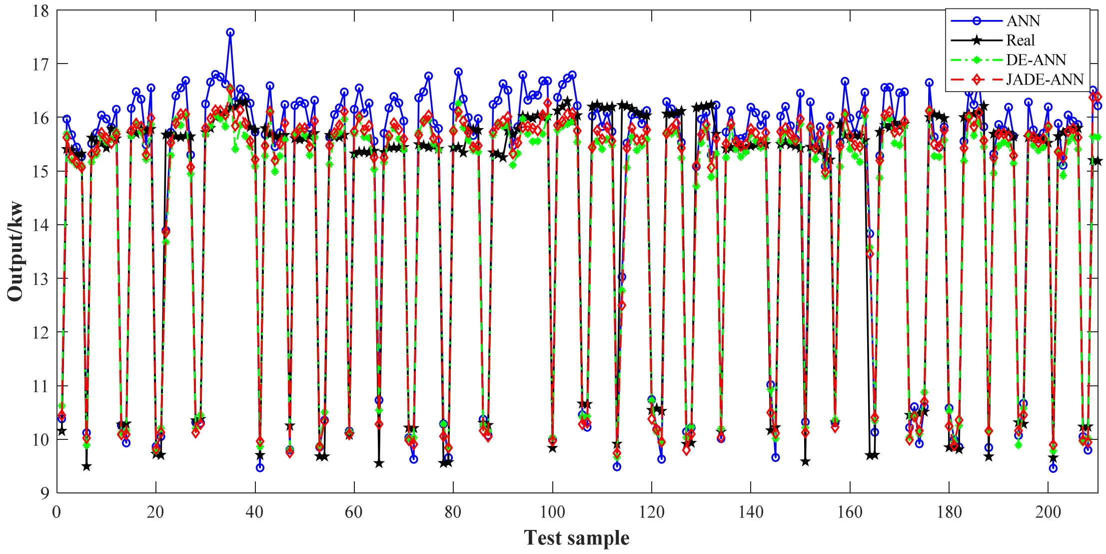

Figure 7. Output comparison of testing sets.

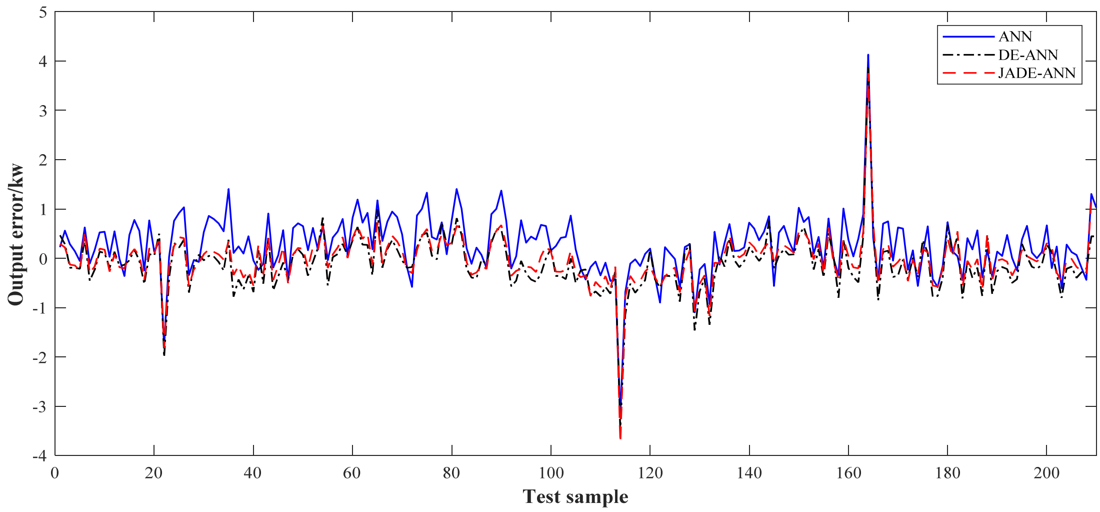

Figure 8. Output error comparison of testing sets.

Table 3 shows the performance parameters of the optimized ANN model. It can be seen that after differential evolution optimizes the initial weight and threshold of ANN, the accuracy of the ANN model has been improved. Specifically, the MAE of the DE-ANN model is reduced by 20.6% compared with the ANN, and the RMSE is reduced by 14.4%. The improved differential evolution algorithm further improves the accuracy of the model. Compared with ANN, the MAE of the JADE-ANN model is reduced by 30.2%, and the RMSE is reduced by 20.5%. Similarly, the coefficient of determination of the model is also increased from 0.9227 to 0.9434 and 0.9512.

Table 3. Performance of three models on the same training set and test set.

Model	R^2	MAE	RMSE
ANN	0.9227	0.4843	0.6698
DE-ANN	0.9434	0.3843	0.5730
JADE-ANN	0.9512	0.3381	0.5322

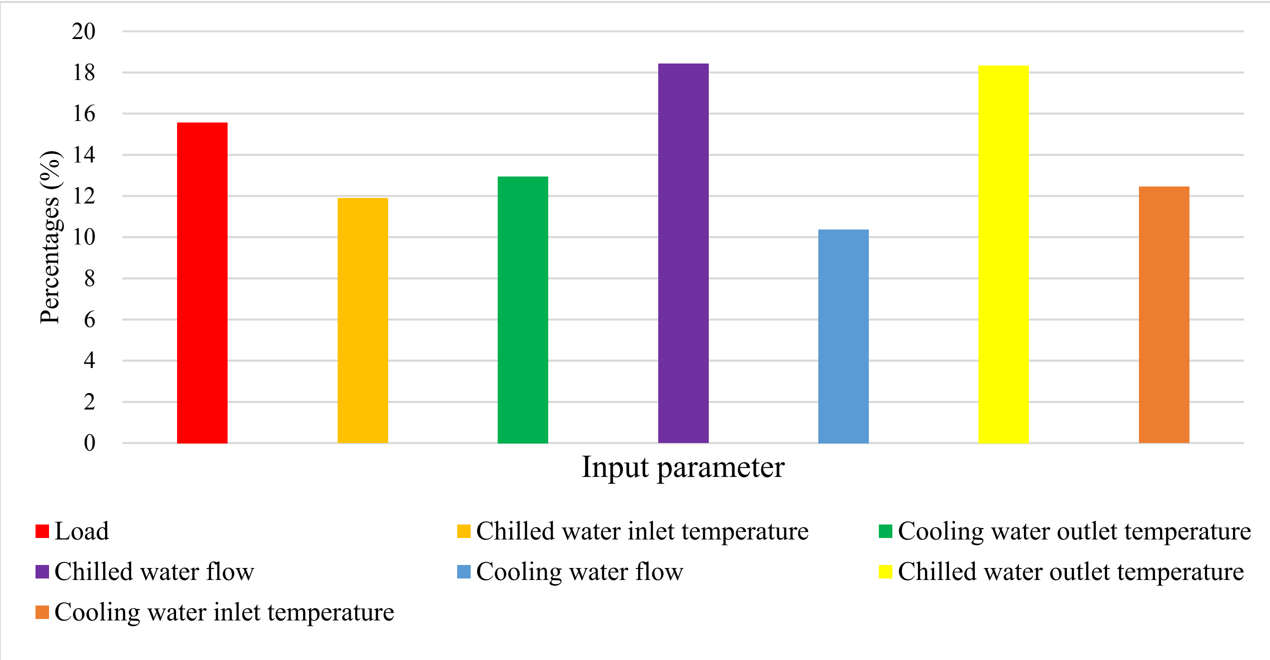

Figure 9. Parameter sensitivity analysis of optimization model.

6.2. Model sensitivity analysis

This analysis involves the influence of parameters on water system energy consumption, which is calculated by Eq (15). Contribution of each variable to total energy consumption is shown in Figure 9. It can be found that the parameters selected in this paper have a significant impact on water energy consumption. The three parameters with the highest contribution rate in the figure are: chilled water flow (18.43%), chilled water outlet temperature (18.35%) and air conditioning load (15.56%). The data shows that in the air conditioning water system, the chilled water system has a greater impact on the total energy consumption of the water system. This also explains why many scholars regard the optimal control of air conditioning chilled water system as the research focus of reducing the energy consumption of air conditioning systems.

$$R_{i,j} = \frac{\sum_{j=1}^{L}(|W_{i,j}W_{j,k}|/\sum_{i=1}^{N}|W_{i,j}|)}{\sum_{i=1}^{N}\sum_{j=1}^{L}(|W_{i,j}W_{j,k}|/\sum_{i=1}^{N}|W_{i,j}|)} \tag{15}$$

In the above formula, $R_{i,j}$ is the relative importance of the input signal. $W_{i,j}$ and $W_{j,k}$ are the connection weights between input layer and hidden layer, hidden layer and output layer respectively. (i = 1, 2,...,N, j = 1,2,...,M. N and M are the number of input signals and output signals respectively.)

7. Conclusions

In this study, the factors affecting the energy consumption of air conditioning water system are considered from the overall perspective, and a prediction model of air conditioning water system energy consumption is established by using the collected data and machine learning technology. By comparing the performance of three commonly used machine learning techniques, ANN was selected as the final modeling technology. To improve the problem that ANN can easily fall into the local optimal solution, an improved differential evolution algorithm is used to optimize the initial weights and thresholds of ANN. The improved model is used to predict the energy consumption of air conditioning water system and good results are obtained.

In future studies, we will focus on deep learning modeling technology and online adaptive updating technology of models to update or modify model parameters in real time, so as to obtain more accurate prediction results.

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Conflict of interest

The authors declared that they have no conflicts of interest in this work.

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