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Research Article

Application of Improved PSO-BP Neural Network in Cold Load Forecasting of Mall Air-Conditioning

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A combination of JMP, PSO-BP neural network, and Markov chain which aims at the low correlation between input and output data and the error of prediction model in the PSO-BP neural network prediction model is proposed. First, the JMP data processing software is used to process the input data and eliminate the samples with low coupling degree. Then, obtaining the cooling load prediction results relies on the training from the PSO-BP neural network. Finally, the final prediction results will be generated by eliminating the random errors using the Markov chain. The results show that the combination of the prediction methods has higher prediction accuracy and conforms to the change rule of the cooling load in shopping malls. Besides, the combination fits the actual application requirements as well.

1. Introduction

At present, the energy consumption of air-conditioning occupies an increasing proportion of whole building energy consumption [1]. Its huge power consumption has increased the pressure on the grid. Some researchers have used ice storage air-conditioning to solve this problem [2]. The operation of ice storage air-conditioning requires a reasonable matching with the cooling capacity of the internal cooler and the ice trough in the peaks and troughs of the electricity price. Firstly, the cooling capacity of the building at every moment in the next day is predicted, and then the cooling capacity should be divided on the basis of the predicted results. Therefore, the dynamic prediction of the cooling load is the core of ice storage air-conditioning.

For the air-conditioning cooling load prediction, most researchers use the data-driven method [3], mainly including support vector machine (SVM), statistical regression, decision tree, genetic algorithm, and neural network algorithm. SVM is a common artificial intelligence method [4], which has the ability to transform nonlinear relations, but it takes too long to deal with data [5, 6]. Statistical regression is a simple and feasible prediction method, but its predictive power is lower than SVM, and it is difficult to choose the predictors of this method [7]. The decision tree method is a technique which is easy to understand and divides data into groups using a tree diagram, but its prediction results often deviate significantly from the actual situations [8], and it cannot address time series and nonlinear data very well [9]. Genetic algorithm is a powerful optimization algorithm for processing complex model problems [10]. When the input data is large and complex, the algorithm can obtain appropriate solutions according to objective functions or subjective judgments, but it also has disadvantages, such as nonunique results and the long calculating time [11, 12]. As a kind of prediction algorithms, neural network is widely used in various fields [13]. One of the neural networks BP (back propagation) is widely used for its powerful nonlinear mapping, self-learning, generalization, and fault tolerance, but the weaknesses of this method are localized minimization and slow convergence. Some researchers have used PSO (particle swarm optimization) [14] to optimize the initial threshold and weight of the BP neural network and to improve the convergence speed and accuracy of BP. However, due to the low matching degree between the input data and the output data and the errors under the process of combining model, the prediction results cannot meet the ideal requirements.

Based on the traditional artificial neural network, this paper shows the results from JMP data analysis software, which analyzes the correlation between input variables and output variables and eliminates irrelevant data. In addition, we used the Markov chain to correct the errors of the artificial neural network. The research shows that the improved model has higher prediction accuracy and convergence speed than those of the traditional artificial neural network prediction method, which is more suitable for the practical application of the project.

2. Thoughts on Dynamic Prediction Method of Air-Conditioning Cooling Load

The key and difficult point of the cooling load forecasting is to improve the prediction accuracy and timeliness. The traditional prediction of the air-conditioning cooling load in shopping malls does not consider the market-running characteristic points, and it cannot distinguish the differences between weekends and business days [15]. Therefore, based on the characteristics of the mall, the data should be reanalyzed and integrated before forecasting. This specific prediction idea is shown in Figure 1.

According to the content above, JMP data analysis software is used to analyze the input data correlation to improve the neural network. The characteristic of the analysis of correlation can eliminate the input and output variables with low coupling degree. It can also fix the problems about slow training speed, and low-precision vulnerability results from the low correlation between input and output variables. Therefore, the prediction accuracy of the neural network can be improved, and it can be applied to the dynamic prediction of cooling load of air-conditioning in shopping mall buildings. In consideration of some relative errors in the predicted results of the combined model, the Markov chain is adopted to further modify the prediction results so that the accuracy can be improved.

3. Construction of Dynamic Prediction Model for Cooling Load of PSO-BP Large Shopping Mall

3.1. The Prediction Model of the PSO-BP Neural Network. The PSO-BP neural network is used to predict the cooling load of air-conditioning in shopping malls. In fact, the PSO algorithm is used to iteratively optimize the weight and threshold of the BP neural network, and then the weight and threshold with the best fitness are obtained for the prediction of the BP neural network.

In order to predict the cooling load of air-conditioning in shopping malls, this paper adopts a three-layer network architecture. The commonly used input data for cold storage air-conditioning cold load prediction include the outdoor dry bulb temperatures T and T–1 at the current and previous moments, respectively, and the solar radiation doses R, R-1, and R-2 at the current, previous, and the first two moments. At the current time, the outdoor humidity is H, the outdoor wind speed is W, and the previous time, the first two times, and the first four times of the cold load are C-1, C-2, and C-4, respectively, with the current time cold load C as the output. In the input layer, the number of neurons is 10 and the output layer is the cold load at time T. The empirical formula (1) can be obtained for nodes of hidden layer of the neural network as 21:

$$A = 2 * B + 1, \tag{1}$$

where A is the number of neurons in the hidden layer and B is the number of neurons in the input layer.

(1) To figure out the fitness of the particles. The fitness value of the particles is determined by the prediction-related data and the data obtained by the PSO algorithm, as shown in the following formula:

$$f = \sum_{i=1}^{N} \left| y_i - \overline{y_i} \right|, \tag{2}$$

where N is the number of samples, y_i is the observed value of sample i, and $\overline{y_i}$ is the predicted value of sample i.

(2) The fitness of the current particle is selected as the best fitness P_{see} of the current particle and the best fitness P_{best} of the historical optimum. The best historical fitness of the current particle and the best global fitness g_{best} are selected as the historical optimal fitness of the current particle.

(3) The velocities and positions of the particles are updated using formulas (3) and (4), respectively:

$$\begin{aligned} V_{ab}(t+1) = V_{ab}(t) + l_1 * r_1 * \left(P_{ab}(t) - X_{ab}(t)\right) \\ + l_2 * r_1 * \left(P_{gb}(t) - X_{ab}(t)\right), \end{aligned} \tag{3}$$

$$X_{ab}(t+1) = X_{ab}(t) + V_{ab}(t+1), \tag{4}$$

where $a = 1, 2, \ldots, n$, $b = 1, 2, \ldots, n$, l_1 is the optimal step size of the individual particles, l_2 is the optimal step size of the particles, r_1 and r_2 are random numbers between 0 and 1, X_{ab} is the position of the particle a, and V_{ab} is the speed of the particle a.

Setting the maximum particle velocity interval as $[0, V_{\max}]$, when the particle velocity is higher than $V_{\max}$, the particle's velocity is back to $V_{\max}$ at this time.

(4) Comparing the current iteration number CurIte with the maximum number of iterations MaxIte: if CurIte ≥ MaxIte, stop iterating; if CurIte < MaxIte, return to step (1).

3.2. The Improvement of the PSO-BP Neural Network Based on JMP and Markov Chain. Although the prediction accuracy of the PSO-BP neural network is better than that of some previous neural networks, it still cannot reach the actual

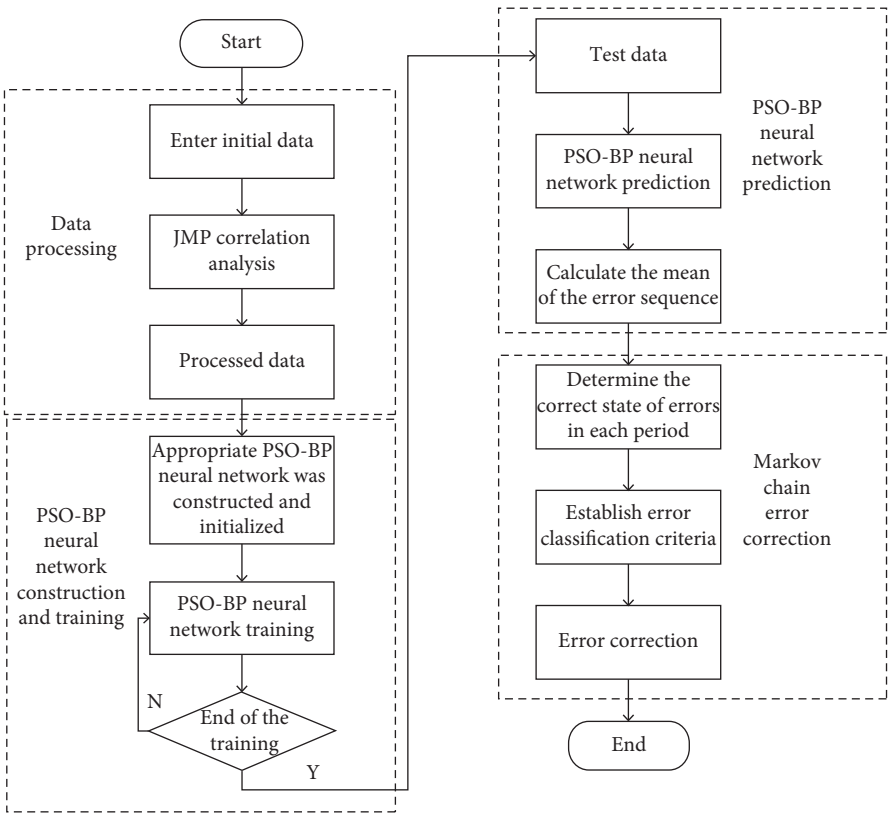

Figure 1: Flow of dynamic prediction method for cooling load.

ideal state of engineering, mainly because there are some deviations in the complexity of input data and combined prediction. Therefore, it is necessary to use the JMP data processing software [16] to process the input data and correct the prediction errors by the Markov chain.

Considering that some of the above data have low correlation between input data and output data, JMP data analysis software is used for correlation analysis and Pearson's correlation significance test is conducted. [0, 0.3] is considered as weak correlation, [0.3, 0.5] as medium correlation, [0.5, 0.7] as strong correlation, and [0.7, 1.0] as strong correlation. The results of correlation analysis are shown in Table 1.

Combining with the analysis results of the foregoing and Table 1, we use the three input parameters R-2, W, and C-4 and good seven variables T, T-1, H-1, R, R-1, 1, and C-C-2 as the input variables of the PSO and BP network prediction models and the parameter C as the output variable; combined with formula (1) for large public buildings, the cooling load prediction model structure is 7-15-1, i.e., 7 input layer nodes, 15 hidden layer nodes, and 1 output layer node.

The Markov chain is a random process with no aftereffects [17]. It can derive the probability distribution of the next moment according to the time condition of a certain condition and obtain the state of the next moment regardless of other moments. The Markov chain is suitable for the correction of prediction problems with fluctuation [18].

The steps of Markov error correction for the predicted value of the above neural network model are as follows:

Table 1: Correlation between input parameters and cooling load at time T.

The input parameters	Data correlation
T	0.7513
T-1	0.7948
R	0.7983
R-1	0.8232
R-2	0.6923
H	0.8963
W	0.0176
C-1	0.9342
C-2	0.8753
C-4	0.6097

(1) The error value matrix $\overline{A}(t)$ is calculated according to the predicted value matrix $\widehat{A}(t)$ and the measured value matrix $A(t)$ obtained by the PSO-BP neural network, and the mean value $\overline{X}$ and the standard deviation S of $\overline{A}(t)$ obtained by formulas (5) and (6) are used to obtain the error state interval:

$$\overline{X} = \frac{1}{n}\sum_{t=1}^{n}\overline{A}(t), \tag{5}$$

$$S = \sqrt{\frac{1}{n-1}\sum_{t=1}^{n}(\overline{A}(t) - \overline{X})}. \tag{6}$$

(2) According to formula (7) and statistical method, the transition probability matrix is obtained according to the error state interval obtained in step (1):

$$P_{ij}^{(t)} = \frac{n_{ij}^{(t)}}{N_i}, \tag{7}$$

where $P_{ij}^{(t)}$ is the probability transition matrix, N_i is the error of state in which i is the total number of occurrences, and $n_{ij}^{(t)}$ is the error of state with i being the number of transitions from state t to state j.

(3) The state vector at step t is obtained by using formula (8) to judge the state interval at step t:

$$P(t) = P^{(0)} \times P^{(t)} = P^{(0)} \times \left(P^{(1)}\right)^t, \tag{8}$$

where P_0 is the probability distribution under the initial condition and $P^{(1)}$ is the one-step probability transfer matrix, as shown in equation (6):

$$P^{(1)} = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1x} \\ p_{21} & p_{22} & \cdots & p_{2x} \\ \vdots & \vdots & \vdots & \vdots \\ p_{y1} & p_{y2} & \cdots & p_{yx} \end{bmatrix}. \tag{9}$$

4. Simulation Analysis of Cooling Load Forecasting in Shopping Mall Buildings

4.1. Research and Analysis on the Mechanism of Cooling Load Change. According to the periodicity and similarity of the changing trend of cooling load, it is speculated that the changing law of cooling load in shopping malls should have similar characteristics. Therefore, taking a commercial center in Xi'an city as an example, the data of cooling load in a week and on a weekend are analyzed, respectively. According to the survey, the cooling load information from Monday to Friday in a week is similar, but it is not quite the same as that on weekends. To take the commercial center as the sample object, the cooling load variation chart, as shown in Figure 2, can be obtained to analyze the cooling load variation during the week and on weekends, and then use the line chart to represent it. It can be shown from Figure 3 that there is a difference in the variation of cooling load within a week and on a weekend. Therefore, in the subsequent experimental simulation, experiments are conducted on analyzing a weekday and a weekend, respectively.

4.2. Case Validation Analysis. According to the previous analysis, this experiment uses the actual data of a commercial center in Xi'an. The commercial center has ten floors, with a height of 40.6 meters and an area of 250,000 square meters. The building air-conditioning area occupies about 187,600 square meters. The mall uses ice storage air-conditioning for cooling in summer.

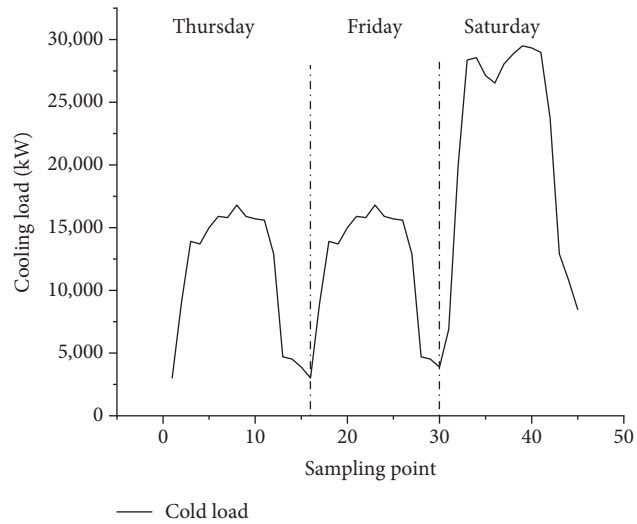

Figure 2: Cooling load variation diagram.

In this experiment, seven variables of outdoor dry bulb temperatures T and $t-1$ at the current moment and the previous moment, solar radiation quantities R and $r-1$ at the current moment and the previous moment, outdoor humidity H at the current moment, and cooling loads $c-1$ and $c-2$ at the previous moment and the first two moments are adopted as input variables of the PSO-BP neural network, and cooling load C at the current moment is taken as the output variable of the neural network. Because of the characteristics of the commercial center, the experiment uses the input variables from 8:00 am to 10:00 pm in the first 50 days of the mall in June and July as training data and the data from July 26th to July 29th as the verification analysis data.

The test data is used for simulation to verify the prediction ability of the network. Figure 3 shows the predicted values of each model, where model 1 is the prediction of the weekday data without any distinctions, model 2 is the prediction of the weekly data but does not eliminate the input data with low correlation, and model 3 distinguishes and predicts the data on weekends and weekdays after eliminating the low correlation of input data. Figure 4 shows the prediction errors among the three models. According to Figures 3 and 4, eliminating the low correlation of input data could cause a better prediction.

It can be found from Figure 4 that the prediction error of model 3 is better than that of models 1 and 2, but it still has a peak error. Therefore, the Markov chain should be used to modify it and to improve the prediction accuracy of the model.

4.3. The Correction of the Markov Chain. The modeling process of the PSO-BP neural network based on the Markov chain modification firstly divides the interval of the range according to the relative error obtained above. The method of interval division is the mean-variance method [19, 20].

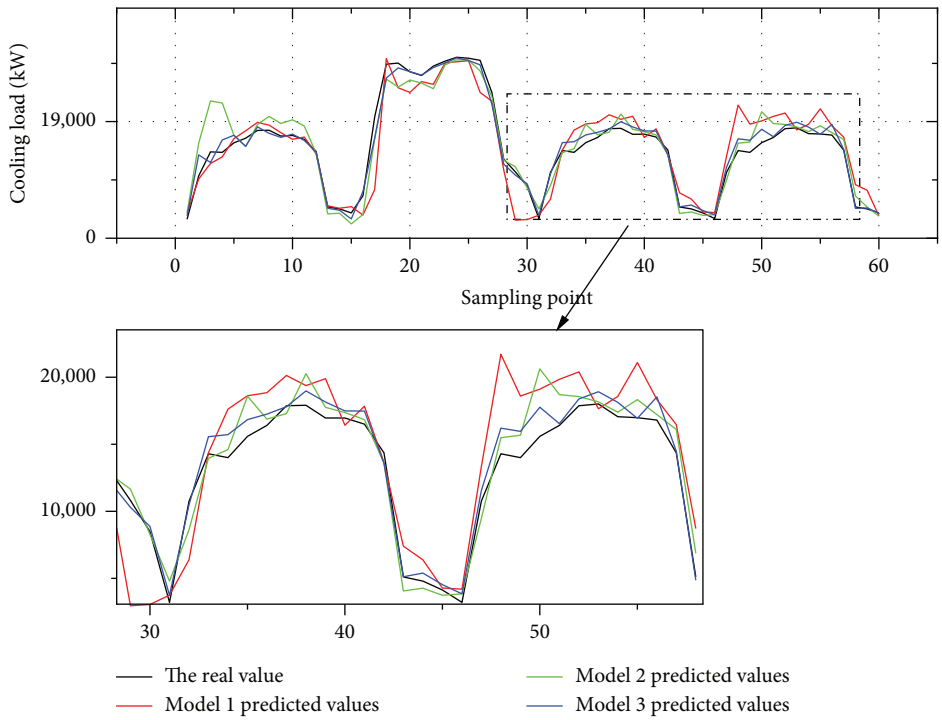

Figure 3: Comparison of prediction results.

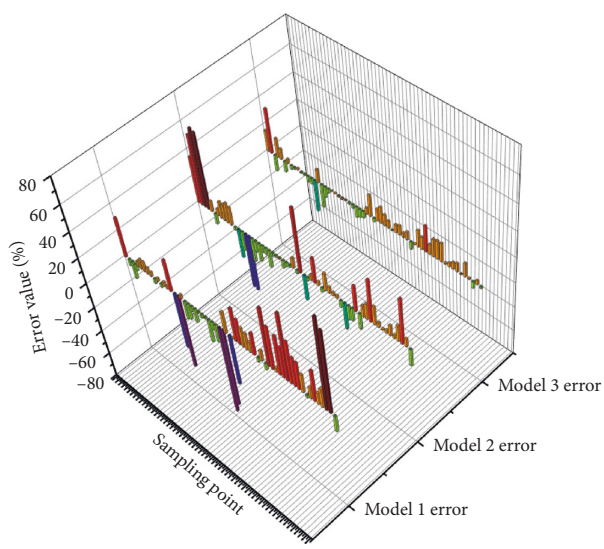

Figure 4: Comparison of prediction errors.

Furthermore, the error is classified according to the divided interval, and the probability transition matrix is constructed according to the classification results to determine the state of the initial vector and the state of the predicted time period, and the modified value of the predicted time period is calculated according to the state of the predicted time period.

According to the relative error of the above analysis, the weekly error mean value $\overline{X}_1 = 5.937$ and mean variance $S_1 = 6.352$ are obtained. The mean value of error over the weekend is $\overline{X}_2 = -0.694$, and the mean variance is going to be $S_2 = 10.421$. After calculation, the state interval of Markov chain within a week and on the weekend is shown in Table 2.

According to the divided state interval, the error values of the PSO-BP model within the prediction week and on the weekend are divided in turn, and the results are shown in Table 3.

According to the error state of Table 2, it is determined that the Markov chain one-step transition probability matrices P_1 and P_2 in the week and on the weekend are as follows:

Table 2: State interval of the Markov chain.

The state interval of a Markov chain within a week	The state interval of the Markov chain on the weekend
$E_1 = [-24.112, -11.111]$	$E_1 = [-5.475, -3.206]$
$E_2 = [-11.111, -5.900]$	$E_2 = [-3.206, 1.895]$
$E_3 = [-5.900, 4.521]$	$E_3 = [1.895, 9.113]$
$E_4 = [4.521, 9.370]$	$E_4 = [9.113, 12.289]$
$E_5 = [9.370, 33.799]$	$E_5 = [12.289, 19.687]$

Table 3: PSO-BP neural network prediction error classification results.

Time	7–26 (weekend)		Time	7–27 (weekend)		Time	7–28 (weeks)		Time	7–29 (weeks)	
	Errors (%)	Status		Errors (%)	Status		Errors (%)	Status		Errors (%)	Status
8	15.843	E_5	8	10.132	E_5	8	16.218	E_2	8	19.687	E_5
9	33.799	E_5	9	−17.486	E_1	9	−2.426	E_4	9	7.364	E_3
10	−12.314	E_1	10	−7.983	E_2	10	8.938	E_4	10	13.364	E_4
11	14.492	E_5	11	−2.809	E_3	11	12.275	E_4	11	14.016	E_4
12	7.951	E_4	12	0.116	E_3	12	8.062	E_4	12	14.018	E_3
13	−8.171	E_2	13	0.167	E_3	13	5.157	E_3	13	0.849	E_3
14	3.333	E_3	14	−0.860	E_3	14	−0.432	E_4	14	2.841	E_3
15	−2.819	E_3	15	−0.966	E_3	15	6.032	E_4	15	5.103	E_4
16	−1.233	E_3	16	−0.352	E_3	16	7.031	E_3	16	6.302	E_3
17	1.223	E_3	17	−1.222	E_3	17	3.094	E_3	17	−0.318	E_3
18	−1.015	E_3	18	−2.479	E_3	18	5.896	E_3	18	10.296	E_3
19	−1.018	E_3	19	−7.976	E_3	19	−5.473	E_3	19	0.853	E_3
20	−4.204	E_3	20	−6.261	E_2	20	0.420	E_1	20	−4.835	E_1
21	−4.323	E_3	21	−4.817	E_3	21	12.708	E_1	21	2.865	E_1
22	−24.112	E_1	22	4.557	E_4	22	9.335	E_2	22	−1.122	E_2

$$P_1 = \begin{bmatrix} 0 & \frac{1}{3} & 0 & 0 & \frac{2}{3} \\ 0 & 0 & 1 & 0 & 0 \\ \frac{1}{18} & \frac{1}{18} & \frac{5}{18} & \frac{1}{18} & 0 \\ 0 & \frac{1}{2} & 0 & 0 & \frac{1}{2} \\ \frac{1}{2} & 0 & 0 & \frac{1}{4} & \frac{1}{4} \end{bmatrix},$$
$$P_2 = \begin{bmatrix} \frac{1}{2} & \frac{1}{2} & 0 & 0 & 0 \\ 0 & \frac{1}{3} & 0 & \frac{1}{3} & \frac{1}{3} \\ \frac{2}{13} & 0 & \frac{8}{13} & \frac{3}{13} & 0 \\ 0 & 0 & \frac{4}{9} & \frac{5}{9} & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix}. \quad (10)$$

According to the error state of Table 2, the state vector of each time period is determined, and the predicted value of the PSO-BP neural network prediction model corrected by the Markov chain is solved according to the state transition vector and the probability transition matrix.

The corrected predicted value (model 4) is predicted by the aforementioned undivided weekly data (model 1), and the weekly data is divided, but the input data is not processed to perform prediction (model 2), which means the weekly data is distinguished and the weekend data is processed by comparing the input data to predict the predicted results (model 3). The results are shown in Figure 5.

RMSPE (root mean square percentage error) was used to evaluate the errors of the four prediction models, and the processing results are shown in Table 4:

The experimental results show that when the improved prediction of the PSO-BP neural network combined with the Markov chain is performed, the maximum number of iterations is set to 2000 times, and the prediction model achieves a prediction accuracy of only 409 steps, which improves the validity of the prediction results. From the results of Figure 5 and Table 4, it can be seen that using the Markov chain to modify the PSO-BP neural network figures out a higher prediction accuracy, and it can meet the requirements of practical engineering applications.

5. Conclusion

Aiming at the problem of cooling load prediction from ice storage air-conditioning in malls, the paper proposes a

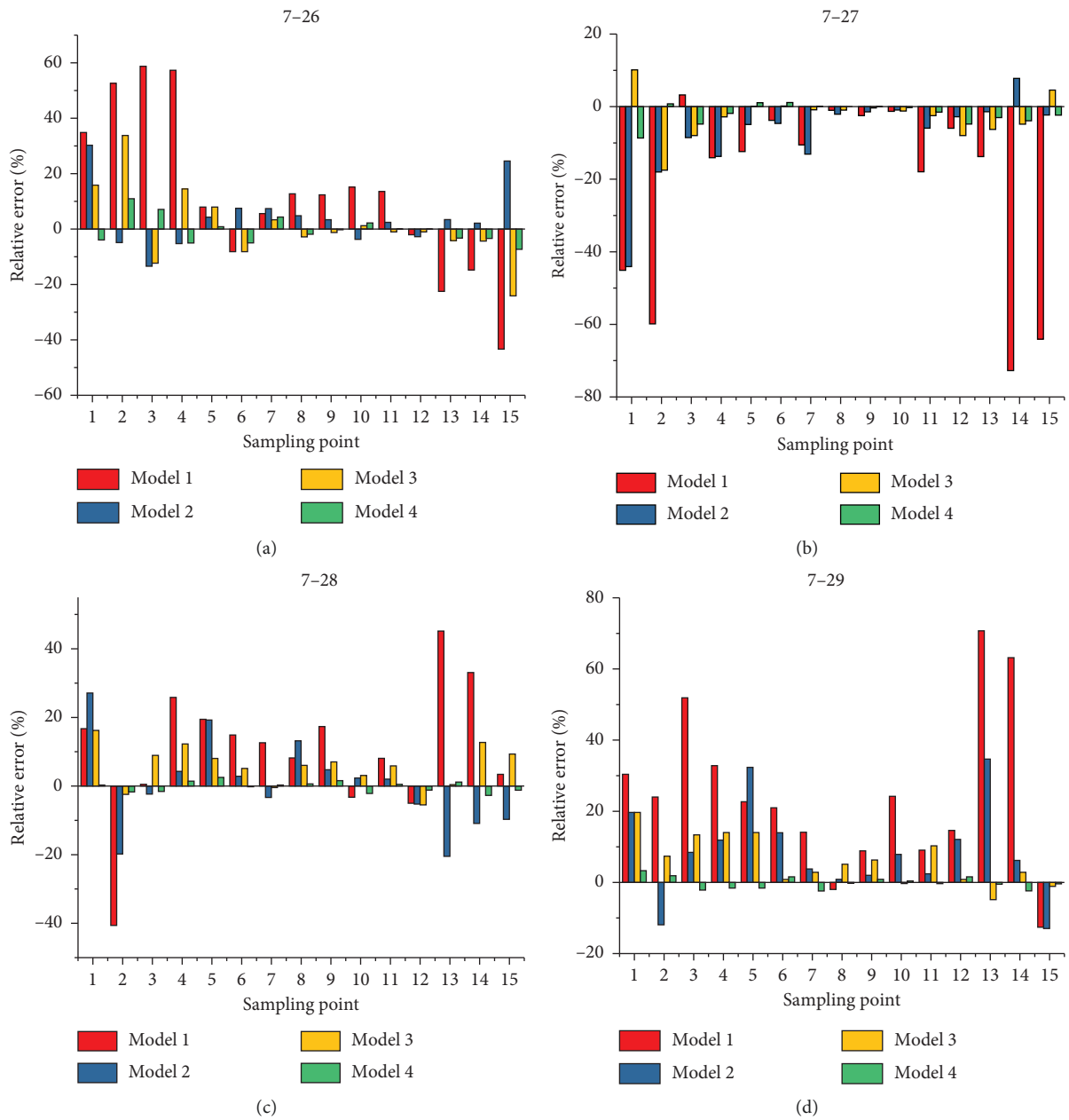

Figure 5: Comparison of results.

Table 4: Prediction model root mean square error.

Using methods	RMSPE (%)
Prediction model 1	26.14
Prediction model 2	20.15
Prediction model 3	9.15
Prediction model 4	3.06

prediction model to improve the PSO-BP neural network and the method which uses the Markov chain to correct the error. The JMP data analysis software is used to analyze the correlation between input and output data. The PSO-BP neural network is used to predict the cooling load of ice storage air-conditioning, and the Markov chain is used to correct the prediction results. Applying the predictive model to the actual mall leads to the following conclusions:

(1) The output cooling load of the ice storage air-conditioning system in the shopping mall at time T is highly correlated with the 7 inputs as follows: the outdoor temperature at time T, the outdoor temperature at time t-1, the solar radiation at time T, the solar radiation at time t-1, the relative humidity at time T, the cooling load at time t-1, and the cooling load at time t-2.

(2) The maximum relative error between the improved model and the unimproved model was reduced from 33.799% to 10.967%, and the root mean square error

of the prediction model RMSPE was reduced from 26.14% to 3.06%.

(3) The prediction results show that the method we use can improve the prediction accuracy. Besides, it is more suitable for practical engineering application.

Nomenclature

$\overline{A}(\cdot)$: Error matrix
$A(\cdot)$: Measured value matrix
$\widehat{A}(\cdot)$: Predictive matrix
$P_{(\cdot)}^{(t)}$: Probability transfer matrix
$P(\cdot)$: State interval
$N(\cdot)$: Total number of errors
$n_{(\cdot)}^{(t)}$: Error number
A: Number of hidden layer neurons
B: Number of neurons in the input layer
C: Cooling load
l: Particle step
R: Solar radiation
T: Outdoor temperature
V: Particle velocity
W: Outdoor wind speed
H: Outdoor humidity
f: Particle fitness
X: Particle position
SVM: Support-vector machine
PSO-BP: Particle swarm optimization-back propagation
BP: Back propagation
PSO: Particle swarm optimization
RMSPE: Root mean square percentage error.

Data Availability

The data used in this paper were from specific research projects, data collection, and a business center in Xi'an, and the data are safe and reliable. However, due to the need of later scientific research and the confidentiality of the market, the data cannot be disclosed for the time being.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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