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Applying support vector machine to predict hourly cooling load in the building

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ABSTRACT

In this paper, support vector machine (SVM) is used to predict hourly building cooling load. The hourly building cooling load prediction model based on SVM has been established, and applied to an office building in Guangzhou, China. The simulation results demonstrate that the SVM method can achieve better accuracy and generalization than the traditional back-propagation (BP) neural network model, and it is effective for building cooling load prediction.

1. Introduction

Predicting the dynamic air-conditioning load in a building is a key point for heating, ventilating, and air-conditioning (HVAC) system design. What is more, it is also useful for HVAC operations including adjusting the starting time of cooling to meet start-up loads, minimizing or limiting the electric on-peak demand, optimizing the costs and energy utilization in cool storage systems, and related energy and cost needs in other HVAC systems [1–3]. However, accurately predicting the building cooling load is a challenging work. Cooling load in the building is affected by many parameters, which can be grouped into two main categories: the optical and thermal properties of building and the meteorological data. Because of the complexity of these affecting parameters, it is very difficult to consider all of them very well during the whole building cooling load prediction process. Many years ago, some researchers began to focus on the prediction of building cooling load [4–11]. Several prediction methods have ever been adopted, such as the admittance and Fourier methods [12], the correlation method [13,14], the transfer function method [15], the neural networks method [16], the Monte Carlo simulation method [17], and so on. At the same time, some building energy consumption and hourly load-simulation software, such as DOE-2, ESP-r, and EnergyPlus, DeST (Designer's Simulation Toolkit) have been developed. They have ever been used to predict the building load in many projects successfully [18–23]. However, using these professional energy software is hard and time-consuming. It is very difficult for the common operators to predict building load using them. Fortunately, among these building cooling load prediction methods, artificial neural networks (ANNs) method is very convenient, and fit for an ordinary operator to implement after the model has been established. What is more, ANN is widely accepted as a technology offering an alternative way to tackle complex and ill-defined problems because of its strong nonlinear mapping ability. Hence it has been popularly applied to predict the building cooling load [16,24] and building energy consumption [25,26].

In recent years, support vector machine (SVM), developed by Vapnik and his coworkers in 1995, has been widely used in classification, forecasting and regression [27–30]. Its practical success can be attributed to solid theoretical foundations based on Vapnik–Chernoverkis (VC) theory. As a novel method, SVM's application in the building filed is vacant until now. Except that Dong et al. have ever utilized SVM to forecast monthly landlord energy consumption of four real buildings in the tropical region [31].

In this paper, we try to introduce the theory of SVM into the forecasting of hourly building cooling load. A building cooling load prediction model based on the SVM theory is established at first. And the optimal parameter setting in the SVM model is studied. Then, the back-propagation neural network model (BP model) and SVM model are both used for the summer hourly cooling load prediction of an office building in Guangzhou, China. The prediction accuracies of these two kinds of models are also compared.

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2. SVM model for forecasting of building cooling load

2.1. SVM

SVM is a novel type of learning machine, gaining popularity due to its many attractive features and promising empirical performance. The main advantage of SVM is that it adopts the structure risk minimization (SRM) principle, which has been shown to be superior to the traditional empirical risk minimization (ERM) principle, employed by conventional neural networks. SRM seeks to minimize an upper bound of the generalization error consisting of the sum of the training error and a confidence level based on VC dimension, which is different from commonly used ERM principle that only minimizes the training error. This method has been proven to be very effective for addressing general purpose classification and regression problems. The basic idea of SVM for regression is to introduce kernel function, map the input space into a high-dimensional feature space via a nonlinear mapping and to perform a linear regression in this feature space [32].

2.2. Building cooling load prediction modeling

2.2.1. Input and output parameters

When the construction of the building is complete, the construction material and design are fixed, and the most important parameters affecting cooling load are the outdoor climate parameters and indoor change of occupancy, starting and stopping of the equipments. However, for the office building, the indoor change of occupancy, starting and stopping of the equipments are regular. Their influences on the building cooling load are relatively small. Among the outdoor climate parameters, the outdoor temperature, humidity and solar radiation are the main meteorological parameters affecting the building cooling load. Hence, this paper takes three of them as the input parameters of the building cooling load prediction model. Furthermore, considering the delay of air temperature and solar radiation intensity's influence on the dynamic cooling load, their history values are also selected as the input parameters.

For the current time τ *(unit: h),* there are mainly six input parameters for the building cooling load prediction model: t_τ, $t_{\tau-1}$, $t_{\tau-2}$, d_τ, l_τ, $l_{\tau-1}$. Here, t_τ, $t_{\tau-1}$, and $t_{\tau-2}$ are, respectively, the outdoor dry-bulb temperature (unit: °C) at the time τ, $\tau-1$, and $\tau-2$. d_τ is the relative humidity (unit: %) at the time τ, l_τ and $l_{\tau-1}$ are, respectively the solar radiation intensity (unit: W/m^2) at the time τ and $\tau-1$. Herein, the data of the past 2 h are used as the input parameters for the reasons of storage effects. The sensitivity analysis of the shorter and longer hours in history on the prediction precision is further discussed in Section 3.6. The hourly building cooling load q_τ is chosen as the model's output.

$$\left.\begin{array}{ll} \underset{\{\alpha_i\},\{\alpha_i^*\}}{\text{Maximize}}: & \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}(\alpha_i-\alpha_i^*)(\alpha_j-\alpha_j^*)\cdot K(X_i,X_j)-\varepsilon\sum_{i=1}^{N}(\alpha_i-\alpha_i^*)+\sum_{i=1}^{N}Y_i(\alpha_i-\alpha_i^*) \\ \text{Subject to}: & \begin{cases}\sum_{i=1}^{N}(\alpha_i-\alpha_i^*)=0 \\ \alpha_i,\alpha_i^*\in[0,C]\end{cases} \end{array}\right\} \tag{7}$$

2.2.2. Normalizing parameters

In order to improve the calculation efficiency, and prevent individual data from overflowing during the calculation, input and output parameters should be normalized as follows:

$$v_i' = \frac{v_i - v_{\min}}{v_{\max} - v_{\min}} \tag{1}$$

$$q_i' = \frac{q_i - q_{\min}}{q_{\max} - q_{\min}} \tag{2}$$

where v_i expresses each input parameter, including the outdoor dry-bulb temperature t_τ, $t_{\tau-1}$, $t_{\tau-2}$, relative humidity d_τ, solar radiation intensity l_τ, $l_{\tau-1}$, q_i is building cooling load q_τ, and $v_{\min}$, $v_{\max}$, $q_{\min}$, $q_{\max}$ express their corresponding minimum and maximum values. v_i' and q_i' represent normalized input and output parameters.

2.2.3. Modeling process

Suppose that all the normalized input parameters compose a vector X_i (i represents one input sample), and Y_i is the normalized building cooling load under the input sample i. When the total number of samples is N, the sample set is defined as $\{(X_i, Y_i)\}_{i=1}^{N}$. Therefore, SVM approximates the relationship between the output and input parameters using the following form:

$$Y = f(X) = W \cdot \phi(X) + b \tag{3}$$

where $\varphi(X)$ represents the high-dimensional feature space which is nonlinearly mapped from the input space X, coefficients W and b are estimated by minimizing the regularized risk function shown

$$\text{Minimize}: \frac{1}{2}\|W\|^2 + C\frac{1}{N}\sum_{i=1}^{N} L_\varepsilon(Y_i, f(X_i)) \tag{4}$$

$$L_\varepsilon(Y_i,f(X_i)) = \begin{cases} 0 & |Y_i - f(X_i)| \le \varepsilon \\ |Y_i - f(X_i)| - \varepsilon & \text{others} \end{cases} \tag{5}$$

In Eq. (4), the first term $\|W\|^2$ is called regularized term. Minimizing $\|W\|^2$ will make the function as flat as possible, thus playing role of controlling the function capacity. The second term is the empirical error measured by the ε-insensitive loss function, which is defined as Eq. (5). This defines a ε tube (Fig. 1) so that if predicted value is within the tube, the loss is zero, while if predicted point is outside the tube, the loss is the magnitude of the difference between the predicted value and the radius ε of the tube. C is the penalty parameter, which is a regularized constant to determine the trade-off between training error and model flatness. To get the estimations of W and b, Eq. (5) is transformed to the primal objective function (6) by introducing positive slack variables ζ_i and ζ_i^*.

$$\left.\begin{array}{ll} \underset{\zeta_i,\zeta_i^*,W,b}{\text{Minimize}}: & \frac{1}{2}\|W\|^2 + C\frac{1}{N}\sum_{i=1}^{N}(\zeta_i+\zeta_i^*) \\ \text{Subject to}: & Y_i - W\cdot\phi(x_i) - b \le \varepsilon + \zeta_i \\ & W\cdot\phi(x_i) + b - Y_i \le \varepsilon + \zeta_i^*,\ i=1,\ldots,N \\ & \zeta_i \ge 0 \qquad \zeta_i^* \ge 0 \end{array}\right\} \tag{6}$$

By introducing kernel function $K(X_i, X_j)$, the dual form of Eq. (6) is obtained as follow:

where α_i, α_i^* are Lagrange multipliers, i and j represent different samples, respectively. Thus, the function (3) becomes the following explicit form:

$$Y = f(X) = \sum_{i=1}^{N}(\alpha_i - \alpha_i^*)K(X_i, X) + b \tag{8}$$

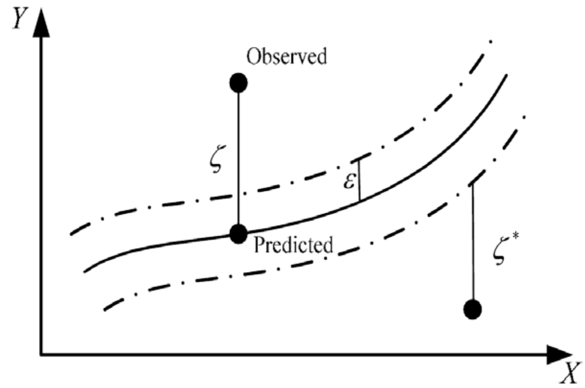

Fig. 1. The parameters for the support vector regression [31,32].

Through selecting the appropriate kernel function, the nonlinear relation between the building cooling load and its correlative influence parameters based on SVM is established.

After the prediction output Y from SVM model is gotten, it should be transformed into the actual prediction value by Eq. (9)

$$\hat{q} = q_{\min} + Y \cdot (q_{\max} - q_{\min}) \tag{9}$$

2.2.4. Choosing kernel function

Any function $K(X_i, X_j)$ satisfying Mercer's condition [33], i.e., $\int\int K(X_i, X_j)f(X_i)f(X_j)dX_i dX_j \geqq 0$ for any square integrable function $f(X)$, can be used as the kernel function. The typical kernel functions include linear function, polynomial function, Gaussian function, and Sigmoid function, etc. Among these functions, the Gaussian function can map the sample set from the input space into a high-dimensional feature space effectively, which is good for representing the complex nonlinear relationship between the output and input samples. Moreover, there is only one variable (the width parameter) in it, which is needed to be determined, thus the high calculation efficiency is ensured. Because of the above advantages, the Gaussian function is used widely. In this paper, Gaussian function is also selected as the kernel function, whose expression is shown as follows:

$$K(X_i, X_j) = \exp\left(-\frac{\|X_i - X_j\|^2}{\delta^2}\right) \tag{10}$$

where δ^2 is the width parameter of Gaussian kernel.

3. SVM cooling load prediction model's application

3.1. Building description

As shown in Fig. 2, an office building located in Guangzhou, China is selected randomly to justify the feasibility of the SVM building cooling load prediction model. Its size is 56 m $*$ 20 m $*$ 14.4 m. The storey height is 3.6 m and the building area with air-conditioning is 3581 m^2. In addition, the exterior windows in the building are at the height of 0.8 m above ground and have the size of 2.5 m $\times$ 2.0 m. The air-conditioning is operated from 8:00 to 21:00 every day. The construction style of the basic building module is described in Table 1. SVM model and BP model are both applied to forecast the summer hourly cooling load of this building.

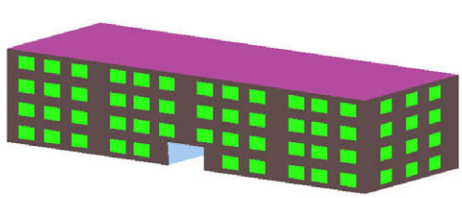

Fig. 2. Appearance of the office building.

3.2. Evaluation indices

The performance measures of SVM models adopted throughout this paper are the root mean square error (*RMSE*) and mean relative error (*MRE*), which are defined as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{q_i - \hat{q}_i}{\hat{q}_i}\right)^2} \times 100\% \tag{11}$$

$$MRE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{q_i - \hat{q}_i}{\hat{q}_i}\right| \times 100\% \tag{12}$$

where $\hat{q}_i$ is the predicted value of q_i.

3.3. Sample collection

The summer of Guangzhou is mainly from May to October. This study puts the hourly climate data and building cooling load in July (31 days) as the training sample and those data in May (31 days), June (30 days), August (31 days) and October (31 days) as the testing sample.

The input parameters of SVM and BP models such as dry-bulb temperature, relative humidity and solar radiation intensity are taken from the climate database of Guangzhou in the typical meteorology year. DeST [34] is used to calculate the office building's hourly cooling loads, which are taken as the basic values to compare with the predicted values from SVM and BP models. DeST is a building environment and energy consumption simulation software developed by Tsinghua University through a more than 10-year study. It adopts the state space method for the load-simulation [35]. Stage design and simulation are its basic features [36]. Its reliability has ever been proven by analytical test, inter-model comparison and experiment results [37]. In the past 10 years, DeST has played an important role in the prediction of building energy consumption in many projects [21–23].

In this study, the building cooling load in July calculated by DeST is used for the output of training sample. The building cooling loads in May, June, August and October calculated by DeST are used to compare with those results predicted by SVM model and BP model.

3.4. Parameter characteristics of SVM

The penalty parameter C and the radius ε are two important parameters. A small value of C will under-fit the training data because too small weight placed on the training data would result in

Table 1
Construction style description of the basic module in the building.

Module	Construction structure	Thermal resistance (m^2 K/W)
Exterior wall	Cement mortar + 24 brick wall + lime mortar	0.3409
Interior wall	Cement mortar + 12 brick wall + lime mortar	0.1904
Roof	Cement mortar + aeroconcrete + reinforced concrete + cement mortar	0.607
Ground	Cement mortar + concrete + cement mortar	0.026
Floor	Cement mortar + reinforced concrete + cement mortar	0.0975
Door	Single-layer, entity, wooden	0.372
Exterior window	Hollow, with light color blind	0.256

large values of prediction error on the test sets. But if C is too large, SVM would over-fit the training set, which means that C will lose its meaning and the objective goes back to minimize the empirical risk only. On the other hand, larger C means larger range of the value of support vectors, accordingly, more data points can be selected as the support vectors in the optimization formulation. If ε is larger, the number of support vectors is fewer and thus the representation of solutions is sparser. But if the ε is too large, it can deteriorate the accuracy on the training data. The optimal values of C and ε are not known beforehand. Hence, some kind of model selection (parameter search) must be done. The goal is to identify optimal values of C and ε so that the model can accurately predict the unknown data.

Ref. [31] used the stepwise searching method to study the performance of SVM based on radial-basis function (RBF) kernel. In this paper, in order to determine the proper values of parameter C and ε, the simulation processes of SVM cooling load prediction model with various parameter settings were also studied. At first, ε is fixed to be 0.1, and we vary the value of C from 2^{-5} to 2^{5} to train the SVM model using the training sample of July data, and record the prediction errors of *RMSE* and *MRE*, and the number of support vectors. The results are shown in Fig. 3. From Fig. 3, we can see that the number of support vectors increases slightly as C increases. It also shows that in terms of parameter C, there are one lowest *MRE* point and one lowest *RMSE* point. *MRE* and *RMSE* first decrease slightly with the increase of parameter C, and then increase after the optimum point. From these results, we can choose parameter C to be $2^3 = 8$.

Then we fix C to be eight, set ε as various values between 2^{-10} and 2^{-1}, and train the SVM model through using the training sample of July data. The results are shown in Fig. 4. From Fig. 4, it can be seen that the *MRE* and *RMSE* firstly almost remain constant, and then suddenly go up largely when ε is between 2^{-2} and 2^{-1}. However, the number of support vectors decreases largely when the ε increases and eventually reaches zero. This indicates that ε does not affect the performance of SVM greatly, while the number of support vectors shows a decreasing function of ε. Considering both the prediction error and the number of support vectors, we choose ε to be $2^{-6} = 0.03125$.

3.5. Selection of the width parameter δ^2 of Gaussian kernel

The width parameter δ^2 of Gaussian kernel directly defines the structure of the high-dimensional feature space $\varphi(X)$, and controls the complexity of the eventual solutions. Generally, large δ^2 results in narrow kernel, and further reduces the prediction error. However, if δ^2 is too large and over a certain limit, the prediction error would increase instead. Therefore, the value of δ^2 should be suitably selected according to the regression problems. In order to identify the proper value, we set C and ε as eight and 0.03125, respectively, and carry out the simulation of SVM cooling load prediction model with various values of δ^2 between 2^{-4} and 2^{10}. The prediction errors of *RMSE* and *MRE*, and the number of support vectors are recorded. The results are shown in Fig. 5. From Fig. 5, we can see that $\delta^2 = 2^2$ is the best for this cooling load prediction problem.

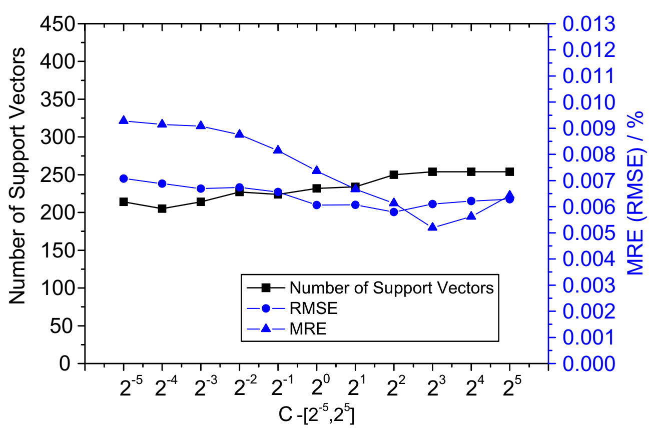

Fig. 3. The results of various C, where $\varepsilon = 0.1$.

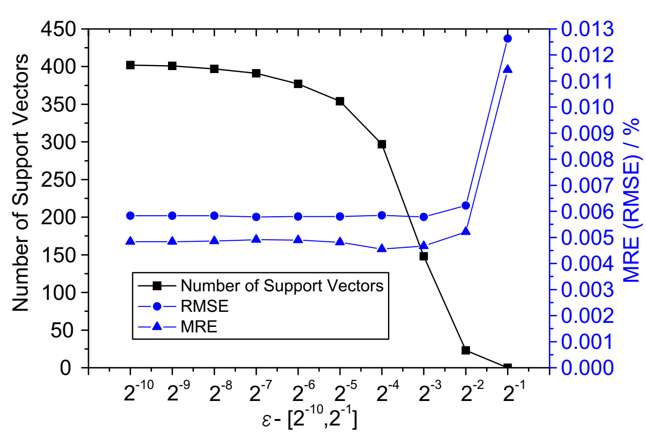

Fig. 4. The results of various ε, where $C = 8$.

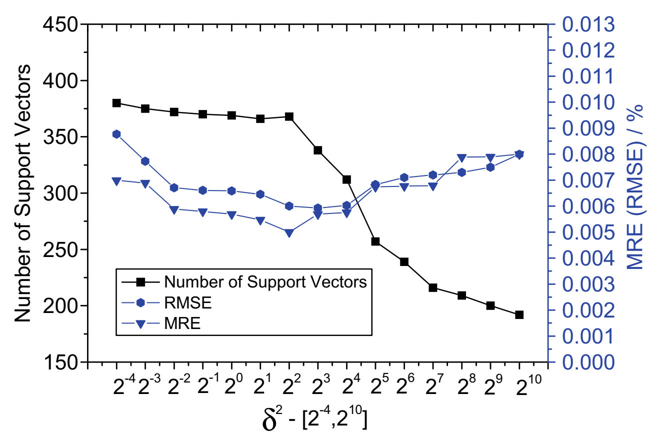

Fig. 5. The results of various δ^2, where $C = 8$, $\varepsilon = 2^{-6}$.

Table 2
Input parameters setting considering various past hours in history.

No.	Input parameters
Case 1	t_τ, $t_{\tau-1}$, d_τ, l_τ
Case 2	t_τ, $t_{\tau-1}$, $t_{\tau-2}$, d_τ, l_τ, $l_{\tau-1}$
Case 3	t_τ, $t_{\tau-1}$, $t_{\tau-2}$, $t_{\tau-3}$, d_τ, l_τ, $l_{\tau-1}$, $l_{\tau-2}$
Case 4	t_τ, $t_{\tau-1}$, $t_{\tau-2}$, $t_{\tau-3}$, $t_{\tau-4}$, d_τ, l_τ, $l_{\tau-1}$, $l_{\tau-2}$, $l_{\tau-3}$

Table 3
The prediction errors of SVM model in different cases (unit: %).

Case	July (training sample)		May (testing sample)	
	RMSE	*MRE*	*RMSE*	*MRE*
Case 1	0.006	0.006	2.401	2.125
Case 2	0.006	0.005	1.146	1.001
Case 3	0.006	0.005	1.144	1.001
Case 4	0.006	0.005	1.143	1.000

3.6. Sensitivity analysis of the storage effects

In view of the delay effects of outdoor dry-bulb temperature and solar radiation intensity on the building cooling load, the data of the past 1 or 2 h in history are chosen as the input parameters. However, the storage effects maybe go further than 2 h in history. In order to analyze the storage effects, we study four cases with different input parameters considering various past hours in history, which are shown in Table 2. For these four cases, SVM model with parameters C, ε and δ^2 determined above is established on the basis of the meteorological data and building cooling load in July. And the established SVM model is used to predict the hourly building cooling load in May. The *RMSE* and *MRE* of the training sample and testing sample under various cases are compared, which is shown in Table 3. From Table 3, we can see that for case 1, in which only the outdoor dry-bulb temperature of the past 1 h in history is considered, the *RMSE* and *MRE* are relatively larger than the other cases. While the data of the past two or more hours in history are considered as the input parameters in cases 2–4, the *RMSE* and *MRE* are almost the same. Therefore, we can select the input

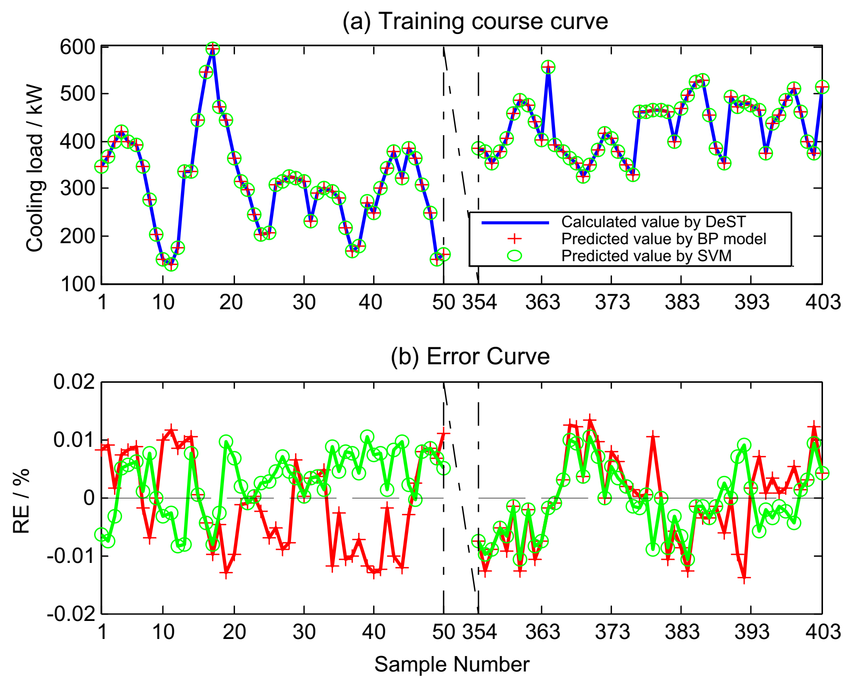

Fig. 6. Training course and relative error (RE) curves of July's sample.

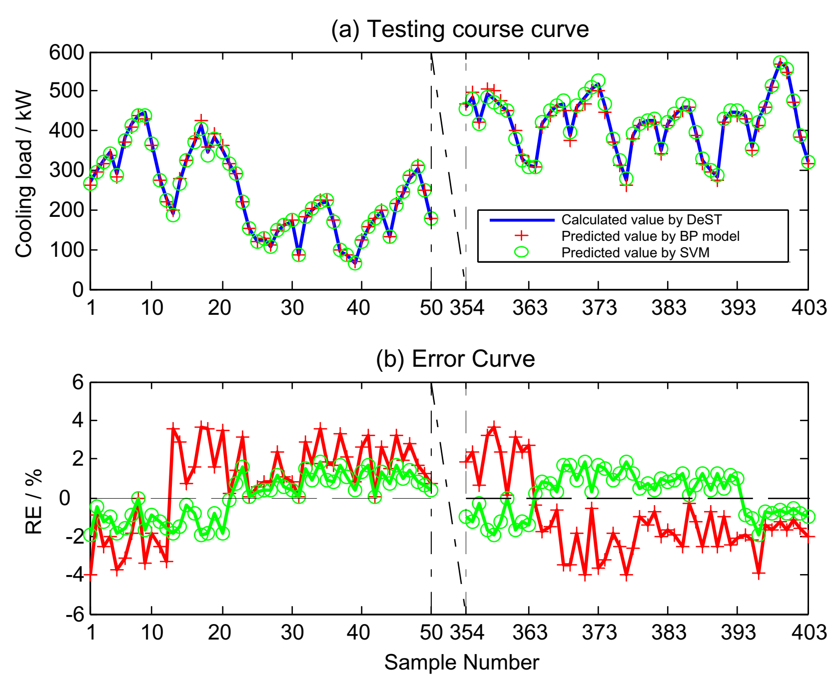

Fig. 7. Testing course and relative error (RE) curves of May's sample.

parameters like case 2, considering both the accuracy and simplicity.

3.7. Prediction results and analysis

After parameters C, ε and δ^2 are selected, and the input climate parameters are determined, SVM model is established on the basis of the meteorological data and building cooling load in July. Based on these input data, we also set up BP model. Back-propagation neural network [38] has the strong nonlinear mapping ability. In this study, three-layered back-propagation neural network is used, consisting of an input layer, a hidden layer and an output layer. The Matlab 7.0/Neural Network Toolbox is used to train and develop the artificial neural networks for the building cooling load estimation. The sigmoid transfer function is selected as the activation function, and it is also trained with a sigmoid-like scaled output vector. The number of neurons in a hidden layer drastically affects the outcome of the network training. It must be sufficient for correct modeling of the problem, and on the other hand, it should be low to ensure generalization. However there is no general rule for

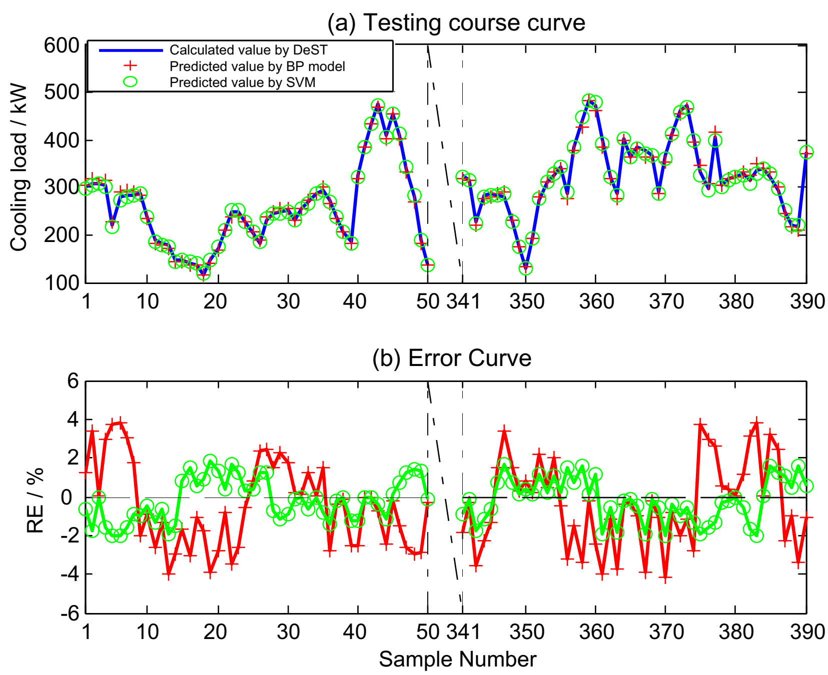

Fig. 8. Testing course and relative error (RE) curves of June's sample.

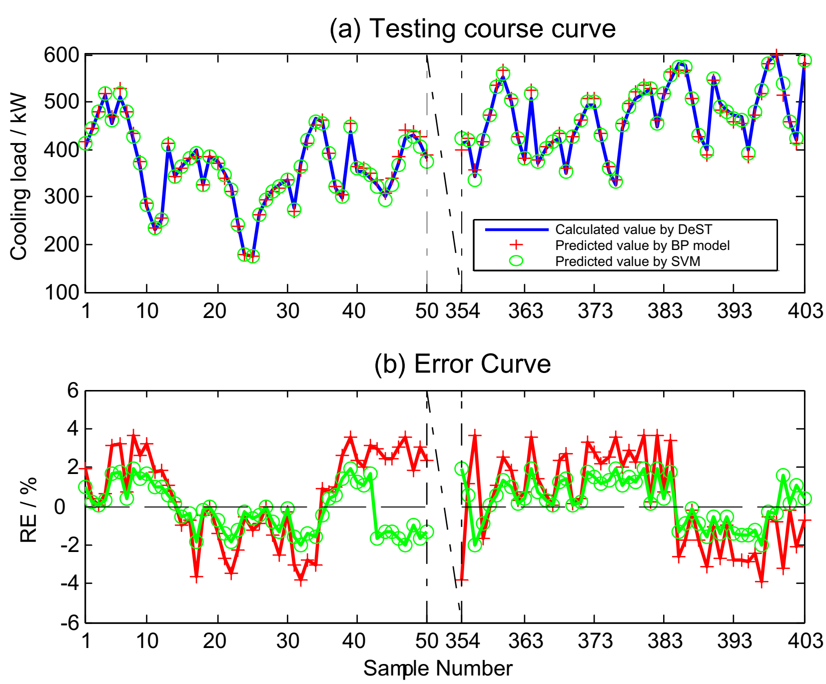

Fig. 9. Testing course and relative error (RE) curves of August's sample.

selecting the number in a hidden layer [39]. Considering the input neurons' number of six, and the output neuron's number of one, we explore the hidden layer neurons' number in the range of 4–13 using stepwise searching method, and find that the optimal value is eight. Considering the limited space, the details are not shown here. Their relative error curves in the training courses are displayed in Fig. 6. Here only a part of hours' results are displayed in order to express the cooling loads and error curves more clearly. It can be seen from it that the prediction relative errors of the training samples under two models are less than 0.02%. The results testify that SVM and BP prediction model are established well to describe the complex relationship between the building cooling load and meteorological parameters.

Next, SVM model and BP model are both used to predict the hourly building cooling load in May, June, August and October. The predicted cooling loads and their relative errors between the prediction value by two models and calculated value by DeST are illustrated in Figs. 7–10. Moreover, the *RMSE* and *MRE* of the training sample and testing sample under two models are compared, which is shown in Table 4.

Figs. 7–10 and Table 4 show that during testing course, the prediction errors of SVM model are less than those of BP model, for the May's testing sample set, the mean square root error and the mean relative error from SVM model are equal to 49.78% and 49.85% of those from BP network model, respectively; for the June's testing sample set, the mean square root error and the mean relative error from SVM model are equal to 49.85% and 49.88% of those from BP network model, respectively; for the August's testing sample set, the mean square root error and the mean relative error from SVM model are equal to 52.54% and 52.60% of those from BP network model, respectively; for the October's testing sample set, the mean square root error and the mean relative error from SVM model are equal to 49.98% and 50.20% of those from BP network model, respectively. The results indicate that using SVM method to predict building cooling load is better than using BP network method. This is because that SRM principle, which is the most outstanding feature of SVM, is implemented to minimize the upper bound of the generalization error rather than the training error, which is applied in neural networks. SVM model can fully utilize the distribution characteristics of training samples to construct distinction function, and through transforming the analyzed problem into a quadratic search optima problem, it does not need more prior information and skill for use. It also has fewer free parameters to optimize compared with neural network. Moreover, SVM deals with small sample sets powerfully, and can carry out statistical learning very well even if the quantity of sample sets is less.

4. Conclusions

This paper applies SVM to forecast the hourly building cooling load. And the performance of SVM with different parameters of the penalty parameter C, the radius ε and the width parameter δ^2 of Gaussian kernel has been investigated and the optimal parameter setting for the application is obtained. The storage effect of historical input parameters for SVM model also has been discussed and the appropriate input parameters are determined. The input parameters considering the outdoor dry-bulb temperature of the

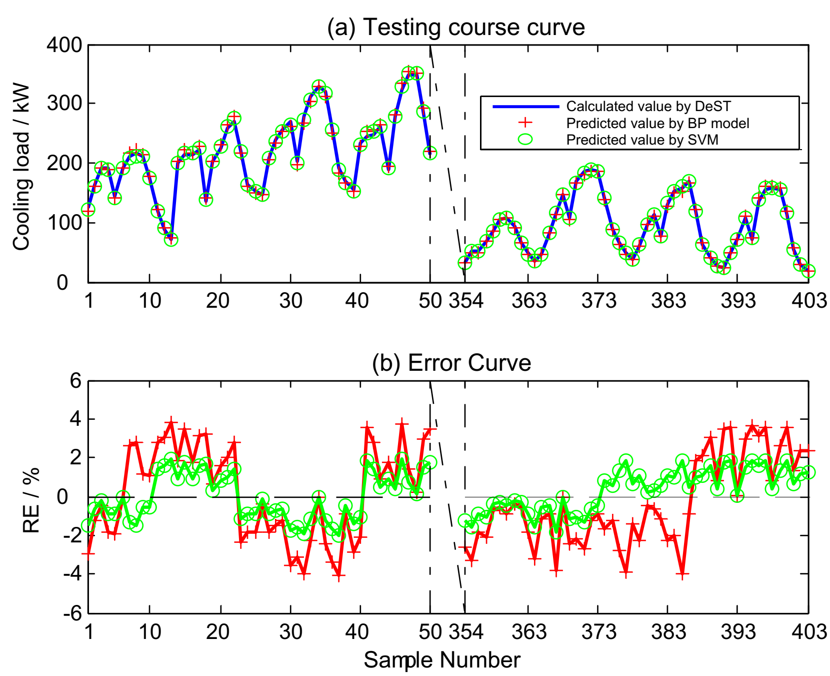

Fig. 10. Testing course and relative error (RE) curves of October's sample.

Table 4
Comparison of the prediction errors of SVM model and BP model (unit: %).

Model	July (training sample)		May (testing sample)		June (testing sample)		August (testing sample)		October (testing sample)	
	RMSE	*MRE*	*RMSE*	*MRE*	*RMSE*	*MRE*	*RMSE*	*MRE*	*RMSE*	*MRE*
SVM	0.006	0.005	1.146	1.001	1.157	1.008	1.168	1.011	1.182	1.016
BP	0.008	0.007	2.302	2.008	2.321	2.021	2.223	1.922	2.365	2.024

past 2 h and the solar radiation intensity of the past 1 h in history are best in view of both the accuracy and simplicity.

Through the comparison to the prediction results of two models, the root mean square error and the mean relative error from SVM model are found to be about 50% of those from BP network model. The results show that SVM method can achieve better prediction accuracy than the conventional back-propagation neural networks. The SVM method's quick and correct learning performance, particularly when the available training set is limited, makes it open a new avenue in load forecasting. The research results demonstrate that SVM method is a promising alternative approach for the prediction of the cooling load in the building.

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