Improving prediction accuracy of cooling load using EMD, PSR and RBFNN

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Abstract. To increase the accuracy for the prediction of cooling load demand, this work presents an EMD (empirical mode decomposition)-PSR (phase space reconstruction) based RBFNN (radial basis function neural networks) method. Firstly, analyzed the chaotic nature of the real cooling load demand, transformed the non-stationary cooling load historical data into several stationary intrinsic mode functions (IMFs) by using EMD. Secondly, compared the RBFNN prediction accuracies of each IMFs and proposed an IMF combining scheme that is combine the lower-frequency components (called IMF4-IMF6 combined) while keep the higher frequency component (IMF1, IMF2, IMF3) and the residual unchanged. Thirdly, reconstruct phase space for each combined components separately, process the highest frequency component (IMF1) by differential method and predict with RBFNN in the reconstructed phase spaces. Real cooling load data of a centralized ice storage cooling systems in Guangzhou are used for simulation. The results show that the proposed hybrid method outperforms the traditional methods.

1. Introduction

District ice storage cooling systems use centrally-located chilling equipment to generate cooling in the form of chilled water so that it can be distributed to the nearby buildings for air conditioning. As energy prices increase, optimal control of district cooling systems has become more critical for energy cost reduction. Among issues of optimal control, accurate cooling load prediction for next-day demand is essential for the optimal scheduling of cooling system operating.

Various strategies have been developed to model cooling load demand. These attempts can be categorized in two approaches: physical-based software simulating methods and statistical methods. The physical-based software simulating methods are based on the thermal knowledge and physical equations of the buildings [1]. The statistical methods are based on the data collected in the cooling system. For district ice storage cooling systems, it is unrealistic to obtain all the building thermal behaviour. For this reason, statistical methods are more suitable for district cooling load prediction. The statistical methods include the single algorithm and the algorithm combinations. Linear-regression analysis [2], the artificial neural networks (ANN) [3], and the support vector machines (SVM) [4] are the primary ones of the single algorithm. The main feature of the algorithm combinations [5] is to combine more than one single algorithm to obtain prediction precision higher than that could be obtained from a single algorithm.

Regression analysis models formulate the cooling load prediction problem by an empirically mathematical function of the main parameters that affect the cooling load, such as temperature,
humidity [6]. Common models reported in the literature include ARX, MLR, and ARMAX models. Generally, such a model is suitable for long-term predicting with large samples. For instance, Yoshida [7] applies this method to predict air-conditioning load based on an ARX model derived from building load simulation. Results show that its average prediction error is 29% in summer and 12% in winter. Li [8] applies four different methods including ARMAX, MLR, ANN and RC network to predict short term building cooling load demand, the results show that the MLR model and the ARMAX model are superior in prediction precision. Usually, regression models require a much shorter training time, but are less capable of modelling nonlinearity.

Artificial neural network and support vector machine have been proved to obtain prediction precision higher than the regression analysis models, due to its capable of modelling nonlinearity. ANN, SVM, modified ANN and SVM have been widely used to predicting, such as power load forecasting, natural gas usage trend forecasting, energy consumption in a building, and etc [9]. It is reported that, in forecasting a building air conditioning load, compared with back propagation neural network (BPNN), the root mean square error and the average relative error obtained by RBFNN are reduced by 36%. It is also reported that, for building air conditioning load prediction, the root mean square error obtained by SVM is about 50% lower than that obtained by BPNN [6].

Cooling load demand depends on many external and internal factors of cooling system, such as outdoor weather parameters, indoor equipment usage, and indoor human activities. Nonlinear interaction of these factors in cooling system leads to chaos of cooling load demand. The chaos especially the self-similarity and non-stationary of cooling load should be considered in cooling load prediction. EMD, which is data-driven technique that represents nonlinear and non-stationary data as a sum of a finite zero-mean components referred to as IMF, can be employed to transform the self-similarity time series into the short-related components. Ying [10] used EMD to forecast an hour-ahead wind speed and power, and Yang [11] integrated EMD, Chaos-based neural network and PSO for financial time series forecasting. EMD has also been used to predict networking traffic [12], price of power [13], and etc. To improve the prediction accuracy for the next-day Cooling load demand of a centralized ice storage cooling systems in Guangzhou, we propose the hybrid EMD-PSR-RBFNN model.

The rest of this paper is organized as follows. Section 2 is a collection of cooling load data, including tests. This serves to confirm that the data are chaos time series. In section 3, we introduce the proposed EMD-PSR-RBFNN model. Section 4 consists of simulations and results of the proposed model and other relevant models. Finally, Section 5 concludes this paper and summarizes the discussion.

2. Data Collection and Proofing of Chaos
This paper adopted the real cooling load time series of a centralized ice storage cooling systems in Guangzhou, the data that is collected a total of 121 days from July 1, 2012 to October 31, 2012, in which the former 106 data are taken as the training set and the remained 15 data as the testing set.

In order to investigate the chaotic nature of the cooling load time series, firstly, we applied mutual information method [14] and Cao method [15] to calculate the delay time and the embedding dimension respectively. Time delay is the delay time between the adjacent two coordinates of reconstructed phase space vector. Mutual information method utilizes the first minimum value of mutual information function to determine the optimum delay time, while the mutual information function is a measure of general random association between two random variables. The delay time of the cooling load time series in this paper is calculated to be 1.

Takens embedding [16] theorem deems that: For infinite and noiseless scalar time series with d-dimensional chaotic attractors, an m-dimensional phase space embedded can always be found in the sense of topological invariant, as long as dimensions \( m \geq 2d + 1 \). By Cao method, the embedding dimension \( m \) of the cooling load time series is calculated to be 5.

Based on the calculated delay time and embedding dimension, Wolf method [17] is applied to calculate the maximum Lyapunov exponent. The maximum Lyapunov exponent of the experimental data is 0.0676, which indicates that the cooling load series has chaotic nature. Phase space reconstruction method of chaotic series is then applied to predict the cooling load demands in this paper.
3. Method

Chaos is a complex behaviour manifested by the low-order deterministic nonlinear dynamical system, which has the characteristic of nonlinearity, self-similarity and etc. In this paper, the proved self-similarity cooling load chaotic series is decomposed with EMD, which broken the self-similarity time series into several short-related IMFs. An IMF combining method is proposed to balance the computation complexity and prediction accuracy, and the differential method is used to smooth the high frequency component of EMD (IMF1) to improve the prediction accuracy further. Then reconstruct the phase space for the combined series and predict with RBFNN algorithm.

3.1. Emd and Combination of IMFs

EMD in Hilbert-Huang transform (HHT) [18] is mainly applied to decompose the original signal into several IMFs and a residue. The essence is to determine the basic shock mode of valid signal in the series by experience. The IMFs which contain local characteristics of cooling load in different time must satisfy the following two conditions: ①in the whole data set, the number of extreme and the number of zero-crossings must either be equal or differ at most by one. ②at any point, the mean value of the envelope defined by local maxima and the envelope defined by the local minima is zero. N.E.Huang, who was the founder of HHT, explained the meaning of these two conditions in the literature [19]. The first condition stipulates that the signal form of IMF is similar to the traditional narrow band requirements for a stationary Gaussian process, which can be characterized as a form of \( a(t)e^{\phi(t)} \), in which \( a(t) \) represents the envelope of the signal, \( \phi(t) \) represents the phase of the signal. The second condition guarantees the symmetry of IMF waveform, and ensures that the instantaneous frequency does not fluctuate after Hilbert transform.

The process of EMD is as follows: Firstly, identify all the local extreme points of cooling load series \( h(t) \). Secondly, connect all the local maxima points and the local minima points by a cubic spline as the upper envelope and the lower envelope, the upper and the lower envelopes should cover all the series between them, the mean of upper and lower envelope value is designated as \( l(t) \). Thirdly, set \( m(t) = h(t) - l(t) \), judge whether \( m(t) \) is an IMF component, if \( m(t) \) satisfies the conditions of IMF, \( m(t) \) is the first IMF of \( h(t) \), otherwise \( m(t) \) is treated as \( h(t) \), and repeat the above processes. Suppose after k iterations, the difference value between signal and the mean of the envelope is \( m_{k,1}(t) = m_{k-1,1}(t) - l_{k-1,1}(t) \), \( m_{k,1}(t) \) is a new series which removes the low frequency, after repeating up to \( k-1 \) times, the difference value is \( m_{k-1,1}(t) \). In order to reduce the computation, when the equation (1) is satisfied, \( m_{k,1}(t) \) is considered as the first IMF, where

\[
SD = \frac{\sum[m_{k,1}(t) - m_{k-1,1}(t)]^2}{\sum[m_{k-1,1}(t)]^2} \leq \varepsilon (1)
\]

The threshold value \( \varepsilon \) is set according to the actual needs. The smaller the threshold is, the closer to the real IMF component \( m_{k,1}(t) \) which satisfies equation (1) is. In this paper, the threshold is set to 0.3. Assuming \( m_{k,1}(t) \) is the first IMF, \( d(t) = h(t) - m_{k,1}(t) \) will be considered as \( h(t) \), repeating the above processes. When the residual component is a monotonic function or its amplitude less than a predetermined value, just stop calculating. So we can get several IMFs, these components can be designated as \( e_{i}(t) \), and the final residual component is \( r(t) \), then

\[
h(t) = \sum_{i=1}^{n} e_{i}(t) + r(t) \tag{2}
\]

The original cooling load series is decomposed as the superposition of a variety of different feature fluctuation series with EMD. The IMFs have different time scale and can be ordered from highest to lowest frequency. In order to highlight the local detail of the high-frequency IMFs which mainly affect
the cooling load prediction accuracy, this paper keeps the high-frequency IMFs and the residual unchanged with the low-frequency IMFs combined together. The details are as follows:

(1) Calculate the means of IMF components \(c_i(t), c_2(t), \ldots, c_q(t)\) in turn; (2) Determine the first component \(c_1(t)\) which the mean deviates from zero significantly; (3) Keep the former \(i-1\) IMFs \(c_i(t), c_2(t), \ldots, c_{i-1}(t)\) (the high-frequency IMFs) and the residual \(r(t)\) unchanged, combine the last \(k-i+1\) IMFs (the low-frequency IMFs) as a low-frequency component according to the equation

\[
\overline{c}_{\text{low}}(t) = \sum_{i=1}^{k} c_i(t) \quad (3)
\]

3.2. Phase Space Reconstructing

Takens theorem [16] considers that the evolution of a component is decided by the interaction of other components in the system, and the information in these related components are implied in the development process of any component. Therefore, phase space reconstructing [20] only need to inspect a component, and reconstruct an equivalent phase space by computing the observing values of certain constant delay points. In section 2, the delay time \(\tau\) and the embedding dimension \(m\) have been obtained to be 1 and 5 respectively. We calculated that the number of sample series after phase space reconstructing is 117.

Assuming the high-frequency IMFs, the combined low-frequency component and the residual forming a time series set \(D = \{x(i), i = 1, 2, \ldots, N\}\), after reconstructing the phase space, we can get the series set \(\overline{D} = \{x(t), y(t)\}, t = 1, 2, \ldots, M\) in phase space domain, in which matrix \(X\) and \(Y\) represent the input and output set respectively, where

\[
\begin{align*}
X(t) &= \begin{bmatrix}
  x(1) & x(1+\tau) & \cdots & x(1+(m-1)\tau) \\
  x(2) & x(2+\tau) & \cdots & x(2+(m-1)\tau) \\
  \vdots & \vdots & \ddots & \vdots \\
  x(M) & x(M+\tau) & \cdots & x(M+(m-1)\tau)
\end{bmatrix} \\
Y(t) &= \begin{bmatrix}
  x(2+(m-1)\tau) \\
  x(3+(m-1)\tau) \\
  \vdots \\
  x(M+1+(m-1)\tau)
\end{bmatrix}
\end{align*}
\]

(4)

3.3. Rbfnn

In the reconstructed phase space, RBFNN algorithm is utilized to predict the cooling load demand. There are three parameters need to be found for RBFNN simulation: the centres of base functions, the variance and the weights between the hidden layer and the output layer. In this paper, the centres of base functions were selected by self-organized method, and Gaussian function is chosen as the radial basis function. Therefore, the activation function of RBFNN is expressed as

\[
R(x_p, c_i) = \exp(-\frac{1}{2\delta^2} \left\| x_p - c_i \right\|^2)
\]

(5)

In equation (5), \(\left\| x_p - c_i \right\|\) is Euclidean norm, \(c_i\) is the centre of Gaussian function, \(\delta\) is the variance of Gaussian function. The output of RBFNN is

\[
y_j = \sum_{i=1}^{k} w_{ij} \exp(-\frac{1}{2\delta^2} \left\| x_p - c_i \right\|^2) \quad j = 1, 2, \ldots, n
\]

(6)

In equation (6), \(x_p = (x_p^1, x_p^2, \ldots, x_p^p)^T\) is the \(p\)-th input sample; \(p = 1, 2, 3, \ldots, P\), \(P\) is the total number of samples; \(c_i\) is the node centre of network hidden layer; \(w_{ij}\) is the weight between the hidden layer and the output layer; \(i = 1, 2, 3, \ldots, h\), \(h\) is the number of hidden layer nodes; \(y_j\) is the actual output of the \(j\)-th output node corresponding to the input samples.

Assuming \(d\) is the desired output, the variance of base functions can be expressed as

\[
\delta = \frac{1}{p} \left\| d_j - y_j c_i \right\|^2
\]
In this paper, $k$ means clustering algorithm [21] is used to calculate the centre points $c_i$, and the least squares method [22] is used to calculate the connection weights $w_{ij}$.

3.4. Hybrid Prediction Model Based on EMD-PSR-RBFNN

This paper proposes a hybrid method based on EMD, PSR and RBFNN (EMDPSRRBFNN) for short-term cooling load demand predicting. The steps are as follows:

Step1: Pre-process the original cooling load series, including data cleansing and data restructuring.

Step2: Decompose the cooling load series with EMD, and then get $k$ IMFs and a residual.

Step3: Combine the IMFs according to the IMF combination methods described in section 3.1.

Step4: Reconstruct the combined time series set $D=\{x(i),i=1,2,\ldots,N\}$ into the series set $\tilde{D}=\{x(t),y(t)\},t=1,2,\ldots,M$ in the phase space.

Step5: Normalize data sets $\tilde{D}=\{x(t),y(t)\},t=1,2,\ldots,M$ of phase space domain, and process the IMF1 by differential method.

Step6: Set up the RBFNN prediction models in the reconstructed phase space for IMF1, IMF2, IMF3, the combined low-frequency component (call it IMF4-IMF6 combined) and the residual respectively, then anti-normalize the predicted values.

Step7: Add the predicted values above together to achieve the final prediction result of the cooling load demand.

4. Simulation and Result

This section discusses the simulation works and results of the proposed EMD-PSR-RBFNN model in predicting the cooling load demand. Works begin with evaluation criteria in section 4.1. The results in section 4.2 verified that EMD model acts as a good filter in non-stationary and self-similarity cooling load time series systems. Simulation results of each EMD component using the PSR-RBFNN are described in section 4.3. Both are displayed in fig.3 and table 3. Following to this, it is the determination of high-frequency components, low-frequency components of EMD. Predicting comparison of different IMFs combination methods are shown in section 4.4. Section 4.5 serves to improve the prediction accuracy of IMF1. Section 4.6 conducts to demonstrate the performance of the proposed EMD-PSR-RBFNN model in predicting cooling load demand. We used models of SVM, LSSVM, RBFNN and SVM, LSSVM, RBFNN based on EMD-PSR for predicting comparison.

4.1. Evaluation Criteria

The root mean square relative error (RMSRE) and the mean relative error (MRE) are used as the evaluation criteria to assess the prediction accuracy, where in equation (7), $y_i$ is the actual load result, $\hat{y}_i$ is the predicted load result, $n$ is the total number of the predicted result,

$$E_{RMSRE} = \left( \frac{1}{n} \sum_{i=1}^{n} \left( \frac{y_i - \hat{y}_i}{y_i} \right)^2 \right)^{1/2} \times 100\% \quad E_{MRE} = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100\%$$

(7)

4.2. EMD and Analyzing of IMFs

4.2.1. Empirical mode decomposing. After EMD to the original cooling load time series, we got six IMFs and a residual, which are shown in figure 1. In figure 1, the horizontal axis represents the samples (days) and the vertical axis represents the cooling load demand (W).
4.2.2. Comparing of stationary. In order to verify the influence of EMD on the stationary of cooling load series, the Hysteron Proteron method [23] is used to test the stationary of the original series and the EMD components. The computing results of the inverse number $A$ and $\lambda$ value are shown in table 1.

![Figure 1](image)

**Figure 1.** Original series and EMD components.

| Parameters | original series | IMF1        | IMF2        | IMF3        | IMF4        | IMF5        | IMF6        | residual |
|------------|----------------|-------------|-------------|-------------|-------------|-------------|-------------|----------|
| inverse number $A$ | 12             | 23          | 31          | 30          | 36          | 18          | 25          | 0        |
| $\lambda$       | -2.3355        | -0.6228     | 0.6228      | 0.4671      | 1.4013      | -1.4013     | -0.3114     | -4.2039  |

According to the Hysteron Proteron method, if the value of $\lambda$ is between -2 to 2, the series should be stationary; otherwise, the series should be non-stationary. As shown in table 1, the original time series is non-stationary and the IMF1 to IMF6 are stationary respectively while the residual is non-stationary. That’s to say, after EMD, the non-stationary original series has been transformed into several stationary series except the residual.
4.2.3. Comparing of self-similarity. In order to verify the influence of EMD on the self-similarity of cooling load series, the variance-time plots method [24] is used to estimate the Hurst index \( H \) for the original cooling load series and each EMD component, the estimation results are shown in table 2.

**Table 2. The Hurst index \( H \).**

| Parameter | Original series | IMF1 | IMF2 | IMF3 | IMF4 |
|-----------|----------------|------|------|------|------|
| \( H \)   | 0.9131         | 0.7327 | 0.3567 | 0.553 | 0.7493 |

The Hurst index \( H \) is the parameter to characterize the self-similarity. When \( H \in (0,1) \), the series is self-similarity. The greater the \( H \) is, the stronger the self-similarity is. As shown in table 2, after EMD, the self-similarity of IMF1~IMF4 reduced significantly. It indicates that EMD reduced the self-similarity of the original cooling load time series. From figure 2 in section 4.2.1, we can see that the waveforms of IMF5, IMF6 and residual approach sinusoidal waveforms gradually which resulting to the random reduced greatly. The calculation error of its Hurst index \( H \) is large and we will not discuss this topic in this paper.

Normally, a self-similar random process is also a non-stationary random process. Long-range dependence time series has the disadvantages of the high model algorithm complexity and poor precision. EMD is an effective method to break the self-similarity time series down into several short-related components.

4.3. RBFNN Prediction for Each EMD Component

Figure 2 shows the EMD components of the original cooling load series and their predicting results with PSR and RBFNN modelling. In figure 2, the horizontal axis represents the samples (days) and the vertical axis represents the cooling load demand (W).

![EMD components and their prediction results of the next 15 days](image)

*Figure 2. EMD components and their prediction results of the next 15 days by PSR-RBFNN.*

Prediction errors corresponding to each EMD component are shown in table 3. As can be seen in table 3 and figure 2, there exists larger prediction errors for the former IMFs (especially the IMF1) when RBFNN modelling, while the prediction errors are smaller for the later EMD components. In section D, we will compare different combination ways of the EMD components to balance the computation complexity and the prediction accuracy.
Table 3. The prediction error of each EMD component with RBFNN modelling

| Evaluation criteria | IMF1 | IMF2 | IMF3 | IMF4  | IMF5  | IMF6  | residual | reconstruction result |
|---------------------|------|------|------|-------|-------|-------|----------|-----------------------|
| RMSRE(%)            | 2.262| 1.571| 0.115| 0.3816| 0.300E-02| 8.19E-03| 2.218     |                       |
| MRE (%)             | 1.540| 0.874| 0.103| 0.3165| 0.381E-02| 1.76E-02| 5.04E-03| 1.516                 |

4.4. Comparing of Prediction Errors for Different IMF Combination Methods

The means of IMF1 to IMF6 are calculated to be -9.9246, 6.4726, -2.9915, 100.369, -83.4171 and -86.3867 respectively. The first IMF whose mean deviates from zero significantly is IMF4. It indicates that IMF1, IMF2 and IMF3 are high-frequency EMD components and represent the influence factor of significant events. In the meanwhile, the IMF4, IMF5, IMF6 are low-frequency EMD components and represent the normal fluctuations factor of cooling load. The residual represents the long-term trend of the cooling load demand.

To illustrate why combining the EMD components as mentioned in section 3.1, this section gives the prediction error of different combination ways of the EMD components respectively in table 4 and table 5, then compares the results of table3, table 4 and table 5. In addition to the different combination ways of the EMD components, the combined components are all predicted respectively with RBFNN model after PSR.

According to the IMFs combination method mentioned in section 3.1, keep the IMF1, IMF2, IMF3 and the residual unchanged, and superimpose IMF4, IMF5, IMF6 into a new low-frequency component (call it IMF4~IMF6 combined). The prediction error of each combined component is shown in table 4. We can find that the predicting accuracy of the new combined low-frequency component and the residual are excellent, but the prediction errors of the high-frequencies, especially the IMF1, are so great.

Table 4. The prediction error after combining IMF4~IMF6.

| Evaluation criteria | IMF1 | IMF2 | IMF3 | IMF4~IMF6 combined | residual | reconstruction result |
|---------------------|------|------|------|---------------------|----------|-----------------------|
| RMSRE(%)            | 2.267| 1.571| 0.115| 0.3889              | 8.19E-03 | 2.221                 |
| MRE(%)              | 1.539| 0.874| 0.103| 0.3333              | 5.04E-03 | 1.517                 |

The prediction error of another IMFs combination method is shown in table 5. In which, IMF1~IMF3 are superimposed into a new high-frequency component, IMF4~IMF6 are superimposed into a new low-frequency component, and keep the residual unchanged as before. Table V shows that the prediction error of superimposing IMF1~IMF3 is so high that the final error (RMSRE) of the cooling load prediction runs up to 3.695%.

Table 5. The prediction error after combining IMF1~IMF3 and combining IMF4~IMF6.

| Evaluation criteria | IMF1~IMF3 combined | IMF4~IMF6 combined | residual | reconstruction result |
|---------------------|---------------------|---------------------|----------|-----------------------|
| RMSRE(%)            | 3.8561              | 0.3889              | 8.19E-03 | 3.695                 |
| MRE(%)              | 2.2082              | 0.3335              | 5.04E-03 | 2.112                 |

By comparing table 3 and table 4, we find that the prediction accuracy are almost the same for the two IMFs combination methods, in which table 3 shows the prediction errors of keeping all the EMD components alone and table 4 shows the prediction errors of combination method mentioned in section 3.1, the RMSRE are 2.221% and 2.218%, the MRE are 1.516% and 1.517% respectively. In other words, whether the low-frequency EMD components (IMF4~IMF6) combining or not, the prediction errors are similar.

Comparing table 4 and table 5, we find that the RMSRE of the former method is 2.221% and the later method is 3.695%. That is to say, when combining the high-frequency EMD components (IMF1~IMF3), the prediction accuracy will get worse.
Therefore, to take the prediction accuracy and the computation complexity into account, this paper selects the combination method of EMD components which is proposed in section 3.1.

4.5. Improving Prediction Accuracy for High Frequency Component of EMD

Figure 3(a) and table 3 in section 4.3 show that the stochastic of IMF1 leads to the poor prediction accuracy. Differential [25] is found as a good method for pre-processing the IMF1 before RBFNN prediction.

Table 6 shows the RESRE and MRE of the IMF1 prediction with RBFNN after zero to six order differential operation. It is evident that the RESRE and MRE of the IMF1 prediction after one order differential operation is the minimum, which are 1.9% and 1.3% respectively. Obviously, one order differential pre-process to IMF1 is the first choice.

Table 6. The prediction error of IMF1 with RBFNN after 0–6 order differential operation.

| Differential order | RMSRE(%) | MRE(%) |
|--------------------|----------|--------|
| 0                  | 2.27     | 1.54   |
| 1                  | 1.90     | 1.30   |
| 2                  | 2.46     | 2.02   |
| 3                  | 5.97     | 4.81   |
| 4                  | 11.61    | 9.4327 |
| 5                  | 23.13    | 18.55  |
| 6                  | 47.25    | 40.11  |

Comparing to table 4, the only change to table 7 is that the IMF1 is pre-processed by one order differential operation. Table 7 shows that the RESRE and MRE of the IMF1 prediction with RBFNN are decreased from 2.267% to 1.903% and 1.539% to 1.3035% respectively. And the final prediction errors are decreased from 2.221% to 1.794% and 1.517% to 1.288% respectively. The differential operation to IMF1 improved the prediction accuracy indeed.

Table 7. The RBFNN prediction error of each component after combining IMF4–IMF6 and pre-processing IMF1 with differential.

| Evaluation criteria | IMF1 after differential | IMF2 | IMF3 | IMF4–IMF6 combined | residual | reconstruction result |
|---------------------|-------------------------|------|------|--------------------|----------|----------------------|
| RMSRE (%)           | 1.903                   | 1.571| 0.115| 0.3889             | 8.19E-03 | 1.794                |
| MRE (%)             | 1.3035                  | 0.874| 0.103| 0.3333             | 5.04E-03 | 1.288                |

4.6. Comparison with Different Prediction Methods
In order to discuss the influence of different prediction methods on the prediction accuracy, three single prediction methods and three hybrid prediction methods are compared. The single prediction methods are LSSVM (least square support vector machine), SVM, and RBFNN. The hybrid prediction methods are EMD-PSR-SVM, EMD-PSR-LSSVM, and EMD-PSR-RBFNN (the proposed method). The process of hybrid prediction methods are: decomposing the original cooling load series with EMD, then combining the IMFs as mentioned in section 3.1, reconstructing the phase space for the combined EMD components, predicting with different single algorithms finally. The IMF1 of the three hybrid prediction methods are all pre-processed with differential method. The RMSRE and MRE of different prediction methods are shown in table 8.

Table 8. Prediction Error of Different Models.

| Evaluation criteria | LSSVM | SVM | RBFNN | EMD-PSR-SVM | EMD-PSR-LSSVM | EMD-PSR-RBFNN |
|---------------------|-------|-----|-------|-------------|---------------|---------------|
| RMSRE(%)            | 5.589 | 5.736| 5.093 | 3.10        | 3.762         | 1.794         |
| MRE(%)              | 4.924 | 4.455| 3.251 | 2.53        | 3.511         | 1.288         |
Table 8 shows that RESRE and MRE of the three hybrid prediction methods are smaller than the three single prediction methods. Among the hybrid prediction methods, the prediction accuracy of the proposed EMD-PSD-RBFNN is the maximum.

5. Conclusion
Predicting non-stationary and nonlinear cooling load demand for next day is very challenging, since there are many correlated independent variables involved. This paper introduced a new model comprised the EMD algorithm, the PSR, and the RBFNN. While the EMD functions as a filter for self-similarity and non-stationary cooling load time series, the RBFNN algorithm predicts the EMD-PSR components.

We proved the chaotic nature of the real operation cooling load time series of a district ice storage cooling systems in Guangzhou. The results in section 4.2 verified that EMD model acts as a good filter in non-stationary and self-similarity cooling load time series systems. In terms of the EMD component combination, different EMD component combination methods results to different prediction accuracy. To balance the computation complexity and prediction accuracy, the combination method is excellent.

We found that the prediction accuracy of high-frequency EMD component is lower than the prediction accuracy of low-frequency EMD components in section 4.3. The results in section 4.5 verified that differential method can be used to improve the prediction accuracy of high frequency EMD component.

Moreover, we compared the accuracy of the cooling load prediction using ‘the proposed EMD-PSR-RBFNN’ method with other algorithms. The results show that the hybrid prediction EMD-PSR models outperform the models not processed by EMD-PSR, and the proposed EMD-PSR-RBFNN model outperforms the other two hybrid prediction methods.

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