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Combined Forecasting Model of Cloud Computing Resource Load for Energy-Efficient IoT System

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ABSTRACT Cloud computing is generally considered as a special energy-efficient form for the Internet of Things (IoT) resource usage. Dedicated server systems for cloud services, better capacity utilization and economies of scale because of the use of larger and more energy-efficient data centers are the reasons why cloud solutions typically use less energy than traditional on-premise systems. To scientifically and rationally configure the hardware and software resources of the cloud computing, the research on forecasting a cloud computing resource load becomes a research focus. However, the widely-used single forecasting model cannot contain all the characteristics of the cloud computing resource load sequence, resulting in inaccurate forecasting results. In this paper, a combined forecasting approach of cloud computing resource load based on wavelet decomposition is proposed, which combined the grey model and cubic exponential smoothing model. It can well preserve details and reduce noise. Firstly, the cloud computing resource load sequence is decomposed into several frequencies by the wavelet decomposition method. The decomposed load sequences with different characteristics are divided into different resolution scale subspaces in deferent frequencies. The noise of the load sequences is reduced by the wavelet threshold denoising method. And then, the load sequences are reconstructed according to the wavelet coefficients. The reconstructed load sequence not only contains less noise but also reserves detailed information. Consequently, it is closer to the real data and more regular. Experimental results show that our proposed combined forecasting model with wavelet decomposition can provide more accurate forecasting results than each single forecasting model or the combined forecasting model without using the wavelet decomposition method. Thus, our proposal is demonstrated to be efficient for forecasting the cloud computing resource load and helping to reduce energy consumption.

INDEX TERMS Cloud computing resource load, wavelet decomposition, combined forecasting model, grey model, cubic exponential smoothing model.

I. INTRODUCTION

The IoT is one of the major revolutions of Information and Communication Technology (ICT) following the invention of computers and the Internet. Most of the IoT send their processing, storing and running applications and data to the cloud. Cloud computing is a blend of conveyed, parallel, multitenant computing model established on various advancements, for example, virtualization, network, benefit and autonomic computing. Cloud computing innovation enables clients to get solid computing and memory assets and in the meantime, the user isn't keen on the area and settings

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of these assets [1]. With the development of cloud computing, the processing is transferred to the cloud means that data centers and transmission networks need more capacity, which brings new resource integration and usage patterns [2]. Research shows that energy consumption in data centers is increasing due to cloud services [3]. Data centers consume five times energy as much as the devices themselves. From 2010 to 2025, the energy consumption of networks and data centers is expected to increase substantially. Energy consumption of the German network is expected to increase by 89% and data centres by 56%. The extrapolated global development has even increased network and data centers by 142% and 107%, respectively. How to rationally allocate and schedule resources (such as CPU utilization, memory utilization, network load, etc.), reduce energy consumption and improve the utilization of cloud computing resources has become a challenge for the industry [4]. Then, the research on forecasting a load of cloud computing resource is carried out. A load sequence of cloud computing resource has two characteristics: On the one hand, a resource load sequence shows a trend of growth on a large time scale, while it shows obvious randomness and volatility on a small time scale, and such fluctuations are also periodic and regular in a certain time scale; On the other hand, the information contained in a load sequence of the cloud computing resource collected in practice is usually incomplete and uncertain, and the collected resource load sequence cannot represent a complete business logic relationship [5], [6].

Since cloud computing resources are easily affected by complex and changeable factors, some random perturbation errors will inevitably exist in the collected resource load sequences over time, resulting in low forecasting accuracy. To solve the above problems, considering the advantages of wavelet in time-frequency domain analysis, Mallat introduced the idea of multiscale analysis into wavelet analysis, proposed a concept of multiresolution analysis, and proposed a corresponding fast algorithm of decomposition and reconstruction, namely Mallat algorithm [7]. The data preprocessing algorithm of wavelet decomposition is applied to the cloud computing resource load sequence. The cloud computing resource load sequence is decomposed into several frequencies by the wavelet decomposition method. The decomposed load sequence with different characteristics is divided into different resolution scale subspaces in different frequencies. And then, the load sequence is reconstructed according to the wavelet coefficients. The reconstructed load sequence not only contains less noise, but also reserves the detailed information, and thus which is more regular and closer to the real data [8]. That provides a good data source for forecasting the load of cloud computing resource in the next step.

At present, the familiar cloud computing resource load forecasting methods are regression analysis method, fuzzy logic method, exponential smoothing method, gray forecasting method, time series method, support vector machine method, and artificial neural network method, etc. Among them, the regression analysis method can better describe the overall changing trend of cloud computing resource load sequence, but it cannot well reflect the random components, and its forecasting result is not accurate [9]. The fuzzy logic method transforms cloud computing resource load sequences into a fuzzy rule base [10]. Since the learning ability of fuzzy forecasting is weak and the theory of fuzzy system identification is not complete, the single fuzzy method is not perfect to forecast cloud computing resources. The exponential smoothing method has both the characteristics of the whole period average and the moving average [11]. It does not discard the past data, but it gradually weakens the influences, that is, with the data moving away, it gives a weight to gradually converge them to zero. The time series forecasting method forecasts the future load level that may be reached in the next period or in the next several years, according to the development process, direction or trend, which are reflected by the cloud computing resource load sequence [12]. The grey forecasting method seeks for the changing regularities by processing the original data of cloud computing resource load, which generates a resource load sequence with strong regularity, and then establishes a corresponding differential equation model to forecast the development trend of resource load [13], [14]. The artificial neural network method and the support vector machine method have strong fitting ability for the complex factors of cloud computing resource [15]–[17]. But for the data sequences with different structures, the forecasting results have great differences and the stability of the forecasting effect is low.

The above familiar load sequence forecasting methods have their own advantages, but there are also some limitations in the forecasting of cloud computing resource load sequence. In view of the characteristics of cloud computing resource load sequence, this paper selects the grey forecasting method and the cubic exponential smoothing forecasting method to respectively forecast the historical load sequences of cloud computing resource. Among them, the grey forecasting method is a method to study the problems of minority data, poor information and uncertainty, which can effectively describe the incompleteness and uncertainty of cloud computing resource load sequence [18]. The grey forecasting method directly seeks the inherent regularity of the cloud computing resource load sequence and forecasts the unknown field through the known information, so as to understand the load of the whole cloud computing resources. The cubic exponential smoothing method is quite effective for nonlinear and non-stationary cloud computing resource load forecasting, and can adjust the forecasting value continuously with the trend change of cloud computing resource load sequence. The cubic exponential smoothing method considers the timeliness of the cloud computing resource load sequence, which is beneficial to the forecasting of the randomness and volatility of the resource load sequence on a small time scale. However, a single forecasting model cannot contain all the characteristics of cloud computing resource load sequence, and the forecasting error is big.

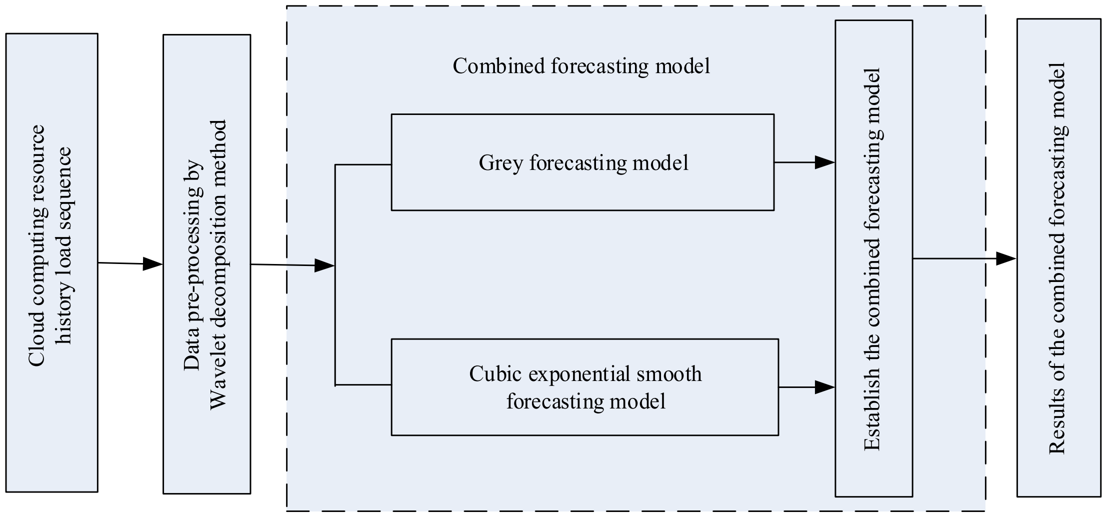

FIGURE 1. Combined forecasting model with Wavelet decomposition.

Therefore, the development direction of cloud computing resource load forecasting is the combination forecasting model [19], that is, according to the characteristics of multifarious forecasting methods, the combined forecasting model is established with the idea of complementary advantages to improve the forecasting accuracy.

To sum up, on the one hand, due to the load sequences collected in the field have much noise, the forecasting results are not often accurate. Therefore, the denoising technology should be adopted to preprocess the original data; On the other hand, there are some limitations in the application of a single forecasting model, and the accuracy of forecasting result is low. In order to solve the above problems, a combined forecasting model with wavelet decomposition is proposed. The modeling steps are shown in Figure 1. Firstly, the cloud computing resource history load sequence is processed by the wavelet decomposition method to weaken the fluctuation of data sequence and reduce the randomness. Then, the grey forecasting model and the cubic exponential smooth forecasting model are used for forecasting analysis, and the Induced Ordered Weighted Average (IOWA) operator [20], [21] is introduced to replace the equal weight in the combined forecasting model. The optimal weight coefficients are given to each single forecasting model according to the forecasting accuracy order. The minimal sum of error square value is as a practical guideline to establish the combined forecasting model.

The structure of this paper is organized as follows. Section I introduces the current research background of forecasting models of cloud computing resource load for energy-efficient IoT system. Section II presents wavelet theories in detail and how to use them in our proposal. In Section III, two single forecasting models and the combined model are put forward. The experiment and analysis are presented in Section IV, and we compare our proposed model with other several popular models. Section V concludes this paper.

II. WAVELET THEORY

The wavelet theory provides an adaptive local multiresolution analysis method in the time domain and the frequency domain, which can well describe the instability characters of load sequence. The theory of wavelet decomposition and reconstruction proposed by Mallat is an important kind of the wavelet theory. Firstly, this paper introduces the theory of Mallat's wavelet decomposition and reconstruction. Secondly, based on Mallat's wavelet theory, the wavelet threshold denoising method is applied to the cloud computing resource load sequence [22].

A. MALLAT'S WAVELET THEORY

1) WAVELET DECOMPOSITION

Firstly, the wavelet decomposition algorithm is applied to the cloud computing resource load sequence s to generate two coefficient sets: the low-frequency coefficient set cA_1 and the high-frequency coefficient set cD_1, as shown in Figure 2. Where, Lo_D is the low-pass filter and Hi_D is the high-pass filter. cA_1 is obtained by convolving s with the low-pass filter Lo_D. cD_1 is obtained by convolving s with the high-pass filter Hi_D, and $\downarrow 2$ denotes that the down-sampling scale is 2.

The same framework is used to further decompose the low-frequency coefficient cA_1 into two parts, that is, cA_1 is replaced with cA_2 and cD_2, and so on. The flow chart of multilayer wavelet decomposition algorithm is shown in Figure 3.

Using the above method, the low-frequency part is decomposed again as a load sequence, and the decomposition structure of load sequence s on the j^{th} layer is $\left[cA_j, cD_j, \ldots, cD_1\right]$. For example, if $j = 3$, the decomposition structure is shown in Figure 4. Where, C is the wavelet decomposition vector and L is the length vector of the corresponding wavelet component.

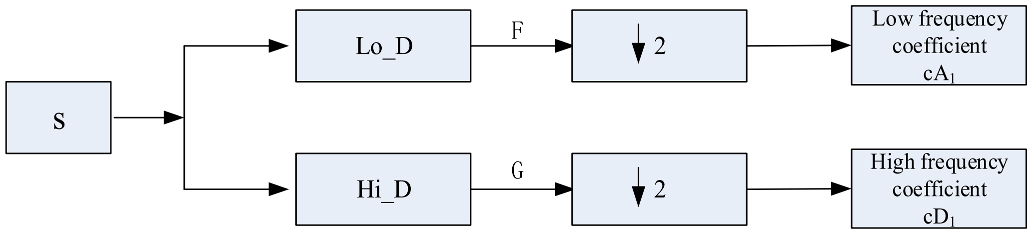

FIGURE 2. Wavelet decomposition.

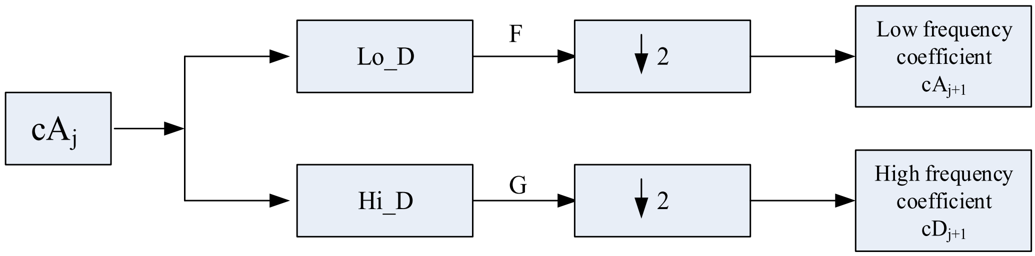

FIGURE 3. Multilayer wavelet decomposition.

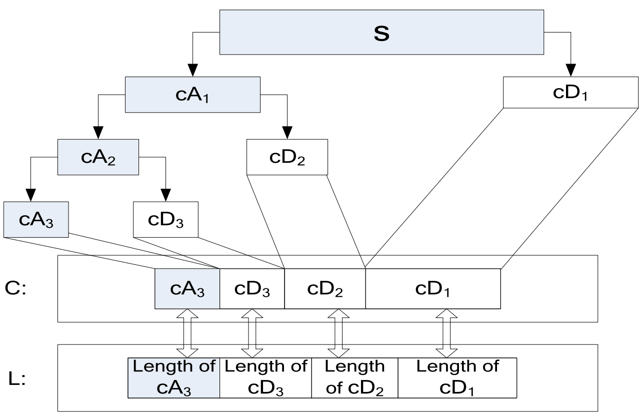

FIGURE 4. Three-layer wavelet decomposition structure.

2) WAVELET RECONSTRUCTION

In the load sequence, the low-frequency component represents the characteristics of the load sequence, while the high-frequency component contains noise. After the high-frequency parts (e.g. cD_1, cD_2, cD_3) being processed with a given threshold, which are decomposed under each scale, then the load sequence is reconstructed by composing them with cA_3. The load sequence of cloud computing resource without noise is obtained.

The reconstruction algorithm is an inverse process of the decomposition algorithm. Its principle is to reintegrate the components obtained by decomposition into the original load sequence without any loss of information. The wavelet decomposition process includes filtering and down-sampling, then it is necessary to carry out reconstruction filtering and up-sampling in the wavelet reconstruction process. Up-sampling is realized by inserting zero values between adjacent sampling points. The length of load sequence components is doubled to reach the same length of sampling data consistent with the load sequence that needs to be reconstructed. The wavelet reconstruction algorithm is shown in Figure 5. Where, Lo_R is the reconstructed low-pass filter, Hi_R is the reconstructed high-pass filter, and $\uparrow 2$ denotes that the scale of up-sampling is 2. cA_{j+1} and cD_{j+1} are the low-frequency coefficient and high-frequency coefficient of the $(j+1)^{\text{th}}$ layer respectively, and cA_j is the low-frequency coefficient of the j^{th} layer obtained by reconstruction.

B. WAVELET THRESHOLD DENOISING THEORY

Based on Mallat's wavelet theory, the wavelet decomposition and reconstruction algorithm can be used to reduce the noise of the load sequence. There are several kinds of wavelet denoising methods, such as spatial domain correlation denoising method, modulus maximum reconstruction denoising method, and wavelet threshold denoising method. Among them, the spatial domain correlation denoising method is easy to increase the false alarm probability and keep the noise as the load sequence. The modular maximum reconstruction denoising method requires the use of complex alternating projection method for reconstruction, which is easy to cause the deviation of reconstruction load sequence, and the algorithm is complex and slow. Therefore, the wavelet threshold denoising method is adopted in this paper for cloud computing resource load sequence denoising [23].

The process of wavelet threshold denoising method is divided into three steps, as shown in Figure 6.

Step 1. Wavelet decomposition. According to the practical needs of data, the appropriate wavelet basis is selected and the number of layers of corresponding wavelet decomposition is determined, and then the n-layer wavelet decomposition is carried out for the cloud computing resource load sequence [24].

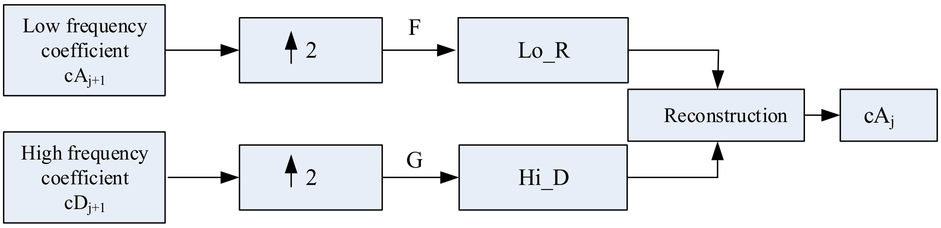

FIGURE 5. Wavelet reconstruction.

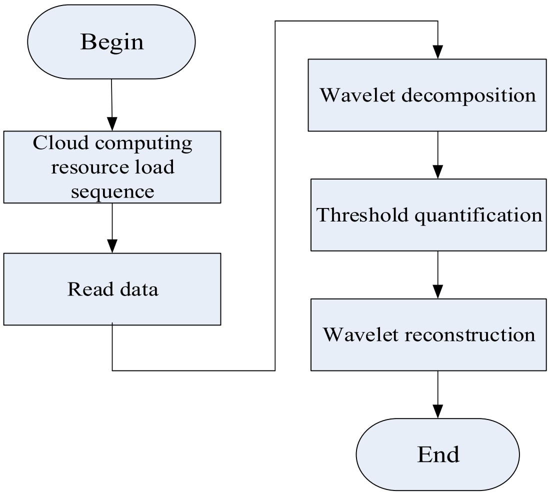

FIGURE 6. Wavelet threshold denoising.

Step 2. Threshold quantification. An appropriate threshold is selected to quantize the high-frequency coefficients of each layer. The coefficient below the threshold is set to 0, and the coefficient above the threshold is retained [25].

Step 3. Wavelet reconstruction. According to the low-frequency coefficients of the last layer of wavelet decomposition and the high-frequency coefficients of each layer after quantizing, the load sequence is reconstructed, and then the denoised cloud computing resource load sequence is obtained.

1) WAVELET DECOMPOSITION

In the process of wavelet decomposition, the key step is how to select an appropriate wavelet basis, which is directly related to the quality of denoising. Generally speaking, there are five aspects ought to be considered for selection the wavelet basis function: (1) Orthogonality; (2) Symmetry; (3) Compact support; (4) Regularity; (5) Vanishing moment [26], [27]. The orthogonality can make analysis simple and is beneficial to accurately reconstruct the load sequence. The symmetry makes the wavelet filtering linearly so that the load sequence will not be distorted, and it can improve the speed of the algorithm. The compact support can avoid leakage in the time domain and can avoid the influence of cross-terms in the frequency domain, which can ensure good space local properties. The regularity determines the smoothness effect of load sequence reconstruction and affects the resolution in the frequency domain. The longer the support set is, the better the regularity will be. The vanishing moment reflects the concentration of energy, and a high enough vanishing moment is beneficial to detect the singularity of the signal [28].

Considering the characteristics of cloud computing resource load sequence comprehensively, there must be two requirements for the wavelet basis function: (1) It has good frequency domain resolution, that is, the wavelet basis function has good regularity; (2) The wavelet basis function must be symmetric to ensure that the load sequence is not distorted. From the above requirements, the wavelet basis function with better performance can be selected according to the actual situation.

2) THRESHOLD QUANTIFICATION

In the wavelet denoising process of cloud computing resource load sequence, the selection of threshold value is directly related to the effect of denoising. If the threshold value is too large, some useful information will be removed as noise. If the threshold value is too small, a lot of noise will remain in the load sequence. Therefore, the selection of threshold is the key to the whole wavelet analysis process.

There are two ways to select the threshold, namely the global threshold and the hierarchical threshold. The method of global threshold value is to make unbiased likelihood estimation for the load sequence, and then determine a threshold value according to the principle of minimum variance between the noise reduction load sequence and the original load sequence in the worst case, and then apply the threshold value to the coefficients of each layer. The hierarchical threshold is determined according to the estimated noise intensity. Different thresholds are selected in different scales to refine the wavelet decomposed load sequence, which is more consistent with the actual situation and is benefit to the improvement of noise smoothing effect. In this paper, the Birge-Massart strategy [29] is selected to determine the hierarchical threshold of each layer in the wavelet denoising process. The steps are as following:

Step 1. For each decomposition layer j, the coefficients of the layer greater than j are all retained;

Step 2. For the i^{th} $(1 \le i \le j)$ layer, only n_i coefficients with the largest absolute value are retained, and n_i is determined by Equation 1.

$$n_i = M\,(j + 2 - i)^{\beta} \tag{1}$$

where, β, M are empirical coefficients, and β is selected for the purpose of compression or noise reduction, and in this paper $\beta = 2$ is selected for the denoising purpose.

The action mode of threshold is as that after the threshold value is obtained, there are two ways to apply the threshold value on the cloud computing resource load sequence: the hard threshold value and the soft threshold value. Let the selected threshold be λ, α_i is the wavelet coefficient estimation, and d_i is the wavelet coefficient before processing [30]. The action mode of hard threshold is:

$$\alpha_i = \begin{cases} d_i & |d_i| \geq \lambda \\ 0 & |d_i| < \lambda \end{cases} \tag{2}$$

The action mode of soft threshold is:

$$\alpha_i = \begin{cases} sign(d_i)(|d_i| - \lambda) & |d_i| \geq \lambda \\ 0 & |d_i| < \lambda \end{cases} \tag{3}$$

where,

$$sign(t) = \begin{cases} 1 & t \geq 0 \\ -1 & t < 0 \end{cases} \tag{4}$$

Both of the threshold modes are widely used. However, the wavelet coefficient of the hard threshold action mode will be discontinuous at λ, and the reconstructed load sequence maybe oscillate. Therefore, the soft threshold action mode is selected in this paper.

Wavelet reconstruction is an inverse process of the wavelet decomposition, so we will not describe it in detail again.

III. FORECASTING MODEL

A. SINGLE FORECASTING MODEL

1) GREY FORECASTING MODEL

The grey forecasting model (GM(1,1) model) makes a system, which with unclear and insufficient overall information, clear on the aspects of structure, model and relation. The GM(1,1) model is a dynamic sequence processing method in the grey system theory [13], [14]. Let $x^{(0)}$ be a non-negative sequence:

$$x^{(0)} = \left\{ x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n) \right\} \tag{5}$$

where, $x^{(0)}(k) > 0, \quad k = 1, 2, \ldots$. $x^{(1)}$ is the first-order accumulation sequence of $x^{(0)}$:

$$x^{(1)} = \left\{ x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n) \right\} \tag{6}$$

where, $x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i), \quad k = 1, 2, \ldots, n$.

The corresponding differential equation of GM(1,1) model is:

$$\frac{dx^{(1)}(t)}{dt} + \alpha x^{(1)}(t) = u, \quad t = 1, 2, \ldots, n \tag{7}$$

where, α is the development grey number, u is the grey action value. The parameter vector $A = \begin{pmatrix} \alpha \\ u \end{pmatrix}$ can be solved by the least square method:

$$A = \left(B^T B\right)^{-1} B^T Y_n \tag{8}$$

where,

$$B = \begin{vmatrix} -\frac{1}{2}\left(x^{(1)}(1) + x^{(1)}(2)\right) & 1 \\ -\frac{1}{2}\left(x^{(1)}(2) + x^{(1)}(3)\right) & 1 \\ \cdots & \cdots \\ -\frac{1}{2}\left(x^{(1)}(n-1) + x^{(1)}(n)\right) & 1 \end{vmatrix}, \quad Y_n = \begin{vmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \cdots \\ x^{(0)}(n) \end{vmatrix}$$

Substitute the calculated parameters α and u into Eq. (7), and solve the equation, and take $x^{(1)}(0) = x^{(0)}(1)$. Then the grey forecasting model is obtained:

$$\hat{x}^{(1)}(t+1) = \left[x^{(0)}(1) - \frac{u}{\alpha} \right] e^{-\alpha t} + \frac{u}{\alpha} \tag{9}$$

According to Eq. (9), the simulated values of successively accumulated values $\hat{x}^{(1)}(t+1)$ are obtained, and then the real forecasted values are obtained by one more subtraction:

$$\hat{x}^{(0)}(t+1) = \hat{x}^{(1)}(t+1) - \hat{x}^{(1)}(t) \tag{10}$$

where, $t = 1, 2, \ldots, n$.

2) CUBIC EXPONENTIAL SMOOTHING FORECASTING MODEL

The exponential smoothing method is used to smooth the historical data to eliminate the influence of random factors. The cubic exponential smoothing method is needed when the historical parameter sequence has a curvilinear tendency [11]. Let the load sequence be $X_1, X_2, X_3, \ldots, X_n$ and let S denote the exponential smoothing value. The first exponential smoothing value in the first t^{th} period is denoted as $S_t^{(1)}$, the second exponential smoothing value is denoted as $S_t^{(2)}$, and the third exponential smoothing value is denoted as $S_t^{(3)}$. The initial smoothing value is:

$$S_0^{(1)} = S_0^{(2)} = S_0^{(3)} = \frac{X_1 + X_2 + X_3}{3} \tag{11}$$

The equations for calculating the exponential smoothing values are:

$$S_t^{(1)} = \alpha X_t + (1 - \alpha) S_{t-1}^{(1)} \tag{12}$$

$$S_t^{(2)} = \alpha S_t^{(1)} + (1 - \alpha) S_{t-1}^{(2)} \tag{13}$$

$$S_t^{(3)} = \alpha S_t^{(2)} + (1 - \alpha) S_{t-1}^{(3)} \tag{14}$$

where, $\alpha \in [0, 1]$ is the smoothing coefficient, which is determined by the actual situation. Generally, it is selected according to the minimum mean square error, that is, exponential smoothing forecasting is made for different α values, and the mean square errors are calculated respectively, and then the minimum mean square error α is taken as the smoothing coefficient.

For the forecasted index value Y_{t+T} with the forecasting cycle of T days and the base number of t^{th} day, the mathematical model of the cubic exponential smoothing model is:

$$Y_{t+T} = a_t + b_t T + c_t T^2 \tag{15}$$

where, a_t, b_t, c_t are the smoothing coefficients and the calculation equations are:

$$a_t = 3S_t^{(1)} - 3S_t^{(2)} + 3S_t^{(3)} \tag{16}$$

$$b_t = \frac{\alpha}{2(1-\alpha)^2}\left[(6-5\alpha) S_t^{(1)} - 2(5-4\alpha) S_t^{(2)} + (4-3\alpha) S_t^{(3)}\right] \tag{17}$$

$$c_t = \frac{\alpha^2}{2(1-\alpha)^2}\left[S_t^{(1)} - 2S_t^{(2)} + S_t^{(3)}\right] \tag{18}$$

B. COMBINED FORECASTING MODEL

The combined forecasting model comprehensively considers the results of several single forecasting models and makes a forecast using an appropriate weight coefficient to weight each model. In the actual forecasting process, the forecasting accuracy of each single forecasting model is not invariable, and the randomness of the forecasting accuracy at each time point leads to the fact that the value of the objective function of the traditional combined forecasting model is not the optimal square sum of global errors, which has some defects. Then in this paper, the IOWA operator is introduced [21], and the weight of each single forecasting model is assigned according to the order of forecasting accuracy at the corresponding forecasting time point, and the combination forecasting model based on IOWA operator is established by taking the minimum square sum of errors as a criterion.

1) IOWA OPERATOR

Let $\langle v_1, a_1\rangle, \langle v_2, a_2\rangle, \ldots, \langle v_m, a_m\rangle$ be m two-dimensional arrays, and let:

$$f_w(\langle v_1, a_1\rangle, \langle v_2, a_2\rangle, \ldots, \langle v_m, a_m\rangle) = \sum_{i=1}^{m} w_i a_{v-index(i)} \tag{19}$$

where, f_w is an $m-$ dimension IOWA operator, which is generated by $v_1, v_2, \ldots, v_m$, and v_i is the induced value of a_i. $W = [w_1, w_2, \ldots, w_m]^T$ is the weighted vector of IOWA, meeting the following conditions: $\sum_{i=1}^{m} w_i = 1, w_i \geq 0$, $i = 1, 2, \ldots, m$; $v - index\,(i)$ denotes the subscript of the i^{th} largest number in $v_1, v_2, \ldots, v_m$ according to the order from large to small.

2) STEPS OF THE COMBINED FORECASTING MODEL

Let $\{x_t,\ \ t = 1, 2, \ldots, N\}$ as the observation sequences, there are m kinds of feasible single forecasting models to forecast them, and $x_{it}\ \ (i = 1, 2, \ldots, m,\ \ t = 1, 2, \ldots, N)$ denotes the forecasted value of the i^{th} forecasting model on the t^{th} day. x_t denotes the actual value of cloud computing resource load on the t^{th} day.

The concrete modeling steps of the combined forecasting model are as following:

Step 1. Calculate the forecasting accuracy $v_{it} \in [0, 1]$ of the i^{th} kind of single forecasting model on the t^{th} day:

$$v_{it} = \begin{cases} 1 - \left|(x_t - x_{it})/x_t\right| & \left|(x_t - x_{it})/x_t\right| < 1 \\ 0 & \left|(x_t - x_{it})/x_t\right| \geq 1 \end{cases} \tag{20}$$

where, $i = 1, 2, \ldots, m,\ \ t = 1, 2, \ldots, N$.

The forecasting accuracy v_{it} is regarded as the induced value of the forecasted value x_{it}, so that the forecasting accuracy of m kinds of single forecasting models on the t^{th} day and the forecasted values of their corresponding sample sections constitute m two-dimensional arrays: $\langle v_{1t}, x_{1t}\rangle, \langle v_{2t}, x_{2t}\rangle, \ldots, \langle v_{mt}, x_{mt}\rangle$.

Step 2. Calculate the IOWA operator value of the combined forecasting model on the t^{th} day:

$$f_{IOWA}(\langle v_{1t}, x_{1t}\rangle, \langle v_{2t}, x_{2t}\rangle, \ldots, \langle v_{mt}, x_{mt}\rangle) = \sum_{i=1}^{m} w_i x_{v-index(it)} \tag{21}$$

where $v - index\,(it)$ denotes the subscript of the t^{th} largest forecasting accuracy in $v_{1t}, v_{2t}, \ldots, v_{mt}$; $W = [w_1, w_2, \ldots, w_m]^T$ denotes the weight coefficient of each single forecasting model in the combined forecasting model. Obviously, in the cloud computing resource forecasting process, the IOWA value is the forecasted value of the combination forecasting model on the t^{th} day.

Step 3. Calculate the forecasting error of the combined forecasting model on the t^{th} day:

$$e_{v-index(it)} = x_t - f_{IOWA} = x_t - \sum_{i=1}^{m} w_i x_{v-index(it)} \tag{22}$$

Step 4. Take the minimum error square sum $S\,(w)$ of N days combined forecasting model as the objective function to construct the optimization programming model.

$$\begin{aligned} \min S\,(w) &= \sum_{t=1}^{N} e_t^2 = \sum_{t=1}^{N}\left(x_t - \sum_{i=1}^{m} w_i x_{v-index(it)}\right)^2 \\ &= \sum_{i=1}^{m}\sum_{j=1}^{m} w_i w_j \left(\sum_{t=1}^{N} e_{v-index(it)} e_{v-index(jt)}\right) \end{aligned}$$

$$s.t.\ \begin{cases} \sum_{i=1}^{m} w_i = 1, & i = 1, 2, \ldots, m \\ w_i \geq 0, & i = 1, 2, \ldots, m \end{cases} \tag{23}$$

Step 5. Calculate the weighting coefficient of a single forecasting model in the combined forecasting model according to the above optimization programming model.

$$W = [w_1, w_2, \ldots, w_m]^T \tag{24}$$

Step 6. According to the calculated weighted coefficients, substitute them into Eq. (21) to obtain the combined forecasting values of cloud computing resource load sequence.

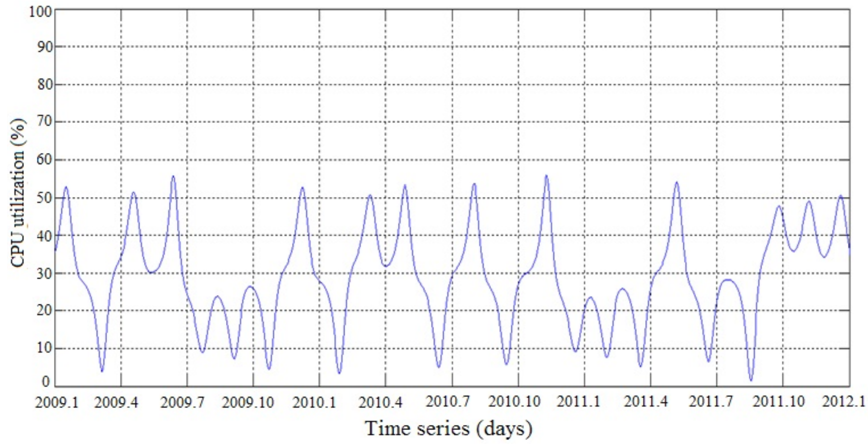

FIGURE 7. CPU utilization of cloud computing resource load sequence.

IV. EXPERIMENT AND ANALYSIS

In order to test and evaluate the forecasting effect of the combined forecasting model based on wavelet decomposition applied to the cloud computing resource load sequence. This paper takes the cloud computing resource load (CPU utilization) sequence of a company from January 2009 to January 2012 as an example to make forecasting. One day is an observation period, and there are 1095 days observation data. The trend is shown in Figure 7. Firstly, the CPU utilization load sequence from day 1 to day 1090 was selected, and combined with the wavelet decomposition principle, the CPU utilization load sequence from day 1091 to day 1095 is forecasted. Secondly, the forecasting results of each forecasting model are compared with the actual data to find out the forecasting model whose forecasting accuracy is the highest.

A. WAVELET DENOISING

In the process of wavelet decomposition, there are two problems: how to choose the best wavelet basis and how to determine the number of decomposition layers. The compact support and the regularity are contradictory. The shorter the compact support set is, the better the time domain localization is. While, the worse the regularity is, the worse the frequency domain localization will become. Therefore, to select appropriate vanishing moment parameters, db4, sym4 and coif4 are selected as wavelet basis in this paper [27]. The more wavelet decomposition layers are, the better the stability of approximation signals and the stability of detail signals are, and the more the accuracy of the forecasted value will be. However, in fact, due to the calculation error in the decomposition process itself, the more layers there are, the greater the error will be. Therefore, the number of decomposition layers usually adopts 3-5 [31].

The Root Mean Square Error (RMSE) and the Signal to Noise Ratio (SNR) are used to compare the denoising effects when we use different wavelet bases and different decomposition layers, which can determine the optimal wavelet basis and decomposition layers, as shown in Table 1.

TABLE 1. Denoising effects' comparison among different wavelet bases and different decomposition layers.

Wavelet basis	Decomposition layers	RMSE	SNR
db4	3	3.1615	15.21
db4	4	3.1472	14.33
db4	5	3.0926	19.13
sym4	3	3.1609	15.83
sym4	4	3.1498	14.11
sym4	5	3.1068	18.27
coif4	3	3.1612	15.98
coif4	4	3.1522	14.61
coif4	5	3.1008	16.83

In the wavelet denoising performance indexes, the smaller the RMSE is, the better the denoising effect is. The higher the SNR is, the better the denoising effect is. It can be seen from Table 1 that when the db4 wavelet is selected as the wavelet basis and the number of decomposition layers is 5, the denoising effect is the best. Then, the db4 wavelet basis function is adopted for 5-layer wavelet decomposition, and the threshold values of each layer coefficients are determined according to the Birge-Massart strategy [29]. Moreover, the soft threshold is applied to coefficients of each layer, and the load sequence after denoising is obtained through wavelet reconstruction. The CPU utilization of the cloud computing resource load sequence before and after denoising are shown in Figure 8. Obviously, the CPU utilization of the cloud computing resource load sequence after denoising is beneficial to improve the noise smoothing effect.

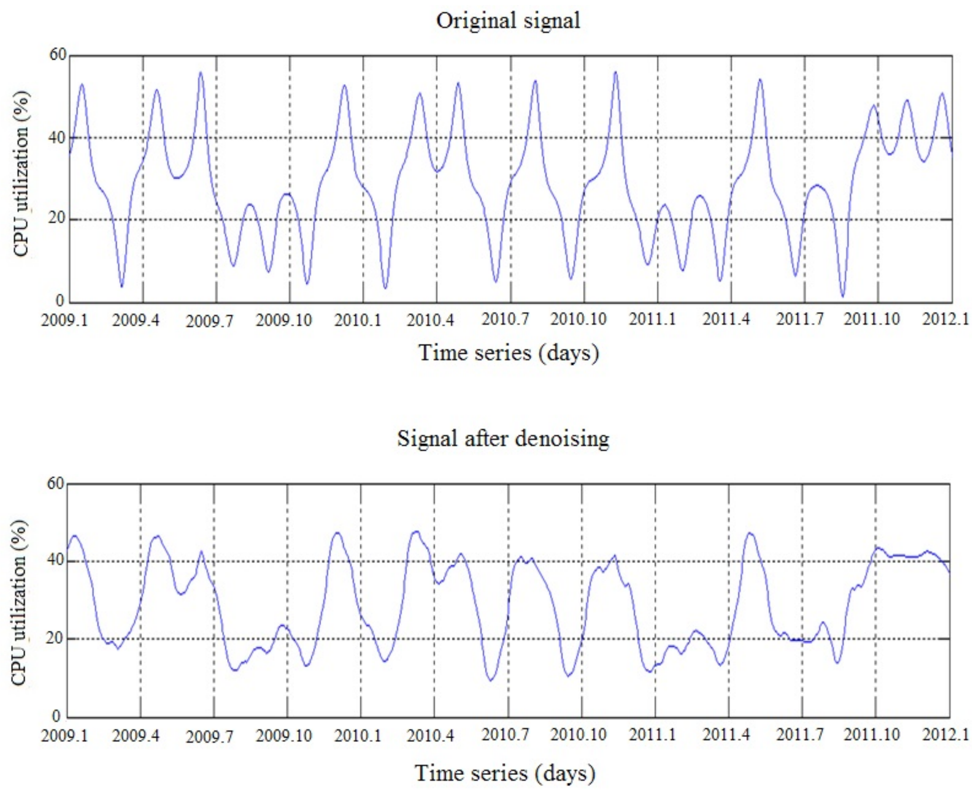

FIGURE 8. CPU utilization of cloud computing resource load sequence before and after denoising.

B. ACCURACY OF EACH FORECASTING MODEL

1) GREY FORECASTING MODEL

In the grey forecasting process, firstly, the least square method is used to solve the value of parameter vector $A = (B^T B)^{-1} B^T Y_n$ of the grey forecasting model. Secondly, according to the parameter vector $A = \begin{pmatrix} \alpha \\ u \end{pmatrix}$, the results of the grey number α and grey action u can be obtained. The parameter a, u is substituted into Eq. (7) to solve the grey forecasting response function. Finally, according to the grey forecasting response function, the results of grey forecasting model can be calculated. The parameters and test results of the grey forecasting model are shown in Table 2.

TABLE 2. Comparison of parameters and test results for the grey forecasting model.

Grey forecasting model	Without wavelet denoising	After wavelet denoising
Grey number α	0.0441	0.0553
Grey action u	33.2871	35.6521
Posterior variance ratio C	0.2132	0.1582
Small error probability P	88.94%	93.57%

The evaluation of the grey forecasting model is related to the posterior variance ratio C and the small error probability P. The smaller the C value is, and the larger the P value is, the better the result is. It can be seen from Table 2 that the grey forecasting model based on wavelet denoising is superior to the grey forecasting model without wavelet denoising in terms of the posterior square difference ratio C and the small error probability P.

2) CUBIC EXPONENTIAL SMOOTHING FORECASTING MODEL

(1) The load sequence without wavelet denoising is used for the cubic exponential smoothing forecasting model. Firstly, determine the initial smoothing value: $S_0^{(1)} = S_0^{(2)} = S_0^{(3)} = \frac{X_1+X_2+X_3}{3} = 36.272$. The different mean square error value α is between [0, 1], at an interval of 0.02, and they are calculated respectively. Through experiments, the minimum mean square error value $\alpha = 0.68$ is taken as the smoothing coefficient. Assume that the forecasting period is T $(T = 1, 2, \ldots, 5)$ days, and the forecasted value Y_{1090+T} of the base data on the t^{th} $(t = 1090)$ day is plugged in the smoothing coefficient equation. Calculate the smoothing coefficients $a_{1090} = 40.1290$, $b_{1090} = -1.2260$, $c_{1090} = 0.0860$, then the equation of the cubic exponential smoothing forecasting model is $Y_{1090+T} = 40.1290 - 1.2260\ T + 0.0860T^2$.

(2) The load sequence after wavelet denoising is used for the cubic exponential smoothing forecasting model. Firstly, determine the initial smoothing value $S_0^{(1)} = S_0^{(2)} = S_0^{(3)} = \frac{X_1+X_2+X_3}{3} = 35.951$. The different mean square error

TABLE 3. Forecasting results of cloud computing resource load sequence.

Time series / day	Actual CPU utilization / %	Grey forecasting model		Cubic exponential smoothing forecasting model		Combined forecasting model	
		Without wavelet denoising	After wavelet denoising	Without wavelet denoising	After wavelet denoising	Without wavelet denoising	After wavelet denoising
1091	37.157	35.618	36.987	38.989	38.221	36.720	37.575
1092	36.044	34.332	35.667	38.021	37.032	35.538	36.317
1093	35.086	32.987	34.992	37.225	36.112	34.372	35.525
1094	34.276	32.112	33.876	36.601	35.461	33.580	34.631
1095	33.606	31.231	32.775	36.149	35.079	32.839	33.872
Mean absolute error / %		5.65	1.08	6.17	3.27	1.79	0.99

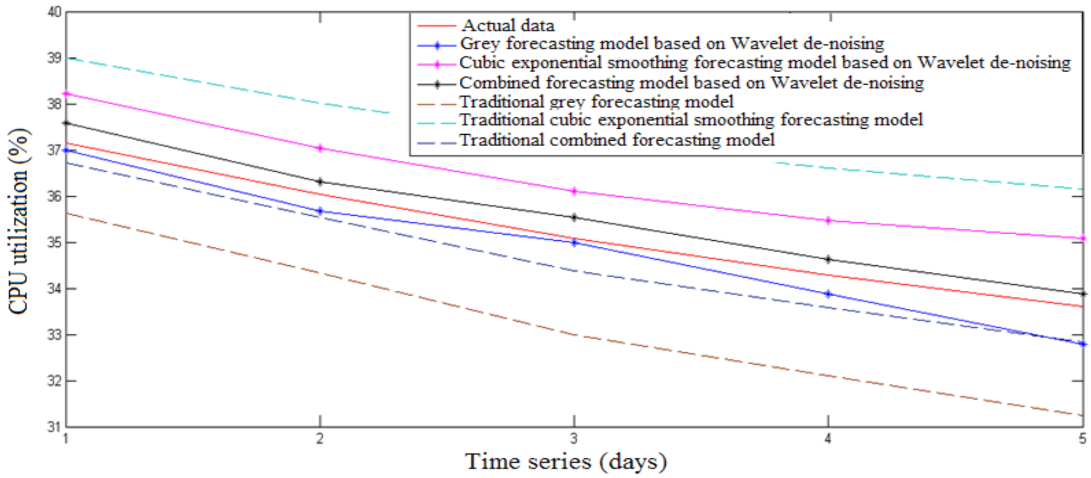

FIGURE 9. CPU utilizations' comparison among different forecasting models in cloud computing.

value α is between [0, 1], at an interval of 0.02, and they are calculated respectively. Through experiments, the minimum mean square error value $\alpha = 0.74$ is taken as the smoothing coefficient. Assume that the forecasting period is T $(T = 1, 2, \ldots, 5)$ days, and the forecasted value Y_{1090+T} of the base data on the t^{th} $(t = 1090)$ day is plugged in the smoothing coefficient equation. Calculate the smoothing coefficients $a_{1090} = 39.6790$, $b_{1090} = -1.5925$, $c_{1090} = 0.1345$, then the equation of the cubic exponential smoothing forecasting model is $Y_{1090+T} = 39.6790 - 1.5925\ T + 0.1345T^2$.

3) COMBINED FORECASTING MODEL

The results of the two single forecasting models are taken as the input sequence x_{1t}, x_{2t} of the combined forecasting model, and the IOWA operator is used to forecast the CPU utilization of the cloud computing resource load sequence from 1091 to 1095 days. The optimal weight coefficients of the combined forecasting model without wavelet denoising are $w_1 = 0.6731$, $w_2 = 0.3269$ and the forecasting value is: $0.6731 \times x_{1t} + 0.3269 \times x_{2t}$. The optimal weight coefficients of the combined forecasting model based on wavelet denoising are $w_1 = 0.5238$, $w_2 = 0.4762$, and the forecasting value is $0.5238 \times x_{1t} + 0.4762 \times x_{2t}$. The forecasting results and the mean absolute error of each single forecasting model and the combined forecasting model are shown in Table 3.

From Table 3 we can find: (1) The mean absolute error of each single forecasting model based on wavelet denoising is smaller than that of the single forecasting model without wavelet de-nosing, which verifies the necessity of wavelet denoising in the forecasting model. (2) The mean absolute error of the combined forecasting model based on wavelet denoising is smaller than that of the single forecasting model and the combined forecasting model without wavelet denoising, which indicates that the combined forecasting model based on wavelet denoising is more suitable for the forecasting of cloud computing resources.

The CPU utilizations' comparison diagram among various forecasting models is shown in Figure 9. Among the seven forecasting value fitting curves in Figure 9, the curve of the combined forecasting model based on wavelet denoising is the closest to the real value curve, which fully demonstrates that the combined forecasting model based on wavelet denoising can improve the forecasting accuracy.

V. CONCLUSION

In this paper, a combined forecasting model of cloud computing resources based on wavelet denoising is proposed. On the one hand, the noise of cloud computing resource load sequence has been reduced, and the necessity of wavelet denoising in the combined forecasting model is verified. On the other hand, it shows that the combined forecasting model has advantages over the traditional single forecasting model, and it can improve the forecasting accuracy of cloud computing resource load sequence. Therefore, the further exploration of the wavelet denoising theory and the combined model is significant to forecast the load of cloud computing resource.

The present contribution provides data to help to reasonably allocate and schedule cloud computing resources to improve the utilization of cloud computing resource and reduce energy consumption. In the overall evaluation of cloud computing, we also should consider the potential of cloud solutions (green-by-cloud) to save resources in the IoT.

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