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Resource Demand Optimization Combined Prediction under Cloud Computing Environment Based On IOWGA Operator

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Abstract

On demand resource forecasting in cloud computing is an crucial guarantee for achieving effective management of all virtualized resources and reducing data center energy consumption. According to single forecasting model cannot integrate all the valid information which leads to the decline in prediction accuracy. This paper proposed an optimal combination prediction model for cloud computing resource requirement. This model is based on generalized Dice coefficient and the induced ordered weighted geometric mean (IOWGA) operator, as well as improved Elman neural network and grey forecasting model. It is able to accurately reflect the random information and trend information in cloud computing load thus will enhance the overall prediction accuracy. The experiment results show this method is feasible and effective.

Key words*: cloud computing; combination prediction; IOWGA operator; neural networks; information resources management*

1. Introduction

Cloud computing wins its popularity by its clear commercial mode and calculating mode, and is widely accepted in the industrial and academic field. Cloud computing is the conceptual combination and evolution of virtualization, utility computing, XaaS and EST. It is also the latest development of distributed computing, parallel computing and grid computing, or can be called a commercial realization [1] of these computer scientific concepts. Cloud computing can achieve various distributive computing, storage and network resources integration, in addition, it can achieve multi-layered virtualization and abstraction, providing large-scale resources to the users in a process of reliable service [2]. To effectively administrate the massive resources (CPU, memory, bandwidth and hardware) in order to response to dynamic, uncertain and diverse users demand, and at the same time of timely and effectively providing resources, to reduce the operation cost and power consumption are the difficulties that the cloud computing runner and service provider should face[3]. The resource demand prediction analysis of cloud computing is and essential step in solving these difficulties. We can use the historical data to precisely predict the demand load in the future span, and then, we can use the related server operation mechanism and virtualization technique to realize the reasonable distribution of the whole cloud computing data center, and provide the cloud computing runner with powerful decision support.

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In the past researches on resource demand prediction, methods like linear regression, pattern matching and fuzzy prediction are used. Among the numerous single prediction techniques, artificial neural network model has high fault tolerance, associability, self-organization and self-learning ability, and has powerful nonlinear mapping and diffusion function to effectively use the random information in the data. In addition, the gray GM(1,1) model, researching on systems with small sample and poor information, has the advantage of low sample demand, convenient calculating, precise prediction, high testability, and is adept at mastering the overall trend of the statistics. Cloud computing resource demand load is a complex nonlinear system being influences by many elements. Under the multiple influences, single model can hardly describe the complex inner changing rules or reflect the external environment changing, and therefore restrain the development of the prediction accuracy. So combined prediction method is an ideal choice of raising the prediction accuracy on the base of existing single prediction model. However, the traditional combined prediction is to weight the different single prediction models differently, the weighted average coefficient of the same single prediction approach is invariable every time. But practically, for a specific single prediction approach, the prediction results are different at different point of time, which means that the prediction accuracy may be sometimes high and sometimes low. Therefore the now existing combined prediction approaches have shortcomings. Professor Cheng Youhua[7-8] raised the combined prediction approach based on induced ordered weighted geometry averaging (IOWGA) operator which effectively overcame the shortcomings mentioned above.

Based on elaborating cloud computing data centre resource management mode and operation mechanism, this essay uses IOWGA operators based on general Dice coefficient, improved Elman neural network algorithm and combined prediction approach of gray GM(1,1) model to deal with resource demand load prediction problems under cloud computing environment, making good complementary of neural network model and gray GM(1,1) model. Experimental result indicates that combined prediction model can adapt the cloud computing resource demand load influenced by various elements better than single prediction model. The prediction accuracy has risen effectively.

2. Clouds Computing Resource Management Structure and Operating System

The resources under cloud computing environment are of tremendous amount, abundant diversity and frequent changes. Different from distributing environment, diverse resources would form a standard virtual resource pool after virtualization under cloud computing environment, providing the users with personalized information service at any place in the cloud, without specifying the position of the resources or the calculating process. Therefore, at the same time of making the users concentrating on information service and reducing the cost of resource requirement, cloud computing also enables the operator of unified administration of diverse resources. Figure 1 shows the resource management structure of cloud computing.

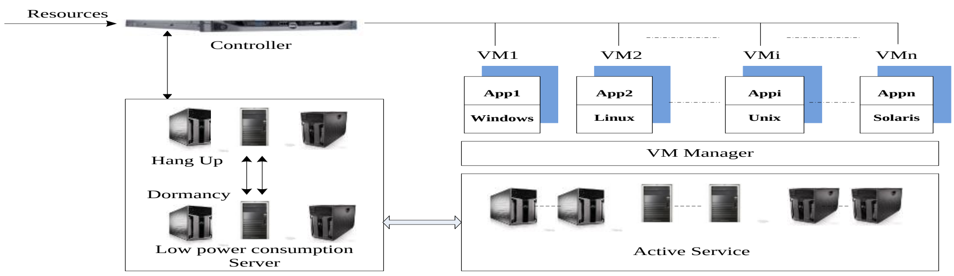

Figure 1. Resource Management Structure of Cloud Computing

As shown in the figure above, cloud computing resource management structure adopts double layer model which includes high layer controller and under layer virtualization manager. Virtualization manager is mainly in charge of virtualization setting and monitoring the related resources. When the resources are required, the virtualization manager would response the request and establishes virtual machine (VM), produce diverse virtual operating system (Windows, Linux, Unix, Solaris and est.) and other related application programs base on it. Resources provider could provide the two as a service package to the users. The controller has to coordinate and administrate the diverse resources in the resource pool, and is mainly in charge of VM setting, load balancing and online server setting. Specifically, when the resource demand constantly grows, the controller could rapidly activate the server in sleeping mode or low-power mode, and switch the server to active mode. When the resource demand reduces, the controller would be able to switch the active server back to low-power mode; the application resources originally on the servers would be transported to other operating active servers by Live Migration [9] technique. This process is called server consolidation. By using server consolidation, we can largely raise the resource utilization, reduce unnecessary energy consumption, lower the operation cost.

By the elucidation above on cloud computing resource management structure and operating mechanism, we can see that if we can predict the amount of resource demand in the next time quantum, and require the information of future resource load, we can prepare in advance. Using the migration mechanism to timely switch on or off the servers would effectively prevent the servers' paralyzing or even website failure caused by undersupplying, or the low utilization and energy waste caused by over supplying. Therefore, the reasonable prediction of resource demand under cloud computing environment is of essential practical significance because it could optimizing resource allocation, and realizes effective administration of diverse resources.

3. Instant Analyses

Based on the above-mentioned argument, this essay constructed a IOWGA operator combination optimization prediction model by using improved Elman wavelet neural network and gray GM (1, 1) prediction model, and optimized the two by using IOWGA operator based on Dice coefficient in a broad sense. This essay also use the combination model to achieve the resource demand prediction under cloud computing.

3.1. Improved Elman Wavelet Neural Network

Elman wavelet neural network was put forward by Elman in 1990. In the dynamic regression network, it has many characteristics such as structure simple and sensitive to the history of the state of the data. Despite input layer, hidden layer and output layer Elman wavelet neural network has an association layer. While the improved Elman neural network adds a feedback connection of a fixed gain $\alpha(0<\alpha<1)$ to the original network, thus the neurons output of the association layer is:

$$x_{ck}(t)=\alpha x_{ck}(t-1)+H_k(t-1) \tag{1}$$

In this equation, $x_{ck}(t)$ is the neurons output of association layer k at time t, $H_k(t-1)$ is the neurons output of association layer k at time $t-1$. In this paper, we assume that the input layer has n nodes, both hidden layer and association layer has m nodes, and output layer has r nodes. $x_j(t)$ is the neurons input of association layer j at time t, and $y(t)$ is its output, so $x_j(t)\in R^n$, $y(t)\in R^r$ and $x_{ck}(t)\in R^m$.

$W_i^1(t)$, $W_{ij}^2(t)$ and $W_{ik}^3(t)$ respectively represents the connection weight between hidden layer and output layer, input layer and hidden layer, Therefore, the nonlinear state space expression of MEWNN is

$$y(t) = \sum_{i=1}^{m} W_i^1(t-1)H_i(t) \tag{2}$$

$$H_i(t) = \varphi\left(\frac{h_i(t) - b_i(t)}{a_i(t)}\right) \tag{3}$$

$$h_i(t) = \sum_{j=1}^{n} W_{ij}^2(t)x_j(t-1) + \alpha\sum_{k=1}^{m} W_{ik}^3(t-1)x_{ck}(t-1) + \sum_{k=1}^{m} W_{ik}^3(t-1)H_k(t-1) \tag{4}$$

The $\varphi(X)$ in this expression is a wavelet function. *Morlet* wavelet function is used in this article and its expression is:

$$\varphi(X) = \cos(1.75X)e^{-X^2/2} \tag{5}$$

$b_i(t)$ is the wavelet coefficient of dilatation, while $a_i(t)$ is The wavelet translation factor. As the dynamic characteristic of the Elman network is only provided by the internal connection, it doesn't need directly using the state as input, or training signal, this is the Elman network's advantage over the static feedforward network. The improved Elman neural network has a better ability of high order system identification comparing to the original Elman neural network.

3.2. GM(1.1)

Put forward by Prof. Deng Julong, the $GM(1,1)$ grey prediction model has been employed in many areas. The modeling mechanism is: Assuming that the original time sequence is $X^{(0)} = \left\{x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n)\right\}$, $x^{(0)}(i) > 0$, $i = 1, 2, \cdots, n$. After an accumulation the result is $X^{(1)} = \left\{x^{(1)}(1), x^{(1)}(2), \cdots, x^{(1)}(n)\right\}$ and $x^{(1)}(j) = \sum_{i=1}^{j} x^{(0)}(i)$, $j = 1, 2, \cdots, n$. The albino differential equation of *GM* (1,1) is:

$$dx^{(1)}/dt + ax^{(1)} = b \tag{6}$$

The grey differential equation of *GM* (1,1) is:

$$x^{(0)}(j) + az^{(1)}(j) = b \tag{7}$$

In this equation a is development coefficient, b is grey action. $\hat{a} = [a,b]^T$ is set as parameter vector, and $z^{(1)}(j) = \frac{1}{2}[x^{(1)}(j-1) + x^{(1)}(j)]$ is set as background value. Least square method is used to solve the equation and get $\hat{a}$.

$$\hat{a} = [a,b]^T = (B^T B)^{-1} B^T Y_n \tag{8}$$

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \cdots & \cdots \\ -z^{(1)}(n) & 1 \end{bmatrix}, \qquad Y_n = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \cdots \\ x^{(0)}(n) \end{bmatrix}.$$

Thus the grey prediction equation is:

$$\hat{x}^{(0)}(j+1)=\hat{x}^{(1)}(j+1)-\hat{x}^{(1)}(j)=(1-e^{a})[x^{(1)}(1)-\frac{b}{a}]e^{-aj},\quad j=0,1,2,\cdots,n-1 \tag{9}$$

3.3. IOWGA Operator Optimization Assembled Prediction Model Based On Generalized Dice Coefficient

In the former studies of assembled prediction model based on IOWGA operator, scholars have put forward several optimizing criterions such as vector angle, Grey Relational Grade and Theil coefficient to construct the assembled model. This paper further proposed an IOWGA operator optimization assembled prediction model based on generalized Dice coefficient. Dice coefficient is an effective coefficient to show the similarity between time series vector, which has been widely used in data mining [12]. Referring to reference 7 and 13, the definitions of IOWGA operator are:

Definition1: Assume that R^+ is the positive set of real numbers, and an n-dimension IOWGA operator has a Mapping Relation: $IOWGA_w^G: R^{+^n}\rightarrow R^+$,

$$IOWGA_w^G(<u_1,a_1>,<u_2,a_2>,\cdots,<u_n,a_n>)=\prod_{i=1}^{n}b_i^{w_i} \tag{10}$$

$W=(w_1,w_2,\cdots,w_n)^T$ is the index weighting vector related to $IOWGA_w^G$ it makes $w_i\in[0,1]$, $i=1,2,\cdots,n$, $\sum_{i-1}^{n}w_i=1$. b_i is the ith member of $(a_1,a_2,\cdots,a_n)$, and u_i is the induced value of a_i

Assume a time series is $\{x_t,t=1,2,\cdots,N\}$, there are m kind of single prediction methods, x_{it} is the prediction value of method i presented at time t, $i=1,2,\cdots,m$, $t=1,2,\cdots,N$.

Definition 2: p_{it} is:

$$p_{it}=\begin{cases}1-\left|x_t-\frac{x_{it}}{x_t}\right|, & if\left|x_t-\frac{x_{it}}{x_t}\right|<1,\\ 0, & if\left|x_t-\frac{x_{it}}{x_t}\right|\geq 1,\end{cases} \tag{11}$$

p_{it} is called the prediction precision of single prediction method i at time t, $i=1,2,\cdots,m$, $t=1,2,\cdots,N$, $p_{it}\in[0,1]$. Set the prediction precision p_{it} as the induced value of prediction value x_{it}, single prediction method i at time t, hence the prediction precision and induced value of m kind of single prediction methods will compose m double dimensional array

$<p_{1t},x_{1t}>,<p_{2t},x_{2t}>,\cdots,<p_{mt},x_{mt}>$. Then the prediction precision of single prediction methods at time t are arranged in descending order:

$$\hat{x}_t=IOWGA_w^G(<p_1,a_1>,<p_2,a_2>,\cdots,<p_n,a_n>)=\prod_{i=1}^{m}x_{p-index(it)}^{w_i} \tag{12}$$

In this equation, $p-index(it)$ is the subscript of prediction precision i, $\hat{x}_i$ is the assembled prediction value. The empowerment coefficient of assembled prediction value is only related to the prediction precision of single prediction model at that time.To facilitate the processing, we take the form of logarithmic error of the time series. Take the logarithm of both sides of equation (12) we can get:

$$\ln \hat{x}_t = \sum_{i=1}^{m} w_i \ln x_{p-index(it)},\ t = 1,2,\cdots,N \tag{13}$$

$X = (\ln x_1, \ln x_2, \cdots, \ln x_N)^T$ is the logarithm vector value of actual time series; $X_i = (\ln x_{i1}, \ln x_{i2}, \cdots, \ln x_{iN})^T$ is the logarithm vector of prediction value obtained by prediction model i, $i = 1,2,\cdots,m$; $\hat{X} = (\ln \hat{x}_1, \ln \hat{x}_2, \cdots, \ln \hat{x}_N)^T$ is the logarithm vector value of assembled prediction value.

Definition 3: δ_i and δ are:

$$\delta_i = \frac{2\sum_{i=1}^{N} \ln x_t \ln x_{it}}{\sum_{i=1}^{N} (\ln x_t)^2 + \sum_{i=1}^{N} (\ln x_{it})^2},$$

$$\delta = \frac{2\sum_{t=1}^{N} \ln x_t \ln \hat{x}_t}{\sum_{t=1}^{N} (\ln x_t)^2 + \sum_{t=1}^{N} (\ln \hat{x}_t)^2} \tag{14}$$

δ_i is the generalized Dice coefficient between the logarithm vector of prediction value X_i and the logarithm vector of actual value X in single prediction method i. δ is the generalized Dice coefficient between the logarithm vector of IOWGA operator assembled prediction value $\hat{X}$ and the logarithm vector of actual value X, $i = 1,2,\cdots,m$. Then we define $Inf_{ij} = \sum_{t=1}^{N} \ln x_{p-index(it)} \ln x_{p-index(jt)}$, $i, j = 1,2,\cdots,m$, and the $m \times m$ matrix $Inf = (Inf_{ij})_{m\times m}$ is the assembled prediction information matrix of IOWGA operator based on generalized Dice coefficient. Then:

$$\begin{aligned}
\sum_{t=1}^{N} (\ln \hat{x}_t)^2 &= \sum_{t=1}^{N} \Big(\sum_{i=1}^{m} w_i \ln x_{p-index(it)}\Big)^2 \\
&= \sum_{i=1}^{m}\sum_{j=1}^{m} w_i w_j \Big(\sum_{t=1}^{N} \ln x_{p-index(it)} \ln x_{p-index(jt)}\Big) \\
&= \sum_{i=1}^{m}\sum_{j=1}^{m} w_i w_j Inf_{ij} \\
&= W^T Inf W
\end{aligned} \tag{15}$$

Equation (14) can be rewrite as:

$$\delta = \frac{2\sum_{i=1}^{m} w_i \sum_{t=1}^{N} \ln x_t \ln x_{p-index(it)}}{\sum_{t=1}^{N} (\ln x_t)^2 + W^T InfW} \tag{16}$$

In order to make the assembled prediction value close to the actual and estimated value, we hope that the

Dice coefficient between the logarithm vector of assembled prediction value $\hat{X}$ and the logarithm vector of actual estimated value X is as big as possible, the bigger the coefficient is the more effective this method will be. When $\hat{X} = X$, the Dice coefficient reaches the maximum. In order to reduce the prediction error as much as possible, the IOWGA operator assembled prediction model basing on generalized Dice coefficient is shown in equation (17):

$$Max \quad \delta(w_i) = \frac{2\sum_{i=1}^{m} w_i \sum_{t=1}^{N} \ln x_t \ln x_{p-index(it)}}{\sum_{t=1}^{N} (\ln x_t)^2 + W^T InfW}$$

$$s.t. \sum_{i=1}^{m} w_i = 1, \quad w_i \geq 0 \tag{17}$$

At this point, IOWGA operator assembled prediction model based on generalized Dice coefficient has been built, as long as the weighted vector $W = (w_1, w_2, \cdots, w_n)^T$ is obtained, $W = (w_1, w_2, \cdots, w_n)^T$, the he optimal predictive value of resource requirements can be found easily under the cloud computing environment.

4. Instant Analyses

Among basic resources like CPU, internal storage, broadband and storage in cloud computing, this article uses CPU as the experimental subject (The demand prediction of other resources are the same as this method), furthermore we adopt the CPU resources using historical data of SDSC [14] as simulation data. SDSC provide a variety of network infrastructure resources and services, including data storage management, high performance computing and data analysis service for scientists, engineers, students and business people and so on. These services are advocated and ongoing in cloud computing, so take advantage of the historical data in SDSC as computing simulation data is reasonable. Before getting the prediction value, we need to train the neural networks. We take 1500 historical time series data points as the training sample, and predict the value of the subsequent 30 data points; the training data is shown in Figure 2.

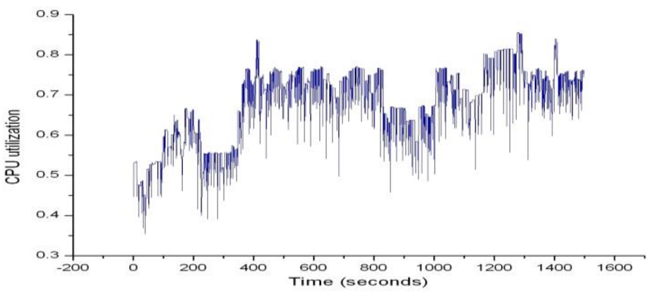

Figure 2. Neural Network Training Data Set

Table1 shows the actual value of CPU utilization (%) and the predicted value by the improved Elman wavelet neural network algorithm (MEWNN) and the $GM(1,1)$ prediction model. From Table 1, we can see that the prediction result of the improved Elman wavelet neural network algorithm is ideal. In order to obtain better prediction results, on the basis of the predicted value obtained by the above two kinds of single prediction method, we construct a double dimensional array of the prediction precision of moment t and its corresponding interval sample prediction value, take the first three time points as example:

$$\hat{x}_1 = IOWGA_w^G(< p_{11}, x_{11} >, < a_{21}, x_{21} >) = 51.3^{w_1} 55.2^{w_2};$$

$$\hat{x}_2 = IOWGA_w^G(< p_{12}, x_{12} >, < p_{22}, x_{22} >) = 38.6^{w_1} 42.7^{w_2};$$

$$\hat{x}_3 = IOWGA_w^G(< p_{13}, x_{13} >, < p_{23}, x_{23} >) = 30.6^{w_1} 32.0^{w_2}$$

$$\cdots \quad \cdots \quad \cdots$$

Table 1. Value of Single Prediction Method

Time (Second)	Actual Value (%)	MEWNN (%)	Grey Model (%)	Time (Second)	Actual Value (%)	MEWNN (%)	Grey Model (%)
1	48.6	51.3	55.2	16	48.7	50.9	53.7
2	40.5	42.7	38.6	17	59.6	58.6	54.6
3	28.1	30.6	32.0	18	65.8	60.3	70.7
4	38.9	36.3	35.1	19	72.9	79.1	68.1
5	49.2	45.4	53.8	20	82.3	85.4	82.5
6	55.6	59.8	54.3	21	76.5	71.6	86.9
7	57.4	57.7	62.7	22	74.8	75.5	68.3
8	59.1	63.5	55.2	23	64.1	69.3	67.7
9	60.8	58.8	64.2	24	79.2	73.1	71.6
10	64.7	63.0	58.4	25	80.8	79.6	84.9
11	68.8	71.6	63.1	26	85.2	92.2	89.8
12	59.5	65.2	53.9	27	75.7	68.5	72.2
13	63.8	69.3	66.0	28	71.3	75.4	76.4
14	69.1	73.8	75.9	29	83.8	91.9	88.1
15	44.6	40.1	37.2	30	75.1	79.3	81.2

Finally, we get the optimal assembled prediction model of the case through equation (17):

$$Max \quad \delta(w_1, w_2) = \frac{1020.2w_1 + 1030.8w_2}{508.9w_1^2 + 1028.2w_1w_2 + 519.6w_2^2 + 511.4}$$

$$s.t. \sum_{i=1}^{2} w_i = 1, \quad w_i \geq 0 \tag{18}$$

By using $Matlab2010b$ optimization toolbox, we obtain the optimal solution in for w_1 and w_2 in equation (18): $w_1^* = 0.647$, $w_2^* = 0.353$ .Then we get the he optimal predictive value of CPU resource requirements can be found easily under the cloud computing environment using the IOWGA operator assembled prediction model based on generalized Dice coefficient. In order to verify its effectiveness, this article takes 3 models into comparison, *i.e.*, ARMA, BP NEURAL NETWORK and Exponential Smoothing. Figure 4 is the schematic diagram of different prediction model; we can find that among the results of the above prediction models, the prediction value of our method is closest to the actual value, which intuitively reflects its good prediction performance.

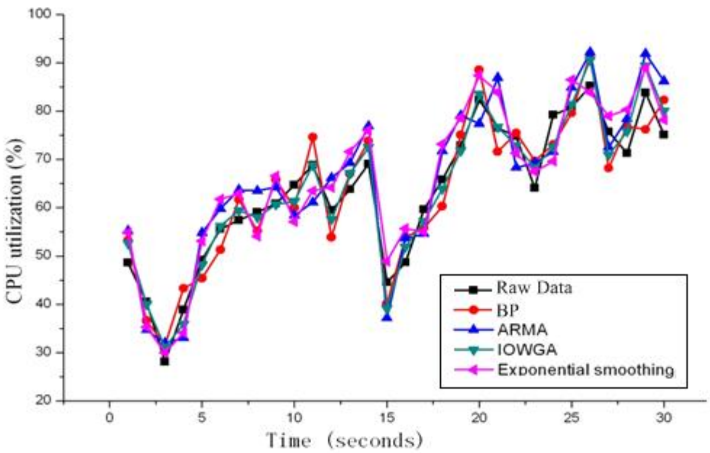

Figure 3. Schematic Diagram of Different Prediction Model

In order to further evaluate the prediction effect, the following error indicators for measuring precision of the conventional evaluation index are chosen, the effect of any of the above prediction model is presented in table 2.

(1) Mean average percent error (MAPE):

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{(x_t - \hat{x}_t)}{x_t}\right|$$

(2) Mean square percent error (MSPE):

$$MSPE = \frac{1}{N}\sqrt{\sum_{t=1}^{N}[(x_t - \hat{x}_t)/x_t]^2}$$

(3) Mean absolute error (MAE):

$$MAE = \frac{1}{N}\sum_{t=1}^{N}\left|x_t - \hat{x}_t\right|$$

(4) Mean square error (MSE):

$$MSE = \frac{1}{N}\sqrt{\sum_{t=1}^{N}(x_t - \hat{x}_t)^2}$$

Table 2. Effect Evaluation of Different Prediction Methods

Evaluation criteria	Paper Model	ARMA	BP NEURAL NETWORK	exponential smoothing
MAPE	0.0461	0.1332	0.0881	0.1142
MSPE	0.0103	0.0859	0.0495	0.7991
MAE	2.7983	9.6170	5.3377	10.3092
MSE	0.6182	1.9653	1.0063	1.5449

From table 2, we can see that the assembled prediction model constructed in this paper have shown great superiority in various evaluation index. Compared with the traditional single prediction model the prediction precision of our method has a significant increase. In the process of practical application it also can accurately extract the data contained in all kinds of information content, which has a broad application prospect.

5. Conclusions

This essay starts from the problem of cloud computing resources demand forecasting, and raises the improved Elman wavelet neural network on the base of resource management architecture and operation mode. The essay also combines the neural network with gray GM (1, 1), and build up a combination optimization prediction model of IOWGA operator based on Dice coefficient in general. The prediction method shows its validity, reasonability and practicality by the result of applying it to historical data.

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