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Electricity Sales Prediction Model of Electricity Market of the Non-linear Regression Combination with the Optimal Weight

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Abstract. The model to estimate electric sales in electric market of the optimal weighting non-linear regression combination is brought forth to improve the accuracy of electricity sales forecast. Firstly, the least square method is used to estimate the nonlinear regression equation in order to obtain the result sets of the prediction sequence. Secondly, the design method of minimizing the calculation of fitting variance and weighting com-bination to calculate the residual sequence and weighting of the Radial Basis Function (RBF) neural network and the least squares vector machine, finally the result sets of residual sequence concluded. At the end, a nonlinear decreasing strategy of inertia weight is introduced on the basis of cuckoo algorithm to optimize the extended search space of model parameters and the model solution. The simulation results show that the model can accurately and comprehensively reflect the law of electric sales and improve the accuracy of sales prediction.

Keywords: cuckoo algorithm, electricity power market, least squares support vector machine, RBF neural network

1 Introduction

The publication of article 9 of electric reform marked the beginning of a new round of electricity market [1]. In the new competitive electricity market, small users can choose their own sales company under the network bidding cloud platform. The dynamic price is one of the main features of the new electricity market [2], and various power companies are following the electricity market reform, showing new

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vitality. In the six months between March and August 2015 alone, more than 50 new independent power companies were established [3]. In addition to mitigating risks, trading for power companies, and pricing, other methods providing an accurate forecast of sales volume have become key factors in surviving the competitiveness of the power market. Therefore, designing a sales forecasting model for a sales company is a problem that must be solved [4]. There are mainly three aspects affecting the forecast sales volume.

(1) Sales factors and overall nonlinear volatility: The sales volume depends on various sales factors of the sales company on the cloud platform [5], such as company rating, price, renewable energy ratio, and so on. As a whole, these factors have a certain relationship with the sales volume [6], and have obvious characteristics of time volatility and growth trend. Volatility also presents a complex nonlinear function characteristic [7].

(2) Limitations of forecasting methods: In forecasting modeling, there may be large forecasting errors in data restriction [8]. Because it is difficult to accurately and fully consider the changing characteristics of forecasting with the single forecasting method, it is unable to guarantee the accurate prediction of sales volume in any situation [9].

(3) Uncertainties in predicting model parameters: Different parameters in the prediction model lead to large differences in prediction accuracy [10]. Choosing the right parameters is the key to improving the prediction accuracy of the sales volume [11].

At present, there are mainly two types of prediction models: Type I is the prediction method of time series modeling, including time series, gray prediction, moving average, exponential smoothing, causal analysis, judgmental analysis, and combined forecasting [12-13]. The second category is based on the prediction of intelligent models [14], including artificial neural network [15], least square support vector machine [16], as well as regression and fuzzy logic law. In [17], Xu et al. used gray prediction to solve the overall forecast of linear growth of China's electricity consumption. However, the proposed IRGM model does not predict the sales of non-linear and floating sales companies very well. In [18], Chen et al. used exponential smoothing method to solve the problem of short-term load forecasting. However, the smoothed parameter α has a greater influence on the forecasting result. The non-stationary data will make the forecasting result less than ideal. In [19], Yan et al. proposed a prediction model based on ARMA and BP_AdaBoost. BP_AdaBoost solves the disadvantages of BP neural network such as into local minima and slow convergence speed. However, the generalization ability of the prediction results is weak. In [20], Li et al. used LS-SVM for short-term wind load prediction. LLSVM solves the problem of under-learning and dimensionality disaster in neural networks. However, the training of small samples is bound to waste a large amount of sequence data.

In summation, this paper first predicts the growth trend of sales volume through nonlinear regression analysis, and constructs the mapping relationship between the factors and the sales volume. Secondly, it designs a method to minimize the combined weights of variance. Finally, using the improved cuckoo algorithm to optimize the parameters of the prediction model, the prediction accuracy is more accurate, providing a reference for the sales company in the new electricity market and improving competitiveness.

2 Construction of the Prediction Model of Electricity Sales Considering Prediction and Residual Sequence

Suppose the forecasting model has actual sales volume at time t, then the sales volume at the next time $t+1$ is S'_{t+1}. The model is expressed by the following formula:

$$S'_{t+1} = S'_t + \varepsilon'_t, t = 1,2,...,T . \quad \textbf{(1)}$$

In this equation, the result sets of prediction sequence of electricity sales is S'_t ($t=1,2,..,T$), and the result sets of residual sequence is ε'_t ($t=1,2,..,T$). The following two parts of the model are mainly considered:

Prediction result sets S'_t. Because of the nonlinear increasing in electricity sales, the original data sequence of sales is S_t ($s_1,s_2,...$,sN) can be presented in quadratic curve equation St as below:

$$S_t = x + yt + zt^2 + r_t, x, y, z > 0; t = 1,2,...,T . \quad \textbf{(2)}$$

In this equation, r_t is residual error; x, y, and z are equation parameters; and T is number of times. In a certain period, electricity sales conform to the growth law of quadratic equation. When set $t1=t2$, $t2=t2$, the nonlinear regression model is transformed into a linear model. Thereby,

$$S = x + yt_1 + zt_2 + r\ . \quad \textbf{(3)}$$

By using the least squares method, model parameters are estimated and the values are x', y', z'. Finally, the prediction equation of the new electricity sales growth trend is:

$$S'_t = x' + y't + z't^2, t = 1,2,...,T\ . \quad \textbf{(4)}$$

Predicted data sequence can be obtained via the prediction equation of growth trend, that is $S'_t(s'_1,s'_2,...,s'_N)$.

Result sets ε'_t of residual error sequence. At time t, the difference between the original data sequence S_t of electricity sales and the estimated data sequence is called residual error t, marked as ε_t. That is:

$$\varepsilon_t = S_t - S'_t, t = 1,2,...,T\ . \quad \textbf{(5)}$$

By using radial residual error ε'_{1t} obtained by the minimum fitting residual error combination of RBF neural network, plus the generalized residual ε'_{2t} obtained by the prediction model of the least squares support vector machine, the prediction result of residual sequence is $\varepsilon'_t(\varepsilon'_1,\varepsilon'_2,...,\varepsilon'_N)$.

Based on the result sets of prediction sequence, prediction model of electricity sales RBF Neural Network Blend Least Squares Vector Machine (RLBLEND) is established. Therefore, the final equation of prediction model can be expressed as:

$$S'_{t+1} = a' + b' + c't^2 + \left(\sum_{t=1}^{n} w_n \varepsilon'_{nt}\right). \quad \textbf{(6)}$$

In this equation, $t=1,2,...,T$, $n=1,2$, and $w_n(n=1,2)$ are weighting coefficients of radial and generalized residual errors, respectively.

3 Prediction Method of Residual Error Sequence

3.1 Prediction of Radial Residual Error Based on RBF Neural Network

RBF Neural Network is a feed-forward network of hidden functions with an excellent capability of nonlinear mapping.

It is important to forecast the input and output factors of the model. According to the analysis of the electricity sales and the factors in the California market, given the training samples of N historical data of electricity sales, the company rating G_t, the price P_t, the renewable energy ratio R_t, the energy reward A_t and the cancellation cost D_t are input to the hidden layer as a neural network. At the time of t residual ε_t is regarded as the output factor, and the radial residual ε_{1t} is marked. The RBF neural network residual prediction model is shown in Fig. 1.

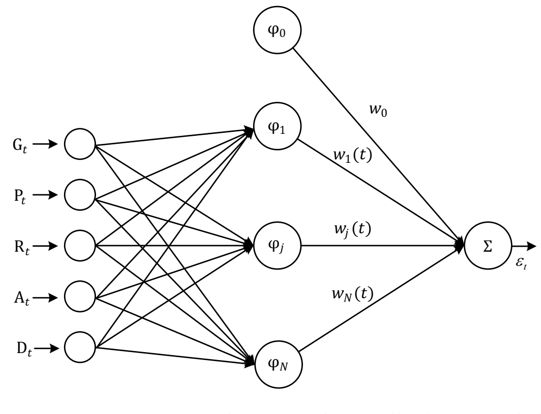

Fig. 1. RBF neural network prediction model

RBF network contains N hidden layers of neural network. Excitation function in *jth* unit is selected as Gaussian function, that is:

$$\varphi_j[I(t),G(t)] = \exp\{-\frac{[I(t)-G(t)]^2}{2\gamma^2}\}. \tag{7}$$

In this equation, when $j=1,2,...,N,\ i=1,2,...,6$, at the time t, γ is the square deviation of the function; $I(t)$ is the training sample input; $G(t)$ is function center; $w_i(t)$ is the weight value of hidden and outputting layers. As in Fig. 1, $\varphi_0=1$, the neural network with generalizing board with the hidden layer of outputting 1 is set up. In model training, basis function center is confirmed by self-organizational learning of Fuzzy Cognitive Map (FCM) clustering algorithm. Square deviation of basis function is as below:

$$\gamma = \frac{c_{\max}}{\sqrt{2h}}. \tag{8}$$

In this equation, c_{max} taking the maximum place of center, the connecting weighting between hidden and outputting layers is immediately obtained by the least square method, that is:

$$w_i = \exp(\frac{h}{c_{\max}^2}\|x_p - c_t\|^2). \tag{9}$$

In this equation, $p=1,2,..,N$, the outputting of neural network is finally:

$$O = w_0 + \sum_{j=1}^{N} w_j\varphi_j[I(t),G(t)]. \tag{10}$$

After the n^{th} iteration of this network, outputting value of $O(n)$ is corresponding the target value, that is radial residual error is ε_n. Target function is defined as:

$$J(n) = \frac{1}{2}\sum_{p=1}^{N} E(n) = \frac{1}{2}\sum_{p=1}^{N}[\varepsilon_n - O(n)]^2. \tag{11}$$

Equation (9) is taken to negative gradient direction in order to adjust weight coefficient of the network.

$$w_j(n+1) = w_j(n) - \eta\frac{\partial J(n)}{\partial w_j(n)}. \tag{12}$$

When setting value after the iteration of certain times is less than target function $J(n)$, iteration terminates and relating coefficient are confirmed, training of neural network completed.

3.2 Generalized Residual Error Prediction Based on Least Squares Support Vector Machine

Subject to the limited sample training set, the least squares support vector machines can achieve the ultimate generalization ability taking the complexity of the model and the preferred learning projects, and finally can realize the characteristics of risk minimization [21].

Combined the least squares support vector machines, prediction model of residual error sequence is established. At the same time, residual error sequence is also the training sample. Given the training sample of N historical data of residual error $\{X_n,\varepsilon_N\}$, and the input value of the sample X_t, outputting value ε_N, and the generalizing residual error ε_{2t}, optimized target function of the least squares support vector machines is:

$$\begin{cases} J(w,e) = \dfrac{\mu}{2}w^T w + \dfrac{1}{2}\gamma\sum_{i=1}^{N} e_i^2 \\ \text{s.t.} \quad y_i = w^T\phi(x_i) + b + e_i, i = 1,2,...,N \end{cases} \tag{13}$$

In this equation, $\varphi(\bullet)$ is mapping function of nuclear space, w is weight vector, e_i is residual error, b is biasing value, and μ and γ are adjustable parameters.

Using Lagrange multiplier method, target function is transferred to solve the maximum value of single parameter α. Function is as below:

$$L(w,b,e,\alpha)=J(w,e)-\sum_{i=1}^{N}\alpha_i\{w^T\varphi(x_i)+b+e_i-y_i\}\ . \quad \textbf{(14)}$$

For w, b, e_i and $\alpha_{i,}$ below equation can be obtained by separate derivation=0:

$$\begin{cases} \dfrac{\partial \mathrm{L}}{\partial \mathrm{w}}=0\rightarrow w=\sum_{i=1}^{N}\alpha_i\varphi(x_i) \\ \dfrac{\partial \mathrm{L}}{\partial \mathrm{b}}=0\rightarrow \sum_{i=1}^{N}\alpha_i=0 \\ \dfrac{\partial \mathrm{L}}{\partial e_i}=0\rightarrow \alpha_i=\gamma e_i \\ \dfrac{\partial \mathrm{L}}{\partial \alpha_i}=0\rightarrow w^T\varphi(x_i)+b+e_i-y_i \end{cases} . \quad \textbf{(15)}$$

In this equation, when i=1,2,...,N, linear function of α and b is obtained according to above four conditions:

$$\begin{bmatrix} 0 & 1_v^T \\ 1_v & \Omega+\dfrac{1}{\gamma}I_N \end{bmatrix}\begin{bmatrix} b \\ \alpha \end{bmatrix}=\begin{bmatrix} 0 \\ y \end{bmatrix}. \quad \textbf{(16)}$$

In this equation, nuclear matrix Ω is:

$$\Omega=\varphi(x_i)^T\varphi(x_i)=K(x_i,x_l)\ . \quad \textbf{(17)}$$

$y=[y_1,...,y_2,...,y_N]$,$1_v=[1,1,...,1]$,$\alpha=[\alpha_1,\alpha_2,...,\alpha_N]$.
Finally, equation of LSSVM (Least Squares Support Vector Machine) is:

$$y(x)=\sum_{i=1}^{N}\alpha_iK(x,x_i)+b\ . \quad \textbf{(18)}$$

In this paper, representative RBF nuclear function is used to construct the prediction model of LSSVM. The equation is:

$$K_{RBF}=\exp\left(\frac{-\|x-x_i\|^2}{2\sigma^2}\right)=\exp(-g\|x_i-x_j\|^2),g>0\ . \quad \textbf{(19)}$$

It is obvious that during the calculation of the least square support vector machines two parameters are designed as adjustable parameters as μ and γ. Cuckoo Search is used to provide the optimization in this essay.

4 Weight Calculation of Minimum Fitting Residual Error Combination

The residual errors of the two prediction methods are respectively radial residual error ε_{1t} and generalized residual error ε_{2t}. Therefore, fitting residual error of both of them is:

$$h_{ii}=\sum_{t=1}^{n}\varepsilon_{it}^2,i=1,2\ . \quad \textbf{(20)}$$

Provided that RBF neural network and the combined weight of the least square support vector machines are separately w_1 and w_2, the fitting result of combined model is:

$$\varepsilon'_t=w_1\varepsilon'_{1t}+w_2\varepsilon'_{2t}(t=1,2,...,n) \quad \textbf{(21)}$$

If the prediction results want to reach certain credibility, a minor fitting residual error is necessary in the prediction, so as to get a higher fitting degree of the results. w_1 and w_2 are solved by minimum fitting residual error.

$$\begin{cases} \min Z = \sum_{t=1}^{n} (\varepsilon'_t - \varepsilon_t)^2 \\ \text{s.t.} w_1 + w_2 = 1, w_1, w_2 \geq 0 \end{cases} . \quad \textbf{(22)}$$

Concerning above equation (20) and (21), above equation can be written as below matrix equation:

$$\begin{cases} \min Z = N^T H N \\ \text{s.t. } e^T N = 1, N \geq 0 \end{cases} . \quad \textbf{(23)}$$

In this equation, $H = \begin{bmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \end{bmatrix}$; $N = \begin{bmatrix} n_1 \\ n_2 \end{bmatrix}$; $e = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$. To obtain the weight coefficient of radial and generalized residual error, nonlinear programming of decision variable N of above equation needs to be solved.

5 Prediction Model Resolution of Electricity Sales Based on Cuckoo Search with Extended Searching Space

5.1 Cuckoo Search

The features of cuckoo search (CS) are less parameters, simple operation, easy implement, random searching paths and the ability to find the optimization [22]. When a cuckoo searches a place to lay eggs and searching radius is within the egg laying scope, the place is one of the candidate solution. When the radius is out of the scope, the way a cuckoo flies is conform to Levy Flight, that is:

$$Le'vy \sim P(L_j) L_j^{-\lambda}, 1 < \lambda < 3 . \quad \textbf{(24)}$$

In this equation, L is the length of steps and its value is random. At the time of t, the place of i cuckoos is x^t_i. And the place at the time of $t+1$ is updated as below:

$$x_i^{t+1} = x_i^t + L \oplus Le'vy(\lambda) . \quad \textbf{(25)}$$

In this equation, $\oplus$ is the point-to-point multiplication. When the place is updated, $r \in [0, 1]$ is compared with the probability P_n of the birds owner's discovery of the birds. If $r<P_n$, x^t_i is unchanging, or x^t_i will change randomly.

5.2 Calculation Cuckoo Search with Extended Searching Space

The accuracy of prediction model of electricity sales is mainly impacted by parameters. Basic CS calculation will cause a insufficient parameter optimization of estimate model of electricity sales and a low speed of convergence rate because of its weak adaptive and searching ability.

The introduce of inertia weight coefficient makes cuckoo search has ability to extend the searching to new area, so that the prediction model parameters of electricity sales are rapidly optimized and the accuracy is enhanced. That is weight cuckoo search with extended searching space Weight Cuckoo Search (WCS). The equation is:

$$X_i^{t+1} = w \cdot x_i^t + a \oplus L(\lambda), i = 1,2,...,N . \quad \textbf{(26)}$$

In this equation, w is inertia weight declination strategy. When w is larger, overall searching for optimization will be conducted. At this time, local optimum will be substituted. Reversely, when w is smaller, convergence speed of the calculation can be increased, contributing to local optimum. Nonlinear searching strategy of CS can not reflect the actual optimization. So a new inertia weight nonlinear declination strategy is needed to be introduced to better searching. W changes as:

$$w = \left(\frac{2}{i} \right)^{0.3} . \quad \textbf{(27)}$$

In this equation, i represents the times of iterations.

WCS with extended searching space is used to better the parameters of RLBLEND model and construct RLBLEND model. The optimizing steps are as below:

(a) initializing parameters μ, γ, and parameter setting of WCS;

(b) using normalized sample set $\{x_i, y_i\}$ to train LLSVM;

(c) initializing probability parameter $P_a=0.8$ to generate randomly nest place. Each nest place has a corresponding two-dimensional vector (μ,γ) and technology matches the cross-validation variance of training set to find out the best nest x_b and the corresponding minimum variance E_{min};

(d) introducing inertia weight to calculate the length of Levy step. And the length will be employed to obtain a new range of nest places and calculated the corresponding prediction error;

(e) by the comparison of the old and new nests, the better one will be the substitution to obtain the best nest place k_t;

(f) calculating the prediction error k_t and using nest place with the smaller prediction error to substitute the worse one to obtain a new nest place p_t;

(g) via the nest place $p_{t,}$ if E_{min} meets the final model accuracy, the search will terminate, or the procedure returns to (d);

(h) nest place obtained after the accuracy is sufficient will ensure the optimized parameter of RLBLEND.

Cuckoo algorithm flow with extended searching space is shown in Fig. 2.

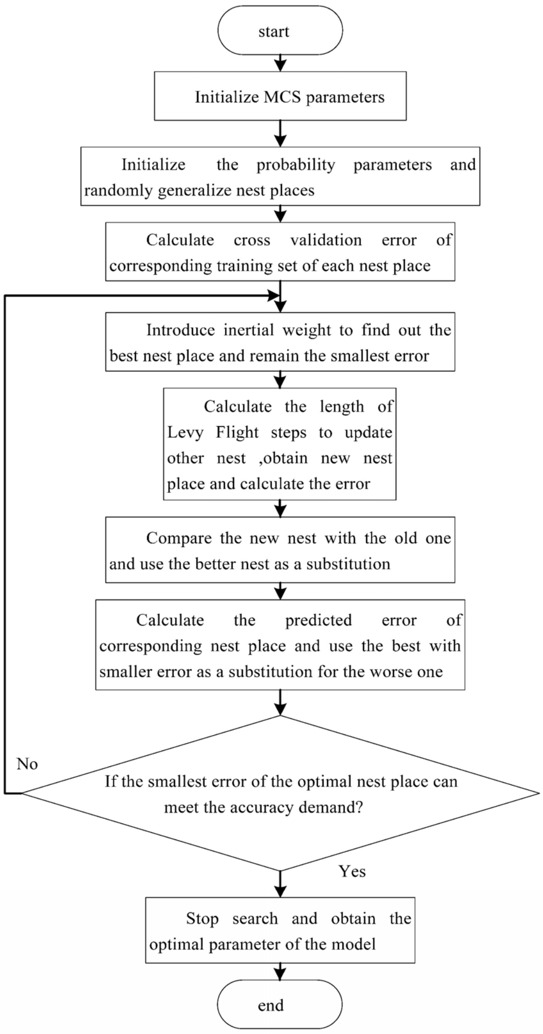

Fig. 2. Extended search space for cuckoo algorithm flow

6 Simulation Contrast Experiment

6.1 Data Source

Data is from the electricity data of LifeEnergy Company in the California electricity market from the January 1 of 2014 to December 31 of 2014 [23], with a total number of 8760. The former 8660 data constitutes model training sample, and the later 100 Data serves as test samples, respectively being subject to error analysis and fitting analysis of the experiment. The original test set is shown in Fig. 3.

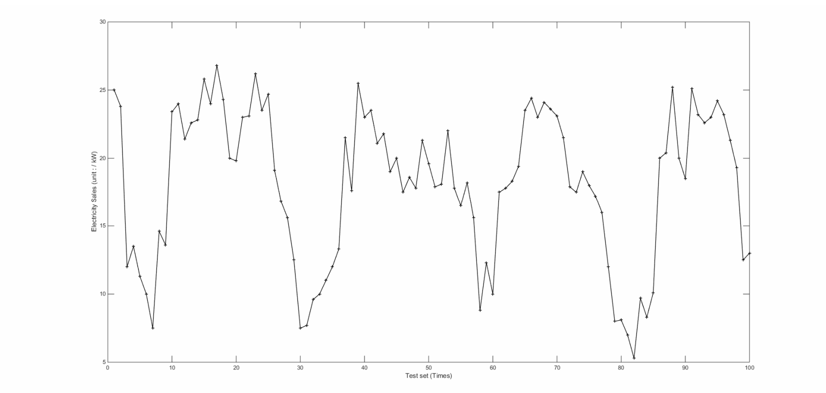

Fig. 3. Raw data set

6.2 Contrast Model and Performance Evaluation Criterion

The prediction model of electricity sales in electricity market of optimum weight nonlinear regression combination serving as the reference, Traditional RBF neutral network and the least squares support vector machines are selected to conduct contrast experiment. Among the restructured data of electricity sales of power supply firms, the later 100 data is regarded as testing sets and other data is training data.

The experiment mainly study two parts. The first experiment studies the fitting degree and changing curve between actual electricity sales and the prediction model results.

The second experiment studies the accuracy of prediction. It adopts root mean square error (RMSE) and mean absolute percentage error (MAPE) as evaluation criteria. RMSE is used to evaluate the deviation between the observed value and truth value. MAPE is the average absolute value of the deviation of all single observed value and arithmetic mean, better reflecting the actual error of predicted value. They are defined as below:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - y'_t)^2} \,. \tag{28}$$

$$MAPE = \frac{\sum_{t=1}^{n}|(y_t - y'_t)/y_t|}{n} \times 100\% \,. \tag{29}$$

In the equation, y_t represents actual value; y'_t represents predicted value; n represents the number of samples.

6.3 Conclusions and Analysis

Experiment I. The fitting and measuring of electricity sales in terms of three samples

The quadratic curve equation is formed as below based on the historical data of the power supply enterprise's electricity sales:

$$Y_t = a + bt + ct^2 + u_t, t = 1, 2, ..., 8660 \,. \tag{30}$$

The growth trend is obtained by the usage of the ordinary least squares method as below:

$$Y'_t = 23.8134 + 4.0121t + 0.001t^2 \ . \tag{31}$$

The experimental results reveal that when confidence level is less than 5%, the parameters in this equation are unequal to zero and fitting coefficient reaches 97.03%, the higher fitting degree indicating that the equation is in line with the growth trend of the company's electricity sales in a certain period. The time t is taken into equation (31) to obtain the initial prediction sequence of electricity sales tendency in a certain period. Three sets of models are used to train the residual sequence, and the estimation results of the later 100 data combined the initial prediction sequence are compared with actual data results sets. The fitting degree and the changing curve of the model are studied.

The fitting and test of electricity sales by RBDNN model. The outputting results of the actual electricity sales measured by RBFNN model and the curve are shown as Fig. 4. The analysis uncovers that the model regarding the overall simulation prediction tend is pretty good, but some points undergo a large fitting error. The reason lies in that neutral network is apt to being stuck into local optimum. Consequently, in spite of a good overall fitting, the prediction accuracy of electricity sales is not good enough.

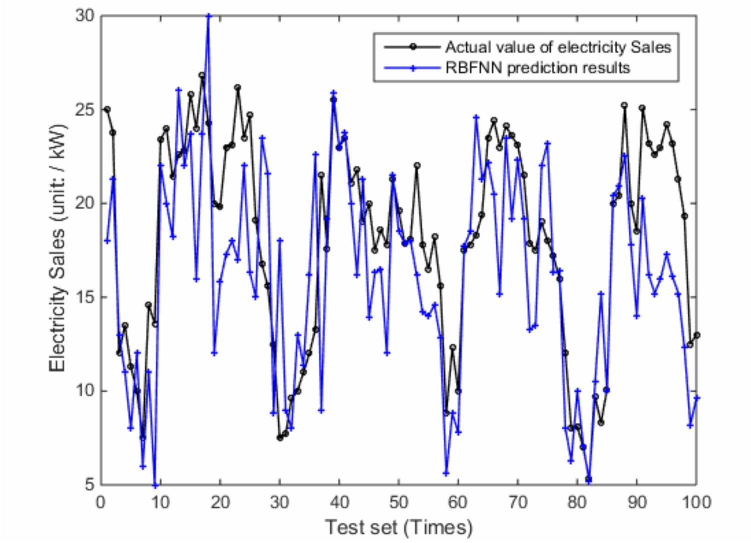

Fig. 4. The Curve of Predictive Results and Actual Output of RBFNN Model

The fitting and measuring of electricity sales by LSSVM. The curve of the model, with the help of the trained sample set learned by LSSMV model, is shown in Fig. 5.

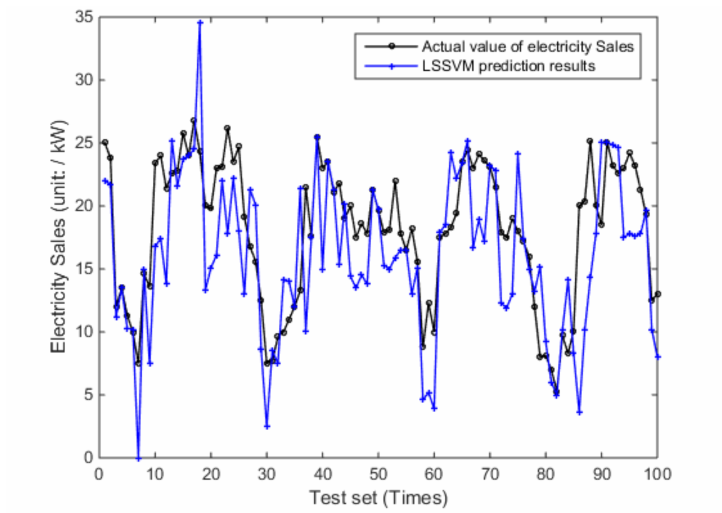

Fig. 5. The curve of predictive results and actual output of LSSVM model

The fitting degree of electricity sales data by LSSVN is good, and the prediction effect concerning single point slightly exceeds RBFNN model. Obviously, LSSVM has the better generalized capacity of the existing electricity sales data compared with traditional RBFNN model. Further, it overcomes the shortcoming in over fitting of neutral network.

The fitting and test of electricity sales by RLBLEND model. Cuckoo with extended searching space is used to optimize the parameters of RLBLEND model and the constructed RLBLEND model is used to predict electricity sales in order to obtain the curve shown in Fig. 6.

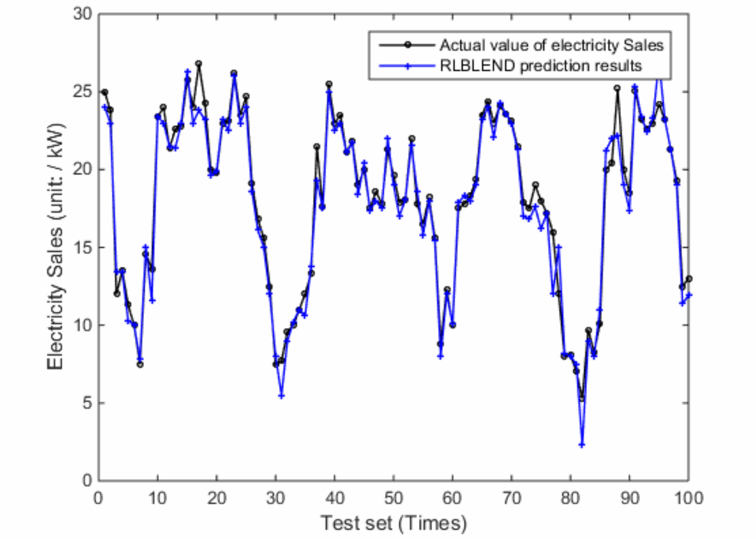

Fig. 6. The curve of predictive results and actual output of RLBLEND model

Compared with the previous contrast models, aside from the more accurate fitting and overall tend, RLBLEND model is more precise and has the optimal practicability.

Experiment II. The analysis of model error comparison

The three groups of models are used to calculate the prediction result error by adopting RMSE and MAPE to study the actual error of prediction value. Performance evaluation standard of the three models is shown in Table 1. The comparison of the first 30 data of the test set in each model with their prediction results and prediction errors is shown in Table 2.

Table 1. Performance evaluation criteria results

Prediction model	RMSE	MAPLE/%
RBFNN	4.90	14.85
LSSVM	4.52	13.61
RLBLEND	1.06	2.90

Table 2. Comparison of prediction results and prediction errors of each model

Serial number	Test set	RBFNN Result	RBFNN Prediction error	LLSVM Result	LLSVM Prediction error	RLBLEND Result	RLBLEND Prediction error
1	25	22	3	18	7	24	1
2	23.8	21.7	2.1	21.3	2.5	23	0.8
3	12	11.2	0.8	13	-1	13.4	-1.4
4	13.5	13.5	0	11	2.5	13.4	0.1
5	11.3	10.3	1	8	3.3	10.3	1
6	10	10.2	-0.2	12	-2	10	0
7	7.5	0	7.5	6	1.5	7.8	-0.3
8	14.6	14.9	-0.3	11	3.6	15	-0.4
9	13.6	7.5	6.1	5	8.6	11.6	2
10	23.4	16.8	6.6	22	1.4	23.4	0

Table 2. Comparison of prediction results and prediction errors of each model (continue)

Serial number	Test set	RBFNN Result	RBFNN Prediction error	LLSVM Result	LLSVM Prediction error	RLBLEND Result	RLBLEND Prediction error
11	24	17.4	6.6	20	4	23	1
12	21.4	13.8	7.6	18.2	3.2	21.5	-0.1
13	22.6	25.2	-2.6	26	-3.4	21.4	1.2
14	22.8	21.6	1.2	22	0.8	23	-0.2
15	25.8	23.7	2.1	23.7	2.1	26.3	-0.5
16	24	24	0	16	8	23	1
17	26.8	24.5	2.3	23.7	3.1	23.8	3
18	24.3	34.5	-10.2	30	-5.7	23.2	1.1
19	20	13.3	6.7	12	8	19.6	0.4
20	19.8	15.1	4.7	15.8	4	19.9	-0.1
21	23	16.1	6.9	17.3	5.7	23.2	-0.2
22	23.1	22	1.1	18	5.1	22.5	0.6
23	26.2	17.8	8.4	17	9.2	26	0.2
24	23.5	22.2	1.3	22	1.5	23	0.5
25	24.7	18	6.7	16.3	8.4	24	0.7
26	19.1	13	6.1	15	4.1	18.6	0.5
27	16.8	21.3	-4.5	23.5	-6.7	16.1	0.7
28	15.6	20.1	-4.5	21.6	-6	15	0.6
29	12.5	8.6	3.9	8.8	3.7	12	0.5
30	7.5	2.5	5	18	-10.5	8	-0.5

Below conclusion are obtained based on simulation experiment:

(1) Both traditional RBF neutral network and LSSVM have a better overall fitting degree in prediction ability, so they can be seen as a certain reference for prediction of power supply companies' electricity sales. But they are not precise enough in single estimation.

(2) After RLBLEND prediction model introduces nonlinear decreasing strategy weight to basic CS algorithm, convergence speed of parameter optimization is faster. And it combines the edges of each model to acquire the best prediction results of electricity sales, greatly improving the accuracy of electricity sales.

Among the three prediction models, RLBLEND shows the smallest error and best prediction results, featuring larger advantages and better stability.

7 Conclusions

Taking the prediction sequence of growth tend regarding power suppliers' electricity sales and the residual prediction sequence of electricity sales, prediction model of nonlinear regression combination with optimal weight of electricity sales in electricity market is brought forth. At the same time, the minimum fitting variance combination with weight calculation is designed to obtain two sets of weight coefficient that have advantages of both RBF neutral network and LLSVM. Finally cuckoo algorithm with extended search space is designed to realize model resolution. The model overcomes the drawback in single prediction measurement to get better prediction results of electricity sales, which provided strong foundation for the determination of power supply companies in electricity market. The next step will be to consider the external objective factors that affect the electricity sales volume, including the electricity side factors and the government regulatory factors, so as to comprehensively consider the sales volume and further improve the prediction accuracy.

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