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PLS-SVR Optimized by PSO Algorithm for Electricity Consumption Forecasting

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Abstract: The development of smart grid and electricity market requires more accurate electricity consumption forecasting. The impact of different parameters of Support vector regression (SVR) on electricity consumption forecasting, and the parameters of SVR model were preprocessed through Particle Swarm Optimization (PSO) to get the optimum parameter values. For the input variables of forecasting model are normalized to reduce the influence of different units on SVR model, and using the partial least square method (PLS) can solve the multicollinearity between the independent variable. A actual data is employed to simulate computing, the result shows proposed method could reduce modeling error and forecasting error, and compared with back-propagation artificial neural networks (BP ANN) and single LS-SVR algorithm, PSO-PLS-SVR algorithm can achieve higher prediction accuracy and better generalized performance.

Keywords: Forecasting, Support vector regression, Particle Swarm Optimization, electricity consumption

1. Introduction

Energy is the foundation of economic development, and electricity is one of the major energy sources. With the improvement of living standards and the acceleration of industrialization, due to the huge amount of capital investment and the lengthy construction time required in electricity capacity expansion projects[1]. In order to meet the massive requirement of industry, and to make the economy develop smoothly, it is very important to make a nation's electricity policy is crucial importance, as it will not only guide the electric utility industry of the country, but will also affect the electricity consumption and atmospheric conditions[2,3]. A good electricity consumption is a prerequisite for the effective development of energy policies, as it can reduce the future electricity consumption error in electric power planning. Therefore, producing accurate electricity consumption forecasts is very important.

In recent years, the forecasting method for electricity consumption can be divided into three categories: time series predictive model, statistical regression analysis predictive model, and artificial intelligence predictive model[4–10]. Time series models, such as the autoregressive integrated moving average (ARIMA) model and grey model, which requires only the historical data of prediction objects to forecast its future evolution, have been widely used in electricity demand forecasting. The forecasting precision of the model depends on the stability and regularity of original data sequence.

In contrast, statistical regression analysis explores the relationship between dependent variable and independent variables, and build regression forecasting model for them. However, the forecasting results depend on the selection of independent variables.

Artificial intelligence forecasting techniques, such as artificial neural networks and support vector regression, are widely applied in forecasting approaches, and have extremely good forecasting performance. However, a large number of training data have been usually required to produce accurate forecasting results.

Since electricity consumption is generally influenced by environment and economy, such as temperature, industry increasing valueconsumer price index, gross domestic product, and so on. Therefore, it is helpful to eliminate multicollinearity among variables before electricity consumption forecasting. PLS can decrease effectively the correlation between the input influence factors. As a supervised feature extraction method, PLS

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was superior to unsupervised principle component analysis (PCA)[11].

Support Vector Machine (SVM), proposed by Vapnik[12], is especially used to the problem of deal with statistical learning of small samples. It has better generalization capability to ANN and Fuzzy model. By solving a quadratic programming problem, SVM can solve the practical problems well such as small sample, nonlinear, high dimension and local minimum. SVM is used to solve the problems including classification and Function fitting regression. Applying the SVM in regression analysis, we can get support vector regression. At present SVR has been widely used in many fields [13–16], and it has good prediction ability. However, there are few studies on parameters optimization method of SVR. In practical application, they mostly determine parameters by experience or using the trial method to get to, which cause as the improper parameter selection and makes the final prediction result is bad.

This study employs the electricity consumption data from 2004 to 2009 in Jiangsu Province of China to explore the forecasting performance of the SVR model in practical application. By implementing the Particle Swarm algorithm and cross validation to optimize the parameters of PLS-SVR, we construct PSO-PLS-SVR forecasting model. The experimental results show that the SVR approach not only has precise forecasting results using small amounts of data, but also meets forecasting requirements of governments.

The rest of this paper is organized as follows. Section 2 introduces the building of procedure of the PLS-SVR forecasting model, and Section 3 uses PSO optimizes the parameters of PLS-SVR, while Section 4 presents its performance and compares it with that of other forecasting methods. Finally, Section 5 concludes this study.

2. The Principle of PLS-SVR Model

2.1. PLS Regression Model

PLS is a reasonably new Multivariate statistical method of data analysis, which is a method for constructing predictive models when the explanatory variables are many and highly collinear. Its main focus is to extract the potential components, which uses data of multiple dependent variables and independent variables for analyzing and modeling.

First, let E_0^T and F_0^T are separately the transposed matrix of E_0 and F_0, then we can obtain the eigenvector w_1 associated with the largest eigenvalue of the matrix $E_0^T F_0 F_0^T E_0$, the component t_1 is:

$$\begin{aligned} w_1 &= \frac{E_0^T F_0}{\left\|E_0^T F_0\right\|}; \\ t_1 &= E_0 w_1; \\ p_1 &= \frac{E_0^T t_1}{\|t_1\|^2}; \\ E_1 &= E_0 - t_1 p_1^T. \end{aligned} \tag{1}$$

In the same way, we can obtain the eigenvector w_h associated with the largest eigenvalue of the matrix $E_0^T F_0 F_0^T E_0$, the component t_h is:

$$\begin{cases} w_h = \dfrac{E_{h-1}^T F_{h-1}}{\left\|E_{h-1}^T F_{h-1}\right\|}; \\ t_h = E_{h-1} w_h; \\ p_h = \dfrac{E_{h-1}^T t_h}{\|t_h\|^2}; \\ E_h = E_{h-1} - t_h p_h^T. \end{cases} \tag{2}$$

If the rank of $X_{n\times p}$ is A, we can use cross validation method for identifying, then,

$$\begin{cases} E_0 = t_1 p_1' + \cdots + t_A p_A', \\ F_0 = t_1 r_1' + \cdots + t_A r_A' + F_A, \end{cases} \tag{3}$$

Where $r_1', \ldots, r_A'$ is a row vector of regression coefficient, F_A is error matrix. Concerning the least square regression equation of F_A is

$$\hat{F}_0 = t_1 r_1 + t_2 r_2 + \cdots + t_h r_h, \tag{4}$$

because $t_1, t_2 \ldots, t_A$ can express as the linear combination of $E_{01}, E_{02}, \ldots, E_{0A}$, Hence, according to the property of PLS regression,

$$t_i = E_{i-1} W_i = E_0 W_i^* \quad (i = 1, 2, \cdots, h), \tag{5}$$

where $W_i^* = \prod_{k=1}^{i-1} (I - W_k P_k^T) W_i$.

Then equation (5) substitute into equation (4),

$$\begin{aligned} \hat{F}_0 &= r_1 E_0 W_1^* + r_2 E_0 W_2^* + \cdots + r_h E_0 W_h^* \\ &= E_0 (r_1 W_1^* + r_2 W_2^* + \cdots + r_h W_h^*). \end{aligned} \tag{6}$$

Let $y^* = F_0$, $x_i^* = E_{0i}$, $\alpha_i = \sum_{k=1}^{h} r_k W_{ki}^*$ $(i = 1, 2, \cdots, m)$. Then, equation (6) can be revert to the regression equation of standardized variable as follows

$$\hat{y}^* = \alpha_1 x_1^* + \alpha_2 x_2^* + \cdots + \alpha_m x_m^*. \tag{7}$$

Equation (7) can be written down raw variable y, and its PLS regression equation of estimated value $\hat{y}$ is obtained,

$$\hat{y} = \left[E(y) - \sum_{i=1}^{m} \alpha_i \frac{S_y}{S_{x_i}} E(x_i)\right] + \alpha_1 \frac{S_y}{S_{x_i}} x_1 + \cdots + \alpha_m \frac{S_y}{S_{x_m}} x_m. \tag{8}$$

2.2. LS-SVR Model

Suppose a set of data (x_i, y_i), $i = 1, 2, \ldots, n$, $x \in R^n$ are given as inputs, $y \in R^n$ are the corresponding outputs. *SVM* regression method is to find a nonlinear map from input space to output space and map the data to a higher dimensional feature space through the map, then the following estimate function is used to make linear regression.

$$y = f(x, \omega) = \omega^T \varphi(x) + b, \tag{9}$$

where $\varphi(x)$ maps the input data to a higher dimensional feature space, ω is a weight vector, and b is the threshold value. $f(x)$ is the regression estimate function which constructed through learning of the sample set. In the *LS-SVR* for function estimation, the objective function of optimization problem, is defined as

$$\min_{\omega,b,\xi} J(\omega, b, \xi) = \frac{1}{2}\omega^T \omega + \frac{1}{2} C \sum_{i=1}^{N} \xi_i^2 \tag{10}$$

$$s.t. \quad y_i = \phi(x_i)\omega + b\xi_i, i = 1, \ldots, N, \tag{11}$$

where $\omega \in R^h$ is the weight vector and $\varphi(\cdot)$ is non-linear mapping function, $\xi_i \in R^{N*1}$ is relaxation factor, $b \in R$ is the skewness, while $R > 0$ is penalty factor. We can easily get the function as

$$L(\omega, b, \xi_i, \alpha_i) = \frac{1}{2}\|\omega\|^2 + \frac{1}{2} C \sum_{i=1}^{N} \xi_i^2 - \sum_{i=1}^{N} \alpha_i \left[\varphi(x_i)\omega + b + \xi_i - y_i\right]. \tag{12}$$

According to the KTT, we get

$$\begin{bmatrix} 0 & E^T \\ E & \varphi\varphi^T + C^{-1}I \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix}. \tag{13}$$

Then, we have the *LS-SVR* regression function model,

$$f(x) = \sum_{i=1}^{N} \alpha_i K(x_i, x_j) + b, \tag{14}$$

$$K(x_i, x_j) = \phi(x_i)\phi(x_j) = \exp(-\|x_i - x_j\|)/2\delta^2, \tag{15}$$

in which the regularization parameter C and kernel breadth δ is the crucial parameters of *LS-SVR*.

2.3. PLS-SVR Model

The processing of *PLS-SVR* is divided into following steps:

Step 1: *PLS* for feature extraction of the raw data

From compute the equation (1) and equation (2) we can contain the vector t_i, p_i and w_i. They respectively constitute the score matrix $T_{\text{train}} = [t_1, \ldots, t_h]$, load matrix $p = [p_1, \ldots, p_h]$ and correlation coefficient matrix $w = [w_1, \ldots, w_h]$ of training samples.

Step 2: *LS-SVR* Modeling

After h dimensions have been extracted. Which can use T_{train}, y_{train} train the *LS-SVR* model, it contain *Lagrange* multiplier and bias term b of the optimal parameter. On this basis, the following equation can be written,

$$\begin{bmatrix} 0 & E^T \\ E & \varphi\varphi^T + C^{-1}I \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ y_{train} \end{bmatrix}. \tag{16}$$

Then using equation (16) can result in coefficient b and α.

Step 3: *PLS-SVR* model prediction

Calculate the prediction value of test sample data is

$$y_{predict}(t) = \sum_{i=1}^{N} \alpha_i K(x_i, x_j) + b \tag{17}$$

Finally, we can get the flow chart of PLS-SVR forecasting model see Figure 2.1.

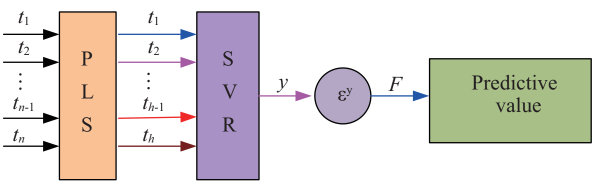

Figure 2.1 The construction of PLS-SVR model

3. PSO-PLS-SVR Forecasting Model

3.1. Parameter Selection and Optimization of PLS-SVR Based on PSO

By the process of SVR algorithm, we know that ε of the insensitive loss function, penalty factor C and σ^2 of the radial basis function are different, then we can have different SVR model. Therefore, we focus on the choosing of ε, and finding the approximate optimal of (C, σ^2) using SVR with particle swarm algorithm, thus construct the PSO-SVR model for regression forecasting.

The core idea of the PSO algorithm to get best parameters is considering (C, σ^2) to be the location of particle while at the same time, setting a reasonable target function. When each particle is searching location, its aim is to minimize or maximize target function, thus can locate its optimization location in history or group field, and change its location on the second foundation.

Letting the target function as the mean square error function,

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2, \quad (18)$$

where y_i is the actual value, $\hat{y}_i$ is the predictive value.

We note (C,σ^2) is $x = (x_1,x_2)$, which consists of particle group. So the location of i the particle can be expressed as $x_i = (x_{i1},x_{i2})$. Let the velocity of i the particle be $v_i = (v_{i1},v_{i2})$, its historical optimal spot is $p_i = (p_{i1},p_{i2})$ and its global optimum is $p_g = (p_{g1},p_{g2})$. So the particle location and velocity change based on the function as follows:

$$\begin{cases} v_{ij}^{(t+1)} = wv_{ij}^{(t)} + c_1\delta_1(p_{ij}^{(t)} - x_{ij}^{(t)}) + c_2\delta_2(p_{gj}^{(t)} - x_{ij}^{(t)}) \\ x_{ij}^{(t+1)} = x_{ij}^{(t)} + v_{ij}^{(t+1)}, \quad j = 1,2 \end{cases} \quad (19)$$

where c_1 and c_2 are called learning factors, which usually are 2. δ_1 and δ_2 are pseudo-random numbers in $[0,1]$. w is inertia weightwhose value will influence the explore and development ability of algorithm. We let it to be time-varying weight.

Set $w \in [w_{\min}, w_{\max}]$, $w_i = w_{\max} - \frac{w_{\max} - w_{\min}}{Iter\_\max} * i$, Where $Iter\_\max$ stands for the maximum iteration times. Let $[w_{\min}, w_{\max}] = [0.1, 0.9]$.

Next we use the Cross Validation Method to optimize PSO-PLS-SVR modelso we can find out the more reasonable parameter set (C,σ^2), thus can get smaller estimated error. The common K Cross validation (K-CV) method is to divide the sample set into K groups. The $K-1$ groups are trained sets and the other group is the test group. Then repeat this K times. After all the K groups becoming the test set, we have K models. Finally, we use the average of the mean square errors produced by the K models.

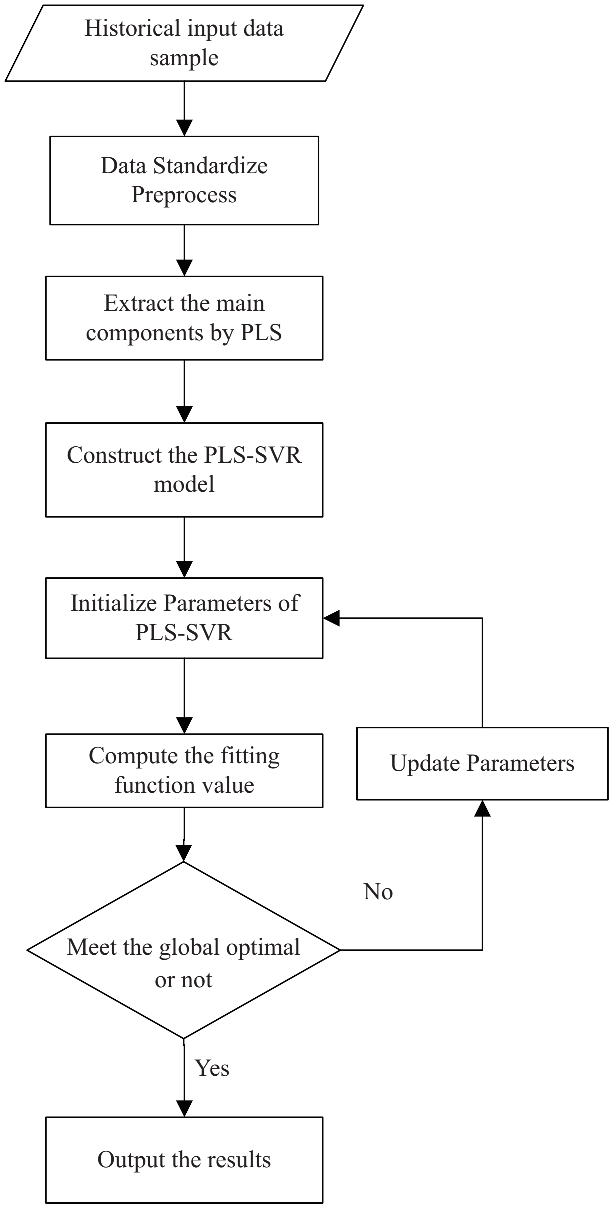

Figure 3.1 The flow chart of PSO-PLS-SVR model

3.2. The modeling process of PSO-PLS-SVR prediction model

The construction of the PSO-PLS-SVR model is described in detail, below:

4. Data and experimental results

4.1. Data analysis and preprocess

The experiment aims to examine the effectiveness of the forecasting model proposed in this paper. This study selects the overall electricity consumption of Jiangsu Province from January 2007 to October 2009. We consider the data of January 2007 to July 2009 to be the trained sets, and thus construct PSO-PLS-SVR forecasting model. We think the data from August to October 2009 are the predictive test sets.

Meanwhile, in order to eliminate of dimension influence, we apply the 0-1 standard method, that is

$$x^* = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (20)$$

So the new data sets are all in $[0,1]$, and the data sets also eliminate the diversity units, which can interfere with the forecasting results.

Due to electricity consumption trends fluctuate by influencing factors. Thus we choose the influencing factors include Average Month Temperature (AMT), Social Retail Sales of Consumer Goods (SRSCC), Industry Increasing Value (IIV), Consumer Price Index (CPI) and Gross Value of Export-Import (GVEI). Hence, we select five influencing factors as input variable. Considering there has multicollinearity between the influencing factors. This paper use PLS to extract the main component variable. Finally, we can get the main influencing include AMT, IIV and GVEI. Then we can get the standardized data for the experimental analysis as shown in Table 4.1.

As the error ε of non-sensitive loss function is too small, even though it can enhance the accuracy of trained model, and it can reduce generalization ability. On the contrary, if ε is too bigger, the constructed model hardly can depict the change of electricity consumption. After repeated experiment, we define ε to 0.01. It can both guarantee the fitting accuracy and the generalization ability of model.

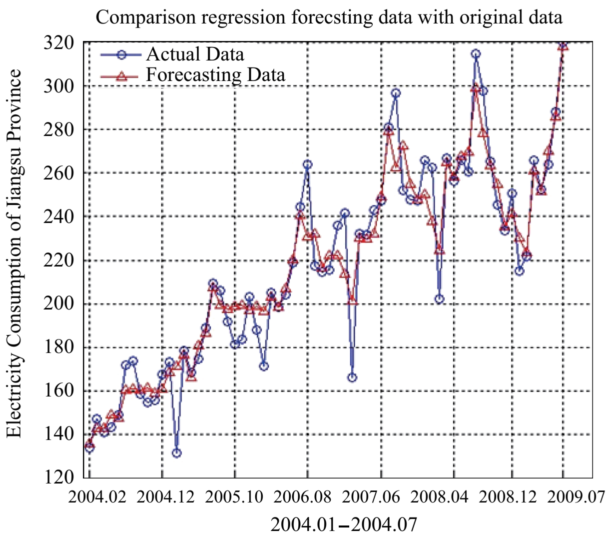

Figure 4.1 The comparison of forecasting result

4.2. Experiment study

In this sub-section, we construct and analyze the experiment of the proposed model in this paper using matlab tools, the predictive result of regression forecasting using PSO-PLS-SVR forecasting model is showed in figure 4.1.

Table 4.1 The standardized data of electricity consumption

Month	Actual Data	AMT	IIV	GVEI
2007.11	−0.5499	−0.6467	−1.1757	−0.4207
2007.12	0.0625	−1.1832	−1.2434	0.1248
2008.01	−0.0437	−1.5365	−1.5636	−0.2124
2008.02	−2.0560	−0.9902	1.331	−1.5246
2008.03	0.0895	−0.6829	0.5339	0.1136
2008.04	−0.2572	−0.1138	0.2403	−0.2385
2008.05	0.0595	0.6943	1.1632	0.2638
2008.06	−0.1167	0.9105	0.7437	−0.2017
2008.07	1.6960	1.2406	−0.1792	1.2472
2008.08	1.1227	1.3658	0.5759	1.0246
2008.09	0.0481	0.7853	−0.389	0.1357
2008.10	−0.6237	0.1593	-1.1861	−0.5021
2008.11	−1.0194	−0.6487	−1.2701	−1.3251
2008.12	−0.4391	−1.1837	−1.1738	−0.5072
2009.01	−1.6331	−1.4337	−1.4782	−1.5941
2009.02	−1.4136	−0.9801	1.2635	−1.7118
2009.03	0.0658	−0.5924	0.4737	0.2031
2009.04	−0.3840	−0.1036	0.3104	−0.4170
2009.05	0.0017	0.7132	1.0946	0.2205
2009.06	0.7970	0.8903	0.8213	0.5281
2009.07	1.8568	1.1205	−0.2247	1.3639
2009.08	1.7928	1.2736	0.6168	1.5812
2009.09	0.6358	0.6902	−0.4125	0.7264
2009.10	0.3084	0.1473	−1.2536	0.2631

Besides, we give out the regression fitting results and Relative Errors (RE) from November 2007 to July 2009, the prediction results and relative errors from August to October 2009. It is showed in the Table 4.2.

Where the relative error is $RE = (\hat{y}_i - y_i)/y_i$, y_i is the real value, $\hat{y}_i$ is the predicted value.

From the result of Table 4.2, PSO-PLS-SVR leads to a satisfactory result of electricity consumption from August to October 2009, and the relative errors confines in 10%. Moreover, the relative errors of last two months are confines to 5%.

In order to assess the rationality of the model is proposed in this paper. We compare the PSO-PLS-SVR model with the BP Neural network model and LS-SVRthe analysis result is showed as Table 4.3 and Table 4.4.

Where $MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2$,

Table 4.2 The fitting regression forecasting relative errors

Month	Actual Value	Predictive Value	Relative Error
2007.11	247.42	247.6248	0.08%
2007.12	265.77	250.3068	−5.82%
2008.01	262.59	237.8922	−9.41%
2008.02	202.29	224.3531	7.91%
2008.03	266.58	264.6364	−0.73%
2008.04	256.19	258.1686	0.77%
2008.05	265.68	267.5641	0.71%
2008.06	260.4	269.3166	3.42%
2008.07	314.72	299.0822	−4.97%
2008.08	297.54	277.8595	−6.61%
2008.09	265.34	263.3971	−0.73%
2008.10	245.21	254.8402	3.93%
2008.11	233.35	235.2366	0.81%
2008.12	250.74	241.7309	−3.59%
2009.01	214.96	230.0365	7.01%
2009.02	221.54	223.4283	0.85%
2009.03	265.87	260.982	−1.84%
2009.04	252.39	251.4928	−0.36%
2009.05	263.95	270.2079	2.37%
2009.06	287.78	285.8141	−0.68%
2009.07	319.54	317.6724	−0.58%
2009.08	317.62	287.4877	−9.49%
2009.09	282.95	295.7437	4.52%
2009.10	273.14	261.7786	−4.16%

$R^2 = \frac{\left(\sum_{i=1}^{n}(y_i-\bar{y})(\hat{y}_i-\bar{\hat{y}})\right)^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2\sum_{i=1}^{n}(\hat{y}_i-\bar{\hat{y}})^2}$, y_i is the actual value, $\hat{y}_i$ is the predictive value, $\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i$, $\bar{\hat{y}} = \frac{1}{n}\sum_{i=1}^{n} \hat{y}_i$.

MSE measures the deviation of predictive value from the actual value. The *MSE* is smaller shows that deviation degree is smaller, and the predictive precision of the forecasting model is more accurate.

R^2 measures the fitting degree of the forecasting modelthe value of R^2 is the bigger ($0 \leqslant R^2 \leqslant 1$), the fitting degree of the model is higher. Meanwhile, it reflects the extent that the dependent variables can be explained by the independent variables.

Besides, from Table 4.3 and Table 4.4, we can see that the PSO-PLS-SVR model is superior to BP Neural Network and LS-SVR both from MSE and fitting degree.

Table 4.3 Relative error comparison with other forecasting method ($\varepsilon = 0.01$, $K = 3$)

Month	PSO-PLS -SVR	BP-ANN	LS-SVR
2007.11	0.083%	7.54%	8.97%
2007.12	−5.82%	−12.55%	−10.68%
2008.01	−9.41%	5.87%	−2.98%
2008.02	7.91%	−2.95%	9.13%
2008.03	−0.73%	−10.85%	−7.25%
2008.04	0.77%	8.42%	5.21%
2008.05	0.71%	6.58%	−4.51%
2008.06	3.42%	−13.52%	9.61%
2008.07	−4.97%	7.26%	−8.13%
2008.08	−6.61%	-9.53%	4.16%
2008.09	−0.73%	7.15%	−3.52%
2008.10	3.93%	−6.86%	−5.38%
2008.11	0.81%	9.24%	6.48%
2008.12	−3.59%	6.25%	−7.53%
2009.01	7.01%	5.51%	−4.25%
2009.02	0.85%	−8.25%	5.36%
2009.03	−1.84%	11.15%	1.84%
2009.04	−0.36%	−6.78%	−5.21%
2009.05	2.37%	−8.45%	−8.35%
2009.06	−0.68%	−9.21%	−3.36%
2009.07	−0.58%	5.32%	2.13%
2009.08	−9.49%	−12.54%	−3.25%
2009.09	4.52%	−9.27%	8.16%
2009.10	−4.16%	−11.02%	9.14%

Table 4.4 The analysis result of other error evaluation indicators

	PSO-PLS-SVR	BP-ANN	LS-SVR
MSE	0.00489006	0.0841958	0.0602458
R^2	92.3001%	85.3185%	89.5624%
(C,σ^2)	(49.0636,8.5909)	–	–

5. Conclusion

The research of this paper is based on SVR to construct model for electricity consumption forecasting. We solve the problems of parameters selection. We use the particle swarm optimization to find out approximate optimal value and at the same time, and recur to the PLS method to lower input dimensions. Thus we can construct PSO-PLS-SVR forecasting model. From the final forecasting results, we can draw a conclusion confidently that the model proposed with higher accuracy which compared with BP Neural Network and LS-SVR forecasting model. On the one hand, SVR can solve the non-linear, big volatility problem. On the other hand, the parameters selection problems can also be solved by particle swarm optimization algorithm.

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