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Mid-Long Term Load Forecasting Based on Combination Forecasting Model

J. G. Zhou†, W. Liu†*, & Q. Song‡

†School of Economics and Management, North China Electric Power University, Baoding, 071003, China,
*Email: 2216449490@qq.com

‡State Grid Jining Power Supply Company, Jining, 272100, China

ABSTRACT: The load forecasting of mid-long term power system has diversity, complexity and many uncertainties, which is a typical nonlinear system. In this paper, multiple linear regression analysis method will be used to select factors from all of the relevant factors, which can optimize the network structure, and reduce the input space dimensions of the combination forecasting. Then the combination forecasting model is used for forecasting, which is based on the RBF neural network and support vector machine. The empirical results show that the forecasting accuracy is higher after screening factors, and the forecasting accuracy of combination forecasting model is higher than the single forecasting models' whether the factors are screened or not, which verifies the validity of the model.

KEYWORDS: Power Load Forecasting; Multiple Linear Regression; Radial Basis Function Neural Network (RBFNN); Support Vector Machine (SVM), Combination Forecasting.

INTRODUCTION

Load forecasting of electric power system is the premise of network planning, production run, generator maintenance and other work arrangements [1]. According to the time interval, the predicted points of load forecasting can be divided into long, medium, short and ultra short-term [2]. Load forecasting of long-term power system is an important basis for the work of departments of electric power system about planning, marketing, market trading, scheduling etc [3].

Load forecasting of long-term power system which is influenced by the economic, social, demographic, climate and other factors is a typical nonlinear system and there is diversity, complexity and many uncertainties [3,4].For a long time, domestic and foreign scholars do a lot of research on the theory and method of power load , the main forecasting methods are: grey forecasting method, regression forecasting method, elastic coefficient method, neural network method and combination forecasting method [5-9]. As for artificial neural networks, scholars use the learning function of neural network to let the computer learning the mappings contained historical load data, and then use this mapping to predict the future load. The artificial neural network is an advanced means of long term load forecasting because it has many fine features such as large-scale distributed parallel processing, nonlinear mapping ability, self-organizing, self-learning, associative memory etc. After study found that radial basis neural network [11] and support vector machine [12] have a unique advantage in solving problems of nonlinear systems, this article will use a combination of both methods to build a optimal model of combination forecasting. Because the strong correlation of the load data will affect the network structure and the accuracy of prediction, we select multiple linear regression analysis to analyze the related factors of long term load forecasting, choose the main factors and exclude the small impact factors. Using a combination forecasting method based on multiple linear regression analysis in this paper not only can optimize the network structure, improve the accuracy of prediction, meet the need of realistic forecasting, and can verify the validity of the method though an example.

THEORETICAL BASIS

Multivariate Linear Regression

Multiple linear regression analysis is a method which is used to study a interdependence relationship between a random variable or a dependent variable Y with one or more independent variables(X1 ~ Xn), using statistical analysis methods and functions to analysis and make a formal description of the relationship about the substance, features, and variation. It is a simple method had the strong ability to explain the advantages of the relationship

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between the variables and has a wide range of applications in the social, economic, technological, and many fields of natural science. The formal description of the model of multiple linear regression analysis as shown in Eq.1:

$$Y=\beta_0+\beta_1X_1+\beta_2X_2+\ldots\ldots+\beta_nX_n+\varepsilon. \tag{1}$$

Where β_0 is the constant term, it represents the estimated value of the population mean of dependent variable Y when all independent variables to 0. $\beta_1 \sim \beta_n$ represent the regression coefficients, there are two types: standardized regression coefficients and non-standardized regression coefficients.

We add independent variables which have significant impact on the dependent variable to the regression model to construct multivariate linear regression analysis model through a variety of ways of regression analysis. We select the variables impacted on the dependent variable greatly by the way of stepwise regression, and at the seam time excluded the variables impacted smaller to build the regression equation.

Radial Basis Neural Network

Radial basis function (RBF) method is a technique interpolated in a high-dimensional space. The first to use this technique was by Bromhead and Love in 1998, they proposed a new method of neural network learning. RBF neural network which is proposed on the basis of drawing lessons from biological local regulation and the knowledge of overlap receiving area is a artificial neural network by using a local reception on a domain to perform network mapping and has the characteristics of optimal approaching and global approaching.RBF neural network also has many other good characteristics such as simple structure, concise training and fast convergence of learning. It can approach any nonlinear function and has been widely used in time series analysis, pattern recognition, nonlinear control, and graphics processing. Therefore, RBF neural network is a ideal choice for long term load forecasting.

Support Vector Machine

Support Vector Machine (SVM) is proposed by Vapnik etc. It is on the basis of statistical learning theory of the VC dimension theory and the principle of structural risk minimization. In order to obtain the best outreach capacity, SVM can make a best compromise between complexity of models and learning ability based on a limited sample of information. Support vector machine show many unique advantages in solving nonlinear and the recognition of high dimensional pattern and be able to promote the use of problems of other machine learning such as function fitting. Therefore, the application of support vector machine can better solve the problem of long term load forecasting.

ESTABLISHMENT OF COMBINATION FORECASTING MODEL

Combination forecasting method synthesizes the results of a variety of forecasting methods to make a accurate prediction according to establishing a combined forecasting model. Because the combination forecasting model can use a variety of sample information to a large extent, consider problems more systematic and comprehensive than single forecasting model. It can effectively reduce the impact of random factors by a single predictive model, thereby improving the accuracy and stability of prediction. In this paper, we use the method of the combination of SVM and RBF neural network model to establish a model of constant weight combination to improve the accuracy of prediction.

RBF Neural Network Model

RBF neural network based on the theory of function approximation is a class of forward network whose learning is equivalent to finding the best-fit plane of training data in a multidimensional space. Each hidden layer neuronal transfer function of the network constitutes a base function of the fitting plane. Generally use Gaussian function, which was expressed as Eq.2:

$$R_i(x)=\exp(-\frac{\|x-c_i\|^2}{2\sigma_i^2})\ \text{i=1, 2,…, m.} \tag{2}$$

Where: x is n-dimensional entered vector; c_i is the center of i-th basis function;σ_i is the planning factor of the i-th base function; *m* is the number of hidden nodes. $\|x-c_i\|$ is the norm of the vector x-c_i, it usually represents the distance between x and c_i; there is a unique maximum of $R_i(x)$ at c_i , with the increasing of $\|x-c_i\|$, Rix decay to zero rapidly. For a given input,only a small portion near the center of *x* is activated. Set input layer entered as X = (x1, x2, ..., xn, ..., xn), the actual output is Y = (y1, y2, ..., yk, ..., yp).The input layer achieve a linear mapping from

$X \rightarrow R_i(x)$, the output layer achieve anonlinear mapping from R (X) $\rightarrow$ y_k, k-th neuronal network output in the output layer is Eq3:

$$y_k = \sum_{i=1}^{m} w_{ik} R_i(x) \qquad \text{k=1, 2,…, p.} \tag{3}$$

Where: n is the input layer nodes; m is the hidden nodes; p is the output layer nodes; w_{ik} is the connection weights of the i-th neuron of hidden layer and the k-th neuron of output layer; $R_i(x)$ is the action function of i-th neuron of the hidden layer. From a structural point of view of RBF network, when the weight and the threshold of neurons of the hidden layer and output layer are determined, at the seam time the output of the network is determined too. So learning process of RBF network is a modification of weights and thresholds of each network layer. We select newrb function to create an approximate RBF network.

Support Vector Machine Model

Assuming that there is a sample training set (x_i, y_i) where $x_i = R^n$ is input space, y_i is the output value. Construct a linear function as Eq.4:

$$f(x) = w\varphi(x) + b \quad . \tag{4}$$

Wherein w is the input weight vector of space; b is the threshold. Insensitive loss function (ε) takes the form as Eq.5:

$$|y_i - f(x_i)| = \{ \begin{matrix} 0, |y_i - f(x_i)| < \varepsilon \\ |f(x_i) - y_i| - \varepsilon, \text{else} \end{matrix} \quad . \tag{5}$$

Empirical risk function is as Eq.6:

$$R_{emp} = \sum_{i=1}^{I} |y_i - f(x_i)| \tag{6}$$

According to the structural risk minimization of statistical theory, the regression function of support vector machine is determined by minimizing the risk function of mechanism, so SVM regression algorithm can be expressed as the following optimization problem constrained by conditions as Eq.7:

$$\min\left(\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{I}|y_i - f(x_i)|\right)$$

$$s.t.\{ \begin{matrix} y_i - w\varphi(x) - b \le \varepsilon + \xi \\ w\varphi(x) + b - y_i \le \varepsilon + \xi^* \end{matrix} . \tag{7}$$

Where ξ and ξ* respectively denote the upper and lower training error, ξ and ξ*≥0.

Due to the high dimensionality of feature space, directly solving the formula is almost impossible, we use dual skills of Wolfe and introduce the dot product kernel function k (x_i, x_j), turn the problem into seeking the dual problem such as Eq.8.

$$\max\left[\left(\alpha, \alpha^*\right) - \frac{1}{2}\sum_{i=1}^{I}\sum_{j=1}^{I}(\alpha, \alpha^*)^T(\alpha, \alpha^*)\langle x_i, x_j\rangle + \sum_{i=1}^{I}(\alpha, \alpha^*)\right]$$

$$s.t.\sum_{i=1}^{I}(\alpha,\alpha^*)=0,0\le\alpha,\alpha^*\le C. \tag{8}$$

The regression estimation function is Eq.9:

$$f(x)=\sum_{i=1}^{I}(\alpha,\alpha^*)k(x_i,x)+b. \tag{9}$$

Assuming that there are m stages data of electric load and n impact indicators totally. X = {x_1, x_2, ..., x_m} is a set of inputs, Y = {y_1, y_2, ..., y_m} is a set of outputs.

Combination Forecasting Model

Combined Forecasting Model

Combine support vector machine model with RBF neural network model to establish the following combination forecasting model as Eq.10:

$$Y_t=\alpha*T_t+\beta*I_t+\varepsilon. \tag{10}$$

Where Y_t is predicted value; T_t is the predictive value of RBF neural network model; I_t is the predicted value of support vector machine model; t is time numbers;α, β are the weight coefficient, respectively represent proportionality coefficient of the predictive value of the RBF neural network model and SVM share in the entire combined forecasting model ;ε represents the error value of electric load forecasting caused by other factors, in a certain time can be regarded as constant.

In the above formula the constraints of 3 numerical values(α, β, and ε) as Eq.11:

$$s.t.\begin{cases}\alpha+\beta\le 1;\\ 0<\alpha,\beta<1;\\ \varepsilon\ge 0\end{cases} \tag{11}$$

Determination of Weight

In the combined model the commonly used methods of empowerment are the method of arithmetic mean, reciprocal method of mean square, reciprocal method of variance, coefficient method of binomial, simple weighting method, optimal weighting method and method of ordered weighted etc. The first three methods are more common, in which the accuracy of the calculation of reciprocal method of variance higher than the other models. We select reciprocal method of variance solving the parameter values such as α, β and ε and so on such as Eq.12.

$$w_j=\frac{D_j^{-1}}{\sum_{j=1}^{J}D_j^{-1}},\ \text{j=1, 2,…, J.} \tag{12}$$

Where D_j is the sum of squared errors of j-th model, the method assign the high weight to the model which squared error is small as Eq.13.

$$D_j=\sum_{j=1}^{N}(x_t-x_t(j))^2\ . \tag{13}$$

EMPIRICAL RESEARCH

In this section we select the relevant data from 1990 to 2012 of China to do a empirical research. Total consumption of electricity is the dependent variable, the influencing factors: GDP, per capita GDP, the value added of the primary industry, the value added of secondary industry, the value added of tertiary industry, the total population, total investment in fixed assets,total retail sales of social consumer goods, the actual using of foreign investment and the level of consumption, the data in Table 1. There are several factors that have a strong correlation, they will affect the network structure and the accuracy of the prediction of the model. Firstly, we choose the multiple linear regression analysis to analyze the factors affecting the long-term electric load forecasting, excluding the factors that have small influence. Then we use the data before screening and screened to make a comparative analysis of electric load forecasting.

Factors Analysis of Electric Load Forecasting Based on Multiple Linear Regression

It is not the more independent variables the better for a model. We select the factors whose ability to explain the dependent variable is stronger, at the seam time the factors also have to make regression equation achieve optimal. Concrete practice:First, seting the value of the critical of probability of F teststatistic is 0.05 (variables added probability) and 0.10 (excluding variable probability), and then using the backward stepwise regression exclud independent variables whose probability more than 0.10 from the regression equation, until we achieve the optimal regression equation. Multiple linear regression analysis of the data in Table 1.

Table 1. The original sample data.

Yea r	Total social consumptio n / (million kilowatt hours)	Gross domesti c product / (billion yuan)	Gross domesti c product per capita / (billion yuan)	First industria l added value / (billion yuan)	Second industria l added value / (billion yuan)	Third industria l added value / (billion yuan)	Total populatio n / (million yuan)	Total investmen t in fixed assets / (billion yuan)	Total retail sales of social consumer goods / (billion yuan)	Actual utilization of foreign capital / (million yuan)	Resident consumptio n level / (yuan)
199	6230.4	6626.63	692.84	2654.90	2537.63	1626.01	114333	4517.00	8,300.10	1,028,900	833
199	6804.0	7081.87	740.65	2736.19	2628.78	1860.93	115823	5594.50	9,415.60	1,155,400	932
199	7455.4	7662.49	801.37	2869.88	2788.94	2110.71	117171	8080.10	10,993.70	1,920,300	1,116
199	8426.5	8823.93	922.84	3253.62	3272.34	2395.83	118517	13072.30	14,270.40	3,896,000	1,393
199	9260.4	10644.1	1113.20	4300.53	3771.37	2928.38	119850	17042.10	18,622.90	4,321,300	1,833
199	10023.4	12103.5	1265.83	5192.35	4231.67	3291.99	121121	20019.30	23,613.80	4,813,300	2,355
199	10764.3	12881.4	1347.19	5705.51	4453.24	3512.52	122389	22974.00	28,360.20	5,480,500	2,789
199	11284.4	13076.6	1367.61	5680.34	4472.60	3670.56	123626	25006.95	31,252.90	6,440,800	3,002
199	11598.4	12960.4	1355.45	5631.08	4266.51	3837.83	124761	28481.20	33,378.10	5,855,700	3,159
199	12305.2	12795.3	1338.19	5460.11	4150.80	3888.32	125786	29933.53	35,647.90	5,265,900	3,346
200	13472.4	13055.4	1365.39	5395.21	4211.18	4049.21	126743	33004.61	39,105.70	5,935,600	3,632
200	14633.5	13323.4	1393.42	5542.03	4220.63	4208.25	127627	37311.76	43,055.40	4,967,200	3,887
200	16331.5	13403.5	1401.79	5643.76	4183.20	4285.98	128453	43614.76	48,135.90	5,501,100	4,144
200	19031.6	13750.3	1438.07	5787.36	4300.98	4392.97	129227	55713.32	52,516.30	5,614,000	4,475
200	21971.4	14702.9	1537.69	6706.97	4581.81	4601.40	129988	70663.52	59,501.00	6,407,200	5,032
200	24940.3	15279.3	1597.97	6673.40	4845.35	4757.77	130756	89008.01	68,352.60	6,380,500	5,596
200	28588.0	15861.0	1658.81	6814.86	5059.55	4927.09	131448	110288.6	79,145.20	6,707,600	6,299
200	32711.8	17072.3	1785.50	7822.31	5334.62	5341.68	132129	137686.5	93,571.60	7,833,900	7,310
200	34541.4	18397.8	1924.12	8739.03	5749.13	5706.85	132802	173284.7	114,830.1	9,525,300	8,430
200	37032.2	18286.3	1912.45	8767.42	5532.38	5870.92	133450	225191.7	132,678.4	9,180,400	9,283
201	41934.5	19500.2	2039.42	9675.17	5858.58	6272.77	134091	278121.9	156,998.4	10,882,10	10,522
201	47000.9	21022.2	2198.59	10872.5	6248.60	6776.85	134735	344205.0	183,918.6	11,769,80	12,570
201	49591.0	21419.8	2240.17	11469.8	6177.69	7072.41	135404	414054.5	210,307.0	11,329,40	14,110

Table 2. Model Summary [f].

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.998[a]	.996	.993	1105.43054
2	.998[b]	.996	.994	1072.46554
3	.998[c]	.996	.994	1042.72509
4	.998[d]	.996	.994	1015.17538
5	.998[e]	.995	.994	1042.02579

a. Predictors: (Constant), Resident consumption level, Total population, Actual utilization of foreign capital, Second industrial added value, First industrial added value, Total investment in fixed assets, Third industrial added value, Total retail sales of social consumer goods

b. Predictors: (Constant), Resident consumption level, Total population, Actual utilization of foreign capital, Second industrial added value, Total investment in fixed assets, Third industrial added value, Total retail sales of social consumer goods

c. Predictors: (Constant), Resident consumption level, Total population, Actual utilization of foreign capital, Second industrial added value, Third industrial added value, Total retail sales of social consumer goods

d. Predictors: (Constant),Total population,Actual utilization of foreign capital, Second industrial added value, Third industrial added value,Total retail sales of social consumer goods

e. Predictors: (Constant), Total population, Second industrial added value, Third industrial added value, Total retail sales of social consumer goods

f. Dependent Variable: Total social electricity consumption

The data in Table 2 show the statistics of regression model, in which R squared is coefficient of determination to primarily measure the goodness of fit of the regression model or to illustrate the extent of the variation of the depedent variable explainted by the independent variable. As for R-squared it is the bigger and the better. In general, R-squared greater than 0.8 indicate that the fitting effect of sample points is very well for equation. The regression is divided into five steps to complete the form Model 1, Model 2, Model 3, Model 4 and Model 5, different factors for each model selected. It is shown that the correlation coefficient R and the coefficient of determination R square for each model are large, indicating the fitting effectan of the model is excellent.

Table 3. Excluded Variables[f].

Model					Partial	Collinearity Statistics
		Beta In	t	Sig.	Correlation	Tolerance
5	Gross domestic product	.256[e]	.208	.838	.050	.000
	Gross domestic product per capita	.257[e]	.208	.837	.051	.000
	First industrial added value	.032[e]	.117	.908	.028	.004
	Total investment in fixed assets	-.086[e]	-.199	.844	-.048	.001
	Resident consumption level	.585[e]	.994	.334	.234	.001
	Actual utilization of foreign capital	-.152[e]	-1.402	.179	-.322	.021

Data in Table 3 show the variables excluded by the backward regression in the process of regression analysis. The paper only shows the variables excluded by the last step considering space requirements. Finally we can obtaine the independent variable that are the total population, the second industrial added value, the third industrial added value and total retail sales of social consumer goods. 6 factors(GDP, per capita gross domestic product, the first industrial added value, fixed asset investment, the residents consumption level and the actual use of foreign investment) have been gradually removed. Note that the selected elements is related to the original data, therefore with the change of time and the influencing factors, the screening results will be dynamic changes. Thus, the independent variable to predict is not static in the future studies, each study need to be screened with the changes of historical data.

Electric Load Forecasting Based on Combination Forecasting Model

We select the data from 1990 to 2009 as a training set which are used to forecast total consumption of electricity from 2010 to 2012. Combination forecasting will be done twice, the data of before screening and screened are used to predict by the method of multivariate regression analysis. Then we will do a comparative analysis about the forecasting results. Before factor screening the dependent variable is total consumption of electricity, independent variables are 10 factors of GDP, per capita gross domestic product, the first industrial added value, the second industrial added value, the total population, fixed asset investment, total retail sales of social consumer goods, the actual use of foreign investment and consumption level. After factor screening the dependent variable is total consumption of electricity, independent variables are 4 factors of second industrial added value, third industrial added value, total population and total retail sales of social consumer goods. Forecasting results are shown in Table 4.

(1) Before Factor Screening

There are 10 independent variables in the model of combined forecasting before factor screening. Calculating the mean square error: the mean square error of RBF neural network model is 2782.30, the mean square error of SVM model is 387.11, the mean square error of combined forecasting model is 330.60.View of this, the degree of fit of the predicted value of the combination forecasting model and the actual value is higher, combined forecasting is necessary. From the view of data in the table, the different bewteen the predicted value of SVM model and the actual value of total consumption of electricity is not very big, the relative error of prediction and actual values of 2010 and 2011 is less than 1%, relative error in 2012 is only 2% or less. The accuracy of the prediction of RBF neural network is relatively low, and the fit is also relatively poor.

(2) After Factor Screening

There are 4 independent variables in the model of combined forecasting after screening by the analysis of multiple linear regression. Calculating the mean square error: the mean square error of RBF neural network model is 329.64, the mean square error of SVM model is 262.54, the mean square error of combined forecasting model is 240.15. View of this, the degree of fit of the predicted value of the combination forecasting model and the actual value is higher, combined forecasting is necessary. From the view of data in the table, the different bewteen the predicted value of RBF neural network model and SVM neural network model and the actual value of total consumption of electricity is not very big, the relative error of prediction of SVM neural network model and actual values is less than 1%, the relative error of prediction of RBF neural network model and actual values is 1%, the fit and accuracy of two models are very high. From the view of mean square error, the accuracy of SVM neural network model is higher than RBF neural network model.

Table 4. Result of forecasting and relative error.

Year	Actual value	Before factor screening					
		RBF predictive value	Relative error	SVM predictive value	Relative error	Combined forecast value	Relative error
2010	41934.5	40618.9501	-3.14%	42184.13	0.60%	42152.83	0.52%
2011	47000.9	43487.63599	-7.47%	47231.42	0.49%	47156.55	0.33%
2012	49591	46566.11162	-6.10%	50169.02	1.17%	50096.96	1.02%
Mean square error		2782.30		387.11		330.60	
Year	Actual value	After factor screening					
		RBF predictive value	Relative error	SVM predictive value	Relative error	Combined forecast value	Relative error
2010	41934.5	42114.69444	0.43%	41910.41	-0.06%	41989.7	0.13%

2011	47000.9	46528.44788	-1.01%	47038.5	0.08%	46840.54	-0.34%
2012	49591	49856.16142	0.53%	50043.54	0.91%	49970.81	0.77%
Mean square error		329.64		262.54		240.15	

(3) Comparative Analysis

As can be seen by the data in Table 4, either single or combination forecasting model the accuracy of prediction of after factor screening is greater than before. This shows that the multiple linear regression analysis extract the main factors from the original factors, at the seam time reserve the useful information of original data, optimize the network structure, effectively improve the prediction accuracy and meet the need of realistic forecast. Whether screening factor or not, the accuracy of prediction of combination forecasting model are higher than a single forecasting model. It shows that the combination forecasting model is scientific and rational, it combines the advantages of two predictive models to improve the accuracy and stability of the forecast.

CONCLUSIONS

In this paper, we use the multiple linear regression analysis to screen out factors of high degree of influence from all relevant factors, not only retain the useful information of original data, but also optimize the network structure, reducing the dimension of the input space of combination forecasting model. Combination forecasting model based on radial basis function neural networks and support vector machine combina the advantages of two predictive models, making the forecasting more comprehensive to improve the accuracy and stability. The analyses of examples verify the effectiveness of combination forecasting model we build. It will be widely used in the research of load forecasting of power system.

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