Software Engineering
2018; 6(1): 7-11
http://www.sciencepublishinggroup.com/j/se
doi: 10.11648/j.se.20180601.12
ISSN: 2376-8029 (Print); ISSN: 2376-8037 (Online)

Research on the Power Demand forecasting in Beijing-Tianjin-Tangshan Area Considering the Special Time Influence Based on Support Vector Machine Model

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To cite this article:
Zhonghua He, Tao Zhang, Fuqiang Li, Yuou Hu, Nana Li. Research on the Power Demand forecasting in Beijing-Tianjin-Tangshan Area Considering the Special Time Influence Based on Support Vector Machine Model. *Software Engineering*. Vol. 6, No. 1, 2018, pp. 7-11. doi: 10.11648/j.se.20180601.12

Received: December 13, 2017; **Accepted**: January 6, 2018; **Published**: January 19, 2018

Abstract: The accuracy of the power demand forecast will directly affect the planning, safety and stability of the power system. The power demand is greatly affected by the factors related to economic development. In addition, special events will also have impacts on the electricity consumption of industries, service industries and residents. In this paper, gray relational analysis and support vector machine intelligent algorithm are used to build a rolling power demand forecasting method based on the development of power economy. By considering the impact of special periods on power demand, this paper forecasts the power demand for special period in Beijing, Tianjin and Tangshan. Finally, the analysis shows that the electricity demand in Beijing, Tianjin and Tangshan in 2017 is 3,337 billion kwh.

Keywords: Beijing-Tianjin-Tang Region, Support Vector Machines, Special Period, Power Demand Forecasting

1. Introduction

Power demand forecasting is significant to the power planning, power system automation and safe generation, which is an important work for the power sector. According to the relationship between economic development and power demand growth, the demand for electricity is greatly affected by special events [1]. During the period of 2011-2015, the special events in Beijing-Tianjin-Tangshan area mainly included: the grand military parade on September 3, 2015, APEC meeting on 7-12 November 2014, the annual Spring Festival, May Day, and the national days. These kind of special events always cause industrial production halt, and increase the power demand for service industry and household, which make a certain impact on the demand of electricity. Therefore, it is necessary to study on the annual power demand forecasting considering the influence of special time in Beijing-Tianjin-Tangshan area, so as to guide the region power balance, medium and long term power supply, and power grid construction.

Different scholars have applied a variety of methods to the field of load forecasting and achieved varying degrees of success. These prediction methods can be divided into three categories: classical forecasting methods, traditional forecasting methods and modern forecasting methods [2-3]. Classic prediction methods including electricity consumption per unit output method, maximum number of hours, elasticity coefficient method, load density method and so on. These methods make full use of the experience of experts and relevant staff, combined with the correlation between variables to direction of the future trend of power load forecast [4]. Traditional forecasting methods mainly include regression analysis, time series method and trend analysis, which have higher requirements on data. Different models have different results, and the appropriate model should be selected in combination with local development [5]. Modern forecasting methods including the artificial neural network prediction method, gray prediction method and support vector machine forecasting method. Modern forecasting methods can deal with the nonlinear relationship between load and influencing factors, which can achieve power load prediction of the various factors [6].

First of all, the power demand forecasting model based on SVM is constructed. By using the gray relational analysis method, the key influencing factors of power demand in Beijing, Tianjin and Tangshan are obtained. Fully considering the impact of economic development, industrial structure and other factors on power demand forecasting. This paper uses SVM to forecast the trend of power demand. In particular, this paper fully considers the impact of special periods on regional electricity demand, and corrects the original data and forecast results.

2. Research Method

Support vector machine is a new method of machine classification developed on the basis of statistical learning theory. This method uses non-linear mapping algorithm to map low-dimensional input space samples to high-dimensional attribute space, which makes it possible to analyze the nonlinear characteristics of samples [7-9]. The SVM algorithm is essentially a convex optimization problem, so that the local optimal solution that the learner can obtain must be the global optimal solution. SVM uses the structure risk minimization theory to construct the optimal segmentation hyperplane in the attribute space, so the global optimal solution can be obtained. These features are beyond the reach of other algorithms, including neural networks [10]. Therefore, SVM is superior to other learning methods in many aspects, both theoretically and foreground. LS-SVM is an extension of SVM. It constructs the optimal decision surface by projecting the nonlinearity of input vector into the high-dimensional space of projection and then applies the principle of risk minimization to transform the inequality of SVM into the solution of equations. Thus reducing the computational complexity and speeding up the computation [11-12]. The specific principle of the model is as follows:

A given sample is set as $T=\{(x_i,y_i)\}_{i=1}^{N}$, N is the total number of samples; the regression model of the sample is:

$$y(x)=w^t\cdot\phi(x)+b$$

Where $\phi(x)$ is the training sample projected onto a high-dimensional space, w is the weight vector, b is the bias;

For LS-SVM, the optimization problem becomes:

$$\min\frac{1}{2}w^T w+\frac{1}{2}\gamma\sum_{i=1}^{N}\xi_i^2 \tag{1}$$

$$s\cdot t\ \ y_i=w^T\varphi(x_i)+b+\xi_i \tag{2}$$

Where, $i=1,2,3,\ldots N$

In order to solve the above problem, the Lagrange function is established:

$$\begin{aligned}L(w,b,\xi,a_i)&=\frac{1}{2}w^T w+\frac{1}{2}\gamma\sum_{i=1}^{N}\xi_i^2\\&-\sum_{i=1}^{N}a_i\left[w^T\varphi(x_i)+b+\xi_i-y_i\right]\end{aligned} \tag{3}$$

Where a_i is the Lagrange multiplier. Derive each variable of the function and make them zero:

$$\begin{cases}\dfrac{\partial L}{\partial w}=0\rightarrow w=\sum_{i=1}^{N}a_i\varphi(x_i)\\ \dfrac{\partial L}{\partial b}=0\rightarrow\sum_{i=1}^{N}a_i=0\\ \dfrac{\partial L}{\partial b}=0\rightarrow a_i=\gamma\xi_i\\ \dfrac{\partial L}{\partial b}=0\rightarrow w^T+b+\xi_i-y_i=0\end{cases} \tag{4}$$

Eliminating w and ξ_i translates into the following questions:

$$\begin{bmatrix}0 & \boldsymbol{e}_n^T\\ \boldsymbol{e}_n & \boldsymbol{\Omega}+\gamma^{-1}\cdot I\end{bmatrix}\cdot\begin{bmatrix}b\\ \alpha\end{bmatrix}=\begin{bmatrix}0\\ y\end{bmatrix} \tag{5}$$

Where, $\Omega=\varphi^T(x_i)\varphi(x_i)$, $e_n[1,1,\ldots1]^T$, $a=[a_1,a_2,\ldots a_n]$, $y=[y_1,y_2,\ldots y_n]^T$;

Solving the above linear equations yields:

$$\begin{bmatrix}0 & e_n^T\\ e_n & \Omega+\gamma^{-1}\cdot I\end{bmatrix}\cdot\begin{bmatrix}b\\ a\end{bmatrix}=\begin{bmatrix}0\\ y\end{bmatrix} \tag{6}$$

Where, $K(x_i,x)$ is the kernel function, and the commonly used kernel functions are: (1) Polynomial kernel function: $(x^T x_i+1)^p$, the index p is specified by the user in advance; (2) Radial basis kernel function: $\exp\left(-\frac{1}{2\sigma^2}\|x-x_i\|^2\right)$, σ^2 is width; (3) Sigmoid kernel function: $\tanh(\beta_0 x^T x_i+\beta_1)$, the value of β_0, β_1 satisfies the Mercer theorem. This paper selects radial basis kernel function $\exp\left(-\frac{1}{2\sigma^2}\|x-x_i\|^2\right)$.

Substituting the input variables for the forecast of electricity demand in North China into formula (6), and get the industry's electricity consumption forecast results.

3. Power Demand Forecast in North China Based on Support Vector Machine

3.1. Electricity Demand Influencing Factors Screening Based on the Gray Correlation Method

Medium and long-term demand forecast involves the long-term development of a region, which is closely related to power system planning, design and dispatching. In recent years, the relationship of demand for electricity has undergone major changes, demand characteristics also showed some new features. In the study of medium and long term demand forecasting, it is necessary to fully consider the influence of relevant factors and accurately grasp the changing law of demand characteristics, so as to effectively improve the accuracy of forecasting results. In recent years, with the vigorous development of China's power industry, the influencing factors of power demand have become more and more complicated. In order to accurately grasp the development law of power demand in North China from 2015 to 2020, other related factors must be added to get better forecast results.

(1) Determine the reference sequence and the compare sequences

On the gray correlation analysis of the Beijing-Tianjin-Tang electricity demand and economic development, taking the total electricity consumption (2005-2015) as a reference series, taking the electricity-related indicators of economic and social development (2005-2015) as a comparative series. The selected indicators of social development related to the demand for electricity in Beijing, Tianjin and Tangshan are shown in Table 1.

Table 1. *Economic and Social Development Indicators Related to the Demand for Electricity in Beijing, Tianjin and Tangshan.*

Economic Growth	Gross Regional Product GDP
	Investment in fixed assets
	Total exports
Industrial Structure	The added value of secondary industry as a share of GDP
	The added value of third industry as a share of GDP
population growth	The total resident population at the end of the year
Livelihood indicators	Urban residents disposable income
Technological progress	Power consumption intensity
	Electricity efficiency

(2) Calculate the gray correlation coefficient of the whole society's electricity consumption and economic development index

The original data of Beijing-Tianjin-Tangshan electric power consumption and related economic development indicators from 2005 to 2015 are treated as non-dimensional. Then calculate the relative degree of correlation and the relative degree of correlation between each comparison sequence and the reference sequence, and then calculate the comprehensive correlation degree of each comparison sequence and reference sequence. In the calculation of comprehensive relevance, this topic treats the absolute relevance and the relative relevance of each comparison sequence and reference sequence as equally important, take 0.5. This shows that in the calculation of the comprehensive relevance of each comparison sequence and reference sequence, this topic focuses on both the geometry of the comparison sequence and reference sequence, as well as the rate of change of each comparison sequence relative to the starting sequence. The final gray correlation coefficient is shown in Table 2.

Table 2. *The Gray Correlation Coefficient of Total Electricity Consumption and Economic Development Index.*

Index		Gray correlation coefficient	Rank
Economic Growth	Gross Regional Product GDP	0.637895	2
	Investment in fixed assets	0.634068	3
	Total exports	0.520109	6
Industrial Structure	The added value of secondary industry as a share of GDP	0.512597	7
	The added value of third industry as a share of GDP	0.502584	8
population growth	The total resident population at the end of the year	0.484361	9
Livelihood indicators	Urban residents disposable income	0.525854	5
Technological progress	Power consumption intensity	0.620753	4
	Electricity efficiency	0.764675	1

According to the results of the gray relational analysis of the electricity consumption and economic development indicators of the whole society in Beijing, Tianjin and Tangshan, came to the conclusion that power efficiency, GDP, the proportion of secondary industry value added are key factors affects the power demand of the whole society in Beijing, Tianjin and Tangshan. Therefore, this paper intends to build a model of the relationship between the annual electricity demand and economic development of the entire society in Beijing, Tianjin and Tangshan from three aspects: power efficiency, GDP and the added value of third industry as a share of GDP. And using the least square support vector machine method to predict the annual power demand.

3.2. Multifactor Power Demand Prediction Based on Support Vector Machine

Power efficiency, GDP, the proportion of secondary industry value added is the main key factor that affects the whole society power demand in Beijing, Tianjin and Tangshan. Therefore, this paper intends to build the relationship model between the annual electricity demand and economic development of the whole society in Beijing, Tianjin and Tangshan from three aspects: electricity efficiency, GDP and the proportion of added value of secondary industry. Because there are too few samples, it can't use the relationship model to predict the annual electricity demand of Beijing, Tianjin and Tangshan. Considering the strong recognition ability and high prediction accuracy of support vector machines in the case of small samples, this paper uses SVM to provide a rolling prediction of annual power demand in Beijing, Tianjin and Tangshan.

This paper uses the least-squares support vector machine (SVM) algorithm to predict the annual electricity demand of Beijing, Tianjin and Tangshan. The data of electricity consumption has been normalized preprocessed. The first rolling forecast is based on the actual electricity consumption, GDP, the added value of secondary industries and power efficiency of Beijing, Tianjin and Tangshan in 2005-2013 as input variables, and the output variables is the annual electricity demand of Beijing, Tianjin and Tangshan in 2014; The second rolling forecast is based on the actual electricity consumption, GDP, the added value of secondary industries and power efficiency of Beijing, Tianjin and Tangshan in 2006-2014 as input variables, and the output variables is the annual electricity demand of Beijing, Tianjin and Tangshan in 2015; and then Beijing-Tianjin-Tangshan annual electricity demand can be forecasted in the same way. (Figure 1).

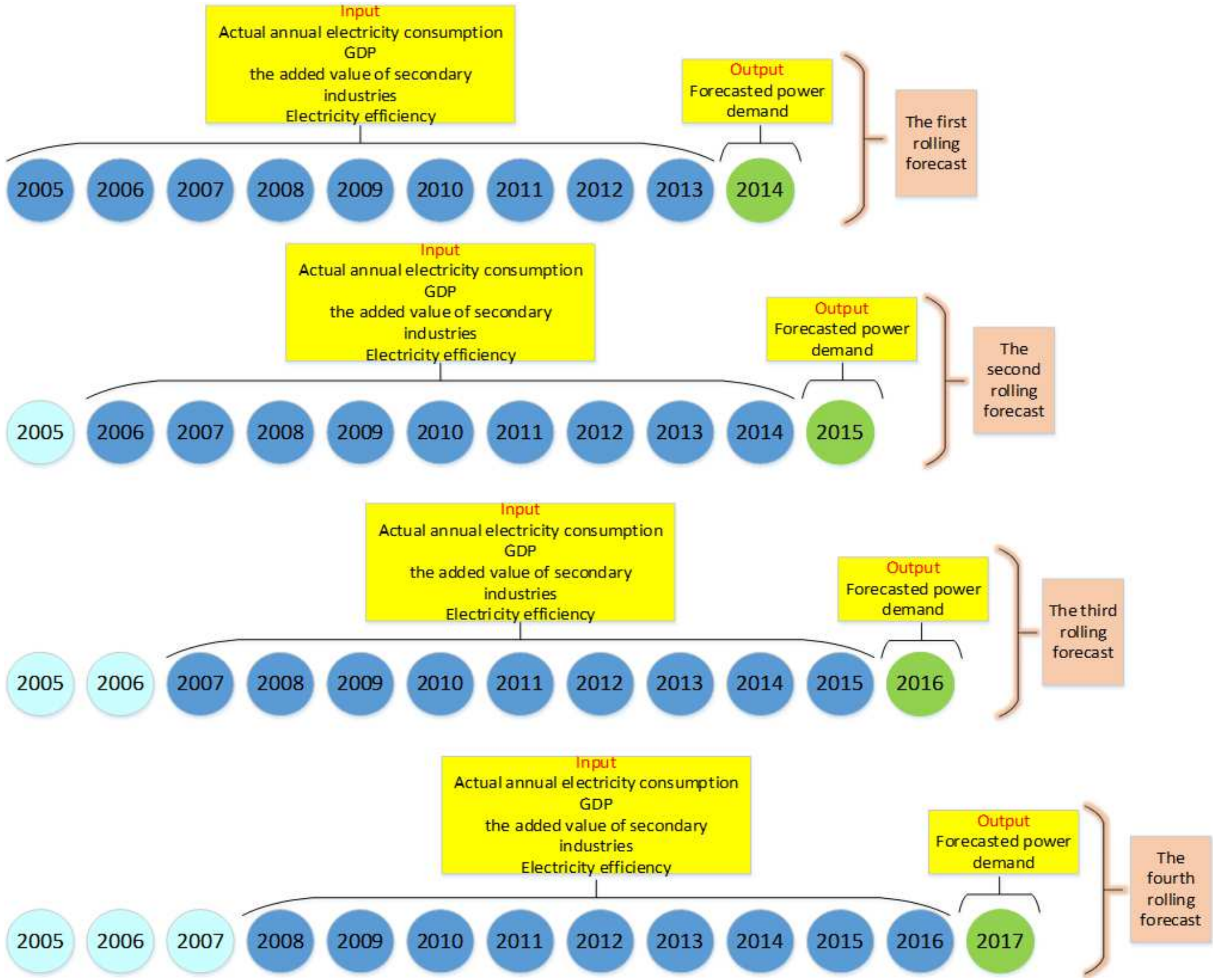

Figure 1. *Electricity Demand Rolling Forecast of Beijing-Tianjin-Tang region.*

Based on the analysis of the characteristics of annual electricity demand and GDP in Beijing, Tianjin and Tangshan, in order to predict the annual electricity demand of Beijing, Tianjin and Tangshan in 2016 and 2017, this paper bases on historical data of Beijing, Tianjin and Tangshan to estimate the annual GDP growth rate, the added value of secondary industries and electricity efficiency changes. Since entering the "Twelfth Five-year Plan" period, GDP of Beijing, Tianjin and Tangshan has increased at an average annual rate of 9.31%, with the added value of the secondary industry accounting for an annual decrease of 1.85% and the power efficiency has increased by 6.39% annually. In February

2016, the "Plan for Economic and Social Development of Beijing, Tianjin and Hebei Province during the 13th Five-Year Plan" was promulgated and put forward. By 2020, the overall strength of the Beijing-Tianjin-Hebei region will be further enhanced, and the economy maintained a medium and high-speed growth. The structure Adjustment will made important progress. Considering that the economy in Beijing, Tianjin and Tangshan will maintain medium and high-speed growth during the 13th Five-Year Plan period, the industrial structure will be effectively adjusted and the technological progress will make the power efficiency effectively improved. Therefore, this paper sets the GDP of Beijing, Tianjin and Tangshan in 2016 and 2017 respectively to increase by 8.5%, the added value of secondary industries of Beijing, Tianjin and Tangshan in 2016 and 2017 as 35.5% and 35% respectively, and the electricity Efficiency in 2016 and 2017 increased by 6%.

4. Conclusion

Comparing to the actual power consumption of Beijing, Tianjin and Tangshan in 2005-2013, it can be seen that the estimation error is small by using LS-SVM algorithm, so the intelligent algorithm is reasonable. Therefore, based on the actual and predicted scenarios, the intelligent algorithm is used to predict the annual electricity demand for Beijing, Tianjin and Tangshan in 2014-2017. The forecast results are shown in Table 3-4.

Table 3. *The Estimation Results and Estimation Error of Consumption Electricity in Beijing-Tianjin-Tangshan Region (Unit: 100 million kwh).*

Year	Annual actual value of the whole society electricity	Estimated annual electricity consumption of the whole society	Error
2005	1636.84	1635.2	-0.10%
2006	1870.10	1873.6	0.19%
2007	2177.20	2177.4	0.01%
2008	2262.21	2260	-0.10%
2009	2490.02	2490.8	0.03%
2010	2836.21	2834.4	-0.06%
2011	3069.69	3069.7	0.00%
2012	3162.23	3163.6	0.04%
2013	3361.46	3361.3	0.00%

Table 4. *The Correction Value of Annual Electricity Consumption of Beijing-Tianjin-Tang region in 2014-2017.*

Year	Actual	Prediction	Prediction considering the special period	Error
2014	3390.61	3333.9	3328.04	-1.85%
2015	3260.30	3356.6	3350.17	2.76%
2016		3307	3302.31	
2017		3337	3332.27	

Acknowledgements

This study is supported by the Project of North China Grid Limited Company: Analysis of the influence of electricity instead on power demand of north China power grid (SGTYHT/16-JS-201).

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