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Electricity Demand Forecasting For High Energy-Intensive Industries of Inner Mongolia in China

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Abstract

Since the development of high energy-consuming industries has an important impact on the total electricity consumption, it is essential to predict the electricity demand of these industries. A procedure based on LS-SVM algorithm and scenario analysis is proposed to forecast the electricity consumption of high energy-intensive industries in Inner Mongolia, which takes three affecting factors into consideration, including the output value, the proportion of output accounting for GDP, and electricity consumption intensity. The prediction results show that the prediction accuracy of LS-SVM is rather high with an average error rate of 2.03%. The electricity demand of energy-intensive industries in Inner Mongolia will reach 2136.9~2175.1 million kWh in 2015, and reach 2514.4 ~ 2966.9 million kWh in 2020. Meanwhile, the annual growth rate among 2013 to 2020 will be 5.18%~7.48%. In addition, 377.5 million kWh will be saved in 2015, and 791.8 million kWh will be saved in 2020.

Keywords: *Electricity demand; Energy-intensive industries; LS-SVM; Scenario analysis*

1. Introduction

The rapid economic development of Inner Mongolia is inseparable with its energy-intensive industries which have the characteristic of “high energy consumption” and “high emission”. In recent years, the energy-intensive industries have been the focus of energy saving and management, which will affect the development and electricity demand of these industries. Therefore, in order to provide guidance for the power planning and construction, it is necessary to make a prediction for the high energy-intensive industries of Inner Mongolia in China.

Since the 1970s, scholars have done a lot of works on the research of electricity demand forecasting. The prediction methods mainly contain: unit consumption method, elastic coefficient method, neural network method, trend extrapolation method, time series method, regression forecasting technique, and gray prediction method. Literature [1] predicted the per capita electricity based on the regression equation between the per capita electricity and per capita net income. Literature [2] proposed a modified model based on neural network and gray prediction method, and forecasted the electricity consumption in Taiwan. Literature [3] used the elastic coefficient and fuzzy method to project the electricity demand in the east China under the background of energy saving and emission reduction. However, these methods have some disadvantages in some aspects. Unit consumption method needs to do a lot of statistical analysis, which is difficult to ensure accuracy more or less [4,5]. The learning process of neural network method is usually slow and it is insensitive to emergencies as well [6-8].The grey prediction model is not suitable for long-term forecast[9,10]. In addition, research on the electricity demand prediction for high energy-intensive industries is still scarce. Therefore, on the basis of previous studies, it is necessary to put forward a more rational model which contains of

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multi-factors to project the electricity consumption energy-intensive industries in Inner Mongolia.

The remainder of the paper is organized as follows: Section 2 presents the basic information about the least squares support vector machine (LS-SVM). In the section 3, the electricity demand is analyzed based on LS-SVM under different scenarios for the energy-intensive industries in the Inner Mongolia. The conclusions and some recommendations are drawn in Section 4.

2. LS-SVM Algorithm

The least squares support vector machine (LS-SVM) is an extension of support vector machine (SVM), which maps the input vector into a high-dimensional space with a form of nonlinearity and construct an optimal decision[11,12]. This algorithm transforms the inequality equations into equation system to do computations under a principle of minimization risk, which reduces the computational complexity and speed up the processing speed[13].

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

$$y(x) = \boldsymbol{w}^t \bullet \varphi(x) + b \tag{1}$$

Where, $\varphi(*)$ is the function which maps the training samples into a high-dimensional space, $\boldsymbol{w}$ is the weighted vector, b is the bias.

In the algorithm of LS-SBM, the optimization problem is shown as follows [14]:

$$\begin{aligned} & min \ \frac{1}{2}\boldsymbol{w}^T\boldsymbol{w} + \frac{1}{2}\gamma\sum_{i=1}^{N}\xi_i^2 \\ & s \cdot t \ \ y_i = \boldsymbol{w}^T\varphi(x_i) + b + \xi_i, \\ & i = 1,2,3,\ldots N; \end{aligned} \tag{2}$$

In order to solve above problem, a Lagrange function is established as follows[15]:

$$\begin{aligned} L(\boldsymbol{w}, b, \xi_i, \alpha_i) = {} & \frac{1}{2}\boldsymbol{w}^T\boldsymbol{w} + \frac{1}{2}\gamma\sum_{i=1}^{N}\xi_i^2 \\ & - \sum_{i=1}^{N}\alpha_i[\boldsymbol{w}^T\varphi(\mathrm{x}_i) + b + \xi_i - y_i] \end{aligned} \tag{3}$$

Where, α_i is the Lagrange multiplier.

Derivative for each variable function, and make it to zero:

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

Eliminate the $\boldsymbol{w}$ and $\xi_{\boldsymbol{i}}$, and change the above problem as follows[16]:

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

Where, $\boldsymbol{\Omega} = \varphi^T(x_i)\varphi(x_i)$, $\boldsymbol{e}_n = [1,1,..., 1]^T$, $\alpha = [\alpha_1, \alpha_2, ..., \alpha_n]$, $y = [y_1, y_2, ..., y_n]^T$,

Solve the above linear equations as follows:

$$y(x) = \sum_{i=1}^{N} \alpha_i K(\boldsymbol{x}_{\boldsymbol{i}}, \boldsymbol{x}) + b \tag{6}$$

Where, $K(\boldsymbol{x}_i, \boldsymbol{x})$ is the kernel function.

There are three kinds of common kernel functions which are shown as below:

(1) The polynomial kernel function: $(\boldsymbol{x}^T \boldsymbol{x}_i + 1)^p$, p is specified by users in advance[17].

(2) The radial basis kernel function: $\exp\left(-\frac{1}{2\sigma^2}\|\boldsymbol{x} - \boldsymbol{x}_i\|^2\right)$, σ^2 is the width[18].

(3) “Sigmoid” kernel function: $tanh\,(\beta_0 \boldsymbol{x}^T \boldsymbol{x}_i + \beta_1)$, β_0, β_1 satisfy the Mercer theorem[19].

In this paper, the radial basis kernel function $\exp\left(-\frac{1}{2\sigma^2}\|\boldsymbol{x} - \boldsymbol{x}_i\|^2\right)$ is selected as the kernel function the LS-SVM algorism.

3. Electricity Demand Forecasting For Energy-Intensive Industries

3.1. Variable Selection and Data Sources

The energy intensive industries of Inner Mongolia mainly include seven industries: the oil processing, coking and nuclear fuel processing industry; chemical raw materials and chemical products manufacturing; non-metallic mineral products; ferrous metal smelting and rolling processing industry; non-ferrous metal smelting and rolling processing industry; electric power, heat production and supply industry, and coal mining and washing industry.

Large numbers of relevant literatures has proved that the growth of electricity demand can be decomposed into three factors: industry output growth effect caused by economic growth, industrial structure effect caused by changes of economic structure, and the efficiency effect caused by the progress of science and technology [20-22]. Therefore, in order to project the electricity demand of energy-intensive industries in Inner Mongolia with a high accuracy, three variables are selected as the input variables to forecasting the electricity demand, namely, the output value, the proportion of output accounting for GDP, and electricity consumption intensity. Meanwhile, the electricity consumption of energy-intensive industries in Inner Mongolia is the output variable.

In particular, the sample date are the electricity demand, input value, the proportion of output accounting for GDP, and electricity consumption intensity in Inner Mongolia from 1989-2011.Specific training data are shown as Table 1.

Table 1. The Data of Training Samples

Time	Electricity consumption（Million kWh）	Output value（One hundred million yuan）	Electricity consumption intensity（kWh/ Ten thousand yuan）	Proportion of output accounting for GDP(%)
1989	69.24	144.82	4781.55	27.88%
1990	74.58	166.15	4488.57	29.75%
1991	78.98	186.15	4242.60	31.01%
1992	88.00	207.55	4240.06	31.15%
1993	96.08	212.31	4525.44	28.54%
1994	102.05	188.89	5402.43	22.84%
1995	111.23	184.97	6013.31	20.31%
1996	125.39	196.65	6376.13	18.87%
1997	134.34	222.69	6032.59	19.30%
1998	139.47	321.08	4343.58	25.15%
1999	147.66	372.88	3960.01	26.83%
2000	161.05	424.35	3795.20	27.57%
2001	178.67	462.25	3865.22	27.13%
2002	215.44	531.28	4055.09	27.55%
2003	297.34	710.81	4183.18	31.27%
2004	389.88	1121.60	3476.10	40.95%
2005	516.02	1542.77	3344.75	45.49%
2006	703.30	2029.66	3465.12	50.27%
2007	956.37	2636.45	3627.49	54.76%
2008	1020.51	3622.69	2816.99	63.86%
2009	1020.61	4490.37	2272.88	67.71%
2010	1209.41	5338.30	2265.53	69.99%
2011	1436.61	6590.29	2179.89	75.56%

Data resource：the data of electricity consumption are cited from the statistical data of north China power grid (1989-2011);Economic data are cited from China's economy yearbook (1990-2012). It is essential to note that all economic data are standardized on the base period of 2000.

3.2. The Analysis of Development Scenarios

Since the “Energy conservation and emissions reduction comprehensive work plan of the state council” was published, Inner Mongolia has been actively promoting the adjustment of industrial structure and energy structure through publishing energy saving and emission reduction, low carbon development action plans. On the one hand, in order to promote the adjustment of industrial structure, a lot of backward production capacities have been eliminated. Meantime, some low-consumption and low-emission industries have been developed to adjust and optimize the energy consumption structure. In particular, industrial is the focus of energy conservation and emissions reduction work. By 2015, the Output current consumption of above designated size industrial enterprises at least 17% lower than in 2010. At the same time, strengthen the technical support and government support to promote technology innovation. On the other hand, the “12th five-year plan" has clarified that the annual GDP growth rate should reach 12% and the unit GDP energy consumption should be at lease reduced by 15%.

In the first two years of the "Twelfth five-year" period, the average annual GDP growth of the Inner Mongolia has reach 12.90%, which is more than the expected goal. However, from the perspective of the GDP growth trend since 2010, there will be a downward trend of the GDP in the Inner Mongolia. In the 2005-2012, the average annual growth of the output value of energy-intensive industries in the Inner Mongolia is 24.06%, which is higher than the growth of the GDP at 7.80%. Currently, some new energy base and chemical industry base have been established in the Inner Mongolia. Meanwhile, affected by the policies, Inner Mongolia will no longer approve the iron and steel, electrolytic aluminum, cement and plate glass industries. Considering the above factors comprehensively, two development scenarios will be set to predict the growth of the output value of energy-intensive industries.

For the development trend of electricity intensity of energy-intensive industries, we also set two scenarios according to the objectives in the "Energy conservation and emissions reduction comprehensive work plan of the state council" and "12th five-year plan". The specific development scenarios are shown in Table 2.

Table 2. Development Scenarios

Scenarios	Time	Annual growth rate of output value	Annual growth rate of electricity intensity	Industrial structure
A	2013-2015	14%	-3%	70%
	2016-2020	10%	-5%	65%
B	2013-2015	18%	-6%	70%
	2016-2020	13%	-8%	65%

3.3. Analysis of Prediction Results

In this paper, the training samples are the data from 1989-2011, and the test samples are the data in 2012. Input the training samples and test samples into LS-SVM, respectively. The prediction results are shown in Table 3 and Figure 1.

Table 3. The Prediction Results in 2015 and 2020

Variables	Time	A	B
Output value	2015	10086.17	11185.56
	2020	16243.87	20608.66
Electricity consumption intensity	2015	2320.69	2248.91
	2020	2204.65	2069.00
Proportion of output accounting for GDP	2015	70%	70%
	2020	65%	65%
Electricity consumption	2015	2136.9	2175.1
	2020	2514.4	2966.9

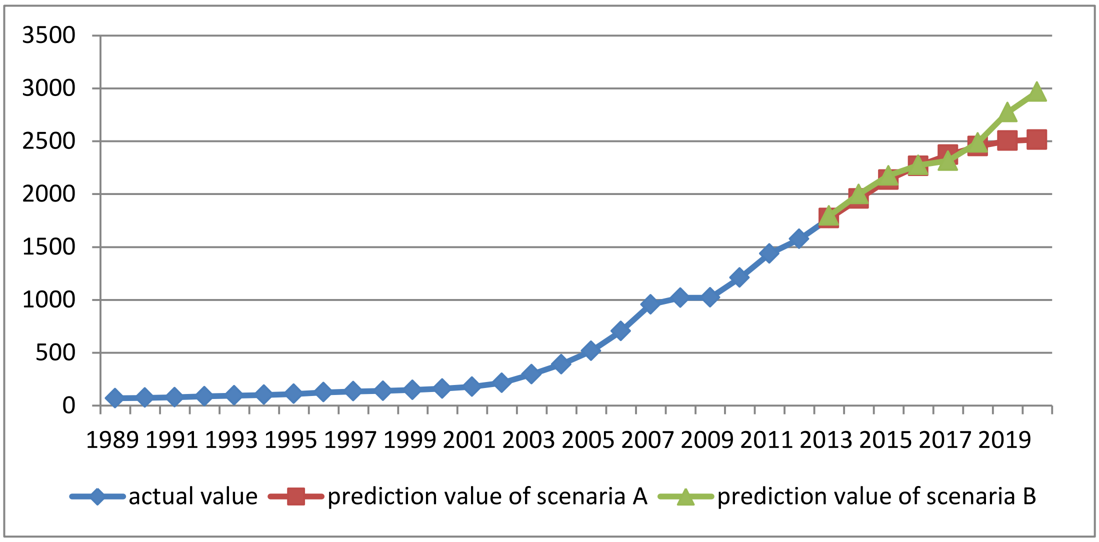

Figure 1. The Prediction Results under Scenario A and B

In general, the average error rate $ARE = \sum_{i=1}^{K} \frac{\left(X_i - \hat{X}_i\right)}{X_i} \times \frac{1}{K} \times 100\%$. Where, X_i is the measured value; $\hat{X}_i$ is the predicted value, K is the number of samples. The accuracy analysis results of the LS-SVM in forecasting the electricity demand are shown in Table 4.

Table 4. The Average Error Rate of the Algorism

Algorithm	ARE of Training Set	ARE of Testing Set	ARE of Whole Set
LS-SVM.	0.7542%	3.3068%	2.03%

According to the prediction results, the prediction accuracy of LS-SVM is rather high with an average error rate of 2.03%, which shows the efficiency of this method in forecasting the electricity demand of energy-intensive industries.

On the other hand, the electricity consumption of energy-intensive industries in Inner Mongolia will keep a high tendency in the future. In particular, the electricity demand will reach 2136.9 and 2175.1 million kWh under scenario A and B, respectively. The electricity demand will reach 2514.4 and 2966.9 million kWh, respectively. What's more, the energy-intensive industries in the Inner Mongolia have a great energy saving potential in the future. Based on the scenario analysis results above, we can conclude that 377.5 million kWh will be saved in 2015, and 791.8 million kWh will be saved in 2020.

4. Conclusions and Recommendations

4.1. Conclusions

The energy-intensive industries are the impetus to promote the economic development of Inner Mongolia, which has a broad market space and strong industry expansion drive. However, owning to the "high investment, high pollution and low output" characteristics of energy-intensive industries, some policies have been provide to restrict the development of energy-intensive in the future. Under the background of energy saving and emission reduction, the electricity demand of energy-intensive industries will be affected by relative policies. In order to forecasting the demand tendency, a procedure based on LS-SVM is provided in this paper, which take “the output value”, “the proportion of output accounting for GDP”, and “electricity consumption intensity” into consideration. Meanwhile, according to the current development situation and policy requirements, two scenarios are provided to analyze the electricity demand situation in the future. There are some conclusions can be drawn in this paper.

(1) The average error rate of prediction is 2.03%, which shows the efficiency of the LS-SVM in forecasting the electricity demand of energy-intensive industries in the Inner Mongolia.

(2) The electricity demand of energy-intensive industries in Inner Mongolia will reach 2136.9~2175.1 million kWh in 2015, and reach 2514.4 ~ 2966.9 million kWh in 2020. Meanwhile, the annual growth rate among 2013 to 2020 will be 5.18%~7.48%, which show a high growth tendency of electricity demand. Based on the scenario analysis results above, we can conclude that 377.5 million kWh will be saved in 2015, and 791.8 million kWh will be saved in 2020.

4.1. Recommendations

Therefore, in order to realize the green transformation of energy-intensive industries in Inner Mongolia, some recommendations are provided as follows:

(1) Energy-intensive industries should enhance the development and application of green technology so as to reduce the electricity consumption intensity.

On the one hand, the government of Inner Mongolia should introduce the industrials with high-techniques. On the other hand, the alliance among enterprises should be encouraged to research and develophigh-end green technology, so as to transformthe mode of economic development.

(2) Speed up the development of renewable energyandadjust the energy structure of energy-intensive industries.

Since the Inner Mongoliais still in a rapid economic development stage, the development of infrastructure construction consumes large numbers ofraw coal, crude oil, steel, cement and other energy. Therefore, in order to guarantee of economic growth under the situation of rapid development and energy saving, the consumption of non-renewable energy should be reduced. Meanwhile, more and more renewable energy should be used to adjust the energy structure in the future.

(3) In order to realize the sustainable development of economy, the “GDP” accounting system should be replaced by the “green GDP”.

The traditional GDP accounting system can only reflect the situation of economic development. Therefore, the government only pays attention to the development of economy and ignores the energy consumption and environment damage in the process of economic. In order to fundamentally solve the contradiction between economic development and environmental pollution, the “green GDP” should be proposed to instead of the traditional “GDP”. Only the “green GDP” in which the environmental cost has been deducted can reflect the economy situation representatively.

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