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RESEARCH ON CHINESE ENERGY CONSUMPTION USING AN IMPROVED PSO-LSSVR MODEL BASED ON A STOCHASTIC PROCESS

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ABSTRACT

Energy is a complex system affected by multiple factors, accurate energy demand forecasts provide the basis for the formulation and implementation of energy planning. This paper builds a new model and predicts China's energy consumption. This study drew three main conclusions. First, aco-integration test and Granger causality test can help users discover the relationships between China's energy demand and its influencing factors. Second, the improved PSO-LSSVR model showed its superiority over other models in terms of forecasting energy demand, which further improved prediction accuracy. Third, the forecasting results indicate that China's energy demand will peak in 2034, and that the peak is 6.7 billion tonnes of coal equivalent (tce). Based on the forecasting results, the paper offers suggestions related to China's energy development policy.

Keywords: Markov chain, Chinese energy demand forecasting, PSO-LSSVR algorithm, Co-integration test, Granger causality test

1. INTRODUCTION

With the further development of China's economy, a major challenge has become how to reasonably predict future energy consumption so as to make correct and reasonable decisions. The *BP Statistical Review of World Energy (2017)* [1] reports that China's energy consumption accounts for 23% of global energy consumption in 2016. The prediction of China's peak energy consumption can help China cope with global climate negotiation, formulate energy policies to ensure energy security. The *World Energy Outlook 2018*, published by the International Energy Agency (IEA) forecast, international energy trade will increasingly flow from the Middle East, Russia, Canada, and the United States to Asia by 2040 [2]. China is Asia's largest economy. According to the IEA's *Renewable Energy 2018 - Analysis and Forecast to 2030*, China's absolute increment ranks first. It pointed out that China will lead global growth in increments during the forecast period and will surpass the EU as the largest renewable energy consumer [3]. Currently, predictions about China's energy consumption vary, and opinions differ as to when China's energy consumption will peak. This study sought to construct a hybrid forecasting model to investigate the peak and peak time of China's energy consumption, and to analyze reasons for the peak. Therefore, to conduct relevant research on the energy demand of China is necessary.

Energy is a nonlinear complex system, influenced by many factors. A co-integration test is more conducive to capturing the long-term relationship between variables than other methods, and the Granger causality test can prevent the causality result of the bivariate model from being affected by the deviation of missing variables [4]. With respect to energy demand forecasting models, they can be classified as univariate time series prediction models and multivariate time series prediction models. Univariate methods [5], mine the rules in historical data for further predictions. To ensure the accuracy, they are applicable primarily for short-term prediction. Multivariate methods are used multiple linear regression models, log-linear regression models [6]. Taking the prediction precision into consideration, they are applied for long-term predictions. Recently, artificial intelligence (AI) methods have become more and more popular in forecasting files for its mapping and good forecast ability. The AI methods used generally include mostly artificial neural networks [7], and particle swarm optimization [8].

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Cortes [9] proposed SVM, which has excellent performance in solving small-sample, nonlinear, high-dimension problems. SuyKens et al. [10] improved least squares support vector regression (LSSVR) in 1999, the least squares formulation of SVR, which has better generalization abilities and powerful computation. However, there are still disadvantages to LSSVR, so PSO is introduced to improve the LSSVM. However, the application of PSO-LSSVR in energy demand prediction is little. In addition, this paper introduces the Markov chain,. Scholars have discussed the Markov chain in depth. Romanovschi [11] have introduced its characters. Therefore, it can be used to observe the problem of energy consumption prediction from another aspect to correct PSO-LSSVR model errors.

2. ALGORITHM INTRODUCTION

2.1 Least square support vector regression

With a nonlinear map $\phi(\cdot)$, the sample from the original space R^n is mapped into the feature space $\varphi(x_k)$. Once the values of α and b are found, the fitting function is represented as follows:

$$f(x) = \sum_{k=1}^{l} \alpha_k K(x, x_i) + b \tag{1}$$

Where $K(x,x_i) = \varphi(x)^T \cdot \varphi(x_l)$ is the Kernel function, which expresses nonlinear mapping with the space from low to high dimensional. It can help SVR deal with nonlinear data, and keep the linear relationship in high-dimensional space. Based on the different Kernel function's analysis, RBF was selected in this study.

2.2 Particle swarm optimization algorithm

PSO is initialized with a random population including m particles, which is $X = \{X_1, X_2, \ldots, X_m\}$. Each particle is a point in a D-dimension space and a feasible solution in the solution space. Particles change their position by moving in the solution space until arriving at the optimal solution. Using different parameters as input can produce different forecasting accuracy by modeling. Therefore, it can select optimization parameters while modeling. The PSO model optimizes the parameter σ^2 and γ in LSSVM, which can improve prediction accuracy.

2.3 Markov Chain

A.A.Markov proposed this process in 1906. Based on the definition and nature of the Markov chain one-step transition probability matrix, the definition of the element means the current state is i and the next state is j. So, based on the definition of the one-step transition probability matrix, each row element of the one-step transition probability matrix is added to 1. [11]

3. CASE STUDY

In this paper, GDP is measured in 10^{13} CNY (in constant 1978 price in China). The total population at the end of a year is measured in 10^7 (POP). Energy structure is indicated by total coal consumption (TCC). Residential consumption levels (RCL, in constant 1978 price in China) are measured in per capita consumption outlay, which is measured in 10^{13} CNY. Urbanization rate is defined the ratio of urban population in the total population (UR). And the energy demand is measured in Mtce (million tons coal equivalent) and shown as ED, or energy demand. All these data are obtained from the China Statistical Yearbook [12].

3.1 Analysis of the relationship between energy demand and its influencing factors

The main factors influenced energy system can be expressed by the following indicators: GDP, POP, TCC, RCL and UR. We will discuss how the Unit root, Johansen co-integration and Granger causality test were used to analyze the dynamic relationship between China's total energy demand and its influencing factors under the environment of Eviews 9.0.

The unit root test and Johansen co-integration test are aimed to prevent the occurrence of spurious regression [13]. As the result of the test, there do exist co-integration relationships between GDP, POP, TCC, RCL, UR, and total energy demand in China. And then, Granger causality test can further determine the causal relationship between total energy demand and its influencing factors. As the result of the test, the GDP, RCL and ED are the bilateral causality. UR, POP, and TCC are the one-way Granger reason of total energy demand. In conclusion, GDP, POP, TCC, RCL, and UR are chosen as variables for the PSO-LSSVR model when forecasting the energy demand of China.

3.2 Forecasting energy demand based on PSO-LSSVR

We fit China's total energy demand from 1978 to 2016 with PSO-LSSVR model by Matlab. We first found the best parameters of the LSSVR model: $\gamma = 19.5636$ and $\sigma^2 = 63$. And then we used the PSO model to optimize the LSSVR model, where the parameters of the PSO model were set as follows: the particles number is 20, the acceleration factors are 1.5 and 1.7, and maximal iterations number is 60.

3.3 Optimization of predictive models

Based on previous research, we divided the state space by the standard normal distribution table and obtained the state classification. We used the fitted and true values of 1978–2016 to obtain the average relative error, and to normalize the relative error sequence. We recorded this model as Model 2. In this way, the state the error may reach in the next moment and the expectation of relative error is obtained by weighted averaging. Combining the fitting values of the current year, the predicted value of Model 2 is further obtained. As the result in Fig. 1, Model 2 optimized by stochastic process has better accuracy.

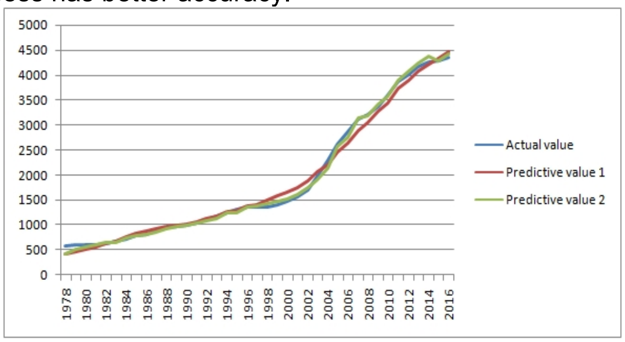

Figure 1. The improved prediction of China's energy demand.

4. RESULTS AND DISCUSSION

4.1 Factor setting

This section analyzes the future changes in factors affecting China's total energy demand. We used the existing data, combined with related professional estimates, to predict the value of the factors affecting China's total energy demand from 2017 to 2050. According to the professional forecast [14–19], we set in this paper that the average annual growth rate of GDP in 2018–2020, 2021–2025 and 2026–2050 are 7%, 5.9% and 5%, respectively, the population of China will be 14.3 billion and 1.39 billion in 2035 and 2050, respectively, and the total population of 2017–2050 in China is set according to the trend extrapolation method, the proportion of coal will fall to 20% in 2050, and the total coal consumption of 2017–2050 will be set according to the trend extrapolation method, the growth rate of real RCL at the average annual growth rate of 8.0% , and China's urbanization rate will reach 70% and 80% in the years 2035 and2050, respectively, and the urbanization rate from 2017 to 2050 is estimated according to the trend extrapolation method.

4.2 Forecasting results

In this section, we show the results from using the Matlab programming language and previous scenario settings to implement the PSO-LSSVR model to predict total energy demand from 2017 to 2050. According to the theory of Markov chain, we determine the state that the error may reach. Based on these steps, we can obtain the 2017–2050 results by weighted average. Thus, the total energy demand for 2017–2050 based on the model2 can be obtained. Fig.2 shows the results.

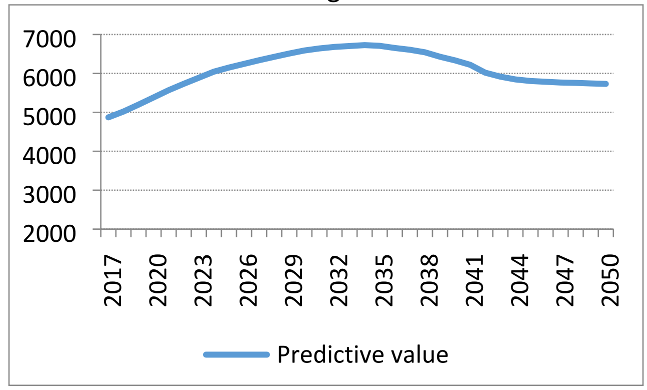

Figure2. model2's 2017-2050 forecast results

As Fig.2shown, the energy consumption growth is also gradually slowing. However, with the development of Chinese economy, China's energy consumption will continue to grow until 2034. The peak is near 6.7 billion tce. China's total energy demand will be reduced to about 5.7 billion tons of standard coal, and will gradually stabilize for the total population declines and the urbanization process slows by 2050.

According to relevant estimates, as of 2035, about 70% of the country's population will have actually entered cities and their surrounding areas, which indicates that China's urbanization process will basically be completed at that time. The total population may also peak at that time. As the total population declines and the urbanization process slows, the demand for total energy may also decrease accordingly.

5. CONCLUSIONS AND POLICY SUGGESTIONS

In this paper, PSO-LSSVM model optimized by Markov chain, is proposed to forecast China's total energy demand for the period 2017–2050. It is better than other forecasting models significantly. The main conclusions of this paper are summarized as follows:

Firstly, according to the co-integration and Granger causality test, this study finds the causal relationship between total energy demand and its influencing factors (GDP, RCL, ECS, POP and UR). We can conduct further factor analysis based on the test results.

Secondly, we introduce intelligent algorithms into the applied energy research. And the mathematical method is used to improve the intelligent algorithm and build a new model. New model has obvious advantages over other models in dealing with complexity of energy systems. From the results of the fitting (Fig.1), the improved PSO-LSSVM prediction model with the Markov chain has been demonstrated to be more accurate than single models. New models can also be applied to other forecasting areas.

Finally, considering the historical trend and future changes of factors affecting China's energy demand, the proposed model predicted that demand will steadily grow to a peak of 6.727 billion tce in 2034, slowly decrease to 5.731 billion tce in 2050, and gradually stabilize. This result can help us grasp the changing trend of China's energy demand and make suggestions.

To help China achieve sustainable economic development, this paper provides the following suggestions to help guide China's energy development, based on this study's forecasted results.

Adjust the economic structure. In terms of economic structure, the demand for high-energy, inefficient products has shifted to low-energy, high-efficiency products, which has improved economic efficiency and reduced energy demand. China should increase the industrial structure adjustment, accelerate technology and equipment upgrades, and promote energy-saving production. To improve China's energy security, China should optimize management links, promote energy-efficient, and improve energy resource utilization and mining efficiency.

Accelerate energy structure adjustment and develop renewable energy. To reduce ecological pollution, China should accelerate the adjustment of energy structure and increase the proportion of clean energy, such as hydropower, wind power, and nuclear power. China should further promote optimization of the energy structure, and develop local new energy and renewable energy according to local conditions. China can expand the green consumer market by accelerating the cultivation of energy-saving service markets and actively promoting market mechanisms.

Adhere to energy conservation and reduce energy consumption. Energy conservation and consumption reduction is an effective way to solve the problem of low energy efficiency in China and meet the economic development needs. It is recommended to focus on controlling industrial energy consumption, relying on technological innovation to improve energy efficiency, rationally guiding transportation energy consumption, and gradually decreasing consumption levels in residential and commercial services.

It is clear from the model comparisons that the PSO-LSSVR model has better prediction performance than others. But the state space is still divided into a limited number of state intervals. We hope to use the other process instead of the current Markov chain in future research. The PSO-LSSVR model will improve the accuracy of the modified model. In addition, we hope to further analyze the convergence of the correction model and explore the effects of multiple models.

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