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Incorporating the influence of China's industrial capacity elimination policies in electricity demand forecasting

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A B S T R A C T

Elimination of high-emitting industrial capacity can be an effective way to control and relieve air pollution but it will also influence demand. Accurate forecasting of electricity demand requires consideration of the impact of capacity elimination policies. This paper applies a modified firefly algorithm improved by Gaussian disturbance to optimize the parameters of Support Vector Machine (SVM) in order to quantify the impact of capacity elimination policies. We consider three policy scenarios and three growth scenarios in our analysis. The results demonstrate that modified firefly algorithm (MFA) can improve the forecasting performance of SVM and electricity demand forecasting considering the influence of capacity elimination policies, and provide good reference for policy analysis and electricity demand analysis.

1. Introduction

With the rapid economic development and industrialization in China, social energy consumption and air pollution have increased greatly. Energy intensive industries such as iron, steel, nonferrous metal, construction material, and chemical manufacturing are not only the pillar industries in China but also the main source of air pollution. In order to control air pollution effectively, China has issued policies for capacity elimination of the heavy industries. Energy consumption and pollution emissions will be strictly limited, which will influence the industrial electricity consumption accordingly. Therefore, electricity demand forecasting that considers the impact of policies to eliminated backward high-emitting industrial capacity is worthy of attention.

Electricity demand forecasting has evolved from traditional to more intelligent methods. The traditional electricity demand forecasting method focuses on an inherent law of electricity demand and linear time series data and correlations between electricity demand and economic factors. Intelligent forecasting methods can deal with more difficult and nonlinear problems. Artificial neural network (ANN) is a common artificial intelligence-based forecasting technology.

ANN is a nonlinear system that imitates the human brain's neural network to learn and deal with problems. It consists of a number of neurons with parallel computing functions and the weights connecting them. The nonlinear mapping between inputs and outputs is realized by an incentive function (Haykin, 2009; Xia et al., 2011; Park et al., 2013). ANN can fit a history curve by discretionarily approaching nonlinear systems (Park et al., 2013; Kowm et al., 2014; Bagnasco et al., 2014). BP neural network (Li and Huang, 2014; Xiao and Liu, 2014; Zhang et al., 2014), RBF neural network (Li et al., 2014; Chang, 2015), and Kohonen neural network (Farhadi and Moghaddas-Tafreshi, 2006) are the most used ANN models. However, ANN is easily affected by initial weights and training samples, and has the disadvantages of slow convergence speed and low computational efficiency. SVM is a kind of machine learning method based on VC dimension theory and structural risk minimization principle. The method possesses generalization ability, global optimization ability, and fast calculation speed (Ye et al., 2012; Fan et al., 2009) under the condition of limited sample size.

The prediction accuracy is affected by its parameters. Many researchers have optimized the parameters by using a variety of intelligent optimization algorithms, such as particle swarm optimization (PSO) (Yang and Meng, 2014), genetic algorithm (GA) (Meng et al., 2014), simulated annealing (SA) (Liu and Huang, 2015), and differential evolution (DE) (Zhao et al., 2013). The algorithms above can improve the performance of SVM greatly. However, they

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still suffer from trapping into the local optimum, which leads to the failure of system training.

This paper uses a firefly algorithm (FA) to optimize the parameters of SVM. A firefly algorithm is a population-based stochastic optimization algorithm developed by imitating the biological characteristics of firefly luminescence (Yang, 2010a). FA has been successfully applied in the field of economic dispatching (Yang et al., 2012), portfolio optimization problems (Bacanin and Tuba, 2014), and more. In order to further improve the performance of FA, this paper will improve FA by using a Gaussian disturbance to promote searching ability and avoid trapping in a local optimum.

When considering the impact of policy in the process of electricity demand forecasting, policy quantification is the most effective and feasible tool. Policy quantification methods such as descriptive statistical analysis (Fu et al., 2013), policy indicators alternative (Levy et al., 2000; Roughgarden and Schneider, 1999), and policy assignment (Ji and Wu, 2015) can obtain the quantification value for model processing. However, such methods ignore the connotation and meaning of policy itself. Furthermore, the impact of policy may be overvalued or undervalued compared to real conditions. Content analysis (Weber, 1990) is another common tool to quantify policy. Content analysis (Fallon, 2016) relies on identifying from written transcripts, examples of indicators of obviously critical and uncritical thinking, from which several critical thinking ratios can be calculated. This method fully decomposes policy categories and applies statistical method to analyze their statistical characteristics, but content analysis still cannot excavate the meaning of specific policy categories. Therefore, model innovation has been paid more attention than the policy impacts of changing electricity demand. In order to fully measure the impact of industrial capacity elimination policy, this paper takes full account of the background of air pollution control to propose a new policy quantification method for evaluating capacity elimination policies. At the same time, the modified firefly algorithm will be used in the selection of SVM parameters. This paper aims to improve the accuracy of electricity demand forecasting in China by optimizing the forecasting model and quantifying the impact of capacity elimination policies on electricity demand. Our research can be used to help ensure the stability and economic efficiency of power system operations, and promote rational planning of the power grid. In addition, the research results can provide a reference for government policy-makers to issue more reasonable and effective policies to reduce high-emitting industrial capacity and protect the environment.

The layout of this paper is designed as follows: In the first section, the air pollution status and background in China is described. The second section reviews the industrial capacity elimination policies in China and proposes the policy quantification method. The SVM model and modified firefly algorithm are detailed in the third section. In Section 4, a case study is given and the results of the electricity demand forecasting analysis are presented. Section 5 provides our conclusions.

2. Capacity elimination policy quantification

2.1. Policy review

As a developing country, China started its industry rather late; consequently the air pollution problem emerged later then in developed countries. Therefore, research on air pollution prevention and control in China is lagging. In the 1970s, China began to deal with air pollution problems, and was able to form a relatively complete legal system in fewer than 50 years. In 2012 air pollution broke out and “haze-fog” became a popularized term in China. The average haze days in 2013 were 35.9 days (Ministry of Environmental Protection, 2014), reaching a peak since 1961. In response, the Chinese government issued several policies on air pollution prevention and control, such as the *Air Pollution Prevention and Control Action Plan*, *2014–2015 Energy Saving and Emission Reduction and Low Carbon Development Action Plan*. At the same time, capacity elimination policies were actively explored and many relevant policies have been issued in China since 2014.

As shown in Table 1, six main capacity elimination policies issued since 2014 clarified the objectives of energy consumption per unit GDP and non-fossil energy consumption, declared the development route, and provided specific capacity elimination measures.

2.2. Capacity elimination policy quantification

Capacity elimination policies have bee were fully implemented since 2014, so we quantify the impact of capacity elimination policies for the 2014–2018 period. The quantification rule is shown in (1):

$$P_{effect} = P_0 - P_1 \tag{1}$$

Where, P_0 is the level of production in the absence of capacity elimination policies during 2014–2018, estimated according to historical data for 2001–2013; P_1 represents the production under the capacity elimination policies, where the production in 2014 and 2015 is the actual value, and the production in 2016–2018 is estimated based on the targets set according to relevant policies. P_{effect} is the capacity reduction, which is regarded as the effect value of capacity elimination policies.

3. Models

3.1. SVM

SVM can convert a nonlinear separable problem in low space to a linear problem in Hilbert space (Sudheer et al., 2014). Fig. 1 illustrates the structure of SVM for regression.

Here, K_n is kernel function, and n represents the number of vectors, m represents the number of inputs.

The nonlinear relationship between the input x and output $f(x)$ can be described by a regression function described in (2):

$$f(x) = w^T \varphi(x) + b \tag{2}$$

where w is the vector of weight coefficients and b is bias constant. $\varphi(x)$ represents a nonlinear mapping from input space to the feature space. SVM uses $\{(x_1, y_1), (x_2, y_3), \cdots, (x_i, y_i)\}(i = 1, \cdots, \ell)$ to train (2). w and b can be estimated by minimizing the objective function given as:

Minimize

$$\frac{1}{2}\|w\|^2 + C\sum_{i=0}^{\ell}\left(\xi + \xi^*\right) \tag{3}$$

where ξ and ξ^* are slack variables. C is the trade-off parameter that determines the degree of the empirical error.

The constraint conditions are described as follows:

$$\begin{cases} y_i - w\varphi(x_i) - b \le \varepsilon + \xi_i \\ w\varphi(x_i) + b - y_i \le \varepsilon + \xi_i^* \; (i = 1, 2, \cdots, \ell) \\ \xi_i, \xi_i^* \ge 0 \end{cases} \tag{4}$$

After optimizing the problem above, the coefficient of w can be obtained: