Research on the Substitute Potential of Beijing-Tianjin-Hebei Electric Energy under Multiple Scenarios Based on PSO-SVM Algorithm

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Abstract. To control the haze of Beijing-Tianjin-Hebei, the government has promoted the "electric energy substitution" (EES) strategy of replacing scattered coal and direct fuel with electric energy. In order to explore the potential of EES in Beijing-Tianjin-Hebei region, this paper takes GDP, population, and technological progress as influencing factors, considers multiple scenarios based on the "decoupling" theory, and establishes a regional energy substitution potential prediction model based on particle swarm optimization support vector machine (PSO-SVM). The market potential of electric energy substitution is predicted and analyzed through scenario analysis. Based on the prediction results, suggestions for promoting electric energy replacement strategy are proposed.

1. Introduction

Nowadays, the air quality in Beijing-Tianjin-Hebei region which is the center of economy, culture and politics in northern China has deteriorated rapidly. It is caused by the growth of energy consumption and the irrationality of the energy structure. As the leading energy consumption, the massive consumption of coal and oil seriously threatens the atmospheric environment in the Beijing-Tianjin-Hebei region. Therefore, the government has promoted the EES strategy of “replacing coal and oil with electricity”. The implementation of EES strategy is essentially the adjustment of energy structure. Since the stable supply of energy directly affects the operation and development of the regional economy, the accurate prediction of the market growth potential brought by the replacement of electric energy in the Beijing-Tianjin-Hebei region is the premise of the scientific planning of the regional electric energy industry.

In order to manage the atmospheric environment, Chinese government has implemented "using electricity in stead of coal" EES strategy, replacing coal and oil with clean, efficient, and convenient electrical energy to ease the environmental pollution caused by emissions. Beijing-Tianjin-Hebei region, as an important economic circle and urban agglomeration in China, is both an important driving force for the development of China power industry and a pilot region for China new round of power market reform. Beijing and Tianjin are adjacent to each other, and the State Grid Corporation of China is advancing the frontier regions for the implementation of EES strategy. Therefore, accurately predicting the potential of EES in the Beijing-Tianjin-Hebei region can not only promote the overall experience of “coal to electricity” and explore a feasible propulsion model in other regions of China, but also accurately plan power grids, save planning resources, and avoid wasting resources.

As a new concept of energy consumption, EES has been widely recognized. Current studies on EES tend to predict energy demand, and researches on the potential of EES are also focused on the urban
level. Fan[1] employed regression techniques to forecast electricity demand under the scenario analysis model and explored the impact of low-carbon economy on electricity demand with variables such as GDP, population; Lin[2] analyzed long-term power demand growth rate of China with the constraints of electricity market demand from macroeconomic perspective. Yin[3] forecasted the future demand for major terminal energy in Beijing, and analyzed the alternative potential of coal and petroleum in various industries through the establishment of a grey energy demand forecasting model. Based on the correlation between energy conservation and emission reduction in Beijing, Zhao Yinhui[4] constructed a model to discuss the environmental and economic benefits of EES of Beijing; All of them have promoted the progress of EES to a certain extent, however, there are few theoretical studies on regional EES potential. With the full opening of China EES progress, we need to study the potential of EES to guide the actual work.

This paper takes region as the research object, quantifies the potential of EES, and builds different development scenarios based on regional economic development, policy support, and EES technology to forecasts EES potential. It not only provides certain theoretical support for electric power industry related management departments to judge the market changes of EES and formulate EES policies, but also is important for increasing the proportion of electric energy consumption in China. In the related research on regional potential for electricity substitution, scenario analysis is commonly used. According to the IPAT method, an IPAT model for EES in Beijing-Tianjin-Hebei is established to evaluate its EES potential. A variety of EES scenarios are designed and particle swarm optimization support vector machine (PSO – SVM) is nested in the IPAT model to predict urban energy consumption and electric energy consumption.

2. Model construction

2.1. IPAT model

The IPAT model was first proposed by American ecologist Ehrlich [5] in the 1970s, which reflects the impact of economic development on the environment through three factors: population (P), affluence (A), and technology (T). The relationship [6] can be expressed as follow:

\[ I = P \times A \times T \]  

(1)

The IPAT model is used to study the relationship between environment, population, affluence, and technology. Similarly, EES is also affected by the combined effects of population, affluence, and technology. The technological progress factors can be indicated by proportion of electric energy consumption intensity accounting for the electric sharing in terminal energy consumption. The more mature the EES, the greater the proportion. Therefore, the IPAT model for EES can be decomposed into the following formula:

\[ I_t = R_t \times A_t \times \left( \frac{E_e}{G} \right)_t \times \left( \frac{De}{E_e} \right)_t \]  

(2)

Where \( I_t \) denotes the total amount of EES in t-th year; \( Pt \) is the total population in t-th year; \( At \) is GDP per capita in t-th year; \( De \) represents the amount of terminal energy substitution; \( E_e \) denotes terminal energy consumption; \( G \) is GDP; \( \left( \frac{E_e}{G} \right)_t \) denotes the terminal electric energy consumption intensity in t-th year; \( \frac{De}{E_e} \) is the proportion of EES in the total amount of terminal electric energy consumption, ie the alternative structure of the electric energy terminal.

Assuming that \( \alpha \) represents the population growth rate, \( \beta \) is the average annual growth rate of GDP per capita, \( \gamma \) is the increase rate of the terminal power consumption intensity, which represents the degree of technological progress, and \( \delta \) represents the rate of proportion change of EES in the terminal power consumption, that is, the rate of structural changes in electric terminals substitution. This parameter is mainly affected by the optimization adjustment of government-led industrial and the guiding role of clean energy consumption, and terminal clean energy mainly refers to electrical energy. Therefore, \( \delta \) can be regarded as the government support for EES. Compared with the situation of EES in the base year, the factors in the t-th year are as follows:
\[ P_t = P_0 \times (1 + \alpha) \]  
\[ A_t = A_0 \times (1 + \beta) \]  
\[ \left( \frac{E_e}{E} \right)_t = \left( \frac{E_e}{E} \right)_0 \times (1 + \gamma) \]  
\[ \left( D_e E_e \right)_t = \left( D_e E_e \right)_0 \times (1 + \delta) \]

Where \( P_t \) and \( P_0 \) are the total population of the \( t \)-th year and base year respectively; \( A_t \) and \( A_0 \) are the GDP per capita of the \( t \)-year and base year separately; \( D_e \) is the terminal energy substitution; \( E_e \) is the terminal power consumption. Therefore, the change of total amount of energy substitution be expressed as:

\[ I_t = I_0 \times [(1 + \alpha) \times (1 + \beta) \times (1 + \gamma) \times (1 + \delta)] \]

Where \( I_t \) and \( I_0 \) are the total amount of energy substitution in \( t \)-th and base year respectively.

2.2. Multiple scenario setting basis

The power industry is a pillar industry of the country. Inadequate power supply will severely constrain the economic development and rapid economic development will increase the demand for the electricity market [7]. Therefore, there is a certain correlation between economic growth and the development of EES. By analyzing relevant theories of economics, policies, etc., and combining the decoupling theory, the basis for the scenarios analysis of EES potential can be obtained [8]. This paper builds three different alternative scenarios based on the drivers of regional economic development, power substitution policy support, and technology. The specific scenario settings are shown in table 1.

Table 1. Scenario settings.

| Scenario Analysis | Specific scenarios                                      | Scenario explanation                                                                 |
|-------------------|--------------------------------------------------------|--------------------------------------------------------------------------------------|
| Scenario 1        | Keeping the current electricity substitution process and taking no steps forward. | Without considering the effect of technological progress and policy support on the EES, that is, electrical energy substitution and economic development are in an uncoupling phase. |
| Scenario 2        | Adding a technology index to the original energy substitution process. | The introduction of technology is promoted on the basis of the existing alternative development of electrical energy, and the decoupling of electrical energy replacement from economic development has been achieved. |
| Scenario 3        | On the basis of increasing technical progress, we will strengthen government support for terminal energy substitution and provide policy support. | On the basis of Scenario B, increasing the driving force of policy support for EES and achieving complete decoupling of EES from economic development. |

2.3. Decoupling theory

Since the substitution of electric energy is related to economic growth, it can be measured by the decoupling theory [9]. Therefore, the degree of dependence between economic growth and terminal energy substitution can be expressed with GDP per capita change rate and the change rate of EES. The degree of decoupling of development can be used as an important assessment basis for technological progress and policy guidance.

Decoupling degree > 1: The growth rate of EES is greater than economic development speed. Economic growth depends on the degree of EES, so the development stage is of undetached [11].

Decoupling degree ≤ 1: The growth rate of EES is less than the economic growth rate or consistent with the economic development speed. Economic growth does not depend entirely on or rarely depends on the degree of EES. Economic growth and energy replacement process are in the decoupling stage [12].
3. Methodology

3.1. Support Vector Machine (SVM) Model

The development of EES in China is relatively late, with few data, and it is influenced by many factors. The accuracy of general method prediction is low. SVM [9] can handle small samples, nonlinearity and high dimensionality problems, and are suitable for EES. Therefore, SVM is used to predict cumulative EES.

In order to ensure the accuracy of the algorithm training, the experimental data is divided into m training set samples \((x_i, y_i)\), \(i = 1, 2, \ldots, m\), \(x_i \in R^n, y_i \in R\), where \(x_i\) and \(y_i\) represent the input column vectors and output values of the i-th training sample, respectively. Creating a linear regression function in the high-dimensional feature space:

\[
f(x) = \omega \psi(x) + b \tag{8}
\]

where: \(\omega\) is the weight vector, \(\omega \in H\); \(b\) is the intercept, \(b \in R\). The nonlinear problem needs to be transformed into a linear problem: The non-linear mapping \(\psi(\cdot)\) is used to map the experimental data into a high-dimensional feature space (Hilbert), and the nonlinear regression is performed by minimizing the upper bound risk.

To avoid the effect of noise in the experimental data, the equation (9) needs to be modified: the \(\varepsilon\) linear insensitivity loss function and the penalty factor \(C\) are introduced; if the fitting error is allowed, slack variables \(\xi_i, \xi_i^*\) are introduced, then the SVM can be converted into the following optimization problems:

\[
\begin{align*}
\min & \left( \frac{1}{2} \| \omega \|^2 + C \sum_{i=1}^{m} (\xi_i + \xi_i^*) \right) \\
\text{s.t.} & \quad y_i - \omega \psi(x_i) - b \leq \varepsilon + \xi_i \\
& \quad \omega \psi(x_i) + b - y_i \leq \varepsilon + \xi_i^* \\
& \quad \xi_i \geq 0, \xi_i^* \geq 0
\end{align*} \tag{9}
\]

In order to simplify the above solution process, the constraint problem is transformed into the Lagrange dual problem:

\[
L = \frac{1}{2} \| \omega \|^2 + C \sum_{i=1}^{m} (\xi_i + \xi_i^*) - \sum_{i=1}^{m} a_i (\varepsilon + \xi_i - y_i - \omega \psi(x_i) + b) - \sum_{i=1}^{m} a_i^* (\varepsilon + \xi_i^* + y_i - \omega \psi(x_i) - b) - \sum_{i=1}^{m} (\eta_i \cdot \xi_i - \eta_i^* \cdot \xi_i^*) \tag{10}
\]

The regression of nonlinear SVM is mapped to high-dimensional feature space through the inner product form. To avoid generating “dimensional disaster” for much samples, the kernel function instead of the inner product is used to define the formula of the kernel function when solving the above optimization problem:

\[
K(x_i, x_j) = \psi(x_i) \cdot \psi(x_j) \tag{11}
\]

This article selects a typical RBF kernel function:

\[
K(x_i, x_j) = \exp(-g\|x_i - x_j\|^2) \tag{12}
\]

Where \(g\) is the variance in the kernel function, the penalty parameter \(C\) and the kernel function parameter \(g\) are the key parameters in the support vector model.
The final regression function is:

\[ f(x) = \sum_{i=1}^{m} (\alpha_i - \alpha^*_i) \cdot K(x_i, x_j) + b \]

(13)

3.2. Particle swarm optimization support vector machine

The accuracy of SVM is influenced by the penalty parameter C and the nuclear parameter g of RBF. C affects the generalization ability or training error of the model. g may cause overfitting or under-learning, which affects the prediction accuracy of the EES. In addition, the potential for EES is affected by many factors such as policy incentives and has high sample uncertainty. Particle swarm optimization (PSO) can find the global optimal solution of the problem with a large probability in processing multi-objective optimization. Compared with the traditional stochastic method, PSO has high computational efficiency and robustness, and can effectively adapt to the sample sequence with higher uncertainty [10].

PSO - SVM calculates the SVM penalty coefficient parameter C and kernel function parameter g based on historical cumulative energy substitution and technical, policy, and economic influencing factors, and uses it as the initial position of the particle, then utilizes the particle swarm algorithm to find the optimal SVM parameter, finally establishes a new SVM network and obtains cumulative EES. This article selects PSO for parameter optimization. The steps are as follows:

Step 1: Initialization. The PSO population size is set to 20, the maximum number of iterations is 200, the initial velocity is initially 1, the initial velocity of the particle is a random number between [0, 1], and the initial parameter calculated by the SVM is the particle initial position.

Step 2: Fitness evaluation. Calculating the individual fitness value and initialize the individual optimal and global optimal.

Step 3: Optimization. Comparing the fitness value and extremum to update their speed, finding the position of the optimal particle, that is, the optimal solution \( C_{PS} \) and \( g_{PS} \).

\[ V_{n+1} = V_n + c_1 r_1(Q_n - X_n) + c_2 r_2(Q_g - X_g) \]  
(14)

\[ X_{n+1} = X_n + V_{n+1} \]  
(15)

Where \( t \) is the current number of iterations; \( c_1 \) and \( c_2 \) are acceleration factors; \( r_1 \) and \( r_2 \) are random numbers generated by the random function in the interval [0,1]; \( m \) represents the inertia weight; \( Q_n \) is the individual extreme point of particle \( n \); \( Q_g \) is the population extremum of the population; \( V_n \) is the velocity of the n-th particle; \( X_n \) is the position of the particle \( n \).

Step 4: End condition checking. Seeking the maximum evolutionary generation, then ending the optimization and outputting the optimal parameters \( C \) and \( g \).

4. Analysis of the EES potential

In 2013, the State Grid Corporation of China proposed the development strategy of EES. Therefore, 2013 was set as the base year TB. According to the analysis of energy consumption data in Beijing, Tianjin and Hebei, the electricity consumption in 2013 accounted for 2.1% of total terminal energy. The formula for the calculation of energy substitution in a given year is:

\[ D_{et} = (E_{et} - \frac{E_{et}}{E_{TB}} \cdot E_t) \]  
(16)

Where \( D_{et} \) is the amount of EES; \( E_{et} \) is the actual electric energy consumption of the t-th year; \( E_t \) is the total terminal energy consumption in the t-th year, \( \frac{E_{et}}{E_{TB}} \) is 2.1%.

Therefore, the formula for calculating EES potential in the t-year is:

\[ F_t = D_{et} \cdot [(1 + \alpha) \times (1 + \beta) \times (1 + \gamma) \times (1 + \delta)]^t \]  
(17)

4.1. Energy consumption forecasting

Taking the historical data of energy consumption in Beijing, Tianjin and Hebei from 2004 to 2015 (Table 2) as a sample, forecasting the data in 2016 using PSO - SVM, and inputting the forecast results into the sample sequence to predict the next year in sequence, as shown in table 3.
Table 2. The EES Related Data from 2004 to 2015 in Beijing-Tianjin-Hebei.

| Year | Terminal energy consumption (Hundred million ton standard coal) | Actual electricity consumption (Ten thousand ton standard coal) |
|------|---------------------------------------------------------------|---------------------------------------------------------------|
| 2004 | 1.73                                                          | 17                                                            |
| 2005 | 1.98                                                          | 24                                                            |
| 2006 | 2.18                                                          | 22                                                            |
| 2007 | 2.36                                                          | 21                                                            |
| 2008 | 2.43                                                          | 47                                                            |
| 2009 | 2.54                                                          | 59                                                            |
| 2010 | 2.62                                                          | 270                                                           |
| 2011 | 2.81                                                          | 180                                                           |
| 2012 | 2.88                                                          | 467                                                           |
| 2013 | 2.97                                                          | 598                                                           |
| 2014 | 2.93                                                          | 892                                                           |
| 2015 | 2.94                                                          | 1023                                                          |

Table 3. Forecasting results.

| Year | Terminal energy consumption Predictive value (Hundreds of millions ton standard coal) | Electricity consumption Predictive value (Ten thousand ton standard coal) |
|------|--------------------------------------------------------------------------------------|------------------------------------------------------------------------|
| 2016 | 5.94                                                                                 | 1532.53                                                                |
| 2017 | 6.14                                                                                 | 1978.14                                                                |
| 2018 | 6.33                                                                                 | 2123.75                                                                |
| 2019 | 6.53                                                                                 | 2669.35                                                                |
| 2020 | 6.73                                                                                 | 2914.96                                                                |

4.2. Parameter settings

The population, economic development, EES technology and relevant policy support of scenario 1, scenario 2 and scenario 3 are predicted. The change of each parameter is represented by α, β, γ, and δ respectively, and the actual value of each parameter is calculated.

(1) Population

With reference to the predictions and judgments of Beijing-Tianjin-Hebei “Population and Social Development Report 2014” and “Report on the Population Development Strategy,” changes in the population growth rate of Beijing-Tianjin-Hebei in the future are comprehensively analyzed. Given Beijing-Tianjin-Hebei construction industry cluster, the introduction of institutions of higher learning and the construction of the Central City community, etc., combining with the existing planning and forecasting research results, it is estimated that the population growth rate will be 6.06‰ in 2016-2020.

(2) Economic parameters

In terms of economy, the rapid economic development has a positive effect on EES. According to the analysis of “2015 Hebei Province Economic Yearbook”, “2015 Beijing Economic Yearbook” and “2015 Tianjin Economic Yearbook”, the economic growth of Beijing, Tianjin, and Hebei in 2014 was 6.5%. In 2014, Beijing-Tianjin-Hebei economic growth rate was 6.5%, and economic growth maintained at a level of 6.8% during 2015, and its economic performance was generally stable. The economic growth rate of Beijing-Tianjin-Hebei from 2016 to 2020 is expected to be about 8%.

(3) Technical level

Assuming that the related technologies for EES have stagnated in scenario 1, the terminal energy demand and terminal electricity consumption intensity remains at the current level. EES process is not decoupled from economic development due to the lack of technological progress. Supposing that EES technology and economy development in tandem, terminal energy demand increases substantially with the advancement of EES technology. The terminal electricity consumption intensity increases, and
the growth level is consistent with the level of economic development in each stage, so that the degree of decoupling of electric energy substitution from economic development is approximately 1 in scenario 2.

(4) Policy support
At the aspect of electricity substitution policy, assuming that in scenario 1, Beijing-Tianjin-Hebei does not take any measures to promote the development of EES and the implementation of EES depends on economy development. Scenario 2 and scenario 3 are based on the government’s electricity replacement policy.

In accordance with the above theoretical basis, population, GDP per capita, technological progress, and policy support parameters for scenarios 1, 2, and 3 are set to predict the change of terminal energy structure development, as shown in Table 4. Where $\alpha$ is the annual growth rate of population; $\beta$ is the annual growth rate of GDP per capita; $\gamma$ is the growth rate of EES technology; $\delta$ represents the rate of change in policy support.

| Scenario Settings | $\alpha/%$ | $\beta/%$ | $\gamma/%$ | $\delta/%$ |
|-------------------|-----------|-----------|-----------|-----------|
| Scenario 1        | 0.6       | 8         | 0         | 0         |
| Scenario 2        | 0.6       | 8         | 5.71      | 0         |
| Scenario 3        | 0.6       | 8         | 5.71      | 4.5       |

4.3. Potential calculation analysis
The following results can be obtained by substituting the above-mentioned energy consumption prediction values and related policy support strengths, technical, and economic development parameters into the formula, as shown in Figure 1.

![Figure 1. Alternative electric demand forecast in different scenario.](image)

By analyzing the EES potential under different scenarios in figure 1, the following conclusions can be drawn:

1. In scenario 1, Beijing-Tianjin-Hebei EES potential are 297.31 hundred million(hm) kWh, 581.1 hm kWh, 877.09 hm kWh, 1436.06 hm kWh, and 1683.1 billion kWh, respectively, and the rate of electrical energy substitution growth is slow.

2. In Scenario 2, the EES potential were respectively 351.21 hm kwh, 775.38 hm kwh, 1152.66 hm kwh, 2022.48 hm kwh and 2920.23 hm kwh, whose growth rate approximately 5.71% compared with scenario 1, indicating that under the continuous promotion of policies, EES has achieved rapid development.

3. In Scenario 3, the EES potential were 400.78 hm kwh, 1163.16 hm kwh, 1807.31 hm kwh, 3154.7 hm kwh, and 4382.28 hm kwh, respectively, whose growth rate was about 4.5% compared with scenario...
2, indicating that under the dual promotion of policy support and technology, the EES potential has been greatly improved.

(4) The EES potential will show a significant growth trend until 2020 both in scenario 1, scenario 2 and scenario 3, as shown in Figure 1. Due to lack of technology and related policies, the growth rate of EES potential in scenario 1 is smaller than that of scenario 2 and 3. The growth rate of EES potential in scenario 3 is greater than that of scenario 2 because of government support added. Compared with Scenario 1, Scenario 2 and Scenario 3 are significantly faster in terms of the progress in EES.

5. Conclusion
Compared with coal, oil, natural gas and other energy sources, electric energy is cleaner, more convenient and safer. The regional government should introduce policies that support EES strategy based on the regional economy, environment, and energy consumption, strengthen policy support and guide society to actively choose electric energy instead of high-pollution, low-efficiency energy, expand the market for EES and actively develop EES technology, and further promote the rapid development of EES in China. At the same time, foreign electrification technology should be widely cited to improve the level of regional electrification.

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