Research on Multi-scenario Intelligent Forecasting Model of China's Electric Power Consumption Driven by Policy

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Abstract. Electricity is the symbol of modern industrial civilization, the basic input of production and the necessities of people's life. With the development of economy, the electric power industry plays an increasingly important role in the national economy. Accurate judgment of power demand is the premise of scientific planning, and its basis is a correct understanding of the law of power consumption, as well as a scientific understanding of the inherent relationship between power demand and economic development. Therefore, this paper systematically studies the relevant data of China from 1993 to 2018, carefully analyses the relationship between economic development and power consumption, reveals the basic law of power consumption and economic development, and on this basis, sets up different scenarios around industrial structure and power consumption structure, and makes multi-scenario prediction of China's electricity demand in the coming 2020, 2030 and 2050 years, with a view to providing China's electricity demand. Force demand planning and related policy formulation provide some reference.

1. Introduction

As the basic industry and social public utilities of the national economy, electricity has a great impact on economic and social development, and its proportion in energy consumption is also rising. With the rapid development of population growth, urbanization and industrialization, as well as the continuous improvement of living standards, the world is facing huge demand for electricity. Accurate judgment of power demand is the premise of scientific planning, and its basis is a correct understanding of the law of power consumption, as well as a scientific understanding of the inherent relationship between power demand and economic development.

The research on the relationship between electricity consumption and economic growth has always been one of the focuses of attention of economists and policy makers. It is of great significance to grasp the correlation and strength between them for the coordinated development of economy and power industry and the formulation of relevant policies. Pao used the co-integration and error adjustment model to study Taiwan's 1980-2007 data. The results showed that there was a co-integration relationship between electricity consumption and economic growth, and there was only one-way Granger causality between economic growth and electricity consumption in both short and long term [1]. Chandran et al. added price variable in research on Malaysia. Cointegration test showed that there was a long-term equilibrium relationship among electricity consumption, real GDP and price, and there was only one-way causality between electricity consumption and economic growth. Using the lag model of autoregressive distribution, the elasticity of electricity consumption to economic growth was estimated to be about 0.7 [2]. Solarin and Shahbaz studied the relationship between electricity consumption,
urbanization and economic growth in Angola by co-integration and Granger causality analysis. The results showed that there was a two-way Granger causality between urbanization and electricity consumption [3]. Karanfil and Li examined the long- and short-run dynamics between electricity consumption and economic activities by using panel data of per capita electricity consumption and per capita GDP of 160 countries for the period of 1980-2010, accounting for the degree of electricity dependence and the level of urbanization and concluded that the electricity-growth nexus was highly sensitive to regional differences, countries' income levels, urbanization rates and supply risks [4]. Samu and Bekun et al. explored the relationship between electricity consumption, real gross domestic product per capita and carbon dioxide emissions in Zimbabwe, and the test showed that there existed a long-run equilibrium relationship between electricity consumption, carbon dioxide emissions and real gross domestic product per capita [5].

The purpose of studying the relationship between electricity consumption and economic growth is to forecast electricity demand and provide reference for national development planning. Some scholars have studied electricity demand forecasting. Azadeh and Ghaderi et al. found that the model combining genetic algorithm with neural network algorithm was more suitable for the prediction of Iranian power consumption and can get smaller relative error [6]. Kavaklioglu predicted Turkey's electricity consumption, and the results showed that electricity consumption can be modeled using Support Vector Regression and the models can be used to predict future electricity consumption [7]. Kiran et al. used a model combining artificial bee colony algorithm and particle swarm optimization to predict Turkey's electricity consumption, and confirmed that the prediction accuracy of this model is higher than that of ant colony algorithm [8]. Azadeh and Taghipour et al. compared the prediction accuracy of genetic algorithm, artificial immune system and particle swarm optimization when forecasting electricity consumption, and experiments showed that the artificial immune system algorithm can obtain more accurate prediction results by using its clonal selection technology under the premise of fixed random variables [9].

This paper considers the influencing factors of power demand from two aspects of economic development and power consumption, and takes them as the auxiliary index of power demand forecasting evaluation index system. The least squares support vector machine model and particle swarm optimization algorithm are introduced. Based on the relevant data of China from 1993 to 2018, scenarios are set around industrial structure and power consumption structure, so as to China's future. Multi-scenario forecasting of power demand in 2020, 2030 and 2050 is expected to provide reference for China's power demand planning and related policy formulation.

2. Theoretical basis

2.1. Selection of influencing factors

There are many and complex factors affecting electricity demand. From the two levels of economic development and electricity consumption, this paper chooses six factors as forecast indicators: per capita GDP, urbanization level, industrial structure, per capita electricity consumption, power consumption structure and power consumption intensity.

(1) Per capita GDP (recorded as AGDP)

GDP can provide a complete picture of the economic situation, which is an important indicator of the economic strength of a country or region. Calculation formula:

\[ AGDP = \frac{GDP}{Population} \]  

(1)

(2) Urbanization level

The level of urbanization is an important symbol of industrialization and modernization of a country. It is an inevitable trend of social and economic development. The level of urbanization rate (recorded as UR) can usually reflect the degree of development of a country or region. Calculation formula:
(3) Industrial structure
For different industries, different power intensity, the adjustment between industries has a significant impact on the consumption of electricity in the whole society. In this paper, the proportion of added value of secondary industry to GDP (recorded as SG) is used to express. Calculation formula:

\[
SG = \frac{\text{The second industrial increment in value}}{\text{GDP}}
\]

(4) Per capita electricity consumption
In this paper, China's per capita electricity consumption (recorded as AE) is used to represent the level of electricity consumption. Calculation formula:

\[
AE = \frac{\text{Social power consumption}}{\text{Population}}
\]

(5) Power consumption structure
In this paper, the power consumption structure is represented by the ratio of the added value of electricity consumption in the secondary industry to social power consumption (recorded as SE). Calculation formula:

\[
SE = \frac{\text{Value-added of electricity consumption in the second industry}}{\text{Social power consumption}}
\]

(6) Power consumption intensity (recorded as F)
Electricity consumption intensity refers to the amount of electricity consumed per unit of GDP, which can reflect the efficiency of electricity consumption and indirectly reflect the level and scale of production technology in this industry.

\[
F = \frac{\text{Social power consumption}}{\text{GDP}}
\]

2.2. Least Squares Support Vector Machine Algorithm
Least Square Support Vector Machine (LSSVM) is an improved algorithm from the traditional standard Support Vector Machine (SVM). It was originally proposed by Suykens and Vandewalle [10]. By innovating the setting of the objective function of SVM, the time-consuming quadratic programming (QP) problem is transformed into the solving problem of linear equations, which reduces the complexity of the model, reduces the memory consumption in the training process and greatly improves the solving speed. The principle of the algorithm is introduced below.

Given a set of sample vectors of n-dimensional input and one-dimensional output, the sample under a single technical scheme can be expressed as \((x_i, y_i) \mid x_i \in \mathbb{R}^n, y_i \in \mathbb{R}, i = 1, 2, \ldots, l\). The sample is mapped from the original space to the high-dimensional feature space by a non-linear mapping \(\phi(x)\). And the non-linear estimation function \(f(x) = \omega \cdot \phi(x) + b\) is transformed into the linear estimation function in the high-dimensional feature space. The weight vector and the offset of the regression function are expressed by \(\omega\) and \(b\) separately. According to the structural risk minimization principle, minimize \(\omega\) and \(b\) as follows:

\[
R = \frac{1}{2} \|\omega\|^2 + cR_{emp}
\]

Where, \(\|\omega\|^2\) is used to control the complexity of the model; \(c\) is a regularization parameter to control the penalty degree of the sample exceeding the error; \(R_{emp}\) is the error control function, that is,
the insensitive loss function $\varepsilon$. LSSVM chooses the square of error $\xi_i$ as the loss function when optimizing the target, so the optimization problem is as follows:

$$
\min \frac{1}{2} \| \varphi \|^2 + c \sum_{i=1}^{l} \xi_i^2 \\
\text{s.t. } y_i \left[ \omega^T \varphi(x_i) + b \right] - 1 + \xi_i = 0 \quad (i=1,2,\cdots,l)
$$

Where, $\xi_i$ is the relaxation factor. So in order to solve this problem, the Lagrange function is established as follows:

$$
L(\omega, b, \xi_i, \alpha) = \frac{1}{2} \| \varphi \|^2 + c \sum_{i=1}^{l} \xi_i^2 - \sum_{i=1}^{l} \alpha_i \left[ y_i \left[ \omega^T \varphi(x_i) + b \right] - 1 + \xi_i \right]
$$

Where, $\alpha_i (i=1,2,\cdots,l)$ is Lagrange multiplier. According to the KKT optimization conditions, the partial derivatives of $L$ to $\omega$, $b$, $\xi_i$ and $\alpha$ are obtained respectively, and they are equal to 0. The results are as follows:

$$
\begin{bmatrix}
0 \\
y^T \\
y \cdot Z \cdot Z^T + c^{-1} I
\end{bmatrix}
\begin{bmatrix}
b \\
\alpha
\end{bmatrix}
= 
\begin{bmatrix}
0 \\
I
\end{bmatrix}
$$

(10)

Then, an arbitrary symmetric function satisfying Mercer’s condition is introduced as the kernel function. The parameters of the kernel function determine the complexity of the spatial distribution of the sample data and have a great influence on the performance of the model. $\alpha$ and $b$ are obtained by least square method. Finally, the decision function of LSSVM regression analysis is obtained as follows:

$$
f(x) = \sum_{i=1}^{l} \alpha_i K(x, x_i) + b
$$

(11)

2.3. Particle Swarm Optimization Algorithm

Particle Swarm Optimization algorithm (PSO) algorithm is a global search algorithm. It was initially inspired by birds’ foraging behavior and was used to solve global optimization problems [11]. The main idea of PSO algorithm is to initialize the location and velocity of a group of random particles and search for the optimal solution by iteration under certain conditions. The best position of each particle in the search process is defined as the individual extreme value $P_{best}$, and the best position of the current population is defined as the global extreme value $G_{best}$. In each iteration, the particle updates its speed and position in the next iteration according to the change of the two.

In a d-dimensional search space, there are m particles representing possible solutions to the problem $X = \{x_1, x_2, \cdots, x_m\}$, where $X_i = \{x_{i1}, x_{i2}, \cdots, x_{id}\}$ represents the position of the $i$ particle, $d$ is the number of LSSVM parameters, here $d=2$. Individual fitness is expressed by the mean square error generated by each training set sample in LSSVM training, and the fitness function is constructed as follows:

$$
MSE \left( \tilde{y}_i \right) = \frac{1}{n} \sum_{i=1}^{n} (y_i - \tilde{y}_i)^2
$$

$$
f(x) = MSE(x)
$$

(12)

The velocity of particles in D dimensional space is defined as $V_i = \{v_{i1}, v_{i2}, \cdots, v_{id}\}$, $P_i = \{p_{i1}, p_{i2}, \cdots, p_{id}\}$ is the best position $P_{best}$ (the minimum fitness) that the particle can search for itself, $P_t = \{p_{t1}, p_{t2}, \cdots, p_{td}\}$ is the best position $G_{best}$ for the entire population. The velocity and position update of the $i$ particle is determined according to the following formula:
\[ v_{i+1} = \omega v_i + c_1 \text{rand}(i)(P_i - X_i) + c_2 \text{rand}(i)(G_i - X_i) \]

\[ x_{i+1} = x_i + v_{i+1} \]  

where, \( \omega \) is the weight factor of inertia; \( t \) is the number of iterations; \( c_1 \) and \( c_2 \) are acceleration factors, representing the step length of particle flying towards its optimal position and overall optimal position; \( \text{rand}(i) \) is a random number uniformly distributed in the interval [0,1].

If the number of iterations reaches the maximum number of iterations or the precision reaches the preset accuracy, the iteration cycle will be withdrawn and the global optimal parameters will be returned. PSO can be used to optimize kernel function parameters and penalty coefficient in LSSVM model, thus artificial exhaustion can be avoided and better fitting effect can be obtained.

3. Construction of Optimal Algorithms Model and Empirical Analysis

3.1. Sample Sources and Data Statistics

Taking the relevant data of China from 1993 to 2018 as samples, the paper calculates six preliminary indicators: per capita gross domestic product (AGDP), urbanization rate (UR), the proportion of added value of secondary industry to gross domestic product (SG), per capita electricity consumption (AE), the ratio of added value of secondary industry to social electricity consumption (SE) and power consumption intensity (F), as shown in Table 1. The following data are from the website of China Electricity Council and China National Bureau of Statistics.

| Year | AGDP (yuan/person) | UR (%) | SG (%) | AE (kWh/person) | SE (%) | F (kWh/yuan) | Power Consumption |
|------|--------------------|--------|--------|-----------------|--------|--------------|------------------|
| 1993 | 3027               | 27.99% | 46.18% | 695.93          | 6.82%  | 0.230        | 8201.08          |
| 1994 | 4081               | 28.51% | 46.16% | 759.04          | 6.07%  | 0.186        | 9046.49          |
| 1995 | 5091               | 29.04% | 46.75% | 820.54          | 5.85%  | 0.161        | 9867.77          |
| 1996 | 5898               | 30.48% | 47.11% | 868.16          | 4.26%  | 0.147        | 10570.29         |
| 1997 | 6481               | 31.91% | 47.10% | 897.43          | 2.03%  | 0.138        | 11039.11         |
| 1998 | 6860               | 33.35% | 45.80% | 913.68          | 0.83%  | 0.133        | 11347.30         |
| 1999 | 7229               | 34.78% | 45.36% | 965.27          | 4.49%  | 0.134        | 12092.28         |
| ...  | ...                | ...    | ...    | ...             | ...    | ...          | ...              |
| 2015 | 50028              | 56.10% | 41.11% | 4141.73         | 1.06%  | 0.083        | 56933.00         |
| 2016 | 53680              | 57.35% | 40.07% | 4321.01         | 3.48%  | 0.080        | 59198.00         |
| 2017 | 59201              | 58.52% | 40.54% | 4589.25         | 3.62%  | 0.078        | 63625.00         |
| 2018 | 64644              | 59.58% | 40.65% | 4905.40         | 4.12%  | 0.076        | 68449.00         |

3.2. Modeling and Training of Optimal Algorithms

Six indicators after standardization are used as input parameters of prediction model, and data are used as training samples to be substituted for LSSVM empirical parameter model and PSO-LSSVM optimization parameter model respectively for model training, and power demand is used as expected output.

(1) LSSVM empirical parameter model training

A standard LSSVM model is established and then input data into the model for training. Selecting the empirical parameters \( C = 100 \) and \( \sigma^2 = 0.4 \) as the basic parameters of the LSSVM prediction model: the penalty factor and the kernel function parameter. And selecting Radial Basis function as the kernel function \( K(x,x) \).
The PSO-LSSVM model is used to forecast and analyze power demand. The number of population is set at 30, the acceleration factor $c_1$ is 1.5 and $c_2$ is 1.7, the range of weight factor of inertia $\omega$ is [0.4, 0.95], the maximum number of iterations is 300, the radial basis function is also chosen as the kernel function, the range of penalty coefficient C is [0, 300], and the range of kernel function parameter $\sigma^2$ is [0, 200].

The iteration process of PSO is shown in Figure 1, and the result of parameter optimization is shown in Figure 2. The lowest point represents the optimal parameter combination point. The optimal parameters of LSSVM optimized by PSO algorithm: $C=267.5438$, $\sigma^2=0.2110$ and the minimum fitness is $MSE_{min}=51.4050$.

\[
K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right)
\]  

(14)

(2) PSO-LSSVM optimization parameter model training
The minimum fitness of PSO-LSSVM optimization parameter model is only 0.17% compared with the average value of actual power consumption. The prediction accuracy of PSO-LSSVM optimization parameter model is high and can meet the accuracy requirements of power demand prediction.

4. Multi-scenario Forecast of China's Electric Power Consumption

4.1. Situational Design of Influencing Factors
China's economic structure is dominated by the secondary industry, the three industries are not coordinated, the agricultural foundation is weak, the industry is large but not strong, and the service industry is lagging behind. The Central Economic Work Conference of China held on December 19, 2018, pointed out that the main contradiction in China's economic operation is still the supply-side structural reform, and we must adhere to the supply-side structural reform as the main line.

Optimizing the industrial structure is an important part of deepening the structural reform of supply side. According to China's policy-driven, this paper sets up multiple scenarios around the industrial structure and power consumption structure, dividing the industrial structure and power consumption structure into two scenarios: high and low scenarios, namely, the proportion of added value of the secondary industry to GDP (SG) and the use of the second industry. The value-added of electricity and the ratio of social electricity consumption (SE) are set to two different values, high and low, respectively. The index values of other influencing factors are controlled unchanged to carry out multi-scenario forecasting of China's electricity consumption.

4.2. Scenario parameter setting
Based on the foregoing analysis and data information availability, the parameters of per capita GDP, urbanization level, industrial structure, per capita electricity consumption, power consumption structure and power consumption intensity are selected in scenario analysis, and the relevant parameters of China's electricity demand are set respectively. Specific settings are as follows:

(1) Per capita GDP setting
From 1993 to 2018, the average annual growth rate of China's population was 6.55‰. According to the 13th Five-Year Plan for National Economic and Social Development of the People's Republic of China(the “13th five-year plan”), by 2020, the total population of China will be about 1.420 billion. According to the latest Green Paper on Population and Labour issued by the Chinese Academy of Social Sciences, China's population will reach a peak of 1.442 billion in 2029, starting from 2030. Entering sustained negative growth, it decreased to 1.364 billion in 2050.

During the period of The 12th Five-Year Plan for National Economic and Social Development of the People's Republic of China(the “12th five-year plan”), China's GDP grew from 48.8 trillion yuan in 2011 to 68.6 trillion yuan in 2015, with an average annual growth rate of 7.05%, and the planned target was fulfilled. Based on the fact that the average annual growth rate of GDP in 2011-2018 is 7.96%, this paper sets the average annual growth rate of GDP at 7.5%.Per capita GDP(AGDP) is basically set as shown in Table 2.

| Table 2. Per capita GDP parameter setting. |
|------------------------------------------|
| 2018 | 2020 | 2030 | 2050 | Average annual growth rate |
| Population (billion) | 1.395 | 1.420 | 1.442 | 1.364 | — |
| GDP (billion yuan) | 90030.9 | 104042 | 214433.8 | 910882.7 | 7.5% |
| AGDP (yuan/person) | 64644 | 73269 | 148706 | 667803 | — |

(2) Urbanization level setting
With the continuous development of economy and society, China's urbanization level and residents' consumption level are also rising. From 2010 to 2015, China's non-agricultural population grew from
670 million to 771 million, and the urbanization rate reached 56.1% in 2015, meeting the urbanization requirements of the “12th five-year plan”. According to the requirement that the urbanization level of the “13th five-year plan” reaches 60% and the actual situation that the average annual growth rate of urbanization rate is 1.20% in 2011-2018, this paper sets the average annual growth rate of urbanization rate as 1.05%. The urbanization rate (UR) is basically set as shown in Table 3.

Table 3. Urbanization level parameter setting.

|       | 2018       | 2020       | 2030       | 2050       | Average annual growth rate |
|-------|------------|------------|------------|------------|---------------------------|
| UR    | 59.58%     | 60.84%     | 67.54%     | 83.23%     | 1.05%                     |

(3) Establishment of industrial structure

In the process of industrial restructuring, the changes of secondary industry can better measure the changes of industrial structure and the impact of industrial structure on power consumption. Based on the change of the proportion of the secondary industry and the planning policy objectives from 2011 to 2018, this paper sets the proportion of the added value of the secondary industry to GDP (SG) in different scenarios as shown in Table 4.

Table 4. Industrial structure parameter setting.

|       | 2018       | 2020       | 2030       | 2050       | Average annual growth rate |
|-------|------------|------------|------------|------------|---------------------------|
| SG    |            |            |            |            |                           |
| High  | 40.65%     | 39.56%     | 34.53%     | 26.31%     | -1.35%                    |
| Low   | 40.65%     | 39.44%     | 33.91%     | 25.06%     | -1.50%                    |

(4) Per capita electricity consumption setting

Per capita electricity consumption is determined by the total population and the electricity consumption of the whole society. According to the growth of electricity consumption in the whole society from 2011 to 2018, the annual growth rate of electricity consumption in the whole society is set at 4.81%. Per capita electricity consumption (AE) is basically set as shown in Table 5.

Table 5. Per capita electricity consumption parameter setting.

|       | 2018       | 2020       | 2030       | 2050       |
|-------|------------|------------|------------|------------|
| AE    | (kWh/person) |          |            |            |
| High  | 4905.40    | 5295.22    | 8341.31    | 22565.23   |
| Low   | 4.12%      | 4.61%      | 4.57%      | 3.58%      |

(5) Electricity consumption structure setting

According to the analysis of the factors mentioned above, it can be seen that the second industry still contributes the most to electricity consumption in the three industries, and the value-added power consumption of the second industry is much higher than that of the first industry and the third industry. According to the change of the ratio of the added value of electricity consumption in the secondary industry to social power consumption (SE) from 1993 to 2018, the power consumption structure is set according to the high and low scenarios as shown in Table 6.

Table 6. Electricity consumption structure parameter setting.

|       | 2018       | 2020       | 2030       | 2050       |
|-------|------------|------------|------------|------------|
| SE    |            |            |            |            |
| High  | 4.12%      | 4.61%      | 4.57%      | 3.58%      |
| Low   | 4.12%      | 4.50%      | 4.23%      | 3.32%      |

(6) Power consumption intensity setting

Generally speaking, the intensity of electricity consumption (F) refers to the total amount of electricity consumed per unit country or region's GDP, which is negatively correlated with the level of electricity utilization in that country or region [12]. That is, the lower the intensity of electricity consumption, the higher the level of electricity utilization in the country or region. On the contrary, when the intensity of power consumption is high, it shows that the level of power utilization in this area is low and there is a great space for technological progress. The basic setting of power consumption intensity in this paper is shown in Table 7.
4.3. Forecast of China's Electric Power Consumption under Different Scenarios

According to the above scenario design around industrial structure and power consumption structure, there are four scenarios: high SG high SE (H_{GH}), high SG low SE (H_{GL}), low SG high SE (L_{GH}) and low SG low SE (L_{GL}). Using the particle swarm optimization (PSO) prediction model constructed in Chapter 3, the standardized data of various factors affecting power consumption are taken as independent variables, and the total power consumption is taken as dependent variables. The forecasting results of the PSO prediction model are shown in Table 8, which can predict the changes of China's power consumption in 2020, 2030 and 2050.

| Scenario   | 2020        | 2030        | 2050        |
|------------|-------------|-------------|-------------|
| H_{GH}     | 7892.1      | 10557.8     | 16553.0     |
| H_{GL}     | 7965.0      | 10655.4     | 16705.9     |
| L_{GH}     | 7457.8      | 9976.9      | 15642.2     |
| L_{GL}     | 7513.4      | 10051.2     | 15758.7     |

The corresponding prediction chart is shown in Figure 3.

According to the forecasted value, it can be concluded that under four scenarios, China's total electricity consumption in the future shows different degrees of sustained growth. Taking the L_{GH}
scenario as an example, it is predicted that China's total electricity consumption will reach 750 million kilowatt-hours in 2020, and the total electricity consumption will continue to grow in 2030. The per capita electricity consumption will exceed 7000 degrees. By 2050, China's total electricity consumption will reach 1.56 billion kilowatt-hours, that is to say, China's electricity demand will increase nearly 2.3 times in the next 30 years.

5. Conclusions and suggestions
The forecasting in this paper fully takes into account the fact that China is undergoing major industrial restructuring and the industrial structure has basically reached its maximum value, and the transformation of energy structure characterized by the rising electrification rate. According to the forecasting results, the power demand in China maintains a rapid and sustained growth trend after the period of industrial restructuring. With the rapid development of China's economy, the continuous improvement of people's living standards and the ever-increasing demand for electricity, it is impossible to solve the problems of future electric power development by relying on the existing generating capacity. Therefore, it is necessary to speed up the development of the electric power industry. In the next few years, we can increase investment in power resources, optimize the structure of the power industry and increase annual new energy generation, so as to meet China's growing demand for electricity without increasing carbon emissions, and actively encourage enterprises and residents to replace other fossil energy consumption with electricity consumption.

In the process of promoting the optimization and adjustment of industrial structure, we should pay attention to the coordination of the three major industrial changes. While reducing the capacity of industrial sectors with high energy intensity and high pollution emissions, we should actively introduce various incentives to speed up the development of service industries with low energy intensity and low pollution emissions, so as to fill the industrial gap in the process of structural change and make full use of social idleness. Elements and resources. While speeding up the construction of power market, the government should strengthen macro-control, actively guide and strictly supervise so as to lay a solid foundation for the better and faster development of the power industry and provide a strong guarantee.

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