An Empirical Study on the Identification of Driving Factors for Two Types of Typical Atmospheric Pollutant Emissions from Power Generation in China

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Abstract: Emission of air pollutants from the power generation industry is a major cause for severe air pollution prevention in China. Identifying the important driving factors of air pollutant emissions from power generation, and evaluating the importance of these factors are of great significance to formulate air pollution prevention policies. Based on the classic STIRPAT model, this paper expands the indexes of relevant economic, social and technical factors, and creatively takes the input of power generation environmental protection facilities as an important technical factor to evaluate the contribution of these factors to two typical air pollutants (SO\textsubscript{2} and smoke dust) of power generation. The empirical study results show that the indicators of economic, social and technical factors proposed and expanded in this paper are significant and effective, and "annual operating cost of industrial waste gas treatment facilities", "power consumption intensity of secondary industry" and "power generation structure" are the variables that have the strongest impact on the emission of two typical air pollutants of power generation. These empirical study results provide scientific guidance for further policy making.

1. Introduction
From the perspective of history, energy is the driving force of human civilization [1]. However, since the industrial revolution, a large amount of fossil fuel consumption has triggered a series of negative environmental effects on a global scale, such as: air pollution, shortage of resources and transportation capacity, huge greenhouse gas emissions, etc., which also restrict the development of human society. As the largest developing country, China has become the world's largest energy consumer in recent years and is facing extremely severe pressure to prevent and control air pollution. According to statistics from the Health Measurement and Evaluation Institute (IHME) of the University of Washington, PM2.5 emissions from fossil fuel combustion and the resulting smog weather have become one of the most important risk factors threatening the health of Chinese residents. More than 1.6 million people in China die from such air pollution, accounting for 30\% of the global death toll from such air pollution every year. According to the air quality report of China's Ministry of Ecological Environment, in the 10 cities with the highest concentration of PM2.5 in March 2018, the
The average concentration of PM2.5 in the atmosphere is about 5.5-7.3 times of the safety standard published by the World Health Organization (WHO) [2]. This grim situation is largely attributable to China's huge energy consumption [3]. And some studies further pointed out that China's energy consumption structure has long been dominated by coal, which has become a major factor for frequent haze weather and deterioration of air quality in recent years [4].

According to statistics from the 2018 Annual Report on Coal Industry Development, coal consumption in China in 2018 ranks first in the world, reaching 3.96 billion tons. In the coal consumption, the demand for power generation is the first. The power generation consumed about 2.1 billion tons of coal in that year, accounting for 53% of the total coal consumption in that year. According to the latest China Environmental Statistics Annual Report 2015 data, power generation contributed more than 60% of SO2 and Nitrogen Oxide emissions and more than 30% of soot emissions from the sources of air pollutants in China from 2011 to 2015.

Therefore, the prevention and control of power generation air pollution is an important part of China's current and future air pollution prevention and control, and is an important part of building a beautiful China. Based on the statistical results of two types of typical power generation air pollutant emissions in China, it is of great significance to identify the driving factors of these pollutant emissions for further targeted improvement of power generation air pollutant emission prevention and control policies in the future.

2. Literature Review

Analyzing the driving factors of air pollutants and greenhouse gas emissions from power generation can be divided into the following two methods: the econometric models, and the method to decompose the power generation air pollutants and greenhouse gas emissions into the product of several main factors.

2.1 Research and Review of Econometric Methods

Research using the first method requires long-term and large amounts of statistical data. The literature [5] uses the conventional multiple linear regression method to estimate the main factors of air pollutant emission and its evolution trend with time series in China's provincial or municipal areas. Among these factors, energy demand and coal consumption for power generation have become one of the main factors of air pollution to varying degrees. The literature [6] calculates the contribution rate of regional differences of regional industrial structure, population density and other factors to different degrees of atmospheric pollutants by using the method of spatial measurement. In addition, the literature [7] confirms that factors such as coal-fired power generation and motor vehicle exhaust emissions significantly contribute to the emission of air pollutants.

Although econometric methods can eliminate the negative effects of endogenous and collinearity problems of explanatory variables through model and algorithm improvement, the defects of this method are also obvious. First, it is strongly dependent on data quality. Second, based on statistical analysis, the demonstration of causality among various factors is relatively weak. Considering the limitation of data samples in reality and the causality between complicated variables such as energy consumption and economic development, how to identify the main driving factors of two typical air pollutant emissions in China's power generation industry by using small sample data is the key of this paper.

2.2 Research and Review on Factor Decomposition Model

The starting point of the factor decomposition model is to decompose the explained variable into the product of several explained variable indicators, and to determine the weight or share of the explained variable indexes when the target is reached. Common factorization models include IPAT model and STIRPAT model. Compared with pure econometric methods, factor decomposition models all have the advantage of not requiring much data sample size, and these decomposition models are compatible with econometric methods and have the functions of estimation accuracy and causal relationship.
identification. Among them, Ehrlich and Holdren put forward the classic IPAT model [8] in 1971, which takes three direct factors (population, wealth and technology) that affect the environment as the main driving factors. Many theoretical and empirical studies using IPAT model show that [9], the four variables of environment, population, wealth and technology are closely related, and the environmental deterioration mainly comes from the three direct drivers of population, wealth and technology, and the interaction among these three drivers. However, IPT model is insufficient, and it was developed in literature [8] that, Dietz T and Rosa E.A improved IPAT model into the STIRPAT model. The model is usually expressed in linear form after taking logarithm and has good expansibility. STIRPAT model has been widely used in the study of environmental drivers [10]. In IPAT model and STIRPAT model, there are three main driving factors: population, wealth and technology. The key to this study is the reasonable selection or expansion of explanatory indicators for the three types of factors. Some existing studies have provided reference for the expansion of these indicators. For example, in the study of changes in carbon emission intensity of power generation in Asian countries, literature [11] first proposed the decomposition of industrial technical factors into two indicators: power generation structure and power generation intensity. The literature [12] further decomposes the power generation technical factors into three factors: power consumption intensity, power generation intensity and power generation structure.

In summary, the decomposition of population and wealth factors is relatively uniform. But the existing researches have not taken the power generation environmental protection technology input as an important decomposition of technical factors. Based on the existing literature, this paper creatively introduces the operating cost of power generation environmental protection facilities as an important decomposition of technical factors, and reasonably constructs the identification model of driving factors of air pollutants and greenhouse gas emissions in power generation industry, so as to comprehensively evaluate the main driving factors of air pollutants emissions from power generation in China at present, thus providing support for further targeted policy enlightenment.

3. Research Methods

3.1 Extended STIRPAT Model Construction

In view of the fact that the factor decomposition model does not require high data sample size and can take into account the advantages of estimation accuracy and causal relationship identification, this paper adopts STIRPAT model and reasonably expands the technical factor decomposition method based on the classic STIRPAT model to apply the research objective of this paper.

Ehrlich and Holdren further propose a classic IPAT model to identify and evaluate the key drivers of human activities' impact on the natural environment [13]. The general form of the model is:

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

(1)

In equation (1), \( I \) indicates the impact of human activities on the natural environment, \( P \) indicates the population size, \( A \) indicates the wealth per capita (or GDP per capita), and \( T \) indicates the technical level (such as GDP average energy consumption and other technical and economic indicators). This model has been further developed in practical application. Dietz and Rosa put forward STIRPAT model in 1994 [8]. The general form of STIRPAT model is:

\[ I = a \cdot P^b \cdot A^c \cdot T^d \cdot \mu \]  

(2)

In equation (2), \( P \), \( A \) and \( T \) respectively represent population size, wealth per capita and technical level. Constant term \( a \) and index term \( b \), \( c \), \( d \) are parameters to be estimated. Different dimensions indicate the degree of impact on the environment, \( \mu \) is a random perturbation term.

This article mainly expands on the technical level items in the model. The selected variables and explanations are shown in Table 1.
Table 1 Variables in the STIRPAT model

| Variables                          | Indicator | Explanation                                      | Units       |
|-----------------------------------|-----------|--------------------------------------------------|-------------|
| Environmental effects             | $I_j$     | Pollutants emitted by generation                 | $10^4$ tons |
| Population                        | $P$       | Total population                                 | $10^4$ people |
| Urbanization rate                 | $U$       | Urbanization rate                                | %           |
| Per capital wealth                | $A$       | Per capital wealth                               | $10^4$ CNY/person |
| Industrial Power Consumption Intensity | $SE_i$   | Industrial Power Consumption Intensity           | kWh/CNY    |
| Power generation structure        | $GS$      | Percentage of thermal power generation           | %           |
| Coal consumption rates of power generation | $FI$      | Coal consumption rates of power generation       | g/kWh      |
| Operation cost of waste Gas treatment facilities | $FE$      | Operation cost of waste Gas treatment facilities | $10^4$ CNY/year |

From Table 1, the expanded STIRPAT model of this study is rewritten into logarithmic form as follows:

$$
\ln I_{jt} = \ln a + b_1 \cdot \ln P_t + b_2 \cdot \ln U_t + c \cdot \ln A_t + \left( \sum_{i=1}^{n} d_i \ln SE_{it} \right) + e_1 \cdot \ln GS_t + e_2 \cdot \ln FI_t + e_3 \cdot \ln FE_t
$$

(3)

In equation (3), the subscript of each variable $t$ indicates the year in which the variable takes its value. In this way, the problem of identifying the driving factors of power generation air pollutant emissions is the coefficient of each variable in the estimation equation (3).

3.2 Parameter Estimation Methods

The typical parameter estimation method generally adopts the ordinary least squares (OLS), but the OLS method for parameter estimation also has defects: it is highly dependent on the data quality of explanatory variables. When the extended STIRPAT model is adopted, the decomposition of social, economic and technical factors is likely to lead to multicollinearity of explanatory variables. Therefore, it is necessary to adopt appropriate parameter estimation methods to eliminate the adverse effects. Partial Least Squares (PLS) is an effective method to eliminate multicollinearity. It establishes the planning relationship between explained variables and independent variables by extracting orthogonal principal components in independent variable data space, thus determining the function between explained variables and explained variables. The procedure for estimating parameters by partial least square method is as follows [14,15]:

Let $Y$ as the interpreted variable vector and $X$ as the interpreted variable vector. The explanatory variable matrix is recorded as $X = (x_{ij})_{n \times p}$. The data matrix of $Y$ after standardization is denoted as $Y = (y_{ij})_{n \times 1}$. Among them, $n$ represents the number of observation data; $i, j$ are natural numbers, $1 \leq i \leq n, 1 \leq j \leq p$.

First, the explanatory variable data are standardized, and the standardization process is shown in equation (4).

$$
X_{ij}^* = \frac{x_{ij} - \overline{x_j}}{s_j}
$$

(4)
In equation (4), \( X_j = \frac{1}{n} \sum_{i=1}^{n} X_{ij} \) is the mean value of the \( j \) explanatory variable vector \( X_j \), \( S_j \) is similar to the standard deviation of the explanatory variable \( X_j \), and the explanatory variable is normalized as in equation (5).

\[
y_i^* = \frac{y_i - \bar{y}}{s_y}
\]

where \( \bar{y} \) and \( s_y \) respectively represent the mean and standard deviation of the interpreted variables.

After normalization, the explanatory variable matrix \( E_0 = (x_{ij}^*)_{n \times p} \). The interpreted variable matrix is recorded as \( F_0 = (y_i^*)_{n \times 1} \).

Then, according to the standardized explanatory variable matrix \( E_0 \), the first principal component is extracted. The calculation process is as shown in equation (6).

\[
t_1 = \frac{E_0^T \cdot F_0}{E_0^T \cdot F_0} \cdot E_0
\]

In equation (6), \( t_1 \) represents the first principal component.

The regression expressions of \( E_0 \) and \( F_0 \) with \( t_1 \) are equations (7) and (8).

\[
E_0 = t_1 \cdot p_1^T + E_1
\]

\[
F_0 = t_1 \cdot r_1 + F_1
\]

In the next step in equations (7) and (8), principal components are continuously extracted using residual matrix. The residual matrices are, respectively, replaced with \( E_1 \) and \( F_1 \). Equations (6), (7) and (8) are iterated repeatedly to extract principal components: \( t_2 \), \( t_3 \) ... \( t_k \).

The fourth step is to determine the optimal number of principal components according to the cross-validation test. The \( i \) th sample is extracted from \( n \) samples, the first three steps are repeated in the remaining \( n-1 \) samples, \( k \) principal components are extracted, and a regression equation is synthesized, and the extracted \( i \) th sample is brought into the regression equation to calculate the fitting error. Then, other individual samples in all sample sets are sequentially extracted, and the above steps are repeated to obtain a prediction error square sum index of \( Y \), which is recorded as \( \text{PRE}_k \). The expression of \( \text{PRE}_k \) which is equation (9).

\[
\text{PRE}_k = \sum_{i=1}^{n} (y_i - \hat{y}_{k(-i)})^2
\]

In equation (9), \( y_i - \hat{y}_{k(-i)} \) represents the fitting error calculated by substituting the \( i \) th sample into the regression equation after extracting the \( i \) th sample and \( k \) principal components.

In addition to \( \text{PRE}_k \), the other item for cross-validation test is \( SS_{k-1}, SS_{k-1} \) means that all sample points are used to fit \( k-1 \) principal components for regression modelling, and then each
sample point is brought in to calculate the sum of squares of residuals to obtain the sum of squares of errors of \( Y \). \( SS_{k-1} \) can be expressed as equation (10).

\[
SS_{k-1} = \sum_{i=1}^{n} (y_i - \hat{y}_{(k-1) i})^2
\]  

(10)

In equation (10) \( y_i - \hat{y}_{(k-1) i} \) represents the fitting error calculated by substituting the fitting value of the \( k-1 \) sample point after the \( i \) th samples are used and the principal components are extracted for modelling.

The criterion for cross validity test \( Q_h^2 \) is equation (11):

\[
Q_h^2 = 1 - \frac{PRE_i}{SS_{k-1}}
\]  

(11)

The criteria for cross-validation test is as follows: when \( Q_h^2 \geq (1 - 0.95^2) \), it is shown that increasing the number of principal component extractions is beneficial to improving the fitting accuracy of the partial least squares regression model; Otherwise, there is no need to increase the number of principal components extracted, and the above iteration and calculation process of extracting principal components should be stopped.

Finally, after determining the number of principal components to be extracted, the partial least squares regression equation can be determined. If the number of principal components to be extracted is \( k \), determined from the previous step, then

\[
F_0 = \sum_{j=1}^{k} r_j \cdot t_j
\]

From equations (7) and (8), we can further obtain:

\[
w_j^* = \prod_{j=1}^{k-1} (I - w_j p_j^T) \cdot w_j
\]

\[
E_0 = \begin{pmatrix} E_0^T \cdot E_0 \end{pmatrix}, \quad \text{where } \quad I \text{ is the order identity matrix } n \times n
\]

In equation (6), \( \begin{pmatrix} E_0^T \cdot E_0 \end{pmatrix} \) is the weight value of each explanatory variable vector. In order to quantify and measure the weight of each variable, it can be calculated according to equation (12):

\[
VIP_i = \sqrt{\frac{n}{\sum_{j=1}^{k} R(y; t_j) \cdot w_{ji}^2}} \cdot \sum_{j=1}^{k} R(y; t_j)
\]  

(12)

In equation (12), \( VIP_i \) is the weight value of the \( i \) th variable; represents the explanatory ability of the \( j \) th principal component \( t_j \) to the explained variable. Equation (12) can provide a basis for analyzing the importance of explanatory variables.

4. Results Analysis and Discussion

4.1 Data Collection

Air pollutants in power generation in China mainly include smoke dust, SO\(_2\), Nitrogen Oxides and greenhouse gas CO\(_2\). Limited by statistical accuracy, this paper selects two types of typical power generation air pollutants (SO\(_2\) and smoke dust) as explanatory variables. The data of explanatory variables and explained variables are shown in Tables 2 and 3. These data come from China Environmental Statistics Yearbook, China Statistics Yearbook, China Electric Power Yearbook, etc.
All monetary units are based on 1990 prices.

### Table 2 Interpreted variable statistics

| year | SO$_2$ ($10^4$ tons) | Smoke dust ($10^4$ tons) |
|------|----------------------|--------------------------|
| 2004 | 929.30               | 328.00                   |
| 2005 | 1112.32              | 391.79                   |
| 2006 | 1204.10              | 348.10                   |
| 2007 | 1147.12              | 298.58                   |
| 2008 | 1059.94              | 251.01                   |
| 2009 | 932.99               | 222.82                   |
| 2010 | 899.79               | 199.57                   |
| 2011 | 901.19               | 215.60                   |
| 2012 | 797.03               | 222.79                   |
| 2013 | 720.63               | 270.28                   |
| 2014 | 621.19               | 272.42                   |
| 2015 | 842.00               | 164.90                   |

### Table 3 Variable statistics

| year | population | Urbani zation rate | Per capital wealth | Industrial Power Consumption Intensity | Power generation structure | Coal consumption rates of power generation | Operation cost of waste Gas treatment facilities |
|------|------------|-------------------|-------------------|----------------------------------------|---------------------------|---------------------------------------------|-----------------------------------------------|
|      |            |                   |                   | NO.1 NO.2 NO.3                          |                           |                                             |                                               |
| 2004 | 129,988    | 41.76             | 5,620.570         | 0.097 0.413 0.074                      | 81.80                     | 376                                         | 111,294.679                                   |
| 2005 | 130,756    | 42.99             | 6,224.833         | 0.101 0.417 0.078                      | 81.54                     | 370                                         | 165,960.054                                   |
| 2006 | 131,448    | 43.90             | 6,980.992         | 0.010 0.422 0.079                      | 83.75                     | 367                                         | 390,616.627                                   |
| 2007 | 132,129    | 44.94             | 7,934.107         | 0.104 0.425 0.074                      | 83.34                     | 356                                         | 555,537.733                                   |
| 2008 | 132,802    | 45.68             | 8,654.449         | 0.089 0.367 0.075                      | 81.22                     | 345                                         | 769,688.948                                   |
| 2009 | 133,450    | 46.59             | 9,431.156         | 0.091 0.374 0.092                      | 81.81                     | 340                                         | 1,048,519.089                                 |
| 2010 | 134,091    | 47.50             | 10,414.974        | 0.091 0.384 0.095                      | 80.81                     | 333                                         | 1,135,419.947                                 |
| 2011 | 134,735    | 51.27             | 11,379.184        | 0.090 0.390 0.099                      | 82.45                     | 329                                         | 2,046,532.234                                 |
| 2012 | 135,404    | 52.57             | 12,224.356        | 0.085 0.374 0.102                      | 78.72                     | 325                                         | 1,838,110.574                                 |
| 2013 | 136,072    | 53.70             | 13,112.756        | 0.083 0.387 0.111                      | 78.58                     | 321                                         | 1,863,207.567                                 |
| 2014 | 136,782    | 54.77             | 13,997.757        | 0.080 0.360 0.103                      | 75.43                     | 319                                         | 2,159,499.208                                 |
| 2015 | 137,462    | 56.10             | 14,863.257        | 0.079 0.343 0.102                      | 73.71                     | 312                                         | 2,254,095.570                                 |

#### 4.2 Data Characteristic Analysis

According to the basic data of explanatory variables in Table 3, it is determined whether there is multicollinearity between variables. The calculation of correlation coefficient between explanatory variables is shown in Table 4.

### Table 4 The correlation coefficients among variables

|        | lnP  | lnU  | lnA  | lnSE1 | lnSE2 | lnSE3 | lnGS | lnFI | lnFE |
|--------|------|------|------|-------|-------|-------|------|------|------|
| lnP    | 1.0000 | 0.9880 | 0.9959 | 0.1886 | -0.8149 | 0.8969 | -0.8089 | -0.9895 | 0.9425 |
| lnU    | 0.9880 | 1.0000 | 0.9794 | 0.1747 | -0.7676 | 0.9091 | -0.8100 | -0.9683 | 0.9147 |
| lnA    | 0.9959 | 0.9794 | 1.0000 | 0.1970 | -0.8024 | 0.9023 | -0.7584 | -0.9952 | 0.9661 |
| lnSE1  | 0.1886 | 0.1747 | 0.1970 | 1.0000 | -0.2829 | 0.1478 | -0.2367 | -0.2575 | 0.1315 |
| lnSE2  | -0.8149 | -0.7676 | -0.8024 | -0.2829 | 1.0000 | -0.6417 | 0.8127 | 0.8331 | -0.7434 |
From the correlation coefficients among variables shown in Table 4, it can be seen that there is a strong positive correlation between $\ln P$, $\ln U$, $\ln A$ and $\ln FE$. There is a strong negative correlation between $\ln FI$ and $\ln P$, $\ln U$, $\ln A$ and $\ln FE$. If OLS method is used to estimate the parameters, the estimation results will have insufficient interpretation ability due to the multicollinearity problems in the data. PLS method is needed to eliminate the adverse effects.

4.3 Partial Least Squares Parameter Estimation Results and Tests

The parameter estimation steps of PLS method introduced in section 3.2 are shown in table 5.

Table 5 The parameter estimated

| Variables | When the interpreted variable is $SO_2$ | When the interpreted variable is smoke dust |
|-----------|----------------------------------------|------------------------------------------|
| $\ln P$   | 0.778                                  | 0.511                                    |
| $\ln U$   | 0.261                                  | 0.068                                    |
| $\ln A$   | 0.032                                  | 0.033                                    |
| $\ln SE1$ | 0.087                                  | 0.007                                    |
| $\ln SE2$ | 0.022                                  | 0.103                                    |
| $\ln SE3$ | 0.402                                  | 0.043                                    |
| $\ln GS$  | 1.392                                  | 0.017                                    |
| $\ln FI$  | -0.155                                 | -0.181                                   |
| $\ln FE$  | 0.019                                  | 0.013                                    |
| Intercept | -7.917                                 | 0.249                                    |

In order to test the fitting effect of the above parameters estimated by partial least square method, the values in table 5 are brought into the regression equation to obtain fitting values, which are compared with the original values of samples. The comparison is shown in fig. 1.

As can be seen from Fig 1, all decision points are evenly distributed near the diagonal, which indicates that the parameter fitting effect in table 5 is acceptable. In the Figs 2, the confidence ellipse with a 95% confidence interval are shown. It can be seen that all data fall in the ellipses evenly, it is
indicating that the distribution of observation results is uniform and no specific points appear. It confirms that the parameter estimates in table 5 can fit the extended STIRPAT model. The economic, social and technical parameters estimated are effective.

4.4 Results Analysis and Discussion
According to equation (12) in section 3.2, the variable weight is only related to the data structure of explanatory variables. The weight of each explanatory variable in the model is calculated as shown in Fig. 3.

![Fig 3 The weight of the variables](image)

From Fig 3, the specific analysis and discussion are as follows:

First, the treatment of terminal fuel and flue gas is the most important means in the treatment of air pollutant emissions in the power generation industry. These technologies have the characteristics of direct effect and quick effect. The promotion and application of these technologies and the continuous improvement of standards are pushing the annual operating cost of industrial waste gas treatment facilities in the power generation industry to keep increasing.

Second, the "power consumption intensity of the secondary industry" has an important impact on the current emission of air pollutants from power generation in China. This is closely related to China's economic structure: China is one of the few countries in the world with complete economic and industrial sectors. From 2004 to 2014, China's secondary industry contributed more than 56% of GDP each year, and maintained an increasing trend (nearly 60% in 2014). The electricity consumption of the secondary industry accounted for more than 80% of the electricity consumption of the whole society. Efforts to adjust and optimize the power consumption intensity of the secondary industry are important measures to curb the emission of air pollutants from two types of typical power generation in China.

Third, continuous attention should be paid to the improvement and optimization of the two technical indexes of "power generation structure" and "power generation energy consumption". The aim of optimizing power generation structure and reducing power consumption is to reduce China's dependence on coal-fired thermal power and improve the efficiency of coal-fired power generation so as to control the growth rate of coal consumption for power generation.

Fourth, the promotion of population growth and urbanization to the emission of air pollutants and greenhouse gases in the power generation industry cannot be ignored. The first three measures need to be strengthened to offset the adverse effects of population growth and urbanization.

5. Conclusions and Policy Implications
Based on the classic STIRPAT model, this paper expands social, economic and technological factors, innovatively introduces "annual operating cost of industrial waste gas treatment facilities" into technological factors, and evaluates the main driving factors of two typical air pollutant emissions from power generation in China. Empirical research shows that at present, "annual operating cost of industrial waste gas treatment facilities", "power consumption intensity of secondary industry" and "power generation structure" are the variables that have the strongest impact on the emission of two typical air pollutants of power generation.

According to the results of empirical research, the main policy implications are as follows: Firstly, the annual operating cost on industrial waste gas treatment facilities in the power generation industry
should be continuously maintained; Secondly, reducing the power consumption intensity of the secondary industry and optimizing the power generation structure are important starting points and focal points for future policies. In addition, the above policy intensity should fully take into account population growth and urbanization rate.

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