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Original Research Paper

Forecast and Control Study on Energy Consumption of China

Tian-Bao Guo, Yu-Ling Dong and Yun-Feng Wang†
College of International Economics and Trade, Jilin University of Finance and Economics, 130117,Changchun, China
†Corresponding author: Yun-Feng Wang

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ABSTRACT

Energy is an essential material for social development, as well as vital strategic material for a countries' economy. Therefore, the society pays more attention to it. This article builds a non-linear model to forecast the energy consumption amount of China during 2015 to 2017 based on supported vector. Meanwhile, principles such as grey correlation, genetic algorithms and principal component analysis are being manipulated to ensure the comprehensive, objective and authenticity for model processing operation. All these efforts enhance the accuracy and dynamic fitness of the model.

INTRODUCTION

In past studies, many scholars were committed to predict the total energy consumption. So, the existing literature form into a number of commonly used forecast models, for example, gray association forecast, time sequence ARIMA model, neural network, consume elasticity method and so on. Many of the above methods are based on linear relationships between variables, and energy consumption is a typical nonlinear adaptive system, which leads to different degrees of impact on prediction accuracy.

On the various energy consumption influence factors, scholars mainly focus on economic factors, price, technology, structure and system, etc. From the perspective of economic factors, Kraft (1978) first proposed the existence of a causal relationship between economic growth and energy consumption, and they used the annual data from 1947 to 1974 to make empirical analysis. Wang Huogen & Shen Lisheng (2008) introduced a production function and established three elements model, used the panel co-integration theory to test energy consumption and economic growth of China. Panel unit root showed energy, GDP as the first-order difference stationary variable. Granger panel causality showed that there was only causality between energy consumption and GDP. From the perspective of the price factor, after using relevant economic theory to analyse the study, Birol & Keppler (2000) concluded that raising energy prices by economic means can improve energy efficiency, and thereby reduce energy intensity. From the perspective of technical factors, Richard et al. (1999) believed that technological progress was an important factor affecting energy consumption intensity of China, and also was a main reason causing energy intensity decline in recent years. From the perspective of structural factors, Lin Boqiang (2001) used the co integration and error correction model to study determinants of energy needs of China, and the results showed that long-term equilibrium relationship between total energy consumption and industrial structure existed. From the perspective of institutional factors, through studying the relationship between taxation and energy consumption, Mulder et al. (2003) found that levying taxes in energy price would stimulate accelerated diffusion and use of new energy-saving technologies, and impel enterprises to replace the capital with labour, thus reduce the total energy consumption.

In terms of energy forecasting, existing literature formed all kinds of prediction models. Lu Erpo (2005) established a combination model of deterministic and stochastic time series to predict energy demand from 2004 to 2020 in China. Zhang Yanzhi et al. (2007) divided the energy system into the energy sector and the non-energy sector and used input-output model to predict energy demands of Jiangsu Province in 2010, 2015 and 2020. Liang Na et al. (2008) established the Grey Forecast of total energy consumption in China, while taking advantage of the RBF neural network to estimate line parameters and GM (1,1) Model. Zeng Sheng (2011) used the energy consumption elasticity coefficient method to predict total energy consumption of China in the coming years. Zhang Yuejun et al. (2013) used SVM to analyse energy demand model from 1978 to 2010 and to predict Beijing energy demand from 2012 to 2020.

In terms of strategies and suggestions, this article reviewed the main points of the domestic research. Wu Guohua et al. (2011) suggested that China should establish two control indicators of total energy consumption and energy consumption per unit of GDP to form the constraint index system of energy consumption from the "Twelve Five". Meanwhile, the state should strengthen management intensity in energy consumption. Xing Lu et al. (2012) believed that the management mechanism which was government led and the control of total energy should be established in China, gradually a market-oriented policy system would be formed, and a scientific and accurate energy statistics and analysis system should be established to achieve total energy consumption classification control and optimized control.

Based on existing literature, we can find that most scholars used single variable or bivariate to study energy consumption factors and the factors selected were the lack of objective evidence. This article, considering the practical situation used gray correlation to identify thirty-two energy consumption factors, while using the genetic algorithm to determine model parameters, and forecast total energy consumption from 2015 to 2017 in China. This paper tries to find the new way of forecasting and control total energy consumption in China.

EMPIRICAL ANALYSIS OF IMPACT FACTORS

Model establishment (Grey Relational Analysis, GRA): Due to many factors of total energy consumption in China, the associated uncertainty exists between the various factors. In order to make quantitative description for the degree of correlation of the energy consumption of China and reveal the main characteristics of energy consumption system of China, this article uses Grey Relational Analysis (GRA) to determine the degree of association between the various factors and total energy consumption of China. Different from regression analysis methods used in previous studies including regression analysis, principal component analysis, correlation analysis and variance analysis etc., GRA has main advantage that there are not too many demands in sample size and sample data distribution, small computing amount, and the final result consistent with the qualitative analysis. The basic idea of gray correlation analysis is based on the degree of sequence closer to the geometry of the curve to determine which contact is close. If the geometry of the curve is closer, the corresponding association between greater degree sequence, whereas the correlation degree is smaller. Specific steps of gray correlation analysis are as follows:

1. Determine the reference sequence reflecting the characteristics of the system behaviour and the comparison sequence affecting system behaviour. The reference sequence (Y) is a dependent variable sequence reflecting the characteristics of the system behaviour. The comparison sequence X_i is several independent variable sequences consisting of system factors, respectively denoted by:

$$Y=\{Y(t), t=1,2,3,\ldots,n\} \quad \ldots(1)$$

$$X_i=\{X_i(t), t=1,2,3,\ldots,n\}, i=1,2,3,\ldots,m \quad \ldots(2)$$

Among them, n represents the length of the reference sequence and comparison sequence, m represents the number of comparison sequences.

2. Carry on the dimensionless processing for the reference sequence and the comparison sequence. Since there are different meanings among the various factors in the system, which will lead to the inconsistent dimension data . In order to correct conclusion, before making gray correlation analysis, generally we need to carry on dimensionless processing for each sequence. This article processes the original sequence with the method of selection of initial value .

$$Y=\{\frac{Y(t)}{Y(1)}, t=1,2,3,\cdots,n\} \quad \ldots(3)$$

$$X_i=\{\frac{X_i(t)}{X_i(1)}, t=1,2,3,\cdots,n\}, i=1,2,3,\cdots,m \quad \ldots(4)$$

3. Grey correlation coefficient calculation of the reference sequence and the comparison sequence. Measure of correlation degree between the reference sequence and the comparison sequences is usually the difference between the curves, in mathematics, with the associated statement to indicate, that is correlation coefficient $\varphi(j)$ between the reference sequence and the comparison sequences at different moments, formula calculation as follows:

$$\varphi_i(j)=\frac{\min_i \min_j |Y(j)-X_i(j)|+\delta \max_i \max_j |Y(j)-X_i(j)|}{|Y(j)-X_i(j)|+\delta \max_i \max_j |Y(j)-X_i(j)|} \quad \ldots(5)$$

Therein, δ represents discrimination coefficient, the value of range 0<δ<1, generally, δ= 0.5,$|Y(j)-X_i(j)|$ represents absolute differences between each point of the reference sequence Y and each point of the comparison sequence X_i behalf of minimum secondary differences. δ max, $\max_j | Y(j)-X_i(j)|$ represents the secondary maximum difference.

4. Calculation of correlation degree ρ. Since the correlation coefficient $\varphi(j)$ is the comparison of the correlation degree between reference sequences and the comparative sequence at different time, its value is not unique. In order to compare the overall degree of correlation between sequences, the correlation coefficient need to be requantized. That is to calculate its average value as measure standard of correlation degree between the reference sequence and the comparison sequences. Calculation formula of correlation degree ρ is as follows:

$$\rho(Y,X_i)=\frac{1}{n}\sum_{j=1}^{n}\varphi_i(j), i=1,2,3,\cdots,m \quad \ldots(6)$$

Empirical analysis on total energy consumption and its influencing factors of our nation: This article uses relevant data of total energy consumption of China and its influencing factors from 1980 to 2012 as the sample, to determine the degree of association between variables by calculating grey correlation degree of total energy consumption of China and various factors. By calculating, the factors of total energy consumption of China which the grey correlation is more than 85% (Table 1).

FORECAST OF TOTAL ENERGY CONSUMPTION IN CHINA

Data Description

This article takes the data from 1980 to 2012 of total energy consumption of China and its influencing factors as the sample, in which this article constructs SVM model by the data from 1980 to 2007 and tests generalization capability of model by the data from 1980 to 2007 the sample data. In this process, selecting more than 85% the gray correlation factors constructs the SVM Model.

GA-SVM Model Description

Genetic algorithm: For the classification using SVM classification method, we need to select the kernel function according to the characteristics of the sample data. This paper takes RBF kernel function for the study. While introducing the kernel function, we also introduced two unknown parameters that are the error punishment factor C and nuclear width §. Therefore, before using SVM to analyse, we need to set these two unknown parameters in advance. For solving this problem, the usual approach is to select the experience value for the unknown parameters.

However, the value of these parameters are not always effective, it is difficult to determine optimum global model. So, this paper takes global optimization ability of the Genetic Algorithm to find the optimal unit of unknown parameters.

In 1969, Holland from American Michigan University, proposed the Genetic Algorithm which is an adaptive mechanism of the global genetic and evolutionary nature of biological reference and the formation of optimized stochastic search algorithm, in essence, the search process was not dependent on specific issues. The simulation of genetic algorithm was selection copy, crossover and mutation phenomena, which was produced in the genetic and evolutionary process. The conduction was mainly through the selection operator, crossover and mutation operator , thereby producing generation after generation of new population, until the search results meet the given convergence condition location. The main steps of the algorithm are as follows:

1. The production of parameter value coding and initial group: Since the error punishment factor C and nuclear width σ taking positive numbers, in order to make the range of the unknown parameters large enough, this article takes the binary string (that is, each only two values 0 and 1) to represent unknown parameters C and σ . At the same time, the number of defined genes herein chromosome are twenty, so that after the binary coding available, the binary string of error punishment factor C and nuclear width σ .

$$X = x_1x_2x_3\cdots x_{10}, \quad Y = y_1y_2y_3\cdots y_{10} \quad ...(7)$$

So the chromosomes:

$$XY = x_1x_2x_3\cdots x_{10}y_1y_2y_3\cdots y_{10} \quad ...(8)$$

The chromosome is an operation target of genetic algorithm, each of which represents a different value in different individuals. Defined error punishment factor C and kernel width mapping functions are as follows:

$$\sigma = f_\sigma \cdot X, \quad C = f_c \cdot Y \quad ...(9)$$

In this paper, the number of the population is set to 20, the maximum hereditary algebra is 100. Using random methods to generate initial population, $S(k)$ while the set of algebraic counter t=1.

2. Determine the fitness function: The fitness function is a real-valued function of all correspondence between all individual groups and fitness, its role is equivalent to solving the objective function in optimization problems. The objective function of this article is to make the model chosen MSE minimum, so the fitness function of this paper is the MSE of training and data, MSE is defined as:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(Y(i) - \hat{Y}(i))^2 \quad ...(10)$$

Among them, N is the number of samples, $Y(i)$ is the actual value of the i^{th} sample, $\hat{Y}(i)$ is the predicted value of the samples.

3. Calculating the individual fitness value: The known sample data is set into the training sample set and the test sample sets, the each unknown parameter value of the initial population $S(k)$ is set into the SVM model, then a different SVM has been calculated using the training sample set corresponding to a different predictive value. After the resultant value is substituted into the formula for calculating the MSE obtained corresponding MSE, which indicates that, the smaller the value the greater the fitness of the individual.

4. Judging whether individuals meet the termination condition: If the termination condition meets or reaches the maximum genetic algebra, then select the largest individual

Table 1: Energy consumption influence factors and gray correlation value.

No.	Influence factor	Gray correlation degree
1	R&D full-time equivalent staff(million people year)	0.998895719
2	urbanization ratio	0.995543914
3	The proportion of electricity consumption	0.995121374
4	The proportion of energy consumption in manufacturing	0.993710464
5	The proportion of tertiary industry to GDP	0.99340781
6	Total population (million people)	0.992396384
7	The proportion of industrial energy consumption	0.991525282
8	The proportion of coal consumption	0.991252932
9	Energy efficiency	0.990924314
10	Energy price index	0.990910621
11	The proportion of secondary industry to GDP	0.990838125
12	The proportion of household energy consumption	0.990714303
13	The proportion of agriculture, animal husbandry and fishery energy consumption	0.990425155
14	GDP growth rate	0.9902786
15	The proportion of oil consumption	0.990227448
16	Engel's coefficient of urban	0.990121024
17	The proportion of natural gas consumption	0.989976633
18	Engel's coefficient of countryside	0.989918532
19	The proportion of R&D to GDP	0.989703274
20	The proportion of primary industry to GDP	0.989631506
21	Energy intensity	0.987259254
22	Carbon emission intensity	0.987246924
23	Research funding expenditure (billion Yuan)	0.945452325
24	FDI(billion dollars)	0.944386548
25	Labor productivity	0.940592108
26	Urban (Yuan)	0.937955379
27		0.931189663
28	Per capita GDP (Yuan)	0.916777106
29	Patent application weight	0.915379186
30	Marketization index	0.911054772
31	R&D funding expenditure (billion Yuan)	0.907583057
32	GDP (billion Yuan)	0.892165373

of fitness in $S(k)$ as a result. And the GA algorithm ends, otherwise the next step.

5. Performing selection operator operation: According to selection opportunity determined by the selection probability $P_s(x_i)$, randomly selecting one individual from S(k) and copying chromosomes each time, repeating N times, and then the resulting N chromosomes composing groups $S_1(k)$.

6. Performing crossover operation: According to chromosome number *c* participating in crossover determined by crossover probability $P_c(x_i)$, randomly selecting N chromosomes from $S_1(k)$, pairing cross operation, and with a new generation of chromosomes, getting new groups.

7. Performing mutation operator operation: According to variation times *m* determined by variation probability $P_m(x_i)$, randomly selecting *m* chromosomes from $S_2(k)$, respectively performing mutation operation, and replacing the original chromosome with the new generation of chromosomes, getting the new groups $S_3(k)$.

8. The group as a new generation population, which is replacing $S(k)$ with $S_3(k)$, t=t+1 , going to step two (Fig. 1).

Support Vector Machine

For a given sample data sets $\{(X_i, Y)\}$, X is the input vector, Y is the output vector, sample size is n. The use of a non-linear mapping function θ maps various input factors of energy consumption X_i into a high-dimensional space ($\theta(x_1), \theta(x_2), \theta(x_3), \cdots, \theta(x_n)$), followed by non-linear regression,

$$f(x) = w \cdot \theta(x) + b \quad ...(11)$$

The mathematic form of non-linear and inseparable issues of SVM is:

$$\text{Min } \frac{1}{2} \| w \|^2 + C \sum_{i=1}^{n} \xi_i \quad ...(12)$$

$$s.t. \begin{cases} y_i (w\theta(x_i) + b) \geq 1 - \xi_i (i = 1, 2, \ldots, n) \\ \xi_i \geq 0 \end{cases} \quad ...(13)$$

Among them, C is the punishment factor, which indicates the degree of punishment error. The greater the degree of punishment is, the more punishment is severe.

ξ is the slack variable which indicates that there is the violation constraint situation for model in a certain extent, so that you can tolerate noise and outliers, and be able to care for more training points. Using Lagrange multiplier method introduces α as a Lagrange multiplier vector. And then the above problem can be transformed into the calculation of the dual quadratic programming:

$$\text{Max } L(\alpha)=\sum_{j=1}^{n}\alpha_j-\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}y_iy_j\alpha_i\alpha_jK(x_i,x_j) \quad ...(14)$$

$$s.t.\begin{cases}\sum_{i=1}^{n}y_i\alpha_i=0\\ 0\le\alpha_i\le C, i=1,2,3,\ldots,n\end{cases} \quad ...(15)$$

Among them, $K(x_i,x_j)$ is a kernel function . So we can obtain optimal solution:

$\alpha^*=(\alpha_1^*,\alpha_2^*,\alpha_3^*,\cdots,\alpha_n^*)^T$, w^* & b^* calculated as result:

$$\begin{cases}w^*=\sum_{i=1}^{n}(\alpha_i-\alpha_i^*)x_i\\ b^*=y_i-\sum_{i=1}^{n}y_i\alpha_i^*K(x_i,x_j)\end{cases} \quad ... (16)$$

The final decision function can be obtained as:

$$f(x)=\operatorname{sgn}\left[(\sum_{i=1}^{n}\alpha_i^*y_iK(x_i,y_i)+b^*)\right] \quad ...(17)$$

For the kernel, there are four more usually used kernel functions as follows:

1. Linear Kernel: $K(x_i,x_j)=(x_i,x_j)$
2. Tow-layer Tangent Kernel: $K(x_i,x_j)=\tan(\beta_0(x_i,x_j)+\beta_1)$, among them, β_0 and β_1 are parameters;
3. d-order Polynomial Kernel: $K(x_i,x_j)=(a(x_i,x_j)+b)^c$, among them, a, b and c are parameters.
4. Radical Basis Function, $K(x_i,x_j)=\exp(-\frac{1}{\delta^2}(x_i-x_j)^2)$, δ present valet.

The total energy consumption data of China is more in line with the radial basis function kernel, while RBF kernel function with respect to its other three nuclear functions has the following advantages:

- Wide application. After selecting the parameter, there is no limit to the distribution of its sample.
- The Kernel function is in line with normal distribution and better analytical, so that it is easy to make theoretical analysis.
- Expressions simple and easy to implement. Even if increasing input variables, it cannot increase excessive complexity.
- Better smoothness and there exists derivative for any order.
- Better symmetry.
- Better generalization.
- RBF core values between zero to one, greatly simplifies the calculation process.

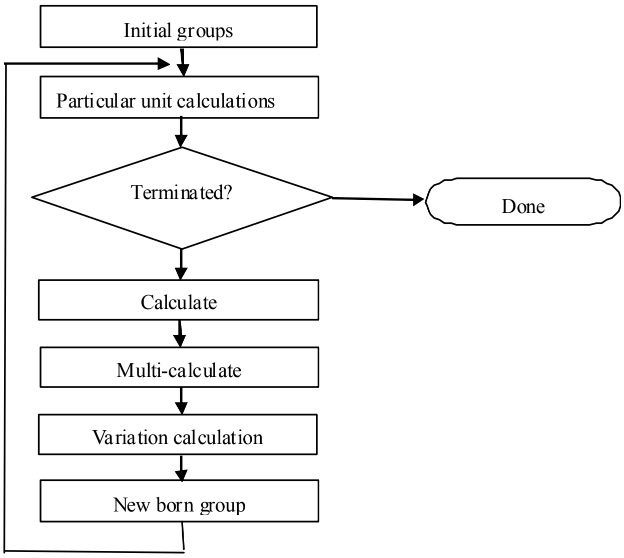

Fig 1: Genetic algorithm logic framework

Therefore, based on the above reasons, the kernel function of SVM model selects RBF type in this article.

In addition, since the input variables and output variables of the model dimension are not consistent, the data are quite different in magnitude. Therefore, before inputting the model, the input data and output data are normalized dimensionless. This article transforms various indicators into data between zero to one by selecting a normalized way:

$$x=\frac{x_i-x_{\min}}{x_{\max}-x_{\min}} \quad ...(18)$$

Empirical Analysis

We will choose the factors of total energy consumption of China as input data of SVM model, then the total energy consumption as output data, model and simulate historical data from 1980 to 2006. But before training and predicting sample data, we need to determine the unknown parameters of SVM model that are error punishment factor C and nuclear width σ . In order to get global optimal solution of these two unknown parameters, we began by the GA algorithm optimization of unknown parameters. And the final prediction results produce mean square error (MSE) as a measure. Select the appropriate value based on the results of the performance test set. Finally, when the error penalty factor C is 20.038, and nuclear width σ is 0.023, it means better forecasting effect. Using the above parameters to establish SVM model, the availability of training samples of the mean square error and correlation coefficients are respectively:

$$MSE_{train} = 0.000106; \ R_{train} = 99.58\%$$

The mean square error of test samples and correlation coefficients are respectively:

$$MSE_{test} = 0.000220$$

So we can see, the use of these models to predict the total energy consumption of China is the better forecasting. Take the test samples (total energy consumption of China from 2008 to 2014) for prediction, the predicted and actual values of total energy consumption in comparison, and the use of the results to predict the percentage of error for each measure. The error percentage is defined as follows:

$$\varepsilon_i = \frac{|\, y_i - \hat{y}_i \,|}{y_i} \times 100\%$$

Table 2 shows that, the use of GRA-GA-SVM model predicts total energy consumption from 2008 to 2014. The error percentage of prediction is within 3%. The average percentage error is only 1.19%. And the correlation coefficient between the estimated and actual values is up to 99.88 percent, which indicates that the predicted and actual values are closely related. This shows that the model is effective to predict the total energy consumption of China, has strong promotion ability, and can be used as an effective way to predict total energy consumption of China in the future.

In order to verify the above model to predict outstanding advantages in energy consumption of China, this paper selects the commonly used ARIMA model in economic forecasting and GM (1,1) model to predict total energy consumption of China, same prediction ideas as the SVM model which this paper establishes using total energy consumption of China from 1980 to 2007 as the training sample model, then predicts the total energy consumption of China from 2008 to 2014, make comparison between the predictive value and the actual value, as measured basis with error percentage, make comparison of predictive performance among GA-GA-SVM model, ARMA (1,2,3) model and GM (1,1) model (Table 3).

The comparison results show that the prediction error of GM (1,1) model is more than 10%, indicating that the effect of forecasting is poor and prediction method is not effective, and it can be seen that the model is not available to predict total energy consumption of China. Although the percentages of predictive error of ARIMA (1,2,3) model are lower than 5%, the average error percentage was 3.37%. Compared with the GRA-GA-SVM model, its predictive performance was quite less.

Thus, on the whole, this paper selects GA-GA-SVM model to predict the total energy consumption of China from 2015 to 2017. At this point we need to predict the 32 factors selected, after predicting by PCA-GA-SVM, using the above trained GRA-GA-SVM model, predict the total energy consumption of China in the future. The results obtained are shown in Table 4.

CONTROL MEASURES

Based on China's annual data from 1980 to 2014, this article uses gray correlation analysis to determine 32 energy factors and build GA-GA-SVM model to predict the total energy consumption in China for next three years, making conclusions as follows:

1. On economic factors, technical factors, the industrial structure and urbanization dimension, its gray correlation values are more than 85%, indicating that the impact of energy consumption in China is a multi-dimensional distribution.
2. From 2015-2017 the predicted value shows that, the total amount of China's energy consumption will continue to rise, but the growth rate gradually weakened. According to the above conclusion, the paper argues that the total energy consumption of China has shown a good trend, it will gradually make the Chinese economy into the "high growth, low consumption," situation. However, from factor analysis point of view, the characteristics of multi-dimensional distribution challenge to energy conservation of China, or China's energy path is still a long way to go. In view of this, the article proposes the following recommendations:

In the level of energy consumption and industrial structure, its various indicators and energy consumption correlation distribute in the vicinity of 99 percent, which indicates that the impact of energy consumption and industrial structure on energy consumption of China is relatively obvious. Therefore, it requires us to adjust the industrial structure and optimize energy consumption structure. For example, in the industrial structure, the government should encourage the development of low-power services and emerging industries, and gradually reduce the proportion of heavy industry in GDP. In terms of energy consumption structure, it should effectively control the production of energy consumption,

Table 2: The ratio between the actual values and the error of predicted values of total energy consumption from 2008 to 2014.

Year	Actual value	Predictive value	Error percentage
2008	291448	292347.0571	0.31%
2009	306647	307920.9987	0.42%
2010	324939	327430.2873	0.77%
2011	348002	352875.0455	1.40%
2012	362000	370809.3795	2.43%
2013	375000	380025.3612	1.34%
2014	383000	389062.4982	1.58%

Table 3: The ratio of error of the predictive values among GA-GA-SVM model, ARIMA model and GM model.

Year	Actual Value	Predictive value of ARIMA (1,2,3) model	Error percentage	Predictive value of GM (1,1) model	Error percentage
2008	291448	283196	2.83%	252799.1	13.26%
2009	306647	298766	2.57%	265945.0	13.27%
2010	324939	314807	3.12%	279774.6	13.90%
2011	348002	331318	4.79%	294323.3	15.42%
2012	362000	348299	3.78%	309628.6	14.47%
2013	375000	367350	2.04%	331162.5	11.69%
2014	383000	366033	4.43%	328116.1	14.33%

Table 4: The predictive value of the total energy consumption of China from 2015 to 2017.

Year	Total (ten thousand tons standard coal)	Growth rate (%)
2015	401307.4	4.78
2016	413667.6	3.08

promote the importance of living energy consumption savings. In the level of urbanization, there is very clear correlation degree between energy consumption and energy savings, which means that the infrastructure construction, the increase of the proportion of urban population, etc. make the total energy consumption of China rise.

And after the 18th National Congress of Communist Party of China, the central government has made it clear to urbanization as a future growth point of China's economy, which implies that the establishment of future cities will bring greater energy consumption. Therefore, the government should actively and steadily push forward the process of urbanization, and uphold the "low-carbon energy city" concept, to avoid wasting resources.

In the level of market factors, the correlation degree between index of marketization, energy prices and total energy consumption is relatively low which indicates that China's energy market has not achieved the optimal allocation of energy resources yet. This is because the government is still to implement energy price management mechanism, to a certain extent on disrupting the laws of the market. Therefore, in the future energy consumption control, the government should continue to learn and explore energy pricing mechanism with Chinese characteristics, and gradually achieve energy price market situation, try to work as role of "night watchman".

In the level of technical factors, there is relatively low correlation degree between other factors and energy consumption, in addition to "R & D personnel full-time equivalent", which shows that China has not yet played a role in the use of energy-saving technologies. So, faced with the dual pressure of control total energy consumption and environmental protection, domestic enterprises should play the role of mainstay, it must vigorously promote energy-saving technologies in the production process to update and improve the proportion of funding for innovative energy-saving technologies. Of course, in the road of exploring the control of the total energy consumption, the Chinese government should continue to explore, the need to guide the downward trend in energy consumption through system innovation. The Chinese government should continue to explore and guide the downward trend in energy consumption through system innovation. Meanwhile, China's outstanding enterprises should also be added to the ranks of energy saving, through the implementation of new technologies, new ideas, new methods energizing energy conservation.

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