

# Neural Network in the Anticipation of Electricity Use: An Investigation from Micro and Macro Perspectives

Mingyuan Zhou<sup>1,a,\*</sup>, Yufeng Xiao<sup>2,b</sup> and Yanqing Ma<sup>3,c</sup>

<sup>1</sup>YK Pao School, Shanghai, China

<sup>2</sup>Wuhan Britain-China School, Wuhan, Hubei, China

<sup>3</sup>Shanghai Weiyu High School International Department, Shanghai, China

<sup>a</sup>1879600231@qq.com, <sup>b</sup>xiaoyufeng2021@163.com, <sup>c</sup>fs20090832@163.com

\*Corresponding author

**Keywords:** Wavelet analysis, BP neural network, Seasonal adjustment model.

**Abstract.** In our contemporary fiscal lives continuously expanded by technological innovations, electricity is playing an increasingly momentous role. That said, ameliorating electricity consumption anticipation has become a most imminent and pressing issue. Considering the large quantity and high frequency of electric load data (96\*197 groups), this paper, from a micro perspective, combines wavelet decomposition with BP neural network to forecast the electric load data of users. The results show that the prediction results are better than that of purely using BP neural network. In addition, from a macro perspective, this paper analyzes the essential factors of electricity consumption in China. Through establishing seasonal adjustment model, our research predicts China's electricity consumption in the next 10 years. The result indicates that the electricity consumption reaches its peak of 2008.541 billion kWh in the third quarter of 2024, and the power supply should be planned well in advance.

## 1. Introduction

Electricity, the predominant source of energy in modern society, plays an irreplaceable role not only in our daily lives, but also in the contemporary economy. More or less, almost every modernized industry relies heavily and bases upon the electricity, which largely increases their operational efficiency and productivity. Hence, the electricity use becomes the main focus of this paper.

With the acceleration of economic development, demand for electricity becomes increasingly large, especially in densely populated metropolis or highly industrialized cities. However, problems occur from time to time, take blackouts happened in New York for instance; its 1977 blackout generated a cost of 345.7 million dollars, and the one occurred recently in 2019 directly led to a cost of 500 thousand dollars for StubHub in just ticket refund (Baik.e.baidu.com, 2019). Apart from these direct monetary cost, operational process may be ceased and millions of products may become waste, criminal activities and societal chaos may be triggered... With electricity being deprived, we mankind are of little difference compared to our primitive ancestors, and under such situation, the productivity may face steep reduction, resulting in devastating impact to the global economy. Thus, such scenarios pose a problem with great urgency to solve -- how to deal with blackouts caused by overdemand and undersupply.

Due to large amount of data and users' irregular habits, it is difficult to use traditional model to predict the electricity use of a typical user. Thanks to the advancement of analytical methods, machine learning in particular, we are now able to predict future trends of electricity demand in a relatively proper and accurate manner based on the massive amount of historical data collected from some typical individual households and governmental statistics. In this paper, we are going to combine these above analytical methods and various of models in order to provide the most accurate prediction possible, and our prediction includes two parts.

The first part explores the issue from a micro perspective by investigating the electricity use of a typical user. The data collected from typical individual households are substantial and has a high-

frequency. Hence, in this part, we predict the electricity load of the individual households with the help of wavelet analysis and machine learning. We can thus, based on the results, make conclusion about the pattern of the fluctuation of electricity consumption within a day. Subsequently, the process could be extended to the prediction of the whole electricity load.

The second part explores the electricity use on a macro level, and in this part, we will make prediction on the basis of data about regional consumption of electricity by employing some econometric models. We mainly investigate the causal effect and the correlation between regional electricity consumption and some possible influential factors include (gross domestic product, population, seasonal factor etc.).

Our result of prediction may function as auxiliary to the authority that is responsible for electricity supply of a region (The State Grid Corporation of China), thus helping them to plan the electricity supply more effectively so as to avoid such blackout situation as well as those undesirable results brought along.

**2. Data Selection**

In the micro analyses and modeling, we employ a single user's electric load data, lasting from September 1, 2015 to March 15, 2016 with a time interval of 15 minutes. In this time span, due to the deficiency of data at certain time periods, this paper focuses on the available data. Electricity load data are as follows:

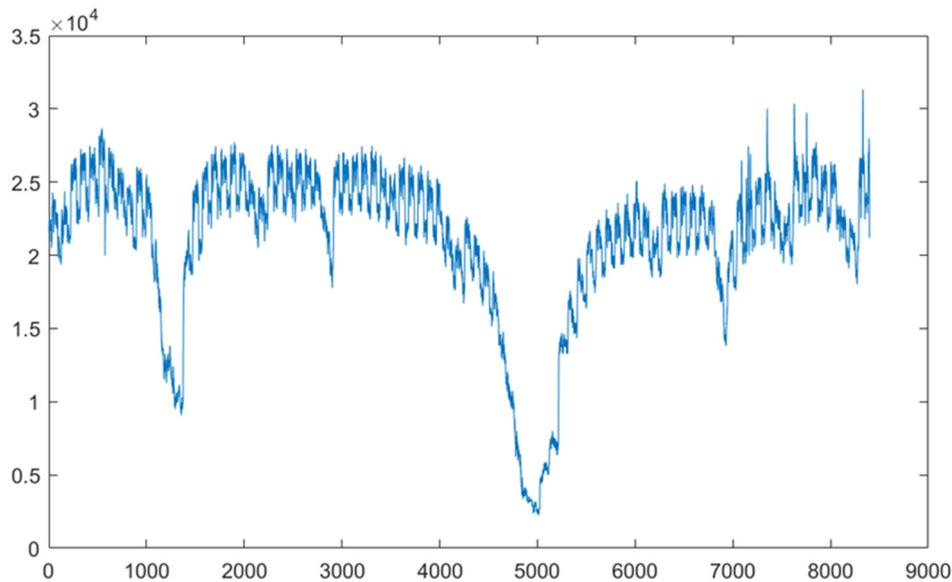


Fig. 1. Characteristics of the electricity load of a typical user

In the macro analyses and modeling, we study the aggregate electricity consumption of China. Through examining the demand for electricity and analyzing the determinants of electricity consumption, our research forecasts China's electricity consumption in the near future. Compared to the micro data, macro data are less in amount and frequency. Therefore, we utilize the tradition method to measure the data.

The macro data used in our research are from official and authoritative databases, and sources are as listed below:

Table 1. Sources of Data

Data	Sources
Electrical Load	HBSIAM
Aggregate Electricity Consumption	National Statistics Bureau, CNKI China Economic and Social Development Database
Gross Value of Industrial Output	National Statistics Bureau
Gross Value of Service Output	National Statistics Bureau
Population	National Statistics Bureau, the United Nations

### 3. Prediction of Electrical Loads: From a Micro Perspective

The increase in electrical load is likely to cause circuit and transformer failures, which in turn leads to power outages in many factories or cities. Therefore, forecasting the residential and industrial power loads will help ensure the safety of urban electricity consumption and maintain the stable development of the urban economy. The data used in this paper are high-frequency data, and the amount of data is enormous. It is often difficult to describe this complicated pattern of change in traditional models, and it is no longer suitable for the prediction of such high-frequency data. Thus, this time, we will adopt the methodology of machine learning algorithm. In addition, considering that the user's power consumption behavior has certain regularity, that is, the user's power consumption varies at different times every day. Therefore, this paper first decomposes the original data, that is, the user's original power load data is divided into daily average electricity consumption; then, the data and the power load data at different times of the day are predicted separately.

The prediction method for daily average electricity consumption data is analyzed by neural network. For the power load data of different time periods in one day, we first perform wavelet decomposition and then analyze the data and make appropriate prediction through BP neural network. The process is shown below:

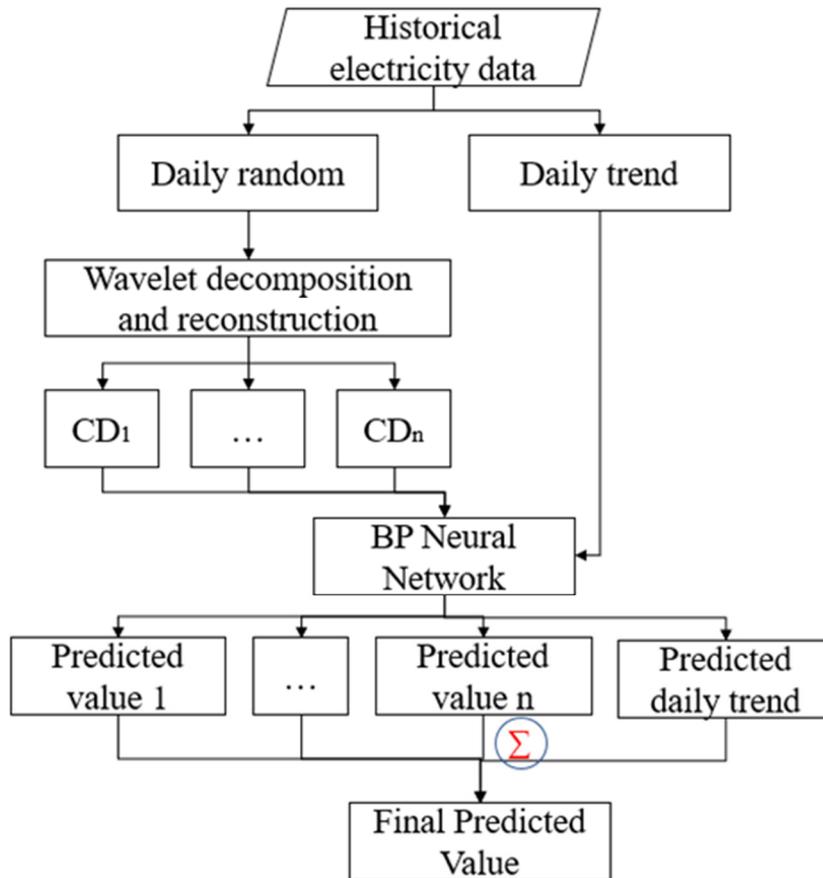


Fig. 2. Flowchart

#### 3.1 Wavelet Decomposition

In the process of decomposing data, Fourier transform have certain limitations. Therefore, the original sequence will be decomposed in the form of wavelet decomposition into three different frequency power load data which will be predicted by BP neural network. Compared to the Fourier transform that uses a series of sine waves, time variation can be captured in wavelet analysis. Wavelet analysis uses a series of finitely attenuated wavelet bases instead of sine waves in the Fourier transform. In the analysis, the wavelet needs to satisfy two conditions, which are respectively expressed as:

$$\int_{-\infty}^{+\infty} \psi^2(u)du = 1 \text{ and } \int_{-\infty}^{+\infty} \psi(u)du = 0 \tag{1}$$

The continuous wavelet transform formula is:

$$WT(a, b) = \int_{-\infty}^{\infty} f(t) \times \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right) dt \tag{2}$$

Where  $a$  is the scale of the wavelet function, controlling the scaling process, and  $b$  is the translation of the wavelet function. The roles of these two variables are the same as the periodic transformation and displacement in the trigonometric function; that is, the corresponding wavelet can be stretched and translated to conform to the original process shape of the data. For the prediction process of power load, the implementation of this method has the following steps:

*Step 1:* Select appropriate decomposition series to perform wavelet decomposition on the historical data of the electrical load to obtain wind speed components of different frequencies;

*Step 2:* Perform two interpolation reconstruction on each frequency component after wavelet decomposition, and let the length of the electrical load data to reach the length of the original data without changing the frequency characteristics of each component;

*Step 3:* According to the frequency characteristics of each component quantity, select the appropriate neural network prediction model and train it separately;

*Step 4:* Appropriate weighted summation of the obtained predicted values of the electric load of different frequencies, and the obtained electric load is the final predicted value of the electric load.

### 3.2 Neural Network Prediction Model

With the dramatic development of big data and artificial intelligence, the machine learning model based on the neural networks has been widely employed and applied in the field of prediction. Neural network models usually consist of input layer, hidden layer and output layer. Through pilot testing, our neural network model contains six hidden layers, and its structure is illustrated as below:

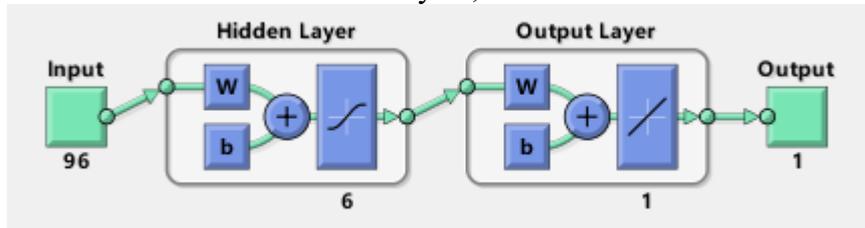


Fig. 3. Neural network structure (from matlab)

Given the train set  $D = \{(x_1, y_1), \dots, (x_m, y_m)\}$ , where  $x_i$  represents the  $i$ -th observation with  $d$ -dimensional variables, the input to the  $h$ -th neuron of the input layer is:

$$\alpha_h = \sum_{i=1}^d v_{ih} x_{im}, \quad m=1, 2, \dots, M \tag{3}$$

Among them,  $X_{im}$  is the  $m$ -th input sample of the  $h$ -th neuron. And the input that the  $j$ -th output layer receives could be shown as follows:

$$\beta_j = \sum_{h=1}^q w_{hj} b_h \tag{4}$$

Where  $b_h$  denotes the output of the hidden  $h$ -th neuron. Usually, the Sigmoid function is used for the hidden and output layer of neuron. Assume that the output using the neural network is  $\hat{y}_k = (\hat{y}_1^k, \hat{y}_2^k, \dots, \hat{y}_m^k)$ , the mean square error of the forecasting is shown as follows:

$$E_k = \frac{1}{2} \sum_{j=1}^l (\hat{y}_j^k - y_j^k)^2 \tag{5}$$

According to the BP algorithm rule, we use gradient descent to update the above process. Given the learning rate  $\eta$ , the adjustment range of the parameter is:

$$\Delta w = -\eta \frac{\partial E}{\partial w}, \frac{\partial E}{\partial w} = \frac{\partial E}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial \beta} \cdot \frac{\partial \beta}{\partial w} \tag{6}$$

And the objective of BP algorithm is to minimize the cumulative error of the training sets. The goal of BP algorithm is:

$$\min E = \frac{1}{m} \sum_{k=1}^m E_k \tag{7}$$

### 3.3 Cross Validation

Unlike to traditional method that only divides the data into a training set and a testing set, we adopt the cross validation in this paper in order to evaluate the effectiveness of the prediction of quantity consumed of electricity generated by our model. Through Cross Validation, we can examine the extent of accuracy of our prediction, and thus guaranteeing the effectiveness of our models.

Firstly, cross validation divides the dataset of electricity consumption  $D$  into  $K$  mutually-exclusive subsets, and this relationship can be shown as below:

$$D = D_1 \cup D_2 \cup \dots \cup D_k, D_i \cap D_j = \phi (i \neq j) \tag{8}$$

During our prediction, we use the union set of  $(k-1)$  subsets as training sets, and the remained subset as the testing set; thus, we can obtain  $K$  sets of training/testing sets. In order to compare the error of the model, we use the average relative percentage error and the mean square error as the evaluation criteria for the prediction accuracy. The average relative percentage error and the mean square error result are as follows:

$$E_{MR} = \frac{1}{n} \sum_{i=1}^n \frac{\hat{Y}_i - Y_i}{Y_i}, E_{MA} = \sqrt{\frac{1}{n} \sum_{i=1}^n \left(\frac{\hat{Y}_i - Y_i}{Y_i}\right)^2} \tag{9}$$

In above equation,  $Y_i$  refers to real value the remained subset, while  $\hat{Y}_i$  refers to the predicted value of the remained subset.

Through repeat the training and testing procedure by  $K$  times, then find out the mean error rate of those  $K$  error rates generated, we can obtain the evaluation methods we used in this paper, which uses the relative inaccuracy as the criteria to measure the accuracy of the models.

To illustrate, following graphs are shown to describe the procedure of this method by using an example dataset  $D$  contains ten subsets  $D_1, D_2, \dots, D_{10}$ :

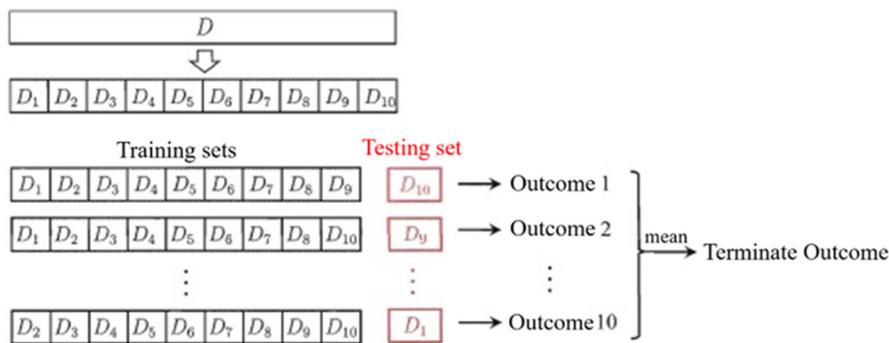


Fig. 4 Schematic diagram of cross validation

### 3.4 Result Analysis

We will first process the user load data, calculate its daily average trend and remove the disturbance term of the daily average trend. The results are shown in the following figure:

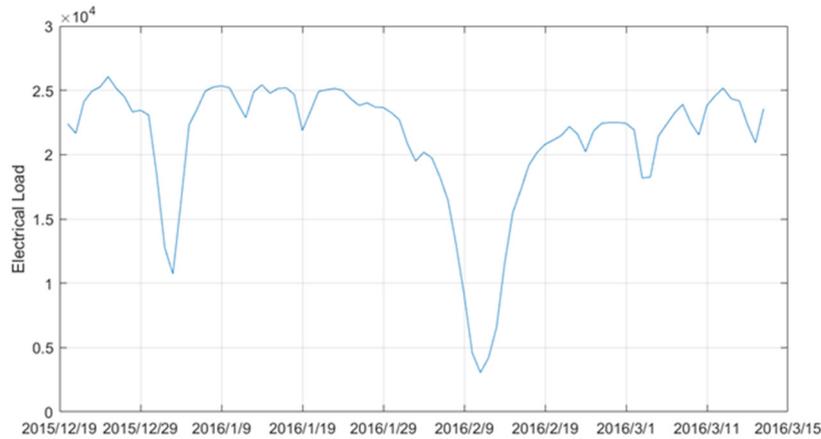


Fig. 5 User's daily average power load

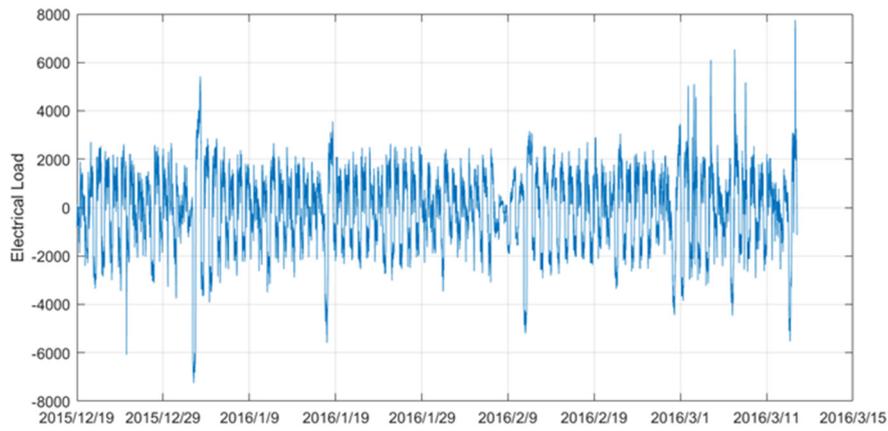


Fig. 6 User's power load after subtracting the mean value

It can be seen from the above figure that the user's electricity load data has obvious regularity, and the average daily electricity load is lower near the holidays (two low points in the above figure, corresponding to New Year's Day and Spring Festival respectively), and used by non-holiday users. The electrical load fluctuations are relatively stable, about 20,000.

3.4.1 Wavelet decomposition:

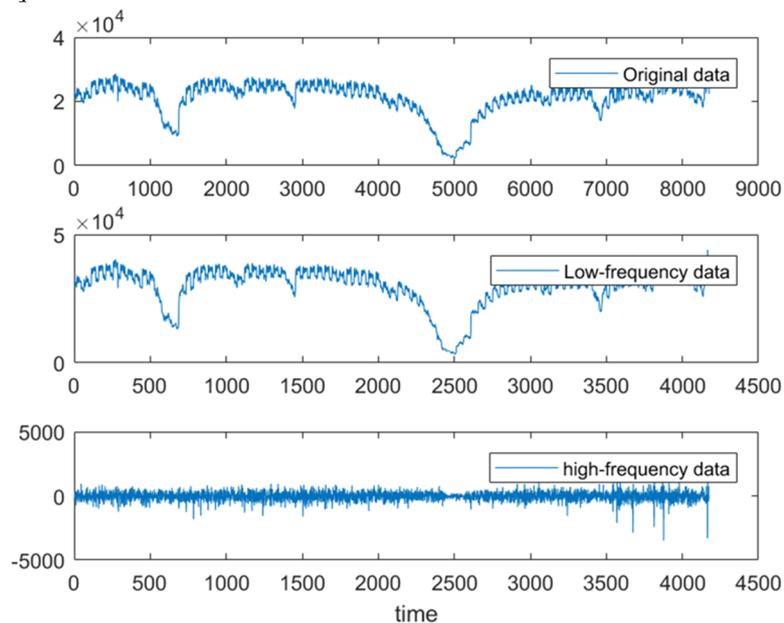


Fig. 7 Original data and data using Wavelet analysis

Similar to Chang et.al (2019) in studying the short-term wind speed process, in order to reduce the randomness of the power load data and wavelet decomposition of the data, we use ‘haar’ wavelet to analyze. After decomposing the user's electrical load data, the power load components of different frequencies can be obtained. The result is shown in the following figure:

Since the frequency of wavelet decomposition is lower than the original sequence frequency, this paper performs spline interpolation reconstruction to make the sequence length of the decomposed high frequency and low frequency equal to the original sequence length.

3.4.2 Forecast result:

The electric load data of a typical user predicted by the BP neural network and the actual electric load are used. The data results are as follows:

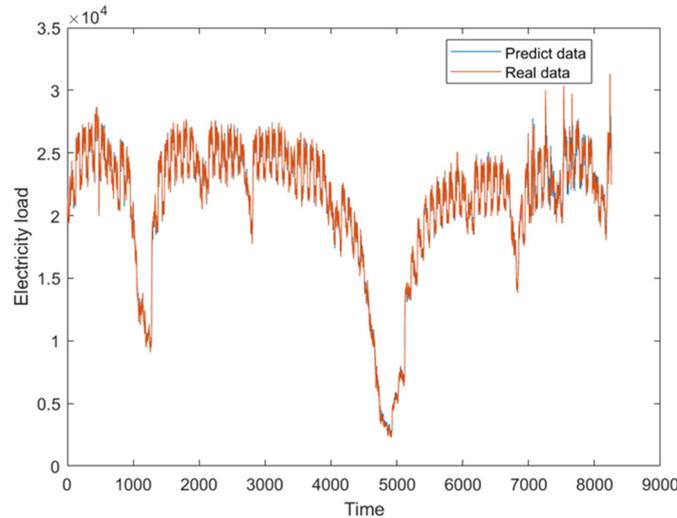


Fig. 8 Real and predicted load data

It can be seen from the above figure that the actual and predicted power load trends are relatively close and the direction of change is the same. The actual electricity consumption concurs with the predicted electricity consumption, shown by the overlap of two trend lines. This indicates BP neural network has better forecasting effect for short-term and high-frequency data. Generally, the relative percentage error of the electric load predicted directly by BP neural network is about 2%, with an average of 1.946%. However, after wavelet decomposition of the original data, BP neural network is used to predict low-frequency and high-frequency load respectively. The relative error percentage and mean square error results are as follows:

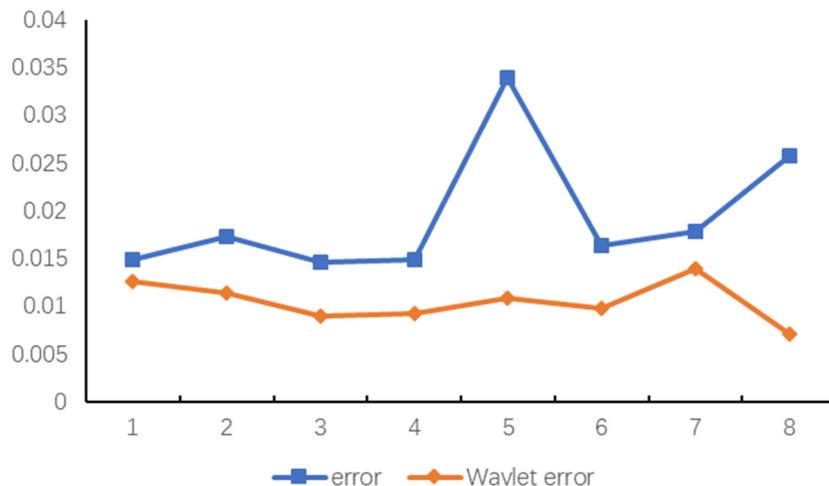


Fig. 9 Relative percentage error

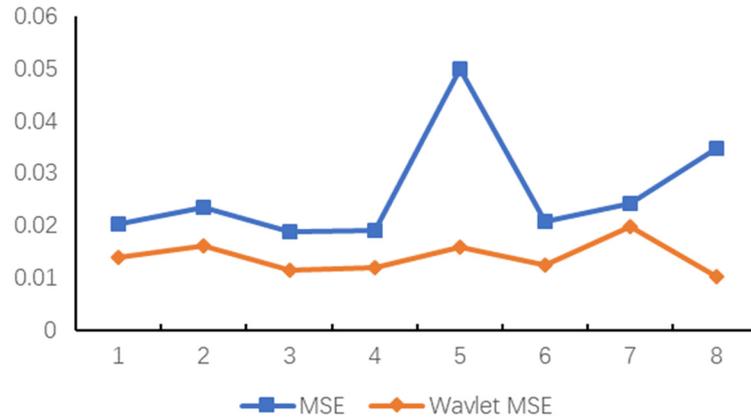


Fig. 10 Mean squared error

As shown in the above figure, the average relative percentage error and the mean square error of BP neural network prediction after wavelet decomposition are 1.05% and 1.395%, respectively. These two results have less error than that of using BP neural network directly, which shows that for high frequency electric load data, the prediction effect of BP neural network after wavelet decomposition and reconstruction is better. This provides us an important reference for short-term electric load forecasting.

#### 4. Prediction of Electricity Use: From a Macro Perspective

In the above sections, we consider the user's power usage behavior from a micro perspective and predict the power load data by combining wavelet analysis with neural network. Now we analyze the electricity consumption data of the society from a macro perspective, and take into account the factors such as seasonality, economic growth, and demographic changes. This time, the analysis will be extended from a single user to China as a whole. First, it is necessary to know the relationship between electricity consumption and seasonality, economic growth and demographic changes, then forecast the seasons, economic growth, and population changes separately. Subsequently, we can utilize the obtained data to conduct a horizontal analysis of the changes in electricity consumption. Through the regression model, the relationship between seasonality, economic growth, and population change and electricity consumption can be quantitatively derived. Since the electricity consumption index is indirectly derived from these three indicators, the prediction of these three indicators is directly related to the prediction results. In order to improve the accuracy of predication, a population-based Leslie matrix model is used for population prediction; considering the characteristics of China's current GDP growth is relatively stable, the ARIMA model is used for GDP prediction; the seasonal index is calculated by the moving average method.

Finally, the predicted results of electricity consumption are obtained based on the calculated results of seasonality, economic growth and demographic changes. By comparing the predicted results with the actual results, the predicted results of the model can be analyzed. The following figure reflects the results of the entire society's electricity consumption in the past 20 years. It can be clearly seen from the figure that the electricity consumption has the trend of seasonal fluctuation. Specifically, the electricity consumption in the fourth quarter is higher than that in the first quarter.

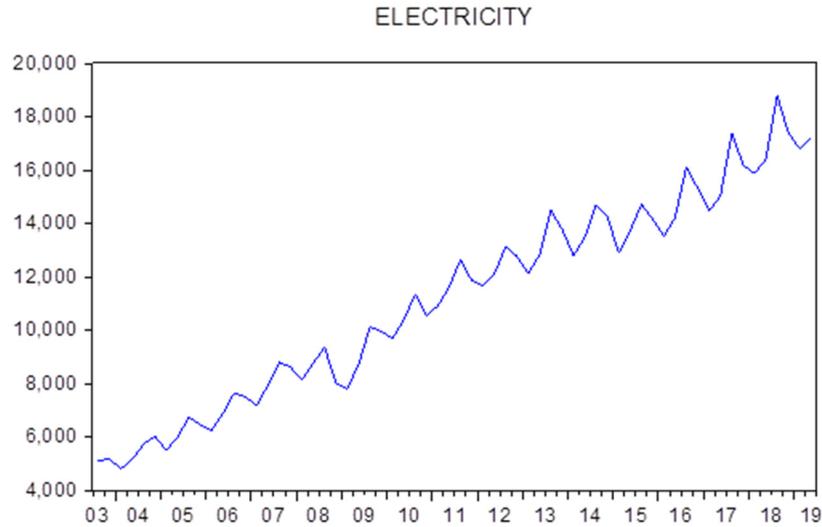


Fig. 11 Total electricity consumption from 2003 to 2019

### 4.1 Establishment of Macro Electricity Model

Taking into account the demand for electricity consumption of the population, we select industrial output value, service industry output value and population as variables that influence electricity consumption. Based on the seasonal variation of power usage, in order to calculate the seasonal cycle effect, the seasonal cycle model established in this paper is as follows:

$$Elec_t = (\beta_0 + \beta_1 Indu_t + \beta_2 Serv_t + \beta_3 N_t) \cdot S_j + e_t \tag{10}$$

The formula in parentheses  $(\beta_0 + \beta_1 Indu_t + \beta_2 Serv_t + \beta_3 N_t)$  indicates the long-term trend of electricity consumption;  $Indu_t$  represents China's industrial output value data;  $Serv_t$  represents China's service industry output value;  $N_t$  indicates population. According to the seasonal characteristics of electricity demand,  $S_j$  is defined as the seasonal index, indicating the range of cyclical changes. The seasonal index is calculated as follows:

(1) Using the regression model to calculate the long-term trend model of electricity consumption without seasonal cycle changes

$$Elec^*_t = \hat{\beta}_0 + \hat{\beta}_1 Indu_t + \hat{\beta}_2 Serv_t + \hat{\beta}_3 N_t \tag{11}$$

(2) Calculate the cycle index for each cycle

$$P_t = \frac{Elec_t}{Elec^*_t}, t = 1, 2, \dots, T \tag{12}$$

(3) Calculate the average seasonal index

$$S^*_j = \frac{P_j + P_{j+4} + \dots + P_{j+4(n-1)}}{n}, j = 1, 2, 3, 4 \tag{13}$$

(4) Standardize the average seasonal index

$$\bar{S} = \frac{1}{4} \sum_{j=1}^4 S^*_j \tag{14}$$

(5) Calculate the final seasonal index  $S_j$  as shown below

$$S_j = \frac{S^*_j}{\bar{S}} \tag{15}$$

Through the process above, we can finally get the seasonal cycle model of the aggregate electricity consumption from a macro perspective, predicting the electricity consumption in China through establishing relationship to industrial output value, service industry output value, population and seasonal factors. The results are as follows:

$$Elec_t = (\hat{\beta}_0 + \hat{\beta}_1 Indu_t + \hat{\beta}_2 Serv_t) \cdot \hat{S}_j \tag{16}$$

### 4.2 Model Solving

We first find out the long-term trend of the demand for electricity consumption. Using the least squares method, we then use software ‘Eviews’ to regress the following formula. The regression form is as follows:

$$Elec_t = \beta_0 + \beta_1 Indu_t + \beta_2 Serv_t + \beta_3 N_t + \varepsilon_t \tag{17}$$

The data collected ranged from the third quarter of 2003 to the second quarter of 2019. Since the population data is annual, the quarterly data of the population can be obtained by interpolating the cubic spline, and the results are as follows.

Table 2. Electricity consumption regression result

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-107175.7	20097.15	-5.332883	0.0000
INDUSTRY	0.077245***	0.013069	5.910391	0.0000
SERVICE	-0.024036*	0.013118	-1.832286	0.0719
POP	0.859839***	0.156234	5.503539	0.0000

Note: \*\*\*, \*\*, \* represents the result is significant at 1%, 5%, 10% significance level respectively.

The R-squared of the above regression is 0.9777, and the F value is 922.3546. The fitting effect of the model is very significant. As shown in the table above, the coefficient before the industrial output value is 0.077245, which means that when the other conditions are unchanged, as the industrial output value increases by 100 million yuan, the electricity consumption will increase by 0.077245 billion kWh, and the result is significant at 1%; the coefficient before the service industry is -0.024036, which may be related to the greater impact of industrial output on electricity consumption, resulting in a negative coefficient; the coefficient before the population is 0.859839, indicating that it remains unchanged under other conditions. In the case of a population surge of 10,000 people, the electricity consumption will increase by 0.859839 billion kilowatts.

Through the above methods, the relationship between the total social electricity consumption, industrial output value, service industry output value, population and seasonal factors can be finally obtained as:

$$\begin{cases} Elec_t^* = (-107175.7 + 0.077245 \times Indu_t - 0.024036 \times Serv_t + 0.859839 \times N_t) \times S_j \\ S_1 = 0.9864, S_2 = 0.9786, S_3 = 1.0635, S_4 = 0.9732 \end{cases} \tag{18}$$

### 4.3 Prediction for Future Electrical Consumption

In fact, we can employ the time series model to predict the future gross value of industrial output and gross value of service output respectively. Nevertheless, China’s economy has already passed the high growth stage and is starting to enter the medium-high growth stage.

#### 4.3.1 Predictive Modeling for GDP:

Gross domestic product (GDP) is the total monetary value of all final goods and services produced within the boundaries of a country in a specific time period. As an exceptionally important macroeconomic indicator, GDP reflects the level of development and growth rate of a country’s economy. In addition, according to Xiong (2011), due to the upward fluctuation tendency of the quarterly GDP, we decide to employ an autoregressive integrated moving average model (ARIMA). As we use the time series model to predict the future change in GDP, we utilize the ADF to test the stationarity of the series. The ADF test is as below:

$$Y_t = \alpha_0 + \rho \Delta Y_t + \varepsilon_t \tag{19}$$

After processing China’s quarterly GDP statistics with logarithm, the result of ADF test is shown below:

Table 3. Result of unit root test

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-3.259058	0.0215
Test critical values: 1% level	-3.548208	
5% level	-2.912631	
10% level	-2.594027	

From the table above, the logarithms of GDP values is significant at the 5% significance level, proving the stationarity of the result, which can be used in the following research. Therefore, in the ARIMA (p, q, d) model, d has the value of 0. To determine the appropriate model form, the research obtains the lag order based on the Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC), as illustrated below:

Table 4. Information Criterion Results

Information criteria	AR(1)	AR(2)	AR(3)	AR(4)
AIC	-1.539444	-1.801666	-1.771834	-3.949102
SBC	-1.471408	-1.698740	-1.630984	-3.774573

By employing least squares method, estimated ARIMA(4,0,0) model, the acquired result is as below:

Table 5. Regression results

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.773840	0.092396	8.375242	0.0000
LGDP(-1)	0.049114	0.046807	1.049290	0.2986
LGDP(-2)	0.014823	0.047272	0.313573	0.7550
LGDP(-3)	-0.044342	0.047183	-0.939787	0.3514
LGDP(-4)	0.923507	0.046209	19.98550	0.0000

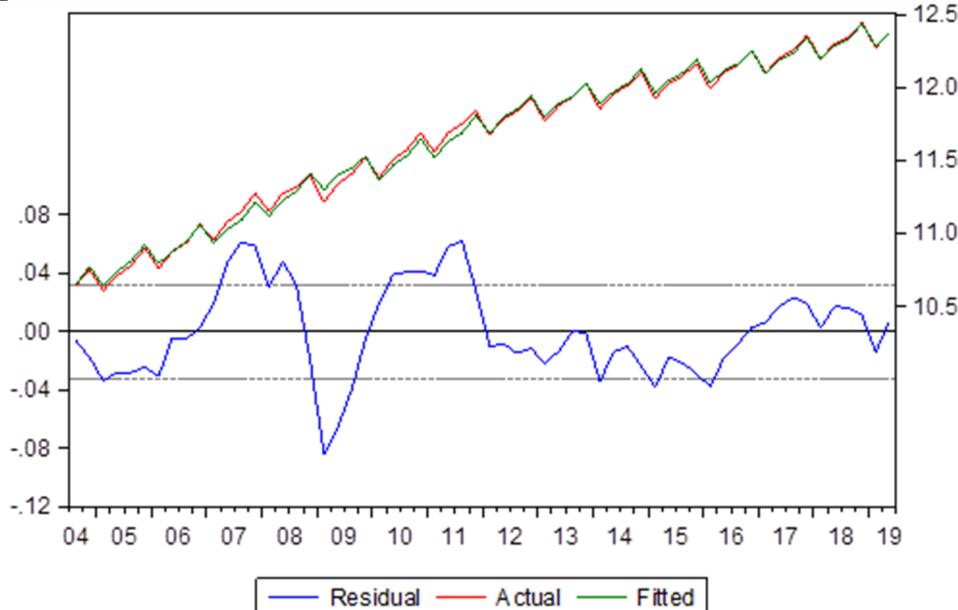


Fig. 12 Actual and Predicted Quarterly log GDP

Shown in the Figure 5-2, the predicted quarterly log GDP is significantly close to the actual quarterly GDP. Therefore, we determine that it is an appropriate and effective method to model the approximate future GDP. Predicting the future GDP series within ten years, the model forecasts the change in China’s gross value of industrial output and gross value of service output. Under the

assumption that China’s economic structure remain unchanged, China’s predicted GDP can be illustrated as:

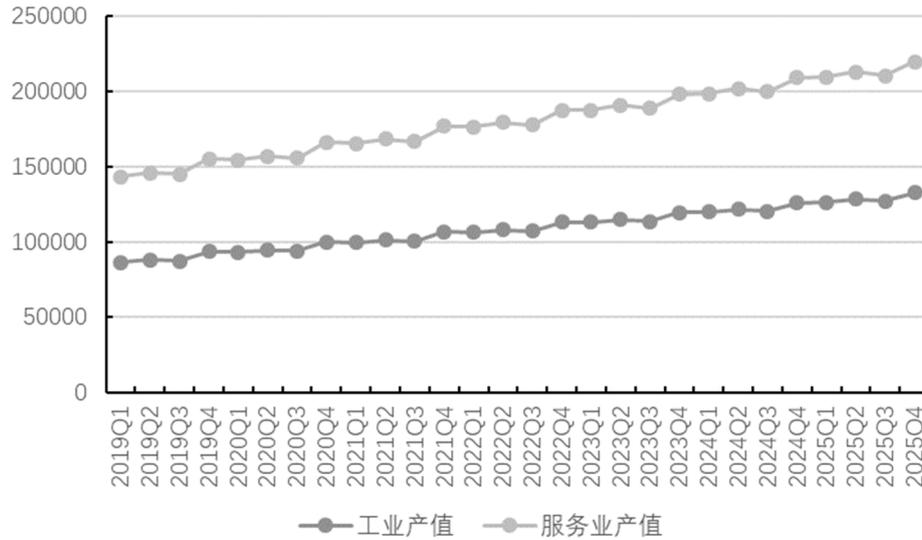


Fig. 13 Industry and service products in the future

4.3.2 Predictive Modeling for Population:

There are various methods for population forecasts. However, considering China now has a very low birth rate, our model assume that the fertility rate is approximately 1.5 based on the data in the book <Green Book of Population and Labor No.19> published by Chinese Academy of Social Science. The model predicts China’s quarterly population in the next ten years through spline interpolation. With the current demographic structure, the future population can be modeled as:

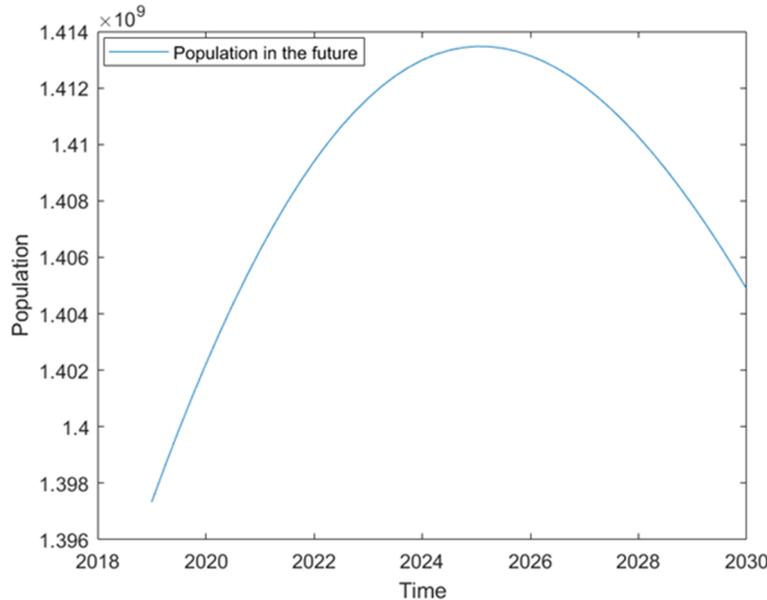


Fig. 14 Future Population Change

4.3.3 Future Electrical Consumption:

Assuming China’s economic structure remains unchanged - that is, the proportion of industrial output and service output remain the same – and based on our predictive population model, the prediction of China’s electricity consumption in the near ten years is shown below:

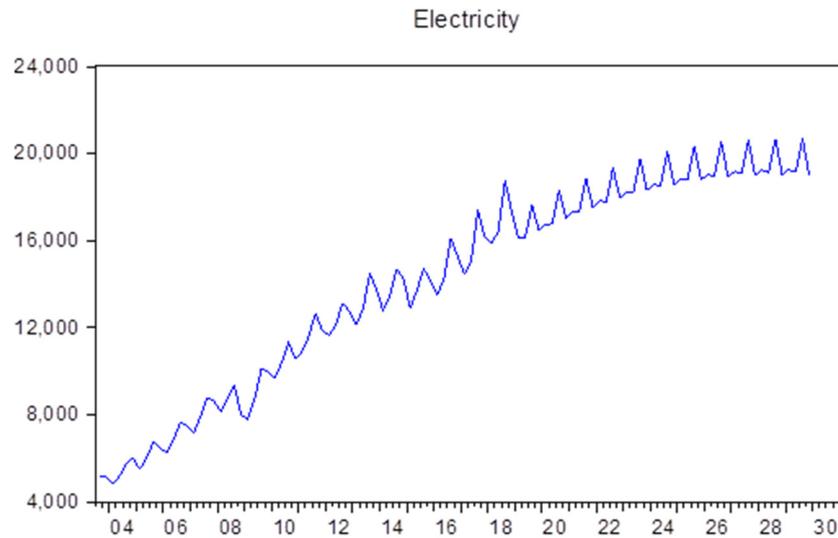


Fig. 15 Prediction of Future Electrical Consumption

From the figure above, along with the rapid economic development of China, the demand for electricity has boosted dramatically and continuously, increasing from 500 billion kilowatt-hour in 2004 to 2000 billion kilowatt-hour in 2020. Thus, the State Grid Corporation of China should improve the electricity supply, avoiding the incidences and issues of electrical power shortage and ensuring the stable growth of the economy. Nonetheless, with China’s economic slowdown, low population growth rate, industrial structure’s changes and other factors, the growth rate of electrical consumption is also slowing down. The figure below provides the prediction of China’s electrical consumption in the next five years:

Table 6 Electricity consumption prediction by quatrter

Quarter	Consumption Prediction (kilowatt-hour in billion)	Quarter	Consumption Prediction (kilowatt-hour in billion)	Quarter	Consumption Prediction (kilowatt-hour in billion)
2019Q1	1611.631	2021Q1	1732.779	2023Q1	1824.229
2019Q2	1615.017	2021Q2	1732.207	2023Q2	1819.927
2019Q3	1764.031	2021Q3	1885.761	2023Q3	1975.629
2019Q4	1646.637	2021Q4	1753.846	2023Q4	1831.274
2020Q1	1675.745	2022Q1	1782.343	2024Q1	1858.497
2020Q2	1677.138	2022Q2	1779.852	2024Q2	1852.520
2020Q3	1828.738	2022Q3	1934.746	2024Q3	2008.541
2020Q4	1703.871	2022Q4	1796.306	2024Q4	1858.910

### 5. Conclusion

Under the global background of frequent electricity crisis, this paper conducts analyses and forecasts China’s electricity consumption from micro (user’s electric load) and macro (society’s electricity consumption) perspectives respectively. Our research is concluded as following:

First, the BP neural network based on wavelet decomposition and reconstruction has an accurate predictability on the user's electric load. For high-frequency data, the traditional models, such as regression models, are not suitable for big data analysis and prediction due to the limited relationship. Therefore, this paper mainly employs BP neural network model to forecast the electric load data. Results show that, compared with directly using the BP neural network model, the predictability of BP neural network after wavelet decomposition and reconstruction is better. The relative percentage error decreases from 1.946% to 1.05%, and the mean square error decreases from 2.64% to 1.395%, which illustrate the higher prediction accuracy of this model. Therefore, according to this piece of information, relevant departments can effectively forecast the electricity load of a certain area and find hidden dangers in time.

Second, China's electricity consumption will continue to rise in the future. Through establishing the seasonal adjustment model, we discovered that the peak of electricity consumption in China occurred in the third quarter. Moreover, China's electricity consumption will reach a small peak around 2024. Therefore, the State Grid Corporation of China should research and make the electrical power plan in advance to ensure the safe and reliable use of electricity and stable economic operation in China.

### **Acknowledgment**

As a team, each member has contributed equally and diligently to the final completion of this paper. Yanjing Ma was responsible for micro section modeling; Yufeng Xiao was responsible for coding and finding relevant data; Mingyuan Zhou was responsible for macro section modeling. We appreciate each member's effort.

We wish to express sincere gratitude to our instructor, Mr. Peter McCombe, who guided us through the modeling and writing process.

We also thank to our parents for their support and help in life.

Lastly, thanks to S.-T. Yau High School Science Award for providing us such precious opportunity to apply our modeling knowledge to the relevant economic problems.

### **References**

- [1] S. K. Goyal, An integrated inventory model for a single supplier-single customer problem, *International Journal of Production Research*, vol.15, pp. 107-111, 1977.
- [2] Y. Chang, et al. Short-Term Wind Speed Combined Forecasting using Wavelet Analysis and Neural Network. *Journal of Huaqiao University (Natural Science)*, 40(4), pp.556-560.
- [3] T. Du, X. Wang & X. Wang, A combined model of wavelet and neural network for short term load forecasting. *International Conference on Power System Technology*, 2002.
- [4] D. Fan, S. Wang, W. Zhang, Study on Application of Seasonal Cycle Model in China's Power Load Forecasting. *Power System Technology*, 36(7), pp.106-110, 2012.
- [5] L. Li, X. Lai, X. Chen, Research on Inner-plant Optimal Operation of Hydropower Station Based on Improved Wolf Swarm Algorithm. *Water Resources and Power*. 37(5), pp. 192-195, 2019.
- [6] L. Shen, A Study on the Relationship between Industrial Structure Evolution and Changes in Electricity Consumption in Zhejiang province, 2013.
- [7] Z. Xiong, Research on GDP Time Series Forecasting Based on Integrating ARIMA with Neural Networks. *Journal of Applied Statistics and Management*, 30(2), pp. 306-314, 2011.
- [8] H. Zhang, J. Yang, Research on Intelligent Prediction of Short-Term Electric Load Based on Wavelet Decomposition. *Telecom Power Technology*. 36(2), pp.38-39, 2019.
- [9] J. Zhang, et al. Saturated Load Forecasting Based on Per Capita Electricity Consumption and Per Capita Electricity Load. *East China Electric Power*. 42(4), pp.0661-0664, 2014.
- [10] Z. Zhou, *Machine Learning*. Tsinghua University Press, 2016.
- [11] Chinese Academy of Social Sciences, *Population and Labor Green Paper: China Population and Labor Issues Report No. 19*.