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Research Article

An Improved Artificial Colony Algorithm Model for Forecasting Chinese Electricity Consumption and Analyzing Effect Mechanism

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Electricity consumption forecast is perceived to be a growing hot topic in such a situation that China's economy has entered a period of new normal and the demand of electric power has slowed down. Therefore, exploring Chinese electricity consumption influence mechanism and forecasting electricity consumption are crucial to formulate electrical energy plan scientifically and guarantee the sustainable economic and social development. Research has identified medium and long term electricity consumption forecast as a difficult study influenced by various factors. This paper proposed an improved Artificial Bee Colony (ABC) algorithm which combined with multivariate linear regression (MLR) for exploring the influencing mechanism of various factors on Chinese electricity consumption and forecasting electricity consumption in the future. The results indicated that the improved ABC algorithm in view of the various factors is superior to traditional models just considering unilateralism in accuracy and persuasion. The overall findings cast light on this model which provides a new scientific and effective way to forecast the medium and long term electricity consumption.

1. Introduction

With the development of economy and technology, particularly in thirty years or so of reform and opening-up, Chinese electricity consumption achieves a sustained and rapid development. However, as illustrated in Figure 1, along with the economic development entering the "new normal," the national economy is in a period of transition from rapid growth to steady growth and the electricity consumption has been fluctuating.

Starting in 2012, on account of the decline in electricity consumption proportion of high energy-intensive industries, the growth of electricity demand in power industry has slowed down significantly. Pumping capital into installed capacity in early time brought about relative surplus buyer's market and the buying-market has gradually formed in recent years [1, 2]. Nevertheless, electric power replacement, as one of the major initiatives to realize energy consumption transition and solve environmental pollution problems in the current situation, is conducive to increase the proportion of electricity in the energy consumption. As a result, facing the new normal and power supply and demand contradiction, it is important to explore Chinese electricity consumption influence mechanism and forecast electricity consumption which is significant for scientifically formulating electrical energy plan and guaranteeing the sustainable economic and social development [3–5].

At present, studies on forecasting medium and long term electricity consumption have proposed multiple methods which contain traditional linear regression, time series and emerging grey prediction [6–10], and so forth. While these methods only rely on electricity consumption data to predict the future and ignore the various factors closely related, actually, electricity consumption is relevant to numerous multidimensional and dynamically changing factors and some correlation may exist between them. The parameter set of higher complexity is necessary to express the changing tendency under the impact of these factors.

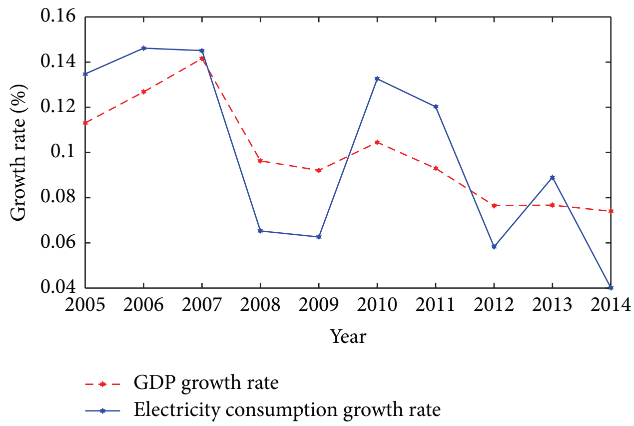

Figure 1: GDP growth rate and electricity consumption growth rate.

What is more, it is improper to use Artificial Neural Network (ANN) and Kalman Filtering for medium and long term electricity consumption forecast in years, because these methods usually need large amounts of data [11, 12]. And they could not show the relationship between each influencing factor and electricity consumption excellently or provide a good guidance for electrical energy plan.

Combined with the feedback at home or abroad, the historical situation of Chinese electricity use, and the change in demand of "new normal" electricity, this paper puts forward the main influence mechanism between electricity consumption and the variables from economy, society, industry, and environment. Thereby, an improved ABC method is suggested to forecast electricity consumption.

This study will make a significant contribution that will be embodied in the following two aspects: firstly, this study provides a full and objective analysis of influence mechanism between the electricity consumption and the variables from economy, society, industry, and environment and elucidates the relationship between them by mathematical statistics method based on a large amount of literature data and the actual situation of Chinese development; secondly, an improved ABC method was used to forecast electricity consumption by creating intended model. Given the example calculation, the model presented herein can assess the effect of various factors on the electricity consumption clearly and confer further advantages on medium and long term forecasting. In the field of prediction, many scholars regard ABC method as an auxiliary algorithm for numerical optimization, and little attention has been focused on a direct use of the advantages of the ABC method to build a model to predict medium and long term electricity consumption in the last years. Taken together, our studies have certain innovation and application value.

This paper is divided into six sections. After a brief introduction, Section 2 presents the influence factors and forecasting methods of electricity consumption. Section 3 describes the data in detail and Section 4 presents the ABC algorithm and the improvement in this paper. Numerical results which are then discussed are described in Section 5. The conclusions of the paper are summarized in Section 6.

2. Literature Review

Electricity, as a special commodity which has difficulty in storing, has to be fully prepared for the forecast, cohesion, and balance of total supply and demand. And as a result, a healthy grid situation will be manifest that the reasonable demand will be met by scientific supply and the problem of regional excess and overall energy shortage will be gradually solved. The objective of accurate modeling of the electricity consumption calls for attention to a few extremely important points. The first point is to discern all of the necessary variables that are bound up with electricity consumption in a given area [13]; the second point is to choose a suitable modeling methodology according to the characteristics of the electricity consumption that can handle the difficulties of the consumption modeling task and obtain the accurate result.

2.1. The Literature of the Influence Factors of Electricity Consumption. On account of the effect of socioeconomic development and the changes in policy environment, the factors which could act on electricity consumption tend to be nonlinear and nonstationary and it is conceivable that the relationship between the input variables and the output variable is undiscovered [14–16].

Previous studies have established that many different variables have been used to model the electricity consumption. Table 1 presents a brief summary of some of the important recent studies on the field.

The first aspect is to ascertain a causal relationship between the economic factors and electricity consumption. Along with economic growth, the productivity and living reveal a growing reliance on electricity demand, and, more than that, the interaction between electricity consumption and economy growth is becoming more and more obvious. In the light of most theories and empirical researches, the economic development which regards real GDP, fixed assets investment, and foreign direct investment as the test variables is central to electricity consumption.

In a study undertaken by Karanfil and Li [17], it was shown that the relationship between electricity consumption and economic growth was affected at the national income level, geographic location, development level, and other factors considering the power dependence and urbanization with the panel data of 160 countries from 1980 to 2010. Ciarreta and Zarraga have demonstrated that the strong causality from electricity consumption to real GDP has characteristics of unidirectional and negative in the perspective of dynamic during a certain time period [18]. Bianco et al. [19] developed linear regression models using historical electricity consumption, gross domestic product (GDP), GDP per capita, and population and the models showed annual electricity consumption was strongly related to the selected variables. Moreover, their time sequence would maintain a state of relative balance in the long term. Tang et al. [20] have highlighted that electricity consumption and economic growth in Portugal have a bidirectional causality from a long term point of view adopting boundary detection method, Granger causality test based on vector error correction model, and other statistical methods. Polemis and Dagoumas

Table 1: Summary of literature review on relationship between factors and electricity consumption.

Number	Authors	Country	Time period	Methodology	Variables	Relationships
1	Karanfil and Li [17]	160 countries	1980–2010	Cointegration techniques	Electricity consumption, economic growth	There exists a causal relationship between electricity consumption and economic growth.
2	Ciarreta and Zarraga [18]	European countries	1970–2007	A panel data approach	Electricity consumption, economic growth	There exists a negative and strong causality from electricity consumption to GDP.
3	Bianco et al. [19]	Italy	1970–2007	Linear regression models	Electricity consumption, GDP, GDP per capita, and population	Annual electricity consumption was strongly related to the selected variables.
4	Tang et al. [20]	Portugal	1974–2009	Multivariate models	Electricity consumption, economic growth	There exists a long run Portugal Granger causality between electricity consumption and economic growth.
5	Polemis and Dagoumas [21]	Greece	1970–2011	Cointegration techniques	Electricity consumption, economic growth	There exists a bidirectional causality between electricity consumption and economic growth.
6	Zaman et al. [22]	Pakistan	1975–2010	The bounds-testing procedure	Electricity consumption, population	There exists a positive relationship between population growth and electricity consumption.
7	Kavaklioglu [23]	Turkey	1975–2006	The ε-SVR models	Electricity consumption, population	There exists a strong causality between population and electricity consumption.
8	Liddle and Lung [24]	105 countries	1971–2009	Heterogeneous panel methods	Electricity consumption, urbanization	There exists a causal relationship between electricity consumption and urbanization.
9	Solarin and Shahbaz [25]	Angola	1971–2009	The VECM Granger causality test	Electricity consumption, urbanization, and economic growth	There exists a bidirectional causality between electricity consumption, economic growth, and urbanization.
10	Zachariadis and Pashourtidou [26]	Cyprus	1960–2004	Time series analysis techniques	Electricity consumption, the residential and the services sectors	There exist long-term elasticities of electricity consumption above the residential and the services sectors.
11	Pao [11]	Taiwan	1990–2002	Statistical models	Electricity consumption, national income, population, GDP, and CPI	POP and NI influence electricity consumption the most, but GDP the least.
12	Zhang et al. [27]	China	1985–2010	Principal component analysis	Electricity consumption, industrial factors	There exists a positive correlation between electricity consumption and industrial factors.
13	Meng and Niu [28]	China	1990–2007	Partial least square modeling	Electricity consumption, gross domestic product of industry	The primary and the secondary industry take more electricity consumption increasing than the tertiary one.
14	Shahbaz et al. [29]	United Arab Emirates	1975–2011	The VECM Granger causality	Electricity consumption, CO_2 emissions	There exists a negative correlation between electricity consumption and CO_2 emissions.
15	Cowan et al. [30]	The BRICS countries	1990–2010	Panel causality analysis	Electricity consumption, CO_2 emissions	The differing results have been achieved for the BRICS countries.

[21] using the same statistical methods have indicated the causal correlation between electricity consumption and economic growth in the case of Greece is bidirectional. Especially in the past ten years, a relatively strong impact is performed from the electricity consumption to GDP.

The second aspect takes the social factors that affect the electricity consumption into consideration. With regard to the development of any country, the social factors are thought to be prerequisite and impact on the development of economy and industry directly. Social factors mainly contain three aspects; they are population, urbanization level, and people living standard. For electricity consumption, it is a core problem whether the growth of electricity consumption can match the trend of population, economic, and social development [22]. And one can even say the social changes in all aspects will make a far-reaching difference in electricity sales market in the future.

Before Kavaklioglu [23] conducted a study of electricity consumption forecast in Turkey utilizing the ε-SVR models, he obtained that the electricity consumption would rise accordingly as the growth of the population allowing for the influence factors including GNP, population, imports, and exports. Collecting urbanization level and other related factors index data of 105 countries from 1971 to 2009, Liddle and Lung [24] clearly pointed out that the improvement of urbanization level would bring the increase in electricity consumption largely based on heterogeneous panel methods; nevertheless the connection found that the relationship between urbanization level and electricity consumption was not a simple linear relationship. In both Solarin and Zachariadis investigations on the correlativity between economic growth, urbanization, and electricity consumption, the findings raised the same conclusion that electricity consumption not only with economic growth but also with urbanization level is in a significant causal relationship in the long term [25, 26]. Another study aimed at the interrelation of electricity consumption and consumer price index (CPI) certified CPI has an effect on electricity consumption in Taiwan [11]. The electricity price was involved in some discussions while as for China it is not an effective index by reason that the price of Chinese electricity consumption is fixed and rarely changed.

The third aspect focuses on industrial factors. Industrial structure refers to the structure of a country or a region's economic industry and their mutual relations. Researches could measure a country or a region's industrial structure from multiple angles, such as the output value structure, labor structure, and relative labor productivity.

Regarding industrial factors including industrial output value, commodity exports, and added services industry value, Zhang et al. [27] utilized principal component analysis and carried on the analysis to show the existence of the positive correlativity between electricity consumption and industrial factors. Meng and Niu [28] have stated that the relationship between electricity consumption and its factors was not as complexity as imagined, so that it was not complicated to achieve the relationship between them using multivariate regression model. Through partial least square modeling, the results of variables importance analysis were elucidated that the secondary industry took more electricity consumption increasing than the primary and the tertiary one [31]. Therefore, most of the studies chose the secondary industry contribution to the GDP as the main indicator measuring the industrial structure during the period.

The fourth aspect is with respect to the environmental factors. In the process of construction of low-carbon society, electricity development plays an important role. Practice has proven that greenhouse gas emissions have been the top in all industries during the link of electricity production which is predominantly coal-fired. Meanwhile, the emissions during the link of using electricity are less than the emissions of other primary energy (mainly including coal, oil, and natural gas) for the environment. Hence, the mutual influence mechanism has existed distinctly between electricity consumption and environmental factors.

The result of Shahbaz et al.'s study pointed out a negative correlation relationship and a back donation between electricity consumption and carbon emissions in United Arab Emirates [29]. In allusion to the different situations of the BRICS countries, Cowan et al. [30] verified that electricity consumption was the Granger causality of CO_2 emissions in India, while there was no Granger causality between electricity consumption and CO_2 emissions in Brazil, Russia, China, and South Africa.

The summary of literature review on relationship between factors and electricity consumption is shown in Table 1.

2.2. The Literature of Forecasting Methods regarding Electricity Consumption. The common methods among the research studies on electricity consumption forecast derive from traditional consumption method, elasticity coefficient method, regression analysis, gray prediction method, Support Vector Machine (SVM), and then modern intelligent algorithms, such as Neural Network, and Wavelet Analysis method, and other meta-heuristics, such as Genetic Algorithms and Particle Swarm Optimization. In addition, prediction accuracies have discrepancies owing to different methods.

At present, the scientific research strength of medium and long term electricity consumption forecast has less adequacy than short term load forecast technology because of its more impact factors, the small amount of historical data, and having more difficulties in making accurate quantitative research.

Via the statistical analysis to determine the relationship between variables, the traditional forecast method, such as grey prediction and regression analysis, shows a good fitting capacity whereas the forecast results cause big error in the future changing trend. Fitting degree and prediction precision perform unsatisfactorily although many scholars use some combination methods to ameliorate the accuracy especially when the model has many variables [32–38]. SVM method can better deal with the nonlinearity and uncertainty among factors influencing the long term power consumption, but it still has some risks appearing local minimum value [39].

So far, some intelligence algorithms, such as ANN, Genetic Algorithm (GA), and Ant Colony Optimization, have received particular attention in estimating electricity consumption and especially in short term electricity consumption forecasting since they can handle current data to an arbitrary degree of accuracy [40, 41].

Through the comparison with conventional regression model, Azadeh et al. showed the estimation of Iran electricity consumption done by GA is more fitted than regression method [42]. They also used an integrated GA and ANN to estimate and predict electricity consumption while the relative error of the method was small [43]. Kiran et al. verified the results of forecasting electricity consumption in Turkey by ABC and PSO techniques outperformed the results forecasted by Ant Colony Optimization [44]. Azadeh et al. compared three meta-heuristics, namely, GAs, Artificial Immune System (AIS), and Particle Swarm Optimization (PSO), with each other in estimation of electricity consumption in the selected countries. With fitted random variables, AIS method with the Clonal Selection Algorithm shows satisfactory results and has been selected as the preferred method [45].

Some of these algorithms require large amounts of historical load data processing to let the computer learning mapping relationships predict the future of the load. Some have strong randomness and fall into local optimum. Modeling the consumption carried out with these algorithms has strong robustness and nonlinear mapping ability to solve current data, but they are not good for prediction since they do not use any mathematical models and present a slow learning convergence speed and a weak generalization ability.

In consequence, with the purpose of exhibiting good global optimization and robustness characteristics as well as accuracy in prediction, it is necessary to build a forecast model under the support of mathematical theory coalescing both mathematical analysis methods and intelligent algorithms.

3. Data Source

This study is based on annual data of electricity consumption, real gross domestic product (GDP), fixed asset investment (FAI), foreign direct investment (FDI), population, urbanization level, household consumption level, real GDP of secondary industry, and carbon emission covering a time period from 1990 to 2014 in China. The time series data are collected from International Monetary Fund Data and Statistics (IMF 2015) and World Bank, world development indicators (WDI, 2015). The real GDP series are transformed from the nominal GDP in constant 1990 prices. These factors selection is based on the above literature analysis and Chinese actual conditions.

In the process of modeling and predicting of electricity consumption, the real GDP and fixed assets investment need to be deemed as important factors into consideration. Although there is no strict sense of the causality between electricity consumption and economic growth in China, electricity consumption as a reflection of the power industry development in the economic system can ahow a country or a region's economic operation. Meanwhile FDI is thought to act as a vital economic factor in view of the advancement of energy internet globalization.

Population and urbanization level, as important factors, should be taken into account in the study as well. There is explanation of urbanization level that it is generally represented with the proportion of urban population accounting for total population. And it is exceedingly significant index to measure economic development of a country or area. In accelerating the process of urbanization, it brings a series of electrification development of the society, which will lead to increasing power consumption, and increasing population will also pull the economic development and growth in electricity consumption sequentially.

It can give no cause for much criticism of the interaction between electricity consumption and industrial structure. The adjustment of the industry is an important cause of promoting economic development and fluctuating of electricity consumption due to the different electricity consumption per unit GDP of industrial sectors.

Apart from that, carbon emission is supposed to be an essential factor in the study of electricity consumption in virtue of a strategy of low carbon energy development via improving the power conversion efficiency and realizing the energy alternative which build electricity as the core.

Table 2 shows the primary data of electricity consumption and the factors mentioned before.

On account of different numerical size and dimension of various factors, this paper applies the method of Z-Score to normalizing them according to the annual order. The process is as follows:

$$X_i' = \frac{\left(X_i - \overline{X}\right)}{S_i}. \quad (1)$$

X_i and X_i' represent primary data and normalized data, respectively, $\overline{X}$ is the average value, and S_i is the standard deviation. The values of these standardized variables fluctuate around zero. Greater than zero is above the average and less than zero is under the average. The normalized data is shown in Table 3.

In order to find some relationship between electricity consumption and various factors, the contrast of change trend of these variables is illustrated by Figure 2.

In Figure 2, we can see the change trend of electricity consumption is same to these factors. And we can trust there must be some relationship between electricity consumption and these factors. Moreover, correlation analysis of the factors and electricity consumption also show the intimate connection between them. Because the counting process is subordinate, the results of correlation analysis are exhibited in Supplementary Material, available online at http://dx.doi.org/10.1155/2016/8496971.

4. Methodological Framework

4.1. Introduction of ABC Algorithm. Artificial Bee Colony (ABC) algorithm, as a swarm intelligence optimization algorithm, has a superior convergence speed on the basis of the intelligent behavior of honey bees. The main characteristic of ABC algorithm is that it only needs to contrast the advantages or disadvantages with other solutions rather than

Table 2: Primary data of various factors and electricity consumption.

Year	Real GDP (billion RMB)	FAI (billion RMB)	FDI (million dollars)	Population (million people)	Urbanization level (%)	Household consumption level (RMB)	Real GDP of secondary industry (billion RMB)	Carbon emission (million tons)	Electricity consumption (billion kW·h)
1990	1882.5	451.7	10289	1143	0.2641	1510	743	2458	623
1991	1954.8	559.5	11550	1158	0.2694	1701	1252	2591	680
1992	2134.2	808.0	19202	1172	0.2746	2027	1481	2723	759
1993	2438.1	1307.2	38955	1185	0.2799	2577	1719	2877	843
1994	2778.5	1704.2	43206	1199	0.2851	3496	2001	3029	926
1995	3141.9	2001.9	48133	1211	0.2904	4283	2104	3228	1002
1996	3485.0	2291.4	54804	1224	0.3048	4839	2290	3323	1076
1997	3833.9	2494.1	64408	1236	0.3191	5160	2372	3314	1128
1998	4190.4	2840.6	58557	1248	0.3335	5425	2588	3312	1160
1999	4518.5	2985.5	52659	1258	0.3478	5854	2650	3423	1231
2000	4862.8	3291.8	59360	1267	0.3622	6280	3010	3514	1347
2001	5272.8	3721.3	49670	1276	0.3766	6860	2531	3674	1463
2002	5710.4	4350.0	55010	1285	0.3909	7703	2940	4025	1647
2003	6228.9	5556.7	56140	1292	0.4053	8472	3807	4723	1903
2004	6853.7	7047.7	64072	1300	0.4176	9422	3742	5521	2197
2005	7545.2	8877.4	63805	1308	0.4299	10493	4052	6326	2494
2006	8398.6	10999.8	67080	1314	0.4434	11760	4493	6926	2859
2007	9463.5	13732.4	78340	1321	0.4589	13786	5171	7518	3271
2008	10803.5	17282.8	95253	1328	0.4699	15781	5499	7663	3438
2009	11843.9	22459.9	91804	1335	0.4834	17175	6439	8037	3643
2010	12934.8	25168.4	108820	1341	0.4995	19109	7849	8472	4192
2011	14286.4	31148.5	117698	1347	0.5127	21810	7738	9206	4693
2012	15615.1	37469.5	113294	1354	0.5257	24565	7982	9415	4976
2013	16809.6	44629.4	118721	1361	0.5373	26955	8368	9674	5322
2014	18098.9	51276.1	119705	1368	0.5477	28844	8811	9761	5523

comprehending the special information of the problem. Gradually, the global optimal value will emerge through the local optimization of each individual worker bee.

However, many intelligent algorithms have been brought forward in recent decades such as Particle Swarm Optimization (PSO) and Artificial Neural Network (ANN) algorithm and Genetic Algorithm (GA). In many areas, it cannot be denied that these algorithms have solved a great deal of problems and made difference [46–51]. But in this paper, these algorithms could be not so appropriate. Obviously, the most important reason is that the data quantity is too lacking to use these intelligent algorithms and it could lead to a huge error which does not want to be seen. Fortunately, the initial purpose of putting forward ABC algorithm is to solve the optimization problem of multivariate function [52]. And Akay and Karaboga analyzed the size of the population for ABC algorithm and drew a conclusion that ABC algorithm did not have to use a big value of colony size to solve optimization problems [53]. Just because of these, the improved ABC algorithm is believed to solve the problem in the field of electricity consumption although this is the first attempt.

4.2. Traditional Algorithm Procedure of ABC. In ABC algorithm, the swarm is composed of employed bees, onlookers, and scouts and the location of a food source is abstracted into a point of D-dimensional space. The process of finding the optimal food source is the procedure of searching for the optimal solution. The position of the swarm represents the solution of optimization problem and the benefit of the source symbolizes the adaptive value of the optimization problem.

The bees search all of the food sources recurrently and location of food source is denoted with a D-dimensional vector quantity:

$$X_j = (x_1, x_2, \dots, x_D), \quad j \in [1, D]. \tag{2}$$

Table 3: Normalized data of various factors and electricity consumption.

Year	Real GDP	FAI	FDI	Population	Urbanization level	Household consumption level	Real GDP of secondary industry	Carbon emission	Electricity consumption
1990	−1.11	−0.78	−1.75	−1.93	−1.41	−1.12	−1.34	−1.12	−1.07
1991	−1.08	−0.78	−1.71	−1.71	−1.34	−1.10	−1.13	−1.07	−1.04
1992	−1.03	−0.76	−1.47	−1.51	−1.27	−1.05	−1.04	−1.02	−0.99
1993	−0.97	−0.74	−0.85	−1.31	−1.20	−0.96	−0.95	−0.96	−0.93
1994	−0.90	−0.71	−0.72	−1.11	−1.13	−0.90	−0.83	−0.90	−0.88
1995	−0.84	−0.68	−0.57	−0.92	−1.06	−0.86	−0.79	−0.83	−0.83
1996	−0.77	−0.66	−0.36	−0.73	−0.92	−0.79	−0.72	−0.79	−0.79
1997	−0.71	−0.65	−0.06	−0.55	−0.77	−0.70	−0.68	−0.80	−0.76
1998	−0.65	−0.62	−0.24	−0.38	−0.62	−0.66	−0.60	−0.80	−0.74
1999	−0.59	−0.61	−0.43	−0.23	−0.47	−0.60	−0.57	−0.75	−0.69
2000	−0.51	−0.59	−0.22	−0.09	−0.33	−0.51	−0.43	−0.72	−0.62
2001	−0.44	−0.56	−0.52	0.05	−0.18	−0.38	−0.62	−0.66	−0.55
2002	−0.34	−0.52	−0.35	0.17	−0.03	−0.30	−0.45	−0.52	−0.43
2003	−0.23	−0.44	−0.32	0.28	0.12	−0.18	−0.10	−0.26	−0.27
2004	−0.10	−0.36	−0.07	0.40	0.25	−0.09	−0.13	0.05	−0.09
2005	0.05	−0.22	−0.08	0.51	0.38	0.02	−0.01	0.36	0.10
2006	0.24	−0.07	0.02	0.61	0.53	0.19	0.17	0.59	0.33
2007	0.49	0.09	0.37	0.71	0.69	0.35	0.45	0.82	0.58
2008	0.67	0.27	0.90	0.81	0.81	0.61	0.58	0.87	0.69
2009	0.87	0.76	0.79	0.91	0.95	0.81	0.96	1.01	0.82
2010	1.12	0.84	1.32	1.01	1.12	1.05	1.53	1.18	1.16
2011	1.37	1.18	1.59	1.10	1.27	1.32	1.48	1.46	1.47
2012	1.58	1.72	1.46	1.20	1.41	1.65	1.58	1.54	1.65
2013	1.82	2.22	1.63	1.30	1.54	1.96	1.73	1.64	1.87
2014	2.06	2.67	1.66	1.41	1.67	2.22	1.91	1.68	1.99

The formula of determining the initial solution is

$$x_{ij} = x_{\min,j} + \text{rand}(0,1)\left(x_{\max,j} - x_{\min,j}\right), \quad j \in [1, D],\ i \in [1, SN]. \tag{3}$$

C and SN are the cycle index and the number of honey bees, respectively. The bees select the food source in accordance with the roulette wheel. Fitness$_i$ is the adaptation degree:

$$\text{fitness}_i = \begin{cases} \dfrac{1}{1 + f(X_i)} & f(X_i) \geq 0 \\ 1 + \left|f(X_i)\right| & f(X_i) < 0. \end{cases} \tag{4}$$

P_i, the selected probability, is

$$P_i = \frac{\text{fitness}_i}{\sum_{j=1}^{FN} \text{fitness}_j}. \tag{5}$$

The bigger value of P_i means the better nectar source and then the better nectar source will gather more scouts. So the onlookers could find the best nectar source. The search formula of onlookers updating the location of nectar source by employed bees is

$$v_{ij} = x_{ij} + r_{ij}\left(x_{ij} - x_{kj}\right), \quad j \neq k,\ j \in [1, D],\ i \in [1, SN]. \tag{6}$$

Hereinto, $k \in (1, 2, 3, \ldots, SN)$, $j \in \{1, 2, \ldots, D\}$, $r_{ij} \in [1, 1]$. However, this method also has disadvantages such as dealing with multiobjective or multiextreme problems. Consequently, it is always used to optimize the parameters and thresholds in other algorithms as an auxiliary method which can reduce the training time [54].

4.3. ABC Model in This Paper. This paper suggests that influence factors and electricity consumption are regarded as independent variables ($A = a_1, a_2, a_3, \ldots, a_D$) and dependent variable separately. In the previous studies, Bianco et al. [19] and Meng and Niu [28] both have developed linear regression models to forecast electricity consumption and the models showed an outstanding outcome. So there is linear function between the variables:

$$\text{Tec} = f(a_1, a_2, a_3, \ldots, a_D). \tag{7}$$

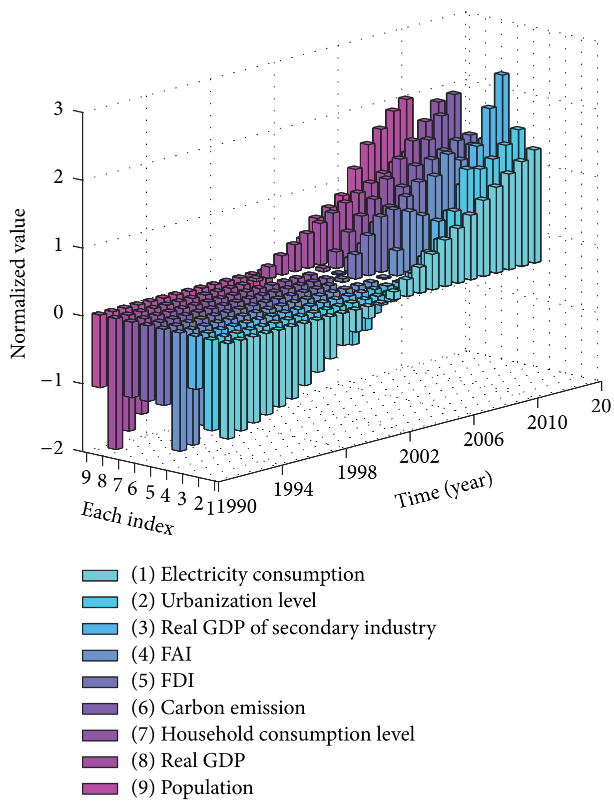

Figure 2: The contrast of change trend between electricity consumption and various factors.

This can also be written as follows:

$$a_1x_1 + a_2x_2 + a_3x_3 + \cdots + a_Dx_D + x_{D+1} = 0. \quad (8)$$

Apparently, $X = [x_1, x_2, x_3, \ldots, x_D, x_{D+1}]$ is the solution of the linear equations. By choosing N years data, we can obtain an equation set containing N equations with $(D+1)$ unknowns: $x_1 - x_{D+1}$. *Specific equations are as follows*:

$$\begin{gathered} a_{11}x_1 + a_{21}x_2 + a_{31}x_3 + \cdots + a_{D1}x_D + x_{D+1} = 0, \\ a_{12}x_1 + a_{22}x_2 + a_{32}x_3 + \cdots + a_{D2}x_D + x_{D+1} = 0, \\ a_{13}x_1 + a_{23}x_2 + a_{33}x_3 + \cdots + a_{D3}x_D + x_{D+1} = 0, \\ \vdots \\ a_{1N}x_1 + a_{2N}x_2 + a_{3N}x_3 + \cdots + a_{DN}x_D + x_{D+1} = 0. \end{gathered} \quad (9)$$

Similarly, this is equivalent to obtain the minimum of the equation below:

$$\begin{aligned} &\min F(A) \\ &= \sum_{N=1}^{N} \left[f\left(a_{1N}, a_{2N}, a_{3N}, \ldots, a_{DN}\right) - \mathrm{Tec}_N \right]^2, \quad (10) \\ &\qquad \mathrm{lb} \le a_{DN} \le \mathrm{ub}. \end{aligned}$$

The subsequent procedure is using Artificial Bee Colony (ABC) algorithm to solve the multivariate linear equations and get coefficient $X = [x_1, x_2, x_3, \ldots, x_D, x_{D+1}]$. Then the relationship between the various factors and electricity consumption is explicit.

As a general rule, if an equation set has solutions, the number of independent variables $(D+1)$ should be greater than or equal to the number of equations (N). Nevertheless, in this paper, $(D+1)$ will be less than N and consequently it will result in no solution in this equation set. Under this circumstance, ABC algorithm cannot be used directly. Therefore, there are two improvements used in traditional ABC algorithm. To begin with, we apply multivariate linear regression (MLR) to ABC algorithm so that the no solution equation set can be solved. In other words, although the solution equation set is no solution, an optimal solution can be found when the error becomes the minimum. Secondly, we set a cycle index CYCLE2 which should be at least as big in order to avoid running into local optimum as much as possible. The concrete implementation steps are as follows.

Step 1 (initialization parameter). Set the population size SN, the maximum of iterative times CYCLE1, each iteration step size V, cycle index CYCLE2, the upper bound ub and lower bound lb, data volume N, and the number of independent variables $D+1$; ε is $F(A)$ and Lim is limit.

Step 2 (generate the initial solution). In the light of (3), it will generate SN initial solutions randomly. Then according to (4) and (5), calculate the fitness and selected probability of each solution. At last choose the best fitness nectar source as the initial solution.

Step 3 (iterative optimization). Scouts search the neighborhood of the nectar source and calculate the fitness and the probability according to (4) and (5). If near honey is better than original nectar source, record new nectar source location and send to employed bees. Onlookers choose the nectar source according to P_i and record new nectar source location according to (6). Then search the neighborhood of the new nectar source until there is no better one. At this moment, the number of iterations needs to be plus 1.

Step 4 (limit judge). Save the current location of nectar source; if the number of iteration is beyond the maximum iterations CYCLE1, Step 2 is in return. Do like this CYCLE2 times.

Step 5 (find the optimal solution). Select the best solution from CYCLE2 nectar sources and it is perceived to be the optimal solution.

The program flow chart is shown in Figure 3.

This study forecasts the electricity consumption using an improved Artificial Bee Colony (ABC) algorithm to solve the multivariate linear equations. The data from 1990 to 2009, 20 years in the aggregate, is the basis and the data from 2010 to 2014, 5 years, is used to test. So in this paper specific parameter is as follows: $SN = 40$, CYCLE1 $= 200$, $V = 0.0001$,

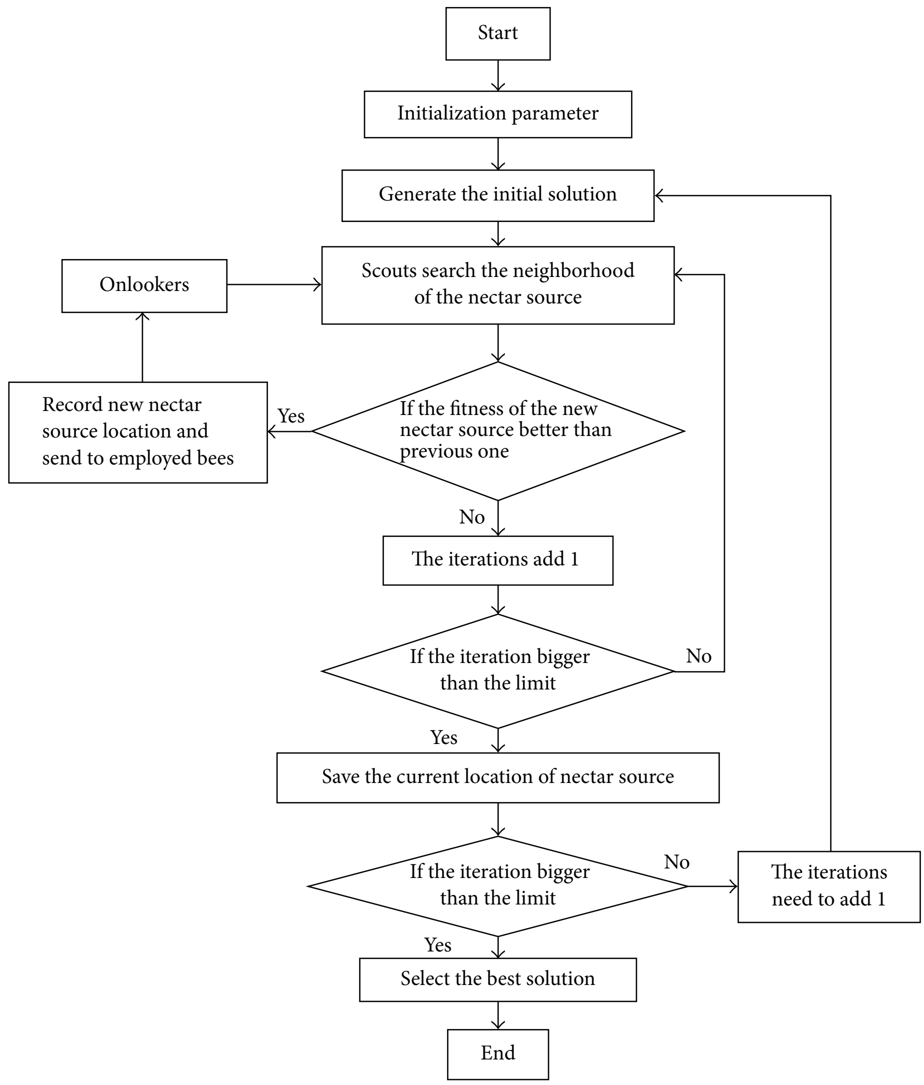

Figure 3: The program flow chart of the improved ABC model.

CYCLE2 = 1000, ub = 1 and lb = −1, Lim = 0.01, $D = 8$, and $N = 20$. There are some explanations about the determination of parameters:

(1) Usually, the population size SN is always 40 and there is no necessity to change in this paper.

(2) Because of $D + 1 = 9$, as a computational algorithm, stochastic algorithm is a pseudorandom algorithm, so CYCLE1 = 200 is enough to insure that every variable can be turned to when $D = 8$.

(3) V and CYCLE2 can improve the accuracy of the prediction. Under ideal conditions, V should be as small as possible and CYCLE2 should be as big as possible. However, in consideration of the actual conditions, we valued $V = 0.0001$ and CYCLE2 = 1000.

(4) Because the data has been standardized, the coefficient can not be beyond $[-1, 1]$. So ub = 1 and lb = −1.

(5) Lim is a parameter which is used to control the end time. If Lim < 0.01, ε is small enough for us to do prediction. So we valued Lim = 0.01.

To test whether the algorithm is correct or not, the following models are chosen to compare: (I) quadratic regression; (II) Artificial Neural Network (ANN); (III) Genetic Algorithm (GA); (IV) Particle Swarm Optimization (PSO).

As one of the most primitive prediction models, the quadratic regression mode should be selected to clarify whether this kind of models is still adaptive or not in such a complex circumstance. ANN algorithm is a representation of early artificial intelligence algorithm. It can tell us whether the emerging intelligence algorithm is better than the old one. GA and PSO are used to represent two classes of meta-heuristics separately and they will prove whether the improved ABC algorithm is superior to others.

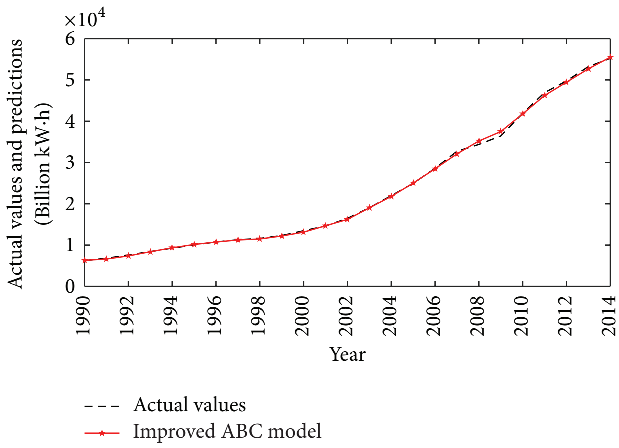

Figure 4: Numerical results of the improved ABC model.

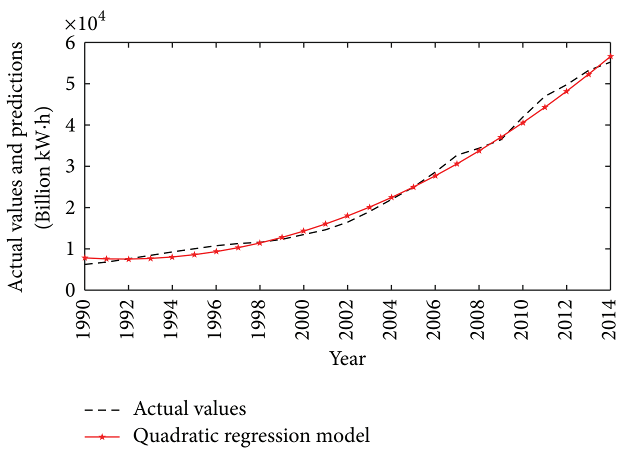

Figure 5: Numerical results of the quadratic regression model.

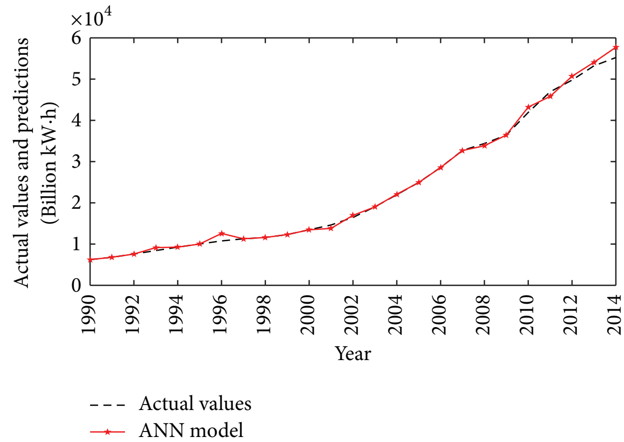

Figure 6: Numerical results of the ANN model.

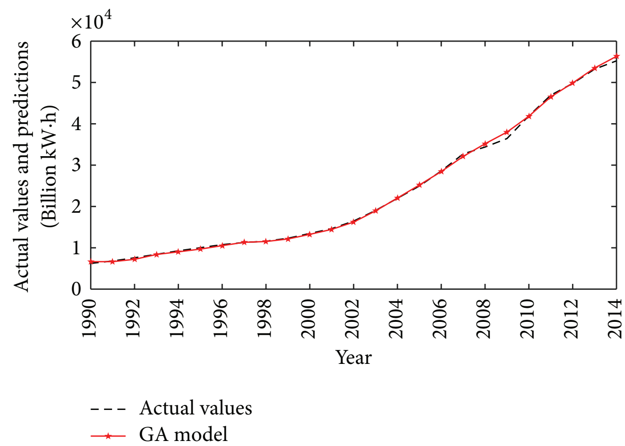

Figure 7: Numerical results of the GA model.

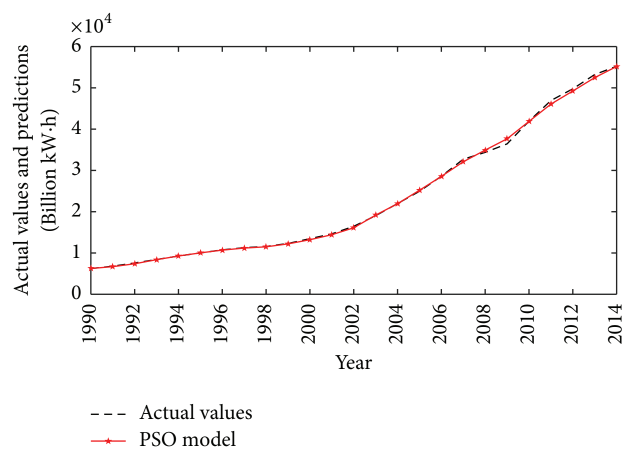

Figure 8: Numerical results of the PSO model.

5. Result and Discussion

In this test, five algorithms run on matlab2015b and experimental results are shown in Figures 4–8.

Numerical results of the improved ABC model compared with actual values are shown in Figure 4.

Numerical results of the quadratic regression model compared with actual values are shown in Figure 5.

Numerical results of the ANN model compared with actual values are shown in Figure 6.

Numerical results of the GA model compared with actual values are shown in Figure 7.

Numerical results of the PSO model compared with actual values are shown in Figure 8.

Although there are figures of five models prediction results, we can not clearly see whether the results of electricity consumption based on the improved ABC algorithm are superior to the results based on other models only by our eyes. For the purpose of better reflection of differences, Table 4 was made and it provided precise predictions and the error between predictions and actual values. The performance of the proposed method is evaluated by two indices, namely, the mean absolute error (MAE) and the mean absolute percentage error (MAPE). The forecasting error of these models is shown in Table 4.

The forecasting error curves of these models are shown in Figure 9.

From error comparisons, the predicted effect of various methods can be clearly seen.

Table 4: The forecasting error of these models.

Prediction methods	Year	TEC (billion kW·h)	Predictions (billion kW·h)	AE	APE	MAE	MAPE
The improved ABC model	2010	41923.00	41779.58	143.42	0.342%	388.95	0.928%
	2011	46928.00	46231.69	696.31	1.484%		
	2012	49762.64	49455.53	307.11	0.617%		
	2013	53223.00	52698.57	524.43	0.985%		
	2014	55233.00	55506.47	273.47	0.495%		
The quadratic regression mode	2010	41923.00	40563.41	1359.59	3.243%	1576.54	3.761%
	2011	46928.00	44276.43	2651.57	5.650%		
	2012	49762.64	48187.10	1575.54	3.166%		
	2013	53223.00	52295.45	927.55	1.743%		
	2014	55233.00	56601.46	1368.46	2.478%		
The ANN model	2010	41923.00	43212.85	1289.85	3.077%	1335.66	3.186%
	2011	46928.00	45814.30	1113.70	2.373%		
	2012	49762.64	50693.92	931.28	1.871%		
	2013	53223.00	54074.38	851.38	1.600%		
	2014	55233.00	57725.06	2492.06	4.512%		
The GA model	2010	41838.90	41870.05	31.15	0.074%	659.23	1.576%
	2011	46503.54	46059.59	443.96	0.955%		
	2012	49881.91	49236.22	645.69	1.294%		
	2013	53493.77	52476.52	1017.25	1.902%		
	2014	56330.92	55172.84	1158.08	2.056%		
The PSO model	2010	41923.00	41870.05	52.95	0.126%	450.89	1.076%
	2011	46928.00	46059.59	868.41	1.851%		
	2012	49762.64	49236.22	526.42	1.058%		
	2013	53223.00	52476.52	746.48	1.403%		
	2014	55233.00	55172.84	60.16	0.109%		

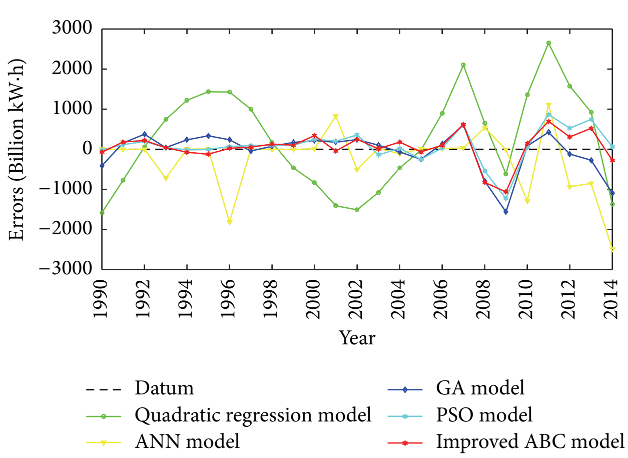

Figure 9: The forecasting errors curves of these models.

To begin with, the accuracy of quadratic regression mode is the worst. It is expected that the errors will be even bigger if the forecast period becomes longer. ANN model is better than quadratic regression mode at accuracy. However there is still a greater error from actual value. Maybe it due to the training data is too little. So quadratic regression mode and ANN model are not so appropriate to forecasting Chinese electricity consumption under this situation.

What is more, the GA model and PSO model make a progress in accuracy and the MAE and MAPE are also small enough to the actual application. However, this paper proved that the improved ABC algorithm combined with multivariate linear regression model is better than others in accuracy and it is more appropriate to forecast the electricity consumption in such a circumstance.

Thirdly, along with the running of these meta-heuristics algorithm, the error, namely, ε_i $(i = 1, 2, 3, \dots, 1000)$, will be created. Rank ε_i in descending order is shown in Figure 10.

From Figure 10, it is obvious that the change of ε becomes smaller and smaller and the solution corresponding to the min-ε is perceived to be the optimal solution. Although all these three models can find an optimal solution and their optimal solutions do not have much difference, we also can find the convergence speed of the improved ABC algorithm is faster than GA and PSO. So, in this paper, the improved ABC algorithm is proved to be the best model to forecasting Chinese electricity consumption.

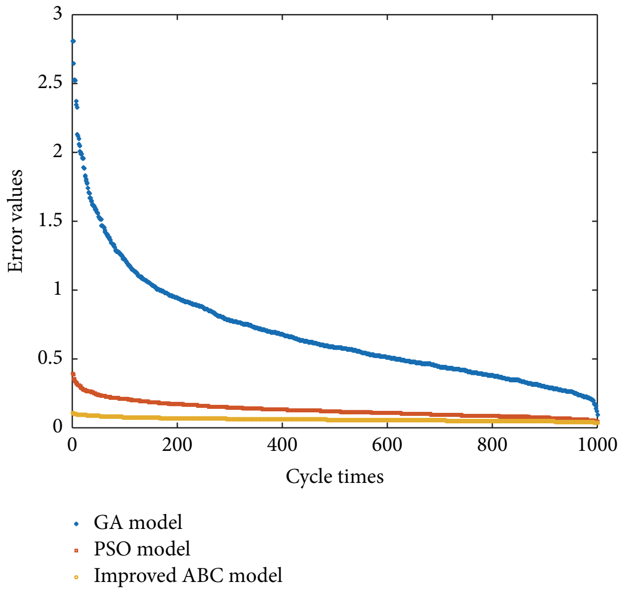

FIGURE 10: ε_i in descending order of GA, PSP, and the improved ABC algorithm.

Finally, the optimal solution of the improved ABC algorithm, corresponding to the min-ε, is $X = (0.385, 0.434, 0.584, 0.486, 0.375, 0.722, 0.265, 0.052, 0.883)$. Thereinto, 0.883 is the constant term. 0.052 is the coefficient of population. 0.722 is the coefficient of carbon emission. From the coefficients we can see that the population is unimportant influencing electricity consumption and there is close relation between carbon emission and electricity consumption. As for other factors, although they are not the most important factors, they should be taken into account.

Therefore, while forecasting the electricity consumption, it should not only focus on itself. The preferable way is to reference various factors associated with electricity consumption and find the relationship between them. It is reliable to get the electricity consumption through predicting the various factors' change in the future.

6. Conclusions

This paper suggests an improved ABC algorithm to explore the influencing mechanism of various factors on Chinese electricity consumption and forecast electricity consumption. Though arranging the research achievement, the historical situation of Chinese electricity use, and the change in demand of "new normal" electricity, eight factors are brought forward. By employing improved ABC and the eight factors, this paper investigates the influence mechanism of Chinese electricity consumption and builds a corresponding prediction model. Experiments proved that the model can well predict the Chinese electricity consumption in the future and have an advantage over simple ANN model and quadratic regression model in accuracy. It provides a new scientific and effective way to forecast the medium and long term electricity consumption.

Abbreviations

ABC: Artificial Bee Colony
MLR: Multivariate linear regression
ANN: Artificial Neural Network
GDP: Gross domestic product
GNP: Gross national product
CPI: Consumer price index
SVM: Support Vector Machine
FAI: Fixed asset investment
FDI: Foreign direct investment.

Competing Interests

The authors declare no conflict of interests.

Authors' Contributions

Professor Jingmin Wang planned the work. Under her guidance and encouragement, Jing Nie summarized the development of the research status and designed the model presented in this work. Jian Zhang implemented the main part of the different prediction methods and error analysis.

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