Intelligent Swarm Firefly Algorithm for the Prediction of China's National Electricity Consumption

Guangfeng Zhang[a], Yi Chen [b,*], Yun Li[b,**], Hongnian Yu[b], Shaomin Wu[c]

[a]*GREQAM, School of Economics, Aix-Marseille University, Marseille, 13236, France*
[b]*School of Computer Science and Network Security, Dongguan University of Technology, Dongguan 523808, China*
[c]*Kent Business School, University of Kent, Canterbury, Kent CT2 7PE, UK*

Abstract

China's energy consumption is the world's largest and is still rising, leading to concerns of energy shortage and environmental issues. It is, therefore, necessary to estimate the energy demand and to examine the dynamic nature of the electricity consumption. In this paper, we develop a nonlinear model of energy consumption and utilise a computational intelligence approach, specifically a swarm firefly algorithm with a variable population, to examine China's electricity consumption with historical statistical data from 1980 to 2012. Prediction based on these data using the model and the examination is verified with a bivariate sensitivity analysis, a bias analysis and a forecasting exercise, which all suggest that the national macroeconomic performance, the electricity price, the electricity consumption efficiency and the economic structure are four critical factors determining national electricity consumption. Actuate prediction of the consumption is important as it has explicit policy implications on the electricity sector development and planning for power plants.

Key words: energy consumption, nonlinear modelling, swarm firefly algorithm, parameters determination

1. Introduction

China's energy industry faces massive challenges although China's macroeconomic performance has attracted the whole world's attention. China is the largest energy consumer and the largest user of coal-derived electricity. However, there are several serious issues concerning China's electricity industry

*e-mail: chenyi@dgut.edu.cn tel: +86-769-2286-1349 fax: +86-769-2286-1828
**e-mail: yun.li@ieee.org tel: +86-769-2286-1349 fax: +86-769-2286-1828

including electricity shortage, environmental damage, electricity pricing reform and electricity efficiency, all of which affect the national electricity production and consumption. (1) China has been facing electricity shortage, particularly seasonal electricity shortage, there were 24 out of 31 provinces facing electricity shortage in 2004, and 19 provinces experienced a power blackout in 2008. (2) Electricity production causes huge environmental issues. See an early paper by Rosen et al., (1995)[1]. All forms of electricity generation have a different degree of environmental impact. The majority of the electricity in China, about 83% in 2011, is generated from coal which is primarily the most widely used and most polluting fuel for electricity generation. (3) China's economy growth is strongly believed as a key driver of the increase in energy consumption. Empirical studies have extensively used state-of-the-art econometrics to identify a close connection between electricity consumption and economic growth in China. See Shiu and Lam (2004)[2],Yuan et al. (2007)[3], Yu et al. (2010)[4], Xiao et al. (2012)[5] and Chen et al. (2007)[6]. China's extraordinary economic growth of the last decade is probably not sustainable, but there is no doubt that China's energy consumption will consistently rise far above the current level. (4) Efficiency issues have been consistently challenging and painful for China's energy sector. An energy efficiency could refer to using energy more efficiently through more efficient end-uses or more efficient generation. Practically, these include electricity production technical efficiency, end-user consumption efficiency and external environmental efficiency. Recent studies by Lesourd and Genoud (2012)[7] and Liu and Zheng (2012)[8] examined both technical efficiency and environmental of coal-fired power plants of China, and their studies indicate the environmental damage is mainly due to the rapid economic development although institutional reforms and policies have been effective in promoting fuel efficiency. Series paper by Rabl (2012)[9], Ami and Rabl (2012)[10] and Spadero, and Ami and Rabl (2012)[11] have explicitly proposed methodologies to evaluate health impact of air pollution in China, and they have specifically examined the damage costs on human health due to air pollutants emitted by power plants. These issues have been among those focuses of policy makers and academic researchers.

Within such a context, we aim to investigate the issue of China's national electricity consumption, with a particular focus on the dynamic nature of electricity consumption and fundamental determinants, given the rapid economic growth, economic structure change, on-going electricity pricing reform in China. Existing studies have generally used linear temporal methods to examine the impact of major economic fundamentals, particularly national economic performance and electricity price, on the national electricity demand, see Shiu and Lam (2004)[2],Yuan et al. (2007)[3], Yu et al. (2010)[4], Chen et al. (2007)[6] and Xiao et al. (2012)[5], but one common technical shortcoming of these studies is that these studies have specifically assumed a linear association between electricity consumption and determinants, which is actually not consistent with the reality and ignore the issues we discussed in the last section.

The firefly algorithm (FA) was firstly proposed by Yang et al. (2008, 2011, 2012) [16, 17, 18], based on which, some further works on FA have been performed by a few researchers. For its characteristics of few input parameters, easy to understand, and implement, it has been applied to various fields: Sayadi et al. (2013)[19] applied an FA for manufacturing cell formation discrete optimisation problems. Fister et al. (2013)[20] published a comprehensive review of Firefly algorithms. Karthikeyan et al. (2014)[22] developed a hybrid discrete FA for multi-objective flexible job shop scheduling problem. Zouache et al. (2016)[21] proposed a quantum-inspired firefly algorithm with particle swarm optimisation, which adapted the firefly approach to solving discrete optimisation problems. Besides, some works on a few nature-inspired meta-heuristics and applications have been carried out, such as: Water wave optimisation[23], population classification in fire evacuation[24], rapid learning algorithm for vehicle classification[26], multi-objective optimisation for spatial-temporal efficiency in a heterogeneous cloud environment[27], multi-objective artificial wolf-pack algorithm [28], etc. This paper introduces a firefly algorithm with a variable population (FAVP) for the electricity consumption prediction.

This study aims to develop a quantitative model of China's national electricity demand with comprehensive analysis including more determination fundamentals. Specifically, we use a swarm firefly algorithm to implement the data analysis, with which parameters are determined in a nonlinear manner. We conduct the sensitivity analysis to demonstrate the dynamic association between electricity demand and determination factors including national macroeconomic performance, which is gross domestic product (GDP) in this context, economic structure, and energy usage efficiency, and our forecasting exercises demonstrates how the nonlinear modelling capture the dynamic nature of electricity demand in China, which can be applied to other economies for the similar issues.

The rest of the paper is organised as follows. Following this introduction section, Section 2 conceptually introduces our model and data used in our empirical analysis. Section 3 presents the technical methodology, which includes a brief introduction to the swarm firefly algorithm which is used in our parameter determination, and an introduction to the fitness function which is used in our simulation exercise. In Section 4, our data analysis is presented, which involves model estimation, parameter sensitivity analysis, and forecasting of national electricity consumption. Finally, Section 5 presents a brief conclusion and the potential future research.

2. Model and Data

Electricity demand is generally assumed to be significantly determined by national macroeconomic performance and electricity price, see Shiu and Lam (2004)[2],Yuan et al. (2007)[3], Yu et al. (2010)[4], Xiao et al. (2012)[5] and Chen et al. (2007)[6]. Meanwhile, professional analysis and academic studies also suggest that consumption efficiency and economic structure hold a significant impact on a national electricity demand, see EIA (2013)[12], MITEI (2013)[13], Toshi et al. (2011)[14] and Acaravici (2010)[15].

As stated in equation (1), we think it is critical to include these two factors in our conceptual model and data analysis due to the dynamic nature of economic structure and consumption efficiency. We use GDP to represent macroeconomic performance, use producer production price to represent electricity price, use the ratio of residential spending to the industrial output to represent the economic structure, and use GDP per unit of electricity consumption to represent electricity consumption efficiency.

$$\hat{E}_C\left(c, \alpha_i, \beta_j\right) = c + \sum_{i=1}^{4}\left(\alpha_i x_i^{\beta_i}\right) + \xi \tag{1}$$

Where electricity consumption $\hat{E}_C$ is function of constant c, parameters α_i and β_i, and error term ξ. α_i and β_i are the parameters to be estimated in a nonlinear framework, $i = 1, 2, 3, 4$, and theoretically we assume β_i is an integer and might take any value in the set of [-∞,∞].

Our empirical model simulation uses annual data over 1980-2009, and data over 2010-2012 is used to test the models' out-of-sample performance. The data for electricity consumption (GWh) is collected from the Electricity Information of the International Energy Agency (IEA, 2011), and the data for the following series are from World Bank Database (WDI): real GDP (constant LCU), electricity production (GWh), electric power consumption per capita (kWh). The annual producer price index for the power industry is from China Statistical Database of the National Bureau of Statistics of China. All these variables are taken in logarithm in the data analysis.

3. Methodologies

3.1. Swarm firefly algorithm with variable population

The FAVP is inspired by the swarm behaviours of the firefly in the summer sky, which can be idealised as four behavioural rules based on the flashing characteristics of firefly swarm, as follows:

- All firefly individuals (FF_i) are unisex, which always move towards its neighbours with better brightness. The brightness (also called light intensity) I, is stated in equation (2), in which r is the distance between two fireflies FF_i and FF_j, I_0 is the initial brightness, γ is the absorption coefficient for the decrease of the brightness, m is the multi-state factor of distance r, $m \geq 1$.

$$I(r) = I_0 \exp\left(-\gamma r^m\right) \tag{2}$$

- For any two fireflies FF_i and FF_j, the firefly's attractiveness ρ is proportional to its brightness, in which,
  - if FF_j is brighter than FF_i, the FF_i will move towards FF_j;
  - the brightness of FF_i and FF_j will decrease while their distance increase;
  - if no FF_i is brighter than the others, they will move randomly;
- The brightness of a firefly is determined by the fitness function.
- The population P of fireflies varies from generation to another to accelerate the calculation process. The variable population P is given in equation (3), in which P_N is the non-replaceable population and P_R is the replaceable population.

$$P = P_N + P_R \tag{3}$$

The attractiveness ρ_{ij} of FF_i to FF_j is defined by equation (4), where ρ_0 is the initial attractiveness at an initial distance r_0 and the rest parameters are same as equation (2).

$$\rho_{ij}(r) = \rho_0 \exp\left(-\gamma r_{ij}^m\right) \tag{4}$$

The distance between any two fireflies FF_i and FF_j is an Euclidean distance as stated in equation (5) at positions x_i and x_j, where $x_{i,k}$ and $x_{j,k}$ are the k-th component of the spatial coordinates x_i and x_j respectively of the FF_i and FF_j, d is the number of dimensions.

$$r_{ij} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^{d} (x_{i,k} - x_{j,k})^2} \tag{5}$$

The movement of FF_i to FF_j is given by equation (6), where ε is the random movement in case of equal brightness generated by a uniformly distribution in the range of [0,1]; $\eta \in [0,1]$ is a randomisation factor determined by the practices;

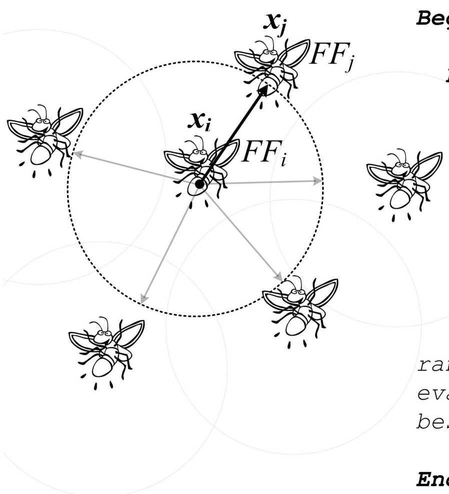
$$x_{i+1} = x_i + \rho_{ij}(r) \cdot (x_j - x_i) + \eta \cdot \left(\varepsilon - \frac{1}{2}\right) \tag{6}$$

The FAVP's workflow is given in Figure 1, which can be briefly stated as: calculation starts and initialises parameters of FAVP; population generation P by equation (3); compares the brightness I_i and I_j between any two of the individuals fireflies; moves the fireflies according to the brightness comparison results and updates the brightness, distance values; ranks current solutions by fitness; keep running the calculation until reaches the terminal conditions.

3.2. Fitness Function Definition

In this section, two trend indices are defined to assess the evolutionary optimisation process, which are the index of mean of the average precision (mAP) and the index of mean of standard derivation (mSTD).

As stated in equation (7), the index of mAP is a score of mean of the average precision for vector f_j, in which $i = 1, \cdots, p$, p is the population of the data set, $AVG(\cdot)$ is the average function. The index of mSTD is defined in equation (8), in which $VAR(\cdot)$ is the variance function.




```
Begin (1)

  t = 0 ;
  Initialise all parameters:
   x_i with variable population P, fitness(x_0),
   Light Intensity I_i, Initial Distances Di, etc.

    While ( Not termination-condition) do
      Begin (2)
         t  =  t + 1;
        FOR i = 1: Population
           FOR j = 1: Population
              IF( I_j > I_i)
                Move firefly i towards firefly j;
              ENDIF
              update distance;
              light intensity;
              attractiveness
           ENDj
        ENDi
      rank all fireflies;
      evaluation fitness(x);
      best solutions;

      End (2)

End (1)
```

Figure 1: Firefly Algorithm with Variable Population Workflow[29, 30]

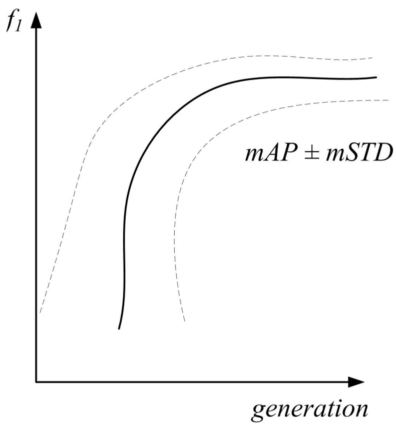


Figure 2: mAP $\pm$ mSTD Over the Full Generations

$$\text{mAP}\left(f_j\right) = \frac{1}{p}\sum_{j=1}^{p}\left(AVG\left(f_j\right)\right) \tag{7}$$

$$\text{mSTD}\left(f_j\right) = \frac{1}{p}\sum_{j=1}^{p}\left(\sqrt{VAR\left(f_j\right)}\right) \tag{8}$$

As shown in Fig. 2, the solid curve is the mAP scores for each vector f_j as given in equation (7) and the dashed curves are the mAP $\pm$ mSTD for each vector f_j as given in equation (8), which demonstrates the evolutionary trend of the optimisation process (generation vs. fitness f) with the upper and lower boundaries.

In this section, an index of the mean average precious(mAP) of the root mean square (RMS) errors of $\hat{E}_c$ and E_c, as given in equation (1), is defined as the fitness to evaluate the optimisation process, which is to minimise the RMS errors. Specifically, the fitness function $\digamma$ of electricity consumption efficiency prediction is given in equation (9), and the problem is to maximise the $\digamma$, which is to maximise the -mAP scores of the RMS of $\hat{E}_c$ and E_c, as given in equation (10), and the $s.t.$ conditions of c, α_i, β_j are given in Table 1.

$$\digamma\left(c, \alpha_i, \beta_j\right) = \left\{-mAP\left(RMS(\hat{E}_c - E_c\right)\right\} \tag{9}$$

$$
\begin{array}{ll}
Maximise: & F(c, \alpha_i, \beta_j) \\
s.t. & \lfloor\rfloor \leq c, \alpha_i, \beta_j \leq \lceil\rceil
\end{array}
\tag{10}
$$

The overall modelling, optimisation and prediction flowchart is shown in Figure 3, which shows the overall technical roadmap to perform our work and it has five steps, as follows:

1 collect and prepare raw data for the modelling;

2 data pre-handling and normalisation when it is necessary;

3 electricity consumption modelling, as discussed in Section 2;

4 fitness function definition for optimisations, as given in Section 3.2;

5 the FAVP, as given in Section 3.1.

4. Simulations

The optimisations are performed by the $SwarmFirefly$, which is a toolbox for MATLAB developed by Chen[29]. According to previous research and engineering applications, the initial parameters are initialised in Table 1, in which a max generation 100 is the termination condition of each round test; the total test number is 100; the randomness factor is 0.2; the randomness reduction is 0.98; the population is 50, in which the non-replaceable P_N and replaceable population P_R are 40 and 10, respectively; the ranges of c, α_i, β_j are [-100,100], [-10,10] and [0,3] respectively.

As can be observed in Figure 4, the fitness curve of mAP $\pm$ mSTD are represented, in which the fitness curves go up very quickly from generation 1 to 20 to reach a plateau point (about generation 20), and then from generation 20 to 100, the curves keep steady over the rest generations and the fitness move to the convergence, which indicates the high efficiency of the swarm firefly algorithm.

Figure 5 compares the data of electricity consumption in theory and real from the years 1980 to 2009, in which small circles 'o' are the real data from China yearbook, solid line is the 'mean' of the FAVP optimised data(theory data), the dashed line and the dash-dot line are the 'mean$\pm$'std' of the theory data. This figure demonstrates the agreement of the theory data and

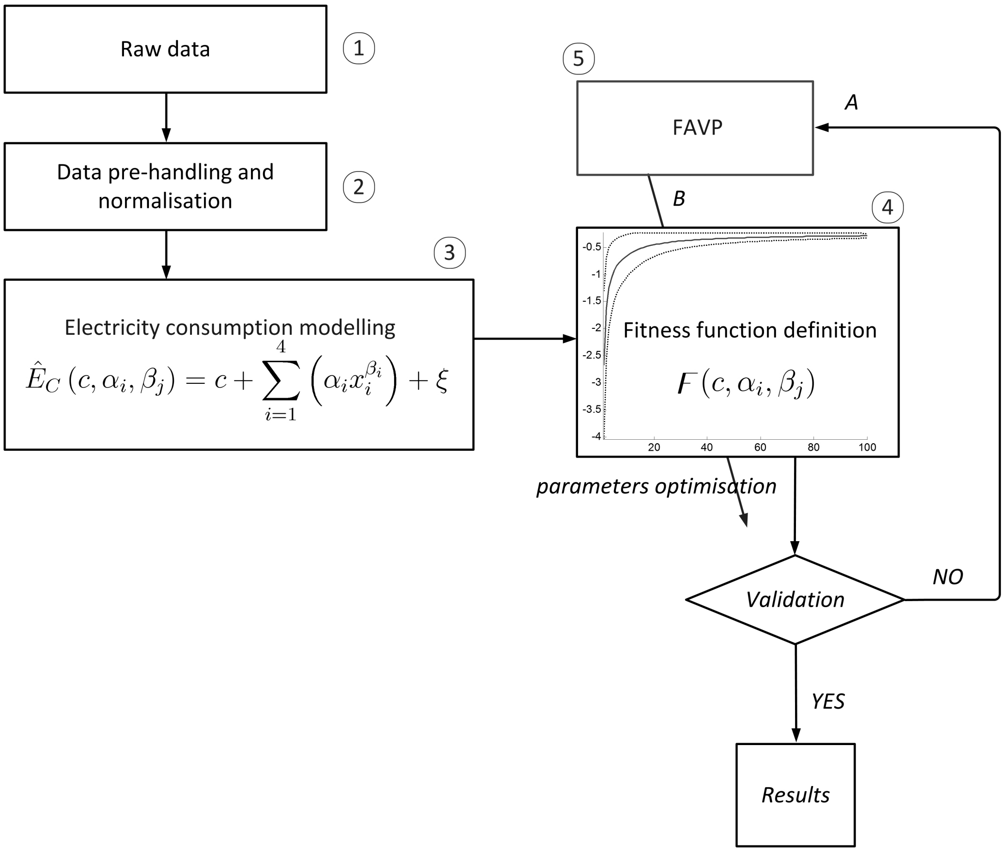


Figure 3: The over-all modelling, optimisation and prediction flowchart

Table 1: Parameters Initialisation for Swarm Firefly Optimisation

max generations	100
test number	100
randomness	0.2
randomness reduction	0.98
population	50
non-replaceable population	40
replaceable population	10
absorption coeffcient	1
c	[-100,100]
α_i	[-10,10]
β_j	[0,3]

real data, which validates the feasibility of the proposed nonlinear modelling approach.

According to the section 2, four variables including GDP, electricity price, consumption efficiency and economic structure are considered in this nonlinear modelling. Fixing any three series at their mean values, Figure 6 to Figure 9 demonstrate how electricity consumption E_c respond to the fourth series' variation respectively, which explicitly indicate that the nation's electricity consumption E_c decreases at an increasing speed with the increase in the electricity price; electricity consumption E_c increases with an increasing speed when the GDP increase; electricity consumption E_c decreases with an increasing speed when the electricity consumption efficiency is improved; and electricity consumption E_c goes up acceleratingly when China's industrialization gets more intensive.

Table 2 gives the normalised optimal parameters by the FAVP, which are to be restored to original scale for practical usage, that is E_c prediction value for the years of 2010, 2011 and 2012 in this case. As shown in Figure 10, the forecasting errors of the E_c the years 2010 to 2012 are stated in percentage, and Table 3 lists the specific error values of the training process of the years 1980 to 2009 and the prediction process of the years 2010 to 2012. We also compared the errors by the FAVP, FA and genetic algorithm (GA), as shown in Table 3, which shows that the FAVP's results have been out-performed the FA and GA's results in this case.

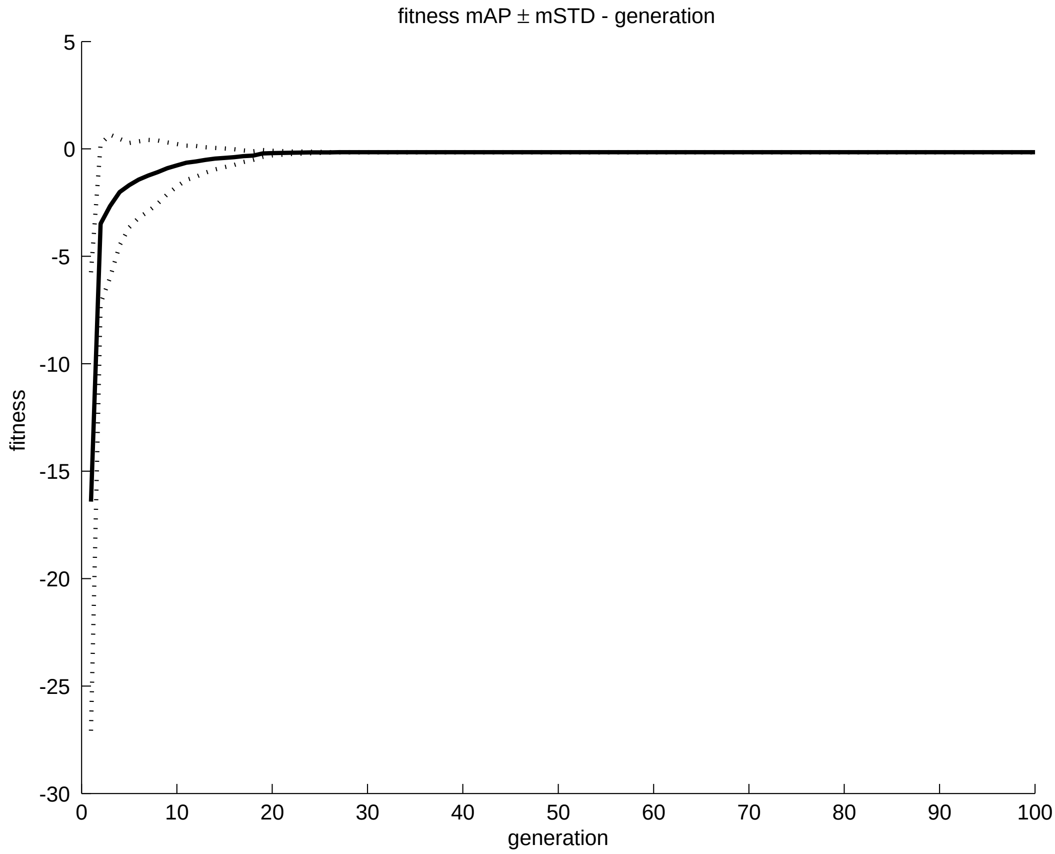


Figure 4: Fitness Curve of mAP $\pm$ mSTD

Table 2: Optimal Parameters by FAVP

parameter	*mean* $\pm$ *std*
c	-1.9696 $\pm$ 4.3775
α_1	4.8243 $\pm$ 2.7687
α_2	-0.2830 $\pm$ 1.7892
α_3	-0.3336 $\pm$ 1.9921
α_4	-0.5481 $\pm$ 2.0203
β_1	1.4790 $\pm$ 1.5137
β_2	2.0049 $\pm$ 1.9311
β_3	1.5875 $\pm$ 1.4019
β_4	1.5748 $\pm$ 1.3035

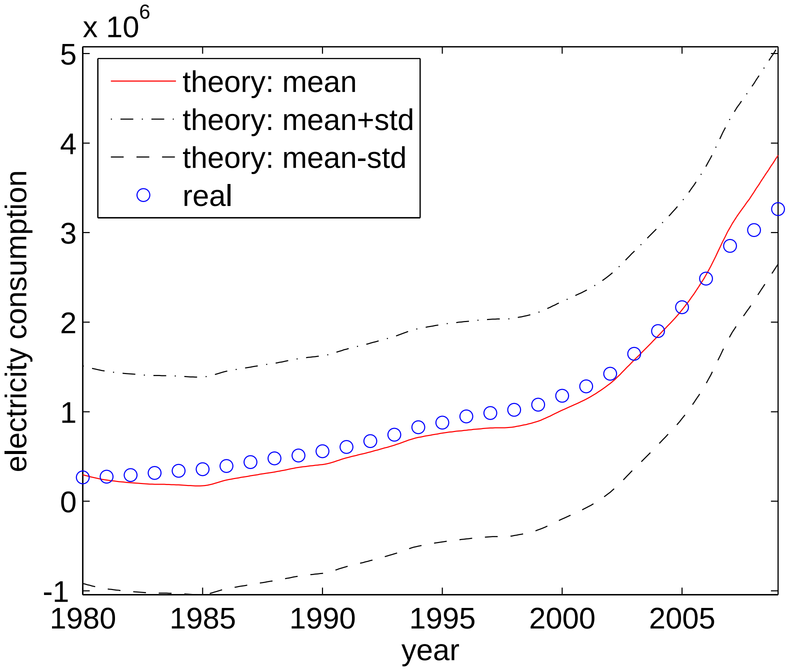


Figure 5: Actual and Theoretical Electricity Consumption Over 1980-2010

Table 3: Forecasting Errors (%) of Electricity Consumption over the years 2010-2012

Method	1980 to 2009	2010	2011	2012
FAVP	4.7187 ± 1.4112	-5.3853 ± 0.4453	-3.4613 ± 0.1287	-1.5917 ± 0.2367
FA	5.6443 ± 2.3355	-7.5785 ± 2.4567	4.5789 ± 3.5672	3.5624 ± 1.3568
GA	6.7543 ± 5.3456	6.1358 ± 3.7555	7.8964 ± 6.3568	4.5678 ± 2.6781

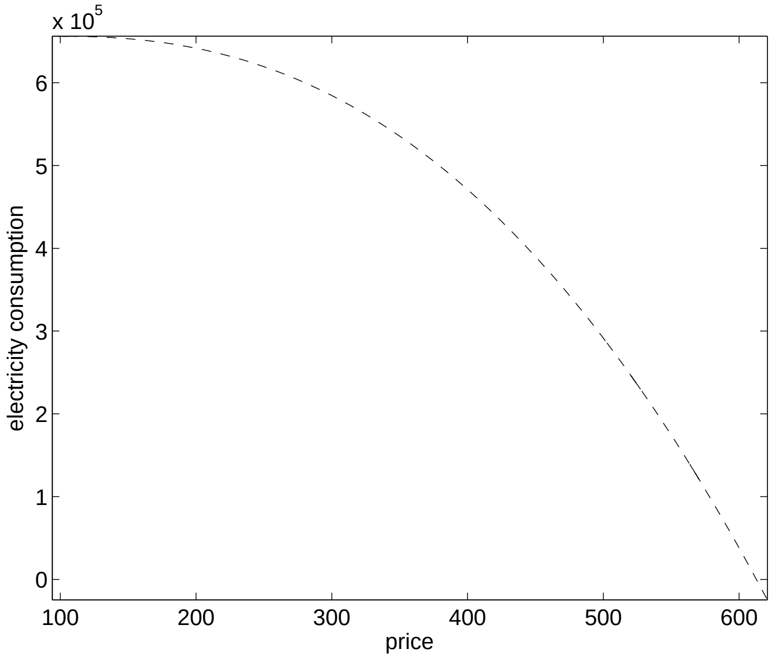


Figure 6: Changes of electricity consumption with price

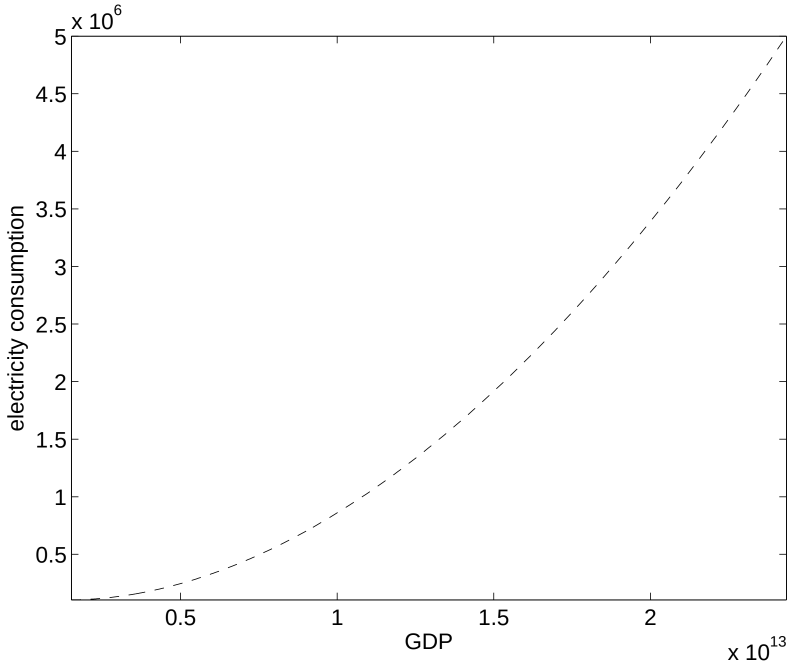


Figure 7: Changes of electricity consumption with GDP

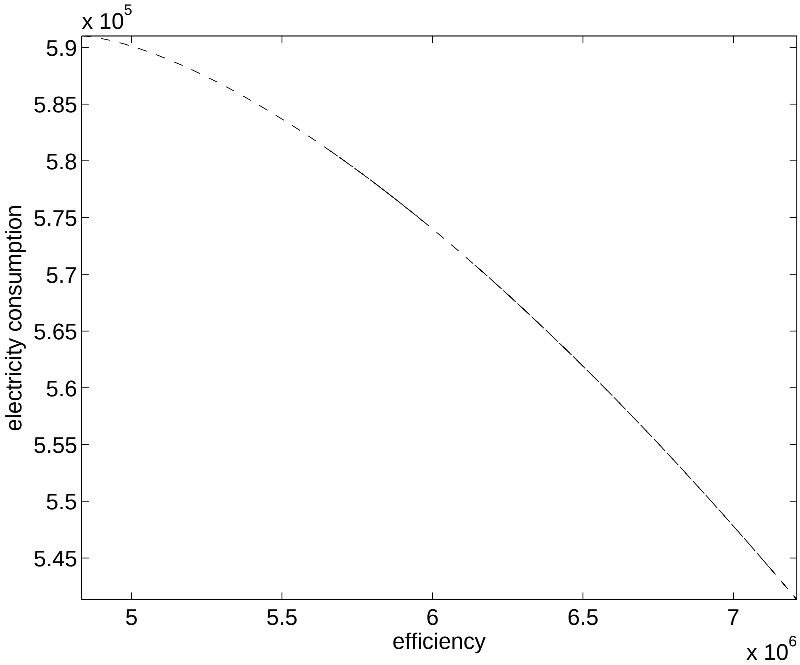


Figure 8: Changes of electricity consumption with efficiency

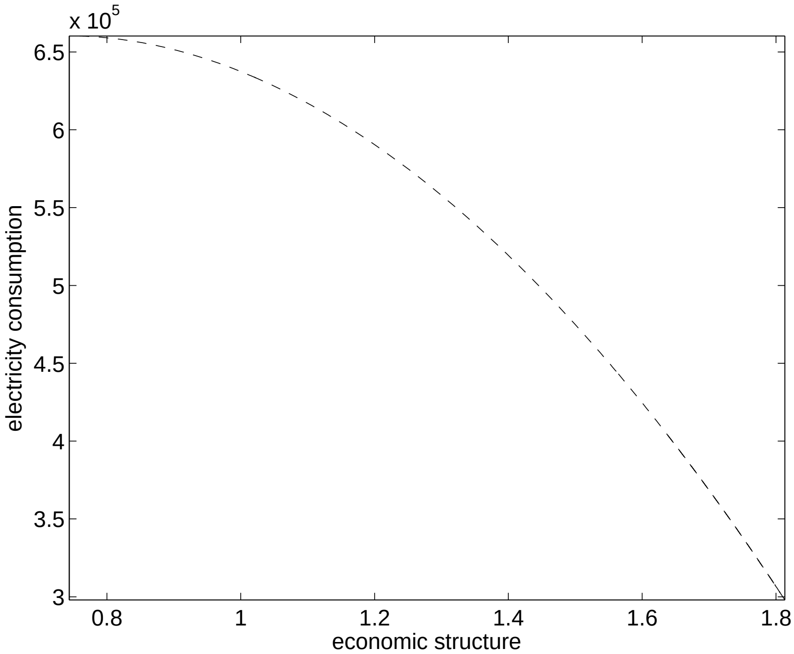


Figure 9: Changes of electricity consumption with economic structure

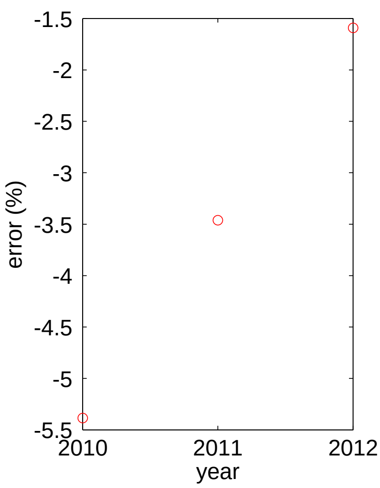


Figure 10: Error in percentage of E_c prediction of year 2010 to 2012

5. Conclusions and Future Works

It is critically important for policy makers and energy investors to be aware of the energy demand which affects the actual policy alternation and policy investment. Our empirical study stimulates China's national electricity demand for the urgency from the rapidly increasing China's electricity demand and economic growth, and side issues from electricity demand and economic growth such as electricity shortage and environmental damage from electricity demand and production. This study adopts a nonlinear approach to model China's national electricity demand and our study suggests that macroeconomic performance, electricity prices, economic structure and electricity consumption efficiency are important factors which affect the national electricity demand of China. Our study also indicates the nonlinear and dynamic impact on electricity demand from those determinants, which suggest we should adjust our energy policy due to the nonlinear association between electricity consumption and economic fundamentals. This study could provide practical policy indication in terms of energy investment and governmental energy policy. As an ANN is a black-box data-fitting model whose parameters would not bear a physical interpretation as many other modelling methods do, especially in extrapolation or prediction[31], we proposed this EC model and the FAVP approach to perform the prediction. In our future work, we plan however to compare with an EC-based ANN and the Bayesian method[32] for this application in our future work. In this work, nonetheless, our EC model has delivered a prediction with an acceptable error rate. Further, the associated FAVP has been compared with the FA and GA methods and has outperformed these existing methods.

References

[1] Rosen, R., et al. (1995) Promoting Environmental Quality in a Restructured Electric Industry, Prepared for the National Association of Regulatory Utility Commissioners. Boston: Tellus Institute. December 15.

[2] Shiu, A., Lam,P. (2004) Electricity consumption and economic growth in China, Energy Policy, Volume 32, Issue 1, Pages 47-54.

[3] Yuan, J., Zhao, C., Yu, S., Hu,Z. (2007) Electricity consumption and economic growth in China: Cointegration and co-feature analysis, Energy Economics, Vol. 29, Iss. 6, pp. 1179-1191.

[4] Yu, Y., Hu, J., Lin, W., and Jiang,W. (2010) 12th five-year plan: Dianli fazhan ruogan wenti yanjiu [Research on Electricity Development and Problems '], China Electricity Publisher

[5] Xiao, S., Xu, M., Zhu., T., Zhang, X. (2012) The Relationship between Electricity Consumption and Economic Growth in China, Physics Procedia, Vol. 24, Part A, pp. 56-62.

[6] Chen, S., Kuo, H., Chen,C. (2007) The relationship between GDP and electricity consumption in 10 Asian countries, Energy Policy, Vol. 35, Iss.4, pp.2611-2621.

[7] Lesourd, J., Genoud,S.(2012) On Thermal Efficiencies and Technical Efficiencies of Chinese Conventional Power Plants: A Stochastic Frontier Approach, manuscript

[8] Liu, G., Zheng,J.(2012) Technical and Environmental Efficiency in Chinese Coal-fired Power Plants (2004-2008)

[9] Rabl, A.(2012) How to Use the Externe Methodology in China, manuscript

[10] Ami, D., Rabl,A. (2012) Transfer values of Monetary Valuation of Health Impacts of Air Pollution in China

[11] Ami, D., A. Rabl, Spadero,J. (2012) Monetary Valuation of Health Impacts of Air Pollution in China

[12] EIA (2013) Electricity demand patterns matter for valuing electricity supply resources

[13] MITEI, (2013) Engaging energy demand

[14] Arimura,T.H., Li,S.-J., Newell,R.G., Palmer,K. (2011) cost-Effectiveness of Electricity Energy Efficiency Programs, NBER Working Paper No. 17556

[15] Acaravici, A. (2010) Structural Breaks, Electricity Consumption and Economic Growth: Evidence from Turkey. Journal for Economic Forecasting 0(2), pages 140-154.

[16] Yang, X. S.(2008) Nature-Inspired Metaheuristic Algorithms. Frome: Luniver Press

[17] Yang, X. S. (2011) Chaos-Enhanced Firefly Algorithm with Automatic Parameter Tuning, International, Journal of Swarm Intelligence Research.

[18] Fister Jr.,I., Yang X.S., Fister I., Brest J. (2012) Memetic firefly algorithm for combinatorial optimization. In: Fifth international conference on bioinspired optimization methods and their applications, pp.75C86

[19] Sayadi M.K., Hafezalkotob, A., Naini, S.G.J. (2013) Firefly-inspired algorithm for discrete optimization problems: an application to manufacturing cell formation. Journal of Manufacturing Systems, Vol. 32, Iss. 1, pp. 78C84

[20] Fister,I., Fister Jr.,I., Yang X.S., Brest,J. (2013) A comprehensive review of firefly algorithms, Swarm and Evolutionary Computation, Vol.13, pp. 34C46.

[21] Zouache,D., Nouioua,F., Moussaoui,A. (2016) Quantum-inspired firefly algorithm with particle swarm optimization for discrete optimization problems, Soft Computing, Vol.20, Iss.7, pp.2781C2799.

[22] Karthikeyan, S., Asokan,P., Nickolas,S. (2014) A hybrid discrete firefly algorithm for multi-objective flexible job shop scheduling problem with limited resource constraints, The International Journal of Advanced Manufacturing Technology, Vol. 72, Iss. 9, pp.1567C1579

[23] Zheng,Y.-J. (2015) Water wave optimization: A new nature-inspired metaheuristic, Computers and Operations Research, Vol. 55, pp.1C11

[24] Zheng,Y.-J., Ling,H.-F., Xue,J.-Y., Chen,S.-Y. (2015) Population Classification in Fire Evacuation: A Multiobjective Particle Swarm Optimization Approach. IEEE Transactions on Evolutionary Computation, Vol.18, Iss. 1, pp. 70-81

[25] Zhang,Y.H., Sun,X.-M., Wang, B.-W. (2016) Efficient algorithm for k-barrier coverage based on integer linear programming, China Communications,Vol. 13, Iss. 7, pp.16-23

[26] Wen,X.Z., Shao,L., Xue,Y., Fang,W. (2015) A rapid learning algorithm for vehicle classification, Information Sciences, Vol. 295 Iss.C, pp. 395-406

[27] Liu,Q., Cai,W.-D., Shen,J., Fu,Z.-J., Liu,X.-D., Linge,N. (2016) A speculative approach to spatial-temporal efficiency with multi-objective optimization in a heterogeneous cloud environment, Security and Communication Networks, Vol.9, Iss. 17, pp. 4002-4012

[28] Chen,Y., Wang,Z.-L., Yang,E.-F., Li,Y. (2017) Pareto-Optimality Solution Recommendation Using Multi-objective Artificial Wolf-pack Algorithm, Proceedings of the 10th IEEE International Conference on Software, Knowledge, Information Management and Applications, Chengdu, China, 15-17 December 2016.

[29] Chen, Y. (2013) SwarmFireFly - The Firefly Swarm Algorithm (FFSA), Retrieved from http://www.mathworks.co.uk/matlabcentral/fileexchange/38931

[30] Chen, Y., Zhang, G.F., Jin, T.D., Wu, S.M., Peng, B. (2014) Quantitative modelling of electricity consumption using computational intelligence aided design. Journal of Cleaner Production, Vol.69, 143-152

[31] Foo,Y.W., Goh,C., Lim,H.C., Li,Y. (2015) Evolutionary Neural Network Modeling for Energy Prediction of Cloud Data Centers.International Symposium on Grids and Clouds (ISGC) 2015, 15 -20 March 2015, Academia Sinica, Taipei, Taiwan

[32] Li, Y., Moutinho, L., Opong, K. K., and Pang, Y. (2015) Bayesian prediction with linear dynamic model: principle and application. In:

Moutinho, L. and Huarng, K.-H. (eds.) Quantitative Modelling in Marketing and Management [2nd ed.]. World Scientific: Hackensack, NJ, pp. 323-342. ISBN 9789814696340 (doi : 10.1142/9789814696357 − 0013)

Contents

List of Figures

List of Tables