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

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## 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

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## 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

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16 including electricity shortage, environmental damage, electricity pricing re-  
17 form and electricity efficiency, all of which affect the national electricity pro-  
18 duction and consumption. (1) China has been facing electricity shortage, par-  
19 ticularly seasonal electricity shortage, there were 24 out of 31 provinces facing  
20 electricity shortage in 2004, and 19 provinces experienced a power blackout  
21 in 2008. (2) Electricity production causes huge environmental issues. See an  
22 early paper by Rosen et al., (1995)[1]. All forms of electricity generation have  
23 a different degree of environmental impact. The majority of the electricity in  
24 China, about 83% in 2011, is generated from coal which is primarily the most  
25 widely used and most polluting fuel for electricity generation. (3) China's  
26 economy growth is strongly believed as a key driver of the increase in energy  
27 consumption. Empirical studies have extensively used state-of-the-art econo-  
28 metrics to identify a close connection between electricity consumption and  
29 economic growth in China. See Shiu and Lam (2004)[2], Yuan et al. (2007)[3],  
30 Yu et al. (2010)[4], Xiao et al. (2012)[5] and Chen et al. (2007)[6]. China's  
31 extraordinary economic growth of the last decade is probably not sustain-  
32 able, but there is no doubt that China's energy consumption will consistently  
33 rise far above the current level. (4) Efficiency issues have been consistently  
34 challenging and painful for China's energy sector. An energy efficiency could  
35 refer to using energy more efficiently through more efficient end-uses or more  
36 efficient generation. Practically, these include electricity production technical  
37 efficiency, end-user consumption efficiency and external environmental effi-  
38 ciency. Recent studies by Lesourd and Genoud (2012)[7] and Liu and Zheng  
39 (2012)[8] examined both technical efficiency and environmental of coal-fired  
40 power plants of China, and their studies indicate the environmental dam-  
41 age is mainly due to the rapid economic development although institutional  
42 reforms and policies have been effective in promoting fuel efficiency. Se-  
43 ries paper by Rabl (2012)[9], Ami and Rabl (2012)[10] and Spadero, and  
44 Ami and Rabl (2012)[11] have explicitly proposed methodologies to evaluate  
45 health impact of air pollution in China, and they have specifically examined  
46 the damage costs on human health due to air pollutants emitted by power  
47 plants. These issues have been among those focuses of policy makers and  
48 academic researchers.

49 Within such a context, we aim to investigate the issue of China's national  
50 electricity consumption, with a particular focus on the dynamic nature of  
51 electricity consumption and fundamental determinants, given the rapid eco-  
52 nomic growth, economic structure change, on-going electricity pricing reform  
53 in China. Existing studies have generally used linear temporal methods to

54 examine the impact of major economic fundamentals, particularly national  
55 economic performance and electricity price, on the national electricity de-  
56 mand, see Shiu and Lam (2004)[2], Yuan et al. (2007)[3], Yu et al. (2010)[4],  
57 Chen et al. (2007)[6] and Xiao et al. (2012)[5], but one common technical  
58 shortcoming of these studies is that these studies have specifically assumed a  
59 linear association between electricity consumption and determinants, which  
60 is actually not consistent with the reality and ignore the issues we discussed  
61 in the last section.

62 The firefly algorithm (FA) was firstly proposed by Yang et al. (2008,  
63 2011, 2012) [16, 17, 18], based on which, some further works on FA have  
64 been performed by a few researchers. For its characteristics of few input pa-  
65 rameters, easy to understand, and implement, it has been applied to various  
66 fields: Sayadi et al. (2013)[19] applied an FA for manufacturing cell formation  
67 discrete optimisation problems. Fister et al. (2013)[20] published a compre-  
68 hensive review of Firefly algorithms. Karthikeyan et al. (2014)[22] developed  
69 a hybrid discrete FA for multi-objective flexible job shop scheduling problem.  
70 Zouache et al. (2016)[21] proposed a quantum-inspired firefly algorithm with  
71 particle swarm optimisation, which adapted the firefly approach to solving  
72 discrete optimisation problems. Besides, some works on a few nature-inspired  
73 meta-heuristics and applications have been carried out, such as: Water wave  
74 optimisation[23], population classification in fire evacuation[24], rapid learn-  
75 ing algorithm for vehicle classification[26], multi-objective optimisation for  
76 spatial-temporal efficiency in a heterogeneous cloud environment[27], multi-  
77 objective artificial wolf-pack algorithm [28], etc. This paper introduces a  
78 firefly algorithm with a variable population (FAVP) for the electricity con-  
79 sumption prediction.

80 This study aims to develop a quantitative model of China's national elec-  
81 tricity demand with comprehensive analysis including more determination  
82 fundamentals. Specifically, we use a swarm firefly algorithm to implement  
83 the data analysis, with which parameters are determined in a nonlinear man-  
84 ner. We conduct the sensitivity analysis to demonstrate the dynamic associa-  
85 tion between electricity demand and determination factors including national  
86 macroeconomic performance, which is gross domestic product (GDP) in this  
87 context, economic structure, and energy usage efficiency, and our forecasting  
88 exercises demonstrates how the nonlinear modelling capture the dynamic na-  
89 ture of electricity demand in China, which can be applied to other economies  
90 for the similar issues.

91 The rest of the paper is organised as follows. Following this introduction

92 section, Section 2 conceptually introduces our model and data used in our  
 93 empirical analysis. Section 3 presents the technical methodology, which in-  
 94 cludes a brief introduction to the swarm firefly algorithm which is used in our  
 95 parameter determination, and an introduction to the fitness function which  
 96 is used in our simulation exercise. In Section 4, our data analysis is pre-  
 97 sented, which involves model estimation, parameter sensitivity analysis, and  
 98 forecasting of national electricity consumption. Finally, Section 5 presents a  
 99 brief conclusion and the potential future research.

## 100 2. Model and Data

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

108 As stated in equation (1), we think it is critical to include these two fac-  
 109 tors in our conceptual model and data analysis due to the dynamic nature  
 110 of economic structure and consumption efficiency. We use GDP to represent  
 111 macroeconomic performance, use producer production price to represent elec-  
 112 tricity price, use the ratio of residential spending to the industrial output to  
 113 represent the economic structure, and use GDP per unit of electricity con-  
 114 sumption to represent electricity consumption efficiency.

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

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

119 Our empirical model simulation uses annual data over 1980-2009, and  
 120 data over 2010-2012 is used to test the models' out-of-sample performance.  
 121 The data for electricity consumption (GWh) is collected from the Electricity  
 122 Information of the International Energy Agency (IEA, 2011), and the data  
 123 for the following series are from World Bank Database (WDI): real GDP

124 (constant LCU), electricity production (GWh), electric power consumption  
 125 per capita (kWh). The annual producer price index for the power industry  
 126 is from China Statistical Database of the National Bureau of Statistics of  
 127 China. All these variables are taken in logarithm in the data analysis.

### 128 3. Methodologies

#### 129 3.1. Swarm firefly algorithm with variable population

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

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

$$I(r) = I_0 \exp(-\gamma r^m) \quad (2)$$

- 139 • For any two fireflies  $FF_i$  and  $FF_j$ , the firefly's attractiveness  $\rho$  is pro-  
 140 portional to its brightness, in which,
  - 141 . if  $FF_j$  is brighter than  $FF_i$ , the  $FF_i$  will move towards  $FF_j$ ;
  - 142 . the brightness of  $FF_i$  and  $FF_j$  will decrease while their distance  
 143 increase;
  - 144 . if no  $FF_i$  is brighter than the others, they will move randomly;
- 145 • The brightness of a firefly is determined by the fitness function.
- 146 • The population  $P$  of fireflies varies from generation to another to ac-  
 147 celerate the calculation process. The variable population  $P$  is given in  
 148 equation (3), in which  $P_N$  is the non-replaceable population and  $P_R$  is  
 149 the replaceable population.

$$P = P_N + P_R \quad (3)$$

150 The attractiveness  $\rho_{ij}$  of  $FF_i$  to  $FF_j$  is defined by equation (4), where  $\rho_0$   
 151 is the initial attractiveness at an initial distance  $r_0$  and the rest parameters  
 152 are same as equation (2).

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

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

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

157 The movement of  $FF_i$  to  $FF_j$  is given by equation (6), where  $\varepsilon$  is the  
 158 random movement in case of equal brightness generated by a uniformly dis-  
 159 tribution in the range of  $[0,1]$ ;  $\eta \in [0,1]$  is a randomisation factor determined  
 160 by the practices;

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

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

### 167 3.2. Fitness Function Definition

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

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

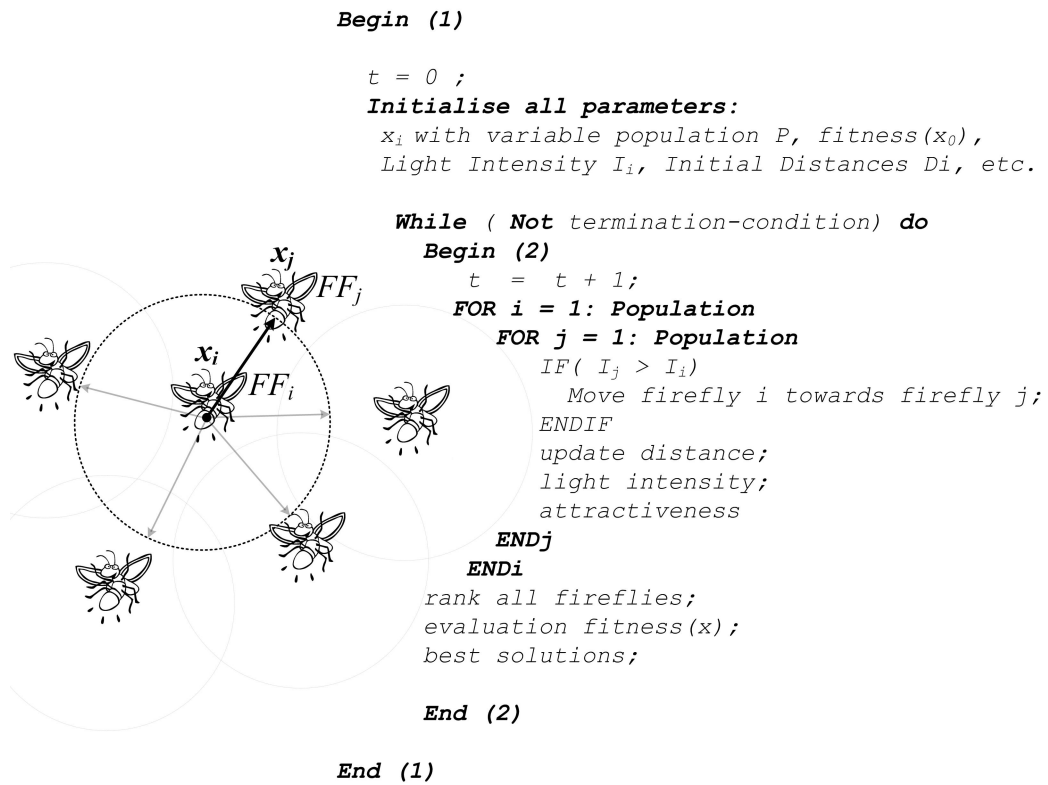


Figure 1: Firefly Algorithm with Variable Population Workflow[29, 30]



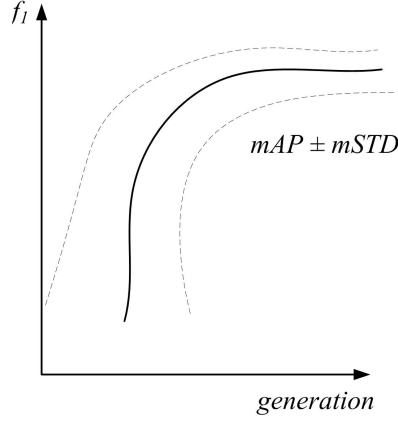


Figure 2: mAP  $\pm$  mSTD Over the Full Generations

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

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

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

180 In this section, an index of the mean average precious(mAP) of the root  
 181 mean square ( $RMS$ ) errors of  $\hat{E}_c$  and  $E_c$ , as given in equation (1), is defined  
 182 as the fitness to evaluate the optimisation process, which is to minimise the  
 183  $RMS$  errors. Specifically, the fitness function  $F$  of electricity consumption  
 184 efficiency prediction is given in equation (9), and the problem is to maximise  
 185 the  $F$ , which is to maximise the -mAP scores of the  $RMS$  of  $\hat{E}_c$  and  $E_c$ , as  
 186 given in equation (10), and the *s.t.* conditions of  $c, \alpha_i, \beta_j$  are given in Table  
 187 1.

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

$$\begin{aligned}
& \text{Maximise : } F(c, \alpha_i, \beta_j) \\
& \text{s.t.} \quad \square \leq c, \alpha_i, \beta_j \leq \square
\end{aligned} \tag{10}$$

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

- 191 1 collect and prepare raw data for the modelling;
- 192 2 data pre-handling and normalisation when it is necessary;
- 193 3 electricity consumption modelling, as discussed in Section 2;
- 194 4 fitness function definition for optimisations, as given in Section 3.2;
- 195 5 the FAVP, as given in Section 3.1.

#### 196 4. Simulations

197 The optimisations are performed by the *SwarmFirefly*, which is a tool-  
198 box for MATLAB developed by Chen[29]. According to previous research  
199 and engineering applications, the initial parameters are initialised in Table  
200 1, in which a max generation 100 is the termination condition of each round  
201 test; the total test number is 100; the randomness factor is 0.2; the random-  
202 ness reduction is 0.98; the population is 50, in which the non-replaceable  $P_N$   
203 and replaceable population  $P_R$  are 40 and 10, respectively; the ranges of  $c$ ,  
204  $\alpha_i$ ,  $\beta_j$  are [-100,100], [-10,10] and [0,3] respectively.

205 As can be observed in Figure 4, the fitness curve of  $mAP \pm mSTD$  are  
206 represented, in which the fitness curves go up very quickly from generation  
207 1 to 20 to reach a plateau point (about generation 20), and then from gen-  
208 eration 20 to 100, the curves keep steady over the rest generations and the  
209 fitness move to the convergence, which indicates the high efficiency of the  
210 swarm firefly algorithm.

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

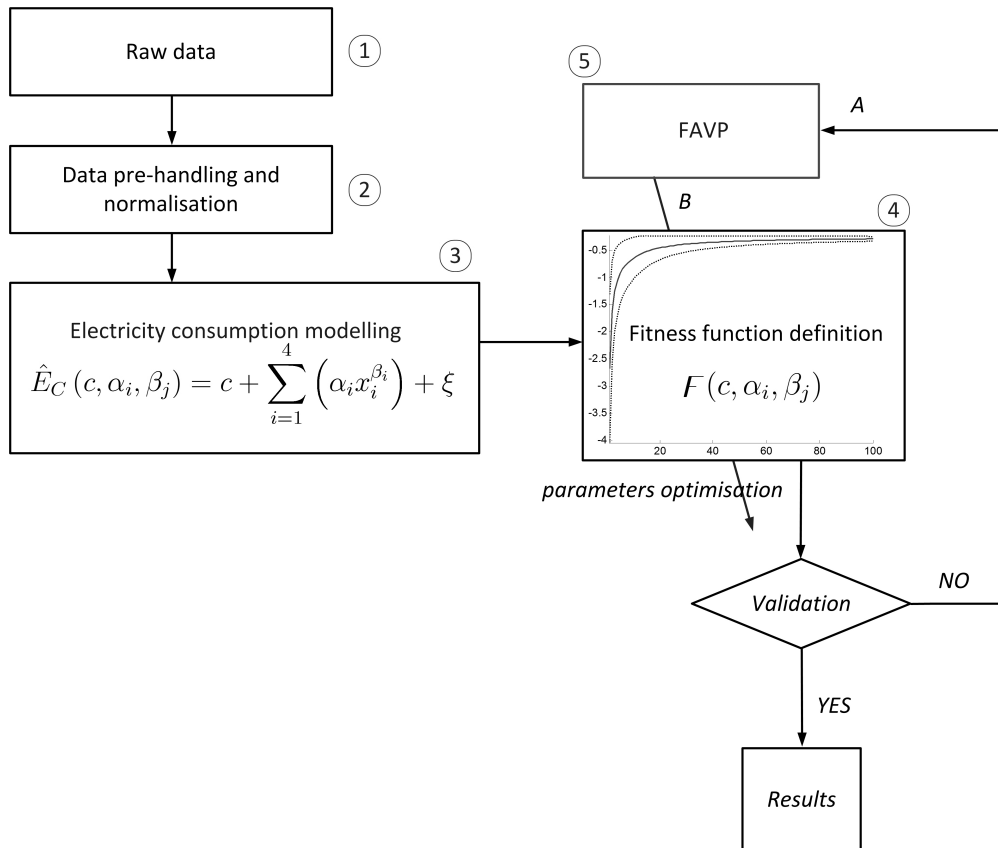


Figure 3: The over-all modelling, optimisation and prediction flowchart

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 coefficient	1
$c$	[-100,100]
$\alpha_i$	[-10,10]
$\beta_j$	[0,3]

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

218 According to the section 2, four variables including GDP, electricity price,  
 219 consumption efficiency and economic structure are considered in this non-  
 220 linear modelling. Fixing any three series at their mean values, Figure 6 to  
 221 Figure 9 demonstrate how electricity consumption  $E_c$  respond to the fourth  
 222 series' variation respectively, which explicitly indicate that the nation's elec-  
 223 tricity consumption  $E_c$  decreases at an increasing speed with the increase in  
 224 the electricity price; electricity consumption  $E_c$  increases with an increasing  
 225 speed when the GDP increase; electricity consumption  $E_c$  decreases with an  
 226 increasing speed when the electricity consumption efficiency is improved; and  
 227 electricity consumption  $E_c$  goes up acceleratingly when China's industrial-  
 228 ization gets more intensive.

229 Table 2 gives the normalised optimal parameters by the FAVP, which are  
 230 to be restored to original scale for practical usage, that is  $E_c$  prediction value  
 231 for the years of 2010, 2011 and 2012 in this case. As shown in Figure 10, the  
 232 forecasting errors of the  $E_c$  the years 2010 to 2012 are stated in percentage,  
 233 and Table 3 lists the specific error values of the training process of the years  
 234 1980 to 2009 and the prediction process of the years 2010 to 2012. We also  
 235 compared the errors by the FAVP, FA and genetic algorithm (GA), as shown  
 236 in Table 3, which shows that the FAVP's results have been out-performed  
 237 the FA and GA's results in this case.

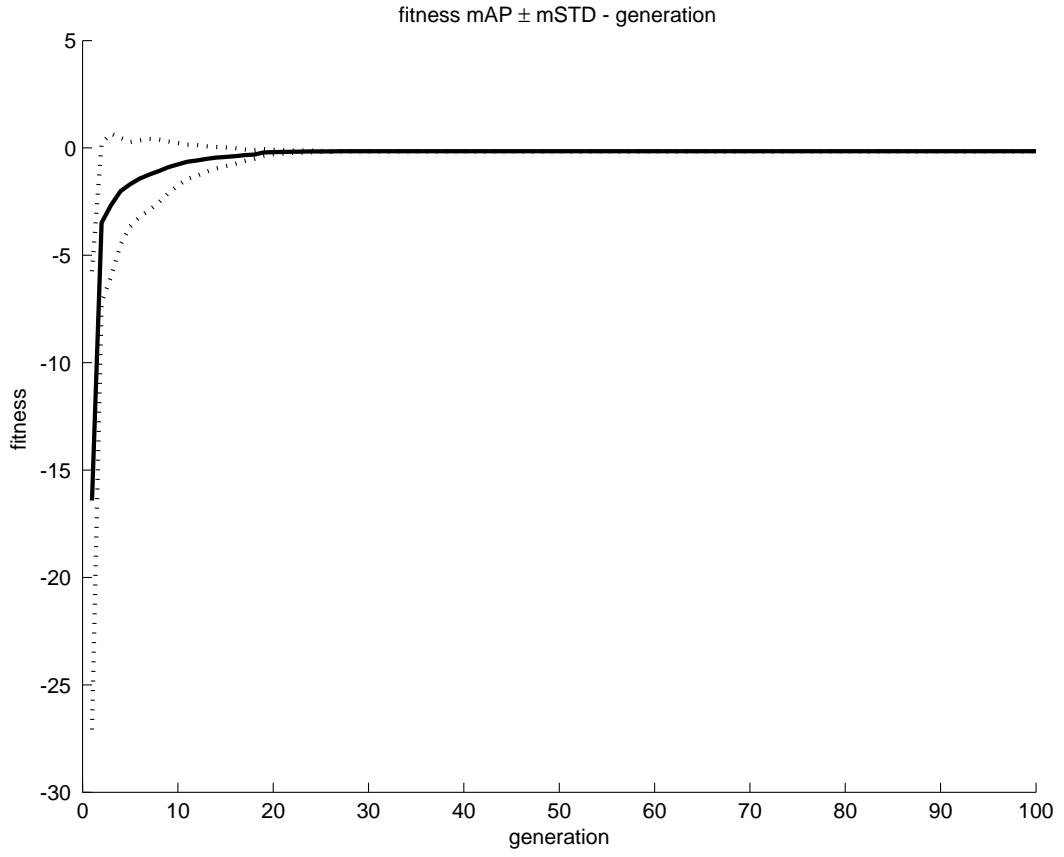


Figure 4: Fitness Curve of mAP  $\pm$  mSTD

Table 2: Optimal Parameters by FAVP

<i>parameter</i>	<i>mean <math>\pm</math> std</i>
$c$	$-1.9696 \pm 4.3775$
$\alpha_1$	$4.8243 \pm 2.7687$
$\alpha_2$	$-0.2830 \pm 1.7892$
$\alpha_3$	$-0.3336 \pm 1.9921$
$\alpha_4$	$-0.5481 \pm 2.0203$
$\beta_1$	$1.4790 \pm 1.5137$
$\beta_2$	$2.0049 \pm 1.9311$
$\beta_3$	$1.5875 \pm 1.4019$
$\beta_4$	$1.5748 \pm 1.3035$

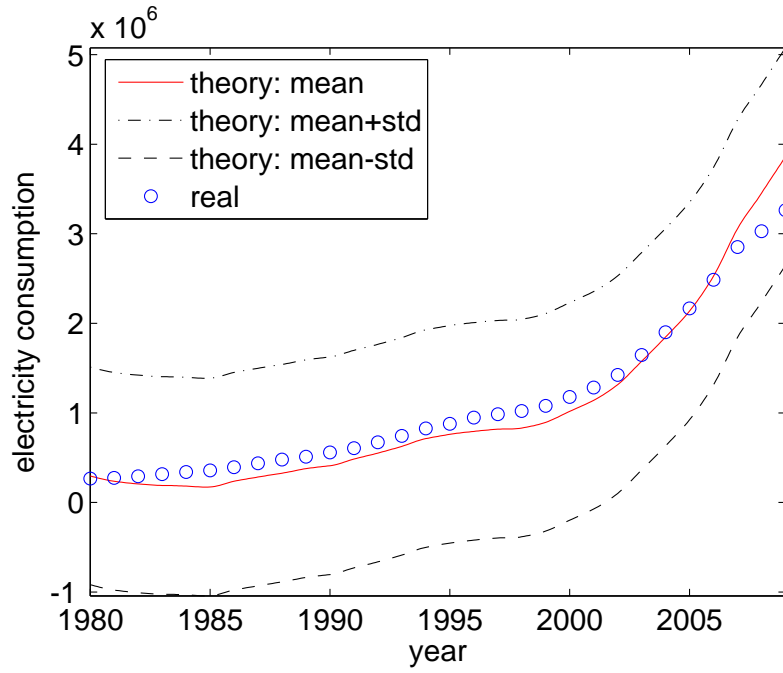


Figure 5: Actual and Theoretical Electricity Consumption Over 1980-2010

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

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

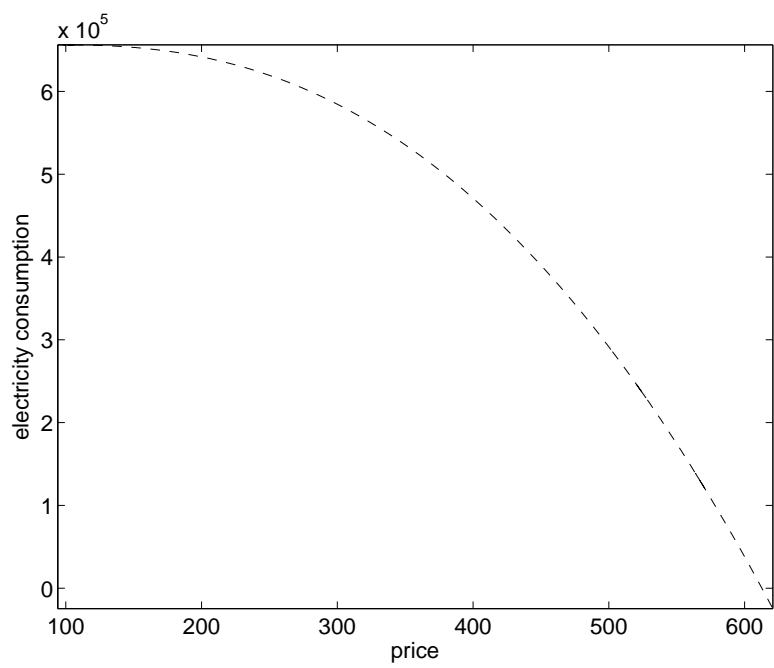


Figure 6: Changes of electricity consumption with price

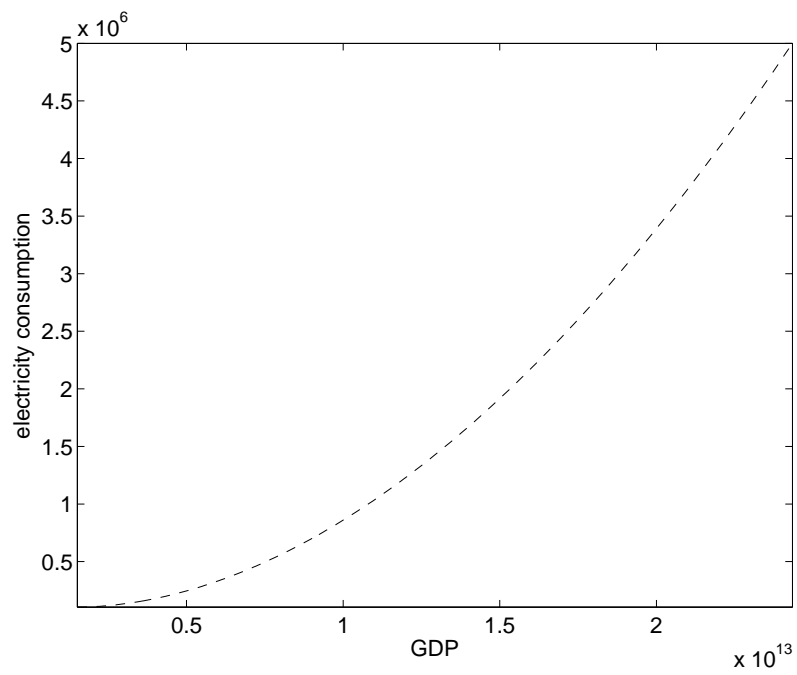


Figure 7: Changes of electricity consumption with GDP



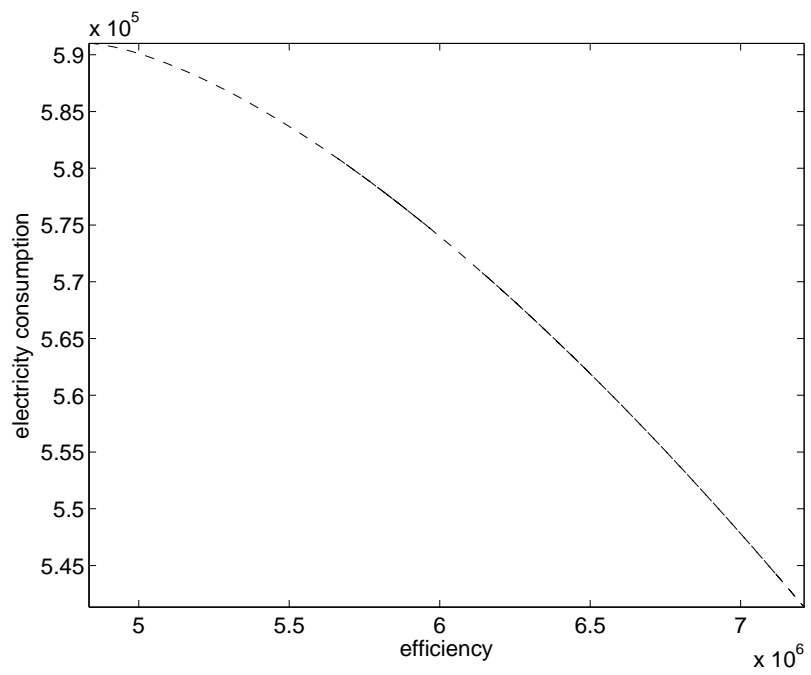


Figure 8: Changes of electricity consumption with efficiency

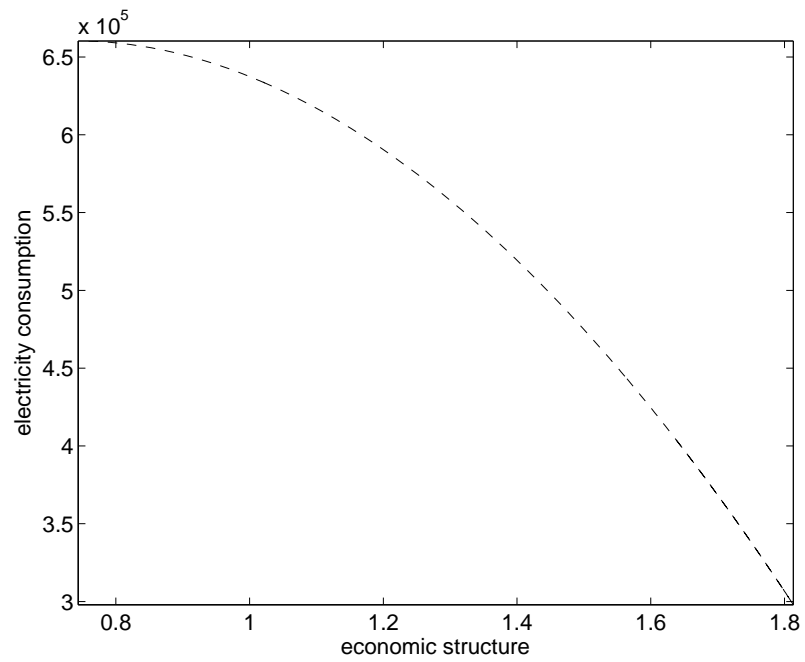


Figure 9: Changes of electricity consumption with economic structure

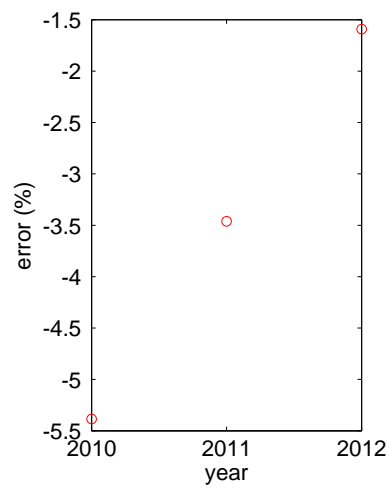


Figure 10: Error in percentage of  $E_c$  prediction of year 2010 to 2012

## 238 5. Conclusions and Future Works

239 It is critically important for policy makers and energy investors to be  
240 aware of the energy demand which affects the actual policy alternation and  
241 policy investment. Our empirical study stimulates China's national electric-  
242 ity demand for the urgency from the rapidly increasing China's electricity  
243 demand and economic growth, and side issues from electricity demand and  
244 economic growth such as electricity shortage and environmental damage from  
245 electricity demand and production. This study adopts a nonlinear approach  
246 to model China's national electricity demand and our study suggests that  
247 macroeconomic performance, electricity prices, economic structure and elec-  
248 tricity consumption efficiency are important factors which affect the national  
249 electricity demand of China. Our study also indicates the nonlinear and dy-  
250 namic impact on electricity demand from those determinants, which suggest  
251 we should adjust our energy policy due to the nonlinear association between  
252 electricity consumption and economic fundamentals. This study could pro-  
253 vide practical policy indication in terms of energy investment and govern-  
254 mental energy policy. As an ANN is a black-box data-fitting model whose  
255 parameters would not bear a physical interpretation as many other modelling  
256 methods do, especially in extrapolation or prediction[31], we proposed this  
257 EC model and the FAVP approach to perform the prediction. In our future  
258 work, we plan however to compare with an EC-based ANN and the Bayesian  
259 method[32] for this application in our future work. In this work, nonetheless,  
260 our EC model has delivered a prediction with an acceptable error rate. Fur-  
261 ther, the associated FAVP has been compared with the FA and GA methods  
262 and has outperformed these existing methods.

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