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Shiwei Yu
Yi-Ming Wei
Ke Wang

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Center for Energy and Environmental Policy Research
Beijing Institute of Technology
No.5 ZhongguancunSouth Street, Haidian District
Beijing 100081
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Yi-Ming Wei
Director of Center for Energy and Environmental Policy Research, Beijing Institute of Technology

For more information, please contact the office:

Address:
Director of Center for Energy and Environmental Policy Research
Beijing Institute of Technology
No.5 Zhongguancun South Street
Haidian District, Beijing 100081, P.R. China

Access:
Tel:+86-10-6891-8551
Fax:+86-10-6891-8651
Email:ceeper@vip.163.com
Website: http://ceep.bit.edu.cn/english/index.htm

China's Primary Energy Demands in 2020: Predictions from An MPSO-RBF Estimation Model

Shiwei Yu[a,b,c*] Yi-Ming Wei[b,c] Ke Wang[b,c]

(a.School of Economics and Management, China university of geosciences, Wuhan, 430074

b. Center for Energy and Environmental Policy Research, Beijing Institute of Technology, Beijing, 100181

c. School of Management and Economics, Beijing Institute of Technology, Beijing, 100181)

Abstract: In the present study, a Mix-encoding Particle Swarm Optimization and Radial Basis Function (MPSO-RBF) network-based energy demand forecasting model is proposed and appliedto forecast China's energy consumption until 2020. The energy demand isanalyzed for the period from 1980 to 2009 based on GDP, population, proportion of industry in GDP, urbanization rate, and share of coal energy. The results reveal that the proposed MPSO-RBF based model has fewer hidden nodes andsmaller estimated errors compared with other ANN-based estimation models. The average annual growth of China's energy demand will be 6.70%, 2.81%, and 5.08% for the period between 2010 and 2020 in three scenarios and could reach 6.25 billion, 4.16 billion, and 5.29 billion tons coal equivalentin 2020.Regardless of future scenarios, China's energy efficiency in 2020 will increase by more than 30% compared with 2009.

Keywords: China's energy demand; forecasting；Radial Basis Function (RBF) neural network; energy intensity

1. Introduction

Worldwide energy consumption is rising sharply, owing to increasing human population, continuing pressure for better living standards, and emphasis on large-scale industrialization in developing countries, thus sustaining positive economic growth rates. As the largest developing country in the world, China's economy and gross energy consumption have been growing rapidly for more than 60 years, especially with reforms and the opening up of its economy. Reports indicate that China's gross domestic product (GDP)

*Corresponding author.Tel:+86 027 67883215;fax: +86 027 67883201

E-mail address:ysw81993@sina.com (S.YU)

grew by an average rate of 9.8% from 1980 to 2009[1]. Despite the 2008 global economic crisis, China's GDP in 2010 remained at a high growth rate of 10.3%, and reached RMB (Chinese currency) 39.80 trillion[2]. Meanwhile, China's energy consumption increased from 602.8 million tce ("standard" tons coal equivalent) in 1980 to 3.25 billion tce in 2010, with an annual growth rate of 5.8%, an increase of 5.9% compared with 2009[2]. Giventhese developments, China overtook the United States as the world's largest energy consumer after 2009[3]. The rapid growth energy consumption has also brought about considerable pressure on China's energy supply. China became a net importer of petroleum products once again in 1993, and, ever since 1997, China's energy self-reliance rate has been below 100%.Compared with developed countries, China's future energy demand will keep growing at a rapid pace. Thus, accurate forecasts of energy demands are very important and fundamental to rational energy planningformulation. The estimation can guide the Chinese government during consideration of necessary actions concerning supply security, environmental quality, and other important aspects of formulating energy policies.

Many studies related to energy consumption forecasts are available in the literature, which can be mainly classified into the following five categories: the econometric category, including time series[4-6], regression[7, 8], and ARMA model[9, 10],the bottom up model-LEAP[11-13], the grey forecasting category [14, 15], the artificial intelligence forecasting category[16-23], and the hybrid forecasting category[15, 24-27]. The literature is abundant and has grown steadily. A brief overview of the different categories of energy forecasting can be found in the review paper surveyed by Suganthia and Samuelb[28]. With the complexity and nonlinearity of mostenergy demand systems, the artificial intelligence forecasting category has becomethe most popular approach amongst thefive categories in recent years. In this category, Artificial Neural Networks (ANN) is one of the intelligent modelsthat can elucidate complex relationships between input and output patterns that would be difficult to model with conventional algorithms. Instead of complex rules and mathematical routines, ANN is able to learn the key information patterns within a multidimensional information domain. In addition, they are fault-tolerant and robust. The greatest advantage of a neural network is its ability to model complex nonlinear relationship without a priori assumptions of the nature of the relationship like a "black box"[29, 30].

Thus far, a number of studies focus on utilizing the ANN model to predict the national energy demand [20, 21, 24, 31-35], electricity load[25, 36-39] and transport energy demand[8, 22, 40] are available. Among these various forecasting methods, the multilayer perceptron (MLP), especially Back Propagation (BP) network, is the most popular. However, some dilemmas have been encountered when dealing with a time series forecasting problem. First, it is not easy to determine a suitable number of hidden neurons. In the above-mentioned studies, the number is mainly achieved via trial and error, which is inefficient and time-consuming. Second, the optimization solution could be trapped in a local optimum as training the weights by BP error gradient algorithm. The improper weightsmay fail to set the mapping between input and output variables. Finally, BP algorithms adjust weights and bias complying with a certain rule. It is thus impossible to adjust the structure self-adaptively in a fixed topology[41].

This has led us to investigate the energy forecasting performance of other ANN models, such as the radial basis function (RBF) neural network. The RBF neural network is another three-layered feedforward neural network model wherethe activation function of the hidden units isdetermined by the distancebetweenthe input vector and a prototype vector.RBFnetwork can approach any continuous function with any precisionand can avoid the redundant calculation of BP network. Furthermore, it has more rapid calculationrate, stronger extrapolating capability and non-linear mappingfunction [42].

In our earlier study, a Mix-encoding Particle Swarm Optimization Radial Basis Function (MPSO-RBF) network has been proposed in theory[43]. However, this model has not been utilized to energy demands modelling. In the present study, a proper MPSO-RBF based model is proposed to forecast the energy demands of China in 2020 based on socio-economic indicators, such as GDP, population, economic structure, urbanization rate, and energy structure. China's energy efficiency in 2020 also has been estimated in three scenarios.

2. Energy consumption and economic indicators of China

Energy consumption is a function of several affecting factors, such as per capitaGDP, relative prices, economic structure, available technology, and lifestyles [44, 45]. Several authors have explored the relationship between energy consumption and certain aspects of economic development, population, economic structure, urbanization rate, and energy structure. Based on the availability of Chinese data, the present study selected GDP (economic development), annual total population, the share of industrial added value to GDP (indicating the economic structure), the ratio of urban population to the total population (urbanization rate), and the share of coal consumption from the total primary energy consumption (energy structure) as independent variables.

Energy consumption and selected economic indicators are described in Fig.1. All annual data from 1980 to 2009 were obtained from the China Statistical Yearbook (1980–2010) and the China Statistical Energy Yearbook (1980–2010), compiled by the National Bureau of Statistics (NBS).

From 1980 to 2009, the annual growth rate of China's primary energy consumption was 5.8% while the economic growth was 9.8% (this calculation factored in constant prices in 1990), showing an annual average energy consumption elasticity coefficient of 0.59, which basically achieves the goal "ensure economic output with energy double quadruple." After 2002, however, the growth rate accelerated. Between 2002and2009,with the annual growth rate at 9.3%, energy consumption nearly doubled in a short span of seven years, during which the elasticity coefficients of 2003 and 2004 exceeded 1; this period is considered to be the fastest growth period of energy consumptionover the last 30 years, as shown in Fig. 1.

Due to the difference of the energy consumption index in different industries, the change of industrial structure and industrial productivity is bound to influence energy consumption. With industrial output value accounting for the proportion of GDP in 1980–2009, Chinese industry proportion has been hovering between 38%–42% (see Fig.1). In recent years, with China's gradual transformation of its economic development model, a large number of enterprises with high energy consumption and high emission levels have been shut down. Industrial output value accounted for the proportion of GDP began a slow decline from 2006, dropping from 41.76% in 2005 to 39.72% in 2009.

Industrialization and urbanization always complement each other. Since the Chinese economy has grown rapidly over the last 30 years, the level of Chinese urbanization has also increased. China is in the middle stages of urbanization; therefore, the city population and rate of urbanization have seen significant increases. As shown in Fig.1, the proportion of urban residents in China rose from 19.4% in 1980 to 46.6% in 2009, with an average annual growth rate of 3.1%. However, a large gap in the urbanization rate continues to exist, with middle-income countries experiencing an average level of 61% and high-income countries experiencing a 78% growth rate[46]. China's current levels of urbanization are expected to increase its total energy consumption.

Population growth is an important factor that drives the amount and type of energy use. China is the most populous country in the world, with a population of 1.33 billion in 2009. The country's one-child policy of one couplehas had a significant impact on its energy use, with China experiencing an average population growth rate of 1.1%from 1980 to 2009, whereas theannual population growthrate peaked at above 1.4% during the period between1985 and 1990.The growth rate in1988 reached a maximum of 1.58% and after that growth declined year by year, showing only 0.51% in 2009. In the error correction model, the elastic coefficient of energy consumption and population was only 0.46, that is to say with the population growing at 1%, energy consumption only increased 0.46% [47]. However, because of China's large population base, small changes in population can cause great changes in energy demand, bringingeven greater pressure on energy resources.

The characteristics of China’s energy endowment include rich coal, less oil, and gas shortage, making China one of the world's few remainingcountries relying on coal for primary energy consumption. From 1980 to 2009, the proportion of coal consumption in primary energy was maintained at over 70%, except for a few years in 2000 to 2004, when it was just slightly lower than 70%. Furthermore, from 1984 to 1992, the proportion exceeded 75%, increasing up to 76.2%(see Fig.1). In 2009, the proportion of coal consumption accounted for 70.4% of total primary energy used, which is much higher than the world average of 29.1%[48].

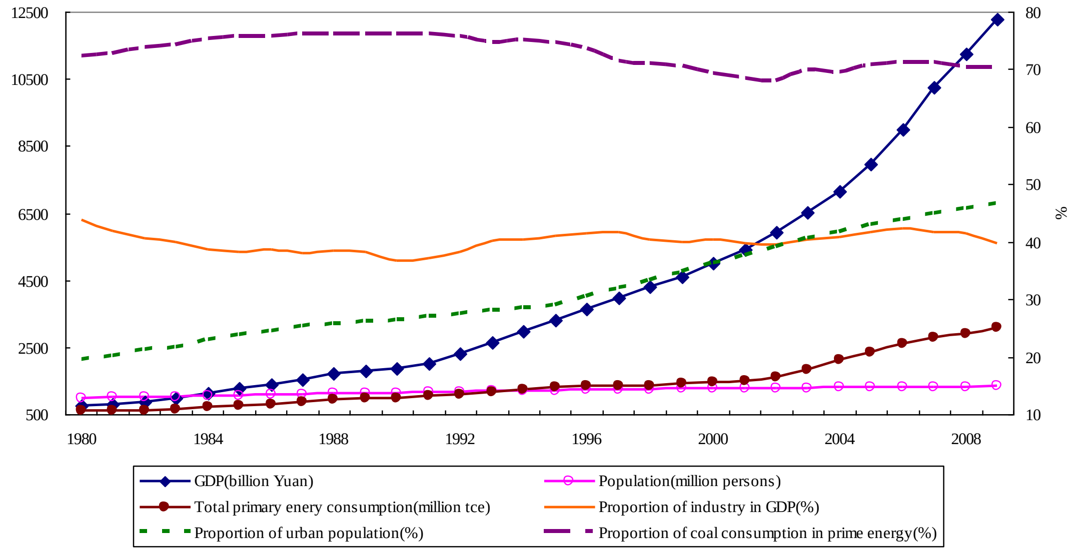

Fig. 1. Energy consumption and selected economic indicators (1980–2009).

3. Methodology

3.1 The study framework

An energy system is a complex nonlinear system; its development and evolution are affected and restricted by a variety of factors, such as the internal sub-system and external environment. To better establish the complex non-linear relationship between energy consumption and its factors, the present study takes advantage of non-linear mapping capabilities of RBF networks in complex systems modeling and the global intelligence capability of PSO optimization algorithm to form a new MPSO-RBF prediction model. The research framework is depicted in Fig.2. First, normalized historical data are divided into two parts, the training set and the test set, which are utilized to train RBF network parameters (e.g., network structure, weights) and test the model prediction performance, respectively. Second, the training set is inputted into the RBF network in random order, errors E are calculated between the outputs of the network and the actual values,and network's structure and weights are optimized by MPSO-BP algorithm. Third, test set is inputted into the optimized RBF network, which meets the maximum number of evolution generations or $E \le \varepsilon$, and the mean absolute percentage forecast error (MAPE) of the test set is computed. Finally, different scenarios are set according to the historical trends of independent variables and the Chinese government's planning scheme. The related scenario data are inputtedinto the validated RBF and China's energy demand from 2010 to 2020 are predicted.

In Fig. 2, $y(i)$ and $\hat{y}(i)$ are the observed and estimated energy demands of the i-th training data, respectively, and $E = \frac{1}{2}\sum_{i=1}^{N}(y(i)-\hat{y}(i))^2$. $\max\_g$ is the maximum number of iterations of the proposed model by the training data and ε is the threshold error of thegiven data. $MAPE = \frac{1}{M}\sum_{i=1}^{M}\frac{|t(j)-\hat{t}(j)|}{t(j)}$ where $t(j)$ and $\hat{t}(i)$ are the j-th RBF forecastand actual values, respectively, N and M are the sizes of the training and test sets, respectively, and η is the threshold of the test forecast $MAPE$.

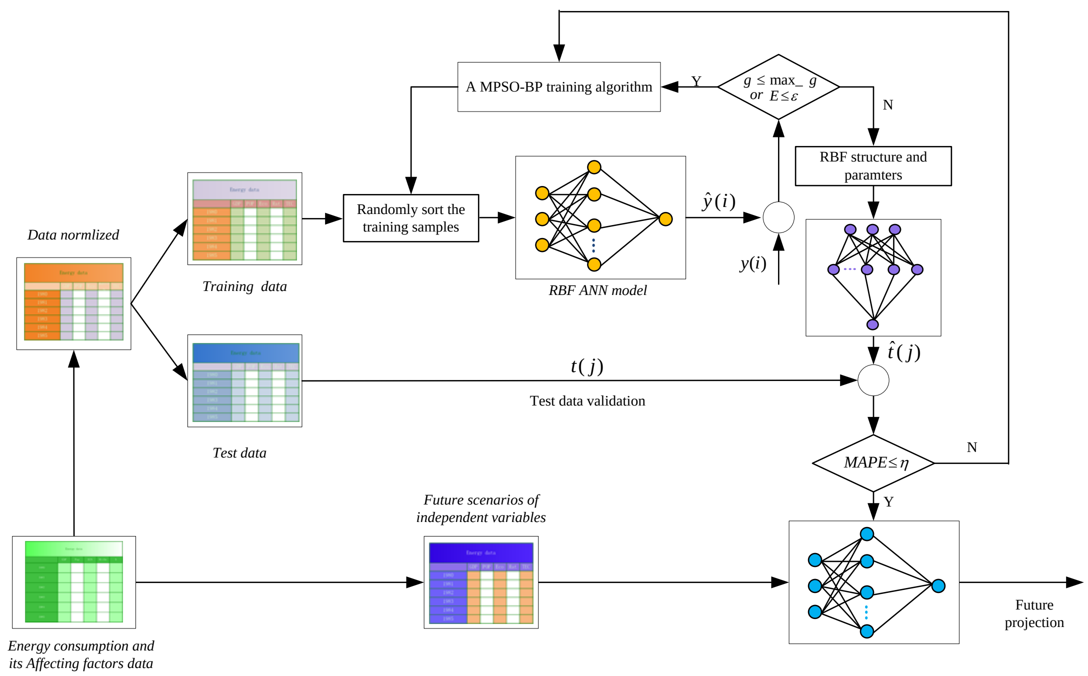

Fig. 2.

Diagram of the proposed MPSO-RBF ANN energy estimation model

3.2The MPSO-RBF forecasting Model

The MPSO-RBF network model, whichthe topology structure and parameters are simultaneous optimized by a mix-encoding particle swarm optimization and BP algorithm (MPSO-BP)[43].To solve the problem of determining the proper structure and the optimum parameters, a hybridMPSO-BP algorithm is proposed. In the hybrid algorithm,every particle structure consists of both binary and real parts. In the binary part, if the value coded in binary code is 1, the neuron is selected. However, if the value is “0,” the neuron is unselected. While thereal part are corresponding to the center c_i, the width σ_i, and the weight w_i of the RBF networks. The model is depicted in Fig.3.

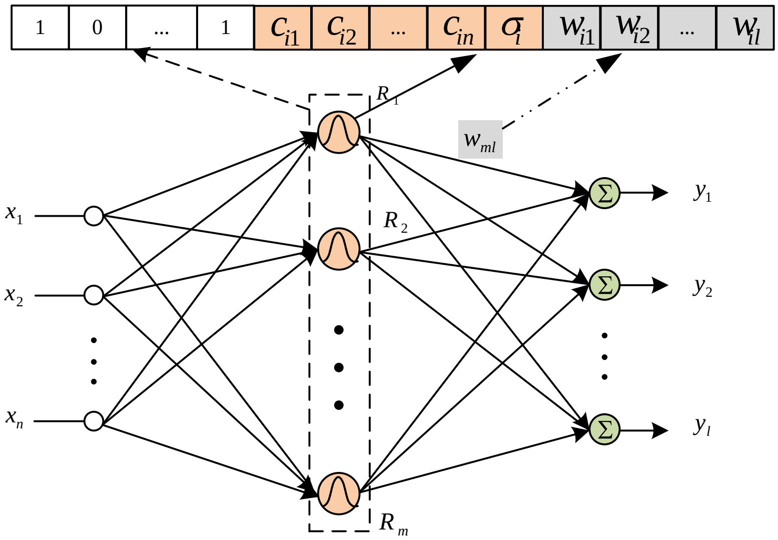

Fig.3. The structure of MPSO-RBF model

The hybridMPSO-BP algorithmis briefly described as the following:First, the structure of the RBF network, namely the number of hidden nodes, and the parameters are optimized by MPSO.Second, the BP algorithm, as a fast local gradient guide searcher, is applied to tune the real parts of particles corresponding to centers, width and weightsof a certain network structure. Finally, the parameters obtained by BP are set against the corresponding particle and the next iteration is performed. Furthermore, a special fitness function is introduced to ensure accuracy with few centers.

More details are described and illustrated by the flowchart in Fig. 4.In Fig.4 $d1$ and $d2$ are the length of binary part and real part of each particle. pop_size is the particles’ population size. $\max\_gen$ and $\max\_k$ are the max iterations of MPSO and BP algorithms ,respectively. χ isa restriction factor. c_1 and c_2 denote the cognitive and the social parameters,respectively. $rand_1$ and $rand_2$ are random numbers distributed uniformly in the interval $[0,1]$. $\chi = \frac{2}{\left|2-\varphi-\sqrt{\varphi^2-4\varphi}\right|}$, For $\varphi > 4$, where $\varphi = c_1 + c_2$, usually $c_1 = c_2 = 2.05$.

P_i^k represents the best previous position particle i has obtained until iteration k; P_g^t isthe best position obtained from P_i^k in the swarmor local neighborhood at iteration k.

Detailed descriptions of the MPSO-RBF network and BP training algorithm for RBF be found in references [43].

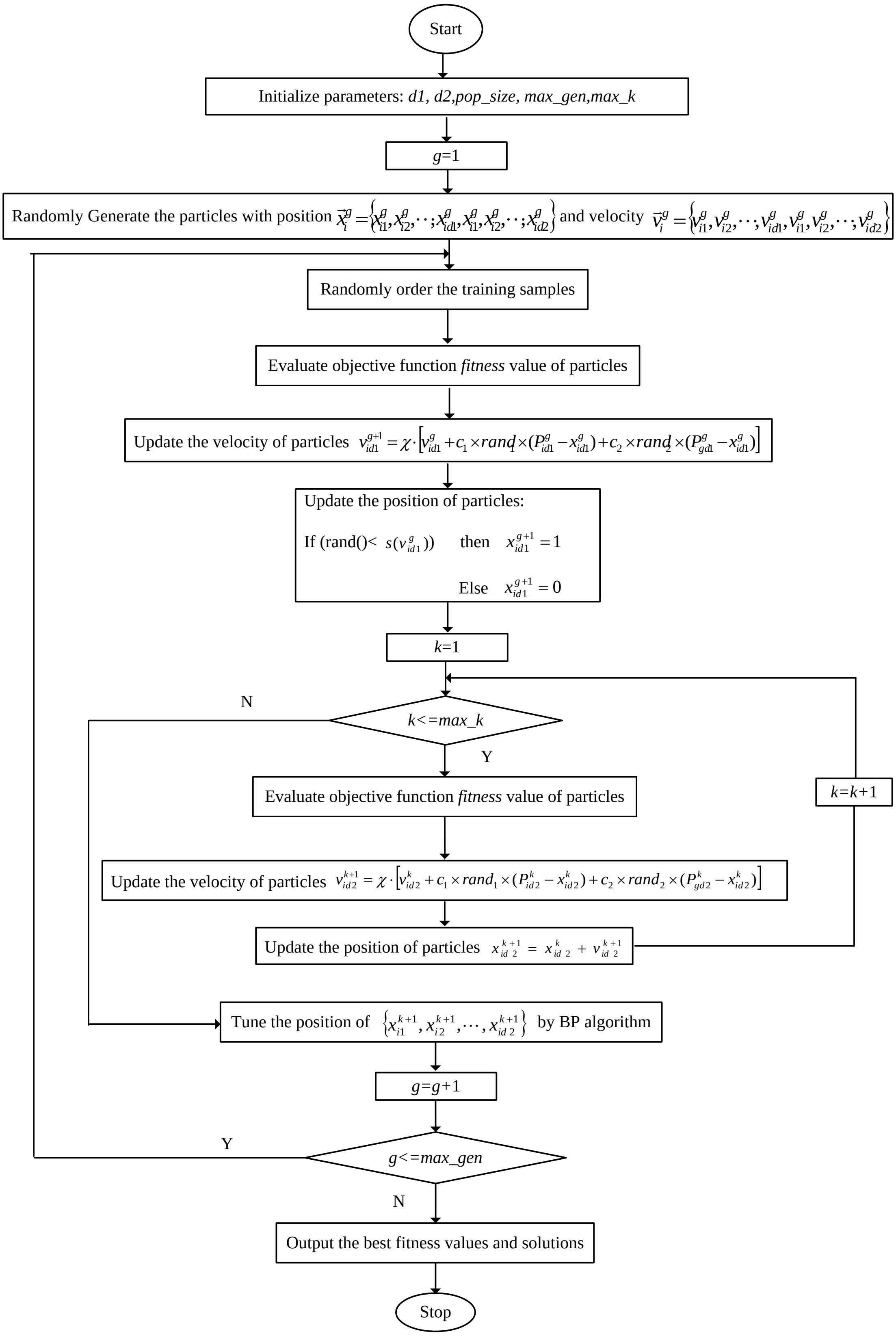

Fig. 4. The flowchart of the MPSO-BP algorithm.

4. Modeling results

Common parameters for the MPSO-RBF model were as follows: Population size $pop\_size = 40$; generation number $\max\_gen = 150$; $\max\_k = 100$.The max number of RBF is 10 (i.e., $d1 = 10$). Five selected economic indicators were applied to forecast the primary energy demand in the present study. Therefore, there were 5 input nodes and 1 neuron in the output layer, and the length of every particle was 80. The initial particle positions belonged to $[-5,5]$. Historical data of China's energy and corresponding selected economicindicatorsfrom 1980 to 2009 were divided into the training set, 1980–2004, and the test set, 2005–2009. The structure and parameters optimized by the proposed MPS-BP algorithm werebased on 10 independent runs under different random seeds. After the algorithm reached the stop criterion, the best structure was 5-4-1, indicating thatthere are only four radial basis nodes in the hidden layers. The fitness values against iteration and the selected RBF numbers against iteration are shown in Figs.5and 6, respectively. The test MAPE is 0.78% and the NRMSE is 0.0251. A comparison between actual and estimated values of energy consumption (training and test data) is shown in Fig.7. Fig.8shows the MAPE of simulation by the MPSO-RBF model.

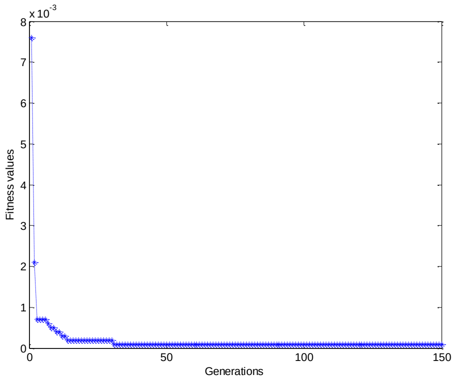

Fig.5. Fitness values against iteration

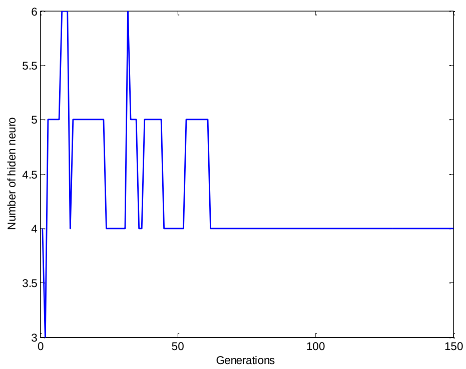

Fig.6. Selected RBF numbers against iteration

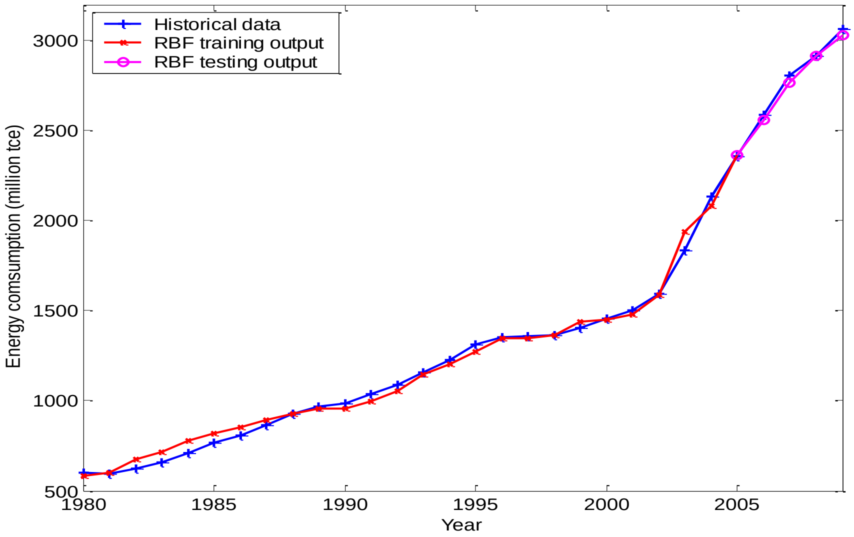

Fig. 7. Comparison between actual and estimated values of energy consumption (1980–2009)

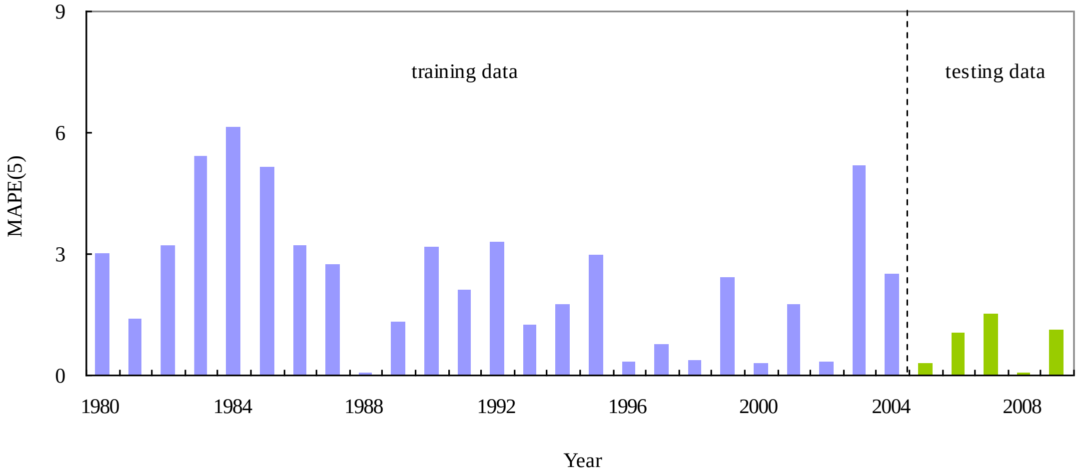

Fig. 8. Trends of percentages of estimated errors of forecasting models (1980–2009)

Table 1 lists the comparison of structure and MAPE in the present study with other authors. Results indicate that the proposed MPSO-RBF model has a simpler network structure and higher estimating precision than other ANN models.

Table 1

The comparison of structure and MAPE[a] in the present study with other authors

Authors	ANN Structure	Training algorithms	Target/Country	MAPE(%)
Limanond et al [8]	Four layers MLP (5-5-5-1)	Back-propagation	ransport energy-Thailand	0.0263[b]
Ekonomou[20]	Four layers MLP (4-20-17-1)	Levenberg-Marquardt	Total energy-Greece	3.52
Azadeh et al.[24]	Four layers MLP (5−3−3−1)	Resilient propagation and momentum and weight decay	Industrial sectors-Iran	0.99
Sözen and Arcaklioglu[32]	Three layers BP (2-4-1)	Levenberg-Marquardt	Net electricityenergy-Turkey	0.93
Pao [34]	Three layers BP (2-5-1)	Back-propagation and momentum	Electricity energy-Taiwan	2.56
Coşkun [37]	Three layers BP (4-4-4)	Back-propagation and momentum	Four-sector net electricity energy-Turkey	8.17
Murat Ceylan[40]	Three layers BP (3−14−1)	Back-propagation	Transport energy-Turkey	13.01
The present study	Three layers RBF (5-4-1)	MPSO-BP algorithm	Total energy-China	0.78/0.025 [b]

[a]Average relative to the test period of each model

[b]Normalized root mean square error(NRMSE) of the test data.

From Table 1, based on historical data, the proposed MPSO-RBF model properly establishedthe non-linear mapping between energy consumption and five factors that affect it, including economic growth, population growth, economic structure,urbanization rate, and share of coal energy. Thus, the future energy consumption of China can be adequately estimated by the model, and the forecasting results may guide the Chinese government in implementing future energy policies.

5. Future scenarios estimations

5.1. Scenario settings

To predict future energy demand andguide the energy policy making, three scenarios are analyzed in the present study. ScenarioA,business-as-usualscenario, is a case of high economic growth, where past trends continue in the future and no new policies for energy saving and environmental protection are implemented. Scenario Bis mostly based on the 12th Five-Year Plan of China, which reflects a shift toward a more sustainable energy pathway realized by policies and measures aimed at improving energy efficiency and reducing energy consumption. Scenario C is a trade-off between Scenarios A and B. Different scenario settings are shown in Table 2. Table 3 summarizes the projected independent variables in 2015and 2020 in thedifferent scenarios. All of theses scenarios are primarilygoverned by five factors, namely, economic growth, population growth, economic structure, urbanization rate,and share of coal energy.

Different scenario settings are shown in Table 2. Table 3 summarizes the projected independent variables in 2015and 2020 in thedifferent scenarios.

Table 2

Scenario settings

Scenarios	Years	GDP growth rate peryear	Population growth rate peryear	Share of industry in GDP growth rate peryear	Urbanization growth rate peryear	Coal share growth rate peryear
A	2010–2015	9.80%	0.60%	-0.20%	2.00%	-0.14%
	2016–2020	9.00%	0.50%	-0.25%	1.80%	-0.20%
B	2010–2015	7.00%	0.50%	-1.32%	1.63%	-0.70%
	2016–2020	6.00%	0.40%	-1.50%	1.50%	-0.80%
C	2010–2015	9.00%	0.55%	-0.60%	1.80%	-0.42%
	2016–2020	8.00%	0.45%	-0.90%	1.60%	-0.50%

Table 3

Index values by 2015 and 2020 in thedifferent scenarios

Affecting factors	Years	Scenario A	Scenario B	Scenario C
GDP (million Yuan)	2015	21488	18971	20812
	2020	33063	25388	30579
Population (million persons)	2015	1383.5	1375.3	1379.4
	2020	1418.6	1403.0	1410.7
Share of industry in GDP (%)	2015	39.20	36.70	38.30
	2020	38.60	34.00	36.60
Urbanization rate (%)	2015	52.47	51.34	51.85
	2020	57.30	55.30	56.14
Coal share in primary energy consumption (%)	2015	69.80	67.50	68.60
	2020	69.10	64.80	66.90

5.2.Future estimating results and discussion

According the scenarios setting, the MPSO-RBF model obtained using the method discussed in Section 4 is utilized to forecast the energy demands of China from 2010 to 2020. The predictions are shown in Fig.9.

In scenario A, China's energy demand will reach 4.66 billion tce in 2015, with an annual growth of 7.12% from 2010 to 2015. In 2020, demand will reach 6.26 billion tce. The average annual growth from 2010 to

2020 is 6.70%, which means that even if no energy policies are further implemented, the growth rate will still be lower than the 2002–2009 growth rates of 9.3% but greater than the 5.8% growth rate during the period between 1980 and 2009. In scenario B, due to slower GDP growth and associated energy-control policy implementation, China's energy consumption growth rate will substantially slow down. The average annual growth is 3.57%, only one-third of the growth rate from 2002 to 2009.The energy demand is expected to reach 3.78 billion and 4.16 billion tce in 2015 and 2020, respectively. From 2010 to 2020, the average annual growth rate is 2.81%, only half of the historical growth from 1980 to 2009. Scenario B showsideal conditions. In scenario C, the expected growth rate of GDP is 8% to 9% but the energy consumption growth rate for the period between2010 and 2015 is expected to be 5.89%. The growth rate is from 2010 to 2020 is expected to be 5.08%, lower than the annual average growth from 1980 to 2009. The energy demand in 2020 will be 5.29 billion tce, 1.72 times the consumption in 2009.

The energy intensity (energy consumption per unit of GDP) trends of three scenarios are shown in Fig.10. The energy intensity declinesfastest in scenario C, while the smallest decline found is in scenario A. In 2020, compared with 2009, the energy intensity is forecasted to decrease by 32.15%, 48.0%, and 42.9% in three different scenarios. This means that regardless of future scenarios, China's energy use will increase in 2020by more than 30% compared with that in 2009. In the next 10 years, China should seek to lower its energy consumption to support higher economic growth.

In 2020, the difference in energy demands between scenarios A and B is 2.10 billion tce. Comparing the settings of the two scenarios, significant differencesin GDP growth, proportion of industry in GDP, and share of coal energy may be found. In scenario B, GDP growth, proportion of industry in GDP, and share of coal energy fall significantly compared with scenario A. Toreverse the situation where China’s growth rate of energy consumption has approached the GDP growth rate since 2002 (the average energy elasticity was found to be 0.88 between 2002 and 2009), China must abandon the efforts to pursue high economic growth and instead focus on industrial restructuring, elimination of high energy consumption and high pollution industries, vigorous development of tertiary industries, gradual reduction of the proportion of industry in GDP, adjustment of the energy structure, and development of clean energy to reduce the use of coal energy. In addition, China should stabilize its population growth and steadily promote urbanization.

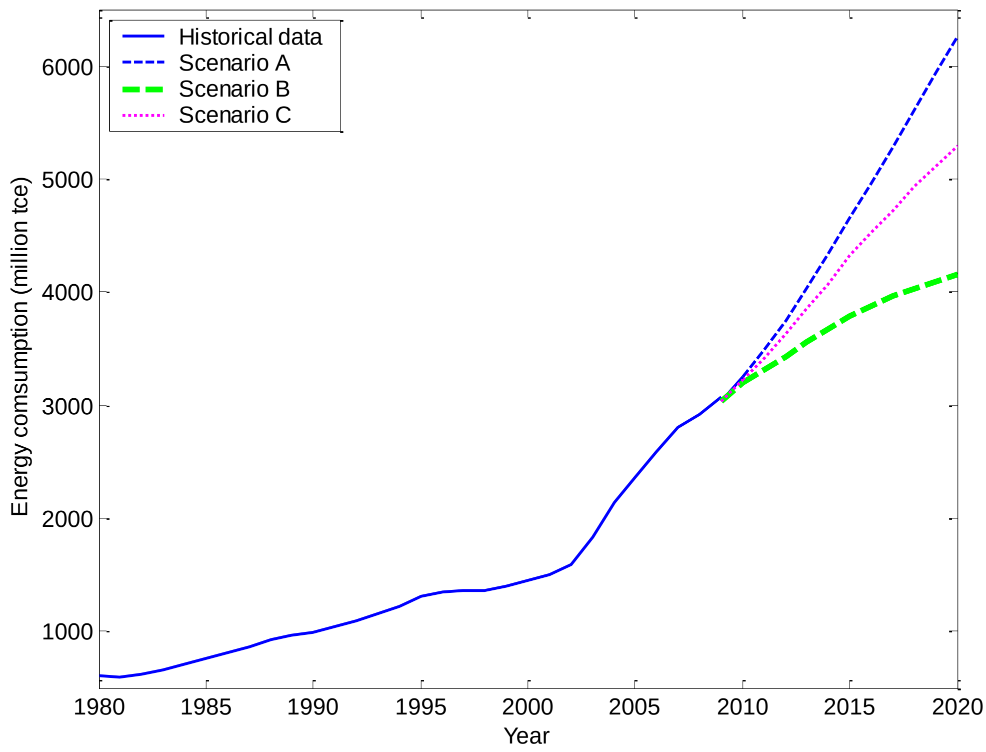

Fig.9. Energy demand forecasts for different scenarios (2010-2020)

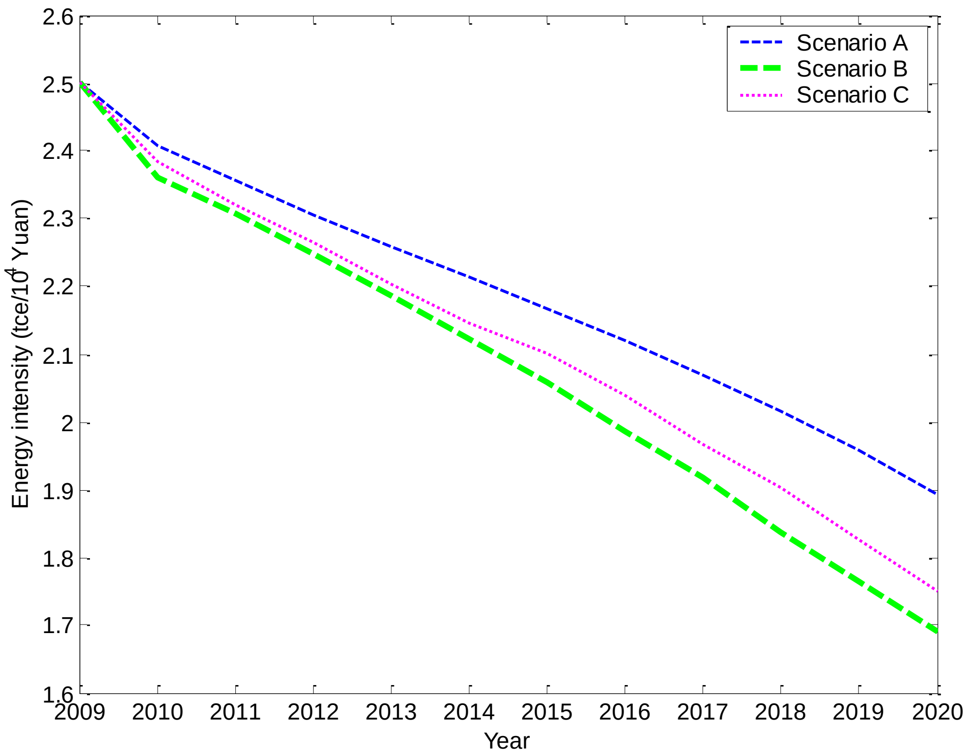

Fig.10. Energy intensity of different scenarios (2010-2020).

6. Conclusions

In the present study, an MPSO-RBF-based energy demand forecasting model isproposed and used to forecast China's energy consumption in 2020. The energy demand isanalyzed for the period between 1980 and 2009 based on GDP, population, proportion of industry in GDP, urbanization rate, and share of coal energy. The following conclusions can be drawn from the study.

(1)The mix-coding PSO-optimized RBF network model effectively establishesa non-linear forecasting model for China's energy demand. There are only four nodes of hidden layers, and the MAPE of the test year (2005–2009) is 0.78 % of the model, which has fewer hidden nodes but smaller estimated errors compared with other ANN-based energy estimation models.

(2) Givenbusiness-as-usual, planning, and middle scenarios, China's energy demands will reach 6.25 billion, 4.16 billion, and 5.29 billion tce in 2020, respectively, with average annual growths of 6.70%, 2.81%, and 5.08% for the period between 2010 and 2020.

(3) Different degrees of energy intensity decline could be expected in 2020. Regardless of future scenarios, China's energy efficiencywill increase in 2020 by more than 30% compared with 2009. This means that, compared with the historical years from 1980 to 2009, China will be able to lower its energy consumption while still supporting higher economic growth in the next 10 years.

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