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Scenario Analysis of Natural Gas Consumption in China Based on Wavelet Neural Network Optimized by Particle Swarm Optimization Algorithm

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Abstract: Natural gas consumption has increased with an average annual growth rate of about 10% between 2012 and 2017. Total natural gas consumption accounted for 6.4% of consumed primary energy resources in 2016, up from 5.4% in 2012, making China the world's third-largest gas user. Therefore, accurately predicting natural gas consumption has become very important for market participants to organize indigenous production, foreign supply contracts and infrastructures in a better way. This paper first presents the main factors affecting China's natural gas consumption, and then proposes a hybrid forecasting model by combining the particle swarm optimization algorithm and wavelet neural network (PSO-WNN). In PSO-WNN model, the initial weights and wavelet parameters are optimized using PSO algorithm and updated through a dynamic learning rate to improve the training speed, forecasting precision and reduce fluctuation of WNN. The experimental results show the superiority of the proposed model compared with ANN and WNN based models. Then, this study conducts the scenario analysis of the natural gas consumption from 2017 to 2025 in China based on three scenarios, namely low scenario, reference scenario and high scenario, and the results illustrate that the China's natural gas consumption is going to be 342.70, 358.27, 366.42 million tce ("standard" tons coal equivalent) in 2020, and 407.01, 437.95, 461.38 million tce in 2025 under the low, reference and high scenarios, respectively. Finally, this paper provides some policy suggestions on natural gas exploration and development, infrastructure construction and technical innovations to promote a sustainable development of China's natural gas industry.

Keywords: natural gas consumption forecasting; particle swarm optimization; wavelet neural networks; scenario analysis

1. Introduction

With fast growing urbanization and economic development, worldwide energy consumption has increased by 30% in the last 25 years [1]. Compared with other fossil fuels such as coal and oil, natural gas is more efficient, clean and cheap, and thus many countries including China have been trying to increase the consumption of natural gas to improve the environment quality. In China, natural gas consumption has increased with an average annual growth rate of about 10% between 2012 and 2017, and the total natural gas consumption accounted for 6.4% of consumed primary energy resources in 2016, up from 5.4% in 2012, making China the world's third-largest gas user. Moreover, in the 13th Five-Year Plan of China, the development and natural gas industry has been adopted as an important task of the government. In such circumstances, forecasting natural gas consumption is a very important aspect of any country's energy policy and planning. Improper estimation of the natural gas consumption may subject final consumers to economic losses and lead to mismanagement of supplies and infrastructures [2]. Therefore, accurately forecasting of natural gas consumption is of great significance for all the market participants to organize indigenous production, foreign supply contracts and infrastructures in a better way.

In the past few years, many efforts have been made, and many models have been proposed for different forecasting problems in the energy area. The proposed models can be generally classified into the following three categories: (1) statistical models; (2) artificial intelligence forecasting models; and (3) hybrid forecasting models. As for the statistical models, the widely used models mainly include auto-regressive moving average (ARMA), auto-regressive integrated moving average (ARIMA), grey forecasting model (GM) and generalized autoregressive conditional heteroscedasticity (GARCH). For example, Xu et al. established a new model with improved GM-ARMA based on HP Filter to forecast the final energy consumption in Guangdong Province, China [3]. Sen et al. used ARIMA based models for forecasting energy consumption and greenhouse emissions, and obtained satisfied results [4]. Zeng and Li presented a self-adapting intelligent grey model for predicting the natural gas demand in China during 2015–2020 [5]. Wang and Wu forecasted the energy market volatility using both univariate and multivariate GARCH-class models [6].

The most often used artificial intelligence forecasting models include artificial neural network (ANN), extreme learning machine (ELM), support vector machine (SVM) and least squares support vector machine (LSSVM). For example, Wang et al. proposed a novel hybrid electricity price forecasting model by combining a two-layer decomposition technique and back propagation (BP) neural network, and the results show the efficiency of the proposed model [7]. Geng et al. established a predictive modeling method based on the ELM integrated fuzzy C-Means integrating analytic hierarchy process (FAHP-ELM) for energy saving and forecasting problems [8]. Ahmad provided a review on applications of ANN and SVM for building electrical energy consumption forecasting [9]. Barman et al. proposed a hybrid forecasting model by integrating the grasshopper optimization algorithm and SVM model for the electricity load forecasting under local climatic conditions in Assam, India [10]. Niu and Dai established a new short-term load predicting method by combining the empirical mode decomposition, gray relational analysis, and modified particle swarm optimization with the LSSVM model. The former two modules were applied to process the original load series, and the latter was used to predict the preprocessed subsequences [11]. Among the above various forecasting methods, artificial neural networks (ANNs) have become the most used for energy related forecasting problems due to their attractive properties such as fault tolerance, strong ability in pattern recognition and distributed associative memory [12]. Therefore, in the past several years, many different ANN-based forecasting models have been established for different forecasting problems [13,14]. However, many studies have illustrated that ANN-based models trained using gradient-based approaches such as back propagation or its variants have some weaknesses when applied to various complex fields such as power load forecasting [12,14].

Based on the above considerations, to further improve the forecasting performance of the ANN-based models, many researchers have proposed various hybrid forecasting models based on ANNs. For example, Fard and Akbari-Zadeh [15] investigated the short-term load forecasting problem using a hybrid method based on wavelet, ANN and ARIMA model, and the experiments illustrated its good performance. Moreover, in standard ANN-based models, the initial weight values are usually determined randomly which may result in low robustness and convergence speed. To overcome the disadvantages of standard ANNs, some researchers have combined the optimization algorithms such as genetic algorithms (GA) and particle swarm optimization algorithms (PSO) with ANNs for constructing the forecasting models in which the optimization algorithm is used for training the connection weights of the network or optimizing design of the network structure [16]. For instance, Muralitharan et al. proposed a novel neural network based optimization approach for energy demand prediction, and the proposed neural network includes the following two steps: (1) the conventional neural network approach is employed to find the required energy demand prediction at the consumer end; and (2) neural network based genetic algorithm (NNGA) and neural network based particle swarm optimization (NNPSO) approaches are implemented where the weights of the neural network are automatically adjusted. The experimental result reveals that the proposed NNGA approach performs better for short term load forecasting and proposed NNPSO is more suitable for the long term energy prediction [17]. Ren et al. established a modified elman neural network (ENN) with a new learning rate scheme, and the experiments demonstrated the effectiveness of the proposed scheme from the aspects of convergence speed and consumption time with some popular schemes such as the original ENN, and PSO-ENN which uses PSO algorithm to search the best structure of ENN [18].

Based on aforementioned studies, the main novelties and contributions of this study can be denoted in the following two respects: (1) This study establishes a novel ANN-based hybrid model by combining the PSO algorithm, wavelet analysis and a modified learning rate scheme for the scenario analysis of natural gas consumption in China. Even through some of the previous studies have proposed some ANN-based hybrid models, such as ENN with a novel learning rate scheme [18], GA-ANN [19], differential evolution (DE) algorithm optimized WNN [20], and DE-ELM [21], and have proven the efficiency of the proposed models, the ANN-based hybrid model combining PSO algorithm and wavelet neural network with a modified learning rate scheme needs to be paid more attention. (2) This study conducts the scenario analysis of natural gas consumption from 2017 to 2025 in China based on three scenarios: low scenario, reference scenario and high scenario.

The reminder of the paper is organized as follows. Section 2 introduces the main methodology adopted in this paper. Section 3 introduces the combination strategies and proposes the PSO-WNN hybrid forecasting model. Section 4 first presents the main factors affecting China's natural gas consumption and then tests the performance of the proposed forecasting model. Section 5 first establishes three different scenarios according to three different development situations, and then analyzes the natural gas consumption under the three scenarios and provides some suggestions. Section 6 concludes this paper.

2. Methodology

The research methods used in this study include particle swarm optimization algorithm and wavelet neural network. Brief descriptions of those methods are stated as follows.

2.1. Particle Swarm Optimization (PSO)

Particle swarm optimization (PSO) is an efficient intelligent algorithm for solving the optimized problems [22]. Similar to other swarm-based evolutionary computations, this algorithm also adopts the population concept and evolving iteration to achieve the optimization purpose. At the beginning of the algorithm, all the designed variables are collected to be a parameter vector which is called the particle or the individual from the viewpoint of PSO. Each particle also represents a candidate solution of the optimized problem, and a pre-specified number of particles further constitute a population. In the PSO algorithm, the particle movement is fully dominated by two particular particles: the individual best denoted by P_{best} and the global best denoted by G_{best}. The velocity updating formula of the algorithm utilizes these two particles' information to produce a new particle velocity. After that, next particle position is then derived by the position updating formula using the particle velocity. Based on the evolutionary mechanisms, all particles guided by the global best eventually converge to some system optimum of the optimized problem by successively executing a certain number of iterations.

In the PSO algorithm, let $X = [x_1, x_2, ..., x_n]$ be a particle, where $x_i, i = 1, 2, ..., n$, is the ith system variable of the optimized problem and n is the number of variables. To find the solution of the optimized problem, the following two formulas should be used to guide the particle movement in the iteration process of PSO algorithm.

$$v_{ij}(k+1) = \omega \cdot v_{ij}(k) + c_1 \cdot r_1 \cdot \left(pbest_{ij}(k) - x_{ij}(k) + c_2 \cdot r_2\right) \cdot \left(gbest_j(k) - x_{ij}(k)\right) \quad (1)$$

$$x_{ij}(k+1) = x_{ij}(k) + v_{ij}(k+1) \quad (2)$$

where Equations (1) and (2) represent the velocity formula and position formula, respectively; x_{ij}, $pbest_{ij}$, and $gbest_j$ are the jth position component of the ith particle, the ith individual best, and the global best, respectively; v_{ij} is the jth velocity component of the ith particle; ω is the inertia weight which balances the global and local search; c_1 and c_2 are two positive constants; r_1 and r_2 are two uniformly random numbers chosen from the interval [0,1]; and k is the iterative counter.

The pseudocode of PSO algorithm is listed in Algorithm 1.

Algorithm 1 Pseudocode of PSO algorithm.

Begin
Create the particle swarm and initialize particles
repeat
For all $x_i \in Pop$ **do**
Compute fitness of each particle $f(x_i)$
If $f(x_i) < P_{best}$
Replace P_{best} by x_i, i.e., $P_{best} = x_i$
End if
If $f(x_i) < G_{best}$
Replace G_{best} by x_i, i.e., $G_{best} = x_i$
End if
Update the particles using the following two equations
$v_{ij}(k+1) = \omega \cdot v_{ij}(k) + c_1 \cdot r_1 \cdot \left(pbest_{ij}(k) - x_{ij}(k) + c_2 \cdot r_2\right) \cdot \left(gbest_j(k) - x_{ij}(k)\right)$
$x_{ij}(k+1) = x_{ij}(k) + v_{ij}(k+1)$
End for
Until the termination condition is satisfied
Output the best particle position
End

2.2. *Wavelet Neural Network (WNN)*

The wavelet theory, proposed by Morlet in 1980, appears to be more effective than Fourier transform in studying particularly non-stationary time series [23,24]. Fourier transform gives frequency domain representation for temporal processes of signal or function that is only available in the time domain. Fourier analysis provides frequency information that can only be extracted for the complete duration of the signal, and it provides no information about the local variations in time and requires the signal to be stationary. Fourier transforms decompose stationary signals into linear combinations of sine and cosine waves, while the continuous wavelet transforms decompose non-stationary signals into linear combinations of the wavelets.

The continuous wavelet transform begins with:

$$W_f(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} f(t)\psi\left(\frac{t-b}{a}\right)dt \quad (3)$$

where $W_f(a,b)$ are the wavelet coefficients; a is scaling function used to stretch or compress mother wavelet $\psi(t)$ that is related to the frequency of the signal; b is the translation function used to shift mother wavelet $\psi(t)$ to a time domain of the signal; and $f(t)$ is the input signal. The mother wavelet $\psi(t)$ is defined as follows.

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \tag{4}$$

In this study, the Morlet function (Equation (5)) is taken as the mother wavelet in the analysis process.

$$\psi(t) = Ce^{-t^2/2}\cos 1.75t \tag{5}$$

In terms of the theory of wavelet and the learning ability of neural network, wavelet and the neural networks can be integrated into the wavelet neural network (WNN) to improve the approximation ability, especially on the catastrophe points, of the neural networks. In WNN, wavelet basis functions are used as node activation functions, WNN introduces the wavelet decomposition property into a general neural network, and combines the advantage of time–frequency location of the wavelet transform and self-learning capability of artificial neural networks. Thus, it is approximate and robust.

The WNN in this paper is designed as a three-layer structure with an input layer, a hidden layer, and an output layer. Each layer has one or more nodes. Figure 1 shows the schematic diagram of the proposed three-layer WNN.

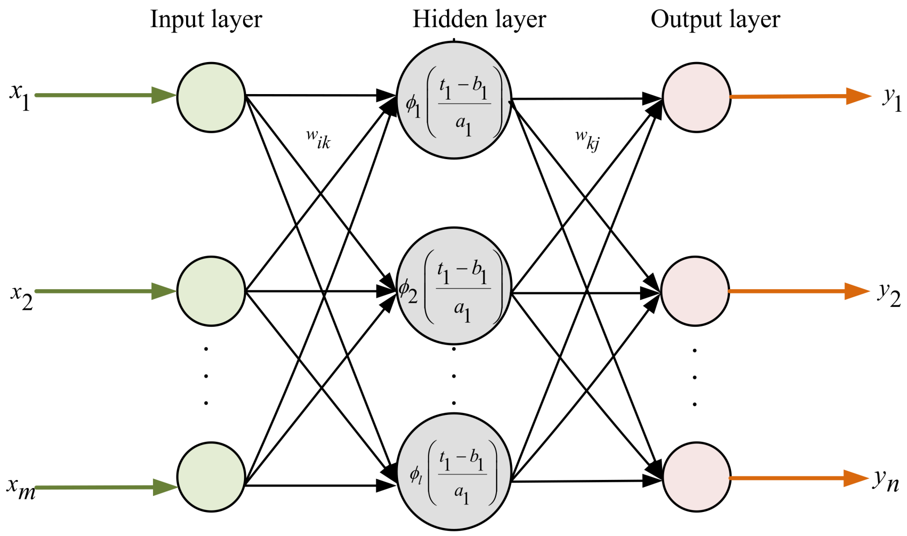

Figure 1. Basic structure of the WNN model.

3. Hybrid PSO-WNN Forecasting model

To avoid falling into the local optimum, the weight values of WNN and the parameters of wavelet, a and b, are optimized using PSO algorithm, see the Figure 2. Let $X = (x_1, \ldots, x_m)$ and $Y = (y_1, \ldots, y_n)$ be the input and output vectors of WNN, and l,W_{ik} and $W_{kj}(i = 1, 2, \ldots, m, k = 1, 2, \ldots, l, j = 1, 2, \ldots, n)$ be the total number of hidden neurons, weight values of the input layer and output layer, respectively. Moreover, suppose that the hybrid forecasting model has a number of P studying samples which are denoted by $I = [X_1, \ldots, X_P], O = [Y_1, \ldots, Y_P]$, where $X_p = \left[x_{1p}, \ldots, x_{mp}\right], Y_p = \left[y_{1p}, \ldots, y_{np}\right], p\,(= 1, \ldots, P)$ represents the p_{th} input sample. Let $Z_k = \left[z_{k1}, \ldots, z_{kp}\right]$ be the output of the k_{th} hidden neuron. In the PSO algorithm, the four parameters w_{ik},w_{kj} and a_k, b_k are coded as one particle, and then the detailed steps of this hybrid PSO-WNN forecasting model can be described as follows.

Step 1: Initialization. Initialize the neural network structures including the number of layers, the number of nodes in each layer, the weight values of WNN, $w_{ik,}$ and w_{kj}, and the parameters of wavelet, a and b. Initialize the parameters of PSO algorithm including the two positive constants c_1 and c_2, the maximum particle velocity, and the total number of particles denoted by $popsize$.

Step 2: Population generation. Code the four neural network parameters including $w_{ik,}w_{kj}$ and a_k, b_k as the particle position vector, i.e.,

$$pos(i) = \left[\omega_{ik}, \omega_{kj}, a_k, b_k\right] \tag{6}$$

where $pos(i)$ represents the position of the ith particle. Then, randomly generate a number of $popsize$ particles as an initial population denoted by $pop(0)$ using both random and artificial ways. The position of each particle represents one feasible solution.

Step 3: Fitness calculation. Calculate the difference between network's output and real values and take this difference as the fitness function of PSO algorithm, i.e.,

$$f = \frac{1}{2P}\sum_{p=1}^{P}\sum_{j=1}^{n}\left(y_{jp} - o_{jp}\right)^2 \tag{7}$$

then, calculate the fitness of each particle according to Equation (7), and take the smallest fitness value as the initial values of P_{best} and G_{best}.

Step 4: Update the P_{best}. Compare the fitness of each particle $(f(x_i))$ with P_{best}. If $f(x_i) < P_{best}$, then replace P_{best} by $f(x_i)$, i.e., $P_{best} = f(x_i)$.

Step 5: Update the G_{best}. Compare the fitness of each particle $(f(x_i))$ with G_{best}. If $f(x_i) < G_{best}$, then replace G_{best} by $f(x_i)$, i.e., $G_{best} = f(x_i)$.

Step 6: Update the position and velocity vectors of particles using the Equations (1) and (2).

Step 7: Stop the PSO algorithm if one of the following is reached: (1) the current iteration number has reached the maximum number of generations; or (2) the fitness value of the particles remains constant for 50 iterations. Then, output the best particle which includes the best combination of $w_{ik,}w_{kj}$ and a_k, b_k, and go to **Steps 8–10** for training the WNN using the training sample. Otherwise, return to **Step 3**.

Step 8: Calculate the output vector. Input the p_{th} sample, obtain the output of the k_{th} hidden neuron through the following Equation (8).

$$Z_{kp} = \psi\left[(\sum_{i=1}^{m} w_{ik}x_{ip} - b_k)/a_k\right] \tag{8}$$

where ψ is the Morlet wavelet function, $\psi(x) = \cos(1.75x)\exp\left(\frac{-x^2}{2}\right)$. For the p_{th} sample, calculate the output of the j neuron in the output layer through the following way:

$$Z_{jp} = w_{j0} + \sum_{k=1}^{l} w_{jk}\left(\psi\left[\sum_{i=1}^{m}\left(w_{ik}x_{ip} - b_k\right)/a_k\right]\right) \tag{9}$$

where w_{j0} is the threshold value of the j neuron in the output layer.

Step 9: Update $w_{ik,}w_{kj}$ and a_k, b_k according to Equations (10)–(13).

$$w_{ik}(t+1) = w_{ik}(t) - \eta\frac{\partial E(t)}{\partial w_{ik}(t)} + \mu\Delta w_{ik}(t) \tag{10}$$

$$w_{kj}(t+1) = w_{kj}(t) - \eta\frac{\partial E(t)}{\partial w_{kj}(t)} + \mu\Delta w_{kj}(t) \tag{11}$$

$$a_k(t+1) = a_k(t) - \eta\frac{\partial E(t)}{\partial a_k(t)} + \mu\Delta a_k(t) \tag{12}$$

$$b_k(t+1) = b_k(t) - \eta\frac{\partial E(t)}{\partial b_k(t)} + \mu\Delta b_k(t) \tag{13}$$

Step 10: Train the network until a set of w_{ik}, w_{kj} and a_k, b_k that satisfies $E = \frac{1}{2P}\sum_{p=1}^{P}\sum_{j=1}^{n}(y_{jp} - o_{jp})^2 < \xi$, where ξ is the pre-specified error and $O_p = [o_{1p}, \ldots, o_{np}]$ is the real value vector related to input sample X_p, is found.

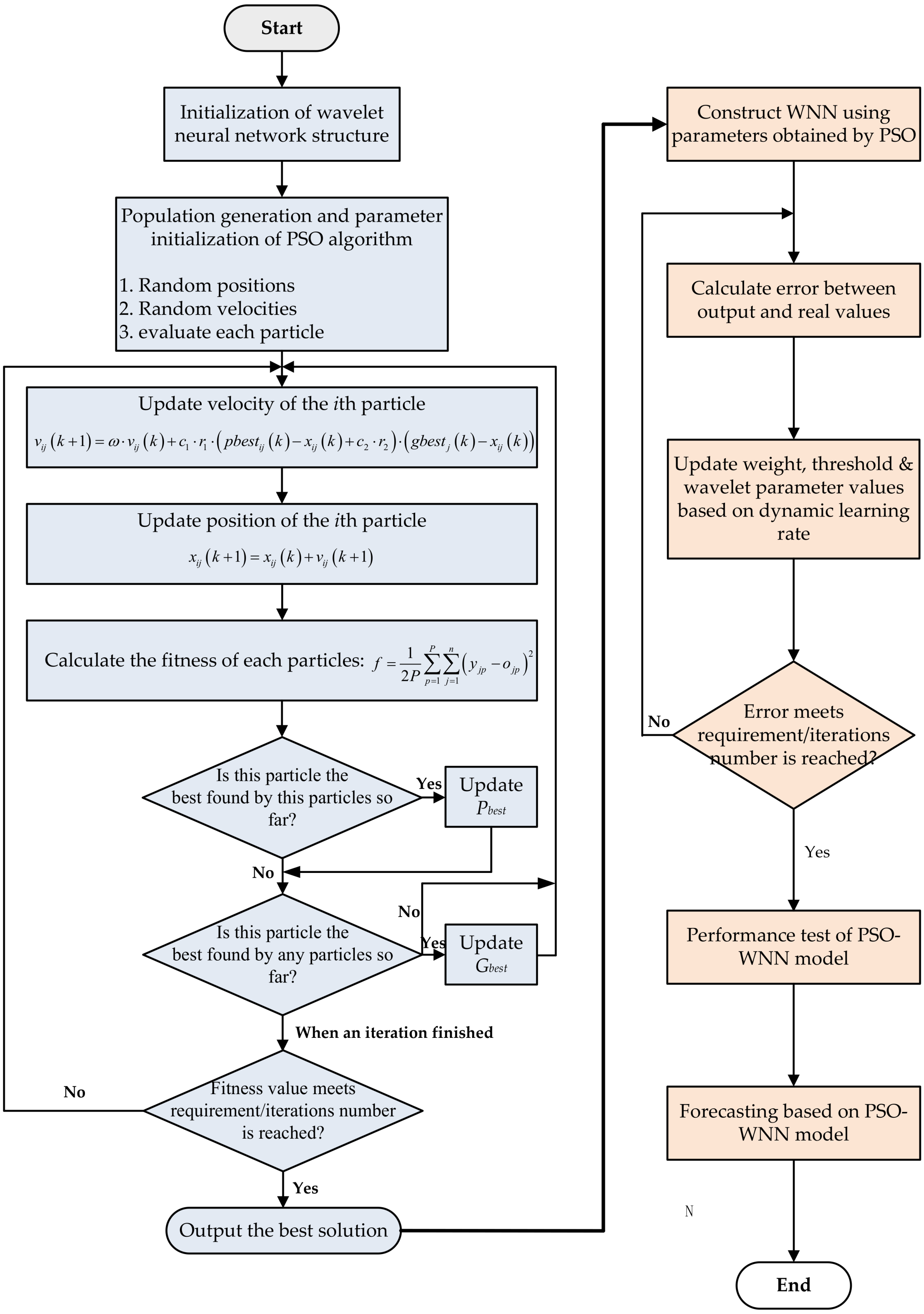

Figure 2. Flowchart of hybrid PSO-WNN forecasting model.

In the training stage of WNN, a dynamic learning rate mechanism is adopted to update the parameter values to improve the convergence speed of WNN, and the steps of this dynamic learning rate mechanism is presented as follows.

Step 1: In the training process of the network, if the total error denoted by ER_{t+1} of $(t+1)^{th}$ iteration is larger than that of t^{th} iteration, and the difference between them is larger than the pre-specified value ς (specified as 3% in this study), then this updating process is ignored and modify the learning rate by $\eta_{t+1} = (1-\alpha)\eta_t$.
Step 2: If $ER_{t+1} < ER_t$, then update $w_{ik,}w_{kj}$ and a_k, b_k. Modify the learning rate by $\eta_{t+1} = (1+\alpha)\eta_t$.
Step 3: If $ER_{t+1} > ER_t$, while the increasing rate is less than ς, update $w_{ik,}w_{kj}$ and a_k, b_k and keep the current learning rate value.
Step 4: The above process of updating the learning rate can be summarized as follows.

$$\eta_{t+1} = \begin{cases} (1+\alpha)\eta_t & E(t+1) \leq E(t) \\ (1-\alpha)\eta_t & E(t+1) > E(t)(1+\varsigma) \\ \eta_t & E(t) < E(t+1) \leq E(t)(1+\varsigma) \end{cases} \tag{14}$$

According to the entropy function theory, for the minimization function, entropy function has faster convergence than mean square error. Thus, in the above updating process of the learning rate value, we set the error function ER as follows:

$$ER = \sum_{p=1}^{P} \sum_{j=1}^{n} \left(z_{pj} \ln o_{pj} + \left(1 - z_{pj}\right) \ln\left(1 - o_{pj}\right) \right) \tag{15}$$

4. Performance Test of the Hybrid PSO-WNN Forecasting Model

In this section, the real data collected from 1995 to 2016 is adopted to test the performance of the proposed hybrid PSO-WNN forecasting model. Before the performance test process, we firstly analyze the factors affecting natural gas consumption in China.

4.1. Affecting Factors of Natural Gas Consumption in China

Natural gas consumption is generally affected by several factors such as GDP, gas price, economic structure, per-capita gas consumption, and proportion in the energy consumed [25]. China's energy system is huge and complex with many uncertainties due to the driving forces of energy requirements. Thus, scientific studies on issues surrounding energy demand and consumption forecasting are challenging to conduct. Even more complicated are the factors affecting the energy consumption in China. The detailed description of key factors is presented as follows.

1. Economic growth. Previous studies show that China's economic growth is the Granger cause of energy consumption growth. Energy demand and consumption tends to grow in line with GDP, although typically at a lower rate. Natural gas, which not only plays the role of important energy in the social development, but also an important raw chemical material in the industrial production, is the important original force of the economic development. Therefore, economic growth reflects the consumption of natural gas. However, due to the huge population of China, the GDP may not be related to an individual's income. Thus, in this study, per capita GDP is used to measure the economic growth.
2. Total amount of gas production (TP). The energy production has close relation with consumption. Natural gas, which is a non-renewable resource, should be produced according to the demand. Therefore, natural gas production has a positive or negative effect on consumption. In recent years, the increasing proportion of natural gas in the energy production structure promotes the growth of consumption.

3. Household consumption level (HCL). With increasing of household consumption level, the public environmental awareness and quality of life improve greatly, which promote the wide use of natural gas in China.
4. Population with access to gas (PAG). The population with access to gas is an important index to reflect the number of gas users. The population with access to gas increases with the development of gas infrastructure, which will drive more gas consumption.
5. Urbanization ratio (UR). Urban and rural residents behave differently in terms of gas use and consumption level. Urban residents have access to better gas services because of better gas supply infrastructure such as urban gas pipelines. It is obviously that urban population growth stimulates the gas consumption. However, rural residents are less privileged in this aspect since they could not afford commercial gas consumption due to their income level. At current stage, China's rural residents contribute little to the total gas consumption. Therefore, urbanization ratio is considered as an important gas consumption factor.
6. Gas price (GP). According to accepted economic theory, price is the primary factor that affects consumption and the important lever for the balance of supply and demand. Price has a significant effect on consumer behavior. When the gas price is too high, users will use some other energy sources such as electricity or coal. In China, even though the gas pricing mechanisms has been changed from the previous cost-plus pricing method to the net market value pricing method, the current gas pricing process is still regulated by the government, and thus cannot fully reflect the scarcity of natural gas [26]. Therefore, the gas price is not considered as an affecting factor in this study.

4.2. Correlation Analysis between the Affecting Factors and Natural Gas Consumption

Correlation analysis measures the relationship between two variables, and its resulting value called the "correlation coefficient" shows if changes in one variable (independent variable) will results in changes in the other one (dependent variable), which helps us understand an indicator's predictive abilities [27,28]. The direction of the dependent variable's change depends on the sign of the coefficient. If the coefficient is a positive number, then the dependent variable will move in the same direction as the independent variable; if the coefficient is negative, then the dependent variable will move in the opposite direction of the independent variable. The correlation coefficient can range $[-1, 1]$. A low correlation coefficient suggests that the relationship between two variables is weak or nonexistent. A high correlation coefficient indicates that the dependent variable will usually change when the independent variable changes. There are several correlation coefficients, and the most common of these is the Pearson correlation coefficient which is adopted in this paper. Table 1 shows the general decision range of two variables' correlation.

Table 1. The general decision range of two variables' correlation.

Absolute Value of Correlation	Correlation Level	Absolute Value of Correlation	Correlation Level
$\lvert r \rvert = 1$	Linear	$\lvert r \rvert > 0.95$	Significant
$\lvert r \rvert \geq 0.8$	Strong	$0.5 \leq \lvert r \rvert \leq 0.8$	Moderate
$\lvert r \rvert < 0.5$	Weak	$\lvert r \rvert = 0$	Nonexistent

According to the actual data for 1995–2016, which were obtained from China Statistical Yearbook [29], the Pearson correlation coefficient of affecting factors listed in Section 4.1 and natural gas consumption are calculated using the SPSS 19.0, as shown in Table 2.

Table 2. Correlation degree between the affecting factors and natural gas consumption.

No.	Affecting Factors	Correlation Degree	Correlation Level	Sorting of Correlation Degree
1	GDP per capita (GDP)	0.8396	Strong	5
2	Total amount of gas production (TP)	0.9834	Significant	1
3	Household consumption level (HCL)	0.9751	Significant	2
4	Population with access to gas (PAG)	0.9737	Significant	3
5	Urbanization ratio (UR)	0.8725	Strong	4
6	length of Pipeline (LP)	0.6971	Moderate	6

Table 2 indicates that there is a significant or strong correlation between natural gas consumption and affecting factors including per capita GDP (unit: RMB yuan), total amount of gas production (unit: million tce ("standard" tons coal equivalent)), household consumption level (unit: RMB yuan), population with access to gas (unit: ten thousand people), urbanization ratio (unit: percent), and, therefore, the combination of these five affecting factors has strong predictive ability for forecasting the natural gas consumption in China.

4.3. Models Comparison

The data of natural gas consumption and the above five affecting factors between 1995 and 2016 are collected from China Statistical Yearbook [29], as shown in Table 3. The per capita GDP, total amount of gas production, household consumption level, population with access to gas and the urbanization ratio are taken as the inputs of the forecasting models, and the amount of natural gas consumption is adopted as the output.

Table 3. Consumption of China's natural gas and values of affecting factors between 1995 and 2016.

Year	Per Capita GDP	TP	HCL	PAG	UR	NGC
1995	5091	2451.65	2355	859.8	29.04	23.61
1996	5898	2660.64	2789	1470.0	30.48	24.33
1997	6481	2802.66	3002	1656.2	31.91	24.46
1998	6860	2856.35	3159	1908.1	33.35	24.51
1999	7229	3298.38	3346	2225.1	34.78	28.11
2000	7942	3646.30	3721	2581.0	36.22	32.33
2001	8717	4028.50	3987	3240.0	37.66	37.33
2002	9506	4369.02	4301	3686.0	39.09	39.00
2003	10,666	4641.46	4606	4320.2	40.53	45.33
2004	12,487	5506.14	5138	5627.6	41.76	52.96
2005	14,368	6486.57	5771	7104.4	42.99	62.73
2006	16,738	7893.68	6416	8319.4	44.34	77.35
2007	20,505	9149.32	7572	10,189.8	45.89	93.43
2008	24,121	10,656.58	8707	12,167.1	46.99	109.01
2009	26,222	11,259.38	9514	14,543.7	48.34	117.64
2010	30,876	12,470.47	10,919	17,021.2	49.95	144.26
2011	36,403	13,673.44	13,134	19,027.8	51.27	178.04
2012	40,007	14,269.46	14,699	21,207.5	52.57	193.02
2013	43,852	15,640.00	16,190	23,783.4	53.73	220.96
2014	47,203	17,007.70	17,778	25,972.94	54.77	242.70
2015	50,251	17,350.85	19,397	28,561.47	56.10	253.64
2016	53,980	18,338.00	21,228	30,855.57	57.35	279.04

To demonstrate the applicability and effectiveness of the proposed PSO-WNN model, the standard ANN and WNN based models are adopted as the two benchmark models, and all the models are programmed in MATLAB language. The data are divided into two sets, in which the first set including the first 18 years of data (from 1995 to 2012) is taken as the training sample, and the second set including the remaining data (from 2013 to 2016) is adopted as the test sample.

This paper adopts the mean absolute percentage error (MAPE) to test the efficiency of the proposed hybrid PSO-WNN model. The computational formulas of MAPE is provided as follows:

$$MAPE = \frac{1}{P}\sum_{p=1}^{P}\left|\frac{Y_p - O_p}{Y_p}\right| \tag{16}$$

where P is the number of samples, and Y_p and O_p are the forecast and real values of natural gas consumption. The fitting values and its relative errors of ANN, WNN and PSO-WNN models are shown in Table 4. Moreover, to well present the difference between these three forecasting models, the performance of ANN, WNN and PSO-WNN models are shown in Figure 3.

Table 4. Performance comparison of ANN, WNN and PSO-WNN models.

Year	Actual	ANN Fittings	∣Error∣ (%)	WNN Fittings	∣Error∣ (%)	PSO-WNN Fittings	∣Error∣ (%)
1995	23.61	25.71	8.89	23.82	0.89	24.06	1.91
1996	24.33	25.65	5.43	22.52	7.44	24.11	0.90
1997	24.46	25.87	5.76	25.03	2.33	23.89	2.33
1998	24.51	25.76	5.10	26.19	6.85	24.82	1.26
1999	28.11	26.87	4.41	27.21	3.20	28.55	1.57
2000	32.33	30.22	6.53	29.28	9.43	32.68	1.08
2001	37.33	32.94	11.76	36.41	2.46	37.92	1.58
2002	39.00	37.82	3.03	36.71	5.87	38.12	2.26
2003	45.33	43.07	4.99	46.26	2.05	44.29	2.29
2004	52.96	54.70	3.29	55.86	5.48	55.99	5.72
2005	62.73	66.02	5.24	61.37	2.17	61.75	1.56
2006	77.35	76.83	0.67	75.69	2.15	76.28	1.38
2007	93.43	91.10	2.49	89.25	4.47	92.28	1.23
2008	109.01	103.90	4.69	112.88	3.55	112.71	3.39
2009	117.64	122.17	3.85	120.78	2.67	119.12	1.26
2010	144.26	140.87	2.35	145.61	0.94	141.60	1.84
2011	178.04	170.27	4.36	173.86	2.35	179.81	0.99
2012	193.02	187.46	2.88	187.32	2.95	197.13	2.13
MAPE	-	-	4.76	-	3.74	-	1.93
Year	**Actual**	**Forecast Value of ANN**	**∣Error∣ (%)**	**Forecast Value of WNN**	**∣Error∣ (%)**	**Forecast Value of PSO-WNN**	**∣Error∣ (%)**
2013	220.96	209.71	5.09	216.59	1.98	223.70	1.24
2014	242.70	256.60	5.73	234.43	3.41	247.14	1.83
2015	253.64	270.85	6.79	265.42	4.64	261.09	2.94
2016	279.04	297.22	6.52	297.07	6.46	288.11	3.25
MAPE	-	-	6.03	-	4.12	-	2.31

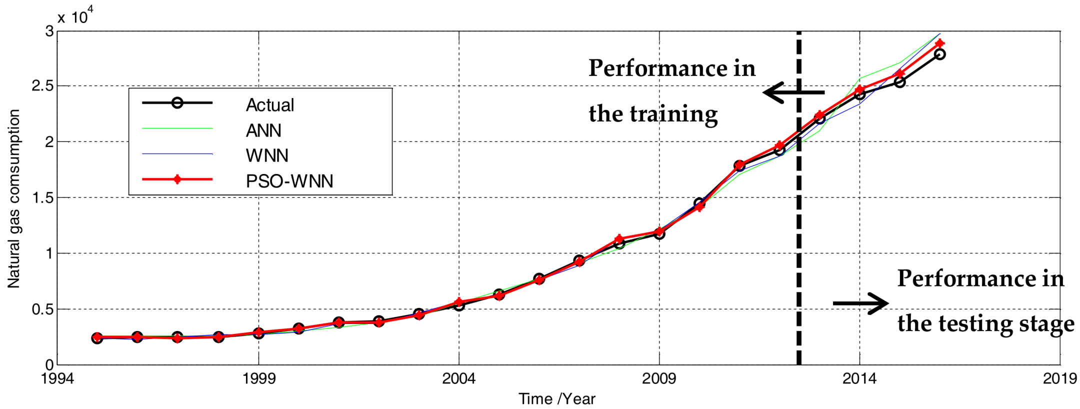

Figure 3. Performance of ANN, WNN and PSO-WNN models.

In Table 4 and Figure 3, it is obviously that the PSO-WNN model preforms better than ANN and WNN based models in both simulation and forecasting stages, which illustrates the good forecasting performance of PSO-WNN model. The reason that the PSO-WNN model outperform ANN and WNN based models can be interpreted by the following three aspects: (1) by combining the wavelet analysis and neural network, the WNN obtains strong function approximation ability, especially on the catastrophe points; (2) by adjusting the wavelet parameters and applying a dynamic learning rate mechanism for updating the connection weight values, WNN can effectively make up the disadvantage of falling into local optimum of traditional ANNs; and (3) by optimizing the connection weight values and wavelet parameters using PSO algorithm, the convergence efficiency and forecasting precision of WNN are effectively improved.

5. Scenario Analysis of Natural Gas Consumption in China during 2017–2025

Natural gas consumption is influenced by many factors which contain uncertainty that will be passed on to the forecast. To reduce this uncertainty, scenario analysis can be applied to investigate different outcomes depending on alterations in the underlying assumptions. Scenario analysis is a process of analyzing possible future events by considering alternative possible outcomes [30,31]. Thus, scenario analysis, which is a main method of forecasting, does not try to show one exact picture of the future. Instead, it presents consciously several alternative future developments.

In this paper, three different scenarios are established and categorized as high, reference and low scenarios. Parameters such as per capita GDP, total amount of gas production, household consumption level, population with access to gas, and urbanization ratio are chosen to reflect the storylines of the different scenarios. The increasing rates of these five affecting factors and their corresponding values are shown in Tables 5 and 6.

Table 5. The increasing rate of each affecting factor in Low, Reference and High scenarios.

Scenarios Settings	Per Capital GDP	TP	HCL	PAG	UR
Increasing rate in low scenario	6.0%	5.0%	12.0%	9.0%	1.5%
Increasing rate in reference scenario	7.0%	6.0%	14.0%	11.0%	2.0%
Increasing rate in high scenario	8.0%	7.0%	16.0%	13.0%	2.5%

Table 6. Results for each scenario under different settings of affecting factors.

	Year	Per Capital GDP	TP	HCL	PAG	UR (%)	NGC
Low-scenario	2017	57,218.80	19,254.90	23,775.36	33,632.57	58.21	297.18
	2018	60,651.93	20,217.65	26,628.40	36,659.50	59.08	313.52
	2019	64,291.04	21,228.53	29,823.81	39,958.86	59.97	328.89
	2020	68,148.51	22,289.95	33,402.67	43,555.16	60.87	342.70
	2021	72,237.42	23,404.45	37,410.99	47,475.12	61.78	356.06
	2022	76,571.66	24,574.67	41,900.31	51,747.88	62.71	369.24
	2023	81,165.96	25,803.41	46,928.34	56,405.19	63.65	382.53
	2024	86,035.92	27,093.58	52,559.75	61,481.66	64.60	395.15
	2025	91,198.07	28,448.26	58,866.92	67,015.01	65.57	407.01
Refer-scenario	2017	57,758.60	19,438.28	24,199.92	34,249.68	58.50	299.97
	2018	61,801.70	20,604.58	27,587.91	38,017.15	59.67	319.77
	2019	66,127.82	21,840.85	31,450.22	42,199.03	60.86	339.59
	2020	70,756.77	23,151.30	35,853.25	46,840.93	62.08	358.27
	2021	75,709.74	24,540.38	40,872.70	51,993.43	63.32	376.18
	2022	81,009.42	26,012.80	46,594.88	57,712.71	64.59	393.11
	2023	86,680.08	27,573.57	53,118.16	64,061.10	65.88	408.84
	2024	92,747.69	29,227.99	60,554.70	71,107.83	67.19	423.96
	2025	99,240.03	30,981.67	69,032.36	78,929.69	68.54	437.95

Table 6. *Cont.*

	Year	Per Capital GDP	TP	HCL	PAG	UR (%)	NGC
High-scenario	2017	58,298.40	19,621.66	24,624.48	34,866.79	58.78	301.36
	2018	62,962.27	20,995.18	28,564.40	39,399.48	60.25	323.06
	2019	67,999.25	22,464.84	33,134.70	44,521.41	61.76	345.03
	2020	73,439.19	24,037.38	38,436.25	50,309.19	63.30	366.42
	2021	79,314.33	25,719.99	44,586.05	56,849.39	64.89	387.67
	2022	85,659.48	27,520.39	51,719.82	64,239.81	66.51	409.00
	2023	92,512.23	29,446.82	59,994.99	72,590.98	68.17	428.22
	2024	99,913.21	31,508.10	69,594.19	82,027.81	69.88	445.78
	2025	107,906.27	33,713.67	80,729.26	92,691.43	71.62	461.38

Based on the above three scenario settings, this study takes the five affecting factors and the natural gas consumption as the input and output of PSO-WNN forecasting model, respectively. Based on this proposed model, the natural gas consumption in China from 2017 to 2025 has been analyzed under low, reference and high scenarios, and the results are listed in Table 6 and Figure 4. From Figure 4, the following three observations can be obtained.

1. Based on the results of scenario analysis, the China's natural gas consumption is going to be 342.70, 358.27, 366.42 million tce ("standard" tons coal equivalent) in 2020, and 407.01, 437.95, 461.38 million tce in 2025 under the low, reference and high scenarios, respectively.
2. The natural gas consumption in the high, reference and low scenarios have a similar increasing trend, while, over time, the gap of natural gas consumption between high and low cases becomes larger and larger.
3. In all three scenarios, natural gas consumption increases relatively rapid from 2017 to 2020, while, after 2020, it increases relatively slow and has the trend to be relatively stable after 2025, which may be interpreted as, in the first four years (2017–2020), the five affecting factors have direct and important influences on the natural gas consumption, while, afterwards, many other factors such as policy and international energy environment, which are not considered in this study, will have influences on the forecasting results.

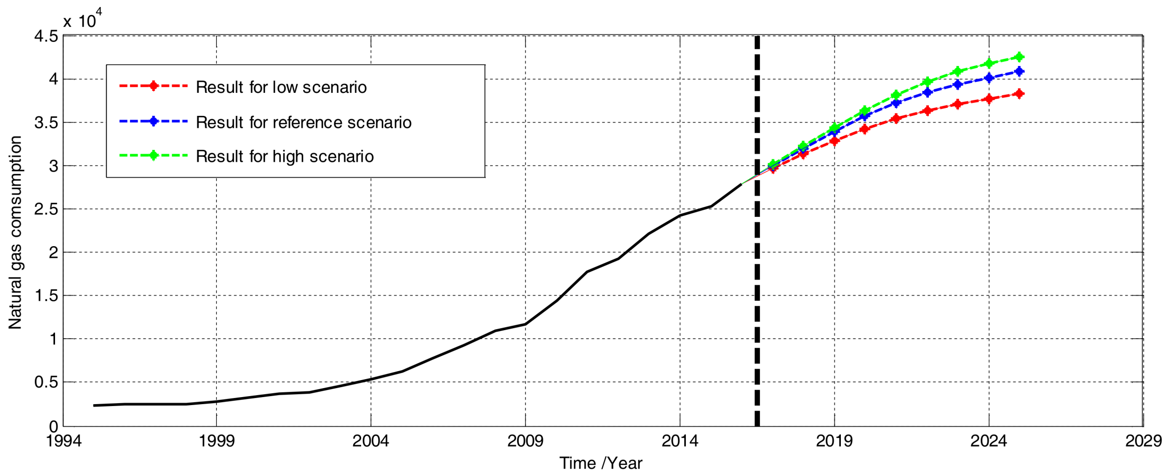

Figure 4. Natural gas consumption for each scenario (2017–2025).

6. Conclusions

Accurately forecasting natural gas consumption becomes very crucial for all market participants to organize indigenous production, foreign supply contracts and infrastructures in a better way. This paper first presents the main factors affecting China's natural gas consumption, and then establishes a hybrid forecasting model by combining the Particle Swarm Optimization algorithm and Wavelet Neural Network. Finally, this study conducts scenario analysis of natural gas consumption from 2017 to 2025 in China based on low, reference and high scenarios. Based on the results, the following conclusions and strategic enlightenments are obtained:

1. The combination of five affecting factors, namely per capita GDP, total amount of gas production, household consumption level, population with access to gas and urbanization ratio, obtained using the correlation analysis, has significant or strong predictive ability for natural gas consumption in China.
2. The PSO-WNN model successfully predicts gas consumption as reflected by a MAPE value of 2.32% for prediction, and outperforms others. Based on the experiment shown in Figure 4, it is obviously that WNN model performs better than ANN model, which can be explained as, by combining the wavelet and neural work, WNN obtains strong function approximation ability, especially on the catastrophe points. Moreover, by adjusting the wavelet parameters and applying a dynamic learning rate mechanism for updating the connection weight values, WNN can effectively avoid falling into the local optimum. PSO-WNN model outperforms WNN model, which can be interpreted as the optimization of network weights and wavelet parameters using PSO algorithm effectively improves the forecasting precision and reduces fluctuation of WNN model.
3. Natural gas consumption in China will keep a relatively rapid growing tendency. According to the results of scenario analysis, the China's natural gas consumption is going to be 342.70, 358.27, 366.42 million tce ("standard" tons coal equivalent) in 2020, and 407.01, 437.95, 461.38 million tce in 2025 under the low, reference and high scenarios, respectively. To satisfy the increasing demand of natural gas consumption, the Chinese government should take some constructive measures: (a) The Chinese government should promote new exploration and development of natural gas reserves, especially in the southwest and northwest regions of China. The current estimation of natural gas resources indicates a URR of 22 trillion cubic meters, mainly distributed in southwest and northwest China; (b) The Chinese government should promote infrastructure construction such as enlargement of natural gas pipeline networks; (c) The Chinese government should accept that natural gas imports are unavoidable in future, thus seeking new suppliers and forging new relationships and collaborations in the gas sector are essential.

The proposed hybrid PSO-WNN model has satisfactory performance for natural gas consumption forecasting, which can be adopted as an important tool for government or company energy related decision-making processes.

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Abbreviations

ANN	Artificial neural network
ENN	Elman neural network
WNN	Wavelet neural network
PSO	Particle swarm optimization
PSO-WNN	Wavelet neural network optimized by particle swarm optimization algorithm
ARIMA	Auto-regressive integrated moving average
ARMA	Auto-regressive moving average

GM	Grey forecasting model
GARCH	Generalized autoregressive conditional heteroscedasticity
ELM	Extreme learning machine
SVM	Support vector machine
LSSVM	Least squares support vector machine
FAHP	Fuzzy C-Means integrating analytic hierarchy process
BP	Back propagation
GA	Genetic algorithm
GDP	Gross domestic product
TP	Total amount of gas production
HCL	Household consumption level
PAG	Population with access to gas
UR	Urbanization ratio
LP	Length of Pipeline
GP	Gas price
MAPE	Mean absolute percentage error

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