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Development of two intelligence-based scenarios for prediction of future natural gas consumption

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Abstract: In this paper, two intelligence-based scenarios are developed in order to predict natural gas consumption in Iran. These scenarios are based on hybrid artificial intelligence (AI) and metaheuristic algorithms. The first scenario is the bats scenario, in which the bat algorithm (BA) is combined with the artificial neural network (ANN) in order to predict future natural gas consumption. The second scenario is based on hybrid ANN and particle swarm optimization (PSO), which is named as a birds scenario. The comparison of the proposed models (ANN-BA and ANN-PSO) showed that the bats scenario is superior to the birds scenario in the prediction of natural gas consumption. The obtained results were reported in terms of determination coefficient and mean square error.

Key words: Artificial intelligence; Natural gas consumption; Bats scenario; Birds scenario; Artificial neural network

1. Introduction

Natural gas is known as a very important energy source in the world. In recent years, the growth of natural gas consumption has been faster than with other types of energy sources, such as oil. By considering total energy consumption in Iran, the percentage share of natural gas consumption has dramatically increased over the past decades. Iran, as a member of OPEC, would be top holders of proven oil and natural gas reserves compared to other countries. The energy policy in Iran is based on an increase of gas usage due to this fact that there are large gas reserves, and also because of the advantages of gas versus oil.

Forecasting and planning natural gas consumption has played a significant role in different aspects of energy policy. In this regard, many investigations have been performed at different levels: at a world level (Valero, 2010; Mohr and Evans, 2011), at national level (Siemek et al., 2003; Gutierrez et al., 2005; Forouzanfar et al., 2010), in both industrial (Sanchez & Berzosa, 2007; Huntington, 2007) and residential sectors (Yoo et al., 2009), at the level of gas distribution systems (Potocnik et al., 2007; Sabo et al., 2011), in both the commercial and residential sectors, and finally, at the level of individual customers (Vondracek et al., 2008).

Successful applications of various techniques have been reported, such as autoregressive integrated moving average (ARIMA), support vector regression (SVR), artificial neural networks (ANNs) and adaptive network-based fuzzy inference system (ANFIS), in the field of prediction of demand and production. Soldo (2012) provides a good overview of different approaches that have so far been used in the field of natural gas consumption forecasting.

In spite of the suitable flexibility of ANN models in doing a variety of tasks including prediction, classification, and function approximation, sometimes an optimal solution could not be obtained. This issue stems from the inappropriate selection of the ANN structure or inadequate adjustment of weights during the training process of the network. Over the last decade, evolutionary algorithms (EAs) have been widely employed to address these problems. Several different attempts have been proposed by various researchers in order to find an optimal solution in ANN training, by using EAs such as genetic algorithms (GA), particle swarm optimization (PSO) and bat algorithms (BA). These procedures are the most popular optimization algorithms, which employ a population of individuals to solve the problem at hand (Yu et al., 2012; Unler, 2008).

The PSO algorithm is a stochastic optimization technique developed by Eberhart and Kennedy (1995). It is inspired by the collective behaviour of animals such as flocks of birds, and contributes to engineering applications. It is highly capable of solving nonlinear optimization functions in multidimensional space. BA is a new population-based metaheuristic approach presented by Yang (2010). This technique, which is based on the hunting behaviour of bats, makes it easy to find the possible solution of the problem by using bat positions. In this method, the quality of the solution

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is indicated by the best position of a bat to its prey. BA has been tested for continuous constrained optimization problems (Yang, 2010).

The aim of this paper is to provide two scenarios based on hybrid ANN and EAs for the prediction of future natural gas consumption. The first and second scenarios are named as birds and bats, respectively. This study seeks to examine the capability of two scenarios in forecasting future natural gas consumption in Iran. In the current research, the radial basis function (RBF) network is considered as a basic structure of the ANN model to develop scenarios.

The remainder of this paper is organized as follows. In the next three sections, the concepts of the RBF network, PSO, and BA algorithms, respectively, are briefly reviewed. Section 5 presents the formulations and structures of the proposed hybrid models (ANN-PSO and ANN-BA). In Sections 6 and 7, the efficiency criteria and case study (natural gas consumption) are introduced, and in Section 8 the efficiency of proposed scenarios for the prediction of natural gas consumption are evaluated, discussed, and compared with each other. Concluding remarks are in the final section of the paper.

2. Radial Basis Function Neural Network (RBFNN)

Neural networks are black box models which invigorate us to perform non-linear mapping between input and output data with arbitrary accuracy. The breadth literature of Radial Basis Function Neural Network (RBFNN) can be found in Broomhead and Lowe (1988). RBFNN has been extensively used by the researchers over the last decades. This popularity is due to its simple structure and training efficiency. RBFNN consists of three layers including input layer, hidden radial basis layer, and an output layer. The hidden layer contains neurons with non-linear functions called basis functions wherein the inputs involving linear combinations of scalar weights and the input vector $x = [x_1, x_2, \dots, x_n]$ are entered into them. Afterwards, all input vector are imposed to each hidden neuron in hidden layer. In each hidden node the incoming vectors are mapped through the radial basis functions. The output layer results in a vector $y = [y_1, y_2, \dots, y_m]$ for m outputs by linear combination of the outputs of the hidden nodes to produce the final output. Thus, the network output can be obtained by:

$$y = f(x) = \sum_{i=1}^{k} W_i \psi_i(x) + \beta_i \qquad (1)$$

Where $f(x)$, $\psi_i(x)$ and W_i are the output of network, radial basis function of the ith hidden node and hidden-to-output weight corresponding to the ith hidden node, respectively. Also k denotes the total number of hidden nodes. The hidden layer neurons has bias β_i.

The radial basis function as multidimensional function describes the distance between a given input vector and a predefined center vector. Among the different types of radial basis function, normalized Gaussian function is usually used as the radial basis function which is derived by:

$$\psi_i(x) = \exp\left[\frac{\|x - \mu_i\|^2}{2\sigma_i^2}\right] \qquad (2)$$

Where μ_i and σ_i are the center and spread width of the ith node, respectively. The basic structure of RBFNN is shown in Fig. 1. Each hidden neuron in a RBFNN computes the Euclidean distance between input vector and the center of that unit. The Euclidean distance is given by:

$$\varepsilon = \|x - \mu_i\| \qquad (3)$$

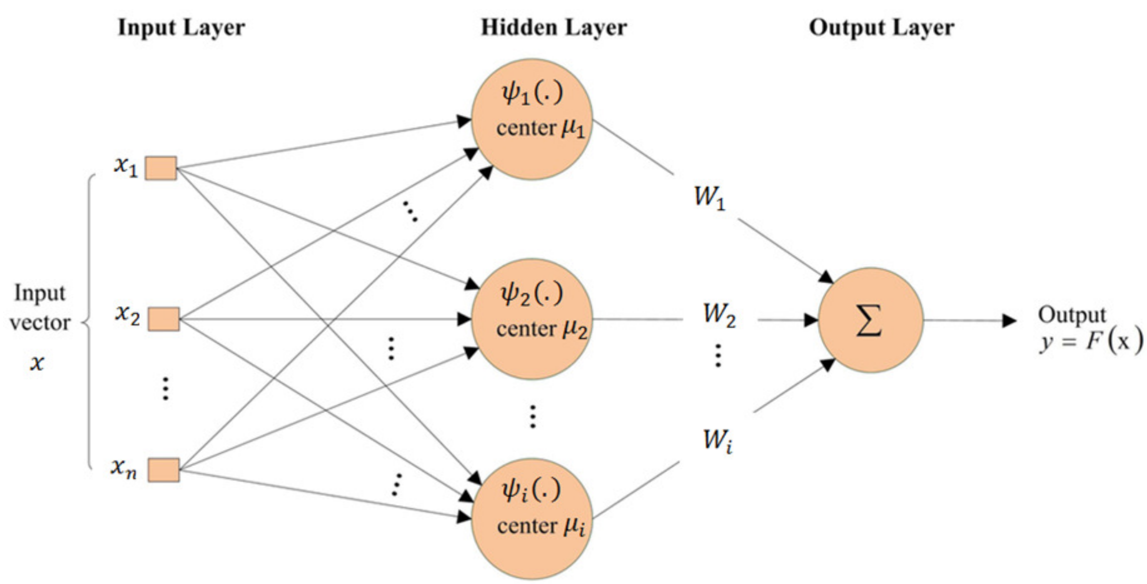

Fig. 1: The basic structure of RBFNN

The number and location of centers in the hidden layer play a significant role in the performance of the RBFNN model. There are two scenarios for training of RBFNN. (a) Determination of radial basis function parameters (i.e., spread width and Gaussian center). To this end, the K-means clustering procedure is commonly used. (b) Determination of output weight through supervised learning method. For this purpose, usually the Least-Mean-Square (LMS) or Recursive Least-Square (RLS) are used.

3. Particle Swarm Optimization (PSO)

The underlying motivation of PSO algorithm is based on social behavior of flocks of birds. This technique makes it possible to solve complex optimization problems. It has been widely used in various types of engineering applications. The PSO algorithm is a population based optimization method in which birds use the information of whole group for finding their direction. Hence, during each flight (iteration), birds as particles update their velocities and positions by the best experience of whole group ($Gbest$) and their own ($Pbest$). The number of variables in each problem determines the dimension of particles (Tichi et al., 2010).

Suppose that F represent function quality that measure how close the solution to the optimal solution and t is the current time, the best position taken by the particle is updated as follows (Engelbrecht, 2007):

$$Pbest_i^{(t+1)} = \begin{cases} Pbest_i^{(t)} \, if F\left(X_i^{(t+1)}\right) \geq F\left(Pbest_i^{(t)}\right) \\ X_i^{(t+1)} if F\left(X_i^{(t+1)}\right) < F\left(Pbest_i^{(t)}\right) \end{cases} \quad (4)$$

$X_i^{(t)}$ is the current location of the particle i. The best position in the swarm ($Gbest^{(t)}$) at time t is calculated as follows:

$$Gbest^{(t)} \in \left\{Pbest_0^{(t)}, \dots, Pbest_{N_s}^{(t)}\right\} \left| F\left(Gbest^{(t)}\right) = min\left\{F\left(Pbest_0^{(t)}\right), \dots, F\left(Pbest_{N_s}^{(t)}\right)\right\} \right. \quad (5)$$

N_s is the total number of particles in the swarm. The velocity is updated according to:

$$V_i^{(t+1)} = WV_i^{(t)} + c_1 r_1\left(Pbest_i^{(t)} - X_i^{(t)}\right) + c_2 r_2\left(Gbest^{(t)} - X_i^{(t)}\right) \quad (6)$$

In which; $V_i^{(t)}$ represents the velocity of the particle i at time t and i is the($i = 1,2,\dots,N$), where N represents the number of birds in swarm. W is the weight of inertial value of {0,1}. c_1 and $c_2$are the constants and acceleration coefficients, respectively. r_1 and r_2 are random values in the range (0,1) sampled from a uniform distribution. Finally, position of the particle is updated by the following formulation:

$$X_i^{(t+1)} = X_i^{(t)} + V_i^{(t+1)} \quad (7)$$

Fig. 2 shows the trajectory of a particle in a swarm is adjusted by using the velocity and position updates, according to Eq. 6.

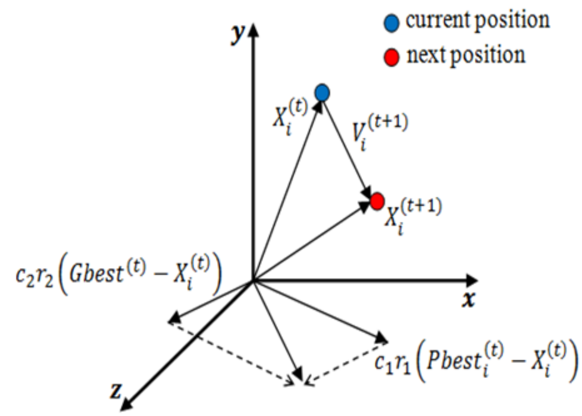

Fig. 2: Trajectory of the particle in the PSO

Fig. 3 represents a flowchart of the PSO algorithm. The first step of the PSO algorithm is to create a 'population' of particles uniformly distributed over the entire search space. Then each particle's position according to the objective function is evaluated. If a particle's current position is better than its previous best position, it should be updated. The ensuing task is to determine the best particle (according to the particle's previous best positions). The next step is to update particles' velocities using Eq. 6 and move particles to their new positions through Eq. 7 This process will be continued until stopping criteria are satisfied.

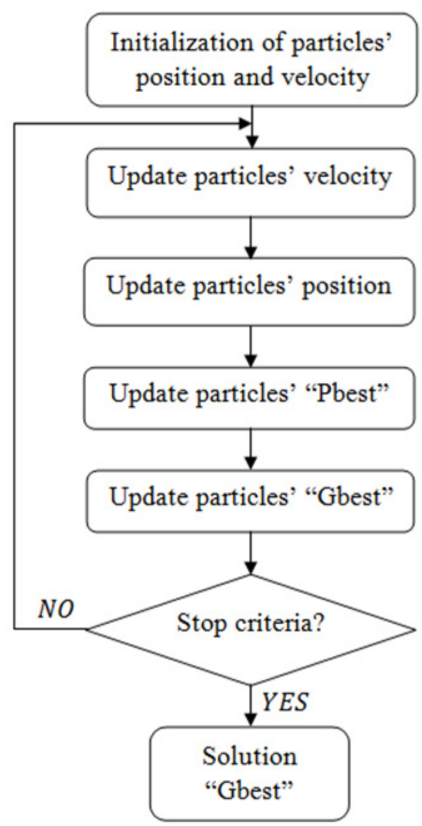

Fig. 3: The flowchart of PSO Algorithm

4. Bat Algorithm (BA)

Bat Algorithm (BA) as new meta-heuristic method was presented by Yang in 2010. This algorithm is based on the echolocation behavior of bats. The capability of echolocation of microbats is fascinating as they can find their prey and discriminate different types of insects even in complete darkness. These bats emit a loud and short pulse of sound, wait it hits into an object and, after a fraction of time, the echo returns back to their ears (Griffin et al., 1960). Thus, bats can compute how far they are from an object. BA as new optimization technique has attracted attention of researchers from different fields. Such technique has been developed to behave as a band of bats tracking prey/foods using their capability of echolocation (Nakamura et al., 2012). In order to model this algorithm, Yang (2010) has idealized the following rules:

1. All bats use echolocation to sense distance, and they also "know" the difference between food/prey and background barriers in some magical way.
2. A bat b_i fly randomly with velocity v_i at position x_i with a fixed frequency f_{min}, varying wavelength λ and loudness A_0 to search for prey. They can automatically adjust the wavelength (or frequency) of their emitted pulses and adjust the rate of pulse emission $r \in [0,1]$, depending on the proximity of their target.
3. Although the loudness can vary in many ways, Yang (2010) assume that the loudness varies from a large (positive) A_0 to a minimum constant value A_{min}.

At first, the initial parameters named position (x_i), velocity (v_i) and frequency (f_i) are initialized for each bat b_i. For each time step t, being T the maximum number of iterations. By updating the velocity and position of virtual bats through the following equations, the movement of them is obtained.

$f_i = f_{min} + \beta(f_{min} - f_{max})$ (8)

$v_i^{(t)} = v_i^{(t-1)} + f_i\left(x_i^{(t-1)} - x_{cgbest}\right)$ (9)

$x_i^{(t)} = x_i^{(t-1)} + v_i^{(t)}$ (10)

In which, $\beta \in [0,1]$ is a random vector drawn from a uniform distribution. The results of Eq. 8 (f_i) is applied in order to control the pace and range of the movement of the bats. The variable x_{cgbest} is the current global best location (solution) which is located after comparing all the solutions among all the m bats. In order to improve the variability of the possible solutions, Yang (2010) has proposed to employ random walks by which each bat takes a random walk creating a new solution for itself based on the best selected current solution.

$x_{New} = x_{Old} + \varepsilon\bar{A}(t)$ (11)

Where $\varepsilon \in [-1,1]$ is a random number which attempts to the direction and strength of the random walk, while $\bar{A}(t)$ is the average loudness of all the bats at this time step. The update of the velocities and positions of bats have some similarity to the procedure in the PSO algorithm (Kennedy and Eberhart, 1995). For each iteration of the algorithm, the loudness A_i and the emission pulse rate r_i are updated, as follows:

$A_i^{(t+1)} = \alpha A_i^{(t)}$ (12)

$r_i^{(t+1)} = r_i^0[1 - \exp(\gamma t)]$ (13)

where $\alpha$and γ are ad-hoc constants. At the first step of the algorithm, the emission rate $r_i^{(0)}$ and the loudness $A_i^{(0)}$ are often randomly chosen. Typically, $A(0) \in [1,2]$ and $r_i^{(0)} \in [0,1]$.

The steps of Bat Algorithm are as follows:

Objective function $f(x), x = (x^1, \ldots, x^n)$

Initialize the bat population x_i and $v_i, i = 1,2, \ldots, m$

Define pulse frequency f_i at $x_i, \forall i = 1,2, \ldots, m$

Initialize pulse rate r_i and the loudness $A_i, i = 1,2, \ldots, m$

1. While $t < T$
2. for each bat b_i, do
3. Generate new solutions through Equations (8, 9 and 10)
4. If $rand > r_i$, then
5. Select a solution among the best solutions
6. Generate a local solution around the best solution
7. If $rand < A_i$, and $f(x_i) < f\left(x_{cgbest}\right)$,then
8. Accept a new solution
9. Increase r_i and reduce A_i
10. Rank the bats and find the current best x_{cgbest}

5. Proposed Models

5.1. Hybrid ANN-PSO model

The efficiency of the RBFNN model mainly relies on the centre and the width of the radical basis function of the hidden layer, and the weight values of the output layer. Usually, the learning strategy in the RBFNN faces difficulties due to finding the optimal solution only in local space. This would cause the network's parameters to be set inappropriately. To deal with this deficiency, many approaches have been proposed over the past decades. PSO is one of these procedures with the advantages of fast convergence speed and strong global search capability. Hence, in the current research, a PSO algorithm was used in order to improve the efficiency of the traditional RBFNN model. The parameters of the RBFNN model were optimized as follows:

1. Initialization of particle swarm and RBFNN (i.e., acceleration coefficients of particle swarm, particle velocity and position). The minimum error and the maximum number of iterations are to be taken into account. RBFNN should be initialized, the centres and the width represent particles, and the values of the weights and the bias are created randomly.
2. The second step of the optimization process is to select the best position of each particle and the global best position of the swarm. The fitness value of each particle is obtained using Eqs. 4 and 7. The speed and position are updated using Eqs. 6 and 7.

3. The iteration should be stopped if the requirements of the minimum error are met. Otherwise, return to step 2.

4. The value of the best position attained by the particles is of the parameters of the RBFNN model. By the same token, the search position of each particle is evaluated using the mean square error to the point of finding the optimal parameters, and developing the optimal RBFNN model. These obtained parameters are to be used in order to verify the proposed model. This process is carried out via a test dataset. It is worthy of note that the ANN-PSO model is calibrated using the training dataset. The pseudocode of PSO-based RBFNN is presented in Fig. 4.

```
for Each particle(i)
Initialize particle position and velocity
end for
while Maximum iteration is not attained
  for Each particle
    Calculate fitness value (Mean Square Error in RBF Network)
    if Fitness function of particle(i) is better than fitness function of Pbest(i)
      Then put particle(i) into Pbest(i)
       end if
       end for
  Put the best of Pbests in terms of fitness function into Gbest
  for Each particle(i)
    Calculate particle velocity based on Eq. (6)
    Update particle position (center, width and weight) based on Eq. (7)
  end for
  end while
```

Fig. 4: The pseudo code of the hybrid RBF-PSO algorithm

5.2. Hybrid ANN-BA model

The second presented hybrid model is the ANN-BA, with which optimization of the parameters of RBFNN have been attempted through the evolutionary procedure of the bat algorithm. The training process of the RBFNN model was implemented using hybridization of the BA concept into the structure of RBFNN. Centre (μ), width (σ), weight (W) and bias of the cells in a layer output (β) are the parameters of RBFNN, which were considered for the purpose of optimization. For the proposed model (ANN-BA), the first task is to initialize the parameters and population of the BA (i.e., m, λ, A_0, r, f_{min}, f_{max}). The frequency (f_i), velocity (v_i) and position (x_i) must also be initialized. Then, for each bat (b_i) and time step t, the RBF training process is accomplished. If the fitness function (MSE) meets the stopping criteria then the optimum RBFNN is concluded; otherwise, the frequency, velocity, and position should be updated using Eqs. (8), (9) and (10). The final step is to keep the best RBFNN parameters (i.e., μ, σ, W and β). These optimized parameters are used in order to verify the proposed model (verification process) by the use of the test dataset. It should be noted that the proposed model is calibrated by using the training data.

6. Efficiency criteria

The following measures of evaluation have been used to compare the performance of the proposed models.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(Y_i - P_i)^2}{\sum_{i=1}^{N}(Y_i - \overline{Y}_i)^2} \quad (14)$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(Y_i - P_i)^2 \quad (15)$$

where R^2, MSE, N, Y_i, P_i and $\overline{Y}_i$ are determination coefficient, Mean Squared Error, number of observations, observed data, computed values and mean of observed data, respectively.

7. Case study

Due to upmost importance of the energy consumption in the context of making energy policy, large numbers of models dealing with different sources of energy have been developed in order to predict the future status of energy consumption. Natural gas consumption as main source of energy in Iran plays a vital role in the various sectors including economical and industrial sectors.

The data used in this study is from the natural gas consumption of Iran. The time series data (Fig. 5) for 33 years (from 1980 to 2012) were used in the modeling process (the first 25 years for training and the rest 8 years for the verification). The statistic characteristics of natural gas consumption in annual time scale are tabulated in Table 1.The data set before going through the network were normalized between 0 and 1.

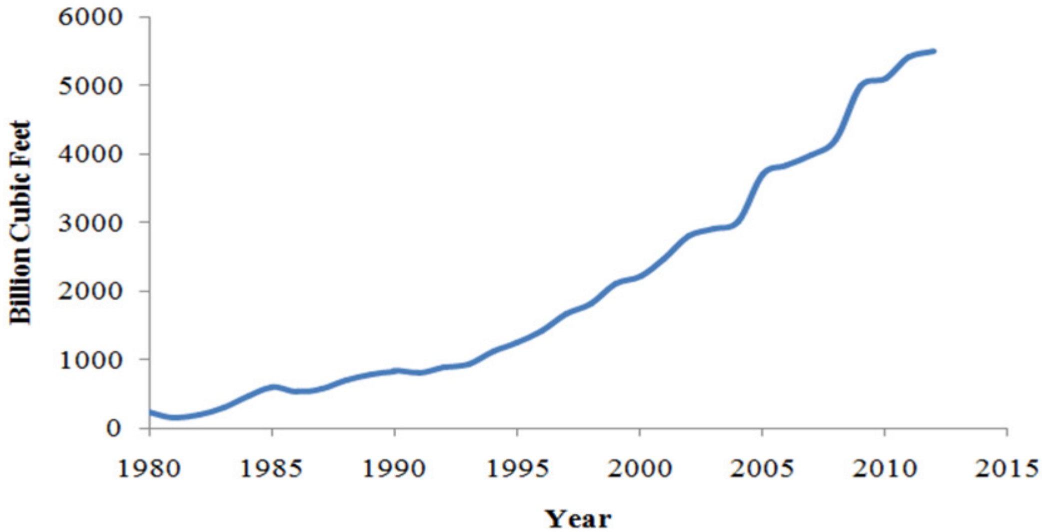

Fig. 5: Natural gas consumption of Iran

Table 1: Statistic characteristics of natural gas consumption (billion cubic feet) data

Max	Min	Mean	Standard deviation
Calibration data set			
3020.84	155	1233.87	898
Verification data set			
5511.04	3707.3	4597.13	736.79

8. Results and discussion

The main aim of this research is to develop two intelligence-based scenarios, called ANN-PSO and ANN-BA, in order to predict the future natural gas consumption in Iran. In this section, the proposed models are examined for modeling purposes. The first task in developing such models as those mentioned above is to identify the input variables. To this end, in the current research, the best input combination was determined using stepwise regression analysis (SRA), in which the lagged time series more related to output (gas consumption one year ahead) were considered as inputs of the proposed models. The statistical software SPSS 17.0 (Ho, 2006) was used to apply the SRA considering $F_e = 3.84$ and $F_r = 2.71$. These parameters can lead to the best-fitted regression model with the highest R-Square. The results obtained at this stage were time series at time step $t-1$, $t-2$, $t-3$, $t-4$ and $t-5$. In the second stage, the proposed models were built using training data. Then, the developed models were verified by means of the test data.

In the current research, firstly the suitable topology of RBFNN is identified, and is then taken into account in order to develop scenarios. To achieve this task, RBFNN was trained and verified with different numbers of hidden neurons (1-10). In this step, the appropriate structure of RBFNN was determined and it was concluded that the six hidden neurons resulted in the best performance of the model. The minimum MSE value for the training dataset was 2.54×10^6 (billion cubic feet) and for the verification stage it was 2.61×10^7 (billion cubic feet). The R^2 for the testing period was found at 0.78.

During the modeling process the appropriate selection of parameters of PSO and BA affects the performance of the proposed models. In this research, a trial-and-error procedure was to be used to identify the suitable parameters. The first scenario is the birds scenario (ANN-PSO), by which the future consumption of natural gas was predicted. By the same vein, the appropriate parameters of the PSO algorithm were explored by employing different values of parameters. The weight of inertial value (W) between [0.7,0.8], $c_1 = c_2 = 2$, velocity V=2, the size of the swarm and the number of iterations are 25 and 1000, respectively. The second scenario is the bats scenario (ANN-BA), in which the BA algorithm parameters were identified; the number of bats and iterations were set to 20 and 1000, respectively: $f_{min} = 0$, $f_{max} = 1$, $\alpha = 0.8$ and $\gamma = 0.7$.

Afterwards, the calibrated models were used in order to predict the natural gas consumption one year ahead. This step was carried out by means of a test date set. The obtained results showed the bats scenario to be more superior to the birds scenario in the prediction of future natural gas consumption in Iran (Fig. 6).

According to the bats scenario, the determination coefficient and the MSE for the calibration stage were obtained by the ANN-BA model as 0.97 and 2.48×10^6 (billion cubic feet), respectively.

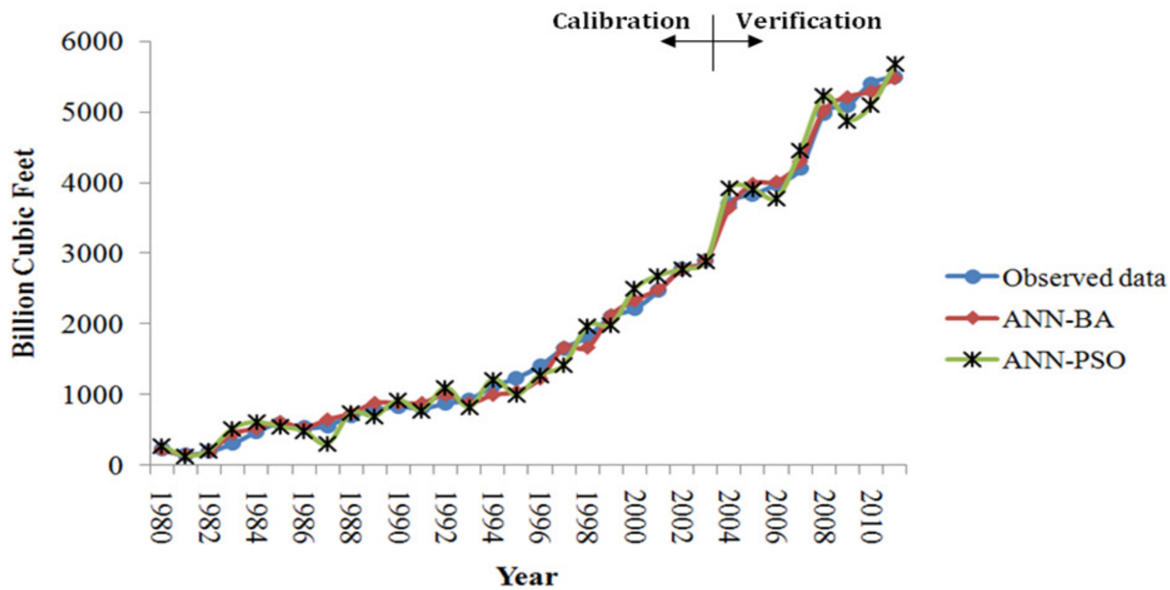

Fig. 6: Comparison of proposed models for natural gas consumption prediction in Iran

The same metrics as above for the verification stage were also acquired as 0.93 and 2.27×10^7 (billion cubic feet), respectively. The ANN-BA model shows a higher determination coefficient and lower MSE compared with the ANN-PSO (R^2=0.88, MSE=2.31×10^7) method. Fig. 7 shows the scatter plot of both of the proposed models.

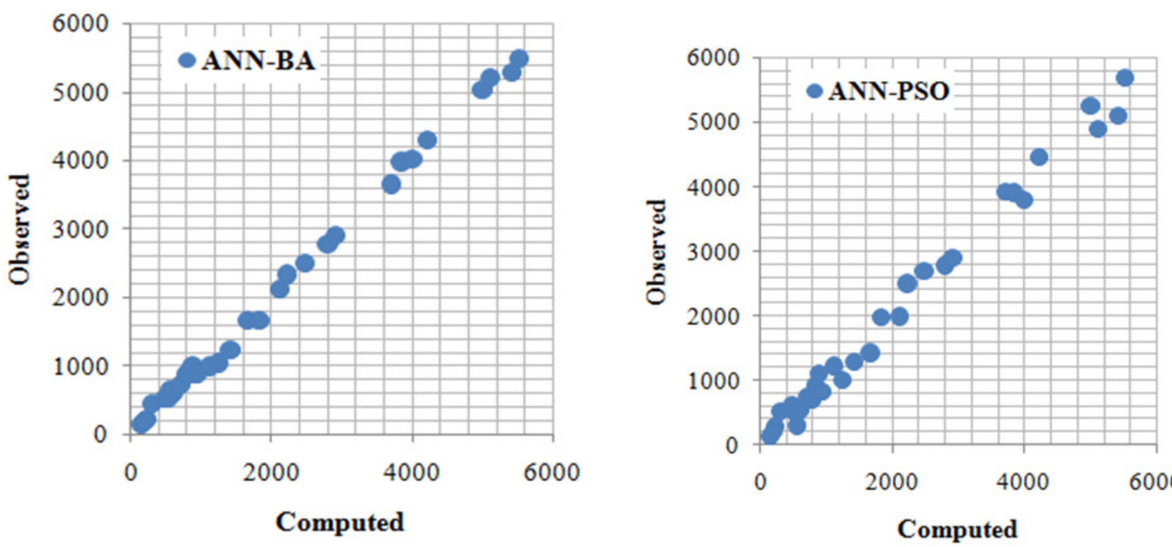

Fig. 7: Scatter plot between observed and computed data based on proposed models

It was elicited that the ANN-BA can significantly approximate the general behaviour of the time series. Whereas the feasible estimation of extreme energy consumption is usually the most important factor in the policymaking programme, therefore, it is worthwhile to develop models as they can capture the peak values of the time series. In the same way, the extreme values of the testing period were closely estimated by the bats scenario.

Despite conclusive evidence regarding the R^2 and MSE as to the superiority of the bat scenario, in order to ensure the privilege of the bat scenario over the birds scenario in the prediction of natural gas consumption the hypothesis testing was furnished.

The best-fit model out of ANN-BA and ANN-PSO would be chosen by hypothesis testing. To meet this purpose, the following hypothesis was proposed:

H0: There is no difference between the prediction accuracy of ANN-BA and ANN-PSO.

H1: There is a difference between the prediction accuracy of the proposed models.

Because of this issue that the data used for the prediction of both scenarios are the same, the paired t-test (two samples for mean) was carried out on prediction accuracy (relative error percentage) to test the hypothesis.

Since $P - value\,(0.0015) < 0.002$, H0 was rejected at a confidence level of $\alpha = 0.002$. The outcomes of the paired t-test in terms of mean of deviation, standard deviation and t-test value are 2.34, 4.65 and -3.152, respectively.

The evidence indicated that the average prediction error (μ) of ANN-BA is significantly lower than that of ANN-PSO. Once again, the ANN-BA model was identified as a rigorous method for the prediction of natural gas consumption in Iran.

The BA can be considered as the most robust optimization algorithm to the point of improving the performance of the data-driven models. This issue stems from this fact that it incorporates a combination of PSO, simulated annealing (SA), and harmony search (HS) using a certain combination of parameters.

9. Conclusion

This paper proposes two intelligence-based scenarios named bats and birds in order to predict the future natural gas consumption in Iran. The results showed that the bats scenario (ANN-BA) is better than the birds scenario (ANN-PSO) for modeling purposes. It was concluded that the bat algorithm is more capable than the PSO procedure in training the RBFNN model, although the PSO algorithm is able to find the global minimum but has a low rate of convergence in finding the optimal solution. From this point of view, the bat algorithm is vigorous due to this fact that it uses the principle of frequency tuning and changes the emission rate of impulses, which can lead to a good affinity from ideal solutions. This algorithm can increase the efficiency of the RBFNN model because of the creation process of a balance between exploration and exploitation and acceleration of the training time. The obtained results showed that the bat scenario is superior to the birds scenario for the prediction of natural gas consumption in Iran.

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