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Carbon Monoxide Prediction Using Artificial Neural Network And Imperialist Competitive Algorithm

[1]Somaiyeh Mahmoudzadeh, [1]Zalinda Othman, [2]Amir Mehdi Yazdani and [1]Azuraliza Abu Bakar

[1]Faculty of Information Science and Technology, Universiti Kebangsaan Malaysia, 43600 Bangi, Selangor, Malaysia
[2]Department of Electrical and Computer Engineering, Naein Branch,Islamic Azad University, Naein, Iran

Abstract: Carbon monoxide (CO) is one of the main air pollutants produced by incomplete combustion process particularly in the urban areas and exposing to the CO polluted environments will definitely affect human health. Therefore, providing a comprehensive computer modeling based on the current and previous related information for further study, analyses and decision making is of paramount importance. There are number of approaches in air pollution modeling and prediction such as traditional statistical methods and more recent ones based on the artificial intelligence solutions. Successes of artificial neural networks (ANN) and evolutionary algorithms, like genetic algorithm, in simulating the nonlinear dynamic of environmental phenomena, have introduced them as powerful alternatives amongst researchers. In this paper, the CO concentration prediction problem is solved by a combination of ANN and a socio-political heuristic search method named imperialistic competitive algorithm (ICA). ICA is a global heuristic search method that uses imperialism and imperialistic competition process as a source of inspiration. The multi layer perceptron (MLP) network topology with Levenberg-Marquardt training technique has been applied in the prediction. In order to enhance the efficiency of the corresponding network, ICA has been hybridized in MLP network (ICA-NN) to optimize the network weights. This research utilized a set of that comprise toxic air samples gathered in monitoring network sites in Dallas-Fort Worth during 2001 to 2006. The performance of the proposed approach is measured by the mean squared error, for both training and testing phases. Comparison between the functionality of hybrid ICA-NN and the mentioned MLP network provides the fact that the ICA-NN is superior in terms of reliable performance with acceptable accuracy for CO pollutant prediction.

Key words: Carbon monoxide prediction. artificial neural network. imperialist competitive algorithm. air pollutant

INTRODUCTION

It might, indeed, be true to state that exposing into the environment contaminated by carbon monoxide (CO) may result in appearing of the various diseases such as different kinds of heart disease, lung disorders, asthma, anemia, cancer as mentioned in previous researches (Guven *et al*., 2010, Frankenberg *et al*., 2011, Raub and Benignus,2002, Knect *et al*., 2010). Biologically speaking, CO affects oxygen cycling of several organs and tissues of body in such away that the amount of oxygen in blood is reduced, significantly. Sometimes extra levels of CO poisoning can cause death (Grant *et al*., 1979, Johnson *et al*., 1993). Study on several children has discovered that respiratory disease get worst when air pollution is in high range and also a comprehensive research on older people has clarified that illness like lung disorder expands in areas with high CO emissions (Raub *et al*., 2000). Several attempts have been made by different groups of researchers to establish mathematical or computer based models that could be efficacious in estimating the dangerous pollutants concentration at different areas (Haupt *et al*., 2009). Hence, the consequences of forecasting methodologies can be helpful in encountering environmental problems by offering invaluable information that can be utilized as an alarm for preventing the expanding of the polluted areas in future. Numerous methods are available in air pollution modeling such as traditional statistical and artificial intelligence (AI) approaches. Several AI techniques have been successfully used for air pollution modeling mainly for prediction purposes (Kolehmainen *et al*., 2000). For example, as in Dragomir (2010) that employed K-Nearest Neighbor technique to forecast the air quality index. It was used to classify the levels of pollution, and extended his investigation by predicting the concentration of ozone based on the environmental pollutants and meteorological variables. Another research work done inSahafizadeh and Ahmadi (2009) that proposed k-mean clustering method to enhance a forecasting model of air pollution in Boucher town area by developing appropriate number of clusters to classify dusty day's data. Variety of investigations are available which demonstrate the mastery of artificial neural network (ANN) in offering high performance in comparison with conventional prediction techniques such as statistical models, multiple classification and regression models (Yi and Prybutok, 1996). ANNs are reliable models for

Corresponding Author: Somaiyeh Mahmoudzadeh, Faculty of Information Science and Technology, Universiti Kebangsaan Malaysia, 43600 Bangi, Selangor, Malaysia

detection or estimation of the environmental phenomena such as estimation of different kinds of pollutants (Gardner and Dorling,1999, Hadjiiski and Hopke,2000,Kolehmainen *et al*.,2001). Taking the advantages of the feed-forward networks, based on the backpropagation learning method with momentum term, researchers in Fei Ma *et al*. (2009) implemented ANN for predicting the indoor air quality. Two steps of performance evaluation were applied in this investigation; multiplicands of data calculation (for the regression between documented and approximated values of the output variable), and root mean square error for the testing phase. The results indicated the satisfactory performance of the proposed methodology for predicting the indoor air quality. A comprehensive investigation on applications of ANNs in different fields, especially in atmospheric studies is provided in Gardner and Dorling (1998). They affirmed the efficiency of ANNs in facing non-linear problems, particularly when theoretical information of the problem cannot be prepared. Multi-Layer Perceptron (MLP) network with Levenberg-Marquardt learning method to forecast the ozone concentration in the Corsica Island and remarkable results were published in Paoli *et al*. (2011). Another research work on MLP, as mentioned inMartı´n *et al*. (2008), that used MLP with back-propagation learning rule and k-Nearest Neighbors models to forecast the future peaks of CO. Their study proved that an optimized MLP with endogenous, exogenous and time indicator inputs had the capability of forecasting of hourly ozone concentration with appropriate accuracy.

Nowadays, there are many arguments on how researchers can improve the performance of various models when dealing with time series forecasting problems. Hybrid models aim to enhance the functionality of the simple common models by combining several models, having reasonable efficiency, so that the risk of failure and reaching inappropriate results will be nosedived. The idea for combining models comes from the assumption that either one cannot determine the true data of the generating procedure or that a single model may not be sufficient to identify all the characteristics of the time series. A hybrid method applied inYildirim and Bayramoglu (2006), Adaptive Neuro-Fuzzy, used to predict daily levels of air pollution in accordance with ozone concentration in city of Zonguldak using meteorological and environmental data as predictor variables. Having the merits of decision making based on the human expert knowledge and linguistic variables, one can combine the consequences of fuzzy inference system with the potencies of neural networks such as learning, adjustment, fault-tolerance, homology and generalization to develop a more reliable andefficient model of forecasting. An attempt to forecast the CO concentration in Tehran by applyinga hybrid ANN together with adaptive neuro-fuzzy inference system (ANFIS) method is reported inNoori *et al*. (2010). They employed forward selection and Gamma test methods for the hybridization and thefeature selection phase. The efficiency of the hybrid models in comparison with simple ANN andANFIS models was significant in terms of decreasing the output error. In hybridization based onheuristic search techniques, Imperialist Competitive Algorithm (ICA) is employed to find theoptimum weight of the applied neural network for estimating the oil flow rate of the wells Berneti and Shahbazian (2011).

Comparison between the two approaches expressed the suitability of the hybrid with significant accuracy and moderate convergence rate. The purpose of this study is to offer a predictive model based on the artificial intelligence approaches in order to predict CO density, as one of the major factors in the air pollution problem.

The proposed predictive model is based on the combination of ANN and an algorithm named Imperialist Competitive Algorithm (ICA). ICA is a global heuristic search method that uses imperialism and imperialistic competition process as a source of inspiration. It is a flexible algorithm and its performance is comparable with GA and PSO. In numerous case studies it showed fast performance in reaching on optimum solutions. Furthermore, the risk of falling in local minimum and maximum traps is by far less than others and it is more flexible in encountering with constraints (Sepehri and Lucas, 2008, Khabbazi *et al*., 2009, Alikhani and Abdechiri, 2010, Sayadnavard *et al*., 2010,Jolai *et al*., 2010).

MATERIALS AND METHODS

Data Set:

In recent decades, industries have been expanding and polluting more than ever. Some of the air pollutants level in weather is impacted by the oil and gas industries productions. Considering some pollution data that are quite alarming reveals the fact that people are suffering from terrible health impacts of oil and gas production. In this work, a dataset from Texas Commission on Environmental Quality (TCEQ) has been utilized for testing the developed predictive models (TCEQ, 1996). The dataset consists of CO concentration data that was gathered from monitoring network sites in Region 4-Dallas/Forth Worth during 2001 to 2006 and was been evaluated by the Toxicology Division. Twenty-four-hour air samples collected continuously every six days during 6 years and investigated as representative long-term average concentrations in that area.

Table 1 contains information regarding to the 18 air toxics monitoring sites located in Region 4-Dallas/Forth Worth.

Table 1: The utilized information for CO concentration prediction problem

Variable Name	*Type of Variable*	*Variable Description*
AIRS	*Char*	*AIRS site ID*
CO1HRAV	*Num*	*CO 1-hour average*
DATE	*Num*	*Date*

Multi Layer Perceptron Neural Network (MLP):

The first objective of this study is to develop a superior architecture of ANN by using the advantages of MLP model and Levenberg-Marquardt back-propagation methods as a training function. It provides an accurate performance with minimum error in both training and testing phase. The MLP network has been remarkably utilized in various applications for its capability to solve the nonlinear problems, simplicity and ability to function approximation. It utilizes a supervised learning technique known as back propagation for training the network. That is based on minimizing the sum of squared errors between the required and actual outputs (Rumelhart *et al*., 1986). The back propagation network learns by attending to example. The example should be provided for network in order to do the expected procedure, and then it can change the network's weights until the training procedure is finished. In this way, it can provide the required output for a specific input.

The point that makes a MLP network totally different from other models is that every neuron conducts a nonlinear activation function, which is developed to simulate the frequency of action potentials. For design the neural network topology, the designer or engineer chooses the network structure, learning rule, the performance function and so many other parameters experimentally. The only way to detect the best solution is by examining the different architectures with various parameter adjustments by trial and error approaches (Khashei and Bijari, 2012). The training process can stop when the network can be able to recognize all the samples successfully, but in practice, commonly it is allowed to let the error fall to a lower value first. This proves that the samples are all being recognized correctly. The total error of network can be evaluated by adding up all the errors for each neuron.

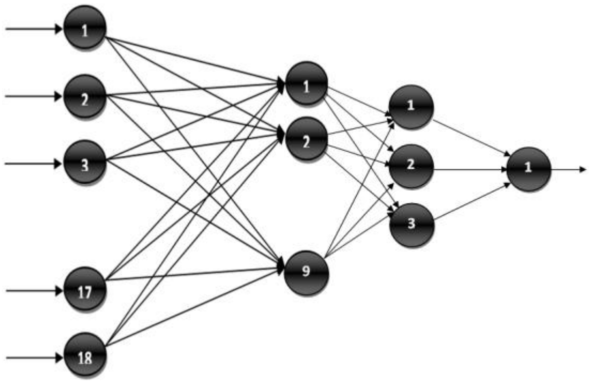

Fig. 1: The MLP network.

Imperialist Competitive Algorithm (ICA):

One of the most new optimization algorithms known as the imperialist competitive algorithm (ICA), affected by socio-political technique of imperialistic competition, has been utilized in this research. The ICA algorithm presented a strong capability in dealing with various optimization problems. This algorithm begins with some initial countries as initial solutions for investigated problem. Some of the best countries, which are considered as the best solutions, are selected to be the imperialist and other countries form the colonies of these imperialists that are partitioned among the imperialists based on the power of each imperialist. After partitioning and creating the initial empires, these colonies start moving toward their relevant imperialist. This movement is a simple model of assimilation policy that has been pursued by some imperialists.

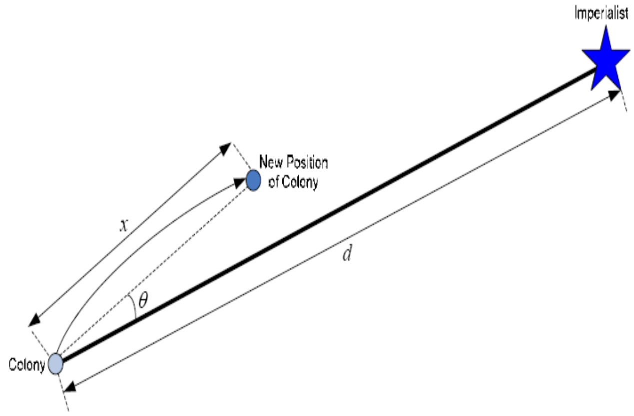

Fig. 2: Movement of colonies toward their relevant imperialist.

Figure 2 shows the assimilation operator that is the movement of a colony towards the imperialist. In this movement, θ and x are random numbers with uniform distribution as illustrated in equation (1) and d is the distance between colony and the imperialist. β and λ are two parameters determine the area in which the colonies suppose to search around their imperialist. Figure 3 shows the whole process in a flowchart as explained above.

$x \sim U(0\,,\,\beta \times d)$
$\theta \sim U(-\gamma, \gamma)$(1)

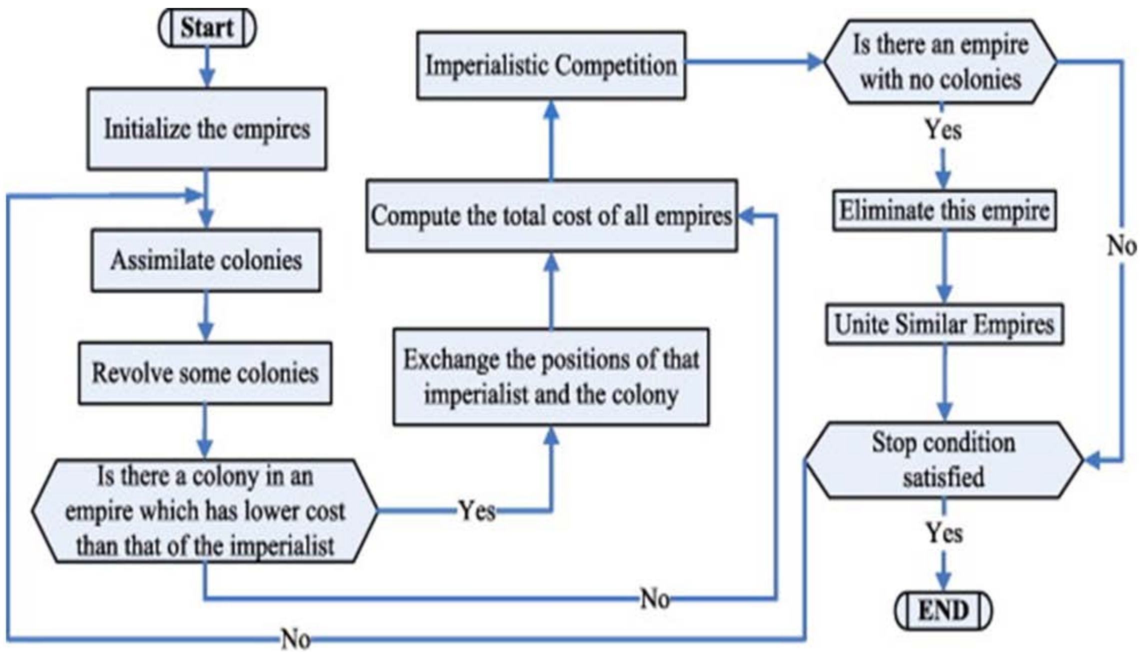

Fig. 3: Pseudo code for ICA.

The displayed algorithm is tested with benchmark functions. The problem is minimization theoccurred errors of neural network.

Hybrid ICA-NN:

In this part, a predictive model for CO pollution prediction based on the combination of neural network and ICA is developed. There are considerable evidences in the state of the art that the ICA can be employed as a strong optimization technique to promote the result of forecasting (Mozafari *et al.*, 2010, Yousefi and Mohammadi, 2011). The ICA uses a global heuristic search in order to optimize the primary weights of a feed forward neural network. The predictive performance of the ICA-NN is strongly higher than that of the regular back propagation neural network. It is because ICA-NN combines local and global seeking skill of the back propagation and ICA, respectively. From another perspective, the hardship in defining appropriate topology for NN is also considerable by using ICA. It can be helpful in selecting the number of neurons in hidden layer, assigning the number of hidden layers and generally in designing optimum geometrical structure of NN (Zhang *et al*., 2009).

RESULTS AND DISCUSSION

Result of MLP network in CO Time Series Prediction:

To evaluate the performance of MLP network for CO density prediction problem, different design of the MLP network architectures are developed and evaluated to find the optimum architecture as listed in Table 2. The chosen best fitted network involves the topology that represents the most effective prediction accuracy with the test data. In the network simulation, 75% of the whole dataset is assigned as training set and 25% of data is remained for testing the networks performance.In this work, three types of training functions, gradient descent, gradient descent with momentum and Levenberg-Marquardt back-propagation are employed in determining the most suitable network. The learning rate parameter of network and the goal for training process are set on different values. Different numbers of epochs are examined in this investigation for training phase. The examined results of different topologies of MLP are demonstrated in Table 2.

Table 2: Mlp Network Performance Results Of Different Parameters Adjustment

Training function	Topology of network	Learning Rate	No. of epochs	Goal of network	Activation function of NN	MSE (Train)	MSE (Test)
Batch gradient descent	(18,9,3,1)	0.07000	1000	0.000020	Tan-sig	0.0813	0.1029
	(18,8,5,1)	0.09000	1500	0.000200	Tan-sig	0.0827	0.1703
	(18,12,6,1)	0.12000	2000	0.002000	Tan-sig	0.0703	0.0837
	(18,6,2,1)	0.20000	2500	0.020000	Tan-sig	0.0700	0.1035
	(18,5,1)	0.00700	3000	0.000090	Tan-sig	0.0918	0.1967
	(18,7,1)	0.00070	3500	0.000009	Tan-sig	0.0983	0.1579
	(18,9,1)	0.00007	4000	0.000007	Tan-sig	0.1594	0.1731
	(18,8,1)	0.15000	4500	0.000005	Tan-sig	0.0553	0.1857
Gradient descent with momentum	(18,9,3,1)	0.07000	1000	0.000020	Tan-sig	0.0847	0.1711
	(18,8,5,1)	0.09000	1500	0.000200	Tan-sig	0.1030	0.1194
	(18,12,6,1)	0.12000	2000	0.002000	Tan-sig	0.1637	0.1931
	(18,6,2,1)	0.20000	2500	0.020000	Tan-sig	0.0806	0.1856
	(18,5,1)	0.00700	3000	0.000090	Tan-sig	0.0903	0.1894
	(18,7,1)	0.00070	3500	0.000009	Tan-sig	0.1242	0.1223
	(18,9,1)	0.00007	4000	0.000007	Tan-sig	0.1321	0.1700
	(18,8,1)	0.15000	4500	0.000005	Tan-sig	0.0587	0.1918
Levenberg-Marquardt	(18,9,3,1)	0.07000	1000	0.000020	Tan-sig	0.0166	0.1906
	(18,8,5,1)	0.09000	1500	0.000200	Tan-sig	0.0131	0.3468
	(18,12,6,1)	0.12000	2000	0.002000	Tan-sig	0.0141	0.8635
	(18,6,2,1)	0.20000	2500	0.020000	Tan-sig	0.0418	0.1924
	(18,5,1)	0.00700	3000	0.000090	Tan-sig	0.0343	0.1205
	(18,7,1)	0.00070	3500	0.000009	Tan-sig	0.0281	0.3390
	(18,9,1)	0.00007	4000	0.000007	Tan-sig	0.0320	0.2601
	(18,8,1)	0.15000	4500	0.000005	Tan-sig	0.0241	0.3128

It is clear from Table 2 that MLP network with Levenberg-Marquardt as a training function presents better results in comparison with two other methods. For example in terms of MSE, the proposed network indicates 0.0166 for training set and 0.1906 for testing set. The numerical results show that the proposed MLP model offers a satisfactory forecasting functionality. The achieved MSE errors for training set are acceptable but by considering the MSE errors for testing set the need of decreasing the percentage of MSE error, in order to improve application of network, is indispensible.Next, based on the results shown in Table 2, some of the best topologies of this method (basedon MSE test and train error) are selected to hybridize with ICA. The results of MLP are stronglyrelated to the activity of the hidden neurons and also the weights between the hidden and outputneurons. The hidden neurons are capable to construct their own representations of the input. Theweights between the input and hidden neurons verify when each hidden neuron is active, and so bymodifying these weights, a hidden neuron can select what it represents. However, improvement oftime series predictor accuracy is important and frequently is a challenging task. Based ontheoretical and empirical evidence, combination of different models can be an effective solution toimproving upon their predictive performance.

Results of ICA-NN in CO Time Series Prediction:

In the proposed methodology, the predicted values of the feed-forward MLP network model aremodified by applying the ICA in order to adjust the weights of connection in existing network'slayers. Empirical results from described datasets indicate that the proposed method is an effectivesolution in order to improve the MLP network accuracy. The model was comprehensively testedfor CO density prediction dataset. The most important parameters are initialized by followingvalues shown in Table 3.

Considering Table 3 we can find out that the (18, 9, 3, 1) topology is compatible with the ICA algorithm in more than two other topologies. Also by comparing different values of examined topology of (18, 9, 3, 1), it is clear that the third one that highlighted in Table 3 gives the most accurate result by considering MSE error as a performance indicator. Therefore, Table 4 shown the selected parameters of ICA used in this work.

Totally 150 number of countries assigned as initial population of imperialistic competition and we have set 0.03 as revolution rate. As described before revolution is the process in which the socio-political characteristics of a country change suddenly. We have selected 10 of the best countries of initial population to form the imperialists and take possession of other 140 ones. The percent of threshold was set on 0.1. Threshold percentage is the percent of search space size, which enables the uniting process of two empires. The MSE (mean square error) of the ICA-NN model for mentioned above parameters adjustment was represented in Figure 4 and 5.

Table 3: Performance of different parameters adjustment of ICA on CO dataset

Selected algorithm	Topology of network	Population size	No. of Decades (iterations)	Num of Initial Imperialists	Revolution Rate	Parameter of Zeta	Parameter of Damp Ratio	Uniting Threshold	Assimilation Coefficient of ICA	Assimilation Angle Coefficient of ICA	MSE(Train)	MSE(Test)
ICA-MLP	(18, 5, 1)	80	30	8	0.3	0.02	0.99	0.02	2	0.5	0.060	0.016
		100	100	12	0.7	0.002	0.099	0.07	1.5	0.7	0.047	0.038
		150	200	10	0.03	0.2	0.8	0.1	2.5	1	0.033	0.016
		200	500	20	0.003	0.5	0.5	0.15	1	1.5	0.039	0.047
	(18,6,2,1)	80	30	8	0.3	0.02	0.99	0.02	2	0.5	0.092	0.015
		100	100	12	0.7	0.002	0.099	0.07	1.5	0.7	0.037	0.019
		150	200	10	0.03	0.2	0.8	0.1	2.5	1	0.039	0.012
		200	500	20	0.003	0.5	0.5	0.15	1	1.5	0.021	0.064
	(18,9,3,1)	80	30	8	0.3	0.02	0.99	0.02	2	0.5	0.083	0.083
		100	100	12	0.7	0.002	0.099	0.07	1.5	0.7	0.033	0.016
		150	200	10	0.03	0.2	0.8	0.1	2.5	1	0.009	0.015
		200	500	20	0.003	0.5	0.5	0.15	1	1.5	0.031	0.022

Table 4: ICA parameters

ICA Parameter	Selected Value
Number of countries	150
Revolution rate	0.03
Threshold Percentage	0.1

These diagrams illustrate the relation between the target and estimated values, which arerespectively obtained from the proposed ICA-NN model. While it is obviously perceived from thegraph, the learning phase in ICA-NN for target and real output lines is constantly assessing theconsequence of the system and shows its ability to handle this problem.

The plots based on regression type also are useful for detecting model inadequacies for timeseries predictors. The appropriateness of the model refers to the difference between the observeddata values and the corresponding model fits. If the residual plot shows much difference in therelationship between the residuals and the predictor variables. The result of the regression diagramfor ICA-NN prediction model for test and train set of data is demonstrated in figure 6 and 7.

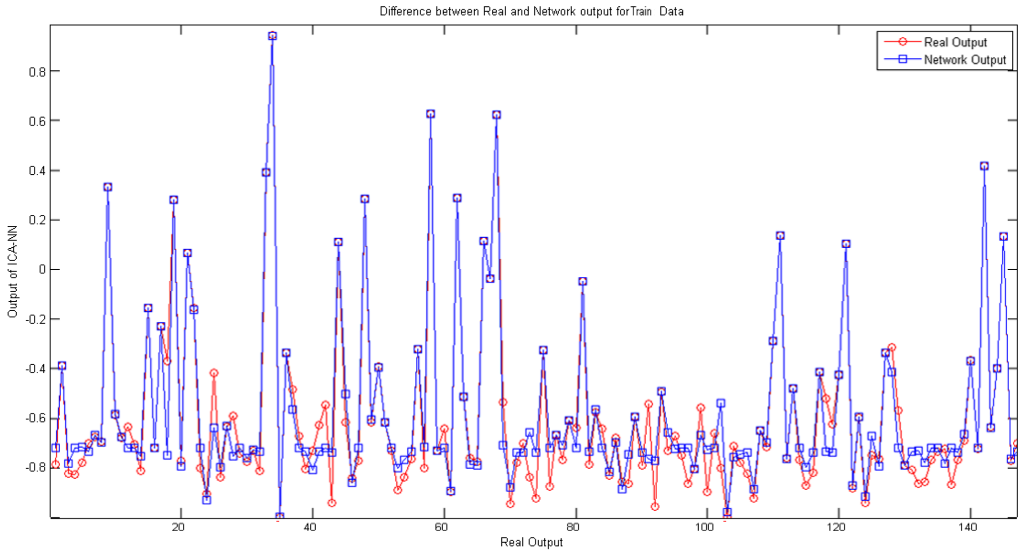

Fig. 4: The difference between real output and output of proposed ICA-NN for the **TRAIN** set

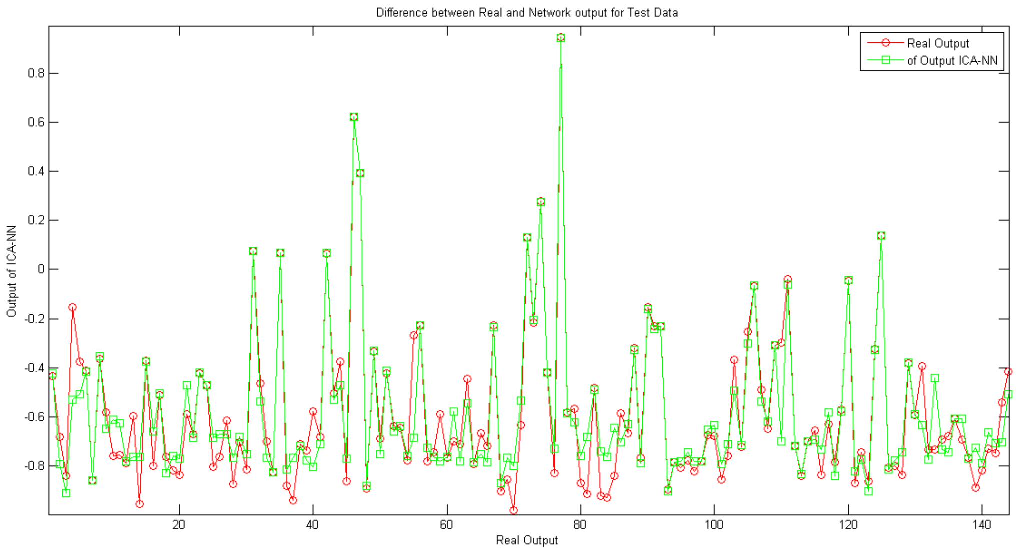

Fig. 5: The difference between real output and output of proposed ICA-NN for the **TEST** set

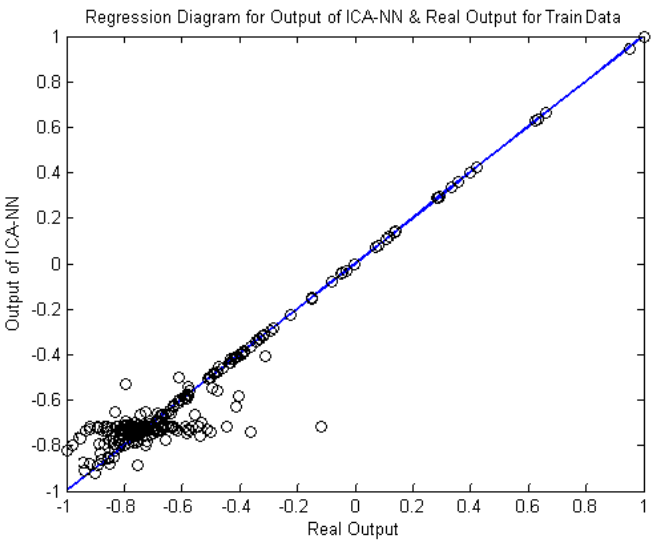

Fig. 6: Regression diagram for TRAIN set in ICA-NN model

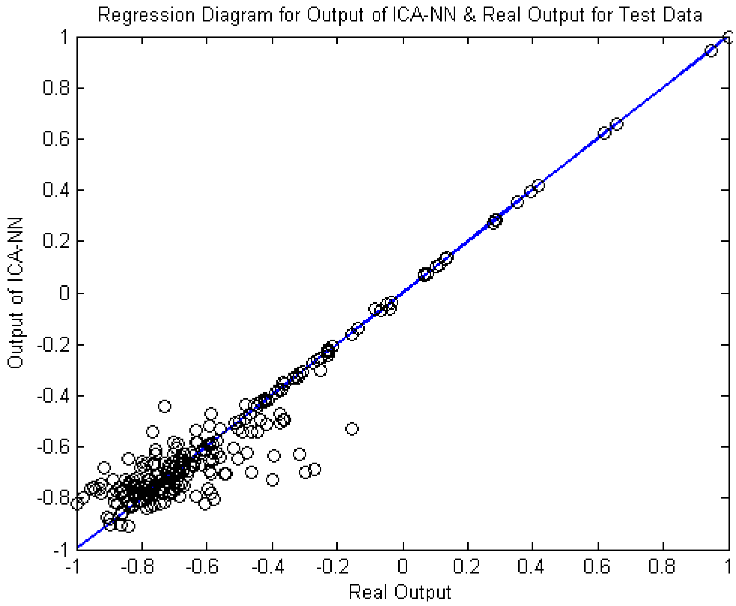

Fig. 7: Regression diagram for TEST set in ICA-NN model

Relying on the capability of the line learning, the proposed ICA-NN hybrid method satisfies the objectives of this research. From this technique, the achieved MSE error for train set is 0.009 and for test set is 0.015, while the generated values for MSE error as performance indicator is 0.0166 and 0.1906 for training and test data in MLP network.

Table 5: Overall performance comparison between two methods

Algorithm	MLP-Topology	MSE(Train)	MSE(Test)
Single Neural Network	(18,5,1)	0.0343	0.1205
	(18,6,2,1)	0.0418	0.1924
	(18,9,3,1)	0.0166	0.1906
Hybrid ICA-MLP	(18,5,1)	0.0330	0.0160
	(18,6,2,1)	0.0390	0.0120
	(18,9,3,1)	0.0090	0.0150

Table 5 proves that in all cases ICA-NN gives better result than MLP network. For instant in (18, 9, 3, 1) topology, the achieved result from ICA-NN for train part of presented dataset shows 0.009 for MSE train error, where MLP network resulted 0.0166 for MSE train error. Considering MSE test error for both used techniques we have 0.1906 for MLP and 0.015 for ICA-NN. In comparison with previous achieved mean squared error result for train and test set our presented hybrid method gives much appropriate result than only MLP model in previous part of this research. These results demonstrated the high ability of hybrid ICA-NN method in time series prediction.

Conclusions:

The main purpose of this article was to utilize artificial intelligence approaches in order to predict CO density. CO pollutant is one of the major factors in the problem of the air pollution. This prediction is based on the gathered information in accordance with CO density measurement index in Texas area. This can be considered as a meritorious solution in order to reduce the harmful effects of the COs and other pollution risks. In this work, the predictive models for air pollution (CO density) detection is based on the combination ANN and a new evolutionary algorithm named Imperialist Competitive Algorithm (ICA). The combination of evolutionary algorithm such ICA algorithm as an optimization factor with different ANNs architectures can strongly increase the basic network accuracy. By using MSE values for the evaluation, ICA-NN represented better performance and it could improve the prediction accuracy of this research. As mentioned above the MSE indicator is conducted for measuring the mean squared errors in a set of forecasts without considering their direction. Generally, it is a factor of measuring accuracy for predictive algorithms. MSE is a quadratic scoring rule that can measure the average magnitude. In this study, the results showed the hybrid ICA-NN algorithm provides an acceptable performance particularly in the prediction accuracy. From the comparison results of the proposed approaches, it can be concluded that the hybrid ICA-NN is more accurate than only NN in predicting CO pollutant.

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