COMPARISON OF ANN AND ANFIS TECHNIQUES IN MODELING DISSOLVED OXYGEN

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ABSTRACT

Dissolved oxygen (DO) is a parameter frequently used to evaluate the water quality on different watersheds and reservoirs. The concentration of DO is so important for the healthy functioning of aquatic ecosystems, and a significant indicator of the state of aquatic ecosystems. In this study, the radial basis neural network (RBNN) and adaptive neuro-fuzzy inference system (ANFIS) method were developed to estimate DO concentration by using various combinations of daily input variables which are pH, discharge, temperature, and electrical conductivity measured by U.S. Geological Survey (USGS). The data of Fountain Creek Stream-Gauging Station (USGS Station No: 07105530) which covers 9 years daily data between1990-1998 were used in the study. The results of the RBNN and ANFIS models were compared with each other. The RBNN model was found to be better than the ANFIS model in estimation of DO concentration.

Keywords: Adaptive neuro-fuzzy inference system (ANFIS), Dissolved oxygen (DO), Radial basis neural network (RBNN).

1. INTRODUCTION

Using the surface waters for the purpose of suitable and safely requires the determination of the water quality. To determine water quality is very important issue for drinking and irrigation water, and many other purposes. For that, there are many national or international standards (EPA [1]; WHO [2]; Council Directive [3]; Official paper (in Turkey) [4]) to determine the water quality around the world. The determination of the water quality is traditionally based on the classification by considering the physicochemical or biological parameters (Hann and Willey [5]; Hem [6]; Radtke et al. [7, 8, 9]; Lewis [10]) according to the water usage range. For example, the concentration of dissolved oxygen (DO) is important for the healthy functioning of aquatic ecosystems, and a significant indicator of the state of aquatic ecosystems. DO is a parameter frequently used to evaluate the water quality on different reservoirs and watersheds. Also, DO concentration is strongly influenced by a combination of physical, chemical, and biological characteristics of streams of oxygen demanding substance including algal biomass, dissolved organic matter, ammonia, volatile suspended solids, and sediment oxygen demand (Kalff [11]; Mullholand et al. [12]).

The development and current progress in the integration of various artificial intelligence techniques (knowledge-based system, genetic algorithm, artificial neural network, and fuzzy inference system) in water quality modeling, sediment transportation, evaporation, DO concentration, and depth integrated estimation of DO etc. have been studied by many researchers. For example, artificial neural networks (ANNs) have been successfully used in various fields of estimation and forecasting (Broomhead and Lowe [13]; Hagan and Menhaj [14]; Haykin [15]; Kisi [16]; Hanbay et al. [17]; Dogan et al. [18]; Ranković et al. [19]; Akkoyunlu et al. [20]; Ay and Kisi [21]). Also, many studies have been successfully implemented for estimating in this context during recent years. Soyupak et al. [22] used the multi-layer perceptron (MLP) to compute the pseudo-steady state time and space dependent DO concentrations in three separate reservoirs with different characteristics using a limited number of input variables. Sengorur et al. [23] used MLP for computing monthly DO values. The correlation coefficient was 0.9186, and the ANN approach was found to be reasonable for modeling DO prediction. Ranković et al. [19] investigated the DO in the Gruža reservoir in Serbia with MLP by using the pH, nitrites, ammonia, Cl, conductivity, Fe, Mn, total P, temperature and nitrate variables. In their study the most effective parameters in estimating DO concentration were found to be pH and temperature. Akkoyunlu et al. [20] used ANN models for estimating the DO concentration of Lake Iznik in Turkey. They used twice measured inputs of pH, TDS, temperature and conductivity to estimate the DO concentration for a one day period. Ay and Kisi [21] modeled DO by using multi-layer perceptron ANN (MLP) and radial basis neural network (RBNN) methods and found that the RBNN performed better than the MLP.

In addition, fuzzy logic has been successfully used for various water resources fields (Lee et al. [24]; Altunkaynak et al. [25]; Duque-Ocampo et al. [26]; Icaga [27]; Dahiya et al. [28]; Lermontov et al. [29]; Rehana and Mujumbar [30]). The considered models for related to problems are sufficient tools to reach results within an acceptable error limits.

In this study, the RBNN and adaptive neuro-fuzzy inference system (ANFIS) methods were developed to estimate DO concentration by using various combinations of daily input variables which are pH, discharge (Q), temperature (T), and electrical conductivity (EC) measured by U.S. Geological Survey (USGS Station No: 07105330). Within the concept of this study, basic information related to the methods and study area are presented in Section 2; the RBNN and ANFIS techniques are summarized in Section 3; the results of the models are discussed in Section 4; and conclusions are given in Section 5.

2. MATERIALS AND METHODS

The daily data of Fountain Creek near Fountain, the station (*Station No: 07105530, Latitude 38°48'11", Longitude 104°47'43")* El Paso County, Colorado in the USA operated by the USGS, were used in this study. The location of the station is shown in

Figure 1. In this station, the daily time series of T, pH, EC, Q and DO were downloaded from the web server of the USGS. Due to the data of some variables were unrecorded, these data were removed from the data set. Therefore, the final data set includes 2063 samples for the station. In this context, there were three phases, the training, testing, and validation. 50% of the data (from April 04, 1990 to February 24, 1994) were used for the training phase, 25% (February 25, 1994 to April 18, 1996) was used for the testing phase and the remaining 25% (April 19, 1996 to January 15, 1998) was used for the validation phase.

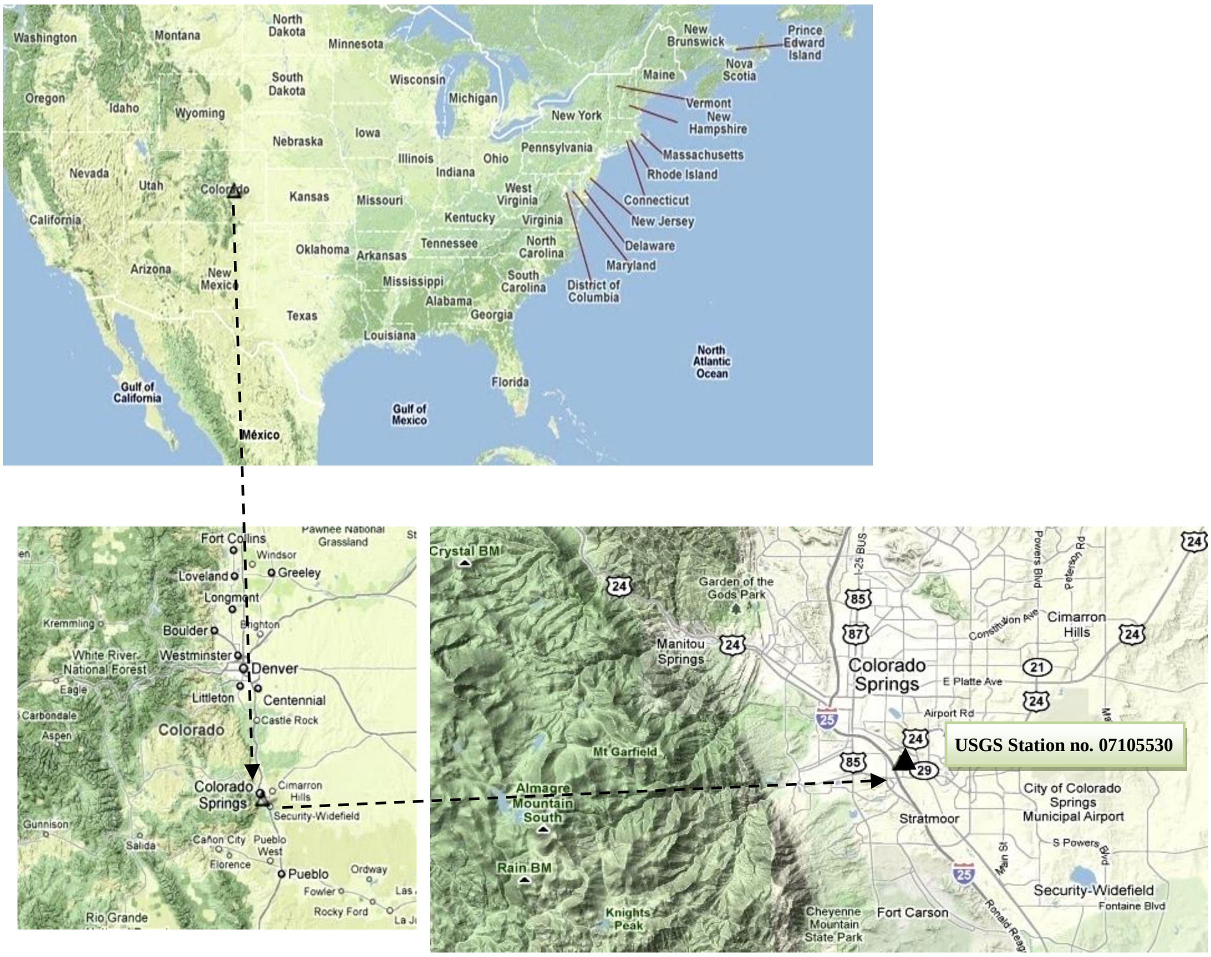

Fig. 1 The location of the Fountain Creek Near Fountain (USGS Station No: 07105530) Station El Paso County, Colorado in America

The RBNN and ANFIS techniques were developed to estimate DO concentration by using various combinations of daily input variables T, pH, EC, and Q measured by the USGS. Results of the RBNN models were compared with those of the ANFIS models. The best model was determined according to root mean square error, mean absolute error and determination coefficient statistics.

3. METHODOLOGY
3.1 Radial basis neural network (RBNN)

RBNN was first introduced into the ANN literature by Broomhead and Lowe [13], Poggio and Girosi [31]. The RBNN has two layers whose output nodes form a linear combination of the basis functions. RBNN is also known as a localized receptive field network because of the fact that the basis functions in the hidden layer produce a significant nonzero response to input stimulus only when the input falls within a small localized region of the input space (Lee and Chang [32]). The relation between inputs and outputs is shown in Figure 2. The RBNN has connection weights between the hidden layer and the output layer only. These weight values can be obtained by linear least-squares method, which gives an important advantage for convergence. Gaussian activation function is widely used as radial basis function. The RBNN method does not perform parameter learning as in the MLP. It performs linear adjustment of the weights for the radial bases. This characteristic gives the RBNN advantage of a very fast converging time without local minima. Because, its error function is always a convex. In this study, different numbers of hidden layer neurons are examined for the RBNN models with a simple trial-and-error method. Detailed information about RBNN theory can be obtained from Haykin [15].

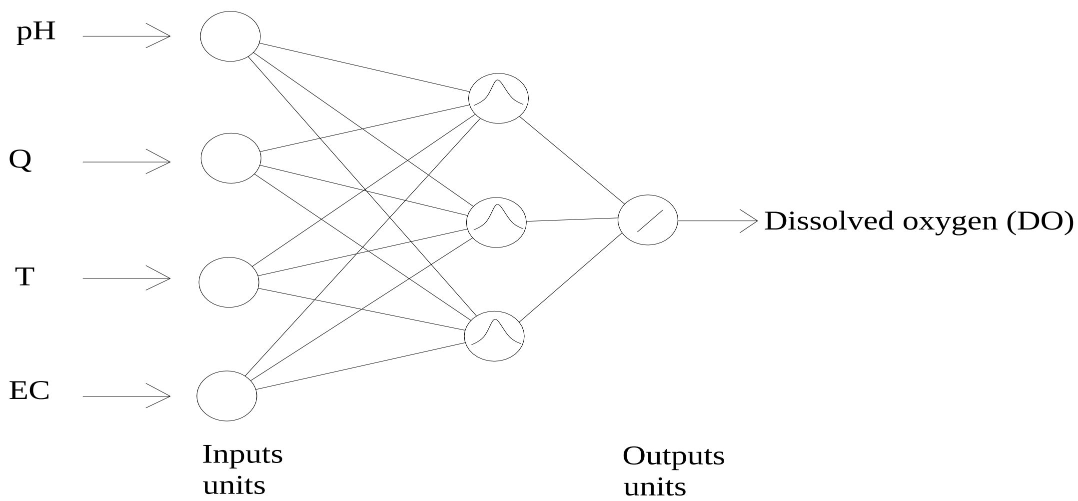

Fig. 2 Schematic diagram of RBNN architecture

3.2Adaptive neuro-fuzzy inference system (ANFIS)

Fuzzy logic (Zadeh [33]; Ross [34]) system models a system with the help of a fuzzy rule or rules. Fuzzy rules are the expressions that state the relationship between the system's inputs and outputs depending on the linguistic variables and in the form of if-then statements. Also, ANFIS technique (Jang [35]) is a network structure consisting of a number of nodes connected through directional links. Each node has a node function with adjustable or fixed parameters. Learning or training phase of network is a process to determine parameter value to sufficiently fit the training data. The basic learning rule is the well-known backpropagation method which seeks to minimize sum of squared differences between network's outputs and desired outputs (Kaya et al. [36]).

Depending on the types of inference operations upon ''if-then rules", most fuzzy inference systems can be classified into three types; Mamdani's system, Sugeno's system. Mamdani's system is the most commonly used, meanwhile, Sugeno's system is more compact and computationally efficient; the output is crisp, so, without the time consuming and mathematically intractable defuzzification operation, it is by far the most popular candidate for sample-data based fuzzy modeling and it lends itself to the use of adaptive techniques (Takagi and Sugeno [37]). More information about ANFIS technique can be found in Jang [35].

Each model result was evaluated by using the root means square error (RMSE), mean absolute error (MAE), and determination coefficient (R^2) criteria (see Eq.1, Eq.2, and Eq.3). Basically, the optimal model can be identified that the RMSE and MAE should be minimal, and R^2 should be close to 1.

$$R^2 = 1 - \frac{\sum_{j=1}^{N}\left[(Y)_{observed,j} - (Y)_{predicted,j}\right]^2}{\sum_{j=1}^{N}\left[(Y)_{observed,j} - (Y)_{mean\ \ observed}\right]^2} \tag{1}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Y_{i\,observed} - Y_{i\,predicted})^2} \tag{2}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|Y_{i\,observed} - Y_{i\,predicted}\right| \tag{3}$$

4. RESULTS

In this study the MATLAB [38] Neural Network Toolbox was used for the implementation of the neural networks method. The RBNN and ANFIS methods were used in the analysis. Three phases were employed in modeling, training, testing, and validation. Optimal spread coefficient and number of hidden layers calculated for the RBNN models after trying various values are given in Table 1. In this table RBNN(3,0.5,3) model indicates a RBNN model has three inputs, spread coefficient of 0.5 and number of hidden layers of 3. It is clear from Table 1 that the RBNN(3,0.5,3) model was found to be better than the others in test phase. However, a slight difference exists between the combination (1) and (3). We can say that the temperature is the most effective parameter in estimation of DO.

To find out the best model in among the all ANFIS models 10 and 100 epochs, 2 and 3 triangle and gaussian membership functions were tried for each model. The optimal ANFIS models obtained for each input combination are given in Table 2. Here, an ANFIS(2,trimf,constant) indicates a model having 2 triangle membership functions for each input and the output is constant. Table 2 shows that the ANFIS(2,trimf,constant) model performed better than the others in test phase

Table 1 RMSE, MAE and R^2 values of the RBNN

Comb. No	Inputs	Model	Training			Testing		
			RMSE	MAE	R^2	RMSE	MAE	R^2
(1)	T	RBNN(1,0.6,1)	0.42	0,31	0.81	0.43	0.34	0.78
(2)	T and pH	RBNN(2,0.3,3)	0.43	0.32	0.80	0.47	0.38	0.74
(3)	**T, pH and EC**	**RBNN(3,0.5,3)**	0.37	0.28	0.85	**0.41**	**0.32**	**0.81**
(4)	T, pH, EC and Q	RBNN(4,1.3,4)	0.35	0.26	0.86	0.44	0.33	0.77

Table 2 RMSE, MAE and R^2 values of the ANFIS

Comb. No	Inputs	Model	Training			Testing		
			RMSE	MAE	R^2	RMSE	MAE	R^2
(1)	**T**	**ANFIS(2,trimf,constant)**	0.41	0.30	0.82	**0.43**	**0.36**	**0.79**
(2)	T and pH	ANFIS(2,trimf,constant)	0.41	0.30	0.83	0.47	0.38	0.78
(3)	T, pH and EC	ANFIS(2,trimf,constant)	0.35	0.26	0.87	0.44	0.35	0.78
(4)	T, pH, EC and Q	ANFIS(2,trimf,constant)	0.33	0.24	0.88	0.55	0.42	0.63

The estimates of the optimal RBNN and ANFIS models in validation phase are compared in Table 3. It is clearly seen from the table that the RBNN slightly performs better than the ANFIS model from the RMSE, MAE and R^2 viewpoints. However, the ANFIS model has only one input T while the RBNN has three inputs T, pH and EC. The validation estimates of RBNN and ANFIS models are illustrated in Figures 3 and 4. It can be seen from these figures that both models gave similar estimates for the low and mean DO values. For the peak DO values, however, both models behaved different with each other. While RBNN underestimates the peak DO values, some overestimations are clearly seen for the ANFIS model.

Table 3 Comparison of RBNN and ANFIS models in validation phase

Inputs	Model	RMSE	MAE	R^2
T, pH and EC	**RBNN (3,0.5,3)**	**0.55**	**0.40**	**0.81**
T	ANFIS(2,trimf,constant)	0.62	0.45	0.78

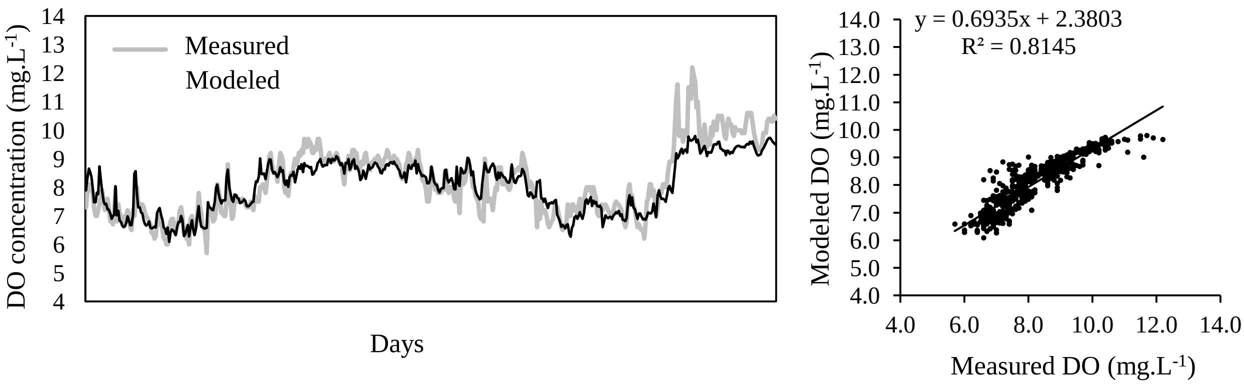

Fig. 3 Measured and modeled DO concentrations by RBNN in validation phase

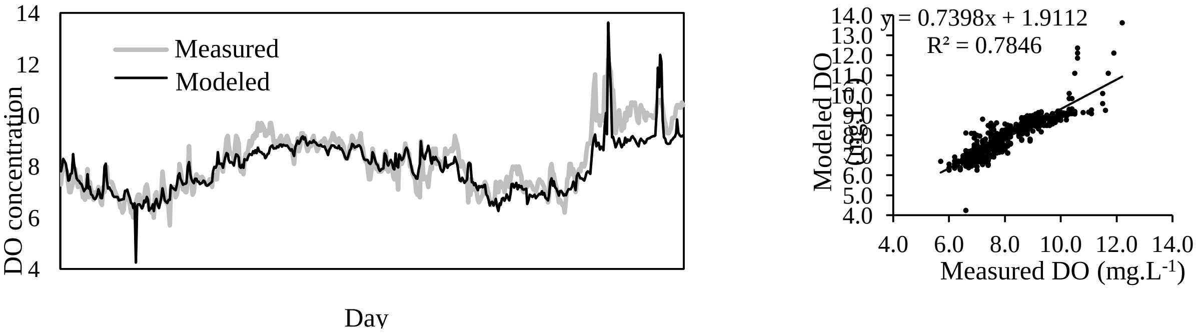

Fig. 4 Measured and modeled DO concentrations by ANFIS in validation phase

5. CONCLUSIONS

Dissolved oxygen (DO) concentration has traditionally been used as a variable of water quality and for water systems. Therefore, modeling of water quality parameters is a very important aspect in the analysis of any aquatic systems. The chemical, physical, and biological components of aquatic ecosystems are very complex and nonlinear. In recent years, computational-intelligence techniques such as neural networks, fuzzy logic, genetic algorithm, and combined neuro-fuzzy systems have become very effective tools to identification and modeling nonlinear systems.

The ability of RBNN and ANFIS methods in estimation of daily DO water quality parameter has been investigated in this study. The performances of the RBNN and ANFIS were compared with each other according to the RMSE, MAE, and R^2 criteria. Results of simulation presented in this paper showed that the RBNN (3,0.5,3) model with three inputs which are T, pH, and EC was found to be slightly better than the ANFIS(2,trimf,constant) model with only one input, T in the validation phase.

The results showed that the temperature (T) is the most effective parameter to estimate DO concentration in this stream-gauging station. ANFIS model can be successfully used in estimation of DO when only temperature data are available.

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