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ORIGINAL ARTICLE

Prediction of dissolved oxygen in Surma River by biochemical oxygen demand and chemical oxygen demand using the artificial neural networks (ANNs)

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KEYWORDS

Radial basis function neural network;
Feed forward neural network;
Dissolved oxygen;
Surma River

Abstract The objective of this study is to develop a feed forward neural network (FFNN) model and a radial basis function neural network (RBFNN) model to predict the dissolved oxygen from biochemical oxygen demand (BOD) and chemical oxygen demand (COD) in the Surma River, Bangladesh. The neural network model was developed using experimental data which were collected during a three year long study. The input combinations were prepared based on the correlation coefficient with dissolved oxygen. Performance of the ANN models was evaluated using correlation coefficient (R), mean squared error (MSE) and coefficient of efficiency (E). It was found that the ANN model could be employed successfully in estimating the dissolved oxygen of the Surma River. Comparative indices of the optimized RBFNN with input values of biochemical oxygen demand (BOD) and chemical oxygen demand (COD) for prediction of DO for testing array were MSE = 0.465, E = 0.905 and R = 0.904 and for validation array were MSE = 1.009, E = 0.966 and R = 0.963. Comparing the modeled values by RBFNN and FFNN with the experimental data indicates that neural network model provides reasonable results.

1. Introduction

The concentration of dissolved oxygen (DO) reflects equilibrium between oxygen-producing processes (e.g. photosynthesis) and oxygen-consuming processes (e.g. aerobic respiration, nitrification, and chemical oxidation) and depends on many factors such as temperature, salinity, oxygen depletion, sources of oxygen and other water quality parameters. Therefore it is very desirable to create a DO model of the Surma River so that water quality can be optimized throughout a time period.

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The water quality models such as River and Stream Water Quality Model (QUAL2K) (Chapra and Pellettier, 2003) and Water Quality Analysis Simulation Program (WASP) (Wool et al., 2006) are very complicated as they require more information of the river system. It makes sense to utilize artificial intelligence (AI) techniques to derive the crucial information about the river water quality. Artificial neural networks have been increasingly used in the prediction of water quality variables (Nash and Sutcliffe, 1970; French et al., 1992; Zhu and Fujita, 1994; Yi-Ming et al., 2003). An ANN learns to solve a problem by developing a memory capable of correlating a large number of input patterns with a resulting set of yields. ANN models mimic somewhat the learning process of a human brain. They operate like a "black box" model, requiring no detailed information about the system (Ahmed et al., 2013). Another advantage of using ANNs is their ability to handle large and complex systems with many interrelated parameters.

Artificial neural networks (ANNs) have been successfully applied in a number of studies focusing on water quality prediction in rivers (Niroobakhsh et al., 2012; Singh et al., 2009), lakes (Stefan et al., 1995), reservoirs (Rankovic et al., 2010; Kuo et al., 2007) and waste water treatment plants (Abyaneh, 2014). Elhatip and Kömür (2008) modeled the water quality parameters in the reservoir of Mamasin Dam. The results illustrated the ability of ANNs to predict the dissolved oxygen of the recharge and discharge areas at the Mamasin Dam site. Li et al. (2007) used the ANN technique to predict the Microcystis spp. population of Lake Dianchi in China. They obtained a correlation of determination (R^2) of 0.911 between the measured and predicted data of Microcystis spp. However, Karul (1999) used total phosphates (TP), NO_3–N, NH_3–N, water temperature, electrical conductivity, pH, turbidity, secchi depth and suspended solids as input variables to predict the chlorophyll-a concentration. In his study, he found correlation coefficient of 0.92. Niroobakhsh et al. (2012) used two ANN networks, multilayer perceptron (MLP) and radial basis function (RBF) to compute the total dissolved solid (TDS) concentrations for the Jajrood River of Iran. In their study, they found that MLP and RBF are able to simulate water quality variables of Jajrood River with more than 90% accuracy. Soyupak et al. (2003) used the neural network model to predict the pseudo steady state time dependent and space dependent dissolved oxygen concentrations in three different reservoirs. The correlation coefficient was more than 0.95 both for the measured and model computed output variables. Singh et al. (2009) computed DO and BOD levels in the Gomti River in India using three-layer feed forward neural networks with back propagation learning. The coefficient of determination for modeled values and observed DO values were 0.70, 0.74, and 0.76 for the training, validation and test sets, respectively. The respective values of root means squared error (RMSE) for the three data sets were 1.50 for training, 1.44 for validation, and 1.23 for testing.

The aim of this paper is to construct a feed forward neural network (FFNN) model and a radial basis function neural network (RBFNN) model to predict the dissolved oxygen in the Surma River, Bangladesh and demonstrate its application to identifying complex nonlinear relationships between input and output variables. The Surma River has been preferred due to its importance in water supply as well as its high ecological importance. The proposed model may contribute to more efficient management as well as to preventive activities.

2. Materials and methods

2.1. Study area and water quality data

The Surma River in Sylhet was selected as the study area for ANN applications. The Surma River is located in the northeastern region of Bangladesh within the administrative districts of Sylhet and Sunamganj. The Surma River has many tributaries and hilly streams joining it from the Khasi–Jaintia Hills of the Indian state of Meghalaya. The Surma River flows through the central part of the Sylhet city, plays a very important role in the economic development of the city. The natural canals passing through the city are responsible for surface runoff conveyance from its urban catchments to the receiving Surma River. However, the water quality of the Surma River is being deteriorated day by day due to human activities and industrial effluents, which are built up on its bank (Ahmed et al., 2010; Alam et al., 2007).

The data set utilized in this study was produced through monitoring of the water quality of the Surma River. Monthly sampling was carried out during the period of three years (2010–2012). Four sampling sites are identified in Fig. 1 and Table 1. One was at the center of the city, where the depth varied from 2 to 10 m, depending on the water level. The second was in the downstream of the central part with a depth ranging from 2.3 to 15 m. The third was near the Shahjalal Bridge, with a depth ranging from 3 to 9 m, about 1 km from the central part. The fourth was in the upstream part, with a depth ranging from 2 to 8 m, 5 km away from the city. For the analysis, 160 samples were selected for the study. The water quality parameters measured were: chemical oxygen demand (COD), biochemical oxygen demand (BOD) and dissolved oxygen (DO). The chemical analyses were performed using standard methods (APHA, 1995). The basic statistics of the measured water quality variables in the Surma River and correlation coefficient with DO are presented in Table 2. As there are only two independent variables and BOD has a very significant influence over DO, BOD has been selected as an individual input variable for RBFN-II and FFNN-II models. Moreover

Table 1 Global Positioning of the sampling points.

Point	Location	Latitude	Longitude
a	Kajir Bazar	24°53′16.32″N	91°51′30.44″E
b	Keane Bridge	24°53′17.16″N	91°52′03.30″E
c	Shahjalal Upashahar	24°52′57.26″N	91°52′43.62″E
d	Burhanudin's Mazar	24°52′37.40″N	91°53′36.70″E

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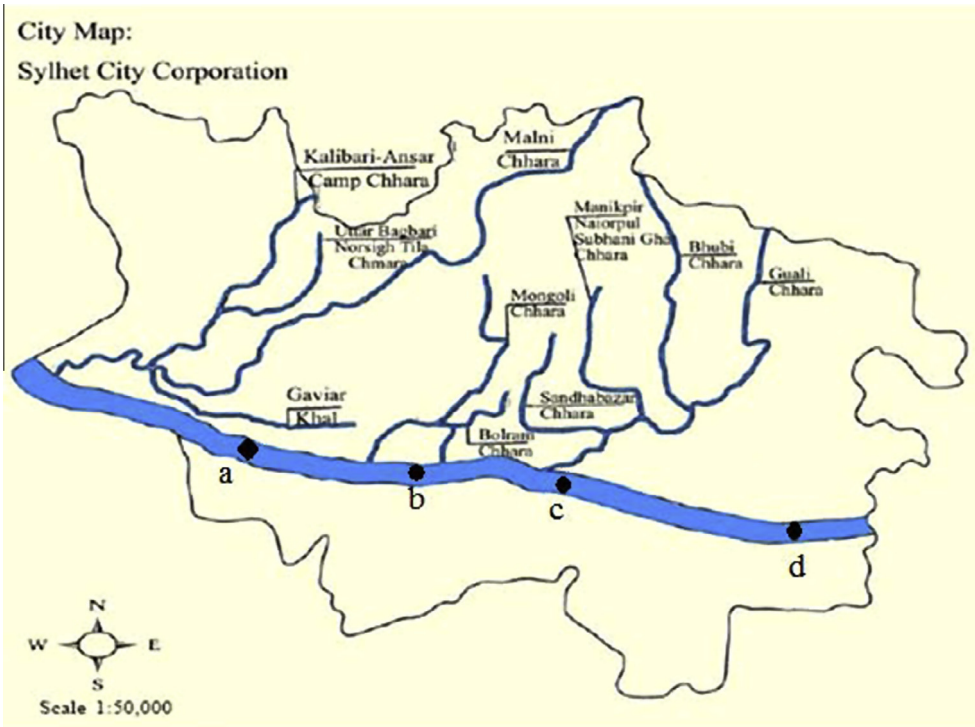

Figure 1 Sampling locations of water samples of the Surma River.

Table 2 Basic Statistics of the measured water quality variables in the Surma River.

Variable	Unit	Minimum	Maximum	Mean	SD	CDO
BOD	mg/l	0.6	17.3	3.79	2.86	0.727
COD	mg/l	2.2	19.43	6.65	2.11	0.557
DO	mg/l	1.9	17.30	5.40	2.45	1.000

SD: standard deviation; CDO: correlation with DO.

Table 3 Data Combination using correlation co-efficient between DO other variables.

Input name	Data combination	Network architecture
FFNN-I	BOD + COD	2-30-1
FFNN-II	BOD	1-20-1
RBFN-I	BOD + COD	2-55-1
RBFN-II	BOD	1-65-1

the RBFN-I and FFNN-I models were constructed with both variables (Table 3).

2.2. Artificial neural network model

The artificial neural networks are composed of a set of artificial neurons which are inspired by biological systems. The model of a neuron is represented in Fig. 2. Back propagation (BP) is a gradient descent algorithm in which the gradient is computed for nonlinear multilayer networks. The ANN parameters (weights and biases) can be adjusted to minimize the sum of the squares of the differences between the actual values and network output values.

The output of a neuron can be expressed as : $\text{out} = f(n)$ (1)

$$\text{Where } n = \sum_{j=1}^{R} \omega_j x_j + b; \quad (2)$$

$x_1, x_2, \ldots\ldots, x_R$ are the input signals;
$\omega_1, \omega_2, \ldots\ldots, \omega_R$ are the weights of the neuron;
b is bias value; and
$f(n)$ is the activation function.

The linear and sigmoid are the most common used activation functions in the construction of artificial neural networks (Rankcovic et al., 2010).

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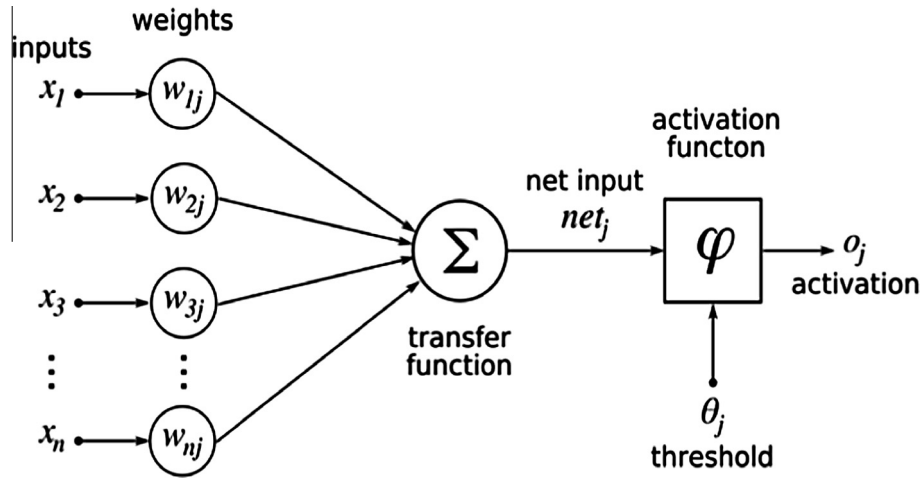

Figure 2 A typical multilayer perceptron ANN architecture (Ahmed et al., 2013).

The linear function is written as

$$f(n) = n \tag{3}$$

and the logistic sigmoid function is defined as

$$f(n) = \frac{1}{1+e^{-n}} \tag{4}$$

However, Haykin (1999) identified a sigmoid function that can be used as a hyperbolic tangent function

$$f(n) = \frac{1-e^{-n}}{1+e^{-n}} \tag{5}$$

The output y at linear output node can be calculated as:

$$y = \sum_{i=0}^{z}\left(\omega_{1,i(2)}\frac{1-e^{-\left(\sum_{j=1}^{R} x_j\omega_{i,j(1)}+b_{i(1)}\right)}}{1+e^{-\left(\sum_{j=1}^{R} x_j\omega_{i,j(1)}+b_{i(1)}\right)}}\right)+b_{1(2)} \tag{6}$$

where R is the number of inputs, z is the number of hidden neurons, $\omega_{i,j(1)}$ is the first layer weight between the input j and the ith hidden neuron, $\omega_{1,i(2)}$ is the second layer weight between the ith hidden neuron and output neuron, $b_{i(1)}$ is a biased weight for the ith hidden neuron and $b_{1(2)}$ is a biased weight for the output neuron. Feed forward neural networks propagate data linearly from input to output and they are the most popular and most widely used models in many practical applications (Rankovic et al., 2010). In this paper, Levenberg–Marquardt algorithm was used as the training algorithm and log-sigmoidal (logsig) was chosen for the activation function.

A radial basis function network has a feed-forward structure consisting of a single hidden layer for a given number of locally tuned units which are fully interconnected to an output layer of linear units (Dibike et al., 1999; Mason et al., 1996). Learning in RBF network is carried out in two phases: first, for the hidden layer, and then for the output layer. The hidden layer is self-organizing; its parameters depend on the distribution of the inputs, not on the mapping from the input to the output. The output layer, on the other hand, uses supervised learning to set its parameters. A RBF hidden unit has one parameter associated with each input unit. These parameters w are not weights placed on the input; rather they are the co-ordinates in input space of a point, that is, the center of the hidden unit output function. The RBF meta model is based on radial basis functions using cones (circular hyperboloid), and it is mathematically represented as follows:

$$f(x) = \sum_{i=1}^{n} w_i \varnothing(||x - x_i||) \tag{7}$$

where n is the number of sampling points; x is the vector of input variables; x is the center of basis function ϕ, $||.||$ is any lp norm (typically is Euclidean norm, this kind of norm is used in this study) and w is the unknown weighting coefficient. Therefore, an RBF is actually a linear combination of n basis functions with weighted coefficients.

RBF can be expressed as a matrix format:

$$f = A\lambda \tag{8}$$

$$\text{where} f = [f(x1), f(x2), \ldots\ldots, f(xm)]^T, A_{ij} = \Phi(||x_i - x_j||)i = 1, 2, \ldots, m; j = 1, 2, \ldots, n \tag{9}$$

The coefficient vector λ is obtained by solving Eq. (9). An RBF using the aforementioned highly nonlinear functions does not work well for linear responses. To solve this problem, we can augment an RBF by including a polynomial function such that.

$$f(x) = \sum_{i=1}^{n} w_i \varnothing(||x - x_i||) + \sum_{j=1}^{m} c_j p_j(x) \tag{10}$$

where m is a total number of terms in the polynomial, and c (j = 1,2, …, m) is the corresponding coefficient.

In this paper, 70% of the total data sets are assigned for training, 15% data sets are allocated for testing and last 15% data sets are assigned for the validation array. The overall performance of the model was evaluated based on the performances of all three modes.

2.3. Performance determination parameters

In the research training of ANN models of different architectures applied an automatic performance analysis of the networks based on the correlation coefficient (R), mean squared error (MSE) and coefficient of efficiency (E) was performed. The R value indicates the strength and direction of a linear relationship between two variables. Therefore, an initial screening of different ANN models was conducted. Then, the

Table 4 Performance parameters of the artificial neural network models.

Model	Mode	E	MSE	R
RBFN-I	Testing	0.905	0.465	0.904
	Validation	0.966	1.009	0.963
	Whole	0.936	0.654	0.944
RBFN-II	Testing	0.846	1.181	0.861
	Validation	0.855	0.942	0.897
	Whole	0.892	1.190	0.892
FFNN-I	Testing	0.997	2.199	0.918
	Validation	0.862	0.693	0.898
	Whole	0.936	0.709	0.936
FFNN-II	Testing	0.938	0.550	0.939
	Validation	0.855	2.925	0.854
	Whole	0.880	1.478	0.870

ANN models were further examined to decide which one is the superlative. For this reason, visual inspection of time-series plots of measured and predicted DO was performed. For the performance analysis, the following parameters were calculated for each ANN model.

1. Correlation coefficient is defined as the degree of correlation between the experimental and modeled values (Rankovic et al., 2010).

$$R = \sum_{k=1}^{N}(y_k - \bar{y})(t_k - \bar{z}) / \sqrt{\sum_{k=1}^{N}(y_k - \bar{y})^2 \sum_{k=1}^{N}(t_k - \bar{z})^2} \quad (11)$$

2. Mean squared error (MSE) measures the average of the squares of the errors. The smaller values of MSE ensure the better performance. The MSE is calculated as:

$$\mathrm{MSE} = \frac{1}{N} * \sum_{k=1}^{N}(t_{k-}y_k)^2 \quad (12)$$

3. The coefficient of efficiency (E) has been widely used to evaluate the performance of hydrologic models. Nash and Sutcliffe (1970) defined the coefficient of efficiency which ranges from minus infinity to 1.0, with higher values indicating better agreement. It is calculated as:

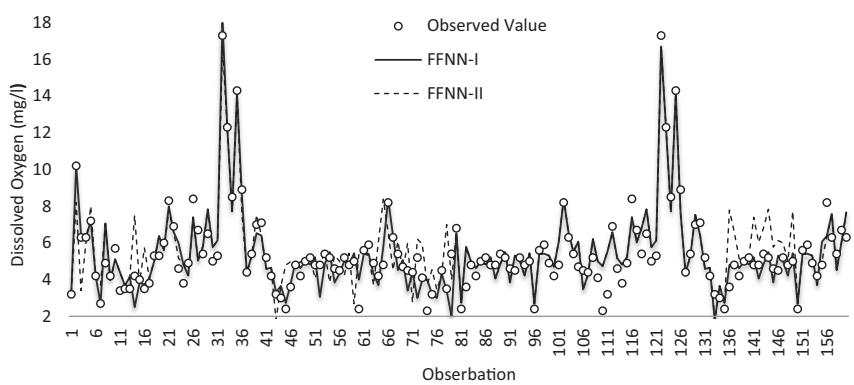

Figure 3 The observed and modeled dissolved oxygen values in whole array using feed forward neural network.

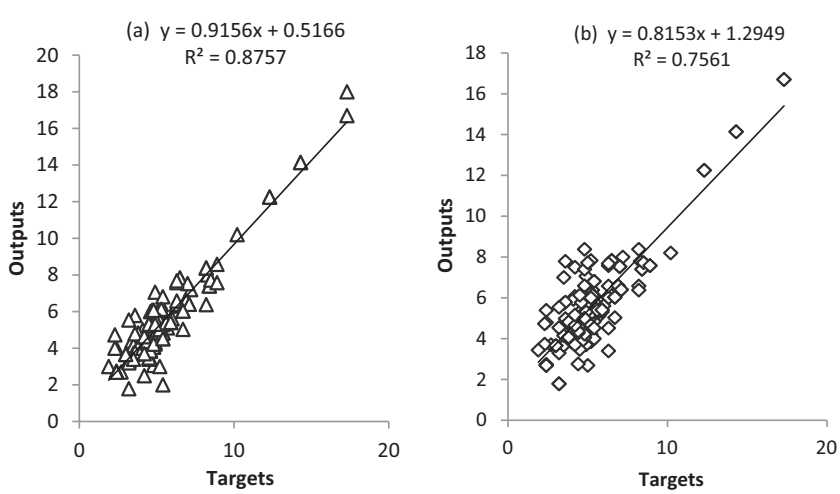

Figure 4 Scatter plot of observed versus modeled dissolved oxygen concentration for feed forward neural network (a) FFNN-I; (b) FFNN-II.

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$$E = 1 - \frac{\sum_{k=1}^{N}(t_k - y_k)^2}{\sum_{k=1}^{N}(t_k - \bar{z})^2} \quad (13)$$

where, y_k and t_k denote the network output and measured value from the kth element; $\bar{y}$ and $\bar{z}$ denote their average respectively, and N represents the number of observations.

3. Results and discussion

The ANN models were trained utilizing different numbers of neuron in the hidden layer, for training, testing, validation and whole array (training + testing + validation) for an input combination. The ANN models that had a higher R value were tabulated and three performance determination parameters were calculated to check the DO prediction capability of two selected ANN models with different network architecture. Among the selected two ANN models, the developed ANN model with RBFNN simulated the DO concentrations of the Surma River more accurately when compared to that with FFNN architecture. The performance parameters for the best DO forecast ANN models are shown in Table 4. The observed and modeled dissolved oxygen values in whole array using feed forward neural network and radial basis function neural network have been illustrated in Figs. 3 and 5. However, the scatter plot of observed versus modeled dissolved oxygen concentration for feed forward neural network and radial basis function neural network is shown in Figs. 4 and 6.

The model RBFN-I with all the input parameters is found as the most appropriate model for dissolved oxygen prediction with high correlation coefficient (R), high coefficient of efficiency (E) and low mean squared error (MSE) value. The respective correlation coefficient for RBFN-I model is 0.904, 0.963 and 0.944 for testing, validation and whole array. However, the MSE and E for the three data sets are 0.465 and 0.905 for testing, 1.009 and 0.966 for validation, and 0.654 and 0.936 for whole set. The prediction ability of RBFN-I is almost similar to Ying et al. (2007) who found the correlation coefficient as 0.94 between the measured and modeled DO values and Soyupak et al. (2003) where they found a correlation coefficient of 0.950 between the measured and modeled variables.

The FFNN-II and RBFN-II models constructed with only BOD showed similar performance for dissolved oxygen prediction with high correlation coefficient and coefficient of efficiency for all arrays (training, testing, validation and whole array). The respective correlation coefficient for RBFN-II model is 0.861, 0.897 and 0.892 for testing, validation and

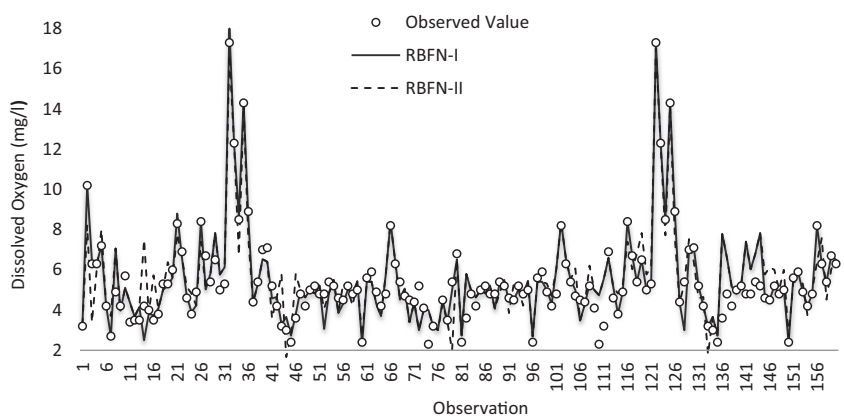

Figure 5 The observed and modeled dissolved oxygen values in whole array using radial basis neural network.

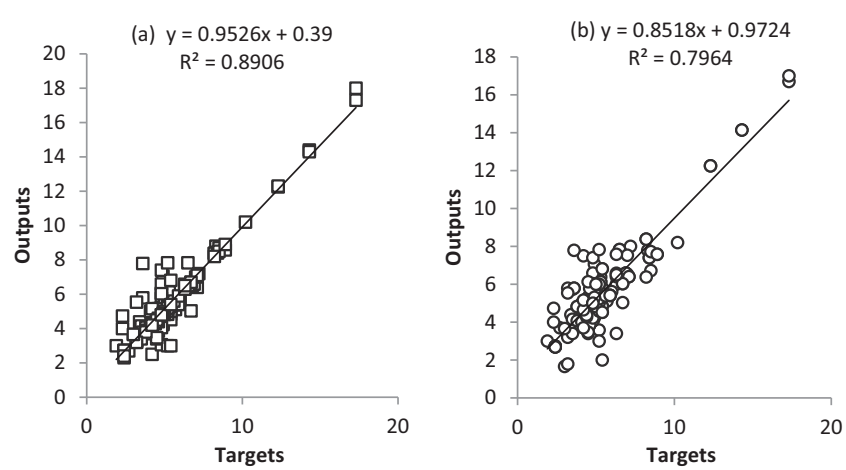

Figure 6 Scatter plot of observed versus modeled dissolved oxygen concentration for radial basis function neural network (a) RBFN-I; (b) RBFN-II.

whole array accordingly. However, the MSE and E for the two data sets are 1.181 and 0.846 for testing, 0.942 and 0.855 for validation, and 1.19 and 0.892 for whole set. However, another ANN model of feed forward neural network, FFNN-II has coefficient of efficiency (E) values of 0.938, 0.855 and 0.880 for testing, validation and whole sets respectively. Moreover, a high value of MSE has been found for the validation array.

The results of this study can be compared with Kuo et al. (2007) who applied an ANN model for predicting the dissolved oxygen in the Te-Chi reservoir. The correlation coefficients for modeled values and observed DO values were 0.75 and 0.72 for training and test data sets, accordingly. Similarly, Singh et al. (2009) found coefficient of determination for modeled values and observed DO values to be 0.85, 0.85, and 0.77, for the training, validation and test sets, respectively. They utilized a three-layer feed forward neural network with back propagation learning to predict DO and BOD levels for Gomti River (India). Rankovic et al. (2010) applied artificial neural network to develop a feed forward neural network (FFNN) model to predict the dissolved oxygen in the Gruza Reservoir, Serbia. They used the Levenberg–Marquardt algorithm to train the FFNN. In their study they found the coefficient of correlation for the test set to be 0.848 and 0.840 for the whole data set. The respective values of root means squared error and bias for the three data sets are 2.25 and 0.14 for training, 1.84 and 0.87 for validation, and 1.38 and −0.22 for testing.

The paper revealed that the proposed ANN models with minimum input parameters such as biochemical oxygen demand and chemical oxygen demand could be successfully used for predicting dissolved oxygen concentrations.

4. Conclusions

In this paper, ANN models were developed to predict dissolved oxygen in the Surma River. The proposed model shows efficiency in forecasting the dissolved oxygen concentration in water bodies. The results showed that the radial basis function neural network model prepared by BOD and COD provided high correlation coefficient (R), high coefficient of efficiency (E) and low mean squared errors (MSE) value for all three modes. However, the feed forward neural networks with two variables provided convincing results. It has been confirmed that DO in the Surma River can be predicted with acceptable accuracy from a small set of variables using feed forward neural network (FFNN) and radial basis function neural network (RBFNN). Dissolved oxygen is an important parameter for the water bodies. The obtained result may be applied to power DO estimations to be utilized in water management and treatment systems.

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