Asian Journal of Chemistry; Vol. 24, No. 1 (2012), 145-149

ASIAN JOURNAL OF CHEMISTRY

www.asianjournalofchemistry.co.in

Modeling Wastewater Treatment Performance of a Vegetated Constructed Wetland Using Neural Network Approach

C.B. ERSU

Department of Environmental Engineering, Cukurova University, 01330 Balcali, Adana, Turkey

Corresponding author: Tel: +90 322 3386779; E-mail: cbersu@yahoo.com

(*Received*: 29 November 2010; *Accepted*: 12 September 2011) AJC-10388

A multi-layer perceptron neural network model with Levenberg-Marquardt algorithm (MLP-LM) was developed based on the performance and operation data of a research worker named Marahatta on a full-scale vegetated submerged wetland system (VSB) operated for a 5 year period. Influent chemical oxygen demand (COD_{inf}), volatile suspended solids (VSS_{inf}), total solids (TS_{inf}) and temperature (T) were determined as the inputs of the model, whereas the output variables were one of the following; (i) effluent chemical oxygen demand (COD_{eff}), (ii) total solids (TS_{eff}) and (iii) volatile suspended solids (VSS_{eff}). Multi-linear regression (MLR) and multi non-linear regression (MNLR) techniques were also used for data analysis to compare the prediction capability. Four criteria used for a statistical comparison were the following: mean square error (MSE), mean absolute error (MAE), mean absolute relative error (MARE) and determination coefficient (R^2). The results showed that MLP-LM approach predicted the performance of the constructed wetland system than the MLR and MNLR techniques.

Key Words: Artificial neural network, Submerged bed system, Constructed wetland, Modeling, Treatment performance, Wastewater treatment.

INTRODUCTION

The type of wastewater treatment technique used for water quality control is becoming more important due to rising environmental issues. At present, there are many traditional and novel technologies applied for wastewater treatment and their construction and operation/maintenance costs may differ in a wide range. With features like acceptable efficiency, easy operation, ecologically friendliness and low cost, constructed wetlands, today, are considered as one of the sustainable treatment alternatives that can be employed for non-point source pollution control[1,2], the treatment of agricultural waste[3-5], domestic wastewater[6-8], industrial waste[9,10], urban run-off/stormwater[11,12] and treatment plant effluents[13,14]. These systems are furthermore applied to strip nutrients of eutrophied surface waters as well as domestic wastewater[15-17]. It must, however, be stressed that wetlands for wastewater treatment have several other functions such as water quality improvement, they can also function as a nature development area, a recreational area, a hydrological buffer or a reservoir[18].

The models applied to predict the system performance of constructed treatment wetlands can be classified into two; (i) simple transport and first-order decay models, (ii) mechanistic or process based models[19]. Among these models is artificial neural network model (ANN), which is a technique inspired by biological neuron processing. The ANN models have a wide application field on several scientific disciplines for time series forecasting, process control and pattern recognition. Their primary advantage over traditional methods is that they do not require the complex nature of the underlying process[20]. Once reliable models for constructed wetlands are useful, they can also be used for evaluating and improving existing design criteria[21]. Artificial neural networks (ANNs) have already been used to simulate the effect of climate change on the discharge and the exportation of dissolved organic carbon and nitrogen from river basins[22], to simulate and forecast residual chlorine concentrations within urban water systems[23], to forecast salinity in water resources[24], to determine the relationship between sewage odour and BOD[25] and to determine the leachate amount from municipal solid waste landfill[26]. Akratos *et al.*[17,27] suggested that artificial neural networks were able to predict biochemical oxygen demand (BOD) and total nitrogen (TN) removal in horizontal subsurface flow constructed wetlands. Very few studies have been conducted on ANN-based prediction of organic matter concentration in the effluents of constructed wetlands[17,27-29].

This study aimed at investigating the process performance of vegetated submerged wetland (VSB) systems based on the observation full-scale applications of wetland systems. One may perform basic statistics, numerical differentiation and integration, evaluate all types of functions solve dynamical systems and partial differential equations, estimate parameters and so forth. Whereas, in current study, a multi-layer perceptron neural network model with a Levenberg-Marquardt algorithm (MLP-LM) was developed based on the performance and operation data of Marahatta[1] on a full-scale vegetated submerged wetland system (VSB) operated for a 5 year period. The aim of this model was to guess the future problems, minimize the pollutions in future, ecosystem rehabilitation, without treatment plant's laboratory, guess the performance, minimize the cost, minimize the margin of error, minimize the manpower, comparing with reactor performance and model performance, to understand relationship between literature parameters.

EXPERIMENTAL

Multi-linear regression (MLR): MLR method constructs a linear relationship between a dependent variable and one or more independent variables. In this method, the dependent variable, y, is regarded as a linear function of p number of independent variables, x_1, x_2,..., x_p. In this case, the linear equation can be formed as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_p x_p + \varepsilon \quad (1)$$

where the residual, ε, is a normally distributed random variable with a mean of zero. The regression coefficients, β_0, β_1, β_2,…, β_p, are computed for the lowest sum of squares of differences between the predicted and observed values[30].

Multi-nonlinear regression (MNLR): Similar to linear regression, non-linear regression also relates a dependent variable to a number of independent variables. Unlike linear regression, the prediction equation for nonlinear regression depends nonlinearly on one or more unknown parameters. Linear regression is often used for forming a purely empirical model, whereas non-linear regression usually arises when there are physical reasons for believing that the relationship between the response and the predictor variables follow a particular functional form. A general mathematical function (model) of a non-linear regression is described below:

$$y = f(x_1, x_2, \ldots, x_n, a_0, a_1, a_2, \ldots, a_m) \quad (2)$$

where a_0, a_1, …, a_m are regression parameters to a set of N tabulated values of x_1, x_2, …, x_n (independent variables) *versus* y (dependent variable). Note that the number of data points must be greater than m + 1 (thus N ≥ m + 1)[31].

Multi-layer perceptron (MLP) neural network: MLP neural network is generally characterized by the presence of one or more hidden layers, the structure of which is shown in Fig. 1. Computation nodes for a MLP network are called "hidden neurons of hidden units". Hidden neurons function to intervene between the external input and the network output in some useful manner. The network can be developed to extract higher order statistics *via* adding one or more hidden layers. In a rather loose sense, the network acquires a global perspective despite its local connectivity due to the extra set of synaptic connections and the extra dimension of artificial neural network (ANN) interconnections. The detailed theoretical information about MLP can be found in Haykin[32]. Here, the MLP is trained using Levenberg-Marquardt technique (LM) due to its more powerful and faster feature compared to conventional gradient descent technique[33-35]. Although MLP can employ more than one hidden layer, one-hidden-layer MLP is used in this study since theoretical works have shown that a single hidden layer is sufficient for MLP to approximate any complex nonlinear function[36,37]. Adaptive learning rates are used to speed up training throughout all MLP simulations and the numbers of hidden layer neurons are determined using trial-and-error method. The sigmoid and linear functions are used for the activation functions of the hidden and output nodes, respectively.

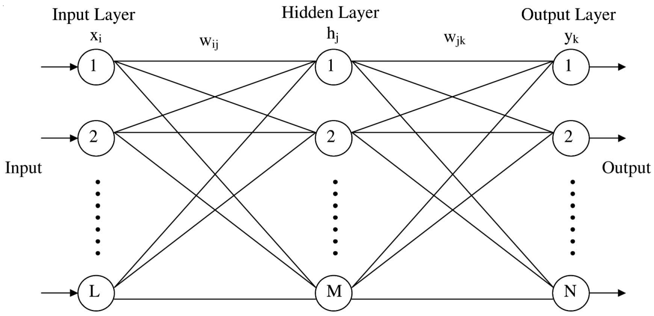

Fig. 1. MLP network model

RESULTS AND DISCUSSION

The data set obtained from the work of Marahatta[1] was randomly divided into two independent parts. To overcome some extrapolation difficulties in prediction of the extreme values, the minimum and maximum values of the parameters used in the modeling were set in the training data. For training phase, 46 data (*ca.* 70 %) were randomly selected and the remaining 19 data (*ca.* 30%) were selected for testing phase. A MATLAB code including ANN toolbox was written for the application of the MLP-LM algorithm.

The four input parameters of the MLP-LM model chosen for the present problem included COD_{inf}, TS_{inf}, VSS_{inf} and temperature (T) and the three output parameters were COD_{eff}, TS_{eff} and VSS_{eff}. Before applying the MLP-LM to the observed data, the training input and output values were normalized using the equation:

$$a\frac{x_i - x_{min}}{x_{max} - x_{min}} + b \quad (3)$$

where x_{min} and x_{max} denote the minimum and maximum of the input and out parameters that are given in Table-1. There are no fixed rules as to which standardization approach should be used for the scaling factors "a" and "b" in particular circumstances, different values can be assigned for these factors[38]. The values of a and b were taken as 0.6 and 0.2, respectively.

TABLE-1
MINIMUM AND MAXIMUM VALUES OF INPUT AND OUTPUT PARAMETERS

Model parameters	Training data set		Testing data set	
	Min	Max	Min	Max
COD_{inf}	147.0	551.7	190.0	489.3
TS_{inf}	360.3	1211.3	517.3	1141.3
VSS_{inf}	14.0	87.5	22.7	87.5
T	4.0	27.1	7.1	24.9
COD_{eff}	5.5	47.0	6.3	45.0
TS_{eff}	210.0	796.7	479.0	663.0
VSS_{eff}	75.5	300.0	130.5	272.5

In current work, the MLR and MNLR techniques were applied to the training dataset. Using MLR and MNLR techniques, the following formulae were found to offer the best statistical measures for fit of training dataset, respectively:

$$COD_{eff} = 17.8 + 0.284\ COD_{inf} + 0.140\ VSS_{inf} + 0.077\ TS_{inf} + 0.263\ T \quad (4)$$

$$TS_{eff} = 280.04 - 0.697\ COD_{inf} + 5.926\ VSS_{inf} + 0.440\ TS_{inf} - 3.69\ T \quad (5)$$

$$VSS_{eff} = 8.36 - 0.0150\ COD_{inf} + 0.380\ VSS_{inf} - 0.0113\ TS_{inf} + 0.233T \quad (6)$$

$$COD_{eff} = 0.989 * COD_{inf}^{0.672} * VSS_{inf}^{0.150} * TS_{inf}^{0.114} * T^{-0.0098} \quad (7)$$

$$TS_{eff} = 18.178 * COD_{inf}^{-0.427} * VSS_{inf}^{0.450} * TS_{inf}^{0.687} * T^{-0.113} \quad (8)$$

$$VSS_{eff} = 119.47 * COD_{inf}^{-0.356} * VSS_{inf}^{0.920} * TS_{inf}^{-0.601} * T^{0.167} \quad (9)$$

Eqns. 4-6 were developed using the MLR technique, while eqns. 7-9 were produced by the MNLR technique. The computed results predicted by the MLR, MNLR and MLP-LM models from the present study were compared with measurements with respect to the mean square error (MSE), mean absolute error (MAE), mean absolute relative error (MARE) and determination coefficient (R^2) statistics. MSE, MAE and MARE statistics are defined as:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(E_i^m - E_i^p\right)^2 \quad (10)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|E_i^m - E_i^p\right| \quad (11)$$

$$MARE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{E_i^m - E_i^p}{E_i^m}\right| \times 100 \quad (12)$$

In eqns. 10-12, E_i^m and E_i^p denote the measured and predicted output parameters, respectively and N is the total number of data. After trying various network structures and iteration numbers, the most appropriate results were obtained from the ANN (4,5,1), ANN (4,3,1) and ANN (4,6,1) models for estimating COD_{eff}, TS_{eff} and VSS_{eff}, respectively.

For the quantitative evaluation of the comparisons of the predicted COD_{eff}, TS_{eff} and VSS_{eff} values using the MLR, MNLR and MLP-LM models with measurements, the results for MSE, MAE, MARE and R^2 statistics are given in Table-2. The results in this table show that, in terms of MSE, MAE, MARE and R^2, the MLP-LM performs much better than those of the MLR and MNLR techniques.

Figs. 2 and 3 show the comparisons of the measured and predicted COD_{eff}, TS_{eff} and VSS_{eff} values obtained using the MLP-LM model for the training and testing phases, respectively. It is seen in these figures that the accurate estimations

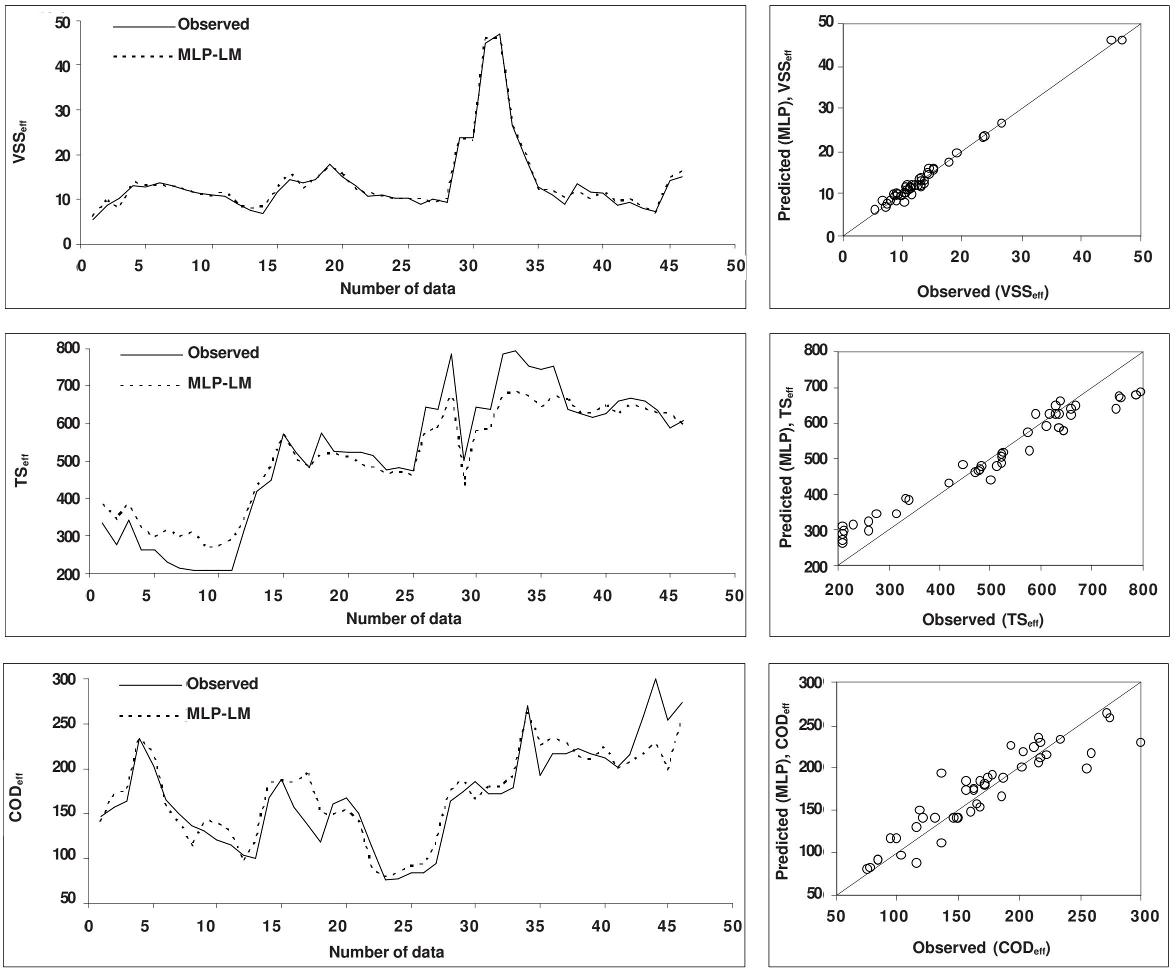

Fig. 2. Model prediction and comparison between observed and predicted effluent VSS, TS and COD during training phase

TABLE-2
STATISTICS OF MLR, MNLR AND MLP-LM MODELS FOR BOTH TRAINING AND TESTING PHASES

Parameter	Criteria	Training			Testing		
		MLR	MNLR	MLP-LM	MLR	MNLR	MLP-LM
COD_{eff}	MSE	1564.83	1658.16	493.62	1628.92	1482.16	488.11
	MAE	30.94	31.63	16.66	34.42	32.41	18.07
	MARE	205.70	18.08	10.30	194.80	14.85	8.97
	R^2	0.479	0.467	0.837	0.234	0.336	0.760
TS_{eff}	MSE	5106.51	6724.49	3138.71	9992.91	11183.95	1447.24
	MAE	55.80	69.50	45.54	89.60	95.52	31.79
	MARE	203.97	16.01	11.29	191.97	17.68	5.69
	R^2	0.840	0.796	0.958	0.617	0.614	0.715
VSS_{eff}	MSE	24.11	25.73	0.74	28.86	33.87	2.94
	MAE	3.21	2.91	0.69	3.38	3.55	1.32
	MARE	207.35	20.63	6.09	219.06	26.92	11.10
	R^2	0.631	0.661	0.989	0.614	0.606	0.960

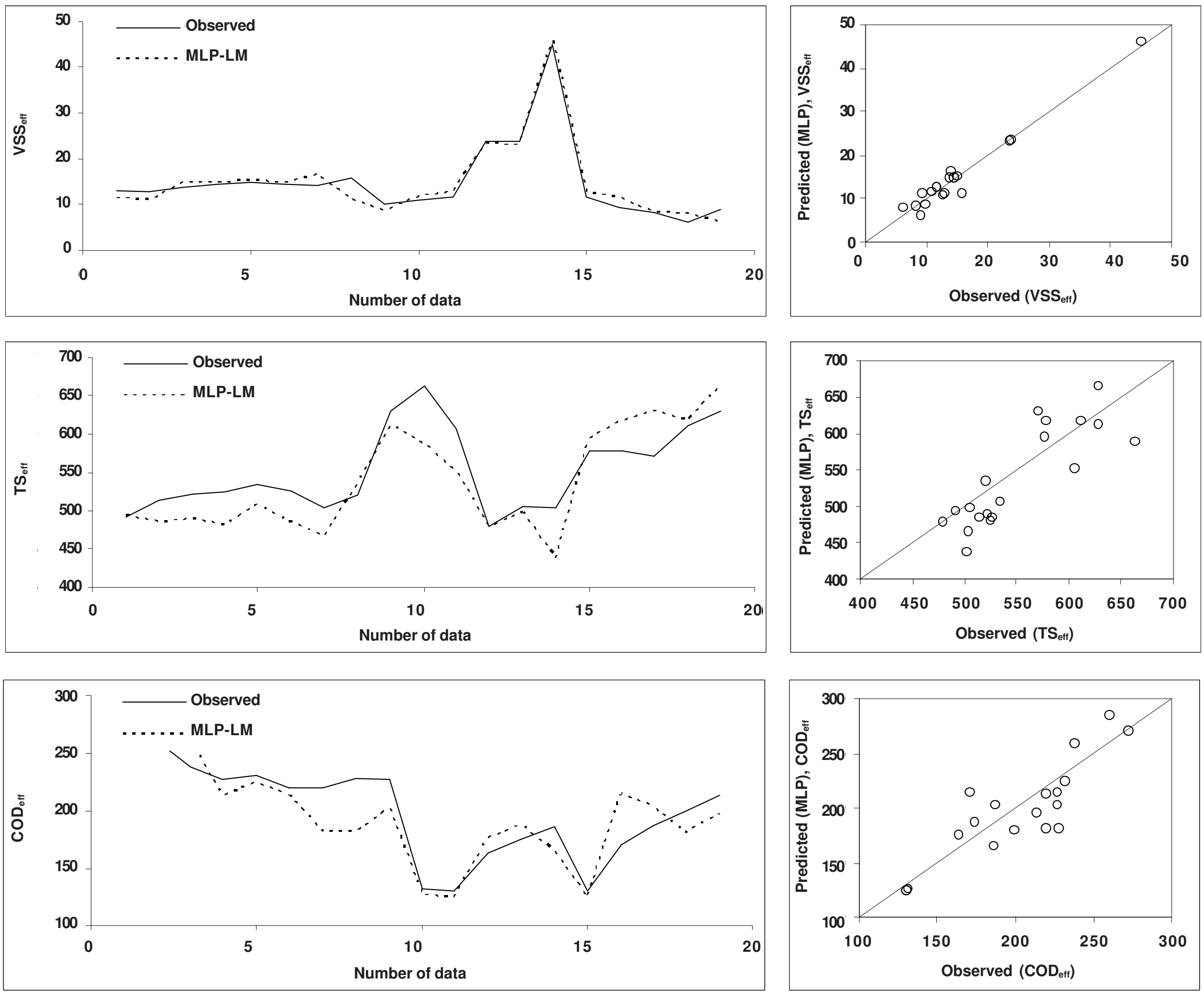

Fig. 3. Model prediction and comparison between observed and predicted effluent VSS, TS and COD during testing phase

for COD_{eff}, TS_{eff} and VSS_{eff} values are achieved by the MLP-LM model.

Conclusion

This study indicates the ability of an artificial neural network approach called as MLP-LM to model the relationships between influent and effluent values of chemical oxygen demand (COD), volatile suspended solids (VSS) and total solids (TS) based on the measured data obtained from the literature. The results showed that the MLP-LM performs better than the MLR and MNLR techniques. The study only used data from the work of Marahatta1 and further work using more data may be required to strengthen these conclusions.

REFERENCES

1. R.C. Marahatta, Ph.D. Thesis, Multi-scale Modeling of a Vegetated Submerged Bed System with Application in Organic Matter Removal and Cloggings, University of Nebraska, Lincoln (2004).
2. H.F. MacDonald, J.C. Bergstrom and J.E. Houston, *J. Environ. Manage.*, **54**, 259 (1998).
3. C.C. Tanner, J.S. Clayton and M.P. Upsdell, *Water Res.*, **29**, 17 (1995).
4. C.C. Tanner, J.S. Clayton and M.P. Upsdell, *Water Res.*, **29**, 27 (1995).
5. J. Kern and C. Idler, *Ecol. Eng.*, **12**, 13 (1999).
6. S. Reed, E. Middlebrooks and R. Crites, Natural Systems for Waste Management and Treatment, McGraw-Hill, New York (1995).
7. R. Kadlec and R. Knight, Treatment Wetlands, CRC Press (1996).
8. A. Al-Ommari and M. Fayad, *Desalination*, **155**, 27 (2003).
9. T. Panswad and O. Chavalparit, *Water Sci. Technol.*, **36**, 183 (1997).
10. P.A. Mays and G.S. Edwards, *Ecol. Eng.*, **16**, 487 (2001).
11. T.H.F. Wong and N.L.G. Somes, *Water Sci. Technol.*, **32**, 145 (1995).
12. J.N. Carleton, T.J. Grizzard, A.N. Godrej, H.E. Post, L. Lampe and P.P. Kenel, *Water Environ. Res.*, **72**, 295 (2000).
13. F.E. Dierberg and P.L. Brezonik, *Water Res.*, **17**, 1027 (1983).
14. E. Llorens, V. Matamoros, V. Domingo, J.M. Bayona and J. Garcia, *Sci. Total Environ.*, **407**, 2517 (2009).
15. J. Huang, R. Reneau and C. Hageborn, *Water Res.*, **34**, 2582 (2000).
16. D.P.L. Rousseaua, P.A. Vanrolleghemb and N.D. Pauwa, *Water Res.*, **38**, 1484 (2004).
17. C.S. Akratos, J.N.E. Papaspyros and V.A. Tsihrintzis, *Bioresour. Technol.*, **100**, 1656 (2009).
18. J. Bays, G. Dernlan, H. Hadjimiry, K. Vaith and C. Keller, In proceedings of of the Water Environment Federation's Technical Exhibition and Conference (WEFTEC), Anaheim, California, 14-18 October (2002).
19. G. Langergraber, D. Giraldi, J. Mena, D. Meyer, M. Peña, A. Toscano, A. Brovelli and E.A. Korkusuz, *Sci. Total Environ.*, **407**, 3931 (2009).
20. P.C. Nayak, Y.R.S. Rao and K.P. Sudheer, *Water Resour. Manag.*, **20**, 77 (2006).
21. G. Langergraber, *Sci. Total Environ.*, **380**, 210 (2007).
22. T.A. Clair and J.M. Ehrman, *Limnol. Oceanogr.*, **41**, 921 (1996).
23. M.J. Rodriguez and J.B. Seirodes, *Environ. Modell. Softw.*, **14**, 93 (1998).
24. H.R. Maier and G.C. Dandy, *Water Resour. Res.*, **32**, 1013 (1996).
25. E.G. Onkal, I. Demir and S.N. Engin, *Environ. Modell. Softw.*, **20**, 843 (2005).
26. F. Karaca and B. Ozkaya, *Environ. Modell. Softw.*, **21**, 1190 (2006).
27. C.S. Akratos, J.N.E. Papaspyros and V.A. Tsihrintzis, *Chem. Eng. J.*, **143**, 96 (2008).
28. R. Pastor, C. Benqlilou, D. Paz, G. Cardenas, A. Espuna and L. Puigjaner, *Resour. Conserv. Recy.*, **37**, 193 (2003).
29. V. Tomenko, S. Ahmed and P.V. Viktor, *Ecol. Modell.*, **205**, 355 (2007).
30. S.C. Chapra and R.P. Canale, Numerical Methods for Engineers with Software and Programming Applications, Mc-Graw-Hill, New York, edn. 4 (2002).
31. A.H. El-Shaarawi and W.W. Piegorsch, Encyclopedia of Environmetrics, Chichester: John Wiley & Sons, Ltd., pp. 1405-1411 (2002).
32. S. Haykin, Neural Networks-A Comprehensive Foundation, Upper Saddle River (NJ), Prentice-Hall, edn. 2, pp. 26-32 (1998).
33. M.T. Hagan and M.B. Menhaj, *IEEE Trans. Neur. Net.*, **5**, 861 (1994).
34. M.Y. El-Bakyr, *Chaos. Soliton Fractals*, **18**, 995 (2003).
35. H.K. Cigizoglu and O. Kisi, *Nordic. Hydrol.*, **36**, 49 (2005).
36. G. Cybenco, *Math. Control Signals Syst.*, **2**, 303 (1989).
37. K. Hornik, M. Stinchcombe and H. White, *Neural Net.*, **2**, 359 (1989).
38. W.C. Dawson and R. Wilby, *Hydrol. Sci. J.*, **43**, 47 (1998).