www.trjfas.org
ISSN 1303-2712
Turkish Journal of Fisheries and Aquatic Sciences 18:1333-1343(2018) DOI: 10.4194/1303-2712-v18_12_01

PROOF RESEARCH PAPER

An Adaptive Neuro-Fuzzy Inference System (ANFIS) to Predict of Cadmium (Cd) Concentrations in the Filyos River, Turkey

Adem Yavuz Sonmez[1,*], Semih Kale[2], Rahmi Can Ozdemir[1], Ali Eslem Kadak[1]

[1] Fisheries Faculty, Kastamonu University, Kastamonu, Turkey.
[2] Faculty of Marine Sciences and Technology, Çanakkale Onsekiz Mart University, Çanakkale, Turkey.

* Corresponding Author: Tel.: +90.366 2802302 ; Fax: +90.366 2802352;
E-mail: aysonmez@kastamonu.edu.tr

Received 12 August 2017
Accepted 22 January 2018

Abstract

Water quality is one of the main characteristics of a river system and prediction of water quality is the key factor in water resource management. Different physical, biological and chemical parameters including heavy metals can be used to assess river water quality. Evaluation of the water quality in the rivers is quite difficult and requires more time and effort because of the fact that many factors affect water quality. Traditional data processing methods are insufficient to solve this problem. Therefore, in this study, an adaptive neuro-fuzzy inference system (ANFIS) model was developed to predict the concentrations of cadmium (Cd) in the Filyos River, Turkey. For this purpose, water samples collected at 7 sampling locations in the river during December 2014-2015 were used to develop ANFIS model. The available data set was apportioned into two separate sections for training and testing the ANFIS model. Developed models aimed to use the least parameters to estimate Cd concentration. As a result, a relatively higher correlation (R^2=0.91) was found between observed and modelled Cd concentrations. The results indicated that the ANFIS model gave reasonable estimates for the concentrations of Cd with a high degree accuracy and robustness. In conclusion, this paper suggests that ANFIS methodology produce very successful findings and has the ability to predict Cd concentration in water resources. The outcomes of this research provide more information, simulation, and prediction about heavy metal concentration in natural aquatic ecosystems. Therefore, ANFIS can be used in further researches on water quality monitoring.

Keywords: ANFIS, cadmium, heavy metal.

Introduction

Metals move to rivers from different sources, such as soils and rocks directly get exposed to surface waters, fallout of atmospheric particulate matter, decomposing dead organic matter, and from anthropological activities, including the release of refined and unrefined liquid wastes into the water resource (Olayinka & Alo, 2004, Sönmez *et al.*, 2016). In particular, releasing of Cd into the aquatic environment from industrial activities is a serious threat for the aquatic ecosystems (Qasaimeh, Abdallah, & Bani Hani, 2012).

Heavy metal dynamics have nonlinear and highly complex relations with each other. Therefore, traditional data processing and modelling methods required several input parameters which are hard to reach and make it a time consuming and expensive process are insufficient to solve the problems related to water quality (Ranković, Radulović, Radojević, Ostojić, & Čomić, 2012; Bayatzadeh Fard, Ghadimi, & Fattahi, 2017). The integration of different techniques and methods will contribute to the future of eco-environmental modelling (Chen, Morales-Chaves, Li, & Mynett, 2006). Soft computing techniques have been commonly used in many areas including environmental modelling and water resource engineering. Modelling complex nonlinear systems is one of the successful applications of artificial intelligence (AI) techniques such as fuzzy inference systems (FIS), artificial neural networks (ANNs), genetic algorithms and knowledge-based systems (Wang, Chau, Cheng, & Qiu, 2009).

Several authors studied various AI techniques in environmental modelling, water quality monitoring and assessment, predicting the concentrations of heavy metals and other quality parameters, and estimation and forecasting in climatic sciences (Soyupak *et al*., 2003; Altunkaynak, Özger, & Çakmakcı, 2005; Kisi, 2005; Ocampo-Duque, Ferré-Huguet, Domingo, & Schuhmacher, 2006; Sengorur, Dogan, Koklu, & Samandar, 2006; Terzi, Keskin, & Taylan, 2006; Dahiya, Singh, Gaur, Garg, & Kushwaha, 2007; Icaga, 2007; Elhatip & Kömür, 2008; Hanbay, Turkoglu, & Demir, 2008; Dogan, Sengorur, & Koklu, 2009; Lermontov, Yokoyama, Lermontov, & Machado, 2009; Rehana & Mujumdar, 2009; Singh, Basant, Malik, & Jain, 2009; Ranković, Radulović, Radojević, Ostojić, & Čomić, 2010; Akkoyunlu, Altun, & Cigizoglu, 2011; Ay & Kisi, 2011, 2014; Areerachakul, 2012; Hisar, Sönmez, Kaya, & Aras Hisar, 2012; Kisi & Ay, 2012; Qasaimeh *et al*., 2012; Sönmez, Hisar, & Yanık, 2012, 2013b; Sönmez, Hasiloglu, Hisar, Aras Mehan, & Kaya, 2013a; Chen & Liu, 2014; Emamgholizadeh, Kashi, Marofpoor, & Zalaghi, 2014; Heddam, 2014; Nemati, Naghipour, & Fazeli Fard, 2014; Yılmaz Öztürk, Akköz, Aşıkkutlu, & Gümüş, 2014; Ahmed & Shah, 2015; Alte & Sadgir, 2015; Csábrági, Molnár, Tanos, & Kovács, 2015, 2017; Nemati, Fazelifard, Terzi, & Ghorbani, 2015; Piotrowski, Napiorkowski, Napiorkowski, & Osuch, 2015; Akpomie, Ekanem, Adamu, & Akpomie, 2016; Kanda, Kipkorir, & Kosgei, 2016; Khadr & Elshemy, 2016; Bayatzadeh Fard *et al*., 2017).

Although heavy metal modelling has been studied by using various statistical and computational approaches, several aspects of their dynamics are still blurred (Akoto, Bruce, & Darko, 2008). Therefore, the purpose of this study was to create an adaptive neuro-fuzzy inference system model to predict the concentrations of Cd in the Filyos River, Turkey and to demonstrate the model application to identify nonlinear complex relationships between input and output variables.

Material and Methods

Study Area and Sampling

Filyos River is geographically located at the southern west coast of the Black Sea in Turkey. It flows through the West Black Sea River Basin and run into Black Sea from Filyos town in Zonguldak city (Figure 1). It is totally 312 km in length. It also has two main branches: Devrek Stream and Yenice Stream and 13300 km^2 drainage area (Kucukali, 2008). Çaycuma and Gökçebey districts situate near the Filyos River and their populations have been increasing day by day. Although the economy of the region is dependent on agriculture and forestry, it has been changed with the construction of some industrial factories such as cement and paper factories (Seker *et al*., 2005). There are substantial differences in the richness of terrestrial ecosystem attributable to the topographical features of the region and the delta of the river is a natural environment with untouched areas (Kucukali, 2014).

The water samples were collected twice at a time by monthly from seven stations at the Filyos River in Turkey between December 2014 and December 2015 (Figure 1). The coordinates of sampling stations were obtained using a handheld GPS device (Table 1). Samples were collected with the Nansen bottle and preserved in the polyethylene (PE) bottles after filtering with 0.45 µm pore size membrane filter. Both the Nansen bottle and PE bottles were washed with

Figure 1. Study area and sampling stations

Table 1. Coordinates of the sampling stations

Station code	Latitude (N)	Longitude (E)
S1	41.552125	32.081409
S2	41.299621	32.096858
S3	41.261114	32.157202
S4	41.211915	32.267908
S5	41.167057	32.579248
S6	41.233736	33.303101
S7	41.037858	33.294250

water to be collected in the sampling stations (Alam, Tanaka, Stagnitti, Allinson, & Maekawa, 2001). Collected water samples were stored in a cooler at +4°C. Heavy metal (Fe, Cu, Mn, Zn, Ni, Cr and Cd) concentrations were determined by Inductively Coupled Plasma Optical Emission Spectrometry (ICP/OES).

Data Preparation and Input Selection

Normalization of water quality parameters is significant for avoiding larger numbers in a uniform range and to be able to scale the data in a same range. Normalization process has an important effect on data preparation to speed up the training time in ANFIS. There are many statistical normalization techniques such as Z-score, min-max, median, sigmoid, and statistical column normalization (Jayalakshmi & Santhakumaran, 2011). In this study, all input data were normalized using Z-score normalization technique for which formula is given in Eq (1). Z-score normalization technique uses standard deviation and mean for each feature through a set of training data for normalizing each input feature.

$$S_i = \frac{(x_i - \mu_i)}{\sigma_i} \quad (1)$$

where, x_i is input data, σ_i is standard deviation of x_i, μ_i is mean of x_i, S_i is normalized x variable as input to ANFIS.

It is important to determine whether the variables have a relationship with one another while modeling Cd values for the Filyos River. For this reason, a coefficient of correlation with Cd was prepared which is tabulated in Table 2.

Adaptive Neuro-Fuzzy Inference System (ANFIS)

A fuzzy system based on the logical rules of premises and conclusions cannot be analyzed with traditional probability theories. Developing fuzzy “if-then” rules is the starting point in constructing a fuzzy system. An effective tool for this purpose is a method that can convert data to the required fuzzy rules. Alternatively, artificial neural networks are capable of generating appropriate relations between input and output variables through learning capabilities based on different training patterns. A combined system of artificial neural networks and fuzzy inference accomplished with using numerical data to predict output can generate an influential tool, adaptive neuro-fuzzy inference system (ANFIS).

ANFIS is a type of neural network focused on Takagi-Sugeno fuzzy inference system. It is an AI technique currently using in hydrological processes (Bisht & Jangid, 2011). ANFIS is firstly introduced by Jang (1993) and it is based on the first-order Sugeno fuzzy model. ANFIS commonly uses either back-propagation or a combination of back-propagation and least square estimation for prediction of membership function parameter (Jang, Sun, & Mizutani, 1997). The most significant purpose of integrating neural networks with fuzzy systems is to exercise learning ability of neural network while the learning capability is a benefit in terms of fuzzy system; on the other hand, there are more benefits for a combined system from the aspect of a neural network.

Takagi-Sugeno type fuzzy inference system is used in ANFIS where every rule’s output can be a constant term or can be a linear combination of input variables addition to a constant term. The weighted average of every rule’s output is the final output. The basic architecture of ANFIS which has two inputs (x, y) and one output (z) is presented in Figure 2.

The rule base of ANFIS contains two Takagi-Sugeno type if-then rules as given below:

Rule 1: If x is A_1 and y is B_1; then $f=p_1x+q_1y+r_1$

Rule 2: If x is A_2 and y is B_2; then $f=p_2x+q_2y+r_2$

where A_1, A_2, B_1 and B_2 are nonlinear parameters while p_1, p_2, q_1, q_2, r_1 and r_2 are linear parameters.

Layer 1 is the fuzzification layer in which x is the input of A_1 and B_1 nodes and y is the input of A_2 and B_2 nodes. A_1, A_2, B_1 and B_2 are used in the fuzzy theory for allocating the membership functions as linguistic labels. The membership relationship between the input and output functions of this layer can be shown as follows:

Table 2. Basic statistics of the measured variables in the Filyos River

Variable	Unit	Mean	SE	SD	Maximum	Minimum	Correlation with Cd
Iron (Fe)	µg L^{-1}	0,2248	0,0019	0,0176	0,1554	0,2810	0,1730
Copper (Cu)	µg L^{-1}	0,0811	0,0001	0,0008	0,0778	0,0830	0,4780
Manganese (Mn)	µg L^{-1}	0,0927	0,0012	0,0107	0,0504	0,0995	0,0000
Zinc (Zn)	µg L^{-1}	1,1559	0,0157	0,1430	0,6769	1,2291	0,0000
Nickel (Ni)	µg L^{-1}	0,0481	0,0002	0,0021	0,0457	0,0529	0,0000
Chromium (Cr)	µg L^{-1}	0,0341	0,0002	0,0014	0,0313	0,0359	0,0000
Cadmium (Cd)	µg L^{-1}	0,0433	0,0002	0,0014	0,0416	0,0464	1,0000

SE: standard error; SD: standard deviation

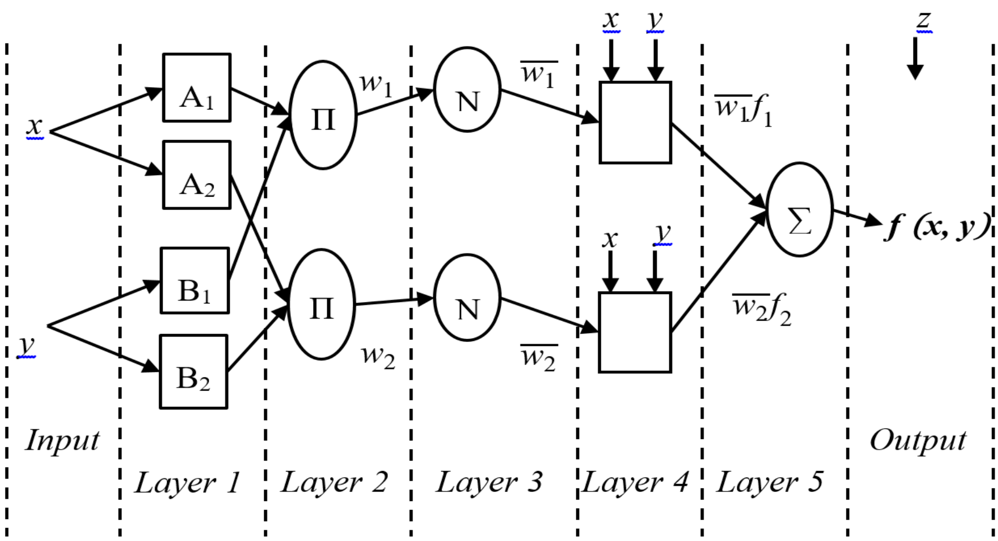

Figure 2. The architecture of ANFIS model.

$$\begin{cases} O_{1,i}=\mu_{Ai}(x), & i=1,2 \\ O_{1,j}=\mu_{Bj}(y), & i=1,2 \end{cases} \quad (2)$$

where μ_{Ai} and μ_{Bi} indicate the membership functions and $O_{1,i}$ and $O_{1,j}$ indicate the output functions.

Layer 2 is the product layer which includes two fixed nodes labeled with Π. The outputs of this layer are w_1 and w_2. These outputs are the weight functions of layer 3 and the product of the input signal can be shown as follows:

$$O_{2,i}=w_i=\mu_{Ai}(x)\mu_{Bi}(y), \quad i=1,2 \quad (3)$$

Layer 3 is the normalized layer, which includes two fixed nodes labeled with N. $\overline{w_1}$ and $\overline{w_2}$ are the outputs of this layer. Normalizing the weight function is the task of this layer in the next process:

$$O_{3,i}=\overline{w_i}=\frac{w_i}{w_1+w_2}, \quad i=1,2 \quad (4)$$

Layer 4 is the defuzzification layer which includes two adaptive nodes. The relationship between the inputs and output of this layer can be shown as follows:

$$O_{4,i} = \overline{w_i}(p_i x + q_i y + r_i), \quad i = 1,2 \quad (5)$$

where p_i, q_i and r_i are the linear parameters of the node and $O_{4,i}$ is the output of this layer.

Layer 5 is the output layer which includes a fixed node labeled with ∑. The output of this layer is comprised all the input components, which denotes the cleaning rates results. The output can be defined as follow:

$$O_{5,i}=\sum_i \overline{w_i} f_i=\frac{\sum_i w_i f_i}{\sum_i w_i}, \quad i=1,2 \quad (6)$$

Matlab software was used to conduct the data computation for ANFIS. ANFIS training includes the gradient descent method and the least squares method. ANFIS training algorithms embedded in the Matlab fuzzy inference toolbox simplify data processing using the training and forecasting functions. Main computation process consists of four stages. Data input is the first stage. Assigning fuzzy sets is the second stage. Some fuzzy sets should be assigned to each type of input and output data for the data input. The system will automatically determine the membership functions for them consistent with range of data and the fuzzy sets in the process of data processing. Using the training function for learning of input data is the third step. ANFIS will learn the data by performing the training data function and collect training errors after the analysis. The last stage is prediction of the output.

Dataset was randomly separated into two equal parts as training and test data. Sub-clustering partitioning technique with Gaussian membership functions was used for generating FIS to fuzzify the input data. The training stage contained an iterative procedure which targeted to calculate optimum values by minimizing the sum of squared differences between training data values and model predictions. Hybrid learning algorithm was selected to train fuzzy inference system. Training process continued until errors maintained the stability.

Results and Discussion

The concentrations of heavy metals including Fe, Cu, Mn, Zn, Ni, Cr and Cd were measured at seven stations in Filyos River. Basic statistics of the dataset is given in Table 2. ANFIS method in Matlab software was used to develop a model to predict Cd concentration. In ANFIS modelling, observed dataset was divided into three stages for training, testing and validation. Gaussian membership function (gaussmf) was considered for input and linear membership function was considered for output parameters. Hybrid algorithm was used to define the optimum number of parameters to describe the FIS.

Training data was consisted of 75% of dataset while 25% of dataset was assigned for testing in ANFIS. Average error value was found as 0.00019036 for both training and testing with 100 epochs (Figure 3). The relationships between input and output variables including three rules are illustrated in Figure 4.

ANFIS model was developed with a high correlation coefficient for training, testing and validation between 0.868 and 0.978. The higher the R-squared ANFIS models were filtered using different membership functions for different combinations of the variables. Performance of the models was evaluated for training and testing. Table 3 displays the mean absolute deviation (MAD), mean squared error (MSE), root mean square error (RMSE), mean absolute percentage error (MAPE), Nash-Sutcliffe efficiency (E), and coefficient of determination (R^2).

Observed and modelled values of Cd concentrations are illustrated in Figure 5. Figure 5

Figure 3. Plot for FIS output, training data, and average error value for testing and training with 100 epochs.

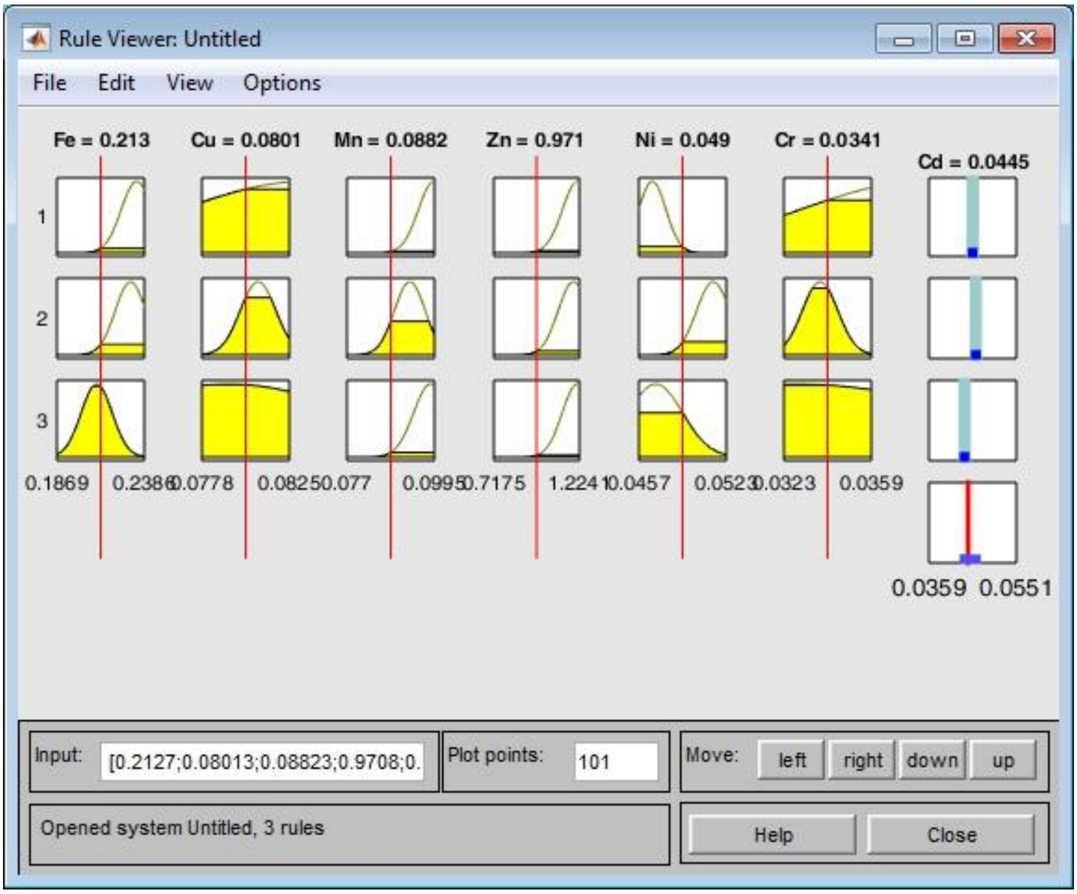

Figure 4. Rules of ANFIS model illustrating the relationships between input and output variables.

Table 3. The performance parameters of ANFIS model for testing, training, and whole stage

Stage	MAD	MSE	RMSE	MAPE	E	R^2
Training	0,00013468	0,00000004	0,00019313	0,30969120	0,980557449	0,978
Testing	0,00052381	0,00000058	0,00076345	1,16788005	0,675131021	0,868
Whole	0,00023313	0,00000018	0,00041873	0,52682332	0,90772321	0,913

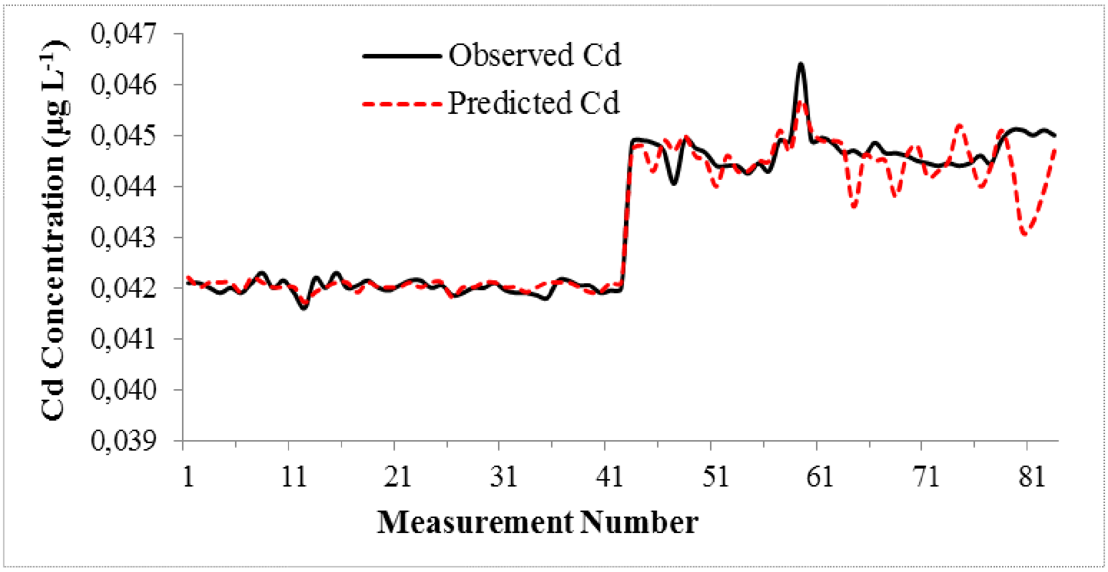

Figure 5. Comparison of measured and modelled Cd concentrations in the Filyos River water.

demonstrates the comparison of observed and predicted Cd concentrations and Figure 6 illustrates the scatter plot for the model of predicted and observed Cd concentration in the Filyos River. The respective correlation coefficient of 0.913 was found between observed and modelled Cd values.

Kemper and Sommer (2002) estimated the concentrations of heavy metal in soils from using back-propagation neural network (BPNN) and multiple linear regression (MLR). Almasri and Kaluarachchi (2005) forecasted the distribution of nitrate in groundwater using the modular neural networks. Rooki, Doulati Ardejani, Aryafar, and Bani Asadi (2011) anticipated heavy metals in acid mine drainage using BPNN, general regression neural network (GRNN), and MLR in Shur River, Iran. Yılmaz Öztürk *et al*. (2014) applied fuzzy logic assessment method for heavy metal pollution in Apa Dam Lake and indicated that fuzzy logic methods suggested more precise evaluation than traditional classification methods. Qasaimeh *et al*. (2012) used ANFIS for heavy metal sorption in aquatic environments and found a higher correlation of 0.98 between observed data and modelled results. Yesilnacar and Sahinkaya (2012) used ANN for prediction of sulfate and sodium adsorption ratio in an unconfined aquifer in Turkey. Valente, Ferreira, Grande, de la Torre, and Borrego (2013) performed FIS to predict the metal concentrations of an acid mine drainage. Sönmez *et al*. (2013b) conducted a comparative analysis of water quality assessment methods for heavy metal pollution in Karasu Stream. The authors used four assessment methods to evaluate heavy metal pollution in the stream and highlighted that fuzzy mathematical models were more reasonable. Sönmez *et al*. (2013a) used fuzzy logic evaluation method to assess the water quality in terms of heavy metal pollution in Karasu Stream and they recommended fuzzy logic evaluation method as a tool to predict heavy metal concentrations and water quality assessment. El Badaoui, Abdallaoui, Manssouri, and Lancelot (2013) used ANN of multilayer perceptron type to predict of heavy metal concentrations in Moroccan aquatic sediments. Chang *et al*. (2014) applied the neuro-fuzzy networks to evaluate the concentration of arsenic in Huang gang Creek, Taiwan. Keskin, Düğenci, and Kaçaroğlu (2015) applied ANN to estimate water pollution in Turkey. Ghadimi (2015) used ANN to anticipate the heavy metal concentrations in the groundwater of Arak, Iran. Akpomie *et al*. (2016) used statistical tools to predict heavy metal concentrations and developed a mathematical model for computer modelling of heavy metal concentrations. Bayatzadeh Fard *et al*. (2017) used AI techniques to predict heavy metal concentrations in the groundwater resources of Lakan lead-zinc mine, in Khomein, Iran. The authors developed different models namely ANN, hybrid ANN with biogeography-based optimization (ANN-BBO), and multi-output adaptive neural fuzzy inference system (MANFIS) to estimate the heavy metal concentrations. They indicated that MANFIS model was a reliable method to predict heavy metal concentrations with a high degree of robustness and accuracy.

A relatively higher correlation (R^2=0.91) was achieved between observed and modelled Cd concentrations (Table 3). The prediction ability of ANFIS model is nearly similar to (Soyupak *et al*., 2003; Zhao, Nan, Cui, & Guo, 2007; Akpomie *et al*., 2016). Akpomie *et al*. (2016) found a correlation coefficient of 0.86 for Cd concentration. Similarly, Soyupak *et al*. (2003) found the coefficient of determination as 0.95 and Zhao *et al*. (2007) found it as 0.94 between observed and modeled DO values. Singh *et al*. (2009) found the coefficient of correlation for observed and modelled DO values as 0.85, 0.77, and, 0.85 for the training, testing and validation, respectively. Figure 7 shows the surface view plots of the anticipated fuzzy rules. These 3D plots illustrate

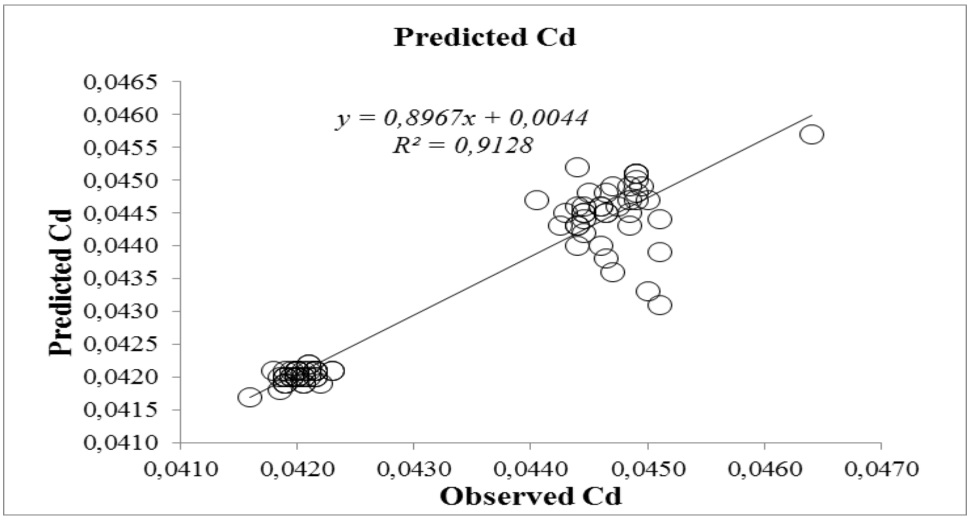

Figure 6. Scatter plot for the model of predicted and observed Cd concentrations in the Filyos River.

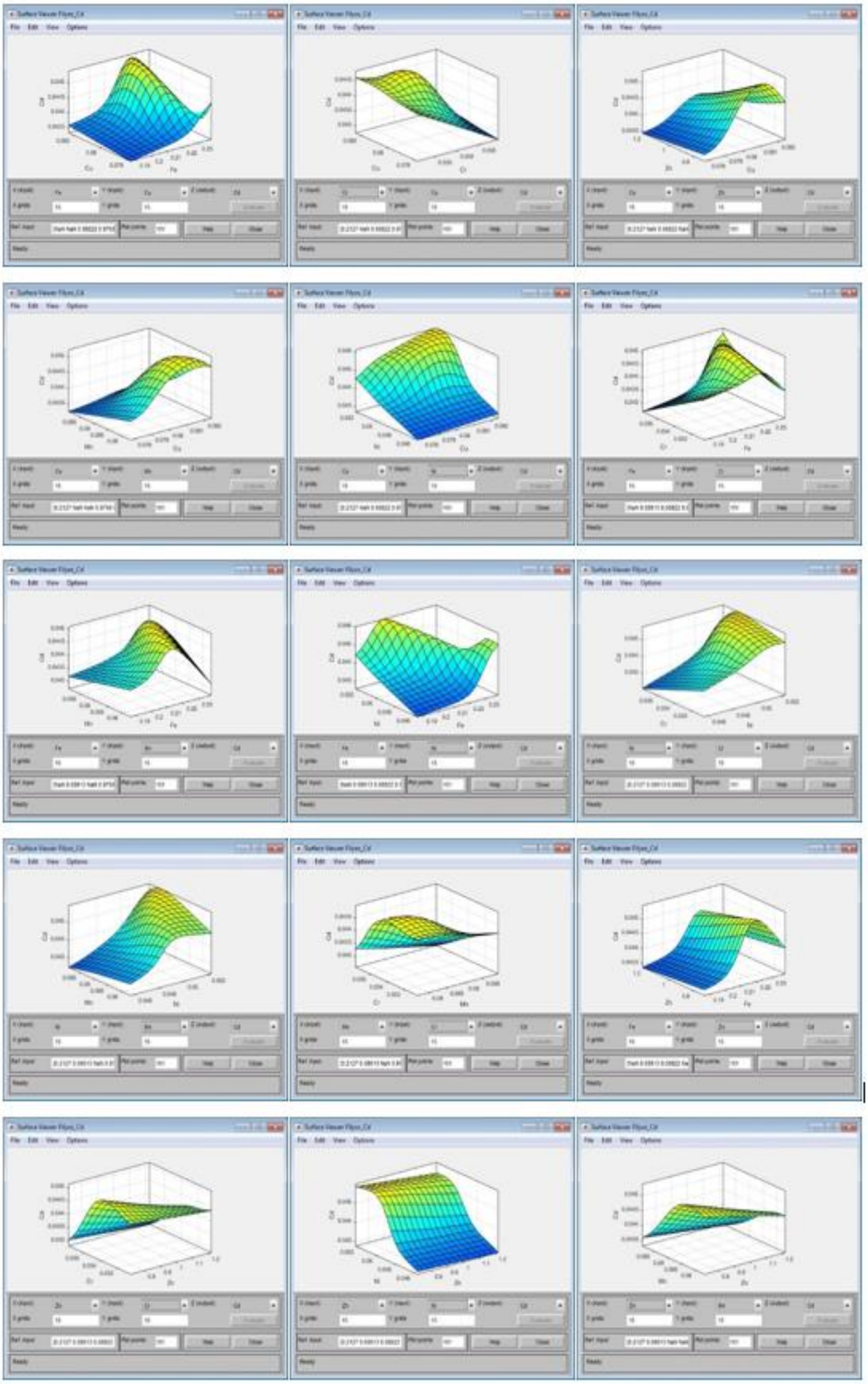

Figure 7. Surface view of the relationships between input and output variables.

the relationships between input and output variables.

A relatively higher correlation between observed and modeled values of Cd concentrations could be related to the experimenting with comparatively smaller dataset for input variables in the study. Several authors found a higher correlation coefficient in different aquatic environments for different variables (Soyupak *et al*., 2003; Sengorur *et al*., 2006; Zhao *et al*., 2007; Dogan *et al*., 2009). On the other hand, Nemati *et al*. (2015) found relatively poor results from ANFIS model between observed and modelled values of dissolved oxygen. Singh *et al*. (2009) found relatively lower correlation between observed and modelled values of DO. Singh *et al*. (2009) stated that the relatively lower correlation might be by the reason of longtime sampling duration, sampling locations, distributed large areas, and non-homogenous characteristic of the water quality variables.

ANFIS takes advantages of the outstanding learning algorithms of ANN and superb prediction functions of FIS. It can make available the calculation without mathematical modeling and provide a good solution for the problem of the non-linear prediction. ANFIS has an adaptive background and use training data to generate a fuzzy inference system. Therefore, ANFIS was chosen in the study. The obtained results of the study can be compared with related researches that discussed in the paper. The results demonstrated that suggested ANFIS models are capable to predict the Cd concentration in rivers using restricted dataset.

Conclusion

In this study, ANFIS models were developed to predict the Cd concentration in Filyos River. The results of the study indicated that ANFIS methodology produced very successful findings and had the ability to predict Cd concentration in water resources. It was determined that the ANFIS model was a reliable method to predict heavy metal concentrations in water resources with an acceptable degree of robustness and accuracy. Use of adaptive neuro-fuzzy inference system is significant for unclear system which has no experience with data behavior. The outcomes of this research provide more information, simulation, and prediction about heavy metal concentration in natural aquatic ecosystems. Therefore, ANFIS can be used in further researches on water quality monitoring.

Acknowledgement

This study was supported by The Scientific and Technological Research Council of Turkey (TÜBİTAK Project No: 114O145). An earlier version of this paper was presented at International Congress on Environmental Researches and Technology (ICERAT 2017) in Belgrade, Serbia.

References

Ahmed, A.A.M., & Shah, S.M.A. (2015). Application of adaptive neuro-fuzzy inference system (ANFIS) to estimate the biochemical oxygen demand (BOD) of Surma River. *Journal of King Saud University - Engineering Sciences*, 29(3), 237-243. https://dx.doi.org/10.1016/j.jksues.2015.02.001

Akkoyunlu, A., Altun, H., & Cigizoglu, H.K. (2011). Depth-Integrated Estimation of Dissolved Oxygen in a Lake. *Journal of Environmental Engineering*, 137(10), 961-967. https://dx.doi.org/10.1061/(ASCE)/EE,1943-7870.0000376

Akoto, O., Bruce, T.N., & Darko, G. (2008). Heavy metals pollution profiles in streams serving the Owabi reservoir. *African Journal of Environmental Science and Technology*, 2(11), 354-359

Akpomie, T.M., Ekanem, E.O., Adamu, M.M., & AkpoFmie, J.O. (2016). Computer Modelling of the Concentration of Heavy Metals in Artificial Borings. *World Journal of Analytical Chemistry*, 4(1), 6-10. https://dx.doi.org/10.12691/wjac-4-1-2

Alam, M.G.M., Tanaka, A., Stagnitti, F., Allinson, G., & Maekawa, T. (2001). Observations on the Effects of Caged Carp Culture on Water and Sediment Metal Concentrations in Lake Kasumigaura, Japan. *Ecotoxicology and Environmental Safety*, 48(1), 107-115. https://dx.doi.org/10.1006/eesa.2000.1989

Almasri, M.N., & Kaluarachchi, J.J. (2005). Modular neural networks to predict the nitrate distribution in ground water using the on-ground nitrogen loading and recharge data. *Environmental Modelling & Software*, 20(7), 851-871. https://dx.doi.org/10.1016/j.envsoft.2004.05.001

Alte, P.D., & Sadgir, P.A. (2015). Water Quality Prediction By Using ANN. *International Journal of Advance Foundation And Research In Science & Engineering (IJAFRSE)*, 1, 278-285

Altunkaynak, A., Özger, M., & Çakmakcı, M. (2005). Fuzzy logic modeling of the dissolved oxygen fluctuations in Golden Horn. *Ecological Modelling*, 189(3-4), 436-446. https://dx.doi.org/10.1016/j.ecolmodel.2005.03.007

Areerachakul, S. (2012). Comparison of ANFIS and ANN for Estimation of Biochemical Oxygen Demand Parameter in Surface Water. *International Journal of Environmental, Chemical, Ecological, Geological and Geophysical Engineering*, 6(4), 168-172. https://dx.doi.org/scholar.waset.org/1999.6/3706

Ay, M., & Kisi, O. (2011). Modeling of Dissolved Oxygen Concentration Using Different Neural Network Techniques in Foundation Creek, El Paso County, Colorado. *Journal of Environmental Engineering*, 138(6), 654-662. https://dx.doi.org/1943-7870.0000511.10.1061/(ASCE)EE

Ay, M., & Kisi, O. (2014). Modelling of chemical oxygen demand by using ANNs, ANFIS and k-means clustering techniques. *Journal of Hydrology*, 511, 279-289. https://dx.doi.org/10.1016/j.jhydrol.2014.01.054

Bayatzadeh Fard, Z., Ghadimi, F., & Fattahi, H. (2017). Use of artificial intelligence techniques to predict distribution of heavy metals in groundwater of Lakan lead-zinc mine in Iran. *Journal of Mining &*

Environment, 8(1), 35-48. https://dx.doi.org/10.22044/jme.2016.592

Bisht, D.C.S., & Jangid, A. (2011). Discharge Modelling using Adaptive Neuro - Fuzzy Inference System. *International Journal of Advanced Science and Technology*, 31(1), 99-114

Chang, F.-J., Chung, C.-H., Chen, P.-A., Liu, C.-W., Coynel, A., & Vachaud, G. (2014). Assessment of arsenic concentration in stream water using neuro fuzzy networks with factor analysis. *Science of The Total Environment*, 494-495, 202-210. https://dx.doi.org/10.1016/j.scitotenv.2014.06.133

Chen, Q., Morales-Chaves, Y., Li, H., & Mynett, A.E. (2006). Hydroinformatics techniques in eco-environmental modelling and management. *Journal of Hydroinformatics*, 8(4), 297-316. https://dx.doi.org/10.2166/hydro.2006.011

Chen, W.B., & Liu, W.C. (2014). Artificial neural network modeling of dissolved oxygen in reservoir. *Environmental Monitoring and Assessment*, 186(2), 1203-1217. https://dx.doi.org/10.1007/s10661-013-3450-6

Csábrági, A., Molnár, S., Tanos, P., & Kovács, J. (2015). Forecasting of dissolved oxygen in the river danube using neural networks. *Hungarian Agricultural Engineering*,(27), 38-41. https://dx.doi.org/10.17676/hae.2015.27.38

Csábrági, A., Molnár, S., Tanos, P., & Kovács, J. (2017). Application of artificial neural networks to the forecasting of dissolved oxygen content in the Hungarian section of the river Danube. *Ecological Engineering*, 100, 63-72. https://dx.doi.org/10.1016/j.ecoleng.2016.12.027

Dahiya, S., Singh, B., Gaur, S., Garg, V.K., & Kushwaha, H.S. (2007). Analysis of groundwater quality using fuzzy synthetic evaluation. *Journal of Hazardous Materials*, 147(3), 938-946. https://dx.doi.org/10.1016/j.jhazmat.2007.01.119

Dogan, E., Sengorur, B., & Koklu, R. (2009). Modeling biological oxygen demand of the Melen River in Turkey using an artificial neural network technique. *Journal of Environmental Management*, 90(2), 1229-1235. https://dx.doi.org/10.1016/j.jenvman.2008.06.004

El Badaoui, H., Abdallaoui, A., Manssouri, I., & Lancelot, L. (2013). Application of the artificial neural networks of MLP type for the prediction of the levels of heavy metals in Moroccan aquatic sediments. *International Journal of Computational Engineering Research*, 3(6), 75-81

Elhatip, H., & Kömür, M.A. (2008). Evaluation of water quality parameters for the Mamasin dam in Aksaray City in the central Anatolian part of Turkey by means of artificial neural networks. *Environmental Geology*, 53(6), 1157-1164. https://dx.doi.org/10.1007/s00254-007-0705-y

Emamgholizadeh, S., Kashi, H., Marofpoor, I., & Zalaghi, E. (2014). Prediction of water quality parameters of Karoon River (Iran) by artificial intelligence-based models. *International Journal of Environmental Science and Technology*, 11(3), 645-656. https://dx.doi.org/10.1007/s13762-013-0378-x

Ghadimi, F. (2015). Prediction of heavy metals contamination in the groundwater of Arak region using artificial neural network and multiple linear regression. *Journal of Tethys*, 3(3), 203-215

Hanbay, D., Turkoglu, I., & Demir, Y. (2008). Prediction of wastewater treatment plant performance based on wavelet packet decomposition and neural networks. *Expert Systems with Applications*, 34(2), 1038-1043. https://dx.doi.org/10.1016/j.eswa.2006.10.030

Heddam, S. (2014). Modeling hourly dissolved oxygen concentration (DO) using two different adaptive neuro-fuzzy inference systems (ANFIS): a comparative study. *Environmental Monitoring and Assessment*, 186(1), 597-619. https://dx.doi.org/10.1007/s10661-013-3402-1

Hisar, O., Sönmez, A.Y., Kaya, H., & Aras Hisar, Ş. (2012). Various inference systems for classification of water quality status: A case study. *Marine Science and Technology Bulletin*, 1(1), 7-11

Icaga, Y. (2007). Fuzzy evaluation of water quality classification. *Ecological Indicators*, 7(3), 710-718. https://dx.doi.org/10.1016/j.ecolind.2006.08.002

Jang, J.-S.R. (1993). ANFIS : Adap tive-Ne twork-Based Fuzzy Inference System. *IEEE Transactions on Systems, Man, and Cybernetics*, 23(3), 665-685

Jang, J.-S.R., Sun, C.-T., & Mizutani, E. (1997). Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence. 1 ed. New Jersey, USA, Prentice Hall. 614 pp.

Jayalakshmi, T., & Santhakumaran, A. (2011). Statistical Normalization and Back Propagation for Classification. *International Journal of Computer Theory and Engineering*, 3(1), 89-93

Kanda, E.K., Kipkorir, E.C., & Kosgei, J.R. (2016). Dissolved oxygen modelling using artificial neural network: a case of River Nzoia, Lake Victoria basin, Kenya. *Journal of Water Security*, 2(1). https://dx.doi.org/10.15544/jws.2016.004

Kemper, T., & Sommer, S. (2002). Estimate of Heavy Metal Contamination in Soils after a Mining Accident Using Reflectance Spectroscopy. *Environmental Science & Technology*, 36(12), 2742-2747. https://dx.doi.org/10.1021/es015747j

Keskin, T.E., Düğenci, M., & Kaçaroğlu, F. (2015). Prediction of water pollution sources using artificial neural networks in the study areas of Sivas, Karabük and Bartın (Turkey). *Environmental Earth Sciences*, 73(9), 5333-5347. https://dx.doi.org/10.1007/s12665-014-3784-6

Khadr, M., & Elshemy, M. (2016). Data-driven modeling for water quality prediction case study: The drains system associated with Manzala Lake, Egypt. *Ain Shams Engineering Journal*, 1-9. https://dx.doi.org/10.1016/j.asej.2016.08.004

Kisi, O. (2005). Suspended sediment estimation using neuro-fuzzy and neural network approaches. *Hydrological Sciences Journal*, 50(4), 683-696. https://dx.doi.org/10.1623/hysj.2005.50.4.683

Kisi, O., & Ay, M. (2012). Comparison ANN and ANFIS techniques in modeling dissolved oxygen. *Proceeding of the Sixteenth International Water Technology Conference, IWTC-16* (pp. 1-10). İstanbul, Turkey.

Kucukali, S. (2008). Forecasting the river discharge, thermal and sediment load characteristics: a case study for Filyos River. *Proceeding of 15th River Flow Conference* (pp. 1975-1981). Çeşme, İzmir, Turkey, Kubaba Congress Department and Travel Services.

Kucukali, S. (2014). Environmental risk assessment of small hydropower (SHP) plants: A case study for Tefen SHP plant on Filyos River. *Energy for Sustainable Development*, 19, 102-110. https://dx.doi.org/10.1016/j.esd.2013.12.010

Lermontov, A., Yokoyama, L., Lermontov, M., & Machado, M.A.S. (2009). River quality analysis using fuzzy water quality index: Ribeira do Iguape river watershed, Brazil. *Ecological Indicators*, 9(6), 1188-1197. https://dx.doi.org/10.1016/j.ecolind.2009.02.006

Nemati, S., Naghipour, L., & Fazeli Fard, M.H. (2014). Artificial Neural Network Modeling of Total Dissolved Solid in the Simineh River, Iran. *Journal of Civil Engineering and Urbanism*, 4(1), 8-14

Nemati, S., Fazelifard, M.H., Terzi, Ö., & Ghorbani, M.A. (2015). Estimation of dissolved oxygen using data-driven techniques in the Tai Po River, Hong Kong. *Environmental Earth Sciences*, 74(5), 4065-4073. https://dx.doi.org/10.1007/s12665-015-4450-3

Ocampo-Duque, W., Ferré-Huguet, N., Domingo, J.L., & Schuhmacher, M. (2006). Assessing water quality in rivers with fuzzy inference systems: A case study. *Environment International*, 32(6), 733-742. https://dx.doi.org/10.1016/j.envint.2006.03.009

Olayinka, K.O., & Alo, B.I. (2004). Studies on Industrial Pollution in Nigeria: The effect of Textile effluents on the quality of Groundwater in some parts of Lagos. *Nigerian Journal of Health and Biomedical Sciences*, 3(1), 44-50. https://dx.doi.org/10.4314/njhbs.v3i1.11507

Piotrowski, A.P., Napiorkowski, M.J., Napiorkowski, J.J., & Osuch, M. (2015). Comparing various artificial neural network types for water temperature prediction in rivers. *Journal of Hydrology*, 529, 302-315. https://dx.doi.org/10.1016/j.jhydrol.2015.07.044

Qasaimeh, A., Abdallah, M., & Bani Hani, F. (2012). Adaptive Neuro-Fuzzy Logic System for Heavy Metal Sorption in Aquatic Environments. *Journal of Water Resource and Protection*, 04(05), 277-284. https://dx.doi.org/10.4236/jwarp.2012.45030

Ranković, V., Radulović, J., Radojević, I., Ostojić, A., & Čomić, L. (2010). Neural network modeling of dissolved oxygen in the Gruža reservoir, Serbia. *Ecological Modelling*, 221(8), 1239-1244. https://dx.doi.org/10.1016/j.ecolmodel.2009.12.023

Ranković, V., Radulović, J., Radojević, I., Ostojić, A., & Čomić, L. (2012). Prediction of dissolved oxygen in reservoirs using adaptive network-based fuzzy inference system. *Journal of Hydroinformatics*, 14(1), 167-179. https://dx.doi.org/10.2166/hydro.2011.084

Rehana, S., & Mujumdar, P.P. (2009). An imprecise fuzzy risk approach for water quality management of a river system. *Journal of Environmental Management*, 90(11), 3653-3664. https://dx.doi.org/10.1016/j.jenvman.2009.07.007

Rooki, R., Doulati Ardejani, F., Aryafar, A., & Bani Asadi, A. (2011). Prediction of heavy metals in acid mine drainage using artificial neural network from the Shur River of the Sarcheshmeh porphyry copper mine, Southeast Iran. *Environmental Earth Sciences*, 64(5), 1303-1316. https://dx.doi.org/10.1007/s12665-011-0948-5

Seker, D.Z., Kaya, S., Musaoglu, N., Kabdasli, S., Yuasa, A., & Duran, Z. (2005). Investigation of meandering in Filyos River by means of satellite sensor data. *Hydrological Processes*, 19(7), 1497-1508. https://dx.doi.org/10.1002/hyp.5593

Sengorur, B., Dogan, E., Koklu, R., & Samandar, A. (2006). Dissolved oxygen estimation using artificial neural network for water quality control. *Fresenius Environmental Bulletin*, 15(9), 1064-1067

Singh, K.P., Basant, A., Malik, A., & Jain, G. (2009). Artificial neural network modeling of the river water quality—A case study. *Ecological Modelling*, 220(6), 888-895. https://dx.doi.org/10.1016/j.ecolmodel.2009.01.004

Soyupak, S., Karaer, F., Gürbüz, H., Kivrak, E., Sentürk, E., & Yazici, A. (2003). A neural network-based approach for calculating dissolved oxygen profiles in reservoirs. *Neural Computing & Applications*, 12(3-4), 166-172. https://dx.doi.org/10.1007/s00521-003-0378-8

Sönmez, A.Y., Hisar, O., & Yanık, T. (2012). Determination of Heavy Metal Pollution in Karasu River and Classification of Water Quality. *Atatürk Üniversitesi Ziraat Fakültesi Dergisi*, 43(1), 69-77

Sönmez, A.Y., Hasiloglu, S., Hisar, O., Aras Mehan, H.N., & Kaya, H. (2013a). Fuzzy Logic Evaluation of Water Quality Classification for Heavy Metal Pollution in Karasu Stream, Turkey. *Ekoloji*, 22(87), 43-50. https://dx.doi.org/10.5053/ekoloji.2013.876

Sönmez, A.Y., Hisar, O., & Yanık, T. (2013b). A Comparative Analysis of Water Quality Assessment Methods for Heavy Metal Pollution in Karasu Stream, Turkey. *Fresenius Environmental Bulletin*, 22(2a), 579-583

Sönmez, A.Y., Kadak, A., Özdemir, R.C., & Bilen, S. (2016). Establishing on Heavy Metal Accumulation in Some Economically Important Fish Species Captured from Kastamonu Costal. *Alınteri Journal of Agricultural Sciences*, 31 (2), 84-90. http://dergipark.gov.tr/alinterizbd/issue/24983/285156

Terzi, Ö., Keskin, M.E., & Taylan, E.D. (2006). Estimating evaporation using ANFIS. *Journal of Irrigation and Drainage Engineering*, 132(5), 503-207. https://dx.doi.org/10.1061/共 ASCE 兲 0733-9437 共 2006 兲 132:5 共 503 兲

Valente, T., Ferreira, M.J., Grande, J.A., de la Torre, M.L., & Borrego, J. (2013). pH, electric conductivity and sulfate as base parameters to estimate the concentration of metals in AMD using a fuzzy inference system. *Journal of Geochemical Exploration*, 124, 22-28. https://dx.doi.org/10.1016/j.gexplo.2012.07.013

Wang, W.-C., Chau, K.-W., Cheng, C.-T., & Qiu, L. (2009). A comparison of performance of several artificial intelligence methods for forecasting monthly discharge time series. *Journal of Hydrology*, 374(3-4), 294-306. https://dx.doi.org/10.1016/j.jhydrol.2009.06.019

Yesilnacar, M.I., & Sahinkaya, E. (2012). Artificial neural network prediction of sulfate and SAR in an unconfined aquifer in southeastern Turkey. *Environmental Earth Sciences*, 67(4), 1111-1119. https://dx.doi.org/10.1007/s12665-012-1555-9

Yılmaz Öztürk, B., Akköz, C., Aşıkkutlu, B., & Gümüş, N.E. (2014). Fuzzy Logic Evaluation of Heavy Metal Pollution of Apa Dam Lake. *Journal of Applied Biological Sciences*, 8(3), 14-20

Zhao, Y., Nan, J., Cui, F.-y., & Guo, L. (2007). Water quality forecast through application of BP neural network at Yuqiao reservoir. *Journal of Zhejiang University-SCIENCE A*, 8(9), 1482-1487. https://dx.doi.org/10.1631/jzus.2007.A1482