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Ultrasonic algae control system performance evaluation using an artificial neural network in the Dogancı dam reservoir (Bursa, Turkey): a case study

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ABSTRACT

Ultrasound is a well-established technology, but it has been applied only recently to control algal blooms. The main purpose of this study is to determine the appropriateness of field measurements for evaluating the performance of an ultrasonic algae control system using an artificial neural network (ANN) in the Dogancı Dam Reservoir (Bursa, TURKEY). Within this study, data were obtained using the NeuroSolutions 5.06 model. Each sample was characterized using ten independent variables (time, total organic carbon (TOC), pH, water temperature (T_{water}), dissolved oxygen (DO), suspended solids (SS), the Secchi disc depth (SDD), open-water evaporation (E), heat flux density (H), air temperature (T_{air}), and one dependent variable (chlorophyll-a (Chl-a)). The correlation coefficients between the neural network estimates and field measurements were as high as 0.9747 for Chl-a. The results indicated that the adopted Levenberg–Marquardt back-propagation algorithm yields satisfactory estimates with acceptably low mean square error (MSE) values.

Keywords: Artificial neural networks; Levenberg-Marquardt algorithm; Reservoirs; Ultrasonic algae control

1. Introduction

Reservoirs contain a significant portion of the fresh water on the planet and are special ecosystems because of their unique features. They are used as drinking water reservoirs and for energy production and irrigation. In addition to being part of the landscape, similar to lakes, specific human-induced changes create unique aquatic environments [1].

In total, 48% of reservoirs in the world are used for irrigation operations, 20% produce energy, and the rest provide water to urban and industrial areas or are used for recreational purposes [2]. Due to natural or human-induced pollution, various species (macro and micro) of algae can grow in aquatic environments. These species have shown photosynthetic activity in aquatic environments; however, they often have adverse effects on water quality parameters. Basically, phytoplankton produces oxygen as a result of photosynthesis. However, this positive effect inhibits light penetration and aquatic environment venting due to surface coating. Dead algae in aquatic environments cause taste and odor problems, and some aquatic organisms are killed due to the formation

To identify bloom control methods that consume little energy and reduce water treatment costs and chemical use of water treatment is a challenge. However, recent investigations on the use of ultrasound have confirmed it to be one such method. Successful use of ultrasound in numerous other applications, including wastewater treatment, made it an ideal green solution test candidate for algal bloom control. Ultrasound travels through the liquid medium via an acoustic cavitation mechanism, in which the sound wave transfers through the liquid through series of compression and rarefaction cycles [3]. A few studies have demonstrated algae bloom control using ultrasound irradiation. It has been reported that ultrasound effectively reduced the growth rate of algae by collapsing gas vesicles that control the floatation of cells, fracturing the cells, and inhibiting cell

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division. Furthermore, the extent of algal growth reduction was influenced by the ultrasonic parameters, such as frequency, intensity and time [4–8].

The ultrasonic algae control technology has been recently applied to control algal biomass growth in water reservoirs in most developed countries. In addition, this technology has been, for the first time, applied in Turkey. Because of these reasons, an evaluation of the performance of the ultrasonic algae control system is needed. In this paper, the artificial neural network (ANN) modeling technique is used to establish a model for evaluating the performance of the ultrasonic algae control system used in the Doganci Dam Reservoir (Bursa, Turkey).

An ANN is a non-linear mathematical structure capable of representing the complex non-linear processes that relate the inputs to the outputs of a system. The most important advantage of an ANN approach over classical ones is its capability to deal with uncertain information and incomplete or inconsistent data [9]. ANNs has become a classical artificial intelligence method for the modeling of algae blooms as well as in other scientific and engineering area [10]. Karul et al. [11] used a three-layer Levenberg-Marquardt feed-forward learning algorithm to model the eutrophication process in three water bodies in Keban Dam Reservoir, Mogan, and Eymir Lakes of Turkey. ANN models were used for reservoir volume and level fluctuations [12–13]. Üneş predicted density flow plunging depth in dam reservoir using the ANN [14]. Because there is a lack of literature on the use of artificial neural networks to study the ultrasonic algae control system and because it is for the first time applied to a dam reservoir in Turkey, this study will be a case study. In order to establish a suitable Chl-*a* prediction model, the total organic carbon (TOC), pH, water temperature (T_{water}), dissolved oxygen (DO), the Secchi disc depth (SDD), suspended solids (SS), open-water evaporation (E), heat flux density (H) and ambient temperature (T_{air}) parameters were used as an input layer, and chlorophyll-a (Chl-*a*) was used as an output layer.

2. Methodology

2.1. Ultrasonic algae control system

Ultrasound use was classified as a non-chemical strategy to control algal growth. Ultrasound transducers were submerged in the settling basins and significantly reduced algal growth on the basin walls. This was considered to be the most successful strategy at water treatment works (WTW) in 2005 [3,15]. Ultrasound works using the acoustic cavitation phenomenon, which occurs after sound waves above the 20 kHz frequency are passed through a liquid medium. Ultrasound is transmitted via waves, which alternately compress and stretch within the liquid medium they pass through. During each "stretching" phase (rarefaction), provided that the negative pressure is strong enough to overcome intermolecular binding forces and surface tension, tiny cavities (microbubbles) of water vapor are produced. In succeeding cycles, these cavities grow and then collapse violently and release large amounts of energy. It has been estimated that temperatures and pressures on the order of five thousand Kelvin and a two thousand atmospheres, respectively, are produced during this collapse [16–18].

Effective distance of the ultrasonic algae system is 15–20 m. The system uses 40 W energy. It produces 15W/h electricity and uses an ultrasonic output frequency of 27–47 kHz/s.

In the Doganci Dam Reservoir, 7 points were chosen to establish the system (Fig. 1). At each point, 3 were installed, resulting in 27 total pieces. Because this is the first study in Turkey, the system is planned to be implemented at two branches of the reservoir.

2.2. Study area

2.2.1. The Doganci Dam Reservoir (DDR)

The DDR is a very small reservoir located in the northwest part of Turkey. It is a water supply reservoir, and operation started in 1983. The drainage area of the reservoir is located between the 44°36′ and 44°57′ northern latitudes and the 32°08′ and 32°62′ eastern longitudes. The maximum operation level of the reservoir is 333.80 m above the Mediterranean Sea level. The characteristics of the reservoir at this water level are as follows: the surface area is 1.58 ha, the total water volume is 37.80 hm^3, and the total drainage area of the dam outlet is 446.9 km^2. The Doganci Dam Reservoir is located on the Nilufer River and the Sultaniye Stream [19].

2.3. Field sampling

The water samples were collected from four different stations representing the area affected by the seven points established for the ultrasonic algae control system. The study area and the sampling locations are shown in Fig. 1. Polyethylene bottles (2000 ml) were rinsed and filled with the reservoir water. All collected samples were immediately delivered to the analytical laboratory for further analysis. The first samples were acquired prior to the algae control system installation. Then, after the system was commissioned, regular samplings were performed at the sampling stations at specific time intervals over the 6 week period.

2.4. Analytical methods

The total organic carbon (TOC), pH, water temperature (T_{water}) and dissolved oxygen (DO) were analyzed in the Dobruca drinking water treatment plant laboratories; the Secchi disc depth (SDD), suspended solids (SS) and chlorophyll-*a* (Chl-*a*) were measured in the Uludag University laboratories. SDD was measured by the Secchi disc method (Windaus). SS and Chl-*a* were analyzed according to standard methods [20]. The meteorological data (open-water evaporation (E), heat flux density (H) and air temperature (T_{air})) were obtained from the Meteorological Service.

2.5. Artificial neural network software (ANN)

An artificial neural network (ANN) is a computational structure inspired by the study of biological neural processing [21]. An ANN is a data modeling tool that is capable of capturing and representing complex relationships between inputs and outputs. The network is composed of large num-

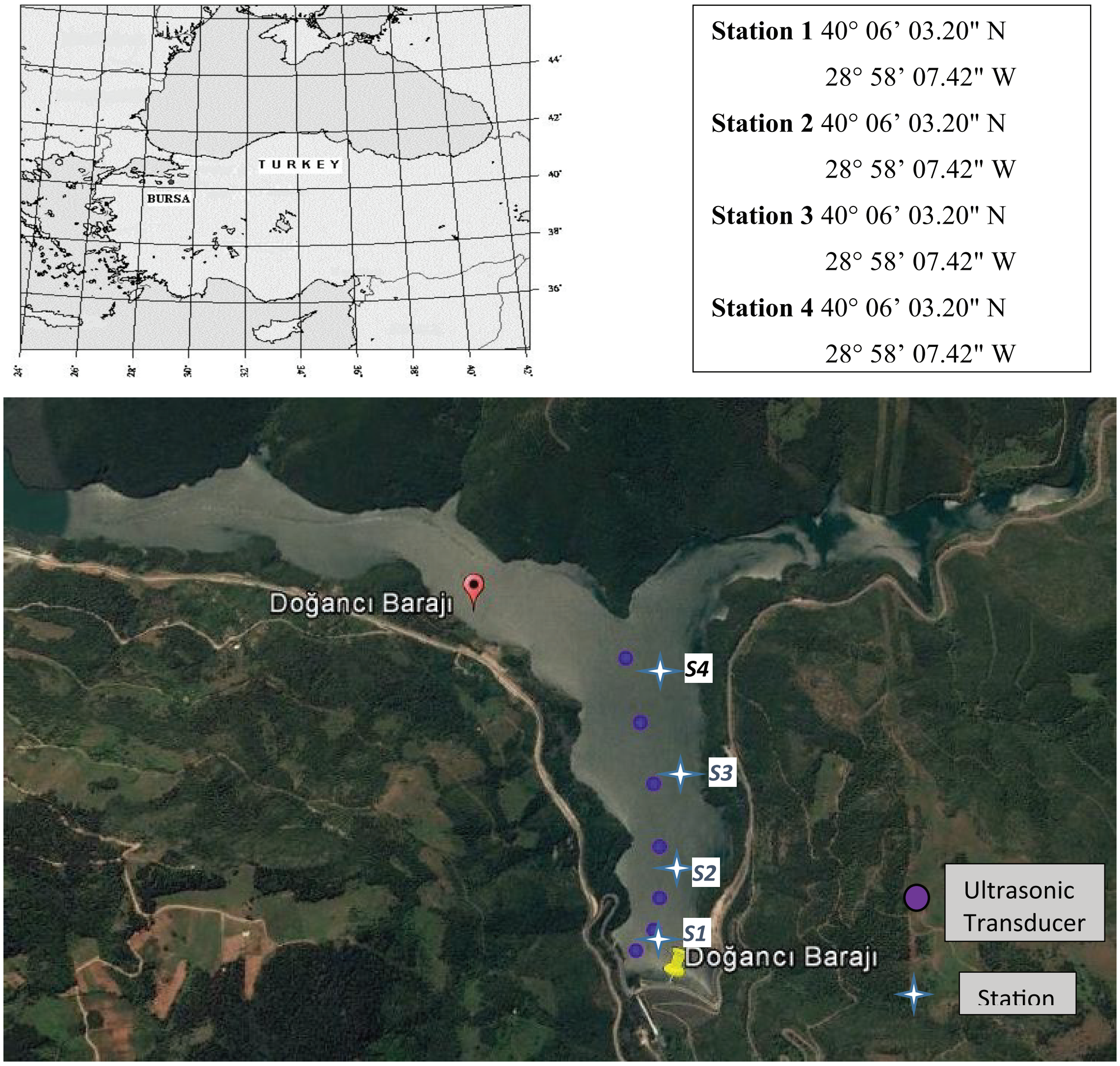

Fig. 1. The view of study area of Doganci Dam Reservoir and sampling stations.

bers of highly interconnected processing elements, which are called "neurons" and are tied together with weighted connections. Each neuron works as an independent processing element and has an associated transfer function, which describes how the weighted sum of its inputs is converted to the results in an output value. Each hidden or output neuron receives a number of weighted input signals from each of the units of the preceding layer and generates only one output value [22].

The multilayer perceptron (MLP) networks are an extension of the perceptron networks because they have one or more hidden layers. Each neuron computes a weighted sum of all incoming signals and, after adding a threshold value, produces the argument to the transfer function, which generates the output of a neuron. The backpropagation algorithm, which involves two phases, is usually used to taint the MLP networks. During the first phase or the feed-forward phase, the free network parameters do not change, and the information of inputs is propagated through the network layer by layer. In the second phase or the backward phase, free parameters of the network (weights and biases) are adjusted to minimize the error of the network, which is calculated according to the measured error [23–25]. In this study, different MLP networks with one single layer and Log-Sigmoid as the transfer function were used to forecast lake levels. It is shown that the incorporation of the Levenberg-Marquardt algorithm into the backpropagation algorithm speeds up the convergence process [26]. The Levenberg-Marquardt algorithm is a second order nonlinear optimization technique that is usually faster and more reliable than any other standard back propagation techniques [27–29].

The training process can be viewed as finding a set of weights that minimize the error (e_p) for all samples in the training set (Q). The performance function is a sum of squares of the errors as follows:

$$E(W) = \frac{1}{2}\sum_{p=1}^{P}\left(d_p - y_p\right)^2 = \frac{1}{2}\sum_{p=1}^{P}\left(e_p\right)^2, P = mT \quad (1)$$

where T is the total number of training samples, m is the number of output layer neurons, W represents the vector containing all the weights in the network, y_p is the actual network output, and d_p is the desired output. When training with the Levenberg-Marquardt algorithm, the changing of weights ΔW can be computed as follows:

$$\Delta W_k = -J_k^T J_k + \left(\mu_k I\right)^{-1} J_k^T e_k \tag{2}$$

Then, the update of the weights can be adjusted as follows:

$$W_{(k+1)} = W_k + \left(\Delta W_k\right) \tag{3}$$

where J is the Jacobian matrix, I is the identify matrix, μ is the Marquardt parameter which is to be updated using the decay rate β depending on the outcome. In particular, μ is multiplied by the decay rate β (0 < β < 1) whenever E(W) decreases, while μ is divided by β whenever E(W) increases in a new step (k) [30].

Therefore, we used this algorithm for training the networks. The adequacy of the ANN is evaluated by considering the coefficient of determination (R^2). In addition, the values of root mean square error (RMSE), the normal root mean square error (NRMSE), the mean absolute error (MAE) and the Normal mean absolute error (NMAE) are used as indices to check abilities of the model [31–35].

The ANN (NeuroSolutions 5.06, NeuroDimension, Inc., Gainesville, Florida) was implemented on the experimental output. All data were tested 20 times with the ANN program. These 20 solutions were repeated 1000 times each, and every 1000 groups were confirmed 3 times in the NeuroSolutions 5.06 program.

2.5.1. Determinite input vector

Firstly, environmental factors were selected as independent variable potentially controlling the Chl-*a* variation referring to literature reports. Next, correlation analysis, principal component analysis was used to filter main factors in this case. As a result, ten major environmental factors (time, total organic carbon (TOC), pH, water temperature ($T_{(water)}$), dissolved oxygen (DO), suspended solids (SS), the Secchi disc depth (SDD), open-water evaporation (E), heat flux density (H) and temperature ($T_{(air)}$)) were selected as potential input variables of prediction models.

3. Results and discussion

The reservoir water quality is a complex function of its morphometry and watershed characteristics, including climate, hydrology, geology, morphology and land uses. Rational planning and operation of water supply systems requires recognition of the cause-effect relationships that influence water quality and, therefore, influence the feasibility and costs of supplying water while meeting the state and federal standards and criteria [36].

Variations in the total organic carbon (TOC), pH, water temperature (T_{water}) and dissolved oxygen (DO), the Secchi disc depth (SDD), suspended solids (SS) and chlorophyll-*a* (Chl-*a*), and the meteorological data (open-water evaporation (E), heat flux density (H) and air temperature (T_{air})) values are graphically illustrated in Fig. 2.

Temperature is an important variable that changes the viscosity and concentration of the water and the speed of biochemical events that occur in the aquatic environment and, consequently, influences the resolution of physiological events that occur in living organisms [37]. The average temperature of the Doganci Dam Reservoir was approximately 13.43 ± 0.21°C during the sampling period. The highest temperature was 15°C, and the lowest temperature was 12.1°C. Temperature is an important factor that increases the biological activity rate and reduces oxygen saturation [38]. According to the obtained results, temperature affected the phytoplankton in the Doganci Dam Reservoir.

In the Doganci Dam Reservoir water column, pH values varied between 8.05 and 8.36, and the average measured value was 8.17 ± 0.05. Based on these values, the pH values >7 indicate that slightly alkaline conditions are dominant in the reservoir. The productivity of alkaline water is high, while acidic water has a low efficiency [39]. The dissolved carbonate in the soil, which is carried by the rain water, is believed to cause alkaline conditions in the Doganci Dam Reservoir. No inverse relationship was found between the pH and oxygen. This condition is thought to be caused by the continuous flow of the reservoir. Specifically, the floating surface of the dam allows for water oxygenation. During the fall season and depending on the temperature, the autumn circulation period is considered to be effective. The DO value varies between 6.84 and 10.28 mg L^{-1}, and the average measured value was 8.31 ± 0.56 mg L^{-1}.

The TOC is a measure of carbon dioxide in the water caused by the oxidation of organic carbon. The increased amount of organic matter is an indicator of water pollution. Organic substances cause the growth of bacteria, fungi and algae in water [40]. The TOC values in drinking water supplies should be in the range of 0.1–25 mg L^{-1} [41]. In this study, the TOC value is at appropriate levels, which indicates that there is no organic contamination.

The Secchi disk depth-light transmittance is a measure of the clarity of the lake. A lower Secchi disk depth value indicates a higher trophic level of the lake. Prior to the ultrasonic algae control system operation, the average measured Secchi disc depth was 3.08 m. After the operation of the system, the average measured Secchi disc depth was 3.24 m. For the last 3 weeks, the SDD had the highest value of 4 m. In the areas where the water supply enters the reservoir, the phytoplankton production was high and the permeability values were low due to the abundance of nutrients. Nutrients were previously high and were lower after the installation of the ultrasonic system, consequently decreasing the dam plankton production and increasing the light transmission.

The factors that affected the amount of suspended solids in water were the phytoplankton concentration and precipitation of flood waters that reached the reservoir. Suspended solids reduce light transmittance and increase the turbidity of the water. By preventing sunlight from reaching water plants and thus affecting photosynthesis, a decrease in the dissolved oxygen in water was observed. Before operation of the system, the average calculated suspended solid value was 1.8 mg L^{-1}. After the operation of the system, it was 1.64 mg L^{-1}.

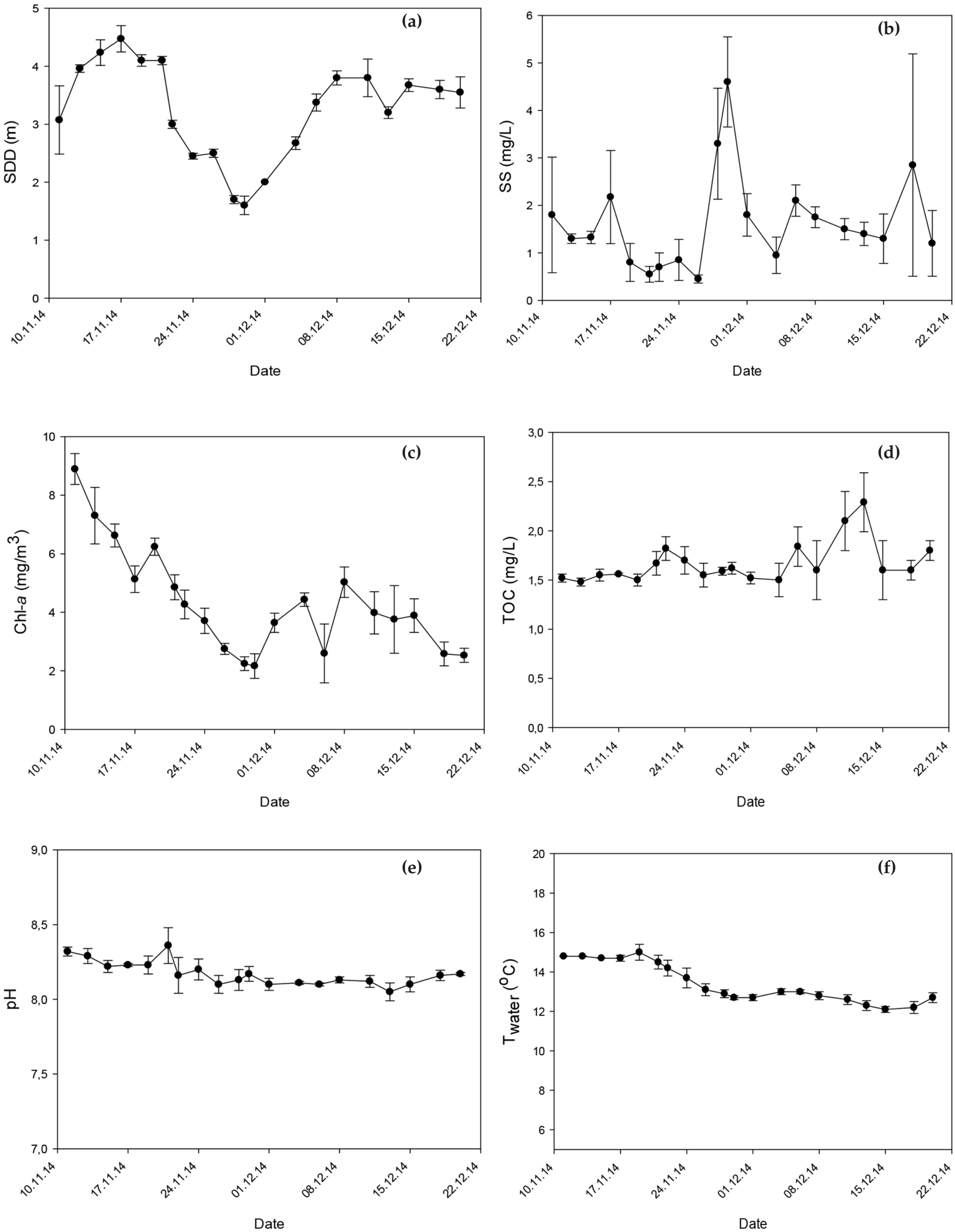

Fig. 2. The graphical illustration of physical, chemical and meteorological data values (a) secchi disc depth (SDD), b) suspended solids (SS), c) chlorophyll-*a* (Chl-*a*), d) total organic carbon (TOC), e) pH, f) temperature (T_{water}) g) dissolved oxygen (DO), h) open-water evaporation (E), i) heat flux density (H) and j) temperature (T_{air})).

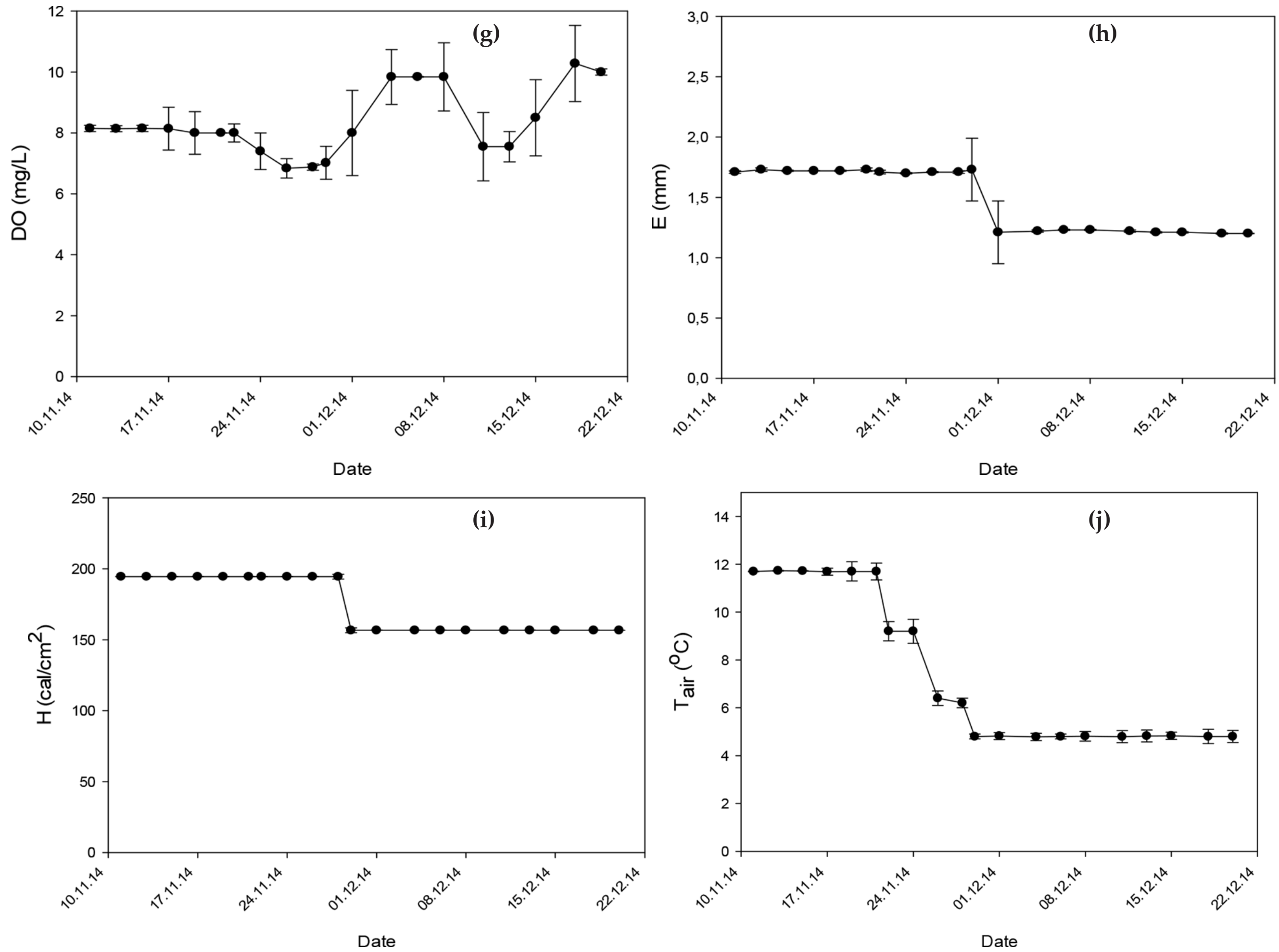

Fig. 2 (Continued). The graphical illustration of physical, chemical and meteorological data values (a) secchi disc depth (SDD), b) suspended solids (SS), c) chlorophyll-*a* (Chl-*a*), d) total organic carbon (TOC), e) pH, f) temperature (T_{water}) g) dissolved oxygen (DO), h) open-water evaporation (E), i) heat flux density (H) and j) temperature (T_{air})).

Chlorophyll-*a* is a pigment that is present in all photosynthetic phytoplankton. The primary production in lakes (primary production) is carried out by chlorophyll in plankton and littoral plants (the plants found in shallow parts of lakes). Therefore, the amount of Chl-*a* is the most important indicator of the phytoplankton biomass and productivity in a lake. Before operation of the system, the average calculated Chl-*a* concentration was 8.9 mg m^{-3}. After operation of the system, it was measured at 4.33 mg m^{-3}. According to the obtained data, a 73% decrease in Chl-*a* concentration was obtained. The Chl-*a* concentration indicates the mesotrophic property of the Doganci Dam Reservoir [42]. At the reservoir area where it divides into two branches, the observed phytoplankton production and light transmittance values were low because of the abundance of nutrients. Fluctuations were observed in Chl-*a* concentrations with the operation of the system. This is thought to have been caused by nutrients that enter the reservoir with precipitation.

The temperature, humidity, solar radiation, rainfall and wind speed data were the measurable point values that revealed meteorological situation in the region. The variations in open-water evaporation levels, heat flux density and air temperatures were examined using data from the meteorological station near the reservoir (Fig. 2).

To explain the water quality changes in reservoir and to determine the appropriateness of the field measurements for evaluating performance of the ultrasonic algae control system, the ANN was applied.

3.1. Application of the ANN

The main purpose of applying the ANN in this study was to determine the appropriateness of the field measurements for evaluating the performance of the ultrasonic algae control system in the Doganci Dam Reservoir. Here, the produced ANN model architecture has a multi-layer, feed-forward and Levenberg–Marquardt back-propagation architecture. In general, a neural net, has a parallel interconnected structure, which consists of (1) an input layer of neurons (independent variables), (2) a number of hidden layers, and (3) an output layer (dependent variables). The number of input and output neurons is determined by the nature of the problem. The hidden layers act as feature detectors, and in theory, there can be more than one hidden

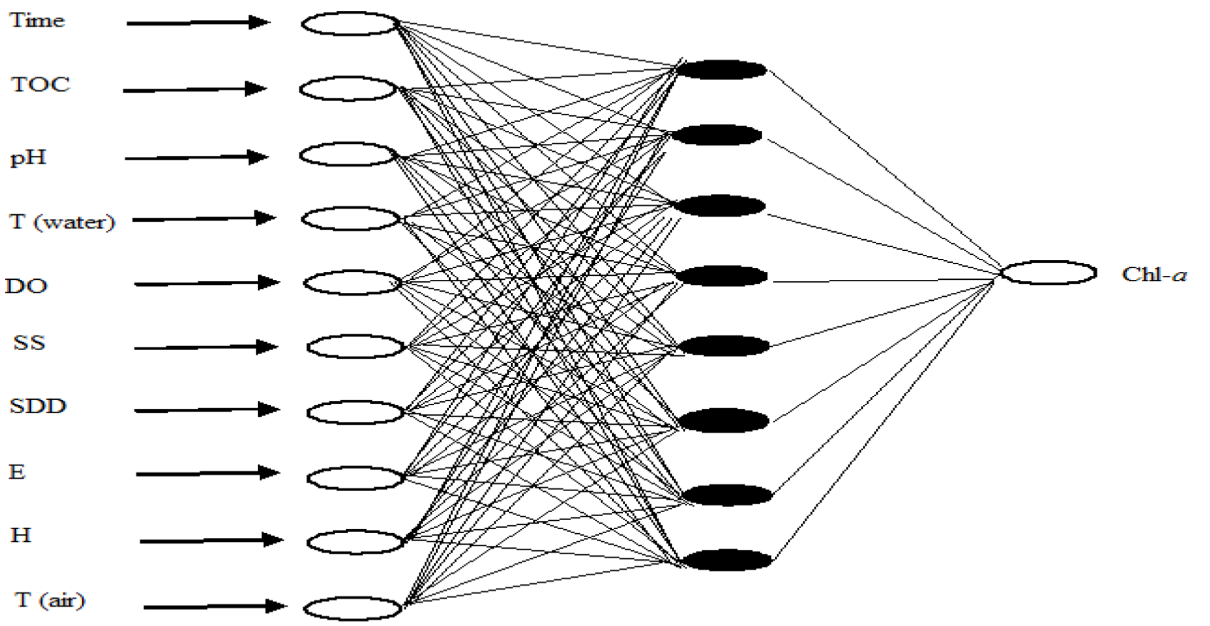

Fig. 3. Artificial neural networks (ANN) optimized structure.

Table 1
Results of the applied model (PE = processing element, MSE = mean square error)

Best networks	Training	Cross-validation
Hidden 1 PEs	10	13
Run #	1	1
Epoch #	192	67
Minimum MSE	2.86 × 10–30	0.001098063
Final MSE	2.86 × 10–30	0.004509149

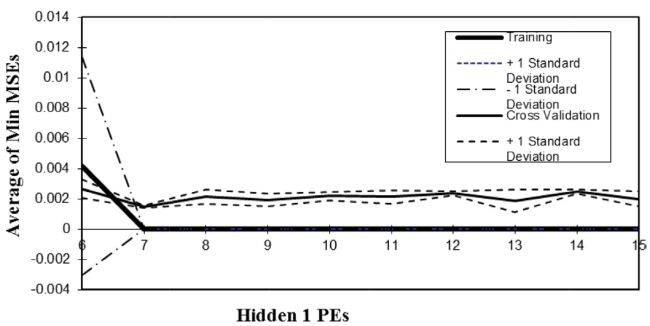

Fig. 4. Average mean square error (MSE) with standard deviation (PE = processing element).

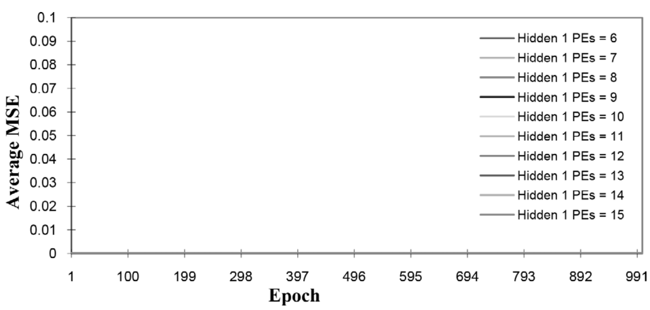

Fig. 5. Average cross-validation.

layer [43]. The ten neurons in the input layer include time, total organic carbon (TOC), pH, water temperature ($T_{(water)}$), dissolved oxygen (DO), suspended solids (SS), the Secchi disc depth (SDD), open-water evaporation (E), heat flux density (H) and temperature ($T_{(air)}$) values. The one neuron in the output layer indicates chlorophyll-*a* (Chl-*a*) values (Fig. 3). Note that the number of hidden layers and the number of neurons in this layer directly affect performance of the network.

In the artificial neural network (NeuroSolutions 5.06) in this study, all data were tested 20 times. The 20 obtained solutions were repeated 1000 times each, and every 1000 groups were confirmed 3 times in the NeuroSolutions 5.06 program. Both the training and cross-validation values are demonstrated in Table 1. Following validation, the standard deviation and application values resembled each other, which demonstrates that there was not a high deviation. All data, obtained as the result of calculations of the ANN, are shown in Fig. 4. The average mean square error (MSE) is shown in Fig. 5.

Fig. 6 shows a comparison between the calculated and experimental values of the output variable for the test sets using the neural network model with 10 hidden layers. Two lines of evidence were used to show success of the predictions. One line is a perfect fit line (predicted data equal to experimental data), on which all data of an ideal model should lay. The other line is the line that fits data the best (from the NeuroSolutions 5.06 program), and a perfect fit is obtained using regression analysis based on minimization of the squared errors. The correlation coefficients (*r*) of

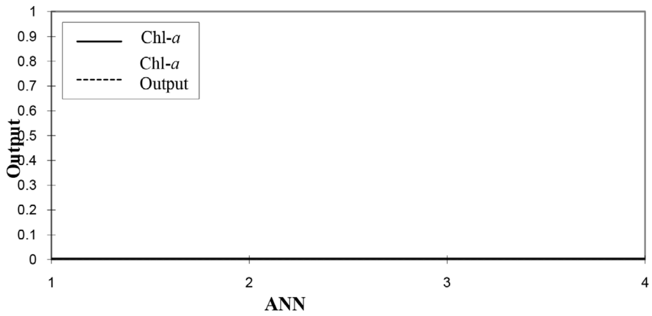

Fig. 6. Desired actual net outputs.

Table 2
Truth values (Chl-*a* = chlorophyll *a*, MSE = mean square error, NMSE = normalized mean square error, MAE = mean absolute error)

Performance	Chl–*a*
MSE	0.212444192
NMSE	0.067179879
MAE	0.407542451
Min Abs Error	0.081598873
Max Abs Error	0.685943664
r	0.974778221

those lines are presented in Table 2. In Fig. 6, the Chl-*a* line has a correlation coefficient of 0.9747 for the test set. Simulations, based on the ANN model, were performed to predict the behavior of the system under different conditions. All of the studied parameters in this work have considerable effects on Chl-*a*. The results confirm that the neural network modeling reproduces experimental data of the ultrasonic algae control system performance, and the data are within the experimental ranges adopted in the model.

4. Conclusion

This study showed that the ANN modelling approach was successfully utilized and is appropriate for evaluating the ultrasonic algae control system performance in the Doganci Dam Reservoir. There have been no reported applications of the use of an ANN for evaluating the ultrasonic algae control system performance in reservoirs in Turkey. The results indicated that the adopted Levenberg–Marquardt back-propagation algorithm yields satisfactory estimates with the acceptably low MSE values. The ANN modelling approach yields high precision estimates with an *r* value of 0.9747 for the Chl-*a* values of the reservoir, if a suitable structure with a sufficient number of neurons is selected.

When evaluated in terms of condition of model application; the average temperature of the Doganci Dam Reservoir was approximately 13.43 ± 0.21°C during the sampling period. Average measured pH value was 8.17 ± 0.05. The TOC values in drinking water supplies should be in the range of 0.1–25 mg L^{-1}. Average measured DO value was 8.31 ± 0.56 mg L^{-1}. The average measured Secchi disc depth was 3.08 m. After the operation of the system the highest value was 4 m. Before operation of the system, the average calculated suspended solid value was 1.8 mg L^{-1}. After the operation of the system, it was 1.64 mg L^{-1}. Before operation of the system, the average calculated Chl-*a* concentration was 8.9 mg m^{-3}. After operation of the system, it was measured at 4.33 mg m^{-3}. According to the obtained data, a 73% decrease in Chl-*a* concentration was obtained.

Because limnological studies and classical modeling efforts for reservoirs are laborious, expensive and time consuming, this approach will, hopefully, be adopted by water authorities as a decision support tool to reduce future monitoring efforts.

References

[1] S. Özyalin, R. Ustaoğlu, Kemer Baraj Gölü (Aydın) net fitoplankton kompozisyonunun incelenmesi, J. Fish. Aquat. Sci., 25 (2008) 275–282 (in Turkish).
[2] ICOLD-International Commission on Large Dams, World Register of Dams. Paris: International Commission on Large Dams, Paris, 1988.
[3] D. Purcell, Control of algal growth in reservoirs with ultrasound, School of Applied Sciences, PhD Thesis, Cranfield University, 2009, p. 248.
[4] K. Nakano, T.L. Jong, M. Matsumura, In situ algal bloom control by the integration of ultrasonic radiation and jet circulation to flushing, Environ. Sci. Technol., 35 (2001) 4941–4946.
[5] T.J. Lee, K. Nakano, M. Matsumara, Ultrasonic irradiation for blue-green algae bloom control, Environ. Technol., 22 (2001) 383–390.
[6] T.J. Lee, K. Nakano, M. Matsumara, A novel strategy for cyanobacterial bloom control by ultrasonic irradiation, Water Sci. Technol., 46 (2002) 207–215.
[7] C.Y. Ahn, M.H. Park, S.H. Joung, H.S. Kim, K.Y. Jang, H.M. Oh, Growth inhibition of cyanobacteria by ultrasonic radiation: Laboratory and enclosure studies, Environ. Sci. Technol., 37 (2003) 3031–3037.
[8] H. Hao, M. Wu, Y. Chen, J. Tang, Q. Wu, Cyanobacterial bloom control by ultrasonic irradiation at 20 kHz and 1.7 MHz., J. Environ. Sci. Heal A., 39 (2004) 1435–1446.
[9] L. Velo-Suárez, J.C. Gutiérrez-Estrada, Artificial neural network approaches to one-step weekly prediction of Dinophysis acuminate blooms in Huelva (Western Andalucía, Spain), Harmful Algae, 6 (2007) 361–371.
[10] J. Jiang, P. Wang, Z. Tian, L. Guo, Y. Wang, A Comparative Study of Statistical Learning Methods to Predict Eutrophication Tendency in a Reservoir, Northeast China, IEEE, 2011.
[11] C. Karul, S. Soyupak, In: F. Recknegel, A Comparison Between Neural Network Based and Multiple Regression Models for Chlorophyll-*a* Estimation, Ecological Informatics, Springer-Verlag 2003, pp. 249–263.
[12] F. Üneş, Precipitation and reservoir volume relationship prediction with artificial neural networks model, National Clean Energy Symposium, Isparta, Turkey, 2006, p. 622.
[13] B. Kunduz, F. Üneş, Reservoir level prediction for Yarseli Dam using artificial neural networks model. National Clean Energy Symposium, Isparta, Turkey, 2006, p. 614.
[14] F. Üneş, Prediction of density flow plunging depth in dam reservoir: an artificial neural network approach, Clean, 38 (2010) 296–308.
[15] S. Kommineni, K. Amante, B. Karnik, eds., Strategies for controlling and mitigating algal growth within water treatment plants, Denver, Colorado, U.S. Water Research Foundation. 2009.
[16] K.S. Suslick, Ultrasound: Its Chemical, Physical, and Biological Effects, New York, USA, VCH publishers, 1988.

[17] K.S. Suslick, Sonochemistry, Science, 247 (1990) 1439–1445.
[18] T.J. Mason, Sonochemistry, Oxford Chemistry Primers, USA, Oxford University Press, 2000.
[19] B. Büyükfidan, N. Büyükfidan, S. Özer, H. Göktaş, S. Kander, Bursa İlinin içme suyunu karşılayan Doganci baraj suyunun fiziksel ve kimyasal özellikleri, Çevre Sorunları Kongresi, İstanbul, Türkiye, 2008 (in Turkish).
[20] AWWA-APHA, Standard methods for the examination of water and wastewater, 21st Edn., American Public Health Association, Bultimore, USA. Washington D.C., 2005.
[21] V.B. Rao, C++ neural networks and fuzzy logic, M&T Books, 1995.
[22] H. Elhatip, M.A. Komur, Evaluation of water quality parameters for the Mamasin dam in Aksaray in the Anatolian part of Turkey by means of artificial neural networks, Environ. Geol., 53 (2008) 1157–1164.
[23] G. Cybenko, Approximation by superpositions of a sigmoidal function, Math. Control Signals Systems, 2 (1989) 303–314.
[24] K. Hornik, M. Stinchcombe, H. White, Multilayer feed forward networks are universal approximators, Neural Networks, 2(5) (1989) 359–366.
[25] M. Talebizadeh, A. Moridnejad, Uncertainty analysis for the forecast of lake level fluctuations using ensembles of ann and anfis models, Expert Syst. Appl., 38 (2011) 4126–4135.
[26] M.T. Hagan, M.B. Menhaj, Training feed forward networks with the Marquardt algorithm, Neural Networks, IEEE Trans., 5(6) (1994) 989–993.
[27] O. Kisi, Multi-layer perceptrons with Levenberg–Marquardt training algorithm for suspended sediment concentration prediction and estimation, Hydrolog. Sci. J., 49 (2004) 1025–1040.
[28] H.K. Cigizoglu, O. Kisi, Flow prediction by three back propagation techniques using k-fold partitioning of neural network training data, Nord Hydrol., 36 (2005) 49–64.
[29] U. Okkan, A. Mollamahmutoğlu, Yiğitler Çayı günlük akımlarının yapay sinir ağları ve regresyon analizi ile modellenmesi, J. Sci. Technol. Dumlupınar Uni, 23 (2010) 33–48.
[30] U. Okkan, H.Y. Dalkilic, Reservoir inflow modeling with artificial neural networks: The case of Kemer Dam in Turkey, Fresen. Environ. Bull., 20 (2011) 3112 R.
[31] P. Coulibaly, F. Anctil, R. Aravena, B. Bobée, Artificial neural network modeling of water table depth fluctuations, Wat. Resour. Res., 37(4) (2001) 885–896.
[32] M. Kumar, N. Raghuwanshi, R. Singh, W. Wallender, W. Pruitt, Estimating evaporate transpiration using artificial neural networks, J. Irrig. Drain. E-ASCE, 128(4) (2002) 224–233.
[33] E. Coppola, F. Szidarovszky, M. Poulton, E. Charles, Artificial neural network approach for predicting transient water levels in a multi layered groundwater system under variable state, pumping and climate conditions, Hydrol. Eng., 8 (2003) 348–360.
[34] A.A. Moghaddam, A. Nadiri, E. Fijani, Ability to study different models of artificial neural networks to evaluate groundwater water level in the hard formation, Paper presented at the Tenth Conference of Geological Society, Tehran, 2006.
[35] P.A. Maedeh, N. Mehrdadi, G.R.N. Bidhendi, H.Z. Abyaneh, Application of artificial neural network to predict total dissolved solids variations in groundwater of Tehran Plain, Iran, Int. J. Environ. Sust., 2(1) (2013) 10–20.
[36] W.W. Walker Jr, Significance of eutrophication in water supply reservoirs, J. AWWA, 75(1) (1983) 38–42.
[37] S. Bulut, R. Mert, K. Solak, M. Konuk, Selevir Baraj Gölü'nün bazı limnolojik özellikleri, Ekoloji, 20 (2011) 13–22 (in Turkish).
[38] B. Taş, Derbent Baraj Gölü (Samsun) su kalitesinin incelenmesi, Ekoloji, 15(61) (2006) 6–15 (in Turkish).
[39] S. Dirican, Evaluation of Kilickaya dam lake water quality, J. Agric. Fac. HR. U., 12(4) (2008) 25–31.
[40] H. Dayıoğlu, M.S. Özyurt, N. Bingöl, C. Yıldız, Kütahya ili içme sularının bazı fiziksel kimyasal ve bakteriyolojik özellikleri, DPÜ Fen Bilimleri Enstitüsü, 7 (2004) 71–90 (in Turkish).
[41] E. Şavik, S. Demer, Ü. Memiş, D.K. Doguç, T.A. Çalışkan, M.T. Sezer, F. Gültekin, N. Özgür, Isparta ve civarında tüketilen suların içerik ve sağlık açısından değerlendirilmesi, S.D.Ü. Tıp Fak. Derg., 19(3) (2012) 92–102 (in Turkish).
[42] Anonymous, Turkey Water Pollution Control Regulations, Tur. Rep. Off. Gaz., Dec. 31, 2004, No. 25687, Turkey, 2004.
[43] T. Yonar, M.Y. Kilic, Chemical oxygen demand and color removal from textile wastewater by UV/H_2O_2 using artificial neural networks, Wat. Environ. Res., 86 (2014) 2159–2165.