Prediction of dissolved oxygen in reservoirs using adaptive network-based fuzzy inference system

Vesna Ranković, Jasna Radulović, Ivana Radojević, Aleksandar Ostojić and Ljiljana Čomić

ABSTRACT

Predicting water quality is the key factor in the water quality management of reservoirs. Since a large number of factors affect the water quality, traditional data processing methods are no longer good enough for solving the problem. The dissolved oxygen (DO) level is a measure of the health of the aquatic system and its prediction is very important. DO dynamics are highly nonlinear and artificial intelligence techniques are capable of modelling this complex system. The objective of this study was to develop an adaptive network-based fuzzy inference system (ANFIS) to predict the DO in the Gruža Reservoir, Serbia. The fuzzy model was developed using experimental data which were collected during a 3-year period. The input variables analysed in this paper are: water pH, water temperature, total phosphate, nitrites, ammonia, iron, manganese and electrical conductivity. The selection of an appropriate set of input variables is based on the building of ANFIS models for each possible combination of input variables. Results of fuzzy models are compared with measured data on the basis of correlation coefficient, mean absolute error and mean square error. Comparing the predicted values by ANFIS with the experimental data indicates that fuzzy models provide accurate results.

Key words | adaptive network-based fuzzy inference system, dissolved oxygen, modelling, reservoir

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INTRODUCTION

Modelling water quality variables is a very important aspect of the analysis of any aquatic system. The chemical, physical and biological components of aquatic ecosystems are very complex and nonlinear. Recently, numerous computational and statistical approaches have been developed, leading to the appearance of ecological informatics (Chon & Park 2006). The future of eco-environmental modelling lies in the integration of different paradigms and techniques (Chen et al. 2006).

The concentration of dissolved oxygen (DO) is important for the healthy functioning of aquatic ecosystems, and a significant indicator of the state of aquatic ecosystems. It is highly desirable to create a DO model for each major reservoir so that water quality can be optimized throughout a time horizon. Although the modelling of DO has been

studied, many aspects of its dynamics are still unclear (Antonopoulos & Gianniou 2003). DO dynamics are highly nonlinear and many useful statistical theories cannot be implemented.

One of the successful applications of artificial intelligence (AI) techniques (knowledge-based systems, genetic algorithms, artificial neural networks and fuzzy inference systems) is to model complex nonlinear systems.

Soft computing techniques have been widely applied in different fields including water resource engineering (Lin et al. 2006; Wang et al. 2009).

Artificial neural networks (ANNs) have been successfully used as tools in the fields of water quality prediction and forecasting. Many researchers have considered neural network modelling of nonlinear dynamic systems. Various

forms of neural networks have been applied for resolving this problem. It is well known that a feedforward neural network (FNN) using the back propagation learning algorithm can approximate a given nonlinear function to any desired degree of accuracy. FNN models were identified, validated and tested for the computation of DO (Dogan *et al.* 2009) and DO and BOD (biochemical oxygen demand) (Singh *et al.* 2009) of river water. A back-propagation algorithm neural network was developed for simultaneous forecasting concentrations of total nitrogen, total phosphorus and DO in the Changle River, southeast China (Chen *et al.* 2010).

Palani *et al.* (2008) demonstrated the application of neural network models for the prediction and forecasting of selected seawater quality variables. Muttil & Chau (2006) employed ANNs and genetic programming for the modelling and prediction of coastal algal blooms. ANNs have been used intensively in the development of a reservoir water quality simulation model (Soyupak *et al.* 2003; Chaves & Kojiri 2007; Kuo *et al.* 2007; Ying *et al.* 2007; Ranković *et al.* 2010).

In recent years fuzzy logic systems have been successfully applied to a number of scientific and engineering problems. The fuzzy system and neural networks have similar mathematical fundamentals, so that a training method used with neural networks could be applied to fuzzy models (Wieland & Mirschel 2008). Fuzzy modelling from measured data is an effective tool for the approximation of uncertain nonlinear systems. In general, there are two types of fuzzy inference models (Jang *et al.* 1997). The Mamdani fuzzy model, in which the antecedent and consequent are fuzzy propositions, has been used to achieve quantitative analysis (Evsukoff *et al.* 2002). The Mamdani model is typically used in expert systems. The second type of fuzzy model is Takagi & Sugeno (1985) (Sugeno & Kang 1988). In this model the consequent is an affine linear function of the input variables. Fuzzy models have already been applied to water quality problems (Liou *et al.* 2003). Firat & Güngör (2008) and Jacquin & Shamseldin (2009) investigated the applicability and capability of fuzzy inference systems in river flow forecasting. Soyupak & Chen (2004) developed a fuzzy logic model to estimate pseudo steady-state chlorophyll-*a* concentrations in a very large and deep Keban Dam Reservoir. Pereira *et al.* (2009) constructed a fuzzy model to compute chlorophyll concentration in a Brazilian upwelling system. Marsili-Libelli (2004) described the

design of an algal bloom fuzzy predictor. Fuzzy pattern recognition is used to model the DO dynamics in the Orbetello lagoon by Giusti & Marsili-Libelli (2009). Altunkaynak *et al.* (2005) used fuzzy logic modelling for predicting the DO concentration in the Golden Horn.

The aim of this paper was to construct an adaptive network-based fuzzy inference system (ANFIS) model to predict the DO in the Gruža Reservoir, Serbia and to demonstrate the model's application to identifying complex nonlinear relationships between input and output variables. Kosko (1994) proved that a fuzzy system can uniformly approximate any real continuous function on a closed and bounded domain to any degree of accuracy. ANFIS is also a universal approximator.

Created models for DO are based on different input variables. Soyupak *et al.* (2003), while suggesting the model for three reservoirs in Turkey, chose the following input variables as an input: season, distance from major source, the depth and temperature.

Sengorur *et al.* (2006) decided that an input would include NO_2–N, NO_3–N, temperature, flow and BOD. Kuo *et al.* (2007) constructed a three-layer FNN for the computation of DO level in the Te-Chi reservoir (Taiwan) using six input variables: month, pH, chlorophyll-*a*, NH_4–N, NO_3–N and water temperature. Ying *et al.* (2007) chose the following eight parameters: temperature, turbidity, pH, alkalinity, chloride, NH_4–N, NO_2–N and hardness, pointing out that each of them affects DO to a certain degree. Singh *et al.* (2009) proposed 11 variables: pH, total alkalinity, total hardness, total solids, COD, NH_4–N, NO_3–N, chloride, phosphate, K and Na. In this paper, the basis for modelling is the parameters used in the previously mentioned models as well as the parameters characteristic for this specific reservoir: manganese (Mn) and iron (Fe). When the oxidation microzone is disturbed under anaerobic conditions in the deepest layers of a hypolimnion (a frequent occurrence during the summer months), phosphate, manganese and ferro ions are liberated from the sediment into the water (Comic & Ostojic 2005). Ranković *et al.* (2010) developed a FNN model to predict the DO in the Gruža Reservoir, Serbia. The input variables of the neural network were: water pH, water temperature, chloride, total phosphate, nitrites, nitrates, ammonia, iron, manganese and electrical conductivity.

Sensitivity analysis was used to determine the influence of input variables on the dependent variable and the following order was obtained: water pH, water temperature, manganese, ammonia, iron, electrical conductivity, nitrites, total phosphate, nitrates and chloride.

It was shown that nitrates and chloride did not have a significant effect on the performance of the ANN model and could be excluded from the input variables. In this paper an ANFIS model for the same reservoir was developed.

The major objective of the study presented in this paper was to construct a high-quality ANFIS model to predict the DO in the reservoir and to demonstrate its application to identifying complex nonlinear relationships between input and output variables. However, it should be noted that although the motivation in this paper was primarily ANFIS development, the process of the proposed input variables selection is such that it can be used for identifying an appropriate set of inputs during AI modelling of other water quality variables.

MATERIAL AND METHODS

Study area and data

The Gruža Reservoir was formed on the Gruža River for the purpose of supplying Kragujevac and the surrounding area with drinking water (Figure 1). Construction of the dam began in 1979, and the reservoir was filled with water in 1985. It is located at an altitude of 238–269 m above sea level (a.s.l.), with a total water volume of $64.6 \times 10^6 \, m^3$, a surface area of 934 ha, and a drainage basin of 318 km². The maximum depth of the reservoir is 31 m, and the reservoir exhibits 3–5 m water level fluctuations. It has a hydraulic residence time of 22 months. More than two thirds of the reservoir has all the characteristics of lowland reservoirs, with shallow depth (mean depth of reservoir is 6.5 m), an unfavourable ratio of trophogenic and tropholytic layers, and banks surrounded by meadows and cultivated land. The soil upon which the accumulation lake was made contains Fe and Mn. A special characteristic is a bridge crossing the reservoir, which carries frequent motor traffic, so that considerable amounts of exhaust fumes are gathered over the reservoir and enter the water by means of diffusion or with precipitation.
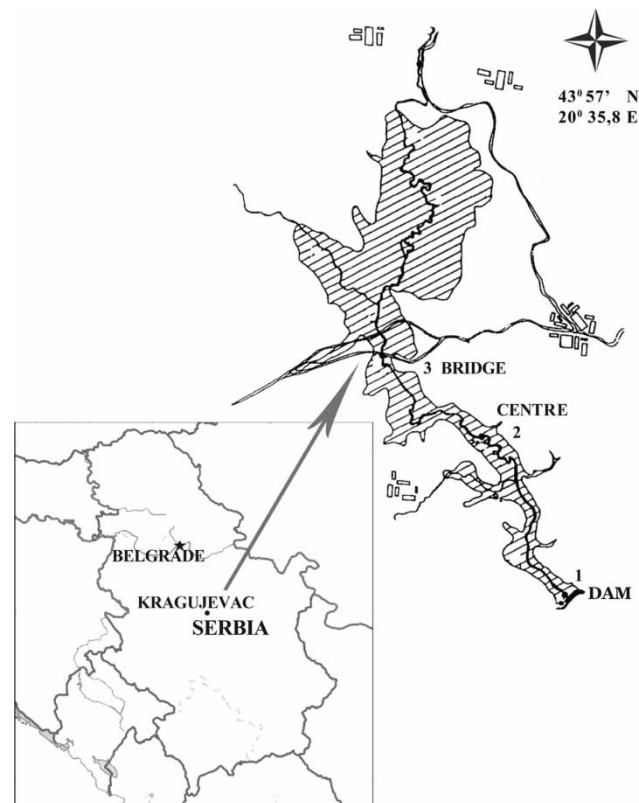

Figure 1 │ The Gruža Reservoir and sampling points (1 – Dam, 2 – Centre, 3 – Bridge).

The large surface in relation to the mean depth favours eutrophication (Ostojić *et al.* 2005). The average values of trophic state parameters indicate that the water of the Gruža Reservoir is eutrophic. It is apparent that the Gruža Reservoir can be classified as a eutrophic water on the basis of total phosphorus content of chlorophyll-*a* and hypertrophic water with respect to transparency (Ostojić *et al.* 2005). It is surrounded by farmland, and receives waste water from a number of neighbouring settlements. The reservoir exhibits thermal stratification from the end of April to the beginning of October (Comic & Ostojic 2005).

The data set used in this study was generated through the monitoring of the water quality of Gruža reservoir. Monthly sampling was carried out during a period of 3 years (2000–2003). Three permanent sampling sites were selected (Figure 1). One was directly beside the dam, where the depth varied from 25 to 30 m, depending on the water level. The second was in the central part with a depth ranging from 14 to 17 m. The third was in the shallowest part, near the bridge, with a depth ranging from 5 to 9 m,

about 200 m from its end, which is under water even when its level is lowest. Samples were collected at intervals of depth of 3 m during the thermal stratification period and at 5 m increments during the mixing period. For the analysis 180 samples with complete data were selected.

The available set of data was divided into two sections as a training test and a test set. In the training process of the ANFIS, 152 samples were used. The ANFIS model was tested using 28 randomly selected data.

ANFIS structure

Supposing that the first-order Takagi–Sugeno fuzzy inference system (FIS) has m inputs $(x_1, x_2, ..., x_m)$ and one output y. Linguistic labels x_j are $A_{1j}, A_{2j}, ..., A_{nj}$. The rule base contains $p = n^m$. For simplicity, it is assumed that the FIS has $m = 2$ and $n = 2$. Then the rule base contains four if–then rules:

R_1: If x_1 is A_{11} and x_2 is A_{12} then $f_1 = q_{11}x_1 + q_{12}x_2 + c_1$
R_2: If x_1 is A_{11} and x_2 is A_{22} then $f_2 = q_{21}x_1 + q_{22}x_2 + c_2$
R_3: If x_1 is A_{21} and x_2 is A_{12} then $f_3 = q_{31}x_1 + q_{32}x_2 + c_3$
R_4: If x_1 is A_{21} and x_2 is A_{22} then $f_4 = q_{41}x_1 + q_{42}x_2 + c_4$

where q_{kj} and c_k; $k = 1, 2, ..., 4, j = 1, 2$, are the consequent parameters. In this inference system the output of each rule is a linear combination of input variables.

The corresponding equivalent ANFIS architecture (Jang 1993) is shown in Figure 2. When f_k is a constant, a zero-order Takagi–Sugeno fuzzy model is formed, which may be considered to be a special case of a Mamdani FIS. The zero-order
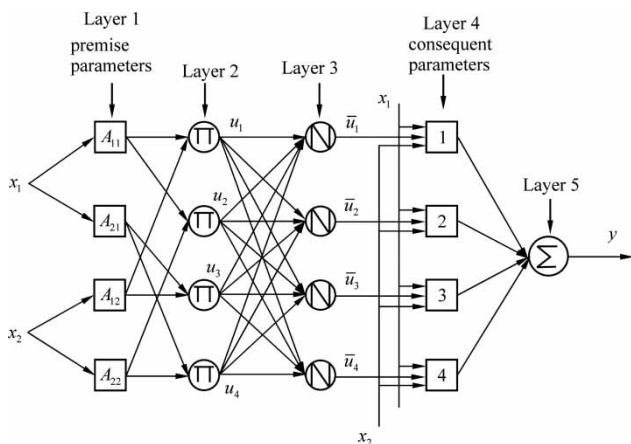
Takagi–Sugeno fuzzy model is functionally equivalent to a radial basis function (RBF) network under certain constraints.

Functional equivalence between a RBF network and ANFIS can be established under these conditions (Jang & Sun 1993).

1. The number of RBF hidden neurons is equal to the number of fuzzy if–then rules.
2. The output of each fuzzy if–then rule is composed of a constant.
3. The membership functions (MFs) within each fuzzy rule are chosen as Gaussian functions with the same variance.
4. The multiplication operator is used to compute the firing strength of each rule.
5. Both the RBF network and the FIS under consideration use the same method (i.e. either weighted average or weighted sum) to derive their overall outputs.

In this study, the third constraint is not satisfied because the *gauss2mf* membership function, but not Gaussian function, is selected.

The ANFIS structure contains five layers.

Layer 1

The outputs of the layer are fuzzy membership grade of inputs $\mu_{A_{ij}}(x_j)$. If the Gaussian MF is adopted, $\mu_{A_{ij}}(x_j)$ is given by:

$$\mu_{A_{ij}}(x_j) = e^{-(x_j - c_{ij})/2\sigma_{ij}^2}, \quad i = 1, 2, \quad j = 1, 2, \tag{1}$$

where c_{ij} and σ_{ij} are the parameters of the MF or premise parameters.

Layer 2

Every node in this layer is a fixed node. The output of nodes can be presented as:

$$u_1 = \mu_{A_{11}}(x_1) * \mu_{A_{12}}(x_2),$$
$$u_2 = \mu_{A_{11}}(x_1) * \mu_{A_{22}}(x_2),$$
$$u_3 = \mu_{A_{21}}(x_1) * \mu_{A_{12}}(x_2),$$
$$u_4 = \mu_{A_{21}}(x_1) * \mu_{A_{22}}(x_2),$$

$*$ denotes T-norm. Nodes are marked by a circle and labelled $\prod$.

Figure 2 | Two-input ANFIS with four rules.

Layer 3

The output of each fixed node labelled N can be presented as:

$$\bar{u}_k = \frac{u_k}{\sum_{k=1}^{4} u_k}, \quad k = 1, 2, 3, 4. \tag{2}$$

Layer 4

Every node in this layer is a square. The outputs of this layer are given by:

$$\bar{u}_k f_k = \bar{u}_k \sum_{j=1}^{2} q_{kj} x_j + c_k, \quad k = 1, 2, 3, 4. \tag{3}$$

Layer 5

Finally, the output of the ANFIS can be presented as:

$$y = \sum_{k=1}^{4} \bar{u}_k f_k = \frac{1}{\sum_{k=1}^{4} u_k} \sum_{k=1}^{4} u_k \left(\sum_{j=1}^{2} q_{kj} x_j + c_k \right). \tag{4}$$

There are four methods to update the parameters of the ANFIS structure, as listed below according to their computation complexities (Jang 1993):

1. Gradient descent (GD): All parameters are updated by the GD.
2. GD and one pass of least square estimation (LSE): The LSE is applied only once at the very beginning to get the initial values of the consequent parameters and then the GD takes over to update all parameters.
3. GD and LSE: This is the hybrid learning.
4. Sequential LSE: using extended Kalman filter algorithm to update all parameters.

In this paper the hybrid learning algorithm that combines the GD and the LSE method is used for updating the parameters. For adapting premise parameters the GD method is used. The LSE method is used for updating the consequent parameters. Each epoch of the hybrid learning algorithm involves a forward and a backward pass in the ANFIS. Jang (1993) described the mathematical background of the hybrid learning algorithm. This algorithm converges much faster since it reduces the dimension of the search space of the back-propagation GD algorithm.

Select input variables and performance criteria

The selection of an appropriate set of input variables from all possible input variables during AI model development is important for obtaining high-quality model. Many of the described methods for input variable selection are based on heuristics, expert knowledge, statistical analysis, or a combination of these. However, although there is a well justified need to consider input variable selection carefully, there is currently no consensus on how this task should be undertaken (May *et al.* 2008).

Jang (1996) presented a heuristic, relatively simple and fast method of input selection for neuro-fuzzy modelling using ANFIS. Finding an optimal solution requires building ANFIS models for each possible combination of input variables (the number of possible combinations is 2^{n_c}, where n_c is the number of candidate variables) which becomes computationally prohibitive for problems involving even a moderate number of candidate input variables. If we have a modelling problem with n_c candidate inputs and we want to find the most influential m inputs as the inputs to ANFIS, we construct $C_m^{n_c} = n_c(n_c - 1) \ldots (n_c - m + 1)/m$ ANFIS models (each with different combination of m inputs), and train them with a single pass of the LSE method (Jang 1996). The proposed method is based on the assumption that the ANFIS model with the smallest root mean squared error (RMSE) after one epoch of training has a greater potential of achieving a lower RMSE when more epochs of training are given. This assumption is not absolutely true, but it is heuristically reasonable.

In this paper, Jang's method was used for the selection of an appropriate set of input variables. An ANFIS model has been trained for 300 epochs. After that number of epochs, the reduction of the RMSE value is negligible. Thus, comparison of trained ANFIS models is justified.

RMSE is calculated by the following expression:

$$\text{RMSE} = \sqrt{\frac{1}{N_o} \sum_{i=1}^{N_o} (y_{mi} - y_i)^2}, \tag{5}$$

where y_i and y_{mi} denote the network output and measured

value from the ith element and N_o represents the number of observations.

The prediction performances of the fuzzy model were evaluated using correlation coefficient (r), mean absolute error (MAE) and mean square error (MSE):

$$\int r = \frac{\sum_{i=1}^{N_o} (y_i - \bar{y})(y_{mi} - \bar{y}_m)}{\sqrt{\sum_{i=1}^{N_o} (y_i - \bar{y})^2 \sum_{i=1}^{N_o} (y_{mi} - \bar{y}_m)^2}}, \tag{6}$$

$$MAE = \frac{1}{N_o} \sum_{i=1}^{N_o} |y_{mi} - y_i|, \tag{7}$$

and

$$MSE = \frac{1}{N_o} \sum_{i=1}^{N_o} (y_{mi} - y_i)^2, \tag{8}$$

where y_i and y_{mi} denote the ANFIS output and measured value from the i-th element; $\bar{y}$ and $\bar{y}_m$ denote their average respectively, and N_o represents the number of observations.

The Pearson correlation coefficient is defined as the degree of correlation between the experimental and predicted values.

RESULTS AND DISCUSSION

In this paper the MATLAB Fuzzy Toolbox was used for the implementation of the fuzzy model. The input variables analysed in this paper were: water pH, water temperature, total phosphate, nitrites, ammonia, iron, manganese and electrical conductivity. The number of possible combinations is $2^8 = 256$. It is necessary to build $C_6^8 = 28$ ANFIS models if we want to find the six most relevant inputs. The training parameters of these models are given in Table 1. It is also important to select proper parameters for the training process, including the initial step size, the step size increase rate and the step size decrease rate. Parameter selection for the training process and their impact on the ANFIS has been addressed in the literature (Jang 1993). The initial step size is defined to 0.01. The step size decrease rate is 0.9 and the step size increase rate is 1.1. Fuzzy partitioning of the input variables of the ANFIS is realized by the selection of the two primary fuzzy sets.

Table 1 | The training parameters of the ANFIS

Number of rules	64
Epoch	300
Membership function	*gauss2mf*
AND method	Product
Implication method	Minimum
Aggregation method	Maximum
Defuzzification method	Weight average

The two-sided Gaussian (*gauss2mf*) MF is taken. The *gauss2mf* is a kind of smooth MF, so the resulting model will generally have a high accuracy in fitting the training data (Wang *et al.* 2005). The function *gauss2mf* $\mu_{A_{ij}}(x_j)$ is a combination of two Gaussian functions. The first function, specified by $\sigma_{ij(1)}$ and $c_{ij(1)}$, determines the shape of the left-most curve. The second function specified by $\sigma_{ij(2)}$ and $c_{ij(2)}$, determines the shape of the right-most curve. Whenever $c_{ij(1)} < c_{ij(2)}$, the *gauss2mf* function reaches a maximum value of 1. Otherwise, the maximum value is less than one.

The ANFIS models in the considered example have 64 rules.

Thus the 496 parameters in this example are composed of 48 premise parameters and 448 consequent parameters when the first order Takagi–Sugeno fuzzy model is used. In this paper, the zero-order Takagi–Sugeno fuzzy model ($f_k = c_k$) is selected. For adapting the premise parameters (48) the GD method is used. The LSE method is used for updating the consequent parameters (64).

From Table 2 it can be seen that the RMSE after 300 epochs is the smallest for model 9 with the inputs: pH, temperature (*Temp*), manganese (Mn), ammonia (*Ammon*), electrical conductivity (EC) and iron (Fe).

The parameters of the MFs of the inputs after training are shown in Table 3.

The rule base of the ANFIS for DO calculation:

Rule 1: If (pH is A_{11}) and (*Temp* is A_{12}) and (Mn is A_{13}) and (*Ammon* is A_{14}) and (EC is A_{15}) and (Fe is A_{16}) then (f_1 is –16.13).

Rule 2: If (pH is A_{11}) and (*Temp* is A_{12}) and (Mn is A_{13}) and (*Ammon* is A_{14}) and (EC is A_{15}) and (Fe is A_{26}) then (f_2 is 61.58).

Table 2 | RMSE after 300 epochs of training

Table 2 | continued

Models	Input variables of the fuzzy models	RMSE after 300 epochs of training
1	pH, ammonia, conductivity, Fe, Mn, nitrites	2.3922
2	pH, ammonia, nitrites, total P, Mn, temperature	2.0739
3	pH, ammonia, conductivity, total P, Mn, temperature	1.5519
4	pH, nitrites, conductivity, Fe, total P, temperature	1.6782
5	pH, nitrites, conductivity, Fe, Mn, temperature	1.8092
6	Nitrites, ammonia, conductivity, Fe, Mn, temperature	2.4739
7	pH, ammonia, conductivity, nitrites, total P, temperature	1.8736
8	Nitrites, ammonia, conductivity, Fe, Mn, total P	2.6808
9	pH, ammonia, conductivity, Fe, Mn, temperature	1.4604
10	pH, ammonia, conductivity, Fe, nitrites, total P	2.2743
11	pH, total P, conductivity, Fe, Mn, temperature	1.4779
12	pH, ammonia, nitrites, Fe, total P, temperature	2.1016
13	pH, ammonia, conductivity, Fe, nitrites, temperature	1.7784
14	Total P, ammonia, conductivity, Fe, Mn, temperature	2.1773
15	Nitrites, ammonia, conductivity, Fe, total P, temperature	2.4259
16	pH, ammonia, nitrites, Fe, Mn, total P	2.5858
17	pH, ammonia, conductivity, Fe, Mn, total P	2.0954
18	pH, ammonia, conductivity, Fe, total P, temperature	1.5299
19	pH, nitrites, total P, Fe, Mn, temperature	2.1888
20	Nitrites, total P, conductivity, Fe, Mn, temperature	2.5663
21	pH, ammonia, conductivity, nitrites, Mn, total P	2.371
22	pH, ammonia, total P, Fe, Mn, temperature	1.6798

(continued)

Models	Input variables of the fuzzy models	RMSE after 300 epochs of training
23	Nitrites, ammonia, conductivity, total P, Mn, temperature	2.4537
24	pH, ammonia, conductivity, nitrites, Mn, temperature	1.9639
25	pH, nitrites, conductivity, Fe, Mn, total P	2.4396
26	pH, nitrites, conductivity, total P, Mn, temperature	1.9829
27	Nitrites, ammonia, total P, Fe, Mn, temperature	2.5497
28	pH, ammonia, nitrites, Fe, Mn, temperature	2.0782

Rule 3: If (pH is A_{11}) and (*Temp* is A_{12}) and (Mn is A_{13}) and (*Ammon* is A_{14}) and (EC is A_{25}) and (Fe is A_{16}) then (f_3 is −16.02).

Rule 4: If (pH is A_{11}) and (*Temp* is A_{12}) and (Mn is A_{13}) and (*Ammon* is A_{24}) and (EC is A_{15}) and (Fe is A_{16}) then (f_4 is 3.449).

Rule 5: If (pH is A_{11}) and (*Temp* is A_{12}) and (Mn is A_{23}) and (*Ammon* is A_{14}) and (EC is A_{15}) and (Fe is A_{16}) then (f_5 is −20.6).

Rule 6: If (pH is A_{11}) and (*Temp* is A_{12}) and (Mn is A_{13}) and (*Ammon* is A_{24}) and (EC is A_{15}) and (Fe is A_{26}) then (f_6 is −359.1).

Rule 7: If (pH is A_{11}) and (*Temp* is A_{12}) and (Mn is A_{13}) and (*Ammon* is A_{24}) and (EC is A_{25}) and (Fe is A_{16}) then (f_7 is 136).

Rule 8: If (pH is A_{11}) and (*Temp* is A_{12}) and (Mn is A_{13}) and (*Ammon* is A_{24}) and (EC is A_{25}) and (Fe is A_{26}) then (f_8 is 5.818).

Rule 9: If (pH is A_{11}) and (*Temp* is A_{12}) and (Mn is A_{23}) and (*Ammon* is A_{14}) and (EC is A_{15}) and (Fe is A_{16}) then (f_9 is 541.6).

Rule 10: If (pH is A_{11}) and (*Temp* is A_{12}) and (Mn is A_{23}) and (*Ammon* is A_{14}) and (EC is A_{15}) and (Fe is A_{26}) then (f_{10} is −81.02).

Rule 11: If (pH is A_{11}) and (*Temp* is A_{12}) and (Mn is A_{23}) and (*Ammon* is A_{14}) and (EC is A_{25}) and (Fe is A_{16}) then (f_{11} is −90.59).

Table 3 | The parameters of the membership functions of the inputs

Input variable	Range	MF	Parameters of the MF
pH	[7.33 8.96]	A_{11}	$\sigma_{11(1)} = 0.2769; c_{11(1)} = 6.841; \sigma_{11(2)} = 0.31; c_{11(2)} = 7.661;$
		A_{21}	$\sigma_{21(1)} = 0.3829; c_{21(1)} = 8.155; \sigma_{21(2)} = 0.2769; c_{21(2)} = 9.449;$
Temp	[3.1 28.5]	A_{12}	$\sigma_{12(1)} = 4.315; c_{12(1)} = -4.52; \sigma_{12(2)} = 3.731; c_{12(2)} = 10.21;$
		A_{22}	$\sigma_{22(1)} = 4.814; c_{22(1)} = 20.43; \sigma_{22(2)} = 4.315; c_{22(2)} = 36.12;$
Mn	[0 9.6]	A_{13}	$\sigma_{13(1)} = 1.631; c_{13(1)} = -2.88; \sigma_{13(2)} = 1.631; c_{13(2)} = 2.88;$
		A_{23}	$\sigma_{23(1)} = 2.549; c_{23(1)} = 6.356; \sigma_{23(2)} = 1.631; c_{23(2)} = 12.48;$
Ammon	[0 6.8]	A_{14}	$\sigma_{14(1)} = 1.155; c_{14(1)} = -2.04; \sigma_{14(2)} = 1.155; c_{14(2)} = 2.039;$
		A_{24}	$\sigma_{24(1)} = 2.116; c_{24(1)} = 4.356; \sigma_{24(2)} = 1.155; c_{24(2)} = 8.84;$
EC	[243 471]	A_{15}	$\sigma_{15(1)} = 38.73; c_{15(1)} = 174.6; \sigma_{15(2)} = 38.73; c_{15(2)} = 311.4;$
		A_{25}	$\sigma_{25(1)} = 38.72; c_{25(1)} = 402.6; \sigma_{25(2)} = 38.73; c_{25(2)} = 539.4;$
Fe	[0 1.1]	A_{16}	$\sigma_{16(1)} = 0.1869; c_{16(1)} = -0.33; \sigma_{16(2)} = 0.04021; c_{16(2)} = 0.3299;$
		A_{26}	$\sigma_{26(1)} = 0.0183; c_{26(1)} = 0.1142; \sigma_{26(2)} = 0.1869; c_{26(2)} = 1.43;$

Rule 12: If (pH is A_{11}) and (*Temp* is A_{12}) and (Mn is A_{23}) and (*Ammon* is A_{14}) and (EC is A_{25}) and (Fe is A_{26}) then (f_{12} is −90.27).

Rule 13: If (pH is A_{11}) and (*Temp* is A_{12}) and (Mn is A_{23}) and (*Ammon* is A_{24}) and (EC is A_{15}) and (Fe is A_{16}) then (f_{13} is 361.4).

Rule 14: If (pH is A_{11}) and (*Temp* is A_{12}) and (Mn is A_{23}) and (*Ammon* is A_{24}) and (EC is A_{15}) and (Fe is A_{26}) then (f_{14} is 742).

Rule 15: If (pH is A_{11}) and (*Temp* is A_{12}) and (Mn is A_{23}) and (*Ammon* is A_{24}) and (EC is A_{25}) and (Fe is A_{16}) then (f_{15} is −129.7).

Rule 16: If (pH is A_{11}) and (*Temp* is A_{12}) and (Mn is A_{23}) and (*Ammon* is A_{24}) and (EC is A_{25}) and (Fe is A_{26}) then (f_{16} is 13.89).

Rule 17: If (pH is A_{11}) and (*Temp* is A_{22}) and (Mn is A_{13}) and (*Ammon* is A_{14}) and (EC is A_{15}) and (Fe is A_{16}) then (f_{17} is 45.94).

Rule 18: If (pH is A_{11}) and (*Temp* is A_{22}) and (Mn is A_{13}) and (*Ammon* is A_{14}) and (EC is A_{15}) and (Fe is A_{26}) then (f_{18} is −21.53).

Rule 19: If (pH is A_{11}) and (*Temp* is A_{22}) and (Mn is A_{13}) and (*Ammon* is A_{14}) and (EC is A_{25}) and (Fe is A_{16}) then (f_{19} is 0.2198).

Rule 20: If (pH is A_{11}) and (*Temp* is A_{22}) and (Mn is A_{13}) and (*Ammon* is A_{14}) and (EC is A_{25}) and (Fe is A_{26}) then (f_{20} is 69.31).

Rule 21: If (pH is A_{11}) and (*Temp* is A_{22}) and (Mn is A_{13}) and (*Ammon* is A_{24}) and (EC is A_{15}) and (Fe is A_{16}) then (f_{21} is −15.18).

Rule 22: If (pH is A_{11}) and (*Temp* is A_{22}) and (Mn is A_{13}) and (*Ammon* is A_{24}) and (EC is A_{15}) and (Fe is A_{26}) then (f_{22} is 45.78).

Rule 23: If (pH is A_{11}) and (*Temp* is A_{22}) and (Mn is A_{13}) and (*Ammon* is A_{24}) and (EC is A_{25}) and (Fe is A_{16}) then (f_{23} is −48.96).

Rule 24: If (pH is A_{11}) and (*Temp* is A_{22}) and (Mn is A_{13}) and (*Ammon* is A_{24}) and (EC is A_{25}) and (Fe is A_{26}) then (f_{24} is −344.1).

Rule 25: If (pH is A_{11}) and (*Temp* is A_{22}) and (Mn is A_{23}) and (*Ammon* is A_{14}) and (EC is A_{15}) and (Fe is A_{16}) then (f_{25} is −998.4).

Rule 26: If (pH is A_{11}) and (*Temp* is A_{22}) and (Mn is A_{23}) and (*Ammon* is A_{14}) and (EC is A_{15}) and (Fe is A_{26}) then (f_{26} is −90.82).

Rule 27: If (pH is A_{11}) and (*Temp* is A_{22}) and (Mn is A_{23}) and (*Ammon* is A_{14}) and (EC is A_{25}) and (Fe is A_{16}) then (f_{27} is 160.2).

Rule 28: If (pH is A_{11}) and (*Temp* is A_{22}) and (Mn is A_{23}) and (*Ammon* is A_{14}) and (EC is A_{25}) and (Fe is A_{26}) then (f_{28} is −17.74).

Rule 29: If (pH is A_{11}) and (*Temp* is A_{22}) and (Mn is A_{23}) and (*Ammon* is A_{24}) and (EC is A_{15}) and (Fe is A_{16}) then (f_{29} is 549.6).

Rule 30: If (pH is A_{11}) and (*Temp* is A_{22}) and (Mn is A_{23}) and (*Ammon* is A_{24}) and (EC is A_{15}) and (Fe is A_{26}) then (f_{30} is 216.3).

Rule 31: If (pH is A_{11}) and (*Temp* is A_{22}) and (Mn is A_{23}) and (*Ammon* is A_{24}) and (EC is A_{25}) and (Fe is A_{16}) then (f_{31} is 298.3).

Rule 32: If (pH is A_{11}) and (*Temp* is A_{22}) and (Mn is A_{23}) and (*Ammon* is A_{24}) and (EC is A_{25}) and (Fe is A_{26}) then (f_{32} is -18.93).

Rule 33: If (pH is A_{21}) and (*Temp* is A_{12}) and (Mn is A_{13}) and (*Ammon* is A_{14}) and (EC is A_{15}) and (Fe is A_{16}) then (f_{33} is 27.98).

Rule 34: If (pH is A_{21}) and (*Temp* is A_{12}) and (Mn is A_{13}) and (*Ammon* is A_{14}) and (EC is A_{15}) and (Fe is A_{26}) then (f_{34} is 61.26).

Rule 35: If (pH is A_{21}) and (*Temp* is A_{12}) and (Mn is A_{13}) and (*Ammon* is A_{14}) and (EC is A_{25}) and (Fe is A_{16}) then (f_{35} is 190.2).

Rule 36: If (pH is A_{21}) and (*Temp* is A_{12}) and (Mn is A_{13}) and (*Ammon* is A_{14}) and (EC is A_{25}) and (Fe is A_{26}) then (f_{36} is -117.2).

Rule 37: If (pH is A_{21}) and (*Temp* is A_{12}) and (Mn is A_{13}) and (*Ammon* is A_{24}) and (EC is A_{15}) and (Fe is A_{16}) then (f_{37} is 114.8).

Rule 38: If (pH is A_{21}) and (*Temp* is A_{12}) and (Mn is A_{13}) and (*Ammon* is A_{24}) and (EC is A_{15}) and (Fe is A_{26}) then (f_{38} is -249.8).

Rule 39: If (pH is A_{21}) and (*Temp* is A_{12}) and (Mn is A_{13}) and (*Ammon* is A_{24}) and (EC is A_{25}) and (Fe is A_{16}) then (f_{39} is -1460).

Rule 40: If (pH is A_{21}) and (*Temp* is A_{12}) and (Mn is A_{13}) and (*Ammon* is A_{24}) and (EC is A_{25}) and (Fe is A_{26}) then (f_{40} is 773.2).

Rule 41: If (pH is A_{21}) and (*Temp* is A_{12}) and (Mn is A_{23}) and (*Ammon* is A_{14}) and (EC is A_{15}) and (Fe is A_{16}) then (f_{41} is -590.5).

Rule 42: If (pH is A_{21}) and (*Temp* is A_{12}) and (Mn is A_{23}) and (*Ammon* is A_{14}) and (EC is A_{15}) and (Fe is A_{26}) then (f_{42} is -420.6).

Rule 43: If (pH is A_{21}) and (*Temp* is A_{12}) and (Mn is A_{23}) and (*Ammon* is A_{14}) and (EC is A_{25}) and (Fe is A_{16}) then (f_{43} is 270).

Rule 44: If (pH is A_{21}) and (*Temp* is A_{12}) and (Mn is A_{23}) and (*Ammon* is A_{14}) and (EC is A_{25}) and (Fe is A_{26}) then (f_{44} is 490.9).

Rule 45: If (pH is A_{21}) and (*Temp* is A_{12}) and (Mn is A_{23}) and (*Ammon* is A_{24}) and (EC is A_{15}) and (Fe is A_{16}) then (f_{45} is 22).

Rule 46: If (pH is A_{21}) and (*Temp* is A_{12}) and (Mn is A_{23}) and (*Ammon* is A_{24}) and (EC is A_{15}) and (Fe is A_{26}) then (f_{46} is 112.6).

Rule 47: If (pH is A_{21}) and (*Temp* is A_{12}) and (Mn is A_{23}) and (*Ammon* is A_{24}) and (EC is A_{25}) and (Fe is A_{16}) then (f_{47} is -30.23).

Rule 48: If (pH is A_{21}) and (*Temp* is A_{12}) and (Mn is A_{23}) and (*Ammon* is A_{24}) and (EC is A_{25}) and (Fe is A_{26}) then (f_{48} is 182.5).

Rule 49: If (pH is A_{21}) and (*Temp* is A_{22}) and (Mn is A_{13}) and (*Ammon* is A_{14}) and (EC is A_{15}) and (Fe is A_{16}) then (f_{49} is 4.394).

Rule 50: If (pH is A_{21}) and (*Temp* is A_{22}) and (Mn is A_{13}) and (*Ammon* is A_{14}) and (EC is A_{15}) and (Fe is A_{26}) then (f_{50} is -74.94).

Rule 51: If (pH is A_{21}) and (*Temp* is A_{22}) and (Mn is A_{13}) and (*Ammon* is A_{14}) and (EC is A_{25}) and (Fe is A_{16}) then (f_{51} is -59.17).

Rule 52: If (pH is A_{21}) and (*Temp* is A_{22}) and (Mn is A_{13}) and (*Ammon* is A_{14}) and (EC is A_{25}) and (Fe is A_{26}) then (f_{52} is -174).

Rule 53: If (pH is A_{21}) and (*Temp* is A_{22}) and (Mn is A_{13}) and (*Ammon* is A_{24}) and (EC is A_{15}) and (Fe is A_{16}) then (f_{53} is -91.47).

Rule 54: If (pH is A_{21}) and (*Temp* is A_{22}) and (Mn is A_{13}) and (*Ammon* is A_{24}) and (EC is A_{15}) and (Fe is A_{26}) then (f_{54} is 715.3).

Rule 55: If (pH is A_{21}) and (*Temp* is A_{22}) and (Mn is A_{13}) and (*Ammon* is A_{24}) and (EC is A_{25}) and (Fe is A_{16}) then (f_{55} is 927.3).

Rule 56: If (pH is A_{21}) and (*Temp* is A_{22}) and (Mn is A_{13}) and (*Ammon* is A_{24}) and (EC is A_{25}) and (Fe is A_{26}) then (f_{56} is 1016).

Rule 57: If (pH is A_{21}) and (*Temp* is A_{22}) and (Mn is A_{23}) and (*Ammon* is A_{14}) and (EC is A_{15}) and (Fe is A_{16}) then (f_{57} is 327.9).

Rule 58: If (pH is A_{21}) and (*Temp* is A_{22}) and (Mn is A_{23}) and (*Ammon* is A_{14}) and (EC is A_{15}) and (Fe is A_{26}) then (f_{58} is 37.17).

Rule 59: If (pH is A_{21}) and (*Temp* is A_{22}) and (Mn is A_{23}) and (*Ammon* is A_{14}) and (EC is A_{25}) and (Fe is A_{16}) then (f_{59} is −966).

Rule 60: If (pH is A_{21}) and (*Temp* is A_{22}) and (Mn is A_{23}) and (*Ammon* is A_{14}) and (EC is A_{25}) and (Fe is A_{26}) then (f_{60} is −170.6).

Rule 61: If (pH is A_{21}) and (*Temp* is A_{22}) and (Mn is A_{23}) and (*Ammon* is A_{24}) and (EC is A_{15}) and (Fe is A_{16}) then (f_{61} is 407.4).

Rule 62: If (pH is A_{21}) and (*Temp* is A_{22}) and (Mn is A_{23}) and (*Ammon* is A_{24}) and (EC is A_{15}) and (Fe is A_{26}) then (f_{62} is 106.3).

Rule 63: If (pH is A_{21}) and (*Temp* is A_{22}) and (Mn is A_{23}) and (*Ammon* is A_{24}) and (EC is A_{25}) and (Fe is A_{16}) then (f_{63} is 8.502).

Rule 64: If (pH is A_{21}) and (*Temp* is A_{22}) and (Mn is A_{23}) and (*Ammon* is A_{24}) and (EC is A_{25}) and (Fe is A_{26}) then (f_{64} is 46.99).

Figures 3 and 4 show the measured and model computed values of DO in test and training + test sets.

Comparisons of measured and ANFIS-predicted values of DO for the test and training + test data sets are shown in Figures 5(a) and 5(b)).

The respective values of MAE and MSE for the two data sets are 0.6670 and 1.23 for the test set, and 1.0373 and 2.1831 for the training + test set.
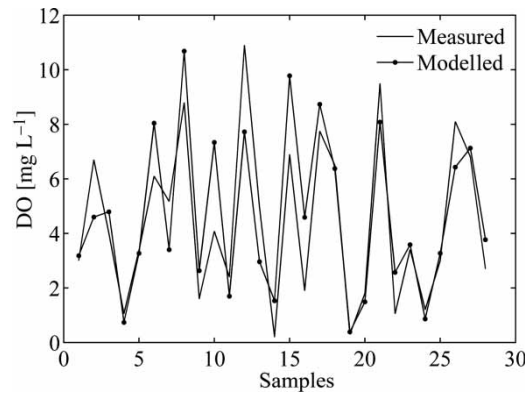

Figure 3 │ The measured and predicted DO values in test set.

Analysing the results shown in Table 2, it can be seen that models 9 and 11 are the two most effective models with five identical inputs and only one different input. It seems that ammonia and total phosphate are at the similar, relatively low, level of importance for the data fitting. An ANFIS model with five input variables: pH, temperature, manganese, electrical conductivity and iron, is created. The training parameters of the ANFIS are the same as in Table 1, except that the number of the rules is 32. RMSE after 300 epochs of training is 1.6275. The coefficient of correlation values for the test and training + test set sets were 0.8217, and 0.8856, respectively. The respective values of MAE and MSE for the two data sets are 1.2897 and 2.786 for the test set, and 1.1847 and 2.67 for the training + test set. The prediction performances of the model with five inputs are worse than performances of the two most effective models from Table 2.
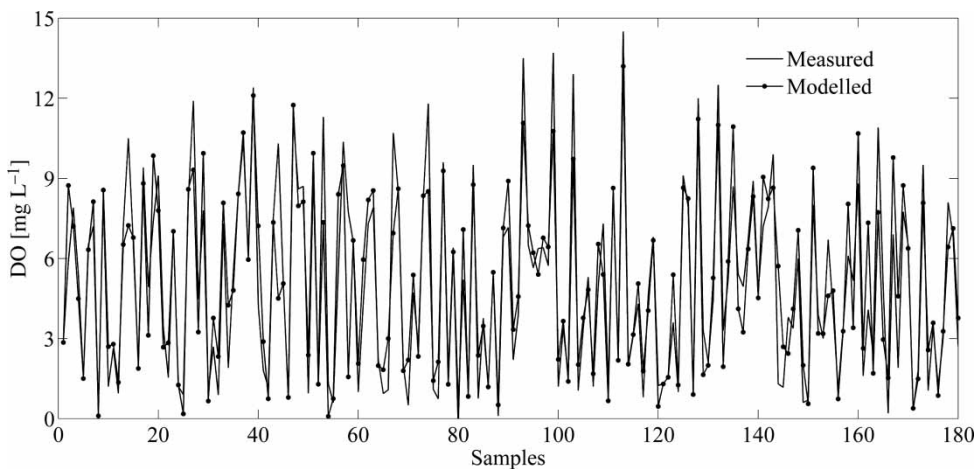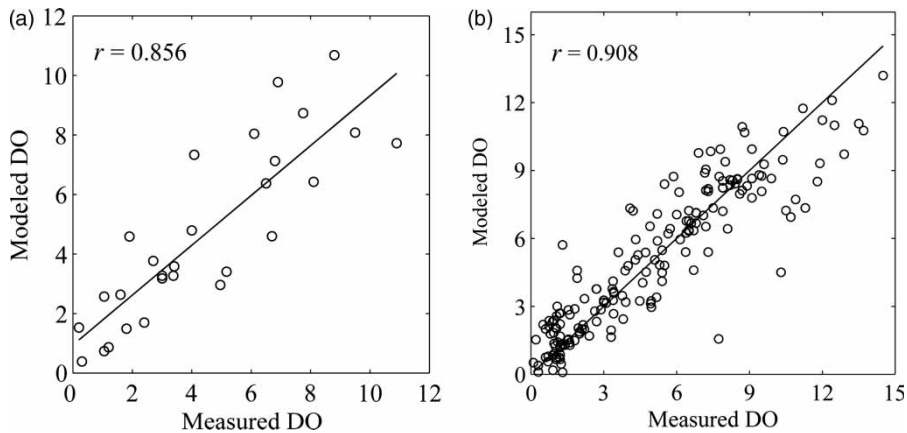

Figure 4 │ The measured and predicted DO values in training + test set.

Figure 5 │ Comparison of the model computed and measured DO values in (a) test set and (b) training + test set.

The results of this study can be compared with results reported in the literature.

Ranković *et al.* (2010) computed DO in the Gruža Reservoir (Serbia) using two-layer feed forward neural networks. The input variables of the neural network were: water pH, water temperature, chloride, total phosphate, nitrites, nitrates, ammonia, iron, manganese and electrical conductivity. Sensitivity analysis is used to determine the influence of input variables on the dependent variable and the following order is obtained: water pH, water temperature, manganese, ammonia, iron, electrical conductivity, nitrites, total phosphate, nitrates and chloride. A FNN model with 10 input variables has coefficient of correlation values for test and training + test sets 0.8478 and 0.9239, respectively. The respective values of MAE and MSE for the two data sets are 1.1790 and 2.7585 for the test set, and 0.5797 and 0.9923 for the training + test set.

In this paper the initial set of the input variables consisted of the eight most effective inputs: pH, temperature, manganese, ammonia, electrical conductivity, iron, nitrites and total phosphate according to results from Ranković *et al.* (2010).

The ANFIS model developed in this paper for the same reservoir and for the same data set, with six selected input variables, determined by Jang's method, has a slightly higher coefficient of correlation values for the test set, but a slightly lower coefficient of correlation values for the training + test set (Figure 5). A relatively low correlation between the measured and model computed output variables, in our investigations, may be attributed to the non-homogeneous nature of the water quality (input and output) variables or due to the fact that set of the input variables used did not include all of the relevant variables.

Both models give similar acceptable results and are potential algorithms to be used as water management tools. FNN is simpler approach in the sense of computational complexity, but on the other hand the ANFIS DO model, with the smaller number of inputs provides a similar accuracy. Ranković *et al.* (2010) concluded that the optimal number of hidden neurons of FNN is 15. Thus, the number of the parameters which are determined by the learning algorithm in FNN was 181.

In this paper, the ANFIS DO model had 112 parameters determined by the training process.

The proposed model shows efficiency in forecasting the DO profiles in eutrophic water bodies, and it is in accordance with results of other authors. It is in accordance with Ying *et al.* (2007) that 'if the correlation between the forecast and actual measured values is fairly good, the forecast model is viable and can be applied to real practice'.

However, although the literature offers some recent successful neural network and fuzzy systems applications related to water quality estimations due to the fact that water quality forecast can be easily affected with high uncertainty and specific circumstances, such as climatological, eco-regional, etc. (Vandenberghe *et al.* 2007). Proposed models could show certain deviations. Thus, it is necessary for proposed models to be adjustable because forecast

model is time-bound and therefore it is necessary to update the model from time to time with actual measured values (Ying *et al.* 2007).

CONCLUSIONS

The aim of this paper was to develop an ANFIS model to predict the DO in water supply reservoir Gruža in Serbia and demonstrate its application to identify complex non-linear relationships between input and output variables. The proposed model shows efficiency in forecasting the DO profiles in eutrophic water bodies. Also, the model is an invaluable tool for studying system dynamics and predicting future states. The fuzzy logic model once developed for a water body, can favourably be used during further monitoring activities, as a predictive management tool. It can be concluded that neuro-fuzzy modelling can be successfully applied for estimations in lakes and reservoirs, and can replace classical approaches, because of its simplicity. An ANFIS application could be used in the future to investigate the applicability of this approach to other reservoirs. As a final conclusion, ANFIS can be a powerful tool for environmental and ecological modelling and assessment.

It should be noted that there are no fixed rules for developing AI techniques in the fields of water quality prediction and forecasting. AI models are usually constructed based on expert knowledge and trial and error adjustment of parameters. Thus, there is no guarantee that the optimal solution will be found. Some future directions for further development are the hybrid combinations of two or more AI methods to produce an even better water quality modelling system.

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