

Estimation of the Change in Lake Water Level by Artificial Intelligence Methods

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Abstract In this study, five different artificial intelligence methods, including Artificial Neural Networks based on Particle Swarm Optimization (PSO-ANN), Support Vector Regression (SVR), Multi-Layer Artificial Neural Networks (MLP), Radial Basis Neural Networks (RBNN) and Adaptive Network Based Fuzzy Inference System (ANFIS), were used to estimate monthly water level change in Lake Beysehir. By using different input combinations consisting of monthly Inflow - Lost flow (I), Precipitation (P), Evaporation (E) and Outflow (O), efforts were made to estimate the change in water level (L). Performance of models established was evaluated using root mean square error (RMSE), mean square error (MSE), mean absolute error (MAE) and coefficient of determination (R^2). According to the results of models, ϵ -SVR model was obtained as the most successful model to estimate monthly water level of Lake Beysehir.

Keywords Adaptive network-based fuzzy inference system · Artificial neural networks · Lake Beysehir · Particle swarm optimization · Support vector regression · Water level

1 Introduction

From the beginning of 20th century, significant changes have been observed in many climatological variables such as temperature, precipitation, evaporation, flow, and water level due to global warming (Qin et al. 2010; Shahid et al. 2012; Burns et al. 2007; Hamed 2008; Shao and Li 2011). These changes lead to significant changes in spatial and temporal distribution of water resources. Reservoirs are important in terms of water resources, and have many benefits, including irrigation of agricultural land, meeting drinking water and utility water demands, making it available for tourism by creating a promenade around it and inland

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waterways transport. On the other hand, in the case of a very high water level, they negatively affect settlements, rail and road transportation, shore-based recreational and educational facilities as well as plantations due to floods (Erkek and Agiralioğlu 2002).

In addition to their benefits, lake waters may cause damage in the case of an increased water level so, in order to obtain maximum benefits from them and bring damage caused by them down to a minimum, change of lake water level should be known in advance and controlled, where necessary. Considering that water level changes in lakes are considerably complex outcomes of many hydrological factors such as precipitations falling on the lake surface or lake watershed, evaporation from free water surface, direct and indirect runoffs from neighbor basins, humidity, air and water temperature, wind speed and groundwater change, etc., it would be an important step to establish the correlation between the change in lake water level and hydro meteorological variables (Kisi et al. 2012).

Lake level prediction can be performed using some complex models taking into consideration the relevant parameters, but susceptibility of lake water levels to these factors might be from one area to the other. Moreover accurate measurement of these factors are often severity and with a great amount of ambiguity. Therefore, instead of using traditional methods with many inputs such as water balance, they are preferable that soft computing techniques (SCTs) which simulate lake water level changes based on previously recorded lake water levels be available for research as well as practical purposes. SCTs are convenient in clarifying the relation between a process output and its input regardless of the water level of understanding the underlying physical processes (Abdel-Hafez 2007).

Lake water level prediction provides useful data on the flood control and water supply and is a challenging task, therefore, forecasting lake water level fluctuations at various time intervals using the records of past time series is an important tool in terms of water resources planning, designing, construction and management (engineering, etc.) (Kisi et al. 2012).

Recently, the use of SCTs such as artificial neural networks (Kisi 2009; Dogan 2005; Sudheer et al. 2002; Shirmohammadi et al. 2013; Wu et al. 2010; Altunkaynak 2007; Solomatine and Dulal 2003; Giustolisi and Laucelli 2005; Cigizoglu 2003; Ondimu and Murase 2007), stochastic models (Kumar et al. 2004; Sveinsson et al. 2003), fuzzy logic, adaptive network -based fuzzy inference system (Afiq et al. 2013; El-Shafie et al. 2007; Keskin et al. 2006; Kisi 2006; Zounemat-Kermani and Teshnehlab 2008; Valizadeh and El-Shafie 2013; Khatibi et al. 2011), support vector machines (Afiq et al. 2013; Wu et al. 2008; Khan and Coulibaly 2006; Cimen and Kisi 2009; Zhao and Wang 2010; Cimen 2008) and Artificial Neural Networks based on Particle Swarm Optimization (Sedki and Ouazar 2010; Mohandes 2012; Chau 2006, 2007; Xi et al. 2012; Tapoglou et al. 2014) are widely used as an appropriate tool for modeling complex nonlinear phenomena covering hydrology and water resources systems.

Soft Computing Techniques (SCTs) are comparatively new statistically-based methods that are becoming commonly used for prediction, evaluation and modeling applications in hydrology and water resources applications. SCTs can be trained to estimate the behavior of real-time phenomena without the need of a physical model to relate the causes and effects of the phenomena. This makes SCT an economic technique for water resources planning, designing, construction and management (engineering, etc.).

The change in lake water level can be generally determined by water balance created by the difference between inflow to and outflow from the lake as well as by models formed using various artificial intelligence methods utilizing hydrological and hydro-meteorological data. For this purpose, various studies were undertaken and the results obtained from the models established using these methods were compared with actual values from observations (Valizadeh et al. 2011; Chang and Chang 2006; Sulaiman et al. 2011; Leahy et al. 2008; Yarar et al. 2009)

Altunkaynak (2007) used ANN for water level changes prediction of Van Lake in Turkey and compared with the traditional ARMAX models in forecasting 1 month-head lake water levels. Khan and Coulibaly (2006) studied the usability of SVM for Lake Erie water level prediction. Guldal and Tongal (2010) used Recurrent Neural Network (RNN) and ANFIS for predicting future lake levels of the Lake Egirdir in Turkey. Talebizadeh and Moridnejad (2011) carried out different ANNs and ANFIS models to forecast the lake water level variations in Lake Urmia in northwest of Iran. Kakahaji et al. (2013) used six models which are two mathematical models (water balance and multiple correlation equation), two dynamic linear models (ARX and BJ), as well as a couple of intelligent models (MLP and LLNF) to predict the lake water level fluctuations of Lake Urmia in Iran. SVM and ANN techniques were used to predict surface water level changes of Van and Egirdir Lakes in Turkey by Cimen and Kisi (2009). Kisi et al. (2012) applied GP, ANFIS, ANN and ARMA models to forecast daily lake water level, three time steps ahead. Chau (2006) used PSO-based neural network technique for river stage estimation in the Shing Mum River of Hong Kong. Ghorbani et al. (2010) used Genetic Programming (GP) to predict the hourly sea water level changes of Hillarys Boat Harbour in Australia and compared with ANNs models. Afiq et al. (2013) investigated the usability of SVM model to forecast the daily dam water level of the Klang gate using daily rainfall and water level data, and compared the data with the results determined using ANFIS model. Sivapragasam and Liong (2004) investigated the sequential elimination approach to determine the optimal training data set and then performed SVR to predict the water level changes. Yarar et al. (2009) assessed the performance of ANN, ANFIS and SARIMA models for the prediction of variations in the water level of Lake Beysehir in Turkey. Shiri et al. (2011) investigated the ability of a neuro-fuzzy (NF) model to estimate the sea level changes in the Hillarys Boat Harbour, Western Australia. Ondimu and Murase (2007) studied the accuracy of an ANN model in reservoir water level prediction.

Lake Beysehir, the 3rd largest lake by size and the largest freshwater lake in Turkey, is currently utilized for the purposes of supplying drinking water, irrigation, fishing and tourism, etc. However, in recent years, the water level of Beysehir Lake considerably fell due to inadequate rainfall and excessive water withdrawal. Nowadays, global climate change and the adverse effects thereof are intensively discussed, and Konya Closed Basin is one of the regions in Turkey where these adverse effects will be seen most. Therefore, the estimation of water level change in Lake Beysehir, which is of importance for the province of Konya, which has an important place in the agriculture of Turkey, and for water resources in the region, is of great importance in terms of efficiency to be provided from the lake.

Accurate prediction of water level variation in lakes and reservoirs in response to hydroclimatological changes is a significant step for the development of sustainable water usage policies, particularly for sophisticated hydrological systems such as Lake Beysehir, Turkey.

For this aim, in this study, models were established using artificial neural networks (ANNs), support vector machines (SVM), the adaptive network-based fuzzy inference system (ANFIS) and artificial neural networks based on particle swarm optimization (PSO-ANN) method to estimate the water level of the Lake Beysehir, Turkey's largest freshwater lake, and the results obtained from the established models were compared with each other.

2 Methodology

2.1 Support Vector Machines (SVM)

In this study, ε -SVR model was used as SVR model. Vapnik (1995) proposed ε -SVR by introducing an alternative ε -insensitive loss function. This loss function allows the concept of

margin to be used for regression problems. The purpose of SVR is to find a function having maximum ε deviation from actual target vectors for all training data given, which should be at the same level as much as possible. In other words, error on any training data should be smaller than ε (Pal and Arun 2006).

The three factors that affect prediction performance of SVM regression are the insensitive error term (ε), the regularization factor (additional capacity control) (C), type of kernel function and kernel parameter. ε constant indicates the range in which error is neglected. As this constant gets smaller, the number of support vectors to be found by SVM increases. C , the regulatory constant, maintains order between system complexity characterized by weight vector and prediction errors measured by insensitive variables. Using these variables in the most appropriate values is highly effective in the success of SVM (Ekici 2007).

Selection of the kernel function as well as model parameters to be used plays an important role in determining SVR performance. However, there isn't any decisive criterion for selecting both kernel function and model parameters (Lin 2006). The Radial Basis Kernel Function is selected for SVR model in this study and expressed as

$$K(x_i, x) = \exp\left(-\gamma\|x_i - x_j\|^2\right) \quad (1)$$

where γ is the parameter of radial basis kernel function which gives the width of the kernel.

2.2 Multi-Layer Perceptron (MLP)

ANN models are often indicated by ANN (i,j,k) network architecture, where i is the number of neurons in the input layer; j, the number of neurons in hidden layer and k, the number of neurons in the output layer. MLP model utilizes a supervised learning method. Learning process is based on the principle of minimizing the error between the output data generated by the network by optimizing weights and the actual output data. Learning rule is a generalized state of Delta Learning Rule based on the method of least squares. Therefore, the learning algorithm is also called Generalized Delta Rule or the Error Back-Propagation Algorithm (Dogan 2005). According to this rule, training is conducted in three stages: a) forward propagation of input training data, b) calculation of error corresponding to target values given, c) adjusting weights by propagating this error backward (Zhao and Wang 2010; Kisi 2009; Khan and Coulibaly 2006).

2.3 Radial Based Neural Network (RBNN)

The basic idea in radial basis neural networks (RBNN) is simply to collect a group of radial basis functions by weighting them so that they approximate to the desired f function (Verleysen and Hlavackova 1994). RBNN is a three layered structure. Input layer is associated with input vector space, and output layer with pattern classes. Thus, the entire structure is reduced to the determination of the structure of the hidden layer and weights between the hidden layer and the output layer. The activation functions of the neurons in the hidden layer are determined by a C_j center and σ_j bandwidth. Activation function is a Gaussian curve defined by the equation:

$$\varphi_j(X) = \exp\left(-\frac{\|X - C_j\|}{2\sigma_j^2}\right) \quad (2)$$

The general equation for the output of neuron j in the output layer is as follows:

$$s_j(X) = \sum_{i=1}^k w_{ij}\phi_i(X) + b_j \tag{3}$$

where w_{ij} is the weight between hidden neuron i and the output neuron j , b_j is the bias constant (Paredes and Vidal 2000).

2.4 Particle Swarm Optimization (PSO)

Particle swarm optimization (PSO) was developed by Eberhart and Kennedy (1995) and, it has been preferred as one of the most popular population based heuristic methods because of its feasibility and simplicity. This algorithm based on the social behavior of biological organisms, specifically birds flocking to a food (Yalcin et al. 2012; Bratton and Kennedy 2007). This behavior associated with that of an optimization search for solutions to non-linear equations in a real-valued search space. The member of social behavior called as swarm’s particle. Each particle has a position in the search space. This algorithm searches the space of an objective function by adjusting the trajectories of the particles. When a particle finds a location that is better than any previously found, then it updates it as the current best for particle (p_i). There is a current best (local best) for all particles (Yang 2008).

The global best (p_g) is referred as a position among all the current best solutions. Until objective no longer improves or the number of iteration, the PSO algorithm updates particles at each step by recalculate the velocity and position of each particle in every dimension using Eqs. 4 and 5.

$$v_{ij} = v_{ij} + c_1r_1(pbest_{ij}-p_{ij}) + c_2r_2(gbest_{ij}-p_{ij}) \tag{4}$$

$$p_{ij} = p_{ij} + v_{ij} \tag{5}$$

where v_{ij} and p_{ij} are velocity and position respectively, c_1 and c_2 are constants, r_1 and r_2 are independent random numbers uniquely generated at every update for each individual dimension, $pbest$ is the local best and $gbest$ is the global best.

The pseudo code of PSO algorithm consists of update steps are illustrated in following (Bratton and Kennedy 2007; Yang 2008).

```

Algorithm 1 The PSO update process
for each time step  $t$  do
    for each particle  $i$  in the swarm do
        update position  $p$  using Eqs 4 and 5
        calculate particle fitness  $f(p)$ 
    update  $p_{best}$ ,  $g_{best}$ 
    end for
end for
    
```

2.4.1 Partical Swarm Optimization Based Artificial Neural Network (PSO-ANN)

PSO is a common used optimization algorithm in literature. Furthermore, the learning procedure of ANN is a process of getting the weights to the appropriate values and this is

called as optimization. Therefore, PSO was preferred to train ANN in this study and called PSO-ANN. In this algorithm connection weights of ANN were used as (assigned) particles in PSO. The process of ANN begins with assigning random values to the connection weights. So the number of weights expresses the dimension of particles. The PSO-ANN network is established according to the each particle. Training samples are presented to the network to be learnt respectively. While this process, the difference (error) between target value and produced value is calculated for each sample. After all training data set is presented to the network, sum of the error (MSE) is calculated to obtain fitness value of particle. In the first step, this fitness value is assigned as local best value (pbest). If this pbest is the best fitness value for all particles, it is accepted global best (gbest). Updating of weights is dependent of gbest and pbest values. If obtained fitness value is bigger than the target error the position value of particles is updating using pbest and gbest in the training process. Then the network is set up according to the new particles and these steps continue until the fitness value reaches the acceptable error value or maximum iterations.

2.5 Adaptive Network Based Fuzzy Inference System (ANFIS)

Adaptive network-based fuzzy inference system is based on the idea of combining the learning ability of artificial neural networks and advantages of fuzzy logic such as human-like decision-making and ease of providing specialized knowledge (Elmas 2003). Actual purpose of adaptive network-based fuzzy inference system is to use artificial neural networks in order to adjust and find the structure and variables of ANFIS system (Elmas 2003; Jang et al. 1997).

ANFIS consists of 6 layers. The functioning of layers in ANFIS structure are the input layer, the fuzzification layer, the rule layer, the normalization layer, the defuzzification layer and overall layer in the order given.

3 Case Study

Lake Beyşehir ($37^{\circ}40'54''\text{N}$, $31^{\circ}43'22''\text{E}$), which is the third largest lake as well as the largest freshwater lake in Turkey, is located within the provincial borders of Konya and Isparta, located in southwest of Turkey (Fig. 1). The water level in the lake often varies from year to year and from season to season. It has an average surface area of 650 km^2 , and it is 1121.93 m above sea level. Its elevation is in the range of 1120 to 1125.5 m. Although a variety of numbers were reported, it is approximately 8.5 m deep, 45 km long, 10–25 km wide, and has a circumference of 120 km. The lake is currently utilized for the purposes of supplying drinking water, irrigation, fishing, commercial business and tourism (Babaloglu 1997).

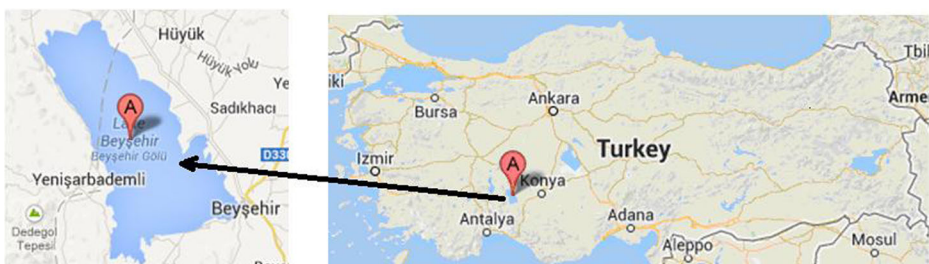


Fig. 1 The location of Lake Beyşehir

In this study, efforts were made to estimate the change in lake water level (L) using monthly inflow - Lost flow (I), Precipitation (P), Evaporation (E) and Outflow (O) values between 1962 and 1990 determined by 4th Regional Directorate of State Hydraulic Works (DSI). For this purpose, the Multi-Layer Perceptron (MLP), which is a conventional ANN model, Radial-Based Neural Network (RBNN), Epsilon-Support Vector Regression (ϵ -SVR), Adaptive Neural Fuzzy Inference System (ANFIS) and Particle Swarm Optimization Based- Artificial Neural Network (PSO-ANN) methods were used, and the performance of the models was evaluated by comparing the estimated values from the models with values from observations.

348-month data between 1962 and 1990 were used to establish the models. 276-month data during the period from 1962 to 1984 of this data was used in training process, and the remaining 72-month data during the period from 1962 to 1984 was used in testing process. I, P, E and O data was used as input variables, while values of change in water level (L) were used as output. Here, level values were given as elevation so the values of change in level per month were calculated by taking the differences in elevation compared to the previous month.

4 Application and Results

In order to estimate the change in monthly water level of Lake Beysehir, the following equation was used to eliminate unit differences in parameters used in input and output layers and the data was made non-dimensional between 0 and 1, before applying MLP, RBNN, ϵ -SVR, ANFIS and PSO-ANN methods

$$X_{norm} = \frac{X_i - X_{min}}{X_{max} - X_{min}} \tag{6}$$

where X_{norm} , X_i , X_{min} and X_{max} represent normalized, observed, minimum and maximum values for all parameters, respectively.

In order to estimate the change in lake water level, models were created using different input combinations comprised of the variables I, P, E, and O, and the effects of individual variable on the change in water level was investigated.

Mean absolute error (MAE), root mean square error (RMSE), mean square error (MSE) and coefficient of determination (R^2) criteria were used to evaluate the success of the models generated by using MLP, RBNN, ϵ -SVR, ANFIS and PSO-ANN methods.

For SVR method, a software package known as LIBSVM Software was employed, while SVR, MLP, RBNN, ANFIS and PSO-ANN were applied using MATLAB 2010b.

$$MAE = \frac{1}{N} \sum_{i=1}^N |Yi_{observed} - Yi_{estimate}| \tag{7}$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (Yi_{observed} - Yi_{estimate})^2} \tag{8}$$

$$MSE = \frac{1}{N} \sum_{i=1}^N (Yi_{observed} - Yi_{estimate})^2 \tag{9}$$

$$R^2 = \frac{\left[\sum_{i=1}^N (Y_{i_{observed}} - \bar{Y}_{observed}) (Y_{i_{estimate}} - \bar{Y}_{estimate}) \right]^2}{\sum_{i=1}^N (Y_{i_{observed}} - \bar{Y}_{observed})^2 \sum_{i=1}^N (Y_{i_{estimate}} - \bar{Y}_{estimate})^2} \tag{10}$$

4.1 Application of MLP Model

The most difficult task in application of MLP is the selection of the number of neurons in hidden layers. There isn't any decisive criterion related to the determination of the number of neurons yet. ANN structure varies depending on the problem. In this study, a 3-layer ANN architecture consisting of a single hidden layer was used to create MLP models. The number of neurons in the hidden layer, learning rate and momentum coefficient were determined by trial and error.

As the activation function, tangent sigmoid and logarithmic sigmoid functions were used in the hidden and output layers, respectively. The number of neurons in the hidden layer was investigated in the range of 1 to 20, whereas learning rate (lr) and momentum coefficient (mc), the parameters affecting convergence rate, were investigated in the range of 0.1 to 0.9. 1000 was taken as the number of iterations in the established MLP models. As a result of the trials made in line with these assumptions, model structures of the most successful MLP models obtained for 5 different input combinations are given in Table 1.

In view of Table 1, according to test data from trials, the most successful MLP structure by the largest R² value was MLP1 (4,2,1) model in M1 combination, in which all parameters were used. In this model, 4 represents the inputs comprised of I-P-E-O; 2, the number of neurons in the hidden layer and 1, the output (L). According to MLP1 model, in which a learning rate (lr) of 0.3 and a momentum coefficient (mc) of 0.9 were obtained, R²=0.991 was obtained for test data. According to input combinations used to determine the monthly change in lake water level, the least successful model was found as MLP4 (1,5,1) model for M4 combination with a minimum R²=0.673, in which total precipitation (P) was used as input and the number of neurons in the hidden layer was obtained as 5 (Buyukyildiz et al. 2013).

4.2 Application of RBNN Model

In order to estimate the change in water level, efforts were made to determine the most appropriate model structure for different input combinations using Radial basis neural network algorithm, and the most successful model was determined by maximum R² value obtained for test data. For this purpose, the number of neurons in the hidden layer, which significantly

Table 1 The lr, mc, and R² values for MLP models in testing period

Model inputs	Model structure	lr	mc	Number of neurons in hidden layer	R ²	
M1	I-P-E-O	MLP1 (4,2,1)	0.3	0.9	2	0.991
M2	I-P-E	MLP2 (3,2,1)	0.7	0.5	2	0.970
M3	P-E	MLP3 (2,5,1)	0.6	0.7	5	0.825
M4	P	MLP4 (1,5,1)	0.7	0.8	5	0.673
M5	E	MLP5 (1,7,1)	0.2	0.1	7	0.701

change the performance of the model, was determined by testing with increments of 1 between 2 and 20, and in the case of spread parameter (σ), with increments of 0.01 between 0.01 and 5.0. The most successful RBNN models obtained for different inputs are given in Table 2. According to the results, the most successful model was established as RBNN1 (4, 6, 4.26, 1) model for M1 combination, for which $R^2=0.9986$ was obtained and I-P-E-O inputs were employed, in this algorithm. In this model, 4 represents the number of inputs (I-P-E-O); 6, the number of neurons in the hidden layer; 4.26, the spread parameter and 1, the output number (L). The input combination in which model success was the least was obtained as RBNN4 (1, 11, 0.02, 1) model ($R^2=0.6891$) for an input number of 1 (P), 11 neurons in hidden layer, a spread parameter of 0.02 and an output of 1 in M4 combination, in which precipitation was used as input.

4.3 Application of ϵ -SVR Model

In the case of estimation of water level by ϵ -SVR, efforts were made to determine the most successful ϵ -SVR model using the same input combinations. In this study, Radial Basis Kernel Function, which has also been widely used in the literature, was used as kernel function. During implementation of ϵ -SVR models, trials were made for different input combinations with an increment of 0.01 in the range of [0.01 0.5] for error term (ϵ), an increment of 1 in the range of [1 100] for regulatory factor (C), an increment of 0.1 in the range of [0.1 8] for γ parameter of Radial Basis Kernel function. C, ϵ , γ and R^2 values of the most successful ϵ -SVR models obtained from these trials are given in Table 3 (Buyukyildiz et al. 2013).

According to ϵ -SVR results obtained for different input combinations, the most successful model was again obtained in ϵ -SVR 1 model in M1 combination, in which all inputs were used. In this model, obtained as ϵ -SVR1 (1, 0.01, 0.1), 1 represents C; 0.01, the ϵ , and 0.1, the γ value. In ϵ -SVR1 (1, 0.01, 0.1) model architecture, a considerably high performance was achieved with an R^2 value of 0.9988 for test data. In SVR application, the least successful performance by R^2 values was in ϵ -SVR4 ($R^2=0.666$) model in M4 combination, in which precipitation was used.

4.4 Application of PSO-ANN Model

The same input combinations were also used to establish the optimum model for estimation of the change in water level by training artificial neural networks with PSO, and the resultant models were compared to determine the most appropriate input combination model.

Learning factors c_1 and c_2 given in Eqs. 4 and 5 were taken as 2. c_1 and c_2 are constants representing acceleration terms, which draws each particle to its best position (p_{best}) and to the

Table 2 The number of neurons in hidden layer, spread parameter (σ) and R^2 values for RBNN models in testing period

Model inputs	Model structure	Spread parameter (σ)	Number of neurons in hidden layer	R^2
M1	I-P-E-O RBNN1 (4,6,4.26,1)	4.26	6	0.9986
M2	I-P-E RBNN2 (3,5,1.59,1)	1.59	5	0.9710
M3	P-E RBNN3 (2,8,1.47,1)	1.47	8	0.8219
M4	P RBNN4 (1,11,0.02,1)	0.02	11	0.6891
M5	E RBNN5 (1,2,0.32,1)	0.32	2	0.7266

Table 3 The C , ε , γ and R^2 values for ε -SVR models in testing period

Model inputs		Model structure	C	ε	γ	R^2
M1	I-P-E-O	ε -SVR 1	1	0.01	0.1	0.9988
M2	I-P-E	ε -SVR 2	4	0.18	0.2	0.971
M3	P-E	ε -SVR 3	45	0.04	0.2	0.816
M4	P	ε -SVR 4	27	0.02	2.3	0.666
M5	E	ε -SVR 5	6	0.26	0.1	0.720

best of the population (g_{best}). c_1 helps the particle move according to its experiences, while c_2 helps it move according to the experiences of the other particles in the population.

In this study, the number of particles was selected as 30, initial inertia weight as $w_{max}=0.9$, perminate inertia weight as $w_{min}=0.4$, and the number of neurons in the hidden layer were investigated in the range of [1 20]. PSO-ANN models were established by taking maximum velocity range which a particle can take as [-1 1], and the number of iterations as 10, 20, 30, 40 and 50 in the respective order for each input combination. The most successful PSO-ANN model structures determined according to the highest R^2 values are given in Table 4 for each iteration (Buyukyildiz et al. 2013).

According to the results of PSO-ANN models obtained for different input combinations and iteration numbers; considering the highest R^2 values, it is clear that the most successful models for each number of iterations were obtained in M1 combinations, in which 4 input parameters were used. The most successful PSO-ANN model by the number of iterations of PSO-ANN models established using M1 combination was obtained with R^2 value of 0.931 for 10 iterations. According to this model obtained as PSO-ANN (4, 5, 1), the number of neurons in the hidden layer against 4 input parameters was found as 5.

If the results in Table 4 are evaluated individually for each input combination, it is apparent that the most successful models in each combination were obtained at different epochs. The most successful network structure in M1 and M2 model combinations was found for 10 epoch, whereas that in M3, M4 and M5 model combinations was obtained at 20, 30 and 50 epochs, respectively.

4.5 Application of ANFIS Model

While both Back propagation and Hybrid learning algorithms were employed to perform ANFIS models to estimate the change in water level of the Lake Beysehir, Grid Partition (ANFIS-GP) and Subtractive Clustering (ANFIS-SC) techniques were utilized to set up the rules. In ANFIS model, types of input and output membership functions and the number of membership functions, which give an acceptable error value with trial-and- error method for each input combination, were determined. Gaussmf, trimf, trapmf functions were used for input membership functions. Values in the range of 2 to 4 were tried as the number of membership functions for each input function. Both constant and linear functions were used as output membership functions. The number of epochs was taken as 100 in ANFIS models established. The results obtained for ANFIS models are given in Table 5.

According to these results, the most successful models created using the Grid Partition and Subtractive Clustering ANFIS techniques were achieved in ANFIS-GP (4, trimf, constant) structure with 16 rules for I-P-E-O input combination using back propagation learning algorithm and in ANFIS-SC (4, 0.7) structure with 2 rules using hybrid learning algorithm. Figure 2 shows ANFIS model structures of these two models. According to these model

Table 4 The PSO-ANN (i,j,k) model structures and R² values for PSO-ANN models in testing period

Model inputs	10 epoch		20 epoch		30 epoch		40 epoch		50 epoch	
	Model structure PSO-ANN (i, j, k)	R ²	Model structure PSO-ANN (i, j, k)	R ²	Model structure PSO-ANN (i, j, k)	R ²	Model structure PSO-ANN (i, j, k)	R ²	Model structure PSO-ANN (i, j, k)	R ²
M1 I-P-E-O	(4,5,1)	0.931	(4,11,1)	0.900	(4,4,1)	0.804	(4,4,1)	0.850	(4,3,1)	0.805
M2 I-P-E	(3,11,1)	0.687	(3,12,1)	0.668	(3,3,1)	0.686	(3,13,1)	0.635	(3,6,1)	0.677
M3 P-E	(2,3,1)	0.765	(2,7,1)	0.775	(2,4,1)	0.752	(2,12,1)	0.773	(2,17,1)	0.760
M4 P	(1,7,1)	0.560	(1,2,,1)	0.582	(1,1,1)	0.601	(1,7,1)	0.592	(1,6,1)	0.594
M5 E	((1,3,1)	0.543	(1,6,1)	0.541	(1,19,1)	0.541	(1,2,1)	0.543	(1,13,1)	0.548

Table 5 The characteristics of ANFIS models in testing period

Model	Inputs	Train FIS Opt. Method	Number of MFs	Input MF type	Output MF type	R ²
ANFIS-GP	I-P-E-O	Back propagation	2 2 2 2	trimf	constant	0.9952
	I-P-E	Back propagation	2 2 2	trimf	constant	0.9714
	P-E	Back propagation	4 4	trimf	constant	0.8188
	P	Hybrid	3	gaussmf	linear	0.6647
	E	Hybrid	4	trimf	constant	0.7206
		Train FIS Opt. Method			Spread coefficient	
ANFIS-SC	I-P-E-O	Hybrid		0.7		0.9936
	I-P-E	Hybrid		0.7		0.9633
	P-E	Hybrid		0.3		0.8075
	P	Hybrid		0.3		0.6618
	E	Back propagation		0.7		0.709

structures, the least successful input combination was the combination in which precipitation (P) was taken as input in both ANFIS techniques. Grid Partition technique was more successful than Subtractive Clustering technique in all combinations in ANFIS models created.

The most successful ANFIS model by R² values obtained in ANFIS-GP and ANFIS-SC models in Table 5 was achieved again in ANFIS-GP (4,trimf,constant) structure with a R² of 0.9952 in back propagation learning algorithm.

RMSE, MAE, MSE and R² values of the most successful models for all methods used are given in Fig. 3a-b and scatter diagrams of the models are given in Fig. 4.

As a result, according to the results obtained from models established in this study, in which MLP, RBNN, ε-SVR, PSO-ANN and ANFIS (ANFIS-GP and ANFIS-SC) models were used to estimate the change in water level of Lake Beysehir, the input combination by which the most successful results were obtained in all methods was I-P-E-O combination (Fig. 3a). The least successful input combination in estimating the change in water level was the combination in which evaporation was taken as input for PSO-ANN model, whereas it was the input combination in which precipitation was used as input in other methods. PSO-ANN models were the least successful model in all combinations. Other methods generally showed performances significantly similar to each other.

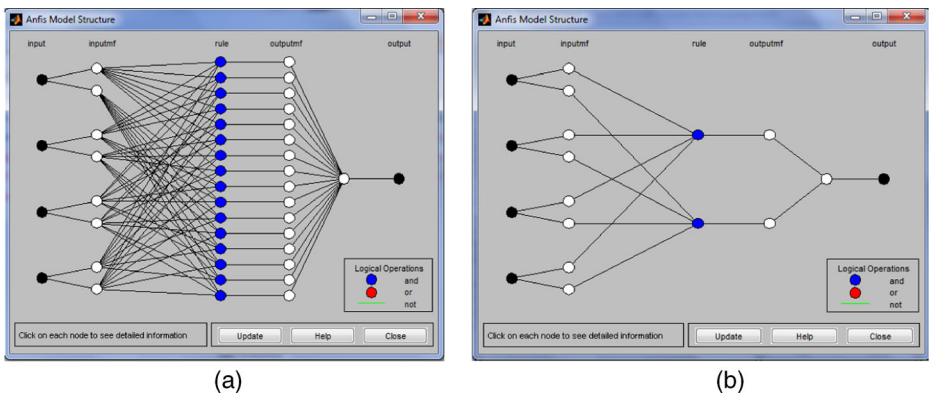
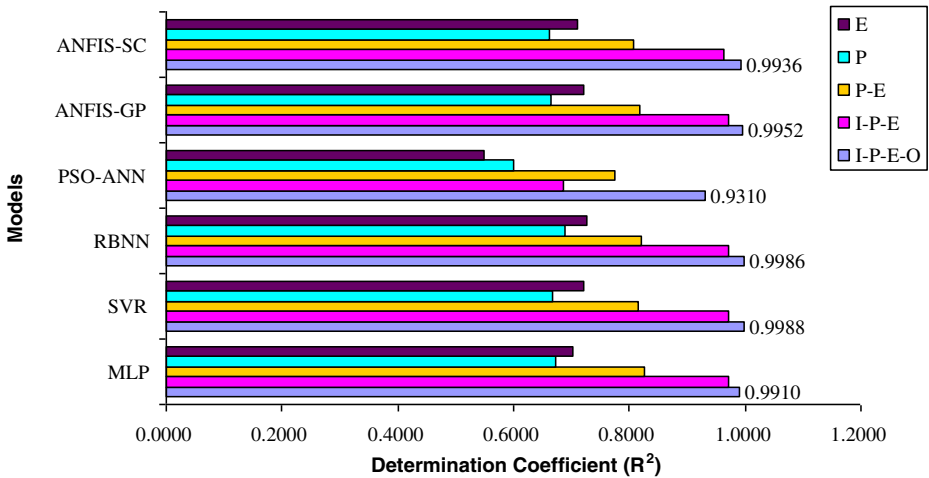
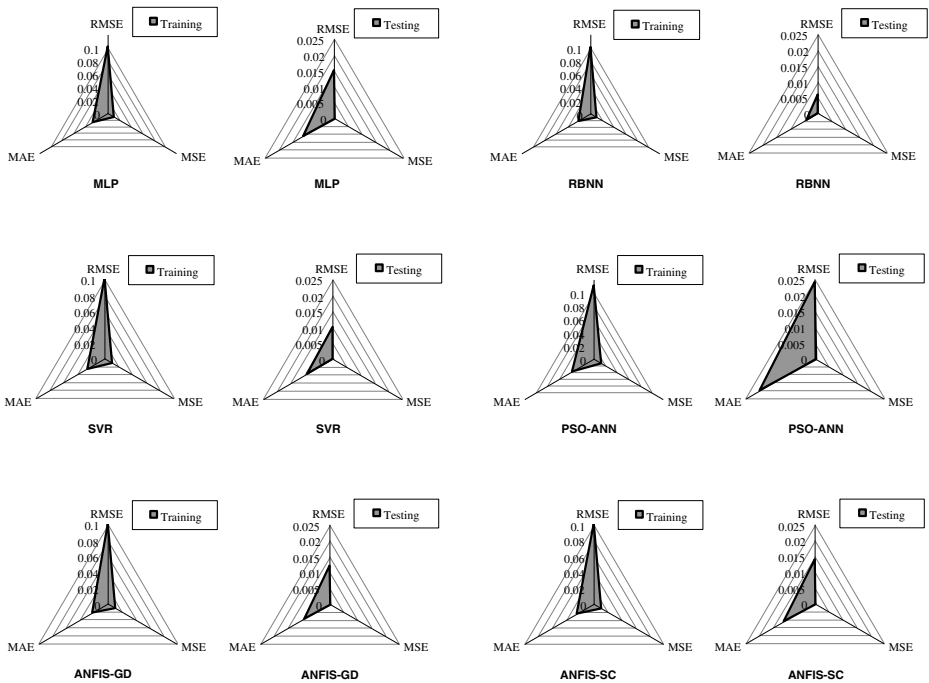


Fig. 2 ANFIS model structures **a)** ANFIS-GP (4, trimf, constant) **b)** ANFIS-SC (4, 0.7)



(a)



(b)

Fig. 3 a) Determination coefficients (R^2) of each combination for the methods used b) RMSE, MAE, MSE values of the most successful models for all methods used

According to determination coefficients in Fig. 3a, the most successful model among the models established to estimate the change in water level was ϵ -SVR (1, 0.01, 0.1) model ($R^2=0.9988$), for which the largest determination coefficient was obtained, if an evaluation is made by testing period. However, ANFIS-GD (4, trimf, constant), ANFIS-SC (4, 0.7), MLP (4,2,1)

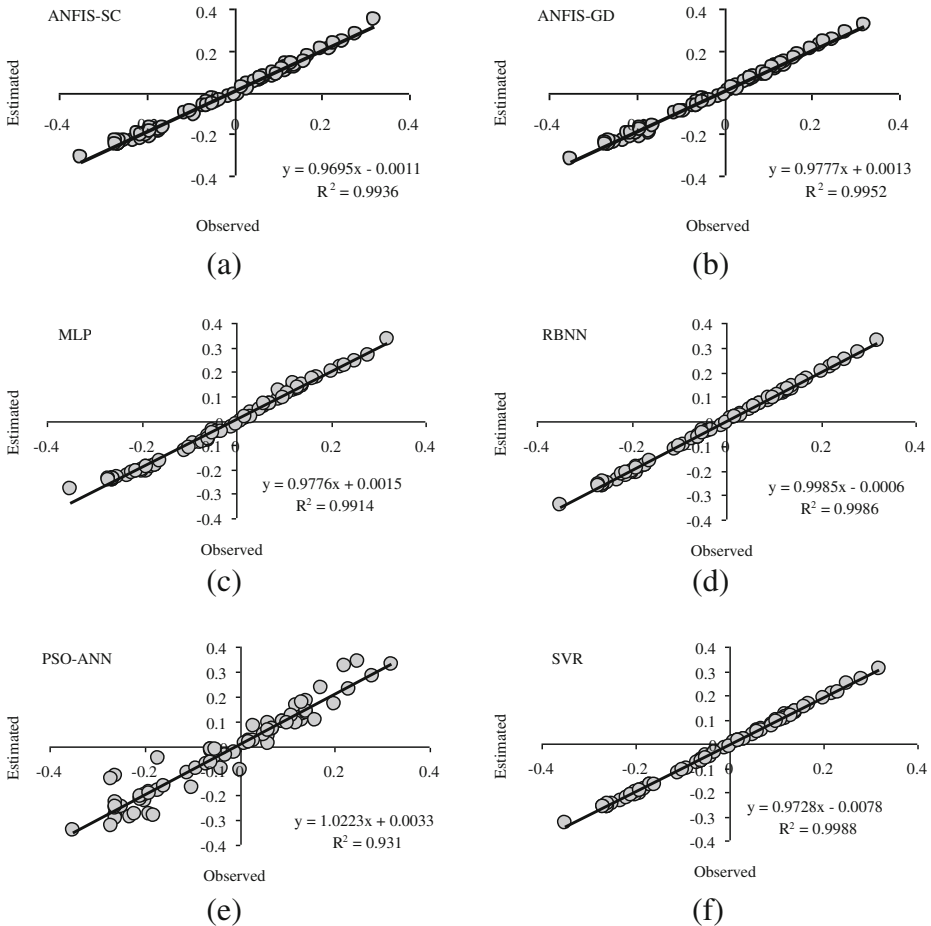


Fig. 4 Scatter diagram of ANFIS-SC, ANFIS-GD, MLP, RBNN, PSO-ANN ε -SVR models in test period – Lake Beyschir

and RBNN (4, 6, 4.26, 6) models also showed a fairly close success to ε -SVR model in terms of R^2 , RMSE, MSE and MAE, which is also evident in scatter diagrams of the respective models. The success of models is also similar to each other by error criteria obtained for training data, while PSO-ANN model was the lowest -performing model in all input combinations, compared to other methods. However, a R^2 value of 0.931 obtained for the most successful PSO-ANN structure also demonstrates that this model achieved a significant success in terms of estimation.

According to Fig. 3b presenting the RMSE, MSE and MAE successes of each used model, the most successful models in predicting water levels were obtained as RBNN (RMSE=0.006 m, MSE=0.000036 m^2 , MAE=0.004 m) and ε -SVR (RMSE=0.01 m, MSE=0.0001 m^2 , MAE=0.009 m) models, and the successes of the MLP, ANFIS-GD and ANFIS-SC models were so much closer to each other. Moreover, the model having the lowest success is determined as the PSO-ANN (RMSE=0.055 m, MSE=0.003025 m^2 , MAE=0.752 m) model. In terms of the detection of the success of the used models, the values obtained for the performance criteria presented in Fig. 3b are in parallel with the R^2 values in Fig. 3a.

It can be clearly seen from the scatter diagrams in Fig. 4 that the success obtained by the models set by the most successful input I-P-E-O (M1) for all the methods used for the water level prediction was considerably high.

5 Conclusion

Planning, designing, construction and management of lakes and reservoirs requires accurate estimations of their water levels. In this study, monthly Inflow - Lost flow (I), Precipitation (P), Evaporation (E) and Outflow (O) observations from the Lake Beyşehir in Turkey were used to predict monthly lake level variations using ϵ -SVR, MLP, RBNN, PSO-ANN and ANFIS methods. While establishing models, different combinations of inflow to the lake - lost flow, precipitation, outflow from the lake and evaporation data were used as input data, and elevation difference between consecutive monthly lake water levels as output data. When performances of models of all input combinations established were investigated, the most successful input combination in each method was M1 combination, in which all I-P-E-O variables were used. When the most successful results in the models established were compared, the most successful method by $R^2=0.9988$ value was ϵ -SVR, however, ANFIS, MLP and RBNN methods also proved to be successful to an extent close to the success of ϵ -SVR method. PSO-ANN method was the lowest-performing method in this study. This high success obtained in all five methods used to estimate the change in water level shows that this type of SCTs can be used to estimate many hydrological parameters required to water resources planning and management.

The use of the estimation power of SCTs can assist Beyşehir Lake administrators to take the necessary precautions in the event of estimated sudden falls or rises in the lake water levels.

Future study will use PSO-SVR and PSO ANFIS models to estimate lake water fluctuations to compare the results of this study

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