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ORIGINAL PAPER

Implementation of supervised intelligence committee machine method for monthly water level prediction

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Abstract
The correct prediction of reservoirs water level variation is one of the important issues for designing, operation of dams, and water supply management. In this study, based on four soft models which are the support vector regression (SVR), adaptive neuro-fuzzy inference system (ANFIS), artificial neural network (ANN), radial basis function neural network (RBFNN), and combinatory use of their results as input to one of these four models, a new structure is proposed. It is named supervised intelligence committee machine (SICM) for monthly reservoir water level prediction of the Karaj Amirkabir dam. Evaluation of the above models is performed by nine error criteria and eventually the best model among them is selected by the vikor decision-making method. The supervised support vector regression (SICM-SVR) is shown high accurate in monthly prediction rather than SVR model with increasing the Nash-Sutcliffe efficiency (NS) from 0.58 to 0.81 (over 39% increase) and decreasing the mean square error (MSE) from 117.8 to 55.78 m^2 (over 52% decrease). According to the vikor analysis among all soft and hybrid models, the SICM-ANN is selected as the best model with NS and MSE equal to 0.94 and 12.85 m^2, respectively. Generally, the proposed method results show that all supervised (hybrid) models have higher performance than soft ones and can be effectively applied to reduce the predicted error of water level.

Keywords Prediction · Reservoir water level · Karaj dam · Supervised intelligence committee machine · Soft models

Introduction

In recent decades, the water crisis and shortage of freshwater resources have been led to many problems in water management and planning, especially during dry periods. For this purpose, the surface water reservoirs of dams play a key role in supplying downstream water needs as one of the essential infrastructures. Due to the dependence of suitable storage of water volume in reservoirs on hydrological parameters, the development of prediction models can be significantly regarded for the accurate study of water level behavior (Sammen et al. 2017; Hipni et al. 2013). For this purpose, the use of artificial intelligence (AI) models have been considerably developed in recent years to predict the hydrological parameters. These models do not need to accurately describe physical parameters and they train simply the systems based on the relations between inputs and outputs (Das et al. 2016). These models are known as soft models (SM) which include different types. It is noted that the hybrid development of soft models is suggested as a solution to improve the forecasting results of the hydrologic parameters by researchers who are Mwale et al. (2014), Kisi et al. (2015), Yadav et al. (2017), Ghorbani et al. (2017), El-Diasty et al. (2018), Nadiri et al. (2019), Meng et al. (2019), and Zhao et al. (2020). Furthermore, there are different ways besides AI models to determine the water level and depth like radar altimetry, satellite imagery, sonar, and echo sounder. Although these techniques are different, they are used in order to determine the depth and water bathymetry by various researchers such as Bandini et al. (2020), Su et al. (2015), Bio et al. (2020), Arseni et al. (2019), and Shang et al. (2019).

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In this section, by considering the previous studies about the soft and hybrid models, the importance of their applications in hydrological variables prediction is investigated. Kisi et al. (2012) predicted the water level of Iznik Lake in western Turkey using the models artificial neural network (ANN), adaptive neuro-fuzzy inference system (ANFIS), and gene expression programming (GEP). The results indicate a high performance of the GEP model compared with the two used models. Valizadeh and El-Shafie (2013) developed ANFIS model based on two types of Gaussian and bell-fit membership functions, to predict the reservoir water level in Klang Gates dam in Malaysia. The results show the high accuracy of the called model compared with the common existing models. The studies for predicting Beysehir Lake water level show that the support vector regression model (SVR) has a high potential than ANFIS, artificial neural network based on particle swarm optimization (PSO-ANN), multi-layer perceptron (MLP), and radial basis function neural network (RBFNN) models (Buyukyildiz et al. 2014). To forecast the water level of cascaded channels, two MLP and recurrent neural network (RNN) models outperformed support vector machine (SVM) in China (Ren et al. 2020). Determining the optimal input using the gamma test (GT) for monthly prediction of reservoir water level of Khanpur dam in Pakistan based on ANN and local regression models was studied by Shamim et al. (2015). The results of the study showed that the use of the gamma test results in a significant improvement of the predicted water level due to the selection of proportional inputs. Das et al. (2016) have used the nonlinear probabilistic model (hybrid Bayesian network (BN)) to estimate the water level of the Mayurakshi reservoir. It is concluded the high accuracy of the proposed approach compared with conventional models like ANN, autoregressive integrated moving average (ARIMA), and the standard Bayesian network. Soleymani et al. (2016) developed the radial basis function-firefly algorithm (RBF-FFA) model to predict the water level of the river. In this study, the firefly algorithm was used to train the RBF soft model. From the obtained results, the high performance of this model in predicting the river water level is achieved. Wang et al. (2020) used the development of a hybrid model to realize accurate multihour sea water level. The forecasting by combining ANFIS model with wavelet decomposition was performed. The results of wavelet-ANFIS (WANFIS) was more accurate than ANN and ANFIS models. Various researchers who are Chen and Lin (2006), Labani et al. (2010), Fijani et al. (2013), Tayfur et al. (2014), Nadiri et al. (2017), Nadiri et al. (2018), and Ambrosio et al. (2019) in order to simultaneously achieve the capabilities of each models have been introduced the hybrid of mentioned models and developing the supervised intelligence committee machine (SICM) model.

Based on the previous researches, the proposed approach receives the results of other soft models as inputs and predicts the desired parameter using a soft model that has not been utilized in the field of reservoir water level prediction. In this paper, the SVR, ANFIS, ANN, and RBFNN models are used because of their ability, novelty, and universality in the water level prediction. These models are applied for providing the SICM model to achieve the development of the efficient prediction model for the proper examination of dam reservoir behavior. The proposed model is evaluated based on the monthly long-term information of the Amirkabir dam in Karaj, including water level, precipitation, evaporation, and inflow and outflow of the reservoir. It is shown that the high ability of the proposed approach improves the prediction results and increases the accuracy of monthly simulation of the reservoir water level. Therefore, the developed structure of this research can be used to predict other hydrological and hydrogeological parameters.

Study area and data set

Due to the importance of strategic dams in providing the water supplies of sensitive areas, in this study, the proposed approach is applied to the concrete and two arched dam of Amirkabir in Karaj. This dam is located in Alborz Province, north of Karaj, and 25 km from Karaj Road to Chalus (Fig. 1). Karaj dam is the first multi-purpose dam in Iran and one of the sources of water supply in Tehran (the capital of Iran). This dam controls the spring floods and prevents damage caused by floods. Also, its lake has created the production of hydroelectric power to help the national electricity grid, Tehran's drinking water provision, the provision of agricultural water in the suburbs of Karaj, the fish breeding conditions, sports, and one of the best spectacular and tourism places (https://en.wikipedia.org).

The presented information of 32 years (1986–2018) on the site of the Water Resources Management Company of Iran (http://dams.wrm.ir) is used to predict the reservoir water level of this dam. The used data as inputs are water level (m), precipitation (mm), evaporation (mm), inflow, and outflow as the units are in (m^3/s). They are converted from daily to monthly with the conversion of their units, according to the above units. In order to better performance of used models and due to the different units, the parameters are converted to normalized values using Eq. (1). Furthermore, the normalized values are non-dimensional (ND) which are summarized in Table 1.

$$X_n = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{1}$$

where X_n, X, $X_{\max}$, $X_{\min}$ are the normalized data, raw data, and highest and lowest values, respectively.

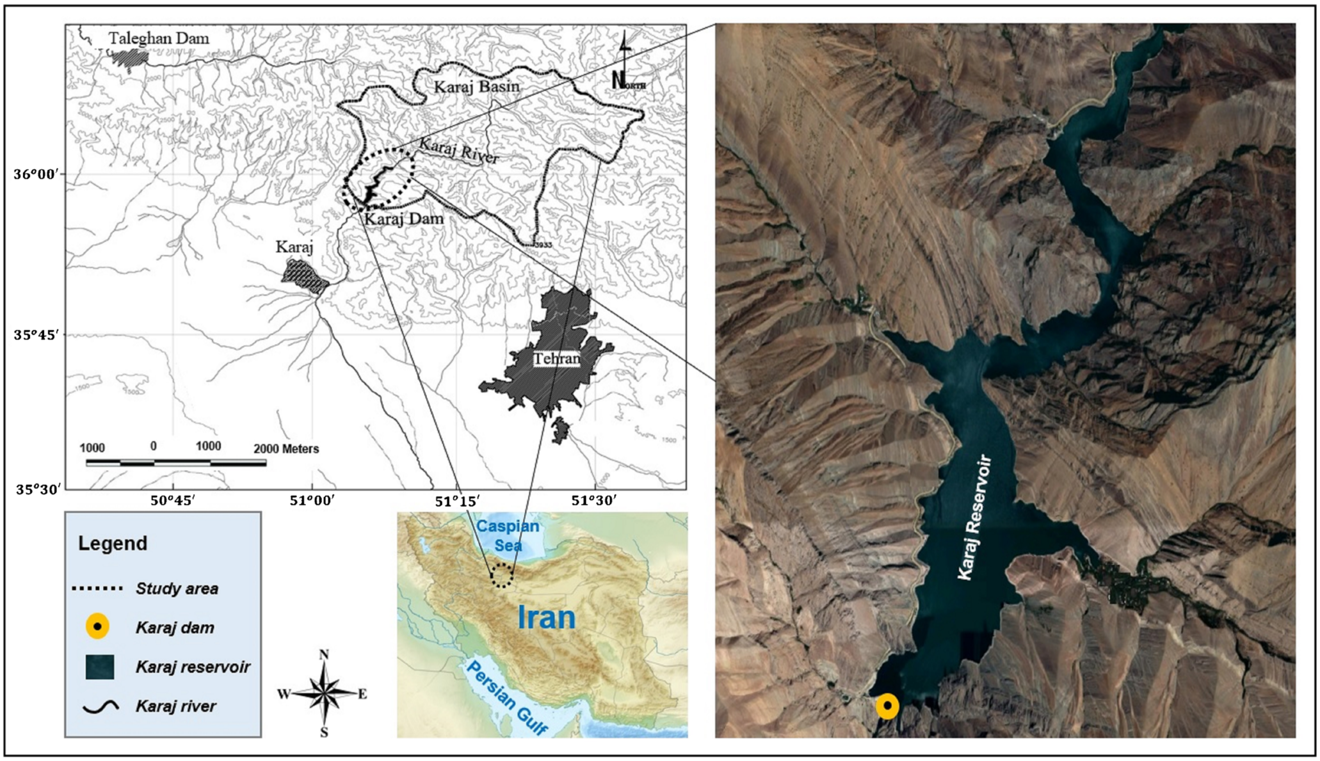

Fig. 1 The location of the Karaj Amirkabir dam

Material and methodology

Support vector regression

The support vector regression (SVR) method is defined based on the principle of the structural error minimization. The input vector x_n is transmitted using nonlinear imaging to a higher dimensional space and this space linear regression is applied to the input vector. The dataset is (x_n, y_n) that x_n and y_n respectively are independent and dependent vectors, where $n = 1, 2, \ldots, N$ and N is the total number of input-output data pairs. The linear regression function is written as following (Vapnik 1998):

$$f(x) = \sum_{n=1}^{N} w_n \phi_n(x) + b \tag{2}$$

where $\{\phi_n(x)\}_{n=1}^{N}$ indicates the input characteristics, $\{w_n\}_{n=1}^{N}$ and b are coefficients that determine by minimizing the following equation (adjusted risk function):

$$P(f(x)) = \frac{C}{N}\sum_{n=1}^{N} E_\varepsilon(y_n, f(x_n)) + \frac{\|w\|^2}{2} \tag{3}$$

$$E_\varepsilon(y_n, f(x_n)) = \begin{cases} 0 & if \quad |y - f(x_n)| \le \varepsilon \\ |y - f(x_n)| - \varepsilon & otherwise \end{cases} \tag{4}$$

Table 1 The initial and normalized values of inputs (water level, precipitation, evaporation, inflow, and outflow)

Initial inputs					Normalized inputs				
WL/m	P/mm	E/mm	I/m^3/s	O/m^3/s	WL/ND	P/ND	E/ND	I/ND	O/ND
1728.750	41.300	13.295	8.577	7.608	0.539	0.186	0.034	0.105	0.119
1734.334	19.300	74.229	21.048	4.837	0.610	0.087	0.191	0.319	0.068
1758.059	106.000	158.616	44.654	19.277	0.910	0.478	0.408	0.724	0.333
1765.127	98.460	238.501	32.631	32.397	0.999	0.444	0.614	0.518	0.573
1764.985	4.110	280.607	17.249	18.632	0.997	0.018	0.722	0.254	0.321

where in Eq. (4), ε and $C$are the insensitive loss function of Vapnik and regulator constant, respectively. The parameter of ε is the difference between observational and computational values (Fig. 2). The parameter of C is defined by the user and determines the exchange curve between the smoothing model and the empirical risk. The parameter of $0.5\|w\|^2$ is a smoothing factor. By introducing the deficiency variables ξ and ξ^* in Eq. (3), the general form of optimization equation in this method is as follows (Shirzad et al. 2014):

$$Minimize\ \left(\phi\left(w,\xi,\xi^*\right) = C\sum_{n=1}^{N}\left(\xi+\xi^*\right)+\frac{\|w\|^2}{2}\right) \tag{5}$$

The limitations of the above objective function are:

$$\begin{cases} y_i - w.\phi(x) - b \le \varepsilon + \xi_i\ ,\ \ \xi_i \ge 0 \\ w.\phi(x) - y_i + b \le \varepsilon + \xi_i^*\ ,\ \xi_i^* \ge 0 \end{cases} \tag{6}$$

According to Lagrange's method for solving the above optimization problem, the Lagrange form the equations should be prepared as follows (Elbisy 2015):

$$Maximize\ \left(\begin{array}{l} H\left(\alpha,\alpha^*\right) = -0.5 \\ \sum\limits_{i=1}^{N}\sum\limits_{j=1}^{N}\left(\alpha_i-\alpha_i^*\right)\left(\alpha_j-\alpha_j^*\right)K\left(x_i,x_j\right) \\ +\sum\limits_{i=1}^{N} y_i\left(\alpha_i-\alpha_i^*\right) - \varepsilon\sum\limits_{i=1}^{N} y_i\left(\alpha_i+\alpha_i^*\right) \end{array}\right) \tag{7}$$

$$\sum_{i=1}^{N}\left(\alpha_i-\alpha_i^*\right) = 0\ ,\ 0 \le \alpha_i, \alpha_i^* \le C \tag{8}$$

where α_n and α_n^* are the Lagrange coefficients, $\alpha_i\alpha_i^* = 0$ and $\alpha_i, \alpha_i^* \ge 0$. Based on the presented equations, it is concluded that the regression function should be considered as the Eq. (9):

$$f(x) = \sum_{i=1}^{N} y_i\left(\alpha_i-\alpha_i^*\right)K(x,x_i)+b \tag{9}$$

$K(x, x_i) = \phi(x_i)\phi(x)$ is the Kernel function that expresses the internal multiplication in an n dimension space. In this research, six common kernel function is used which are radial basis kernel function (Rbf), polynomial kernel function (PoL), Gaussian radial basis kernel function (Gau), exponential radial basis kernel function (Exp), linear (Lin), and nonlinear (MLP). The SVR model is a novel method which is been used in recent studies. Furthermore, this model is employed for water level prediction of lake or sea, and in this paper is used for an artificial resource (dam reservoir).

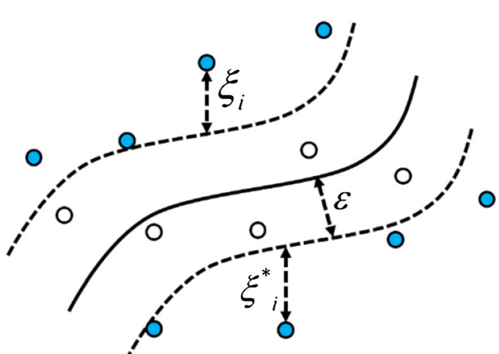

Fig. 2 The variables ofε, ξ, and ξ^*

Adaptive neuro-fuzzy inference system model

The adaptive neuro-fuzzy inference system (ANFIS) is proposed by Jang in 1993. This structure consists of the multilayer adaptive networks that are obtained from the main elements and functions of fuzzy logic systems. Using the concepts of network architecture and training algorithm in neural network topics in neural fuzzy systems, many achievements have been obtained in the modeling and control of complex systems. This method is developed based on the concepts of neural network methods in fuzzy systems. The main purpose of this method is to train the form of membership functions for a fuzzy system that earns from the adaptive properties of neural network methods (Galavi et al. 2013; Valizadeh and El-Shafie 2013; Chen et al. 2019).

There are two main approaches for realizing a FIS which are the Mamdani and Sugeno. In this study, the Sugeno fuzzy system is employed as the preferred FIS approach for water level forecasting. A FIS with two inputs (x_1,x_2) and one output (O) is considered as an example to explain the ANFIS process. Generally, fuzzy rules can be expressed in the following way (Fig. 3): (Wang et al. 2020).

Rule 1:

If x_1 equals I_1 and x_2 equalsJ_1, then $O_1 = a_1x_1 + b_1x_2 + \ldots + r_1$;

Rule 2:

If x_1 equals I_2 and x_2 equalsJ_2, then $O_2 = a_2x_1 + b_2x_2 + \ldots + r_2$;

where x_1 and x_2 are inputs; a_1, b_1, r_1, a_2, b_2, and r_2 are the function parameters of the output (O); I_1, I_2, J_1, and J_2 are the membership functions (MF_S) for the inputs. The basic concept underlying Sugeno's approach comprises five layers, each of which perform different functions. The first layer is the input layer. The output of the i^{th}node in layer 1 is denoted as $O_{1,\ i}$.

$$O_{1,i} = \mu_{A_i}(I), i = 1, 2, \tag{10}$$

$$O_{1,i} = \mu_{B_i}(I), i = 1, 2, \tag{11}$$

where $O_{1,\ i}$ defines the membership grade of a fuzzy set (A_1,A_2,B_1,B_2) and A_i or B_i are the linguistic labels associated with the corresponding input node. The second layer is the rule-node layer. In this layer, the output corresponds to the product of input signals, which is given by:

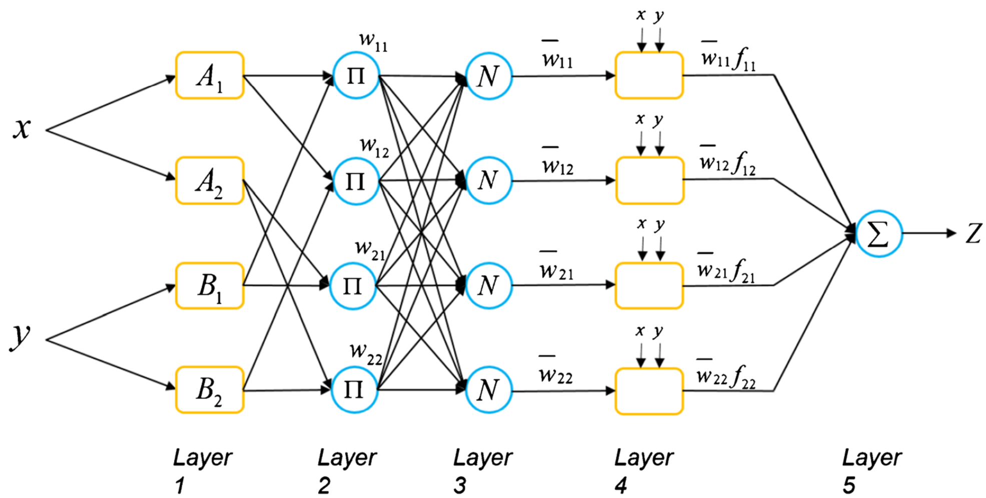

Fig. 3 The general form of ANFIS model

$$O_{2,i} = W_i = \mu_i(I)\mu_i(J), i = 1, 2, \tag{12}$$

where $\mu_i(I)$ and $\mu_i(J)$ denote MFs. The third layer is the normalized layer. In this layer, the weight function is normalized as follows:

$$O_{3,i} = w = \frac{w_i}{w_1 + w_2}, i = 1, 2, \tag{13}$$

The fourth layer is the consequent-node layer, which is also referred to as the defuzzy layer. In this layer, the output obtained from layer 3 is multiplied with the Sugeno fuzzy rule function, as described below:

$$O_{4,i} = \overline{w_i} f_i = w_i(a_i x + b_i x_2 + \ldots + r_i), i = 1, 2, \tag{14}$$

where,a_i, b_i, and r_i denote the parameter set. The sum of all outputs obtained from the penultimate layer is calculated at the single output node (layer 5) (Wang et al. 2020).

$$O_{5,i} = \sum_{i=1}^{n} \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}, n = 2. \tag{15}$$

Generally, the fuzzy and especially ANFIS models are widely employed in many studies with acceptable results. Also, ANFIS is a novel model in this field that satisfies researchers to apply it.

Artificial neural network model

Artificial neural networks (ANN) are flexible mathematical structures that are retrieved from the biological neuron system. In general, the most common ANN structures are known as multi-layer perceptron networks including input, hidden, and output layers and actuator functions. The back-propagation algorithm (BPA) which is provided by Rumelhart et al. (1986) can train a network in many nonlinear issues. This method is used and recommended in many studies to determine the nonlinear relationship between input and output parameters. In this study, a multi-layer perceptron back-propagation (MLP-BP) neural network is employed (Fig. 4) (Sulaiman et al. 2011). The mathematical form of this algorithm is as follows:

$$y_j = f\left[\sum_{i=1}^{n} w_{ji} x_i + b_j\right] \tag{16}$$

where x_i, y_j, b_j, w_{ji}, n, and $f$are the value of the node (neuron) i^{th} in the previous layer, the value of the node j^{th} in the current layer, the oblique vector associated with the node j^{th} in the current layer, weight links between nodal values x_i and y_j, number of nodes in the previous layer, and the actuator function in current layer, respectively. The initial values of weight and oblique vectors can play a decisive role in creating the proper structure for predicting output parameter, as shown in Eq. (16). In order to prevent the network structure from encountering in local optimal values, in this work, 50

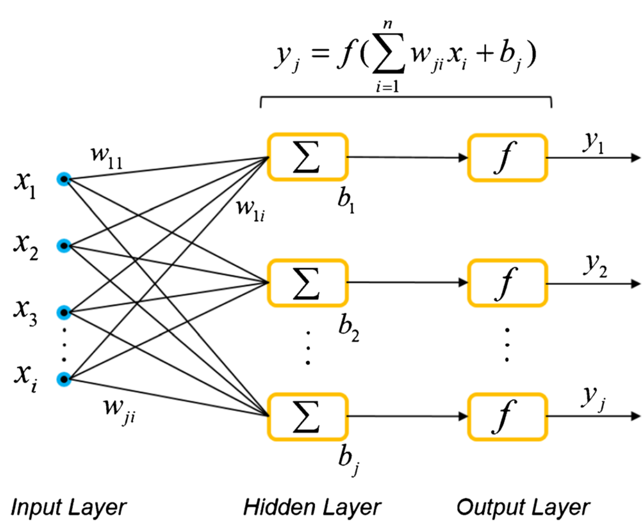

Fig. 4 The general form of ANN model

randomized sets of weight and oblique vectors are created and the network is trained to determine the best weights. In addition, more mathematical details of this soft model can be found in ASCE (2000). The high performance and accuracy of the ANN model in various studies reveal its ability. This model is been using in different fields for a long time with high accuracy. Studying of related researches shows that water level prediction is one of the appropriate fields for using this model.

Radial basis function neural network model

This model is a non-supervised neural network model that first introduced by Broomhead and Lowe (1988). Radial basis function neural network (RBFNN) model consists of three layers such as input, hidden, and output. This model shows a good performance for nonlinear modeling and develops its structure in contrast to the multi-layer perceptron neural network (MLPNN) model in one step. In this model, the learning between input and hidden layers is done by defining the weights which are created based on the clustering algorithms. Thus, Euclidean spacing of input vector i^{th} and weight vector related to the node j^{th} of the hidden layer is defined in the form of the parameter D_j as follows (Csabragi et al. 2017; Buyukyildiz et al. 2014):

$$D_j = \sqrt{\sum_{i=1}^{n} \left(w_{ij}-x_i\right)^2} \tag{17}$$

where n is the number of input parameters. Based on the calculated parameter D_j, the output parameter value is simulated using an appropriate oblique function. According to the recommendations of previous studies, the Gaussian kernel function is the most appropriate oblique function for this model that function form is as follows:

$$f_{(D_j)} = \exp\left[\frac{D_j}{2\sigma^2}\right] \tag{18}$$

where in this equation, σ is a smoothing factor that is determined by network training. The value of σ determines the data scattering rate (Fig. 5). According to Eq. (19), the output of RBF model can be computed with m nodes in the hidden layer (Fig. 6) (Csabragi et al. 2017).

$$Y = \sum_{i=1}^{m} w_j f_{(D_j)} + b \tag{19}$$

where b and w_j are a constant value (bias) and the weight associated with hidden and output layers, respectively.

According to related researches, the neural network models are frequently employed for water level prediction. The RBFNN model has also had acceptable results in this field.

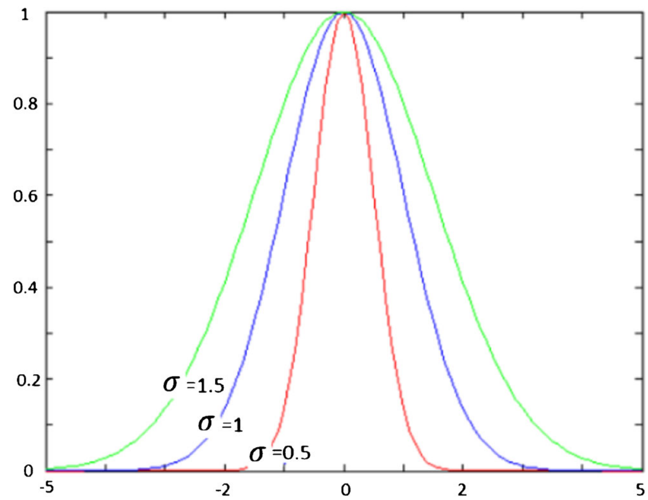

Fig. 5 Value of σ according to the data scattering rate

Supervised intelligence committee machine method

Due to the drawback in each of the simulation models, various researchers improved the simulation results using methods like simple weighting or weighing based on the optimization algorithms on the results of soft models. This method is known as the supervised intelligence committee machine (SICM) that is used in various works. One of these studies is introduced by Chen and Lin (2006) and Labani et al. (2010). These researches result in an improvement of the simulation results. However, they indicate a high error value. In this regard, Tayfur et al. (2014) combined the results of other simulation models by using the artificial neural network to reduce the simulation error. This method includes a number of soft simulation models that it is performed in two stages. In the first stage, it is necessary to simulate the desired parameter

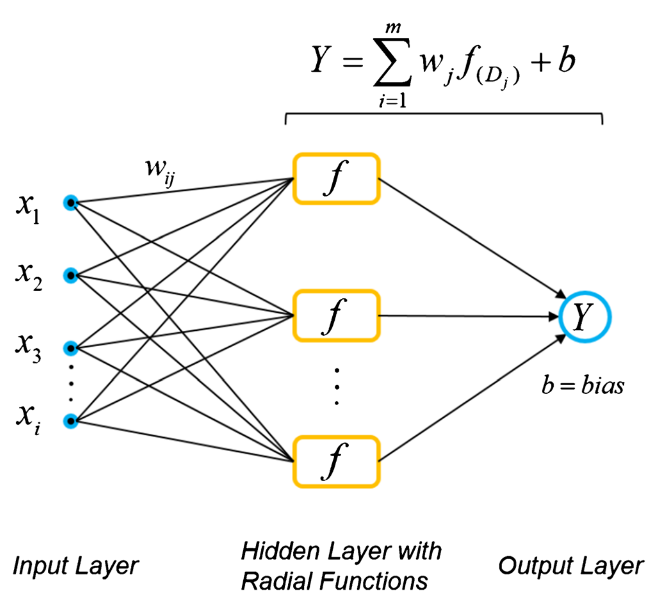

Fig. 6 The general form of RBFNN model

value (which is the reservoir water level in this study) using soft simulation models and the input-output set.

Then, the output of these models will consider as input parameters in the SICM model. In this method, four models are used as a combiner structure of other models to achieve an appropriate solution. According to Fig. 7, the output of soft simulation models including ANN, ANFIS, RBFNN, and SVR is used in the structure of the suggested SICM model. The results of these models are aggregated with each of four simulation models and finally, the monthly reservoir water level is estimated using Eqs. (20) and (21).

$$Q_i = SM_i(WL, P, E, I, O) \tag{20}$$

$$Q_{SICM} = Q_i(SM_i) \tag{21}$$

where WL, P, E, I, and O are input parameters of precipitation, evaporation, input, and output of the reservoir, respectively. The SM_i is a used soft model that include ANN, RBFNN, ANFIS, and SVR due to the simulation ability of the water level parameter. Based on the output of each soft models (Q_i) and their combination using four simulation models, the final output (Q_{SICM}) is obtained with the better estimation of the water level.

In recent years, the use of lonely soft models has not been considered by researchers because the hybrid (supervised) models have shown better performance than soft ones. Thus, the supervised models are frequently used in new papers like this study.

The use of supervised models for the artificial reservoir (dam) is the main novelty of this paper. Also, the neural network models (ANN, RBFNN, and …) are the prevalent and high-performance models in this study and many other types of research (Table 2). According to Table 2, the strengths and weaknesses of this study and other related papers are separately shown. In this table, the reasons for using SVR, ANFIS, ANN, RBFNN, and SICM models are understandable.

The way of choosing best model of SICM

The evaluation and selection of one method among various methods are always considered by decision makers in different disciplines. There are different decision-making methods to compare the results and choosing the best model. In this study, vickor multi-criteria decision making (VMCDM) is used as one of the most widespread methods for decision making and choosing the best option. This method has been developed to solve discrete multi-criteria issues with opposite and disproportionate criteria. The main purpose of this method is ranking the options with the closest approach to the ideal answer for each criterion. The following steps are considered to start the decision-making process using the vikor method (Opricovic and Tzeng 2004):

- The formation of decision matrix (f_{ij}, $i = 1, 2, 3, \ldots, n, j = 1, 2, 3, \ldots, m$): It is an option scoring matrix based on criteria. In this work, four used soft models in the non-hybrid model and four developed hybrid models are as options, and the criteria are the error parameters that are considered for each model. The values of n and m represent the total number of criteria and options, respectively.
- Determining the weight of each criterion: the weight of each criterion (W_i) is determined using the Shannon entropy method (Hanting et al. 2013).
- Determining the positive and negative ideal points for each criterion among all the options that are called f_i^+ and f_i^-, respectively. These values are determined as follows. In this paper, R, IA, EFF, and NS are considered as

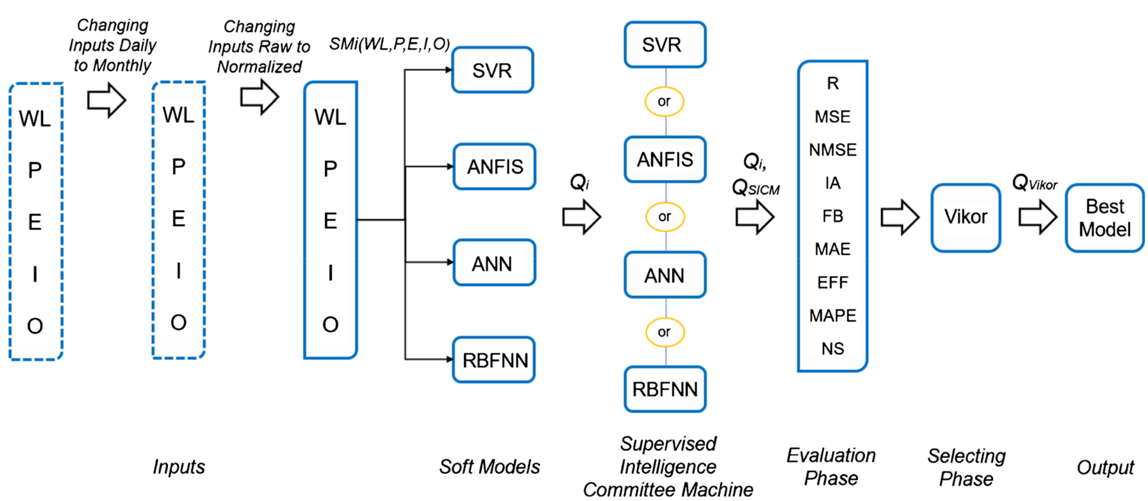

Fig. 7 The proposed SICM model structure for the reservoir monthly water level prediction

Table 2 The strengths and weaknesses of related papers and this study

Research	Type of reservoir	Used models	Advantages	Disadvantages
Buyukyildiz et al. 2014	Natural	The SVR, PSO-ANN, MLP, and RBFNN models	Using several models including hybrid one	A low statistical data set
Kisi et al. 2015	Natural	The SVM-FA, GP, and ANN models	Using a hybrid model	A low number of soft models
Shamim et al. 2015	Artificial	The ANN and local linear regression (LLR)	Using GT method to determine the ideal input	A low number of soft models
Das et al. 2016	Artificial	The ARIMA, ANN, BN, and hybrid BN models	Using a hybrid model–a large statistical data set	a Low number of soft models
Soleymani et al. 2016	Natural	The SVM, MLP, and RBF-FFA	Using a hybrid model	A low number of soft models
Ren et al. 2020	Artificial	The MLP, RNN, and SVM models	Using large number of error criteria	A LOW number of soft models–lack of hybrid model
Wang et al. 2020	Natural	The ANN, ANFIS, WANN, and WANFIS models	Using the hybrid models–the large number of error criteria	A low number of soft models
Zhao et al. 2020	Natural	A hybrid machine learning framework	Using a hybrid model	A low number of models and error criteria
Malekpour and Tabari (this paper)	Artificial	The SVR, ANFIS, ANN, RBFNN, and SICM method	Using the latest and greatest soft models–a large statistical data set-the large number of error criteria–higher results using SICM method	–

positive criteria and MSE, NMSE, FB, MAE, and MAPE as negative criteria.

$f_i^+ = \max_j \left(f_{ij}\right)$ and $f_i^- = \min_j \left(f_{ij}\right)$: for positive criteria: the criteria with the highest amount are more desirable

$f_i^+ = \min_j \left(f_{ij}\right)$ and $f_i^- = \max_j \left(f_{ij}\right)$: for negative criteria: the criteria with the least amount are more desirable

Calculating the amount of sufficient (S_j) and regret (R_j) for each option: According to Eqs. (22) and (23), the sufficient value represents the relative distance option j^{th} and the regret value expresses the maximum distance option j^{th} from the ideal point.

$$S_j = \sum_{i=1}^{n} w_i \left(\frac{f_i^+ - f_{ij}}{f_i^+ - f_i^-}\right) \tag{22}$$

$$R_j = \max\left[w_i \left(\frac{f_i^+ - f_{ij}}{f_i^+ - f_i^-}\right)\right] \tag{23}$$

- The vikor determination for each option:

$$Q_j = V\left(\frac{S_j - S^*}{S^- - S^*}\right) + (1-V)\left(\frac{R_j - R^*}{R^- - R^*}\right), R^* \\ S^* = \min_j (S_j), S^- = \max_j (S_j), \\ = \min_j (R_j), R^- = \max_j (R_j), \tag{24}$$

Table 3 Error criteria values for soft models' evaluation (training stage)

Models	R (ND)	MSE (m^2)	NMSE (ND)	IA (ND)	FB $*10^3$ (ND)	MAE (m)	EFF (ND)	MAPE (ND)	NS (ND)
SVR	0.96	24.7	0.09	0.97	0.43	1.73	0.91	0.11	0.93
ANFIS	0.82	101.85	0.40	0.89	1.10	7.35	0.65	0.42	0.65
ANN	0.86	80.85	0.32	0.92	− 0.72	6.15	0.74	0.35	0.74
RBFNN	0.83	100.54	0.38	0.9	− 1.21	7.29	0.68	0.42	0.68

Table 4 Error criteria values for supervised (hybrid) models' evaluation (training stage)

Models	R (ND)	MSE (m^2)	NMSE (ND)	IA (ND)	FB $*10^4$ (ND)	MAE (m)	EFF (ND)	MAPE (ND)	NS (ND)
SICM-SVR	0.97	14.78	0.05	0.98	0.36	1.3	0.93	0.07	0.95
SICM-ANFIS	0.9	59.38	0.22	0.94	0.83	4.81	0.81	0.28	0.81
SICM-ANN	0.89	63.05	0.24	0.94	− 0.66	5.08	0.77	0.29	0.8
SICM-RBFNN	0.89	62.75	0.24	0.94	− 0.87	5.12	0.8	0.29	0. 8

where V is the weight related to the group maximum desirability. Also, to a high agreement between the decision-making group, the value over 0.5, an agreement with a majority of votes approximately equal to 0.5, and a lower agreement or a rejection of it will be less than 0.5 (Opricovic and Tzeng 2007).

- Ranking options by sorting the ascending ofS_j, R_j, and Q_j values. At this stage, three types of ratings are specified for each option.
- Suggesting the best rating of Q_j (which is the smallest amount ofQ_j) as a better compromise solution if it satisfies the following two conditions:

The first condition (acceptable advantage): If optionsA^1 and A^2 have the first and second rankings among the m options based on the Q_j rating, the following equation is established:

$$Q\left(A^2\right)-Q\left(A^1\right)\geq\frac{1}{m-1} \tag{25}$$

The second condition (acceptable stability in decision making): The option A^1 should be recognized as the top rating at least in the ranking of one of parameters S_j and R_j.

If one of the first or second conditions is not established, a compromise solution set is proposed as follows:

A) If the only second condition is not available, options A^1 and A^2 will accept as the top choices.
B) In the absence of the first condition, options A^1, A^2, …, A^mwill consider as the preferred option. Also, the equation $A^m-A^1\leq\frac{1}{m-1}$ must be true for these options.

Results and discussion

All data are randomly divided into three groups for evaluating the used models. In this study, 85% of the data is applied to train soft models, 10% for calibration testing, and 5% for testing the trained structures. Then, the correlation coefficient (R), mean square error (MSE), normalized mean square error (NMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), index of agreement (IA), fractional bias (FB), efficiency coefficient (EFF), and Nash-Sutcliffe efficiency (NS) criteria are used for the performance evaluation of models (Tabari 2016; Soleymani et al. 2016). Moreover, in this paper, units of MAE and MSE are meter and square meters, respectively, and other criteria are non-dimensional (ND). The equation of all these error criteria is as follows:

$$R=\frac{\sum_{i=1}^{n}\left(X_{mi}-\overline{X}_m\right)\left(X_{ci}-\overline{X}_{ci}\right)}{\sqrt{\sum_{i=1}^{n}\left(X_{ci}-\overline{X}_c\right)\sum_{i=1}^{n}\left(X_{mi}-\overline{X}_m\right)}} \tag{26}$$

$$MSE=\frac{\sum_{i=1}^{n}\left(X_{mi}-X_{ci}\right)^2}{n} \tag{27}$$

$$NMSE=\frac{\left(\overline{X_{mi}-X_{ci}}\right)^2}{\overline{X}_m\overline{X}_c} \tag{28}$$

$$NS=1-\frac{\sum_{i=1}^{n}\left(X_{mi}-X_{ci}\right)^2}{\sum_{i=1}^{n}\left(X_{mi}-\overline{X}_m\right)^2} \tag{29}$$

Table 5 Error criteria values for soft models' evaluation (Testing stage)

Models	R (ND)	MSE (m^2)	NMSE (ND)	IA (ND)	FB $*10^3$ (ND)	MAE (m)	EFF (ND)	MAPE (ND)	NS (ND)
SVR	0.77	117.80	0.45	0.84	1.15	7.79	0.53	0.46	0.58
ANFIS	0.84	96.53	0.37	0.91	0.88	7.62	0.71	0.44	0.70
ANN	0.94	23.37	0.09	0.97	− 0.11	3.66	0.93	0.21	0.89
RBFNN	0.91	37.22	0.14	0.95	− 0.25	4.91	0.95	0.28	0.82

Table 6 Error criteria values for supervised (hybrid) models' evaluation (testing stage)

Models	R (ND)	MSE (m^2)	NMSE (ND)	IA (ND)	FB $*10^4$ (ND)	MAE (m)	EFF (ND)	MAPE (ND)	NS (ND)
SICM-SVR	0.90	55.78	0.21	0.95	0.71	4.41	0.87	0.25	0.81
SICM-ANFIS	0.93	29.48	0.11	0.97	0.48	3.62	0.87	0.21	0.89
SICM-ANN	0.97	12.85	0.04	0.98	− 0.03	2.58	0.94	0.15	0.94
SICM-RBFNN	0.96	17.17	0.06	0.98	− 0.09	2.61	1.13	0.15	0.92

$$MAE = \frac{\sum_{i=1}^{n} |X_{mi} - X_{ci}|}{n} \quad (30)$$

$$MAPE = \frac{1}{n}\left[\sum_{i=1}^{n} \frac{|X_{mi} - X_{ci}|}{X_{mi}}\right] *100 \quad (31)$$

$$IA = 1 - \frac{\sum_{i=1}^{n} (X_{mi} - X_{ci})^2}{\sum_{i=1}^{n} \left(\left|X_{mi} - \overline{X}_m\right| + \left|X_{ci} - \overline{X}_m\right|\right)^2} \quad (32)$$

$$FB = 2\frac{\left(\overline{X}_m - \overline{X}_c\right)}{\left(\overline{X}_m + \overline{X}_c\right)} \quad (33)$$

$$EFF = \left(\frac{\sqrt{\sum_{i=1}^{n} \left(X_{ci} - \overline{X}_m\right)^2}}{\sqrt{\sum_{i=1}^{n} \left(X_{mi} - \overline{X}_m\right)^2}}\right)^2 \quad (34)$$

where X_{mi}, X_{ci}, $\overline{X}_m$, and $\overline{X}_c$ are measured, predicted, average measured, and average predicted values, respectively.

The developed structure of soft and hybrid models is implemented in the software MATLAB2018b. The best models are extracted by adjusting the parameters of each of these models. It should be mentioned that the time delay effect of the input parameters is applied to the models for investigating the results of the reservoir water level prediction. The obtained results show a decrease in the performance of prediction models with time delay. Thus, five parameters without time delay including water level, precipitation, evaporation, inflow, and outflow of the reservoir as inputs and reservoir water level at the end of the month as outputs are considered in all models.

Generally, every model has some limitations and parameters to be determined. By implementing the SVR model for various kernel functions (SVR-RBF, SVR-LIN, SVR-POL, SVR-GAU, SVR-EXP, and SVR-MLP), the SVR-GAU model is selected as the best model because of its lowest error at the test stage and defined error criteria. This issue is also considered for determining the best parameter and related model with other soft models. For example, in this model, the NS and MSE are determined 0.58 and 117.8, respectively. These values are the highest value of NS and the lowest of MSE error, compared with other models. In this model, regulator parameters C and ε are considered as 200 and 0.01, respectively. Also, the range of the parameters' changes is selected in 50–300 and 0.0001–1, respectively. The Sugeno implication is utilized in the ANFIS model. It uses the FIS structure training with the genfis2 command which requires clustering of input and output data. By applying the trial and error processing to achieve the optimum ANFIS model and by selecting the number 1 from the range of 0–1 for the clustering center, the lowest value of MSE is obtained 96.5 m^2. The development of the ANN model with a hidden layer and 9 neurons in it achieves the best ANN model with a Nash efficiency indicator of 0.89 at the test stage. It should be noted that the range of changes in the number of neurons in the hidden layer is chosen by 2–15 neurons. In the RBFNN model, by using the smoothing factor and the number of neurons as 3

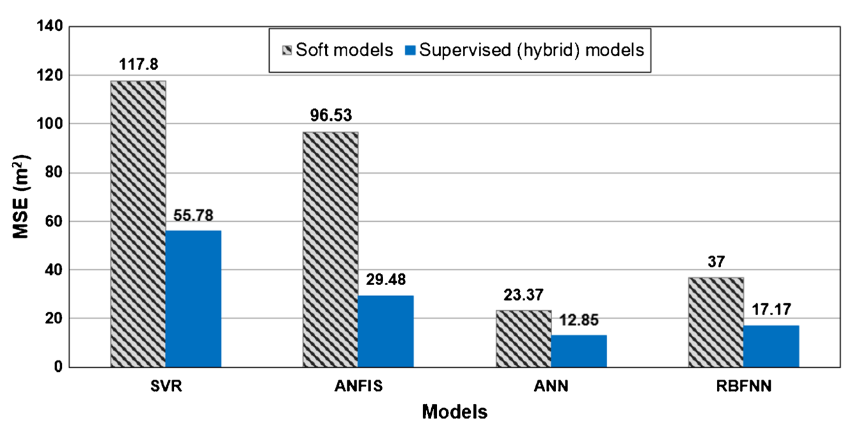

Fig. 8 The MSE criterion comparison of the soft and supervised (hybrid) models at the test stage

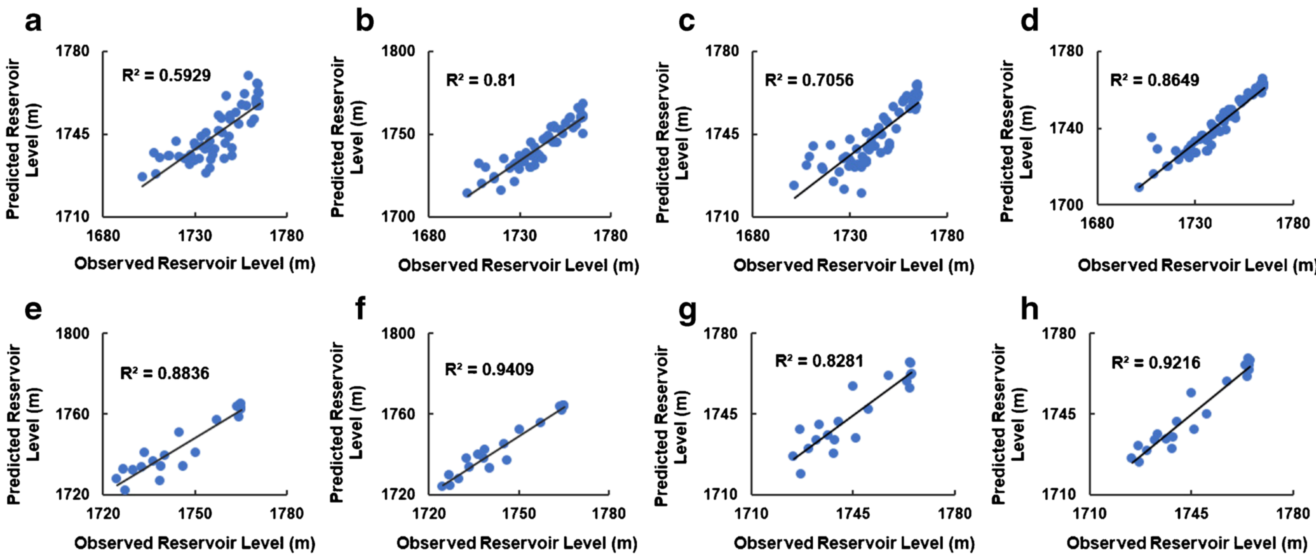

Fig. 9 Scatter plats of the soft and supervised (hybrid) models at the test stage: **a** SVR, **b** SICM-SVR, **c** ANFIS, **d** SICM-ANFIS, **e** ANN, **f** SICM-ANN, **g** RBFNN, and **h** SICM-RBFNN

and 25, respectively, the best prediction is obtained with 37 m^2 for the MSE. The variation range of the smoothing parameters and the number of neurons is set to 0–4 and 5–50, respectively. The values of the nine mentioned error criteria for each model are calculated for evaluating the performance of the developed soft models that are presented in Tables 3, 4, 5, to 6.

Since all four soft models have increased the accuracy of the predicted results, the hybrid use of them can play a significant role in improving predictive results. Therefore, in this study based on the proposed hybrid approach, the results of these four soft models are considered as inputs to each of these models. In fact, the proposed hybrid models are somehow already supervised by soft structures. By implementing the hybrid approaches and calculating the error criteria for each of them, the possibility of comparing and selecting the superior model is provided according to Tables 4 and 6. According to these tables, it is seen that the performance of primary single models is significantly increased in order to achieve a significant reduction in error rates. For example, in supervised SICM-SVR model, the R and MSE are improved by 17% and 52%, respectively, rather than SVR model (Tables 5 and 6; Fig. 8). Also, the parameter of R^2 in the supervised models SVR, ANFIS, ANN, and RBFNN is increased 37%, 22%, 6%, and 12%, respectively. This improvement of SICM models performance is clearly seen in Fig. 9.

Due to the proximity of nine error criteria, the use of the vikor method can be effectively considered in introducing the best model. This method simultaneously use the values of evaluation criteria and achieve the superior model based on Table 7. According to this table, all soft and supervised models are compared and the result of vikor reveals the best model. Also, the values of *Q*, *R*, and *S* parameters are sorted in descending order for more convenience.

Based on the vikor rules, the SICM-ANN model is ranked first and has higher performance in the reservoir water level prediction of the Karaj dam because it has the lowest number of *Q* and *R*. After that, the SICM-RBFNN model with the

Table 7 Results of vikor method for soft and supervised (hybrid) models

Vikor parameters					
Q		*R*		*S*	
SICM-ANN	0	SICM-ANN	0.04	SICM-RBFNN	0.05
SICM-RBFNN	0.10	SICM-RBFNN	0.09	SICM-ANN	0.06
SICM-ANFIS	0.23	ANN	0.23	SICM-ANFIS	0.24
ANN	0.25	SICM-SVR	0.28	ANN	0.29
SICM-SVR	0.50	SICM-ANFIS	0.31	SICM-SVR	0.41
RBFNN	0.58	RBFNN	0.51	RBFNN	0.57
ANFIS	0.64	SVR	0.77	ANFIS	0.81
SVR	0.86	ANFIS	0.80	SVR	0.93

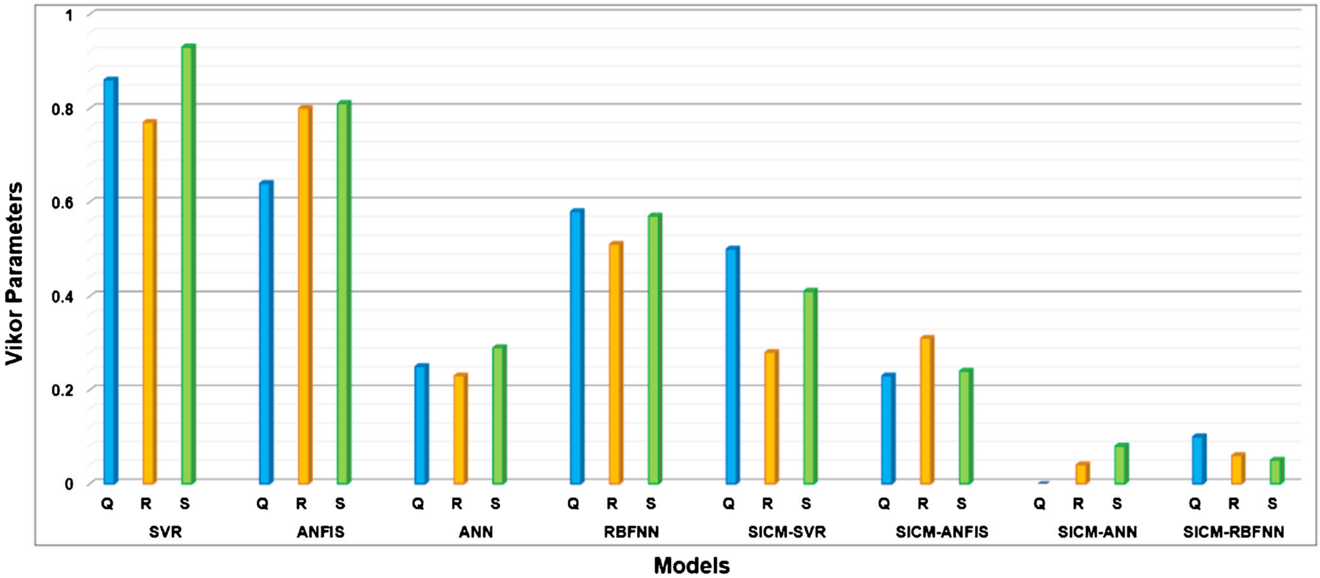

Fig. 10 Vikor parameters for all models

vikor 0.12 is ranked as the second in terms of nine error criteria to predict the output parameter. The results of this multi-criteria decision making (vikor) method are schematically shown in Fig. 10.

In order to check the accuracy of SICM models in comparison with soft models, the time series of reservoir water levels is traced in the test period as shown in Fig. 11. They show that in some places, soft models have not been able to simulate the actual conditions of the reservoir water level of the dam. For example, the predicted water levels by the ANN model for data set in the 381, 386, and 388 rows from the test period data have 45%, 48%, and 46% of error rather than the observed values, respectively (Fig. 11c). This error rate can be seen relatively for other test period data and models (Fig. 11).

The use of predicted water level determines the volume of water in the reservoir and also the exploitation of the dam. Thus, the study of the accuracy of estimated water volume is equivalent to the predicted surface water level. Furthermore,

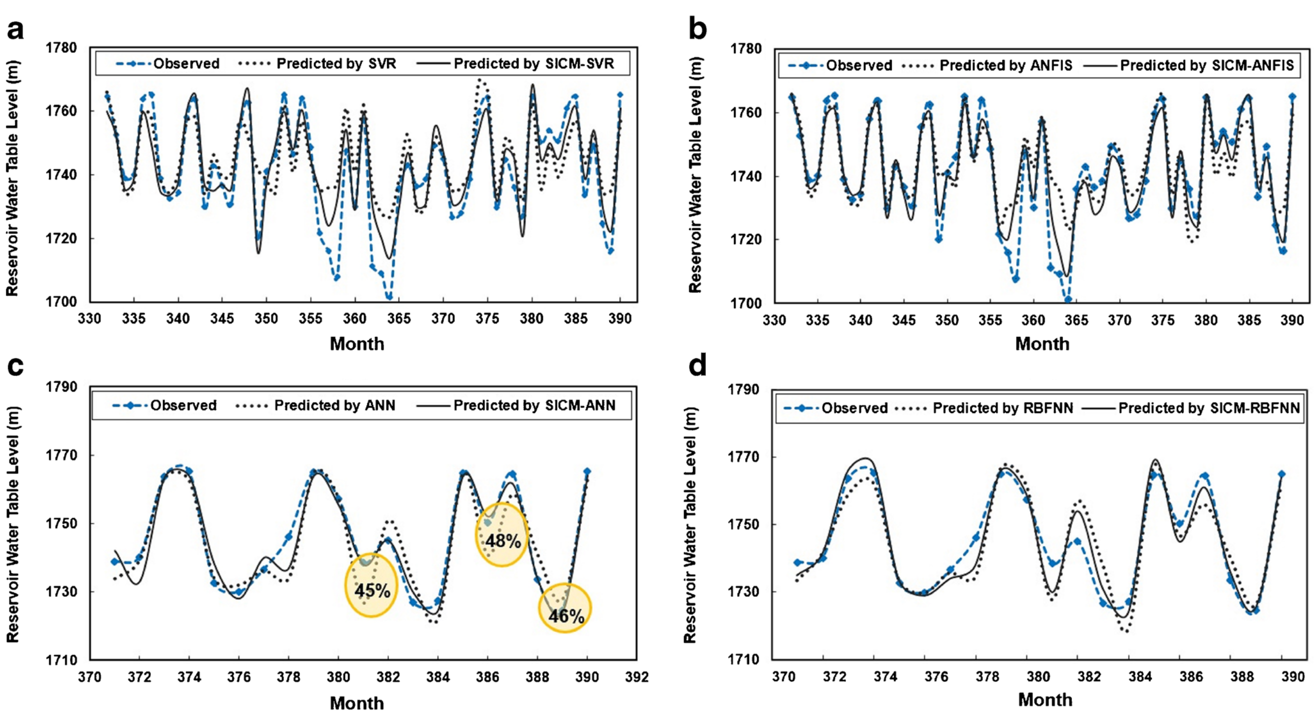

Fig. 11 The comparison of the reservoir water level time series at the test stage: **a** SVR and SICM-SVR, **b** ANFIS and SICM-ANFIS, **c** ANN and SICM-ANN, **d** RBFNN, and SICM-RBFNN models

this issue shows other dimensions of the proposed approach performance and accuracy. Based on the predicted water level values by two superior ANN and SICM-ANN models, it can be seen that the ANN model is estimated 28 m^3 of water in the dam reservoir annually more than SICM-ANN model. This issue can be significantly regarded compared with the 32 m^3 of water which average monthly is released to supply the dam downstream needs. In fact, overestimated than the actual volume of the reservoir increases the risk of water supply and reduces the operational efficiency of the reservoir. Therefore, the development of hybrid approaches is significantly reduced the predicted error and also has significant effects on the management of exploitation in real conditions of the reservoir and prevents the adoption of incorrect decisions by operators.

Conclusion

Based on the importance of the reservoir water level prediction in the management of their exploitation, in this paper, the hybrid approach development of the popular soft models is introduced to predict the reservoir water level of the Amirkabir dam of Karaj. At first, by using precipitation, evaporation, water level, inflow, and outflow parameters from 32 years as input data, single soft models of SVR, ANFIS, ANN and, RBFNN are used for training and validation.

Due to the error reduction and improving the results of the water level prediction, the development of the hybrid model is considered in this study. The produced outputs of four soft models are applied as inputs to each of them. By executing these hybrid models and calculating nine error criteria, the SICM-ANN model is selected as the superior model based on the vikor decision-making method. The review of SICM-ANN and ANN models shows a significant improvement in the results of the water level prediction with a decrease of 81% MSE and increasing the correlation coefficient from 0.94 to 0.97. Wrong water level prediction of dam reservoir increases the risk of water supply and reduces the operational efficiency of the reservoir. Therefore, the use of supervised models is significantly reduced the forecasting error and also has significant effects on the management of exploitation in real conditions of the reservoir and prevents the adoption of incorrect decisions by operators.

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