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Evaluating Performance of Hybrid Neural Network Models in Daily River Flow Estimation

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Abstract

River flow forecasting is of immense importance for reliable planning, designing, and management of water resources projects. This study investigated the performance of wavelet neural network, support vector machine, artificial neural network, and Multiple Models Driven by Artificial Neural Networks (MMANN) in predicting flow time series of the Kashkan River in Lorestan, Iran. Daily flow time series was created from the records of Kashkan hydrometric and rain gauge stations for a 10-year period from 2006 to 2016. To determine the best input-output mapping, estimations were repeated with different combinations of inputs derived from previous daily river flow data. Performance of the models was evaluated in terms of correlation coefficient, root mean square error, and mean absolute error. Performance comparisons showed that the MMANN model with a correlation coefficient of 0.960, root mean square error of 0.021, and mean absolute error of 0.001 generates the best daily flow estimates for the studied river.

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Introduction

River flow forecasting is of vital importance for managing floods and minimizing the associated loss of life and property. Accurate forecasting of river flow can play a key role in the planning and management of water resources, but considering the variety of factors that can influence this phenomenon, it is often difficult to produce flow estimates with good precision. The analytical tools most commonly used for river flow estimation are statistical and regression models, but given their normally linear nature, they are error-prone and often cannot model the time variations of this phenomenon with acceptable precision. Therefore, other models are needed to accurately forecast river flow with all effective factors taken into consideration. Over the years, intelligent modeling systems such as support vector machine (SVM), gene expression programming (GEP) and Bayesian network have been widely used in the prediction of nonlinear phenomena. In recent years, the use of intelligent models in river flow forecasting has received considerable attention from researchers. In the following, several notable examples of studies in this area are reviewed.

In a study carried out by Elsafi (2014), an artificial neural network (ANN) was used to estimate flood discharge at several hydrometric stations along Nile River in Sudan. The results of this study showed that ANN model can provide highly accurate estimates of flood discharge. Uysal and Sorman (2017) used a wavelet-artificial neural network model to predict monthly flows in Çamlıdere basin in Turkey and reported that this model showed excellent flow estimation capability. In a study by Dash et al. (2018) on Kerala basin in India, rainfall modeling was performed with the help of artificial neural networks, which were successful in providing good rainfall estimates.

Ghorbani et al. (2018) investigated the performance of hybrid models based on ANN and SVM in estimating the discharge of Zarrineh River in Iran. The results of this study showed that the ANN-based hybrid model was more accurate than the one based on SVM. In a study conducted by Saez et al. (2018), the Soil and Water Assessment Tool (SWAT) and ANN were used to estimate runoff in two basins in Spain. This study reported that the ANN model outperformed the SWAT model in this application. Ghorbani et al. (2018), analyzed the performance of several hybrid artificial intelligent models in the estimation of monthly flow into the Lake Egirdir in Turkey, and concluded that the hybrid model comprising ANN and the firefly algorithm performed better than other hybrid models. Rai and Nagasaka (2018) used radial basis function network (RBFN) and ANN models to estimate runoff in Kathmandu basin in Nepal and found that RBFN was more accurate in this application.

Darbandi and Pourhosseini (2018) assessed the performance of an ANN-firefly algorithm hybrid model in the estimation of the monthly flow of Ajichay basin in Iran and showed that it provides higher accuracy than the ordinary ANN model. In a study by Wang et al. (2018), the monthly flow of the Clearwater River in the United States was predicted by an ANN-based hybrid, which was shown to outperform the basic ANN model. Asadi et al. (2019) used an ANN model to predict the monthly flow of the Haughton River in Australia and evaluated its performance in terms of correlation coefficient, root mean square error, and Nash-Sutcliffe efficiency. The results showed that the developed ANN model has an acceptable performance in estimating monthly flow.

Other notable studies in this area include Jayawardena et al. (2005), Marwala et al. (2007), Aytek et al. (2008), Taheri, and Ghafouri (2012), Kartika et al. (2013), Xiong et al. (2014), Tayfur et al. (2014), Ghorbani et al. (2016a), Ghorbani et al. (2016b), Shamshirband et al. (2016), Ghorbani et al. (2017), and Raheli et al. (2017).

The Kashkan River is one of the most important rivers in Lorestan, Iran and a major source of agriculture and drinking water for many communities in this area, but over the recent years, a decline in the flow of this river has caused many problems in the local catchment. Accurate simulation of the flow of the Kashkan River can contribute to adopting suitable water management measures. Therefore, this study aimed to predict the daily flow of the Kashkan River using MMANN.

Materials and methods

Study area

The Kashkan River is the most flood-prone river in Lorestan Province in the southwestern part of Iran. With an area 66.97km^2, Kashkan basin covers one-third of the Lorestan area and it is an important tributary of the Karkheh River in the south. In the hydrological division of Iran, this basin is part of the Persian Gulf basin. Kashkan basin is located between 33° 5′ 45″ and 33° 44′ 41″ northern latitudes and 47° 31′ 34″ and 48° 12′ 6″ eastern longitudes. The location of the study area is shown in Figure 1.

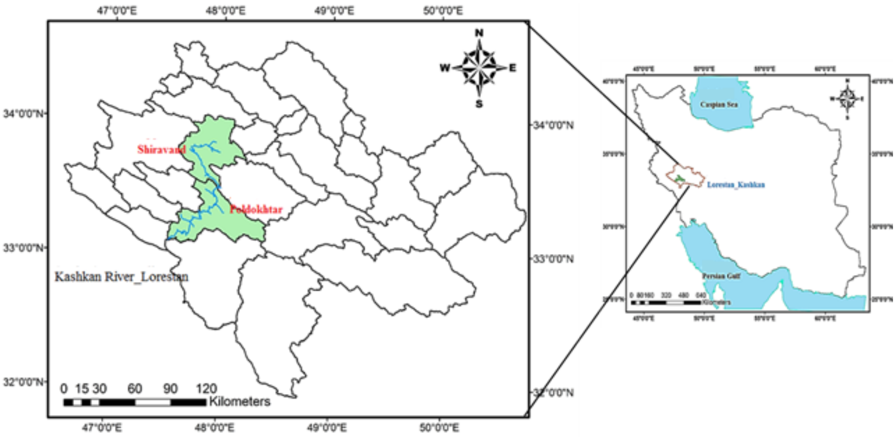

Figure 1. The Study area

Artificial neural network

Artificial neural networks have found extensive application in hydrology and water resources management studies (Nourani et al., 2011). Structurally, an artificial neural network typically consists of an input layer, a number of middle (hidden) layers, and an output layer. The input layer acts as an instrument for importing data and preparing them for processing, the hidden layers consist of the processor nodes, and the output layer produces and presents the values predicted by the network. The first practical applications of artificial neural networks emerged with the introduction of multilayer perceptron networks. It has been shown that among the learning algorithms, using the backpropagation algorithm with feedforward structure, and using three layers is a very rewarding approach for solving complex engineering problems and simulating and predicting hydrological time series (Nourani et al., 2009). The most common activation functions used in backpropagation networks are the sigmoid and hyperbolic tangent functions (Tokar & Johnson, 1999).

Support vector machine

Support vector machine is an efficient learning system based on the theory of constrained optimization that uses the structural risk minimization principle to produce a globally optimal solution (Vapnik, 1995). In SVM regression modeling, the process involves estimating a function based on the dependent variable Y, which itself is a function of several independent variables (x). Like other regression problems, it is assumed that the relationship between independent and dependent variables is characterized by an algebraic function such as f(x) plus some perturbation or allowed error (ε) (Vapnik, 1998).

$$f(x)=W^{T}.\emptyset(x)+b \quad (1)$$

$$y=f(x)+noise \quad (2)$$

where W^T is the transpose of the vector of coefficients, and b is the characteristic constant of the regression function and $\emptyset$ is the kernel function. Here, the goal is to find a functional form for f (x). This is accomplished by training the SVM model with a set of data (training set) (Misra et al., 2009). To obtain W and b, the error function (Equation 3) in the ε-SVM model should be minimized subject to the constraints in Equations (4) and (5) (Hamel, 2009).

$$\frac{1}{2}W^{T}.W+C\sum_{i=1}^{N}\varepsilon_i+C\sum_{i=1}^{N}\varepsilon_i^{*} \quad (3)$$

$$W^{T}.\emptyset(X_i)+b-y_i\le\varepsilon+\varepsilon_i^{*} \quad (4)$$

(5)

$$y_i-W^{T}.\emptyset(X_i)-b\le\varepsilon+\varepsilon_i\ ,$$

$$\varepsilon_i\ ,\ \varepsilon_i^{*}\ge 0\quad ,\quad i=1,2,\dots,N$$

In the above equations, C is a positive integer which determines the penalty applied upon encountering an error during training, $\emptyset$ is the kernel function, N is the number of samples, and ε_i and ε_i^* are the slack variables. The SVM regression function can be rewritten as follows:

$$f(x)=\sum_{i=1}^{N}\bar{\alpha}_i\,\emptyset(x_i)^{T}.\emptyset(x)+b \quad (6)$$

In Equation 6, $\overline{\alpha}_i$ is the mean of the Lagrangian coefficients. It could be difficult to compute $\emptyset(x)$ in its characteristic space (Yoon et al., 2011). To solve this problem, it is typical to build the SVM regression model with a kernel function of the following form.

$$K(X_J, X) = \emptyset(X_i)^T \sqrt{b^2 - 4ac} \quad (7)$$

Different kernel functions can be used to construct different types of ε-SVM. The kernel functions that can be used in SVM regression models include polynomial kernel, and radial basis function (RBF) kernel, and linear kernel, which can be obtained from the following 8-10 equations.

The structure of the SVM model is illustrated in Figure 2. Since RBF, linear and polynomial kernels are the most commonly used kernel functions (Basak et al., 2007; Vapnik and Chervonenkis, 1991), this study also used these three kernel functions. It should be noted that the computations of SVM were performed by coding in MATLAB, and the parameters of the kernel functions were optimized through trial and error.

$$K(x, x_j) = (t + x_i . x_j)^d \quad (8)$$

$$K(x, x_i) = \exp\left(-\frac{\|x - x_i\|^2}{2\sigma^2}\right) \quad (9)$$

$$K(x, x_j) = x_i . x_j \quad (10)$$

Wavelet neural network

Wavelet transform (WT) has been developed as an alternative to short-time Fourier transform (STFT) and specifically to overcome the frequency resolution problems of that transform. Like STFT, WT involves partitioning the signal into several windows and executing the transform procedure on each window separately (Wang et al., 2000). But the most important difference between STFT and WT is that in the latter, not only the window length or frequency resolution but also the window width or frequency scale vary depending on the type of frequency. In other words, WT operates based on the scale rather than frequency and can be viewed as a time-scale transform. Hence, using the wavelet transform, the signal can be expanded at high scales to give a detailed view or compressed at low scales to give a global view of the signal (Wang et al, 2000). A wavelet means a small wave, part or window of the main signal whose energy is concentrated in time. Using the wavelet transform or analysis, a mother signal or time series can be decomposed into multiple wavelets with different resolutions and scales. Therefore, wavelets are translated and scaled samples of the mother signal, which are extremely attenuating oscillate over a finite length. This feature of wavelet transform makes it suitable for local analysis of unsteady and transient time series (Shin et al, 2005).

Wavelet transform has been defined in two forms: continuous and discrete.

Continuous Wavelet Transform (CWT)

Continuous wavelet transform of the function f(t) has been defined as follows (Vapnik, 1998).

$$\begin{aligned} CWT_f^{\psi}(s,\tau) &= \Psi_f^{\psi}(s,\tau) \\ &= \frac{1}{\sqrt{|s|}} \int_{-\infty}^{+\infty} f(t)\psi^*\left(\frac{t-\tau}{s}\right) dt \\ &= \langle f(t), \psi_{s,\tau}(t) \rangle \end{aligned} \quad (11)$$

$$\psi_{s,\tau}(t) = \frac{1}{\sqrt{|s|}} \psi\left(\frac{t-\tau}{s}\right) \quad (12)$$

Equation (12) is a bivariate relationship for s, which is the scale parameter (inverse of frequency), and τ, which is the translation parameter. In the above equations, the symbol * denotes complex conjugate, ψ is the mother wavelet or window function, and $\frac{1}{\sqrt{|s|}}\psi(\frac{t-\tau}{s})$ are the wavelets obtained by the translation and scaling of the mother wavelet (Wang et al, 2000). The term mother is used because all translated and scaled samples (daughter wavelets) are obtained from this function. In other words, the mother wavelet is a template for other windows. The symbol ⟨...⟩ denotes the vector multiplication of two functions in the signal space.

Multiple Models Driven by Artificial Neural Networks

Another strategy for implementing the models discussed in this paper is to run

MMs by an artificial neural network (MM-ANN). Neural networks are parallel information processing systems that imitate the logical processes of the human brain. These systems consist of a set of neurons or nodes placed in multiple layers, with conversion functions and weights and biases which can be adjusted according to inputs to produce the required outputs. Each neuron in each layer is linked to all neurons in the subsequent layer, but the same cannot be said for neurons in each individual layer. These neurons provide suitable conversion functions for the weighted input parameters. The neural network used in this study is a feedforward multilayer perceptron (MLP) that is trained by a backpropagation technique such as the least-squares method. In the topology considered for ANNs, the network consists of three layers: an input layer, a hidden layer, and an output (target) layer. In this study, ANNs are used as artificial intelligence for executing multiple models (AIMM). The strategy used for this purpose is as follows:

(i) There are two levels of supervised learning.
(ii) At level 1 (L1), two models of supervised artificial intelligence models are built: SVM KKT and SVM-FFA. The inputs of these models are determined by their structure, which is unknown and will be determined through trial and error (as discussed in the introduction)
(iii) At level 2 (L2), an ANN is used to execute the models of L1. The inputs of this level are the outputs of the above models. L2 is called MM-ANN.
(iv) The obtained values are used as target values for both L1 and L2 models.
(v) ANN is first executed in the backpropagation mode to identify the parameters of each model and then executed in the feed-forward mode to generate the prediction outputs, which are then compared with the observed values for performance evaluation. The merit of this strategy is the ability to learn on two levels.

Evaluation criteria

The accuracy and performance of the models were evaluated by the use of correlation coefficient (R), root mean square error (RMSE) and mean absolute error (MAE), which are given by the following equations. The best values for R, RMSE, and MAE are 1, 0, and 0, respectively.

$$R=\frac{\sum_{i=1}^{N}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{N}(x_i-\bar{x})^2\sum_{i=1}^{N}(y_i-\bar{y})^2}} \qquad -1\leq R\leq 1 \quad (10)$$

$$RMSE=\sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i-y_i)^2} \quad (11)$$

$$MAE=\frac{1}{n}\sum\left|x_i-y_i\right| \quad (12)$$

In the above equations, x_i and y_i are the values observed and predicted at the i-th time step, N is the number of time steps, and $\bar{x}$ and $\bar{y}$ are the means of observed and predicted values. In addition to the above criteria, the diagrams of distribution and time series of observed-predicted values were also used to further analysis.

Results and Discussion

One of the most important steps in modeling is the selection of a suitable combination of input variables. For this selection, first, the cross-correlation of input and output variables was computed, and then the input parameters that would give a suitable model for predicting the flow of the Kashkan River were selected accordingly. The parameters selected in this step are listed in Table 1. In this table, P(t-2), P(t-1), P(t), Q(t-1,), Q(t-2), Q(t-3), denote river flow at times t-1, t-2, and t-3, and are the model inputs, and the output is Q(t) or river flow at time t. Regarding the training, it should be remembered that the uncertain nature of the mechanisms that govern river flow not only increase the modeling complexity and memory requirement but also decrease its accuracy. Therefore, river flow modeling should be performed using the most effective observational data in the training (Kisi et al., 2006). Since the method of this study involves predicting discharge based on the sequence of discharge in preceding days, only the normalized discharge values with sequences of up to 5 days long were used in the training. As shown in the table, this operation was performed with different combinations of sequences, which are referred to as patterns. Also, given the existence of cross-correlation value of more than 0.500 between input and output data (Table 2), different combinations of input parameters were tested to determine the best model for estimating daily flow rates of Kashan River. For this purpose, we used the daily flow data of Poledokhtar hydrometric station in Lorestan, which consists of 3650 records collected on a daily basis over a 10-year period (2006-2016). Ultimately, 2920 records were selected for training and the remaining 730 records were used for validation of the trained models. This selection was made according to the recommendations that 80% of the data should be randomly selected for training and 20% of the data (consisting of all varieties) should be reserved for testing (Nugy et al, 2002). Table 3 shows the statistical properties of the flow discharge parameter.

Table 1. The cross-correlation between input and output parameters

	P(t)	P(t-1)	P(t-2)	Q(t-1)	Q(t-2)	Q(t-3)
Q(t)	0.74	0.65	0.54	0.7	0.58	0.51

Table 2. Selected compositions of input parameter models, multiple models driven by artificial neural networks, wavelet neural network, support vector machines and artificial neural network

Number	Input	Output
1	P(t)	Q(t)
2	P(t),P(t-1)	Q(t)
3	P(t),P(t-1),P(t-2)	Q(t)
4	P(t),P(t-1),P(t-2),Q(t-1)	Q(t)
5	P(t),P(t-1),P(t-2),Q(t-1),Q(t-2)	Q(t)
6	P(t),P(t-1),P(t-2),Q(t-1),Q(t-2),Q(t-3)	Q(t)

Table 3. The statistical properties of the parameters used in the statistical period

Skewness	Standard deviation	Maximum	Mean	Minimum	Parameter	
1.521	20.129	119	23.435	0.011	Training	Discharge(m^3/s)
1.859	19.573	111	18.572	0.312	Validation and Testing	

Artificial neural network

To determine the best network structure and specifications, daily discharge modeling was performed with MLPs using different numbers of neurons. The output layers of the networks were constructed with the hyperbolic tangent function, which is a commonly used activation function. MPLs were trained by an error backpropagation training algorithm called the Levenberg-Marquardt algorithm to achieve faster convergence in the training phase. Different combinations of activation functions were used in the hidden layer(s). For the training phase, the number of iterations was set to 1000 and performance was evaluated in terms of mean square error. The number of neurons in the input and output layers was set according to the nature of the problem, but the number of hidden neurons was determined by trial and error with the goal of minimizing the error value. To determine the best number of hidden neurons, the algorithm was executed with a gradually increasing number of hidden neurons until there was no further improvement in the accuracy of outputs. Table 4 compares the performance of networks with different structures and specifications. This table also shows the statistical specifications of training and validation data. As can be seen, structure 6 with the correlation coefficient of 0.898 and the root mean square error of 0.071 and mean absolute error of 0.006 in the validation phase was found to be the most suitable structure for modeling of the daily maximum discharge. Figure 2 shows the observed and predicted values of the ANN model in validation phase.

Table 4. The analysis of ANN model results for river flow inputs.

Structure	Training			Testing		
	R	RMSE	MAE	R	RMSE	MAE
1	0.823	0.621	0.208	0.841	0.224	0.092
2	0.837	0.477	0.174	0.852	0.201	0.078
3	0.843	0.317	0.162	0.864	0.162	0.067
4	0.854	0.164	0.036	0.875	0.112	0.034
5	0.863	0.138	0.027	0.891	0.088	0.018
6	0.886	0.115	0.010	0.898	0.071	0.006

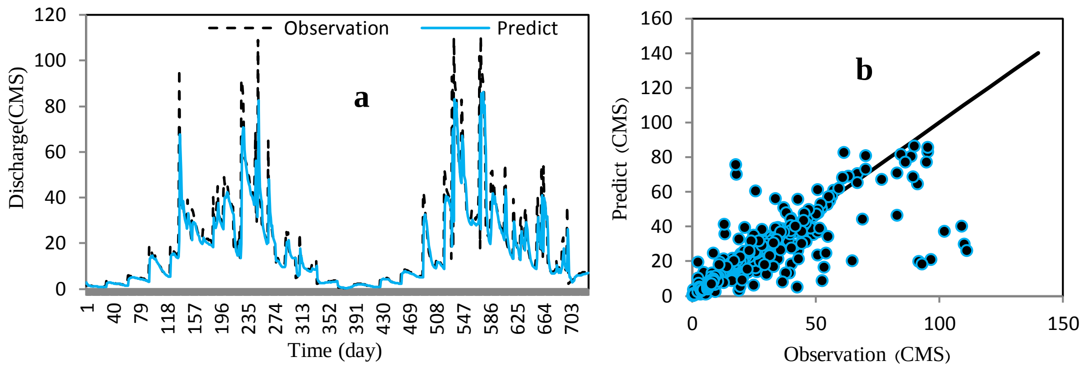

Figure 2. Observed and predicted values of the ANN model in validation phase

Wavelet neural network

Daily discharge of Kashkan station was also modeled with wavelet neural networks with different numbers of hidden neurons and layers. For the wavelet neural network model, first, a suitable wavelet type (symlet) was selected. Then, transform was applied to the data to extract the approximation coefficients and their details. For the activation function, the Mexican hat wavelet function, which is the second derivative of the Gaussian function, was used. The training was performed using the gradient descent algorithm, which is commonly used in the training of neural networks, network error minimization, and adjustment of network parameters. As shown in Table 5, structure 6 with a correlation coefficient of 0.944, root mean square error of 0.025 and a mean absolute value of 0.002 in the validation phase was the most suitable choice for the modeling of discharge at daily time scale. Figure 3 displays the diagram of changes in the predicted and observed values versus time for the best model obtained for the validation data. As can be seen, the wavelet neural network model has had an acceptable performance in the estimation of most of the values. As Figure 3 shows, the wavelet neural network model has performed well in estimating most of the minimum and maximum values and has generated very accurate estimates for these values.

Table 5. The analysis of WNN model results for river flow inputs.

Structure	Training			Testing		
	R	RMSE	MAE	R	RMSE	MAE
1	0.864	0.158	0.084	0.888	0.082	0.052
2	0.871	0.132	0.068	0.894	0.068	0.043
3	0.882	0.114	0.048	0.905	0.057	0.026
4	0.894	0.094	0.020	0.917	0.045	0.012
5	0.908	0.075	0.009	0.935	0.032	0.005
6	0.917	0.038	0.003	0.944	0.025	0.002

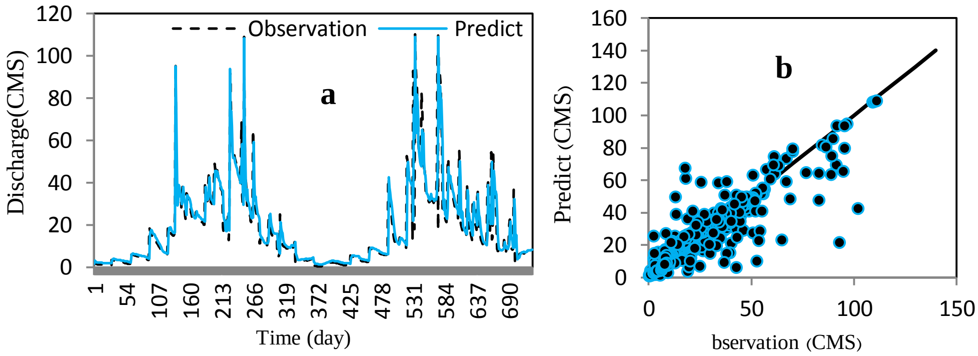

Figure 3. Observed and predicted values of the WNN model in validation phase

Support vector machine

To estimate the daily flow of Kashan River with the SVM model, first, data were normalized to reduce the amplitude of variations in daily flow data of this river. Then, the optimal parameter setting for the SVM model, including the values of ε and C, had to be determined. Given the use of RBF kernel function in the SVM model, and its good accuracy in estimating the daily flow of rivers (Lin et al., 2006; Liong et al., 2002), the characteristic value of this function (γ) had to be determined. The first two parameters (ε and C) were obtained from a network search optimization algorithm and the last variable (γ) was determined through trial and error. It should be noted that given the low speed of the network search optimization algorithm, this task was performed using the modified network search algorithm proposed by Chen and Yu (5), which is known as two-step network search algorithm, in combination with cross-validation. For this purpose, first, large-scale networks were analyzed to determine the range of ε and C for a constant γ. Then, the range thus found was subdivided into progressively smaller networks until the values of ε and C were determined. The same process was repeated for other γ values, thus producing different models for different γ values. Among the developed models, the ones with the lower errors were determined and their ε, C and γ values were extracted. The results obtained for the SVM model are presented in Table 6. According to this table, model structure 6 with a correlation coefficient of 0.905, root mean square error of 0.068m^3/s and a mean absolute error value of 0.003 m^3/s in the validation phase outperformed other structures. As shown in Table 6, the SVM model performed very well in predicting the daily flow values of the Kashkan River even when only one input parameter was used. This means that even if there are gaps in statistical reports, the SVM model can produce good flow estimates based on minimal inputs such as the flow rate of the previous day. Figure 4 shows the diagram of the best model obtained for the validation data. In Figure 4-b, most of the estimates are around the bisector line (y = x), which means good consistency between predicted and observed values. Figure 4-a, which shows the variations of predicted and observed values over time, also demonstrates the good accuracy of the model in estimating most of the values. Figure 4-b also shows that the SVM model has underperformed in estimating some flood flows and peak flows on wet days, as the points corresponding to these estimations are away from the bisector line.

Table 6. The analysis of SVM model results for river flow inputs.

Structure	Training			Testing			SVM Parameters		
	R	RMSE	MAE	R	RMSE	MAE	C	ε	γ
1	0.848	0.659	0.195	0.858	0.211	0.087	10	0.3	0.63
2	0.854	0.461	0.161	0.873	0.194	0.072	10	0.3	0.42
3	0.863	0.306	0.154	0.876	0.156	0.061	10	0.2	0.28
4	0.859	0.157	0.023	0.884	0.107	0.015	10	0.2	0.25
5	0.871	0.124	0.013	0.897	0.085	0.008	10	0.1	0.22
6	0.892	0.104	0.004	0.905	0.068	0.003	10	0.1	0.17

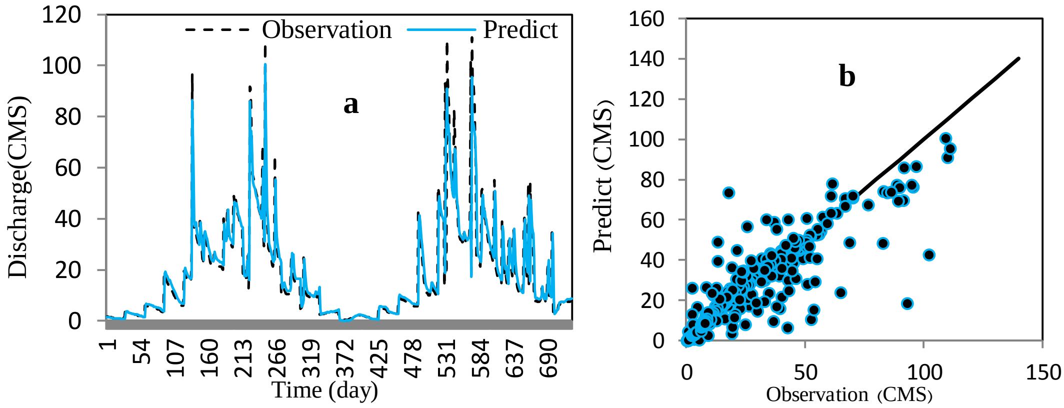

Figure 4. Observed and predicted values of the SVM model in validation phase

Multiple Models Driven by Artificial Neural Networks

The MMANN model was used to compare the results of the developed model with those of conventional artificial intelligence models. As shown in Table 7, structure 6 with a correlation coefficient of 0.960, root mean square error of 0.021, and a mean absolute error of 0.001 in the validation phase is the best structure for modeling discharge at daily time scale. Figure 5 shows the diagrams of estimation accuracy for the best model for the validation data. As these results indicate, the MMANN model has had acceptable performance in estimating all values.

Table 7. The analysis of MMANN model results for river flow inputs.

Structure	Training			Testing		
	R	RMSE	MAE	R	RMSE	MAE
1	0.868	0.145	0.074	0.901	0.075	0.032
2	0.872	0.126	0.053	0.914	0.063	0.021
3	0.886	0.107	0.044	0.928	0.048	0.015
4	0.904	0.084	0.015	0.944	0.034	0.008
5	0.918	0.061	0.007	0.951	0.028	0.002
6	0.926	0.032	0.002	0.960	0.021	0.001

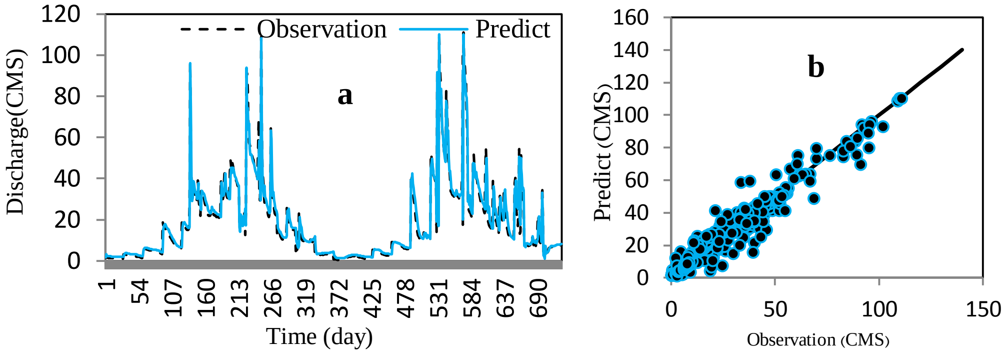

Figure 5. Observed and predicted values of the MMANN model in validation phase

Comparison of model performance

As Table 8 indicates, the comparison of the optimal solutions obtained from different models showed that all four models can simulate the daily flow of the Kashkan River with good accuracy and minimal error. However, among these models, MMANN had the highest correlation coefficient (0.960) and the lowest root mean square error and mean absolute error ($0.021m^3/s$, and $0.001m^3/s$) at the validation phase. The violin plots of the four models are illustrated in Figure 6. In this figure, the average of the estimates of the ANN model is lower than that of other models. The lower bound of the MMANN model indicates that it has outperformed others in estimating minimum values.

Table 7. The analysis of MMANN, SVM, WNN, ANN model results for river flow inputs.

Model	Training			Testing		
	R	RMSE	MAE	R	RMSE	MAE
ANN	0.886	0.115	0.010	0.898	0.071	0.006
SVM	0.892	0.104	0.004	0.905	0.068	0.003
WNN	0.917	0.038	0.003	0.944	0.025	0.002
MMANN	0.926	0.032	0.002	0.960	0.021	0.001

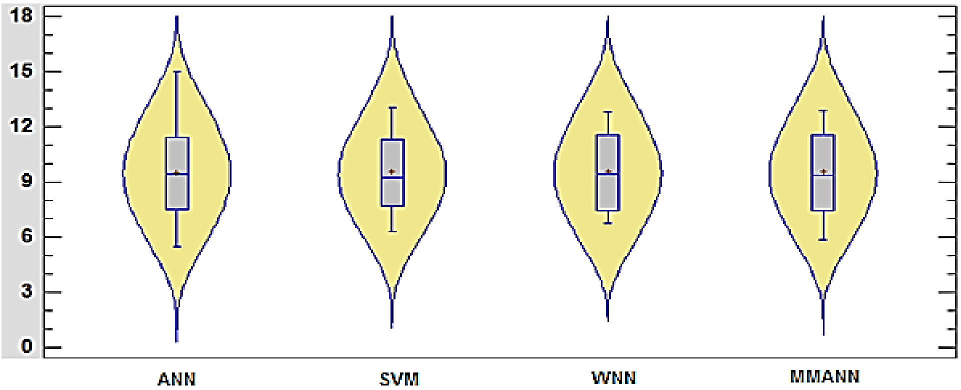

Figure 6. Violin Plot of observed and predicted values of the MANN, WNN, SVM and ANN models in training and testing phase

Conclusion

This study aimed to evaluate the performance of several models in simulating the daily flow of the Kashkan River in Lorestan Province of Iran. The models used for this purpose included artificial neural network, wavelet neural network, support vector machine, etc. The observed flow values were compared with those predicted by the models (Bayesian network, gene expression programming, and support vector machine) based on a set of evaluation criteria. The results of this study can be summarized as follows.

All of the studied models performed better in a structure with 1 to 5 lags than in other structures.

The SVM model was able to accurately predict daily flow values based on minimum inputs. This capability is especially helpful for reaching more accurate estimates in cases where stations have missing records. According to the evaluation criteria, all of the models could generate accurate daily river flow estimates, but among them, the MMANN model was more accurate and less error-prone than ANN and SVM models. Overall, these results suggest that the MMANN model can serve as an effective tool for predicting daily river flows and thus facilitating the development and implementation of surface water management strategies and supporting management decisions with the purpose of maintaining and restoring river discharge.

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Conflict of interest

The authors declare that they have no conflict of interest.

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