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Streamflow Forecasting and Estimation Using Least Square Support Vector Regression and Adaptive Neuro-Fuzzy Embedded Fuzzy c-means Clustering

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Abstract This paper investigates the ability of least square support vector regression (LSSVR) and adaptive neuro-fuzzy embedded fuzzy c-means clustering (ANFIS-FCM) in forecasting and estimation of monthly streamflows. In the first part of the study, the LSSVR and ANFIS-FCM models were tested in 1-month ahead streamflow forecasting by using cross-validation method. Monthly streamflow data belonging to two stations, Besiri Station on Garzan Stream and Baykan Station on Bitlis Stream, in Dicle Basin of Turkey were used. The LSSVR and ANFIS-FCM results were compared with autoregressive moving average (ARMA) models. It was found that the LSSVR models performed better than the ANFIS-FCM and ARMA models in 1-month ahead streamflow forecasting. The ANFIS-FCM models are also found to be better than the ARMA models. The effect of periodicity on forecasting performance of the LSSVR models was also investigated. Adding periodicity component as input to the LSSVR models significantly improved the models' accuracy in forecasting. In the second part of the study, the accuracy of the LSSVR and ANFIS-FCM models was tested in streamflow estimation using data from nearby stream. Based on the results, the LSSVR was found to be better than the ANFIS-FCM and successfully used in estimating monthly streamflows by using nearby station data.

Keywords Streamflow · Forecasting · Estimation · Least square support vector regression

1 Introduction

The forecasting and estimating future streamflows are very important for many of the activities associated with planning and operation of the components of a water resource system such as

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operation of water infrastructures, flood mitigation, dam planning, operation of water reservoirs, distribution of drinking water and planning for navigation. Therefore, forecasting of river flows can be considered as one of the main research topics in hydrology (Awchi 2014).

Traditionally, the autoregressive moving average (ARMA) models have been widely used for forecasting water resources time-series (Maier and Dandy 2000). The main disadvantage of these models is assuming linear relationships among variables. In the real world, however, streamflow pattern is highly nonlinear and non-stationary (Hsu et al. 1995). Nonlinear model such as least square support vector regression (LSSVR), which is suited to complex nonlinear problems, is needed for the analysis of real world temporal data.

In the last decades, the application of artificial intelligence has received much attention in water resources (Kisi 2006, 2007; Guven 2009; Guven and Talu 2010; Kumar et al. 2011; Mustafa et al. 2012; Sanikhani and Kisi 2012; Awchi 2014). Recently, the support vector regression (SVR) has been widely used in solving hydrologic problems (Sivapragasam et al. 2001; Vapnik et al. 1997; McNamara et al. 2005; Awad et al. 2007; Kaheil et al. 2008; Kisi and Cimen 2009; Chen et al. 2010; He et al. 2014). Sivapragasam et al. (2001) used SVR for forecasting rainfall and runoff. The SVR was successfully employed to forecast flood stage by Liong and Sivapragasam (2002), to develop rating curves at three gauging stations in Washington by Sivapragasam and Muttil (2005), to predict water level fluctuations of Lake Erie by Khan and Coulibaly (2006), to forecast long-term discharges by Lin et al. (2006), to predict daily sediments in natural rivers by Cimen (2008), to model daily potential evapotranspiration by Kisi and Cimen (2009), to downscale the daily precipitations by Chen et al. (2010), to predict daily streamflows with weather and climate inputs by Rasouli et al. (2012), to forecast daily dam water levels by Hipni et al. (2013), to improve forecast of annual rainfall-runoffs by Wang et al. (2013), and to forecast daily river flows in the semiarid mountain region by He et al. (2014). The major disadvantage of the SVR method is its higher computational burden for the constrained optimization problems. This drawback of the SVR has been overcome by LSSVR method, which solves linear equations instead of a quadratic programming problem (Wang and Hu 2005). LSSVR has been successfully applied to solve different problems in engineering (Tao et al. 2008; Huang et al. 2009; Deng and Yeh 2010; Pahasa and Ngamroo 2011; Shokrollahi et al. 2013; Kamari et al. 2014; Hemmati-Sarapardeh et al. 2014). Tao et al. (2008) used LSSVR for prediction of bearing raceways super finishing. Huang et al. (2009) predicted effluent parameters of wastewater treatment plant based on LSSVR. Deng and Yeh (2010) applied LSSVR to the airframe wing-box structural design cost estimation. Pahasa and Ngamroo (2011) used LSSVR for power system stabilization by SMES. Shokrollahi et al. (2013) predicted CO_2-reservoir oil minimum miscibility pressure using LSSVR. Kamari et al. (2014) used LSSVR for efficient screening of enhanced oil recovery and prediction of economic analysis. Hemmati-Sarapardeh et al. (2014) determined the reservoir oil viscosity using LSSVR approach. However, there are limited studies in the literature related to application of LSSVR in water resources (Guo et al. 2011; Hwang et al. 2012; Kisi 2012, 2013; Okkan and Serbes 2013). Guo et al. (2011) used LSSVR for prediction of reference evapotranspiration and found promising results. Hwang et al. (2012) forecasted daily water demand and daily inflows by using LSSVR method and compared with neural networks (NN) and multiple linear regression (MLR) models. They indicated that the LSSVR performed better than the NN and MLR methods. Kisi (2012) modeled discharge-sediment relationship by LSSVR and compared with NN and sediment rating curve (SRC) models. The results showed that the proposed model gave better accuracy than the NN and SRC. Kisi (2013) applied LSSVR for modeling daily reference evapotranspiration and compared with feed forward NN and empirical models. He showed that LSSVR model performed better than the NN and other models. Okkan and Serbes (2013) used and proposed LSSVR with wavelet in reservoir inflow modeling. Despite the reported success of employing LSSVR in numerous studies, to the best of our knowledge the capability of LSSVR has not yet been examined in terms of streamflow forecasting.

In the last decades, adaptive neuro-fuzzy (ANFIS) method has also been successfully applied in water resources (Chen et al. 2006; Kisi 2006; Yarar et al. 2009; Kisi et al. 2012; Rezaeianzadeh et al. 2014; Sharma et al. 2015) The ANFIS was successfully employed to forecast flood by Chen et al. (2006); to model daily pan evaporation by Kisi (2006); to estimate level changes of Lake Beysehir by Yarar et al. (2009); to forecast daily intermittent streamflows by Kisi et al. (2012); to forecast flood flows of Khosrow Shirin watershed located in the Fars Province of Iran by Rezaeianzadeh et al. (2014); and to simulate streamflows in El Nino Southern Oscillation (ENSO)-affected watershed by Sharma et al. (2015). In the ANFIS related literature, the grid partition (GP) method were generally used for training. The GP method, however, uses many fuzzy rules and many parameters to be optimized which makes it unsuitable for many input variables (Chen and Gao 2012). Therefore, in the present study, the fuzzy c-means clustering (FCM) was used instead of GP. To the best of the authors' knowledge, no research work has yet been published on the forecasting of monthly streamflows using adaptive neuro-fuzzy embedded fuzzy c-means clustering (ANFIS-FCM) method.

The study aims to investigate the ability of LSSVR and ANFIS-FCM methods in monthly streamflow forecasting and estimation. The effect of periodicity on forecasting performance of the LSSVR and ANFIS-FCM models was also investigated. The LSSVR and ANFIS-FCM techniques were also used to estimate monthly flows of Bitlis Stream using the data of Garzan Stream. The term forecasting is used here for the model applications where the input and output data belonging to the same river station in the study. The term estimation is used when input and output data belong to different stations.

2 Least Square Support Vector Regression

SVR as one of the most efficient and powerful learning machines has been much attended during the last few years (Suykens and Vandewalle 1999; Awad et al. 2007; Kisi and Cimen 2009; Chen et al. 2010; He et al. 2014). Any function can be expressed by SVR in the following format (Suykens et al. 2002) as

$$f(X) = w^T \varphi(X) + b \tag{1}$$

where w shows the m-dimensional weight vector, φ is the mapping function and b is the bias term. Vapnik proposed minimization of the cost function $\frac{1}{2} w^T + c\sum_{i=1}^{M} \left(\xi_k - \xi_k^*\right)$ to calculate w and b (Suykens et al. 2002). This cost function is subjected to the following constraints:

$$\begin{cases} y_k - w^T \varphi(x_k) - b \le \varepsilon + \xi_k, & k = 1, 2, \ldots, M \\ w^T \varphi(x_k) + b - y_k \le \varepsilon + \xi_k^* & k = 1, 2, \ldots, M \\ \xi_k - \xi_k^* \ \ge \ 0 \ , & k = 1, 2, \ldots, M \end{cases} \tag{2}$$

Where x_k and y_k indicate the k_{th} input and output data, respectively; ε stands for the fixed precision of the function approximation; ξ_k and ξ_k^* are the two slack variables. The tuning parameter, c of the SVR controls the amount of deviation from the interested ε. As a matter of fact, one of the tuning parameters of the SVM is c. To minimize the cost function and its constraints, the Lagrangian of this problem should be used (Suykens et al. 2002):

$$L(a,a^*) = -\frac{1}{2}\sum_{k,l=1}^{M}(a_k - a_k^*)(a_l - a_l^*)K(x_k,x_l) - \varepsilon\sum_{k=1}^{M}(a_k - a_k^*) + \sum_{k=1}^{M}y_k(a_k - a_k^*) \quad (3)$$

$$\sum_{k=1}^{M}(a_k - a_k^*) = 0,\ a_k, a_k^* \in [0,c] \quad (4)$$

$$K(x_k,x_l) = \varphi(x_k)^T\varphi(x_l),\ k = 1,2,\ldots,\mathrm{N} \quad (5)$$

Where a_k and a_k^* are Lagrangian multipliers. The final form of the SVR can be obtained as (Esfahani et al. 2015)

$$f(x) = \sum_{k,l=1}^{M}(a_k - a_k^*)K(x,x_k) + b \quad (6)$$

A quadratic programming problem is solved in order to solve the above problem and determine a_k, a_k^* and and b, which is considerably difficult. For improving the original SVR method, Suykens and Vandewalle (1999) proposed the least square modification of the SVR (LSSVR). The LSSVR originated from SVR is a powerful technique for solving non-linear problems, classification, function and density estimation (Kumar and Kar 2009). Figure 1 shows the procedure of LSSVR. The cost function of the LSSVR is

$$minJ(w,e) = \frac{1}{2}w^T w + \frac{\gamma}{2}\sum_{i=1}^{M}e_i^2 \quad (7)$$

that subject to following constraints

$$y_i = w^T\varphi(x_i) + b + e_i \quad (i = 1,2,\ldots,M) \quad (8)$$

where γ is the regularization constant and e_i is the training error for x_i.

To derive solutions w and e, the Lagrange Multiplier optimal programming method is applied to solve Eq. (7); the objective function can be obtained by changing the constraint problem into an unconstraint problem. The Lagrange function L can be given as

$$L(w,b,e,\propto) = J(w,e) - \sum_{i=1}^{M}a_i\{w^T\varphi(x_i) + b + e_i - y_i\} \quad (9)$$

where a_i denotes Lagrange multipliers.

According to the Karush-Kuhn-Tucker (KKT) conditions (Flecher 1987), the optimal conditions can be derived after taking the partial derivatives of Eq. (9) with respect to w, b, e and a, respectively as

$$\begin{cases} w = \sum_{i=1}^{m}a_i\varphi(x_i) \\ \sum_{i=1}^{m}a_i = 0 \\ a_i = \gamma\, e_i \\ w^T\varphi(x_i) + b + e_i - y_i = 0 \end{cases} \quad (10)$$

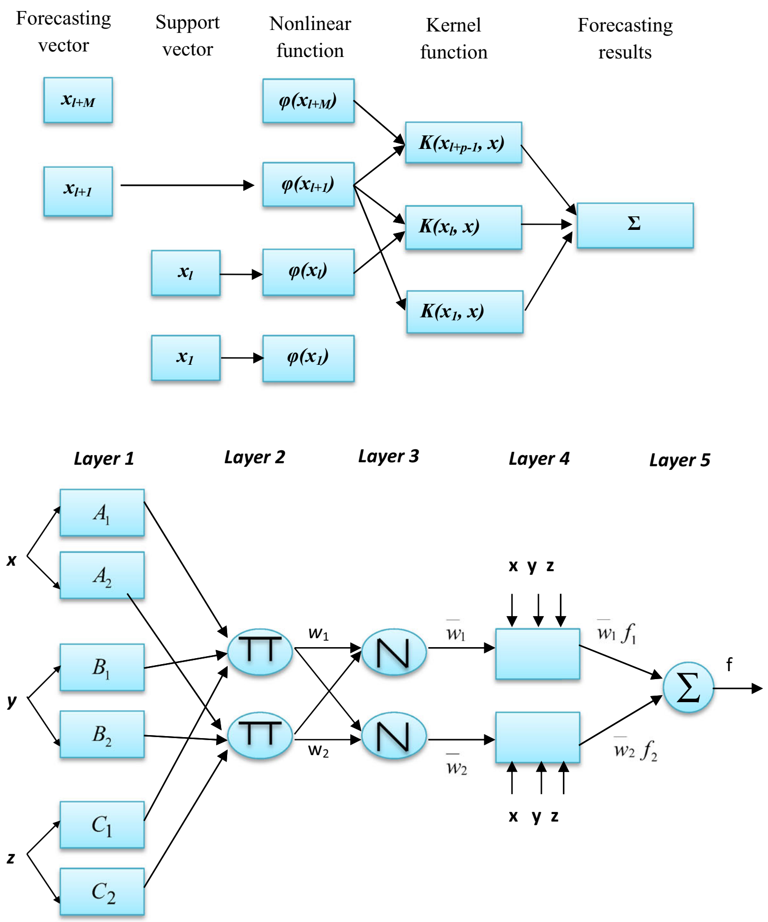

Fig. 1 LSSVR and ANFIS models for streamflow forecasting

After elimination of e_i and w, the linear equations are obtained as

$$\begin{bmatrix} 0 & -Y^T \\ Y & ZZ^T + I/\gamma \end{bmatrix} \begin{bmatrix} b \\ a \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \tag{11}$$

where $Y=y_1, \ldots, y_m$, $Z=\varphi(x_1)^T y_1, \ldots, \varphi(x_m)^T y_m$, $I=[1, \ldots, 1]$, $a=[a_1, \ldots, a_l]$.

Kernel function can be defined as $K(x,x_i)=\varphi(x)^T\varphi(x_i)$, $i=1, \ldots,$ M, according to the Mercer's condition. Thus, the LSSVR becomes

$$f(x) = \sum\nolimits_{i=1}^{m} a_i K(x, x_i) + b \tag{12}$$

The RBF kernel function, commonly used in regression problems, was used in this study. It can be defined as

$$K(x, x_i) = exp\left(-\|x - x_i\|^2 / 2\sigma^2\right) \tag{13}$$

LSSVR has two tuning parameters, γ and σ^2 which are obtained by minimization of the deviation of the LSSVR model from measured values (Shu-gang et al. 2008).

3 Adaptive Neuro-Fuzzy Inference System

ANFIS, first introduced by Jang (1993), is a universal approximator and is capable of approximating any real continuous function on a compact set. ANFIS has a structure composed of a number of nodes connected to each other through directional links. Each node is characterized by a node function consists of fixed or adjustable parameters (Jang et al. 1997).

As an example, for a fuzzy inference system (FIS) having three inputs x, y and z and one output f, the rule base contains two fuzzy if-then rules of Takagi and Sugeno's type can expressed as

$$\text{Rule 1: If } x \text{ is } A_1, y \text{ is } B_1 \text{ and } z \text{ is } C_1 \text{ then } f_1 = p_1 x + q_1 y + r_1 z + s_1 \tag{14}$$

$$\text{Rule 2: If} x \text{ is } A_2,\ y \text{ is } B_2 \text{ and } z \text{ is } C_2 \text{ then } f_2 = p_2 x + q_2 y + r_2 z + s_2 \tag{15}$$

Here f_1 and f_2 indicate the output function of rule 1 and rule 2, respectively. The ANFIS structure is shown in Fig. 1. The node functions in each layer are described below.

Every square node i in layer 1 is an adaptive node with a node function $O_{l,i}$=$\varphi A_i(x)$, for i= 1, 2 where x is the input to the i_{th} node and A_i is a linguistic label (such as "small" or "big") associated with this node function. $O_{l,i}$ is the membership function (MF) of a fuzzy set A (e.g., A_1, A_2, B_1, B_2, C_1, C_2) and it specifies the degree to which the given input x satisfies the quantifier A_i. $\varphi A_i(x)$ is usually chosen to be Gaussian function with maximum equal to 1 and minimum equal to 0 as

$$\varphi A_i(x) = \exp\left(-\left(\frac{x-a_i}{b_i}\right)^2\right) \tag{16}$$

where $\{a_i, b_i\}$ is the parameter set. Parameters of this layer are called as premise parameters. Every circle node in layer 2 is labelled Π which multiply the incoming signals and sends the product out. For instance, w_i=$\varphi A_i(x)\varphi B_i(y)\varphi C_i(z)$, i=1, 2. The output of each node indicates the firing strength of a rule. Every circle node in layer 3 is labelled N. Here the ratio of the ith rule's firing strength to the sum of all rules' firing strengths is calculated by ith node as

$$\overline{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1,\ 2. \tag{17}$$

Every square node in layer 4 has a node function $O_{4,i} = \overline{w}_i f_i = \overline{w}_i(p_i x + q_i y + r_i z + s_i)$ where $\overline{w}_i$ is the output of layer 3, and $\{p_i, q_i, r_i, s_i\}$ is the parameter set. Each parameter of this layer is called as consequent parameters. The single circle node in layer 5 is labelled Σ calculates the final output as the summation of all incoming signals

$$O_{5,i} = \sum_{i=1} \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{18}$$

Thus, an ANFIS network have been constructed which is functionally equivalent to a first-order Sugeno FIS. ANFIS method use linear or constant functions for the output. Detailed information for ANFIS can be obtained from Jang (1993).

In the present study, ANFIS with fuzzy c-means clustering (ANFIS-FCM) were applied. In the FCM method, the data points are grouped by measuring the potential of data points in the feature space. The mountain clustering method is used for estimating number of clusters and the cluster centers (Chiu 1994; Cobaner 2011). The fuzzy c-means clustering (FCM) is a modification of the K-means algorithm which owns some limitations and may not work appropriately with big data set. The FCM minimizes intra cluster variance (Ayvaza et al. 2007) and comprises grouping of data by means of the clustering algorithm. In FCM, the distance or objective squared error function is minimized.

4 Case Studies

In this study, the monthly streamflow data from two stations, Besiri Station (No: 2603) on the Garzan Stream and the Baykan Station (No: 2610) on the Bitlis Stream, in the Firat-Dicle Basin of Turkey were used. Figure 2 illustrates the location of the stations. The drainage areas at these sites are 2450 km^2 for Besiri and 636 km^2 for Baykan. The observed data are 30 years (360 months) long with an observation period between 1965 and 1994 for both stations. The observed data obtained from the report of the Turkish General Directorate of Electrical Power Resources Survey and Development Administration are for hydrologic years, i.e., the first month of the year is October and the last month of the year is September.

In the present study, cross validation method was applied and whole data were divided into four training/testing parts to get effective modeling. In all the applications, three parts were used in training and remaining one part in testing. In each application, test part was changed and thus four different applications were employed. The statistical properties of each data set used in the study are given in Table 1 for the both stations. The observed monthly streamflows show high positive skewness (Csx=1.75 and 2.29). The auto-correlations are quite low showing low persistence (e.g., r_1=0.607, r_2=0.152, r_3=0.102). The auto-correlations of Baykan Station are generally higher than those of the Besiri Station.

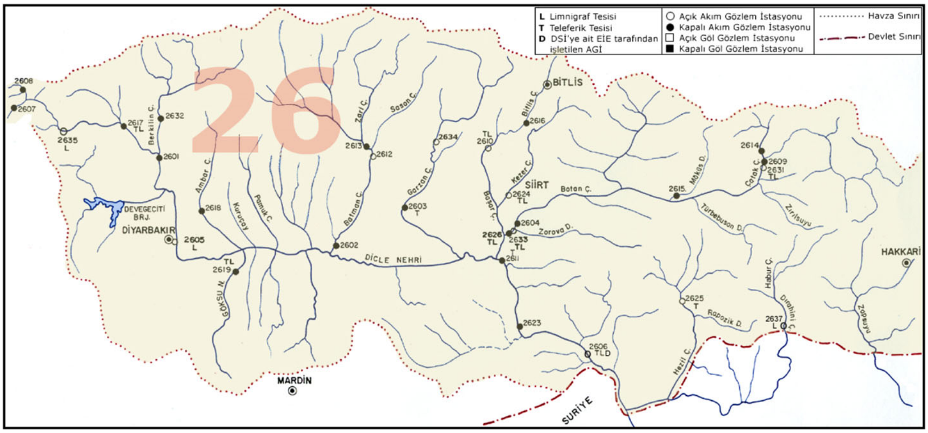

Fig. 2 The Besiri (2603) and Baykan (2610) stations on rivers Garzan and Bitlis (Sanikhani and Kisi 2012)

Table 1 The monthly statistical parameters of data set for Besiri and Baykan stations

Station	Data set	x_{mean} (m^3/s)	Sx (m^3/s)	Csx (m^3/s)	x_{min} (m^3/s)	x_{max} (m^3/s)	r_1	r_2	r_3
Besiri	1994–2002	41.7	54.2	2.06	0	297	0.607	0.152	0.102
	1984–1993	47.1	62.4	2.29	1	354	0.614	0.185	0.054
	1974–1983	42.4	54.1	1.95	2	286	0.622	0.152	0.138
	1964–1973	54.7	66.5	1.75	2.5	309	0.657	0.193	0.054
Baykan	1994–2002	15.8	17.1	1.62	2.0	73.4	0.632	0.152	0.110
	1984–1993	20.2	23.7	2.18	2	126	0.643	0.211	0.041
	1974–1983	18.5	21.4	1.96	2.4	111	0.627	0.138	0.153
	1964–1973	22.7	26.3	1.90	2.6	116	0.639	0.130	0.097

x_{mean}, Sx, Csx, x_{min}, x_{max}, r_1, r_2, r_3 indicate the overall mean, standard deviation, skewness, lag-1, lag-2 and lag-3 auto-correlation coefficients, respectively

5 Application

In the first part of the study, the LSSVR and ANFIS-FCM models were tested in 1-month ahead streamflow forecasting and results were compared with ARMA models. Three input combinations based on current and preceding monthly streamflow values were evaluated. Let assume that the Q_t represents the flow at time t, the input combinations evaluated in the study are; (i) Q_t, (ii) Q_t, Q_{t-1}, (iii) Q_t, Q_{t-1} and Q_{t-2}. The models were evaluated with respect to root mean square errors (RMSE), mean absolute errors (MAE) and determination coefficient (R^2) statistics for each input combination. The RMSE and MAE can be expressed as

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(Q_{i,o}-Q_{i,f}\right)^2} \tag{19}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|Q_{i,o}-Q_{i,f}\right| \tag{20}$$

where N is the number of data, $Q_{i,o}$ is the observed discharge values and $Q_{i,f}$ is the model's forecast.

For each input combination, cross validation method was employed by dividing data into four sets. Different parameters were tried for each LSSVR model and the optimal ones that gave the minimum RMSE error in test period were obtained. The parameters of the optimal LSSVR models for each input combination are provided in Table 2. In this table, M1 indicates model 1 and (0.2, 0.8) shows the regularization constant and width of the RBF kernel, respectively. Various regularization constants and RBF kernels were tried for the LSSVR models. As an example, the variation of test RMSE vs regularization constant and RBF kernel for the M1 model comprising input Qt (input combination i) is shown in Fig. 3 for the Besiri Station. The test results of the best LSSVR models are given for the Besiri Station in Table 3. It is clear from the table that both LSSVR and ANFIS-FCM models give different forecasts for different data sets. According to the average performance of the models, the LSSVR and ANFIS-FCM models comprising current and one previous flow values (input combination ii) perform better than the other models. The input combination (iii) seems to be slightly worse than the input combination (ii) for the both methods. It is clear that the LSSVR and ANFIS-FCM models give the worst results for the M2 data set. The reason behind this may be the fact

Table 2 The parameters of the optimal LSSVR models for each combination – Besiri and Baykan stations

Cross validation	Trainin data set	Test data set	Input combination		
			(i)	(ii)	(iii)
Besiri station					
M1	1964–1984	1994–2002	(0.2,0.8)	(0.7,0.3)	(3.3,0.4)
M2	1964–1974 and 1994–2002	1984–1993	(10,6.5)	(10,0.4)	(10,0.6)
M3	1964–1973 and 1984–2002	1974–1983	(10,2.4)	(0.5,1.0)	(0.1,3.4)
M4	1974–2002	1964–1973	(10,0.3)	(5.2,0.5)	(10,5.0)
Baykan station					
M1	1964–1984	1994–2002	(0.8,1.0)	(0.2,0.5)	(0.3,0.6)
M2	1964–1974 and 1994–2002	1984–1993	(10,7.6)	(10,1.9)	(1.6,1.6)
M3	1964–1973 and 1984–2002	1974–1983	(6.4,0.7)	(0.8,1.0)	(1.0,1.5)
M4	1974–2002	1964–1973	(10,9.5)	(10,0.2)	(10,4.3)

that the maximum streamflow value of the testing data set (x_{max}=354 m^3/s) is higher than that of the training data set (see Table 1). This implies that the trained LSSVR and ANFIS-FCM models face difficulties in making extrapolation in high values in the case of M2. The best LSSVR model was obtained for the M1 and input combination (iii) while the best ANFIS-FCM model was obtained for the M3and input combination (iii). Table 3 clearly indicates that the LSSVR models generally perform better than the ANFIS-FCM models in 1-month ahead streamflow forecasting.

Table 4 shows the test results of the best LSSVR and ANFIS-FCM models for the Baykan Station. According to the average performance of the models, the LSSVR models give similar results for the input combinations (ii) and (iii) and they have better accuracies than the input combination (i). The ANFIS-FCM models, however, have similar accuracy for the input combinations (i) and (iii) and they perform worse than the input combination (ii). Similar to

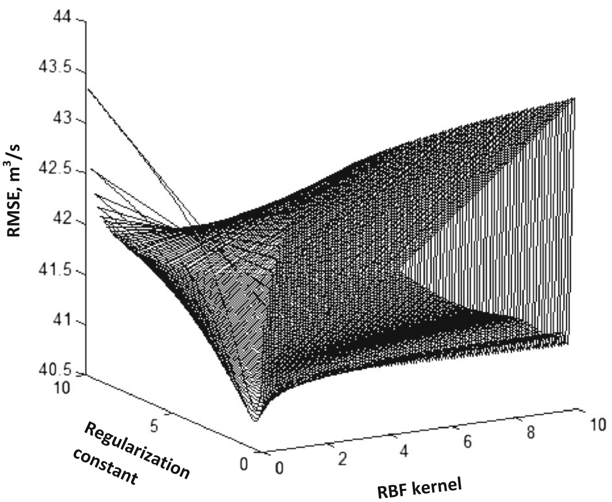

Fig. 3 The variation of test RMSE vs regularization constant and RBF kernel for the LSSVR model – input combination (i) and M1 data set of Besiri station

Table 3 Comparison of the LSSVR and ANFIS-FCM models - Besiri Station

Statistics	Cross validation	Test data set	Input combination			
			(i)	(ii)	(iii)	Mean
LSSVR						
RMSE	M1	1994–2002	40.7	32.0	29.4	34.0
	M2	1984–1993	50.7	40.0	42.7	44.5
	M3	1974–1983	39.7	31.7	37.3	36.2
	M4	1964–1973	47.5	40.7	40.6	42.9
		Mean	44.7	36.1	37.5	39.4
MAE	M1	1994–2002	27.9	21.2	19.0	22.7
	M2	1984–1993	31.6	22.9	24.5	26.3
	M3	1974–1983	24.6	20.0	25.6	23.4
	M4	1964–1973	31.5	24.8	25.7	27.3
		Mean	28.9	22.2	23.7	24.9
R^2	M1	1994–2002	0.435	0.660	0.705	0.601
	M2	1984–1993	0.434	0.648	0.598	0.560
	M3	1974–1983	0.457	0.657	0.555	0.556
	M4	1964–1973	0.504	0.649	0.650	0.601
		Mean	0.458	0.654	0.628	0.580
ANFIS-FCM						
RMSE	M1	1994–2002	42.4	38.5	39.9	40.3
	M2	1984–1993	53.7	41.7	42.2	45.9
	M3	1974–1983	42.7	34.8	34.7	37.4
	M4	1964–1973	46.5	42.1	43.5	44.0
		Mean	46.3	39.3	40.1	41.9
MAE	M1	1994–2002	27.3	23.6	24.5	25.1
	M2	1984–1993	32.3	23.5	23.1	26.3
	M3	1974–1983	26.1	20.3	22.0	22.8
	M4	1964–1973	30.9	25.7	27.1	27.9
		Mean	29.2	23.3	24.2	25.5
R^2	M1	1994–2002	0.393	0.563	0.474	0.478
	M2	1984–1993	0.370	0.619	0.608	0.532
	M3	1974–1983	0.379	0.600	0.609	0.529
	M4	1964–1973	0.522	0.609	0.591	0.574
		Mean	0.416	0.599	0.571	0.528

the Besiri, the LSSVR models give the worst results for the M2 data set while the worst forecasts of the ANFIS-FCM models were obtained for the M2 data set, followed by M2. Here, also the maximum streamflow value of the testing data set (x_{max}=126 m^3/s) is higher than those of the training data set (see Table 1). This confirms the extrapolation difficulties of the LSSVR models for this data set. Here also the best LSSVR model was obtained for the M1 and input combination (iii). The ANFIS-FCM model, however, gave its best forecasts for the M1 and input combination (ii). It is clear from the Table 4 that the LSSVR models generally have better accuracy than the ANFIS-FCM in 1-month ahead streamflow forecasting. Comparison of Tables 3 and 4 clearly shows that the LSSVR and ANFIS-FCM models are

Table 4 Comparison of the LSSVR and ANFIS-FCM models - Baykan Station

Statistics	Cross validation	Test data set	Input combination			
			(i)	(ii)	(iii)	Mean
LSSVR						
RMSE	M1	1994–2002	12.8	10.4	10.1	11.1
	M2	1984–1993	18.0	15.5	15.6	16.4
	M3	1974–1983	15.0	12.3	12.2	13.2
	M4	1964–1973	19.0	14.6	14.9	16.2
		Mean	16.2	13.2	13.2	14.2
MAE	M1	1994–2002	9.07	7.88	7.26	8.07
	M2	1984–1993	11.8	8.94	9.28	10.0
	M3	1974–1983	9.20	7.35	6.92	7.82
	M4	1964–1973	12.3	9.13	8.91	10.1
		Mean	10.6	8.33	8.10	9.00
R^2	M1	1994–2002	0.460	0.664	0.692	0.605
	M2	1984–1993	0.455	0.596	0.592	0.548
	M3	1974–1983	0.470	0.646	0.652	0.589
	M4	1964–1973	0.543	0.691	0.676	0.637
		Mean	0.482	0.649	0.653	0.595
ANFIS-FCM						
RMSE	M1	1994–2002	13.3	11.0	12.9	12.4
	M2	1984–1993	18.7	16.0	17.6	17.4
	M3	1974–1983	16.2	13.6	24.1	18.0
	M4	1964–1973	19.2	15.1	14.3	16.2
		Mean	16.9	13.9	17.2	16.0
MAE	M1	1994–2002	9.12	7.07	7.69	7.96
	M2	1984–1993	11.7	8.63	9.35	9.89
	M3	1974–1983	9.68	7.92	9.67	9.09
	M4	1964–1973	11.9	9.13	8.53	9.85
		Mean	10.6	8.19	8.81	9.20
R^2	M1	1994–2002	0.427	0.628	0.632	0.562
	M2	1984–1993	0.412	0.594	0.513	0.506
	M3	1974–1983	0.390	0.578	0.461	0.476
	M4	1964–1973	0.436	0.666	0.727	0.610
		Mean	0.416	0.617	0.583	0.539

more successful in Besiri Station than the Baykan. The reason of this may be the higher auto-correlations of the Baykan Station in relative to the Besiri.

Different ARMA models were also tested by using same data sets and the optimal ones that gave the minimum RMSE were selected. The results are given in Table 5 for the Besiri and Baykan stations. In Besiri Station, it should be noted that the ARMA model also gave its worst results for the M2 data set similar to the LSSVR and ANFIS-FCM. Comparison of Tables 3 and 5 clearly indicates that the LSSVR and ANFIS-FCM models perform better than the ARMA model for all the data sets. For the Baykan Station, also the worst forecasts were obtained from the M2 model while the M1 model was found to be the best. Comparison of

Table 5 Comparison of the ARMA models

Statistics	Cross validation	Model	Test data set	
Besiri station				
RMSE	M1	ARMA (1,3)	1994–2002	42.8
	M2	ARMA (3,0)	1984–1993	52.2
	M3	ARMA (1,3)	1974–1983	42.6
	M4	ARMA (3,0)	1964–1973	49.0
			Mean	46.7
MAE	M1	ARMA (1,3)	1994–2002	26.3
	M2	ARMA (3,0)	1984–1993	29.3
	M3	ARMA (1,3)	1974–1983	24.1
	M4	ARMA (3,0)	1964–1973	29.3
			Mean	27.3
R^2	M1	ARMA (1,3)	1994–2002	0.408
	M2	ARMA (3,0)	1984–1993	0.462
	M3	ARMA (1,3)	1974–1983	0.430
	M4	ARMA (3,0)	1964–1973	0.522
			Mean	0.456
Baykan station				
RMSE	M1	ARMA (3,2)	1994–2002	12.4
	M2	ARMA (2,1)	1984–1993	18.8
	M3	ARMA (1,3)	1974–1983	15.3
	M4	ARMA (3,2)	1964–1973	18.2
			Mean	16.2
MAE	M1	ARMA (3,2)	1994–2002	8.96
	M2	ARMA (2,1)	1984–1993	11.2
	M3	ARMA (1,3)	1974–1983	8.95
	M4	ARMA (3,2)	1964–1973	12.0
			Mean	10.3
R^2	M1	ARMA (3,2)	1994–2002	0.481
	M2	ARMA (2,1)	1984–1993	0.487
	M3	ARMA (1,3)	1974–1983	0.468
	M4	ARMA (3,2)	1964–1973	0.515
			Mean	0.488

ARMA, LSSVR and ANFIS-FCM models (Tables 4 and 5) shows that the LSSVR and ANFIS-FCM models have better accuracy than the ARMA in monthly streamflow forecasting. The average RMSE accuracy of the ARMA models was increased by 15.6–12.4 % using LSSVR models for the Besiri and Baykan stations, respectively.

In this part of the study, the periodicity effect was also investigated by adding a component α which takes values between 1 and 12 according to the month of the year to be forecast into each input combination. The test results of the periodic LSSVR models are provided in Table 6 for the both stations. According to the average performance of the models, the periodic LSSVR models provide similar accuracy for the different input combinations. Similar to the previous application, the periodic LSSVR model has the worst forecasts for the M2 data set

Table 6 Comparison of the periodic LSSVR models

Statistics	Cross validation	Test data set	Input combination			
			(i)	(ii)	(iii)	Mean
Besiri station						
RMSE	M1	1994–2002	29.6	29.5	27.7	28.9
	M2	1984–1993	42.4	40.4	42.4	41.7
	M3	1974–1983	28.5	28.9	30.3	29.2
	M4	1964–1973	37.4	39.1	39.0	38.5
		Mean	34.5	34.5	34.9	34.6
MAE	M1	1994–2002	18.4	18.4	17.7	18.2
	M2	1984–1993	23.4	23.6	23.9	23.6
	M3	1974–1983	16.1	15.8	18.2	16.7
	M4	1964–1973	24.0	23.1	23.8	23.6
		Mean	20.5	20.2	20.9	20.5
R^2	M1	1994–2002	0.707	0.719	0.745	0.724
	M2	1984–1993	0.603	0.641	0.602	0.615
	M3	1974–1983	0.723	0.712	0.685	0.707
	M4	1964–1973	0.688	0.673	0.678	0.680
		Mean	0.680	0.686	0.678	0.681
Baykan station						
RMSE	M1	1994–2002	9.38	8.92	9.85	9.4
	M2	1984–1993	16.6	15.0	15.3	15.6
	M3	1974–1983	10.7	11.7	12.0	11.5
	M4	1964–1973	15.7	13.5	14.6	14.6
		Mean	13.1	12.3	12.9	12.8
MAE	M1	1994–2002	6.25	5.74	7.15	6.38
	M2	1984–1993	9.67	8.76	9.09	9.17
	M3	1974–1983	6.11	6.36	6.59	6.35
	M4	1964–1973	8.84	7.80	8.53	8.39
		Mean	7.72	7.17	7.84	7.57
R^2	M1	1994–2002	0.726	0.729	0.714	0.723
	M2	1984–1993	0.540	0.621	0.607	0.589
	M3	1974–1983	0.729	0.686	0.664	0.693
	M4	1964–1973	0.625	0.736	0.691	0.684
		Mean	0.655	0.693	0.669	0.672

while the M1 model is found to be the best for the Besiri Station. Comparison of Tables 3 and 6 reveals that adding periodic component into input combinations significantly increases the LSSVR model accuracy. The average RMSE accuracies of the ARMA and LSSVR models were respectively increased by 25.9–12.2 % using periodic LSSVR models for the Besiri Station. The observed and forecasted monthly streamflows by the LSSVR, periodic LSSVR (P-LSSVR), ANFIS-FCM and ARMA for the M1 data set are shown in Fig. 4 in the form of scatterplot. It is clear from the scatterplots that the fit line coefficients *a* and *b* (assume that the fit line equation is $y=ax+b$) of the P-LSSVR model are respectively closer to the 1 and 0 with a higher R^2 value than those of the LSSVR, ANFIS-FCM and ARMA models. In Baykan

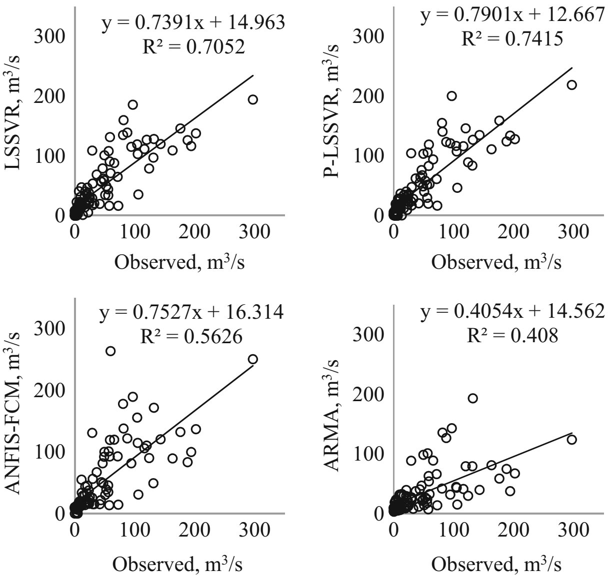

Fig. 4 The observed and forecasted streamflows by the LSSVR, P-LSSVR, ANFIS-FCM and ARMA models for the M1 data set - Besiri station

Station, according to the average accuracy of the models, the periodic LSSVR models provide almost same performance for the input combinations (i) and (iii). Input combination (ii) has slightly better accuracy than the other combinations for the. Here also the periodic LSSVR model has the best forecasts for the M1 data set while the M2 model was found to be the worst. Comparison of Tables 4 and 6 clearly indicates that the LSSVR model accuracy significantly increases by adding periodic component into inputs. The average RMSE accuracy of the ARMA and LSSVR models was respectively increased by 21–9.9 % using periodic LSSVR models for the Baykan Station. Figure 5 illustrates the observed and forecasted monthly streamflows by the LSSVR, periodic LSSVR (P-LSSVR), ANFIS-FCM and ARMA for the M1 data. Similar to the Besiri Station, here also the P-LSSVR forecasts are closer to the observed streamflows than those of the LSSVR, ANFIS-FCM and ARMA. LSSVR and ANFIS-FCM models also perform better than the ARMA model.

In the second part of the study, the ability of the LSSVR and ANFIS-FCM models was tested in streamflow estimation using data from nearby stream. The streamflow estimation using nearby stream's data is an important issue since the downstream or upstream data are missing for many rivers. In this case, the streamflow data of the nearby streams can be used to estimate the missing streamflow data. It should be noted that the Besiri and Baykan stations have drainage basins with similar hydrological characteristics. The data of the Besiri Station were used to estimate monthly streamflows of the Baykan Station. In this application, also cross validation method was employed by dividing data into four parts. The four input combinations were tried as (i) Q_t, (ii) Q_t, Q_{t-1}, (iii) Q_t, Q_{t-1}, Q_{t-2}, and (iv) Q_t, Q_{t-1}, Q_{t-2}, Q_{t-3}. The output is the current flow, Q_t of the Baykan Station. The optimal regularization constant and RBF kernel values obtained by using trial and error method are given in Table 7 for each data set and each input combination. The test results of the LSSVR and ANFIS-FCM models are provided in Table 8. According to the average performance of the models, the best

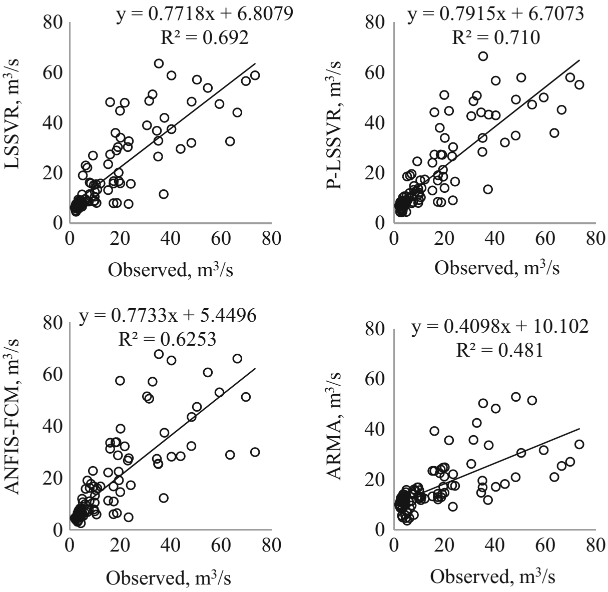

Fig. 5 The observed and forecasted streamflows by the LSSVR, P-LSSVR, ANFIS-FCM and ARMA models for the M1 data set - Baykan station

accuracy of the LSSVR models was obtained from M1 data set while the M4 gave the worst estimates. For the ANFIS-FCM, however, the best accuracy was obtained for the M3 data set while the M4 gave the worst estimates. It is clear from the table that the LSSVR models gave better estimates than the ANFIS-FCM models in cross station application. The observed and estimated flows by LSSVR and ANFIS-FCM models for each data set are shown in Fig. 6. It is clearly seen from the figure that both LSSVR and ANFIS-FCM models closely estimate streamflow data of Baykan Station by using the data of Besiri Station especially for the M1, M2 and M3 data sets. The superior accuracy of the LSSVR models to the ANFIS-DCM models is obviously seen from the figüre.

6 Conclusions

In the present study, the ability of LSSVR and ANFIS-FCM models in forecasting and estimation of monthly streamflows was investigated. In the first part of the study, the

Table 7 The parameters of the optimal LSSVR models in cross-station application

Cross validation	Test data set	Input combination			
		(i)	(ii)	(iii)	(iv)
M1	1994–2002	(0.3,10)	(0.2,4.0)	(0.3,10)	(0.3,10)
M2	1984–1993	(10,5.8)	(10,10)	(10,10)	(10,10)
M3	1974–1983	(7.0,10)	(1.8,10)	(2.0,10)	(2.3,10)
M4	1964–1973	(10,6.1)	(4.6,6.4)	(10,8.9)	(10,6.8)

Table 8 Comparison of the LSSVR and ANFIS-FCM models in estimating monthly river flows of the Baykan Station by using the data of Besiri Station

Statistics	Cross validation	Test data set	Input combination				
			(i)	(ii)	(iii)	(iv)	Mean
LSSVR							
RMSE	M1	1994–2002	4.69	3.95	4.09	4.12	4.21
	M2	1984–1993	5.99	5.29	5.23	5.72	5.56
	M3	1974–1983	4.30	4.79	4.78	4.71	4.65
	M4	1964–1973	12.5	11.8	11.8	11.7	12.0
		Mean	6.87	6.46	6.48	6.56	6.59
MAE	M1	1994–2002	3.47	3.08	3.09	3.11	3.19
	M2	1984–1993	2.93	2.81	2.97	3.28	3.00
	M3	1974–1983	2.64	2.65	2.59	2.51	2.60
	M4	1964–1973	5.91	5.26	5.27	5.26	5.43
		Mean	3.74	3.45	3.48	3.54	3.55
R^2	M1	1994–2002	0.940	0.962	0.958	0.958	0.955
	M2	1984–1993	0.948	0.958	0.959	0.949	0.954
	M3	1974–1983	0.964	0.958	0.959	0.960	0.960
	M4	1964–1973	0.763	0.789	0.788	0.791	0.783
		Mean	0.904	0.917	0.916	0.915	0.913
ANFIS-FCM							
RMSE	M1	1994–2002	5.10	5.56	6.01	5.16	5.46
	M2	1984–1993	6.42	9.21	6.28	5.90	6.95
	M3	1974–1983	5.34	4.79	5.77	5.10	5.25
	M4	1964–1973	12.7	13.3	11.5	11.4	12.2
		Mean	7.39	8.22	7.39	6.89	7.47
MAE	M1	1994–2002	2.88	2.65	3.09	2.70	2.83
	M2	1984–1993	3.29	4.54	3.39	3.37	3.65
	M3	1974–1983	2.88	2.65	2.86	2.66	2.76
	M4	1964–1973	6.01	5.99	5.07	5.39	5.6
		Mean	3.77	3.96	3.60	3.53	3.71
R^2	M1	1994–2002	0.945	0.924	0.931	0.925	0.931
	M2	1984–1993	0.933	0.870	0.934	0.942	0.920
	M3	1974–1983	0.934	0.958	0.924	0.952	0.942
	M4	1964–1973	0.756	0.734	0.797	0.802	0.772
		Mean	0.892	0.872	0.897	0.905	0.891

LSSVR and ANFIS-FCM models were tested in 1-month ahead streamflow by using data from two stations, Besiri Station on Garzan Stream and Baykan Station on Bitlis Stream, in Dicle Basin of Turkey. Cross validation method was also employed in the applications. The LSSVR and ANFIS-FCM forecasts were compared with those of the ARMA models. Both models were found to be better than the ARMA in 1-month ahead streamflow forecasting. The LSSVR model reduced the average RMSE value with respect to the ARMA model by 15.6 and 12.4 % for the Besiri and Baykan stations, respectively. The effect of periodicity component on forecasting ability of the LSSVR models was also examined. It was found that

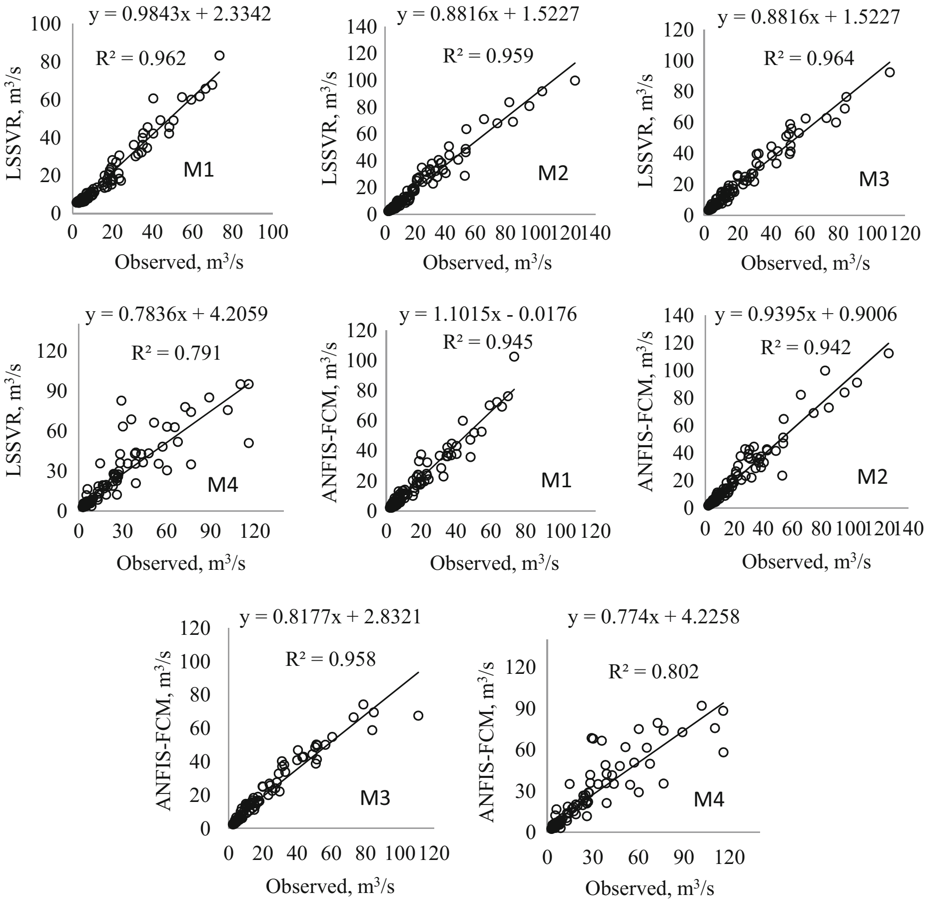

Fig. 6 The streamflow estimates of the Baykan Station by LSSVR and ANFIS-FCM using the data of Besiri station

adding periodicity into the model inputs significantly improved the LSSVR accuracy in forecasting. The average RMSE accuracies of the LSSVR models were increased by 12.2 and 9.9 % using periodic LSSVR models for the Besiri and Baykan stations, respectively. The second part of the study focused on testing the accuracy of the LSSVR and ANFIS-FCM models in streamflow estimation using data from nearby stream. The results indicated that the LSSVR performed better than the ANFIS-FCM and could be successfully used in estimating monthly streamflows by using nearby station data.

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References

Awad M, Jiang X, Motai Y (2007) Incremental support vector machine framework for visual sensor networks. EURASIP J. Adv. Signal Process 2007, Article ID 64270, doi:10.1155/2007/64270

Awchi TA (2014) River discharges forecasting in northern Iraq using different ANN techniques. Water Resour Manag 28:801–814
Ayvaza MT, Karahana H, Aral MM (2007) Aquifer parameter and zone structure estimation using kernel-based fuzzy c-means clustering and genetic algorithm. J Hydrol 343(3–4):240–253
Chen D, Gao C (2012) Soft computing methods applied to train station parking in urban rail transit. Appl Soft Comput 12:759–767
Chen SH, Lin YH, Chang LC, Chang FJ (2006) The strategy of building a flood forecast model by neuro-fuzzy network. Hydrol Process 20:1525–1540
Chen ST, Yu PS, Tang YH (2010) Statistical downscaling of daily precipitation using support vector statistical downscaling of daily precipitation using support vector machines and multivariate analysis. J Hydrol 385(1–4):13–22
Chiu S (1994) Fuzzy model identification based on cluster estimation. J Intell Fuzzy Syst 2(3):267–278
Cimen M (2008) Estimation of daily suspended sediments using support vector machines. Hydrol Sci J 53(3): 656–666
Cobaner M (2011) Evapotranspiration estimation by two different neuro-fuzzy inference systems. J Hydrol 398: 292–302
Deng S, Yeh TH (2010) Applying least squares support vector machines to the airframe wing-box structural design cost estimation. Exp Syst Appl 37(12):8417–8423
Esfahani S, Baselizadeh S, Hemmati-Sarapardeh A (2015) On determination of natural gas density: least square support vector machine modeling approach. J Nat Gas Sci Eng 22:348–358
Flecher R (1987) Practical methods of optimization. John Wiley & Sons
Guo X, Sun X, Ma J (2011) Prediction of daily crop reference evapotranspiration (ET_0) values through a least-squares support vector machine model. Hydrol Res 42(4):268–274
Guven A (2009) Linear genetic programming for time-series modeling of daily flow rate. J Earth Syst Sci 118(2): 137–146
Guven A, Talu NE (2010) Gene-expression programming for estimating suspended sediment in middle euphrates basin, Turkey. CLEAN Soil Air Water 38(12):1159–1168
He Z, Wen X, Liu H, Du J (2014) A comparative study of artificial neural network, adaptive neuro fuzzy inference system and support vector machine for forecasting river flow in the semiarid mountain region. J Hydrol 509:379–386
Hemmati-Sarapardeh A, Shokrollahi A, Tatar A, Gharagheizi F, Mohammadi AH, Naseri A (2014) Reservoir oil viscosity determination using a rigorous approach. Fuel 116:39–48
Hipni A, El-shafie A, Najah A, Karim OA, Hussain A, Mukhlisin M (2013) Daily forecasting of Dam water levels: comparing a support vector machine (SVM) model with adaptive neuro fuzzy inference system (ANFIS). Water Resour Manag 27:3803–3823
Hsu K, Gupta HV, Sorooshian S (1995) Artificial neural network modeling of the rainfall-runoff process. Water Resour Res 31(10):2517–2530
Huang Z, Luo J, Li X et al (2009) Prediction of effluent parameters of wastewater treatment plant based on improved least square support vector machine with PSO. 1st International Conference on Information Science and Engineering (ICISE), Nanjing, pp 4058–4061, **No. 5454606**0 http://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=5454606
Hwang SH, Ham DH, Kim JH (2012) Forecasting performance of LS-SVM for nonlinear hydrological time series. KSCE J Civ Eng 16(5):870–882
Jang J-SR (1993) ANFIS: adaptive-network-based fuzzy inference system. IEEE Trans Syst Manag Cybern 23(3):665–685
Jang J-SR, Sun C-T, Mizutani E (1997) Neuro-fuzzy and soft computing: a computational approach to learning and machine intelligence. Prentice Hall, Upper Saddle River
Kaheil YH, Rosero E, Gill MK, Mc Kee M, Basatidas LA (2008) Downscaling and forecasting of evapotranspiration using a synthetic model of wavelets and support vector machines. IEEE Trans Geosci Remote Sens 46(9):2692–2707
Kamari A, Nikookar M, Sahranavard L, Mohammadi A (2014) Efficient screening of enhanced oil recovery methods and predictive economic analysis. Neural Comput Applic 25:815–824
Khan MS, Coulibaly P (2006) Application of support vector machine in lake water level prediction. J Hydrol Eng 11(3):199–205
Kisi O (2006) Daily pan evaporation modeling using a neuro-fuzzy computing technique. J Hydrol 329:636–646
Kisi O (2007) Evapotranspiration modeling from climate data using a neural computing technique. Hydrol Process 21(6):1925–1934
Kisi O (2012) Modeling discharge-sediment relationship using least square support vector machine. J Hydrol 456–457:110–120

Kisi O (2013) Least squares support vector machine for modeling daily reference evapotranspiration. Irrig Sci 31(4):611–619
Kisi O, Cimen M (2009) Evapotranspiration modelling using support vector machines. Hydrol Sci J 54(5):918–928
Kisi O, Nia AM, Gosheh MG, Tajabadi MRJ, Ahmadi A (2012) Intermittent streamflow forecasting by using several data driven techniques. Water Resour Manag 26(2):457–474
Kumar M, Kar IN (2009) Non-linear HVAC computations using least square support vector machines. Energy Convers Manag 50:1411–1418
Kumar ARS, Ojha CSP, Goyal MK, Singh RD, Swamee PK (2011) Modelling of suspended sediment concentration at Kasol in India using ANN, fuzzy logic and decision tree algorithms. J Hydrol Eng 16(3): 394–404
Lin J-Y, Cheng C-T, Chau K-W (2006) Using support vector machines for long-term discharge prediction. Hydrol Sci J 51(4):599–612
Liong S, Sivapragasam C (2002) Flood stage forecasting with support vector machines. J Am Water Resour Assoc 38(1):173–186
Maier HR, Dandy G (2000) Neural networks for prediction and forecasting of water resources variables: a review of modeling issues and applications. Environ Model Softw 15(10):1–124
McNamara JD, Scalea FL, Fateh M (2005) Automatic defect classification in long-range ultrasonic rail inspection using a support vector machine-based 'smart system'. Hydrol Sci J 46(6):331–337
Mustafa MR, Rezaur RB, Saiedi S, Isa MH (2012) River suspended sediment prediction using various multilayer perceptron neural network training - a case study in Malaysia. Water Resour Manag 26: 1879–1897
Okkan U, Serbes ZA (2013) The combined use of wavelet transform and black box models in reservoir inflow modeling. J Hydrol Hydromechanics 61(2):112–119
Pahasa J, Ngamroo I (2011) A heuristic training-based least squares support vector machines for power system stabilization by SMES. Exp Syst Appl 38(11):13987–13993
Rasouli K, Hsieh WW, Cannon AJ (2012) Daily streamflow forecasting by machine learning methods with weather and climate inputs. J Hydrol 414–415:284–293
Rezaeianzadeh M, Tabari H, Yazdi AA, Isik S, Kalin L (2014) Flood flow forecasting using ANN, ANFIS and regression models. Neural Comput Applic 25:25–37
Sanikhani H, Kisi O (2012) River flow estimation and forecasting by using two different adaptive neuro-fuzzy approaches. Water Resour Manag 26:1715–1729
Sharma S, Srivastava P, Fang X, Kalin L (2015) Performance comparison of adoptive neuro fuzzy inference system (ANFIS) with loading simulation program C++ (LSPC) model for streamflow simulation in El Nino southern oscillation (ENSO)-affected watershed. Exp Syst Appl 42(4):2213–2223
Shokrollahi A, Arabloo M, Gharagheizi F, Mohammadi AH (2013) Intelligent model for prediction of CO2 e reservoir oil minimum miscibility pressure. Fuel 112:375–384
Shu-gang C, Yan-bao L, Yan-ping W (2008) A forecasting and forewarning model for methane hazard in working face of coal mine based on LS-SVM. J China Univ Mining Technol 18:0172–0176
Sivapragasam C, Muttil N (2005) Discharge rating curve extension: a new approach. Water Resour Manag 19(5): 505–520
Sivapragasam C, Liong S-Y, Pasha MFK (2001) Rainfall and runoff forecasting with SSA–SVM approach. J Hydroinformatics 3(3):141–152
Suykens JAK, Vandewalle J (1999) Least square support vector machine classifiers. Neural Process Lett 9(3): 293–300
Suykens JA, Van Gestel T, De Brabanter J, De Moor B, Vandewalle J, Suykens J, Van Gestel T (2002) Least squares support vector machines. World Sci
Tao B, Xu WJ, Pang GB et al (2008) Prediction of bearing raceways superfinishing based on least squares support vector machines. Proceedings of the 4th International Conference on Natural Computation (ICNC) 2, 125–129
Vapnik V, Golwich S, Smola AJ (1997) Support vector method for function approximation, regression estimation, and signal processing. In: Mozer M, Jordan M, Petsche T (eds) Advances in Neural Information Processing Systems 9. MIT Press, Cambridge, pp 281–287
Wang H, Hu D (2005) Comparison of SVM and LS-SVM for regression. Neural Netw Brain 1:2079–2283
Wang W, Xu D, Chau K, Chen S (2013) Improved annual rainfall-runoff forecasting using PSO–SVM model based on EEMD. J Hydroinformatics 15(4):1377–1390
Yarar A, Onucyıldız M, Copty NK (2009) Modelling level changes in lakes using neuro-fuzzy and artificial neural networks. J Hydrol 365:329–334