ORIGINAL ARTICLE

River flow simulation using a multilayer perceptron-firefly algorithm model

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Abstract

River flow estimation using records of past time series is importance in water resources engineering and management and is required in hydrologic studies. In the past two decades, the approaches based on the artificial neural networks (ANN) were developed. River flow modeling is a non-linear process and highly affected by the inputs to the modeling. In this study, the best input combination of the models was identified using the Gamma test then MLP–ANN and hybrid multilayer perceptron (MLP–FFA) is used to forecast monthly river flow for a set of time intervals using observed data. The measurements from three gauge at Ajichay watershed, East Azerbaijani, were used to train and test the models approach for the period from January 2004 to July 2016. Calibration and validation were performed within the same period for MLP–ANN and MLP–FFA models after the preparation of the required data. Statistics, the root mean square error and determination coefficient, are used to verify outputs from MLP–ANN to MLP–FFA models. The results show that MLP–FFA model is satisfactory for monthly river flow simulation in study area.

Keywords Ajichay watershed · Estimation · Firefly algorithm · Multilayer perceptron · River flow

Introduction

River flow simulation is significant for planning and management of catchment area, evaluation of risk and control of droughts, floods, development of water resources, production of hydroelectric energy, navigation planning and allocation of water for agriculture (Khatibi et al. 2012).

Simulation of river flow is great importance for protection and simulation of changes in marine ecosystems. Different methods are used for river flow simulation including time series analysis, fuzzy logic, neurofuzzy, genetic programming, artificial neural networks and recently, chaos theory. Since the 1990s, time series methods utilizing the genetic programming, artificial neural network and fuzzy logic methods have become viable, giving rise to the publication of many scientific studies.

ANNs applied by Anmala et al. (2000) for river flow estimation in three watersheds in Kansas. Simulation show that ANNs model does not provide a significant improvement without time delayed input over other regression models. The river flow at the Kafue Hook Bridge in Vietnam, simulated by Chibanga et al. (2003), separately using ANNs. A system comparison of two types of ANNs applied by Chiang et al. (2004), static and dynamic in their research. Wu et al. (2005) developed the using of ANNs for watershed runoff and river flow simulations. Back propagation (This technique is also sometimes called backward propagation of errors) ANN, runoff models applied by Sarkar et al. (2006) to estimate and prediction daily runoff for a part of the Satluj river basin of India. Comparison of different ANN models applied by Kisi (2007) for short term daily river flow estimation. Kalteh (2008) applied ANNs model for the estimation of streamflow and used Garson's algorithm for determining the relative significant of inputs, neural interpretation diagram, and randomization approach. In 2009, Modarres simulated the Plasjan watershed rainfall–runoff by ANNs model in the western area of the Zayandehrud watershed, Iran. Dorum et al. (2010) studied to set up rainfall–runoff

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relationship using ANN and ANFIS models at hydrometric stations on seven sites in Susurluk watershed. Ghorbani et al. (2016) investigated the applicability of MLP, RBF and SVM models for the estimation of river flow. The results show that the RBF and MLP models are better for estimation monthly river flow. Li et al. (2017) were evaluated implementation of hybrid evolutionary model based on SVR–FFA for water quality indicator simulation. The SVR–FFA model was presented to be a acceptable and robust model for the estimation of WQI. Alweshah et al. (2014) used firefly algorithm with artificial neural network for time series problems and concluded the experimental results showed that the proposed ANN FFA model can effectively solve time series classification problems.

In this paper, a novel simulation approach based on evolutionary facts called MLP–FFA is adopted in this study for the simulation processes. Inputs of models was selected using Gamma test. The result of the proposed algorithm was verified by comparing with MLP–ANN model.

Methodology

Study area, data and performance criteria

Our study is Ajichay watershed. Ajichay (East Azerbaijani) is one of the major rivers in the province of East Azerbaijan. In terms of geographical location is located between the north and longitude of 37°42′–30°38′East 45°40′–47°53′. The watershed starts of the height of 3400 m south and south west slopes of Sabalan mount and about 33 km northeast of the city of Sarab and through the northern city of tabriz in the west Azarshahr at an altitude of 1270 m, the lake ends. The total area of the catchment area is about 12,790 Sq. km. In Fig. 1 presented river watershed. The river is also the largest water supply to the Urmia Lake. Table 1 presents some of the important statistics for the time series used and Fig. 2 shows the variations of monthly data for study stations.

Mutual information

Finding optimum lag time

Mutual information (MI) technique has been used widely in the linear and nonlinear correlation estimation and also input lag time variables selection (Wang et al. 2010). For the given time series sequence $\{x_0, x_1, x_2, \ldots, x_t, \ldots, x_n\}$ the mutual information illustrate the amount of information about the state $x_{t+\tau}$ if the state of x_t is known. The average mutual information is specified by:

$$I(\tau) = \sum_{t=1}^{N-\tau} P(x_t, x_{t+\tau}) . \log\left(\frac{p(x_t, x_{t+\tau})}{p(x_t) . p(x_{t+\tau})}\right), \tag{1}$$

where $P(x_t)$ is the probability density of x_t and the $P(x_t, x_{t+\tau})$ is the common probability density of x_t and $x_{t+\tau}$. The first local minimum of $I(\tau)$ estimates the optimal selection for the lag time necessary for input selection (De Domenico et al. 2013).
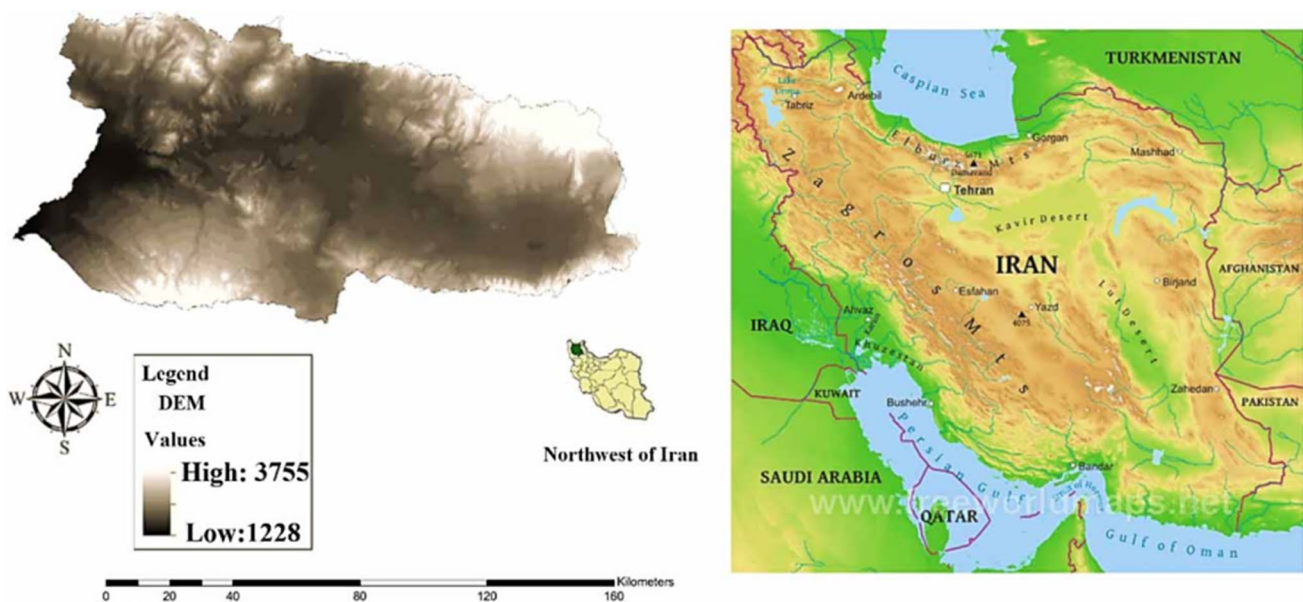

Fig. 1 Location of study area (Ajichay)

Table 1 Statistics of monthly river flow data from Ajichay river

Station	Data set	Number of data	Maximum	Minimum	Mean	Standard deviation (m³/s)	Coefficient of variation
Vanyar	Training	252	107.703	0.002	10.94	18.05	1.65
	Testing	108	65.3	0.013	6.23	11.17	1.79
	Total	360	107.703	0.002	9.52	16.62	1.72
Markid	Training	110	43.11	0	5.16	9.54	1.84
	Testing	46	26.93	0	3.11	5.28	1.69
	Total	156	43.11	0	4.55	8.54	1.87
Arzang	Training	110	32.42	0	2.73	5.61	2.05
	Testing	46	12.06	0	1.27	2.66	2.09
	Total	156	32.42	0	2.31	4.96	2.15

Input variables selection is one of the important problems when developing simulation models. This is due to the influence of correlated lag times to the model accuracies. Thus, mutual information function was performed to specify the numbers of lags (Khatibi et al. 2011).The AMI shows well-defined first minima at time lag 3 months (Fig. 3). Thus, a set of four input sets were designed with lagged t of up to 3 months for 1-month lead time simulation of river flow using MLP–ANN, MLP–FFA methods.

Development of rainfall–runoff simulation models

Two soft computing models including MLP_ANN and MLP_FFA are used for river flow modeling. To evaluate the efficiency of the models for simulating monthly river flow data are divided into two groups, each used separately in the training and testing periods. The models are developed with 70% of data for training and the 20% for testing and then, the data for MLP_ANN model should be normalized and the rang of input data has been used within 0–1.

Multilayer perceptron artificial neural networks (MLP–ANN)

ANNs are parallel data processing system. A neural network consists of a set of neurons arranged in layers and in the case that weighted inputs are used, these nodes provide appropriate inputs by conversion functions. Any layer consists of pre-designated neurons and each neural network includes one or more of these interconnected system. Figure 4 represents a three layered structure that consists of one input layer, one hidden layer and one output layer. The operation process of these networks is so that the input layer accepts the data and intermediate layer processes them and finally the output layer displays the resultant outputs of model usage. For the

time of data modeling stage, coefficients related to present errors in nodes are corrected through comparing the model outputs with recorded input data. Further information on ANNs can be found in e.g. Haykin (1999).

Firefly algorithm

The FFA developed by Yang (2010), is a swarm intelligence optimization technique based on the motion of fireflies. An optimization subject solution can be suppose as factor i.e. firefly which glows in proportion to its type. Each brighter firefly attracts its partners, irrespective of their sex, which makes exploration of the search place very efficient (Lukasik and Zak 2009). The whole swarm moves towards the brightest firefly. So the attractiveness of the fireflies is directly corresponding to their brightness. In addition, the brightness depends on the intensity of the factor (Kayarvizhy et al. 2014).The main issues in FFA development are the formulation of the objective function and the variation of the light intensity. The light intensity $I(r)$, the attractiveness (β) and the Cartesian distance between any two fireflies i and j can be written as:

$$I(r) = I_o \exp(-\gamma r^2) \tag{2}$$

$$\beta(r) = \beta_o \exp(-\gamma r^2) \tag{3}$$

$$r_{ij} = \left\| x_i + x_j \right\| = \sqrt{\sum_{k=1}^{d} (x_{i,k} - x_{j,k})}, \tag{4}$$

where γ is the light absorption factor; $I(r)$ and I_o are the light intensity at distance r and primary light intensity from a firefly, $\beta(r)$ and β_o are the attractiveness β at a spacing r and $r = 0$. The next movement of firefly i can be illustrate as:

$$x_i^{i+1} = x_i + \Delta x_i \tag{5}$$

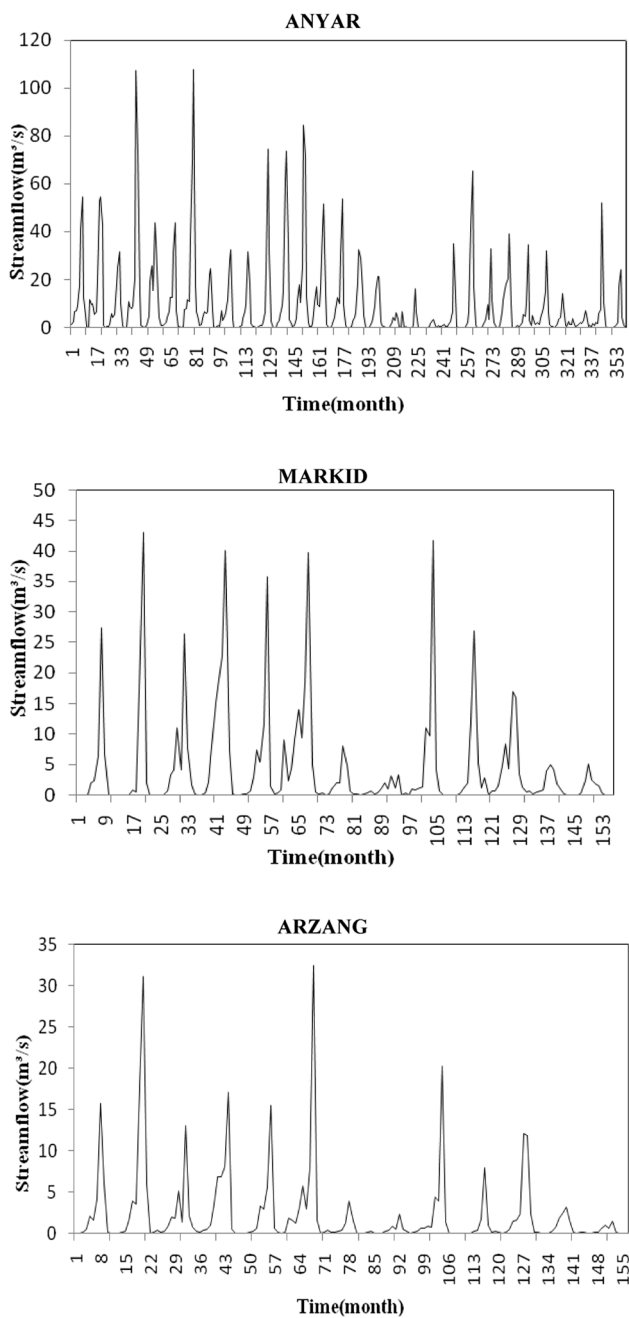$$\Delta x_i = \beta_o e^{-\gamma r^2}(x_j - x_i) + \alpha \varepsilon_i. \tag{6}$$

Fig. 2 Monthly river flow time series at the Ajichay river

Fig. 3 Average mutual information (AMI) function of the study stations time series

In the Eq. (5) attraction is the first term, the second term show the randomization, with α as a randomization factor whose value range is 0–1 and ε_i is the random number vector obtain from a Gaussian distribution (Sudheer et al. 2014).

In this research optimal values of γ, ε and C for the model and in addition optimal values for the weights of the MPL model were computed

Performance evaluation criteria

To evaluate the river flow simulation performances of the developed models, two statistical indices are used. The indices

Fig. 4 Simple configuration of multilayer perceptron neural network (Nkuna and Odiyo 2011)
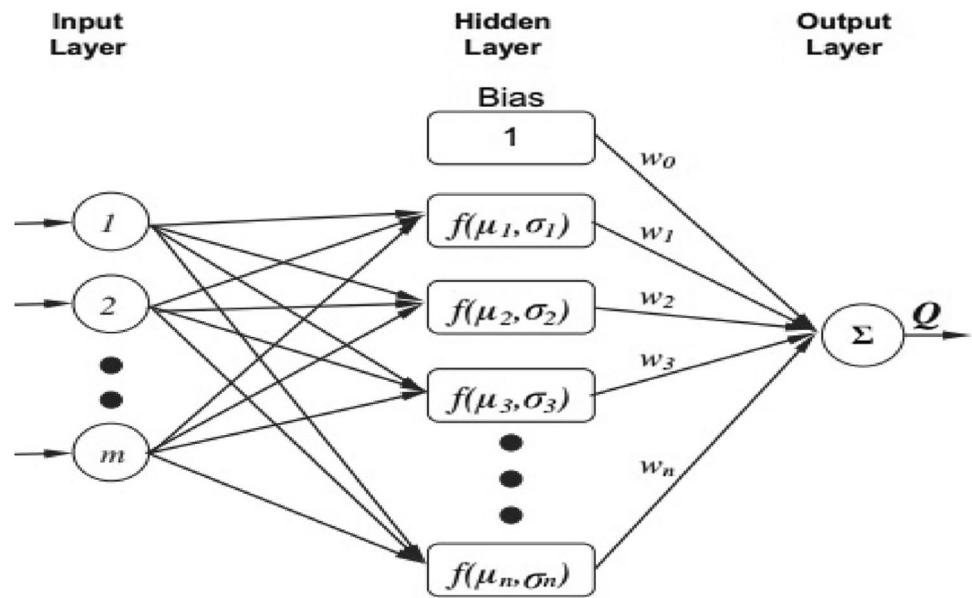
include determination coefficient (R^2) and root mean squared error (RMSE).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(x_i - y_i)^2}{N}} \tag{7}$$

$$R^2 = \left[\frac{\sum_{i=1}^{N}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{N}(x_i - \bar{x})^2 \sum_{i=1}^{N}(y_i - \bar{y})^2}}\right]^2, \tag{8}$$

where x_i and $y_i =$ the observed flow and simulated flow by the developed model, respectively; $\bar{x} =$ the mean of the observed values; $\bar{y} =$ the mean of the simulated values; and $N =$ the number of observed data. The R^2, is used for comparisons of models. A high R^2 implies a good model performance. The RMSE is used to measure estimating accuracy, which produces a positive value by squaring the errors. High value for R^2 (up to one) and low value for RMSE indicate high efficiency of the model (Najafzadeh et al. 2014).

Analysis, results and discussion

Comparison of the models performance for river flow simulation

The three-layer is used for MLP–ANN model with one hidden layer and the common trial-and-error procedure was selected the number of hidden nodes. The network was trained in 100 epochs, learning rate of 0.0012 and momentum coefficient of 0.84. The optimal number of neuron in the hidden layer was identified using a trial and error procedure.

In this research, MLP–FFA model was obtained by combining multilayer perceptron models and firefly algorithm. The results of MLP–ANN and MLP_FFA models for river flow simulation based on there different input settings are presented in this section. The performance of models structure has been evaluated using root mean square error and coefficient of determination.

Table 2 present the simulation performance of MLP–ANN and MLP–FFA models using three different input settings in training (calibration) and testing (validation) periods.

According to Table 2, MLP3 model is the best structure for simulation of Vanyar, Markid and Arzang stations in

Table 2 Statistical analysis of simulated values with ANN–MLP and MLP–FFA models

Station	Model	Model structure			Training		Testing	
		Input combination	Output	Model structure	RMSE (m³/s)	R^2	RMSE (m³/s)	R^2
Vanyar	MLP 1	Q_{t-1}	Q_t	(1, 15, 1)	10.77	0.706	11.065	0.668
	MLP 2	Q_{t-1}, Q_{t-2}	Q_t	(2, 13, 1)	7.596	0.827	8.07	0.805
	MLP 3	Q_{t-1}, Q_{t-2}, Q_{t-3}	Q_t	(3, 8, 1)	6.333	0.878	6.462	0.811
Markid	MLP 1	Q_{t-1}	Q_t	(1, 7, 1)	2.879	0.852	2.389	0.799
	MLP 2	Q_{t-1}, Q_{t-2}	Q_t	(2, 16, 1)	2.872	0.867	2.159	0.815
	MLP 3	Q_{t-1}, Q_{t-2}, Q_{t-3}	Q_t	(3, 10, 1)	2.777	0.919	2.849	0.829
Arzang	MLP 1	Q_{t-1}	Q_t	(1, 13, 1)	2.285	0.848	2.36	0.61
	MLP 2	Q_{t-1}, Q_{t-2}	Q_t	(2, 17, 1)	1.9	0.904	2.075	0.797
	MLP 3	Q_{t-1}, Q_{t-2}, Q_{t-3}	Q_t	(3, 10, 1)	1.585	0.949	1.596	0.866
Vanyar	MLP–FFA 1	Q_{t-1}	Q_t	(1, 15, 1)	6.402	0.885	7.53	0.749
	MLP–FFA 2	Q_{t-1}, Q_{t-2}	Q_t	(2, 13, 1)	5.695	0.901	6.057	0.859
	MLP–FFA 3	Q_{t-1}, Q_{t-2}, Q_{t-3}	Q_t	(3, 8, 1)	4.441	0.94	4.562	0.89
Markid	MLP–FFA 1	Q_{t-1}	Q_t	(1, 7, 1)	4.28	0.825	4.29	0.44
	MLP–FFA 2	Q_{t-1}, Q_{t-2}	Q_t	(2, 16, 1)	4.565	0.781	4.77	0.6
	MLP–FFA 3	Q_{t-1}, Q_{t-2}, Q_{t-3}	Q_t	(3, 10, 1)	2.083	0.956	2.137	0.899
Arzang	MLP–FFA 1	Q_{t-1}	Q_t	(1, 13, 1)	1.714	0.911	1.771	0.725
	MLP–FFA 2	Q_{t-1}, Q_{t-2}	Q_t	(2, 17, 1)	1.425	0.944	1.696	0.727
	MLP–FFA 3	Q_{t-1}, Q_{t-2}, Q_{t-3}	Q_t	(3, 10, 1)	1.189	0.972	1.197	0.928

Ajichay river and it was selected as the optimum model for training and testing data set.

Results of statistical analysis for the Vanyar, Markid and Arzang stations in Ajichay river indicate that the MLP–FFA3 model outperforms the MLP3 model for river flow modeling during the training period. In the testing period, two developed models indicate that river flow values with the same accuracy in terms of statistical indices. In general, RMSE is found to be smaller (lowest for MLP–FFA3) and the MLP–FFA approximate are closer to the observed data. Coefficient of determination (R^2) is highest for MLP–FFA3 in all the cases of training and testing periods. Moreover, scatter plots for simulated and observed monthly river flow values is indicated in Fig. 5 during testing period. It can be seen that the linear trend line of MLP_FFA model is the closest to the 45°. Similarly, it can be seen in Fig. 5 that the MLP–FFA3 model has the best accuracy for the estimation of the monthly river flow at the Ajichay river basin during the testing periods. The estimated time series of river flow using the MLP–FFA3 model are compared with the observed time series during the testing periods. A good fit is observed between the observed and simulated streamflow by

MLP–FFA3 model. It can be found that the developed MLP–FFA3 model out performs the ANN model developed in this research for simulation monthly river flow and is sufficient for modeling river flow. The results of this research show that the MLP–FFA3 model is able to provide a good simulation river flow in study river.

The Taylor diagram

The Taylor diagrams applied to prepare a visual comprehension into performance measures which plots a series of points on a polar plot for the two sets of modeling results: (1) 3 data points for MLP; (2) 3 data points for MLP–FFA and (3) the observed value. The Taylor diagram representation normalized standard deviation (SD) between simulated and observed values along the radial intervals with normalized origins and R^2-values are represented as the direction angles. The expectation is that the observed values have a individual show on the Taylor diagram and the closer the simulated performance measures to the representation of the observed values, the better model performance. Figure 6 shows the Taylor diagram and shows that MLP–FFA enable an important improvement in the model performance and
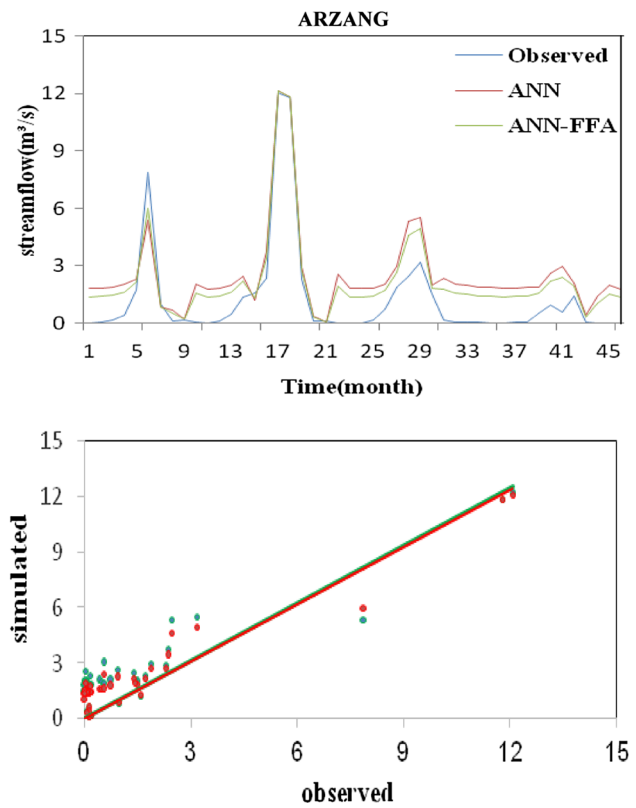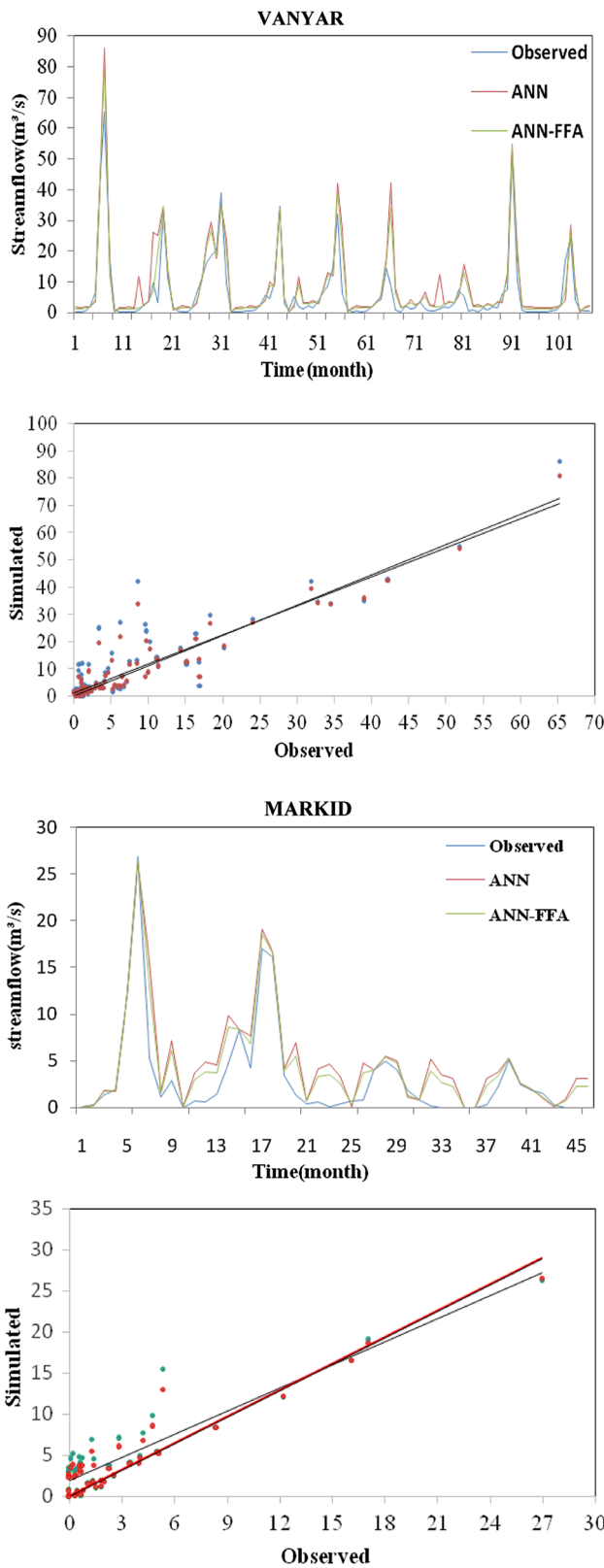
Fig. 5 Comparison between time series plots of simulated and observed values; and scatter plot of observed and simulated values

Fig. 5 (continued)

the performances of modeling strategies likely classified as: MLP, MLP–FFA for both the training and testing status.

Summary and conclusion

In this study, MLP–ANN and MLP–FFA models were employed for modeling river flow using monthly data. Monthly river flow for three stations were used in Ajichay river and evaluated flow. Three different combinations are considered for input data. The inputs to the models include runoff with 3 month lag times (Q_{t-3}, Q_{t-2} and Q_{t-1}). To evaluate the models performances and the effects of input data for river flow, Ajichay watershed was selected as case study. The models, performances are evaluated based on two statistical indices to measure the modeling error and Taylor diagram. The results indicate that third models are the best ones for river flow modeling. Inter-relationships among the variables cannot be distinguished clearly in the ANNs and MLP–FFA models. To overcome this weakness, MI methods was used for pre-processing inputs before using them. The results also reveal that the MLP–FFA3 model in three stations are better than MLP3 model. The results represent that MLP–FFA3 model is capable of river flow modeling with efficiency.

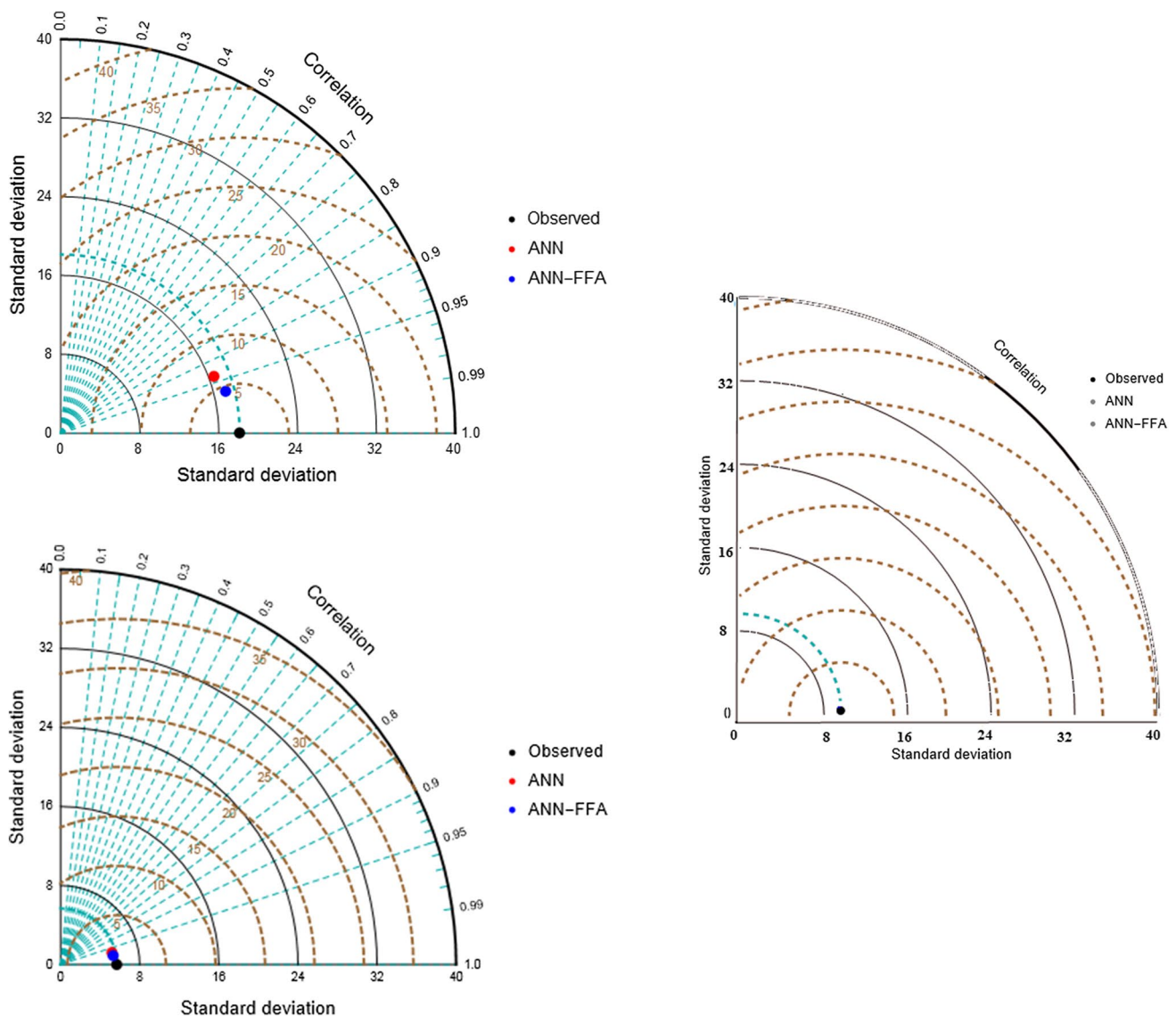**Fig. 6** Taylor diagram: performance measures for training and testing phases: **a** 3 data points of MLP, **b** 3 data points of MLP–FFA

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