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Application of Several Data-Driven Techniques for Rainfall-Runoff Modeling

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ABSTRACT In this study, several data-driven techniques including system identification, adaptive neuro-fuzzy inference system (ANFIS), artificial neural network (ANN) and wavelet-artificial neural network (Wavelet-ANN) models were applied to model rainfall-runoff (RR) relationship. For this purpose, the daily stream flow time series of hydrometric station of Hajighoshan on Gorgan River and the daily rainfall time series belonging to five meteorological stations (Houtan, Maravehtapeh, Tamar, Cheshmehkhan and Tangrah climatologic stations) were used for period of 1983-2007. Root mean square error (RMSE) and correlation coefficient (r) statistics were employed to evaluate the performance of the ANN, ANFIS, ARX and ARMAX models for rainfall-runoff modeling. The results showed that ANFIS models outperformed the system identification, ANN and Wavelet-ANN models. ANFIS model in which preprocessed data using fuzzy interface system was used as input for ANN which could cope with non-linear nature of time series and performed better than others.

Key words: ANFIS, ANN, System identification, Wavelet-ANN, Rainfall-Runoff modeling

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1 INTRODUCTION

Rainfall–runoff (RR) analysis is quite difficult due to presence of complex nonlinear relationships in the transformation of rainfall into runoff. However runoff analysis is very important for the prediction of natural disasters like floods and droughts. It also plays a very important role in the design and operation of various components of water resources projects like barrages, dams, water supply schemes, etc (Aqil *et al.*, 2007). Runoff analysis is also needed in water resources planning, development and flood mitigations. Due to the lack of stream gauges and the obligatory of stream flow observations in Iran, it is necessary to predict the stream flow by using simple approaches. Various types of modeling tools had been used to estimate runoff. These techniques consist of lumped conceptual models, distributed physically based models, deterministic models and black box (time series) models (Lohani *et al.,* 2006).

During the past decades, major progress has been made in the two techniques, the ANFIS and the ANNs. Due to the abilities of the ANN and the ANFIS models in modeling complex nonlinear systems, successful applications of these methods in hydrology modeling have

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been widely reported, including flood forecasting (Campolo *et al.*, 1999; Xiong *et al.*, 2001; Campolo *et al.*, 2003; Bruen and Yang, 2005; Vafakhah, 2012; Yurekli *et al.*, 2012), stage-discharge relationship (Lohani *et al.*, 2006), sediment prediction (Cigizoglu, 2004; Bhattacharya and Solomatine, 2006; Vafakhah, 2013), groundwater level prediction (Daliakopoulos *et al.*, 2005; Mohammadi 2008; Shirmohammadi *et al.*, 2013; Moosavi *et al.*, 2013) and rainfall-runoff modeling (Melching *et al.*, 1991; Hsu *et al.*, 1995; Shamseldin, 1997; Sajikumar and Thandaveswara, 1999; Tokar and Johnson, 1999; Tokar and Markus, 2000; Dibike and Solomatine, 2001; Anctil *et al.*, 2003; Rajurkar *et al.*, 2004; Khan and Coulibaly, 2006; Jain and Srinivasulu, 2006). Recently, wavelet transform analysis has become a popular analysis tool due to its ability to elucidate simultaneously both spectral and temporal information within the signal. This overcomes the basic shortcoming of Fourier analysis, which is that the Fourier spectrum contains only globally averaged information. Therefore, a data pre-processing can be done by time series decomposition into its subcomponents using wavelet transform analysis. This technique is largely applied to times series analysis of non-stationary signals (Nason and Von Sachs, 1999). As an example, Zhou *et al.* (2009) developed a wavelet predictor-corrector model for prediction of monthly discharge time series and showed that the model has higher prediction accuracy than ARIMA and seasonal ARIMA. ANN-wavelet conjunction model was firstly presented by Aussem *et al.* (1998) for financial time series forecasting. Wang and Ding (2003) applied wavelet-network model to forecast shallow groundwater level and daily discharge. Cannas *et al.* (2006) investigated the effects of data pre-processing on the ANN model performance using continuous and discrete wavelet transforms; the results showed that networks trained with pre-processed data, performed better than networks trained on undecomposed, noisy raw signals. Anctil and Tape (2004) decomposed time series by wavelet into three sub-series depicting the rainfall-runoff processes: short, intermediate and long wavelet periods, then multi-layer artificial networks were trained for each wavelet sub-series. Results showed that the short wavelet period fluctuations are thus the key to any further improvement in ANN rainfall–runoff forecasting models. Partal and Cigizoglu (2004) used neurowavelet technique for forecasting river daily suspended sediment load.

In system theory, the definition of a suitable mathematical–physical representation of a dynamic system through transfer functions is called system identification (Erdoğan and Gülal, 2009). System identification is an iterative process, where models are identified with different structures from data and the models performances are compared. The procedure is started by estimating the parameters of simple model structures. If the model performance is poor, the complexity of the model structure could be increased. Ultimately, the simplest model that describes the dynamics of the system well is chosen. A number of researches have been conducted using these models. Baratti *et al.* (2003) forecasted monthly discharge in one of the rivers of Italy by using auto-regressive moving average with exogenous inputs (ARMAX) and ANN with Levenberg– Marquart (LM) algorithm. The comparison results showed that the ANN models are more accurate than the ARMAX models. Castellano-Méndez *et al.* (2004) modeled the monthly and daily behaviors of the runoff of the Xallas river using Box– Jenkins and neural networks methods. The performance of the ANN was an improvement on the Box–Jenkins results. Nayak *et al.* (2004) applied ANFIS to model the daily discharge of the Baitarani River, India, with a catchment size of 14 218 km^2 and compared their model results with the results from the ANN and auto-regressive moving average (ARMA) models. They developed six different models varying the number of antecedent discharge from 1 to 6 in the input vectors, to find the optimum number of inputs. The ANFIS model with two inputs was found to be the best compared to the other five models. The best performing ANFIS model was reported to outperform ARMA but was similar in performance with an ANN model with two neurons in the hidden layer, although ANFIS was much better in peak estimation compared to ANN. Aqil *et al.* (2007) conducted a comparative study of ANN and ANFIS in modeling the daily and hourly runoff behavior for the Cilalawi River in Java, Indonesia. Their results showed that the ANFIS model outperformed the other two models. Shiri and Kisi (2010) compared the application of single neuro-fuzzy (NF) and wavelet-neuro-fuzzy (WNF) models in Derecikviran Station on the Filyos River for daily, monthly and yearly stream flows forecasting. It was found that the WNF model increase the accuracy of the single NF models especially in forecasting yearly stream flows. Talei *et al.* (2010a) investigated the effect of inputs used on event-based runoff forecasting by ANFIS. Fifteen ANFIS models were compared, differentiated by the choice of rainfall and/or discharge inputs used. It was found that models using only rainfall antecedents as inputs performed better in term of goodness-of-fit for discharge at larger lead times (up to eight time steps ahead) while models which included Q(t-1) as input were better in forecasts at shorter lead times (up to two time steps ahead). Talei *et al.* (2010b) compared an application of an ANFIS and Storm Water Management Model (SWMM) in event-based RR modeling in order to evaluate the capabilities of these methods for a sub-catchment of Kranji basin in Singapore. The results of this study show that the selected ANFIS is comparable to SWMM in event-based R–R modeling. In addition, ANFIS is found to be better at peak flow estimation compared to SWMM. Dorum *et al.* (2010) compared ANN, ANFIS and Multi-regression (MR) models at rainfall–runoff relationship on seven streams in Susurluk Basin. Except some stations, acceptable results such as decisiveness coefficient (R^2) value for ANN model and R^2 value for ANFIS model were obtained as 0.7587 and 0.8005, respectively. The high values of predicted errors, belonging to peak values at stations where multi variable flow is seen, affected R2 and RMSE values negatively. Nourani *et al.* (2011) used the SARIMAX (Seasonal Auto Regressive Integrated Moving Average with exogenous input)-ANN and the wavelet-ANFIS models for rainfall–runoff modeling. The obtained results of the models applications for the rainfall–runoff modeling of two watersheds (located in Azerbaijan, Iran) show that, although the proposed models can predict both short and long terms runoff discharges by considering seasonality effects, the wavelet-ANFIS model is relatively more appropriate because it uses the multi-scale time series of rainfall and runoff data in the ANFIS input layer. Nayak *et al.* (2013) modeled Rainfall-runoff for Malaprabha basin in India by using conceptual, data driven and wavelet based computing approach. The results of this study indicate that the WNN model performs better compared to an ANN and NAM model in estimating the hydrograph characteristics such as flow duration curve effectively. Asadi *et al.* (2013) applied a hybrid intelligent model for rainfall-runoff modeling at the Aghchai watershed. They used data pre-processing methods such as data transformation, input variables selection and data clustering for improving the accuracy of the model. The results show that this approach is able to predict runoff more accurately than ANN and ANFIS models. Kisi *et al.* (2013) used ANN, ANFIS

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and gene expression programming (GEP) for modeling rainfall-runoff process. The study provides evidence that GEP is a viable alternative to other applied artificial intelligence and multi linear regression time-series methods. Based on a review of the literature, it appears that the use of all wavelet decomposed sub-series as inputs to the ANN models needs to be explored since averaging or optimizing the selection of only certain sub-series (as has been done in most of the studies to date in the literature) can be viewed as a potentially diminutive approach since all sub-series coefficients are equally important and contain information about the original time series and the use of system identification models in semi-arid watersheds with intermittent flows needs to be explored. The aim of this paper is to compare the accuracy of ARX, ARMAX, ANN, Wavelet-ANN, and ANFIS techniques in modeling rainfall-runoff process.

2 MATERIALS AND METHODS

2.1 Study River

The time series of daily stream flow data collected from Hajighoshan station (station no: 12-063, 55°21′ E, 37°24′ N) on the Gorgan River operated by Iranian Water Research Institute was used in this study. Stream flow or discharge measurement normally involves (1) obtaining a continuous record of stage, (2) establishing the relationship between stage and discharge (rating curve) (3) transforming the record of stage into a record stage. The location of Hajighoshan station is shown in Figure 1.

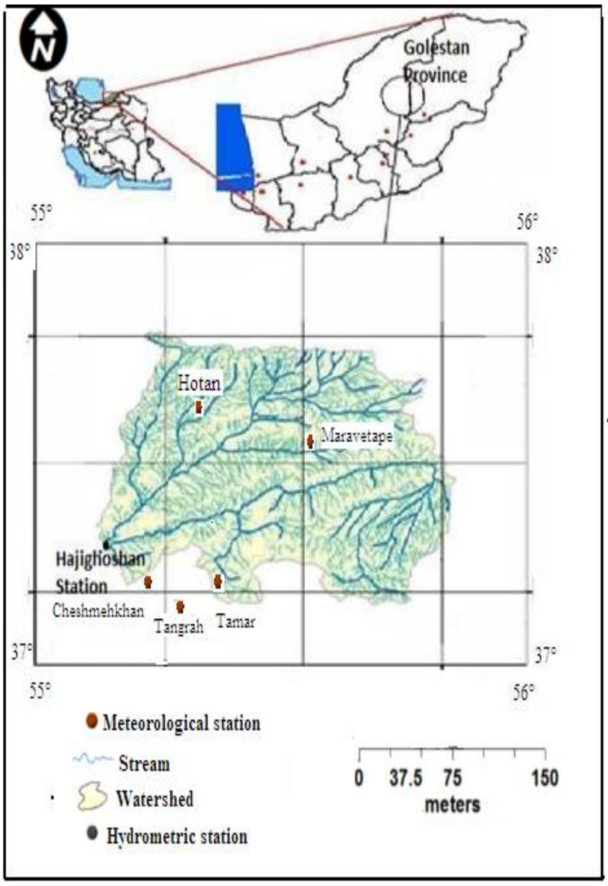

Figure 1 Location of Hajighoshan station in Gorgan River, Mazandaran province, Iran

The used data spans a period of 26 years from 1982 to 2008 (9497 days) for the mentioned station. The rainfall data were comprised the observations belonging to five meteorological stations (Houtan, Maravehtapeh, Tamar, Cheshmehkhan and Tangrah climatologic stations). The average rainfall of Hajighoshan watershed was computed using Thiessen polygon. Table 1 shows Characteristics and effective area different stations in rainfall Hajighoshan watershed.

In the modeling process, the data sets of stream flow and rainfall were scaled to the range between 0.1 and 0.9 for ANN and ANFIS models as follow:

$$N_i = 0.8 \times \left(\frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \right) + 0.1 \qquad (1)$$

where N_i is the normalized value, x_i is the original data and $x_{\min}$, $x_{\max}$ are, respectively, the minimum and maximum of stream flow and rainfall. The 19 year rainfall and stream flow data are used to train the ANFIS and ANN models and the remaining 7 year records are used for testing. For the Hajighoshan station, the daily flow statistics of training, test and entire data set are presented in Table 2.

It can be seen from table that the rainfall and stream flow data show significantly high skewed distribution.

2.2 ARX model (Autoregressive exogenous inputs)

In the ARX model structure, the output at a specific time is considered to be linear combinations of the previous outputs and inputs and the current input. A discrete-time designation of the ARX model is:

$$\begin{aligned} y(t) + a_1 y(t-1) + \ldots + a_{n_a}(t - na) &= b_1 u(t-1) \\ + \ldots + b_{nb} u(t - n_k - n_b + 1) + e(t) \end{aligned} \qquad (2)$$

Where t represents integer time step, e(t) denotes the modeling error, y is the output, u is the input, ei and bj are model parameters to be estimated using the data and na , nb and nk are the orders of the output, input and input–output delay, respectively (Celik and Ertugrul, 2010). In order to build ARX model, daily total precipitation data were used as input for day, 1-day and 2-day-ahead precipitation forecasts. In this study, linear parametric model was used as estimation model. Several delay orders were tested using trial and error procedure. The parameters of na , nb and nk vary from 0 to 9 (Talei *et al.*, 2010a).

Table 1 Characteristics and effective area different stations in rainfall Hajighoshan watershed

Station name	**Geographic coordinates**		**Elevation (m)**	**Annual Precipitation (mm)**	**Effective area**	
	Longitude	**Latitude**			**Hectare**	**Percent**
Houtan	55˚ 28´ 53″	37˚ 56´ 23″	107	275.3	144.14	6.1
Maravehtapeh	55˚ 57´ 19″	37˚ 54´ 31″	216	355	352.09	14.9
Tamar	55˚ 30´ 7″	37˚ 29´ 31″	190	537.8	1127.15	47.4
Cheshmehkhan	56˚ 7´ 02″	37˚ 17´ 48″	1174	232.5	54.35	2.3
Tangrah	55˚ 26´ 00″	37˚ 15´ 51″	438	717.23	675.27	29

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Table 2 The statistical characteristics of the daily rainfall and streamflow data

Variable	Data set	Numbers of data	Average	Standard deviation	Maximum	Minimum	Skewness
Rainfall (mm)	Training	6940	1.44	4.12	53.37	0	4.78
	Test	2557	1.69	4.79	46.04	0	4.60
	Entire	9497	1.51	4.31	5.37	0	4.75
Streamflow (m^3 s^{-1})	Training	6940	1.94	6.64	248	0	17.78
	Test	2557	2.12	8.74	267	0	19.13
	Entire	9497	1.99	7.27	267	0	18.89

2.3 ARMAX Model (Autoregressive Moving average exogenous inputs)

All of the modeling steps in ARMAX are similar to ARX but for the delay orders. The ARMAX model is defined as follows:

$$
\begin{aligned}
&y(t)+a_1 y(t-1)+\cdots+a_{n_a} y(t-na)= \\
&b_1 u(t-nk)+....+b_{n_b} u(t-nk-nb+1)+ \\
&\cdots+c_1 e(t-1)+...+c_{n_c} e(t-nc)+e(t)
\end{aligned}
\quad (3)
$$

where $y(t)$ is the output at time t, ai's and bj's are model parameters to be estimated using the data, na is the number poles of the system, nb is the number of the zeros of the system, nc is the number of previous error terms on which the current output depends and nk is the number of input samples that occur before the inputs affect the current output (Celik and Ertugrul, 2010). The zeros and the poles are equivalent ways of describing the coefficients of the model. The poles relate to the "output-side" and the zeros relate to the "input-side" of this equation. The number of poles (zeros) is equal to number of sampling intervals between the most and least delayed output–input (Ljung, 1995). Similar to ARX model in order to build ARMAX model, daily total precipitation data were used as input to day, 1-day and 2-day ahead groundwater level forecasts. Also linear parametric model was employed as estimation model. Several delay orders were tested using a trial and error procedure. The parameters of na, nb, nc and nk vary from 0 to 9 (Talei *et al.*, 2010a).

2.4 ANFIS

The ANFIS used in the study is a fuzzy inference model of Sugeno type, and is a composition of ANN and fuzzy logic approaches (Jang, 1993). The model identifies a set of parameters through a hybrid learning rule combining the back propagation gradient descent and a least-squares method. It can be used as a basis for constructing a set of fuzzy If-Then rules with appropriate membership functions to generate the previously stipulated input‑output pairs. The Sugeno fuzzy inference system is computationally efficient and works well with linear techniques, optimization and adaptive techniques (Jang 1993). Characteristics of the ANFIS model have been presented in Table 3.

2.5 ANN

The neural network structure in this study possessed a three-layer learning network consisting of an input layer, a hidden layer, and an output layer. The methodology used for adjusting the weights of the ANN model was LM because this technique is more powerful than conventional gradient descent techniques (Hagan and Menhaj, 1994). Sigmoid and hyperbolic tangent activation functions were used for the hidden and linear activation was used for output node(s). The hidden layer node numbers of each model were determined after trying various network structures. The ANN training was stopped after 1000 iterations.

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Table 3 The training parameters of the ANFIS

Parameter	Method
AND method	Prod
Or method	Maximum
Imp. method	Prod
Aggr. method	Maximum
Defuzzification method	wtaver

2.6 Wavelet-ANN

In order to build the hybrid Wavelet-ANN model, sub-series elements which are derived from the use of the discrete wavelet transform on the original time series data have been used as inputs for neural network models. Each sub-series element plays a unique role in the original time series and the performance of each sub-series is distinct. In the first step, the original data (i.e. daily average discharge and daily precipitation) was decomposed into a series of details using a discrete wavelet transformation. Then the decomposition process was iterated with successive approximation signals being decomposed in turn, so that the original time series was broken down into many lower resolution components (Adamowski and Chan, 2011). All of the mentioned variables were decomposed to 1, 2, 3 and 10 levels by eleven different kinds of wavelets i.e. Haar wavelet as a simple wavelet, Daubechies-2 (db2) wavelet as the most popular wavelet (Mallat, 1989), and some irregular wavelets such as db, sym, bior, rboi, and coif wavelets.

2.7 Performance evaluation

The 80 and 20 percent of whole data set was used randomly for training and testing, respectively. Coefficient of correlation (r) and root mean square error (RMSE) were used to evaluate the performances of models and select the best one. In brief, the models predictions are optimum if r and RMSE are found to be close to 1 and 0 respectively. The higher the R value (with 1 being the maximum value) and he lower the RMSE values (with 0 being the minimum value) the better is the performance of the model.

$$r = \sqrt{\frac{(\sum_{i=1}^{n}(Q_o - Q_{Ave})(Q_E - Q_{Ave-E}))^2}{\sum_{i=1}^{n}(Q_o - Q_{Ave})^2(\sum_{i=1}^{n}Q_E - Q_{Ave-E})^2}} \quad (13)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Q_o - Q_E)^2} \quad (14)$$

where Q_o, Q_E, n, Q_{Ave} and Q_{Ave-E} are observed stream flow, estimated stream flow, number of data, mean observed stream flow and mean estimated stream flow.

3 RESULTS AND DISCUSSION

3.1 System identification

In this study, several ARX and ARMAX as system identification models were tested to forecast stream flow. Table 1 shows the best models of ARX and ARMAX chosen in this research. Table 4 shows R and RMSE for different system identification models with the best orders for forecast stream flow for test data set.

3.2 ANN

Table 5 shows the results obtained from employing ANN models with the LM algorithm and best iteration (i.e. 1000) for forecast stream flow.

3.3 ANFIS Model

Table 6 shows the results obtained from employing ANFIS models with the best number of membership functions (i.e. 2 MFs), for the best iteration (i.e. 3,000), and the forecast stream flow for validation data set. As shown in this table, the best membership type selected is bell-shaped.

3.4 Wavelet-ANN

In this part 252 Wavelet-ANN models have been tested for case study. The best ANN model was selected to make hybrid Wavelet-ANN models. Table 7 shows the results of Wavelet-ANN models with the best combination of inputs and the best network (i.e. LM) for test data set.

Table 4 Results of system identification (test data set)

Model inputs		Structure	Test period	
			r	RMSE ($m^3\ s^{-1}$)
	$Q_t= f(P_t)$	4 4 1	0.87	4.88
ARX	$Q_t=f(P_t, P_{t-1})$	6[3 3] [1 1]	0.36	9.71
	$Q_t=f(P_t, P_{t-1}, P_{t-2})$	4[6 6]3 [4 4]	0.21	9.56
	$Q_t= f(P_t)$	7 3 7 1	0.8	6.31
ARMAX	$Q_t=f(P_t, P_{t-1})$	9[777]2[444]	0.34	9.95
	$Q_t=f(P_t, P_{t-1}, P_{t-2})$	7[666]4[333]	0.26	10.9

Table 5 Results of ANN (test data set)

Model inputs	ANN structure	Test period	
		r	RMSE ($m^3\ s^{-1}$)
$Q_t= f(P_t)$	1-14-1	0.36	9.50
$Q_t=f(P_t, P_{t-1})$	2-9-1	0.40	9.69
$Q_t=f(P_t, P_{t-1}, P_{t-2})$	3-11-1	0.21	10.1

Table 6 Results of ANFIS models (test data set)

Membership Function	Model inputs					
	$Q_t= f(P_t)$		$Q_t=f(P_t, P_{t-1})$		$Q_t=f(P_t, P_{t-1}, P_{t-2})$	
	r	RMSE ($m^3\ s^{-1}$)	r	RMSE ($m^3\ s^{-1}$)	r	RMSE ($m^3\ s^{-1}$)
MFgauss	0.87	4.88	0.38	4.77	0.30	10.16
MFgbell	0.93	3.46	0.88	3.92	0.64	9.35
MFpi	0.86	5.17	0.37	4.75	0.30	10.17
MFtri	0.76	4.94	0.37	4.90	0.29	10.16

Figure 3 demonstrates the stream flow forecasts of the ARX, ARMAX, ANN, ANFIS and Wavelet-ANN models in the test period for the Hajighoshan station. The predictions of the ANFIS models are closer to the exact line than those of the ARX, ARMAX, Wavelet-ANN and ANN models. In general, ANFIS performs more efficiently than ARX, ARMAX and ANN and Wavelet-ANN models.

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Table 7 Results of Wavelet-ANN models (test data set)

Model inputs	Models	ANN structure	Test period	
			r	**RMSE (m^3 s^{-1})**
Q_t= f (P_t)	Bior 9	1-4-1	0.36	6
	Coif 4	1-9-1	0.34	5.18
	Db 8	1-9-1	0.35	5.97
	Dmey 6	1-5-1	0.4	5.52
	Haar 9	1-3-1	0.37	5.97
	Rbio 9	1-6-1	0.37	5.99
	Sym 5	1-8-1	0.42	5.25
Q_t=f (P_t, P_{t-1})	Bior 2	2-9-1	0.46	5.26
	Coif 9	2-9-1	0.47	4.88
	Db 2	2-4-1	0.45	5.27
	Dmey 9	2-9-1	0.44	5.62
	Haar 2	2-2-1	0.46	5.26
	Rbio 2	2-4-1	0.45	5.27
	Sym 3	2-5-1	0.41	6.25
Q_t=f (P_t, P_{t-1}, P_{t-2})	Bior 6	3-9-1	0.47	4.84
	Coif 4	3-3-1	0.51	4.39
	Db 6	3-10-1	0.46	4.86
	Dmey 12	3-5-1	0.6	5.69
	Haar 6	3-5-1	0.45	4.91
	Rbio 6	3-7-1	0.46	4.87
	Sym 5	3-8-1	0.36	5.69

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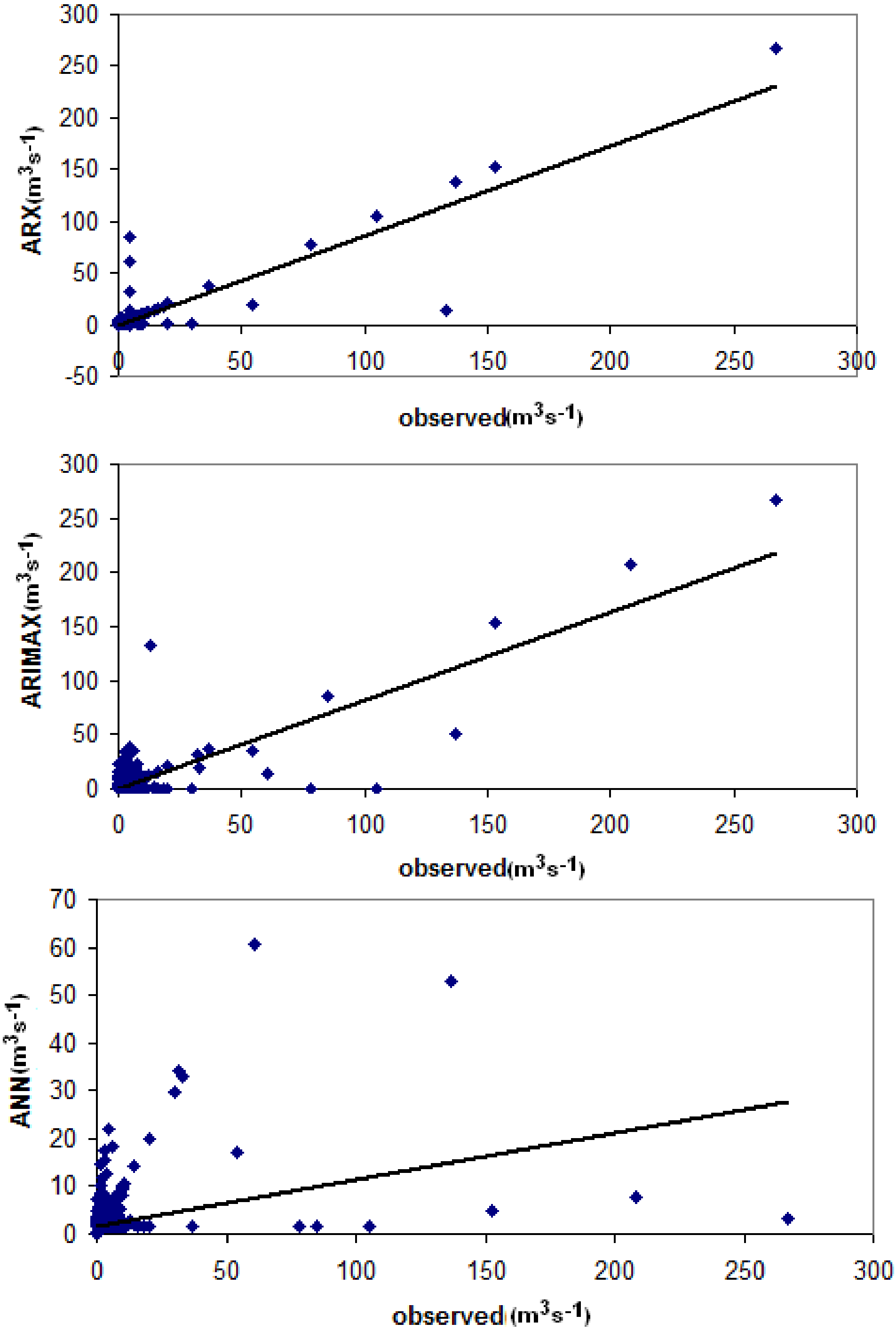

Figure 3 The best models predictions for stream flow (test data set)

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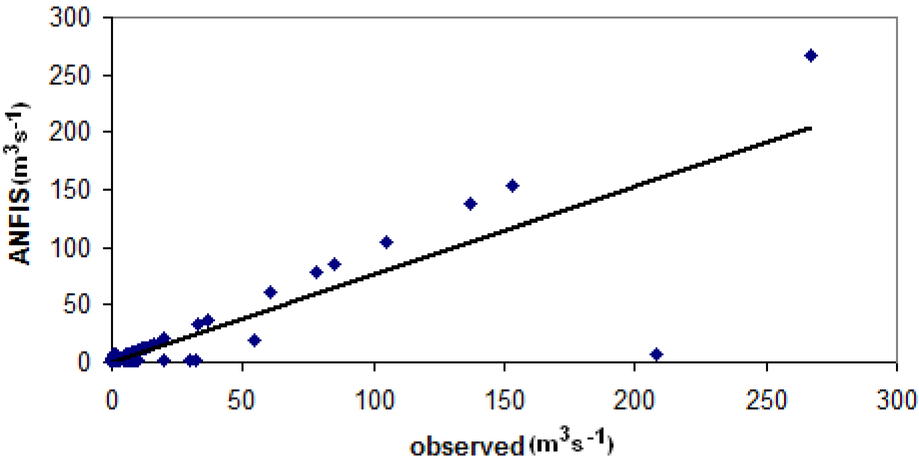

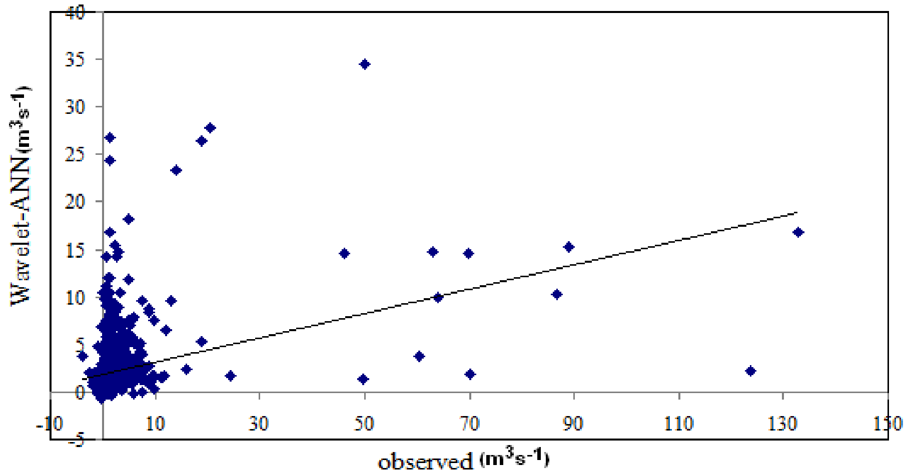

Figure 3 (Continue)

4 CONCLUSIONS

In this study, several data-driven techniques including, system identification, ANFIS, ANN and Wavelet-ANN models were tested and evaluated in order to rainfall-runoff modeling on the basis of performance criteria. The obtained results also showed that ANFIS outperformed all other models. It may be related to the combined effect of fuzzification of the input through membership functions and the ability of ANN. Because the data were first fuzzified and then fed to the ANN model and neural network modeling have been performed on the fuzzified data so, the ability of these modeling advance have been improved (Shirmohammadi *et al.* 2013). These results are in accordance with Nayak *et al.* (2004), Lohani *et al.* (2006), Aqil *et al.* (2007) and Dorum *et al.* (2010).

Nayak *et al.* (2004), Lohani *et al.* (2006), Aqil *et al.* (2007) and Dorum *et al.* (2010) reported slightly better performance of ANFIS than ANN in modeling the daily and hourly runoff behavior. The ANN and Wavelet-ANN seem to be the worst at forecasting peak flows. It may be noted that the ANN and Wavelet-ANN models were built on non-transformed data, and it follows that the transformation of data into the normal domain prior to model development also helps improve peak flow estimation (Vafakhah, 2012). It can be implied that, in general, the ANFIS model provides a superior alternative to system identification, ANN and

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Wavelet-ANN models for developing input–output simulations and for rainfall-runoff modeling. The results of the study are highly encouraging and suggest that an ANFIS approach is viable for rainfall-runoff modeling. An important direction for future work is the use of wavelet-system identification and wavelet-ANFIS models in order to improve the ability of these methods.

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کاربرد فنون داده‌محور برای مدل‌سازی بارش- رواناب

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چکیده در این تحقیق فنون داده‌محور شامل شناسایی سیستم، سیستم عصبی-فازی تطبیقی، شبکه عصبی مصنوعی و شبکه عصبی مصنوعی موجکی برای مدل‌سازی بارش-رواناب به کار برده شدند. بدین منظور، از داده‌های روزانه ایستگاه هیدرومتری حاجی‌قوشان و داده‌های روزانه بارندگی مربوط به پنج ایستگاه هواشناسی هوتن، مراوه‌تپه، تمر، چشمه‌خان و تنگراه از سال‌های ۱۳۶۲ تا ۱۳۸۶ استفاده شد. از معیارهای میانگین مربعات خطا و ضریب همبستگی به منظور ارزیابی کارکرد مدل‌های ANFIS، ANN، Wavelet-ANN , ARX و ARMAX برای تخمین دبی روزانه استفاد شد. نتایج نشان داد که سیستم عصبی-فازی تطبیقی از مدل‌های شناسایی سیستم، شبکه عصبی مصنوعی و شبکه عصبی مصنوعی موجکی کارآیی بالاتری در تخمین دبی روزانه داشت. سیستم عصبی-فازی تطبیقی به دلیل پیش پردازش فازی داده‌ها و ورود فازی داده‌ها به ساختار شبکه عصبی مصنوعی باعث تطابق طبیعت غیر خطی سری زمانی داده‌ها شده و بنابراین کارآیی بهتری از بقیه مدل‌ها داشتند.

کلمات کلیدی: سیستم عصبی-فازی تطبیقی، شبکه عصبی مصنوعی، شناسایی سیستم، شبکه عصبی مصنوعی موجکی، مدل‌سازی بارش-رواناب