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Comparison of the ARMA, ARIMA, and the autoregressive artificial neural network models in forecasting the monthly inflow of Dez dam reservoir

Mohammad Valipour *, Mohammad Ebrahim Banihabib, Seyyed Mahmood Reza Behbahani

Department of Irrigation and Drainage Engineering, College of Abureyhan, University of Tehran, Pakdasht, Tehran, Iran

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SUMMARY

The goal of the present research is forecasting the inflow of Dez dam reservoir by using Auto Regressive Moving Average (ARMA) and Auto Regressive Integrated Moving Average (ARIMA) models while increasing the number of parameters in order to increase the forecast accuracy to four parameters and comparing them with the static and dynamic artificial neural networks. In this research, monthly discharges from 1960 to 2007 were used. The statistics related to first 42 years were used to train the models and the 5 past years were used to forecast. In ARMA and ARIMA models, the polynomial was derived respectively with four and six parameters to forecast the inflow. In the artificial neural network, the radial and sigmoid activity functions were used with several different neurons in the hidden layers. By comparing root mean square error (RMSE) and mean bias error (MBE), dynamic artificial neural network model with sigmoid activity function and 17 neurons in the hidden layer was chosen as the best model for forecasting inflow of the Dez dam reservoir. Inflow of the dam reservoir in the 12 past months shows that ARIMA model had a less error compared with the ARMA model. Static and Dynamic autoregressive artificial neural networks with activity sigmoid function can forecast the inflow to the dam reservoirs from the past 60 months.

1. Introduction

More accurate forecasting of the inflow reservoir has a significantly importance in water resources management due to the role of management and operation of reservoirs, hydroelectric energy generation, and designed structures to control. In this study, three models of ARMA, ARIMA, and autoregressive artificial neural network were used for the monthly inflow to the reservoir.

After publishing the paper of Box and Jenkins (1976), ARIMA and ARMA models or Box–Jenkins models became one of the general time series models to hydrological forecasting. An ARIMA model is a generalization of an ARMA model. Access to basic information requires integration from the series (for a continuous series) or calculating all of the differences of series (for a continuous series). Since the constant of integration in derivation or differences is deleted, the probability of using of these amount or middle amount in this process is not possible. Therefore, ARIMA models are non-static and cannot be used to reconstruct the missing data. However, these models are very useful for forecasting changes in a process (Karamouz and Araghinejad, 2012).

One famous black box model that forecast river flow in recent decades is artificial neural network model. Artificial neural networks are free-intelligent dynamic systems models that are base on the experimental data, and the knowledge and covered law beyond data changes to network structure by trends on these data (Menhaj, 2012). Using of time series models (ARMA and ARIMA) and artificial neural networks has been prevalence very well in different fields of hydrology as follows:

Balaguer et al. (2008) used the method of Time Delay Neural Network (TDNN) and ARMA model to forecast asking for help in support centers for crisis management. The correlation results were obtained for TDNN model and ARMA, 0.88 and 0.97, respectively. This research showed that ARMA model was better than TDNN. Toth et al. (2000) used the artificial neural network and ARMA models to forecast rainfall. The results showed the success of both short-term rainfall-forecasting models for floods forecasting in real time. Mohammadi et al. (2005) forecasted Karaj reservoir inflow using data of snow melting, artificial neural network and ARMA methods, and regression analysis. The 60% of inflow in dam happened between April and June, so forecasting the inflow in this season is very important for dam's performance. The highest inflows were in the spring due to the snow melt because of draining in threshold winter. The results showed that artificial neural network has lower significant faults as compared with other methods (Chegini, 2012). Valipour (2012a) determined critical area of Iran using 50 years of rainfall data and ARIMA model. He resulted that ARIMA model was an appropriate tool to forecasting annual rainfall. Kisi and Cigizoglu (2005) by using dynamic artificial neural networks forecast the monthly inflow, storage, and evaporation on

* Corresponding author. Tel./fax: +98 2126300812.
E-mail address: vali-pour@hotmail.com (M. Valipour).

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Nomenclature

ε_t	random variable	*RMSE*	root mean square error
ω	periodic term	*MBE*	mean square error
B	difference operator	i	number of months
$B(Z_t)$	*D*th seasonal difference measure ω	Q_{ci}	computational discharge in month i
d	non-seasonal difference	Q_{oi}	observational discharge in month i
p	order of non-seasonal autoregressive model	n	number of data
q	order of non-seasonal moving average model	$\overline{Q}_{oi}$	average of observational discharge
P	order of seasonal autoregressive model	E_i	relative error in month i
Q	order of seasonal moving average model	F_i	average of cumulative relative error in the month i
ϕ	parameter of non-seasonal autoregressive model	$\overline{E}$	average of relative error
θ	parameter of non-seasonal moving average model	C_v	variation coefficient of relative error
Φ	parameter of seasonal autoregressive model	b1,b2	first and second biases
Θ	seasonal moving average model	w1,w2	first and second weights

Canak Dere basin. The results for monthly saving and monthly evaporation were satisfactory, but forecasting of the monthly inflow as compared with monthly save and evaporation had a lower accuracy. They used both radial and sigmoid activity functions in dynamic artificial neural network. Their research results showed that sigmoid activity function has a priority over radial activity function. Valipour (2012b) in another research using time series analysis (AR, MA, ARMA, and ARIMA) investigated number of required observation data for rainfall forecasting according to the climate conditions. The results showed that time series models were better appropriate to rainfall forecasting in semi-arid climate. Numbers of required observation data for forecasting of 1 next year were 60 rainfall data in semi-arid climate. Banihabib et al. (2008) also forecast the inflow to the Dez reservoir at daily time scale using static artificial neural network model and simple linear regression model based on discharge data from hydrometric stations located upstream of the desired station on minor and major river branches. This research showed that static artificial neural network is better than linear regression models.

Therefore, considering the above mentioned performed researches, we can know that the efficacy of ARMA, ARIMA and artificial neural network in forecasting hydrologic field and sampling as compared with other statistic models such as linear and nonlinear regression. However, in forecasting inflow to the reservoir, by ARMA and ARIMA methods the maximum numbers of parameters were two. Furthermore, concurrent use of ARMA and ARIMA models has not been done in previous research to compare them and use of autoregressive artificial neural network in forecasting the monthly inflow to reservoir. This study aims to forecast inflow to Dez reservoir using ARMA and ARIMA models, by increasing the numbers of parameters to four parameters for evaluate the accuracy of forecasting, and compare these two models with static and dynamic autoregressive artificial neural network models, based on inflow of Taleh Zang station located on the Dez dam upstream.

2. Materials and methods

Dez basin encompasses some part of the middle peaks of Zagros. The range of basin is 32°, 35′ to 34°, 07′ North latitude and 48°, 20′ to 50°, 20′ east longitude and is located in south-western of Iran. Dez basin is limited from west to Karkheh basin, from north to Ghareh Chay basin and from east and south to Karun basin. Fig. 1 shows locational map of study area. In this research, due to the autocorrelation characteristic of ARMA and ARIMA models for forecasting inflow of entrance station in Dez reservoir, Taleh Zang station data was used, and for this reason, artificial neural network models used in this study were named autoregressive. In order to forecast the goal station discharge (Taleh Zang station at the entrance to the Dez reservoir) at the monthly scale, the station's monthly discharge period from water year 1960–1961 to water year 2006–2007 were selected. In reality, the used data involved 564 data that began from October 1960 and end in September 2007.

In this study, two time series models and artificial neural networks in general, and four ARMA, ARIMA static autoregressive artificial neural network and dynamic autoregressive artificial neural network models were used for forecasting monthly flow of Teleh Zang station individually. These models are explained in the following sections.

ARMA and ARIMA models obtained from a combination of autoregressive and moving average models. For modelling of seasonal time series beside non-seasonal series, $ARIMA(p,d,q)(P,D,Q)_\omega$ is known as multiplicative ARIMA model is defined as follows:

$$\begin{aligned}(1-\Phi_1B^{\omega}-\Phi_2B^{2\omega}-\cdots-\Phi_pB^{P\omega})(1-\varphi_1B-\varphi_2B^2-\cdots\\-\varphi_pB^p)(1-B^{\omega})^D(1-B)^dZ_t\\=(1-\Theta_1B^{\omega}-\Theta_2B^{2\omega}-\cdots-\Theta_QB^{Q\omega})(1-\theta_1B-\theta_2B^2-\cdots\\-\theta_qB^q)\varepsilon_t\end{aligned} \tag{1}$$

where ε_t is the random variable, ω is the periodic term, B is the difference operator as $B(Z_t) = Z_{t-1}$, $(1-B^{\omega})^D$ is the *D*th seasonal difference measure ω, $d = (1-B)^d$ is the *d*th non-seasonal difference, p is the order of non-seasonal autoregressive model, q is the order of non-seasonal moving average model, P is the order of seasonal autoregressive model, Q is the order of seasonal moving average model, ϕ is the parameter of non-seasonal autoregressive model, θ is the parameter of non-seasonal moving average model, Φ is the parameter of seasonal autoregressive model, and Θ is the seasonal moving average model (Karamouz and Araghinejad, 2012). It should be noted that, in Eq. (1) when $d = D = 0$, ARIMA model becomes ARMA model. The next stage is determining the number of ARMA and ARIMA models parameters that perform by Partial Auto Correlation Function (PACF) and Auto Correlation function (ACF) curves (Balaguer et al., 2008; Cryer and Chan, 2008; Mohammadi et al., 2005; Toth et al., 2000). These curves are depicted in Figs. 2 and 3, which the horizontal axis shows the delay time and the vertical axis shows the amounts of ACF and PACF, respectively.

According to these curves, it was observed that the amounts of ACF and PACF in the delays 1 and 2 were high. So choosing up to two autoregressive parameters and two moving average parameters was sufficient (Cryer and Chan, 2008), but in order to investigate the effect of increasing the number of parameters in forecasting accuracy in this study, up to 4 autoregressive parameters and also up to 4 moving average parameters were used. The

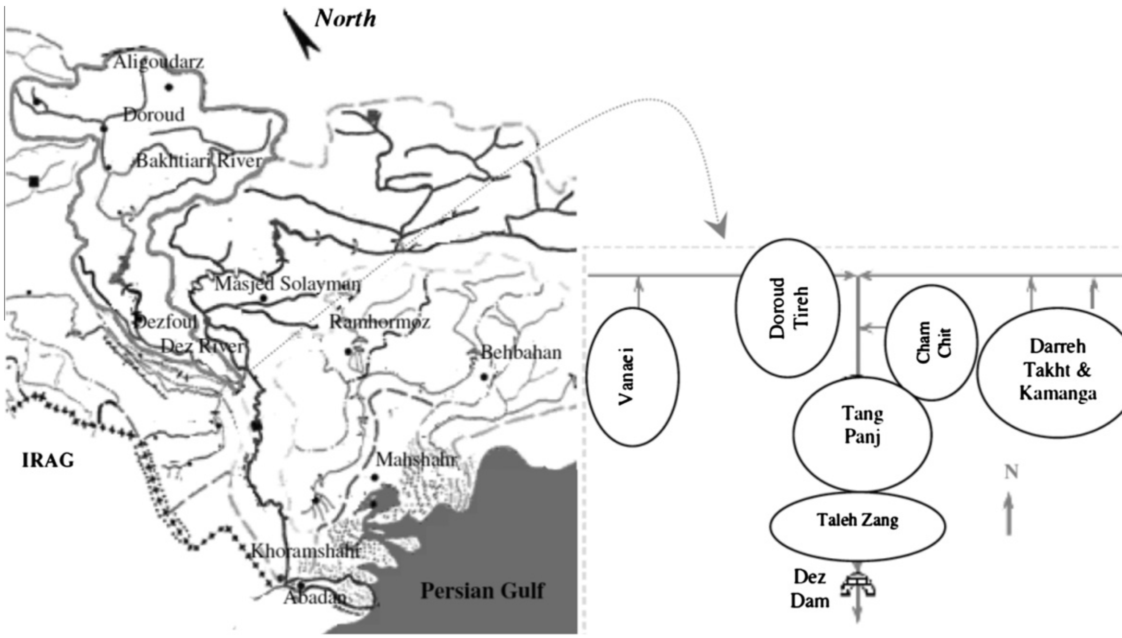

Fig. 1. Locational map of study area.

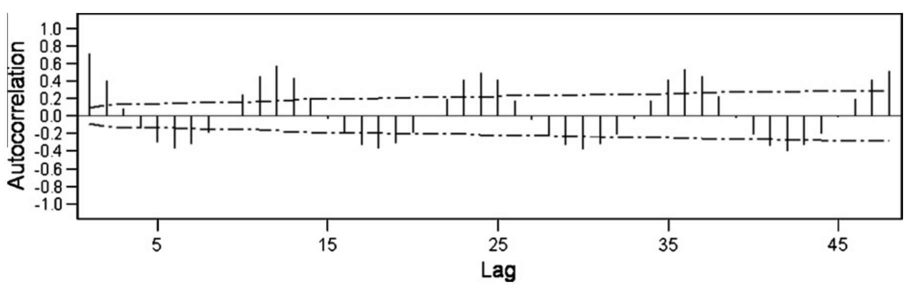

Fig. 2. ACF diagram based on inflow to the Dez reservoir in Taleh Zang station.

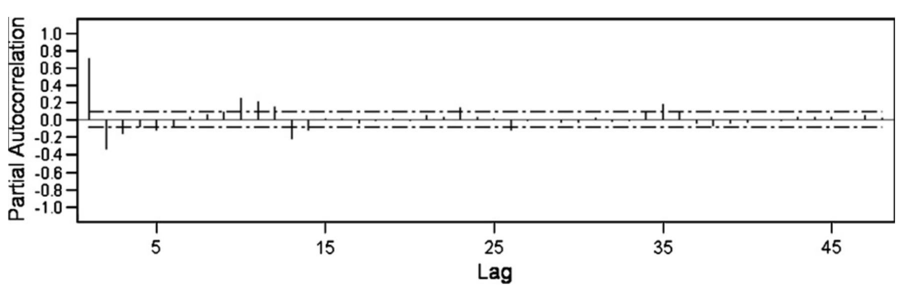

Fig. 3. PACF diagram based on inflow to the Dez reservoir in Taleh Zang station.

next parameters that should be determined are d and D, which defined for ARIMA models. These parameters were considered in practice maximum one or two (Cryer and Chan, 2008). Due to the number of possible scenarios for the parameters, $p = P = q = Q = \{0, 1, 2, 3, 4\}$, and considering two cases for the presence or absence of a constant term in the models, number of ARMA structures used to forecast the inflow to Dez dam was equal to 1250. Also, considering the three modes $d = 1$, $D = 0$, $d = 0$, $D = 1$, and $d = D = 1$, the number of ARIMA structures was equal to $3 \times 1250 = 3750$. The results to determine the parameters p, q, P, Q, d, and D were computed using MINITAB software and are given in Section 4.

In this study, the autoregressive static and dynamic neural network models were applied to forecast monthly reservoir inflow for Taleh Zang station and all necessary steps were programmed in MATLAB software environment. Artificial neural networks used in this study had an input layer, a middle layer and output layer, and they were chosen because they had a high ability to estimate the complex relationships (Chegini, 2012). The difference between static and dynamic neural networks was related to the use of model output as input. In dynamic networks, the model output with a delay, as an input was entered into the network, but in the static artificial neural networks, model output was not used as the input. In this research, neural networks with bias, and hidden and output layer with sigmoid and radial activity function were used. In order to classify data using artificial neural networks, monthly discharge statistics from October 1960 to September 2007 were arranged as Q_1 to Q_{564}. The Q_1 specifies the discharge in October 1960 and the rest was the same manner. The Artificial Neural Networks (ANNs) need to two educational (training) and test (forecasting) sets. Each set contains two sets of data: inputs and the target. Therefore, data division was as follows: in the training set for input data, Q_1 to Q_{264} were used; in target data, Q_{445} to Q_{504}; in the test set (forecasting) for input data, Q_{265} to Q_{444}; and for the target data Q_{505} to Q_{564} were used. Because the number of input data in both training and test sets should be equal, therefore, for final implementation of models, each input matrix contained 180 data, which were identified as three vectors with 60 rows in the following:

$$\text{Training set}: \begin{bmatrix} Q_{85} & Q_{145} & Q_{205} \\ Q_{86} & Q_{146} & Q_{206} \\ & & \vdots \\ Q_{87} & Q_{147} & Q_{207} \\ Q_{144} & Q_{204} & Q_{264} \end{bmatrix} \qquad \text{Testing set}$$

$$: \begin{bmatrix} Q_{265} & Q_{325} & Q_{385} \\ Q_{266} & Q_{326} & Q_{386} \\ & & \vdots \\ Q_{267} & Q_{327} & Q_{387} \\ Q_{324} & Q_{384} & Q_{444} \end{bmatrix}$$

So in training set for calculating the first target data (Q_{455}), Q_{85}, Q_{145} and Q_{205} were used that all belongs to a special month and for remaining data and testing set the same method was used. The cycle of training in ANNs was as follows: first, initial weights and biases were allocated to the training set input data and by their entry into the hidden layer (the effect of number of neurons) and using training function and network education activity functions. A comparison was made between the input data and target data and a communication was established between them. Then forecast was carried out for the new data (test set of input data), and by modifying the weights and biases and the effect of output delay (dynamic network), mentioned cycle was repeated until achieving to an acceptable error (Avarideh, 2012).

The number of neurons in the hidden layer to solve a problem was not known in general in artificial neural networks and should be determined by experimental methods. However, if their numbers was lower than a standard level (as it was also observed in this study), it was possible that learning does not occur in general, which this was called under fitting, and it means that there were not weighting and biases though which network could produce logical outputs close to the correct answers. In contrast, over fitting possibly occurred while the neurons used in this case were excessive. Of course, by increasing the level of target errors, it was possible to prevent severe and unfavourable variations in learning and in turn cancel over training in network. More neurons in the hidden layer caused more degrees of freedom in the network. The more variables were optimized, time of training lengthens, and weight matrix and bias vector become higher. In addition, the higher number of neurons resulted in possibility increasing of answer finding and much chance for preventing from falling in local minimums. Section 4 of this paper reports the results of under fitting and over fitting states. On the other hand, it has been proven that if the number of hidden layer neurons is smaller than or equal to the number of inputs, better results are given (Avarideh, 2012). Therefore, in this study, the best number of neurons in the hidden layer was obtained by different tests. So that, for fixed structures, the number of middle layer neurons were considered 10, 20, and 30–59. Then, for the best structure, about 20 neurons were tested respectively. To avoid more deviation from main topic, all structures were not investigated (for selecting the best number of neurons), and due to the superiority of the sigmoid activity function to radial activity function in this paper, only the results concerning the structures of static and dynamic autoregressive neural network model, with sigmoid activity function was given in Section 5.

3. Criterion to select the best structure of ARMA, ARIMA, and artificial neural network models

In order to select the best structure between ARMA, ARIMA, and artificial neural network models, the root mean square error and the mean bias error were used as follows:

$$RMSE = \sqrt{\sum_{i=1}^{n}(Q_{ci} - Q_{oi})^2/n} \tag{2}$$

$$MBE = \left(\sum_{i=1}^{n}(Q_{oi} - Q_{ci})\right)/n \tag{3}$$

where $RMSE$ is the root mean square error, MBE is the mean square error, i is the number of months, Q_{ci} is the computational discharge in month i, the Q_{oi} observational discharge in month i, and n is the number of data. Finally, for being comparable the results with other similar studies, $RMSE/\overline{Q}_{oi}$ error index are used, where $\overline{Q}_{oi}$ is the average of observational discharge. Remarkably, the amount of $\overline{Q}_{oi}$ for calibration (training) period contain data 445–504 and is equal to 335.7 m^3/s, and for the forecasting period contain data 505–564 and is equal to 199.9 m^3/s. In addition, to determine the time error and the best time of the forecasting, three following criteria were used:

$$E_i = |Q_{ci} - Q_{oi}|/Q_{oi} \tag{4}$$

$$F_i = \sum_{i=1}^{n} E_i \Big/ i \tag{5}$$

$$C_v = \left(\sqrt{\sum_{i=1}^{n}(E_i - \overline{E})^2/n}\right) \Big/ \overline{E} \tag{6}$$

where E_i is the relative error in month i, F_i is the average of cumulative relative error in the month i, $\overline{E}$ is the average of relative error, and C_v is the variation coefficient of relative error.

4. Results and discussion

4.1. Effect of increasing number of parameters on performance improvement of ARMA and ARIMA models

The best values of parameters in the ARMA and ARIMA models have been shown in Table 1. According to Table 1, it was determined that by increasing in number of autoregressive and the moving average parameters, error rate was reduced. Thus, as was clear from Table 1, the best ARMA model has three seasonal autoregressive parameters and four seasonal moving average parameters. The best ARIMA model had four autoregressive parameters, one moving average parameter, one seasonal autoregressive parameter, and one seasonal moving average parameter, and $d = 1$. It was not possible to mention all relevant results of the 5000 structure used to ARMA and ARIMA models in this paper, therefore, only results related to the best structures was presented in Table 1. The benchmark error index $RMSE/\overline{Q}_{oi}$ for the forecasting model ARIMA$(1,1,0)(1,1,2)_{12}$ data was equal to 0.7148 and it was chosen as the best model to forecast inflow to the Dez reservoir in Taleh Zang station, from the all models between ARMA and ARIMA.

Tables 2 and 3 also show obtained coefficients for the ARMA and ARIMA models, respectively.

Table 1
Improving performance of ARMA and ARIMA models due to the increasing number of parameters.

Model	Best structure in considering ACF and PACF (such as previous research)	$RMSE/\overline{Q}$ (training)	$RMSE/\overline{Q}$ (forecasting)	Best structure in current research (increase the number of parameters)	$RMSE/\overline{Q}$ (training)	$RMSE/\overline{Q}$ (forecasting)
ARMA	ARMA$(1,0)(2,1)_{12}$	0.5468	0.8077	ARMA$(0,4)(3,0)_{12}$	0.5603	0.7981
ARIMA	ARIMA$(1,1,0)(1,1,2)_{12}$	0.5514	0.7873	ARIMA$(4,1,1)(1,0,1)_{12}$	0.5589	0.7148

Table 2
Obtained coefficients for the ARMA model.

Constant term	θ_1	θ_2	θ_3	θ_4	Φ_1	Φ_2	Φ_3	χ^2	DF
71.3400	−0.5526	−0.4807	−0.2369	−0.1194	0.3602	0.0716	0.2899	53.5345	41

Table 3
Obtained coefficients for the ARIMA model.

φ_1	φ_2	φ_3	φ_4	Φ_1	θ_1	Θ_1	χ^2	DF
0.2575	0.1056	−0.0979	−0.0061	1.0010	0.6394	0.9522	56.0309	41

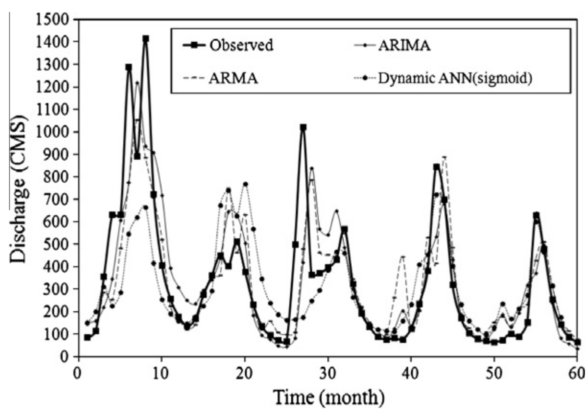

Fig. 4. Obtained results in training period.

According to Tables 2 and 3, the obtained values for the ARMA and ARIMA models with degrees of freedom 41, was lower than its critical value (56.9420) (Wei, 1990). Therefore, it was concluded that the structures used to forecast were accurate. It should be noted that, degrees of freedom 41 was acquired by with a minus of the number of parameters used in each model (except d and D in ARIMA model) from the maximum lag which was visible in Figs. 3 and 4 (48).

4.2. Ability of used models in inflow forecasting

Table 4 shows training and forecasting $RMSE/\overline{Q}_{oi}$ index used for research models. By comparing the results in Table 4, it was found that ARIMA model had a better performance than ARMA model because of making time series stationary, in both training and forecasting phases. According to Table 4, it was determined that dynamic autoregressive artificial neural network used in this study, was superior to static autoregressive artificial neural network models in both training and forecasting stages, because of output delay effect as input to network and increasing the power of network training. The effects of selecting an appropriate activity function were shown in Table 4. By selecting a sigmoid activity function, the forecasting was done in a satisfactory manner, but with a poor activity function (radial) accuracy of forecasting decreases significantly. According to Table 4 as artificial neural networks with sigmoid activity function were superior to artificial

Table 4
Obtained results for inflow to Dez reservoir in Taleh Zang station.

Model	$RMSE/\overline{Q}$ (training)	$RMSE/\overline{Q}$ (forecasting)
Dynamic autoregressive ANN with sigmoid activity function	0.7436	0.6380
Static autoregressive ANN with sigmoid activity function	0.8046	0.6630
ARIMA$(4,1,1)(1,0,1)_{12}$	0.5589	0.7148
ARMA$(0,4)(3,0)_{12}$	0.5603	0.7981
Dynamic autoregressive ANN with radial activity function	0.8211	0.8400
Static autoregressive ANN with radial activity function	1.1009	1.0019

neural networks with radial activity function in both static and dynamic states, $RMSE/\overline{Q}_{oi}$ index, and training and forecasting data for artificial neural networks with sigmoid activity function were calculated for number of middle layer neurons and were presented in Table 5. According to Table 5, by using from neurons more than 20, accuracy of forecasting data reduced because of over fitting. In addition, in static network with neurons less than 6 and in dynamic network with neurons less than 17, forecasting was not done correctly because of under fitting. Table 5 shows that training and forecasting $RMSE/\overline{Q}_{oi}$ index in dynamic autoregressive ANN with sigmoid activity function and 17 neurons in the hidden (middle) layer was lower, and thus this state was appropriate.

Figs. 4 and 5 compare the ability of the superior structures between ARMA, ARIMA, and artificial neural network models, used for training and forecasting.

As is clear from Figs. 4 and 5, although the ARMA and ARIMA models had a better performance in training period into the dynamic autoregressive artificial neural network model with sigmoid activity function, dynamic autoregressive artificial neural network model with sigmoid activity function was superior to the ARMA and ARIMA models in forecasting period, especially peak points.

Problem of used models was forecasting error of peak flows. Figs. 6–8 show comparison of observed data with ARMA, ARIMA, and dynamic autoregressive ANN with sigmoid activity function models in forecasting period, regardless of occurrence time, respectively.

By comparing Figs. 6–8 was indicated that the ARMA model forecasted almost all of discharges less than 260 more than the actual amount cubic meter per second (CMS) and forecasted less than

Table 5
Effect of number of hidden layer neurons on ANN model.

ANN type	Number of hidden layer neurons	$RMSE/\overline{Q}$ (training)	$RMSE/\overline{Q}$ (forecasting)	ANN type	Number of hidden layer neurons	$RMSE/\overline{Q}$ (training)	$RMSE/\overline{Q}$ (forecasting)
Static	10	0.9786	0.7977	Dynamic	10	0.9351	0.7327
Static	20	0.9592	0.8365	Dynamic	20	0.6280	0.9192
Static	30	0.8583	1.0028	Dynamic	30	0.7735	0.7916
Static	40	1.0403	0.8662	Dynamic	40	0.8484	0.8560
Static	50	0.8420	0.8228	Dynamic	50	0.6760	0.8111
Static	59	0.8435	0.9767	Dynamic	59	0.9021	0.9586
Static	1	0.9963	0.8179	Dynamic	1	0.8840	0.7324
Static	2	0.9280	0.7976	Dynamic	2	1.0115	0.7485
Static	3	0.7937	0.7577	Dynamic	3	0.9173	0.7926
Static	4	0.7832	0.8119	Dynamic	4	0.8488	0.8228
Static	5	0.8831	0.8199	Dynamic	5	0.8066	0.7338
Static	6	0.8046	0.6630	Dynamic	6	0.8805	0.7132
Static	7	0.8949	0.7722	Dynamic	7	0.9163	0.8012
Static	8	0.8762	0.7492	Dynamic	8	0.7489	0.7398
Static	9	0.9462	0.8768	Dynamic	9	0.7479	0.6686
Static	11	0.7550	0.8998	Dynamic	11	0.7708	0.7250
Static	12	0.9559	0.7651	Dynamic	12	0.7613	0.7367
Static	13	0.8617	0.7072	Dynamic	13	0.8446	0.7908
Static	14	0.7120	0.8178	Dynamic	14	0.9421	0.7830
Static	15	0.6552	0.8626	Dynamic	15	0.9714	0.8017
Static	16	0.7565	0.8197	Dynamic	16	0.8497	0.8216
Static	17	0.6474	0.8202	Dynamic	17	0.7436	0.6380
Static	18	0.8424	0.8483	Dynamic	18	0.9236	0.8506
Static	19	0.7578	0.8838	Dynamic	19	1.0440	0.7481

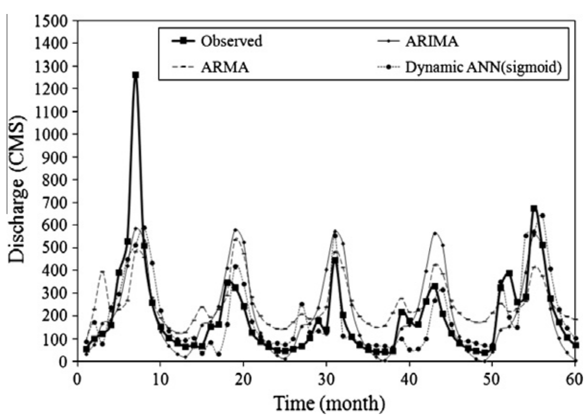

Fig. 5. Obtained results in forecasting period.

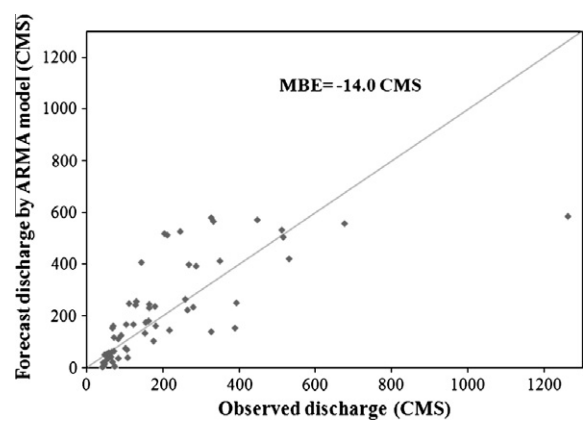

Fig. 7. MBE index for ARIMA model.

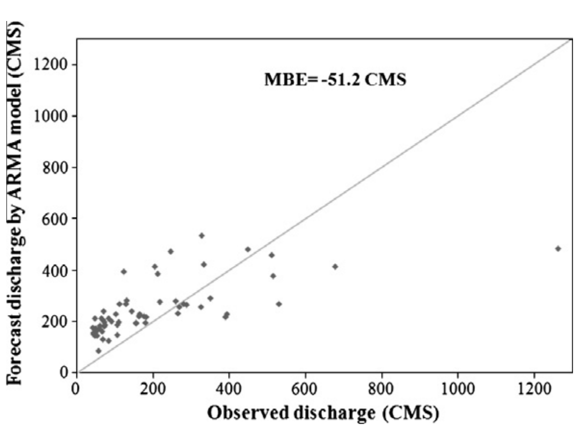

Fig. 6. MBE index for ARMA model.

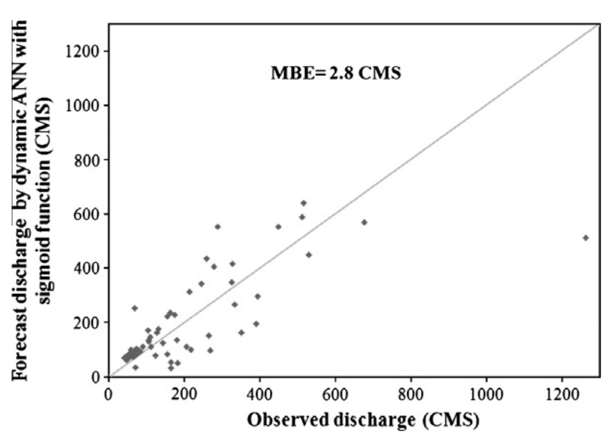

Fig. 8. MBE index for ANN model.

Table 6
Minimum of E and F indexes in forecasting period.

Model	E_{min}	Month	$\overline{E}$	F_{min}	Month	C_v
Dynamic autoregressive ANN with sigmoid activity function	0.0205	Third June	0.4620	0.4091	First September	0.7943
ARMA(0,4)(3,0)$_{12}$	0.0296	Fifth June	1.0611	0.566	First October	0.8746
ARIMA(4,1,1)(1,0,1)$_{12}$	0.0028	Third November	0.5207	0.2433	First July	0.8054

the actual amount other discharges. But ARIMA model because of making of discharge data series stationary, not only establish equality between the number of more and less than forecasted data, but could also forecast data less than 100 CMS with a good accuracy. However, dynamic autoregressive ANN model with sigmoid activity function had a better performance than the ARMA and ARIMA models. This was also confirmed by comparing MBE index. The MBE index close to zero for dynamic autoregressive ANN model with sigmoid activity function indicated the unbiased position of dynamic autoregressive ANN model with sigmoid activity function in forecasting period. In addition, negativity of MBE index indicated (not number) the higher values of excessively forecasted discharge compared to those of forecasted discharge in ARMA and ARIMA models poorly.

4.3. Error changes of used forecasting models based on elapsed time

In order to study the time changes of forecasting by using Eqs. (4)–(6), the best forecasting time for the models was obtained. Table 6 shows the minimum E and F indexes, the month of occurrence of these values, and the C_v index for forecasting period.

Values of $\overline{E}$ and C_v indexes in Table 6 was lower for dynamic autoregressive ANN model with sigmoid activity function than the ARMA and ARIMA models. This represents lower changes in error and implies superiority of dynamic autoregressive ANN model with sigmoid activity function to the ARMA and ARIMA models. For better comparison of E and F indexes in forecasting period, Figs. 9 and 10 could be used, respectively. Fig. 9 shows that changes of relative error are lower in dynamic autoregressive ANN model with sigmoid activity function than those of the ARMA and ARIMA models. Fig. 10 indicates that the average cumulative relative error in dynamic autoregressive ANN with sigmoid activity function and ARIMA model, have less fluctuations than the ARMA model. In other words, dynamic autoregressive ANN with sigmoid activity function and ARIMA models have reached a kind of stagnation in error. As is clear from Table 6, amount of E_{min} index is nearly ten times, and amount of $\overline{E}$ and F_{min} indexes are nearly two times in ARIMA model is less than the ARMA model, which shows a significant reduction in forecast error for ARIMA model than that of the ARMA model. According to Table 6, the lowest rate of F_{min} index has happened in the first month forecast, which it also is clear in

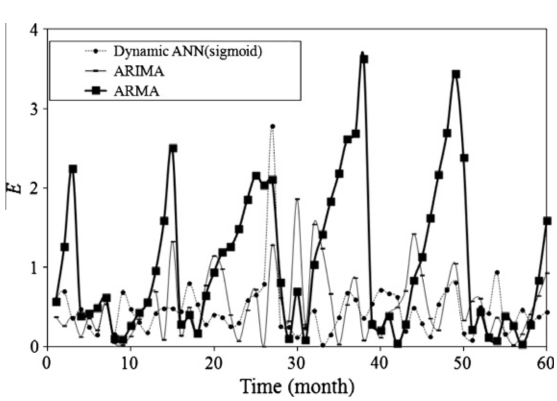

Fig. 9. Changes of E index based on elapsed time.

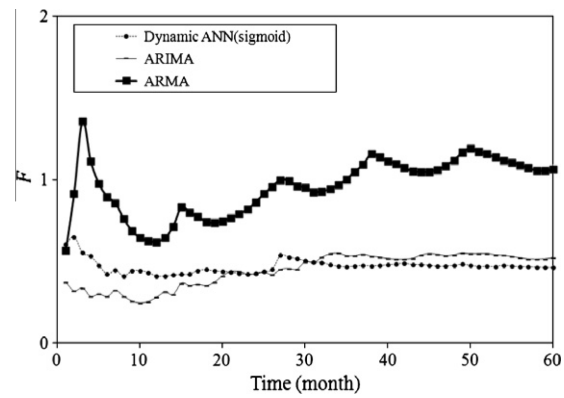

Fig. 10. Changes of F index based on elapsed time.

Fig. 10. Meanwhile the increasing trend of F index is visible in the ARMA model as well as in Fig. 10.

The amount of F_{min} index was not only happened in the tenth month of forecasting in ARIMA model, but also according to Fig. 10, $(F_{\max})_{ARIMA} < (F_{\min})_{ARMA}$. It was an important result to compare the errors in ARMA and ARIMA models. It means that the maximum average cumulative relative error in the ARIMA model was less than the minimum average cumulative relative error in the ARMA model. In other words, the amount of F index in ARIMA model has never reached to the amount of F index in the model ARMA, which it shows again the superiority of ARIMA model to ARMA model. Also in Fig. 10, the amount of F index in the ARIMA model was less than dynamic autoregressive ANN model with sigmoid activity function at the initial 30 months of forecasting. However, F index become lower in dynamic autoregressive ANN model with sigmoid activity function. This was represented a better performance of ARIMA model in short-term forecasting and better performance of dynamic autoregressive ANN model with sigmoid activity function in long-term forecasting. The reason of the better performance of ARIMA model for the short-term forecasting was related to the nature of the hydrological data used in this model. In this model, since the 504 data was fed to this model as a lump sum, the relationship between the data was established only as one monthly. It means that model considers the once-a-month communications between discharges in order to forecast the new month discharges. Thus, the best forecasting horizon does not go beyond a year. In the autoregressive artificial neural network model, input data enter the network as three vectors 60-ary (each vector continues previous vector statistically), where each was related to about 5 years, which start with the first October and ends in the fifth September. Thus, for forecasting each month, not only once-in-a month relationship of each 60-ary vector, but also the communication between each data in these categories of 60-ary with other two categories was considered. It could be better said that if the relationship between the data is regarded as a hydrological parameter, ARIMA model uses one parameter (once-in-a-month communication between previous discharges) and the ANN model uses two hydrological parameters (once-in-a-month communication between each category of 60-ary and communication of every data in this category with two other categories). This showed that artificial neural networks had a better performance in long-term fore-

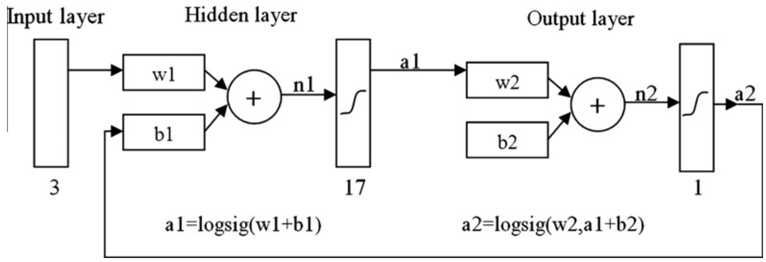

Fig. 11. A graphical structure of dynamic neural network model with number of 3, 17, and 1 neuron(s) in input, hidden, and output layers, respectively (best structure in this study).

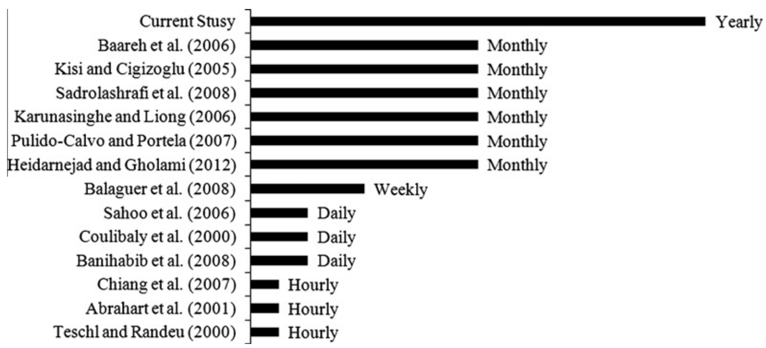

Fig. 12. A compression between current study and previous studies based on forecasting period.

casting. This was confirmed in Figs. 5 and 6. In Fig. 4, peak points related to final 2 years of fitness have been estimated much better than those of first 3 years of fitness have. In Fig. 5 peak points corresponding to the end 3 years of forecasting have been estimated better than those of first 2 years forecasting. According to Figs. 9 and 10 and Table 3, although it was difficult to select the best forecasting time, the monthly inflow could be forecast about 1 year ago by using the ARIMA model. Given that in dynamic autoregressive ANN model with sigmoid activity function, whatever we move forward towards the end of 5-year forecast period, fluctuations decrease, and even the accuracy of forecasting increases (especially in the peaks), and it could be concluded that next 5 years could be forecast by this discharge model.

4.4. Increasing of forecasting period using the best model of current study

Fig. 11 shows a graphical structure of the best model in this study. By using this structure can be forecast inflow to the Dez reservoir for 5 next years. Fig. 12 shows a compression between current study and previous studies (Abrahart et al., 2001; Baareh et al., 2006; Balaguer et al., 2008; Banihabib et al., 2008; Chiang et al., 2007; Coulibaly et al., 2000; Heidarnejad and Gholami, 2012; Karunasinghe and Liong, 2006; Kisi and Cigizoglu, 2005; Pulido-Calvo and Portela, 2007; Sahoo et al., 2006; Sadrolashrafi et al., 2008; Teschl and Randeu, 2006) based on forecasting period. In this study, because of simultaneous effectiveness of dynamic ANN (use from output delay as input to better training) and optimization for number of hidden layer neurons (17), horizon time of forecasting increased from short or mid-term to long-term period.

5. Conclusion

In this paper, ability of ARMA, ARIMA, and autoregressive ANN models was compared in forecasting Dez reservoir inflow at the Taleh Zang station. Monthly discharge data for a period of 42 years were collected from Taleh Zang hydrometrical station and used for training models. Then, the accuracy of forecasting models were investigated by recent 5 years data. To summarize, it could be concluded that:

The accuracy of both models ARMA and ARIMA increased compared to previous studies, because of increase in the number of autoregressive and moving average parameters in these models.

The ARIMA model has a better performance than ARMA model because it makes time series stationary, in both training and forecasting phases. But dynamic autoregressive artificial neural network used in this study is superior to static autoregressive artificial neural network, due to the output delay effect as input to network and increase in the power of network training compared to autoregressive static neural network and in general compared to the ARMA and ARIMA models in both training and forecasting stages.

The effect of selecting the proper activity function and the number of middle layer neurons were identified in this paper as well as. Because by selecting appropriate activity function and number of neurons, forecasting was performed nicely, but by selecting activity function and number of inappropriate neurons forecasting accuracy decreased significantly. Number of appropriate middle layer neurons for static and dynamic networks was 6 and 17 respectively, and an appropriate activity function was sigmoid.

Changes in relative error, cumulative mean relative error, and variation coefficient of relative error in autoregressive ANN models with sigmoid activity function was less than autoregressive ANN with radial activity function and ARMA and ARIMA models; this indicated the superiority of autoregressive ANN models with sigmoid activity function to the other models. By investigating these changes, it was cleared that the ARIMA model could be used for forecasting an appropriate monthly inflow for the next 12 months, and dynamic autoregressive ANN model with sigmoid activity function could be used for forecasting discharge of the next 5 years.

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