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Comparison of ANN and ARIMA techniques for forecasting Kardeh river flow

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ABSTRACT

Because of Iran located in climate of arid and semi-arid, prediction of river flow for programming and water resources management is very important.Present research was carried out with the aim of Kardeh river artificial flow production using neural network and ARIMA model, and evaluating performance of these two models. Data used in this research as monthly time series from 1987 to 2013 was collected from Regional Water Department of Mashhad. Quantity obtained from division of R^2 index for all time durations in ANN model is more than 1 (> 1), that show index is higher for ANN model than ARIMA model. Also quantity obtained from division of RMSE, MSE and MAD indexes for all time duration is lower for ANN model than ARIMA model, however in this study, Kardeh river artificial flow production was Forecasted with use of method of artificial neural network

Key words : *ARIMA, ANN, Forecasting, KardehRiver*

Introduction

With due attention to importance of controlling surfacewaters and also importance of water deficit that in vast parts from Iran was seen, modeling water resources and river flows is one of important subjects for programming long time and better use from them (Sharifi and Salehi, 2006).

Because of Iran located in climate of arid and semi-arid, prediction of river flow for programming and water resources management is very important. Accuracy predictions can help to responsible persons in this matter for adopting accuracy decisions (SedaghatKerdar and Fattahi, 2009).

Probability and statistic common methods on the basis of mathematical equations usually were used for predicting time series by water science Scientifics. These methods are on the basis of time series, regression models and water-shed basin models (Sveinsson *et al.*, 2003). Between these methods, time series method has the most limitation and the lowest accuracy for predicting river flow in long time. water-shed basin models is very complex, and supplying and producing it has much expenses. Regression models have difficulties similar to time series method and water-shed basin models (Souza and Lall, 2003). So researches created one method for predicting in the name of "neural method" that this method was extracted from human brain. Neural method can find relations between variables (Zhang and Hu, 1998).

Kardehriver has formatted from joining two sub rivers of Koushkabad and Al. Water of this river is usable for agriculture and drinkable consumptions. On this river was established Kardeh dam. This dam is located in north of Mashhad plain. Area of this

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water-shed basin is 547 km^2 and precipitation average of region is 283.5 mm (Regional Water Department of Mashhad, 2013).

Researches done by artificial neural network showed that this model has high accuracy for predicting (Aksoy and Dahamsheh, 2009). Parida*et al*., (2006) run off of water-shed basin of semi-arid of Botswanapredicted to year of 2020 using artificial neural network. This research with aim of water resources management in water-shed basin was done.The results of this research showed that run off coefficient about 1% would increase in each year. Makkeasorn*et al*., (2008) on the basis of world climate change, and attention to water resources management as one critical subject in world predicted river flow in water-shed basin of semi-arid in South Texas using two models of artificialIntelligence. They use from thermal data of ocean surface by meteorology future generation radar obtained from temporary meteorology stations, and old data of river flow obtained from measurement stations of USA Geology Department. The results of research showed that precipitation data of future generation radar has the most effect in river flow prediction, and also water surface temperature in Atlantic Ocean has more effect on prediction than water surface temperature in Pacific Ocean.

Present research was carried out with the aim of Kardeh river artificial flow production using neural network and ARIMA model, and evaluating performance of these two models.

Materials and Methods

Auto-Regressive Integrated Moving Average (ARIMA) Model

Introduced by Box and Jenkins (Box and Jenkins,1970), in the last few decades the ARIMA model has been one of the most popular approaches of linear time series forecasting methods. An ARIMA process is a mathematical model used for forecasting. One of the attractive features of the Box-Jenkins approach to forecasting is that ARIMA processes are a very rich class of possible models and it is usually possible to find a process which provides an adequate description to the data. The original Box-Jenkins modeling procedure involved an iterative three-stage process of model selection, parameter estimation and model checking. Recent explanations of the process (Makridakis*et al*, 1998) often add a preliminary stage of data preparation and

a final stage of model application (or forecasting). Also, the *ARIMA (p, d, q)* model for variable *y* is as follow:

$$y_t = f(t) + \Phi_1 y_{t\_1} + 000 + \Phi_1 y_{t-p} + e_t + \theta_1 e_{t-1} + 000 + \theta e_{t-q} \quad ..(1)$$

Where *y* is estimated by the following equation:

$$Y_t = \Delta^d x_t = (1-L)^d x_t \quad .. (2)$$

Where and are the target value and random error at time t, respectively $\Phi_i (i = 1,2,000,p)$ and $\Phi_i (j = 1,2,000, q)$ are model parameters, p and q are integers and often referred to as orders of autoregressive and moving average polynomials

Artificial Neural Network mode

The major advantage of neural networks is their flexible capability of nonlinear modeling. With ANN, there is no need to specify a particular model. Rather, the model is adaptively based on the features presented from the data (Haoffi *et al.*, 2007). This data-driven approach is suitable for many empirical researches where no theoretical guidance is available to suggest an appropriate data generating process. For the purposes of this paper, the feed-forward backpropagation neural network (alsoknown as a MLP4 network) is the neural network model most widely used in time series forecasting, because it is capable of resolving a wide variety of problems (Sarle, 2003). MLP networks made up of an input layer, an output layer and one or more hidden layers of neurons. As the Fig1 shows, each input is weighted with an appropriate *w*. The sum of the weighted inputs andthe bias forms the input to the transfer function *f*.

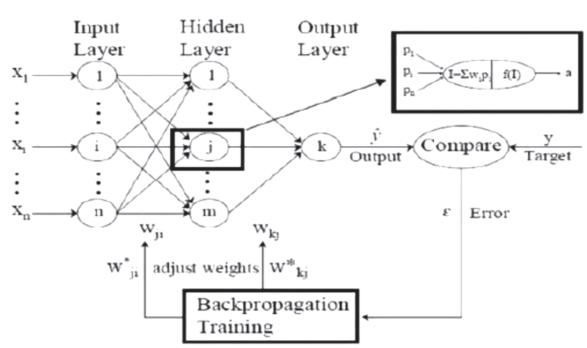

Fig. 1. A typical Back-Propagation neural network

Neurons can use any differentiable transfer function *f* to generate their output. In general,transfer function introduces a degree of nonlinearity that is valuable for most ANNapplications and ideally, it should be continuous, differentiable, and monotonic. Feed-forward networks often have hidden layer(s) of sigmoid neurons followed by an output layer of linearneurons.

Two stages may be considered in the MLP network: the running stage, in which an inputpattern is presented to the trained network and transmitted through successive layers ofneurons until reaching an output, and the training or learning stage in which the weights orparameters of the network are iteratively modified on the basis of a set of input–outputpatterns known as a training set, in order to minimize the deviance or error between the outputobtained by the network and the user's desired output. This is why MLP network learning issaid to be supervised. The learning rule commonly used in this type of network is the backpropagation algorithm or gradient descent method, developed and disseminated byRumelhart, Hinton and Williams (Rumelhart, 1996). In this research, we use the following three-layer feedbacknetworks:

$$F = F\left[\beta_0 + \sum_{j=1}^{J} \beta_j G\left[\sum_{k=1}^{K} \gamma_{kj} X_J\right]\right] \quad (3)$$

Where F is the output function of the output layer unit, 0 is the bias unit (equal to 1), G isthe output function of the hidden layer units j ,denotes the weight for the connectionlinking input k to the hidden unit j , is the weight of outputs from the hidden layers in theoutput layer unit, and X is the input vector.

Forecast Performance Measures

Forecast researchers need measures in order to compare the forecasting performance ofvarious models. Commonly, these measures are including of, MAD, MSE and RMSE thatthe following is their definition and general formulas:

Where y_t, $\hat{y}_t$ and n are the target value, output value and number of observations, respectively. Clearly, the best score for R^2 measure is 1 and for other measures is zero.

Results and discussion

In this part in beginning for selecting better model for prediction of time series data, performance of Autoregressive Integrated Moving Average (ARIMA) and artificial neural network (ANN) models was compared, then better model was selected. In order to R^2 index and errors achieved from prediction of two models for different time ranges with together was compared.

Firstly, ARIMA method is evaluated. In this method variables correlation degree as determined via test of Augmented Dicky Fuller, and results was fixed with firstorder difference Equations. Then forduration of 3, 6, 9 and 12 month,Autoregressive

Table 1. Four common types of forecast performance measures

Measure Definition	Formulate
Absolute fraction of variance (R^2)	$R^2 = 1 - \frac{\sum(\hat{y} - y_t)^2}{\hat{y}_t^2}$
Mean Absolute Deviation (*MAD*)	$MAD = \frac{\sum\lvert\hat{y}_t - y_t\rvert}{n}$
Mean Square Error (*MSE*)	$MSE = \frac{\sum(\hat{y} - y_t)^2}{n}$
Root Mean Square Error (*RMSE*)	$RMSE = \sqrt{\frac{\sum(\hat{y} - y_t)^2}{n}}$

degree was supposed 1, 2, 3 and 4 respectively, and for every which from time duration of models with MA process degree equal to 1, 2, 3 and 4 were estimated, and from better model that had the most amount of *Schwartz Bayesian*index for determining mobile mean degree was used. Then determined structure for prediction was used. And finally this prediction was compared with use of models evaluation indexes with actual data (table 2). In ARIMA model the best structure selected in condition of 3 month is (1, 2, 1), in condition of 6 month is (1, 1, 2), in condition of 9 month is (2, 2, 3) and in condition of 12 month is (1, 2, 4).

In order to evaluating ANN model performance and comparison of it with method of ARIMA in prediction of flow time seriesfor time duration of 3, 6, 9 and 12 months of future, different structures of feedback spreading network (1, 2, 3, 4 and 5 knots in hidden layer) was designed with logistic activation function. Finally for evaluation of this model performance and comparison of it with ARIMA model using models valuation parameters, output data every network was compared with actual data (table 2).In ANN model the best structure selected in condition of 3 month is 1-1-2-3-5, in condition of 6 month is 1-1-2-3-4-5-5, in condition of 9 month is 1-1-2-3-5 and in condition of 12 month is 1-1-2-4-5.Networks structure to this form was designed that the first number shows No. inputs and the last number shows No. outputs, and each number shows No. knots and No. neurons in each knot. According to Table 2, ANN model has more performance for predicting time series than ARIMA model.

In order to compare performance of ARIMA and ANN models for predicting time series was divided quantity related to ANN models test evaluation parameters on quantity related to ARIMA models test evaluation parameters in each time horizon (Table 3). According to table 3, quantity obtained from division of R^2 index for all time duration in ANN

Table 2. Results obtained from ARIMA model and ANN model

Duration (month)	ANN						ARIMA		
	R^2		MAD		RMSE		R^2	MAD	RMSE
	test	train	test	train	test	train			
3	0.981	0.988	0.0028	0.0038	0.0029	0.0039	0.958	0.017	0.021
6	0.980	0.987	0.0042	0.0031	0.0042	0.0031	0.952	0.020	0.024
9	0.0976	0.978	0.0044	0.0034	0.0047	0.0035	0.948	0.021	0.031
12	0.971	0.974	0.0046	0.0039	0.0049	0.0038	0.939	0.022	0.032

Reference: research results

Table 3. Performance comparison of results obtained from ARIMA model and ANN model

RMSE	MAD	R^2	ANN	ARIMA	Duration Time(Month)
0.185	0.223	1.024	1-1-2-3-5	(1,2,1)	3
0.188	0.248	1.044	1-1-2-3-5-5-4	(1,2,1)	
0.195	0.235	1.038	5-3-2-1-1	(1,2,1)	
0.198	0.252	1.039	5-4-2-1-1	(1,2,1)	
0.176	0.235	1.022	1-1-2-3-5	(2,1,1)	6
0.175	0.21	1.029	1-1-2-3-5-5-4	(2,1,1)	
0.179	0.218	1.025	5-3-2-1-1	(2,1,1)	
0.181	0.222	1.028	5-4-2-1-1	(2,1,1)	
0.162	0.235	1.032	1-1-2-3-5	(3,2,2)	9
0.173	0.214	1.034	1-1-2-3-5-5-4	(3,2,2)	
0.151	0.209	1.029	5-3-2-1-1	(3,2,2)	
0.189	0.224	1.034	5-4-2-1-1	(3,2,2)	
0.185	0.228	1.038	1-1-2-3-5	(4,2,1)	12
0.178	0.218	1.041	1-1-2-3-5-5-4	(4,2,1)	
0.165	0.231	1.044	5-3-2-1-1	(4,2,1)	
0.153	0.209	1.034	5-4-2-1-1	(4,2,1)	

Reference: research results

model is more than 1 (R^2> 1), that show R^2index is higher for ANN model than ARIMA model. Also quantity obtained from division of RMSE, MSE and MAD indexes for all time duration is lower for ANN model than ARIMA model.

Conclusion

Present research was carried out with aim of Kardeh river artificial flow production using neural network and ARIMA model, and evaluating performance of these two models. In order to evaluating ANN model performance and comparison of it with method of ARIMA in prediction of flow time series for time duration of 3, 6, 9 and 12 months of future, different structures of feedback spreading network (1, 2, 3, 4 and 5 knots in hidden layer) was designed with logistic activation function.Quantity obtained from division of R^2 index for all time duration in ANN model is more than 1 (R^2> 1), that show R^2index is higher for ANN model than ARIMA model. Also quantity obtained from division of RMSE, MSE and MAD indexes for all time duration is lower for ANN model than ARIMA model, however in this study, Kardeh river artificial flow production was predicted with use of method of artificial neural network

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