International Journal of Applied Engineering Research ISSN 0973-4562 Volume 12, Number 9 (2017) pp. 2006-2016

A Comparative Study of Artificial Neural Networks and Adaptive Nero-Fuzzy Inference System for Forecasting Daily Discharge of a Tigris River

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Abstract
Forecasting of the river discharge is important for convenient water resources management and planning specially in dry and warm region. This study prepares the application and comparison of artificial neural networks (ANNs) with back-propagation algorithm and adaptive nero-fuzzy inference system (ANFIS) for predicting the daily discharge in the Tigris River in Qurnah, Basrah, south of Iraq. The overall strategy in this study is to construct and develop three models for both ANNs and ANFIS techniques to forecast the daily discharge of the river depending on observed data was taken in earlier years. Three statistical parameters (root mean square error, efficiency coefficient and coefficient of correlation) are used to evaluate the performance of the three models in each technique. Depending on results of statistical results, both techniques have the ability to predict the river discharge. Also, it is found that the third model is better than the first and second models in both techniques to predict the daily discharge in the river. At last, in all models, statistical parameters and graphical results showed that the convergence between observed and predicted data is very good by using ANFIS models as compared to ANNs models.

Keywords: Forecasting, Tigris River, Discharge, Artificial Neural Networks, Adaptive nero-fuzzy inference system

INTRODUCTION

The discharge of a river is the volume of water passing through the river cross section at a specific point in a unit of time. As mentioned, forecasting of the river discharge could be very important in the management of water resources. Any seasonal river basin designing for evaluation of water between different consumers cannot achieve without predicting /knowing the amount of water (i.e. flow rate) passes through the river at that time.

Many of the activities linked with the operation and planning of the components of a water resource system require predict of future events. For the hydrologic components, there is a requirement for both long term and short term forecasts of stream flow events, discharge in order to optimize the system or to plan for future development. Many of these systems are large in spatial extent and have a hydrometric data collection network that is very little. These conditions can generate in considerable uncertainty in the information of hydrologic that is available [A. Chowdhary and shrivastava R.K., 2010]. Moreover, the river management for operation strongly depends on accurate and reliable flow forecasts [M. K. Akhtar, et. Al, 2009].

Moreover, the inherently non-linear relationships between input and output variables complicate effort to predict streamflow events. Therefore, it is required to perfection in forecasting techniques. Presently, there are many techniques used in the hydrological of modeling time- series and generating synthetic streamflow assume linear relationships among the variables [A. Chowdhary and shrivastava R.K., 2010]. Models usually integrate simplified forms of physical laws and are generally nonlinear, deterministic and time-invariant, with parameters that represent the watershed characteristics [Hsu, K., et. al, 1995]. Kitanidis and Bras, explain that conceptual watershed model is reliable in predicting the most significant features of the hydrograph [Kitanidis, PK. and Bras, RL., 1980a and Kitanidis, PK. and Bras RL., 1980b]. However, the application and calibration of such a model can typically current various difficulties [Duan, Q., et. al, 1992], needing developed mathematical tools [Duan, Q., et. al, 1992, Duan, Q., et. al, 1994 and Sorooshian, S., et. al, 1993], significant amount of calibration data [Yapo, P., et. al, 1996], and some degree of experience and expertise with the models [Hsu, K., et. al, 1995].The problem with the conceptual models is that empirical regularities or periodicities are not always clear.

Although of requiring to large amount of data and effort of human to calibrate, validate and test the model, physics based methods are useful to understand the entire of underlying process [VanderKwaak, J.E. and Loague, K., 2001]. In the other hand, good advantage of predicting models is that they just require some amount of data, but their drawback is that they appear like a black box in use and also require lengthy parameterization. Multi Linear Regression (MLR), ANFIS, Fuzzy Logic Based System and Artificial Neural Networks are most common used of predicting methods [Wang, Y.-C., et. al, 2008].

Artificial Neural networks (ANNs) have been well suitable and successfully used in diversity fields of hydrology inclusive water resources [Lohani, A.K., et. al, 2011, Huo, Z.,et. al, 2010, Chen, D., et. al, 2010, Agarwal, A., et. al, 2006 and Panagoulia, S., 2006]. ANN models extractor the relationship between the inputs and outputs of a process, without the physics being explicitly provided. These models need only a few number of input variables, such as discharge and rainfall, while, distributed (semi) physically based models require a large number of additional parameters to be provided, such as cross-sections, flow resistance, groundwater flow characteristics, etc. these parameters are difficult to measure or to estimate, mainly because of temporal variability and strong spatial. In addition to this, ANNs models are reliable and computationally fast, which makes them very suitable for early warning and real time applications, such as flood forecasting. On the other hand, the ANN solution is obtained through an optimization method validated during trials and errors [ASCE, 2000a and Brath, A., et. al, 2002].

Another technical used extensively in hydrological studies, which is the fuzzy inference system (FIS). The FIS has been used successfully in rainfall-runoff and real time flood forecasting modeling [Hundecha, Y., et. al, 2001]. In recent years, the integration of neural networks and fuzzy logic has given birth to neuro-fuzzy systems. Neuro-fuzzy systems have the potential to capture the advantages of both ANNs and fuzzy logic in a single framework. Many researchers used this technique for time series of river flow and rainfall-runoff predictions [Hundecha, Y., et. al, 2001, See, L. & Openshaw, S., 2000 and Xiong, L. H.,et. al, 2001].

The main objective of this study is forecasting the daily discharge of Tigris River in Qurnah city, Basrah, south of Iraq by using ANNs and ANFIS techniques then compare the two techniques to investigate applicability and performance as effective tools for applicating in water resources engineering.

STUDY AREA AND DATA SET

The Tigris River is the second largest river in Western Asia. Its basin is shared by four countries: Turkey, Iraq, Syria and Iran. On the other hand contributions from precipitation that originates in the Armenian Highlands, the Tigris is fed by numerous tributaries that rise in the Zagros Mountains in Iraq, Iran and Turkey. The length of Tigris River is 1900 km out of which 1415 Km run inside Iraq. It has a catchment area of about 235,000 Km^2 [Iraqi Ministries of Environment, 2006]. The Tigris has a higher water yield than the Euphrates River. Historically, the natural annual flow of the Tigris at the Iraqi-Turkish-Syrian border was around 21 BCM. In recent years, the flow volume of Tigris River has been influenced by development of large water projects in Turkey and Iraq. This river is heavily dammed in both Iraq and Turkey, in order to provide water for irrigating the arid and semi-desert region boarding the river valley. In accordance with the character of feeding and distribution of precipitation, one can distinguish three periods in the annual cycle of the Tigris river water regime. Flood period (February-June) connected with snow thawing in the mountains, summer low-water period (July-October) and a period of rain flooding (November-February) within the flood period the Tigris River conveys about 75 percent of annual flow, in the dry period about 10 percent and in the period of autumn-winter flood about 15 percent [Iraqi Ministries of Environment, 2006]. Tigris and Euphrates meet near Qurnah, Basrah, south of Iraq. The combined flow, called Shatt Al Arab empties in Arabian Gulf. Qurnah city is a pleasant little place 74 kilometers North West of Basrah at the very tip of the point of Shatt Al Arab as shown in Figure (1). The daily observed measurements of Tigris River discharge for the period (1/12/2013 - 30/9/2016) are measured in Qurnah. The observed data is used as input for all proposed models and the other part used for comparison with the predicted results. The observed data of Tigris River are obtained from water resource Directorate in Basrah city.

DESCRIPTION OF SELECTED TECHNIQUES

Two techniques are used in this study include ANNs and ANFIS to forecast the daily Tigris River discharge in Qurnah, Basrah, South of Iraq.

Artificial Neural Networks (ANNs) :

An artificial neural network (ANN) is a mathematical/computational model inspired by the structure of biological neural networks [J. J. Hopfield, 1982]. The network consists of layer of parallel processing elements, called neurons.

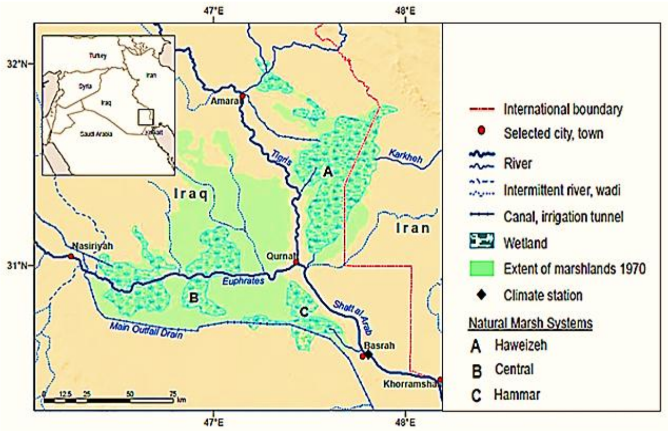

Figure 1: Study area location showing Tigris River in Qurnah, Basrah, South of Iraq

In most networks, the input layer receives the input variables for the problem in hand. This consists of all quantities that can influence the output. The output layer consists of values predicted by the network and thus represents model output. Between the input and output layer there may be one or more hidden layer. The neurons in each layer are connected to the neurons in a proceeding layer by a weight (Wji), which can be adjusted during training. Figure (2) illustrates a three layer neural network consisting of four neurons in input layer, four neurons in hidden layer and two neurons in output layer, with interconnection weights between layers of neurons.

Generally, an ANN model is an adaptive tool which is able to change its own structure based on the external or internal information flowing through during the learning step, and is used to model a complex relationship between input and output parameters. Inputs and output parameters required for creating an ANN model should be chosen based on these facts that the input parameters should be independent from each other and the output variables being a function of the inputs.

The weights of the network are usually initialize randomly and are progressively changed in each iteration during the training process. Training in such networks means that the network has to learn a target function. To do so, each input together with its corresponding output is presented to the network. Learning algorithm tries to adjust the weights in all layers in a way that the error between computed output and correct output become small. The most known and popular learning algorithm is back-propagation learning algorithm. This learning algorithm tries to minimize the overall error of the network based on optimization method called gradient descent. After injection of any input to first layer of the network, the error is calculated based on some predefined error function in the output layer. Then the error is fed back to previous layer (hidden layer) to adjust those weights which connect the hidden layer to output layer. These chained adjustments continue until the adjustment of weights of the first layer.

The back-propagation network is the most popular among ANN paradigms [R P Lippman, 1987]. The back-propagation algorithm gives a prescription for changing the weight (Wji) in any feed forward network to learn a training vector of input-output pairs. It is a supervised learning method in which an output error is fed back through the network, altering connection weight so as to minimize the error between the network output and the target output. Therefore, the back-propagation is used here as an approach to ANN training. The outputs of the hidden layer are gathered and processed by the last or output layer, which delivers the final output of the network. A neuron is a processing unit with n inputs ($x_1, x_2, \ldots, x_n$), and only one output (y), with

$$y = f(x_1, x_2, \ldots, x_n) = A\left[\left(\sum_{i=1}^{n} w_i x_i\right) + b\right] \qquad (1)$$

Where:

w_i : the weight of the neuron

b : the constant bias

A : the activation or transfer function

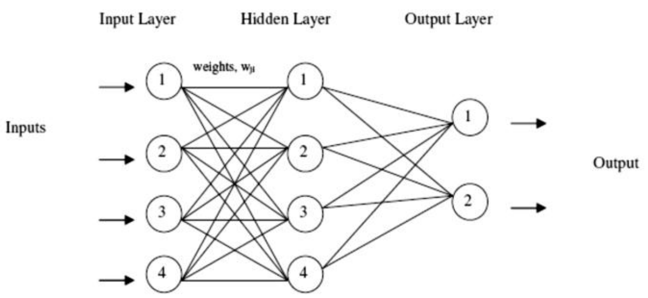

Figure 2: Configuration of three-layer neural network

Adoptive-Neuro Fuzzy Inferance System (ANFIS) :

The adaptive neuro-fuzzy inference system (ANFIS) is a soft computing method in which a given input–output data set is expressed in a fuzzy inference system (FIS). The FIS implements a nonlinear mapping from its input space to the output space. With the ability to combine the verbal power of a fuzzy system with the numeric power of a neural system adaptive network, ANFIS has been shown to be powerful in modeling numerous processes. ANFIS possesses good capability of learning, constructing, expensing, and classifying. It has the advantage of allowing the extraction of fuzzy rules from numerical data or expert knowledge and adaptively constructs a rule base. Furthermore, it can tune the complicated conversion of human intelligence to fuzzy systems. The mapping is accomplished by a number of fuzzy IF–THEN rules, each of which describes the local behavior of the mapping. The fuzzy membership parameters are optimized either by using a back-propagation algorithm or by combination of both back-propagation and least square method. The efficiency of the FIS depends on the estimated parameters. Further description of the ANFIS is given in [Brown, M. and Harris, C., 1995]. Very few studies are available on rainfall–runoff modeling and river flow forecasting using ANFIS together with its performance comparison with an ANN technique [Chau, K. W., et. al, 2005 and Aqil, M., et. al, 2007].

The structure of the ANFIS is similar to that of a neural network (see Figure (3.b)). It maps inputs through input membership functions (MF) and associated parameters. Similarly, output mapping is done through output membership functions and associated parameters. For example, consider that x and y are the two inputs and z is the output. The first-order IF–THEN fuzzy rules can be expressed as follows:

(Rule 1) IF x is A_1 AND y is B_1, THEN $f_1 = p_1x + q_1y + r_1$

(Rule 2) IF x is A_2 AND y is B_2, THEN $f_2 = p_2x + q_2y + r_2$

Where:

A_1, A_2 and B_1, B_2 are the MFs for inputs x and y respectively.

p_1, q_1, r_1, p_2, q_2, r_2 are the associated parameters of the output functions.

The mechanism of fuzzy reasoning for the Sugeno type fuzzy model to derive output function f from a given input vector [x,y] is presented in Figure (3.a). The five-layered ANFIS architecture is illustrated in Fig. 3(b) and is described subsequently.

Layer 1 Each node is assigned a fuzzy membership value using membership functions to form a fuzzy set.

$$o_{1,i} = \mu_{A_i}(x) \quad for\ i = 1,2$$

$$o_{1,i} = \mu_{B_{i-2}}(xy) \quad for\ i = 3,4$$

where x, y are the crisp input to node i, and A_i, B_i are the membership grades of the membership functions μ_A and μ_B, respectively. A generalized Gaussian membership function was used in the present study. Using a generalized Gaussian MF, the output $O_{1,i}$ can be computed as:

$$o_{1,i} = \mu_{A_i}(x) = \frac{1}{1+\left[\frac{x-c_i}{a_i}\right]^{2b_i}} \qquad (3)$$

where $\{a_i, b_i, c_i\}$ is the parameter set that changes the shapes of the MF with maximum equal to 1 and minimum equal to 0.

Layer 2 In this layer, every node multiplies the input signals, denoted in Fig. 3(b) as " **Π** " and represents the rule nodes and the output $O_{2,k}$ that represents the firing strength of a rule and is computed as:

$$o_{2,k} = w_k = \mu_{A_i}(x)\mu_{B_i}(y) \qquad i=1, 2 \tag{4}$$

Layer 3 This layer consists of the averaging nodes, which is labelled as "N" and computes the normalized firing strength equal to:

$$o_{3,k} = \overline{w}_i = \frac{w_i}{w_1+w_2} \tag{5}$$

Layer 4 The node function of this layer is to compute the contribution of each ith rule towards the total output and the function can be defined as:

$$o_{4,i} = \overline{w}_i f_i = w_i(p_i x + q_i y + r_i) \qquad i=1, 2 \tag{6}$$

where, $\overline{w}_i$ is the output of Layer 3 and $\{p_i, q_i, r_i\}$ is the parameter set.

Layer 5 This layer has a single output node, which computes overall output of the ANFIS as:

$$o_{5,l} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{7}$$

The computation of these parameters (or their adjustment) is facilitated by a gradient vector, which provides a measure of how well the fuzzy inference system is modeling the input/output data for a given set of parameters. Once the gradient vector is obtained, any optimization routines can be applied to adjust the parameters and to reduce some error measure, usually defined by the sum of the squared difference between actual and desired outputs. The ANFIS modeling performed using the "subtractive fuzzy clustering" function as which can perform successfully even in less rules. clustering of numerical data forms the basis of many classification and system modeling algorithms. The purpose of clustering is to identify natural groupings of data from a large data set to produce a concise representation of a system's behavior. Data clustering (or cluster analysis) is aim to find the natural grouping(s) of a set of cases, data, or objects.

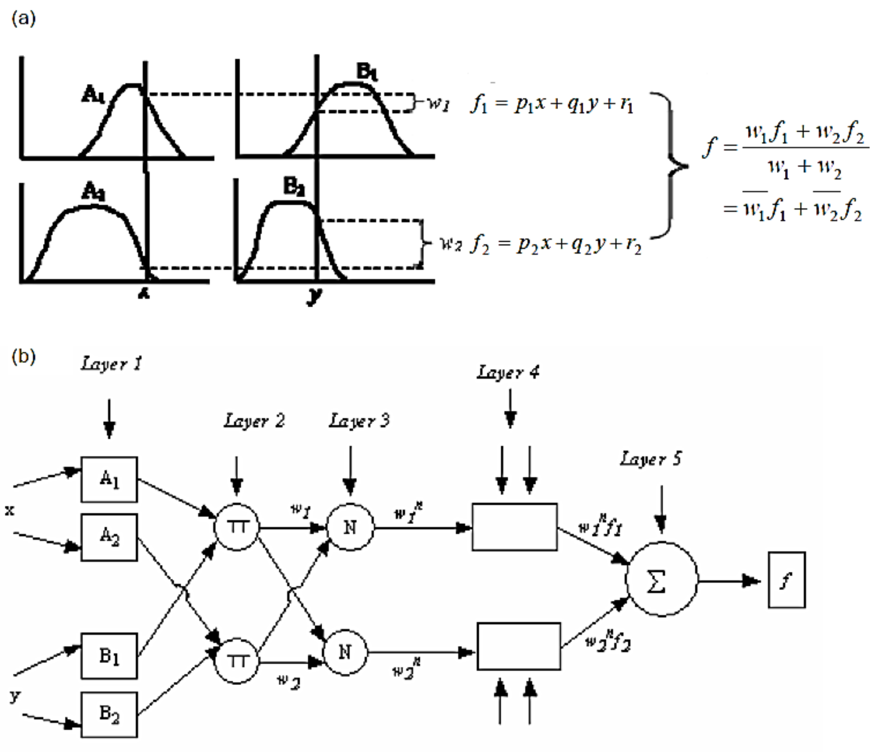

Figure 3: (a) A fuzzy inference system, and (b) the corresponding architecture [Jang, J. S. R.,et. al, 1997]

METHODOLOGY

In this study, three different ANNs and ANFIS models (Table 1) were proposed and their performance compared to determine the best model. The ANNs and ANFIS simulation and analysis of results, were performed using Matlab R2010b.The observed data for the period (1/12/2013 - 30/9/2016) were used in this study. Hence 1025 instances are available for forecast the daily discharge of Tigris River in Qurnah, Basrah, south of Iraq.

As shown in Table (1), the first model (M1) represents the discharge at time t (Q_t) as a function of stage (H) and discharge (Q) of a river release at (t-1). The second model (M2) represents the flow at time t, being a function of stage and discharge of a river release at (t-1) and (t-2). Likewise, Q_t=f (H_{t-1}, Q_{t-1}, H_{t-2}, Q_{t-2}, H_{t-3}, Q_{t-3}) represents the third model (M3), it was proposed by considering the integrated effect of the release values up to three antecedent time step.

Table 1: Proposed three models for ANNs and ANFIS techniques

Model	Input	Output
M1	H_{t-1}, Q_{t-1}	Q_t
M2	H_{t-1}, Q_{t-1}, H_{t-2}, Q_{t-2}	Q_t
M3	H_{t-1}, Q_{t-1}, H_{t-2}, Q_{t-2}, H_{t-3}, Q_{t-3}	Q_t

Two different techniques: ANN and ANFIS are used in this study. The first step in developing the ANNs and ANFIS based on models is the chosen of suitable model architecture and the model inputs and output.

The architecture of ANNs were chosen consist of a frequent network consisting of one input layer, one output layer and one may note size of a hidden layer is one of the most important considerations when solving actual problem using multilayer feed forward networks. The optimal number of neuron in the hidden layer was identified using trial and error procedure by changing the number of neurons. In ANNs the observed data are divided into three statistically part: 60% for training, 20% for validation, and 20% for testing. The training of the neural network is accomplished by adjusting the interconnecting weights till such time that the root mean square error (*RMSE*) between the observed and predicted set of values is minimized.

The ANFIS architecture consists of a five layered special network, with the domains of previous variables separated into a specified number of membership functions. The adjustment of adequate membership function parameters is facilitated by a gradient vector. After determining a gradient vector, the parameters are adjusted and performance function is minimized least squares estimation. The optimal parameters of the ANFIS model can be estimated using the hybrid learning algorithm. On the other hand, a Gaussian membership function (*mf*) is selected to the extracted input clusters. The normal distribution of input data is carried out by using Gaussian function *f*(*x*) as in the following formula:

$$f(x) = \frac{e^{-(x-\mu)^2}}{\sigma\sqrt{2\pi}} \qquad \text{……………..} \ (8)$$

Where:

μ and σ : the parameters of normal distribution showing the mean and standard deviation of data, respectively .

These Gaussian member ship functions are constructed from μ and σ values of the clusters. The input data (observed data) for the three models was divided to 80% and 20% for training and testing, respectively. In ANFIS models, the effective and important parameters in subtractive clustering which controls number of clusters and fuzzy If. Then rules are cluster radius. This parameter is ranged of (0,1). The training error can be controlled by adjusting cluster radius. Specifying a smaller cluster radius usually yields smaller cluster and more rules. A large cluster radius when approaching to one yields few large cluster in the data and few rules. Optimum clustering radius is determined by performing subtractive clustering network for several times, with changing radius values between (0,1) leads to different number of If. Then rules could be established. The best value of clustering radius is associated with lowest value of Root mean squared error (*RMSE*). Output of each membership function (*mf*) is linear equation consist of equation parameters multiply by input variable for example, output *mf1* in M1

$$output\ mf_1 = c_1 H_{t-1} + c_2 Q_{t-1} + c_3$$

In this equation, parameter $c_1$is coefficient corresponding to H_{t-1}, c_2 coefficient corresponding to Q_{t-1}, while c_3 is constant in each equation.

The comparison of performances for both ANNs and ANFIS models through which the best model is chosen, some statistical parameters were relied upon. Three performance evaluation criteria used in this study, (1) Root mean squared error (*RMSE*), it is an often used measure of the difference between values predicted by a model and those actually observed from the thing being modeled. *RMSE* is one of the commonly used error index statistics [Lin, J.Y., et. al, 2006] and it is defined in Eq. (9). (2) Efficiency coefficient (*CE*), it is based on the standardization of residual variance with initial variance, the Coefficient of Efficiency can be used to compare the relative performance of the two approaches effectively [J. E. Nash and J. V. Sutcliffe., 1970]. It is expressed in Eq. (10). (3) Correlation Coefficient (*R*), it represents the linear dependence between observation and their corresponding predictions. [Bisht, D. C. S. and Jangid, A., 2011]. It is expressed as in Eq. (11).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{i=n}\left(Q_m - Q_s\right)^2} \qquad (9)$$

$$CE = 1 - \frac{\sum_{i=1}^{i=n}\left(Q_m - Q_s\right)^2}{\sum_{i=1}^{i=n}\left(Q_m - \bar{Q}_m\right)^2} \qquad (10)$$

$$R = \frac{\sum_{i=1}^{i=n}\left(Q_m - \bar{Q}_m\right)\left(Q_s - \bar{Q}_s\right)}{\sqrt{\sum_{i=1}^{i=n}\left(Q_m - \bar{Q}_m\right)^2 \sum_{i=1}^{i=n}\left(Q_s - \bar{Q}_s\right)^2}} \qquad (11)$$

Where:

Q_m : Measured value

Q_s : Simulated value

$\bar{Q}_m$: Average of measured values

$\bar{Q}_s$: Average of simulated values

n : The number of observations

RESULTS AND DISCUSSION

Three models are constructed for both ANNs and ANFIS to forecast a daily discharge in Tigris River. These models are described in Table (1). Models with the same input combinations as used in the ANNs modeling were trained and tested to forecast the daily discharge of the Tigris River using the ANFIS approach. The performance of the models is evaluated by using the statistical parameters (*RMSE, CE* and *R*).

The ANNs with back-propagation algorithm constructed with fifteen hidden neurons was found to be capable of generalizing input-output data set. One may note the size of a hidden layer is one of the most significant considerations when solving real problems using networks of multilayer feed forward.

Table (2), shows the best values of clustering radius for three models of ANFIS technique. These are 0.1, 0.1 and 0.3 for models M1, M2 and M3 respectively. On the other hand, the Gaussian membership function parameters for the models (M1, M2 and M3) are shown in Tables 3, 4 and 5, respectively.

Depending on the results of statistical parameters as shown in Table (6), two techniques can be evaluated. The statistical criteria values give the impression that the ANFIS and ANNs capable of predicting the daily discharge of the river, but the results of the three models of ANFIS are better than the predicted results of the three models of ANNs. and can be shown in Table (6) for both techniques, that the results of model two (M2) is better than results of model one (M1), because M2 is a function of stage and discharge of a river release at (t-1) and (t-2), while M1 is function to stage and discharge of a river release at (t-1) only. On the other hand, the results of M3 is best than M1 and M2 in both techniques because that M3 is function to six input variables (H_{t-1}, Q_{t-1}, H_{t-2}, Q_{t-2}, H_{t-3}, Q_{t-3}) in three days earlier.

Thus the results of this analysis indicate that the ANFIS is able to obtain the better predicating accuracy of daily discharge in Tigris River. The performances of all forecasting models developed during the testing period are shown in Figures 4, 5 and 6. The convergence between the observed data and the forecasted data in both ANNs and ANFIS is closer in Figure 6, which represent the testing period of M3.

Table 2: *r*, *RMSE* and No. of rules for ANFIS models

clustering radius (*r*)	Model					
	M1		*M2*		*M3*	
	RMSE	*No. of Rules*	*RMSE*	*No. of Rules*	*RMSE*	*No. of Rules*
0.1	**4.035**	**9**	**4.226**	**20**	7.685	19
0.2	8.438	4	6.580	5	6.887	10
0.3	8.456	3	7.946	4	**2.451**	**5**
0.4	9.665	2	7.520	3	4.703	4
0.5	11.561	1	7.598	3	6.703	3
0.6	11.561	1	7.829	2	7.676	3
0.7	11.561	1	8.837	1	7.929	3
0.8	11.561	1	8.837	1	8.913	2
0.9	11.561	1	9.774	1	8.797	1

Table 3: Input and output membership functions parameters for *M1* in ANFIS

Input mf No.	*Parameters for Inputs*			
	H_{t-1}		Q_{t-1}	
	σ	μ	σ	μ
mf_1	3.536	0.58	24.74	56.9
mf_2	3.536	10	24.74	56.9
mf_3	3.536	18	24.74	56.9
mf_4	3.536	28	24.74	56.9
mf_5	3.536	38	24.74	67.8
mf_6	3.536	43	24.74	67.8
mf_7	3.536	51	24.74	67.8
mf_8	3.536	60	24.74	67.8
mf_9	3.536	70	24.74	84.75

Output mf No.	*parameters for Output (Q_t)*		
	C_1	C_2	C_3
mf_1	0.9498	0.8674	-37.84
mf_2	-3.857	0.6182	152.6
mf_3	-0.2172	0.9709	6.25
mf_4	0.1943	1.0120	-0.01434
mf_5	5.2190	2.1410	-363.1
mf_6	0.6594	0.7016	5.871
mf_7	-0.2627	1.0610	13.82
mf_8	-5.4880	0.00673	328.1
mf_9	1.5680	1.0290	-16.890

Table 4: Input and output membership functions parameters for *M2* in ANFIS

Input mf No.	*Parameters for Inputs*							
	H_{t-1}		Q_{t-1}		H_{t-2}		Q_{t-2}	
	σ	μ	σ	μ	σ	μ	σ	μ
mf_1	3.536	0.5	24.74	39.9	3.536	0.48	24.74	38.7
mf_2	3.536	10	24.74	49.5	3.536	9	24.74	47.2
mf_3	3.536	20	24.74	49.5	3.536	20	24.74	47.2
mf_4	3.536	22	24.74	49.5	3.536	27	24.74	47.2
mf_5	3.536	23	24.74	49.5	3.536	27	24.74	53.87
mf_6	3.536	30	24.74	53	3.536	28	24.74	53.87
mf_7	3.536	35	24.74	53	3.536	28	24.74	53.87
mf_8	3.536	40	24.74	53	3.536	30	24.74	53.87
mf_9	3.536	42	24.74	53.6	3.536	33	24.74	53.87
mf_{10}	3.536	48	24.74	53.6	3.536	33	24.74	53.87
mf_{11}	3.536	50	24.74	57.79	3.536	40	24.74	70.02
mf_{12}	3.536	50	24.74	57.79	3.536	40	24.74	70.02
mf_{13}	3.536	52	24.74	69.16	3.536	43	24.74	70.02
mf_{14}	3.536	52	24.74	69.16	3.536	43	24.74	70.02
mf_{15}	3.536	52	24.74	69.16	3.536	50	24.74	70.02
mf_{16}	3.536	58	24.74	69.16	3.536	53	24.74	70.02
mf_{17}	3.536	58	24.74	71.0	3.536	53	24.74	78.9
mf_{18}	3.536	62	24.74	71.0	3.536	58	24.74	78.9
mf_{19}	3.536	67	24.74	69.16	3.536	65	24.74	88.9
mf_{20}	3.536	70	24.74	86.9	3.536	70	24.74	88.9

Output mf No.	*parameters for Output (Q_t)*				
	C_1	C_2	C_3	C_4	C_5
mf_1	-0.9344	0.1738	-1.3530	0.927	111.3
mf_2	0.1431	-0.09655	0.0808	1.047	4.07
mf_3	0.8661	0.4308	0.6316	0.01872	-35.46
mf_4	0.01123	0.3080	-0.4013	0.6211	14.83
mf_5	-4.225	-1.0980	-1.7360	1.7980	370
mf_6	0.6682	0.8042	2.744	0.06466	-250.1
mf_7	1.544	-0.2348	-0.3144	1.0780	-50.54
mf_8	0.1155	-0.3668	0.2526	1.289	-0.9813
mf_9	-0.1557	-0.4235	0.1259	1.325	4.474
mf_{10}	-1.117	-0.3212	-0.5407	1.188	66.04
mf_{11}	0.2854	-0.3364	0.3225	1.346	-21.95
mf_{12}	-1.503	-0.1995	0.9606	1.012	-9.842
mf_{13}	5.262	6.9460	-2.436	-1.546	-381.1
mf_{14}	0.2932	-0.2013	-1.079	0.8784	39
mf_{15}	-0.8757	0.9289	-0.6379	0.1549	83.47
mf_{16}	0.4660	-0.05642	0.08065	-0.0566	80.52
mf_{17}	-0.05003	0.03726	0.3015	0.6867	5.125
mf_{18}	-0.1732	0.02043	0.01535	1.031	4.517
mf_{19}	0.3465	-0.5640	0.5690	1.649	-15.46
mf_{20}	-0.1317	0.7978	-0.1077	0.0989	9.348

Table 5: Input and output membership functions parameters for *M3* in ANFIS

Input mf No.	*Parameters for Inputs*											
	H_{t-1}		Q_{t-1}		H_{t-2}		Q_{t-2}		H_{t-3}		Q_{t-3}	
	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ
mf_1	10.61	2	74.22	51.4	10.61	1	74.22	53	10.61	1	74.22	55.9
mf_2	10.61	26	74.22	51.4	10.61	25	74.22	53	10.61	28	74.22	57
mf_3	10.61	42	74.22	58.2	10.61	40	74.22	59.3	10.61	38	74.22	57
mf_4	10.61	55	74.22	69.1	10.61	55	74.22	69.3	10.61	55	74.22	73.2
mf_5	10.61	71	74.22	74.9	10.61	71	74.22	74.2	10.61	70	74.22	73.2

Output mf No.	*parameters for Output (Q_t)*						
	C_1	C_2	C_3	C_4	C_5	C_6	C_7
mf_1	0.3524	0.6295	-0.3897	-1.803	0.1314	2.131	-0.4199
mf_2	-1.417	-0.5468	2.776	0.626	-0.8498	0.6756	-15.15
mf_3	0.0624	-0.1267	0.07275	0.3402	-0.0292	0.3402	-0.0292
mf_4	-0.1002	-0.5512	-0.06013	1.046	0.000777	0.4378	5.217
mf_5	-0.7647	1.314	-1.668	-0.2562	-0.1468	-0.1822	194.7

Table 6: Statistical performance of the models (M1, M2 and M3) results computed over the test set

ANNs				*ANFIS*			
Model no.	*RMSE*	*CE*	*R*	*Model no.*	*RMSE*	*CE*	*R*
1	5.018	0.752	0.734	1	4.035	0.755	0.812
2	6.712	0.798	0.869	2	4.226	0.848	0.925
3	3.128	0.801	0.918	3	2.451	0.891	0.947

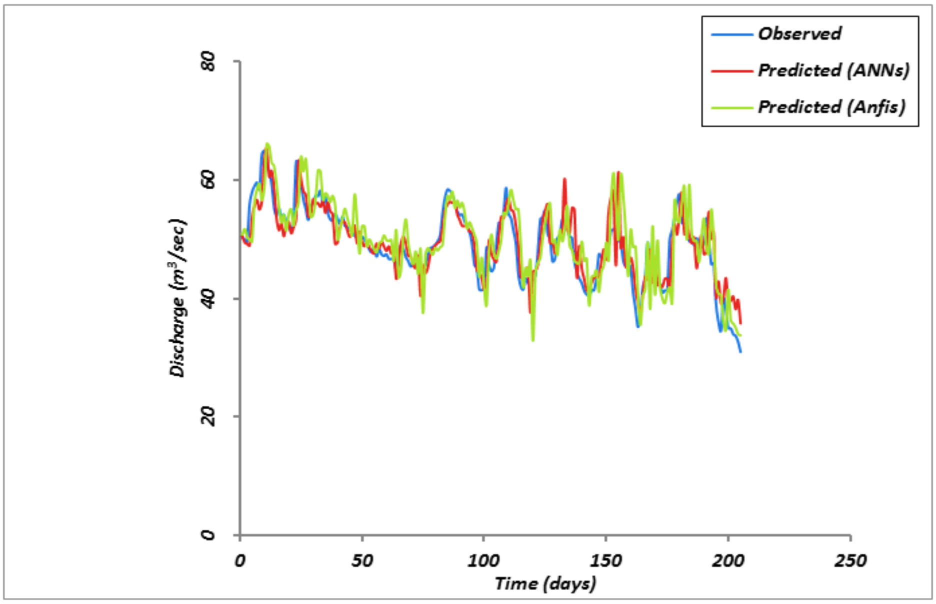

Figure 4: Comparison between observed and forecasted discharge in testing period for M1

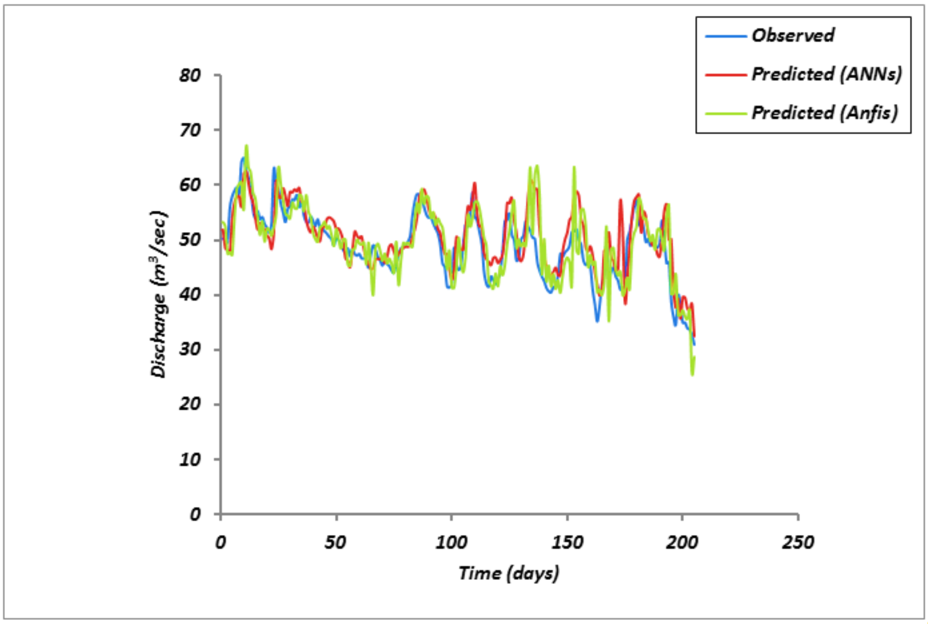

Figure 5: Comparison between observed and forecasted discharge in testing period for M2

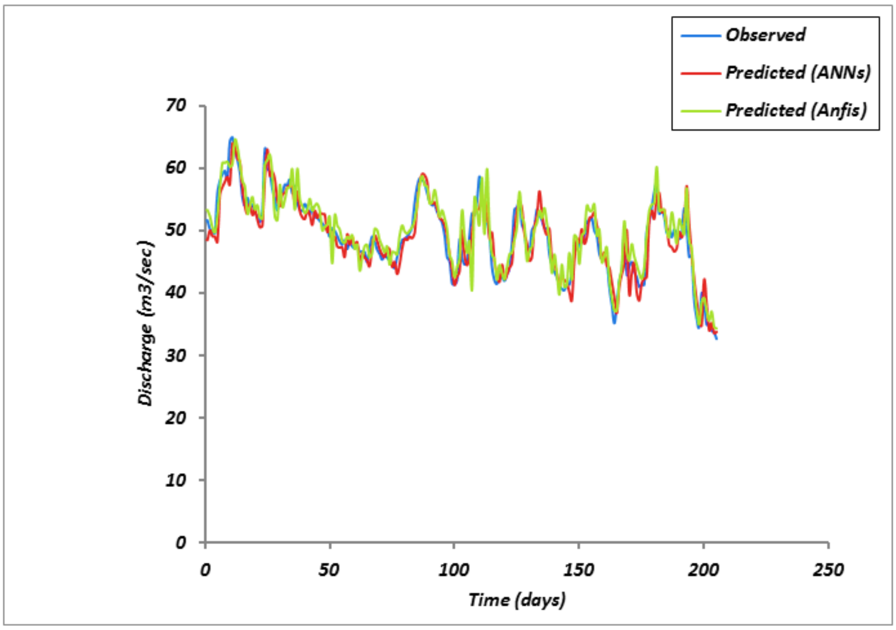

Figure 6: Comparison between observed and forecasted discharge in testing period for M3

CONCLUSIONS

ANNs and ANFIS techniques are developed for forecasting the daily discharge of Tigris River in Qurnah, Basrah, south of Iraq. Three models were constructed for each technique to forecast the daily discharge in the river. The first model (M1) depends on the input data which represent to the stage and discharge of a river for one day earlier, and the input data for the second model (M2) represent to the stage and discharge of a river for two day earlier, while the third model (M3) depends on the stage and discharge for three day earlier as inputs.

Three statistical parameters (*RMSE*, *CE* and *R*) were used to evaluate the performance of the two techniques in this study. It is found in both technique (ANNs, ANFIS), the results of the statistical criteria for M2 are best from those in M1. This indicates that M2 is better than M1 to predict the daily discharge in the river. On the other hand; the statistical parameters for M3 are higher than those in M1 and M2, this means that M3 gives better forecast daily discharge than M1and M2.

In general, the results showed that the ANNs with back-propagation algorithm and ANFIS techniques are powerful tools to simulate the river flow for short term, and the agreement between the observed and forecasted daily discharge of the river is reasonably good in both techniques. But it is important to note that the statistical performance of the ANFIS models is found to be better in comparison to the ANNs models. This indicates the ANFIS technique gives slightly better results than the ANNs techniques for forecasting daily discharge of the river.

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