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# ARTIFICIAL NEURAL NETWORK MODELS INVESTIGATION FOR EUPHRATES RIVER FORECASTING &BACK CASTING

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## ABSTRACT

*The development of stream flow forecasting model is one of the most important aspects in water resources planning and management , since it can help in providing early warning of river flooding as well as in short term operation of water supply system. In this research the best ANN artificial neural networks model for simulation and forecasting of Euphrates river flow downstream Al-Hindiyaha barrage was investigated by applying different architectures of ANN models to the monthly flow of Euphrates river at the mentioned site depending on the previous months data from the same site (this was called Single Site ANN model SSANN )and also by investigating the dependence of Euphrates river flow downstream Al-Hindiyaha barrage on two other sites (Husaybah , Hit)discharges of the same river (which was called Multi Site ANN model MSANN). Another Trial was achieved by investigating different ANN models to predict a missed monthly data for Euphrates river flow at Husaybah gauging station. This trail was achieved first by investigating different MSANN models then by reversing operation of the best forecasting model which was found, this operation was called Back casting technique. The current study had demonstrated a promising application of ANN –stream flow forecasting and back casting for different gaging stations of Euphrates river .*

**Keywords:** ANN, SSANN, MSANN, Forecasting, Back casting.

## 1. INTRODUCTION

The development of stream flow forecasting model is one of the most important aspects in water resources planning and management , since it can help in providing early warning of river flooding as well as in short term operation of water supply system. This task which is the forecasting operation can be considered as a big challenge that is faced by the hydrologists due to uncertainty of parameters estimates and the nonlinearity of physical process. Many traditional models have been developed such as the models which are extracted from stochastic analysis of time series for stream flow forecasting . Since the early nineties , ANNs have been used as an alternative for the traditional models in this field (ASCE.Task Committee on Application of Artificial Neural Networks in Hydrology, 2000). Artificial neural networks (ANN) models, are considered as a category of the data –driven techniques, and have been widely used in stream flow forecasting. Several distinguishing features of ANN models make them valuable and attractive for forecasting tasks (Maier and Dandy, 2000; Samarassinghe, 2006). The main goal of this research is to investigate the best ANN artificial neural networks model for the purpose of simulation and forecasting of Euphrates river flow downstream Al-Hindiyaha barrage ( Latitude 32˚ 43' 01" N, Longitude 44˚ 16' 01" E ,with drainage area 274,100 km2), this is done by applying different architectures of ANN to the monthly discharge of Euphrates river at the mentioned site depending on the previous months data for the same site (this is called Single Site ANN model SSANN )and also by investigating the dependence of Euphrates river discharge downstream Al-Hindiyaha barrage on two other sites (Husaybah , Hit)discharges of the same river (which is called Multi Site ANN model MSANN). Another Trial is achieved by investigating different ANN models to predict a missed data for Euphrates river flow at Husaybah gauging station by using different MSANN models in addition to a reversing operation of the best found MSANN forecasting model , this operation is called Back casting technique.

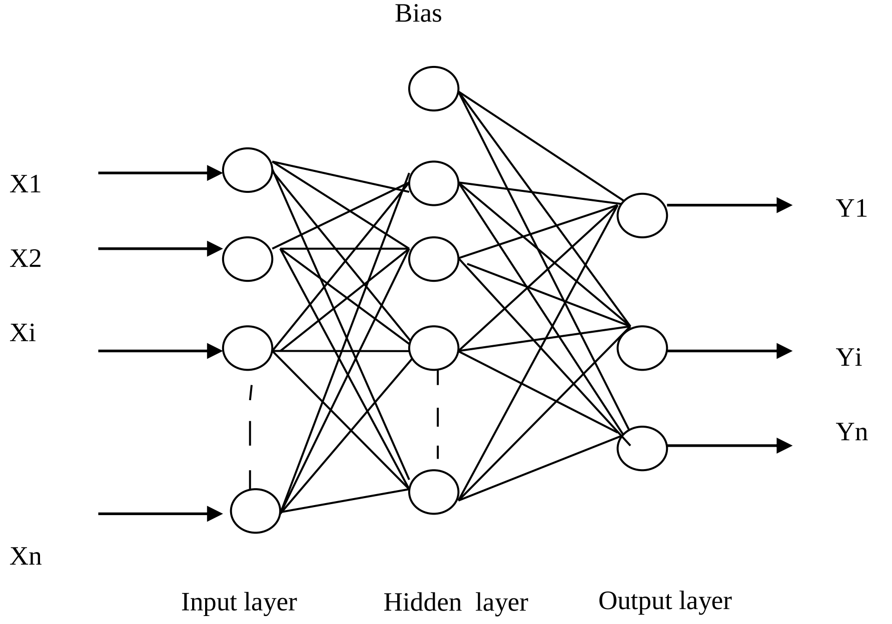
## 2. ARTIFICIAL NEURAL NETWORKS

There are billions of interconnected neurons in human brain which are arranged in such a structure and operate to make humans able to quickly recognize patterns and process data . ANN can be described as a mathematical representation of this structure of human brain. The properties of this mathematical representation can be summarized as its ability to learn from examples, recognize a pattern in the data , process information rapidly and adapt solutions overtime (Kisi, 2005). In any ANN network there are a number of data processing elements called neurons, which are grouped in layers. Neurons of the first layer which is called input layer receive the input vector and transfer the values to the next layer nodes or neurons across connections. This process is continued until the output layer is reached. ANNs can be categorized into two types according to the number of layers :single bi layer and multilayer networks and also can be categorized into feed forward and feed backward networks due to the direction of the information and processing (Haddad *et al.*, 2005).

### A. MLP Networks

Figure (1) shows the general form of the most common used networks which is called Multilayer perceptron

**Figure-1.** Multilayer Perceptron Network




It is clear from the shown figure that each node in a layer is fully interconnected to all nodes in the previous layer and the output of any layer makes the input of the next layer. Most applications in hydrology uses this kind of network with application of back propagation algorithm (BPA) (Coulibaly *et al.*, 2001).

## B. Training networks by Back propagation Algorithm (BPA)

In this study Feed Forward Back Propagation algorithm method is used and the training of BP networks is carried out by presenting training sets to input and output neurons and computation of the error of the network and back propagation it then adjusting weights in order to reduce the error. Since the data which is passing from one neuron to another through the connections are multiplied by weights that control strength of a passing signal. The common used learning rule which is based on back propagation algorithm BPA in multilayer perceptron MLP is Generalized delta rule which uses the equation bellow to adjust the weights that connecting the nodes to others in a directed link .

$$\Delta w_{ij}(n) = -\alpha.\frac{\partial E}{\partial w_{ij}} + \eta.\Delta \mathrm{w_{ij}}(n-1)\text{……………..}(1)$$

Where $\Delta w_{ij}(n)$ and $\Delta \mathrm{w_{ij}}(n-1)$ are weight increments between node i and j during the nth and (n-1)th pass, or epoch (Haddad *et al.*, 2005).

## C. Neurons of Hidden layer and transfer function

Choosing the number of hidden layer nodes is a difficult task to build ANN model , there is no net theory yet to select the appropriate number of neurons in the hidden layer. Here the common trial and error method was used to determine a suitable number of neurons in the hidden layer. For each model different number of neurons at the hidden layer was tried , and the training process was done using Sigmoid function which is:

$$y_i = f\left(\sum w_{ji}\, x_i\right) = \frac{1}{1+e^{-(\sum w_{ji} x_i\,)}} \ldots\ldots\ldots\ldots(2).$$

yi=the output which is bounded between 0 and 1,wji=weight of the connection joining the jth neuron in a layer and x i =value of the ith neuron in the previous layer(Kisi O, 2005). Before applying the ANN, the input data were standardized. This process was done by applying the following equation :

$$Q_{stan} = (Q\text{-}Q_{min})/(Q_{max}\text{-}Q_{min})\ldots\ldots\ldots\ldots\ldots(3)$$

Where Qstan :is the standardized value of flow or any input data, Q: flow values or normal input data ;Qmin: The minimum value of the flow or any input data ; Qmax: the maximum value of the flow values or any input data (Dawson, 1998) .

## 3. STUDY AREA AND DATA SET

The Euphrates river has its springs in the highlands of Eastern Turkey and its mouth at the Persian Gulf. It is the longest river in Southwestern Asia with 2,700 km, and its actual annual volume is 35.9 billion cubic meters (bcm). The Euphrates river is formed in Turkey by two major tributaries; the Murat and the Karasu. These two streams join together around the city of Elazig, and the river Euphrates follows a southeastern route to enter Syria at Karakamis point. After entering Syria, the Euphrates continues its southeastern course and is joined by two more tributaries, the Khabur and the Balikh. Both of these tributaries have their sources in Turkey and they are the last bodies of water that contribute to the river. After entering Iraq, the river reaches the city of Hit, where it is only 53 m above sea level. From Hit to the delta in the Persian Gulf, for 735 km, the river loses a major portion of its waters to irrigation canals and to Lake Hammar. The remainder joins the Tigris river near the city of Qurna, and the combined rivers are called the Shatt al-Arab. The Karun river from Iran joins the Shatt at Basra, and they empty into the Persian Gulf altogether (Biswas, 1994). Euphrates river has three important gaging stations which are at:

1-Husaybah (IRQ-E1): Latitude 34̊ 25' 20 "N, Longitude 41̊ 00' 38" E (period of monthly discharge record for this station is from November 1981 to September 1997).

2-Hit(IRQ-E2): Latitude 33̊ 36' 23" N, Longitude 42̊ 50' 14" E(Drainage area 264,100 square kilometer , period of monthly discharge record: October 1932 to May 1997).

3-Downstrem Al-Hindyah barrage (IRQ-E3): Latitude 32̊ 43' 01" N, Longitude 44̊ 16' 01" E(Drainage area 274,100 square kilometers , period of monthly discharge record: February 1930 to September 1999) (USGS A report prepared in cooperation with MoWR and MoAWR under the auspices of the U.S Department of Defense. Task Force for Business and Stability Operations, 2010). The location of these gaging stations are shown clearly in Figure (2).

**Figure-2.** Locations of stream flow gauging stations for Tigris River and Euphrates River Basins, Iraq.


## 4. METHODOLOGY

As was mentioned in section 2.2 above a Multilayer Feed forward Neural networks(MLP network with back propagation algorithm) is applied for Euphrates river simulation and forecasting at downstream Al Hindyaha barrage first and the same algorithm is used for prediction and back casting the un recorded data for Euphrates river at Husaybah station to estimate the missed monthly data (1932-1981). Generalized delta rule is used for training . In this research two methods were based on for simulation and forecasting stream flow this will be cleared as follows:

### A. SSANN (Single Site Artificial Neural Networks)

In this method the simulation by MLP artificial neural networks is based on the stream flow data at the third site which is downstream Al-Hindyaha barrage (IRQ-E3) at present and previous (lagged or delayed) months, 7different models of forecasting and simulation have been implemented using different number of neurons in hidden layer. Following combinations of ANN models architectures were evaluated:

$Q_3(t+1) = f(Q_3(t))$

$Q_3(t+1) = f(Q_3(t), Q_3(t-1))$

$Q_3(t+1) = f(Q_3(t), Q_3(t-1), Q_3(t-2)).$

.

.

$Q_3(t+1) = f(Q_3(t), Q_3(t-1), Q_3(t-2), Q_3(t-3), Q(t-4)Q_3(t-5), Q(t-6))$

## B. MSANN (Multi Site Artificial Neural Networks)

Another modification of ANN models was tried in this research by investigating the effect of the monthly flow data at two other sites ( Husaybah, Hit) on the monthly flow values of Euphrates river at downstream Al-Hindyaha barrage at the same and previous months. This means that the simulation by MLP artificial neural networks is depending on the correlation between the discharge values for different sites and also for lagged or delayed times. 14 different models of forecasting and simulation have been implemented using different number of neurons in the hidden layer . ANN models form were as:

$Q_3(t+1) = f(Q1(t), Q2(t), Q_3(t))$

$Q_3(t+1) = f(Q1(t), Q2(t), Q_3(t), Q1(t-1), Q2(t-1), Q_3(t-1))$

.

.

$Q_3(t+1) = f(Q1(t), Q2(t), Q_3(t), Q1(t-1), Q2(t-1), Q_3(t-1), Q1(t-2), Q2(t-2), Q_3(t-2), Q1(t-3), Q2(t-3), Q_3(t-3), Q1(t-4), Q2(t-4), Q_3(t-4), Q1(t-5), Q2(t-5), Q_3(t-5), Q1(t-6), Q2(t-6), Q_3(t-6)).$

And

$Q_3(t+1) = f(Q2(t), Q_3(t))$

$Q_3(t+1) = f(Q2(t), Q_3(t), Q2(t-1), Q_3(t-1)).$

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.

.

$$Q_3(t+1) = f(Q2(t), Q_3(t), Q2(t-1), Q_3(t-1), Q2(t-2), Q_3(t-2), Q2(t-3), Q_3(t-3), Q2(t-4), Q_3(t-4), Q2(t-5), Q_3(t-5), Q2(t-6), Q_3(t-6))$$

Note: This methodology is applied also with different architectures to predict missed data of monthly flow values of Husaybah site(IRQ-E1). The details of used ANNs models for this task is presented in Table(3-Group A).

## C. Back casting

Due to the results of MSANN which is applied to forecast the monthly flow values of Euphrates river downstream Al-Hindyaha barrage (IRQ-E3), the best one was selected to achieve the missed data prediction of Husaybah site (IRQ-E1)by reversing the forecasting operation , this is also presented in Table(3-Group B)

## 5. RESULTS AND DISCUSSION

A. Results of Forecasting the Euphrates river flow downstream Al-Hindyaha barrage(IRQ-E3) :

MLP neural networks with back propagation method has been investigated in this paper to forecast stream flow data for Euphrates river in the mentioned site .The three layers network structure which was shown in Figure(1)was applied. To solve this problem, the network was trained by using Matlab (7.12.0) neural networks tools . For investigating the suitability of ANN, a ratio of 70:15:15 for training, validation and testing was considered. Different models were tried with different no of neurons in the hidden layer. To evaluate neural networks performance initialization of connection weights ,training, validation and testing has been performed with ten independent random trails .The correlation coefficient (R) values which provide how well model is close to actual values and Mean square error (MSE) values which indicate the average squared difference between outputs and targets(desired outputs) were found to assess the network performance using equations below

$$\text{MSE} = \frac{\sum_{i=1}^{n}(Q_{observed}(i)-Q_{predicted}(i))2}{n} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(4).$$

$$R = \sqrt{\frac{\sum_{i=1}^{N}\left(Q_{observed}-Q_{observed}{}^{\wedge}\right)(Q_{predicted}-Q_{predicted}{}^{\wedge})}{\sqrt{\sum_{i=1}^{n}\left(Q_{observed}-Q_{observed}{}^{\wedge}\right)^{2}\sum_{1=1}^{n}(Q_{predicted}-Q_{predicted}{}^{\wedge})^{2}}}}\ldots\ldots\ldots..(5).$$

Where the hut denotes the mean of the variable ; n is number of data point. Following is Table(1) which illustrates the architectures , best results of R,MSE and the best no of neurons in the hidden layer for the first SSANN models which was used to simulate Euphrates river at d/s Al-Hinddyaha barrage (IRQ-E3).

**Table-1.** Architecture And R, Mse Results For SSANN Models Used For Euphrates River D/s Al-Hindiyaha Barrage. (Irq-E3).

| no | Model definition | No of neurons in the hidden layer | The best value R | | The minimum MSE | |
|---|---|---|---|---|---|---|
| | | | training | test | training | Test |
| 1 | $Q_3(t+1) = f(Q_3(t))$ | 1,2,3,4,5,**6**,7,8,9 ,10 | 0.75 | 0.85 | 0.01 | 0.059 |
| 2 | $Q_3(t+1) = f(Q_3(t), Q_3(t-1))$ | 2,3,4,5,6,7,8, **9**,10,12,16,18 | 0.72 | 0.87 | 0.0101 | 0.0063 |
| 3 | **$Q_3(t+1) = f(Q_3(t), Q_3(t-1), Q_3(t-2))$ | 2,3,**4**,5,6,8,10,12,14,16,18 | 0.97 | 0.93 | 0.0099 | 0.0061 |
| 4 | $Q_3(t+1) = f(Q_3(t), Q_3(t-1), Q_3(t-2), Q_3(t-3))$ | **2**,4,6,8,10,12,14 ,16,18,20 | 0.75 | 0.84 | 0.0087 | 0.0103 |
| 5 | **$Q_3(t+1) = f(Q_3(t), Q_3(t-1), Q_3(t-2), Q_3(t-3), Q(t-4))$ | 2,4,6,8,10,12,14 ,16,**18**,20 | 0.89 | 0.93 | 0.0070 | 0.0071 |
| 6 | $Q_3(t+1) = f(Q_3(t), Q_3(t-1), Q_3(t-2), Q_3(t-3), Q(t-4)Q_3(t-5))$ | 2,4,6,8,10,12,14 ,16,18,**20** | 0.79 | 0.87 | 0.0096 | 0.007 |
| 7 | $Q_3(t+1) = f(Q_3(t), Q_3(t-1), Q_3(t-2), Q_3(t-3), Q(t-4)Q_3(t-5), Q(t-6))$ | 3,**5**,7,9,10,12,14 ,16,18,20,21 | 0.8 | 0.83 | 0.0073 | 0.0090 |

While Table(2) shows the architectures , best results of R,MSE and the best no of neurons in the hidden layer for MSANN models that used to simulate Euphrates river at d/s Al-Hinyaha barrage (IRQ-E3).

**Table-2.** Architecture And R, Mse Results For MSANN Models Used For Euphrates River D/s Al-Hindiyaha Barrage. (Irq-E3).

| no | Model definition | No of neurons in the hidden layer | The best value R | | The minimum MSE | |
|---|---|---|---|---|---|---|
| | | | training | test | aining | test |
| 1 | $Q_3(t+1) = f(Q1(t), Q2(t), Q_3(t))$ | **<u>3</u>**,4,6,8,10 | 0.61 | 0.87 | 0.054 | 0.029 |
| 2 | $Q_3(t+1) = f(Q1(t), Q2(t), Q_3(t), Q1(t-1), Q2(t-1), Q_3(t-1))$ | 3,**<u>6</u>**,8,104 | 0.577 | 0.7834 | 0.032 | 0.047 |
| 3 | $**Q_3(t+1) = f(Q1(t), Q2(t), Q_3(t), Q1(t-1), Q2(t-1), Q_3(t-1), Q1(t-2), Q2(t-2), Q_3(t-2))$ | 3,4,6,8,10,12,**<u>14</u>** | <u>0.86</u> | <u>0.93</u> | <u>0.0021</u> | <u>0.00153</u> |
| 4 | $Q_3(t+1) = f(Q1(t), Q2(t), Q_3(t), Q1(t-1), Q2(t-1), Q_3(t-1), Q1(t-2), Q2(t-2), Q_3(t-2), Q1(t-3), Q2(t-3), Q_3(t-3))$ | 3,4,6,8,10,12, 14,16,**<u>18</u>**,20 | 0.725 | 0.8 | 0.024 | 0.0148 |
| 5 | $Q_3(t+1) = f(Q1(t), Q2(t), Q_3(t), Q1(t-1), Q2(t-1), Q_3(t-1), Q1(t-2), Q2(t-2), Q_3(t-2), Q1(t-3), Q2(t-3), Q_3(t-3), Q1(t-4), Q2(t-4), Q_3(t-4))$ | 4,6,8,10,12,14,16,18,**<u>20</u>** | 0.98 | 0.77 | 0.00134 | 0.0084 |
| 6 | $Q_3(t+1) = f(Q1(t), Q2(t), Q_3(t), Q1(t-1), Q2(t-1), Q_3(t-1), Q1(t-2), Q2(t-2), Q_3(t-2), Q1(t-3), Q2(t-3), Q_3(t-3), Q1(t-4), Q2(t-4), Q_3(t-4), Q1(t-5), Q2(t-5), Q_3(t-5))$ | 4,6,8,10,12,**<u>14</u>**,16,18,20 | 0.85 | 0.8 | 0.0169 | 0.02 |
| 7 | $Q_3(t+1) = f(Q1(t), Q2(t), Q_3(t), Q1(t-1), Q2(t-1), Q_3(t-1), Q1(t-2), Q2(t-2), Q_3(t-2), Q1(t-3), Q2(t-3), Q_3(t-3), Q1(t-4), Q2(t-4), Q_3(t-4), Q1(t-5), Q2(t-5), Q_3(t-5), Q1(t-6), Q2(t-6), Q_3(t-6))$ | 4,6,8,10,12,**<u>14</u>**,16,18,20 | 0.727 | 0.85 | 0.027 | 0.067 |
| 8 | $Q_3(t+1) = f(Q2(t), Q_3(t))$ | 2,**<u>4</u>**,6,8,10 | 0.7611 | 0.74 | 0.034 | 0.041 |
| 9 | $Q_3(t+1) = f(Q2(t), Q_3(t), Q2(t-1), Q_3(t-1))$ | 2,4,**<u>6</u>**,8 | 0.76 | 0.78 | 0.024 | 0.014 |
| 10 | $Q_3(t+1) = f(Q2(t), Q_3(t), Q2(t-1), Q_3(t-1), Q2(t-2), Q_3(t-2))$ | 2,4,6,8,10,**<u>12</u>**, 14 | 0.84 | 0.805 | 0.0102 | 0.0206 |
| 11 | $Q_3(t+1) = f(Q2(t), Q_3(t), Q2(t-1), Q_3(t-1), Q2(t-2), Q_3(t-2), Q2(t-3), Q_3(t-3))$ | 2,4,6,8,**<u>10</u>**,12, 14,16,18,20 | 0.87 | 0.74 | 0.012 | 0.017 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 12 | $Q_3(t+1) = f(Q2(t), Q_3(t), Q2(t-1), Q_3(t-1), , Q2(t-2), Q_3(t-2), Q2(t-3), Q_3(t-3), Q2(t-4), Q_3(t-4))$ | 2,4,6,8,10,12 , 14,**<u>16</u>**,18,20 | 0.85 | 0.81 | 0.0102 | 0.0201 |
| 13 | $**Q_3(t+1) = f(Q2(t), Q_3(t), Q2(t-1), Q_3(t-1), Q2(t-2), Q_3(t-2), Q2(t-3), Q_3(t-3), Q2(t-4), Q_3(t-4), Q2(t-5), Q_3(t-5))$ | 2,4,6,8,10,12 , 14,16,**<u>18</u>**,20, 22,24 | <u>0.9</u> | <u>0.966</u> | <u>0.0083</u> | <u>0.0012</u> |
| 14 | $Q_3(t+1) = f(Q2(t), Q_3(t), Q2(t-1), Q_3(t-1), Q2(t-2), Q_3(t-2), Q2(t-3), Q_3(t-3), Q2(t-4), Q_3(t-4), Q2(t-5), Q_3(t-5), Q2(t-6), Q_3(t-6))$ | 2,4,6,8,10,12 , 14,**<u>16,</u>**18,20, 22,24 | 0.8 | 0.81 | 0.018 | 0.016 |

Where :

Q1(t):The monthly flow rate of Euphrates river at Al-Husaybah gage(IRQ-E1) station at month t.

Q2(t):The monthly flow rate of Euphrates river at Hit gage station (IRQ-E2) at month t.

Q3(t):The monthly flow rate of Euphrates river at downstream Al-Hindyaha barrage gage station (IRQ-E3) at month t. It is clear from above two tables that there are 4 models which show best results. According to this the best 4 models were selected to achieve the forecasting process. For SSANN models the whole monthly data for the Euphrates river downstream of Al-Hindyaha barrage was used for simulation since the period of recorded data for this gaging station was from 1930-1999 , but the monthly data for period(1995-199)was selected for forecasting and calibration purposes. While for MSANN models the monthly data for period(1881-1997)was selected for simulation and for the forecasting and calibration , monthly data of (1993-1997) was used. Here are the succeeded models equations :

**$Q_3(t+1) = f(Q_3(t), Q_3(t-1), Q_3(t-2))$……………………………….………..…(6).

**$Q_3(t+1) = f(Q_3(t), Q_3(t-1), Q_3(t-2), Q_3(t-3), Q(t-4))$……………….(7).

$**Q_3(t+1) = f(Q1(t), Q2(t), Q_3(t), Q1(t-1), Q2(t-1), Q_3(t-1), Q1(t-2), Q2(t-2), Q_3(t-2))$…………………………………………………..…………………………....(8).

$**Q_3(t+1) = f(Q2(t), Q_3(t), Q2(t-1), Q_3(t-1), Q2(t-2), Q_3(t-2), Q2(t-3), Q_3(t-3), Q2(t-4), Q_3(t-4), Q2(t-5), Q_3(t-5))$…….………………………....(9).

Due to the above results ,the above models were applied to forecast the monthly flow data for Euphrates river downstream Al-Hindyaha barrage, Figures below show the comparisons between forecasted data and observed one .

**Figure-3.**Forecasted monthly flow of (IRQ-E3) vs. observed( SSANN structure 3-4-1).

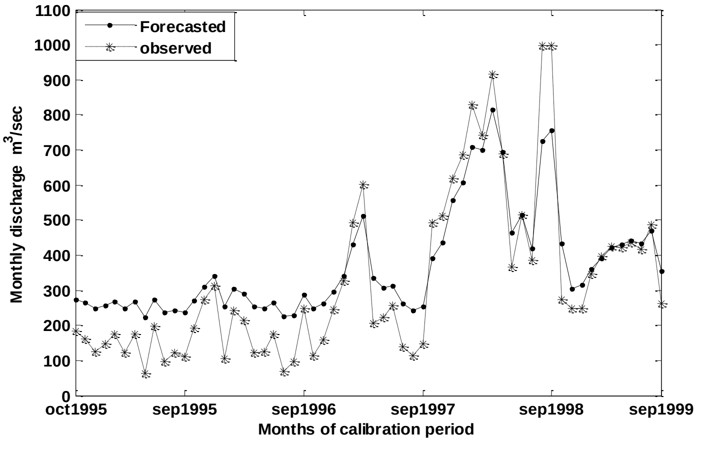



**Figure-4.**Forecasted monthly flow of (IRQ-E3) vs. observed( SSANN structure 5-18-1).

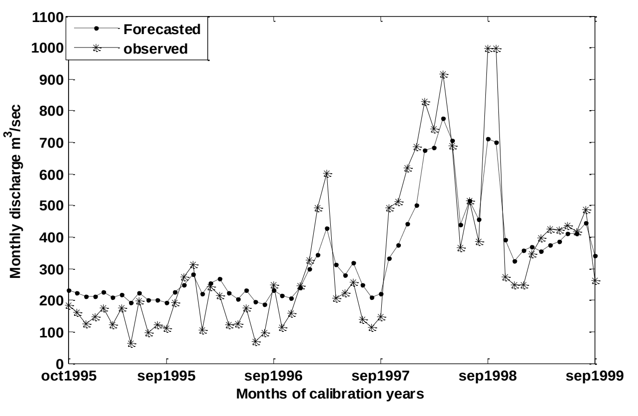



**Figure-5.** Forecasted monthly flow of (IRQ-E3) vs. observed (MSANN structure 9-14-1).

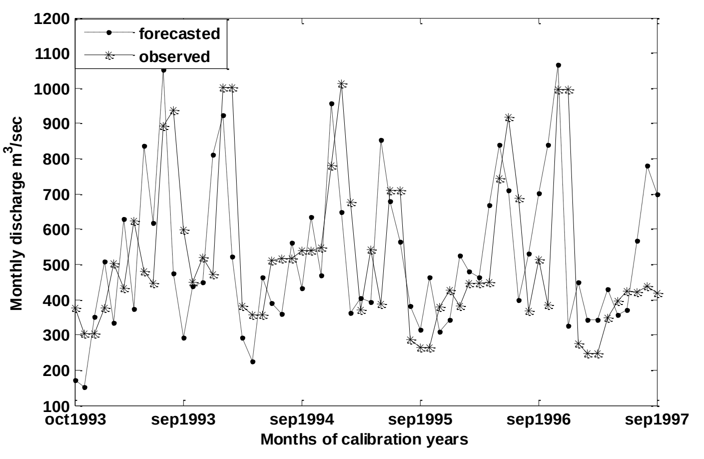
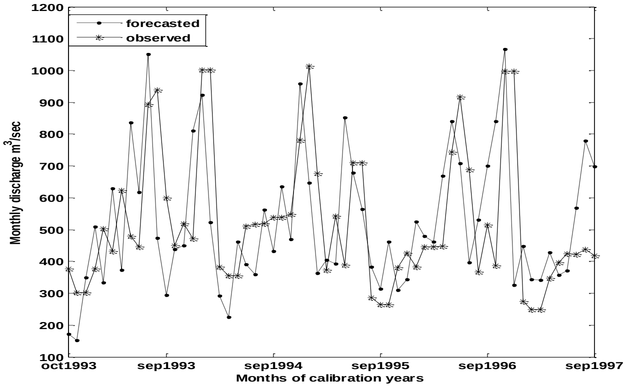


**Figure-6.** Forecasted monthly flow of (IR-E3) vs. observed ( MSANN structure 12-18-1).




## B. Results of Prediction of Missed data of Husaybah (IRQ-E1)

Due to the success of MSANN modeling according to above results , another trial was done to utilize ANN technique for prediction the missed data of Husaybah (IRQ-E1) for the period (1932-1881) as monthly data .This was done by trying different models of MSANN and by referring to the above most successful models after investigating the most high correlation between the three sites discharge values. The applied models are categorized into two groups as: Group A:which treat the flow at the required site as independent on its value, while it is dependent on the other sites data at similar time , and at lagged times also , this is done to ensure more simplified way to predict missed data . Group B: treats the flow at the required site by using the three sites flow for modeling by utilizing from the above best model of MSANN which was tried for (IRQ-E3) site flow , since the operation here is not forecasting but it may be described as back casting (Reversing the above process). Following is Table(3) which presents the test results for applied models.

**Table-3.** Architectures And R, Mse Results For MSANN Models Used For Husaybah(Irq-E3) Simulation

| no. | Model definition | No of neurons in the hidden layer | The best value R | | The minimum MSE | |
|---|---|---|---|---|---|---|
| | **Group A** | | training | test | training | test |
| 1 | $Q_1(t) = f(Q2(t), Q_3(t))$ | 2,4,6,8,10, 12,**14**,20 | 0.789 | 0.89 | 0.0023 | 0.0012 |
| 2 | $Q_1(t) = f(Q2(t), Q_3(t)Q2(t-1), Q_3(t-1))$ | 2,4,6,8,**10**, 12 | 0.971 | 0.912 | 0.0043 | 0.00523 |
| 3 | $Q_1 = f(Q2(t), Q_3(t),, Q2(t-1), Q_3(t-1), Q2(t-2), Q_3(t-2))$ | 2,4,6,8,**10**, 12 | 0.91 | 0.866 | 0.009 | 0.0086 |
| 4 | $** Q_1(t) = f(Q2(t), Q_3(t),, Q2(t-1), Q_3(t-1), Q2(t-2), Q_3(t-2),, Q2(t-3), Q_3(t-3))$ | 2,4,6,8,**10**, 12,14,16 | 0.961 | 0.98 | 0.00507 | 0.00056 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 5 | $Q_1(t) = f(Q2(t), Q_3(t), Q1(t-1), Q2(t-1), Q_3(t-1), Q2(t-2), Q_3(t-2),, Q2(t-3), Q_3(t-3),, Q2(t-4), Q_3(t-4))$ | 2,4,**6**,8,**10,** 12,14,**16***, 18,20 | 0.97 | 0.942 | 0.0013 | 0.00089 |
| 6 | $Q_1(t1) = f(Q2(t), Q_3(t), Q2(t-1), Q_3(t-1), Q2(t-2), Q_3(t-2), Q2(t-3), Q_3(t-3), Q2(t-4), Q_3(t-4), Q2(t-5), Q_3(t-5))$ | 2,4,6,8,10, 12,**14,**16,18,20, 24 | 0.9637 | 0.9124 | 0.0013 | .0066 |
| 7 | $** Q_1(t) = f(Q2(t), Q_3(t), Q2(t-1), Q_3(t-1), Q2(t-2), Q_3(t-2), Q2(t-3), Q_3(t-3), Q2(t-4), Q_3(t-4), Q2(t-5), Q_3(t-5), Q2(t-6), Q_3(t-6))$ | 2,4,6,8,10, **12**,14,16,18,20,24,28 | 0.9811 | 0.947 | 0.00038 | 0.00095 |
| no. | **Group B model** Back casting ,reversing the succeed forecasting model | No of neurons in the hidden layer | The best value R | | The minimum MSE | |
| | | | training | test | training | test |
| 8 | $Q1(t), Q1(t-1), Q1(t-2) = f(Q_3(t+1), Q2(t), Q_3(t), Q2(t-1), Q_3(t-1), Q2(t-2), Q_3(t-2))$ | 5,7,9,**11**,13, 15,17,19,21 | 0.906 | 0.957 | 0.0037 | 0.00469 |

According to the above table more than one model showed a perfect results ,model no.4 can be chosen as the best one due to results of correlation coefficient and mean square errors especially in the test period :

$Q_1(t) = f(Q2(t), Q_3(t), Q2(t-1), Q_3(t-1), Q2(t-2), Q_3(t-2),, Q2(t-3), Q_3(t-3))$……………………………………………………………………………..……(10)

And also model no.7 results was too good,

$Q_1(t) = f(Q2(t), Q_3(t), Q2(t-1), Q_3(t-1), Q2(t-2), Q_3(t-2), Q2(t-3), Q_3(t-3), Q2(t-4), Q_3(t-4), Q2(t-5), Q_3(t-5), Q2(t-6), Q_3(t-6)$………………..(11)

Model. No 8 is also a perfect model to predict the missed data

$Q1(t), Q1(t-1), Q1(t-2) = f(Q_3(t+1), Q2(t), Q_3(t), Q2(t-1), Q_3(t-1), Q2(t-2), Q_3(t-2))$…………………………………………………(12)

Note : In the model (no.8,eq(12)) there are three outputs which means when using this model , three values of the missed data can be predicted this can provide additional calibration of the model . Following are Figures (7,8,9)of comparison between estimated data and observed one for the calibration period

**Figure-7.** Estimated monthly flow of Euphrates river at(IRQ-E1) Vs. observed (MSANN structure 8-10-1).

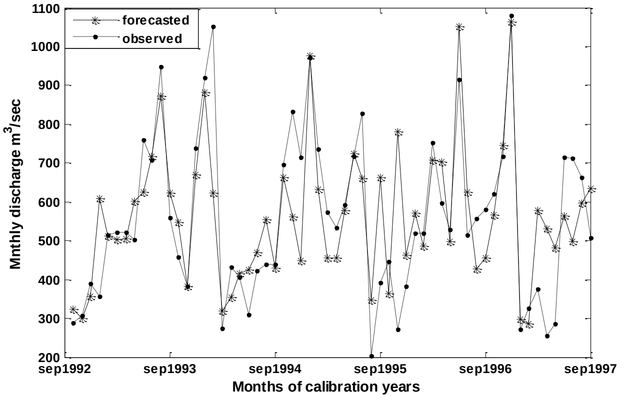



**Figure-8.** Estimated monthly flow of Euphrates river at (IRQ-E1) (MSANN structure14-12-1).

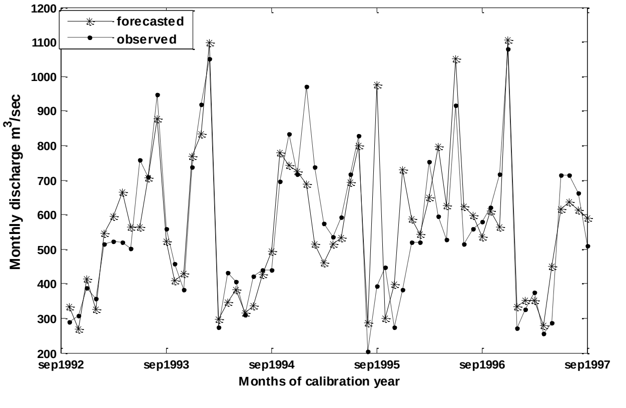
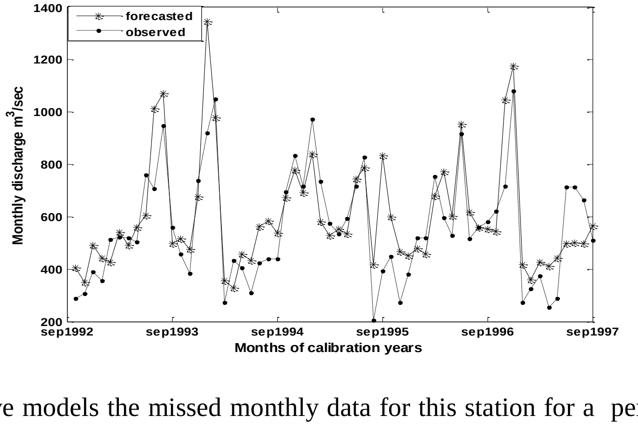
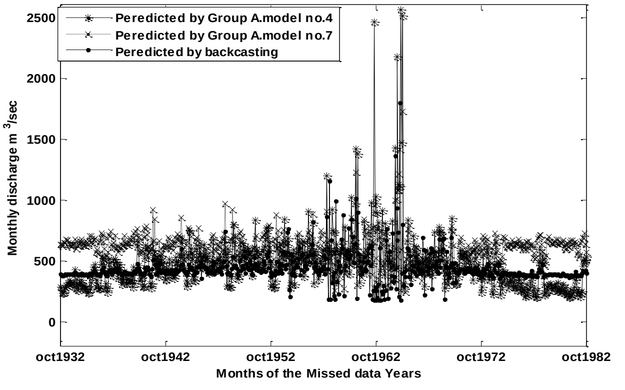



**Figure-9.** Estimated monthly flow of Euphrates river at (IRQ-E1)vs. observed (Back casting 7-11-3).




By using the above models the missed monthly data for this station for a period(1932-1981)years were found and the results were plotted as shown below in Figure (10) which shows the estimated data for un recorded period by the three models

**Figure-10.**The predicted monthly flow data for (IRQ-E1)for a period (1932-1982)by the three successful models




## 6. CONCLUSIONS

The current study has demonstrated a promising application of ANN –stream flow forecasting . Two SSANN models for forecasting the Euphrates river flow at d/s Al-Hindyaha barrage(IRQ-E3) showed good results, the best one was with three inputs which are the monthly flow data for three sequent times, four neurons in the hidden layer. Also two other models of MSANN kind showed promising results, first one was with nine inputs which are the monthly flow values for the three sites of Euphrates river at lagged months 1,2 and 14 neurons in the hidden layer. The second successful MSANN model was with 12 inputs and 18 neurons in the hidden layer, the inputs were the monthly flow data just at two sites. This model was most successful for this site flow which indicates the high correlation between monthly flow data at Hit and monthly flow data d/s Al-Hindyaha barrage . Although of this result the SSANN models produced less training time due to the network size reduction and the results obtained were better . The four mentioned models can be utilized from for forecasting the Euphrates river flow at the required station for future. By referring to results of Al Husaybah site missed data prediction, it is obvious also that two models presented too good results , first one was MSANN model that indicated dependence of monthly data of Husaybah site on the monthly data of the two sequent sites flow at delayed months with 8-10-1 structure. Also The back casting MSANN model showed perfect result to estimate the missed data . These two models are presenting a good promise to estimate missed data for Husayabah gauging station . It is also concluded from this study that by using sigmoid function which was used as a transfer function between the input layer and the hidden layer and between the hidden layer and outputs one can reach best results than by using pure line transfer equation between the hidden layer and the outputs which was tried also.

## 7. ACKNOWLEDGEMENTS

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