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PREDICTION OF TIGRIS RIVER DISCHARGE IN BAGHDAD CITY USING ARTIFICAL NEURAL NETWORKS

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Abstract

Artificial Neural Networks **(ANNs),** with three layers feed- forward network of sigmoid hidden neurons and linear output neurons are performed for predicting Tigris River flow in Baghdad City, middle of Iraq. The network is trained with Levenberg-Marquradt back-propagation algorithm. The number of hidden neurons is estimated according to trial and error procedure. The best model is selected according to trial and error procedure based on root mean square error and coefficient of correlation. The selected model is used to predicate the river discharge for one, two, and three months ahead. Results indicate that the **ANNs** with Levenberg-Marquradt back-propagation algorithm are a powerful tool for forecasting the river discharge for short term duration. But this ability begins to decrease when increasing the period of forecasting.

Key words: Artificial, Neural, Networks, Flow, Tigris, River

التنبؤ بتصريف جريان نهر دجلة في مدينة بغداد باستخدام الشبكات العصبية الصناعية

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البصرة/ العراق

الخلاصة

تمت تهيئة الشبكات العصبية الصناعية لثلاث طبقات بطريقة الطبقات المتعددة الامامية لتابع التحويل الاسي للطبقة المخفية وتابع التحويل الخطي لطبقة الاخراج للتنبؤ بتصريف نهر دجلة في مدينة بغداد، وسط العراق. استخدمت خوارزمية للانتشار العكسي في تدريب الشبكة. أختير عدد العقد طبقا لعملية التجربة والخطأ. حدد افضل نموذج بطريقة ألتربيعي لتنبؤ بتصريف مجرى النهر لشهر، شهرين، الخطأ معدل الارتباط وجذر المحاولة والخطا وبالاعتماد على معامل وثلاثة اشهر لاحقة. حيث بينت النتائج ان الشبكات العصبية المتعددة الامامية المدربه بخوارزمية أداة فاعلة للتنبؤ بتصريف النهر للامد القصير. حيث تبدا هذه القدرة بالتضائل كلما زادت فترة التنبؤ.

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1 .Introduction

The ability of river stream flow prediction quickly and accurately is critical operation in flood forecasting. Prediction of stream flows is vital important for flood caution, operation of flood-control-purposed reservoir, determination of river water potential, production of hydroelectric energy, allocation of domestic and irrigation water in drought season, and navigation planning in rivers **(Bayazit, 1988).**

In the recent years, new techniques and algorithms have applied as a powerful tool for modeling the problems of water resources. Artificial Neural Networks **(ANNs)** is one of them. ANNs have been used as successfully tool for solving many different types of hydrological problems **(ASCE, 2000). ANN** techniques applied to hydrologic time series and forecasting have shown better performance than the classical techniques **(Govindaraju and Rao, 2000).**

Among the models for stream flow forecasting, **ANNs** have attracted much interest recently **(Coulibaly, et.al, 2000).** The main reason for this popularity is that, as is the case with other black-box models, they seem to be easy to use. Unlike conceptual modeling, no hydrological parameters are need to drive functional relationships between the independent and the dependent variables; these are determined automatically in the calibration process. However, these conceptual models require accurate geometric data, which may not be available in many locations and may be costly. It is also not possible to integrate observed data directly at desired locations to improve the model results. In this respect, **ANNs** provide a quick and flexible approach for data integration and model development.

In this study, the prediction of Tigris River flow in Baghdad City, Capital of Iraq by using **ANNs** approach is the main objective of this research, In addition to investigate the capability of **ANN** model for forecasting the stream flow for one, two, and three months ahead.

2. Artificial Neural Networks

ANNs are based on the present understanding of the biological nervous systems. An **ANN** is a massively parallel-distributed information processing system that has certain performance characteristics resembling biological neural networks of the human brain **(Haykin, 1994).** The network consists of layers of parallel processing elements, called neurons. In most networks, the input layer receives the input variables for the problem at 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 layer and output layer there may be one or more hidden layer as shown in **Figure 1.**

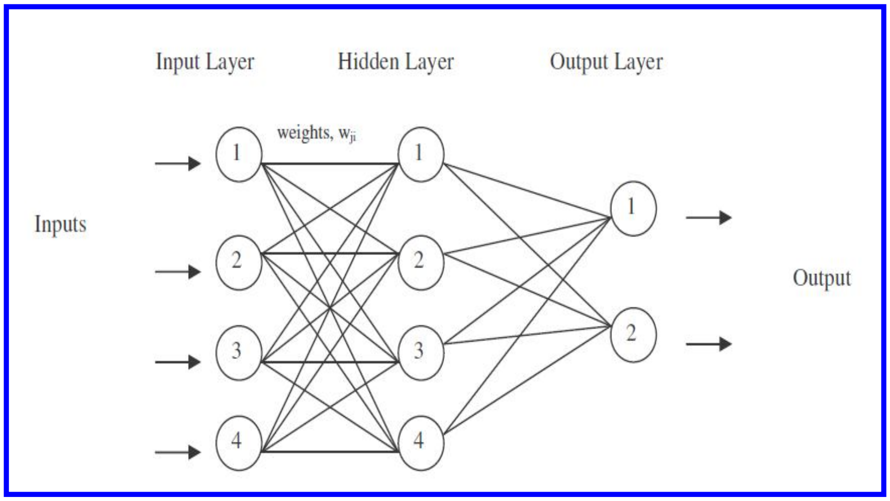

Fig.1 Configuration of Three-Layer Neural Network.

Today Neural Networks can be trained to solve problems that are difficult for conventional computers or human beings. Neural Networks are good for fitting functions and recognizing patterns. In fact, there is a proof that a fairly simple neural network can fit any practical function. Through the process of the neural model, the scalar input (*p*) as shown in figure (2) is transmitted through a connection that multiplies its strength by the scalar weight (w) to form the product (Wp). The transfer function net input (*n*) again scalar is the sum of the weighted input (Wp) and the bias (*b*), which produce the scalar output (*a*). (*f*) is a transfer function, typically a step function or a sigmoid function.

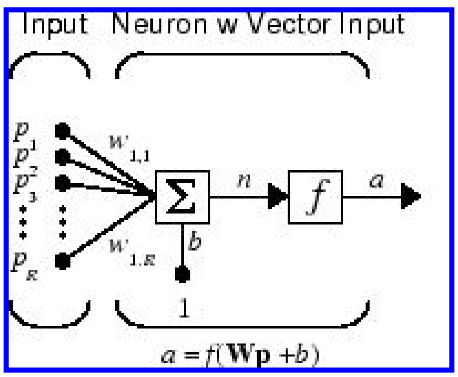

Fig.2 A Neuron with Multiple Scalars Input.

The central idea of neural networks is the parameters can be adjusted, so that the network exhibits some desired or interesting behavior. The training of the network is complete by adjusting the weight or bias parameters to achieve some desired end.

Back-propagation is perhaps the most popular algorithm for training **ANNs.** The back-propagation algorithm gives a prescription for changing the weights, wji **(see Figure 1)** 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 weights so as to minimize the error between the network output and the target output. The average of all square error (E) for the outputs is computed to make the derivative easier. Once the error is computed, the weights can be updated one by one. The following equation is used for the connection weights adjustment **(Jun Han, 2002).**

$$\Delta w_{ji}(n) = -\varepsilon * \left(\frac{\partial E}{\partial w_{ji}}\right) + \alpha * \Delta w_{ji}(n-1) \ldots\ldots\ldots\ldots\ldots\ldots\text{eq.(1)}$$

Where:-

$\Delta w_{ji}(n)$ and $\Delta w_{ji}(n-1)$: weight increment between node j and i during the nth and (n-1)th the pass, or epoch.

ε : learning rate.

α : momentum.

Three layer feed forward neural network used in this study, which have been widely used for water resources modeling, because these layers are sufficient to generate arbitrarily complex output signals **(Lippman, 1987)**. The output of the hidden layer are gathered and processed by the output layer. A neuron is a processing unit n inputs (x_1, x_2, …., x_n) and one output (y), with

$$y = f(x_1, x_2, \ldots, x_n) = A[(\textstyle\sum_{i=1}^{n} w_i x_i) + b] \ldots\ldots\ldots\ldots\ldots\text{eq.(2)}$$

Where:-

w_i : the weight of the neuron.

b : the constant bias.

A : the activation function.

1. Study Area and Data Set

Baghdad is capital of Iraq, central Iraq as shown in **Figure 3**. Its location on the Tigris River about 530 km from the headwaters of the Arabian Gulf, is in the heart of ancient Mesopotamia. The Tigris River is one of the main rivers in the Middle East. Its total length is 1900 kilometers out of which 1415 kilometers run inside Iraq. It has a catchment area of about 235,000 square kilometers **(Iraqi Ministries of Environmental, water resources, Municipalities and public works, 2006)**. 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 Environmental, water resources, Municipalities and public works, 2006)**. The monthly average discharge of Tigris River for the period (1954-2002) is used in this study (Ministry of Irrigation, General Faculty of Dams and Reservoir, 2002). The summary statistics of the raw data are shown in **Table 1.** The highest annual discharge (1692 m^3/s) occurred at 1988, while the lowest annual discharge (392, 391 m^3/s) occurred during the year 2000 and 2001 respectively.

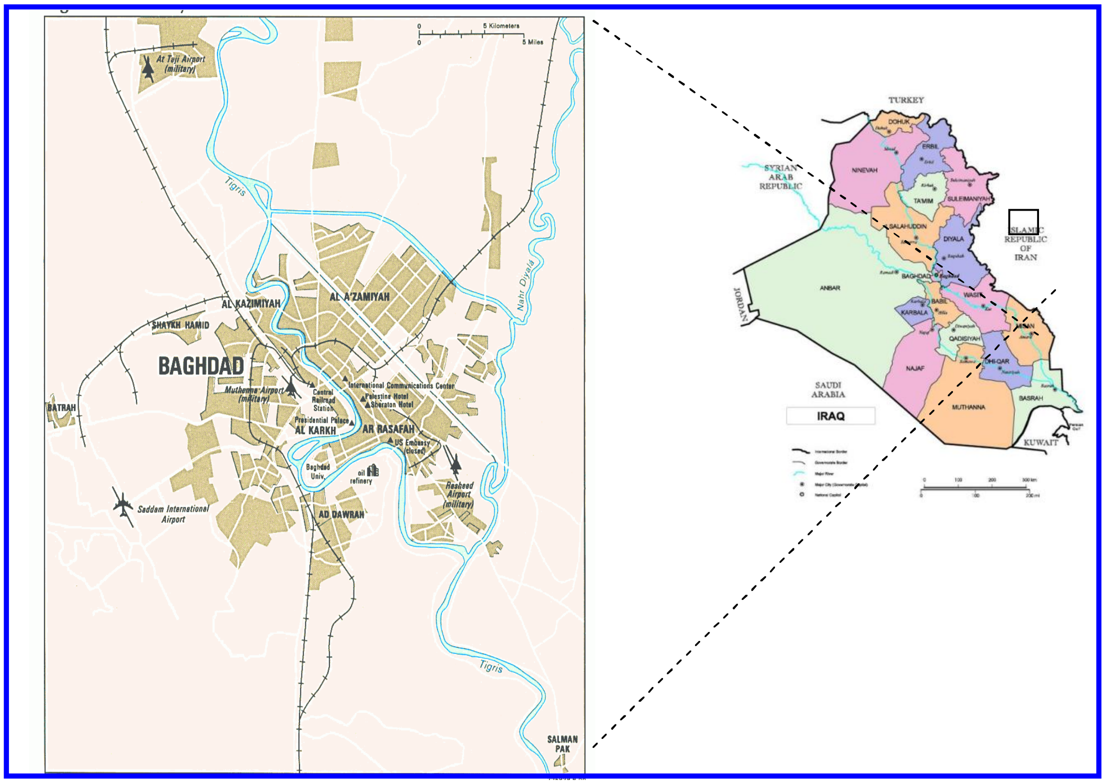

Fig. 3 Location of Study Area in Reference to Map of Iraq.

Table 1 Basic Statistics of Data Set.

Basic Statistics	Value	Number of Observations
Minimum	391	583
Maximum	1692	
Average	768.8	
Standard Deviation	372.3	
Skewness Coefficient (Cs)	1.81	
Kurtosis Coefficient (Ck)	4.54	

4.Methodology

Three layers feed- forward network with sigmoid hidden neurons and linear output neurons are used in this research. The network is trained with Levenberg-Marquradt back-propagation

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algorithm. The data set is scaled by using mapminmax function, according to this scale, the range of the input lies inside the range ($-1 \leq x \leq 1$). Hence the total number of observations is 583 samples, these observations are divided into three statistically parts. 70% (409 samples) for training, these are presented to the network during training, and the network is adjusted according to its error. 15% (87 samples) is used as a validation part; these are used to measure network generalization, and to halt training when generalization stops improving. The last part of data set is testing part (15%, 87 samples), these have no effect on training and so provide an independent measure of network performance during and after training. The early stopping method is selected to overcome overfitting problem. The number of hidden neurons is estimated according to trial and error procedure. 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 adjusting of inter-connecting weights is accomplished using the back-propagation algorithm. A trial and error procedure based on root mean square error (Eq.3) and coefficient of correlation **(Eq.4)** are used to select the best network architecture and perform of **ANN** for predicting the discharge of Tigris River.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_i - x_i)^2}{N}} \quad \text{..........................eq.(3)}$$

$$R = \frac{\sum_{i=1}^{N}(x_i - \bar{x})^2 (y_i - \bar{y})^2}{\sqrt{\sum_{i=1}^{N}(x_i - \bar{x})^2 \sum_{i=1}^{N}(y_i - \bar{y})^2}} \quad \text{.......................eq.(4)}$$

Where:-
x_i : the observed values at the i-th time step.
y_i : the simulated values.
N : the number of time increments.
$\bar{x}$ and $\bar{y}$: are the mean value of the observations and simulations.

5.Results and Discussion

Two models are adopted for selecting the best one. These models are described as follow:-
M_1, $Q_t = f(Q_{t-1})$.......................................eq.(5)
M_2, $Q_t = f(Q_{t-1}, Q_{t-2})$ ....eq.(6)
Where:-
Q_t : discharge at a specified time.
Q_{t-1}, Q_{t-2} : discharges at t-1 and t-2 respectively.
Root mean square error (RMSE) and coefficient of correlation (R) are used for evaluating the performance of models. **Table 2** shows the summary results for M_1, M_2 computed over the test set, with marked values corresponding with best performance according to the criteria in each column.

Table 2 The Results of M_1, and M_2 Computed over the Test Set.

Model	R	RMSE
M_1	0.945	118.12
M_2	0.914	123.27

Figures 4 and 5 show the observed versus calculated for M_1 and M_2 respectively. M_1 is selected according to the above statistical parameters for prediction the river discharge for one, two, and three months ahead as shown in **Figures 6 to 8**. These figures show the ability of neural networks as a powerful tool to predicate the river discharge for short term duration. But this ability begins to decrease when increasing the period of forecasting. The performance of the neural networks could be improves by using additional information that related to the variable under consideration, such as rainfall. Also the efficiency of **ANN** could be increased by using Hybrid models, such as Hybrid Wavelet-Genetic programming approach **(Nourani, et.al, 2012).**

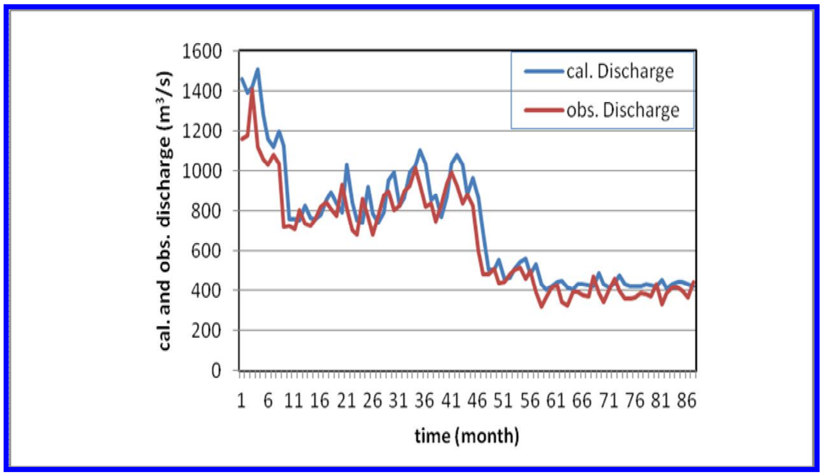

Fig.4 Observed and Calculated River Discharge for M_1 Model.

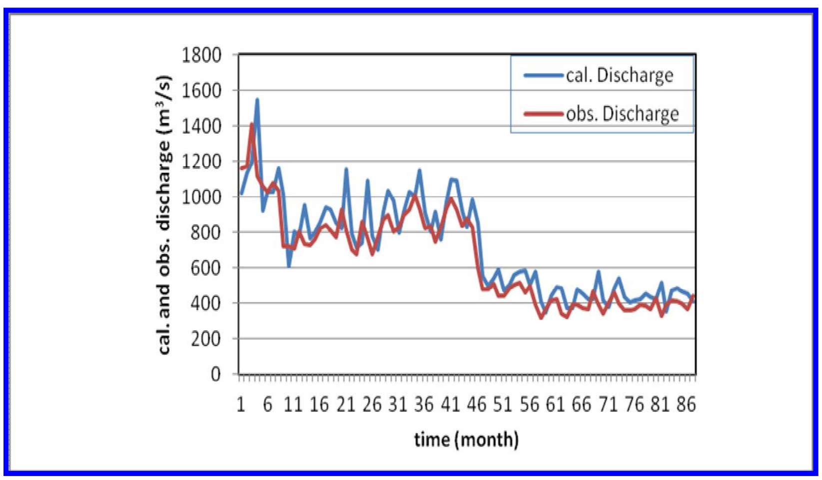

Fig.5 Observed and Calculated River Discharge for M_2 Model.

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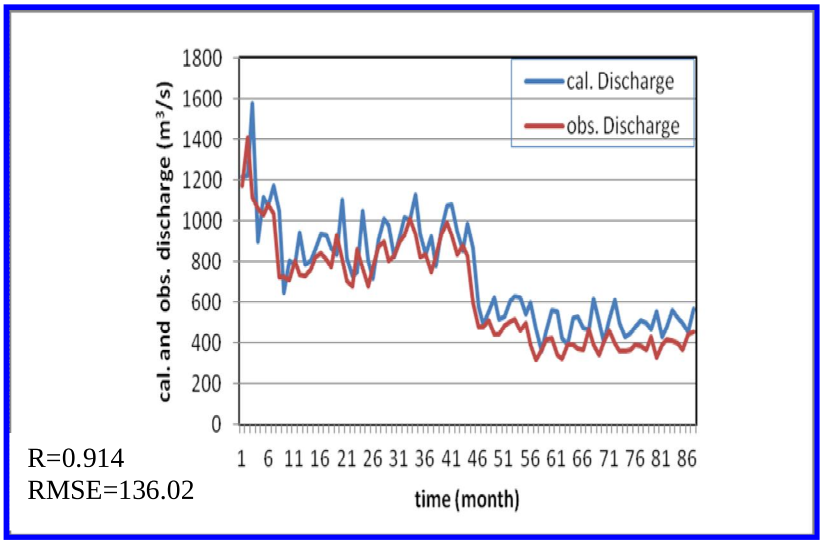

Fig.6 Observed and Calculated River Discharge for One Month Ahead Prediction.

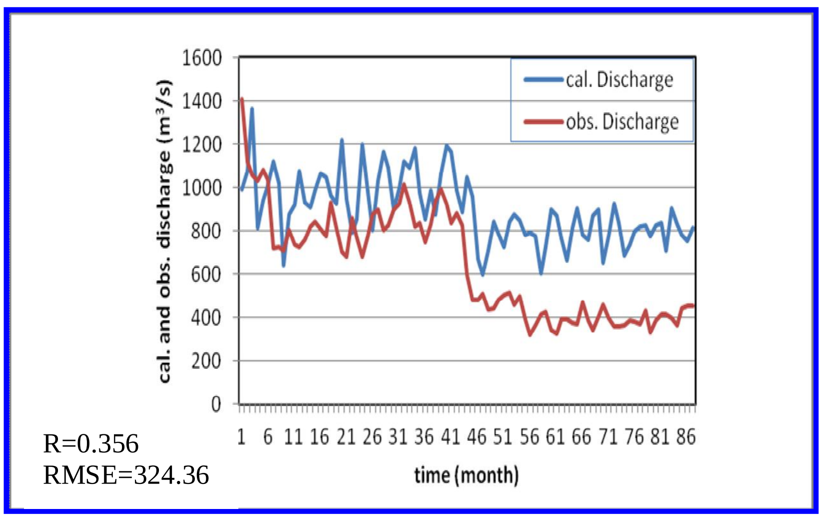

Fig.7 Observed and Calculated River Discharge for Two Months Ahead Prediction.

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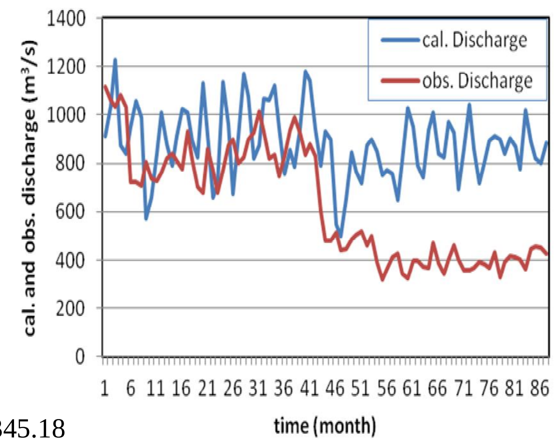

R=0.118
RMSE=345.18

Fig.8 Observed and Calculated River Discharge for Three Months Ahead Prediction.

2. Conclusions

Three layers feed- forward network with sigmoid hidden neurons and linear output neurons are used for predicting Tigris River discharge in Baghdad City, middle of Iraq. Back-propagation is used here for training **ANNs**.The back-propagation algorithm gives a prescription for changing the weights in any feed forward network to learn a training vector of input-output pairs. The results showed that the artificial neural network with back-propagation algorithm is a powerful technique for predicting the river discharge for one month. But the efficiency of **ANN** is begun to decrease when increasing the length of forecasting period. It appears from experiments that a single **ANN** cannot produce accurate forecasts for lead times higher than the characteristic lag (travel) time of the particular river. The ability of **ANN** for modeling both short and long term patterns could be increased by using of multi-scale time series of rainfall and runoff data as the genetic programming inputs.

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