Performance Of Artificial Neural Networks , Support Vector machine and Fuzzy logic networks ANFIS In Monthly Streamflow Forecasting For Diyala, Adhim and Elkhazer Rivers Northern Iraq.

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Abstract-Streamflow forecasting is needed for proper water resources planning and management. Since The most challenging task for water resources engineers and managers is a streamflow forecasting. In this study a brief application and comparison of artificial neural network, Support vector machine SVM and adaptive neuro system ANFIS approaches are employed for three case studies which were Diyala River , Adhim and Elkhzer Rivers northern Iraq. Different training algorithms and different artificial neural networks such as Levenburg Marqudat LMNN , Scaled conjugate gradient SCGNN , radial basis function networks RBNN and generalized regression networks GRNN were selected in modeling and generation of synthetic streamflow for the mentioned case studies. Two other methods were also applied to the mentioned case studies which are support vector machine SVM and adaptive neuro fuzzy interference ANFIS model which integrates both neural networks and fuzzy logic principles. A comprehensive comparison between the applied models was done to determine the best performance for each case study . The performance of applied networks and models were determined according to well known test parameters R^2, E nash, Rbias ,MAPE, MAE. It has been found in this study that Levenburg Marqudat is faster and have better performance than Scaled conjugate gradient algorithm in training operation while the radial basis networks and generalized regression networks presented the best performance among all kinds of networks for Diyala and Adhim rivers while the best performance for Elkhazer river was only by radial basis function networks.

Index Terms: ANN, LMNN, SCGNN, RBNN, GRNN , SVM, ANFIS

1.INTRODUCTION

Streamflow forecasting is required for many activities involving water resources systems .The most important advantages that can be obtained from an exact streamflow forecasting include an enhanced ability to estimate the volumes and timing for flood events, improved water use efficiency through better anticipation of river inflows and a concomitant reduction in operational losses due to over releases from water storages(Dutta., et. al 2001,2007). Streamflow forecasting is very important in many areas such as dam planning, flood mitigation and domestic water supply. Most of the used methods in streamflow forecasting are based on the statistical analysis of the observed stream data which were measured in the past(Arslan A 2012). Many of these methods provide very complex or too demanding tools for practical cases(Kaya , et. al 2002). Many traditional methods were applied to different streams in order to simulate these streams and to provide better mathematical models which reflect the stream behavior . Arslan A., 2012 produced a modified form of Thomas Fiering model to simulate Khasa Chy river northern Iraq. The same researcher used the traditional Markove Autoregressive AR model for forecasting the same river for future years . Artificial neural networks have been proven to be an efficient alternative to traditional methods which were used for simulation and forecasting streamflow (Levenberg. L,1994),. Previous studies have demonstrated that the ANN has received much attention for stream flow forecasting (Dolling, et. al.2003 - Firat, M.,2008 -Hu, T.S , 2001- Shamseldin., 2007-Wang., 2009). Zealand et. al. (1999) investigated the utility of artificial neural networks (ANNs) for short term forecasting of streamflow . Al aboodi., 2009, 2013 produced a comprehensive study for prediction of Tigris river discharges using different types of artificial neural networks . Muhammed J R 2005 investigated the utility of artificial neural networks (ANNs) for Khabor stream northern Iraq. (Kişi 2005) applied the artificial neural networks (ANNs) in forecasting mean monthly streamflow and compared the applied models with AR models. The same researcher (2008)applied different artificial neural networks techniques for river flow forecasting for two case studies at Turkey . In addition to these models the adaptive neuro interference fuzzy system was used by many researchers for same purpose. A model Based on simulating rainfall-stream flow using fuzzy logic and ANN was produced by Tayfur and Singh (2006). Ballini et. al (2001) developed a neuro fuzzy network model for forecasting the inflow of Brazilian hydroelectric plants. In this study four different artificial networks with ANFIS and support vector machine models were applied for prediction of the future flows of Diyala River 35° 08′ 00″ N, 45° 45′ 00″ E.,ElKhazer stream 36° 18′ 00″ N, 43° 33′ 00″ E and Adhim River 34° 30′ 00″ N, 44° 31′ 00″ E northern Iraq. Description of these models are represented below.

2.METHODOLOGY:

2.1. ARTIFICIAL NEURAL NETWORKS .

Artificial neural networks (ANN) have been developed as mathematical models similar to biological nervous systems. The basic processing elements of neural networks are called artificial neurons. In a simplified mathematical model of the neuron, the effects of the synapses are represented by connection weights that modulate the effect of the associated input signals, and the nonlinear characteristic exhibited by neurons is represented by a transfer function. The neuron impulse is then

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computed as the weighted sum of the input signals, transformed by the transfer function. The learning capability of an artificial neuron is achieved by adjusting the weights in accordance to the chosen learning algorithm. The architecture of a neural networks consists of three basic components which are called layers: input layer, hidden layer(s), and output layer. In feed-forward networks, the signal flow is from input to output units(Bishop., 1995).

2.1.1. Feed forward networks training methods

In this study two Different methods in training the feed forward artificial neural networks were tried which are Levenburge –Maqurdaut and scaled conjugate gradient methods. The aim of training a network is to reduce the error between the outputs of the networks with the desired one. Each training algorithmic attempts to reduce the calculated error by adjusting weights and biases(Levenberg. L,1994). A typical feed forward neural network structure is illustrated in Figure(1).

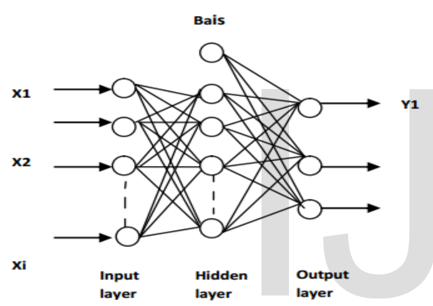

Fig. 1. Typical Feed forward Neural Network.

2.1.1.a. Levenberg-Marquardt(LMNN).

The Levenberg-Marquardt (LM) training method can be described as the most effective method for feed-forward neural networks with respect to the training precision. The LM algorithm is an iterative technique that locates the minimum of a multivariate function that is expressed as the sum of squares of non-linear real-valued functions(.Marquardt., 1963). Levenberg-Marquardt Learning was first introduced to the feed forward networks to improve the speed of the training. This method is a modification to Guass-Newton method which has an extra term to prevent the cases of ill-conditions. The training process in this method is based on minimizing an error function, in each iteration, such as the one in equation below :

$F(X_k) = \frac{1}{N}\sum_{i=1}^{N} v_i (X_k)^2$…………1.

where N is the number of samples used to train the feed forward artificial neural network; xk is the vector of parameters, in this case,the set of weights at iteration k; vi(xk)= Ti-Yi(xk), Ti isthe ith desired output for the sample, and Yi(xk) is the ith FANN output during iteration k. (.Marquardt., 1963)., (Levenberg. L,1994).

2.1.1.b . Scaled Conjugate Gradient (SCGNN).

The Scaled Conjugate Gradient (SCG) algorithm denotes the quadratic approximation to the error E ina neighborhood of a point w by:

$E_{qw}(y) = E(w) + E'(w)^T y + \frac{1}{2} y^T E''(w) y$ … 2.

In order to determine the minimum to Eqw(y)the critical points for Eqw(y) must be found. The critical points are the solution to the linear system (Kisi, O ., 2005).

$$E_{qw}(y) = E''(w)y + E'(w)y \text{ … … … .3}$$

2.1.2.Radial basis Functions Networks(RBFNN)

RBFNN is a network which is composed of three layers, the input layer, the hidden(Kernel) layer and the output layer. The important property of RBF networks is that the outputs of the input layer are determined by calculating the distance between the network inputs and hidden layer centers. The second layer is the linear hidden layer and outputs of this layer are weighted forms of the input layer outputs. Each neuron of the hidden layer has a parameter vector called center. A radial basis function $\emptyset$ is one whose output is symmetric around an associated center c_i. The general expression of the network can be given as:

$y_j^{\wedge} = \sum_{i=1}^{I} w_{ij} \emptyset(\|x - c_i\| + \beta_j)$……………………4.

The norm is usually taken to be the Euclidean distance and the radial basis function is also taken to be Gaussian function and defined as:

$\varphi(r) = \exp(-\alpha_i . \|x - c_i\|^2)$……………………5.

where,

I:Number of neurons in the hidden layer ;J :is the number of neurons in the output layer ,wij :is the weight of the ith neuron and jth output;φ:is the Radial basis function;αi :is the Spread parameter of the ith neuron;xis the Input data vector ,ci : is the Center vector of the ith neuron;βj :is the Bias value of the output jth neuron and ŷj :is the Network output of the jth neuron.(Maier., 1996),(Robert,., 2005).

2.1.3. Generalized regressing neural networks (GRNN)

Generalized Regression Neural Networks (GRNNs), are classified as a probabilistic neural networks. The structure of the generalized regression neural networks are composed from four layers: input layer, pattern layer, summation layer, and output layer. The first layer is fully connected to the second, pattern layer, where each unit represents a training pattern and its output is a measure of the distance of the input from the stored patterns. Each pattern layer unit is connected to the two neurons in the summation layer: S-summation neuron and D-summation neuron. The S-summation neuron computes the sum of the weighted outputs of the pattern layer while the D-summation neuron calculates the un weighted outputs of the pattern neurons. (Moller ., 1993). The connection weight between a neuron in the pattern layer and a S-summation neuron is the target output value corresponding to given input pattern. For D-summation neuron, the connection weight is unity. The output layer only divides the output of each S-summation neuron by that of each D-summation neuron, yielding the predicted value corresponding to an unknown input vector. The operation of the D-summation neuron includes a parameter called the spread factor, whose optimal value is often determined by trials (Kim., B, 2014)

2.2 Adaptive Neuro Fuzzy Inference System (ANFIS).

Jang introduced ANFIS model at 1993. A basic structure of ANFIS model is illustrated in Figure(2) .This model consists a number of nodes connnected through directional links . These nodes are characterized by node function with fixed or adjustable parameters . Training phase of neural networks is a process to determine parameter values to sufficiently fit the training data. The basic learning rule is the well known backpropogation method which seeks to minimize some measure of error, usually sum of squared differences between networks outputs and desierd outputs (Kaya et al., 2002).

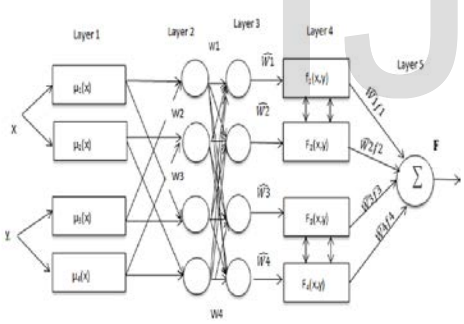

Fig. 2. Structure of ANFIS Networks

2.3 Support Vector Machine .

Support Vector Machine" (SVM) is a supervised machine learning algorithm which can be used for both classification or regression challenges. However, it is mostly used in classification problems. In this algorithm, the data item will be plotted as a point in n-dimensional space (where n is number of features we have) with the value of each feature being the value of a particular coordinate. Then, a classification will be performed by finding the hyper-plane that differentiate the two classes very . SVM is learning method that is widely used for data analysing and pattern recognizing .The algorithm was invented by Vapnik (1995) and the current standard incarnation was proposed by Vapnik (Buyukyildiz et al. 2014).

3. Case Studies.

In this study the monthly flow values for three case studies which were Diyala River , Adhim and Elkhazer Rivers northern Iraq were used to apply the above different methods. For Diyala river the record period was from 1931-2004 as monthly flow value measured in m3/sec. The record period of monthly flow values for the Adhim river was extending from 1945-1997 while for Elkhazer River monthly data was extended from 1932-2004.(Saleh., K, 2010).

Diyala River: is an important tributary of the Tigris River, rising in the Zagros Mountains of western Iran near Hamadan as the Sirvan River and flowing westward across lowlands to join the Tigris just below Baghdad, Iraq. Its total length is 275 miles (443 km). The upper Diyala drains an extensive mountain area of Iran and Iraq. For 20 miles (32 km) it forms the frontier between the two countries (Encyclopedia Britannica ., 2015).

Adhaim River: is an important tributary of the Tigris River, originates in Iraq converges with the Aksu tributary, which passes through Tuzhurmatu. The Adhaim tributary rises from the foothill region in Iraq. It forms from three main streams which are joined upstream of Injana. Further downstream it flows south-westwards and joins the Tigri 15km downstream of Balad. Its total basin area is 13000km2 and its length is 230km. The mean annual long term discharge at Injana is 25 cumecs (0.8bcm).This fluctuates from year to year. For instance, it increased to 55 cumecs (1.73bcm) in 1969 and decreased to5 cumecs (0.l6bcm) in 1960(Hamdan.,1988).

Khazer River is a river of northern Iraq, a tributary of the Great Zab River. The net yearly recharge rate of the valley water table is 111.6 mm/year and the region is considered to be fertile.The area around the Khazer River is however, geologically active and crosses three anticlines from the north to the south and this has greatly affected the course of the river. (Hussein A, Encyclopedia Britannica ., 2015). Figure(3) illustrates the location of the corresponding case studies).

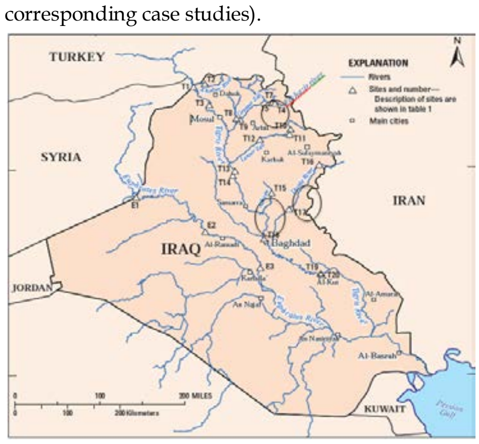

Fig. 3. The locations of Diyala , Adhiam and Elkhazir Rivers.

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4. Applications and Results

4.1. Case Study I Diyala River

The monthly flow of Diyala River data was normalized before applying the mentioned methods above using the following formula:

$$\frac{X_{i-}\ X_{min}}{X_{max-}\ X_{min}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots.6.$$

Where Xi ,Xmin, X max are the data , minimum and maximum of the series respectively. (Kisi O, 2005).

4.1.1. Application of LMNN on Diyala River

In general The feed forward neural networks can have more than one hidden layer ,however many pervious works have shown that using one hidden layer is suitable for any ANN to deal with non linear problems. It was proven by many researches that one hidden layer may be enough for most forecasting problems therefore one hidden layer was used in this work. A difficult task for designing any neural network is choosing the input parameters combinations and the number of hidden layer neurons since the architecture of the ANN affects its computational complexity and its generalizations capability (Kilinc., 2005). The neuron numbers for the hidden layer were tried to range from 2-38 neurons.

The performance of the different models were investigated using following parameters

$$\mathrm{ENash} = 1 - \frac{\sum_{t=1}^{n}(A_t - F_t)^2}{\sum_{t=1}^{n}(A_t - F_{mean})^2} \ldots\ldots\ldots\ldots7.$$

The range of E lies between 1.0 (perfect fit) and $-\infty$

$$\mathrm{R\ bias} = 100 * \frac{\sum_{t=1}^{n}(F_t - A_t)}{\sum_{t=1}^{n} A_t} \ldots\ldots\ldots\ldots\ldots8.$$

The optimal value of Rbias is 0.0, with low-magnitude values indicating accurate model simulation. Positive values indicate overestimation bias, whereas negative values indicate model underestimation bias .

$$R^2 = \frac{(\sum_{t=1}^{n}(A_t - A_{mean})(F_t - F_{mean}))^2}{\sum_{t=1}^{n}(A_t - A_{mean})^2 \sum_{t=1}^{n}(F_t - F_{mean})^2} \ldots\ldots\ldots9$$

A high R2 value (i.e. close to unity), indicates a good model fit with observed data(Chokmani., 2003- Tiryaki., 2014). Another two test parameters which are mean absolute error and mean absolute percentage error are used which can be defined as in the following formulas .

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|A_t - F_t| \ldots\ldots\ldots10$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|A_t - F_t|}{A_t} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 11.$$

Multiplying by 100 makes it a percentage error (Tiryaki., 2014). The results for the best investigated LMNN models for different input combinations are illustrated in the following Table(1).

Table(1) The performance of LMNN on Diyala River

LMNN/Diyala River						
Input Parameters	Model structure	E_{nash}	R_{Bias}	R^2	MAE	MAPE
Qt-1	1-28-1	0.58	0.15	0.58	64.1	53.78
Qt-1, Qt-2	2-36-1	0.74	0.15	0.74	47.33	52.78
Qt-1, Qt-2, Qt-3	3-28-1	0.8	-0.02	0.8	42.76	42.55
Qt-1, Qt-2, Qt-3, Qt-4	4-19-1	0.78	0.12	0.78	46.11	41.77
Qt-1, Qt-2, Qt-3, Qt-4,Qt-5	5-23-1	0.86	-0.12	0.86	38.58	37.34
Qt-1, Qt-2, Qt-3, Qt-4,Qt-5, Qt-6	**6-34-1**	**0.9005**	**-0.063**	**0.9006**	**31.05**	**35.47**

4.1.2. Application of SCGNN on Diyala River.

After applying the same procedure for normalization the monthly flow values of Diyala River the training algorithm was changed to Scaled Conjugate gradient method for the same previously applied input combinations . The performance of this feed forward networks was dropped if compared with the pervious used algorithm. This was found after calculating the same test parameters which are shown in Table (2) below .

Table(2) The performance of SCGNN on Diyala River

SCGNN/Diyala River						
Input Parameters	Model structure	E_{nash}	R_{Bias}	R^2	MAE	MAPE
Qt-1	1-12-1	0.57	1.02	0.57	64.83	53.82
Qt-1, Qt-2	2-32-1	0.64	0.04	0.64	53.7	43.14
Qt-1, Qt-2, Qt-3	**3-21-1**	**0.64**	**0.589**	**0.64**	**52.78**	**43.08**
Qt-1, Qt-2, Qt-3, Qt-4	4-23-1	0.63	-1.41	0.63	53.86	46.14
Qt-1, Qt-2, Qt-3, Qt-4,Qt-5	5-22-1	0.62	1.77	0.63	54.27	57.16
Qt-1, Qt-2, Qt-3, Qt-4,Qt-5 , Qt-6	6-6-1	0.62	1.63	0.63	54.23	53.15

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4.1.3. Application of RBFNN on Diyala River.

In this application different values of the spread were tried , the best number of neurons in the hidden layer was selected according to the best values of the test parameters . The selected input combinations of monthly flow values data were as in the previous applications .The performance parameters showed a clear increasing in the efficiency and performance by using this kind of networks .This is illustrated in Table(3) below. The best result was found for the structure (6-0.1-1).

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Table(3) The performance of RBFNN on Diyala River.

RBFNN/Diyala River						
Input Parameters	Spread value	E_{nash}	R_{Bias}	R^2	MAE	MAPE
Qt−1	0.001	0.92	0.55	0.92	26.96	47.68
Qt−1, Qt−2	0.01	0.9	0.55	0.91	28.17	51.75
Qt−1, Qt−2, Qt−3	0.1	0.94	0.72	0.94	19.21	41.2
Qt−1, Qt−2, Qt−3, Qt−4	0.1	0.94	0.55	0.94	20.87	41.31
Qt−1, Qt−2, Qt−3, Qt−4,Qt−5	0.1	0.95	-0.53	0.95	21.76	37.33
Qt−1, Qt−2, Qt−3, Qt−4,Qt−5 , Qt−6	**0.1**	**0.96**	**0.4**	**0.96**	**21.16**	**36.34**

4.1.4.Application of GRNN on Diyala River .

Results of generalized regressing networks are illustrated in Table (4).These results were found after testing all the input combinations which were selected for the above previously applied networks and after investigating different values of spread values. The best result is remarked with bold font with spread value 0.001 and for just two inputs which are Qt−1, Qt−2.

Table(4) The performance of GRNN on Diyala River

GRNN/Diyala River						
Input Parameters	Spread value	E_{nash}	R_{Bias}	R^2	MAE	MAPE
Qt−1	0.001	0.71	0.86	0.71	12.63	23.15
Qt−1, Qt−2	**0.001**	**0.99**	**0.065**	**0.99**	**5.79**	**8.335**
Qt−1, Qt−2, Qt−3	0.01	0.93	0.186	0.93	8.1	17.41
Qt−1, Qt−2, Qt−3, Qt−4	0.01	0.97	0.066	0.97	13.7	17.86
Qt−1, Qt−2, Qt−3, Qt−4,Qt−5	0.01	0.98	-0.071	0.98	9.64	13.6
Qt−1, Qt−2, Qt−3, Qt−4,Qt−5 , Qt−6	0.01	0.99	-0.079	0.99	9.7	11.2

The efficiency of the forecasting process was improved after using radial basis function networks and highly increased after using generalized regression networks. Figure(3-a) shows the comparison between the best applied models among all different tested types of networks on Diyala River.

4.1.5.Application of Support Vector Machine SVM on Diyala River .

The found results for support vector machine models which were applied with the same scenarios of input combinations are illustrated in Table (5). The results of this kind of models did not show a good performance since the found statistical parameters were not indicating to a good performance ,this is very clear from the Table .

Table(5) The performance of GRNN on Diyala River

SVM/Diyala River					
Input Parameters	E_{nash}	R_{Bias}	R^2	MAE	MAPE
Qt−1	0.4754	-4.14	0.4721	87	203.15
Qt−1, Qt−2	0.449	-7.4	0.4204	76.8	180.335
Qt−1, Qt−2, Qt−3	0.41	-7.8	0.4111	98	170.41
Qt−1, Qt−2, Qt−3, Qt−4	0.3905	-8.0	0.4000	87.7	17.86
Qt−1, Qt−2, Qt−3, Qt−4,Qt−5	0.3671	-10.0	0.3897	76.09	133.6
Qt−1, Qt−2, Qt−3, Qt−4,Qt−5 , Qt−6	0.2929	-10	0.3112	67.445	118.2

4.1.6.Application of ANFIS models on Diyala River .

After applying the models of adaptive neuro fuzzy interference with same input combinations scenarios on the monthly flow values of Diyala River . The performance of this applied technique was better than SVM models performance but not as well as ANN models . This was found after calculating the same test parameters which are shown in Table (6) below.

Table(6) The performance of GRNN on Diyala River

ANFIS/Diyala River					
Input Parameters	E_{nash}	R_{Bias}	R^2	MAE	MAPE
Qt−1	0,46	-10.06	0,456	68.83	89,57
Qt−1, Qt−2	0,55	-10.,24	0,5511	63.7	80,870
Qt−1, Qt−2, Qt−3	0.42	-9.2	0,4245	57.78	89,80
Qt−1, Qt−2, Qt−3, Qt−4	0,440	-9.1	0,4645	58.86	77,8800
Qt−1, Qt−2, Qt−3, Qt−4,Qt−5	0,495	-5.17	0,4958	64.27	83,2600
Qt−1, Qt−2, Qt−3, Qt−4,Qt−5 , Qt−6	0,4903	5.069	0,495	64.23	84,5200

As a general finding for this case study the efficiency of the forecasting process was improved after using radial basis function networks and highly increased after using generalized regression networks. Figure(4-a) shows the comparison between the best applied models among all different tested types of networks on Diyala River. The Figure does not consist the Support vector SVM and by ANFIS models.

4.2. Case Study II Adhiam River.

The same normalization method was applied to the series and the same input combinations for Adhiam River were tried to the selected artificial neural networks and for SVM and ANFIS models. The results of the applied models are discussed below.

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4.2.1. Application of LMNN on Adhiam River.

The results for The best investigated LMNN models for different input combinations are illustrated in the following Table(7).

Table(7) The performance of LMNN on Adhiam River .

LMNN/Adhiam River						
Input Parameters	Model structure	E_{nash}	R_{Bias}	R^2	MAE	MAPE
Qt−1	1-20-1	0.31	-2.06	0.31	19.69	185.34
Qt−1, Qt−2	2-24-1	0.5	-0.32	0.5	17	168.17
Qt−1, Qt−2, Qt−3	3-22-1	0.57	-0.17	0.58	15.2	173.9
Qt−1, Qt−2, Qt−3, Qt−4	4-24-1	0.71	-5.81	0.71	13.56	160.65
Qt−1, Qt−2, Qt−3, Qt−4,Qt−5	5-23-1	0.73	-0.59	0.73	11.02	124.89
Qt−1, Qt−2, Qt−3, Qt−4,Qt−5 , Qt−6	**6-26-1**	**0.79**	**-0.33**	**0.79**	**10.44**	**119.38**

4.2.2. Application of SCGNNon Adhiam River.

After changing the training algorithm to Scaled Conjugate gradient method for the same previously applied input combinations for Adhiam River, the performance of this feed forward net works was highly dropped if compared with the pervious used algorithm. This was found after calculating the same test parameters which are shown in Table (8) below .

Table(8) The performance of SCGNN on Adhiam River .

SCGNN/Adhaim River						
Input Parameters	Model structure	E_{nash}	R_{Bias}	R^2	MAE	MAPE
Qt−1	1-32-1	0.34	3.07	0.34	19.57	114.05
Qt−1, Qt−2	2-32-1	0.39	-3.32	0.4	18.67	113.84
Qt−1, Qt−2, Qt−3	3-34-1	0.39	-3.05	0.4	18.2	113.77
Qt−1, Qt−2, Qt−3, Qt−4	**4-38-1**	**0.43**	**-3.97**	**0.43**	**18.59**	**103.86**
Qt−1, Qt−2, Qt−3, Qt−4,Qt−5	5-28-1	0.4	-0.26	0.4	17.92	123.7
Qt−1, Qt−2, Qt−3, Qt−4,Qt−5 , Qt−6	6-18-1	0.38	-0.51	0.38	18.19	123.74

4.2.3. Application of RBFNN on Adhiam River.

Different spread values were tested for the selected input combinations of monthly flow values data and the performance parameters showed a clear increasing in the efficiency and performance .This is illustrated in Table(9) below. The best result was found for the structure (3-0.01-1) but with under estimation values.

Table(9) The performance of RBFNN on Adhiam River .

RBFNN/Adhaim River						
Input Parameters	Spread value	E_{nash}	R_{Bias}	R^2	MAE	MAPE
Qt−1	----	----	-----	------	------	---------
Qt−1, Qt−2	0.01	0.93	0.28	0.93	4.25	11.7
Qt−1, Qt−2, Qt−3	**0.01**	**0.94**	**-0.109**	**0.94**	**4.63**	17.28
Qt−1, Qt−2, Qt−3, Qt−4	0.01	0.94	-0.38	0.94	4.68	15.9
Qt−1, Qt−2, Qt−3, Qt−4,Qt−5	0.01	0.91	-0.25	0.91	6.17	**22.32**
Qt−1, Qt−2, Qt−3, Qt−4,Qt−5 , Qt−6	0.01	0.92	-0.3	0.92	5.91	19.12

4.2.4. Application of GRNN on Adhiam River.

Results of generalized regressing networks are

Table(10) The performance of GRNN on Adhiam River .

GRNN/Adhiam River						
Input Parameters	Spread value	E_{nash}	R_{Bias}	R^2	MAE	MAPE
Qt−1	0.1	0.49	3.523	0.49	15.72	103.28
Qt−1, Qt−2	0.01	0.95	0.432	0.95	3.08	17.68
Qt−1, Qt−2, Qt−3	0.01	0.98	0.42	0.98	3.96	13.21
Qt−1, Qt−2, Qt−3, Qt−4	**0.01**	**0.99**	**0.031**	**0.99**	**1.55**	**12.12**
Qt−1, Qt−2, Qt−3, Qt−4,Qt−5	0.01	0.86	-0.67	0.86	9.41	13.12
Qt−1, Qt−2, Qt−3, Qt−4,Qt−5 , Qt−6	0.01	0.89	-0.49	0.89	7.26	13.89

illustrated in Table (10).The Table shows an increasing in the performance after investigating the test parameters. The best result was found for the model of structure(4-0.01-1).

4.2.5. Application of Support Vector Machine SVM on Adhiam River

Results of SVM models are illustrated in Table (11).The Table shows a clear decreasing in the performance after investigating the test parameters, since this model couldn't describe the stream behavior .

ISSN 2229-5518

Table(11) The performance of SVM on Adhiam River .

SVM/Adhiam River					
Input Parameters	E_{nash}	R_{Bias}	R^2	MAE	MAPE
Qt−1	0.29	3.723	0.29	25.70	121
Qt−1, Qt−2	0.295	2.732	0.295	13.00	98.68
Qt−1, Qt−2, Qt−3	0.298	2.72	0.298	10.97	83.21
Qt−1, Qt−2, Qt−3, Qt−4	0.299	1.8142	0.299	10.55	92.12
Qt−1, Qt−2, Qt−3, Qt−4,Qt−5	0.286	-1.887	0.286	15.45	93.12
Qt−1, Qt−2, Qt−3, Qt−4,Qt−5 , Qt−6	0.289	-1.79	0.289	14.27	101

4.2.6. Application of ANFIS on Adhiam River.

Results of ANFIS models are illustrated in Table (12). The results of test parameters for ANFIS models were also not so encouraging.

Table(12) The performance of ANFIS on Adhiam River .

ANFIS/Adhiam River					
Input Parameters	E_{nash}	R_{Bias}	R^2	MAE	MAPE
Qt−1	0.111	14.604	0.111	26.64	167.0
Qt−1, Qt−2	0.131	5.905	0.1345	25.55	165.90
Qt−1, Qt−2, Qt−3	0.119	5.9395	0.1376	31.54	11.4700
Qt−1, Qt−2, Qt−3, Qt−4	0.123	8.484	0.1325	31.501	100.03
Qt−1, Qt−2, Qt−3, Qt−4,Qt−5	0.1432	9.1735	0.293	35.88	103.70
Qt−1, Qt−2, Qt−3, Qt−4,Qt−5 , Qt−6	-0.346	16.65	0.2011	38.49	117.900

Among all the applied models on the Adhim River the high performance of generalized regression networks could be noticed from Figure (4-b)which illustrates the comparison between different applied models on Adhiam River.

4.3. Case Study III Elkhazer River.

Following section represent the view of most important results of the applied models on monthly flow data of Elkhazer river .

4.3.1. Application of LMNN on Elkhazer River.

The results for the best investigated LMNN models for different input combinations are illustrated in the following Table(13). The best architecture for LMNN models which were applied on the monthly flow data of Elkhazer river was found to be with two

Table(13) The performance of LMNN on Elkhazer River .

LMNN/ Elkhazer River						
Input Parameters	Model structure	E_{nash}	R_{Bias}	R2	MAE	MAPE
Qt−1	1-25-1	0.74	-0.56	0.74	29.69	285.32
Qt−1, Qt−2	**2-32-1**	**0.77**	**-0.57**	**0.77**	**27**	**278.12**
Qt−1, Qt−2, Qt−3	3-22-1	0.67	-0.54	0.67	25.2	273.19
Qt−1, Qt−2, Qt−3, Qt−4	4-24-1	0.64	-0.51	0.64	23.56	260.6
Qt−1, Qt−2, Qt−3, Qt−4,Qt−5	5-21-1	0.65	-0.59	0.65	21.02	234.8
Qt−1, Qt−2, Qt−3, Qt−4,Qt−5 , Qt−6	6-30-1	0.66	-0.493	0.66	20.44	229.8

input combinations Qt−1, Qt−2 and 32 neuron at the hidden layer

4.3.2. Application of SCGNNon Elkhazer River.

After changing the training algorithm to Scaled Conjugate gradient method for the same previously applied input combinations for Elkhazer stream , the performance of this feed forward net works was also highly dropped if compared with the pervious used algorithm. This was found after calculating the same test parameters which are shown in Table (14) below .

Table(14) The performance of SCGNN on Elkhazer River .

SCGNN/ Elkhazer River						
Input Parameters	Model structure	E_{nash}	R_{Bias}	R^2	MAE	MAPE
Qt−1	1-18-1	0.29	6.07	0.29	65.34	528.38
Qt−1, Qt−2	2-14-1	0.23	-8.32	0.233	64.9	535.03
Qt−1, Qt−2, Qt−3	3-16-1	0.119	-7.05	0.12	76	788.78
Qt−1, Qt−2, Qt−3, Qt−4	4-38-1	0.21	-10.97	0.219	66.78	755.52
Qt−1, Qt−2, Qt−3, Qt−4,Qt−5	5-28-1	0.24	-5.26	0.24	66.9	767.621
Qt−1, Qt−2, Qt−3, Qt−4,Qt−5 , Qt−6	6-18-1	0.38	-3.051	0.38	18.19	954.42

4.3.3. Application of RBFNN on Elkhazer River.

For the application of RBFNN models on Elkhazer river different spread values were tested for the selected input combinations of monthly flow values data and the performance parameters showed a clear increasing in the efficiency.This is illustrated in Table(15) below. The best result was found for the structure (6-0.01-1) but with under estimation values.

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Table(15) The performance of RBFNN on Elkhazer River .

RBFNN/ Elkhazer River						
Input Parameters	Spread value	E_{nash}	R_{Bias}	R^2	MAE	MAPE
Qt-1	----	----	-----	------	------	---------
Qt-1, Qt-2	0.01	0.90	0.28	0.90	5.5	21.7
Qt-1, Qt-2, Qt-3	0.01	0.87	-0.19	0.87	7.63	27.6
Qt-1, Qt-2, Qt-3, Qt-4	0.01	0.88	-0.38	0.894	12	31.9
Qt-1, Qt-2, Qt-3, Qt-4,Qt-5	0.01	0.91	-0.65	0.91	6.3	22.32
Qt-1, Qt-2, Qt-3, Qt-4,Qt-5 , Qt-6	**0.01**	**0.95**	**-0.075**	**0.95**	**5.96**	**19.23**

4.3.4. Application of GRNN on Elkhazer River.

Results of generalized regressing networks for Elkhazer river are illustrated in Table (16).The Table shows a decreasing in the performance if compared with the previous method after investigating the test parameters. The best result was found for the model of structure(6-0.01-1).

Table(16) The performance of GRNN on Elkhazer River .

GRNN/ Elkhazer River						
Input Parameters	Spread value	E_{nash}	R_{Bias}	R^2	MAE	MAPE
Qt-1	0.1	0.59	-0.46	0.59	39.69	299
Qt-1, Qt-2	0.01	0.55	-0.47	0.55	37	287.1
Qt-1, Qt-2, Qt-3	0.01	0.68	-0.54	0.68	34	293.19
Qt-1, Qt-2, Qt-3, Qt-4	0.01	0.69	-0.41	0.69	33.7	299.6
Qt-1, Qt-2, Qt-3, Qt-4,Qt-5	0.01	0.56	-0.49	0.56	31.02	299.8
Qt-1, Qt-2, Qt-3, Qt-4,Qt-5 , Qt-6	**0.01**	**0.79**	**-0.493**	**0.79**	**30.43**	**229.8**

4.3.5. Application of Support Vector Machine SVM and ANFIS models on Elkhazer River

The test parameters results of SVM models and ANFIS models for Elkhazer river were not reflecting the success of these methods in describing the stream behavior at all therefore the results were not included here. For this stream the best model was radial basis function networks with six input combinations and 0.01 spread value .The best no of neurons at the hidden layer was 150 neuron. Figure(4-c) illustrates the comparison between the applied models for this stream.

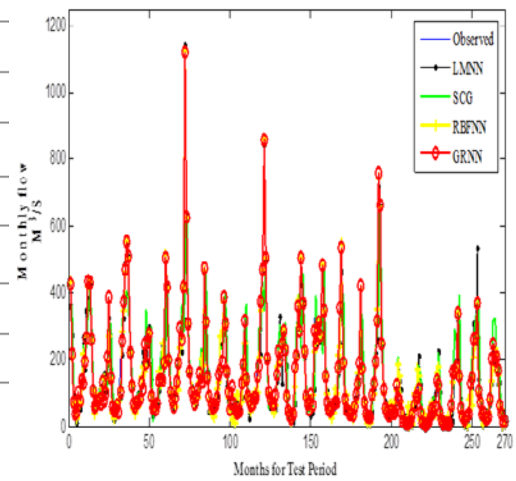

Fig.4-a.The Performance of applied models on Diyala River for test period

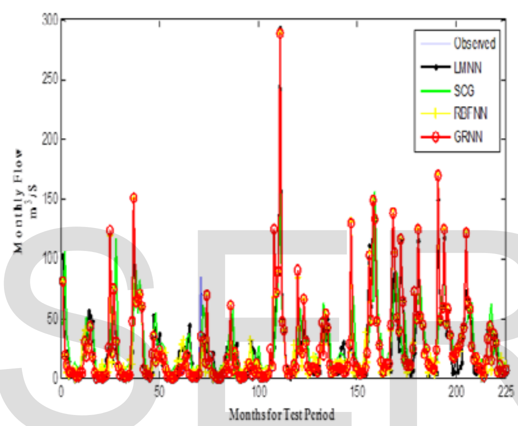

Fig.4-b.The Performance of applied models on Adhiam River for test period.

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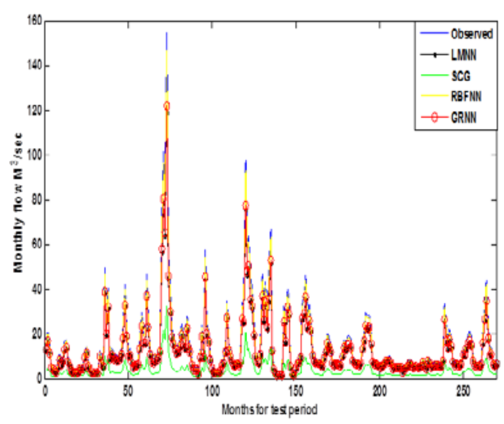

Fig.4-c.The Performance of applied models on Elkhazer River for test period

5. Conclusions

In the presented study the monthly flow values for three case studies were estimated using Feed forward neural networks with two different training algorithms LM Levenberg-Maqurdat and SCG scaled conjugate gradient then by using another two neural networks which are radial basis function neural networks RBFNN and generalized regression neural networks GRNN. Another two additional methods which are support vector SVM machine and adaptive neuro fuzzy interference ANFIS were applied on the same case studies. The performance of the applied models were decided due to the best values of R2,Enash and R Bias and lowest values of MAE , MAPE. It was seen that some models provided quite close estimations to observed values. It was concluded from the case studies results that using LM training method takes a small fraction of time than SCG method and performs better .The RBFNN also was found to be more efficient than LMNN and SCGNN while the best performance for both Dyala and Adhim rivers was found to be for GRNN networks with small spread values. The concluded results for Elkhazer river was quite different since the best results was found by applying radial basis function networks . It can be concluded from the present study that it is very difficult to know which training algorithm or which type of networks will perform the best for a given streamflow since each stream has its properties which distinguish its behavior from others.

REFERENCES:

[1] Ali H. Al aboodi(2014)."Prediction of Tigris river discharge in Baghdad city using Artificial Neural networks"Kufa journal of engineering (K.J.E), 5 (2) , 107-116.

[2] Ali H. Al aboodi ., Amar S. , Sarmad A Abas.2009. Dawod. "Prediction of Tigris River Stage in Qurna, South of Iraq, Using Artificial Neural Networks". Engineering and Technology journal, Baghdad 13(27),2456-2448

[3] Arslan A .Chelang . 2012 ". Stream flow Simulation and Synthetic Flow Calculation by Modified Thomas Fiering Model" .Al-Rafidain Engineering.20 (4), 118-127.

[4] Arslan A. Chelang ., Kadir. J., M . 2013. " Khassa Chay Stream Flow Forecasting by Markove Autoregressive AR. Model. ". Al-Rafidain Engineering 21 (3) , 99-110

[5] Ballini, R , Soares, S., Andrade, M. G., (2001)." Multi step a head streamflow forecasting by a neuro fuzzy network model " I .Proceeding of the annual conference of the north Americal fuzzy information processing society , (2) 992-997.

[6] Bishop, C.M. Neural Networks for Pattern Recognition.1995, Oxford University Press, Oxford, UK.

[7] B. Kim, S. Kim, and K. Kim. "Modeling of plasma etching using a generalized regression neural network. "Vacuum 71 ,2003,497–503.

[8] Buyukyildiz, M., Tezel, G., Yilmaz, V., 2014. " Estimation of the Change in Lake Water Level by Artificial Intelligence Methods". Water Resour Manage. 28: 4747–4763.

[9] Chokmani K, Ouarda TBMJ., Hamilton S, Ghedira MH, Gingras H . " Comparison of ice-affected streamflow estimates computed using artificial neural networks and multiple regression techniques ". Journal of Hydrology 2003;349(3-4): 383–396

[10] Dutta D, Herath S, MusiakeK. " Flood inundation simulation in a river basin using a physically based distributed hydrologic model ".HydrolProcess2000;14(3):497–520

[11] Dutta D, Alam J, Umeda K, Hayashi M, Hironaka S . " A two dimensional hydrodynamic model for flood inundation simulation: a case study in the Lower Mekong River basin". Hydrol Process 2007;21:1223–1237

[12] D.W.Marquardt. "An Algorithm for the Least-Squares Estimation of Nonlinear Parameters". SIAM Journal of Applied Mathematics.1963; 11(2), 431-441.

[13] Dolling, O.R., E.A. Varas,. ".Artificial neural networks for streamflow prediction ". Journal ofHydraulic Research.2003; 40(5): 547-554.

[14] Firat, M., . "Comparison of Artificial Intelligence Techniques for river flow forecasting." Hydrol. Earth Syst. Sci.,2008; (12): 123-139.

[15] Hu, T.S., K.C. Lam, S.T. Ng, "River flow time series prediction with a range-dependent neural network". Hydrological Sciences2001;24(5): 729–745.

[16] Hamdan B Nomas 1988. "The water resources in Iraq assessment" . A Thesis submitted to the Social Science Faculty University of Durham for the Degree of Doctor of Philosophy

[17] Hussein A. Jassas & Broder J. Merkel 2015 . "Investigating groundwater recharge by means of stable isotopes in the Al-Khazir Gomal Basin, northern Iraq". Environmental Earth Sciences June 2015, Volume 73, Issue 12, pp 8533-8546.

[18] Jang JSR (1993)."ANFIS : Adaptive network based Fuzzy interference system" IEEE Trrans. Syst. Management and Cybemetics, 23(3),. 665-685.

[19] Kaya, M.D., Haşiloğlu, A. S., Yeşilyurt, H., (2002). "To Estimate The Design Of Functional Sizes Of Chairs And Desks On The Basis Of Iso 5970 Using Adaptive Neuro-Fuzzy Inference System"., Fsscımıe'02, May 29-31

[20]K. Levenberg. "A Method for the Solution of Certain Non-linear Problems in Least Squares". Quarterly of Applied Mathematics.1944;2(2):164-168.

[21] Keskin, M.E. and D. Taylan., "Artificial Models for Inter basin Flow Prediction in Southern Turkey".Journal of Hydrology Engineering2009; 752-758.

[22] KilincI ,Ci. Gizoglu H Kerem., and AynurZoran . "A Comparison Of Three Methods For The Prediction Of Future Stream Flow Data". 2005;State Hydraulic Works (DSI) Turkey 14th. Reg. Directorate of DSI Istanbul/TURKEY.

[23] Kisi O, Uncuoglu E . "Comparison of three back propagation training algorithms for two case studies ".Indian journal of engineering and &Materials sciences , 2005(12) : 434-442

[24] Kisi, O., . "River flow forecasting and estimation using different artificial neural network technique". Hydrology Research2008; 39(1): 27-40.

[25] Maier, H. R., and Dandy, G. C. "Use of artificial neural networks for prediction of water quality parameters". Water Resour. Res.,1996;1013–1022.

[26]Moller,A.,. "Scaled-Conjugate-Gradient-Algorithm-for-Fast-Supervised-Learning,-Neural Networks". Water Resour. Res.,1993;6 (4),525-533.

[27] Muhamad, J.R. and J.N. Hassan, . "Khabur River flow using artificial neural networks". Al-Rafidain Engineering,2005; 13(2): 33-42.

[28] Robert, J.; Howlett, L.C.J. "Radial basis function networks 2: New Advances in Design". PhysicaVerlag: Herdelberg, Germany, 2001, ISBN: 3790813680

[29]Singh, M.C. Deo. "Suitability of different neural networks in daily flow forecasting". Applied Soft Computing, No. 7 .2007;968–978.

[30] Saleh K Dina . "Stream Gage Descriptions and Streamflow Statistics for Sites in the Tigris River and Euphrates River Basins, Iraq 2010 ". A Report Prepared in cooperation with MoWR and MoAWR under the auspices of the U.S. TR 540., Department of Defense, Task Force for Business and Stability Operations. U.S. Department of the Interior -U.S. Geological Survey.

[31] Shamseldin, A.Y., K.M. O'Connor, A.E. Nasr, . "A Comparative Study of Three Neural Network Forecast Combination Methods for Simulated River Flows of Different Rainfall-Runoff Models". Hydrological Sciences Journal 2007; 52(5): 896-916.

[32] Tiryaki S, Ozsahin S, YildirimI . "Comparison of artificial neural network and multiple linear regression models to predict optimum bonding strength of heat treated woods". International Journal of Adhesion and Adhesives 2014;55: 29–36

[33] Wang, W.C., K.W. Chau, . "A comparison of performance of several artificial intelligence methods for forecasting monthly discharge time series". Journal of Hydrology 2009; 374:3-4. 294-306.

[34]Zealand C., Burn D., Simonovic S. " Short-term Streamflow Forecasting Using Artificial Neural Networks". Journal of Hydrology 1999; 214, 32-48.
[35] Encyclopedia Britannica :http//www.britannica.com/Eb checked/topic/166851/Diyala River, Date of access 28/3/2015
[36] Tayfur G, and V, P, Singh (2006)."Rainfall-Runoff modeling using artificial neural networks "J.Hydrol. Engg.4 232-239.