Performance Of DifferentArtificial Neural Networks In Monthly StreamflowForecasting For DiyalaAnd Adhim Rivers Northern Iraq

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Abstract:

Streamflowforecasting 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 networks approaches are employed for two case studies which were Diyala River .and Adhim River northern Iraq. Different training algorithms and different artificial neural networks such as LevenburgMarqudat LMNN , Scaled conjugate gradient SCGNN , radial basis function networks RBNN and generalized regression networks GRNN were selected in modelling and generation of synthetic streamflow for the mentioned case studies. The performance of applied networks were determined according to well known test parameters R^2, E_{nash}, R_{bias} ,MAPE, MAE. It has been found in this study that LevenburgMarqudat 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 .

Keywords: ANN, LMNN, SCGNN, RBNN, GRNN .

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[4-5].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 basedon the statistical analysis of the observed stream data which were measured in the past.Many of these methods providevery complex or too demanding tools for practical cases[13]. In recent years Artificial neural networks have been proven to be an efficient alternative to traditional methods which were used for simulation and forecastingstreamflow[14] .Previous studies have demonstrated that the ANN has received much attention for stream flow forecasting [7-8-9-12-22-24].Zealand et. al. (1999) investigated the utility of artificial neural networks (ANNs) for short term forecasting of streamflow.[25]. 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 in for river flow forecasting[14-15].In this study four different artificial networks were applied for prediction of the future flows ofDiyala River 35° 08′ 00″ N, 45° 45′ 00″ E. and Adhim River 34° 30′ 00″ N, 44° 31′ 00″ E northern Iraq. Description of these models are represented below.

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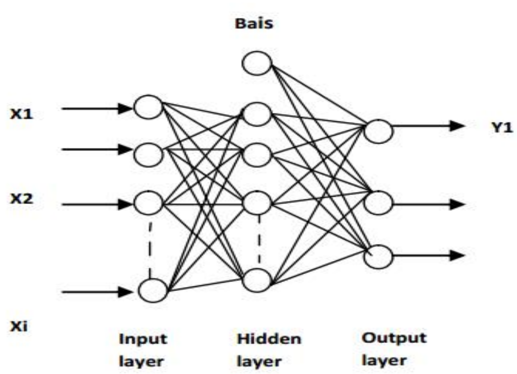
2.Methodology:

Artificial neural networks (ANN) have been developedas mathematical models similar to biologicalnervous systems. The basic processing elements of neural networks arecalled artificial neurons. In asimplified mathematical model of the neuron, the effectsof the synapses are represented by connection weights thatmodulate the effect of the associated input signals, and thenonlinear characteristic exhibited by neurons is representedby a transfer function. The neuron impulse is then computedas the weighted sum of the input signals, transformed bythe transfer function. The learning capability of an artificialneuron is achieved by adjusting the weights in accordanceto 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-forwardnetworks, the signal flow is from input to output units[1].

2.1. 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 Conjeguate 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[14].A typicalfeed forward neural network structure is illustrated in Figure(1).



Figure(1) Typical Feed forward Neural Network.

2.1.1. Levenberg-Marquardt(LMNN).

The Levenberg-Marquardt (LM) training method can be described as the most effective method for feed-forward neural networkswith 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[6-11].Levenberg-Marquardt Learning was first introduced to the feed forward networks to improve the speed of the training. This method is a modification toGuass-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 errorfunction, in each iteration, such as the one inequation 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; x_k is the vector of parameters, in this case,the set of weights at iteration k; $v_i(x_k)= T_i-Y_i(x_k)$, T_i isthe ith desired output for the sample, and $Y_i(x_k)$ is the ith FANN output during iteration k.[6-11-14].

2.1.2. 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

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

In order to determine the minimum to $E_{qw}(y)$thecritical points for $E_{qw}(y)$ must be found. The critical points are the solution to the linear system [17].

$$E_{qw}(y) = E^{"}(w) y + E'(w) y \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots .3$$

2.2. 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:

$y_j^{\hat{}} = \sum_{i=1}^{I} w_{ij} \emptyset(\|x - c_i\| + \beta_j$.......................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 thenumber of neurons in the output layer ,*wij* :is the weight of the *i*th neuron and *j*thoutput;φ:is the Radial basis function;*αi* :is theSpread parameter of the *i*thneuron;**x**is theInput data vector ,**c***i :* is theCenter vector of the *i*th neuron;*βj* :is the Bias value of the output *j*th neuron and *ŷj :*is theNetwork output of the *j*th neuron.[19].

2.3. 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. [20]. 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 [2].

3. Case Study

In this study the monthly flow values for two case studies which were Diyala River and Adhim River northern Iraq were used to apply the above different ANNs on . The record period of monthly for the Adhimriver was extending from 1945-1997 while for Diyala river the record period was from 1931-2004.DiyalaRiver: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[26].Adhaim River:is an important tributary of the Tigris River, originates in Iraq converges withthe Aksu tributary, which passesthrough Tuzhurmatu.The Adhaim tributary rises from the foothill region in Iraq. It forms from three main streams which are joined upstreamof Injana. Further downstream it flows south-westwards andjoins the Tigri 15km downstream of Balad.Its totalbasin area is 13000km^2 and its length is 230km. The meanannual long term discharge at Injana is 25 cumecs (0.8bcm).This fluctuates from year to year. For instance, itincreased to 55 cumecs (1.73bcm) in 1969 and decreased to5 cumecs (0.l6bcm) in 1960 .[10].Figure (2) illustrates the location of the two corresponding rivers .

Figure(2) The locations of Diyala and Adhiam Rivers.

4. Applications and Results

4.1Case Study I Diyala River

The monthly flow of DiyalaRiver 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 X_i ,X_{min}, $X_{\ max}$ are the data , minimum and maximum of the series respectively[14].

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 [16]. The neuron numbers for the hidden layer were tried to range from 2-38 neurons.
The performance of the ANN different models were investigated using following parameters

$$E_{Nash} = 1 - \frac{\sum_{t=}^{n}(A_t - F_t)^2}{\sum_{t=1}^{n}(A_t - F_{mean})^2}$$ ……..7. The range of E lies between 1.0 (perfect fit) and $-\infty$

$$R_{Bias} = 100 \times \frac{\sum_{t=1}^{n}(F_t - A_t)}{\sum_{t=1}^{n} A_t}$$ ….........8.The optimal value of R_{bias} is 0.0, with low-magnitude values

indicating accurate model simulation. Positive values indicate overestimation bias, whereas negative values indicate model underestimation bias .

$$R^2 = \frac{\left[\sum_{t=1}^{n}(A_t - A_{mean})(F_t - F_{mean})\right]^2}{\sum_{t=}^{n}(A_t - A_{mean})^2 \sum_{t=1}^{n}(F_t - F_{mean})^2}$$ ....9.A high R^2 value (i.e. close to unity), indicates a good model fit with observed data[3-24].

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 .

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|A_t - F_t\right|$$ ....10.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|$$ ....11.Multiplying by 100 makes it a percentage error [24].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 net works 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	3.02	0.57	64.83	53.82
$Qt-1$, $Qt-2$	2-32-1	0.64	2.04	0.64	53.7	43.14
$Qt-1$, $Qt-2$, $Qt-3$	**3-21-1**	**0.64**	**1.589**	**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

4.1.3. Application of RBFNN onDiyala 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).

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 onDiyala 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**	**0.65**	**0.99**	**5.79**	**8.335**
$Qt-1$, $Qt-2$, $Qt-3$	0.01	0.93	0.86	0.93	8.1	17.41
$Qt-1$, $Qt-2$, $Qt-3$, $Qt-4$	0.01	0.97	0.66	0.97	13.7	17.86
$Qt-1$, $Qt-2$, $Qt-3$, $Qt-4$,$Qt-5$	0.01	0.98	-0.71	0.98	9.64	13.6
$Qt-1$, $Qt-2$, $Qt-3$, $Qt-4$,$Qt-5$, $Qt-6$	0.01	0.99	-0.79	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.

4.2. Case Study II Adhiam River.

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

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(5).

Table(5) 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	-0.06	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	-4.59	0.73	11.02	124.89
$Qt-1$, $Qt-2$, $Qt-3$, $Qt-4$,$Qt-5$, $Qt-6$	**6-26-1**	**0.79**	**-3.33**	**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 combinationsforAdhiam 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 (6) below .

Table(6) 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	0.07	0.34	19.57	114.05
$Qt-1$, $Qt-2$	2-32-1	0.39	-0.32	0.4	18.67	113.84
$Qt-1$, $Qt-2$, $Qt-3$	3-34-1	0.39	-0.05	0.4	18.2	113.77
$Qt-1$, $Qt-2$, $Qt-3$, $Qt-4$	**4-38-1**	**0.43**	**-0.97**	**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(7) below. The best result was found for the structure (3-0.01-1) but with under estimation values.

Table(7) 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	1.28	0.93	4.25	11.7
$Qt-1$, $Qt-2$, $Qt-3$	**0.01**	**0.94**	**-1.1907**	**0.94**	**4.63**	17.28
$Qt-1$, $Qt-2$, $Qt-3$, $Qt-4$	0.01	0.94	-1.38	0.94	4.68	15.9
$Qt-1$, $Qt-2$, $Qt-3$, $Qt-4$,$Qt-5$	0.01	0.91	-1.25	0.91	6.17	**22.32**
$Qt-1$, $Qt-2$, $Qt-3$, $Qt-4$,$Qt-5$, $Qt-6$	0.01	0.92	-1.3	0.92	5.91	19.12

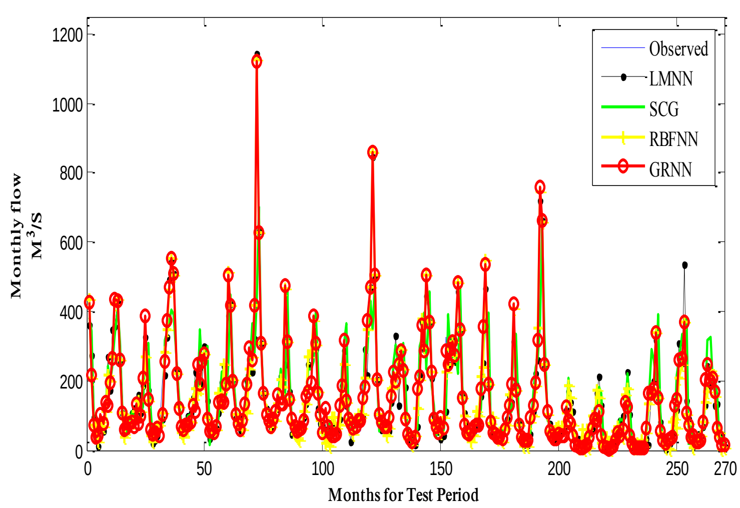
4.2.4. Application of GRNN on Adhiam River.

Results of generalized regressing networks are illustrated in Table (8).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).

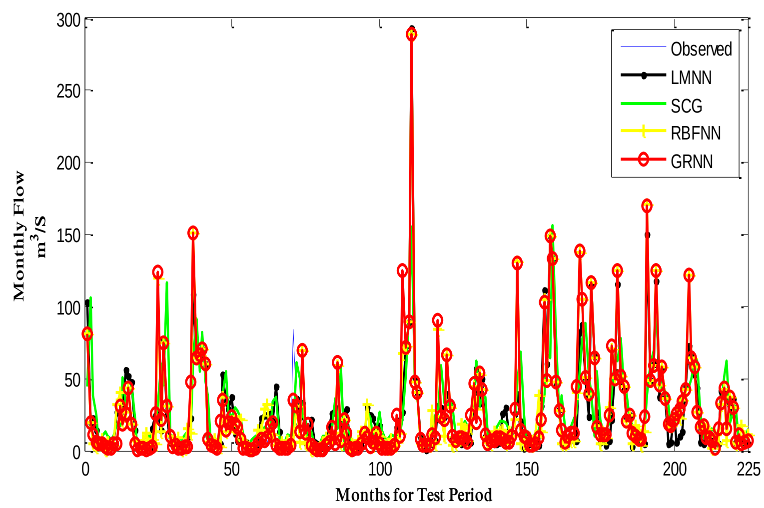
Table(8) The performance of GRNN on Adhiam River .

GRNN/Adhiam River						
Input Parameters	**Spread value**	E_{nash}	R_{Bias}	R^2	**MAE**	**MAPE**
$Qt-1$	0.1	0.49	0.523	0.49	15.72	13.28
$Qt-1$, $Qt-2$	0.01	0.95	0.432	0.95	3.08	7.68
$Qt-1$, $Qt-2$, $Qt-3$	0.01	0.98	0.42	0.98	0.96	3.21
$Qt-1$, $Qt-2$, $Qt-3$, $Qt-4$	**0.01**	**0.99**	**0.3142**	**0.99**	**0.55**	**2.12**
$Qt-1$, $Qt-2$, $Qt-3$, $Qt-4$,$Qt-5$	0.01	0.86	-0.67	0.86	5.41	3.12
$Qt-1$, $Qt-2$, $Qt-3$, $Qt-4$,$Qt-5$, $Qt-6$	0.01	0.89	-0.49	0.89	4.26	3.89

The high performance of generalized regression networks could be noticed from Figure (3-b)which illustrates the comparison between different applied models on AdhiamRiver.



(a)



(b)

Figure(3)The Performance of applied models on(a) Diyala River and on (b)Adhiam Riverfor test period .

5. Conclusions

In the presented study the monthly flow values for two 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 . The performance of the applied models were decided due to the best values of R^2,E_{nash} and R_{Bias} and lowest values of MAE , MAPE..It was seen that three models providedquite close estimations to observed values. It was concluded from both case studies results that using LM training method takes a small fraction of time than SCG methodand performs better .The RBFNN also was found to be more efficient than LMNN and SCGNN while the best performance for both two case studies was found to be for GRNN networks with small spread values. It can be concluded from the present study that it is very difficult to know which training algorithm or which type of neural networks will perform the best for a given streamflow forecasting since each stream has its properties which distinguish its behavior from others.

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