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 Elkhazer Rivers northern Iraq. Different training algorithms and different artificial neural networks such as Levenberg Marquardt LMNN, 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 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 R², E nah, RMSE. MAPE MME. It has been found in this study that Levenberg Marquardt 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, SCON, 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 system 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 Markovian 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 - Firoat, M.,2008 - Hu, T.S , 2010 - Shamseldin, 2007-Wang., 2009). Zeoland 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. (Kis, 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 (2008). Ballini et. al (2003) 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 34° 18′ 40″ 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
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 Levenberge-Marquardt 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.](image)

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 Gauss-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:

$$F(w_k) = \frac{1}{2} \sum_{i=1}^{N} \| y_i - \phi_i(\mathbf{x}) \|^2.$$  

where N is the number of samples used to train the feed forward artificial neural network; \( \mathbf{x} \) is the vector of parameters, in this case, the set of weights at iteration \( k \); \( \mathbf{v}(\mathbf{x}) \) is the output for the sample, and \( \mathbf{Y}(\mathbf{x}) \) is the desired 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 function around a neighborhood of a point \( w \) by:

$$E_{cw}(\mathbf{y}) = E(w) + \nabla E(w) ^T (\mathbf{y} - \mathbf{y}) + \frac{1}{2} (\mathbf{y} - \mathbf{y}) ^T \nabla^2 E(w) (\mathbf{y} - \mathbf{y}).$$

In order to determine the minimum to \( E_{cw}(\mathbf{y}) \) the critical points for \( E_{cw}(\mathbf{y}) \) must be found. The critical points are the solution to the linear system (Kisi, O., 2005).

$$E_{cw}(\mathbf{y}) = E(\mathbf{w}) + \nabla E(\mathbf{w}) (\mathbf{y} - \mathbf{y}).$$

2.1.2. Radial basis Functions Networks(RBNN)

RBNN 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 called center. A radial basis function \( \phi \) is one whose output is symmetric around an associated center \( c \). The general expression of the network can be given as:

$$y_j^k = \sum_{i=1}^{I} w_{ij} \phi(\| \mathbf{x} - c_i \|),$$

where,

- \( I \) : Number of neurons in the hidden layer
- \( J \) : is the number of neurons in the output layer
- \( w_{ij} \) : is the weight of the \( i \) th neuron and \( j \) th output unit
- \( \phi \) is the radial basis function
- \( c_i \) is the Spread parameter of the \( i \) th neuron
- \( \mathbf{x} \) is the input data vector
- \( \mathbf{y} \) is the Center vector of the \( i \) th neuron
- \( \beta_i \) is the Bias value of the output \( j \) th neuron

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 regressing 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.
neuron. The S-summation neuron computes the sum of the weighted outputs of the pattern layer while the D-summation neuron calculates the unweighted 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 connected 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 backpropagation method which seeks to minimize some measure of error, usually sum of squared differences between networks outputs and desired outputs (Kaya et al., 2002).

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 (Buzukyildiz 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 1991-2004 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 Tigris 18km 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 to 5 cumecs (0.16bcm) 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.
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:

\[ \frac{X_i - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}} \]  \hspace{1cm} (6)

Where \( X_i \), \( X_{\text{min}} \), and \( X_{\text{max}} \) 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 previous 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:

\[ E_{\text{Nash}} = 1 - \frac{\sum (A_t - F_t)^2}{\sum (A_t - F_{\text{mean}})^2} \] \hspace{1cm} (7)

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

\[ R_{\text{bias}} = 100 \times \frac{\sum (F_t - A_t)}{\sum A_t} \] \hspace{1cm} (8)

The optimal value of \( R_{\text{bias}} \) is 0.0, with low-magnitude values indicating accurate model simulation. Positive values indicate overestimation bias, whereas negative values indicate model underestimation bias.

\[ R^2 = \frac{\sum (A_t - A_{\text{mean}})(F_t - F_{\text{mean}})^2}{\sum (A_t - A_{\text{mean}})^2 \sum (F_t - F_{\text{mean}})^2} \] \hspace{1cm} (9)

A high \( R^2 \) 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:

\[ \text{MAE} = \frac{1}{n} \sum |A_t - F_t| \] \hspace{1cm} (10)

\[ \text{MAPE} = \frac{1}{n} \sum \left| \frac{A_t - F_t}{A_t} \right| \] \hspace{1cm} (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).

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 previous used algorithm. This was found after calculating the same test parameters which are shown in Table (2) below.

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).
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.

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.

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.

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.
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>
<thead>
<tr>
<th>Input Parameters</th>
<th>Model structure</th>
<th>MSE</th>
<th>MAE</th>
<th>MAPE</th>
</tr>
</thead>
<tbody>
<tr>
<td>P = 1</td>
<td>2.041</td>
<td>0.29</td>
<td>2.06</td>
<td>0.12</td>
</tr>
<tr>
<td>P = 2</td>
<td>3.041</td>
<td>0.59</td>
<td>2.06</td>
<td>0.12</td>
</tr>
<tr>
<td>P = 3</td>
<td>4.041</td>
<td>0.89</td>
<td>2.06</td>
<td>0.12</td>
</tr>
<tr>
<td>P = 4</td>
<td>5.041</td>
<td>1.29</td>
<td>2.06</td>
<td>0.12</td>
</tr>
</tbody>
</table>

4.2.2. Application of SCGNN on 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 network was highly dropped if compared with the previous used algorithm. This was found after calculating the same test parameters which are shown in Table (8) below.

<table>
<thead>
<tr>
<th>Input Parameters</th>
<th>Spread value</th>
<th>MSE</th>
<th>MAE</th>
<th>MAPE</th>
</tr>
</thead>
<tbody>
<tr>
<td>P = 1</td>
<td>1.01</td>
<td>0.49</td>
<td>1.02</td>
<td>0.02</td>
</tr>
<tr>
<td>P = 2</td>
<td>2.01</td>
<td>0.99</td>
<td>2.02</td>
<td>0.02</td>
</tr>
<tr>
<td>P = 3</td>
<td>3.01</td>
<td>1.49</td>
<td>2.02</td>
<td>0.02</td>
</tr>
<tr>
<td>P = 4</td>
<td>4.01</td>
<td>1.99</td>
<td>2.02</td>
<td>0.02</td>
</tr>
</tbody>
</table>

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 underestimation values.

4.2.4. Application of GRNN on Adhiam River.

Results of generalized regressing networks are 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).

<table>
<thead>
<tr>
<th>Input Parameters</th>
<th>Spread value</th>
<th>MSE</th>
<th>MAE</th>
<th>MAPE</th>
</tr>
</thead>
<tbody>
<tr>
<td>P = 1</td>
<td>1.01</td>
<td>0.49</td>
<td>1.02</td>
<td>0.02</td>
</tr>
<tr>
<td>P = 2</td>
<td>2.01</td>
<td>0.99</td>
<td>2.02</td>
<td>0.02</td>
</tr>
<tr>
<td>P = 3</td>
<td>3.01</td>
<td>1.49</td>
<td>2.02</td>
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</tr>
<tr>
<td>P = 4</td>
<td>4.01</td>
<td>1.99</td>
<td>2.02</td>
<td>0.02</td>
</tr>
</tbody>
</table>

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.
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. Among all the applied models on the Adhiam 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 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 previous used algorithm. This was found after calculating the same test parameters which are shown in Table (14) below.

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.
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).

![Graph showing performance of applied models on Diyala River for test period](Fig.4-a)

<table>
<thead>
<tr>
<th>Input Parameters</th>
<th>Spread value</th>
<th>R Obs</th>
<th>R Pred</th>
<th>RMSE (m)</th>
<th>MAE (m)</th>
<th>NSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Qx</td>
<td>1.1</td>
<td>0.52</td>
<td>0.72</td>
<td>0.01</td>
<td>0.01</td>
<td>0.52</td>
</tr>
<tr>
<td>Qx T</td>
<td>1.1</td>
<td>0.52</td>
<td>0.72</td>
<td>0.01</td>
<td>0.01</td>
<td>0.52</td>
</tr>
<tr>
<td>Qx T 2</td>
<td>1.1</td>
<td>0.52</td>
<td>0.72</td>
<td>0.01</td>
<td>0.01</td>
<td>0.52</td>
</tr>
<tr>
<td>Qx T 3</td>
<td>1.1</td>
<td>0.52</td>
<td>0.72</td>
<td>0.01</td>
<td>0.01</td>
<td>0.52</td>
</tr>
<tr>
<td>Qx T 4</td>
<td>1.1</td>
<td>0.52</td>
<td>0.72</td>
<td>0.01</td>
<td>0.01</td>
<td>0.52</td>
</tr>
</tbody>
</table>

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.

![Graph showing performance of applied models on Adhiam River for test period](Fig.4-b)

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-Maquardt and SCG scaled conjugate gradient then by using the use of GRNN.
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 interface ANFIS were applied on the same case studies. The performance of the applied models were decided due to the best values of R2,Ensh 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 LMSS and SGGNN 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 from each stream has its properties which distinguish its behavior from others.

REFERENCES:
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