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RIVER FLOW FORECASTING USING DIFFERENT ARTIFICIAL NEURAL NETWORKS FOR TWO CASE STUDIES AT TURKEY.

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Abstract

This paper provides an application of different kinds of Artificial neural networks in predicting the mean monthly riverflow. In this research , based on the monthly flow vales which are btained from Tukey State of water works and for Two case studies at Turkey , the performance of different types of ANN was investigated. It was concluded that there is no specific characterstic of any basin that would suggest the use of a model of ANN rather than another .

Key words : River flow , ANN, LMNN, SCGNN, RBFNN , GRNN.

Introduction:

The amount of water that would be carried by a stream in the future is very important since it directly affects the design and operation of many water resources structures. stream flow data are very important for many areas of water engineering such as dam planning, flood mitigation, operation of water reservoirs, distribution of drinking water and drainage water, hydropower generation in dry periods and planning of river transport. So the amount of water carried by a stream in the future is one of the main research topics related of hydrology (Al aboodi, 2014).. 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 ., (2000) , Dutta et.al.,(2007). There are many mathematical methods which are used for future streamflow forecasting such as those given by .Hurst(1951), Matalas(1967), Box and Jenkins (1970), and Delleur et al., (1976) . Unlike mathematical models that require brief information of all the contributing variables, a trained artificial neural network can estimate process behavior even with incomplete information. Ones the ANN have been properly trained, they are able to provide accurate results even for cases they have never seen before .Hecht-Nielsen (1991), Haykin (1994). In this paper a comprehensive investigation of the best type of artificial neural networks for predicting future values of two case studies at Turkey was achieved.

Artificial Neural Networks:

ANNs can be considered as a powerful modeling Tool in comparison to the statistical methods Ceylan I , (2008). Thus, ANNs have been used in most engineering problems and applications such as forecasting ,optimization, classification and pattern recognition .Canakci et. Al., (2012) . They are composed of several highly interconnected computational units or nodes. Each node performs a simple operation on an input to generate an output that is forwarded to next node in the sequence. This parallel processing allows for great advantages in data analysis. ANNs are widely used in various branches of hydraulic engineering and their property to approximate complex and nonlinear equations makes it useful tools in econometric analysis. Each network comprises an input layer, an output layer and one or more hidden layers . Hassan AM et.al., (2009). The neurons in the networks are interconnected using weight factors(wij). A neuron(j) in a given layer receives information (xi) from all the neurons in the preceding layer (Fig. 1). It sums up information(netj) weighted by factors corresponding to the connection and the bias of the layer(θj), and Transmits output values(yj) computed through applying a mathematical function(f(.)) to netj, to all neurons of the next layer. This process is formulated in Equations. (1) and(2), and illustrated in Fig.(1-a,b). Ozsahin S (2013).

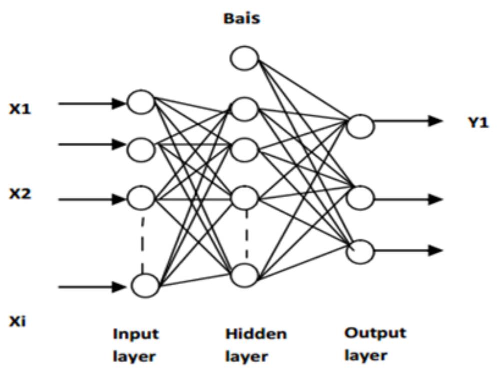


Figure (1-a)

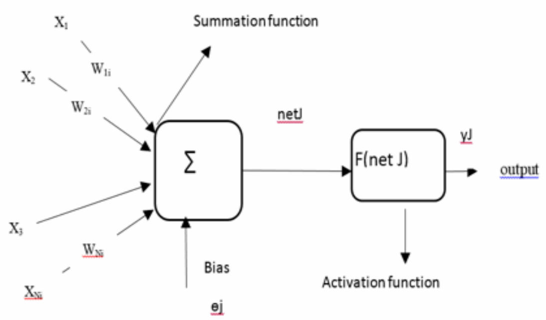


Figure (1-b)

Figure(1). Multi-layered ANN architecture and neuron sketch.

$$net\ j = \sum_{i=1}^{n} x_i w_{ij} - \theta_j \qquad \text{.....................................(1).}$$

$$y_i = f(net\ j) \qquad \text{..........................(2).}$$

Training The ANNs :

The training process is based on minimizing an error function, in each iteration, such as the one in equation (3):

$$F(X_k) = \frac{1}{N}\sum_{i=1}^{N} V_i(X_k)^2 \quad \text{...........................(3).}$$

where *N* is the number of samples used to train the FANN; *xk* is the vector of parameters, in this case, the set of weights at iteration *k*; *vi(xk)= oi-yi(xk)*, *oi* is the *i*th desired output for the sample, and *yi(xk)* is the *i*th FANN output during iteration *k*. Kisi (2005)

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.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

Scaled Conjugate Gradient (SCGNN).

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

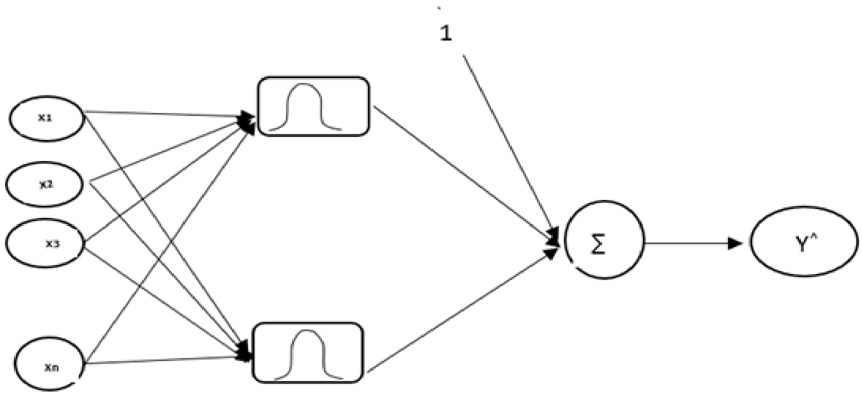
$$E_{qw}(y) = E(w) + E'(w)^T y + \frac{1}{2} y^T E^{"}(w) y \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 4.$$

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 Moller et. al ., (1993).

$$E_{qw}(y) = E^{"}(w) y + E'(w) y \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 5.$$

Radial basis Functions Networks(RBFNN)

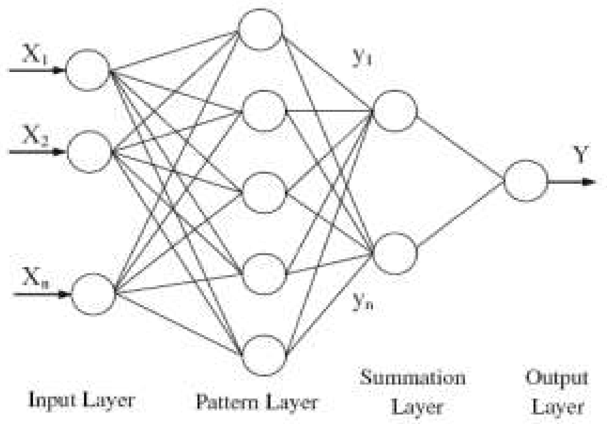
Radial Basis Function (RBF) is a powerful, fast learning, and self-organized neural network. It is better than BP network in approximation, classification and learning speed, especially in processing highly nonlinear problems . RBF neural network was proposed by Moody and Darken (1980). It includes three layers: aninput layer, a hidden radial basis neuron layer and a linear neuron output layer. Its structure is illustrated in Figure(2).



Figure(2) Structure of Radial Basis Function Neural Networks.

Generalized regressing neural networks (GRNN).

A GRNN is a variation of the radial basis neural networks, which is based on kernel regression networks . A GRNN does not require an iterative training procedure as back propagation networks. It approximates any arbitrary function between input and output vectors, drawing the function estimate directly from the training data. In addition, it is consistent that as the training set size becomes large, the estimation error approaches zero, with only mild restrictions on the function. Kim B, et. Al. , (2004).



(Kim B, et. Al 2004).

Figure(3). General structure of GRNN

Case Studies:

In this study two different streams from two different basins at Turkey were selected to acheive the predection prosses on with the discribed different methodology. The selsected basins are :

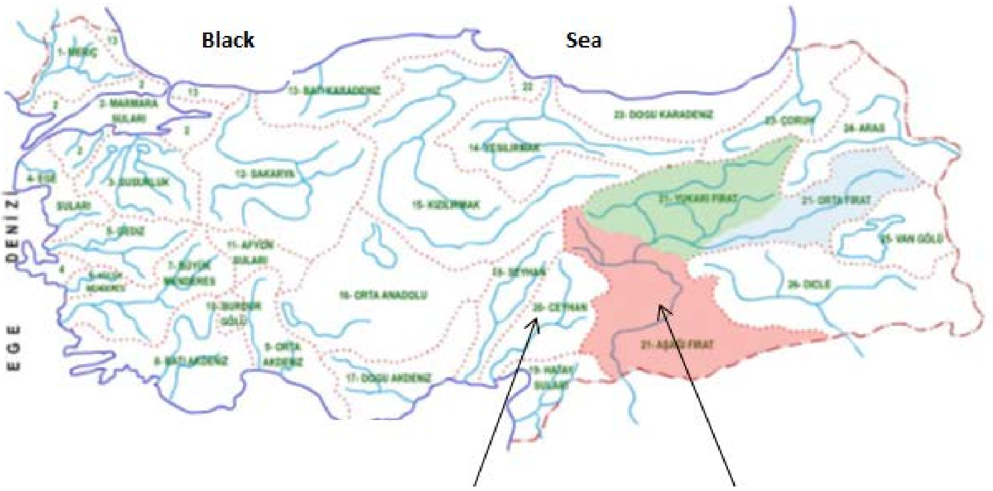
1. Euphrates Basin -Goksu Malpinar River, station no 2115

This stream locates at 38º 09′ 26″ E 37º 29′ 36″ L about 45 km from Adiyaman between Malpinar and seyviran villages its an important tributary of Euphrates River at Turkeye. The precipitation area of this stream is about 3998.8 km^2 with approximate mean value for a long period equal to 54.2 m3/sec.The monthly flow data for this river is extended from 1955-2000. Figure(4,5) below show the location of the river

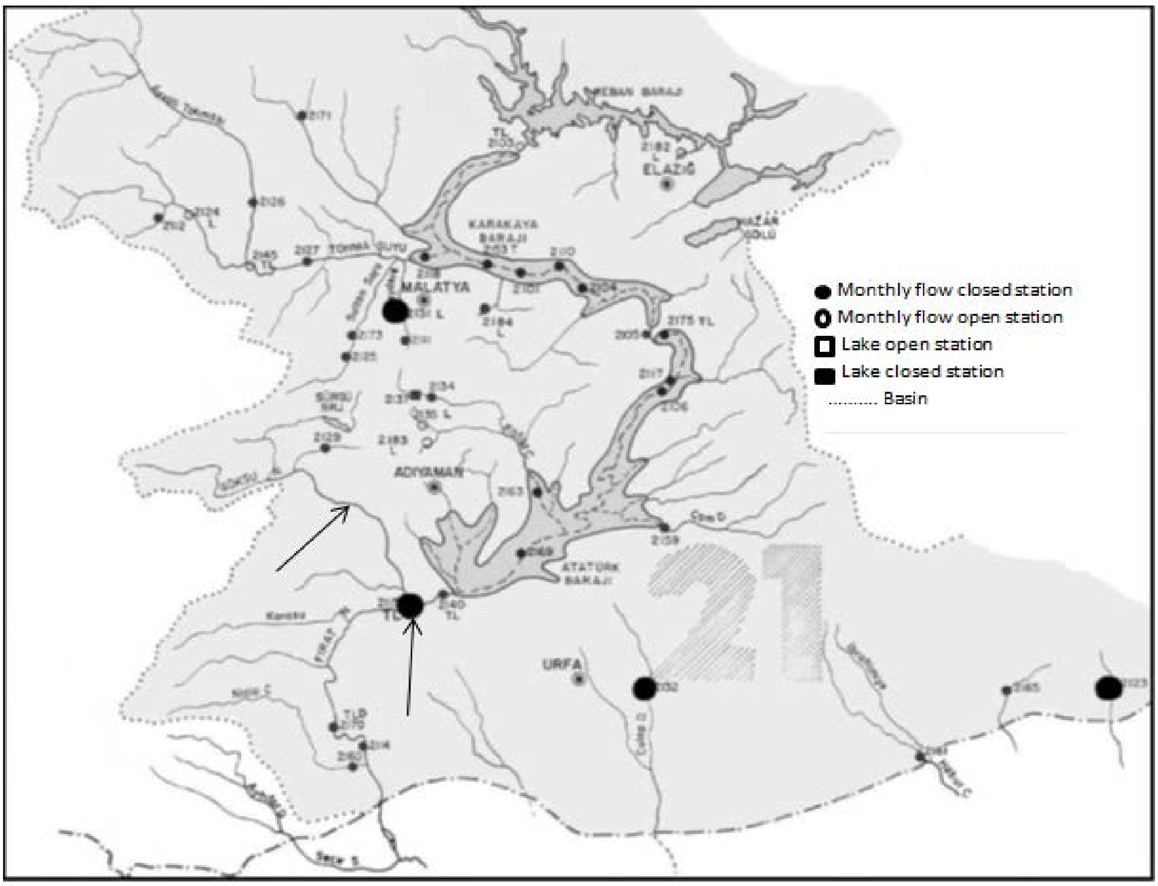
2. Cihan Basin-Goksu Poskoflu River ,station no 2009

This stream locates at 37º 00′ 04″ E 37º 08′ 54″ L about 45 km at Karamanmaras about 18 km from Elbistan road. The precipitation area of this streami about 1387.2 km^2 with approximate mean value for a long period equal to 12.6 m3/sec.The monthly flow data for this river is extended from 1954-2000. In this study the monthly record for this stream was used from 1955-2000. Figure(4,6) below shows the corresponding case study.

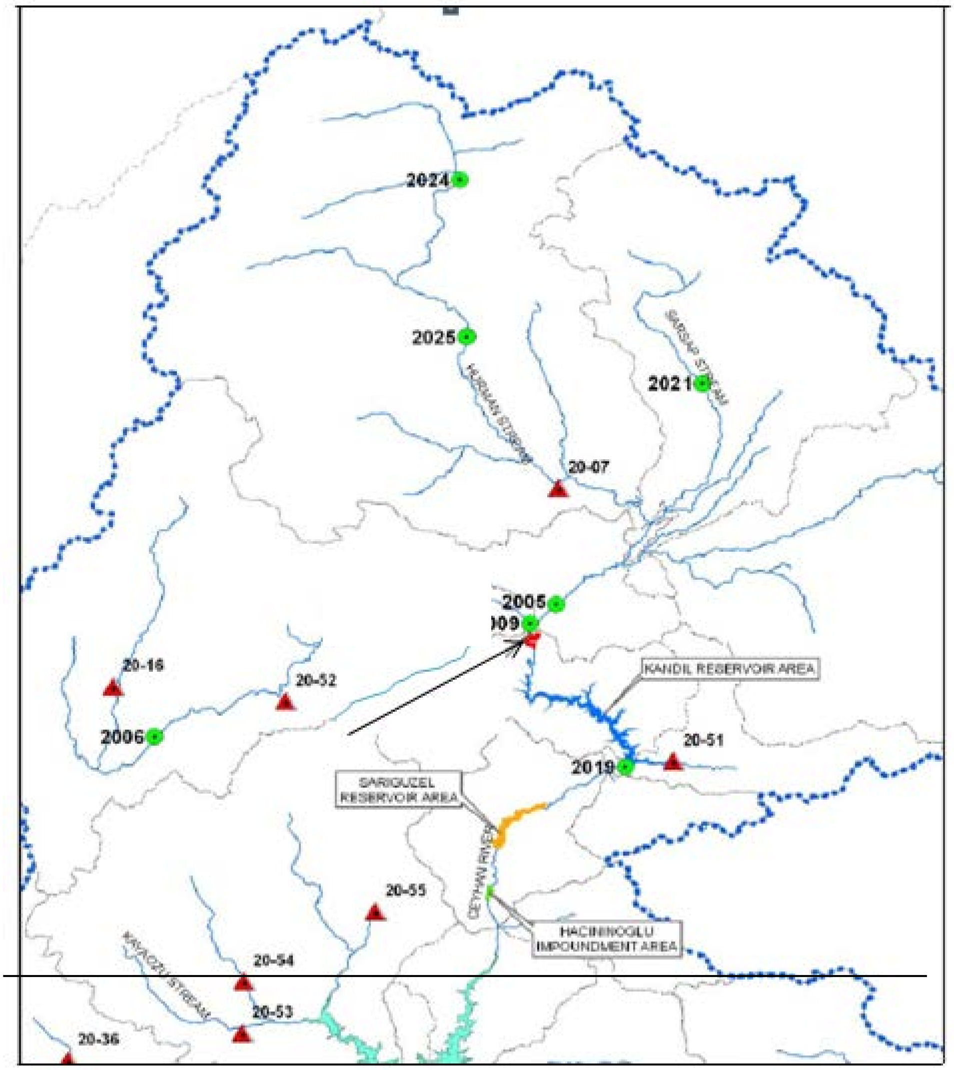
Large Basins of Turkey



Figure(4) The selected basins and Rivers in this research.



Figure(5) Goksu Malpinar River from Euphrates River.



Figure(6) . Gogsu Poskuflu River from Cihan Basin.

Application and Results

The monthly flow values for the two mentioned case studies were first normlized using the followimg formula:

$$X_{norm} = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \quad ....(6).$$

where X_{norm}, X_i, X_{min} and X_{max} indicates normalized, observed, minimum and maximum values for all parameters, respectively. Kisi O(2005). After the normlization process complition the mentioned different artificial neural networks were applied to the both normlized flows for both case studies with different archetectures by using different input combinations as followings:

Q_{t-1}

Q_{t-1}, Q_{t-2}

$Q_{t-1}, Q_{t-2}, Q_{t-3}$

$Q_{t-1}, Q_{t-2}, Q_{t-3}, Q_{t-4}$

$Q_{t-1}, Q_{t-2}, Q_{t-3}, Q_{t-4}, Q_{t-5}$

$Q_{t-1}, Q_{t-2}, Q_{t-3}, Q_{t-4}, Q_{t-5}, Q_{t-6}$

Results For Euphrates Basin -Goksu Malpinar River.

The artificial neural networks different models which were described in the preceding section have been applied to the river flow data for Goksu Malpinar River by using MATLAB Codes. Two sets of data are required. The first set was used to train the network which is referred as training data. The second data set was used to test the performance of the applied network. Different number of combinations were applied by trying different number of inputs as were mentioned in preceding section and by testing different numbers of neurons in the hidden layer for LMNN and SCGNN networks and different values of spread parameter for RBNN and GRNN networks. The determination of the best architecture was determined due to values of statistical evaluation parameters which are the determination coefficient (R^2), Nash-Sutcliffe efficiency (E_{Nash}), percent bias (R_{Bias}), mean absolute error (MAE) and mean absolute percent error (MAPE), These parameters were used to assess the models performances. These evaluation criteria defined as :

$$R^2 = \frac{\left[\sum_{i=1}^{N}(Yi_{observed} - \bar{Y}_{observed})(Yi_{estimate} - \bar{Y}_{estimate})\right]^2}{\sum_{i=1}^{N}(Yi_{observed} - \bar{Y}_{observed})^2 \sum_{i=1}^{N}(Yi_{estimate} - \bar{Y}_{estimate})^2} \quad \text{.....................(7).}$$

$$E_{Nash} = 1 - \frac{\sum_{i=1}^{n}(Yi_{observed} - Yi_{estimate})^2}{\sum_{i=1}^{n}(Yi_{observed} - \bar{Y}_{estimate})^2} \quad \text{...........................(8).}$$

$$R_{Bias} = 100 \times \frac{\sum_{i=1}^{n}(Yi_{observed} - Yi_{estimate})}{\sum_{i=1}^{n} Yi_{observed}} \quad \text{.............................(9).}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Yi_{observed} - Yi_{estimate}}{Yi_{observed}}\right| \quad \text{..............................(10).}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|Yi_{observed} - Yi_{estimate}\right| \quad \text{...........................(11)}$$

Following Tables and Figures illustrate the results of these parameters for the different models and archetectures . The best archetecure was selescted among different choises for each input combination to be veiwed in the Tables. Table (1) gives the values of statistical parameters for test data for GoksuMalpinar River using Levenburg Marquardt neural networks . The table concintratess on the best performance of each archetecture.

Table(1) Results of The statistical parameters for Goksu Malpinar Riverusing LMNN.

Model structure	E_{nash}	R^2	MAPE	MAE	R_{bias}
M1(1-2-1)	0.5486	0.549	43.0302	19.3966	2.1921
M2(2-2-1)	0.5974	0.6018	35.5119	17.4782	3.5116
M3(3-6-1)	**0.6102**	**0.615**	**32.5510**	**16.0688**	**3.8123**
M4(4-4-1)	0.6010	0.6131	33.4325	17.0181	2.9047
M5(5-5-1)	0.5724	0.6009	35.9461	16.9735	5.7100
M6(6-3-1)	0.6073	0.6119	33.8292	16.7055	1.8020

The best netwoek which was trained by Levenburg Marquardt method was found to be by using three input neurons which are Q_{t-1},Q_{t-2},Q_{t-3} and by using six neurons in the hidden layer as it is clear from the results of statistical performance parameters .Since the value of determenation coefficient was found to be 0.6151 while the E nash value was 0.6102 .Values of MAPE and MAE were least values among all the values of other applied networks .R bias value was found 4.4628. Another training algorthim was tested here which is scaled conjegaute gradient with different input combinations and by trying different numbers of of neurons at the hidden layer . Table (2) gives the values of statistical parameters for test data for Goksu Malpinar River using SCG NN .

Table(2) Results of The statistical parameters for Goksu Malpinar River using SCGNN.

Model structure	E_{nash}	R^2	MAPE	MAE	R_{bias}
M1(1-5-1)	0.5423	0.5490	42.4539	19.4370	2.4823
M2(2-4-1)	0.6017	0.6034	33.0959	16.7193	1.8353
M3(3-8-1)	0.6336	0.6500	34.2286	16.5186	3.9291
M4(4-9-1)	0.6420	0.6507	35.8808	16.5399	1.3151
M5(5-9-1)	0.6292	0.6385	33.6389	16.4265	4.0694
M6(6-7-1)	**0.6424**	**0.6528**	**32.3424**	**16.1726**	**1.6832**

The best model among all the applied ones was the last model by using six input neurons and seven neurons in the hidden layer . It is clear that applying SCG algorthims did not improve the performance of the networks. Applying the different values of spread and testing different numbers of neurons at hidden layer for radial basis function networks did not show a good performance for Goksu Malpinar River , this is clear from the results which are illustrated at Table (3). Table(3) gives the values of statistical parameters for test data for GoksuMalpinar River using RBF NN .

Table(3) Results of The statistical parameters for Goksu Malpinar River using RBFNN.

Model structure	E_{nash}	R^2	MAPE	MAE	R_{bias}
1-0.002-67	-1.66e+14	0.1506	5.5238e+08	2.2370e+08	-4.3950e+08
2-0.005-96	-0.2682	0.0074	54.2445	28.9636	-39.0694
3-0.004-100	-0.2959	1.7763e-05	55.6627	29.9471	-43.8725
4-0.09-96	-0.4305	0.1688	63.6584	31.9249	-15.1311
5-0.1-75	-0.1936	0.1826	63.2548	28.4735	-18.4519
6-0.1-200	-0.0626	0.2015	55.7455	26.3363	-15.1615

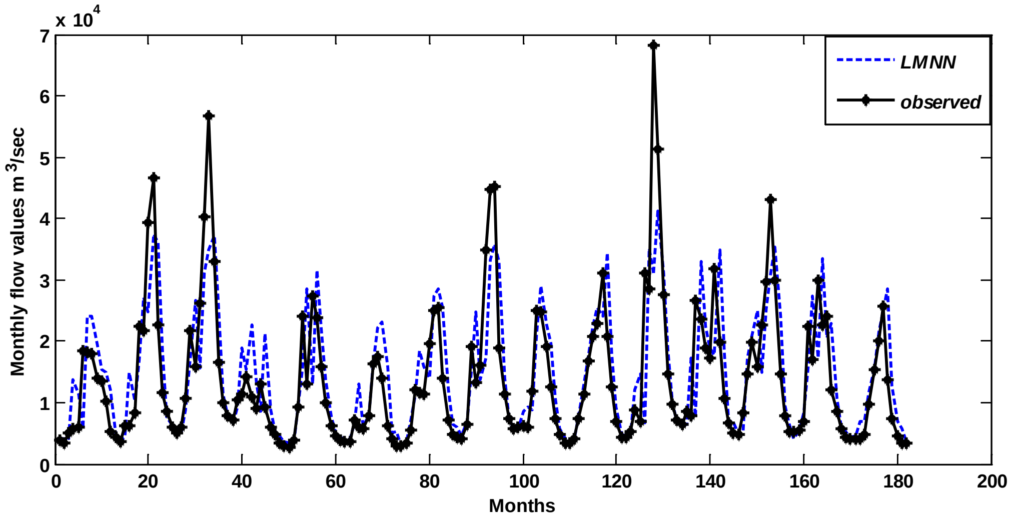
Radial basis function networks were not suitable for discribing the bahivior of Goksu Malpinar River. It is clear from Table (4) that the predictions of the river flow values which are resulted from GRNN generlized regression nueral networks are better than thouse found by RBFNN. Table(4)gives the values of statistical parameters for test data for GoksuMalpinar River using GRNN.

Table(4) Results of The statistical parameters for Goksu Malpinar River using GRNN.

Model structure	**E_{nash}**	**R^2**	**MAPE**	**MAE**	**R_{bias}**
1-1-1	0. 301	0.5295	105.1895	31.1609	5.6114
2-0.9-1	0. 491	0.4289	102.5718	30.7282	4.4408
3-0.1-1	0.5803	0.5868	52.7238	18.9554	3.5534
4-0.1-1	0.5948	0.6070	49.1449	18.0553	3.9024
5-0.1-1	**0.6140**	**0.6286**	**46.7658**	**17.2679**	**3.7755**
6-0.1-1	0.6067	0.6169	46.7815	17.2712	4.4833

The best performance was by using five inputs with o.1 spread value for GRNN. By compaing the applied four different methods for Goksu Malpinar River it can be seen that Levenburg Marquardt networks were the most suitable models for discribing the behavior of Goksu Malpinar stream .

The best LMNN model with(3-6-1) structure performance is illustrated in Figure(7) with an underestimation of peack flow value near 30%.



Figure(7)Peredicted by LMNN vs observed data for Goksu Malpinar for test period.

Results For Euphrates Basin -Goksu Poskoflu River.

The same different artificial neural networks models and methods were applied also to the Goksu poskoflu river from Cihan basin . Following Tables are representing the results of statistical parameters for test period . Table(5) gives the values of statistical parameters for test data for Poskoflu River using Levenburg Marqurdat NN .

Table(5) Results of The statistical parameters for Goksu Poskuflu River using LMNN.

Model structure	E_{nash}	R^2	MAPE	MAE	R_{bias}
M1(1-2-1)	0.5119	0.5128	92.009	5.5105	1.4101
M2(2-3-1)	0.6398	0.6594	78.901	4.8523	5.8167
M3(3-4-1)	0.6706	0.6814	79.887	4.6519	5.4303
M4(4-4-1)	0.6743	0.6757	79.511	4.7751	-0.1574
M5(5-5-1)	0.6532	0.6721	82.6578	5.0404	6.5516
M6(6-5-1)	**0.7053**	**0.7056**	**72.536**	**4.4091**	**0.7930**

The last tried input combination with 6 neurons as input neurons and five neurons at the hidden layer leds to value of E_{nash} as 0.7053 , coefficient of determination equal to 0.7056 while the value of R_{bias} was 0.793 which represent the best results among all the applied archetectures for this kind of networks. By changing the method of training to scaled conjeguate gradient for the same input combinations , an improvement was caught . This is clear from Table(6) which gives the values of statistical parameters for test data for Poskoflu River using SCGNN .

Table(6) Results of The statistical parameters for Goksu Poskuflu River using SCGNN.

Model structure	E_{nash}	R^2	MAPE	MAE	R_{bias}
M1(1-2-1)	0.5116	0.5125	96.781	5.5123	1.4028
M2(2-3-1)	0.6543	0.6564	88.209	4.6183	2.4773
M3(3-5-1)	0.6798	0.6836	89.0077	4.6492	3.9237
M4(4-6-1)	0.6732	0.6830	86.340	4.6924	2.6706
M5(5-6-1)	**0.7537**	**0.7610**	75.555	**4.3029**	**5.9997**
M6(6-5-1)	0.7008	0.7071	76.112	4.5182	3.2989

The best network by using SCG method was by using five inputs and six neurons at the hidden layer . After applying the radial basis function neural networks on the Goksu Poskoflu river following results were found . Most applied arechetectures showed very good results, this is illustrated in Table(7) which gives the values of statistical parameters for test data for Poskoflu River using RBFNN .

Table(7) Results of The statistical parameters for Goksu Poskuflu River using RBFNN.

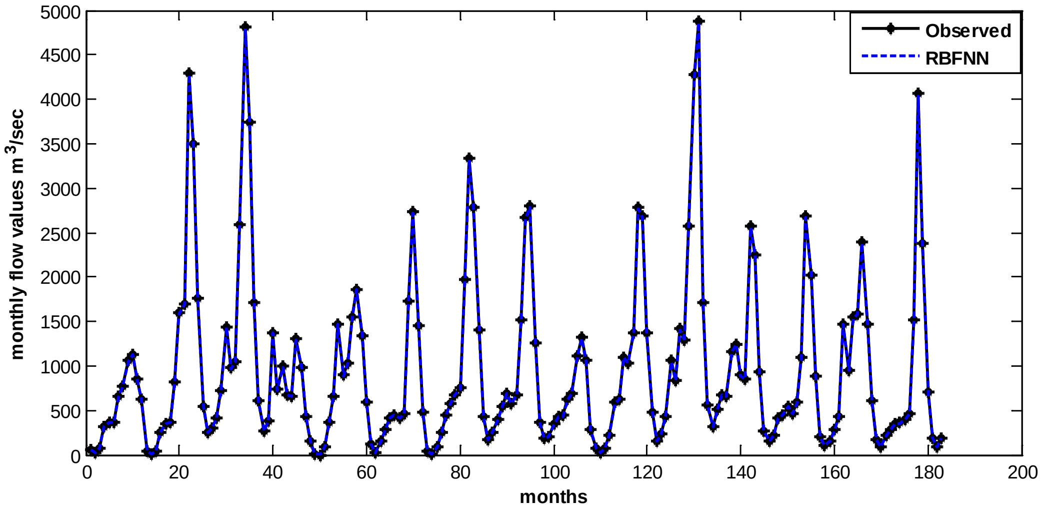
Model structure	E_{nash}	R^2	MAPE	MAE	R_{bias}
1-0.1-300	0.5920	0.5933	83.008	5.0711	1.1645
2-0.01-500	**0.9994**	**0.9993**	**34.0098**	**1.3505**	**-1.0169**
3-0.01-150	0.9573	0.9574	41.098	1.6963	-0.8556
4-0.001-150	0.9480	0.9480	44.779	1.8416	-0.0929
5-0.01-150	0.9515	0.9515	43.332	1.7962	-0.0037
6-0.1-200	0.9230	0.9280	45.502	1.99416	-0.0929

Values of E_{nash} for the most Radial basis and coffecient of determinatin function neteworks were above 0.9 and the values of the other statistical parameters indicated to a very well performance. The best model is indicated with a bold font by using 2 input neurons and 0. 01 spread value with 500 neurons at the hidden layer. The results of the statistical parameters for the applied different generlized regression models are illustrated in Table (8) which gives the values of statistical parameters for test data for Poskoflu River using GRNN.

Table(8) Results of The statistical parameters for Goksu Poskuflu River using GRNN.

Model structure	E_{nash}	R^2	MAPE	MAE	R_{bias}
1-0.1-1	0.4632	0.4647	104.98	6.0761	-1.5816
2-0.1-1	0.5446	0.5588	102.112	5.5475	-0.6260
3-0.1-1	0.5864	0.5994	100.091	5.1968	1.0995
4-0.1-1	0.5446	0.5588	103.009	5.5475	-0.6260
5-0.1-1	0.5957	0.6025	99.890	5.1434	3.9618
6-0.1-1	0.5864	0.5994	88.112	5.1968	1.0995

The performance of generlized regression neural networks was less than performance of Lmn and SCGNN. The best RBFNN model performance which presented best results and best fit between the observed and modelled data is illustrated in the Figure(8).



Figure(8) Peredicted by RBNN vs. observed data for Goksu Poskuflu for test period.

Conclusions

The potential of ANN different Models was tested and investigated to simulate to two rivers which are Goksu Malpinar and Goksu Poskufu from two different basins at Turkey in this paper. Two different training algorthims which are Levenburg Marquradt and Scaled cojeguate gradient were used and two different networks which are radial basis function networks and generlized regression neural nwtworks were applied to the both case studies . All the mentioned models were tested after applying different input combinations and different number of neurons at the hidden layer. For Radial basis function NN and generlized regression NN different spread values were tested. It was found that using the Levenburg Marqurdat Neural Networks provided best match between observed and simulated data for Goksu Malpinar river with value of understimation for peack flow near 30% while the best model for Goksu Poskuflu river was radial basis function neural networks . Based on the results , it is clear that theres is no specific characterstic of the basin that would suggest the use of any model of ANN rather than another .

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