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ABSTRACT

Forecasting streamflow have a significant economic impact, since the forecasting can help in agricultural water management and in providing protection from water shortages and possible flood damage. One of the main research topics related to streamflows is estimating the future flows in a stream. In this study two different forecasting models which are adaptive neuro fuzzy inference system ANFIS and layered recurrent artificial neural networks LRNN were applied to Altinsu Curuh river in eastern Black Sea region at Turkey by using the monthly flow values of the river with different effective hydrological factors from the river basin. A comprehensive comparison between ANFIS model and layered recurrent neural networks was achieved using five important evalution parameters. The performances of both models were found to be comparable. However ANFIS models yielded the best result in estimating and forecasting the river.

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INTRODUCTION

One of the necessities in watershed management is to utilize the stream flow forecating models in developing operation policies. Water reserves for different water users can be controlled and managed through a reliable stream flow forecast. Forecasting Stream flow can have a significant economic -impact, Since this can help in agricultural water management and in providing protection from water shortages and possible flood damage. One of the main research topics related to stream flows is estimating the future flows in a stream. Stream flow forecasting is challenging task because of the complexity of hydrologic systems. Improving the nature of stream flow forecasting has always been an important issue for water resources engineers and hydrologic forecasters. Forecasting of stream flow is very important in the areas such as dam planning, flood mitigation and domestic water supply (Kilinc I *et al.*, 2005). Many various models are used for modeling stream flow. These models can be divided into conceptual, physical and data driven models. In recent decades, artificial intelligence techniques such as Adaptive Neural Fuzzy Inference System (ANFIS), Artificial Neural Network (ANN) have been widely considered owing to their flexibility in modeling the non-linear processes such as rainfall-runoff model (Elom *et al.*, 2012). Many studies have been conducted using ANFIS (Halid nd Ridd., 2002; Navak *et al.*, 2004;Aldrian and Djamil, 2008; Dastorani *et al.*, 2010). Aqil *et al.*, 2007 conducted a comparative study between ANFIS and ANN in modeling continuous daily and hourly behavior of runoff in both daily and hourly time scales. Their results showed that ANFIS had a higher efficiency than other two techniques for forecasting the runoff based on rainfall. Ballini *et. al* 2001 developed a neuro fuzzy network model for forecasting the inflow of Brazilian hydroelectric plants. A daptive Neuro Fuzzy based interference System (ANFIS) introduced in hydrologic forecasting by Jang (1993) for forecasting river flow. A model based on simulating stream flow using fuzzy logic and ANN was produced by Tayfur and Singh (2006). Karunanithi *et al.*, 1994 compared the artificial neural networks ANNs with traditional methods for modeling qualitative and quantitative water resource variables. Other researches Maier and Dandy., 1996; Shamseldin., 1997; Olsson *et al.*, 2004 also used this technique successfully. Zealand *et al.*, 1999 proved the success of training the ANN with back-propagation algorithm for 1-week-ahead stream flow forecasting. Imrie *et al*. 2000 applied the cascade correlation and back-propagation algorithms for short term stream flow forecasting. Hsieh *et al.*, 2003 applied multiple linear regressions (MLR) and feed-forward neural network models using principal components of large-scale climatic indices to predict the seasonal volume of Columbia River in British Columbia. Al aboodi., 2009, 2014 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. In this study a comparision was achived between the performance

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of adaptive neuro interference system ANFIS and Layered recurrent neural networks in forecasting Altinsu Curuh in eastern Black Sea region at Turkey using monthly flow values of the stream and three effective hydrological factors.

METHODOLOGY

Adaptive Neuro-Fuzzy Inference System (Anfis)

The adaptive neuro-fuzzy inference system (ANFIS) can be defined as a soft computing method in which a given input–output data set is expressed in a fuzzy inference system (FIS). The FIS implements anon linear mapping from its input space to the output space. The mapping is accomplished by a number of fuzzy IF–THEN rules, each of which describes the local behaviour of the mapping. The fuzzy membership parameters are optimized either by using a back-propagation algorithm or by combination of both back-propagation and least square method. The efficiency of the FIS dependson the estimated parameters. (Jang *et al*., 1997 and Loukas, 2001). ANFIS could be considered as an integration of neural networks and fuzzy logic and have the potential to capture the benefits of both these fields in a single framework.

ANFIS utilizes linguistic information from the fuzzy logic as well learning capability of an ANN for automatic fuzzy if-then rule generation and parameter optimization (Ali H. Al aboodi., 2014). A conceptual ANFIS consists of five components: inputs and output database, a Fuzzy system generator, a Fuzzy Inference System (FIS), and an Adaptive Neural Network. Most fuzzy inference systems can be classified into three types due to the types of inference operations upon “if-then rules”. These types are Mamdani’s system, Sugeno’s system and Tsukamoto’s system. The most commonly used one is Mamdani’s system. Sugeno’s system is more compact and computationally efficient. The output is crisp, so, without the time consuming and mathematically intractable defuzzification operation, it is by far the most popular candidate for sample-data based fuzzy modeling and it lends itself to the use of adaptive techniques (Takagi and Sugeno, 1985). In first-order Sugeno s system, a typical rule set with two fuzzy IF/THEN rules can be expressed as:

Rule 1: If x is A1 and y is B1, then f1= p1x+q1y+ r1…………………..…………(1).

Rule 2: If x is A2 and y is B2, then f2= p2x+q2y+ r2……………………….……(2).

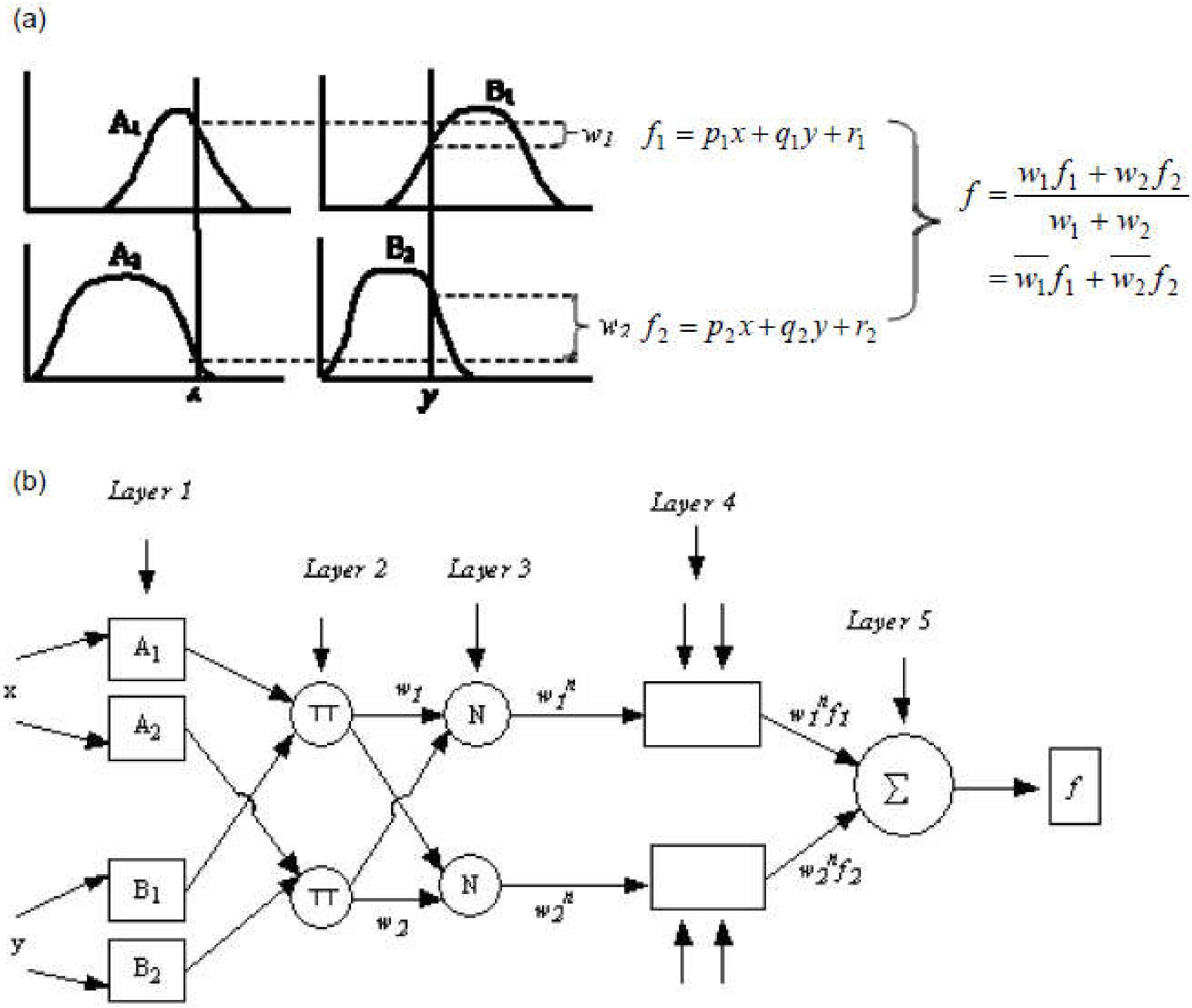

Figure1 Structure of ANFIS Networks. Jang, (1997)

Figure(1) illustrates The five-layered ANFIS architecture and is described subsequently.

Layer 1:Each node in this layer is assigned a fuzzy membership value using membership functions toform a fuzzy set.

$$Q_{1,i} = \mu_{A_i}(x) \text{ for } i = 1,2 \qquad \text{...........(3)}$$

$$Q_{1,i} = \mu_{B_{i-2}}(y) \text{ for } i = 3,4 \qquad \text{...................(4)}$$

where x, y are the crisp input to node i, and Ai, Bi are the membership grades of the membership functions μA and μB, respectively. A generalized bell-shaped membership function was used in the present study. Using a generalized bell-shaped MF, the output O1,i can be computed as:

$$Q_{1,i} = \mu_{A_i}(x) = \frac{1}{1+\left[\frac{x-c_i}{a_i}\right]^{2b_i}} \qquad \text{......................(5)}$$

where {ai, bi, ci} is the parameter set that changes the shapes of the MF with maximum equal to 1and minimum equal to 0.

Layer 2: In this layer, every node multiplies the input and represents the rule nodes and the output O2, k that represents the firing strength of a rule and is computed as:

$$Q_{2,k} = w_k = \mu_{Ai}(x)\mu_{Bi}(y) \quad i = 1,2 \qquad \text{....(6)}$$

Layer 3: This layer consists of the averaging nodes, which is labelled as "N" and computes the normalized firing strength equal to:

$$Q_{3,k} = w_i{}' = \frac{w_i}{w_1+w_2} \qquad i = 1,2 \qquad \text{..........(7)}$$

Layer 4: The node function of this layer is to compute the contribution of each ith rule towards the total output and the function can be defined as:

$$Q_{4,i} = w_i{}'f_i \;\; = w_i(p_i x + q_i y + r_i) \qquad i = 1,2 \qquad \text{........(8)}$$

where, wi is the output of Layer 3 and {pi, qi, ri} is the parameter set.

Layer 5: This layer has a single output node, which computes overall output of the ANFIS as:

$$Q_{5,I} = \sum_i w_i{}'f_i \;\; = \frac{\sum_i w_i \;\; f_i}{\sum_i w_i} \qquad \text{...................(9)}$$

The computation of these parameters is facilitated by a gradient vector, which provides a measure of how well the fuzzy inference system is modelling the input/output data for a given set of parameters.

Once the gradient vector is obtained, any optimization routines can be applied to adjust the parameters and to reduce some error measure, usually defined by the sum of the squared difference between actual and desired outputs. The ANFIS uses a hybrid learning algorithm, the gradient descent method and least square method to update the membership function parameters. Jang, (1997), (NIRANJAN *et al*., 2009)

Neural Network Model

ANN can be described as a mathematical representation of the structure of human brain. The properties of this mathematical representation can be summarized as its ability to learn from examples, recognize a pattern in the data, process information rapidly and adapt solutions overtime (Kisi., 2005., Abdul Sattar Y., 2007). In any ANN network there are a number of data processing elements called neurons, which are grouped in layers. Neurons of the first layer which is called input layer receive the input vector and transfer the values to the next layer nodes or neurons across connections. This process is continued until the output layer is reached. ANNs can be categorized into two types according to the number of layers :single bi layer and multilayer networks and also can be categorized into feed forward and feed backward networks due to the direction of the information and processing (Haddad *et al*., 2005)

Layer recurrent Neural Networks LRNN

Recurrent Neural Networks are useful in situations when there is a temporal (time dependent) relationship in data. They are constructed by taking a feed forward network architecture and adding feedback connections to previous layers. Such networks are trained by the standard back propagation algorithm except that patterns must always be presented in time sequential order. The difference in the structure is that there are some extra nodes next to the input layers that are connected to the hidden layer just like the other input nodes. These extra nodes hold the contents or representation of the contents of one of the layers as it existed when the provides pattern was trained. In this way the network sees previous knowledge it had about previous inputs. This extra set of nodes are called the networks context units and are sometimes referred to as networks long term memory. Figure (2) represents a recurrent neural networks.(Sandy D, 1997; Arslan Ch., 2013).

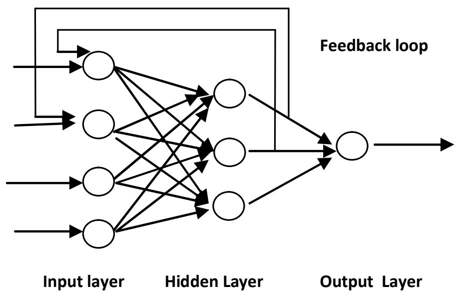

Figure 2 Layer Recurrent Network

Study area Nature of data

The study area for this research is Altins Coruh River, the perennial river in eastern Black Sea region, The river springs from Mescit Mountains in Bayburt and reaches the Black Sea in Batum City of Georgia after a course of 431 kms. Mean annual flow of the river before leaving Turkey's border is about 200 m3/s. There are 11 successive gauging stations, with deferent recording time period, on the main course of the Altisu Coruh River (Ali Danandeh Mehr, 2013). Respect to the spatial and temporal consistency of the stations, the selected gauge station in this study station 2322and observation period (1972–2000) from available data in such a way that provide both the longest and the most reliable records concurrently. Altinsu Coruh is a shared river between Turkey and Georgia. Monthly stream flow prediction at the lower reach of the river, trans-boundary reach, will help both countries' water recourses managers make suitable decisions in dry or wet spellsor to resolve probable conflicts about sharing of river water. In addition to the monthly flow values of the river different hydrological factors around the station position were taken also for the same period. These factors are monthly mean periciptation, maximum periciptationat the month and monthly mean temperature. Figure (3) shows the location of the river.

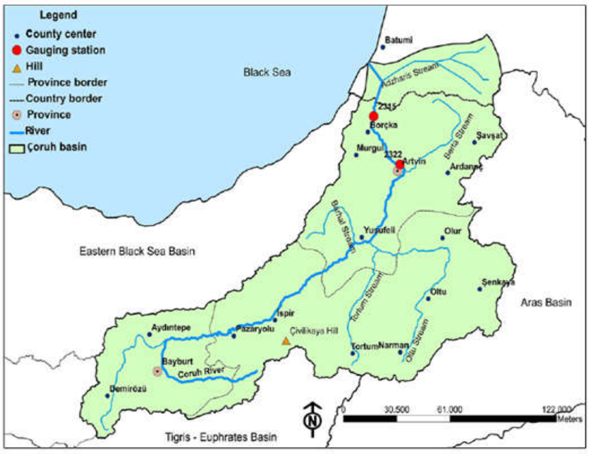

Figure 3 Location of The AltinSu Curuh River (Ali Danandeh Mehr, 2013).

The data set for the stream and hydrological effective factors were divided into training and test sets (198 data set for training and 150 for test since the record period was as monthly record from 1972 to the end of 2000. The performance of both training and test periods for both methods were decided according to the best values of the following parameters:, Nash-Sutcliffe efficiency E_{nash} , percent bias R $_{bias}$, coeeffiicent of determination R^2, mean absolute error MAE and mean absolute percent error MAPE parameters which were used as evaluation criteria. These parameters are defined as:

$$\text{ENash} = 1 \quad \frac{\sum_{t=1}^{n}(A_t - F_t)^2}{\sum_{t=1}^{n}(A_t - F_{mean})^2} \qquad \text{.........10}$$

$$\text{R bias} = 100 \quad \frac{\sum_{t=1}^{n}(F_t - A_t)}{\sum_{t=1}^{n} A_t} \qquad \text{...........11}$$

$$R^2 = \frac{\left(\sum_{t=1}^{n}(A_t - A_{mean})(F_t - F_{mean})\right)^2}{\sum_{t=1}^{n}(A_t - A_{mean})^2 \sum_{t=1}^{n}(F_t - F_{mean})^2} \qquad \text{.................12}$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n} |A_t - F_t| \qquad \text{.................13}$$

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \qquad \text{......................14}$$

where At is the actual value and Ft is the forecasted or simulated value and Fmean, Amean are the mean value of the forecasted and actual series respectivelly (Chokmani *et al.*, 2008; Tiyaki S *et al.*, 2014).

Applications and Results

Data of monthly flow released of Altinsu curuh river at six antecedent time steps Q $_{t-1}$, Q $_{t-2}$, Q $_{t-3}$, Q $_{t-4}$,Q $_{t-5}$, Q $_{t-6}$ were considered as input to the ANN and ANFIS models in addition to the most effective hydrological factors at the region around the stream . These factors were P: monthly mean periciptation, Pmx: maximum periciptation value at the month, T: monthly mean temperature value. Accordingly, six different ANFIS and LRANN models (Table 1) were proposed and their performance compared to determine the best model. Model M1 for example represents the outflow of future value of Altinsu Curuh river at time t (Q(t)) as a function of corresponding monthly flow value to one time step lag, t and the perciptation monthly mean value, maximum percipitation at the month t with monthly mean value of the temperature . Likewise, Q(t) = f[Q(t-1),P,Pmx,T)].All models were trained and tested using a three-layered with a number of functional nodes and connection weights. One hidden layer was decided for all models for training. The number of hidden neurons (HN) in the hidden layer of layered recurrent ANN architecture was varied till the best performance was obtained. The input and output data sets was proccesed by normalizing the data using following equation:

$$X_{norm} = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \qquad \text{..................(15)}$$

where X_{norm}, X_i, X_{min} and X_{max} indicates normalized, observed, minimum and maximum values for all parameters, respectively. (Kisi O, 2005). And then feeding into the ANN models for training and testing. The ANN and ANFIS simulation, and analysis of the results, were performed using MATLAB 7.

Table1 Structure of the applied Models for ANFIS and LRNN

Model name	Model structure
M1	Q_t=f(Q $_{t-1}$, P,P_{mx}, T)
M2	Q_t=f (Q $_{t-1}$, Q $_{t-2}$, P,P_{mx}, T)
M3	Q_t=f(Q $_{t-1}$, Q $_{t-2}$, Q $_{t-3}$, P,P_{mx}, T)
M4	Q_t=f(Q $_{t-1}$, Q $_{t-2}$, Q $_{t-3}$, Q $_{t-4}$, P,P_{mx}, T)
M5	Q_t=f(Q $_{t-1}$, Q $_{t-2}$, Q $_{t-3}$, Q $_{t-4}$,Q $_{t-5}$, P,P_{mx}, T)
M6	Q_t=f(Q $_{t-1}$, Q $_{t-2}$, Q $_{t-3}$, Q $_{t-4}$,Q $_{t-5}$, Q $_{t-6}$, P,P_{mx}, T)

Note: Q t-i represents flow value for i past month, P: monthly mean periciptation, Pmx: maximum periciptation value at the month,T: monthly mean temperature value.

Application of adaptive neuro fuzzy ineference system ANFIS models.

The data set for Curuh River monthly flow, the monthly periciptation, maximum periciptation and the mean monthly temperature were divided into training and test sets then the adaptive neuro fuzzy system method was applied by using different input combinations as was explained before . Models with the mentioned input combinations were trained and tested to predict the monthly flow values using the ANFIS approach. All six models were trained and tested on the data of the same periods. The number of fuzzy membership functions for each input was considered as 3 according to the type of model. The type of membership function used for all the models was of generalized bell (gbell) type, which is a direct generalization of Cauchy distribution used in the probability theory with three parameters, Due to its smoothness and concise expression it is popularly used in many applications to specify the fuzzy sets (Jang *et al.*, 1997). The number of fuzzy rules and the optimum number of parameters required to define the FIS for the best result were decided based upon the number of inputs used and their type, as well as on the number of fuzzy membership functions employed in the model. The parameters of the membership functions were adjusted using the back-propagation algorithm. The outputs function of the ANFIS model was considered as a linear type. Table 2 illustrates the performance indices obtained from all six models trained using the ANFIS technique for training period. Table 3 illustrates the results for test period.

Table 2 The performance of ANFIS models for training

Model	E_{nash}	R_{bias}	R^2	MAE	MAPE
M1	0.8136	-2.5210	0.8151	40.3549	28.6339
M2	0.8649	-0.4285	0.8650	34.1838	23.7609
M3	0.8517	-0.9964	0.8520	38.5664	27.1567
M4	**0.8948**	**0.8952**	**0.8951**	**30.5023**	**20.5415**
M5	0.8850	-0.5241	0.8852	33.2629	23.7116
M6	0.8820	-1.0352	0.8823	32.677	23.5113

Table 3 The performance of ANFIS models for test period

Model	E_{nash}	R_{bias}	R^2	MAE	MAPE
M1	0.7725	3.2316	0.7748	47.6370	31.7451
M2	0.8417	0.4272	0.8417	38.3545	26.9069
M3	0.8339	1.2789	0.8343	38.1889	26.5417
M4	**0.8802**	**-1.2322**	**0.8808**	**33.0893**	**22.0420**
M5	0.8632	0.6821	0.8636	35.0611	24.0357
M6	0.8554	1.3725	0.8560	35.1868	25.0751

As can be seen from the both tables, Model 4 performed better than the other five models with E_{nash} 0.8948, 0.8802 ,R_{bias} 0.8952, -1.2322, R^2 0.98951, 0.8808, MAE 30.5023, 33.0893 and MAPE 20.5415, 22.042, respectively for training and test periods. The ANFIS model produced quite good results.

Application of Layered recurrent neural networks models

As was mentioned before the number of hidden neurons (HN) in the hidden layer of ANN architecture was varied till the best performance was obtained. Each model was trained using a different number of hidden neurons (HN) in the hidden layer and the performance indices were computed to determine the optimum number of hidden eurons. Table (4) illustrates the performance of the layered recurrent networks for training period while Table(5) illustrates the results for the test period for the same input combinations and the best number of neurons at the hidden layer.

Table 4 The performance of LRNN models for training

Model	Neuron No.	E_{nash}	R_{bias}	R^2	MAE	MAPE
M1	10,00	0.8733	2.6131	0.8757	29.3052	21.4700
M2	23,00	0.8222	4.1913	0.8331	41.8698	37.5761
M3	7,00	0.8651	1.3851	0.8646	34.2443	27.9928
M4	5,00	0.8760	4.8248	0.8855	30.7347	22.9259
M5	3,00	0.8620	2.5192	0.8663	33.8453	25.637
M6	**6**	**0.8842**	**1.6479**	**0.8891**	**30.6694**	**21.9177**

Table5 The performance of LRNN models for test

Model	Neuron No.	E_{nash}	R_{bias}	R^2	MAE	MAPE
M1	10,00	0.8029	-0.4673	0.8225	39.171	24.1,00
M2	23,00	0.7676	-1.45	0.8015	57.3334	41.75
M3	7,00	0.8521	0.7034	0.8532	36.826	254664,00
M4	5,00	0.8435	1.82	0.8443	38.4519	27.14700
M5	3,00	0.8474	1.909	0.8477	37.3695	24.4089
M6	**6**	**0.8647**	**2.9192**	**0.8707**	**31.9278**	**21.5641**

Model 6 showed the best performance as evident fromits highest E_{nash} (0.8842 for training and 0, 8647 for test) and lowest MAE (30.966 for training and 31.9278 for test). While the values of T R^2 for this model was the best among all the models (0.8891 for training and 0.8707 for test). The best number of neurons at the hidden layer for this model was found to be 6 neurons for generalizing input–output data sets. Model 6 produced better results during model training and testing. By comparing the performance of the two applied methods it can be seen that the both models produced quite good results for forecasting the monthly flow values of Altinsu Curuh River but the ANFIS model performed better than LRNN. It is observed also that the peak flow were underestimated by 19.825% in ANFIS model for test period and about 22.55 % in LRNN model for the same period , which may be due to the presence of a small number of higher flow values in the test data sets. The superiority of the ANFIS technique to the ANN method may be due to the fuzzy partitioning of the input space and for creating a rule-base to generate the output. Figure (4) presents a comparison between the observed with both ANFIS and LRNN computed flow obtained from the best models during testing.

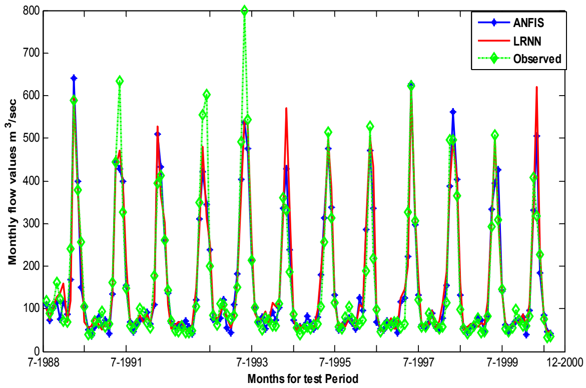

Figure 4 The comparision between the applied models and the observed data for test period

CONCLUSIONS

ANFIS and LRNN models have been proposed and emerged as an alternative approach of Altinsu Curuh river forecasting in eastern Black Sea region at Turkey by taking in consider the antecedent time steps of the monthly flow data of the stream in addition to the most effective hydrological factors at the region around the river. These factors were monthly mean pricipitation, maximum pericipitation at the month and monthly mean temperature. Different input combinations were tried for both models in addition to a comperhensive investigation of the best neurons number at the hidden layer for LRNN models. It was concluded after the completion of this study that the both models produced quite good results for forecasting the monthly flow values of Altinsu Curuh River but the ANFIS model performed better than LRNN. It can be seen that Altisu curuh river could be predicted with considerable accuracy taking the monthly stream values of four consecutive monthly time time lags (Model 4) asinputs using ANFIS model and six consecutive monthly time time lags (Model 6) using LRNN technique in addition to using the effective hydrological factors around the briver basin . The performances of both models were found to be comparable. However ANFIS models yielded the best result as revealed from the E nash, R bias, R2, MAE and MAPE values and deviation of peak flowvalues. It was found also after investigating of neurons number at the hidden layer for LRNN models that six neurons in one hidden layer is the most appropriate in the LRANN architecture that yielding the best results.. The results of the study indicated that ANFIS is a better technique than the LRANN to capture behaviour of the stream and could be used successfully for hydrological applications.

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