Hydrol. Earth Syst. Sci. Discuss., 4, 1369–1406, 2007
www.hydrol-earth-syst-sci-discuss.net/4/1369/2007/

Hydrology and Earth System Sciences Discussions

Papers published in *Hydrology and Earth System Sciences Discussions* are under open-access review for the journal *Hydrology and Earth System Sciences*

Artificial Intelligence Techniques for river flow forecasting in the Seyhan River Catchment, Turkey

M. Firat

Pamukkale University Civil Engineering Deprt, Denizli, Turkey

Received: 15 May 2007 – Accepted: 17 May 2007 – Published: 6 June 2007

Correspondence to: M. Firat (mfirat@pamukkale.edu.tr)

Abstract

The use of Artificial Intelligence methods is becoming increasingly common in the modeling and forecasting of hydrological and water resource processes. In this study, applicability of Adaptive Neuro Fuzzy Inference System (ANFIS) and Artificial Neural Network (ANN) methods, Generalized Regression Neural Networks (GRNN) and Feed Forward Neural Networks (FFNN), for forecasting of daily river flow is investigated and the Seyhan catchment, located in the south of Turkey, is chosen as a case study. Totally, 5114 daily river flow data are obtained from river flow gauges station of Üçtepe (1818) on Seyhan River between the years 1986 and 2000. The data set are divided into three subgroups, training, testing and verification. The training and testing data set include totally 5114 daily river flow data and the number of verification data points is 731. The river flow forecasting models having various input structures are trained and tested to investigate the applicability of ANFIS and ANN methods. The results of ANFIS, GRNN and FFNN models for both training and testing are evaluated and the best fit forecasting model structure and method is determined according to criteria of performance evaluation. The best fit model is also trained and tested by traditional statistical methods and the performances of all models are compared in order to get more effective evaluation. Moreover ANFIS, GRNN and FFNN models are also verified by verification data set including 731 daily river flow data at the time period 1998–2000 and the results of models are compared. The results demonstrate that ANFIS model is superior to the GRNN and FFNN forecasting models, and ANFIS can be successfully applied and provide high accuracy and reliability for daily River flow forecasting.

1 Introduction

In last decades, the forecasting and modeling of river flow in hydrological processes is quite important to deliver the sustainable use and effective planning and management of the water resources. In order to estimate hydrological processes such as precipitation, runoff and change of water level by using existing methods, some parameters such as the physical properties of the watershed and river network and observed detail data are necessary. In the literature, there have been many approaches such as, Box and Jenkins (1970) methods of autoregressive (AR), auto-regressive moving average (ARMA), auto-regressive integrated moving average (ARIMA), autoregressive, moving average with exogenous inputs (ARMAX), generally used for modeling of river flow. Some of the earliest examples of the AR type of stream flow forecast models include Thomas and Fiering (1962) and Yevjevich (1963). These approaches have employed conventional methods of the time series forecasting and modeling (Owen et al., 2001; BuHamra et al., 2003; Zhang, 2003; Mohammadi et al., 2006; Arena et al., 2006; Komornik et al., 2006; Toth et al., 2000). Artificial neural networks (ANN) have been recently accepted as an efficient alternative tool for modeling of complex hydrologic system to the conventional methods and widely used for prediction. Some specific applications of ANN to hydrology include modeling rainfall-runoff process (Sajikumar et al., 1999), river flow forecasting (Dibike et al., 2001; Chang et al., 2002; Sudheer and Jain; 2004; Dawson et al., 2002), sediment transport prediction (Fırat and Güngör, 2004), and sediment concentration estimation (Nagy et al., 2002). The ASCE Task Committee reports (2000) did a comprehensive review of the applications of ANN in hydrological forecasting context. Jain and Kumar (2007) proposed a new hybrid time series neural network model that is capable of exploiting the strengths of traditional approaches and ANN. Tingsanchali and Gautam (2000) applied ANN and stochastic hydrologic models to forecast the flood in two river basins in Thailand. GRNN method have also been used for many specific studies (Cigizoglu and Alp, 2006; Kim et al., 2004; Ramadhas et al., 2006; Celikoglu and Cigizoglu, 2007; Celikoglu, 2006). On the other hand, fuzzy logic method was first developed to explain the human thinking and decision system by Zadeh (1965). Several studies have been carried out using fuzzy logic in hydrology and water resources planning (Chang et al., 2001; Liong et al., 2000; Mahabir et al., 2000; Nayak et al., 2004a; Şen and Altunkaynak, 2006). Recently, Adaptive Neuro-fuzzy inference system (ANFIS), which consists of the ANN and

fuzzy logic methods, have been used for several application such as, database management, system design and planning/forecasting of the water resources (Chen et al., 2006; Chang et al., 2006; Nayak et al., 2004b; Fırat and Güngör, 2007; Firat, 2007).

The main purpose of this study is to investigate the applicability and capability of ANFIS and ANN methods for modeling of daily river flow. To verify the application of this approach, the Seyhan catchment located in the south part of Turkey is chosen as the case study area. The River Seyhan is one of the most important water resources in Turkey. The River Seyhan flow change depends on various impacts such as climatic and hydro-meteorological variables of the basin, water usage for agricultural and hydroelectric energy. The models for modeling of river flow with having various input structures are developed and applied to the forecasting of the flows of the River Seyhan.

2 Adaptive Neural Fuzzy Inference System (ANFIS)

The fuzzy logic approach is based on the linguistic uncertainly expression rather than numerical uncertainty. Since Zadeh (1965) proposed the fuzzy logic approach to describe complicated systems, it has become popular and has been successfully used in various engineering problems, (Chen et al., 2006; Chang et al., 2001; Liong et al., 2000; Mahabir et al., 2000; Nayak et al., 2004a; Firat, 2007; Nayak et al., 2004b; Şen, 2001). Fuzzy inference system is a rule based system consists of three conceptual components. These are: (1) a rule-base, containing fuzzy if-then rules, (2) a database, defining the membership function and (3) an inference system, combining the fuzzy rules and produces the system results (Şen, 2001). The first phase of fuzzy logic modeling is the determination of membership functions of input – output variables, the second phase is the construction of fuzzy rules and the last phase is the determination of output characteristics, output membership function and system results (Fırat and Güngör, 2007). A general structure of fuzzy system is demonstrated in Fig. 1.

ANFIS consisting of the combination of the ANN and the fuzzy logic has been shown to be powerful in modeling numerous processes such as rainfall-runoff modeling and real-time reservoir operation (Chen et al., 2006; Chang et al., 2006; Fırat and Güngör, 2007). ANFIS uses the learning ability of ANN to define the input-output relationship and construct the fuzzy rules by determining the input structure. The system results were obtained by thinking and reasoning capability of the fuzzy logic. The hybrid-learning algorithm and subtractive function are used to determine the input structure. The detailed algorithm and mathematical background of these algorithms can be found in Jang et al. (1997). There are two types of fuzzy inference systems, Sugeno-Takagi inference system and Mamdani inference system, in literature. In this study, Sugeno Takagi inference system is used for modeling of daily river flow. The most important difference between these systems is the definition of the consequent parameter. The consequence parameter in Sugeno inference system is a linear equation, called “first-order Sugeno inference system”, or constant coefficient, “zero-order Sugeno inference system (Jang et al., 1997). It is assumed that the fuzzy inference system includes two inputs, x and y, and one output, z. For the first-order Sugeno inference system, typical two rules can be expressed as;

Rule 1 : IF x is A_1 and y is B_1 THEN $f_1 = p_1 * x + q_1 * y + r_1$

Rule 2 : IF x is A_2 and y is B_2 THEN $f_2 = p_2 * x + q_2 * y + r_2$

where, x and $y$are the crisp inputs to the node i, A_i and B_i are the linguistic labels as low, medium, high, etc., which are characterized by convenient membership functions and finally, p_i , q_i and r_i are the consequence parameters. The structure of this fuzzy inference system is shown in Fig. 2.

Input notes (Layer 1): Each node in this layer generates membership grades of the crisp inputs which belong to each of convenient fuzzy sets by using the membership functions. Each node's output O_i^1 is calculated by:

$$O_i^1 = \mu_{A_i}(x) \quad \text{for} \quad i = 1,\ 2 \quad ; \quad O_i^1 = \mu_{B_{i-2}}(y) \quad \text{for} \quad i = 3,\ 4 \tag{1}$$

where μ_{A_i} and μ_{B_i} are the membership functions for A_i and B_i fuzzy sets, respectively. Various membership functions can be applied to determine the membership grades. In this study, the Gauss membership function is used, as;

$$O_i^1 = \mu_{A_i}(x) = e^{\frac{-(x-c)^2}{2\sigma^2}} \tag{2}$$

where, the premise parameters change the shape of membership function from 1 to 0.

Rule nodes (Layer 2): In this layer, the AND/OR operator is applied to get one output that represents the results of the antecedent for a fuzzy rule, that is, firing strength. The outputs of the second layer, called firing strengths O_i^2, are the products of the corresponding degrees obtained from the layer 1, named as w as follows;

$$O_i^2 = w_i = \mu_{Ai}(x)\mu_{Bi}(y), \quad i = 1,2 \tag{3}$$

Average nodes (Layer 3): Main target is to compute the ratio of firing strength of each ith rule to the sum firing strength of all rules. The firing strength in this layer is normalized as;

$$O_i^3 = \bar{w}_i = \frac{w_i}{\sum\limits_i w_i} \qquad i = 1,2 \tag{4}$$

Consequent nodes (Layer 4): The contribution of ith rule towards the total output or the model output and/or the function defined is calculated by Eq. (5);

$$O_i^4 = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i) \qquad i = 1,2 \tag{5}$$

where, $\bar{w}_i$ is the ith node output from the previous layer as demonstrated in the third layer. $\{p_i, q_i, r_i\}$ is the parameter set in the consequence function and also the coefficients of linear combination in Sugeno inference system.

Output nodes (Layer 5): This layer is called as the output nodes in which the single node computes the overall output by summing all incoming signals and is also the last step of the ANFIS. The output of the system is calculated as;

$$f(x,y) = \frac{w_1(x,y)f_1(x,y) + w_2(x,y)f_2(x,y)}{w_1(x,y) + w_2(x,y)} = \frac{w_1 f_1 + w_2 f_2}{w_1 + w_2} \tag{6}$$

$$Q_i^5 = f(x,y) = \sum_i \bar{w}_i . f_i = \bar{w}_i f_1 + \bar{w}_i f_2 = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (7)$$

The objective is to train adaptive networks for having convenient unknown functions given by training data and finding the proper value of the input and output parameters. For this aim, ANFIS applies the hybrid-learning algorithm, consists of the combination of the"gradient descent" and "the least-square" methods. The gradient descent method is used to assign the nonlinear input parameters, as the least-squares method is employed to identify the linear output parameters (p_i, q_i, r_i). The "subtractive fuzzy clustering" function, offering the effective result by less rules, is applied to solve the problem in ANFIS modeling (Nayak et al., 2004b).

3 Artificial Neural Networks

An ANN, can be defined as a system or mathematical model consisting of many nonlinear artificial neurons running in parallel which can be generated as one or multiple layered. In this study Generalized Regression Neural Networks (GRNN) and Feed Forward Neural Networks (FFNN) are used for modeling of daily river flow.

3.1 Feed Forward Neural Networks (FFNN)

A FFNN consists of at least three layers, input, output and hidden layer. The number of hidden layers and neurons are determined by trial and error method. The schematic diagram of a FFNN is shown in Fig. 3. Each neuron in a layer receives weighted inputs from a previous layer and transmits its output to neurons in the next layer. The summation of weighted input signals are calculated by Eq. (8) and this summation is transferred by a nonlinear activation function given in Eq. (9). The results of network are compared with the actual observation results and the network error is calculated

with Eq. (10). The training process continues until this error reaches an acceptable value.

$$Y_{\text{net}} = \sum_{i=1}^{N} Y_i . w_i + w_0 \quad (8)$$

$$Y_{\text{out}} = f(Y_{\text{net}}) = \frac{1}{1+e^{-Ynet}} \quad (9)$$

$$J_r = \frac{1}{2} . \sum_{i=1}^{k} (Y_{\text{obs}} - Y_{\text{out}})^2 \quad (10)$$

$Y_{\text{out is}}$ the response of neural network system, $f(Y_{\text{net}})$ is the nonlinear activation function, Y_{net} is the summation of weighted inputs, Y_i is the neuron input, w_i is weight coefficient of each neuron input, w_0 is bias, J_r is the error between observed value and network result, Y_{obs} is the observation output value. In this study, the back propagation learning algorithm, the supervised learning and sigmoid activation function are used in training and testing of models.

3.2 Generalized Regression Neural Networks

A Generalized Regression Neural Networks (GRNN) is a variation of the radial basis neural networks, which is based on kernel regression networks (Cigizoglu and Alp, 2006). A GRNN doesn't require an iterative training procedure as back propagation networks. A GRNN consists of four layers: input layer, pattern layer, summation layer and output layer as shown in Fig. 4.

The number of input units in input layer depends on the total number of the observation parameters. The first layer is connected to the pattern layer and in this layer each neuron presents a training pattern and its output. The pattern layer is connected to the summation layer. The summation layer has two different types of summation, which are a single division unit and summation units. The summation and output layer together perform a normalization of output set. In training of network, radial basis and linear activation functions are used in hidden and output layers. Each pattern layer unit is connected to the two neurons in the summation layer, S and D summation neurons. S-summation neuron computes the sum of weighted responses of the pattern layer. On the other hand, D summation neuron is used to calculate unweighted outputs of pattern neurons. The output layer merely divides the output of each S-summation neuron by that of each D-summation neuron, yielding the predicted value to an unknown input vector x as (Kim et al., 2004);

$$Y_i' = \frac{\sum_{i=1}^{n} y_i \,.\, \exp\left[-D(x, x_i)\right]}{\sum_{i=1}^{n} \exp\left[-D(x, x_i)\right]} \tag{11}$$

$$D(x, x_i) = \sum_{k=1}^{m} \left(\frac{x_i - x_{ik}}{\sigma}\right)^2 \tag{12}$$

y_i is the weight connection between the ith neuron in the pattern layer and the S-summation neuron, n is the number of the training patterns, D is the Gaussian function, m is the number of elements of an input vector, x_k and x_{ik} are the jth element of x and x_i, respectively, σ is the spread parameter, whose optimal value is determined experimentally.

4 Study area and available data

In this study, the applicability and capability of ANFIS and ANN methods, GRNN and FFNN, is investigated in forecasting and modeling of daily river flow. To illustrate the applicability of the ANFIS and ANN methods, The Seyhan River, located in the south of

Turkey, is chosen as case study area. It has been operated for irrigation, hydropower generation, domestic use and recreation facilities. The Seyhan River and its drainage basin are shown in Fig. 5.

5 River flow forecasting by Artificial Intelligence Techniques

5.1 Input variables

The river flow process in any cross section of river system can be characterized as the function of various variables such as, spatial and temporal distribution of rainfall, catchment and river physical characteristics. The relationship of between river flow and influential variables can be expressed by;

$$Q(t) = f(X(t)) + \varepsilon_t \tag{13}$$

where, $Q(t)$ denotes the river flow in any cross section of river system, $X(t)$ is the input vector, which consists of many variables such as spatial and temporal distribution of rainfall, catchment and river physical characteristics at various time lags, ε_t is the random error. In the river flow modeling and forecasting, these parameters affects the performance of the forecasting model because input vector includes the number of antecedent values of these variables. Owing to the complexity of this process, most conventional approaches are often unable to provide sufficiently accurate and reliable results. There is one River flow gauging station, Seyhan River Üçtepe (1818), equipped with automatic daily flow recorders, on Seyhan River as shown in Fig. 5. Totally 4383 daily river flow data were obtained from river flow station of Üçtepe (1818) on Seyhan River for the time period 1986–2000 and Fig. 6 shows the time series data of daily river flow.

The minimum value; $x_{\min}$, maximum value; $x_{\max}$, mean; $\bar{x}$, standard deviation; s_x, variation coefficient c_{vx}, skewness coefficient; c_{sx}, for total observed data sets are given in Table 1.

5.2 Model structure

One of the most important steps in developing a satisfactory forecasting model is the selection of the input variables. Hence, cross- correlations between input and output variables are calculated in order to apply the methods for modeling. Different combinations of the antecedent flows of river flow gauge station are used to construct the appropriate input structure. The structures of forecasting models are shown in Table 2.

Where; Q_t represents the River flow at time (t), $Q(t-1)$,... $Q(t-n)$ are the river flow respectively at times $(t-1)$ ... $(t-n)$. It is evident that the training data sets should cover all the characters of the problem in order to get effective estimation. The observed data were divided into three parts: training data set, testing data set and verification data set. The verification data set consisted of the last two years (at time period 1998–2000). The training and testing data set include the daily river flow record at time period 1986–1998 years and the time periods of training/ testing are shown in Table 3.

The training and testing experiments with ANFIS and ANN methods are carried out considering various input layer structures with data set given in Fig. 6. The performances of the models both training and testing data are evaluated and compared according to Correlation Coefficient (CORR), Efficiency (E) and Root Mean Square Error (RMSE).

$$\mathrm{CORR} = \frac{\sum_{i=1}^{N} (Q_D - \overline{Q_D}).(Q_Y - \overline{Q_Y})}{\sqrt{\sum_{i=1}^{N} (Q_D - \overline{Q_D})^2.(Q_Y - \overline{Q_Y})^2}} \tag{14}$$

$$E = \frac{E_1 - E_2}{E_1} \quad E_1 = \sum_{t=1}^{N} Q_D - \overline{Q_D})^2, \ E_2 = \sum_{t=1}^{N} (Q_Y - Q_D)^2 \tag{15}$$

$$\mathrm{RMSE} = \left[\sum_{i=1}^{N} \frac{(Q_D - Q_Y)^2}{N} \right]^{0.5} \tag{16}$$

where, Q_Y is the forecasted river flow, Q_D is the field observation of river flow, $\overline{Q_Y}$ is the average of the forecasted river flows, $\overline{Q_D}$ is the average of the observation river flow. The correlation coefficient is a commonly used statistic and provides information on the strength of linear relationship between the observed and the computed values. The efficiency (E) is one of the widely employed statistics to evaluate model performance. The values of CORR and E close to 1.0 indicate good model performance. RMSE evaluates the residual between measured and forecasted sediment yield. Theoretically, if this criterion equals zero then model represents the perfect fit, which is not possible at all.

5.2.1 ANFIS model

In this study firstly, the seven models having various input variables are trained and tested by ANFIS method and the performances of models for river flow forecasting models are compared and evaluated based on training and testing performances. The best fit model structure is determined according to criteria of performance evaluation. The performances of the ANFIS models are shown in Fig. 7.

As can be seen in Fig. 7, the ANFIS models are evaluated based on their performance in testing sets. The models have shown significant variations in the criteria of the performance evaluation given in Fig. 5. It shows that the lowest value of the RMSE and the highest values of the RMSE and CORR are R-I M2 ANFIS model. R-I M2 ANFIS model, which consists of two antecedent flows in input, has shown the highest efficiency, correlation and the minimum RMSE and R-I M2 was selected as the best-fit model for modeling of river flow in the Seyhan catchment. The performance of the R-I M2 ANFIS model is shown in Table 4.

It appears that the ANFIS model is accurate and the value of RMSE is small enough, and correlation coefficients and efficiencies are very close to unity. The results of the ANFIS model are compared with the observed flows in order to evaluate the performance of the training/testing of the model. Figure 8 shows the scatter diagrams of the estimated values of the training/testing of the ANFIS models and observed values.

The results of the ANFIS model demonstrate that the ANFIS can be successfully applied to establish accurate and reliable time series forecasting models. In order to get a true and effective evaluation of the performance of ANFIS method, the models were also trained and tested by GRNN and FFNN methods.

5.2.2 ANN models

In this study, secondly, the GRNN and FFNN methods are used for modeling of daily river flow. In the training and testing of ANN models, the same data set is used and performances of models are also evaluated and compared based on given above criteria. The performances of the GRNN models are given for both training and testing data sets in Fig. 9.

As can be seen in Fig. 9, the results of all GRNN models trained were compared and evaluated according to their performances in training and testing sets. The values of the E and CORR of R-I M2 GRNN model are higher than those of other models. In addition the value of R-I M2 GRNN model is also lower than that of other models. As a result, R-I M2 GRNN model is selected as the best fit forecasting model according to criteria of performance evaluation. In order to get a true and effective evaluation, the best fit model structure having two input variables has also been trained and tested by FFNN. The FFNN model having two input variables was trained and tested using the same non-transformed data set. The error backpragation algorithm and sigmoid activation function was used for the training and testing of FFNN model. The number of hidden layers and numbers of hidden neurons in hidden layer, the learning rate, the coefficient of momentum and epochs were selected by trial and error method during the training. Figure 10 shows the variation of the E, CORR and RMSE criteria with the number of the hidden neurons in hidden layer for testing data sets.

As can be seen in Fig. 10, the FNN model, which has five hidden neurons in hidden layer, has shown the best fit performance. The training parameters of the FFNN model such as, the learning rate (0.02), the coefficient of momentum (0.7) and epochs (2000) were selected by trial and error method during the training. The performances of R-I M2 GRNN and R-I M2 FFNN models are given for both training and testing sets in Table 5, Figs. 11 and 12.

Comparing the performances of GRNN and FFNN forecasting models, it can be seen that the value of the RMSE of the GRNN model is lower than FFNN model. In addition, the values of E and CORR of the GRNN model are also higher than FFNN model. It may be noted that a trial and error procedure has to be performed for FFNN model to develop the best network structure, while such a procedure is not required in developing a GRNN model. The results suggest that the GRNN method is superior to the FFNN method in the modeling and forecasting of the river flow.

5.2.3 Auto-regressive model

In the traditional analysis techniques, the data set must be divided to periodical component, trend component, internal dependent component and independent (random) components. Trend is the evidence of the increase or decrease of process parameters (mean and standard deviation) by time. It is understood that there is a periodical component when the parameters of the process show variation in a determined period. BOX-COX transformation was applied to the data to converge the data to normal distribution. The periodicity of the daily means and standard deviations were calculated by using Fourier series to arrange the periodicity in the data.

$$DNY(t) = \frac{DY(t) - \overline{DY}}{\sigma_{DY}} \tag{17}$$

where $DNY(t)$ is the normalized time series variable, $DY(t)$ is the original time series variable, $\overline{DY}$ is the mean of the original time series data and σ_{DY} is the standard deviation of the original time series data. AR (2) model, which includes input variables of

R-I M2 model, is used to compare the responses of the R-I M2 ANFIS, ANN models. The structure of AR model can be expressed by following Eq. (18);

$$Q(t) = \sum_{i=1}^{N} \alpha_i Q(t-i) + \varepsilon(t) \tag{18}$$

where, $Q(t)$ is the daily river flow, $Q(t-i)$ is the river flow at $(t-i)$ time, α is the auto-regressive parameter to be determined (i) is an index representing the order of AR model and $\varepsilon(t)$ is the random error. Once the estimates of the traditional time series model coefficients have been obtained using the training data set, the model can be validated by computing the performance statistics during both training and testing data sets.

5.2.4 Verification of forecasting models

The best fit R-I M2 ANFIS, GRNN and FFNN models are verified by verification data set including totally 731 daily river flow values at the time period 1998–2000 years. The performances of all methods for both testing and verification data sets are given in Table 6.

Comparing verification performances of ANFIS, GRNN and FFNN models, the value of RMSE of ANFIS model is lower than those of GRNN and FFNN model. On the other hand, the values of E and CORR of ANFIS model are also higher than those of GRNN and FFNN models. The results suggest that the ANFIS method is superior to the ANN methods in the modeling and forecasting of river flow. The comp Once the estimates of the traditional time series model coefficients have been obtained using the training data set, the model can be validated by computing the performance statistics during both training and testing data sets. Comparison of the verification results of models are demonstrated in Fig. 13.

6 Conclusions

In this study, applicability and capability of Artificial Intelligence techniques, ANFIS and ANN, for daily river forecasting was investigated. To illustrate the capability of ANFIS and ANN methods, Seyhan River, located in the south of Turkey, was chosen as a case study and estimation models having various input variables were established. The performances of the models and observations were compared and evaluated based on their performance in training and testing sets. The R-I M2 ANFIS model having two antecedent flow variables was selected as the best fit river forecasting model according to criteria of performance evaluation. The models were also trained and tested by GRNN and FFNN methods for the same set of data and results were reported to get more accurate and sensitive comparison. Comparing the results of training and testing of forecasting models, it can be seen that the value of the RMSE of ANFIS model is lower than those of ANN methods, GRNN and FFNN. The values of the E and CORR of ANFIS model are higher than those of GRNN and FFNN models. On the other hand, Comparing verification performances of ANFIS, GRNN and FFNN models, the value of RMSE of ANFIS model is also lower than those of GRNN and FFNN model. In addition, the values of E and CORR of ANFIS model are also higher than those of GRNN and FFNN models. The results suggest that the ANFIS method is superior to the ANN methods in the modeling and forecasting of river flow.

References

Arena, C., Cannarozzo, M., and Mazzola, M. R.: Multi-year drought frequency analysis at multiple sites by operational hydrology – A comparison of methods, Phys. Chem. Earth, 31, 1146–1163, 2006.

ASCE Task Committee.: Artificial neural networks in hydrology-II: Hydrologic applications, J. Hydrol. Eng., ASCE 5(2), 124–137, 2000.

Box, G. E. P. and Jenkins, G.: Time Series Analysis, Forecasting and Control, Holden-Day, San Francisco, CA, 1970.

BuHamra, S., Smaoui, N., and Gabr, M.: The Box–Jenkins analysis and neural networks: prediction and time series modeling, Appl. Math. Model., 27, 805–815, 2003.
Celikoglu, H. B.: Application of radial basis function and generalized regression neural networks in non-linear utility function specification for travel mode choice modeling, Math. Comput. Model., 44, 640–658, 2006.
Celikoglu, H. B. and Cigizoglu, H. K.: Public transportation trip flow modeling with generalized regression neural Networks, Adv. Eng. Software, 38, 71–79, 2007.
Chen, S. H., Lin, Y. H., Chang, L. C., and Chang, F. J.: The strategy of building a flood forecast model by neuro-fuzzy network, Hydrol. Processes, 20, 1525–1540, 2006.
Chang, F. J., Hu, H. F., and Chen, Y. C.: Counter propagation fuzzy–neural network for river flow reconstruction, Hydrol. Processes, 15, 219–232, 2001.
Chang, F. J., Chang, L. C., and Huang, H. L.: Real-time recurrent learning neural network for stream-flow forecasting, Hydrol. Processes, 16, 2577–2588, 2002.
Chang, F. J. and Chang, Y. T.: Adaptive neuro-fuzzy inference system for prediction of water level in reservoir, Adv. Water Resour., 29, 1–10, 2006.
Cigizoglu, H. K. and Alp, M.: Generalized regression neural network in modelling river sediment yield, Adv. Eng. Software, 37, 63–68, 2006.
Cigizoglu, H. K.: Generalized regression neural network in monthly flow forecasting, Civil Engineering and Environmental Systems, 22(2), 71–84, 2005.
Dawson, C. W., Harpham, C., Wilby, R. L., and Chen, Y.: Evaluation of artificial neural network techniques for flow forecasting in the River Yangtze, China, Hydrol. Earth Syst. Sci., 6, 619–626, 2002,
http://www.hydrol-earth-syst-sci.net/6/619/2002/.
Dibike, Y. B. and Solomatine D. P.: River Flow forecasting Using Artificial Neural Networks, Phys., Chem. Earth (B), 26, 1–7, 2001.
Fejer, B. C., Farley, D. T., Woodman, R. F., and Calderon, C.: Dependence of equatorial F-region vertical drift on season and solar cycle, Geophys. Res. Lett., 86, 215–218, 1981.
Fırat, M. and Güngör, M.: Estimation of the Suspended Concentration and Amount by using Artificial Neural Networks, IMO Technical Journal, 15(3), 3267–3282, 2004.
Fırat, M. and Güngör, M.: River Flow Estimation using Adaptive Neuro-Fuzzy inference System, Mathematics and Computers in Simulation, in press, http://www.sciencedirect.com/science/journal/03784754, 2007.
Firat, M.: Watershed modeling by adaptive Neuro- fuzzy inference system approach, Ph.D.

thesis, Pamukkale University, Turkey, (in Turkish), 2007.
Jain, A. and Kumar, A. M.: Hybrid neural network models for hydrologic time series forecasting, Appl. Soft Computing, 7, 585–592, 2007.
Jang, J. S. R, Sun, C. T., and Mizutani, E.: Neuro-Fuzzy and Soft Computing, PrenticeHall, ISBN 0-13-261066-3, 607 s., United States of America, 1997.
Kim, B., Lee, D. W., Parka, K. Y., Choi, S. R., and Choi, S.: Prediction of plasma etching using a randomized generalized regression neural network, Vacuum, 76, 37–43, 2004.
Komornik, J., Komornikova, M., Mesiar, R., Szökeova, D., and Szolgay, J.: Comparison of forecasting performance of nonlinear models of hydrological time series, Phys. Chem. Earth, 31, 1127–1145, 2006.
Liong, S. Y., Lim, W. H., Kojiri, T., and Hori, T.: Advance Flood forecasting for Flood stricken Bangladesh with a fuzzy reasoning method, Hydrol. Processes, 14, 431–448, 2000.
Mahabir, C., Hicks, F. E., and Fayek, A. R.: Application of fuzzy logic to the seasonal runoff, Hydrol. Processes, 17, 3749–3762, 2000.
Mohammadi, K., Eslami, H. R., and Kahawita, R.: Parameter estimation of an ARMA model for river flow forecasting using goal programming, J. Hydrol., 331, 293–299, 2006.
Nagy, H. M., Watanabe, K., and Hirano, M.: Prediction of Sediment Load concentration in Rivers using Artificial Neural Network Model, J. Hydrol. Eng., 128, 588–595, 2002.
Nayak, P. C., Sudheer K. P., and Ramasastri, K. S.: Fuzzy computing based rainfall-runoff model for real time flood forecasting, Hydrol. Process, 17, 3749–3762, 2004a.
Nayak, P. C., Sudheer, K. P., Ragan, D. M., and Ramasastri, K. S.: A Neuro Fuzzy computing technique for modeling hydrological time series, J. Hydrol., 29, 52–66, 2004b.
Owen, J. S., Eccles, B. J., Choo, B. S., and Woodings, M. A.: The application of auto–regressive time series modelling for the time–frequency analysis of civil engineering structures, Eng. Struct., 23, 521–536, 2001.
Ramadhas, A. S., Jayaraja, S., Muraleedharan, C., and Padmakumar, K.: Artificial neural networks used for the prediction of the cetane number of biodiesel, Renewable Energy, 31, 2524–2533, 2006.
Sajikumar, N. and Thandaveswara, B. S.: A non-linear rainfall–runoff model using an artificial neural network, J. Hydrol., 216, 32–55, 2000.
Sudheer, K. P. and Jain, A.: Explaining the internal behaviour of artificial neural network river flow models, Hydrol. Processes, 18, 833–844, 2004.
Tingsanchali, T. and Guatam, M. R.: Application of tank, NAM, ARMA and neural network

models to flood forecasting, Hydrol. Processes, 14, 1362–1376, 1999.
Thomas, H. A. and Fiering, M. B.: Mathematical synthesis of streamflow sequences for the analysis of river basin by simulation, in: Design of Water Resources Systems, edited by: Mass, A., Harvard University Press, Cambridge, MA, 459–493, 1962.
Toth, E., Brath, A., and Montanari, A.: Comparison of short-term rainfall prediction models for real-time flood forecasting, J. Hydrol., 239, 132–147, 2000.
Şen Z.: Fuzzy Logic and Foundation, ISBN: 9758509233, 172 p, Bilge Kültür Sanat Publisher, Istanbul, 2001.
Şen Z.: Artificial Neural Network, Water Foundation Publisher, Istanbul, 2004.
Şen, Z. and Altunkaynak, A.: A comparative fuzzy logic approach to runoff coefficient and runoff estimation, Hydrol. Processes, 20, 1993–2009, 2006.
Yevjevich, V.: Fluctuations of Wet and Dry Years, Part-I. Research Data Assembly and Mathematical Models, Hydrology Paper 1, Colorado State University, Fort Collins, CO, 1963.
Zhang, G. P.: Time series forecasting using a hybrid ARIMA and neural network model, Neurocomputing, 50, 159–175, 2003.

Table 1. The Statistical Parameters for data sets.

Data Set	Variable	$x_{\min}$	$x_{\max}$	$\bar{x}$	s_x	c_{sx}
Training/Testing (1987–1998)	$Q(t)$ (m^3/s)	54.00	912.00	147.93	110.26	2.26
Verification (1998–2000)	$Q(t)$ (m^3/s)	60.80	712.00	134.52	95.42	2.37

Table 2. The structure of the models for forecasting of river flow.

Model	Input structure	Output
R-I M1	$Q(t-1)$	$Q(t)$
R-I M2	$Q(t-1)Q(t-2)$	$Q(t)$
R-I M3	$Q(t-1)Q(t-2)Q(t-3)$	$Q(t)$
R-I M4	$Q(t-1)Q(t-2)Q(t-3)Q(t-4)$	$Q(t)$
R-I M5	$Q(t-1)Q(t-2)Q(t-3)Q(t-4)Q(t-5)$	$Q(t)$
R-I M6	$Q(t-1)Q(t-2)Q(t-3)Q(t-4)Q(t-5)Q(t-6)$	$Q(t)$
R-I M7	$Q(t-1)Q(t-2)Q(t-3)Q(t-4)Q(t-5)Q(t-6)Q(t-7)$	$Q(t)$

Table 3. The structure of the training and testing data sets.

Date of training set	Date of testing set	Date of verification set
1 Oct 1986–30 Sep 1994	1 Oct 1994–30 Sep 1998	1 Oct 1998–30 Sep 2000

Table 4. Comparison of the performances of the R-I M2 GRNN and FFNN models.

Model	Testing Data Set			Training Data Set		
	RMSE	E	CORR	RMSE	E	CORR
R-I M2 ANFIS	26.95	0.941	0.970	29.43	0.945	0.964

Table 5. Comparison of the performances of the R-I M2 GRNN and FFNN models.

Models	Testing Data Set			Training Data Set		
	RMSE	E	CORR	RMSE	E	CORR
R-I M2 GRNN	32.076	0.917	0.952	42.520	0.848	0.921
R-I M2 FFNN	43.830	0.845	0.924	48.475	0.803	0.900

Table 6. Comparison of the performances of the R-I M2 GRNN and FFNN models.

Models	Testing Data Set			Verification Data Set		
	RMSE	E	CORR	RMSE	E	CORR
R-I M2 ANFIS	26.950	0.941	0.970	33.972	0.873	0.935
R-I M2 GRNN	32.076	0.917	0.952	37.189	0.860	0.928
R-I M2 FFNN	43.830	0.845	0.924	43.595	0.808	0.899
R-I M2 AR(2)	38.420	0.840	0.928	39.344	0.823	0.914

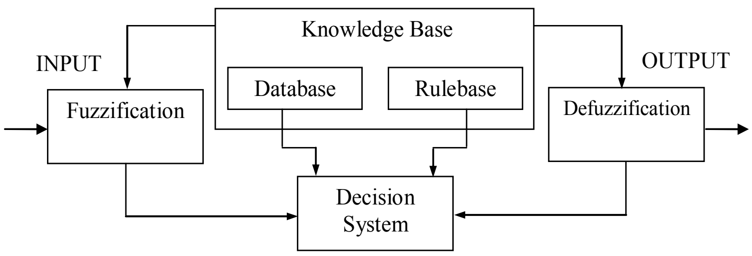

Fig. 1. The general structure of the fuzzy Inference System.

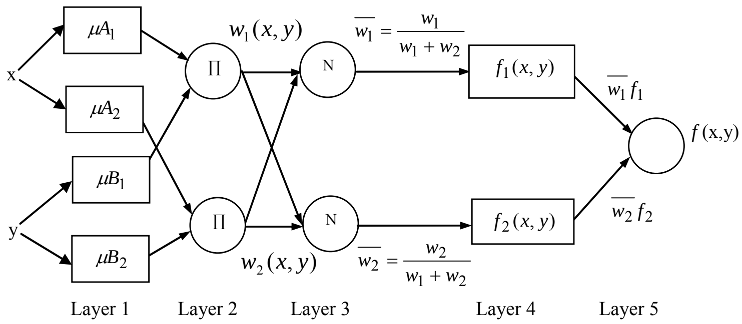

Fig. 2. The scheme of Adaptive Neuro-Fuzzy Inference System.

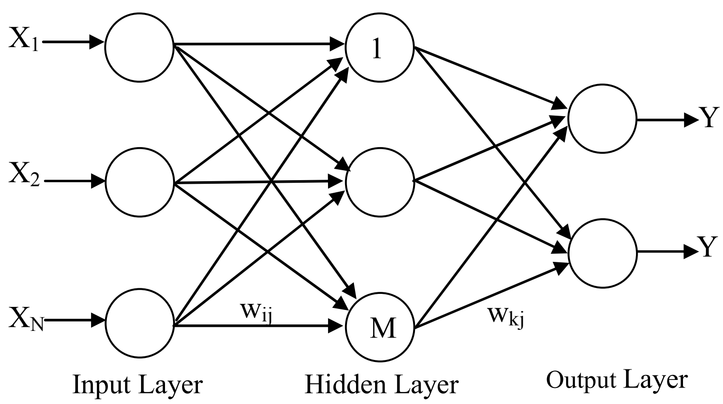

Fig. 3. General structure of a FFNN.

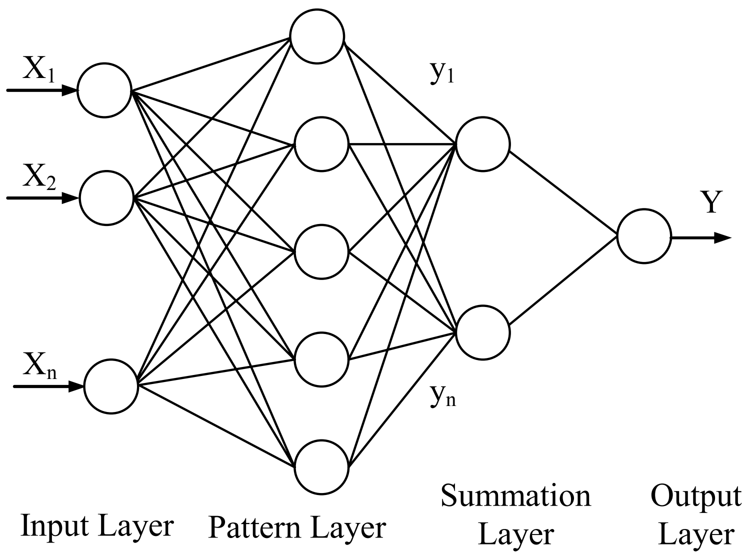

Fig. 4. The general structure of a GRNN.

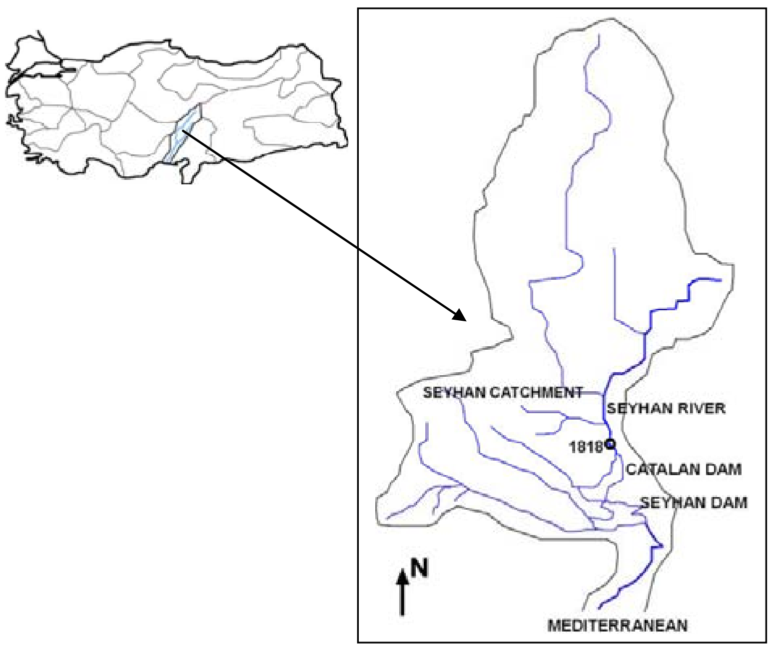

Fig. 5. The Seyhan River and its drainage area.

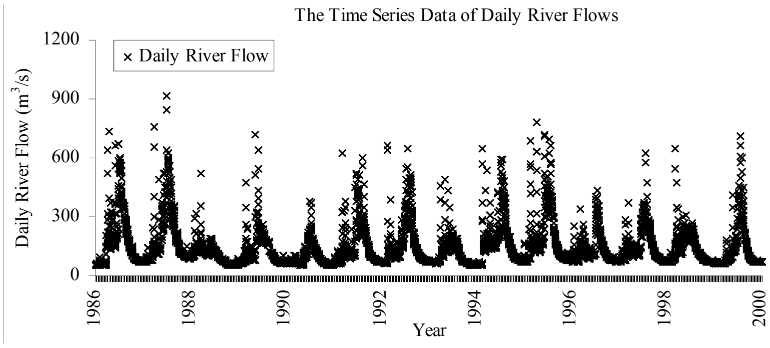

Fig. 6. The time series data of daily river flow.

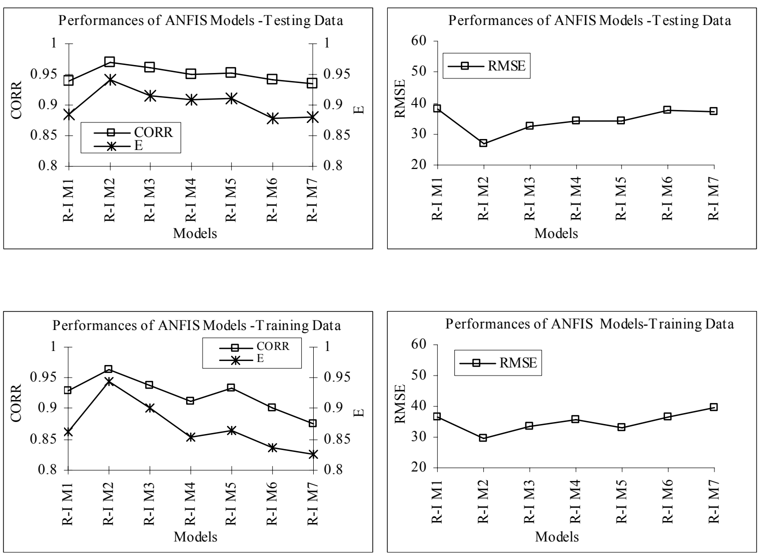

Fig. 7. The performances of ANFIS models.

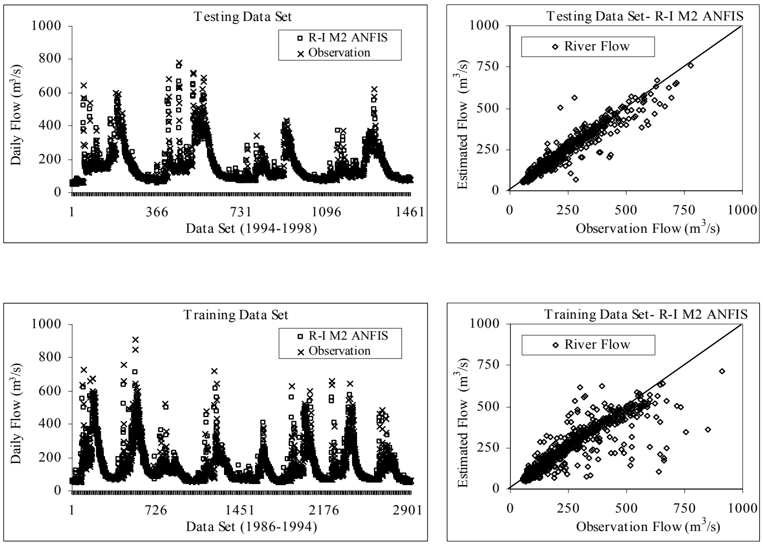

Fig. 8. The results of training and testing of the R-I 2 ANFIS model.

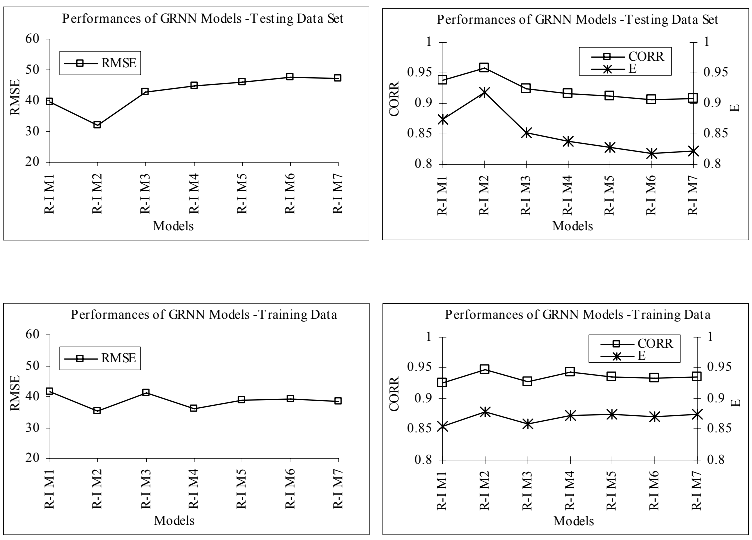

Fig. 9. The performances of GRNN models.

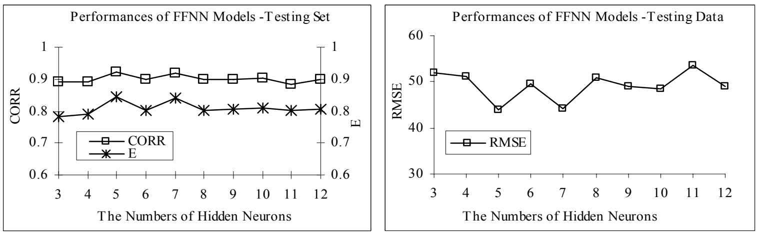

Fig. 10. The performances of FFNN model for various hidden neurons.

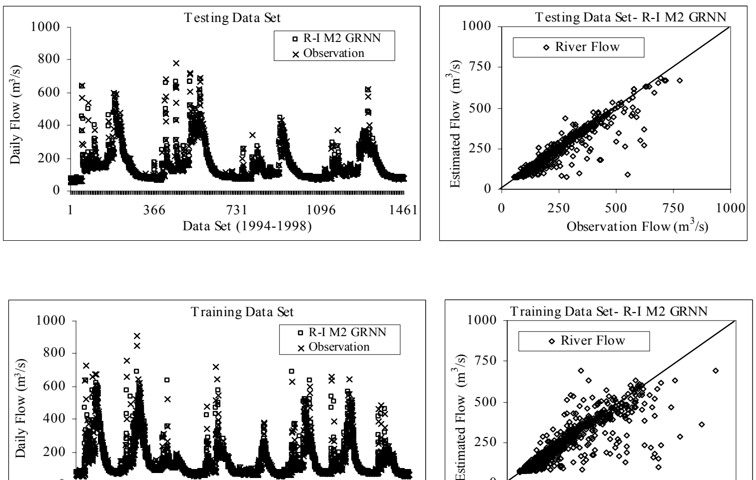

Fig. 11. Results of training and testing of R-I 2 GRNN models.

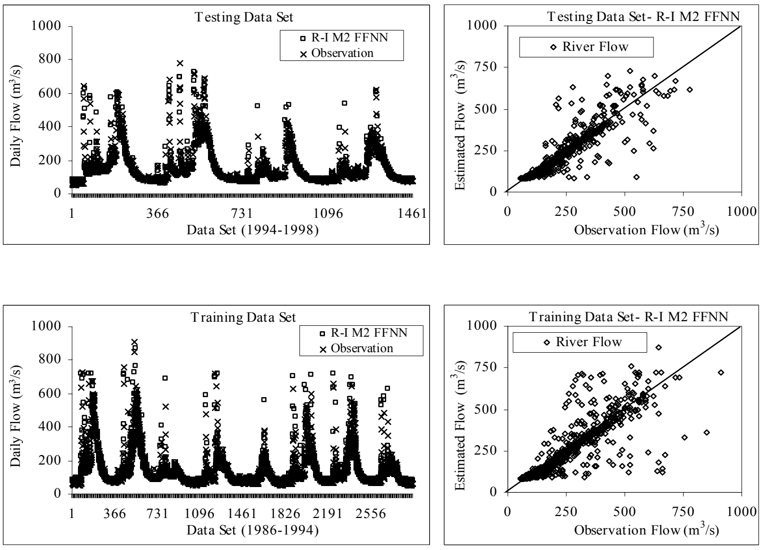

Fig. 12. Results of training and testing of R-I 2 FFNN models.

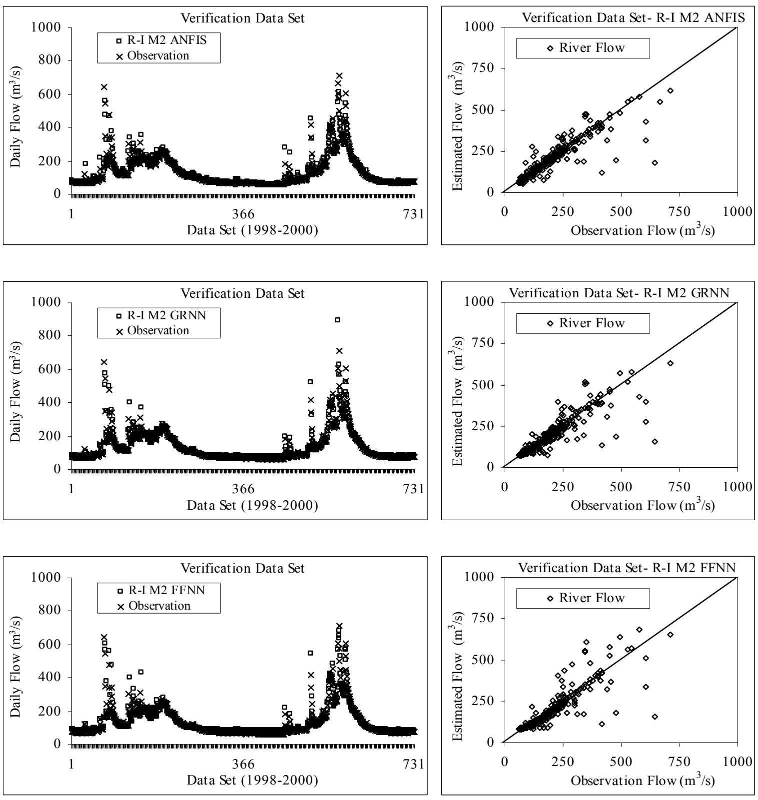

Fig. 13. Comparison of the verification results of ANFIS and ANN methods.