RAINFALL RUNOFF RELATIONSHIP USING NEURAL NETWORKS AND FUZZY LOGIC

[1]Dr.C.S.V. Subrahmanya Kumar [2]Dr.G.K.Viswanadh
[1]Professor, [2] Professor & OSD to VC
[1]Department of Civil Engineering [2]Department of Civil Engineering
[1]ACE Engineering College, Hyderabad, India, [2]J.N.T.U College of Engineering, Hyderabad, India

ABSTRACT
Rainfall-runoff models are used to describe the hydrological behavior of a catchment. The relationship between rainfall and runoff is known to be highly non- linear, time varying and spatially distributed. This relationship is important in dealing with water resources management schemes. Recently, soft computing techniques such as Artificial Neural Networks, Fuzzy Logic, Adaptive Neuro- Fuzzy Inference System have emerged to model the various hydrological processes. This study presents the application of Artificial Neural Networks and Fuzzy Logic to model rainfall- runoff for Osmansagar catchment, Hyderabad, India. To study the performance of the models, various statistical indices such as Threshold statistics, Average absolute relative error, Correlation coefficient, Mean square error, Nash coefficient of efficiency were estimated.. The Nash coefficients of efficiency of the ANN and Fuzzy model were found to be 95% and 92 % during training/ calibration and 91% and 96% during testing / validation. The correlation coefficients between the observed and computed series for both the models are 0.97, 0.96 respectively during training /calibration and 0.97, 0.99 respectively during testing/validation periods. The results indicate that ANN and Fuzzy logic can effectively be used to establish relationship between rainfall and runoff.
Key words: Rainfall, Runoff**,** Artificial Neural Networks, Fuzzy Logic

I.INTRODUCTION

Runoff prediction is one of the most important aspects in hydrology, useful in water resources development, planning and management. A wide variety of rainfall- runoff models have been developed and used for flood forecasting. The transformation from rainfall to basin runoff involves many hydrological components like initial soil moisture, evaporation, evapotranspiration, infiltration and so on. All these hydrological components are believed to be highly non-linear, time varying, spatially distributed and cannot be properly described by simple models. The various models available are statistical, conceptual and black box to model rainfall-runoff process. Recently, soft computing techniques such as fuzzy logic, Artificial Neural Networks, Adaptive Neuro-Fuzzy Inference System have emerged to model the various hydrological processes. Artificial neural networks (ANNs) have been proposed as black box models which are efficient tools for modeling and prediction in hydrology. ANNs are supposed to possess the capability to reproduce the unknown relationship existing between a set of input variables of the system and one or more output variables. An ANN is described as an information processing system that is composed of many nonlinear and densely interconnected processing elements or neurons. ANNs have proven to provide better solutions when applied to (i) complex systems that may be poorly described or understood, (ii) problems that deal with noise or involve pattern recognition and (iii) situations where input is incomplete or ambiguous by nature. Notable contributions in the field of hydrologic applications are French et al. 1992; Roger and Dowla 1994; Hsu et al. 1995; Tokar 1996.

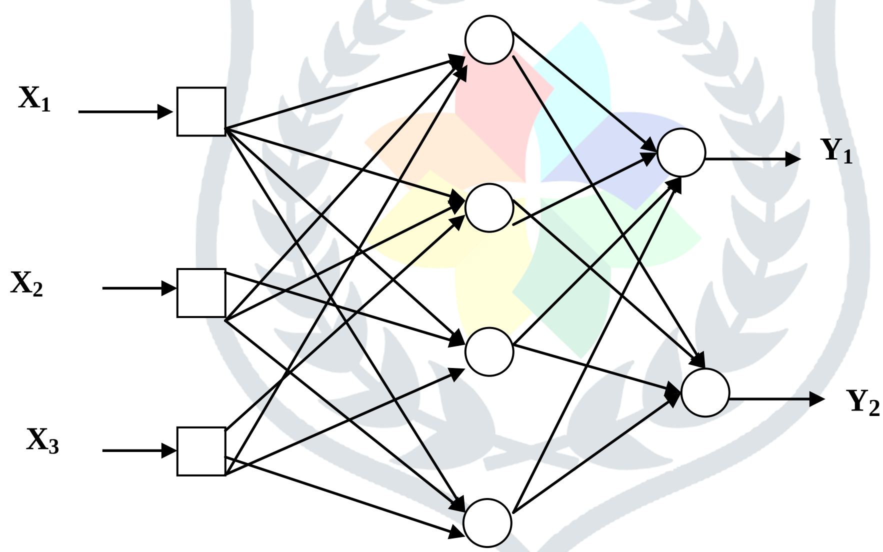
A fuzzy rule based modeling is a qualitative modeling scheme by which one describes system behavior using a natural language (Sugeno, 1993). In using a fuzzy logic based approach in modeling cause and effect, relationships are described verbally rather than using known governing physical relationships. In this methodology, the cause and effect relationships, can be established based on the observed trends. Therefore a detailed knowledge of the underlying physical processes is not required.

The main advantages the fuzzy application are that the fuzzy theory is more logical and scientific in describing the properties of an object. The most unique characteristic of this theory, is its operation on various membership functions (MF) instead of the crisp real values of the variables. Fuzzy logic is a useful tool in handling dynamic, imprecise, non linear and noisy data, especially when the underlying physical relationships are not fully understood. A few attempts have been made to implement such an approach in modeling hydrological processes. Notable among them are, Bardossy and Disse (1993) used Fuzzy concepts in modeling infiltration. See & Openshaw (1999, 2000) have demonstrated the applicability of hybrid models constructed by integrating conventional and Artificial intelligent approaches in river level and flood forecasting. P.C.Nayak et al. (2005) have used Neuro-Fuzzy concepts in flood forecasting. Abebe et al. (2000) have shown the applicability of fuzzy rule based models for reconstruction of missing precipitation events. In this paper a brief overview of ANN and Fuzzy logic is presented and the applicability of these methods to rainfall- runoff modeling is demonstrated for Osmansagar catchment, Hyderabad, A.P.

ARTIFICIAL NEURAL NETWORKS BASED MODELING APPROACH

An ANN is a massively parallel distributed information processing system that has certain performance characteristics resembling biological neural networks of the human brain (Haykin, 1994). ANN plays an important role in the field of hydrology, since the analysis of hydrologic systems deals with high degree of empiricism and approximation. As large number of publications have appeared in the recent past, to avoid duplication, the main concepts are highlighted in this section.

An ANN is composed of many non- linear and densely interconnected processing elements or neurons. In an ANN architecture, neurons are arranged in groups called layers. Each neuron in a layer operates in logical parallelism. Information is transmitted from one layer to another in serial operations (Hecht- Nielsen, 1991). A network can have one or several layers. The basic structure of a network usually consists of three layers- the input layer, where the data are introduced to the network, the hidden layer(s), where the data are processed, and the output layer, where the results for the given input are produced. The neurons in the hidden layer(s) are connected to the neurons of a neighbouring layer by weighing factors that can be adjusted during the model training process. The networks are organized according to training methods for specific applications. Fig. 1 illustrates a three layer artificial neural network The most distinctive characteristic of an ANN is its ability to learn from examples. Learning or training of an ANN model is a procedure by which ANN repeatedly processes a set of test data (input – output data pairs) , changing the values of its weights. In the training or learning process, the target output at each output node is compared with the network output, and the difference or error is minimized by adjusting the weights and biases through some training algorithm. In the present study, the training of ANNs was accomplished by Levenberg- Marquardt algorithm with back-propagation (LMBP). Back- propagation is the most commonly used supervised training algorithm in the multilayer feed forward networks.



. Fig. 1. A Typical Three Layer Feed forward ANN configuration

FUZZY LOGIC BASED MODELING APPROACH

Fuzzy logic modeling is based on the theory of fuzzy sets (Zadeh, 1965). Unlike in binary set, the boundary in a fuzzy set is not clearly defined and partial membership of elements is possible. Each element of the set is assigned a membership value which can be between 0 and 1. The function that assigns this value is referred to as the MF associated with the fuzzy set. The membership functions are of triangular shapes, trapezoidal shapes ,Gaussian functions etc. The use of these triangular and trapezoidal MF are shown in Fig.2 and Fig.3. The Gaussian function can increase the computational effort and provides no noticeable improvement in performance (Welstead, 1994).

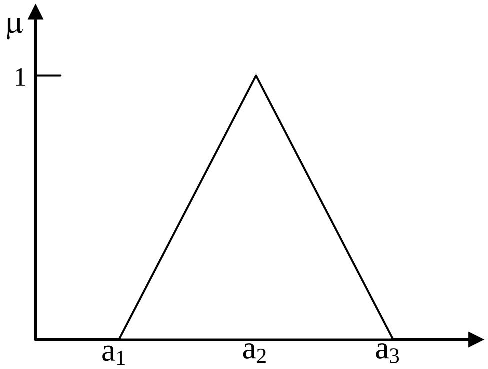


Fig.2 Membership function of a triangular fuzzy number

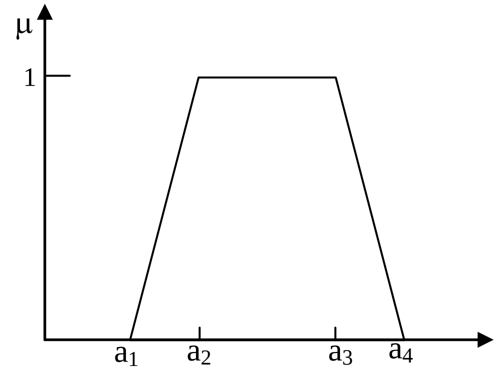


Fig.3 Membership function of a trapezoidal fuzzy number

Quantitative rules pertaining to physical science are normally derived by mathematical functions which, for every element in the domains assign a unique output value. There are also certain classes of rules applied to linguistic variables, which do not have unique numerical values.

In this paper the basis of fuzzy logic is to consider hydrological variables in a linguistically uncertain manner, in the forms of subgroups, each of which is labeled with successive word attachments such as "low", "medium", "high" etc. In this way, the variable is considered not as a global and numerical quantity but in partial groups which provide better room for the justification of sub- relationships between two or more variables on the basis of fuzzy words.

The basic structure of fuzzy modeling, commonly known as fuzzy inference system (FIS), is a rule based or knowledge system consisting of three conceptual components:

(i) a rule base that consists of a collection of fuzzy IF- THEN rules; (ii) a data base that defines the MF used in fuzzy rules ; and (iii) a reasoning mechanism that combines these rules into a mapping routine from the input to the outputs of the system, to derive a reasonable output conclusion.

The FIS can take either fuzzy sets or crisp values as input, but the overall outputs are always fuzzy sets. A FIS implements a non linear mapping from its input space to output space. This mapping is accomplished by a number of fuzzy IF – THEN rules from the rule base; each of these rules describes the local behavior of the mapping. The parameters of the IF – THEN rules are known as antecedents or premise and the output parameters are known as consequents in fuzzy modeling. The antecedents define a fuzzy region of the input space ,and the consequents specify the corresponding output. Hence the efficiency of the FIS depends on the number of IF- THEN rules used for computation.

The steps involved in the application of fuzzy logic to model the dynamic systems are fuzzification, logic decision and defuzzification. Fuzzification involves the identification of the impulse or the input and the response variables, the division of both input and output variables into different domains, and choosing a MF. Ideally, for 'n' domains and 'p' input variables there could be n^p different IF-THEN rules. Hence the domain partitioning has to be done carefully; otherwise it may lead to over parameterization.

Fuzzy Logic decision involves the design of the IF-THEN rules, and the determination of output fuzzy set. In case of rules on binary sets the conditions of the rule are either completely fulfilled or not, and in case of rules on fuzzy sets , partial fulfillment of the conditions is possible. The consequence of the actual rule for a given set of model variable values depends on the degree to which they fulfill the condition of the rule. The truth value corresponding to the fulfillment of the conditions of a rule for a given set of values of the arguments is referred to as the degree of fulfillment of the rule and has values in the interval [0,1]. This value is determined based on the membership value of each of the arguments and the logical connectors used (Bardossy and Duckstein, 1995).

Defuzzification involves the determination of crisp output from the fuzzy outputs of the IF-THEN inference system. The various defuzzification methods are max-membership value, centroid method, weighted average method, mean- max membership etc.

Normally in any approach , several rules are partially satisfied for a given set of model variables and hence there are several associated fuzzy consequences, which are combined into an overall fuzzy consequence . The combined rule consequence is then converted into a crisp real number using defuzzification techniques. The defuzzification technique commonly used is the mean defuzzification in which the centroid of the overall fuzzy consequence is taken as the crisp output of the fuzzy rule system.

In the applications of the fuzzy system in control and forecasting, there are mainly two approaches, the first one being the Mamdani approach and the other Takagi- Sugeno approach (Kruse et al, 1994). In the present study of rainfall - runoff modeling, Mamdani approach (Mamdani and Assilian, 1975), has been applied. In this methodology, there are three clear procedures, i.e., fuzzification, logic decision and defuzzification , as described earlier. In the Takgi _ Sugeno approach (Takagi and Sugeno, 1985), amalgamates the logic decision and defuzzification procedures into one composite procedure. It does not have an explicit defuzzification method.

STUDY AREA

Osmansagar catchment in Hyderabad, A.P, India, was selected to demonstrate the methodology to develop a relationship between maximum annual rainfall- runoff using an ANN and Fuzzy Logic. The catchment has a drainiage area of 750 sq km. The area is situated between 17.2^{o} – 17.5^{o} N latitude and 78.25^{o} to 78.35^{o}E longitude. The climate in the study area is semi arid and the average annual rainfall is around 800mm. The maximum annual rainfall- runoff data considered in this study is 60 years. The models were trained /calibrated and then tested or validated.

Fig: 4 A View of Osmansagar Catchment with Osmansagar Reservoir

ANN RAINFALL- RUNOFF MODEL

A three layer ANN model was employed to study the rainfall – runoff relationship. The number of neurons in the hidden layer is finalised by trial and error. In the trial process during training, the number of neurons in the hidden layer was varied between 1 and 5. The configuration that gives the minimum MSE and maximum correlation coefficient was selected for each of the options. Before applying the ANN, the input data was normalized to fall in the range of 0 and 1.

$$NV = (IV - MinV) / (MaxV - MinV) \quad (1)$$

Where NV is the normalized value, IV is the initial value of the variable, MinV is the smallest value of all inputs and MaxV is the greatest value of all the inputs. In the present study, the training of ANNs was accomplished by Levenberg- Marquardt algorithm with back- propagation (LMBP). Sigmoid function is used as the activation function in the network training process. The hidden neurons are optimized by trial and error and the final ANN architecture arrived consists of three hidden neurons. Once the ANN model has been successfully executed, model outputs in the form of normalized values are converted by inverse transformation.

FUZZY RAINFALL- RUNOFF MODEL

In this model, rainfall and runoff variables are considered as eight partial subgroups, namely, "low", "medium low", "medium", "medium high", "high low", "high medium", "high", "very high". A small number of fuzzy subgroups selection leads to unrepresentative prediction whereas large number imply unnecessary calculation. Fig.(5) shows the relative positions of the fuzzy words employed in this paper.

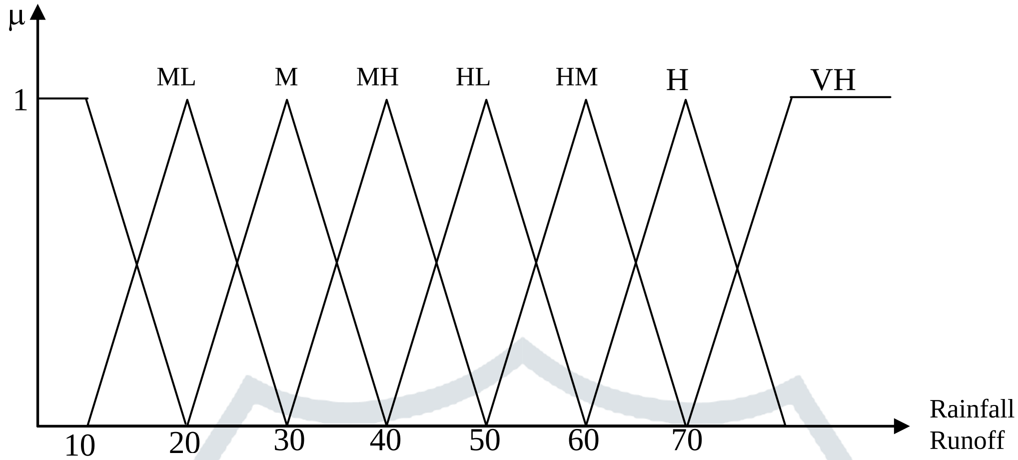


Fig. 5 Fuzzy subgroups of rainfall and runoff

Each one of the middle fuzzy words is shown as triangle with maximum membership degree at its apex. The most left and right fuzzy words, namely "low' and "very high" are presented as trapeziums. It is significant to consider that neighbouring fuzzy subsets interefere with each other providing fuzziness in the modeling. The following eight systems of rules were considered for the description of fuzzy rainfall- runoff modeling. These rules are as follows.

i) IF rainfall is L THEN runoff is L or
ii) IF rainfall is ML THEN runoff is ML or
iii) IF rainfall is M THEN runoff is M or
iv) IF rainfall is MH THEN runoff is MH or
v) IF rainfall is HL THEN runoff is HL or
vi) IF rainfall is HM THEN runoff is HM or
vii) IF rainfall is H THEN runoff is H or
viii) IF rainfall is VH THEN runoff is VH

Where L, ML, M, MH, HL, HM, H, VH are abbreviations for fuzzy subgroups of "low", "medium low", "medium", " medium high"," high low", "high medium", "high", and " very high", respectively.

In hydrological studies, it is necessary to deduce from these combined fuzzy subgroups a single value or aggregated result which is referred to as defuzzification.as mentioned earlier. The method of defuzzification used in this paper is centroid defuzzification method. In general, given a fuzzy set with membership degree defined on the interval [a,b] of variable 'x', the centroid defuzzification prediction 'x' is defined as,

$$\bar{x} = \frac{\int_a^b x\mu(x)dx}{\int_a^b \mu(x)dx} \qquad (2)$$

PERFORMANCE EVALUATION CRITERIA

The performance of the models resulting from both training / calibration and testing/ validation phases is evaluated using various measures of goodness-of-fit. The various statistical parameters such as Threshold statistics (TS_x), Correlation coefficient (R), Mean square error (MSE), Average absolute relative error (AARE), and Nash coefficient of efficiency (η) were evaluated for both the models .

Threshold statistics gives the distribution of errors whereas AARE gives average prediction error without any bias. MSE provide information about the predictive capabilities of the model. Correlation coefficient measures the degree to which two variables are related. Nash coefficient of efficiency and coefficient of correlation assess the efficiency of the models. The relationship of these performance indices are given below.

1) THRESHOLD STATISITCS (TS_X)

The threshold statistic is defined for a certain level of absolute relative error, say x% and is designated as TS_x . The TS_x may be defined as the percentage of data points forecasted for which absolute relative error is less than x%. Mathematically, it is represented as,

$$TS_x = (n/N) * 100 \quad (3)$$

where 'n' number of data points forecasted whose absolute relative error is less than *x*% and 'N' the total number of data points predicted. Threshold Statistics were computed for absolute relative error levels of 5%, 10%, 25%, 50%, and 100% in this study.

2) AVERAGE ABSOLUTE RELATIVE ERROR (AARE)

The average absolute relative error (AARE) is the average of the absolute values of the relative errors in forecasting certain number of data points. Mathematically, AARE is computed as,

$$RE(t) = \frac{y_p(t) - y_o(t)}{y_o(t)} * 100 \quad (4)$$

$$AARE = \frac{1}{n} \sum |RE(t)| \quad (5)$$

Where $y_o(t)$ is the observed runoff value at time t, $y_p(t)$ is the predicted runoff value at time t, RE(t) is the relative error in forecasting runoff at time t, N is the total number of data points forecasted. Lower AARE values indicate better effectiveness of model prediction .**3) CORRELATION COEFFICIENT (R)**

The correlation coefficient measures the strength of correlation between the computed output and observed output. Its value ranges between -1 and +1. The value close to 1.0 indicates good performance of the model.

$$R = \frac{[y_o(t) - y'_o \ (t)] * [y_p(t) - y'_p \ (t)]}{\sqrt{\sum[\, yo(t) - y'o(t)]2} * \sqrt{[y_p(t) - y'_p \ (t)]2}} \quad (6)$$

Where $y_o(t)$ and $y_p(t)$ are the observed and computed values of a variable and $y'_o(t)$, $y'_p(t)$ are the mean of the observed and computed values

4) NASH COEFFICIENT OF EFFICIENCY (η)

The Nash coefficient of efficiency compares the computed and the observed values of the variable and evaluates how far the model is able to explain the total variance in the data set. This is calculated using the following equation.

$$\eta = \frac{[y_o(t) - y'_o \ (t)]^2 - y_p(t) - y_o \ (t)]^2}{\sum[y_o(t) - y'_o \ (t)]^2} * 100 \quad (7)$$

Where $y_o'(t)$ is the mean of observed values and all other variables are same as explained earlier. Higher the value of efficiency better is the model performance. The efficiency above 90% indicates very satisfactory performance.

6) MEAN SQUARE ERROR (MSE)

The Mean square error(MSE) is computed as,

$$MSE = 1/N * \sum [\, y_p(t) - y_o(t) \,]^2 \quad (8)$$

Lower the value of MSE , better is the performance.

RESULTS & DISCUSSION :

In ANN approach, a standard back propagation algorithm is employed for training and the hidden neurons are optimized by trial and error. The final architecture consists of three hidden neurons. In fuzzy logic modeling, Mamdani approach was adopted to develop relationship between and runoff. Eight subgroups were formulated to model the process. Both the models are trained/calibrated using the same data sets. The various statistical parameters such as Threshold statistics (TS_x), Correlation coefficient (R) , Mean square error (MSE) , Average absolute relative error (AARE) and Nash coefficient of efficiency (E) were evaluated for both the models during Training/Calibration , Testing/Validation periods and the values are presented in Table.1 and Table 2.

Table.1 Statistical performance indices (Training/Calibration)

Model	TS5	TS10	TS25	TS50	TS100	R	MSE	AARE	η
ANN	27.5	65	92.5	95	100	0.973	20.31	10.71	0.95
Fuzzy	34.2	57.5	82.5	97.6	100	0.961	42.38	12.24	0.92

Table.2 Statistical performance indices (Testing/Validation)

Model	TS5	TS10	TS25	TS50	TS100	R	MSE	AARE	η
ANN	15.8	57.9	94.73	94.73	100	0.971	14.55	12.26	0.91
Fuzzy	63.2	84.2	94.7	100	100	0.989	6.54	6.8	0.96

The models developed in this study have Nash coefficient of efficiency more than 90% during Training/Calibration , Testing/Validation periods indicating very satisfactory performance. The AARE values in both the models is less than 12.5%, thus indicating better model prediction.

The graphical representation of runoff variation for both the models during training / calibration and testing / validation phases is presented in Fig.6 and Fig.7.

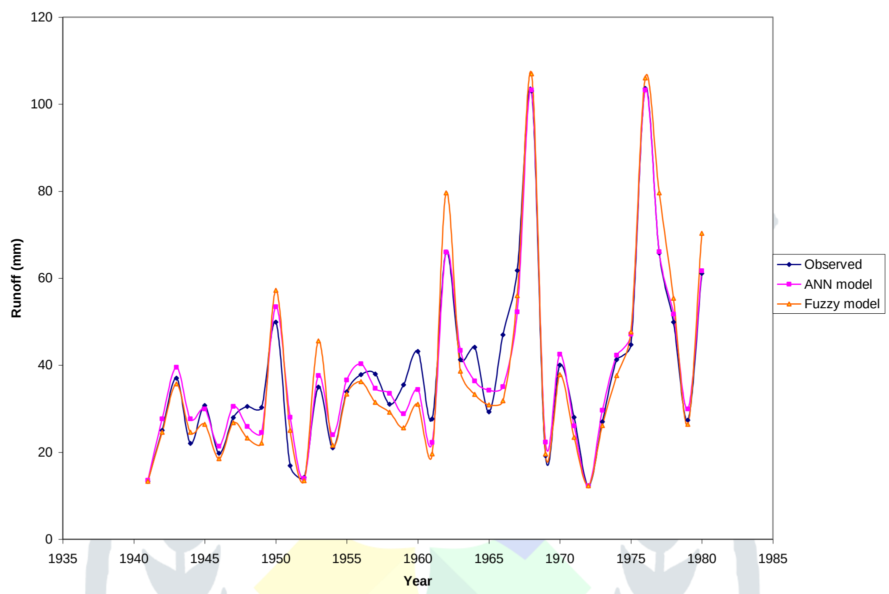


Fig.6 Variation of observed & computed runoff values (training/ calibration periods)

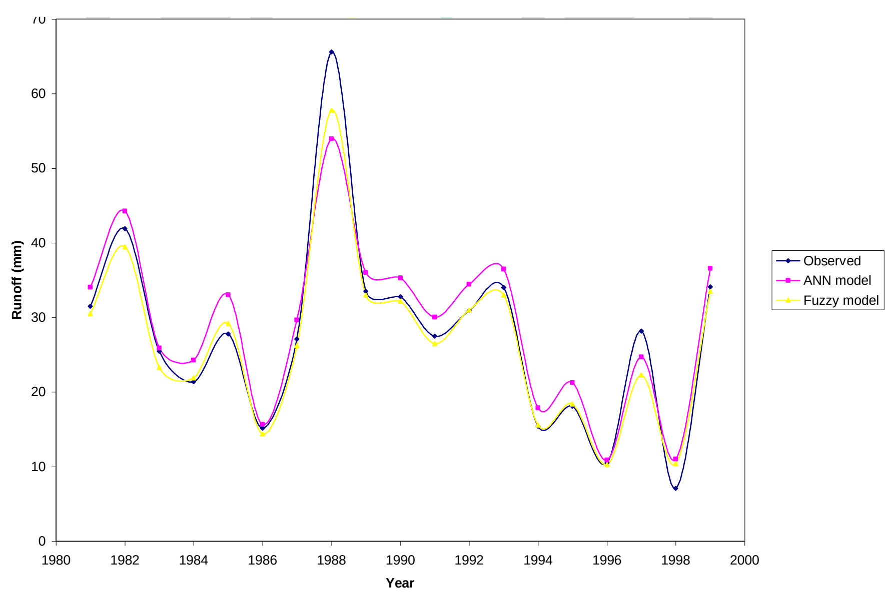


Fig.7 Variation of observed & computed runoff values (testing/ validation periods)

CONCLUSIONS

The applicability of ANN and Fuzzy logic based approaches has been illustrated to develop rainfall- runoff model in Osmansagar catchment. When applying such approaches, knowledge of the underlying physical processes is not prerequisite. Five different performance evaluation criteria were computed for both the models during both Training/Calibration , Testing/Validation periods. The performance of both the models in terms of performance evaluation criteria were found to be reasonably good. The results of the study are highly encouraging and suggest that soft computing techniques such as artificial neural networks and fuzzy logic based models can be used as effective tools for develop relationship between rainfall and runoff.

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