ANN AND FUZZY LOGIC IN HYDROLOGICAL MODELLING AND FLOW FORECASTING

A THESIS

Submitted in partial fulfilment of the requirements for the award of the degree

of

DOCTOR OF PHILOSOPHY

in

HYDROLOGY

By

ANIL KUMAR LOHANI

DEPARTMENT OF HYDROLOGY
INDIAN INSTITUTE OF TECHNOLOGY ROORKEE
ROORKEE-247 667 (INDIA)

DECEMBER, 2007

INDIAN INSTITUTE OF TECHNOLOGY ROORKEE
ROORKEE

CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in the thesis entitled **ANN AND FUZZY LOGIC IN HYDROLOGICAL MODELLING AND FLOW FORECASTING** in partial fulfilment of the requirements for the award of the degree of Doctor of Philosophy and submitted in the Department of Hydrology, Indian Institute of Technology Roorkee, Roorkee is an authentic record of my own work carried out during a period from July, 2002 to December, 2007 under the supervision of Dr. N.K. Goel, Professor & Head, Department of Hydrology, Indian Institute of Technology Roorkee and Dr. K.K.S. Bhatia, Scientist F, National Institute of Hydrology, Roorkee.

The matter in the thesis has not been submitted by me for the awards of any other degree of this or any other Institute.

(ANIL KUMAR LOHANI)

This is to certify that the above statement made by the candidate is correct to the best of our knowledge.

N. K. Goel
Professor & Head
Department of Hydrology
Indian Institute of Technology, Roorkee
Roorkee-247667

K. K. S. Bhatia
Scientist F
National Institute of Hydrology
Jal Vigyan Bhawan
Roorkee-247667

Date: December 12, 2007

The Ph.D. viva-voce Examination of Mr. Anil Kumar Lohani, Reseach Scholar, has been held on________________

Signature of Supervisors

Signature of External Examiner

ABSTRACT

During last few decades, scientific and engineering community has acquired extensive experience in developing and using soft computing techniques. Artificial neural networks (ANNs) and fuzzy logic based systems have emerged as potential soft computing techniques. In hydrological literature, a number of studies based on ANN have been reported. However, use of fuzzy logic is a relatively new area of research in the field of hydrology and water resources. In areas like stage-discharge relationship, stage-discharge-sediment relationship, rainfall-runoff modeling and hydrological forecasting etc., the fuzzy logic approach remains almost unattempted. Therefore, the present study has been undertaken to explore the potential of fuzzy logic based approaches in these areas and compare their performance with artificial neural network models. The objectives of the present study can be summarized as follows:

i. To develop ANN, fuzzy rule-based and regression models for stage-discharge relationships, and compare their performance in modeling hysteresis.

ii. To develop and test ANN, fuzzy rule-based and regression models for deriving stage-discharge-sediment relationships, and compare their performance for estimation of river sediment load.

iii. To investigate potential of ANN and fuzzy rule-based approaches for modeling rainfall-runoff relationships using different model structures and compare their performance with linear transfer function based models.

iv. To develop fuzzy rule-based models for flood forecasting in order to provide accurate enough forecasts for very short lead periods and compare their performance with ANN models.

River discharge is one of the most important inputs in various hydrological models and it is very important to estimate the discharge in a river reliably. Traditionally, hydrologists use regression equation based rating curves for flow estimates. However, this approach fails to model the non-linearity in the relationship and particularly in the cases where hysteresis is present in the data. Focusing on the ANN and fuzzy rule based models, different stage-discharge relationships were developed and compared using data of Jamtara, Manot, Mandla, Satarana and Hirday Nagar gauging stations lying in Narmada basin. Suitability of fuzzy modelling for substantially less data was also verified. Furthermore, hypothetical data for loop rating curve were used to explore hysteresis modelling capabilities of the models. The results show that the fuzzy modeling approach is superior than the conventional and artificial neural network (ANN) based approaches. Comparison of the models on hypothetical data set also reveals that the fuzzy logic based approach models the hysteresis effect (loop rating curve) more accurately than the ANN approach. In order to estimate bias of the fuzzy, ANN and curve fitting models for different output ranges the testing data sets of all the gauging sites were scaled so as to lie in the range of zero to one and than poled together. The average underestimation and overestimation errors were computed and plotted for different discharge ranges. The results indicates that fuzzy models provide a very accurate estimation in all ranges of river discharges in the study area.

Many practical problems in water resources require knowledge of the sediment load carried by the rivers or the load the rivers can carry without danger of aggragadation or degradation. Hence, the measurement of sediments being transported by a river is of vital interest for planning and designing of various water resources projects. The conventional methods available for sediment load estimation are largely empirical, with sediment rating curves being the most widely used. The rating relationships based on regression technique are generally not adequate in view of the inherent complexity of the problem. ANN and fuzzy logic algorithm were developed using available data of two gauging sites in the Narmada basin in India. The results suggests that the fuzzy model is able to capture the inherent nonlinearity in the river gauge, discharge and sediment relationship better than the ANN and conventional regression method, and is able to estimate sediment concentration in the rivers more accurately. A comparative analysis of predictive ability of these models in different ranges of flow indicates that the fuzzy modeling approach is slightly better than the ANN. The models were also compared to each other in estimation of total sediment load since it is important in water resources management. It was found that the curve fitting approach poorly estimates the total sediment load. While, the fuzzy logic model estimates were considerably better than the ANN model. Comparison of results showed that the fuzzy rule based model could be successfully applied for sediment concentration prediction as it significantly improves the magnitude of prediction accuracy.

More applications and research is needed to support the utility of ANN and fuzzy logic technique in the area of rainfall-runoff modelling and to help in establishing their full practical use in dealing the real world problems. Therefore, in this study ANN, fuzzy rule based and linear transfer function models were constructed for estimating catchment discharge by developing rainfall-runoff models for Manot sub-basin of Narmada River system. Different model structures were constructed by considering eleven combinations of input data vectors under four different categories: (i) only rainfall as input, (ii) rainfall and antecedent moisture content as input, (iii) rainfall and runoff as input, and (iv) rainfall, runoff and antecedent moisture content as input. The performance of the models were examined using the model performances indices such as: root mean square error, the correlation coefficient, model efficiency and volumetric error. The results indicate that the fuzzy logic based approach is capable of modelling the rainfall-runoff process more accurately in comparison to ANN and linear transfer function based modeling approaches.

Another fundamental aspect of many hydrological studies is the problem of forecasting the flow of a river in a given point of its course. Therefore, real time flood forecasting models were developed using ANN and fuzzy logic methods. Finally, to improve the real time forecasting of floods, a modified Takagi Sugeno fuzzy inference system termed as threshold subtractive clustering based Takagi Sugeno (TSC-T-S) fuzzy inference system has been introduced using the concept of rare and frequent hydrological situations. The proposed fuzzy inference systems provide an option of analyzing and computing cluster centers and membership functions for two different hydrological situations generally encountered in real time flood forecasting. Accurate forecasting of floods at shorter lead periods is a very important task for flood management in Narmada basin, Central India. The methodology has been tested on hypothetical data set and than applied for flood forecasting using the hourly rainfall and river flow data of upper

Narmada basin upto Mandla gauging site. The available rainfall-runoff data has been classified in frequent and rare events and suitable TSC-T-S fuzzy model structures were suggested for better forecasting of river flows. The performance of the model during calibration and validation was evaluated by model performance indices such as root mean square error, NS model efficiency and coefficient of correlation. A new performance index termed as peak percent threshold statistics was proposed to evaluate the performance of flood forecasting model. The developed model was tested for different lead periods using hourly rainfall and discharge data. Further, the proposed fuzzy model results were compared with artificial neural network (ANN) and subtractive clustering based T-S fuzzy model (SC-T-S fuzzy model). It was concluded from the study that the proposed TSC-T-S fuzzy model provide reasonably accurate forecast with sufficient lead-time.

The results presented in this thesis are highly promising and suggest that fuzzy modeling is a more versatile and improved alternative to ANN approach. Furthermore, fuzzy logic algorithm has the ability to describe the knowledge in a descriptive human-like manner in the form of simple rules using linguistic variables. The ANN and fuzzy logic methodology presented in this thesis can provide a promising solution to various hydrological modeling and forecasting problems. However, the analysis of the results reported in this work leave sufficient scope and opens new dimensions for further investigations, which could not be taken up owing to time constraint.

ACKNOWLEDGEMENTS

I would like to express my deep and sincere gratitude to my supervisors, Dr. N.K. Goel, Professor, Department of Hydrology, Indian Institute of Technology, Roorkee and Dr. K.K.S. Bhatia, Scientist F & Head Research Coordination Management Unit, National Institute of Hydrology, Roorkee. Their wide knowledge and logical way of thinking have been of great value for me. Their understanding, encouraging and personal guidance have provided a good basis for the present thesis.

I express my sincere gratitude to Prof. D.K. Srivastava, Prof. Ranvir Singh, Prof. U.C. Choubey, my Doctoral scrutiny committee members, Prof. B.S. Mathur, Prof. D.C. Singhal, Dr. M. Perumal, Dr. H. Joshi, Dr. D.S. Arya and Dr. Manoj Jain, Department of Hydrology for their constant encouragement and valuable suggestions during the course of this research work. I am also thankful to Mr. Ashok Basistha, Mr. H.G. Gundekar, Mr. B. Sahoo and other fellow research scholars for their interaction and association at Department of Hydrology, I.I.T., Roorkee.

I am also thankful to the Dr. K.D. Sharma, Director, N.I.H. for extending research facilities to carry out this work. I am grateful to Shri R.D. Singh, Scientist F & Head Surface Water Hydrology Division, NIH for his invaluable suggestions during the study and providing a stimulating and fun environment to learn and grow.

I warmly thank Shri Rakesh Kumar, Dr. Sanjay Kumar Jain, Dr. Avinash Agarwal, Mr. Jaiveer Tyagi, Mr. R.P. Pandey, Mr. Senthil Kumar, Dr. Sanjay Kumar and Dr. Manohar Arora, for their valuable advice and friendly help.

I must surely thank Shri N.K. Bhatnagar and Shri R.K. Nema for their sincere help in conducting the data collection.

I owe my loving thanks to my wife Geetu and my son Swapnil. Without their encouragement and understanding it would have been impossible for me to finish this work.

(Anil Kumar Lohani)

Place: Roorkee
Date: 12.12.2007

TABLE OF CONTENTS

CHAPTER	TITLE	PAGE No.

CHAPTER		TITLE	PAGE No.
	7.7	STUDY AREA AND DATA USED	158
	7.8	MODEL INPUT SELECTION	159
	7.9	RESULTS AND DISCUSSION	162
		7.9.1 ANN Model	162
		7.9.2 Fuzzy Model	162
		7.9.3 Modeling Hypothetical Data Set	168
		7.9.4 Modeling Observed Flow Data	172
		7.9.4.1 Forecasting at very short time (1 hour lead)	172
		7.9.4.2 Forecasting at >1 hour lead time	180
	7.10	SUMMARY AND CONCLUSIONS	194
8		**CONCLUSIONS AND SCOPE FOR FURTHER RESEARCH**	196
	8.1	CONCLUSIONS	196
	8.2	SCOPE FOR FURTHER RESEARCH	198
		REFERENCES	200

LIST OF TABLES

LIST OF FIGURES

CHAPTER-1

INTRODUCTION

1.1 GENERAL

Scientific and engineering community has acquired extensive experience in developing and using soft computing techniques during last few decades. Artificial neural networks (ANNs) and fuzzy logic based systems have emerged as potential soft computing techniques. These methods offer several advantages over conventional methods. Neural network technology has offered many promising results in the field of hydrology and water resources simulation. Fuzzy logic is another soft computing technique, which has very recently received attention in hydrology. Zadeh (1965) introduced the basic concepts of fuzzy logic with a new theory called "Fuzzy Sets" and opened a wide spectrum of applications in many fields. It is a paradigm for an alternative design methodology which can be applied in developing both linear and non-linear systems. The discipline of fuzzy logic, fuzzy systems, and fuzzy modeling has witnessed its greatest success in real-world automatic control applications, including subway control, autonomous robot navigation, auto-focus cameras, image analysis, and diagnosis systems. In the fuzzy logic approach the Boolean logic is extended to handle the concept of partial truth which implies that the truth takes a value between a completely true value and a completely false value.

A number of studies based on ANN have been reported in hydrological literature. Modelling in hydrology and water resources using fuzzy logic is a relatively new area of research although last decade has witnessed quite a few studies mainly in reservoir operation and water resources management. In other important areas like stage-discharge relationship, stage-discharge-sediment relationship, rainfall-runoff modeling and hydrological forecasting etc., the fuzzy logic approach remain almost rarely attempted. Therefore, the present study has been undertaken to explore the potential of fuzzy logic based approaches in these areas and compare their performance with artificial neural network models.

1.2 OBJECTIVES

The objectives of the present study can be summarized as follows:

i. To develop ANN, fuzzy rule-based and regression models for stage-discharge relationships, and compare their performance in modeling hysteresis.

ii. To develop and test ANN, fuzzy rule-based and regression models for deriving stage-discharge-sediment relationships, and compare their performance for estimation of river sediment load.

iii. To investigate potential of ANN and fuzzy rule-based approaches for modeling rainfall-runoff relationships using different model structures and compare their performance with linear transfer function based models.

iv. To develop fuzzy rule-based models for flood forecasting in order to provide accurate enough forecasts for very short lead periods and compare their performance with ANN models.

1.3 LAYOUT OF THE THESIS

The work has been organised in the form of eight chapters as follows:

Chapter-1: It introduces the research work, its need and briefly describes the objectives of the study.

Chapter-2: It presents a general review of the historical development of the techniques developed in the field of fuzzy logic and its practical application in various fields.

Chapter-3: It presents the details of the study area where fuzzy logic and ANN based approaches have been applied. SWDES and HYMOS software are used to deal with the primary and secondary processing of the available surface water data of the study areas.

Chapter-4: Focusing on the subtractive clustering based fuzzy rule based model, this chapter explores the effect of varying length of data in modeling stage-discharge relationship. Hypothetical data for loop rating curve have been used to explore hysteresis modelling capabilities of the fuzzy model. Furthermore, the fuzzy model results are compared with the ANN and regression models. The ANN and fuzzy modeling description, explained in meaningful and operative terms, is the foundation for the rest of the analyses carried out in this thesis.

Chapter-5: This chapter presents another application of fuzzy rule based model in development of stage-discharge-sediment relationship. Further, ANN and conventional regression methods are developed and compared with the results obtained from fuzzy models. Results of all the three models (ANN, fuzzy logic and regression) are also compared in predicting river sediment load.

Chapter 6: This chapter demonstrates a methods for constructing fuzzy rule based model for rainfall-runoff modeling. Results are compared with the models developed using ANN and linear transfer function based models.

Chapter 7: This chapter provides identification of a modified subtractive clustering method to develop fuzzy model for real time flood forecasting by considering frequent and rare events. The methodology is first tested on hypothetical data set and then applied to actual observed flow data. New performance evaluation criteria have also been developed and introduced for testing the forecasting capability of the model. Further, ANN models are developed and compared with the fuzzy models.

Chapter-8: This chapter summarises the findings of present study and scope for further research.

CHAPTER-2

REVIEW OF LITERATURE

2.1 INTRODUCTION

Over the past decade, there has been a widespread interest in the field of soft computing. Soft computing techniques such as artificial neural networks and fuzzy logic have rendered it possible to simulate human expertise in narrowly defined domain during the problem solving by integrating descriptive knowledge, procedural knowledge, and reasoning knowledge. Neural network technology has provided many highly promising results in the field of hydrology and water resources. Fuzzy logic based techniques have emerged as convincing alternatives to traditional procedures in the analysis and prediction of various real world phenomena. It has also opened up new avenues to hydrological modeling research. However, compared to ANNs, a few studies of fuzzy model were applied in hydrology and water resource forecasting. A comprehensive review of the application of ANN to hydrology can be found in the ASCE Task Committee (2000a, 2000b) and in Maier and Dandy (2000). It is extremely important and timely to review the development and applications of fuzzy logic based modeling approaches. Therefore, this chapter deals with the review of literature on historical development of fuzzy logic and its applications in various fields. Reviews pertaining to the relevant aspects of the study problems are presented in the respective chapters.

2.2 SOFT COMPUTING

The term soft computing was proposed by Zadeh (1994) and further explained by Kaynak and Rudas (1995) and Jang et al. (2002). Accordingly the soft computing is defined as: "A collection of methodologies that aim to exploit the tolerance for imprecision and uncertainty to achieve tractability, robustness, and low solution cost. Its principal constituents are fuzzy logic, neural networks, and probabilistic reasoning including genetic algorithms, chaos theory and parts of learning theory." Soft computing is likely to play an increasingly important role in many application areas, including software engineering. The role model for soft computing is the human mind. Each of these constituent methodologies has its own strength, as summarized in Table 2.1 (Jang et al., 2002). The interrelationship between these computing techniques is presented in Figure 2.1.

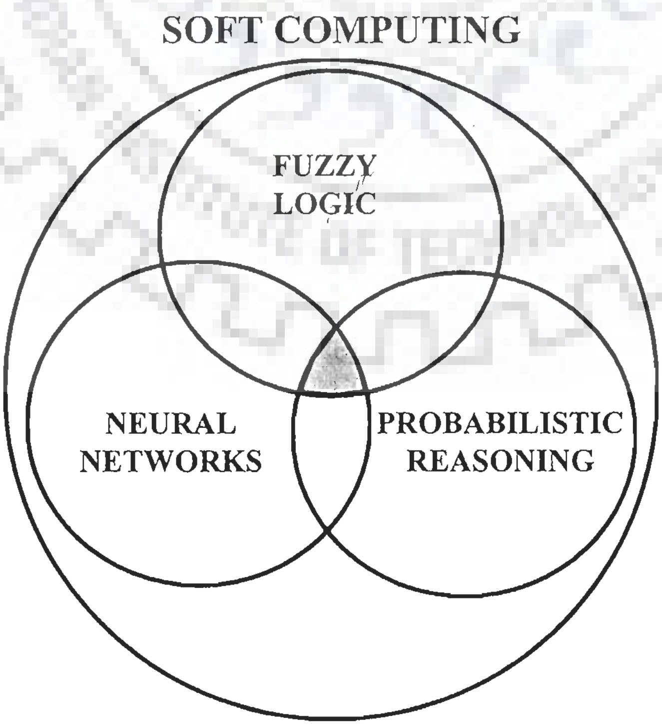

Figure 2.1: Intersection of Soft Computing Techniques

Table 2.1: Strength of soft computing methods

Methodology	Strength
ANN	Learning and adaptation
Fuzzy set theory	Knowledge representation via fuzzy if-then rules.
Genetic algorithm	Systematic random search.

Zadeh (1994) pointed out that these soft computing methods are complementary rather than competitive. Many researchers have proposed various forms of integration of fuzzy logic and neural networks (Lin and Lee, 1996). Further, Malhotra and Malhotra (1999) reported that the solutions derived from soft computing are generally more robust, flexible, and economical than those provided by hard computing.

2.3 HISTORICAL DEVELOPMENT OF FUZZY LOGIC

The classical logic is referred to as bivalent and statements are said to be either true or false. This is Aristotle's legacy. He stated that A and not- A was null, an empty set. This was considered to be philosophically correct for over 2000 years. However, it is also interesting to note that two centuries earlier Buddha held a very different world view. Rather than a clear cut perspective of a black and white world, he saw a world filled with contradictions. Buddha stated that a rose, could be a certain degree completely red, but also at the same time it was to a degree not red, i.e. the rose can be red and not red at the same time. This is in clear contradiction with an Aristotle World view (Gorman, 1998).

The idea of grade of membership, which is the concept that became the backbone of 'fuzzy set theory' and 'fuzzy logic' was introduced by Zadeh (1965) as an extension of

Boolean logic to enable modelling of uncertainty. According to him the essential characteristics of fuzzy logic are:

- In fuzzy logic, exact reasoning is viewed as a limiting case of approximate reasoning.
- In fuzzy logic, every thing is to a matter of degree.
- Any logic system can be fuzzified.
- In fuzzy logic, knowledge is interpreted as a collection of elastic or equivalent fuzzy constraints on a collection of variables.
- Inference is viewed as a process of propagation of elastic constraints.

Zadeh (1965) introduced fuzzy set theory as a mathematical discipline. Subsequently, to establish the mathematical framework for computing with fuzzy sets, a number of properties of fuzzy sets have been defined by various researchers. These included the definition of the height, support, core, α-cut, cardinality, normality and convexity of a fuzzy set. Definitions of set-theoretic operations such as union and intersection can be extended from ordinary set theory to fuzzy set. As membership degree are no longer restricted to {0,1} but can have any value in the interval {0,1}, these operations can not be uniquely defined.

Zadeh (1973) introduced the concept of a linguistic variable, that is, a variable whose values are words rather than numbers. The concept of a linguistic variable has played and is continuing to play a pivotal role in the development of fuzzy logic and its applications.

Mamdani and Assilian (1975) proposed a fuzzy inference system popularly known as Mamdani fuzzy inference system. The Mamdani fuzzy inference system was the first attempt to control a stream engine and boiler combination by a set of linguistic control rules obtained from experienced human operators. In Mamdani's application, two fuzzy inference systems were used as two controllers to generate the heat input to the boiler and throttle opening of the engine cylinder, respectively to regulate the stream pressure in the boiler and the speed of the engine. Since the plant takes only crisp values as inputs, therefore a defuzzifier has been used to convert a fuzzy set to a crisp value.

Tsukamoto (1979) proposed a fuzzy model in which the consequent of each fuzzy if then rule is represented by a fuzzy set with a monotonical membership function. As a result the inferred output of each rule is defined as a crisp value induced by the rule's firing strength. Since each rule infers a crisp output, the Tsukamoto fuzzy model aggregates each rule's output by the method of weighted average and thus avoids the time consuming process of defuzzification. The Tsukamoto fuzzy model is not used often since it is not as transparent as either the Mamdani or Sugeno fuzzy models.

Pedrycz (1984) presented the identification algorithm in fuzzy relational model. Fuzzy relational models, which can be regarded as a generalization of the linguistic model, encode associations between linguistic terms defined in the system's input and output domains by using fuzzy relations.

Takagi and Sugeno (1985) developed a model where the consequent is a crisp function of the antecedent variables rather than a fuzzy proposition. It can be seen as a combination of linguistic and mathematical regression modeling in the sense that the antecedents describe fuzzy regions in the input space in which the consequent functions are valid.

A complete treatment of fuzzy set properties and operations is given by Zimmermann (1996) and Klir and Yuan (1995). Table 2.2 summarizes the classes of aggregation operators for fuzzy sets:

Table 2.2: Classification of aggregation operators (Adopted from Zimmermann, 1996)

Sl. No.	Intersection Operators t-norms	Union Operators t-conorms	Averaging operators
1	Minimum algebraic product	Maximum algebraic product	
2	Bounded sum	Bounded difference	
3	Hamacher product	Hamacher sum	
4	Einstein product	Einstein sum	
5	Drastic product	Drastic sum	
6			Arithmetic mean, Geometric mean
7			Symmetric summation and difference
8	Hamacher intersection operators	Hamacher union operators	
9	Yager intersection operators	Yager union operators	
10	Dubois intersection operators	Dubois union operators	
11			"fuzzy and", "fuzzy or" compensatory and, convex combination of maximum and minimum, or algebraic product and algebraic sum

Jang (1993) proposed a class of adaptive networks that are functionally equivalent to fuzzy inference systems. The proposed architecture is referred to as ANFIS which stands for Adaptive Network based Fuzzy Inference System or semantically equivalently, Adaptive Neuro Fuzzy Inference System. The proposed scheme also described how to decompose the parameter set to facilitate the hybrid learning rule for ANFIS architectures representing both the Sugeno and Tsukamoto fuzzy models. It was also demonstrate that under certain minor constraints, the radial basis function network (RBFN) is functionally equivalent to the ANFIS architecture for the Sugeno fuzzy model. The effectiveness of ANFIS with the hybrid learning rule was tested through four simulation examples: (i) modeling of two input nonlinear function, (ii) modeling of three input nonlinear function, (iii) on line identification of control system, and (iv) predicting chaotic time series.

Chiu (1994) presented an efficient method for estimating cluster centers of numerical data. This method can be used to determine the number of clusters and their initial values for initializing iterative optimization-based clustering algorithm. When combined with linear least squares estimation, it provides an extremely fast and accurate method for identifying fuzzy models. Further, Mathworks (1994) introduced "The Fuzzy Logic Toolbox" for MATLAB as an add-on component to MATLAB in 1994 (MathWorks, 1994).

Jang and Mizutani (1996) presented the results of applying the Levenberg-Marquardt method, a popular nonlinear least squares method, to the ANFIS architecture. Through empirical studies, they discussed the strength and weakness of using such an efficient nonlinear regression techniques for neuro fuzzy modeling and explained the trade-offs between mapping precision and membership function interpretability. Although the Levenberg-Marquardt method can achieve a better mapping precisions, it also evolves the membership functions to an extent such that the linguistic interpretability of the final membership functions become quite week. They referred to this situation as the dilemma between precision and interpretability.

Zadeh (1998) mentioned that the status of fuzzy logic in 1998 is vastly different from what it was in 1978. He further stated that the mathematical foundations of fuzzy logic are well established; the basic theory is in place; the impact of fuzzy logic on the basic sources and especially on mathematics, physics and chemistry is growing in visibility and importance; and fuzzy logic based applications are extending in a wide variety of directions.

Chen et al. (2000) proposed a new scheme to estimate the membership values for fuzzy set. The scheme takes input from empirical experimental data which reflects the expert's knowledge on the relative degree of belonging of the members. First, they suggested an alternative (indirect) index for the expert(s) to submit. The index reflects the expert's assessment on the comparison of the degree belonging of each pair of elements. Second, based on the raw data which is generated via the use of the index, they proposed an optimization framework for calibration. It is then suggested that the membership values of the fuzzy set are the solution of this optimization problem.

Abonyi et al. (2002) introduced a new clustering algorithm, that can easily be represented by an interpretable Takagi-Sugeno fuzzy model. Similar to other fuzzy clustering algoriths, the proposed "modified Gath-Geva algorithm" is employed in search of clusters. This new technique was demonstrated on the benchmark nonlinear processes. It was found that the proposed technique improves the interpretability of the model.

Angelov (2004) developed and tested a recursive approach for adaptation of fuzzy rule-based model. Cluster centers calculated using on-line clustering of the input–output data with a recursively calculated spatial proximity measure are then used as prototypes of the centres of the fuzzy rules. The recursive nature of the algorithm, used to design an evolving fuzzy rule-base in on-line mode, adapts to the variations of the data pattern. It is reported that the proposed algorithm is instrumental for on-line identification of Takagi–Sugeno models, exploiting their dual nature and combined with the recursive modified weighted least squares estimation of the parameters of the consequent part of the model. Furthermore, the resulting fuzzy rule-based models have high degree of transparency, compact form, and computational efficiency and making them strongly competitive candidates for on-line modelling, estimation and control in comparison with the neural networks, polynomial and regression models.

Table 2.3 describes the history of fuzzy logic after its initiation by Zadeh in 1965. It is incomprehensive and includes just some events but can be used for illustration of the fuzzy logic development.

Table 2.3: Brief history of development and practical applications of fuzzy logic

Year	Development and applications of Fuzzy Logic
1965	Concept of fuzzy sets theory by Lotfi Zadeh (USA)
1966	Fuzzy logic (P. Marinos, Bell Labs.)
1972	First working group on fuzzy systems in Japan by Toshiro Terano Fuzzy Measure (M. Sugeno, TIT)
1973	Paper about Fuzzy algorithm by Zadeh (USA)
1974	Steam engine control by Ebrahim Mamdani (UK)
1977	First Fuzzy expert system for loan applicant evaluation by Hans Zimmerman (Germany).
1979	Hitachi was developing a new, automatic train for the Sapporo subway. Fuji Electric applied fuzzy logic in waste water treatment plant.
1980	Cement kiln control by F.L. Smith & Co. - Lauritz P. Holmblad (Denmark) – the first permanent industrial application. Fuzzy logic chess and backgammon program – Hans Berliner (USA)
1981	Expert System “EXPERT” for Rheumatology, Ophtalmology (Weiss, Kulikowski)

Year	Development and applications of Fuzzy Logic
1982	Expert System "SPERIL" for Earthquake Engineering (Ishizuka et al.)
1982	Control of cement kilns (Holmblad and Østergaard)
1984	Water treatment (chemical injection) control (Japan) Subway Sendai Transportation system control (Japan)
1985	First fuzzy chip developed by Masaki Togai and Hiroyuke Watanabe in Bell Labs (USA) Takage-Sugeno Fuzzy Model
1985	Expert System "CADIAG-2" for Internal medicine (Adlassnig et al.)
1985	Automatic train operation (Yasunobu and Miyamoto)
1986	Fuzzy expert system for diagnosis illnesses in Omron (Japan)
1987	Container crank control , Tunnel excavation , Soldering robot , Automated aircraft vehicle landing , Second IFSA Conference in Tokyo , Togai Infra Logic Inc. – first fuzzy company in Irvine (USA)
1987	Expert System "FAULT" for Financial Accounting (Whalen et al.)
1988	Kiln control by Yokogawa First dedicated fuzzy controller sold – Omron (Japan)
1988	Expert System "OPAL" for Job shop scheduling (Bensana et al.)
1988	Expert System "EMERGE" for Chest pain analysis (Hudson, Cohen)
1989	Creation of Laboratory for International Fuzzy Engineering Research (LIFE) in Japan First Fuzzy Logic Air Conditioner
1989	Expert System "ESP" for Strategic planning (Zimmermann)
1990	Fuzzy TV set by Sony (Japan) Fuzzy electronic eye by Fujitsu (Japan) Fuzzy logic systems institute (FLSI) by Takeshi Yamakawa (Japan) Intelligent system control laboratory in Siemens (Germany)

Year	Development and applications of Fuzzy Logic
1991	Fuzzy AI Promotion Centre (Japan) Educational kit by Motorola (USA)
1993	Adaptive neuro fuzzy inference system (ANFIS)
1993	Traffic systems (Hellendoorn)
1994	Subtractive Clustering based TS fuzzy model
1994	Fuzzy Logic Toolbox in MATLAB
1996	Use of Levenberg-Marquardt method in ANFIS
2004	Recursive approach for adaptation of fuzzy rule-based model

Source: Reznik, 1997; Zimmermann (1996) and Babuska (2001)

2.4 CONCLUDING REMARKS

From the above review it is evident that 'Soft Computing' techniques in various forms are moving forward to model highly intricate systems. The mathematical foundation of fuzzy logic is well established. Further, the fuzzy logic approach has been tested, evaluated and applied in the field of signal processing and in various other areas as it suited to complex non linear models. Researchers have only begun evaluating the potential of fuzzy logic approach in hydrologic modeling studies. Review of literature on recent trends of gauge-discharge modeling, gauge-discharge-sediment modeling, rainfall-runoff modeling and flood forecasting using ANN and fuzzy rule based methods are presented in the respective chapters.

CHAPTER 3

STUDY AREA AND DATA USED

3.1 INTRODUCTION

Various methods/models developed in the study have been applied to the Narmada river basin. The river Narmada is the fifth largest river of India and the largest west flowing river in peninsular India. Hydrological data collected from various agencies for this study have been computerized using SWDES software developed by the DHV consultants under India Hydrology Project Phase-I (1996-2002). Further, the hydrological time series data have been processed using HYMOS Software Package (HYMOS, 2001). For the processing of the spatial and location specific data, digitization has been carried out manually. The conversion process has been checked by GIS software Integrated Land and Water Information System (ILWIS) by spatial data overlapping and comparing with the original traces. The map layers of spatial data alongwith location of stations were transferred to HYMOS software for further processing and analysis of hydrological data. The processed hydrological data of the study areas have been used for the development of hydrological models discussed and presented in chapters 4 to 7. This chapter presents the description of study area, data collected and the methodology adopted in validation and processing of hydrological data.

3.2 STUDY AREA

The Narmada river basin is bounded on the north by the Vindhyas, on the east by the Maikala range on the south by the Satpuras and on the west by the Arabian Sea. Most of the basin is at an elevation of less than 500 meters above mean sea level. A small area around Pachmarhi is at a height of more than 1000 meters above mean sea level. The Narmada basin extends over an area of 98,796 sq. km. and lies between longitudes 72° 32' E to 81° 45'E and latitudes 21° 20' N to 23° 45'N. Figure 3.1 shows the map of the Narmada river basin.

The Narmada river rises in the Amarkantak Plateau of Maikala range in the Shahdol district of Madhya Pradesh at an elevation of 1057 meters above mean sea level. The river travels a distance of 1312 km before it falls into Gulf of Cambay in the Arabian Sea near Bharuch in Gujarat. The first 1079 km are in Madhya Pradesh. In the next length of 35 km, the river forms the boundary between the States of Madhya Pradesh and Maharashtra. Again, in the next length of 39 km, it forms the boundary between Maharashtra and Gujarat. The last length of 159 km. lies in Gujarat. The river has 41 tributaries of which 22 are on the left bank and 19 on the right.

The climate of the basin is humid tropical ranging from sub-humid in the east to semi-arid in the west with pockets of humid or per humid climates around higher hill reaches. The normal annual rainfall for the basin works out to 1,178 mm. South west monsoon is the principal rainy season accounting for nearly 90% of the annual rainfall. About 60% of the annual rainfall is received during July and August months. The Narmada basin consists mainly of black soils and the different varieties are deep black soil, medium black soil and shallow black soil. In addition mixed red and black soil, red and yellow soil and skeletal soil are also observed in pockets.

3.2.1 Hydrometeorological Data Observation Network

The number of raingauge stations in the basin was 21 in 1891 which has risen to 205 stations by 1980. Of these nearly 120 raingauge stations have data for more than 40 years. There are about 50 self recording raingauge stations (SRRG), maintained by either India Meteorological Department or other agencies like the flood forecasting division of Central Water Commission, State Irrigation Departments, etc. India Meteorological Department is maintaining class II or class I observatories at 18 locations in and around Narmada basin where the observations of dew point, temperature are made twice a day at 0300 GMT (0830 IST) and 1200 GMT (1730 IST). Systematic observations of gauge and discharge were started in Narmada basin only in 1947 by the then Central Water Ways, Irrigation and Navigation Commission.

3.2.2 Data Collection

Hydrometeorological and hydrological data of upper Narmada basin have been collected from Water Resources Department, Bhopal (M.P.); Narmada Control Authority, Indore; Chief Engineer, Narmada Basin, Central Water Commission, Bhopal and India Meteorological Department. Daily and hourly rainfall, gauge/discharge and other meteorological data have been collected from above departments. Further, daily values of sediment concentration data have also been collected. Rainfall data are received as a discrete time series on daily basis from above mentioned departments. The hydrometeorological data used in study are given in Table 3.1

Table 3.1: Inventory of data used in study

Sl. No	Station	Data Type	Frequency	Period
1	Jamtara	Gauge	Hourly	1991-1995
2	Manot	Gauge	Hourly	1989-1998
3	Mandla	Gauge	Hourly	1991-1998
4	Satarana	Gauge	Hourly	1989-1993
5	Hriday Nagar	Gauge	Hourly	1989-1993
6	Jamtara	Discharge & Sediment	Daily	1989-1993
7	Manot	Discharge & Sediment	Daily	1989-1993
8	Mandla	Discharge & Sediment	Daily	1989-1993
9	Satarana	Discharge & Sediment	Daily	1989-1993
10	Hriday Nagar	Discharge & Sediment	Daily	1989-1993
11	Narayanganj	Rainfall	Daily	1993-1998
12	Bichhia	Rainfall	Daily	1993-1998
13	Baihar	Rainfall	Daily	1993-1998
14	Palhera	Rainfall	Daily	1993-1998
15	Manot	Rainfall	Daily	1993-1998
16	Gondia	Rainfall	Daily	1993-1998
17	Nimpur	Rainfall	Daily	1993-1998
18	Jamtara	Rainfall	Hourly	1991-1995
19	Dindori	Rainfall	Hourly	1991-1995
20	Malankhand	Rainfall	Hourly	1991-1995

3.3 HYDROLOGICAL DATA PROCESSING

HYMOS is an information system for storage, processing and presentation of hydrological and environmental data (HYMOS, 2001). It combines an efficient database structure with powerful tools for data entry, validation, completion, analysis, retrieval and presentation. The HYMOS data base is time series oriented with common facilities for spatial analysis. In combination with a GIS for comprehensive geographical data analysis, it covers all data storage and processing requirements for planning, design and operation of water management system.

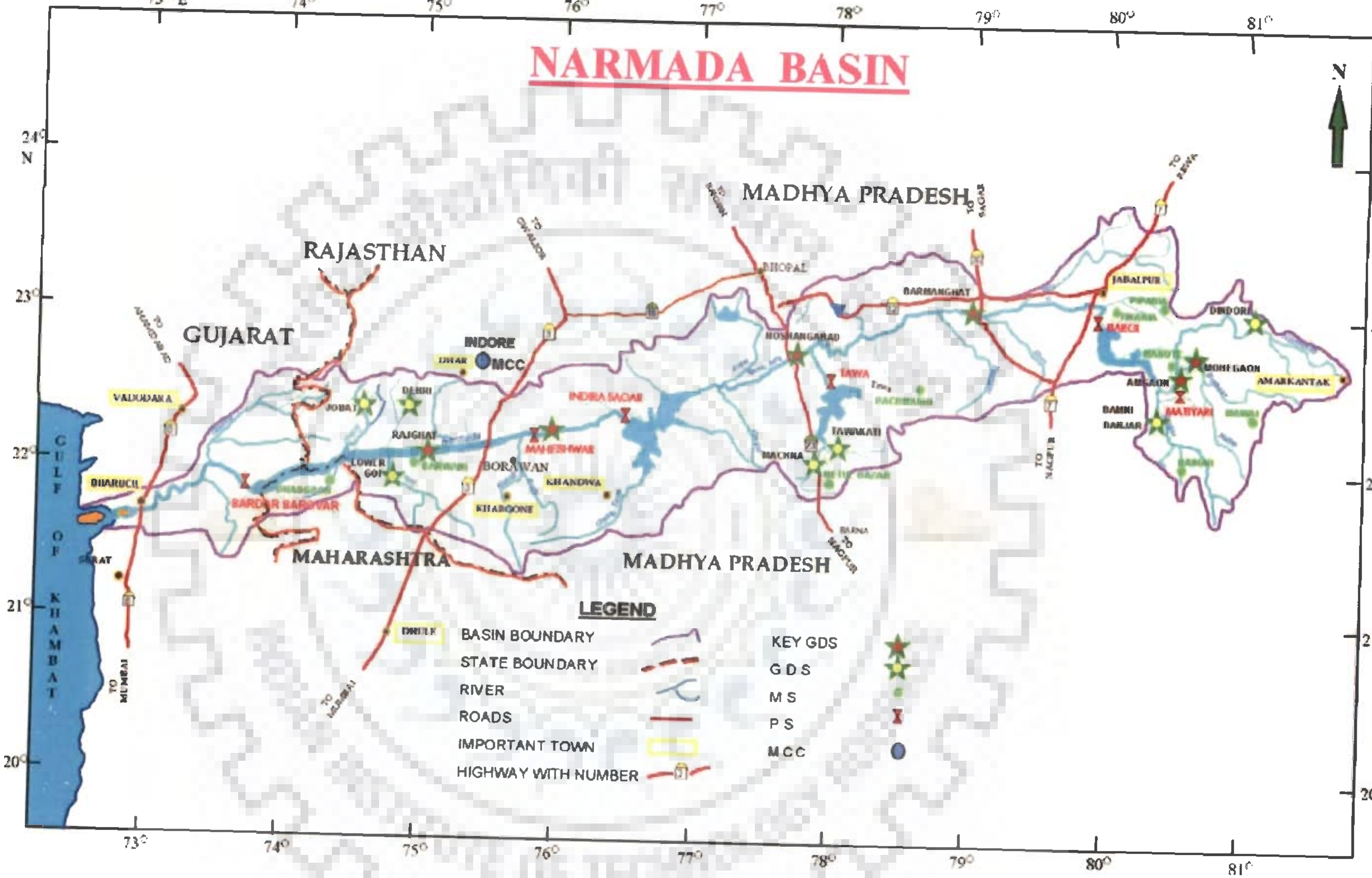

Figure 3.1: Index Map of Narmada Basin

Various physical characteristics of the study areas have been derived from Geograhical Information System (GIS) software Integrated Land and Water Information System (ILWIS) and stored in the HYMOS. Such geographical data have been organised in different map layers so as to make it possible to use one or more such layers at any time. Time series surface water data of the study area were first entered in Surface Water Data Entry System (SWDES) software and then exported to HYMOS. Various operations carried out for processing of rainfall, gauge and discharge data of the study area are broadly classified as primary and secondary data validation.

3.3.1 Primary Validation of Data

Preliminary processing and scrutiny of the data is an essential task before the analysis of observed data. The preliminary processing includes a number of operations on raw data viz.: verification, valid status, reasonable report, quality of data, checking against data limits and warning levels, adjustment of records. Primary processing of available hydrological data of the study areas has been carried out using the checks/operations available in SWDES and HYMOS. During the primary validation various spurious errors and entries on wrong date were corrected.

3.3.2 Secondary Validation of Data

Specific tasks carried out in secondary data processing of available rainfall data on HYMOS includes:

- Screening of data series
- Scrutiny by multiple time series graphs
- Scrutiny by tabulations of daily rainfall series of multiple stations
- Checking against data limits for totals at longer durations

- Spatial homogeneity testing of rainfall (Nearest neighbour analysis)
- Long-term shift in rainfall data
- Correction and Completion of Rainfall Data

The quality and reliability of a discharge series depends primarily on the quality of the stage measurements. Various methods for secondary data processing of flow data used in the present study include:

- Single station validation
- Multiple station validation
- Comparison of streamflow and rainfall

The secondary data validation has been carried out for hourly, daily, monthly and yearly rainfall data. The validation of compiled monthly and yearly rainfall totals helps in bringing out those inconsistencies which are either due to a few very large errors or due to small systematic errors which persist unnoticed for much longer durations. Missing data and data identified as erroneous have been substituted from neighbouring stations using suitable interpolation method. Depending on the type of error missing or erroneous rainfall data of various stations have been corrected and completed using a suitable operation/ procedure mentioned above and available in HYMOS.

After correction and completion of missing and erroneous data an important task is to compile the data in various usable forms. Further, in HYMOS a number of methods are available for estimating areal rainfall from point rainfall. Thiessen polygons for estimation of areal rainfall of the study area have been used in this study. Thiessen polygon (Figure 3.2) has been developed by supplying the GIS map layers of the study area and locations of the gauges in HYMOS.

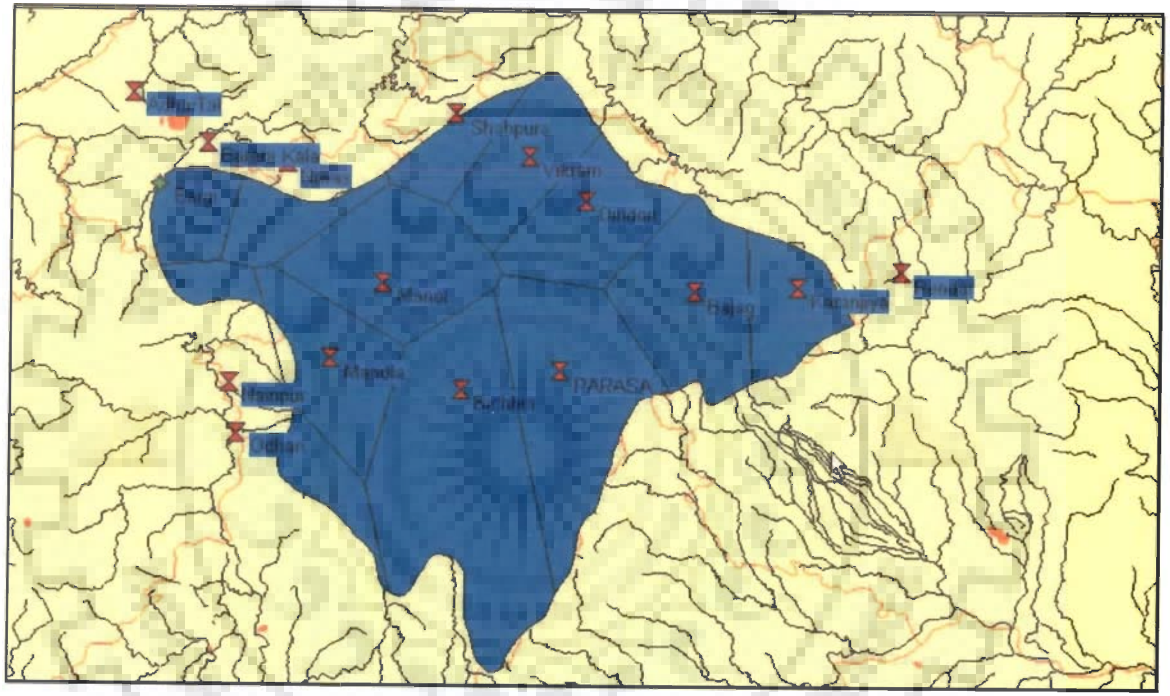

Figure 3.2: Area represented by each raingauge –Thiessen polygon method (Narmada basin up to Mandla)

3.4 CONCLUDING REMARKS

The hydrometeorological and hydrological data are subjected to primary and secondary processing in order to ensure the quality of data and also bring them in the appropriate form required for the purpose of hydrological modeling. As described in this chapter, the data processing studies have been carried out for investigation of spurious systemic errors, inconsistency in data etc. Filling of gaps and correction of spurious data have been carried out from the surrounding stations data using the appropriate methods such as interpolation, distance power method, normal ratio method etc.

It is important to note that the precipitation shows very high variability in short interval data as compared to long interval data. The variability on daily basis is more as compare to ten daily basis or monthly basis. Therefore, in case of precipitation data internal consistency and spatial consistency have been checked and corrected on the basis of daily, ten daily and monthly data. After the primary and secondary validation of data, all the data have been brought in a uniform manner.

The validated data of different gauging sites have been used for the development gauge-discharge, gauge-discharge-sediment rating curve relationships using regression, ANN and fuzzy logic based approaches and presented in Chapter- 4 and 5. The processed rainfall and discharge data have been used for the development of rainfall-runoff models (Chapter-6) using linear transfer function, ANN and fuzzy logic based approaches. Accurate foresting of floods at shorter lead periods is a very important task in Narmada basin. Therefore, the available data have been used to develop a suitable flood forecasting model using fuzzy and ANN techniques. This study is discussed in the subsequent chapter (Chapter-7).

CHAPTER 4

DEVELOPMENT OF STAGE–DISCHARGE RELATIONSHIPS USING ANN AND FUZZY LOGIC

4.1 BACKGROUND

The correct assessment of discharge in a river using the rating curve is very important as it serves the base information for hydrological modeling, forecasting and planning of water resources. The present chapter provides a quantitative framework of analysis based on conventional method, ANN and fuzzy logic principles, aiming to address this issue and attempts to fill the gap of quantitative research that exists in the area. Research findings of this chapter have been published in the form of a research paper entitled "Takagi-Sugeno Fuzzy Inference System for Modeling Stage-Discharge Relationship" in Journal of Hydrology (Vol. 331, pp. 146–160, 2006). Further, a reply of the discussions on this paper has been published as "Reply to comments provided by Z. Sen on Takagi-Sugeno Fuzzy Inference System for Modeling Stage-Discharge Relationship" in Journal of Hydrology (Vol. 337, pp 244-247, 2007). This chapter is organized as follows: First, the existing literature in the area is reviewed. Next, the methodology and an overview of the data used in the study are provided. This is followed by the interpretation of results and a section brings out conclusions.

4.2 INTRODUCTION

Stream flow information is important for effective and reliable planning and management of various water resources activities and the assessment, management and control of water resources can be effective if accurate and continuous information on river-flow is available. Generally a network of river gauging stations provides continuous information on river stage and sparse information of corresponding discharges. Thus, the continuous discharge data corresponding to observed gauge can be obtained by developing a stage discharge relationship and using this relationship to convert the recorded stages into corresponding discharges. This relationship is determined by correlating measurements of discharge with the corresponding observations of stage (Maidment, 1992). However, under certain conditions (flatter gradients and constricted channels) the discharge for a flood on a rising stage differs from that on the falling stage. This phenomenon is called hysteresis and results in a looped stage-discharge curve (Tawfik et al. 1997) for floods with different stage-discharge relations for rising and falling water stages. Rating curve development approaches can be categorized into three main groups: the single curve approach, the raising and falling approach, and the Jone's approach (Tawfik et al. 1997). DeGagne et al. (1996) documented the process of developing a decision support system for the analysis and use of stage-discharge rating curve while other possible models have been proposed by Gawne and Simonovic (1994) and Yu (2000).

The functional relationship between stage and discharge is complex and can not always be captured by the traditional modeling techniques (Bhattacharya and Solomatine, 2005). In the real world, stage and discharge relationship do not exhibit simple structure and are difficult to analyze and model accurately. Therefore, it seems necessary that soft computing methods e.g. artificial neural network (ANN) and fuzzy logic, which are suited to complex non-linear models, be used for the analysis. There are several applications of ANNs in stage-discharge modeling. Jain and Chalisgaonkar (2000) used three layer feed forward ANNs to establish stage discharge relationship. Bhattacharya and Solomatine (2005) have found that the predictive accuracy of ANN model is superior than the traditional rating curves. The effectiveness of an ANN with a radial basis function was explored by Sudheer and Jain (2003). The ANN based approaches have also provided promising results in modeling loop rating curves (Jain and Chalisgaonkar, 2000; Sudheer and Jain 2003).

The purpose of this study is to investigate and explore the potential of an alternate soft computing technique for stage discharge modeling based on fuzzy logic. The ability of fuzzy logic to model nonlinear events makes it even more important to investigate its ability to model stage discharge relationship. Uncertainty in conventional gauge-discharge rating curves involves a variety of components such as measurement noise, inadequacy of the model, insufficiency of river flow conditions, etc. Fuzzy logic based modeling approach has a significant potential to tackle the uncertainty problem in this field and to model nonlinear functions of arbitrary complexity. Other advantage of fuzzy logic is its flexibility and tolerance to imprecise data (Zadeh, 1999). Fuzzy rule based modeling is a qualitative modeling scheme where the system behavior is described using a natural language (Sugeno and Yasukawa, 1993). The transparency of the fuzzy rules provides explicit qualitative and quantitative insights into the physical behavior of the system (Coppola et al. 2002). Fuzzy rule based modeling has been attempted in water resources management, reservoir operation, flood forecasting and other areas of water resources analysis (Bardossy and Duckstein, 1992; Fontane et. al., 1997; Kindler, 1992;

Mujumdar and Sasikumar, 1999; Panigrahi and Mujumdar, 2000; Sasikumar and Mujumdar, 1998; Deka and Chandramouli, 2003).

4.3 OVERVIEW OF FUZZY LOGIC

The classical theory of crisp sets can describe only the membership or non-membership of an item to a set. While, fuzzy logic is based on the theory of fuzzy sets which relates to classes of objects with unsharp boundaries in which membership is a matter of degree. In this approach, the classical notion of binary membership in a set has been modified to include partial membership ranging between 0 and 1 (Zadeh, 1965). The membership function is described by an arbitrary curve suitable from the point of view of simplicity, convenience, speed, and efficiency. A sharp set is a sub set of a fuzzy set where the membership function can take only the values 0 and 1 (Babuška, 1998).

The range of the model input values, which are judged necessary for the description of the situation, can be portioned into fuzzy sets (Hellendoorn, et al., 1997). The process of formulating the mapping from a given input to an output using fuzzy logic is called the fuzzy inference. The basic structure of any fuzzy inference system is a model that maps characteristics of input data to input membership functions, input membership function to rules, rules to a set of output characteristics, output characteristics to output membership functions, and the output membership function to a single-valued output or a decision associated with the output (Jang et al. 2002). In rule based fuzzy systems, the relationships between variables are represented by means of fuzzy if-then rules e.g. "*If* antecedent proposition *then* consequent proposition". Depending on the particular structure of the consequent proposition, three main types of fuzzy models are distinguished as: (1) Linguistic (Mamdani Type) fuzzy model (Zadeh, 1973; Mamdani,

1977) (2) Fuzzy relational model (Pedrycz, 1984; Yi and Chung, 1993) (3) Takagi-Sugeno (TS) fuzzy model (Takagi and Sugeno, 1985). A major distinction can be made between the linguistic model, which has fuzzy sets in both antecedents and consequents of the rules, and the TS model, where the consequents are (crisp) functions of the input variables. Fuzzy relational models can be regarded as an extension of linguistic models, which allow for different degrees of association between the antecedent and the consequent linguistic terms. In the present work, the TS fuzzy model is employed to develop stage discharge rating curve. These models are relatively easy to identify and their structure can be readily analyzed.

4.4 TAKAGI–SUGENO FUZZY INFERENCE SYSTEM

A fuzzy rule-based model suitable for the approximation of many systems and functions is the *Takagi–Sugeno* (TS) fuzzy model (Takagi and Sugeno, 1985). In the TS fuzzy model, the rule consequents are usually taken to be either crisp numbers or linear functions of the inputs

Ri: IF x is A_i THEN $y_i = a_i^T x + b_i, \quad i = 1,2,......M$ (4.1)

Where $x \in \Re^n$ is the antecedent and $y_i \in \Re$ is the consequent of the i^{th} rule. In the consequent, a_i is the parameter vector and b_i is the scalar offset. The number of rules is denoted by M and A_i is the (multivariate) antecedent fuzzy set of the i^{th} rule defined by the membership function

$$\mu_i(x) : \Re^n \longrightarrow [0,1] \quad (4.2)$$

The fuzzy antecedent in the TS fuzzy model is normally defined as an and-conjunction by means of the product operator

$$\mu_i(x) = \prod_{j=1}^{p} \mu_{ij}(x_j) \tag{4.3}$$

where x_j is the j^{th} input variable in the p dimensional input data space, and μ_{ij} the membership degree of x_j to the fuzzy set describing the j^{th} premise part of the i^{th} rule. $\mu_i(x)$ is the overall truth value of the i^{th} rule.

For the input x the total output y of the TS model is computed by aggregating the individual rules contributions:

$$y = \sum_{i=1}^{M} u_i(x).y_i \tag{4.4}$$

where u_i is the normalized degree of fulfillment of the antecedent clause of rule R_i

$$u_i(x) = \frac{\mu_i(x)}{\sum_{i=1}^{M} \mu_i(x)} \tag{4.5}$$

The y_i's are called consequent functions of the M rules and are defined by:

$$y_i = w_{i0} + w_{i1}x_1 + w_{i2}x_2 + \dots\dots\dots + w_{ip}x_p \tag{4.6}$$

where w_{ij} are the linear weights for the i^{th} rule consequent function.

TS fuzzy models are quasi linear in nature. They result in smooth transition between linear sub-models (Figure 4.1), which are responsible for separate sub-space of states. This property of the TS fuzzy model allows separating the identification problem into two sub-problems: (i) appropriate partitioning of the state space of interest by clustering and; (ii) parameter identification of the consequent part.

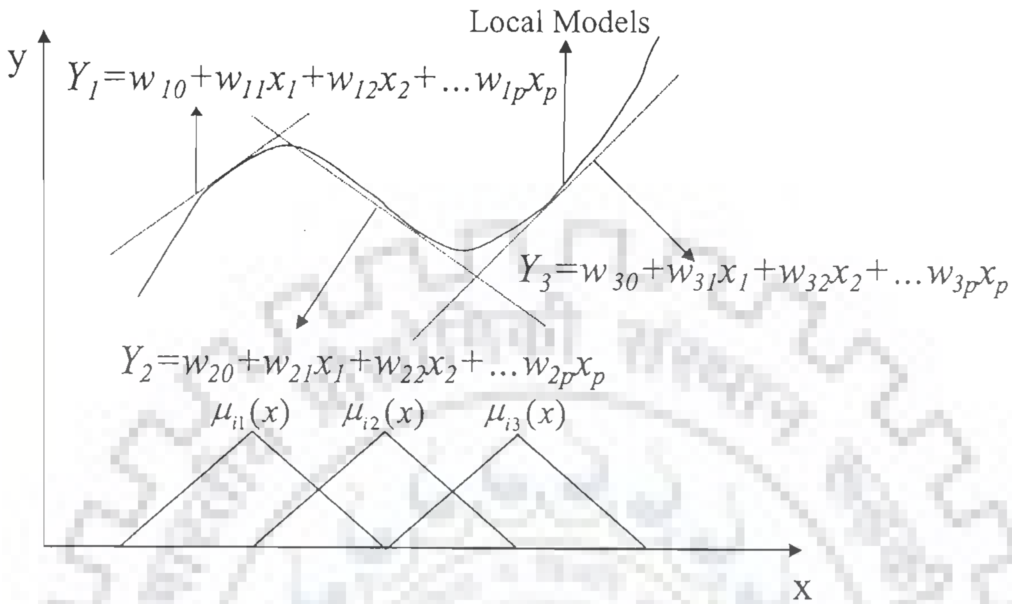

Figure 4.1: Takagi-Sugeno fuzzy model as a smooth piece-wise linear approximation of non-linear function

4.4.1 Generation of TS Fuzzy Model

In general, *TS* fuzzy modeling involves structure identification and parameter identification. The structure identification consists in initial rule generation after elimination of insignificant variables, in the form of IF-THEN rules and their fuzzy sets. Parameter identification includes consequent parameter identification based on certain objective criteria. In many situations, such rules are difficult to identity by manual inspection and therefore are usually derived from observed data using techniques collectively known as fuzzy clustering Höppner et al. (1999). The basic purpose of fuzzy, clustering is to identify natural grouping of the data from a large data set, producing a concise representation of a systems behaviour, similar to traditional clustering procedures, a user can specify the expected number of clusters or let the system "find" the likely number of clusters from input data. Various method have been developed in the literature, such as K-means or C-means clustering (Krishnaiah and Kanal, 1982), fuzzy C-means clustering (Bezdek, 1973, Jang et al., 2002), mountain clustering (Yager and Filev, 1994), Gaustafron-kessel (GK) fuzzy clustering (Gustafson and Kessel, 1979), and subtractive clustering (Chiu, 1994,1996).

Fuzzy C-means clustering method is an iterative technique that starts with a set of cluster centers and generates membership grades, used to induce new cluster centers. In this approach number of iterations depends on the initial values of the clusters' centers. Mountain clustering method is based on grid of data space that computes the potential value (mountain function) for each point on the grid on the basis of its distance to the actual data point. The greatest potential point (one of the grid vertices) represents the first cluster (highest point on the mountain). Subsequently, the potential for each grid point is adjusted, allowing for the determination of all remaining clusters. Subtractive clustering method (Chiu, 1994) is an extension of the mountain clustering method, where data points (not grid points) are considered as the potential candidates for cluster centers. As a result, clusters are elected from the system training data according to their potential. Therefore, in subtractive clustering method, the computation is simply proportional to the number of data points and independent of the dimension of the problem under consideration (Jang et al., 2002).

4.4.2 Subtractive Clustering

The subtractive clustering approach is used to determine the number of rules and antecedent membership functions by considering each cluster center (D_i) as a fuzzy rule. In this approach each data point of a set of N data points $\{x_1, \ldots\ldots x_N\}$ in a p-dimensional space is considered as the candidate for cluster centers. After normalizing and scaling data points in each direction, a density measure at data point x_i is computed on the basis of its location with respect to other data points and expressed as:

$$D_i = \sum_{j=1}^{N} \exp\left(-\left(\frac{2}{r_a} \right)^2 . \left\| x_i - x_j \right\|^2 \right) \tag{4.7}$$

where r_a is a positive constant called cluster radius.

A data point is considered as a cluster center when more data points are closer to it. Therefore, the data point (x_1^*) with highest density measure (D_1^*) is considered as first cluster center. Now excluding the influence of the first cluster center, the density measure of all other data points is recalculated as

$$D_i = D_i - D_1^* .\mu(x_i^*) \tag{4.8}$$

$$\mu(x_i^*) = \exp\left(-\frac{\left\| x_i - x_i^* \right\|^2}{(r_b/2)^2} \right) \tag{4.9}$$

where r_b (r_b>r_a) is a positive constant that results in a measurable reduction in density measures of neighborhood data points so as to avoid closely spaced cluster centers (Chiu, 1994).

After the density measure for each data point is revised (Equation 4.8), the data point with the highest remaining density measure is obtained and set as the next cluster center x_2^* and all of the density measures for data points are revised again. The process is repeated and the density measures of remaining data points after computation of k^{th} cluster center is revised by substituting the location (x_k^*) and density measure (D_k^*) of the k^{th} cluster center in Equation (4.8). This process is stopped when a sufficient number of cluster centers are generated. A sophisticated stopping criterion for automatically determining the number of clusters is suggested by Chiu (1994, 1996).

The cluster center derived using the subtractive clustering approach represents a prototype that exhibits certain characteristic of the system to be modeled. These cluster centers (x_i^*) can be reasonably used as the centers for the fuzzy rules' premise and antecedent membership function that describes the system behaviour. For j^{th} variable of the input data vector x, the degree to which rule i is fulfilled is defined by Gaussian membership functions:

$$\mu_{ij}(x_i) = \exp\left(\frac{(x_i - x_i^*)^2}{(r_a/2)^2}\right) \tag{4.10}$$

For every unique input vector a membership degree to each fuzzy set greater than 0 is computed, and therefore every rule in the rule base fires. This leads to the possibility of generating only a couple of rules for describing the accurate relationship between input and output data.

4.4.3 Estimation of Linear Consequent Parameters

All linear consequent parameters can be estimated simultaneously using global estimation approach. In the case of global estimation approach the regression matrix X for N data samples becomes:

$$X = [X_1\, X_2\, ...X_j.....X_M] \tag{4.11}$$

Where M are number of rules in the system and

$$X_i = \begin{bmatrix} u_i(x(1)) & x_1(1).u_i(x(1)) & x_2(1).u_i(x(1)) & x_3(1).u_i(x(1)) & x_p(1).u_i(x(1)) \\ u_i(x(2)) & x_1(2).u_i(x(2)) & x_2(2).u_i(x(2)) & x_3(2).u_i(x(2)) & x_p(2).u_i(x(2)) \\ u_i(x(3)) & x_1(3).u_i(x(3)) & x_2(3).u_i(x(3)) & x_3(3).u_i(x(3)) & x_p(3).u_i(x(3)) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ u_i(x(N)) & x_1(N).u_i(x(N)) & x_2(N).u_i(x(N)) & x_3(N).u_i(x(N)) & x_p(N).u_i(x(N)) \end{bmatrix} \quad (4.12)$$

where u_j is the basis function defined in Equation (4.5), $x_j(k)$ is the value of the j^{th} variable in the k^{th} data point. With this the model output as defined in Equation (4.4) becomes:

$$y = X.w \quad (4.13)$$

where w is the parameter vector from Equation (4.6) containing only the linear weights w_{ij} obtained from the membership degree through the multidimensional membership functions. These linear parameters can be estimated by least square method.

4.5 ARTIFICIAL NEURAL NETWORK (ANN)

Artificial neural networks (ANNs) are simplified models of the biological neuron system and as such they share some advantages that biological organisms have over standard computational systems. A biological neuron consists of a *body* (or *soma*), an *axon* and a large number of *dendrites* (Figure 4.2). The dendrites are inputs of the neuron, while the axon is its output. The axon of a single neuron forms synaptic connections with many other neurons. It is a long, thin tube which splits into branches terminating in little bulbs touching the dendrites of other neurons. The small gap between such a bulb and a dendrite of another cell is called a *synapse*.

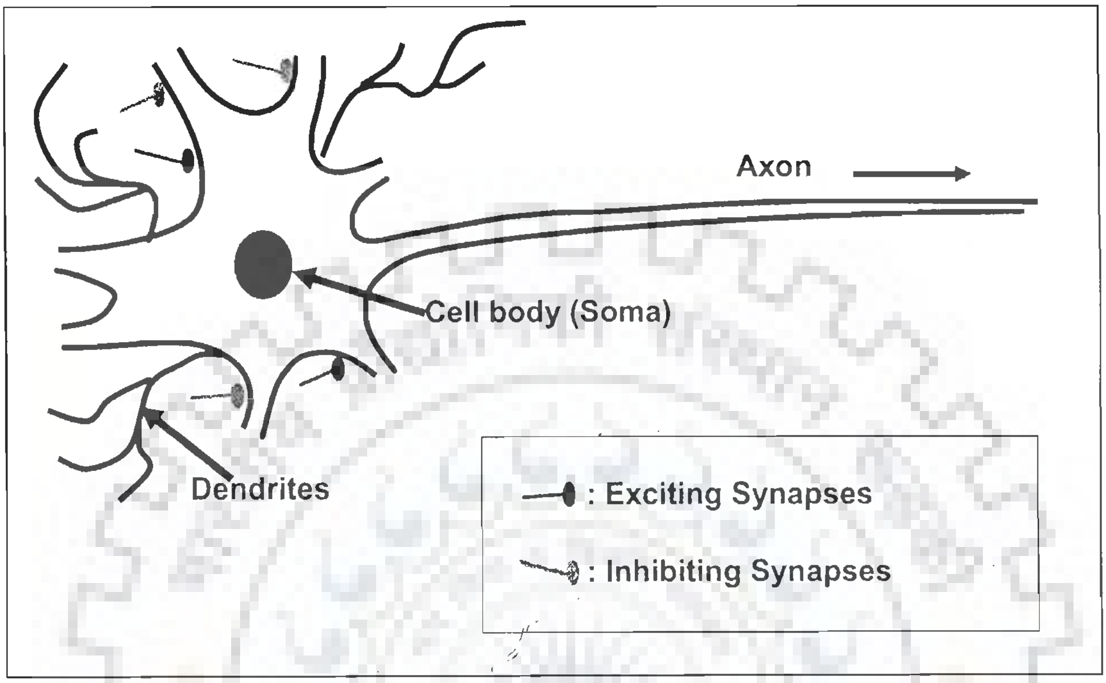

Figure 4.2: Structure of a typical neuron, or nerve cell

Mathematical models of biological neurons (called artificial neurons) mimic the functionality of biological neurons at various levels of detail. A typical model is basically a static function with several inputs (representing the dendrites) and one output (the axon). Each input is associated with a weight factor (synaptic strength). The weighted inputs are added up and passed through a nonlinear function, which is called the *activation function*. The value of this function is the output of the neuron (Figure 4.3).

4.5.1 Neural Network Architecture

A typical ANN model consists of number of layers and nodes that are organised to a particular structure (Mehrotra et al. 1997). There are various ways to classify a neural network. Neurons are usually arranged in several *layers* and this arrangement is referred to as the *architecture* of a neural net. Networks with several layers are called *multi-layer* networks, as opposed to *single-layer* networks that only have one layer. The classification of neural networks is done by the number of layers, connection between the nodes of the layers, the direction of information flow, the non linear equation used to get the output from the nodes, and the method of determining the weights between the nodes of different layers. Within and among the layers, neurons can be interconnected in two basic ways: (1) *Feedforward networks* in which neurons are arranged in several layers. Information flows only in one direction, from the input layer to the output layer, and (2) *Recurrent networks* in which neurons are arranged in one or more layers and feedback is introduced either internally in the neurons, to other neurons in the same layer or to neurons in preceding layers. The commonly used neural network is three-layered feed forward network due to its general applicability to a variety of different problems (Hsu et al., 1995) and is presented in Figure 4.4.

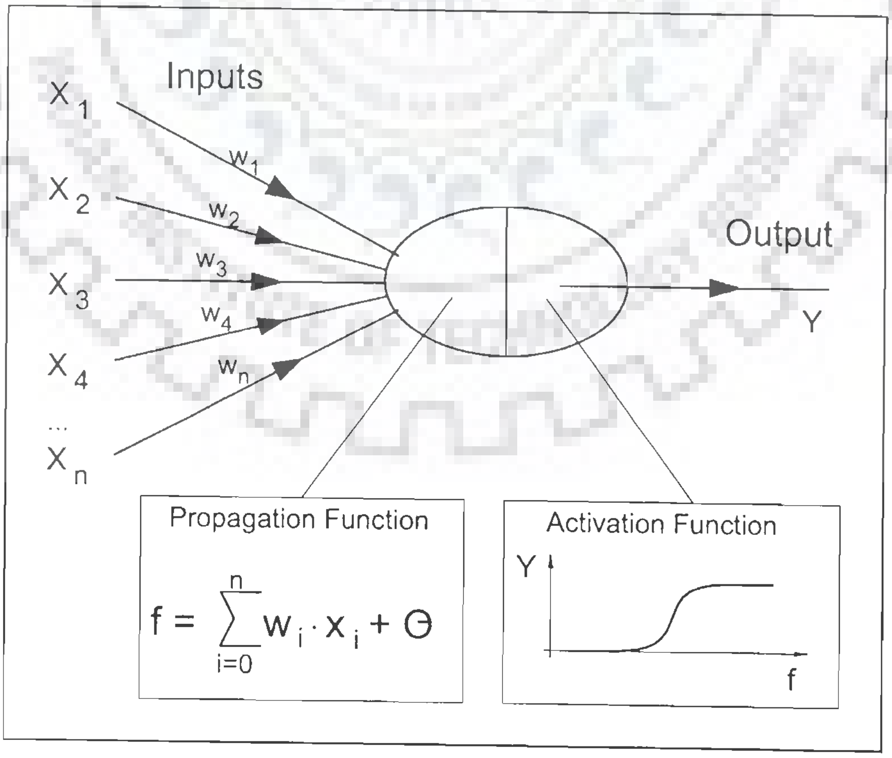

Figure 4.3: Processing Element of ANN

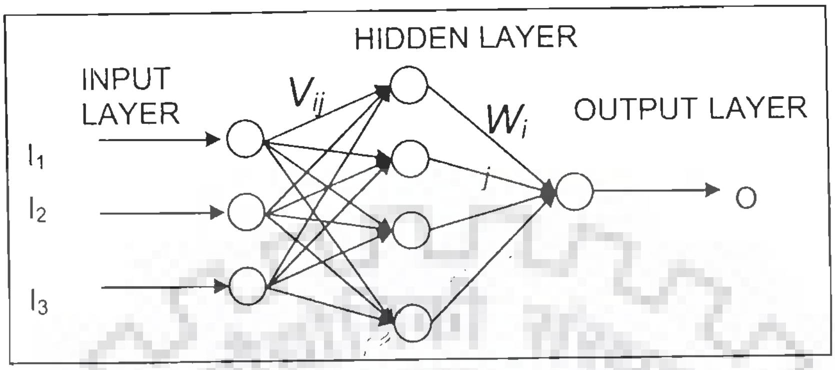

Figure 4.4: A Typical Three-Layer Feed Forward ANN (ASCE, 2000a)

4.5.2 Learning

The learning process in biological neural networks is based on the change of the interconnection strength among neurons. In artificial neural networks, various learning concepts are used (Table 4.1). A comprehensive description of all these learning algorithms can be found in Hecht-Nielsen (1991), Freeman and Skapura (1991).

Table 4.1: Basic learning algorithm

S.N	Algorithm	Initial weights	Learning
1	Hebbian	0	Unsupervised
2	Perceptron	Random	Supervised
3	Delta	Random	Supervised
4	Widrow-Hoff	Random	Supervised
5	Correlation	0	Supervised
6	Winner-take-all	Random(Normalized)	Unsupervised
7	Outstar	0	Supervised

A mathematical approximation of biological learning, called Hebbian learning is used, for instance, in the Hopfield network. Two different learning methods can be recognized: supervised and unsupervised learning: In supervised learning the network is supplied with both the input values and the correct output values, and the weight adjustments performed by the network are based upon the error of the computed output. In unsupervised learning the network is only provided with the input values, and the weight adjustments are based only on the input values and the current network output.

4.5.3 Multi-Layer Neural Network

A multi-layer neural network (MNN) has one input layer, one output layer and a number of hidden layers between them. In a MNN, two computational phases are distinguished:

1. *Feedforward computation.* From the network inputs (xi, $i = 1, \ldots, n$), the outputs of the first hidden layer are first computed. Then using these values as inputs to the second hidden layer, the outputs of this layer are computed, etc. Finally, the output of the network is obtained.
2. *Weight adaptation.* The output of the network is compared to the desired output. The difference of these two values called the error, is then used to adjust the weights first in the output layer, then in the layer before, etc., in order to decrease the error. This backward computation is called error backpropagation. The error backpropagation algorithm was proposed by Werbos (1974) and Rumelhart, et al. (1986) and it is briefly presented in the following section.

Feedforward Computation

In a multi layer neural network with one hidden layer (Figure 4.4), step wise the feedforward computation proceeds as:

I. Forward Pass

Computations at Input Layer

Considering linear activation function, the output of the input layer is input of input layer:

$$O_l = I_l \tag{4.14}$$

where, O_l is the l^{th} output of the input layer and I_l is the l^{th} input of the input layer.

Computations at Hidden Layer

The input to the hidden neuron is the weighted sum of the outputs of the input neurons:

$$I_{hp} = u_{1p}O_1 + u_{2p}O_2 + \ldots.. + u_{lp}O_l \tag{4.15}$$

for $p = 1,2,3,\ldots..m$

where, I_{hp} is the input to the p^{th} hidden neuron, u_{lp} is the weight of the arc between l^{th} input neuron to p^{th} hidden neuron and m is the number of nodes in the hidden layer.

Now considering the sigmoidal function the output of the p^{th} hidden neuron is given by:

$$O_{hp} = \frac{1}{(1 + e^{-\lambda(I_{hp} - \theta_{hp})})} \tag{4.16}$$

where O_{hp} is the output of the p^{th} hidden neuron, I_{hp} is the input of the p^{th} hidden neuron, θ_{hp} is the threshold of the p^{th} neuron and λ is known as sigmoidal gain. A non-zero threshold neuron is computationally equivalent to an input that is always held at -1 and the non-zero threshold becomes the connecting weight values as shown in Figure 4.5.

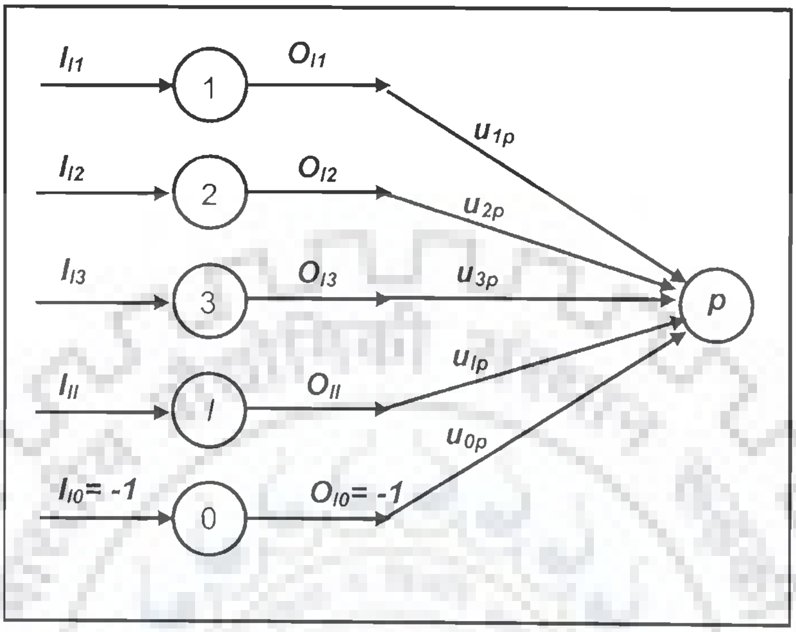

Figure 4.5: Treating threshold in input layer

Computations at Output Layer

The input to the output neurons is the weighted sum of the outputs of the hidden neurons:

$$I_{Oq} = w_{1q}O_{h1} + w_{2q}O_{h2} + \ldots + w_{mq}O_{hm} \tag{4.17}$$

for $q = 1,2,3,\ldots n$

where, I_{Oq} is the input to the q^{th} output neuron, w_{mq} is the weight of the arc between m^{th} hidden neuron to q^{th} output neuron.

Considering sigmoidal function, the output of the q^{th} output neuron is given by:

$$O_{Oq} = \frac{1}{(1+e^{-\lambda(I_{Oq}-\theta_{Oq})})} \tag{4.18}$$

where, O_{Oq} is the output of the q^{th} output neuron, λ is known as sigmoidal gain, θ_{Oq} is the threshold of the q^{th} neuron. This threshold may also be tackled again considering extra 0^{th}

neuron in the hidden layer with output of -1 and the threshold value θ_{Oq} becomes the connecting weight value as shown in Figure 4.6.

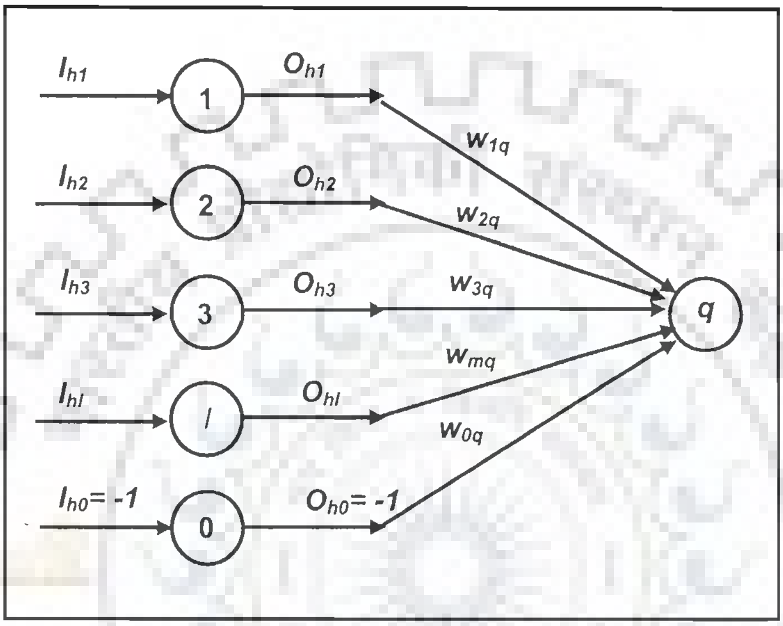

Figure 4.6: Treating threshold in output layer

Computation of Error

The error in output for the r^{th} output neuron is given by:

$$\xi^{l} = \frac{1}{2}\sum_{r=1}^{n}(T_{Or} - O_{or})^2 \tag{4.19}$$

where O_{Or} is the computed output from the r^{th} neuron and T_{Or} is the target output.

Equation (4.19) gives the error function in one training pattern. Using the same technique for all the training patterns the error function become

$$\xi = \sum_{j=1}^{N}\xi^{j} \tag{4.20}$$

where, N is the number of input-output data sets.

Training of Neural Network

Training is the adaptation of weights in a multi-layer network such that the error between the desired output and the network output is minimized.

II. Backword Pass

For k^{th} output neuron, E_k is given by

$$\xi_k = \frac{1}{2}(T_k - O_{ok})^2 \quad (4.21)$$

where, T_k is the target output of the k^{th} output neuron and O_{ok} is the computed output of the k^{th} output neuron.

To compute $\frac{\partial \xi_k}{\partial w_{ik}}$, apply chain rule of differentiation as:

$$\frac{\partial \xi_k}{\partial w_{ik}} = \frac{\partial \xi_k}{\partial O_{Ok}} \cdot \frac{\partial O_{Ok}}{\partial I_{Ok}} \cdot \frac{\partial I_{Ok}}{\partial w_{ik}} \quad (4.22)$$

$$\frac{\partial \xi_k}{\partial O_{Ok}} = -(T_i - O_{Ok}) \quad (4.23)$$

and the output of the k^{th} output neuron is given by

$$O_{Ok} = \frac{1}{(1 + e^{-\lambda(I_{Ok} - \theta_{Ok})})} \quad (4.24)$$

Hence,

$$\frac{\partial O_{Ok}}{\partial I_{Ok}} = \lambda O_{Ok}(1 - O_{Ok}) \quad (4.25)$$

Hence, the derivative of the sigmoidal function is a simple function of outputs.

Now,

$$I_{Ok} = w_{1k} \cdot O_{h1} + w_{2k} \cdot Oh_{H2} + \ldots\ldots + w_{mk} O_{hm} \quad (4.26)$$

It gives

$$\frac{\partial I_{Ok}}{\partial w_{ik}} = O_{hi} \tag{4.27}$$

Hence,

$$\frac{\partial \xi_k}{\partial w_{ik}} = -\lambda(T_k - O_{Ok}) \cdot O_{Ok} \cdot (1 - O_{Ok}) \cdot O_{hi} = -d_k . O_{hi} \tag{4.28}$$

where,

$$d_k = \lambda \cdot (T_K - O_{Ok}) \cdot O_k \cdot (1 - O_{Ok}) \tag{4.29}$$

Therefore, change of weight for weight adjustment of synapses connecting hidden neurons and output neurons is expressed as:

$$\Delta w_{ik} = -\eta \frac{\partial \xi_k}{\partial w_{ik}} = -\eta \cdot O_{hi} \cdot d_k \tag{4.30}$$

where, η is learning rate constant

Learning rate coefficient determines the size of the weight adjustment made at each iteration and hence influences the rate of convergence. Poor choice of the learning coefficient can result in a failure in convergence. For a too large learning rate coefficient the search path will oscillate and converge slowly. For a very small learning rate coefficient the descent will progress in a small steps and thus significantly increase the time of convergence.

Now we compute $\frac{\partial \xi_k}{\partial u_{ij}}$ by applying the chain rule of differentiation as:

$$\frac{\partial \xi_k}{\partial u_{ij}} = \frac{\partial \xi_k}{\partial O_{Ok}} \cdot \frac{\partial O_{Ok}}{\partial I_{Ok}} \cdot \frac{\partial I_{Ok}}{\partial O_{hi}} \cdot \frac{\partial O_{Hi}}{\partial I_{Hj}} \cdot \frac{\partial I_{hj}}{\partial u_{ij}} \tag{4.31}$$

It is already proved that

$$\frac{\partial \xi_k}{\partial I_{Ok}} = \frac{\partial \xi_k}{\partial O_{Ok}} \cdot \frac{\partial O_{Ok}}{\partial I_{Ok}} = -\lambda(T_k - O_{Ok})O_{Ok}(1 - O_{Ok}) = -d_k \tag{4.32}$$

$$\frac{\partial I_{Ok}}{\partial O_{hi}} = w_{ik} \tag{4.33}$$

$$\frac{\partial O_{hi}}{\partial I_{hj}} = \lambda(O_{hi})(1 - O_{hi}) \tag{4.34}$$

$$\frac{\partial I_{hj}}{\partial u_{ij}} = O_{ij} = I_{ij} \tag{4.35}$$

Hence,

$$\frac{\partial E_k}{\partial O_{Ok}} \cdot \frac{\partial O_{Ok}}{\partial I_{Ok}} \cdot \frac{\partial I_{Ok}}{\partial O_{hi}} = -w_{ik} d_k \tag{4.36}$$

$$\frac{\partial \xi_k}{\partial u_{ij}} = \{-w_{ik} d_k\} \cdot \{\lambda(O_{hi})(1 - O_{hi})\} \cdot \{I_{ij}\} \tag{4.37}$$

Therefore, change of weight for weight adjustment of synapses connecting input neurons and hidden neurons is expressed as:

$$\Delta u_{ij} = -\eta \cdot \frac{\partial \xi_k}{\partial u_{ij}} = -\eta[\{-w_{ik} d_k\} \cdot \{\lambda(O_{hi})(1 - O_{hi})\} \cdot \{I_{ij}\}] \tag{4.38}$$

The performance of the backpropagation algorithm depends on the initial setting of the weights, learning rate, output function of the units (sigmoidal, hyperbolic tangent etc.) and the presentation of training data. The initial weights should be randomized and uniformly distributed in a small range of values. Learning rate is important for the speed of convergence. Small values of learning parameter may result in smooth trajectory in the weight space but takes long time to converge. On the other hand large values may increase the learning speed but result in large random fluctuations in the weight space. It is desirable to adjust the weights in such a way that all the units learn nearly at the same rate. The training data should be selected so that it represents all data and the process adequately. The major limitation of the backpropagation algorithm is its slow convergence. Moreover, there is no proof of convergence, although it seems to perform well in practice. Some times it is possible that result may converge to local minimum and there is no way to reduce its possibility. Another problem is that of scaling, which may be handled using modular architectures and prior information about the problem.

4.6 RATING CURVE ANALYSIS

Rating curve is a useful tool to transfer observed stage to corresponding river discharge. It simplifies the need for costly and time consuming discharge measurements. The river discharge is crucial in flood management, water yield computation and hydrologic design. Rating curves are mostly of the form:

$$Q = a(H - H_0)^b \tag{4.39}$$

where Q is the discharge (m^3/s); H is the river stage (m); a and b are constant; and H_0 is the stage (m) at which discharge is nil. A first estimate of H_0 is usually chosen after examining the characteristics of the historical stage data and then by trial and error the final value of H_0 is chosen which gives the best fit i.e. the minimum sum of squares of errors (SSE). In a flood event, the relationship between stage and discharge is not unique. During the rising flood, the flood wave receives less hindrance in propagation than in a falling flood. For the same stage this causes higher discharge during the rising flood than during a falling flood. This effect is known as hysteresis; it results in a loop-rating curve and justifies the premise that the relationship between stage and discharge is not a one-to-one mapping, but has the dependency of discharge on past stage and discharge values. Sometimes the stage data is divided into rising and falling stages separately to take care the hysterisis effect (Bhattacharya and Solomatine, 2005). Then separate regression models (Equation 4.39) are developed for each set. This approach is not without limitations as data separation is often subjective and therefore the use of rating curves need expertise and is prone to errors. Artificial Neural Network (ANN) is a powerful procedure for non linear function mapping. Various attempts have been made to establish the applicability of ANN for gauge–discharge rating curve modeling (Jain and Chalisgaonkar, 2000; Sudheer and Jain, 2003; Bhattacharya and Solomatine, 2005).

4.7 DATA USED

Data from discharge measuring stations in the upper catchment of river Narmada in central India have been considered. The data considered for model calibration were a mix of dry and wet periods, and the validation period was an average year. The data used for analysis consisted of following six sets:

1. The daily stage and discharge record of the Jamtara gauging site on the Narmada River. The catchment area at this site is 4,000 km^2. Here 1281 pairs of gauge and discharge were available. In this case, the first 900 pairs of data were used to fit the conventional rating curve and to calibrate ANN and fuzzy based models, and the remaining 301 for validation.
2. The daily stage and discharge record of the Narmada River at Manot gauging site. The catchment area at this site is 4980 km^2. Here 506 pairs of gauge and discharge were available. In this case, the first 330 pairs of data were used to fit the conventional rating curve and to calibrate ANN and fuzzy based models, and the remaining 176 for validation.
3. The daily stage and discharge record of Narmada River at Mandla gauging site. The catchment area at this site is 13120 km^2. Here 522 pairs of gauge and discharge were

available. In this case, the first 330 pairs of data were used to fit the conventional rating curve and to calibrate ANN and fuzzy based models, and the remaining 192 for validation.

4. The daily stage and discharge record of the Kolar River (a tributary of the Narmada River) at Satarana gauging site. The catchment area at this site is 820 km^2. Here 768 pairs of gauge and discharge were available. In this case, the first 600 pairs of data were used to fit the conventional rating curve and to calibrate ANN and fuzzy based models, and the remaining 168 for validation.
5. The daily stage and discharge record of the Banjar River (a tributary of the Narmada River) at Hriday Nagar gauging site. The catchment area at this site is 1110 km^2. Here 1494 pairs of gauge and discharge were available. In this case (Case-I), the first 900 pairs of data were used to fit the conventional rating curve and to calibrate ANN and fuzzy based models, and the remaining 594 for validation.
6. A data set of 120 pairs of gauge and discharge data of Hirday Nagar gauging site covering both very low and very high values of flow were used to verify suitability of model for substantially less data. In this case (Case-II), the first 80 pairs of data were used to fit the conventional rating curve and to calibrate ANN and fuzzy based models, and the remaining 40 for validation.
7. A hypothetical data set (200 pairs) wherein the rating curve exhibits hysteresis. The hypothetical data sets of serial number 1,3,5,... were used to calibrate the model and data sets at serial number 2,4,6,.... were used to validated the model. The hypothetical data set considered in this study is similar to one considered by Jain and Chalisgaonkar, 2000.

4.8 MODEL DEVELOPMENT

For each data set a rating curve given by Equation 4.39 was fitted using the stage and discharge data selected for model calibration. Observed zero of the gauge values have been used for computing the water depths and subsequently the rating curves are developed by least square method linearly relating the log of the water depth with the log of the flow values. The rating curve regression equations developed have value of a as 85.041, 149.4, 21.90, 10.32, 42.704, 42.702; value of Ho as 360, 443.07, 430.82, 289.4, 436.85, 436.85 and value of b as 1.796, 1.343, 3.139, 2.835, 2.0791, 2.0789 for Jamtara, Manot, Mandla, Satarana, Hridya Nagar (case-I) and Hridya Nagar (case-II) respectively. The current discharge can be better mapped by considering, in addition to the current value of river stage, the stage and the discharge at the previous time steps (Jain and Chalisgaonkar, 2000). Accordingly, the current study analyzed different combinations of antecedent gauge and discharge values. Six TS fuzzy models were developed during the analysis with the corresponding input vectors as follows:

Model 1: $Q_t = f(H_t)$

Model 2: $Q_t = f(H_t, H_{t-1})$

Model 3: $Q_t = f(H_t, Q_{t-1})$

Model 4: $Q_t = f(H_t, H_{t-1}, Q_{t-1})$

Model 5: $Q_t = f(H_t, H_{t-1}, H_{t-2}, Q_{t-1})$

Model 6: $Q_t = f(H_t, H_{t-1}, H_{t-2}, Q_{t-1}, Q_{t-2})$

where Q_t and H_t corresponds to the river flow and gauge at time t.

For the six input-output data vectors ANN models were also developed. The feed-forward back propagation ANN network used in this study consists of input neurons (gauge and discharge of previous time steps) in the input layer and a single output neuron (discharge) in the output layer with one hidden layer. The number of neurons in the hidden layer of the network was finalized after many trials. The newff function available in the Neural Network Toolbox of MATLAB was used to create ANN model. During training the weights and biases of the network were adjusted using gradient descent with momentum weight and bias learning function. The default performance function for feed forward networks is mean square error (the average squared error between the network outputs and the target outputs). In order to handle uncertainties of the randomly generated initial weights and stopping criteria, a number of trials have been made (Faraway and Chatfield 1998, Sahoo and Ray 2006) to see whether consistent results are obtained. The developed model was simultaneously checked for its improvement on testing data on each iteration to avoid over training.

The most significant factors, identified in the previous sections, were used to develop a fuzzy model. This was carried out into two steps: (i) determining cluster centers and hence the number of fuzzy rules and their associated membership functions and (ii) optimizing the model utilizing TS fuzzy technique based on least square estimation (LSE). The clustering partitions a data set into a number of groups such that the similarity within a group is large than that among groups. Most similarity matrices are sensitive to the range of elements in the input vectors, therefore the data set under consideration has been normalized within the unit hypercube. The FIS of TS fuzzy model is generated using subtractive clustering. Program codes were written in MATLAB for different architectures including the fuzzy toolbox. In order to find out optimum cluster centers and thus the optimum fuzzy model, the cluster radius (r_a) of subtractive clustering algorithm was varied between 0.1 and 1 with steps of 0.02. The cluster centers and thus the Gaussian membership function obtained for each case were used to compute consequent parameters through a linear least square method and a model was built. Using the global model performance indices such as root mean square error (RMSE) between the computed and observed discharge, the correlation coefficient and model efficiency (Nash and Sutcliffe, 1970), the optimal parameter combination of the model was sought. Once the optimization process is finished, the optimized membership functions for each input variable and consequent parameters are defined for an optimized TS fuzzy model. The process is repeated for each of the six data sets. Figure (4.7) shows the membership functions for TS fuzzy model 5 developed for Jamtara site. Nine optimized fuzzy rules with nine membership functions for each variable are extracted (Table 4.2). It is evident from Table 4.2 that the output of the TS fuzzy model for each rule is in the form of linear Equation. For every input vector a membership degree to each fuzzy set greater than 0 is computed from the Gaussian membership function. Therefore, all the rules fires simultaneously for each combination inputs and thus provides a crisp output value for a given input data vector using Equation 4.4. The model performance indices and error values (absolute and relative errors) were used to check the ability of the models during the calibration and validation stage.

Rating curves can be more accurately modeled by adding more input information in the form of stage as well as discharge values at previous time steps (Jain and Chalisgaonkar, 2000) as represented by models 3 to 6. In practice the discharge values of previous time steps are not readily available. Therefore, the model calibrated using the

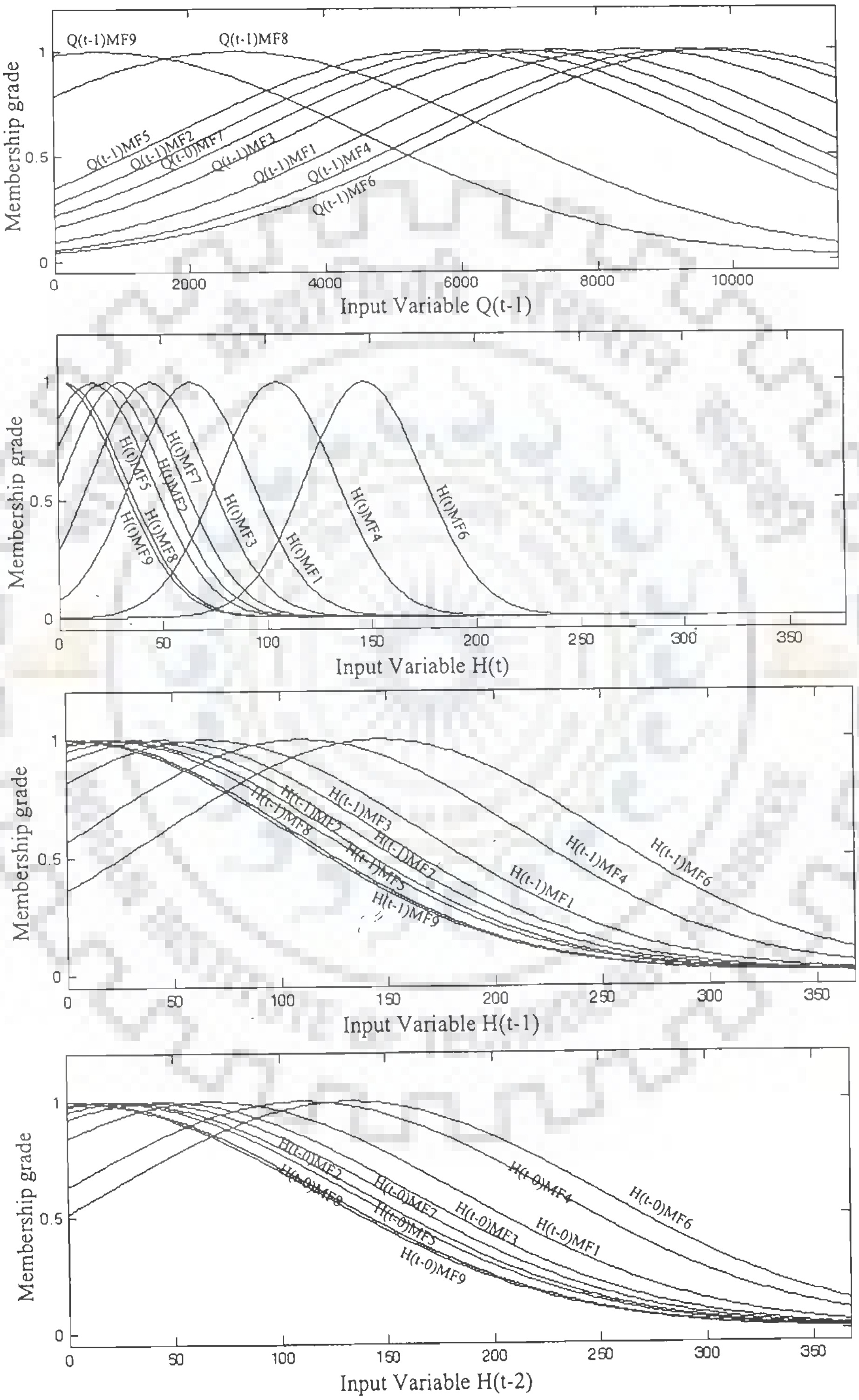

Figure 4.7: Membership Functions of input variables for fuzzy model $Q_t=f(H_t,H_{t-1},H_{t-2},Q_{t-1})$ at Jamtara site

Table 4.2: Fuzzy rules for fuzzy model $Q_t=f(H_t,H_{t-1},H_{t-2},Q_{t-1})$ at Jamtara site

Rule	Rule Description
1	If (H(t-2) is H(t-2)mf1) and (H(t-1) is H(t-1)mf1) and (H(t) is H(t)mf1) and (Q(t-1) is Q(t-1)mf1) then Q(t) is 65.86*H(t-2) - 61.85*H(t-1) + 983.2*H(t) + 1146*Q(t-1) + 1952
2	If (H(t-2) is H(t-2)mf2) and (H(t-1) is H(t-1)mf2) and (H(t) is H(t)mf2) and (Q(t-1) is Q(t-1)mf2) then Q(t) is 268.4*H(t-2) + 492.7*H(t-1) + 3589*H(t) + 3730*Q(t-1) – 1357
3	If (H(t-2) is H(t-2)mf3) and (H(t-1) is H(t-1)mf3) and (H(t) is H(t)mf3) and (Q(t-1) is Q(t-1)mf3) then Q(t) is 4887*H(t-2) + 5995*H(t-1)+96900*H(t) + 17400*Q(t-1) + 53380
4	If (H(t-2) is H(t-2)mf4) and (H(t-1) is H(t-1)mf4) and (H(t) is H(t)mf4) and (Q(t-1) is Q(t-1)mf4) then Q(t) is 9047*H(t-2)+10590*H(t-1)+145400*H(t)+19540*Q(t-1)-76790
5	If (H(t-2) is H(t-2)mf5) and (H(t-1) is H(t-1)mf5) and (H(t) is H(t)mf5) and (Q(t-1) is Q(t-1)mf5) then Q(t) is 785.2*H(t-2) + 1270*H(t-1) + 6190*H(t) + 485.6*Q(t-1) – 13410
6	If (H(t-2) is H(t-2)mf6) and (H(t-1) is H(t-1)mf6) and (H(t) is H(t)mf6) and (Q(t-1) is Q(t-1)mf6) then Q(t) is -74.47*H(t-2) - 196.7*H(t-1) - 2137*H(t) - 158.1*Q(t-1) + 1085
7	If (H(t-2) is H(t-2)mf7) and (H(t-1) is H(t-1)mf7) and (H(t) is H(t)mf7) and (Q(t-1) is Q(t-1)mf7) then Q(t) is -16.5*H(t-2) - 7.963*H(t-1) - 140.7*H(t)-4.747*Q(t-1) + 76.07
8	If (H(t-2) is H(t-2)mf8) and (H(t-1) is H(t-1)mf8) and (H(t) is H(t)mf8) and (Q(t-1) is Q(t-1)mf8) then Q(t) is 0.1015*H(t-2) - 0.2973*H(t-1) - 2.965*H(t)-0.8626*Q(t-1) + 2.92
9	If (H(t-2) is H(t-2)mf9) and (H(t-1) is H(t-1)mf9) and (H(t) is H(t)mf9) and (Q(t-1) is Q(t-1)mf9) then Q(t) is 0.001763*H(t-2) - 0.1055*H(t-1) + 0.2319*H(t) + 0.3554*Q(t-1) + 0.5115

known pairs of gauge-discharge data sets was validated using computed discharge values in input data vector. In this process one/two known values of discharges of previous time steps were used to compute next one/two discharges as the case may be (one for models 3,4,5 and two for model 6). From the next step onwards the computed discharge values were used as input for computation of discharge from Models 3 to 6 following the procedure suggested by Sudheer and Jain (2003). Using computed discharge as input to these models may cause the error to carry over from one step to another. However, such carry over errors may not have any significant affect due to higher accuracy of fuzzy and ANN model (Sudheer and Jain 2003).

4.9 RESULTS AND DISCUSSION

Global model performance indices (Table 4.3) such as root mean square error (RMSE) between the computed and observed discharge, the correlation coefficient and model efficiency (Nash and Sutcliffe, 1970) were used to evaluate the performance of the models. The fuzzy models are compared with the back propagation ANN model and conventional curve fitting approaches using all the six data sets (Table 4.4-4.9). It can be seen from these tables that the RMSE values are significantly higher for the ANN and curve fitting approaches than the fuzzy approach. The fuzzy models also show higher coefficient of correlation. However, a clear cut picture is not evident using only coefficient of correlation as a performance measure. Therefore, the model efficiency was also used to evaluate the performance of various model structures. In general the curve fitting approach shows very poor model efficiency. While, the fuzzy model shows better

Table 4.3: Global performance evaluation criteria

$$\text{Coefficient of Correlation} = \frac{\sum_{i=1}^{N} (Q_o - \overline{Q}_o)(Q_p - \overline{Q}_p)}{\sqrt{\sum_{i=1}^{N} (Q_o - \overline{Q}_o)^2 \sum_{i=1}^{N} (Q_p - \overline{Q}_p)^2}}$$

$$\text{Root Mean Square Error} = \sqrt{\frac{\sum_{i=1}^{N} (Q_{oi} - Q_{pi})^2}{N}}$$

$$\text{Nash Sutcliffe Efficiency} = 100 \times \left[1 - \frac{\sum_{i=1}^{N} (Q_o - Q_p)^2}{\sum_{i=1}^{N} (Q_o - \overline{Q}_o)^2} \right]$$

Where N is the number of observations; Q_o is the observed flow; Q_p is predicted flow; $\overline{Q}_o$ is the mean of the observed flow; and $\overline{Q}_p$ is the mean of the predicted flow.

model efficiency in comparison to an equivalent ANN model. For the practical point of view, the accurate estimation of discharge is in particular important for the low and high flows. Therefore, the results were also compared using average absolute error (AAE = $\frac{1}{n}\{Q_o - Q_c\}$) between observed and computed low flows and average absolute relative error (AARE = $\frac{1}{n}\{(Q_o - Q_c)/Q_o\} \times 100$) between observed and computed high flows. Keeping in view the flow pattern in the selected rivers, top 10% flow values were used to compute average relative errors and rest of the flow values were used to compute average absolute errors. It may be noted from the results (Table 4.4-4.9) that the ANN performs better than the conventional curve fitting models and the fuzzy model outperforms both ANN and curve fitting models in both low flow and high flow region of rating curve. It is also evident from computed errors that fuzzy logic models provide proper discharge estimates in situations where functional relationship between stage and discharge is complex and can not be modeled very accurately by conventional rating curves. As more and more information (input) is added to the model, generally the coefficient of correlation improves and RMSE is reduced. This may be due to auto correlation and cross correlation structure in the input data vector. Increase in inputs beyond a certain limit in the model cause reduction in model performance. This is due to reduction in auto correlation and cross correlation in the input data vector. From Table 4.4-4.9, it is also apparent that model 5, which consists of three antecedent gauges and one discharge in input, showed the highest coefficient of correlation, minimum RMSE and maximum model efficiency, and it is selected as the best fit model for describing gauge-discharge relationship of all the selected gauging sites. Figures 4.8 to 4.13, illustrate that the estimated discharge values from fuzzy and ANN models are generally falls within ±10% of observed discharges. However, the discharge computed by conventional curve fitting approach in general showed more than 10% variation from observed discharges. Furthermore, Figures. 4.8 to 4.13 illustrate that the discharges estimated by fuzzy logic model are very close to observed discharge values. All the three (conventional rating curve, fuzzy model and ANN model) models developed for data sets 1 to 6 are based on varying data lengths from 80 to 900 gauge discharge pairs. This indicates that the irrespective of data length the fuzzy models are always more accurate than the equivalent ANN or conventional rating curve models developed for selected gauging sites.

A model with a minimum RMSE may not be sufficient to eliminate the uncertainty in the model choice. In order to estimate bias of the Fuzzy, ANN and curve

Table 4.4: Values of performance indices and error functions for Fuzzy, ANN and conventional models – Calibration and validation data of Jamtara Site

Fuzzy/ANN Model (Number of Rules/Nodes in hidden layer)	Calibration Data		Validation Data	
	(a) Coefficient of correlation (b) RMSE (m^3/s) (c) Efficiency (%)	(a) AAE (m^3/s) (b) AARE (%)	(a) Coefficient of correlation (b) RMSE (m^3/s) (c) Efficiency (%)	(a) AAE (m^3/s) (b) AARE (%)
Q_t=f(H_t) (5/7)	(a) 0.994(0.985) (b) 125.6(135.7) (c) 91.20(89.72)	(a) 39.81(43,48) (b) 4.85(5.59)	(a) 0.996(0.995) (b) 91.40(99.91) (c) 92.00(90.44)	(a) 42.62(47.72) (b) 6.20(7.41)
Q_t=f(H_t,H_{t-1}) (7/5)	(a) 0.996(0.987) (b) 84.68(98.25) (c) 95.99(94.61)	(a) 35.32(37.23) (b) 4.42(5.12)	(a) 0.996(0.996) (b) 89.74(97.04) (c) 92.28(90.98)	(a) 36.28(41.39) (b) 5.96(6.23)
Q_t=f(H_t,Q_{t-1}) (7/6)	(a) 0.996(0.991) (b) 82.67(93.71) (c) 96.18(95.1)	(a) 29.49(33.41) (b) 4.24(5.11)	(a) 0.996(0.996) (b) 83.72(93.45) (c) 93.28(91.63)	(a) 34.98(37.33) (b) 4.81(5.83)
Q_t=f(H_t,H_{t-1},Q_{t-1}) (8/6)	(a) 0.997(0.994) (b) 65.02(75.44) (c) 97.64(96.82)	(a) 29.22(31.12) (b) 4.22(4.91)	(a) 0.996(0.993) (b) 82.13(89.32) (c) 93.54(92.36)	(a) 31.72(35.32) (b) 4.54(4.82)
Q_t=f(H_t,H_{t-1},H_{t-2},Q_{t-1}) (9/8)	(a) 0.998(0.996) (b) 66.38(73.52) (c) 97.54(96.98)	(a) 28.15(29.33) (b) 4.18(4.90)	(a) 0.997(0.991) (b) 78.87(87.19) (c) 94.04(92.72)	(a) 26.28(32.76) (b) 4.72(4.81))
Q_t=f(H_t,H_{t-1},H_{t-2},Q_{t-1},Q_{t-2}) (12/8)	(a) 0.998(0.996) (b) 72.71(76.05) (c) 97.05(95.77)	(a) 30.84(30.97) (b) 5.09(5.21)	(a) 0.995(0.989) (b) 80.17(88.97) (c) 93.84(92.41)	(a) 28.55(34.21) (b) 6.26(6.25)
Curve Fitting	(a) 0.993 (b) 147.4 (c) 81.45	(a) 67.39 (b) 11.32	(a) 0.989 (b) 117.57 (c) 86.76	(a) 74.22 (b) 17.39

TABLE 4.5: Values of performance indices and error functions for Fuzzy, ANN and conventional models – Calibration and validation data of Manot Site

Fuzzy/ANN Model (Number of Rules/Nodes in hidden layer)	Calibration Data		Validation Data	
	(a) Coefficient of correlation (b) RMSE (m^3/s) (c) Efficiency (%)	(a) AAE (m^3/s) (b) AARE (%)	(a) Coefficient of correlation (b) RMSE (m^3/s) (c) Efficiency (%)	(a) AAE (m^3/s) (b) AARE (%)
Q_t=f(H_t) (4/6)	(a) 0.961(0.946) (b) 84.12(90.40) (c) 92.2(90.99)	(a) 6.82(7.41) (b) 10.74(10.76)	(a) 0.962(0.945) (b) 44.76(57.83) (c) 85.4(75.62)	(a) 7.49(8.11) (b) 13.59(13.63)
Q_t=f(H_t,H_{t-1}) (7/6)	(a) 0.963(0.954) (b) 74.38(87.88) (c) 93.9(91.48)	(a) 6.54(7.10) (b) 9.22(9.14)	(a) 0.964(0.955) (b) 42.35(51.32) (c) 86.92(80.81)	(a) 7.23(7.83) (b) 11.63(11.67)
Q_t=f(H_t,Q_{t-1}) (8/7)	(a) 0.979(0.961) (b) 73.09(78.14) (c) 94.11(93.26)	(a) 5.57(6.44) (b) 9.12(9.02)	(a) 0.975(0.960) (b) 39.04(50.12) (c) 88.89(81.69)	(a) 6.25(6.88) (b) 9.15(9.39)
Q_t=f(H_t,H_{t-1},Q_{t-1}) (8/6)	(a) 0.988(0.962) (b) 70.18(76.18) (c) 94.57(93.60)	(a) 4.26(5.31) (b) 8.23(8.89)	(a) 0.987(0.962) (b) 37.47(49.86) (c) 89.76(81.88)	(a) 4.65(5.23) (b) 8.25(8.27)
Q_t=f(H_t,H_{t-1},H_{t-2},Q_{t-1}) (9/8)	(a) 0.989(0.960) (b) 70.14(80.26) (c) 94.57(92.89)	(a) 3.07(3.49) (b) 7.88(12.23)	(a) 0.988(0.964) (b) 36.36(47.39) (c) 90.37(83.63)	(a) 4.46(5.12) (b) 7.59(15.13)
Q_t=f(H_t,H_{t-1},H_{t-2},Q_{t-1},Q_{t-2}) (14/8)	(a) 0.986(0.961) (b) 72.96(79.67) (c) 94.13(93.00)	(a) 4.40(4.67) (b) 8.10(12.51)	(a) 0.983(0.958) (b) 38.61(48.03) (c) 89.13(83.18)	(a) 4.89(5.03) (b) 8.17(14.78)
Curve Fitting	(a) 0.955 (b) 92.21 (c) 90.62	(a) 18.97 (b) 15.33	(a) 0.951 (b) 64.57 (c) 79.61	(a) 17.32 (b) 14.27

TABLE 4.6: Values of performance indices and error functions for Fuzzy, ANN and conventional models – Calibration and validation data of Mandla Site

Fuzzy/ANN Model (Number of Rules/Nodes in hidden layer)	Calibration Data		Validation Data	
	(a) Coefficient of correlation (b) RMSE (m^3/s) (c) Efficiency (%)	(a) AAE (m^3/s) (b) AARE (%)	(a) Coefficient of correlation (b) RMSE (m^3/s) (c) Efficiency (%)	(a) AAE (m^3/s) (b) AARE (%)
Q_t=f(H_t) (4/6)	(a) 0.964(0.949) (b) 82.44(88.59) (c) 93.95(92.72)	(a) 6.68(7.26) (b) 10.53(10.56)	(a) 0.965(0.948) (b) 45.66(58.99) (c) 87.02(77.06)	(a) 7.64(8.27) (b) 13.86(13.90)
Q_t=f(H_t,H_{t-1}) (7/6)	(a) 0.967(0.958) (b) 72.52(95.43) (c) 95.40(92.94)	(a) 6.38(6.92) (b)8.99(8.91)	(a) 0.968(0.959) (b) 43.07(52.19) (c) 88.31(82.10)	(a) 7.35(7.96) (b) 11.83(11.86)
Q_t=f(H_t,Q_{t-1}) (8/7)	(a) 0.983(0.962) (b) 70.53(75.41) (c) 95.43(94.57)	(a) 5.38(6.21) (b) 8.80(8.70)	(a) 0.979(0.963) (b) 39.63(50.87) (c) 90.13(82.83)	(a) 6.34(6.98) (b) 9.29(9.54)
Q_t=f(H_t,H_{t-1},Q_{t-1}) (8/6)	(a) 0.990(0.968) (b) 67.16(72.90) (c) 95.80(94.82)	(a) 4.08(5.08) (b) 7.88(8.51)	(a) 0.989(0.969) (b) 37.96(50.51) ©90.93(82.94)	(a) 4.71(5.30) (b) 8.36(8.39)
Q_t=f(H_t,H_{t-1},H_{t-2},Q_{t-1}) (9/8)	(a) 0.991(0.972) (b) 66.28(75.85) (c) 95.61(93.91)	(a) 2.90(3.30) (b) 7.45(11.56)	(a) 0.990(0.971) (b) 36.72(47.86) (c) 91.36(84.55)	(a) 4.50(5.17) (b) 7.68(11.21)
Q_t=f(H_t,H_{t-1},H_{t-2},Q_{t-1},Q_{t-2}) (14/8)	(a) 0.989(0.969) (b) 69.68(76.087) (c) 95.40(94.26)	(a) 4.20(4.46) (b) 7.74(11.95)	(a) 0.986(0.970) (b) 39.15(48.70) (c) 90.33(84.30)	(a) 4.96(5.10) (b) 8.27(10.99)
Curve Fitting	(a) 0.957 (b) 90.37 (c) 91.51	(a) 18.59 (b) 15.03	(a) 0.952 (b) 65.86 (c) 81.34	(a) 17.67 (b) 14.56

TABLE 4.7: Values of performance indices and error functions for Fuzzy, ANN and conventional models – Calibration and validation data of Satrana Site

Fuzzy/ANN Model (Number of Rules/Nodes in hidden layer)	Calibration Data		Validation Data	
	(a) Coefficient of correlation (b) RMSE (m^3/s) (c) Efficiency (%)	(a) AAE (m^3/s) (b) AARE (%)	(a) Coefficient of correlation (b) RMSE (m^3/s) (c) Efficiency (%)	(a) AAE (m^3/s) (b) AARE (%)
Q_t=f(H_t) (4/5)	(a) 0.982(0.991) (b) 41.14(32.21) (c) 91.20(94.60)	(a) 2.97(1.11) (b) 12.96(13.03)	(a) 0.981(0.989) (b) 24.03(23.91) (c) 92.06(92.07)	(a) 3.98(3.81) (b) 13.15(13.87)
Q_t=f(H_t,H_{t-1}) (6/8)	(a) 0.993(0.992) (b) 27.06(29.23) (c) 96.19(95.55)	(a) 2.09(2.31) (b) 10.66(11.91)	(a) 0.992(0.989) (b) 19.48(22.48) (c) 94.74(92.99)	(a) 2.56(3.01) (b) 11.03(11.72)
Q_t=f(H_t,Q_{t-1}) (6/5)	(a) 0.994(0.993) (b) 26.29(30.01) (c) 96.40(95.31)	(a) 1.83(1.89) (b) 9.46(9.75)	(a) 0.992(0.992) (b) 19.12(21.19) (c) 94.93(93.77)	(a) 1.92(2.01) (b) 9.86(9.02)
Q_t=f(H_t,H_{t-1},Q_{t-1}) (8/6)	(a) 0.996(0.994) (b) 23.73(27.48) (c) 97.04(96.07)	(a) 1.76(1.76) (b) 8.86(9.01)	(a) 0.993(0.992) (b) 18.89(20.17) (c) 95.05(94.36)	(a) 1.73(1.77) (b) 8.29(8.34)
Q_t=f(H_t,H_{t-1},H_{t-2},Q_{t-1}) (9/8)	(a) 0.997(0.995) (b) 22.08(27.41) (c) 97.46(96.09)	(a) 1.75(2.10) (b) 8.06(8.26)	(a) 0.995(0.994) (b) 18.23(20.17) (c) 95.39(94.35)	(a) 1.77(2.01) (b) 8.05(8.21)
Q_t=f(H_t,H_{t-1},H_{t-2},Q_{t-1},Q_{t-2}) (12/10)	(a) 0.996(0.995) (b) 25.91(28.21) (c) 96.50(95.86)	(a) 1.86(2.05) (b) 8.44(8.91)	(a) 0.994(0.993) (b) 18.24(20.94) (c) 95.39(93.93)	(a) 1.93(2.17) (b) 8.20(8.32)
Curve Fitting	(a) 0.965 (b) 52.36 (c) 81.45	(a) 4.57 (b) 16.39	(a) 0.978 (b) 52.60 (c) 61.66	(a) 5.32 (b) 16.44

TABLE 4.8: Values of performance indices and error functions for Fuzzy, ANN and conventional models–Calibration and validation data of Hriday Nagar Site (Case-I)

Fuzzy/ANN Model (Number of Rules/Nodes in hidden layer)	Calibration Data		Validation Data	
	(a) Coefficient of correlation (b) RMSE (m^3/s) (c) Efficiency (%)	(a) AAE (m^3/s) (b) AARE (%)	(a) Coefficient of correlation (b) RMSE (m^3/s) (c) Efficiency (%)	(a) AAE (m^3/s) (b) AARE (%)
Q_t=f(H_t) (4/5)	(a) 0.988(0.964) (b) 40.37(49.27) (c) 94.8(92.25)	(a) 3.57(4.32) (b) 10.05(10.11)	(a) 0.986(0.961) (b) 70.98(81.21) (c) 85.40(75.62)	(a) 4.26(4.74) (b) 11.12(12.03)
Q_t=f(H_t,H_{t-1}) (6/8)	(a) 0.989(0.964) (b) 36.83(47.78) (c) 95.67(92.71)	(a) 3.09(3.30) (b) 10.00(10.12)	(a) 0.981(0.960) (b) 76.62(84.56) (c) 82.98(80.81)	(a) 3.83(4.06) (b) 10.89(11.10)
Q_t=f(H_t,Q_{t-1}) (6/5)	(a) 0.990(0.974) (b) 40.03(49.01) (c) 94.88(92.64)	(a) 3.04(3.05) (b) 8.15(9.27)	(a) 0.985(0.972) (b) 67.13(78.26) (c) 86.94(82.25)	(a) 2.67(2.89) (b) 8.03(9.01)
Q_t=f(H_t,H_{t-1},Q_{t-1}) (8/6)	(a) 0.992(0.989) (b) 33.76(37.77) (c) 96.37(95.44)	(a) 2.95(3.48) (b) 7.19(7.33)	(a) 0.988(0.982) (b) 63.18(73.95) (c) 88.43(84.15)	(a) 2.16(2.82) (b) 7.72(7.17)
Q_t=f(H_t,H_{t-1},H_{t-2},Q_{t-1}) (9/8)	(a) 0.992(0.990) (b) 30.11(36.32) (c) 97.11(95.79)	(a) 2.94(3.03) (b) 6.99(6.21)	(a) 0.989(0.983) (b) 57.32(69.41) (c) 90.47(86.04)	(a) 1.98(2.23) (b) 6.53(6.02)
Q_t=f(H_t,H_{t-1},H_{t-2},Q_{t-1},Q_{t-2}) (12/10)	(a) 0.991(0.989) (b) 32.82(36.97) (c) 96.56(95.63)	(a) 3.06(3.71) (b) 7.01(7.39)	(a) 0.980(0.980) (b) 59.28(72.55) (c) 89.81(84.75)	(a) 1.77(2.13) (b) 6.74(6.77)
Curve Fitting	(a) 0.961 (b) 76.23 (c) 81.45	(a) 6.31 (b) 12.45	(a) 0.960 (b) 93.4 (c) 74.72	(a) 8.47 (b) 12.81

TABLE 4.9: Values of performance indices and error functions for Fuzzy, ANN and conventional models–Calibration and validation data of Hriday Nagar Site (Case-II)

Fuzzy/ANN Model (Number of Rules/Nodes in hidden layer)	Calibration Data Fuzzy(ANN)		Validation Data Fuzzy(ANN)	
	(a) Coefficient of correlation (b) RMSE (m^3/s) (c) Efficiency (%)	(a) AAE (m^3/s) (b) AARE (%)	(a) Coefficient of correlation (b) RMSE (m^3/s) (c) Efficiency (%)	(a) AAE (m^3/s) (b) AARE (%)
Q_t=f(H_t) (4/4)	(a) 0.991(0.981) (b) 38.72(41.76) (c) 94.15(93.07)	(a) 5.045(5.67) (b) 12.35(12.29)	(a) 0.979(0.979) (b) 94.35(94.62) (c) 84.40(87.32)	(a) 6.32(7.83) (b) 12.19(12.55)
Q_t=f(H_t,H_{t-1}) (4/4)	(a) 0.984(0.982) (b) 31.39(37.82) (c) 96.15(94.42)	(a) 5.02(5.45) (b) 11.21(11.33)	(a) 0.979(0.978) (b) 92.11(93.31) (c) 87.99(87.67)	(a) 6.08(6.17) (b) 11.01(11.82)
Q_t=f(H_t,Q_{t-1}) (5/4)	(a) 0.987(0.984) (b) 27.22(35.19) (c) 97.15(95.19)	(a) 4.94(5.07) (b) 9.78(9.02)	(a) 0.982(0.980) (b) 89.39(92.88) (c) 88.68(87.79)	(a) 5.71(5.77) (b) 9.51(9.47)
Q_t=f(H_t,H_{t-1},Q_{t-1}) (5/4)	(a) 0.987(0.985) (b) 22.88(35.11) (c) 97.95(95.19)	(a) 3.87(4.98) (b) 8.73(8.84)	(a) 0.984(0.981) (b) 85.11(91.23) (c) 89.74(88.22)	(a) 5.13(4.79) (b) 8.65(19.02)
Q_t=f(H_t,H_{t-1},H_{t-2},Q_{t-1}) (5/4)	(a) 0.989(0.986) (b) 20.03(35.02) (c) 98.43(95.21)	(a) 3.09(4.43) (b) 8.21(8.32)	(a) 0.984(0.982) (b) 84.97(88.47) (c) 89.78(88.92)	(a) 4.73(4.67) (b) 8.46(8.54)
Q_t=f(H_t,H_{t-1},H_{t-2},Q_{t-1},Q_{t-2}) (5/5)	(a) 0.989(0.986) (b) 20.49(35.89) (c) 98.36(94.97)	(a) 3.71(4.51) (b) 8.33(8.03)	(a) 0.981(0.981) (b) 85.97(88.46) (c) 89.83(88.92)	(a) 4.79(5.02) (b) 8.83(8.08)
Curve Fitting	(a) 0.965 (b) 94.5 (c) 86.60	(a) 24.62 (b) 14.81	(a) 0.964 (b) 111.63 (c) 82.36	(a) 27.77 (b) 13.78

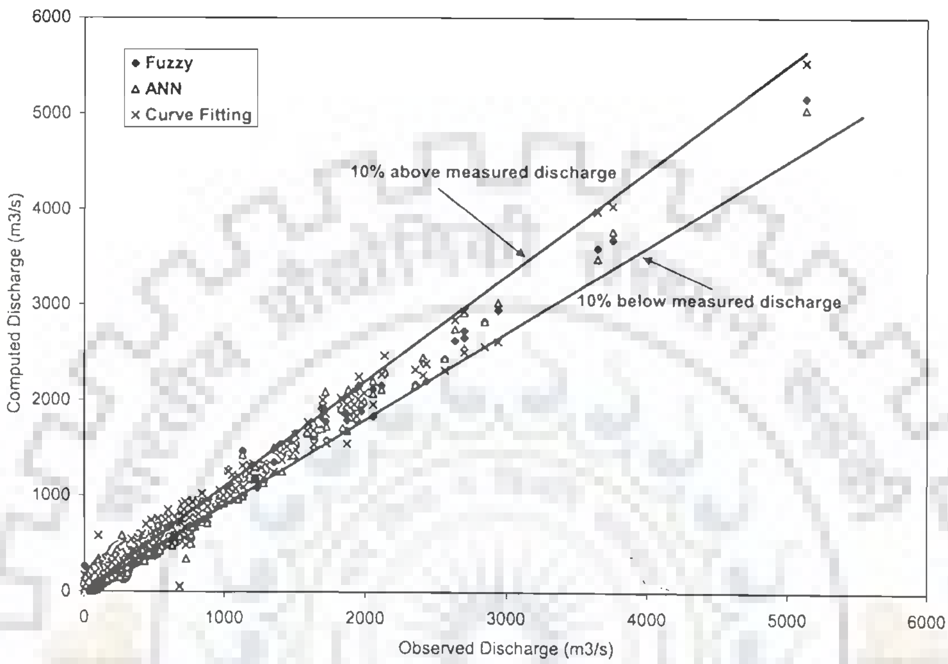

Figure 4.8: A scatter plot of computed and observed discharge data - Jamtara Site

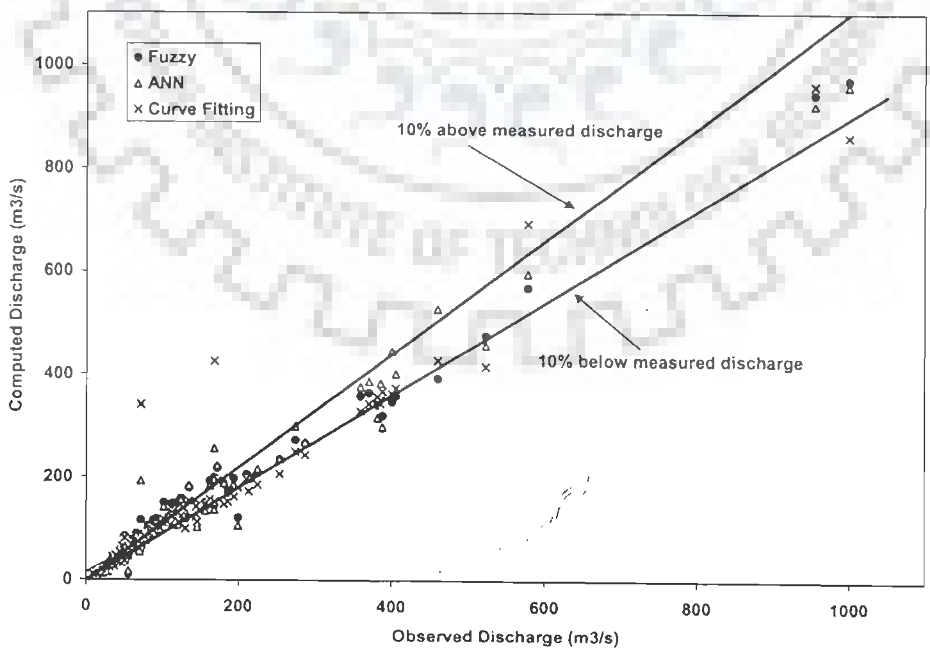

Figure 4.9: A scatter plot of computed and observed discharge data - Manot Site

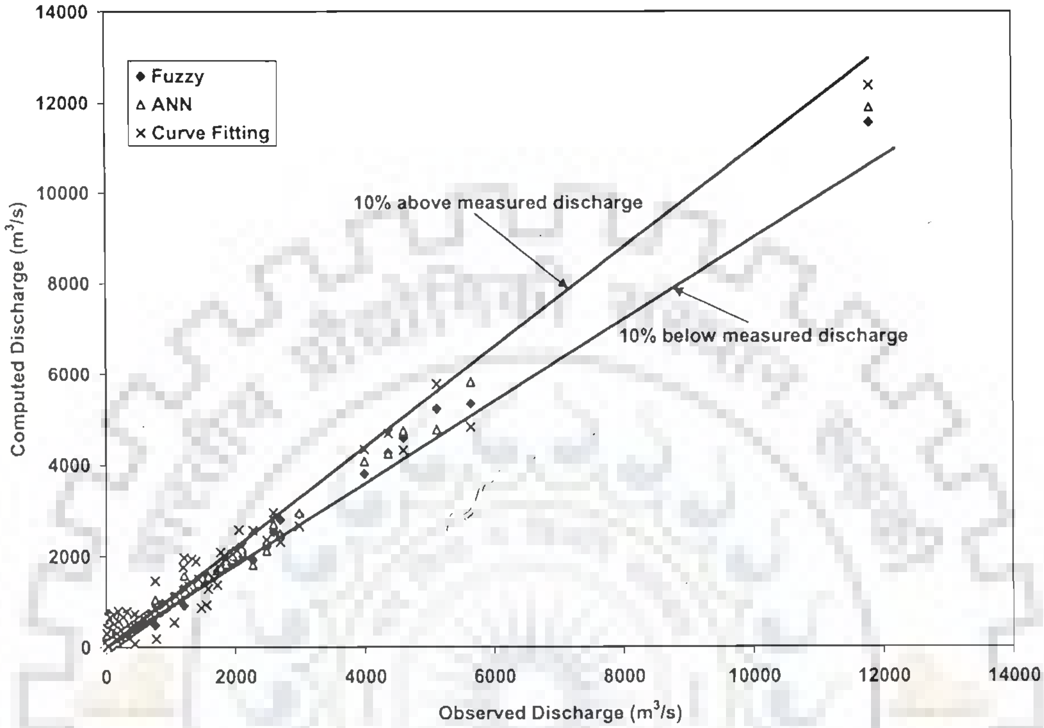

Figure 4.10: A scatter plot of computed and observed discharge data – Mandla Site

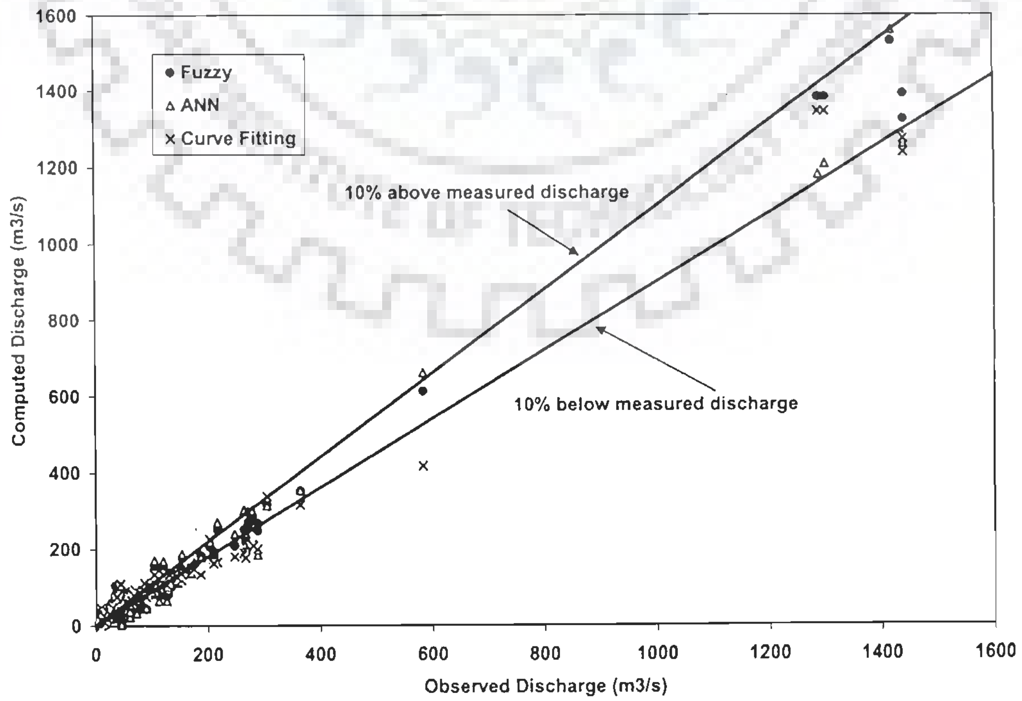

Figure 4.11: A scatter plot of computed and observed discharge data - Satrana Site

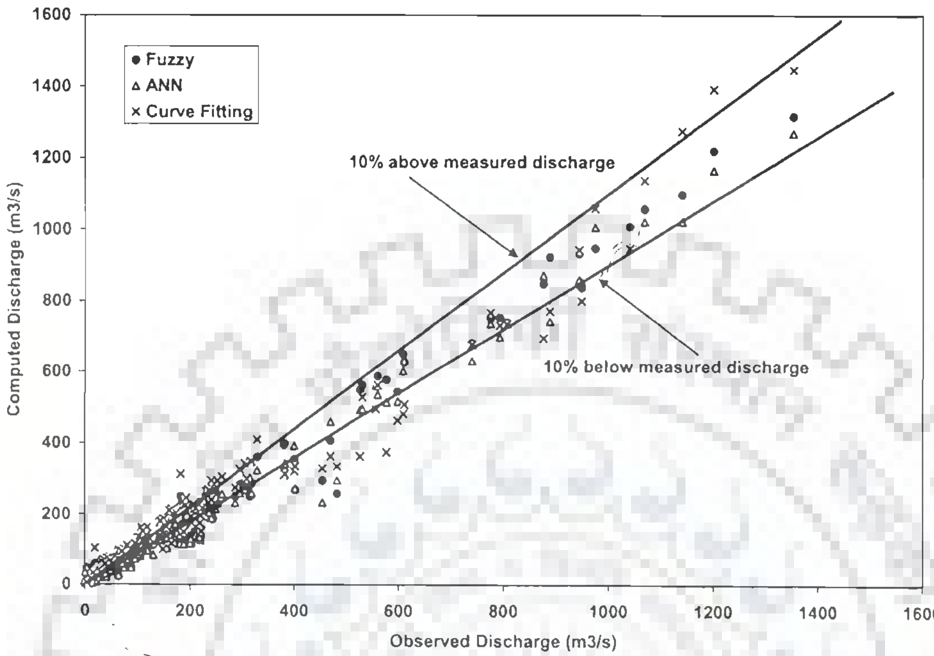

Figure 4.12: A scatter plot of computed and observed discharge data- Hridya Nagar Site (Case-I)

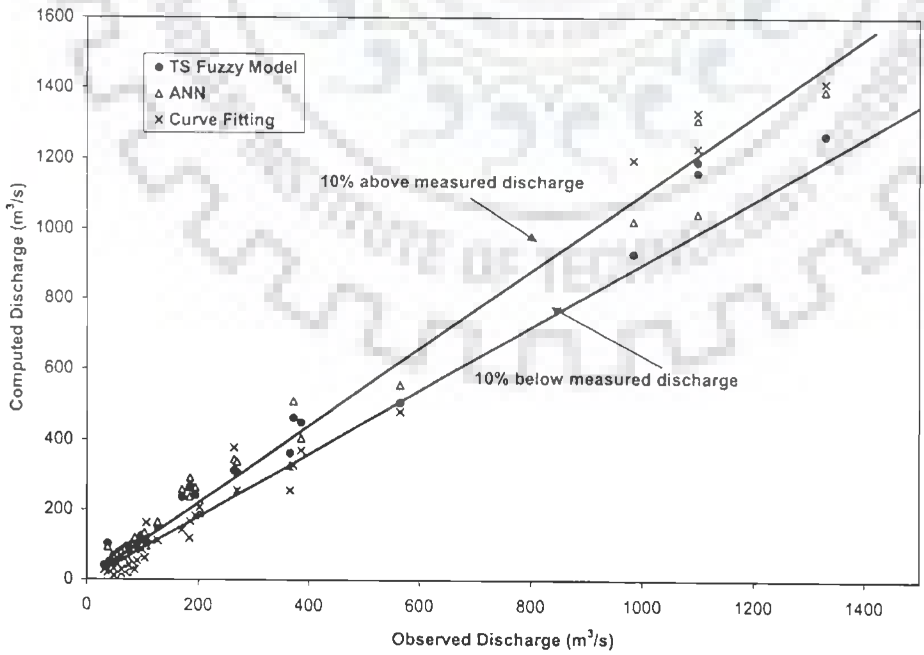

Figure 4.13: A scatter plot of computed and observed discharge data- Hridya Nagar Site (Case-II)

fitting models for different output ranges the testing data sets of all the gauging sites were scaled so as to lie in the range of zero to one and than pooled together. Further, the scaled and pooled data set was divided into two sets (i) data set with the data points for which models generally underestimated discharge, and (ii) data set containing the points for which discharge was overestimated. The pooled average relative underestimation and overestimation errors (PARE) were computed and plotted for the following eight discharge ranges: 0-0.1, 0.1-0.2, 0.2-0.3, 0.3-0.4, 0.4-0.5, 0.5-0.6, 0.6-0.7, and 0.7-1.0 (Figure 4.14) using the following formula:

$$PARE = \frac{1}{n}\sum_{i=1}^{n}\frac{(Qo_i - Qc_i)}{Qo_i} \qquad (4.40)$$

where, Qc_i and Qo_i are computed and observed discharge and n is the number of data points falling in each class.

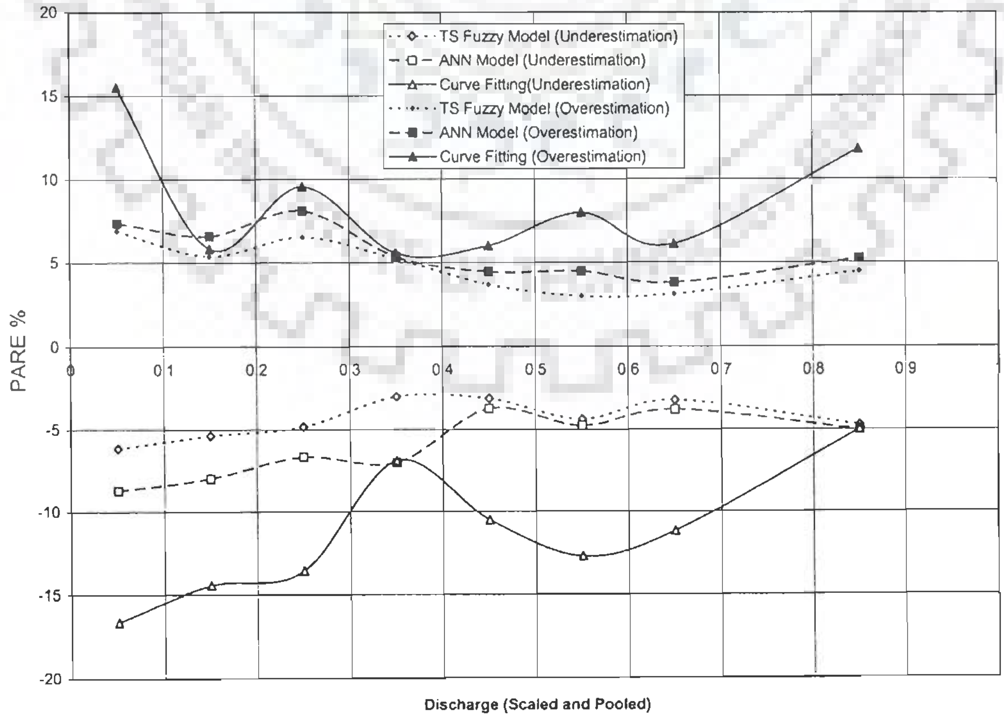

Figure 4.14: Variation of over and under estimation error with ischarge for different models in pooled data set

It is seen that in each range the overestimation and underestimation error of fuzzy model is more or less same and also generally less than the ANN and curve fitting models. This indicates the absence of bias in fuzzy model in all ranges of discharges. The underestimation error in the low flow is more for curve fitting approach and in high flow region all the three models are very close to each other. However, the over estimation error is in the same range for all the three models in low flow situation. While, in high flow situation the over estimation error is very small for fuzzy model. In general fuzzy model gave very accurate estimation for all the flow situations.

4.9.1 Modeling Hysteresis

Using the curve fitting approach the modeling of hysteresis is not possible as it fits an average or steady state curve. Jain and Chalisgaonkar (2000) applied ANN to model hysteresis considering a hypothetical case. In this study almost a similar loop curve is modeled using both ANN and fuzzy logic based approach and the results are presented in Table 4.10. The results indicate that the fuzzy model performs better than the ANN approach for modeling hysteresis. Further, it is seen from this table that the models utilizing more information of previous time periods are useful in estimating the hysteresis more accurately. Here, in this case models 5 and 6 showed highest correlation and minimum RMSE in comparison to other model structures. Figure 4.15 shows the estimated discharges at various stages using curve fitting, ANN and fuzzy models. The results clearly indicate that the conventional curve fitting approach failed to model the hysteresis present in the data. Figure 4.15 shows a slight difference in the middle and upper part of the estimated and hypothetical loops when ANN modeling approach was applied. However, the fuzzy logic based modeling approach models the loop rating curve more accurately throughout entire data range and this can be better observed from Figure 4.16.

TABLE 4.10: Values of performance indices and error functions for Fuzzy, ANN and conventional models–calibration and validation of hysteresis (hypothetical case)

Fuzzy/ANN Model (Number of Rules/Nodes in hidden layer)	Calibration Data		Validation Data	
	(a) Coefficient of correlation (b) RMSE (m^3/s) (c) Efficiency (%)	(a) AE (m^3/s) (b) RE (%)	(a) Coefficient of correlation (b) RMSE (m^3/s) (c) Efficiency (%)	(a) AE (m^3/s) (b) RE (%)
Q_t=f(H_t) (4/4)	(a) 0.939(0.926) (b) 141.1(155.3) (c) 91.21(89.35)	(a) 132.08(141.31) (b) 9.7(9.9)	(a) 0.936(0.919) (b) 144.2(160.7) (c) 90.37(89.67)	(a) 130.13(132.23) (b) 9.1(10.16)
Q_t=f(H_t,H_{t-1}) (5/2)	(a) 0.991(0.981) (b) 122.32(150.69) (c) 93.39(89.97)	(a) 90.42(93.21) (b) 7.50(7.90)	(a) 0.987(0.979) (b) 134.5(155.1) (c) 92.32(89.06)	(a) 110.43(111.56) (b) 7.65 (8.23)
Q_t=f(H_t,Q_{t-1}) (6/3)	(a) 0.997(0.995) (b) 81.54(98.61) (c) 97.06(95.70)	(a) 85.21(89.10) (b) 6.19(6.62))	(a) 0.997(0.996) (b) 86.39(95.23) (c) 95.09(93.77)	(a) 97.56 (100.53) (b) 6.21 (7.25)
Q_t=f(H_t,H_{t-1},Q_{t-1}) (6/8)	(a) 0.998(0.998) (b) 26.81(33.51) (c) 97.11(95.81)	(a) 73.10(75.31) (b) 6.14(6.52)	(a) 0.998(0.997) (b) 27.44(32.29) (c) 97.38(95.70)	(a) 74.78(80.00) (b) 6.10(6.87)
Q_t=f(H_t,H_{t-1},H_{t-2},Q_{t-1}) (8/8)	(a) 0.999(0.999) (b) 14.76(19.93) (c) 98.81(96.70)	(a) 71.25(71.89) (b) 6.08(6.28)	(a) 0.999(0.999) (b) 15.83(21.25) (c) 98.78(96.69)	(a) 72.46(73.58) (b) 6.05(6.88)
Q_t=f(H_t,H_{t-1},H_{t-2},Q_{t-1},Q_{t-2}) (8/8)	(a) 0.999(0.999) (b) 14.98(20.19) (c) 98.24(95.89)	(a) 72.38(73.1) (b) 6.74(6.80)	(a) 0.999(0.998) (b) 15.57(21.48) (c) 98.07(95.61)	(a) 75.15(75.34) (b) 6.35(6.81)
Curve Fitting	(a) 0.843 (b) 161.21 (c) 85.52	(a) 139.42 (b) 7.24	(a) 0.841 (b) 164.93 (c) 84.35	(a) 139.41 (b) 7.24

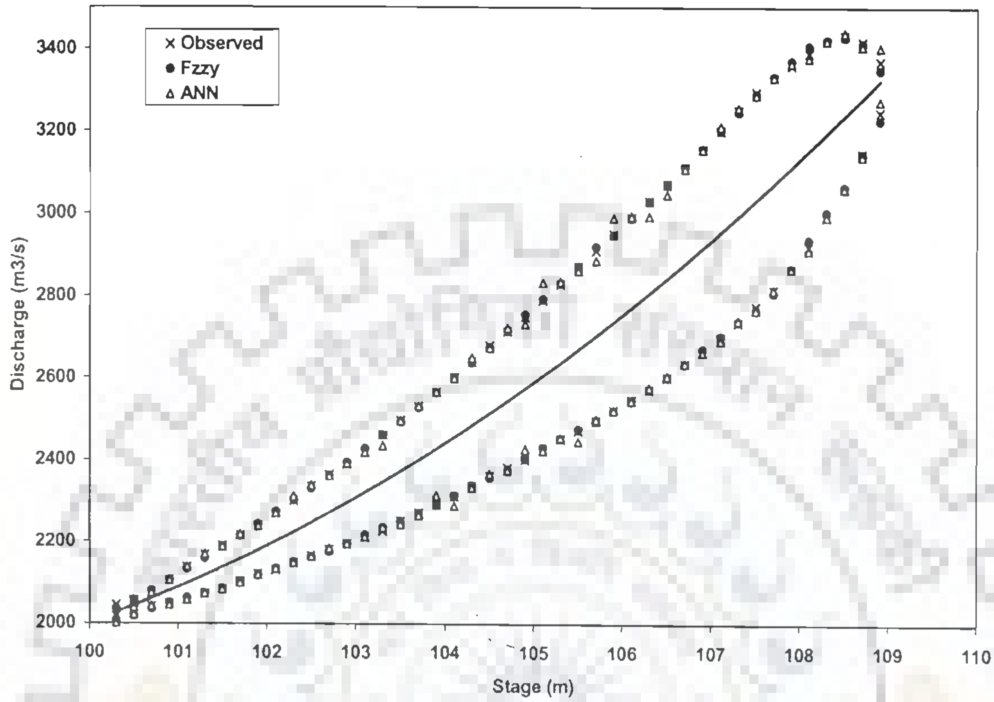

Figure 4.15: Comparison of Computed Discharges at Various Gauges Using Curve Fitting, ANN and Fuzzy Logic – Hypothetical data

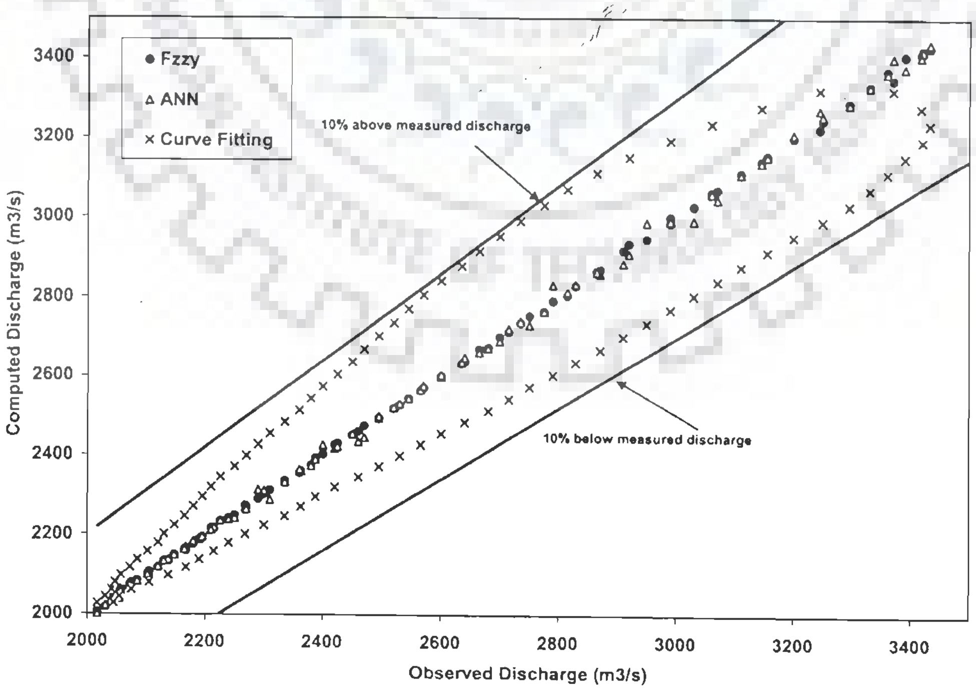

Figure 4.16: A scatter plot of computed and observed discharge data - Hypothetical data

4.10 CONCLUSIONS

Any attempt to improve the modeling of gauge-discharge rating curves is significantly important for rainfall-runoff modeling and flood forecasting. In this study, a fuzzy logic algorithm is developed to estimate the discharge from measured gauge data. The satisfactory estimation of the discharge by the proposed fuzzy models from the 7 different data sets indicates that gauge-discharge modeling can reliably employ the fuzzy model. Also, in this study, the fuzzy model is tested against both the ANN and conventional curve fitting approach. The fuzzy models estimate the discharge more accurately both in case of actual observed data sets of various lengths and hypothetical data set. The ANNs can be synthesized without making use of the detailed and explicit knowledge of the underlying physics and a fuzzy logic algorithm has the ability to describe the knowledge in a descriptive human-like manner in the form of simple rules using linguistic variables. The fuzzy model proposed herein may be concluded to be appropriate for modeling of rating curves.

CHAPTER 5

ANN AND FUZZY LOGIC IN DERIVING STAGE-DISCHARGE-SEDIMENT CONCENTRATION RELATIONSHIPS

5.1 BACKGROUND

Correct assessment of sediment volume carried by a river is of vital interest due to its importance in the design and management of water resources projects. This chapter attempts to derive stage-discharge-sediment concentration relationship using conventional regression method, ANN and fuzzy logic. Research findings of this chapter have been published in the Hydrological Sciences Journal (Deriving stage-discharge-sediment concentration relationship using fuzzy logic, Hydrological Sciences Journal (2007) 52(4), 793-807). This chapter is organized as follows: First, the existing literature in the area is reviewed in some detail. Next, the development of models and an overview of the data used in the study are provided. This is followed by the interpretation of results and a section on conclusions.

5.2 INTRODUCTION

The assessment of volume of sediments being transported by a river is important for estimation of sediment transport in rivers, design of dams, reservoirs and channels, environmental impact assessment and determination of the efficacy of watershed management and other catchment treatment. Sediment rating curves based on regression analysis are widely used to estimate the sediment load being transported by a river. The regression and curve-fitting techniques are not adequate in view of the complexity of the problem (Kisi, 2005). A problem inherent in the rating curve technique is the high degree of scatter, which may be reduced but not eliminated (Jain, 2001). Ferguson (1986) pointed out that the rating curve method, or the duration curve method, using a log-log rating curve, can underestimate sediment loads up to 50% even when the full time series of concentration is available and proposed a simple correction factor based on statistical considerations to remove most of the bias and to improve the accuracy of estimates of river load. Phillips et al. (1999) used high frequency suspended sediment concentration and discharge data to determine the accuracy and precision of suspended sediment flux estimates. The error correction procedure described in their study appears to offer some potential for suspended sediment flux infrequent concentration data. Asselman (2000) applied sediment rating curve method to four different locations along the river Rhino and its main tributaries and pointed out that the rating curves obtained by least square regression on logarithmic transformed data tend to underestimate sediment transport rates by about 10% to more than 50%. Samtani et al. (2004) reported the sediment transport characteristics of Tapi river, India. Sediment rating curves relating instantaneous sediment flux to discharge were established by Van Dijk et al. (2005) for suspended, bed load and total sediment by fitting power equation to all water discharge-sediment discharge data pairs, and no extra variation in sediment load was explained by runoff stage (i.e. raising or falling) and therefore a single curve was used.

Various studies carried out to compare actual and predicted suspended concentration indicate that conventional rating curves can substantially under predict actual sediment concentrations (Walling and Webb, 1988; Asselman, 2000). A number of attempts have been made to discuss statistical inaccuracies related to the curve fitting, and different methods have been proposed for refining the conventional sediment rating curves by applying various statistical correction factors, using non-linear regression, or classifying the discharge and sediment data into different groups (Duan, 1983; Jansoon 1985; Ferguson, 1986, 1987; Walling and Webb, 1988; Singh and Durgunoglu, 1989; De Vries and Klavers, 1994; Phillips, et al., 1999; Asselman, 2000).

The ANNs concept and its applicability to various problems of water resources have been amply demonstrated by various investigators (ASCE Task Committee, 2000a, 2000b). The ANN approach for modelling sediment-discharge process has already produced very encouraging results. Rosenbaum (2000) has demonstrated the applicability of the ANN technique in predicting sediment distribution in Swedish harbors. In order to assess the water quality of the lake Kasumigaura in Japan, Baruah et. al. (2001) developed ANN models of lake surface chlorophyll and sediment content estimated from Landsat TM imagery. Through this study, the authors confirmed that back propagation neural network with only one hidden layer could model both the parameters better than conventional regression techniques. In another study, Jain (2001) applied the ANN approach to establish an integrated stage-discharge-sediment concentration relation for two sites on the Mississipi River. It was pointed out that the bias correction approach proposed by Ferguson (1986) does not yield results better than those obtained by means of ANNs. Nagy et al. (2002) also used neural network to estimate the natural sediment discharge in rivers in terms of sediment concentration and addressed the importance of choosing an appropriate neural network structure and providing field data to that network for training purpose. Tayfur (2002) applied ANNs and physically based models to simulate experimentally observed nonsteady-state sediment discharge data and observed that the ANN models perform better than the physically based models for simulating sediment loads from different slopes and different rainfall intensities. Multilayer perceptrons (MLPs) were also successfully applied by Cigizoglu (2004) to simulate the suspended sediment process in rivers for forecasting of daily suspended data where explicit knowledge of internal sub process is not required. Kisi (2004a) found that a MLP with Levenberg-Marquardt training algorithm generally gives better suspended sediment concentration estimates than the generalized regression neural networks (GRNN), radial basis function (RBF) techniques and multi-linear regression (MLR). Furthermore, comparison of results revealed that the RBF and GRNN showed better performance in estimation of total sediment load. Lin and Namin (2005) reported that an integrated approach which utilizes the advantages of both deterministic methods and ANNs, has the potential to give more reliable predictions of suspended sediment transport under practical and complex conditions. Agarwal et al. (2005) developed generalized batch and pattern learned back propagation artificial neural network based sediment yield models considering high level of iteration and cross validation as criteria to terminate the process of learning. Tayfur and Guldal (2006) developed a three layer feed forward ANN model using back propagation algorithm to predict daily total suspended sediment in rivers by testing several cases of different data lengths of Tennessee basin, in order to obtain optimal period for training ANNs. Further, it was observed that the ANN model shows better performance than the linear black-box model, based on two dimensional unit sediment graph theory (2D-UGST). Applying k-fold partitioning in training data set, Cigizoglu and Kisi (2006) showed that superior sediment estimation performance can be obtained with quite limited data, provided that the sub-training data statistics are close to those of whole testing data set. These studies pointed out that, in general the ANN approach gives better results compared to several commonly used formulas of sediment discharge. Raghuwanshi et al. (2006) demonstrated the ANN capabilities in runoff and sediment yield modeling.

Fuzzy rule based approach introduced by Zadeh (1965) is being widely utilized in various fields of science and technology. It is a qualitative modeling scheme in which the system behavior is described using a natural language (Sugeno and Yasukawa, 1993). The transparency in formulation of fuzzy rules offers explicit qualitative and quantitative insights into the physical behavior of the system (Coppola et al. 2002). The application of fuzzy logic as a modelling tool in the field of water resources is a relatively new concept, although some studies have been carried out to some extent in the last decade and these studies have generated lots of enthusiasm. Bardossy and Duckstein (1992) applied fuzzy rule based modeling approach to a Karstic aquifer management problem. Bardossy and Disse (1993) used fuzzy rules for simulating infiltration. Fontane et al. (1997) and Panigrahi and Mujumdar (2000) applied fuzzy logic for reservoir operation and management problems. The fuzzy modeling approach has also been successfully applied for water quality management (Sasikumar and Mujumdar, 1998; Mujumdar and Sasikumar, 1999). Use of multiobjective fuzzy linear programming for sustainable irrigation planning and optimal land-water-crop planning has been demonstrated by Srinivasa Raju and Duckstein (2003) and Sahoo et al. (2006) respectively. Few attempts have been made to demonstrate the applicability of fuzzy rule based approach in river flow forecasting (Xiong et al. 2001; Chang and Chen, 2001; Lohani et al., 2005a; Lohani et al., 2005b; Nayak et al., 2005a, 2005b) and modeling stage discharge relationship (Lohani et al., 2006, Lohani et al., 2007). Kisi (2004b) developed nine different fuzzy differential evaluation (fuzzy_DE) models to estimate sediment concentration from streamflow. Based on comparison of results, it was concluded that the fuzzy_DE model may provide a superior alternative to the conventional rating curve approach. Another study carried out by Kisi (2005) indicated that the neuro-fuzzy model gives better estimates of suspended sediment than the neural networks and conventional sediment rating curve. Similarly, fuzzy rule-based models using triangular membership functions for sediment concentration forecasts also produce much better results than rating curve models (Kisi et al., 2006).

This study demonstrates the applicability of fuzzy rule based approach in developing gauge-discharge-sediment relationship. The study also aims at an evaluation of fuzzy rule based model with ANN and conventional rating curve for computation of sediment using daily gauge and discharge data of Manot and Jamtara gauging sites in Narmada basin, India.

5.3 FUZZY INFERENCE SYSTEM

Figure 5.1 shows block diagram of a typical fuzzy inference system for setting up stage-discharge-sediment relationship. The premise (IF part) of each rule describes a certain input data situation. The inference system evaluates all premises and calculates a truth value for each rule out of the membership values of the fuzzy sets contained in the premise. The consequent (THEN part) of all rules are calculated where the truth value of the premise is greater than zero. The results of each consequent are then used to compute the overall result, weighted by the truth-value of the rule. As discussed in Chapter 4, *TS* fuzzy model (Takagi and Sugeno, 1985), where the consequents are (crisp) functions of the input variables, has two important aspects involving: (i) structure identification and, (ii) parameter identification.

For deriving stage-discharge-sediment model structure using subtractive clustering, each cluster centre D_i is considered as a fuzzy rule that describes the system behaviour. The cluster centers are identified on the basis of the potential value (P_j) assigned to each data point x_i of a set of N data points in a p- dimensional space of

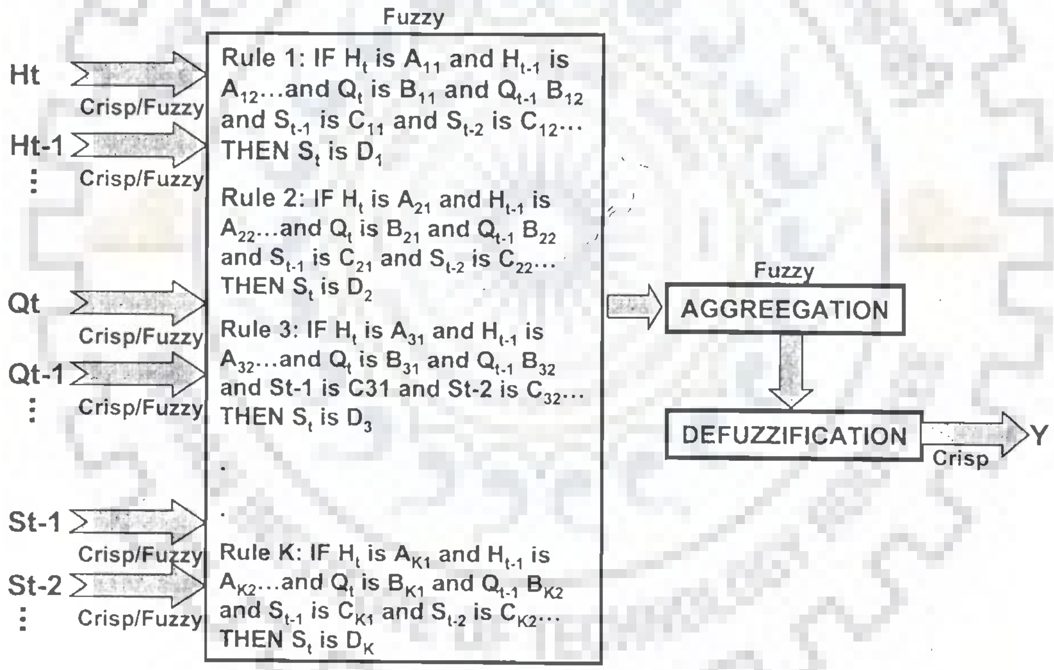

Figure 5.1: Fuzzy Inference System for modeling gauge-discharge-sediment relationship

input vectors constituting current and previous values of gauge and discharge and previous sediment values:

$$P_i = \sum_{j=1}^{N} \exp\left(-4.\frac{\left\| x_i - x_j \right\|^2}{r_a^2} \right) \tag{5.1}$$

where, r_a ($\geq$ 0) and $\left\| x_i - x_j \right\|$ are cluster radius and Euclidean distance respectively.

The data point with highest potential (P_i^*) is considered as first cluster center D_1. Further, the potential of the remaining data points is modified by subtracting the influence of first cluster center. Again, the point with highest modified potential is considered as second cluster center (D_2^*) and the process is repeated to compute other cluster centers. Therefore, the modified potential of the data points after computation of the j_{th} cluster center is expressed as:

$$P_i = P_i - P_j^* \exp\left(-4.\frac{\|x_i - D_j\|^2}{r_b^2}\right) \tag{5.2}$$

where r_b ($r_b > r_a \geq 0$) is the radius that results measurable reduction in potential of neighborhood data points and avoids closely spaced cluster centers. The process is repeated until a sufficient clusters are generated and finally the process is stopped considering the criterion suggested by Chiu (1994). These cluster centers (D_i^*, $i=1,k$) can be used as the centers of the fuzzy rules' premise of input data vector x and the degree to which rule i is fulfilled is defined by Gaussian membership function:

$$\mu_i(x) = \exp\left(-4.\frac{\|x - D_i^*\|^2}{r_a^2}\right) \tag{5.3}$$

A linguistic fuzzy model has fuzzy sets in both antecedents and consequents of the rules. Whereas, in Takagi-Sugeno (*TS*) fuzzy model the consequents are expressed as (crisp) functions of the input variables (Takagi and Sugeno, 1985). A *TS* Fuzzy model consists of a set of rules R_i, $i=1,...,k$:

R_i: IF H_t is A_{i1} AND H_{t-1} is A_{i2} ...... AND H_{t-u} is A_{iu+1} AND Q_t is A_{iu+2} AND Q_{t-1} is A_{iu+3} ...... AND Q_{t-v} is A_{iu+v+2} AND S_{t-1} is A_{iu+v+3} ...... AND Q_{t-wv} is $A_{iu+v+w+2}$

THEN $S_t = f_i(H_t, H_{t-1}, \ldots. Q_t, Q_{t-1} \ldots. S_{t-1}, S_{t-2} \ldots..)$ (5.4)

where H_t, H_{t-1}, …. Q_t, Q_{t-1} …. S_{t-1}, S_{t-2} …. are the antecedents and S_t is the consequent, A_{ij} are fuzzy sets and $f_i(H_t, H_{t-1}, \ldots. Q_t, Q_{t-1} \ldots. S_{t-1}, S_{t-2} \ldots..)$ is linear.

$$f_i(H_t, H_{t-1}, \ldots Q_t, Q_{t-1} \ldots S_{t-1}, S_{t-2} \ldots.) = a_1 H_t + a_2 H_{t-1} + ..a_j Q_t + a_{j+1} Q_{t-1} + a_n S_{t-w} + a_{n+1} \quad (5.5)$$

The output of the *TS* fuzzy model is computed by:

$$y = \sum_{i=1}^{M} f_i(H_t, H_{t-1}, \ldots. Q_t, Q_{t-1} \ldots. S_{t-1}, S_{t-2} \ldots..).\Phi_i(x) \quad (5.6)$$

where, M is the number of fuzzy rules. $\phi_i(x)$ are called basis functions, which normalize the degree of rule fulfillment by using the product t-norm:

$$\Phi_i(x) = \frac{\mu_i(x)}{\beta(x)} \quad (5.7)$$

where,

$$\mu_i(x) = \prod_{j=1}^{p} \mu_{ij}(x_j) \quad (5.8)$$

$$\beta(x) = \sum_{i=1}^{M} \mu_i(x) \quad (5.9)$$

where, x_j is the j_{th} element in current data vector in a p dimensional input data vector. μ_{ij} is the membership degree of x_j to the fuzzy set describing the j_{th} premise part of the i_{th} rule.

The cluster analysis assigns a set of rules and antecedent membership functions that models the data behaviour. Then using global linear least square estimation, the consequent equation (5.6) of each rule is determined. The advantage of this method is that it generates Gaussian membership functions (Equation 5.3) as fuzzy sets, which have, by nature, infinite support, therefore for every special input vector a membership degree (> 0) to each fuzzy set is computed. Thus the relationship between input and output channels is described through a couple of rules.

5.4 CONVENTIONAL SEDIMENT RATING CURVES

The sediment rating curve is a relation between the river discharge and sediment load. Such curves are widely used to estimate the sediment load being transported by a river. Generally, a sediment-rating curve may be plotted showing average sediment concentration or load as a function of discharge averaged over daily, monthly, or other time periods. Using the rating curve, the records of discharge are transformed into records of sediment concentration or load. Mathematically, a rating curve may be constructed by log-transforming all data and using a linear least square regression to determine the line of best fit. The relationship between sediment concentration (or load) and discharge is of the form:

$$S = aQ^b \tag{5.10}$$

The log-log transformation of equation (5.10) is:

$$\log S = \log a + b \log (Q) \tag{5.11}$$

Where, S and Q are suspended sediment concentration (or load) and discharge respectively. a and b are regression constants.

A typical sediment-rating curve is a straight-line plot on log-log paper and a regression equation minimizes the sum of squared deviations from the log-transformed data. This is not the same as minimizing the sum of squared deviations from the original dataset. Therefore, this transformation introduces a bias that underestimates the sediment concentration (or load) at any discharge and it may result in underestimation by as much as 50% (Ferguson, 1986). Ferugson and others have suggested bias correction factors, but their appropriateness is uncertain (Walling and Webb, 1988). Further, depending upon the channel characteristics, two or more curves may be fitted to the data. A major limitation of this approach, however is that it is not able to take into account the hysteresis effect that gives a loop rating curve (Jain, 2001). Therefore, as such, the conventional rating curve technique is not adequate in view of the complexity and importance of the problem and, hence, there remains a scope for further improvement.

5.5 STUDY AREA AND DATA USED

Data from discharge measuring stations in the upper catchment of river Narmada in central India have been considered. The data used for analysis consisted of daily stage, discharge and sediment records for the following two gauging sites:

1. Manot gauging site: The catchment area at this site is 4980 km^2. The average (20 year) annual total suspended sediments at Manot site is 5.82 x 10^6 tones (Gupta and Chakrapani, 2005). Here, 831 pairs of gauge and discharge were available for the monsoon period 1993-1998. The first 500 pairs of data were used to fit the conventional rating curve and to calibrate ANN and fuzzy based models, and the remaining 331 were used for validation.
2. Jamtara gauging site: It is located down stream of Manot site on the Narmada River. The catchment area at this site is 17157 km^2. The average annual total suspended sediments at Jamtara site is 3.32 x 10^6 tones. The Bargi Dam upstream of Jamtara traps a substantial amount of River Narmada suspended sediment (Gupta and Chakrapani, 2005). Here, 406 pairs of gauge, discharge and sediment were available for the monsoon period 1993-1995. The first 250 pairs of data were used to fit the

conventional rating curve and to calibrate fuzzy based models, and the remaining 156 were used for validation.

In this study care was taken to have the training data consisting of two extreme (minimum and maximum observed values)input patterns. To insure that the developed models are capable of whole data set, about 60% of the total samples were used for the calibration and rest of the data set for the validation. The statistical parameters of data sets of two stations are shown in Table 5.1.

Table 5.1: Statistical parameters of data set for the two stations

Data set	Station/Data type	Minimum	Maximum	Mean	Standard Deviation	Coefficient of Skewness
Calibration	**Manot Site** (500 data)					
	Gauge (m)	443.0	455.6	444.6	1.3	3.1
	Discharge($m^3\ s^{-1}$)	0.4	2997.0	273.4	387.7	4.0
	Sediment (mg l^{-1})	7.0	6168.0	785.4	1024.7	4.3
	Jamtara Site (250 data)					
	Gauge (m)	363.5	374.4	365.8	2.3	3.4
	Discharge($m^3\ s^{-1}$)	31.4	7800.0	977.6	1411.9	4.3
	Sediment (mg l^{-1})	6.0	1371.0	151.8	142.7	4.1
Validation	**Manot Site** (331 data)					
	Gauge (m)	443.0	450.0	444.4	0.9	2.3
	Discharge($m^3\ s^{-1}$)	0.4	2060.0	200.0	281.8	3.9
	Sediment (mg l^{-1})	7.0	5888.0	484.9	749.9	3.6
	Jamtara Site (156 data)					
	Gauge (m)	364.1	371.6	365.1	1.6	2.0
	Discharge($m^3\ s^{-1}$)	45.0	4781.0	555.1	1142.8	2.3
	Sediment (mg l^{-1})	7.0	725.0	101.4	141.8	2.6

5.6 MODEL DEVELOPMENT

5.6.1 Conventional Rating Curve Analysis

The rating curves were fitted for two locations in the Narmada river system by least square regression on the logarithms of discharge and sediment concentration data. The rating curves based on least square regression of the log-transformed data seem to underestimate concentration values at high discharges. The degree of underestimation decreases when the bias correction factor is used (Asselman, 2000). A bias correction factor suggested by Ferguson (1986) has been applied to improve the accuracy of sediment concentration estimates from the rating curve. The correlation coefficients and root mean square error (RMSE) of the fitted curves are given in Table 5.2 and 5.3. The developed regression equation was used to compute discharge considering a different set of discharge values (validation data) and the sediment concentration so computed was compared with the observed sediment concentration values.

5.6.2 ANN Models

5. 6.2.1 Model inputs

Identification of inputs and outputs variables is the first step in developing an ANN model. Various researchers have shown that the current sediment load can be mapped better by considering, in addition to the current value of discharge, the sediment, discharge and gauge at the previous time steps (Jain, 2001; Cigizoglu and Alp, 2006). Therefore, in addition to Q_t, i.e., discharge at time step t, other variables such as Q_{t-1}, Q_{t-2}, and S_{t-1}, S_{t-2}, were also considered in the input. In the present study, the following five combinations of input data of stage, discharge and sediment were considered:

Table 5.2: Coefficient of correlation and RMSE for ANN, Fuzzy and conventional models at Jamtara Site

Fuzzy Model	Nodes in hidden layer	Number of Rules/ Gaussian membership functions	Calibration /Training Data				Validation/Test Data			
			ANN		Fuzzy		ANN		Fuzzy	
			R	RMSE (mg l^{-1})	R	RMSE (mg l^{-1})	R	RMSE (mg l^{-1})	R	RMSE (mg l^{-1})
S_t=f(H_t,H_{t-1}, Q_t, Q_{t-1} and S_{t-1})	5	4	0.612	116.1	0.624	101.4	0.613	113.6	0.630	109.79
S_t=f(H_t, H_{t-1}, H_{t-2}, Q_t, Q_{t-1} and S_{t-1})	5	4	0.784	95.1	0.794	84.6	0.790	85.94	0.797	85.57
S_t=f(H_t, H_{t-1}, H_{t-2}, Q_t, Q_{t-1},Q_{t-2} and S_{t-1})	5	4	0.790	84.9	0.802	85.6	0.809	83.79	0.812	83.1
S_t=f(H_t,H_{t-1}, Q_t, Q_{t-1}, Q_{t-2},S_{t-1} and S_{t-2})	5	7	0.813	84.13	0.815	82.83	0.813	83.12	0.815	82.22
S_t=f(H_t, H_{t-1}, H_{t-2}, Q_t, Q_{t-1}, Q_{t-2}, S_{t-1} and S_{t-2})	6	5	0.781	106.2	0.797	92.84	0.798	96.37	0.794	95.68
Curve Fitting with bias correction	R		0.524				0.562			
	RMSE (mg l^{-1})		161.1				141.9			

Table 5.3: Coefficient of correlation and RMSE for ANN, Fuzzy and conventional models at Manot Site

Fuzzy Model	Nodes in hidden layer	Number of Rules/ Gaussian membership functions	Calibration /Training Data				Validation/Test Data			
			ANN		Fuzzy		ANN		Fuzzy	
			R	RMSE (mg l^{-1})	R	RMSE (mg l^{-1})	R	RMSE (mg l^{-1})	R	RMSE (mg l^{-1})
S_t=f(H_t,H_{t-1},Q_t, Q_{t-1} and S_{t-1})	4	5	0.608	789.73	0.617	732.32	0.599	859.43	0.602	780.23
S_t=f(H_t, H_{t-1}, H_{t-2}, Q_t, Q_{t-1} and S_{t-1})	4	5	0.775	685.54	0.779	663.83	0.772	685.35	0.777	683.09
S_t=f(H_t, H_{t-1}, H_{t-2}, Q_t, Q_{t-1}, Q_{t-2} and S_{t-1})	4	6	0.792	665.89	0.794	642.31	0.785	671.49	0.795	660.21
S_t=f(H_t, H_{t-1}, Q_t, Q_{t-1}, Q_{t-2}, S_{t-1} and S_{t-2})	5	7	0.796	659.53	0.797	642.78	0.793	668.12	0.798	656.13
S_t=f(H_t, H_{t-1}, H_{t-2} Q_t, Q_{t-1}, Q_{t-2}, S_{t-1} and S_{t-2})	5	6	0.784	665.63	0.794	642.35	0.791	670.07	0.794	663.37
Curve Fitting with bias correction	R		0.558				0.615			
	RMSE (mg l^{-1})		1168.1				971.73			

1. $S_t = f(H_{t-1}, H_t, Q_{t-1}, Q_t, S_{t-1})$
2. $S_t = f(H_{t-2}, H_{t-1}, H_t, Q_{t-1}, Q_t, S_{t-1})$
3. $S_t = f(H_{t-2}, H_{t-1}, H_t, Q_{t-2}, Q_{t-1}, Q_t, S_{t-1})$
4. $S_t = f(H_{t-1}, H_t, Q_{t-2}, Q_{t-1}, Q_t, S_{t-2}, S_{t-1})$
5. $S_t = f(H_{t-2}, H_{t-1}, H_t, Q_{t-2}, Q_{t-1}, Q_t, S_{t-2}, S_{t-1})$

Where, S_t, H_t and Q_t are the sediment concentration, gauge and discharge at time t, respectively.

5.6.2.2 Training of ANN models

The feed-forward back propagation ANN network used in this study consists of input neurons (gauge, discharge and sediment of previous time steps) in the input layer and a single output neuron (sediment) in the output layer with one hidden layer. The input and output data were scaled between 0 and 1. In the trial runs, the number of neurons in the hidden layer was varied between 2 and 10. After many trials, the number of neurons in the hidden layer of the network was finalized and they vary from 4 to 6. The initial weights were randomly assigned and the activation functions such as sigmoid and linear functions, were used for the hidden and output nodes, respectively. The mean square error (average squared error between the network outputs and the target outputs) was used to measure the performance of a training process. During training, the weights and biases of the network were adjusted using gradient descent with momentum weight and bias learning function. To confirm the consistency in the results, a number of trials have been made and the developed model was simultaneously checked for its improvement on testing data on each iteration to avoid over training.

5.6.3 Fuzzy Model

Five input data vectors considered for ANN models were also applied for the *TS* fuzzy model development. The most significant factors, identified in the previous sections, were used to identify a *TS* fuzzy model. The model identification was carried out in two steps: (i) determining the number of fuzzy rules and their associated membership functions using fuzzy clustering approach and (ii) optimizing the *TS* fuzzy model through least square estimation. The fuzzy clustering partitions a data set into a number of groups in such a way that the similarity within a group is larger than that among groups. The similarity matrices are generally highly sensitive to the range of elements in the input vectors. Therefore, the input-output data sets have been normalized within the unit hypercube. The subtractive clustering approach has been applied for computation of rule base and membership functions. The optimum model structure was determined after trials. In the trials, the cluster radius (r_a) of subtractive clustering algorithm was varied between 0.1 and 1 with steps of 0.02. The cluster centers and thus the Gaussian membership function identified for each case were used to compute consequent parameters through a linear least square method and finally a *TS* fuzzy model was developed. Each fuzzy model has a different number of rules (between 4 and 7). For every input vector a membership degree to each fuzzy set greater than 0 is computed from the Gaussian membership function. Therefore, all the rules fires simultaneously for each combination inputs and thus provides a crisp output value for a given input data vector using equation (5.6). Performance indices such as root mean square error (RMSE) between the computed and observed discharge and the correlation coefficient were used to finalize the optimal parameter combination of the model.

5.7 RESULTS AND DISCUSSION

The value of performance indices for the estimation of sediment concentration of all the models are presented in Table 5.2 for Jamtara site and in Table 5.3 for Manot site. The correlation statistics, which evaluate the linear correlation between the observed and computed sediment concentration, is consistent during the calibration and validation period for all of the models. The correlation coefficients for the conventional rating curve are low in case of both calibration and validation data sets. The conventional sediment curves developed by Asselman (2000) for numerous stations also showed a low value of correlation coefficient between observed and computed sediment. The ANN model shows a significant improvement in estimation of sediment concentration, as indicated by increased correlation coefficient, varying from 0.612 to 0.813 for calibration data sets and 0.613 to 0.813 for validation data sets of Jamtara site, and from 0. 608 to 0.796 for calibration data sets and 0.599 to 0.793 for validation data sets of Manot site (Table 5.2 and 5.3). Further, slightly better correlation is observed with the *TS* fuzzy model in the case of both Jamtara (0.624 to 0.815 calibration data and 0.630 to 0.815 for validation data) and Manot (0.617 to 0.797 calibration data and 0.602 to 0.798 for validation data). The RMSE values obtained for Manote site are generally very high in comparison to those obtained for the Jamtara site (Table 5.2 and 5.3). This is mainly due to very low sediment concentration in the river water at Jamtara. The fuzzy model has the lowest RMSE value when compared with ANN and conventional rating curves. The observed discharge and sediment concentration data of the two sites showed a decrease in the sediment values with the increasing flows after some turning points. This characteristic is known as hysteresis and the higher performance of ANN and fuzzy models is basically due to their capability in capturing this phenomenon. This capability of the ANN and fuzzy model was investigated by plotting sediment concentration estimates versus the observed flows (Figure 5.2 and 5.3) for the periods where hysteresis is present in the data set. This illustration clearly represents that the ANN and fuzzy models reproduce a hysteresis though slightly different from the observed hysteresis. Both ANN and fuzzy models approximated the shape of the hysteresis curve in general with some under- and overestimation. However, the fuzzy model estimates the sediment concentrations more accurately than the ANN models in such conditions.

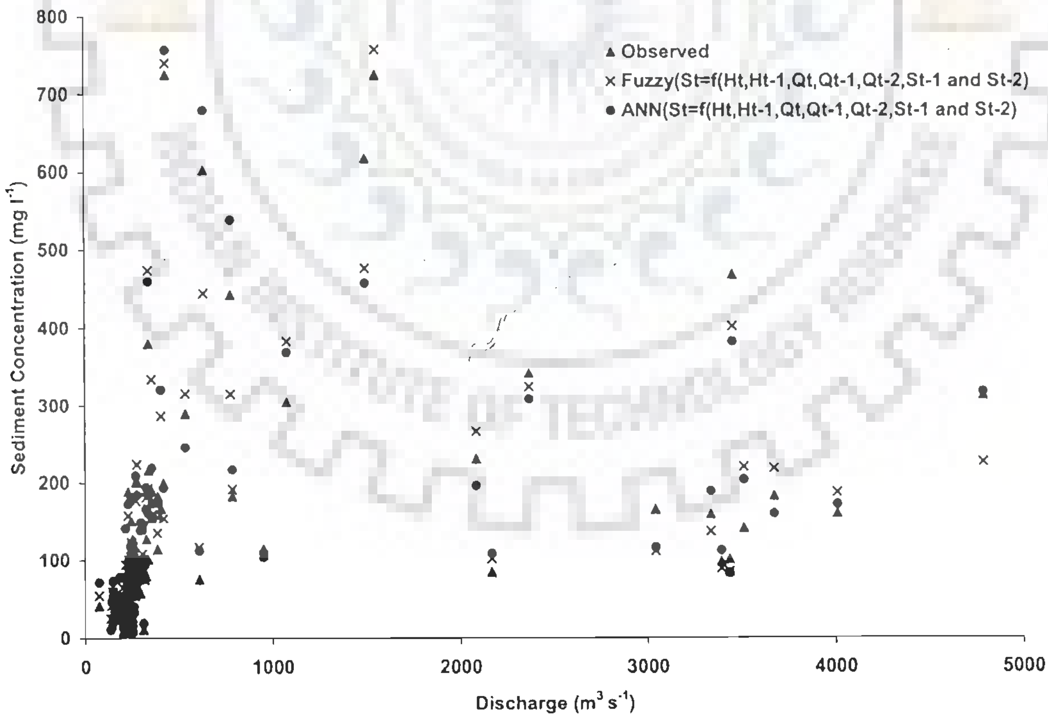

Figure 5.2: The hysteresis regeneration by ANN and Fuzzy Models (S_t=f(H_t, H_{t-1}, Q_t, Q_{t-1}, Q_{t-2}, S_{t-1} and S_{t-2})) for the Jamtara Site –Validation data

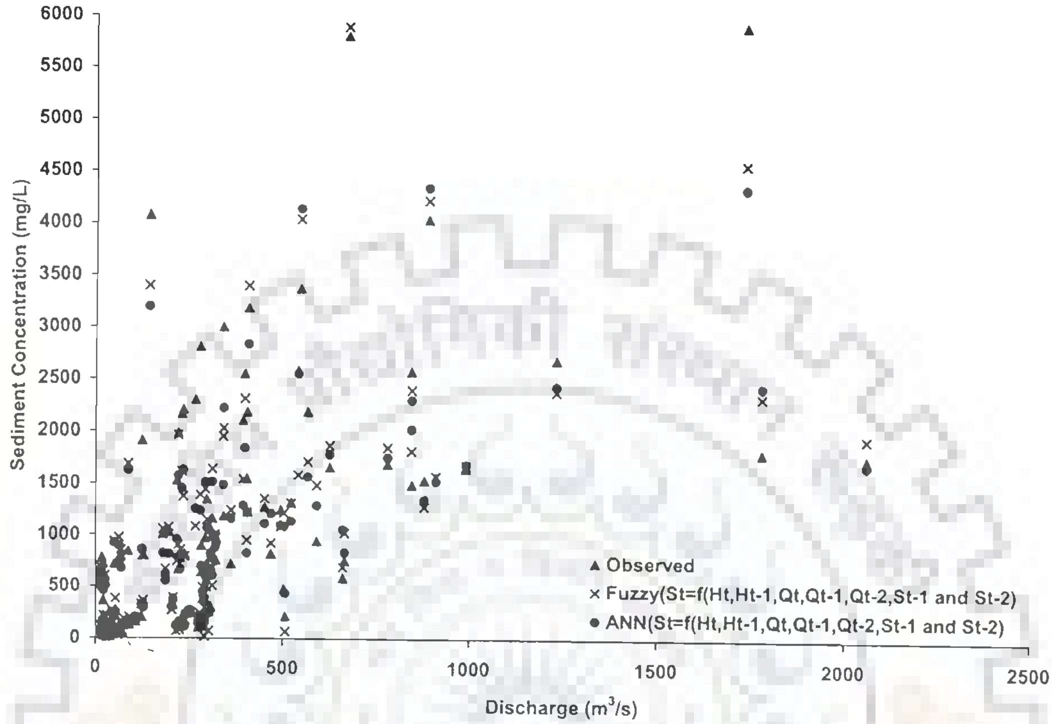

Figure 5.3: The hysteresis regeneration by ANN and Fuzzy Models (S_t=f(H_t, H_{t-1}, Q_t, Q_{t-1}, Q_{t-2}, S_{t-1} and S_{t-2}) for the Manot Site –Validation data

The estimations of sediment concentration for the validation period are compared with the observed sediment concentration values in the form of sediment hydrograph in Figure 5.4 and 5.5. The sediment hydrographs show that the deviations (under- and overestimation) from the observed sediment concentration are in general not very high in the case of the ANN and fuzzy modeling approach. It is also seen from the graph that the conventional approach significantly underestimates the peaks. Further, the recession behaviour is not properly modeled by the conventional curve fitting approach. The calibration and validation results (Table 5.2 and 5.3) indicate that the increase in information in the form of gauge, discharge and sediment of previous time steps improves the model results, which confirms the results obtained by Jain (2001). However, further increase in such information in the input structure shows a declining trend in model output. This may be due to decrease in autocorrelation and cross-correlation after certain lags.

Scatter plots between observed and estimated sediment data with ±20% error band are shown in Figure 5.6 for Jamtara site and in Figure 5.7 for Manot site. These scatter plots indicate that the fuzzy and ANN model can estimate high values of sediment more accurately than the conventional approach. Figure 5.6 illustrates that most of

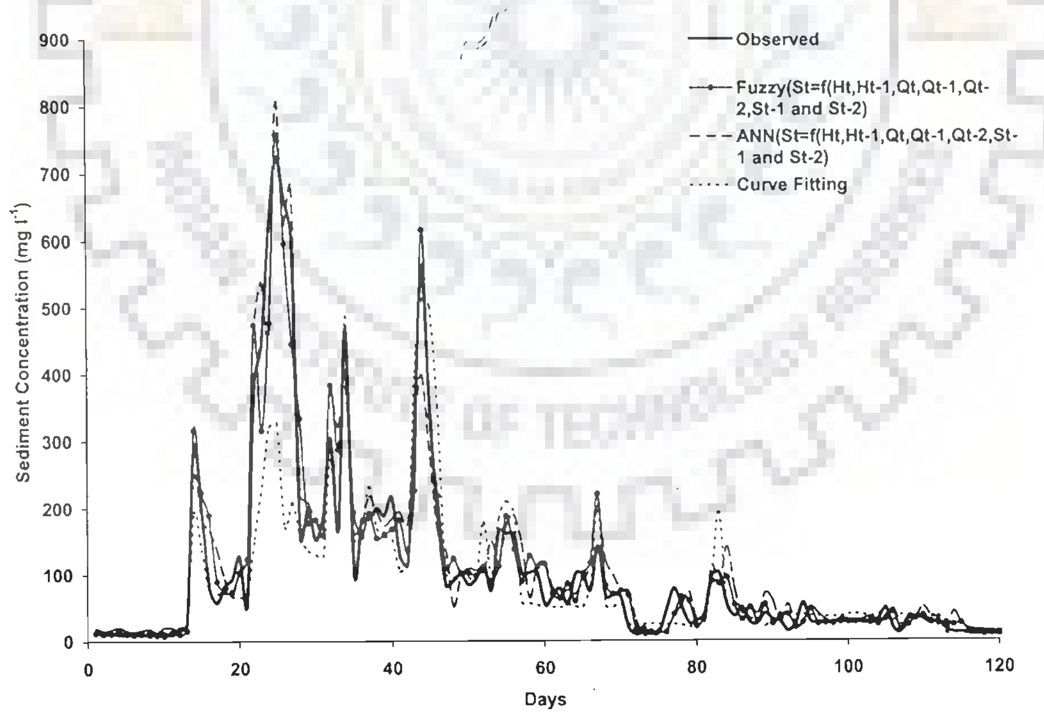

Figure 5.4: Estimated sediment concentration hydrograph by curve fitting, ANN and Fuzzy models (S_t=f(H_t, H_{t-1}, Q_t, Q_{t-1}, Q_{t-2}, S_{t-1} and S_{t-2}) for the Jamtara Site – Validation data

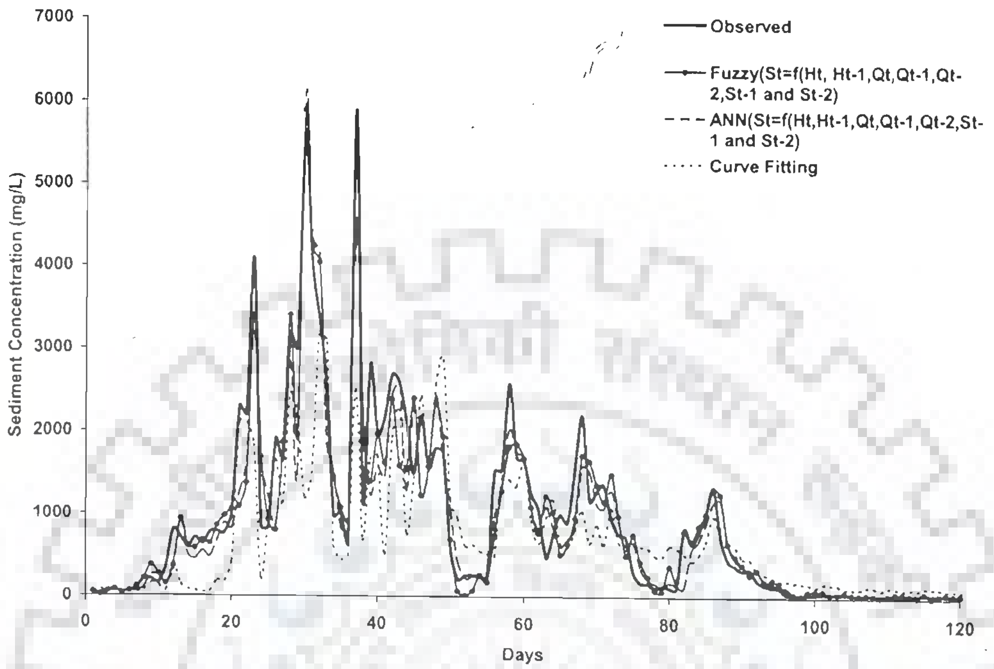

Figure 5.5: Estimated sediment concentration hydrograph by curve fitting, ANN and Fuzzy models ($S_t=f(H_t, H_{t-1}, Q_t, Q_{t-1}, Q_{t-2}, S_{t-1}$ and S_{t-2}) for the Manot Site – Validation data

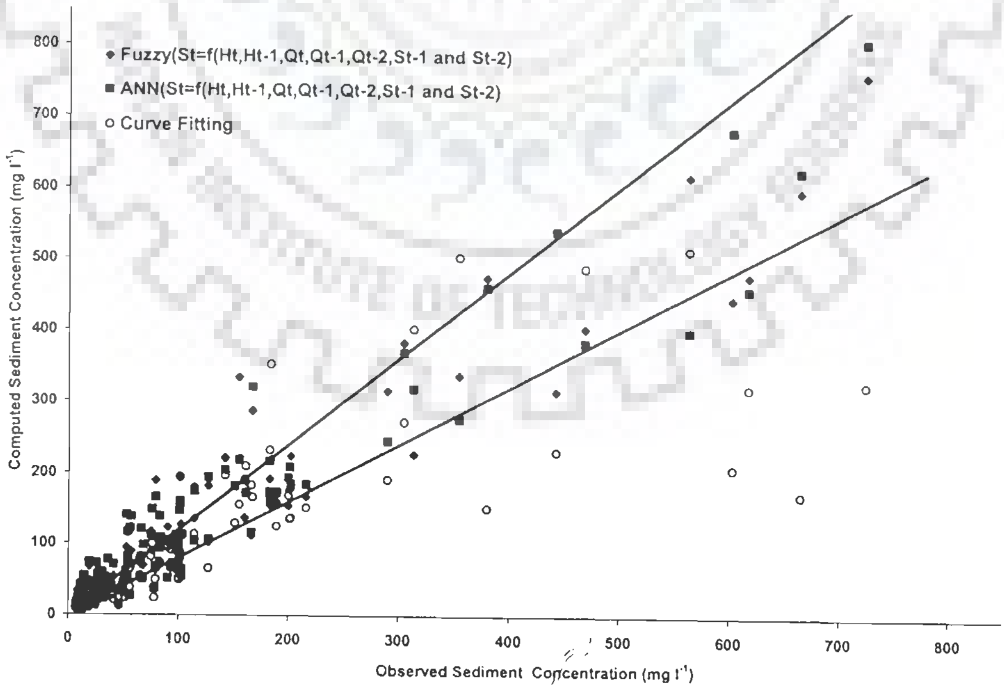

Figure 5.6: Scatter plot comparing estimated and observed sediment concentration with ± 20% error band for the Jamtara Site using – Validation data

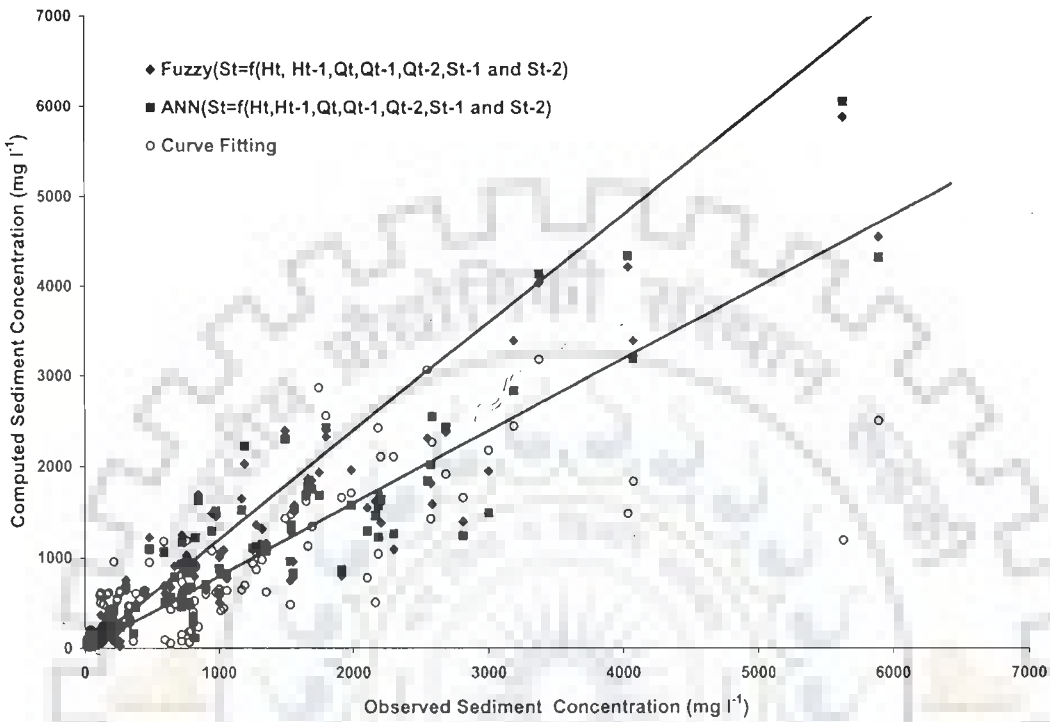

Figure 5.7: Scatter plot comparing estimated and observed sediment concentration with ± 20% error band for the Manot Site –Validation data

the measured sediment values in the high range (>500 mg l^{-1}) of the sediment are estimated more accurately than with the conventional curve fitting approach. In the lower and lower-middle region of error band, the variation is generally more than 20% which is mainly because of narrow band width in that region. The validation result for Manot site (Figure 5.7) also indicates that high sediment concentration values (>3000 mg l^{-1}) are well estimated by fuzzy and ANN models within the ±20% error band.

The models' performance in estimation of total sediment load is also compared, since it is important in water resources management. The total estimated sediment amounts for the gauging sites in the validation periods are given in Table 5.4. The total sediment load estimates for the Manot site by the fuzzy, ANN and curve fitting models are, respectively, 3.52, 5.18 and 21.04 % lower than the observed value and those for Jamtara site are, respectively, 2.63, 4.05 and 23.19% lower than the observed value. The curve-fitting approach poorly estimates the total sediment load. The fuzzy logic model estimates are considerably better than those of the ANN model.

Table 5.4: Estimated sediment load during testing period by curve fitting, ANN and fuzzy models (S_t=f(H_t, H_{t-1}, Q_t, Q_{t-1}, Q_{t-2}, S_{t-1} and S_{t-2}))

Gauging Site	Observed Sediment Load x10^4 tons	Model Results					
		Fuzzy logic		ANN		Curve Fitting	
		Sediment Load x10^4 tons	Relative Error (%)	Sediment Load x10^4 tons	Relative Error (%)	Sediment Load x10^4 tons	Relative Error (%)
Jamtara	151.69	147.70	2.63	145.54	4.05	116.51	23.19
Manot	526.57	507.99	3.52	499.27	5.18	415.77	21.04

For the practical point of view, the accurate estimation of sediment concentration is in particular important for entire spectrum of river sediment concentration conditions (or river flow situations). Generally, a model with a minimum RMSE may not be sufficient to eliminate the uncertainty in the model choice. In order to estimate the bias of the models for different output ranges, observed and computed data of two gauging sites were scaled in the range of 0 to 100 and than pooled together. Further, the scaled and pooled data set was divided into two sets: (i) data set consisting of data points for which models generally underestimates, and (ii) data set consisting of data points for which the model overestimates. The pooled average relative underestimation and overestimation errors (PARE (%)) were computed and plotted for the following eight sediment concentration classes: 0-10, 10-20, 20-30, 30-40, 40-50, 50-60, 60-70, 70-100 (Figure 5.8) using the following formula:

$$PARE\,(\%) = \frac{1}{n}\sum_{i=1}^{n}\frac{(Sc_i - So_i)}{So_i} \qquad (5.12)$$

where, Sc_i and So_i are computed and observed sediment concentration and n is the number of data points falling in each class.

It is seen that in each class, the overestimation and underestimation error of fuzzy and ANN models are more or less uniform and do not show any strong deviation. This indicates the absence of bias in fuzzy and ANN models in all ranges of sediment concentration. The overestimation and underestimation error in very low sediment concentration are markedly high for curve fitting approach. Similarly, in the high sediment region, the underestimation error for curve fitting approach is always greater than that for the fuzzy and ANN models. In general, the fuzzy model gives slightly more accurate estimates than the ANN model for both overestimated and underestimated data sets and in almost all the river stages.

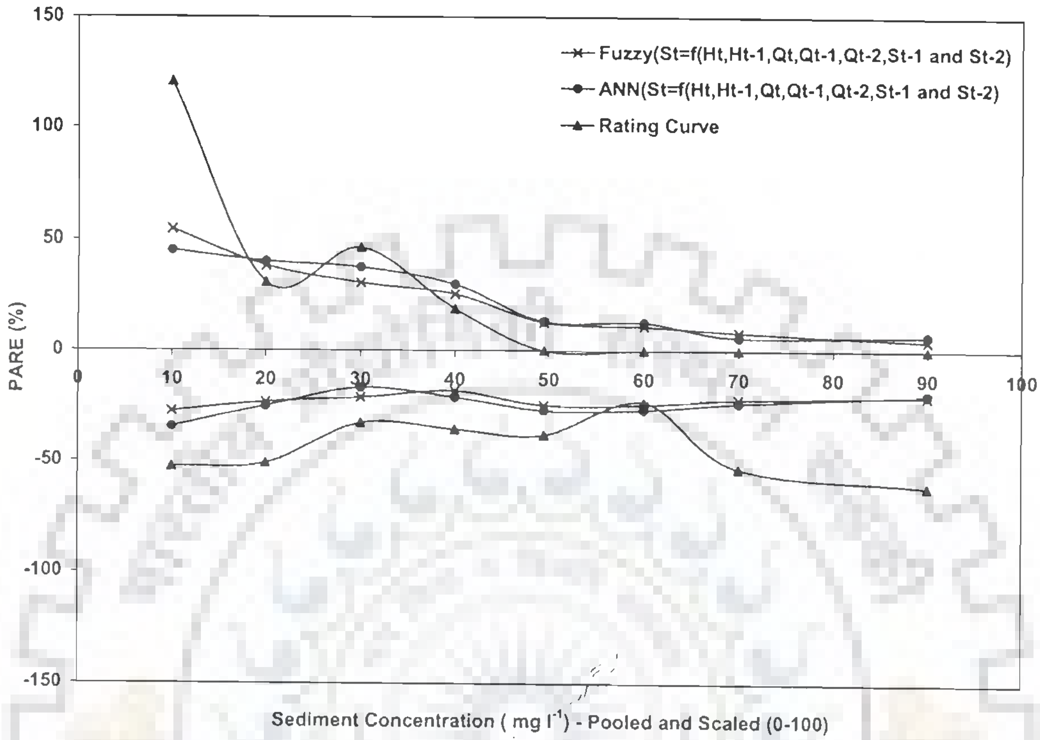

Figure 5.8: Variation of over and under estimation error with sediment concentration for different models in pooled data set

5.8 CONCLUSIONS

Many practical problems in water resources require knowledge of the sediment load carried by the rivers or the load the rivers can carry without danger of aggragadation or degradation. Hence, the measurement of sediments being transported by a river is of vital interest for planning and designing of various water resources projects. The conventional methods available for sediment load estimation are largely empirical, with sediment rating curves being the most widely used. The rating relationships based on regression technique are generally not adequate in view of the inherent complexity of the problem. In this study, ANN and fuzzy logic techniques are applied to model stage-discharge-sediment concentration relationship. The data of two gauging sites in the Narmada basin have been used to compare the performance of fuzzy, ANN and conventional curve fitting approaches. Performance of the conventional sediment rating curves, neural networks and fuzzy rule based models was evaluated using coefficient of correlation, root mean square error and pooled average relative underestimation and overestimation errors (PARE) of sediment concentration. Both ANN and fuzzy models were found to be considerably better than the conventional rating curve method. This is explained by the fact that fuzzy and ANN approaches can successfully capture the hysteresis phenomenon. It is noted that in the fuzzy and ANN approaches, several explanatory variables for past times were used to predict sediment concentration in present time, whereas, the conventional method uses a single explanatory variable, the current discharge. Therefore, the performance of the conventional sediment rating curve is poor in comparison to fuzzy and ANN models. The study suggests that the fuzzy model is able to capture the inherent nonlinearity in the river gauge, discharge and sediment relationship better than the ANN, and is able to estimate sediment concentration in the rivers more accurately. A comparative analysis of predictive ability of these models in different ranges of flow indicates that the fuzzy modeling approach is slightly better than the ANN. The results of the study are highly promising and suggest that fuzzy modeling is a more versatile and improved alternative to the corresponding ANN approach for developing stage-discharge-sediment concentration relationships.

CHAPTER 6

RAINFALL-RUNOFF MODELLING USING ANN AND FUZZY LOGIC BASED MODELS

6.1 BACKGROUND

As mentioned in the previous chapters, little formal research has been devoted to a quantitative investigation of the fuzzy logic based models in hydrological modeling. Therefore, the present study aims to enhance the recent research works on fuzzy logic based rainfall-runoff modeling. Rainfall-runoff modelling, from daily time scale point of view, is now explored with different input model structures, using the linear transfer function, ANN and fuzzy logic. Using the available rainfall-runoff data of the upper Narmada basin, a suitable modeling technique with appropriate model input structure is suggested on the basis of various model performance indices. Research findings of this chapter have been accepted for presentation in the International Conference on Water, Environment, Energy and Society (WEES) – 2009, New Delhi, India.

6.2 INTRODUCTION

The rainfall-runoff process is highly nonlinear, time-varying, spatially distributed, and not easily described by simple models. Therefore, the problem of transformation of rainfall into runoff has been a subject of scientific investigations throughout the evolution of the subject of hydrology. Hydrologists are mainly concerned with evaluation of catchment response for planning, development and operation of various water resources schemes. A number of investigators have tried to relate runoff with the different characteristics which affect it (Dooge, 1959; Rodriguez-Iturbe and Valdes, 1979; Stedinger and Taylor, 1982; Chow et al., 1988; Van der Tak and Bras, 1990; Bevan et al., 1995; Muzik, 1996; Bevan, 2000; Sikka and Selvi, 2005). Various attempts have been made to address this modelling issue either using knowledge based models or data-driven models. A knowledge based model aims to reproduce the system and its behaviour in a physically realistic manner and are generally called physically-based model. The physically based models generally use a mathematical framework based on mass, momentum and energy conservation equations in a spatially distributed model domain, and parameter values that are directly related to catchment characteristics. For the purpose of rainfall-runoff process simulation, conceptual and physical based models are widely used. However, simulating the real-world relationships using these rainfall-runoff models is not a simple task since the various hydrological processes that involve the transformation of rainfall into runoff are complex and variable. Many of the conceptual models widely used in rainfall-runoff modeling are lumped one and the factors in generating runoff are not represented clearly by these models. The time required to construct these models is enormous and thus an alternative modelling technique is sought when detailed modelling is not required in cases such as streamflow forecasting. The linear regression or linear time series models such as ARMA (Auto Regressive Moving Average) have been developed to handle such situations because they are relatively easy to implement. However, such models do not attempt to represent the non-linear dynamics inherent in the hydrologic processes, and may not always perform well. In recent years, data-driven technique e.g. Artificial Neural Network (ANN) has gained significant attention. Many rainfall-runoff models using ANN have been reported in the literature.

This study presents the development of intelligence models based on ANNs and fuzzy logic for prediction of runoff. The fuzzy relations between the input and output variables were inferred from the measured data and they are laid out in the form of IF-THEN statements. The performance of the developed models is compared with linear transfer based models.

6.3 LITERATURE REVIEW

6.3.1 ANN Based Models

In modeling the hydrological processes, ANNs have proven to be good in simulating complex, non-linear systems (Halff et al., 1993; Karunanithi et al., 1994; Hsu et al., 1995; Minns and Hall, 1996; ASCE Task Committee, 2000; Dawson and Wilby, 2001; Anctil et al., 2004; Jain and Srinivasulu, 2004; Rajurkar et al., 2004; Agarwal et al. 2004; Agarwal and Singh, 2004). Daniel (1991), ASCE (2000a, 2000b), and Maier and Dandy (2000) reported comprehensive review and some of the applications of ANN in hydrology and water resources. Hsu et al. (1995) used three layered feed forward neural network with Linear Least Square Simplex (LLSSIM) for the training and compared its performance with the ARMAX model and conceptual SAC-SMA (Sacramento soil moisture accounting) model and found that ANN model gave better results than the other two models. Smith and Eli (1995) presented the ability of a three-layer ANNs to relate spatially and temporally varying rainfall excess to the runoff response of a simple synthetic watershed. Raman and Sunilkumar (1995) developed ANN model with back propagation algorithm to synthesize inflows into reservoirs and found that ANN gave better results than autoregressive model. Dawson and Wilby (1998) developed flood forecasting system with three layered feed forward neural network with back propagation algorithm and compared with conventional flood forecasting system and found that the flood forecasting system by ANN performed better than the other one. Fernando and Jayawardena (1998) used Radial Basis Function Network (RBFN) with Orthogonal Least Square (OLS) algorithm to model runoff forecasting from rainfall patterns. They found that the training was faster in RBFN with OLS algorithm and RBFN performed better than the network with Back propagation algorithm and the ARMAX model. Tokar and Johnson (1999) employed an Artificial Neural Network (ANN) methodology to forecast daily runoff as a function of daily precipitation, temperature, and snowmelt for the Little Patuxent River watershed in Maryland. The sensitivity of the prediction accuracy to the content and length of training data was investigated. Thirumalaiah and Deo (2000) constructed an ANN model for hourly flood runoff and daily river stage. They used Back Propagation algorithm, Conjugate gradient algorithm, Cascade Correlation algorithm for the training of the model and the results are compared with Multiple Regression model and found that ANN performed better than the Multiple regression model. Sajikumar and Thandaveswara (1999) used temporal back propagation neural network to model monthly rainfall-runoff process and they compared the results with Volterra type Functional Series Model. They found that TBP NN performed better than the other model. Elshorbagy et al (2000) used Feed Forward ANN with Back propagation algorithm to predict spring runoff and found that the ANN results were better than the linear and nonlinear regressive model. Tokar and Markus (2000) applied ANN technique to model watershed runoff with back propagation algorithm for the training of the neural network and compared with the results of conceptual models. The results indicate that ANNs can be powerful tools in modeling the rainfall-runoff process for various time scale, topography, and climatic patterns. Zhang and Govindaraju (2000) used modular neural network structure to model the rainfall-runoff process. Bayesian concepts were utilized in deriving the training algorithm. Average monthly rainfall of current and previous months and average monthly temperatures were treated as network inputs, and monthly runoff was treated as output. It was reported by them that modular neural networks predict extreme events of runoff better than the singular neural network models. Sudheer et al. (2001) used ANN technique with back propagation algorithm for the development of rainfall-runoff model. The statistical properties of the data series such as auto, partial and cross correlation values were used to select an appropriate input vector for the model development. The ANN model developed based on this approach performed effectively. Sudheer, et al. (2002) presented a new approach for designing the network structure in an artificial neural network (ANN)-based rainfall-runoff model. They utilized the statistical properties such as cross-, auto- and partial-auto-correlation of the data series in identifying a unique input vector that best represents the process for the basin, and a standard algorithm for training. Jain and Indurthy (2003) carried out a comparative analysis of deterministic, statistical, and artificial neural networks for event based rainfall-runoff modeling. Agarwal and Singh (2004) developed multi layer back propagation artificial neural network (BPANN) models to simulate rainfall-runoff process considering three time scales viz. weekly, ten daily and monthly. They suggested that the variability and uncertainty of data have an impact on the development of generalized BPANN model.

In most of the studies reported above, three-layered feed forward neural network with Back Propagation algorithm were used for the training and validation of the model.

Therefore, three-layered feed forward network and Back Propagation algorithm have been used for training the network in this study also.

6.3.2 Fuzzy Logic Based Models

Zhu and Fujita (1994) compared the performance of three-layered feed forward neural network with back propagation algorithm to forecast the discharge for 1-hr, 2-hr, 3-hr lead-time with fuzzy inference method.

Hundecha et al. (2001) demonstrated the applicability of a fuzzy logic based approach to rainfall-runoff modelling. Individual processes involved in producing runoff from precipitation in a watershed were modeled and their applicability was investigated by incorporating them in a modular conceptual model HBV (Hydrologiska Byråns Vattenbalansavdelning, Bergström, 1972, Bergström and Forsman, 1973). Four different processes taking place in a watershed system i.e. snowmelt, evapotranspiration, runoff and basin response were identified and a fuzzy rule based routine was formulated for each of the modules independently. Daily time series of precipitation, mean temperature and discharge values obtained from different gauging stations in the catchment of the river Neckar in South West Germany were used. Performance of each of the fuzzy rule based modules was found to be almost similar to equivalent HBV module. However, the fuzzy rule based routine for snowmelt showed the best performance. Development of a fuzzy rule based routine for the basin response module was found to be the most difficult. In totality the entire fuzzy logic based model was found to reproduce the observed discharge well with the knowledge of the factors that influence a process.

Han et al. (2002) described a novel attempt to use a fuzzy logic approach for river flow modelling based on fuzzy decision tree (FDT). Daily rainfall and river flow data of

Bird Creek catchment were used to calibrate and validate the fuzzy model. From these data a set of classification rules were generated using MA-ID3 algorithm developed by Baldwin et al. (1998). Features were selected on the basis of maximising the expected information gain as quantified by Shamnon's measure of entropy. Further, an iterative method was applied for ranking the features according to their effectiveness in partitioning the set of defined classes. The calibration data set was classified in five fuzzy sets with a degree of overlap of 0.65 and a decision tree was created. Critically examining the full decision tree, it was depicted that the points tends to cluster in the very low fuzzy sets have a tendency to bias towards zero due to high occurrence of zero rainfall values. The FDT model with only five fuzzy labels performed reasonably well. The performance of the model was not as good as the neural network model in test case. It is reported that the neural network models are black box models which lake the see through ability; while, glass box nature of the fuzzy model could provide some useful insight about the hydrological processes.

Sen and Altunkaynak (2003) proposed fuzzy system modelling, an alternative to the classical regression approach, to determine rainfall-runoff relationships. The conventional linear regression fitted to scatter of rainfall-runoff data ignores the dynamic behaviour of the rainfall-runoff process. The study presented the application of fuzzy and regression methods on monthly rainfall-runoff data of two different drainage basins on the European and Asian sides of Istanbul. The rainfall-runoff data were divided into five subgroups namely "low", "medium low", "medium", "medium high", and "high" with triangle membership functions for the three middle classes and trapeziums membership for the most left (i.e. low) and most right (i.e. high) classes. Considering the direct proportionality features of the rainfall-runoff relationship, five rules were formulated to compute output from fuzzy model. Centroid defuzzification method (Ross, 1995; Sen, 2001) was used to compute crisp output from fuzzy set. The study concluded that the fuzzy system approach provided the runoff estimates more accurately than a regression approach. The runoff estimation accuracy obtained by fuzzy model was within an acceptable relative error of less than 10%.

Ozelkan and Duckstein (2001) proposed a fuzzy conceptual rainfall-runoff (CRR) framework to deal with those parameter uncertainties of conceptual rainfall-runoff models that are related to data and/or model structure. For developing a fuzzy conceptual rainfall-runoff framework, they fuzzified the conceptual rainfall-runoff system and then different operational models are formulated using fuzzy rules. Finally, the parameter identification aspect is examined using fuzzy regression techniques. The model was developed for the Lucky Hills sub-watershed of the Walnut Gulch experimental watershed located south-east of Tucson, Arizona USA. Bi-objective and tri-objective fuzzy regression models are applied in the case of linear conceptual models. The results indicated that the fuzzy CRR models using fuzzy least square regression yielded more stable parameters estimates than those obtained using fuzziness of the rainfall-runoff.

Tayfur and Singh (2003) presented two intelligence models i.e. artificial neural networks (ANNs) and fuzzy logic for predicting runoff due to rainfall. They considered infiltration rate and rainfall intensity as input variables and discharge as output variable for developing a fuzzy logic based model. All the input and output variables intuitively fuzzified considering triangular fuzzy membership functions and the fuzzy relations in the form of IF-THEN statements were infered between the input and output variables.

The model was tested using experimental peak discharge data and runoff hydrographs and the results were compared with physically based model. They reported that the intelligence models can predict discharge from rainfall events and simulate runoff hydrographs satisfactorily.

Vernieuwe et al. (2005) demonstrated three different methods for constructing fuzzy rule based models of the Takagi-Sugeno type for rainfall-runoff modeling. Three fuzzy clustering methods namely grid partitioning, subtractive clustering and Gustafson-Kessal (GK) clustering identification were applied on rainfall and runoff data of Zwalm catchment, Belgium. Hourly precipitation (disaggregated from daily observations) and discharge values of a complete year were used to build the model so as to cover different hydrological conditions observed within the different seasons of the year.

Recent developments and use of fuzzy logic in hydrological modeling indicates that more applications and research is needed to support the utility of fuzzy technique in the area of daily rainfall-runoff modelling and to help in establishing their full practical use in dealing the real world problems.

6.4 DATA USED FOR THE STUDY

Validated and processed data of Narmada catchment up to Manot gauging site covering an area of 4300 sq. km. have been selected for rainfall-runoff modeling. Validated and processed data of daily rainfall at Narayanganj, Bichhia, Baihar, Palhera, Manot, Gondia and Nimpur stations and daily discharge at Manot gauging site have been considered. The available data were divided into two sets, one for calibration and other for validation. The daily rainfall and discharge data from June to September (monsoon period) of the years 1993 and 1996 were used for calibration of the ANN model because these four years of data represent the extreme values of rainfall and discharge. The data of year 1997 and 1998 were used for the validation of the model.

6.5 DEVELOPMENT OF RAINFALL-RUNOFF MODELS

6.5.1 Fuzzy Model for Rainfall-Runoff Dynamics

Selection of the input and output variables is the first step in development of a fuzzy rule based rainfall-runoff model. Runoff at the outlet of a catchment is a function of previous rainfall and runoff values, as well as of the meteorological, topological, and soil and vegetative conditions of the catchment. Theoretically, a non linear and time varying storage function may be useful to express the rainfall-runoff process. There are inherent difficulties in defining such functions particularly when sufficient data are not available and estimation of catchment response is only relying on available rainfall data. Therefore, in the case of a rainfall-runoff model with minimum available data, the output variable describes the runoff that is to be predicted and possible input variables are measured rainfall and runoff data.

In daily rainfall-runoff modeling, proper accounting of loss rate plays an important role. Some researchers use the term loss rates and infiltration rates interchangeably. This led to the idea that stream flow occurs only when infiltration capacities are exceeded and therefore, result entirely from surface runoff. Perhaps, a more appropriate definition of losses would include precipitation that is stored on vegetative surface (interception), in the soils (where soil moisture deficit occur), as detention storage, or water that percolates to ground or is otherwise delayed.

The initial abstraction consists mainly of interception, infiltration, and surface storage, all of which occur before runoff begins (Ponce and Hawkins, 1996). A specified percent of the potential maximum retention is the initial abstraction which is the interception, infiltration and surface storage occurring before the runoff begins. The remaining percent of the potential maximum retention is mainly the infiltration occurring after the runoff begins. This letter infiltration is controlled by the rate of infiltration at the soil surface or by the rate of transmission in the soil profile or by the water-storage capacity of the profile, which ever is the limiting factor. A quick succession of storm reduces the magnitude of potential maximum retention each day because the limiting factor does not have the opportunity to completely recover its rate or capacity through weathering, evapotranspiration, or drainage (Ponce and Hawkins, 1996). During such a storm period the magnitude of potential maximum retention remains virtually the same after the second or third day even if the rains are large so that there is a lower limit to potential maximum retention for a given soil-cover complex. There is a practical upper limit to potential maximum retention, again depending on the soil-cover complex, beyond which the recovery cannot take potential maximum retention unless the soil-cover complex is altered. Change in potential maximum retention is based on the antecedent moisture condition (AMC) determined by the total rainfall in the 5 day period preceding a storm (Ponce and Hawkins, 1996). Therefore, in addition to daily rainfall values, the AMC is also introduced in the input vector of a daily rainfall-runoff model. The number of preceding day's rainfall suitable for the computation of AMC has been decided by the cross correlation analysis of runoff at Manot site and AMC(n) values computed for preceding n days. The correlation matrix between runoff and AMC(n) is developed for n

= 3 to 9 days. The correlation analysis (Figure 6.1) between AMC and runoff suggests that AMC values computed using 7 days rainfall shows maximum value of correlation i.e. 0.835 and can be suitably considered in the input vector of daily rainfall-runoff model of Manot catchment. The following eleven combinations of input data vectors have been considered:

1. Only rainfall as input

   M1 $Q_t = f(P_t, P_{t-1}, P_{t-2}, P_{t-3})$

2. Rainfall and AMC as input

   M2 $Q_t = f(P_t, P_{t-1}, P_{t-2}, P_{t-3}, AMC)$

3. Rainfall and Runoff as input

   M3 $Q_t = f(P_t, P_{t-1}, P_{t-2}, P_{t-3}, Q_{t-1})$

   M4 $Q_t = f(P_t, P_{t-1}, P_{t-2}, P_{t-3}, Q_{t-1}, Q_{t-2})$

   M5 $Q_t = f(P_t, P_{t-1}, P_{t-2}, P_{t-3}, Q_{t-1}, Q_{t-2}, Q_{t-3})$

4. Rainfall, Runoff and AMC as input

   M6 $Q_t = f(P_t, P_{t-1}, P_{t-2}, P_{t-3}, Q_{t-1}, AMC)$

   M7 $Q_t = f(P_t, Q_{t-1}, AMC)$

   M8 $Q_t = f(P_t, P_{t-1}, P_{t-2}, P_{t-3}, Q_{t-1}, Q_{t-2}, AMC)$

   M9 $Q_t = f(P_t, Q_{t-1}, Q_{t-2}, AMC)$

   M10 $Q_t = f(P_t, P_{t-1}, P_{t-2}, P_{t-3}, Q_{t-1}, Q_{t-2}, Q_{t-3}, AMC)$

   M11 $Q_t = f(P_t, Q_{t-1}, Q_{t-2}, Q_{t-3}, AMC)$

where Q_t and P_t are the runoff and precipitation at time t respectively.

The evaluation of a set of fuzzy rules (or rule base) in a fuzzy rule based model for the determination of the runoff value is an important task. The basis of fuzzy logic is to consider hydrologic variables in a linguistically uncertain manner, in the form of subgroups, each of which is labeled with successive fuzzy 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 provided better room for the justification of sub-relationship between two or more variables on the basis of fuzzy words (Sen, 2003). Since rainfall-runoff relationship in general, has a direct proportionality feature, it is possible to write the following rule base for the description of Takagi-Sugeno fuzzy rainfall-runoff model.

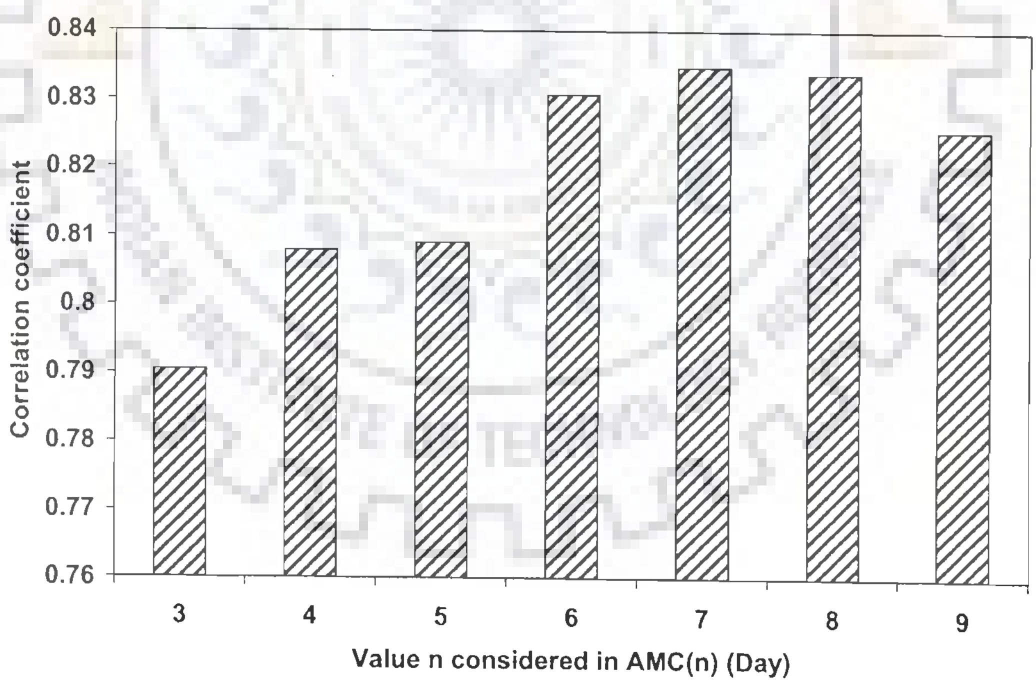

Figure 6.1: Correlation coefficient between AMC(n) and runoff

1. ***Only rainfall as input***

M1 Rule $R_i : IF(P_t, P_{t-1}, P_{t-2}, P_{t-3})$ is C_i THEN

$$Q_t = a_{1i}P_t + a_{2i}P_{t-1} + a_{3i}P_{t-2} + a_{4i}P_{t-3} + c_i \quad (6.1)$$

2. ***Rainfall and AMC as input***

M2 Rule $R_i : IF(P_t, P_{t-1}, P_{t-2}, P_{t-3}, AMC)$ is C_i THEN

$$Q_t = a_{1i}P_t + a_{2i}P_{t-1} + a_{3i}P_{t-2} + a_{4i}P_{t-3} + a_{5i}AMC + c_i \quad (6.2)$$

3. ***Rainfall and Runoff as input***

M3 Rule $R_i : IF(P_t, P_{t-1}, P_{t-2}, P_{t-3}, Q_{t-1})$ is C_i THEN

$$Q_t = a_{1i}P_t + a_{2i}P_{t-1} + a_{3i}P_{t-2} + a_{4i}P_{t-3} + a_{5i}Q_{t-1} + c_i \quad (6.3)$$

M4 Rule $R_i : IF(P_t, P_{t-1}, P_{t-2}, P_{t-3}, Q_{t-1}, Q_{t-2})$ is C_i THEN

$$Q_t = a_{1i}P_t + a_{2i}P_{t-1} + a_{3i}P_{t-2} + a_{4i}P_{t-3} + a_{5i}Q_{t-1} + a_{6i}Q_{t-2} + c_i \quad (6.4)$$

M5 Rule $R_i : IF(P_t, P_{t-1}, P_{t-2}, P_{t-3}, Q_{t-1}, Q_{t-2}, Q_{t-3})$ is C_i THEN

$$Q_t = a_{1i}P_t + a_{2i}P_{t-1} + a_{3i}P_{t-2} + a_{4i}P_{t-3} + a_{5i}Q_{t-1} + a_{6i}Q_{t-2} + a_{7i}Q_{t-3} + c_i \quad (6.5)$$

4. ***Rainfall, Runoff and AMC as input***

M6 Rule $R_i : IF(P_t, P_{t-1}, P_{t-2}, P_{t-3}, Q_{t-1}, AMC)$ is C_i THEN

$$Q_t = a_{1i}P_t + a_{2i}P_{t-1} + a_{3i}P_{t-2} + a_{4i}P_{t-3} + a_{5i}Q_{t-1} + a_{6i}AMC + c_i \quad (6.6)$$

M7 Rule $R_i : IF(P_t, Q_{t-1}, AMC)$ is C_i THEN

$$Q_t = a_{1i}P_t + a_{2i}Q_{t-1} + a_{3i}AMC + c_i \quad (6.7)$$

M8 Rule $R_i : IF(P_t, P_{t-1}, P_{t-2}, P_{t-3}, Q_{t-1}, Q_{t-2}, AMC)$ is C_i THEN

$$Q_t = a_{1i}P_t + a_{2i}P_{t-1} + a_{3i}P_{t-2} + a_{4i}P_{t-3} + a_{5i}Q_{t-1} + a_{6i}Q_{t-2} + a_{7i}AMC + c_i \quad (6.8)$$

M9 Rule $R_i : IF(P_t, Q_{t-1}, Q_{t-2}, AMC)$ is C_i THEN

$$Q_t = a_{1i}P_t + a_{2i}Q_{t-1} + a_{3i}Q_{t-2} + a_{4i}AMC + c_i \quad (6.9)$$

M10 Rule $R_i : IF(P_t, P_{t-1}, P_{t-2}, P_{t-3}, Q_{t-1}, Q_{t-2}, Q_{t-3}, AMC)$ is C_i THEN

$$Q_t = a_{1i}P_t + a_{2i}P_{t-1} + a_{3i}P_{t-2} + a_{4i}P_{t-3} + a_{5i}Q_{t-1} + a_{6i}Q_{t-2} + a_{7i}Q_{t-3} + a_{8i}AMC + c_i \quad (6.10)$$

M11 Rule $R_i : IF(P_t, Q_{t-1}, Q_{t-2}, Q_{t-3}, AMC)$ is C_i THEN

$$Q_t = a_{1i}P_t + a_{2i}Q_{t-1} + a_{3i}Q_{t-2} + a_{4i}Q_{t-3} + a_{5i}AMC + c_i \quad (6.11)$$

where a_{ji} and c_i are the parameters of the consequent part of rule R_i.

Using the linear consequent part of the fuzzy rainfall-runoff model, subtractive clustering based identification method has been applied. The model performance is examined by means of NS efficiency (Nash and Sutcliffe, 1970) and Root Mean Square Error (RMSE) criteria. In order to find the optimal model, the parameters of the subtractive clustering algorithm were finalized after a number of trial runs. In the trials, the parameters of subtractive clustering were varied from 0.5 to 2 for quash factor and o.1 to 1 for the cluster radius (r_a), accept ratio and reject ratio with steps of 0.01. The cluster centers and thus the Gaussian membership function identified for each case were used to compute consequent parameters through a linear least square method and finally a *TS* fuzzy model was developed. The developed model gives crisp output value for a given input data. Fuzzy model developed form the actual data sets have different rules ranging from 4 to 7. Performance indices such as root mean square error (RMSE) between the computed and observed runoff, correlation coefficient and NS efficiency were used to finalize the optimal parameter combination of the model. The effect of error in peak and low observations are taken care by the criteria viz. correlation coefficient and NS efficiency. The error in time to peak is another criterion which is not considered here as it is normally considered in storm studies. In rainfall-runoff modeling, accurate estimation of total volume is an important aspect. Therefore, another criterion known as volumetric error (Kachroo and Natale, 1992) has been considered in this study to hydrologically evaluate the performance of the models under consideration. The volumetric error (V_{er}) is expressed as:

$$V_{er} = \frac{\sum_{i=1}^{n}(Q_{ci} - Q_{oi})}{\sum_{i=1}^{n} Q_{oi}} \times 100 \qquad (6.12)$$

where Q_{ci}, Q_{oi} and n are computed runoff, observed runoff and number of data sets.

6.5.2 Network Architecture for ANNs Model

Three-layered feed forward neural network was considered for the design of the ANN model for the rainfall-runoff process in this study. The network structure is formulated by considering single output neuron in output layer corresponding to the predicted runoff at time t. As described through equation 6.1 to 6.11, computed areal rainfall, preceding runoff at Manot gauging site and antecedent moisture content (AMC) constitutes the input neurons in the input layer. The data are normalised between 0 and 1 before the start of the training of the ANN model. The learning algorithm adopted here was error back propagation algorithm based on the generalised delta rule. After the normalization of data the next step in the development of ANN model was the determination of the optimum number of neurons in the hidden layer. The optimum number of neurons in the hidden layer was identified using a trial and error procedure by varying the number of neurons in the hidden layer from 2 to 10. A number of trial runs were made before the finalization of the number of neurons in the hidden layer of the network. The number of neurons in the hidden layer of the networks of models M1 to

M11 was finalized and they vary from 4 to 6. In the process of model development the initial weights were randomly assigned and the activation functions such as sigmoid and linear functions were used for the hidden and output nodes, respectively. The mean square error (average squared error between the network outputs and the target outputs) was used to measure the performance of a training process. During training the weights and biases of the network were adjusted using gradient descent with momentum weight and bias learning function. As discussed in the previous chapters, a number of trials have been made until consistent results are obtained. Furthermore, the developed model was simultaneously checked for its improvement on testing data on each iteration to avoid over training. Therefore, an ANN with *n* input neurons, *k* hidden neurons and 1 output neurons (*n*-*k*-1) was adopted as the best structure combination to capture the rainfall-runoff relationship inherent in the data sets under consideration. Optimized values of hidden neurons (k) are presented in Table 6.1.

Table 6.1: Optimum number of neurons in hidden layer

ANN Model	No. of Inputs	No. of neurons in hidden layer	No. of outputs
M1	3	4	1
M2	4	4	1
M3	4	4	1
M4	5	4	1
M5	6	4	1
M6	5	4	1
M7	3	4	1
M8	6	5	1
M9	4	4	1
M10	7	6	1
M11	5	4	1

6.5.3 Linear Transfer Function Model

Box and Jenkins (1976) described a linkage between two time dependent variables of a discrete linear system by the following mathematical expression:

$$\psi\alpha_s Z_t = \varepsilon\alpha_s X_t \tag{6.13}$$

where X_t, Z_t are input and output variables at time t. α_s is back shift operator. $\psi\alpha_s$ and $\varepsilon\alpha_s$ are polynomials of order $(1-a_1\alpha_{s1}-a_2\alpha_{s2}....a_p\alpha_{sp})$ and $(b_0+b_1\alpha_{s1}+b_2\alpha_{s2}....b_q\alpha_{sq})$.

Equation (6.13) can be rewritten as,

$$(1-a_1\alpha_{s1}-a_2\alpha_{s2}....a_p\alpha_{sp})\cdot Z_t = (b_0+b_1\alpha_{s1}+b_2\alpha_{s2}....b_q\beta_{sq})\cdot X_t \tag{6.14}$$

or

$$(1-a_1Z_{t-1}-a_2Z_{t-2}....a_pZ_{t-p}) = (b_0X_t+b_1X_{t-1}+b_2X_{t-2}....b_qX_{t-q}) \tag{6.15}$$

or

$$Z_t = \sum_{k=1}^{p} a_k\cdot Z_{t-k} + \sum_{k=0}^{q} b_k\cdot X_{t-k} \tag{6.16}$$

Shifting the base time for variable X from 1 to q, the Equation (6.16) can be expressed as:

$$Z_t = \sum_{k=1}^{p} a_k\cdot Z_{t-k} + \sum_{k=1}^{q} b_k\cdot X_{t-k+1} \tag{6.17}$$

where p and q are time memory or response for input (X_t) and output (Z_t) variables. a, b are parameters or constants.

Equation (6.17) produces a set of 't' linear equations to be solved for $(p+q)$ number of constants. The linear equations can be represented in matrix form as:

$$Z = Y\cdot M + \xi_{\Re} \tag{6.18}$$

where Z = output vector $=[Z_1, Z_2, ...Z_t]^T$ (6.19)

Y = input matrix

$$\begin{bmatrix} 0 & 0 & 0 & . & . & 0 & X_1 & 0 & 0 & . & . & 0 \\ Z_1 & 0 & 0 & . & . & 0 & X_2 & X_1 & 0 & . & . & 0 \\ Z_2 & Z_1 & 0 & . & . & 0 & X_3 & X_2 & X_1 & . & . & 0 \\ Z_3 & Z_2 & Z_1 & . & . & 0 & X_4 & X_3 & X_2 & . & . & X_{4-q+1} \\ Z_4 & Z_3 & Z_2 & . & . & Z_{5-p} & X_5 & X_4 & X_3 & . & . & X_{5-q+1} \\ . & . & . & . & . & . & . & . & . & . & . & . \\ . & . & . & . & . & . & . & . & . & . & . & . \\ . & . & . & . & . & . & . & . & . & . & . & . \\ . & . & . & . & . & . & . & . & . & . & . & . \\ Z_{t-1} & Z_{t-2} & Z_{t-3} & . & . & Z_{t-p} & X_t & X_{t-1} & X_{t-2} & . & . & X_{t-q+1} \end{bmatrix} \tag{6.20}$$

M = time memory vector

$$= [a_1, a_2, \ldots a_p, b_1, b_2, \ldots\ldots b_q]^T \tag{6.21}$$

$\xi_{\Re}$ = error vector

$$= [e_1, e_2, \ldots e_t]^T \tag{6.22}$$

The least square method which minimizes the sum of square of difference between observed and estimated values is used to solve the set of above defined 't' linear equations.

Now, instead of finding the exact solution of Equation (6.18), a search is to be made for $M = \hat{M}$ which minimizes the sum of squared error defined by:

$$E(M) = \sum_{i=1}^{t} (Z_i - m_i^T M)^2 = (Z - M \cdot Y)^T (Z - M \cdot Y) \tag{6.23}$$

where $\xi_{\Re} = Z - Y \cdot M$ is the error vector produced by a specific choice of M. E(M) has a quadratic form and has a unique minimum at $M = \hat{M}$. The squared error in Equation (6.23) is minimized when $M = \hat{M}$, called the least square estimator which satisfies the normal equation:

$$Y^T \cdot Y \cdot \hat{M} = Y^T \cdot Z \tag{6.24}$$

or

$$\hat{M} = [Y^T \cdot Y]^{-1} \cdot Y^T \cdot Z \tag{6.25}$$

6.6 RESULTS AND DISCUSSION

Runoff prediction models for the rainfall-runoff hydrological process have been developed using linear transfer function, artificial neural networks and fuzzy rule based modeling system for Manot catchment using different combinations of input data vectors. The model performance evaluation has been carried out through statistical and hydrological performance evaluation criteria, viz. root mean square error (RMSE), correlation coefficient, Nash Sutcliffe efficiency and volumetric error (V_{er}).

6.6.1 Linear Transfer Function Runoff Prediction Model

The linear transfer function models have been developed for the prediction of runoff. The linear transfer function models are trained using the same input data set as used for the ANN and fuzzy rule based models, to enable a direct comparison. Considering various combinations of input vectors (Equation 6.1 to Equation 6.11) eleven separate models have been developed and mathematically expressed as:

Only rainfall as input

$$Q_t = 10.42P_t + 5.89P_{t-1} + 3.35P_{t-2} + 2.5P_{t-3} \tag{6.26}$$

Rainfall and AMC as input

$$Q_t = 8.95P_t + 3.04P_{t-1} + 0.68P_{t-2} + 0.07P_{t-3} + 1.75AMC \tag{6.27}$$

Rainfall and Runoff as input

$$Q_t = 7.99P_t + 1.12P_{t-1} + 1.11P_{t-2} + 0.52P_{t-3} - 0.61Q_{t-1} \tag{6.28}$$

$$Q_t = 6.34P_t + 0.11P_{t-1} + 0.063P_{t-2} + 0.03P_{t-3} + 0.547Q_{t-1} + 0.08Q_{t-2} \tag{6.29}$$

$$Q_t = 6.32P_t + 0.10P_{t-1} + 0.03P_{t-2} + 0.001P_{t-3} + 0.528Q_{t-1} + 0.09Q_{t-2} + 0.07Q_{t-3} \tag{6.30}$$

Rainfall, Runoff and AMC as input

$$Q_t = 6.30P_t + 0.07P_{t-1} + 0.02P_{t-2} + 0.007P_{t-3} + 0.522Q_{t-1} + 0.67AMC \tag{6.31}$$

$$Q_t = 7.76P_t + 0.526Q_{t-1} + 0.68AMC \tag{6.32}$$

$$Q_t = 4.67P_t + 0.28P_{t-1} + 0.15P_{t-2} + 0.02P_{t-3} + 0.52Q_{t-1} + 0.04Q_{t-2} + 0.67AMC \tag{6.33}$$

$$Q_t = 7.34P_t + 0.511Q_{t-1} + 0.29Q_{t-2} + 0.63AMC \tag{6.34}$$

$$Q_t = 7.45P_t + 0.51P_{t-1} + 0.11P_{t-2} + 0.09P_{t-3} + 0.514Q_{t-1} + 0.10Q_{t-2} + 0.02Q_{t-3} + 0.34AMC \tag{6.35}$$

$$Q_t = 0.75P_t + 0.532Q_{t-1} + 0.11Q_{t-2} + 0.22Q_{t-3} + 0.31AMC \tag{6.36}$$

Performance indices of the linear transfer function models developed in the form of mathematical equations 6.26 to 6.36 are presented in Table 6.2. A comparison of the developed model has been carried out on the basis of model performance indices viz. RMSE, coefficient of correlation and NS efficiency. The linear transfer function runoff prediction models for Manot basin show the values of coefficient of correlation and NS efficiency in the range of 0.54 to 0.766 and 0.400 to 0.658 respectively for the developed models during calibration. Values of coefficient of correlation and NS efficiency vary in the range of 0.539 to 0.758 and 0.347 to 0.584 during the model validation. Root mean square error varies from 163.0 to 284.8 during calibration and 128.6 to 299.5 during validation. An improvement in the model performance is observed by including AMC in the input vector of the linear transfer function models. In the models where only rainfall is the input, Model M2 is the best model with the values of correlation coefficient, NS efficiency and RMSE as 0.563, 0.473, 266.8 respectively during calibration and 0.565, 0.402, 281.0 respectively during validation. Models M3 to M5 with only rainfall and runoff as inputs show that the model M4 performs better than the other two models. The correlation coefficient, NS efficiency and RMSE of Model M4 are 0.702, 0.592, 189.4 respectively during calibration and 0.631, 0.522, 154.4 during validation. It is observed that the inclusion of 3 day previous runoff in the model M5 reduces the model performance. Models M6 to M11 consider rainfall, runoff and AMC in the model input vector. In this category of models, M8 is the best model with values of coefficient of correlation, NS efficiency and RMSE as 0.766, 0.658, 163.0 respectively during calibration and 0.758, 0.584, 128.6 respectively during validation. In general, the performance indices of model calibration and validation indicate that inclusion of Q_{t-3} in the model input vector reduces the model performance. Figure 6.2 to 6.12 illustrates the time series of observed runoff and model predicted runoff for the eleven linear transfer function models for the validation period 1997 and 1998. It is observed that the model M1 and M2 estimates zero runoff values when there is no rainfall during the periods selected in the input model structure. Inclusion of previous day discharge values in the input model structure has direct impact on the model performance.

Table 6.2: Statistical performances indices of Linear Transfer Function Models

Model	Calibration				Validation			
	Coefficient of Correlation	NS	RMSE	Ev	Coefficient of Correlation	NS	RMSE	Ev
Only rainfall as input								
1	0.540	0.400	284.8	35.5	0.539	0.347	299.5	37.7
Rainfall and AMC as input								
2	0.563	0.473	266.8	33.8	0.565	0.402	281.0	35.8
Rainfall and Runoff as input								
3	0.698	0.575	193.7	27.2	0.627	0.451	156.7	-29.0
4	0.702	0.592	189.4	-26.9	0.631	0.522	154.4	-28.7
5	0.700	0.589	190.3	-27.0	0.629	0.508	155.3	-28.9
Rainfall, Runoff and AMC as input								
6	0.699	0.588	192.4	-27.1	0.628	0.501	156.0	-29.0
7	0.693	0.564	193.4	-27.7	0.615	0.500	157.0	-29.5
8	0.766	0.658	163.0	-21.1	0.758	0.584	128.6	-22.7
9	0.764	0.656	163.6	-21.3	0.755	0.582	134.5	-22.9
10	0.761	0.656	163.6	-21.5	0.754	0.580	131.4	-23.2
11	0.761	0.655	164.0	-21.5	0.753	0.581	132.7	-23.2

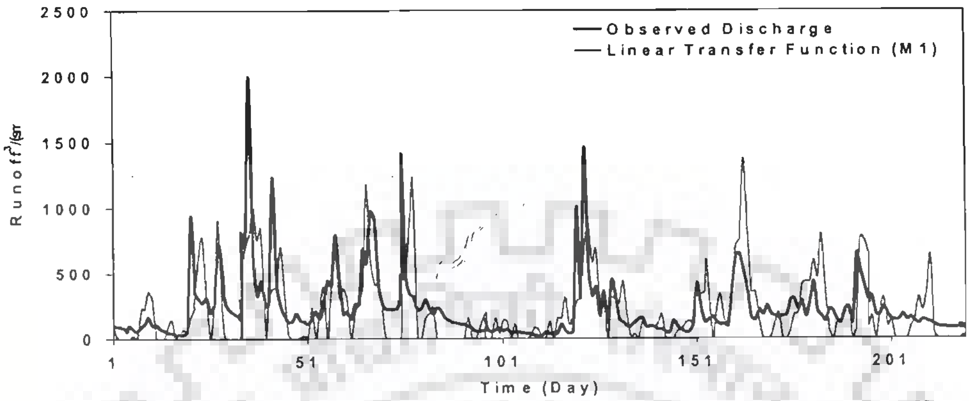

Figure 6.2: Time series of Observed Runoff and Model Predicted Runoff - Linear Transfer Function Model (M1)

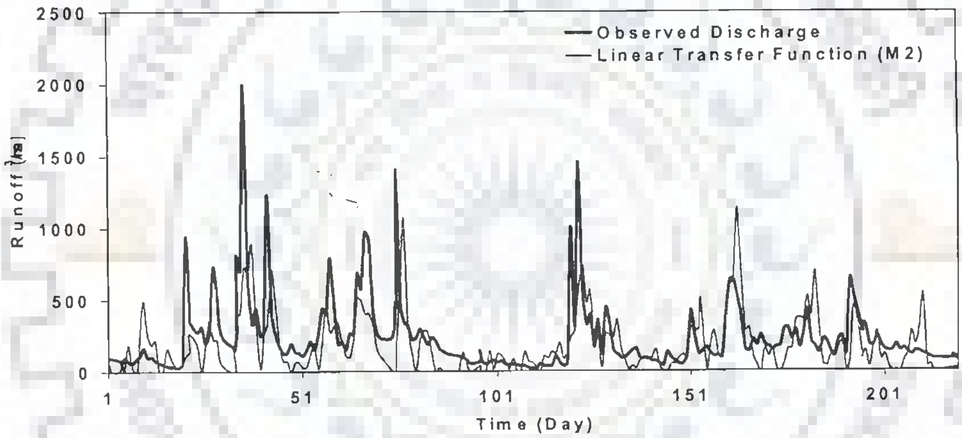

Figure 6.3: Time series of Observed Runoff and Model Predicted Runoff - Linear Transfer Function Model (M2)

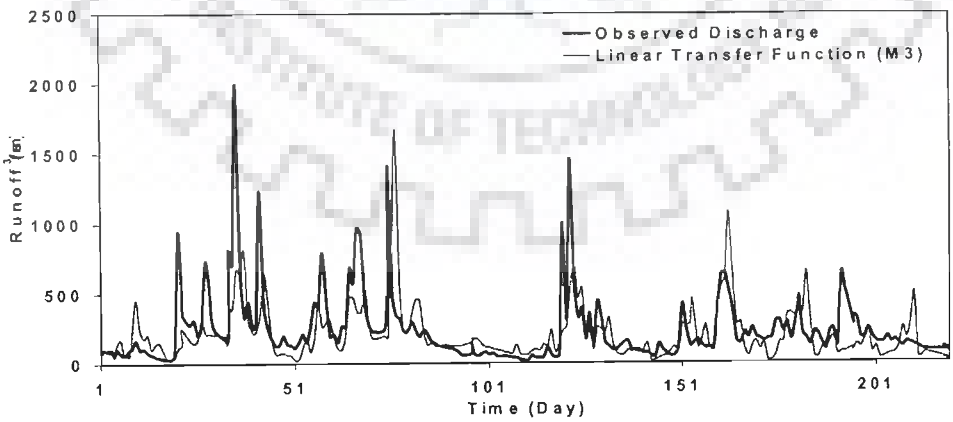

Figure 6.4: Time series of Observed Runoff and Model Predicted Runoff - Linear Transfer Function Model (M3)

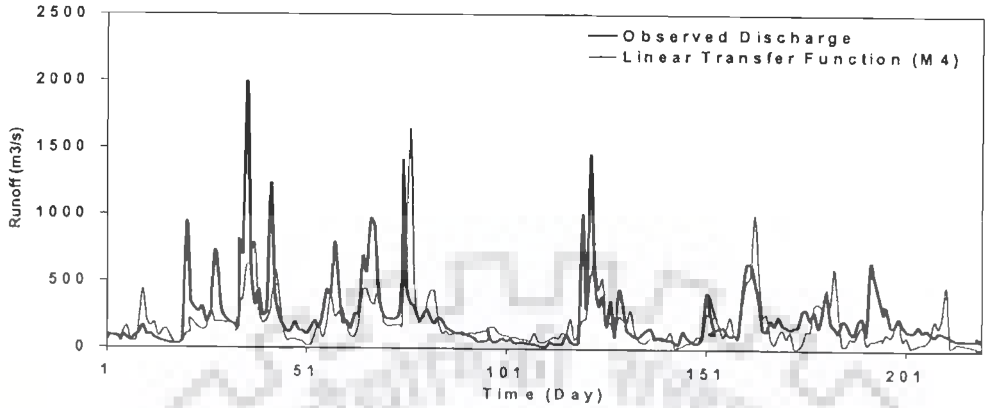

Figure 6.5: Time series of Observed Runoff and Model Predicted Runoff - Linear Transfer Function Model (M4)

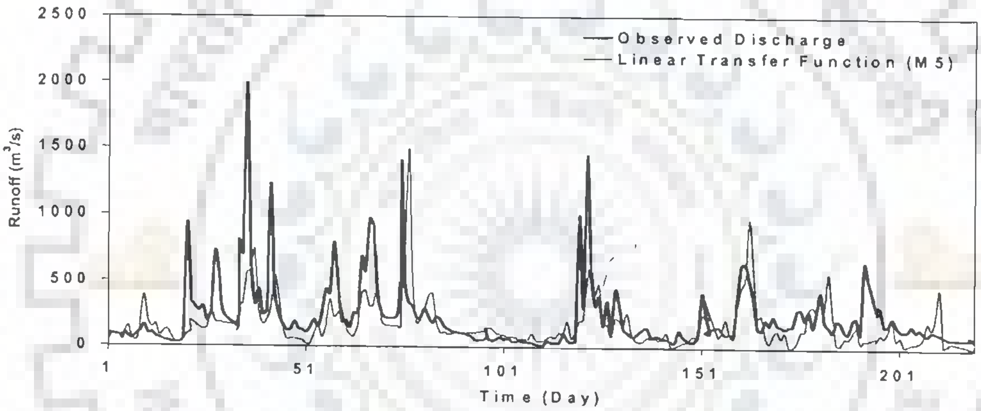

Figure 6.6: Time series of Observed Runoff and Model Predicted Runoff - Linear Transfer Function Model (M5)

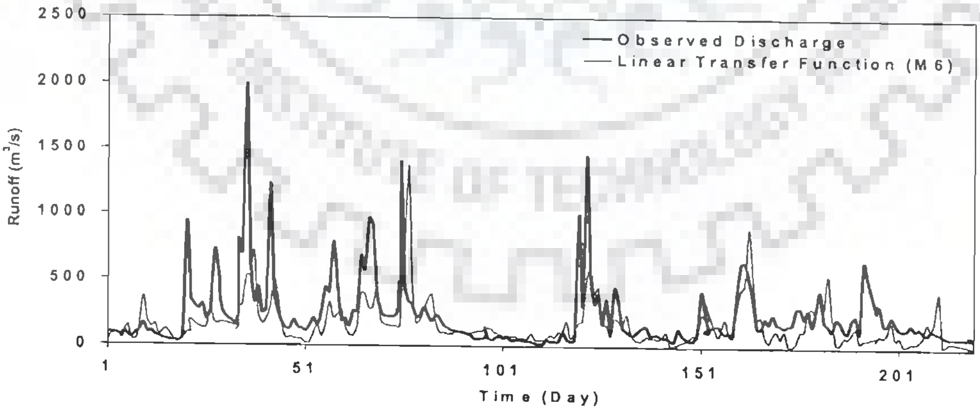

Figure 6.7: Time series of Observed Runoff and Model Predicted Runoff - Linear Transfer Function Model (M6)

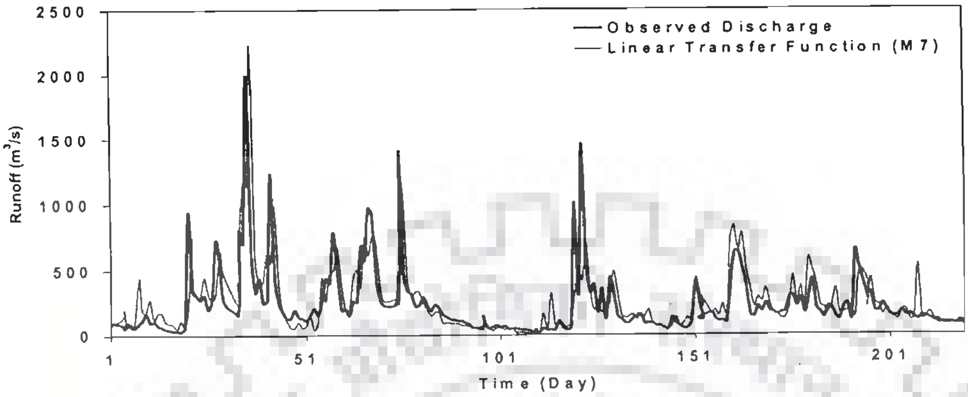

Figure 6.8: Time series of Observed Runoff and Model Predicted Runoff - Linear Transfer Function Model (M7)

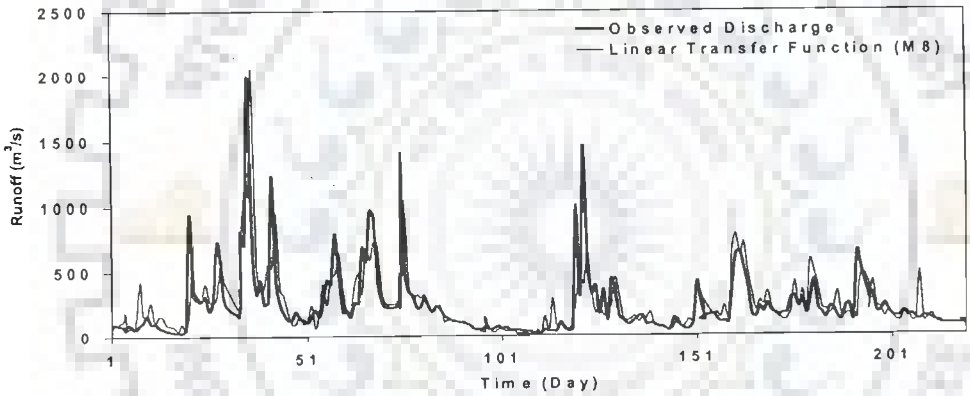

Figure 6.9: Time series of Observed Runoff and Model Predicted Runoff - Linear Transfer Function Model (M8)

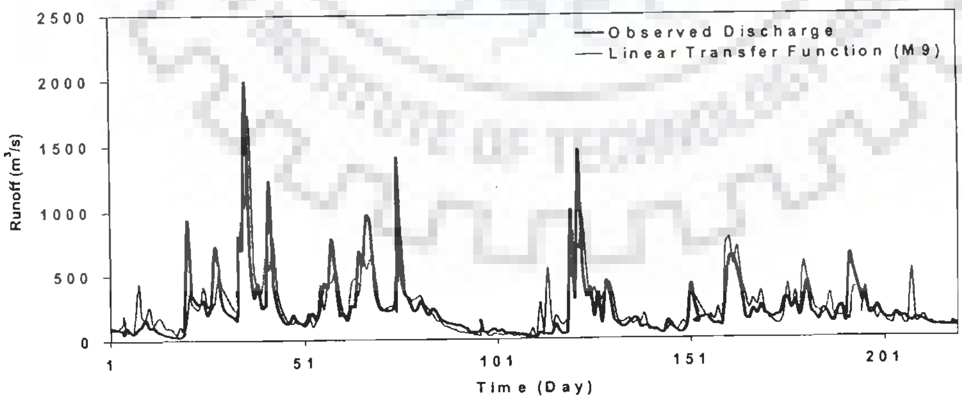

Figure 6.10: Time series of Observed Runoff and Model Predicted Runoff - Linear Transfer Function Model (M9)

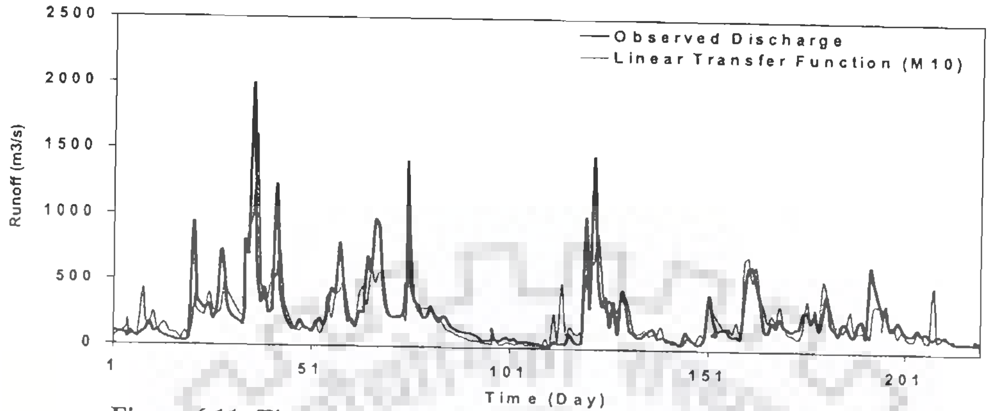

Figure 6.11: Time series of Observed Runoff and Model Predicted Runoff - Linear Transfer Function Model (M10)

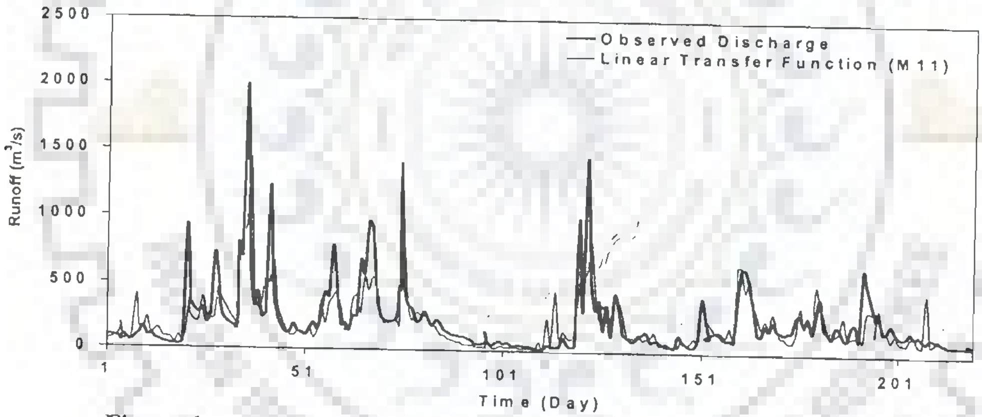

Figure 6.12: Time series of Observed Runoff and Model Predicted Runoff - Linear Transfer Function Model (M11)

6.6.2 ANN Runoff Prediction Model

All the eleven models (M1 to M11) having different input vectors were trained by providing the inputs to the model, computing the output, and adjusting the interconnection weights until the desired output is reached. The error back propagation algorithm has been used to train the network, using the mean square error (RMSE) over the training sample as the objective function. In the process of model development several network architectures with different number of input neuron in input layer, and different number of hidden layer with varying number of hidden neurons have been considered to select the optimal architecture of the network. A trial and error procedure based on the minimum RMSE criterion is used to select the best network architecture.

Table 6.3 presents the performance indices of all the eleven models developed using artificial neural networks. Model performance evaluation criteria RMSE, coefficient of correlation and NS efficiency were used to evaluate the performance of the developed model. It is observed that the values of coefficient of correlation and NS efficiency vary in the range of 0.661 to 0.884 and 0.569 to 0.770 respectively for the developed models during calibration. During the model validation, values of coefficient of correlation and NS efficiency vary in the range of 0.671 to 0.868 and 0.563 to 0.745. Root mean square error varies from 133.2 to 241.2 during calibration and 94.2 to 217.9 during validation. ANN models developed for three different cases i.e. (i) only rainfall in the input vector, (ii) rainfall and AMC in the input vector, and (iii) rainfall, runoff and AMC in the input vector. Models developed under these three classes show distinct performance. The model result indicates that the antecedent moisture content values considered in the input vector show an improvement in the daily rainfall-runoff model performance. Model M1 with only rainfall in the input vector show the values of coefficient of correlation, NS efficiency and RMSE values as 0.661, 0.569, 241.2 during calibration and 0.671, 0.563, 217.9 during validation respectively. Model M2 is defined by including antecedent moisture content in the input vector of model M1. Model M2 show the values of coefficient of correlation, NS efficiency and RMSE values as 0.672, 0.572, 218.6 during calibration and 0.678, 0.574, 216.2 during validation respectively.

This indicates that the inclusion of antecedent moisture content in the input vector has a direct relation with the performance of the model. Now, improvement of model M1 by inclusion of preceding day runoff is very obvious and this is confirmed by the Models M3, M4 and M5. Inclusion of preceding three days of runoff in the input vector, trim down the model performance. Values of coefficient of correlation, NS efficiency and RMSE of model M4 (i.e. 0.869, 0.635, 173.6) are better than the model M5. This indicates that only previous two runoff values are required to predict runoff. Model M6 to M8 are same as Model M3 to M5 except the term antecedent moisture content in the input vector. Model M6 to M8 show an improvement in the model performance by the inclusion of antecedent moisture content. It is depicted from the performances indices of Models M3 to M5 that the values of coefficient of correlation, NS efficiency and RMSE varies in the range of 0.801 to 0.838; 0.649 to 0.662 and 113.3 to 114.7 respectively during validation. Slightly better performance is obtained from the models M6, M8 and M10. For these three models (M6, M8 and M10) values of coefficient of correlation, NS efficiency and RMSE are found in the range of 0.822 to 0.868; 0.654 to 0.745, and 94.2 to 115.1 respectively during validation. In case of model M6, M8 and M10 the performance of the model M10 decreases when compared with model M8. Further, it is found from model M6 and M9 that instead of previous day rainfall values previous day runoff values have more effect on model performance. This may be due to the fact that the preceding day runoff and antecedent moisture contents provide sufficient memory to the daily rainfall runoff model which is otherwise associated with rainfall values. Another important criterion i.e. volumetric error (V_{er}) also indicates a pattern in tune with the correlation coefficient. Figure 6.13 to 6.23 illustrates the time series of observed runoff and model predicted runoff for the eleven ANN models for the validation period 1997 and 1998.

Table 6.3: Statistical performances indices – ANN models

	Calibration				Validation			
Model	Coefficient of Correlation	NS	RMSE	Ev	Coefficient of Correlation	NS	RMSE	Ev
Only rainfall as input								
1	0.661	0.569	241.2	25.7	0.671	0.563	217.9	23.1
Rainfall and AMC as input								
2	0.672	0.572	218.6	19.8	0.678	0.574	216.2	21.2
Rainfall and Runoff as input								
3	0.854	0.612	174.3	14.1	0.801	0.649	114.7	10.9
4	0.869	0.635	173.6	-12.8	0.838	0.662	113.3	-9.7
5	0.862	0.631	174.1	-13.4	0.834	0.656	114.5	-10.3
Rainfall, Runoff and AMC as input								
6	0.858	0.629	176.3	-13.8	0.822	0.654	115.1	-10.6
7	0.854	0.620	179.2	-14.1	0.819	0.649	118.4	-10.9
8	0.884	0.770	133.2	-11.4	0.868	0.745	94.2	-8.6
9	0.878	0.767	136.0	-11.7	0.860	0.742	98.6	-8.8
10	0.883	0.769	137.5	-11.6	0.860	0.743	99.4	-8.7
11	0.885	0.767	137.6	-11.5	0.858	0.742	100.1	-8.6

6.6.3 Fuzzy Logic Runoff Prediction Model

Fuzzy rule based models developed using model structures presented through Equation 6.1 to Equation 6.11 were compared using various statistical model performance indices e.g. RMSE, coefficient of correlation, NS efficiency and volumetric error. Table 6.4 presents these performance indices of all the eleven model structure defined as M1 to M11. The models classified in three different groups were evaluated within the same group and than compared with the models of other group. Inclusion of AMC in the input vector Model M1 results a new model M2. Model results

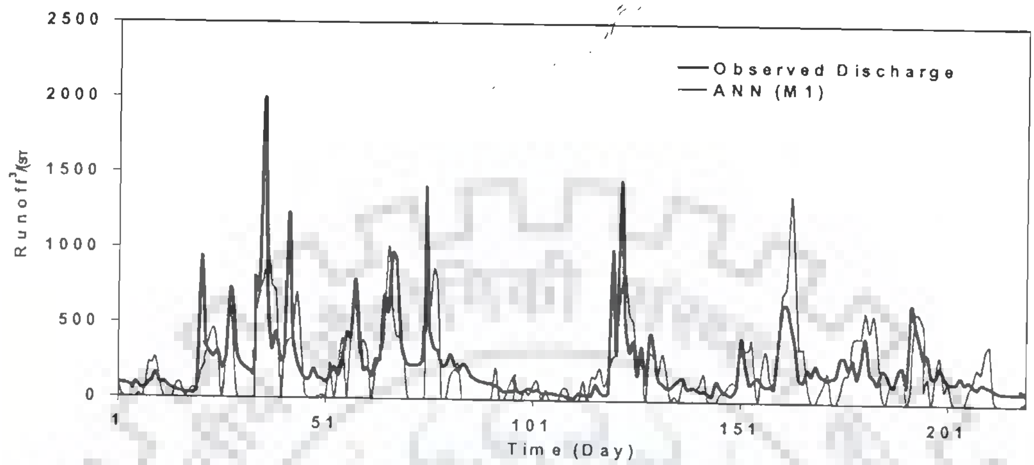

Figure 6.13: Time series of Observed Runoff and Model Predicted Runoff - ANN Model (M1)

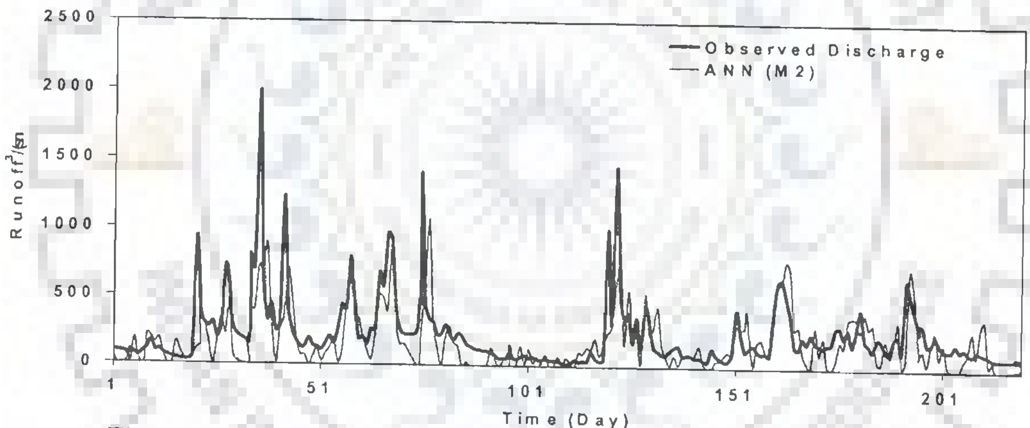

Figure 6.14: Time series of Observed Runoff and Model Predicted Runoff - ANN Model (M2)

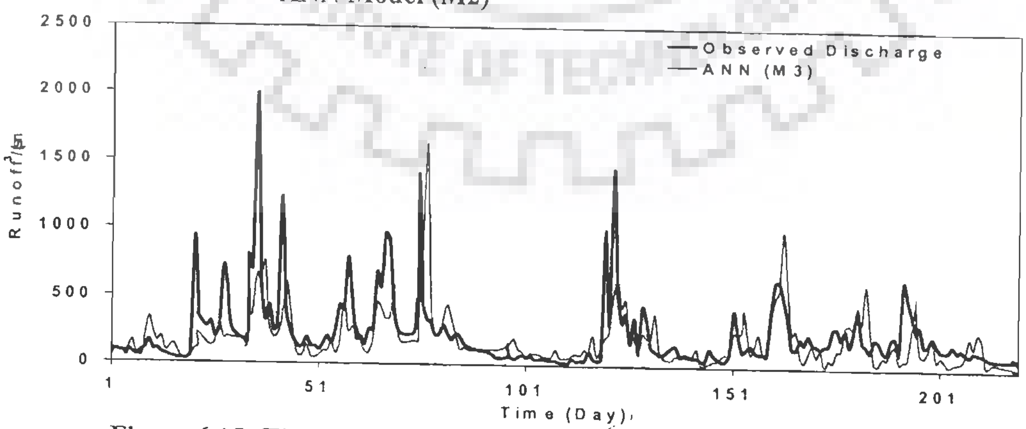

Figure 6.15: Time series of Observed Runoff and Model Predicted Runoff - ANN Model (M3)

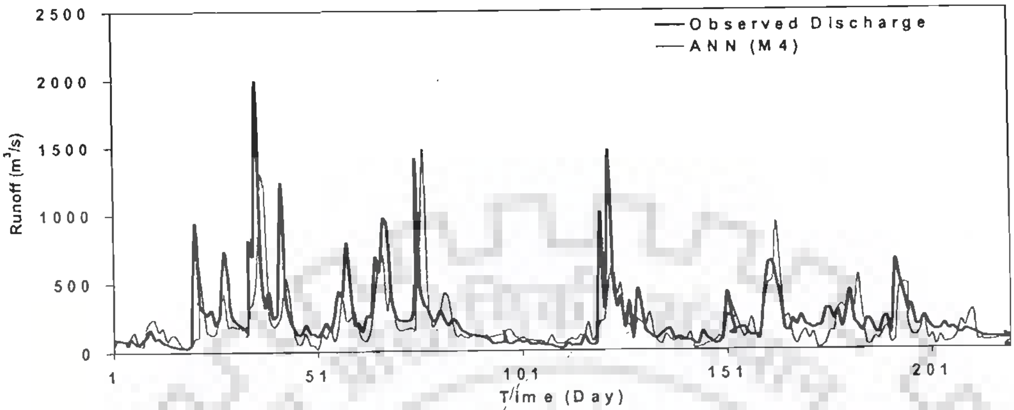

Figure 6.16: Time series of Observed Runoff and Model Predicted Runoff - ANN Model (M4)

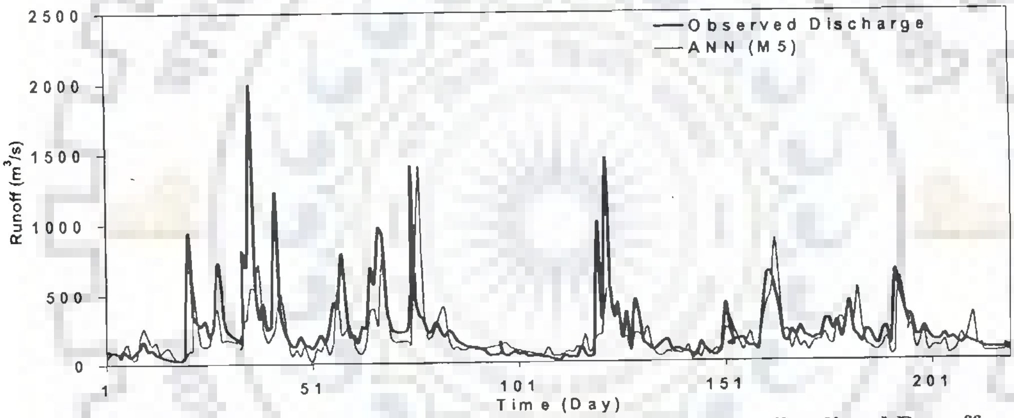

Figure 6.17: Time series of Observed Runoff and Model Predicted Runoff - ANN Model (M5)

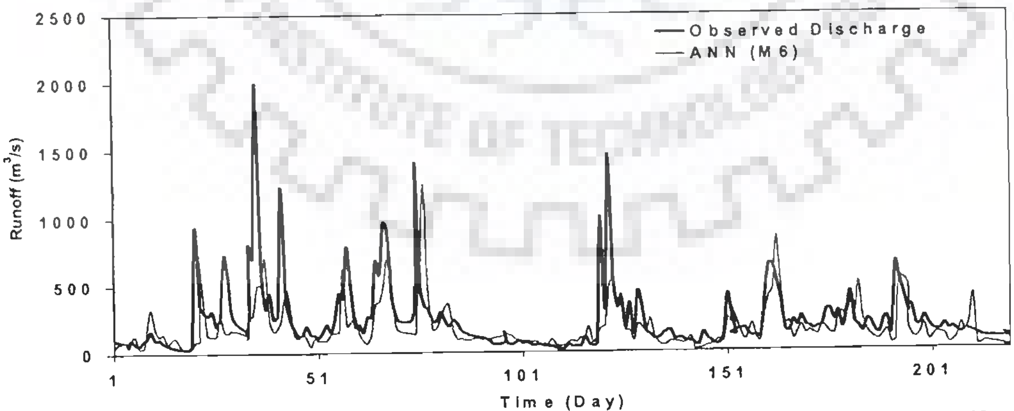

Figure 6.18: Time series of Observed Runoff and Model Predicted Runoff - ANN Model (M6)

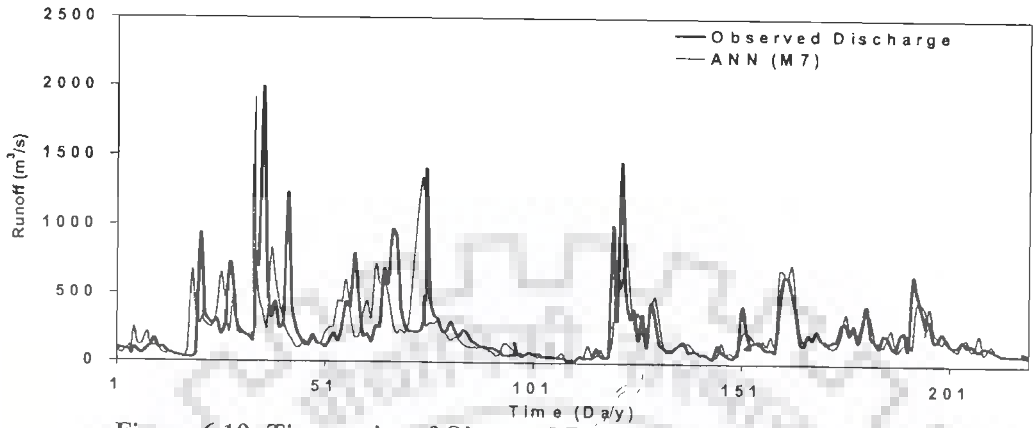

Figure 6.19: Time series of Observed Runoff and Model Predicted Runoff - ANN Model (M7)

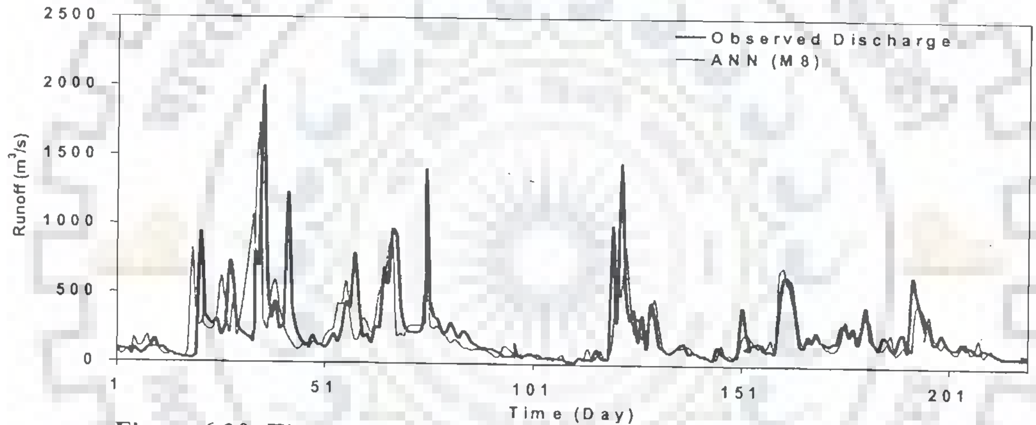

Figure 6.20: Time series of Observed Runoff and Model Predicted Runoff - ANN Model (M8)

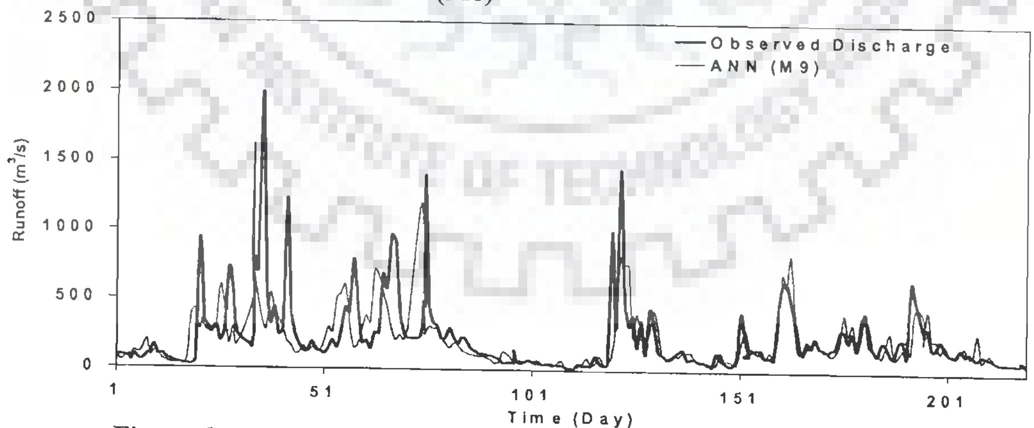

Figure 6.21: Time series of Observed Runoff and Model Predicted Runoff - ANN Model (M9)

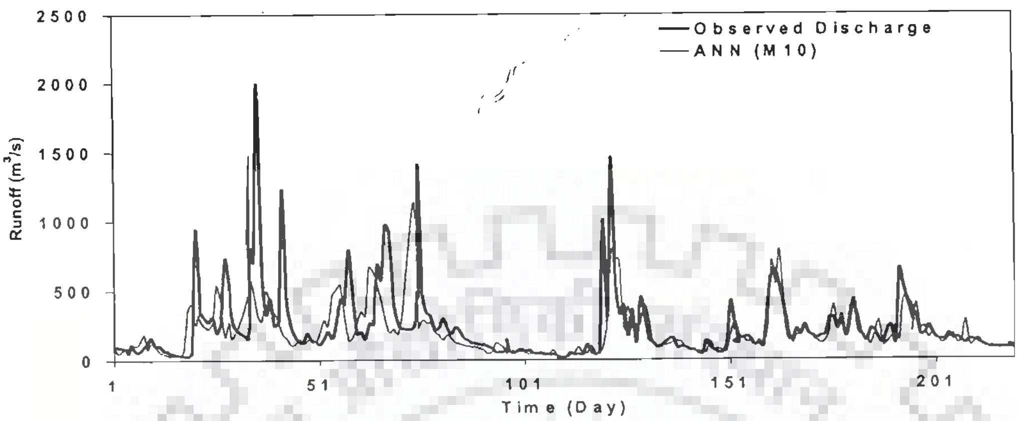

Figure 6.22: Time series of Observed Runoff and Model Predicted Runoff - ANN Model (M10)

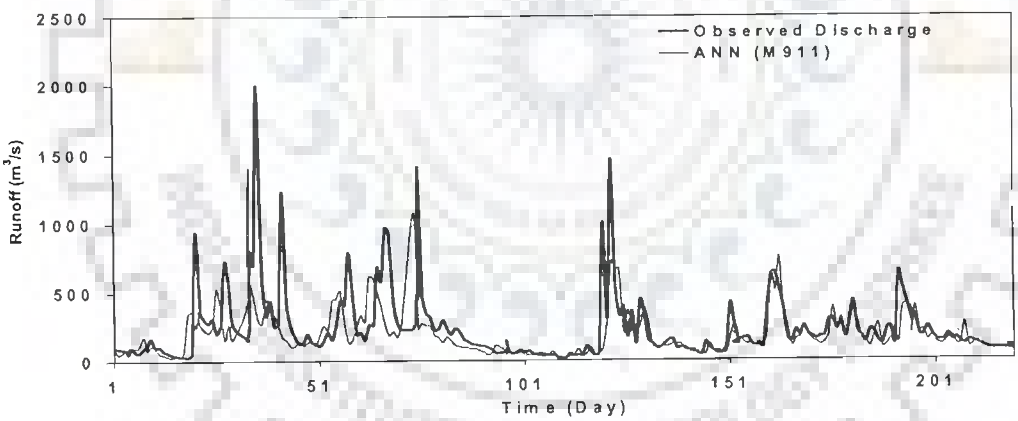

Figure 6.23: Time series of Observed Runoff and Model Predicted Runoff - ANN Model (M11)

(Table 6.4) show that the model M2 performs better than M1 model both during calibration (M1: 0.672, 0.584, 237.2; M2: 0.696, 0.583, 206.4) and validation (M1: 0.683, 0.577, 214.1; M2: 0.693, 0.585, 208.5). Model M3 to M5 were developed for different combinations of precipitation and runoff and they show coefficient of correlation in the range of 0.823 to 0.842, NS efficiency in the range of 0.663 to 0.675, RMSE in the range of 108.7 to 109.4 and volumetric error in the range of -9.66 to 10.3 during validation. A comparison of fuzzy rule based runoff prediction models M3 to M5 indicates that the model M4 is the best model in this group with coefficient of correlation 0.842, NS efficiency 0.675, RMSE 108.7 and volumetric error -9.66. Models M6 to M11 falling in the fourth group also have AMC term in the input vector. Statistical performance indices of these models i.e. coefficient of correlation, NS efficiency, RMSE and volumetric error varies in the range of 0.827 to 0.876; 0.662 to 0.755; 86.9 to 111.6 and -7.42 to -10.9 respectively. These values of performance indices are always higher than the performance indices of group 3 models i.e. models M3 to M5. This also confirms that the model performance improves when the AMC is also included in the input vector of fuzzy rule based runoff prediction models. Further, a comparison of all the eleven models show that the model M8 is the best fuzzy rule based model for the catchment of Narmada up to Manot with coefficient of correlation 0.876, NS efficiency 0.755, RMSE 86.9 and volumetric error -7.5 during validation. Figure 6.24 to 6.34 illustrates the time series of observed runoff and model predicted runoff for the eleven ANN models for the validation period 1997 and 1998.

6.6.4 Comparison of Different Methods

In order to assess the ability of fuzzy rule based runoff prediction models relative to that of neural network and linear transfer function models, ANN and linear transfer function models were also developed using the same input vectors to that of fuzzy models. The performance of ANN, linear transfer function and fuzzy models are compared in terms of the performance indices of the developed models. Plots of

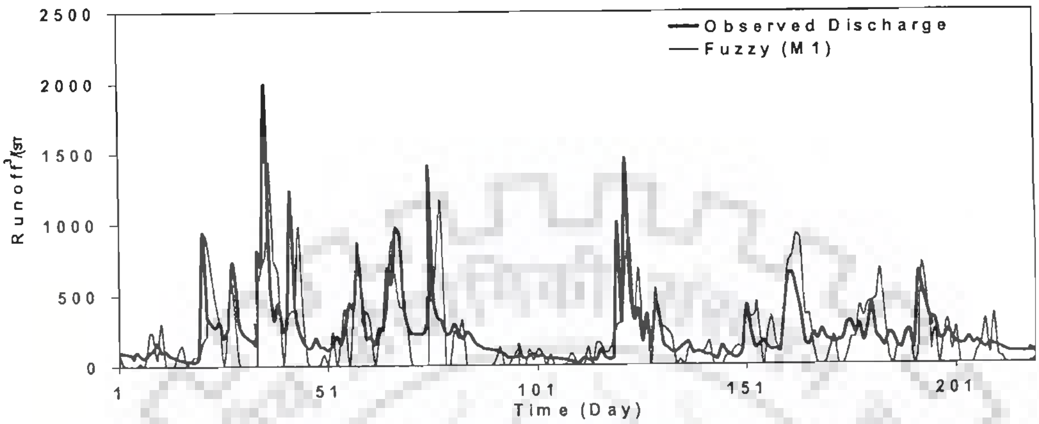

Figure 6.24: Time series of Observed Runoff and Model Predicted Runoff - Fuzzy Model (M1)

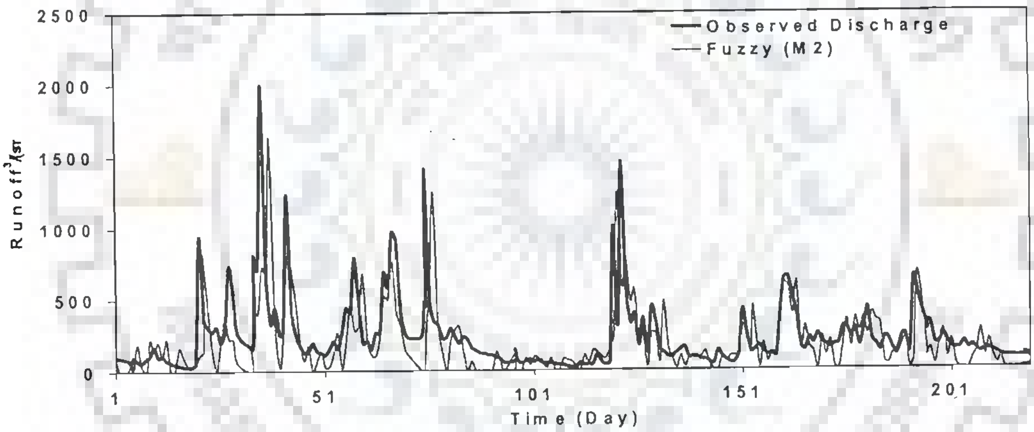

Figure 6.25: Time series of Observed Runoff and Model Predicted Runoff - Fuzzy Model (M2)

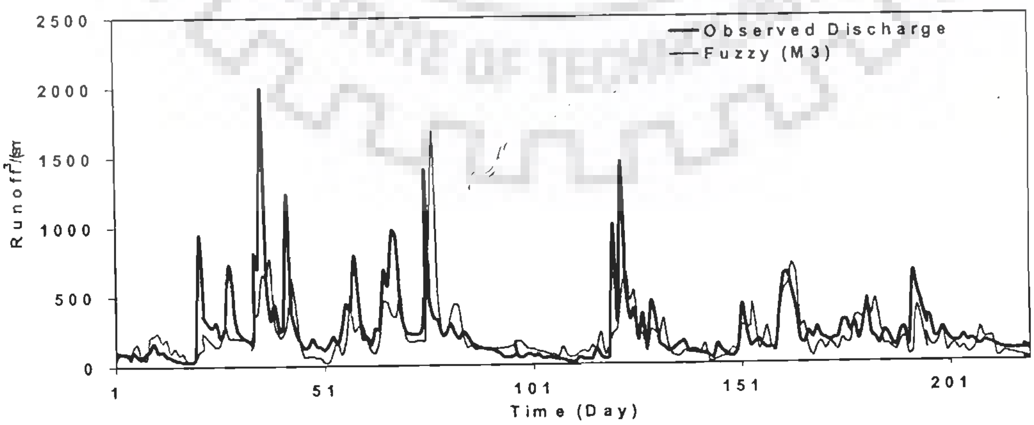

Figure 6.26: Time series of Observed Runoff and Model Predicted Runoff - Fuzzy Model (M3)

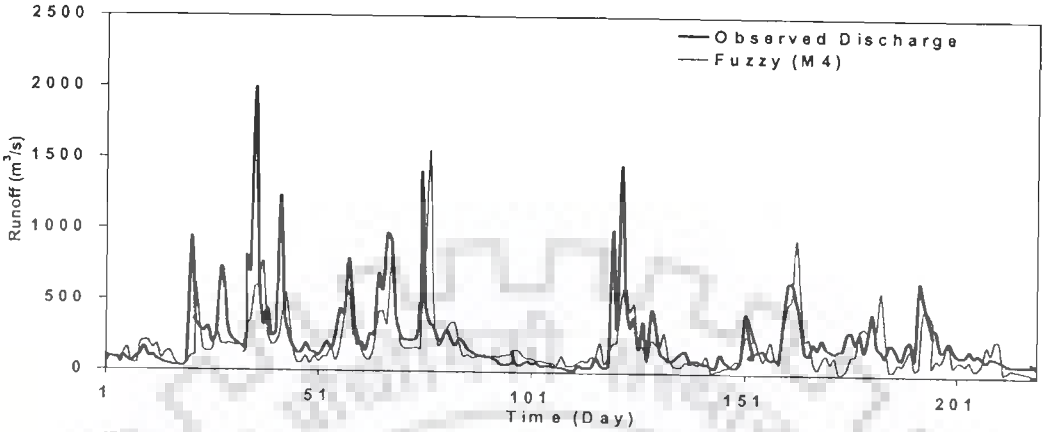

Figure 6.27: Time series of Observed Runoff and Model Predicted Runoff - Fuzzy Model (M4)

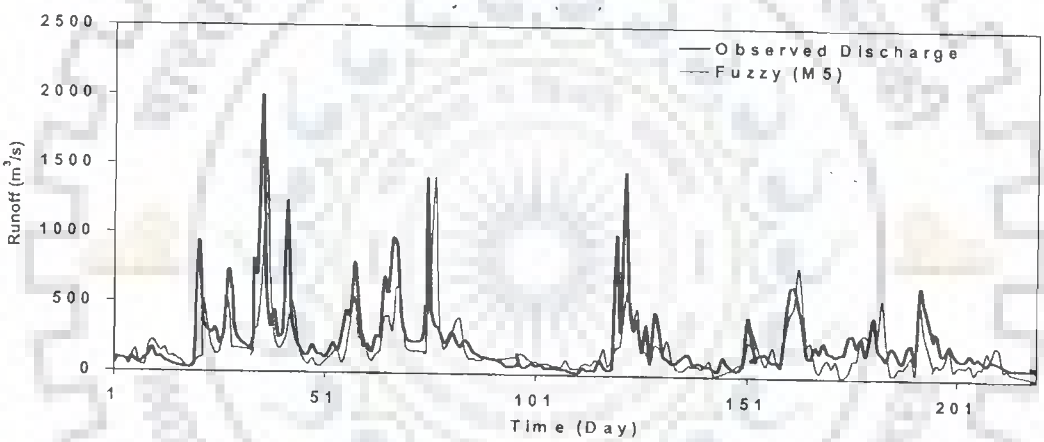

Figure 6.28: Time series of Observed Runoff and Model Predicted Runoff - Fuzzy Model (M5)

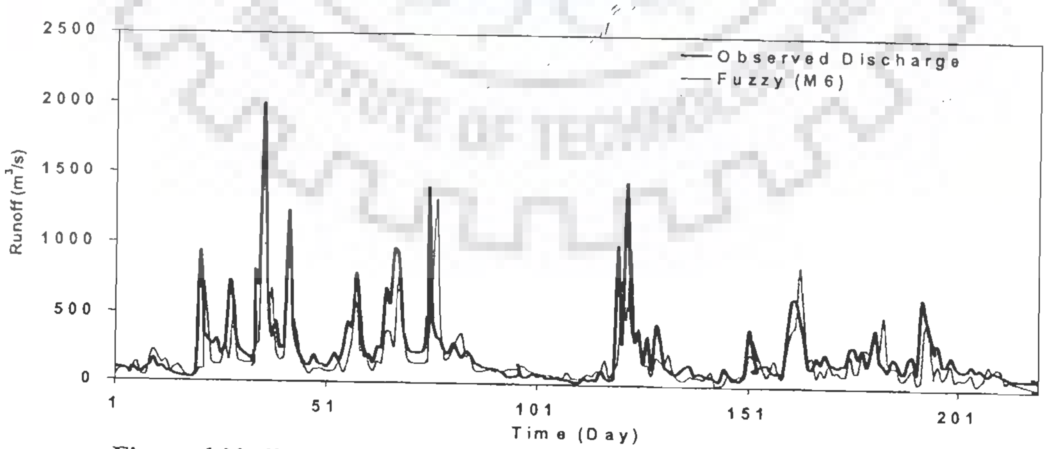

Figure 6.29: Time series of Observed Runoff and Model Predicted Runoff - Fuzzy Model (M6)

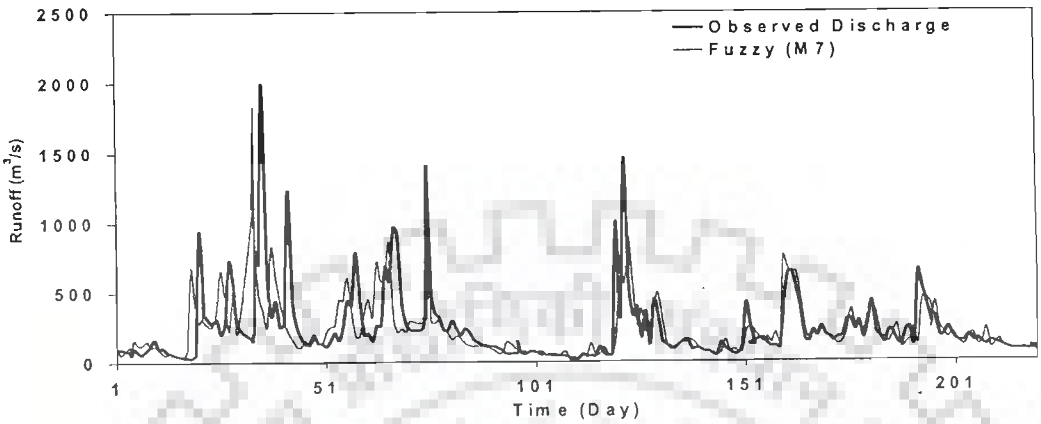

Figure 6.30: Time series of Observed Runoff and Model Predicted Runoff - Fuzzy Model (M7)

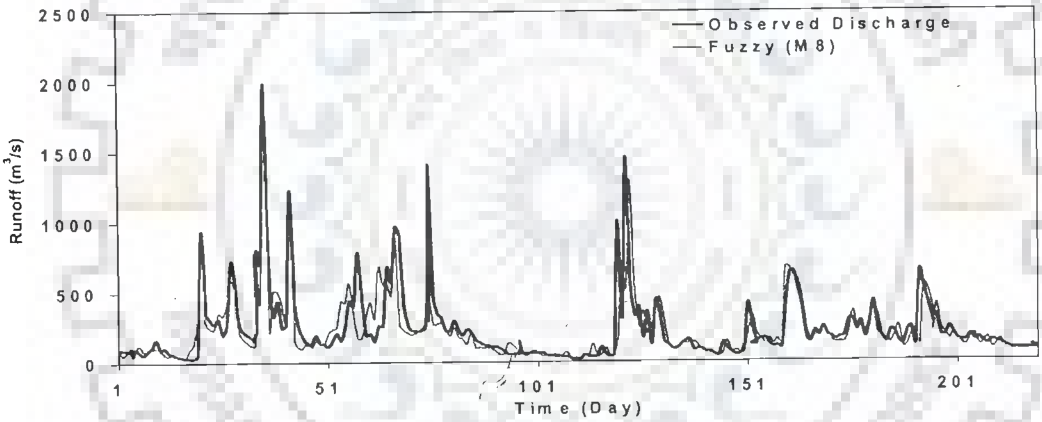

Figure 6.31: Time series of Observed Runoff and Model Predicted Runoff - Fuzzy Model (M8)

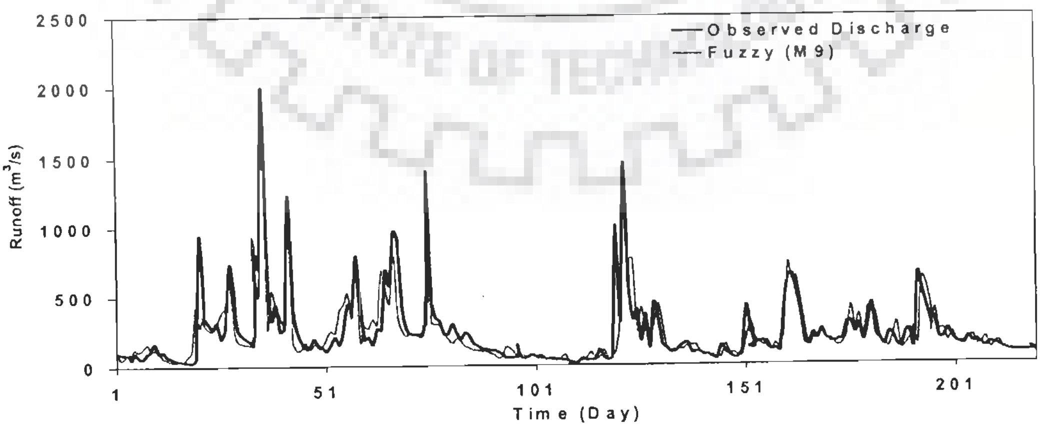

Figure 6.32: Time series of Observed Runoff and Model Predicted Runoff - Fuzzy Model (M9)

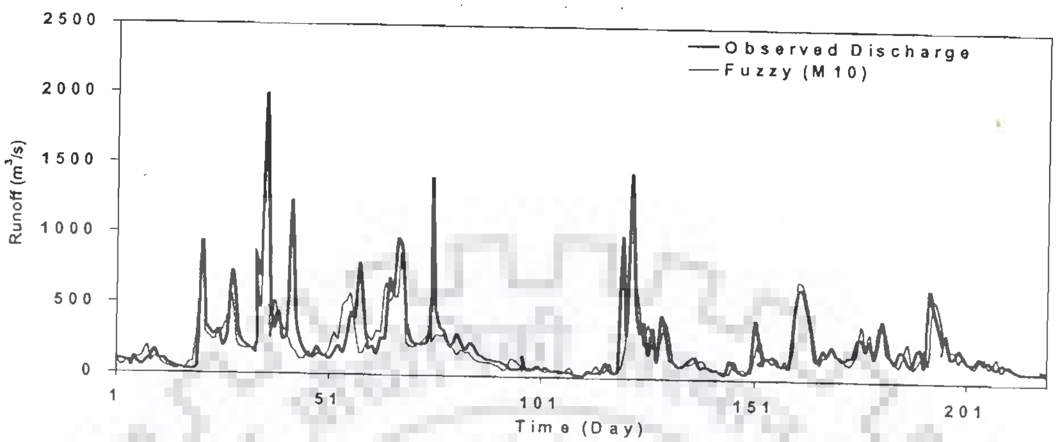

Figure 6.33: Time series of Observed Runoff and Model Predicted Runoff - Fuzzy Model (M10)

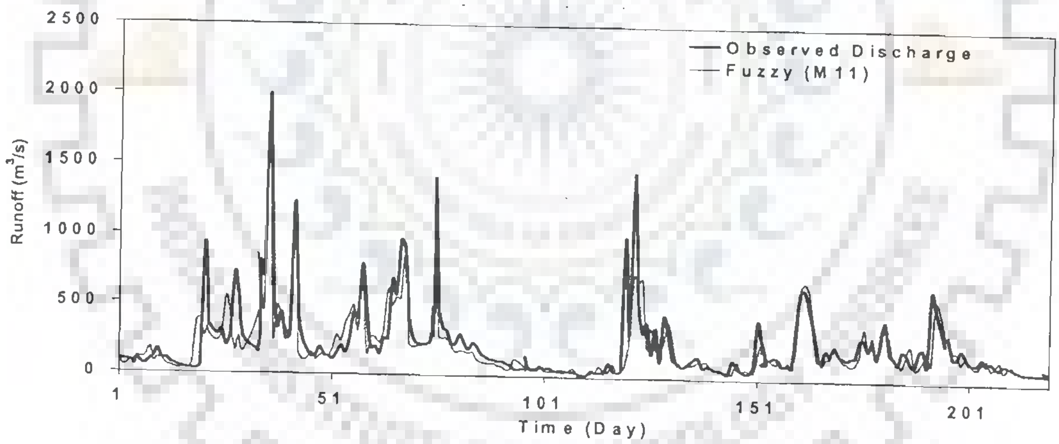

Figure 6.34: Time series of Observed Runoff and Model Predicted Runoff - Fuzzy Model (M11)

correlation coefficient (Figure 6.35 and Figure 6.36), NS efficiencies (Figure 6.37 and Figure 6.38), and RMSE (Figure 6.39 and Figure 6.40) of the developed ANN, fuzzy logic (Model M1 to M11) and linear transfer function models are compared. It is observed from these figures that the inclusion of AMC in the input vector has direct impact on model performance. From the performance indices it is depicted that the linear transfer function model-M8, ANN model-M8 and the fuzzy model-M8 are the best models in their respective groups. Further, a close comparison of the ANN models and the fuzzy models indicates that the fuzzy M8 model is best rainfall-runoff model for the catchment of Narmada upto Manot gauging site. Figures 6.35 to 6.40 and Table 6.2 to 6.4 suggests that though the performance of both the ANN and the fuzzy models are similar during training and validation, the fuzzy models shows a slight improvement over the ANN. It is also evident from these figures that the fuzzy and the ANN models outperform the linear transfer function models. A significant improvement is observed for the fuzzy model in the runoff volume computation compared to ANN.

Table 6.4: Statistical performances indices - Fuzzy models

Model	Calibration				Validation			
	Coefficient of Correlation	NS	RMSE	Ev	Coefficient of Correlation	NS	RMSE	Ev
Only rainfall as input								
1	0.672	0.584	237.2	23.6	0.683	0.577	214.1	21.2
Rainfall and AMC as input								
2	0.696	0.583	206.4	17.6	0.693	0.585	208.5	19.0
Rainfall and Runoff as input								
3	0.870	0.634	170.1	11.7	0.823	0.663	109.2	10.3
4	0.878	0.647	168.7	-11.0	0.842	0.675	108.7	-9.66
5	0.871	0.642	169.3	-11.6	0.838	0.672	109.4	-10.2
Rainfall, Runoff and AMC as input								
6	0.868	0.640	172.1	-11.9	0.838	0.671	110.2	-10.5
7	0.863	0.631	172.8	-12.4	0.827	0.662	111.6	-10.9
8	0.906	0.776	130.5	-8.7	0.876	0.755	86.9	-7.5
9	0.896	0.770	133.9	-8.6	0.871	0.752	94.2	-7.42
10	0.897	0.772	134.2	-8.9	0.870	0.753	94.2	-7.75
11	0.901	0.771	134.5	-8.7	0.869	0.752	95.7	-7.58

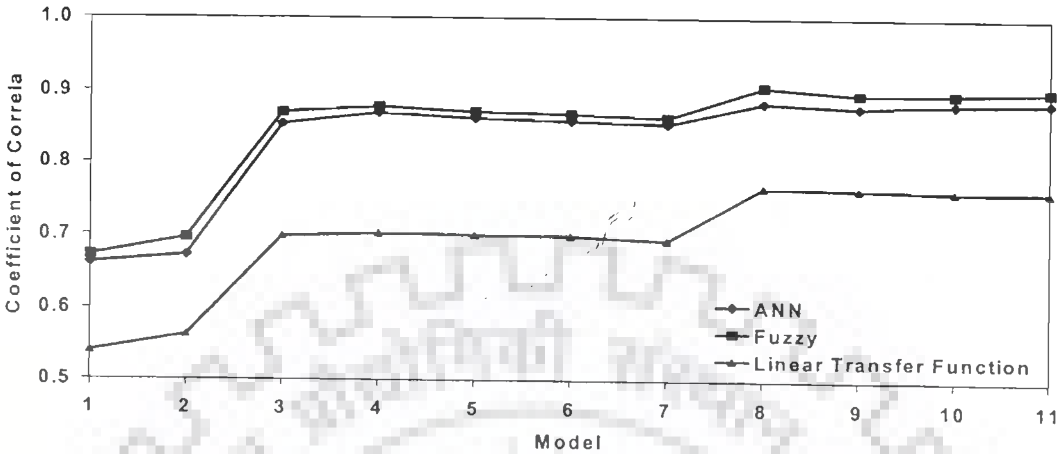

Figure 6.35 : Comparison of correlation coefficients of ANN, Fuzzy and Linear Transfer Function Models - Calibration Data

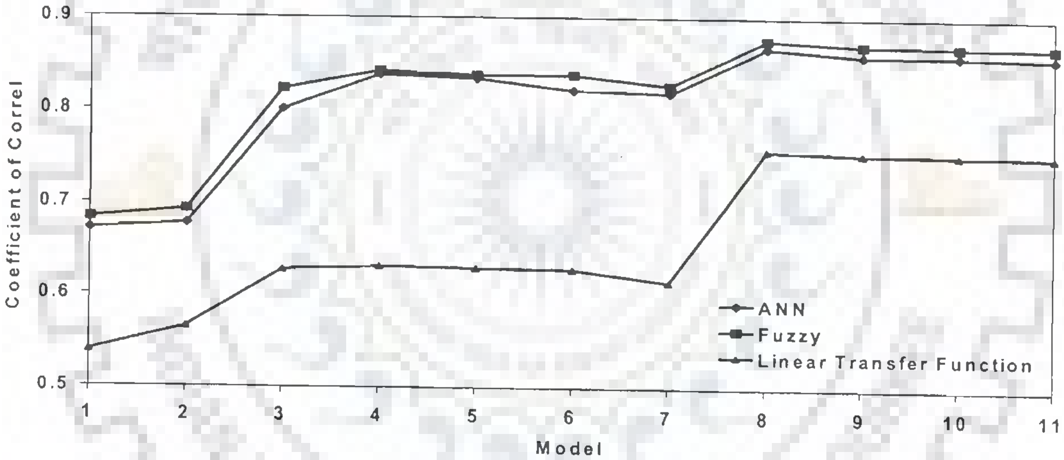

Figure 6.36: Comparison of correlation coefficients of ANN, Fuzzy and Linear Transfer Function Models - Validation Data

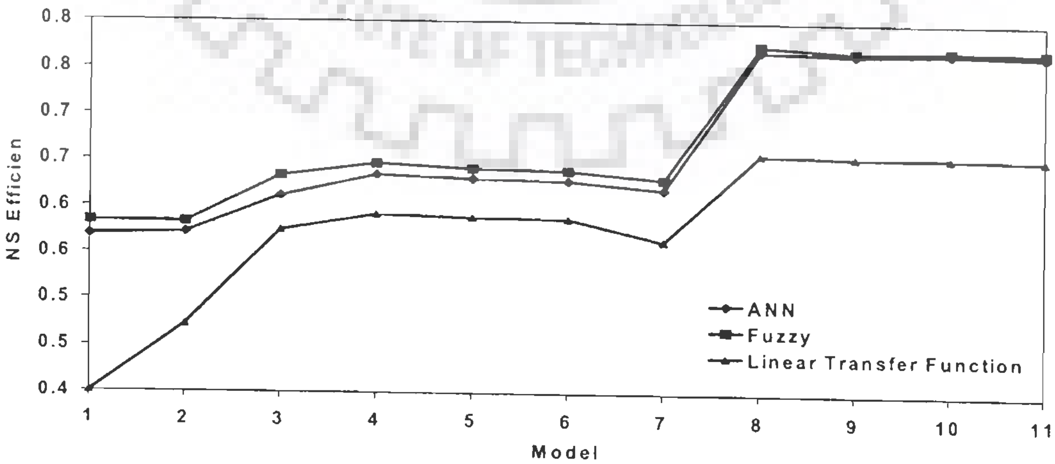

Figure 6.37: Comparison of NS Efficiency of ANN, Fuzzy and Linear Transfer Function Models - Calibration Data

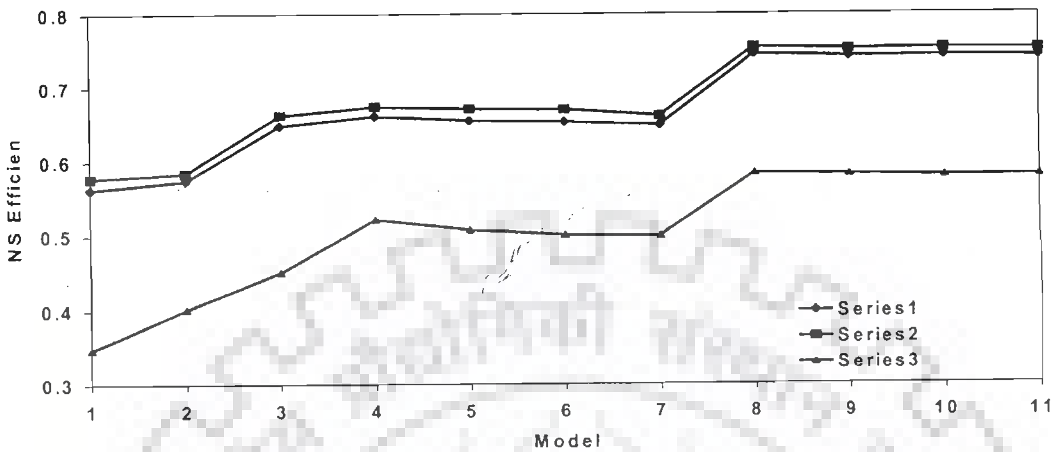

Figure 6.38: Comparison of NS Efficiency of ANN, Fuzzy and Linear Transfer Function Models - Validation Data

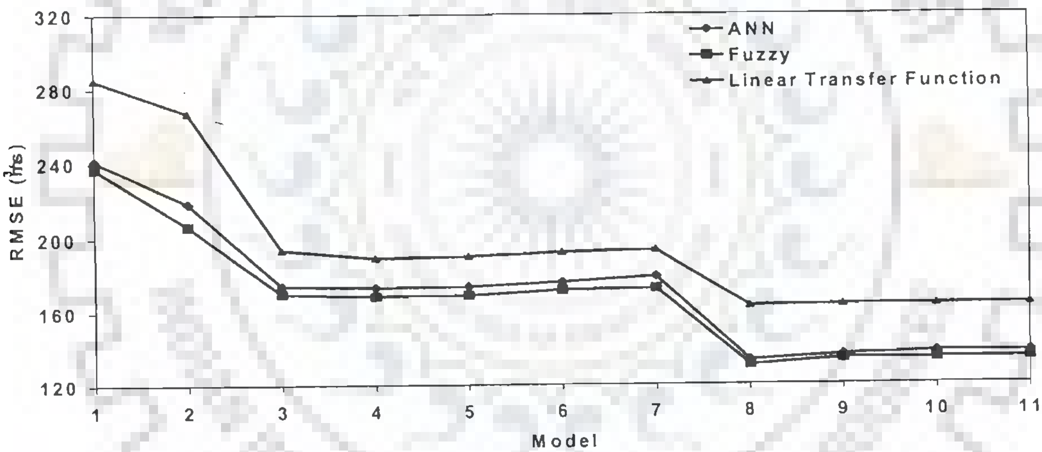

Figure 6.39: Comparison of RMSE of ANN, Fuzzy and Linear Transfer Function Models - Calibration Data

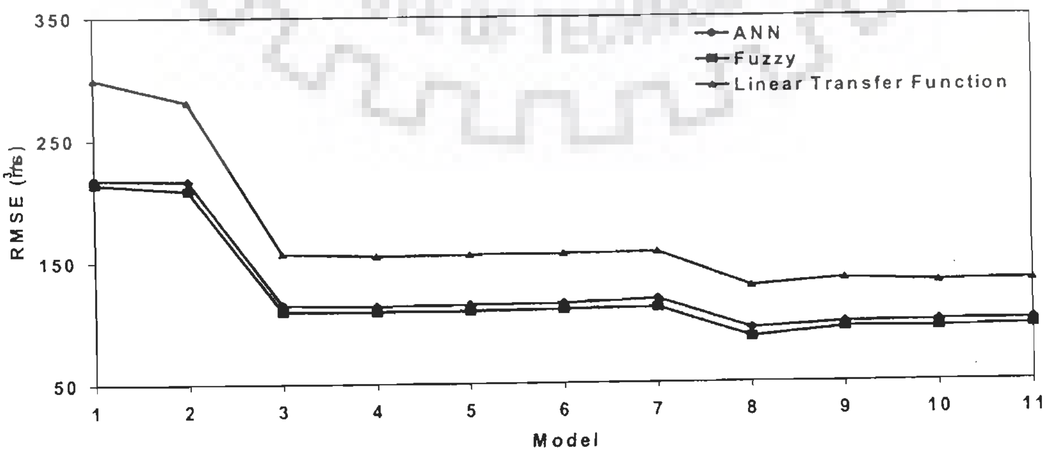

Figure 6.40: Comparison of RMSE of ANN, Fuzzy and Linear Transfer Function Models-Validation Data

6.7 CONCLUSIONS

In this study, linear transfer function, ANN and fuzzy rule based techniques have been used to develop models for the prediction of runoff using rainfall-runoff models for Narmada catchment upto Manot gauging site. Potential of fuzzy rule based technique for modeling of rainfall-runoff process is investigated by comparing results of fuzzy logic based rainfall-runoff models with the three-layered feed forward neural network and linear transfer function based models developed using the same input vectors. The daily rainfall and runoff data of the monsoon season (Mid June to September) from 1993 to 1998 were considered for the development (calibration and validation) of models. The rainfall and runoff data required for the study were processed using HYMOS software. The concept of antecedent moisture content in the fuzzy rule based daily rainfall runoff modeling has been introduced. Through correlation analysis between antecedent moisture content of different periods and runoff, a suitable structure of antecedent moisture content is decided. Rainfall-runoff models developed for 4 major inputs. Further, a detailed analysis and comparison of the models of the same group, models of different groups and the models developed using different modeling techniques have been carried out. The analysis of results indicates that the introduction of antecedent moisture content is very useful for daily rainfall runoff modeling as it improves the performance of the models. The study suggests a suitable daily rainfall-runoff model structure for the study area and concludes that the fuzzy rule based approach outperforms both the ANN and linear transfer function approaches.

FLOOD FORECASTING USING ANN AND FUZZY RULE BASED MODELS

7.1 BACKGROUND

The thesis now goes one step further in the development of a framework for real time flood forecasting. Real time flood forecasting, from a non structural flood management point of view, is now explored in two different ways, using the discharge values estimated from measured gauges as described in Chapter-4 as a starting point: first, by selecting the model structures using the ANN and subtractive clustering based Takagi-Sugeno fuzzy modeling approach discussed and described in Chapter-4. Secondly, by proposing and developing a modified Takagi Sugeno (T-S) fuzzy inference system termed as threshold subtractive clustering based Takagi Sugeno (TSC-T-S) fuzzy inference system by introducing the concept of rare and frequent hydrological situations in fuzzy modeling system and quantifying the accuracy of the inferences made by the proposed model in real time flood forecasting. The current research reveals that the latter has an edge on existing methodology and provides more promising flood forecasts. Some of the results of this study have been presented and published in the form of research papers entitled "Real time flood forecasting using fuzzy logic", Hydrological Perspectives for Sustainable Development Vol. 1, Allied Publishers Pvt. Ltd., New Delhi and "Development of Fuzzy Logic Based Real Time Flood Forecasting System For River Narmada In Central India", International Conference on "Innovation, advances and implementation of flood forecasting technology, 9-13 October 2005, Bergen-Tromsø, Norway".

The chapter is organized in the following manner: Initially, review of the exiting literature on flood forecasting is presented. Modified method i.e. threshold subtractive clustering for computation of clusters is then proposed and mathematically derived in the next section, where its main advantages over the subtractive clustering are summarised. Next sections outline the rationale for proposing the modified fuzzy model as a principle model for data real time flood forecasting. The chapter is then closed by a section on general conclusions.

7.2 INTRODUCTION

Real time flood forecasting systems are used to provide timely warning to people residing in flood plains to prepare the evacuation plan. Experience has shown that loss of human life and property etc. can be reduced to a considerable extent by giving reliable advance information about the floods. Flood forecasting also provide useful information to water management personnel for making optimal decisions related to flood control structures and reservoirs operation.

India, which is traversed by a large number of river systems, experiences seasonal floods. It has been the experience that floods occur almost every year in one part or the other of the country. The rivers of North and Central India are prone to frequent floods during the south-west monsoon season, particularly in the month of July, August and September. Besides structural measures, the real time flood forecasting is one of the most effective non- structural measures for flood management.

The effectiveness of real time flood forecasting systems in reducing flood damage depends upon how accurately the estimation of future stages or flow of incoming flood at selected points along the river is predicted. The techniques available for real time flood forecasting may be broadly classified in three groups: (i) deterministic modeling, (ii) stochastic and statistical modeling and (iii) computational techniques like Artificial Neural Network (ANN) and fuzzy logic. Depending on the availability of hydrological and hydro-meteorological data, basin characteristic, computational facilities available at the forecasting stations, warning time required and purpose of forecast, different flood forecasting techniques are being used in India. In India, most of the techniques for formulating the real time flood forecast are based on statistical approach. For some pilot projects, network model and multi-parameter hydrological models are used. While, the recent techniques like ANN and fuzzy logic are being currently used by the academicians and researchers for the development and testing. In this chapter brief review of the ANN and fuzzy logic based flood forecasting models and their applications is presented. Further, in order to improve the real time forecasting of floods, this chapter proposes a modified Takagi-Sugeno (T-S) fuzzy inference system termed as threshold subtractive clustering based Takagi-Sugeno (TSC-T-S) fuzzy inference system by introducing the concept of rare and frequent hydrological situations in fuzzy modeling system. The proposed modified fuzzy inference systems provide an option of analyzing and computing cluster centers and membership functions for two different hydrological situations generally encountered in real time flood forecasting. The methodology has been tested on hypothetical data set and than applied for flood forecasting using the hourly rainfall and river flow data of upper Narmada basin, Central India. Furthermore, a comparative study of proposed method with subtractive clustering based Takagi-Sugeno and ANN approaches has also been carried out to test its applicability for real time flood forecasting.

7.3 LITERATURE REVIEW

Floods are natural phenomena and are inherently complex to model. Conventional methods of flood forecasting are based on either simple empirical black box models which do not try to mimic the physical processes involved or use complex models which aim to recreate the physical processes and the concept about the behaviour of a basin in complex mathematical expressions. In between these two broad categories of models there is a wide variety of models e.g., deterministic and stochastic, lumped and distributed, event driven and continuous or their combinations (Nielsen and Hansen, 1973; Box and Jenkins, 1976; Lundberg, 1982; Yakowitz, 1985; Wood and Connell, 1985; Burn and McBean, 1985; Yapo et al., 1993; Vogel et al. 1999; Solomatine and Price, 2004), which are the basis of conventional flood forecasting system. Existing flood forecasting models are highly data specific and complex and make various simplified assumptions (Hecht-Nielsen, 1991). For a reliable forecast Singh (1989) has listed three basic criteria i.e. accuracy, reliability, and timeliness. Timeliness of forecasting is extremely important and this can be achieved by simple and robust forecasting models.

Recently there has been a growing interest in soft computing techniques viz. artificial neural networks (ANNs) and fuzzy logic. ANNs are basically data driven approach and are considered as black box models (Bishop, 1994) in hydrological context. These models are capable of adopting the non-linear relationship (Hecht-Nielsen, 1991, Flood and Kartam, 1994) between rainfall and runoff as compared to conventional techniques, which assume a linear relationship between rainfall and runoff. AANs have strong generalization ability, which means that once they have been properly trained, they are able to provide accurate results even for cases they have never experienced before (Imrie et al., 2000). Previous studies have shown that ANNs are capable of reproducing unknown rainfall-runoff relationship adequately (ASCE 2000a, ASCE, 2000b). ANN is also a powerful tool in solving complex nonlinear river flow forecasting problems (Hsu et al., 1995, 2002; Thirumalaiah and Deo,1998a; Thirumalaiah and Deo,1998b; Zealand et al., 1999; Atiya et al., 1999; Campolo et al., 1999; Uvo et al., 2000; Birkundavyi et al., 2002) and in particular when the time required to generate a forecast is very short. Sahoo and Ray (2006) demonstrated that the ANN can outperform rating curves for discharge forecasting. Suitability of some deterministic and statistical techniques along with an ANN to model an event based rainfall-runoff process have been investigated by Jain and Indurthy (2003). There investigation on ANN with varying architecture, training rules and error back propagation establishes the suitability of ANN in flow forecasting. A comprehensive review of the ANN application in prediction and forecasting of water resources variables can be found in works by Maier and Dandy (2000).

Fuzzy rule based method is a qualitative modeling scheme where the system behaviour is described using natural language (Sugeno and Yasukawa, 1993). Dubois et al. (1998) state that the real power of fuzzy logic lies in its ability to combine modeling (constructing a function that accurately mimics the given data) and abstracting (articulating knowledge from the data). See and Openshaw (1999, 2000) indicated that the fuzzy logic can be used with a combination of soft computing technique to create sophisticated river level monitoring and forecasting system. Hundecha et al. (2001) have demonstrated the applicability of fuzzy logic approach in rainfall-runoff modeling. Rule based fuzzy logic modeling techniques for forecasting water supply was investigated by Mahabir et al. (2003). Luchetta and Manetti (2003) have developed a fuzzy logic based approach to the forecasting of hydrological levels, particularly suitable to cope with extreme situations, by setting different rules for trivial and rare situations. Neurofuzzy technique based on the combination of backpropogation and least square error methods for the parameter optimization is applied in short term flood forecasting by Nayak et al. (2005b) and pointed out that the number of parameters grows exponentially with the number of membership functions resulting in large training time. Takagi-Sugeno (T-S) fuzzy technique has been applied to rainfall-runoff modeling and flood forecasting by various researchers (Xiong et al.; 2001; Vernieuwe et al.; 2005 and Jacquin and Shamseldin; 2006). The T-S fuzzy structure identification is obtained directly by fuzzy clustering approach (Chiu, 1994).

The above discussion reveals that the core of the T-S-fuzzy structure identification method is in the clustering and the projection. A limitation of the clustering based T-S-fuzzy model is that if any data point falls away from the cluster or outside the clusters the model performance may not be satisfactory (Nayak et al; 2005a). Particularly in non–structural flood management a slight improvement in the accuracy of the real time flood forecasts has many direct advantages. In order to improve the real time forecasting of floods, the concept of threshold subtractive clustering based Takagi Sugeno (TSC-T-S) fuzzy inference system has been introduced in fuzzy modeling system. In the proposed method the input-output data space is classified into frequent and rare events to preserve generalization capability of the T-S fuzzy model with improved forecasting. The results of the proposed TSC-T-S fuzzy model are evaluated with the forecast from ANN and SC-T-S (or interchangeably used as TS or T-S fuzzy model) fuzzy model at different lead periods.

7.4 FUZZY STRUCTURE IDENTIFICATION

Data driven fuzzy identification is an effective tool for the approximation of uncertain non-linear systems (Hellendoorn and Driankov, 1997). As discussed in Section 4.4.1, the core of the fuzzy structure identification method is in the clustering and the projection. First, the output space is partitioned using a fuzzy clustering algorithm. Second, the partitions (clusters) are projected onto the space of the input variables. The output partition and its corresponding input partitions are the consequents and antecedents, respectively. Then by projecting each cluster onto each input variable, temporary clusters in the input space are obtained. This may be implemented by using the subtractive clustering method that automatically determines the number of cluster. The subtractive clustering method uses the following formula to express the potential as a sum of contribution of Euclidean distance between a given point and all other data points (Chiu, 1994):

$$D_i = \sum_{j=1}^{N} d_{ij} \tag{7.1}$$

$$d_{ij} = e^{-\alpha|x_i - x_j|^2}, \qquad i = 1,2,.......N \tag{7.2}$$

where D_i is the potential of the data point x_i to be a cluster centre, d_{ij} denotes the contribution of every single distance, N is the number of training data samples and $\alpha = 4/r_a^2$; r_a is the cluster radii.

7.5 THRESHOLD SUBTRACTIVE CLUSTERING

In short term flood forecasting application, the number of input-output data pairs is very large. The input data vectors, which are used to train and build the T-S fuzzy model, do not have all the same importance. Particularly, in small to medium size catchments, the river flow shows a very high rate of rise and fall in shorter spells due to upstream rain and such high spikes in the time series of flow data do not show any periodicity. In such cases the time series of river flow values contains both low to medium (frequent events) as well as high to very high flows (rare events). In general the high flow values are very few in numbers but important in forecasting. The main purpose of any flood forecasting model is to predict 'rare events' or catastrophic events (Luchetta and Manetti, 2003). In subtractive clustering approach, an adequate choice of the cluster radius (R_a) matches the input-output pairs to a given accuracy. Generally, R_a value is determined by trial and error and it lies always between 0 and 1. Small value of R_a results in more number of clusters i.e. granular partition with minimum matching error. But this reduces the generalization capability of a fuzzy model. While, a higher value of R_a reflects a rough partition of the input space in separate clusters and hence a separate fuzzy sets (Abonyi et al., 2002). The parameter R_a is used as an input parameter for the generation of subtractive clustering based T-S fuzzy inference system and the same value of cluster radius (R_a) is used for defining membership functions of input variables. Such subtractive clustering based T-S fuzzy model when applied to real time flood forecasting model, try to mimic varying hydrologic situation with similar non-linear membership functions. Furthermore, the clusters obtained from the input (rainfall and/or runoff) are generally biased towards frequent events. Clusters with different radius of influence and thus with different Gaussian membership function widths may serve a better input-output mapping of continuous short interval rainfall-runoff data originating from mixed population. This can be achieved by proposed TSC-T-S fuzzy inference system which deals with the frequent and rare events separately during estimation of cluster and membership functions. By carefully examining the available input–output data pairs, threshold values for each input variable can be decided which subdivides the data into two classes (i) frequent events (N_f) and, (ii) rare events (N_r). Let there are N input-output data pairs in n dimensional data space then

$$N_f + N_r = N \tag{7.3}$$

and

$$\frac{N_f}{N_r} \geq 1 \tag{7.4}$$

In the subtractive clustering the data points have to be normalized in each direction within a unit hypercube. Following the previous definition the normalized data vector is subdivided as a collection of frequent events N_f of data points $\{xf_1, \ldots xf_k, \ldots xf_{Nf}\}$ and rare event N_r of data points $\{xr_1, \ldots xr_l, \ldots xr_{Nr}\}$ in n dimensional data space. Since each data point is considered as a potential cluster centers, a density measure at data point x_k of frequent events is defined as:

$$Df_k = \sum_{j_f=1}^{N_f} \exp\left(-\frac{\left\| xf_k - xf_{j_f} \right\|^2}{\left(\frac{Rf_a}{2} \right)^2} \right) \tag{7.5}$$

Similarly, density measure at data point x_l of rare events

$$Dr_l = \sum_{j_r=1}^{N_r} \exp\left(-\frac{\left\| xr_l - xr_{j_r} \right\|^2}{\left(\frac{Rr_a}{2} \right)^2} \right) \tag{7.6}$$

where Rf_a and Rr_a are the radius of influence of clusters in frequent and rare events.

The data points with highest density measure, denoted by Df_k^* and Dr_l^* are considered as first cluster centers in frequent ($xf_{j_f}^*$) and rare events ($xr_{j_r}^*$). In case of both rare and frequent events the density measure is then recalculated for all other points excluding the first cluster centers by the following formula:

For frequent events

$$Df_k = Df_k - Df_k^* . \sum_{j_f=1}^{N_f} \exp\left(-\frac{\left\| xf_k - xf_{j_f}^* \right\|^2}{\left(\frac{\eta Rf_a}{2} \right)^2} \right) \tag{7.7}$$

For rare events

$$Dr_l = Dr_l - Dr_l^* . \sum_{j_r=1}^{N_r} \exp\left(-\frac{\left\| xr_l - xr_{j_r}^* \right\|^2}{\left(\frac{\eta Rr_a}{2} \right)^2} \right) \tag{7.8}$$

where η is a positive constant and ηRf_a and ηRr_a is the radius defining the neighborhood that has measurable reductions in potential. Further,

$$\eta Rf_a \geq Rf_a \tag{7.9}$$

$$\eta Rr_a \geq Rr_a \tag{7.10}$$

Again, the data point with highest density measure is considered as the next cluster centre. This process is repeated until a sufficient number of cluster centers are generated. A sophisticated stopping criterion using density measures and minimal distance between clusters given by Chiu (1994, 1996) is generally applied (Vernieuwe et al., 2005). After computing the clusters, both frequent and rare events clusters are pooled together.

Further, it may be possible that the highest cluster center in the frequent events and lowest cluster center in the rare event are close enough. Therefore, the two clusters may be clubbed together so as to reduce the closely spaced clusters and thus to improve the generalization capability of the fuzzy model. In subtractive clustering approach proposed by Chiu (1994), when maximum potential ratio lies in between accept and reject ratios a new cluster center is accepted if

$$P_r + d_{min} \geq 1 \tag{7.11}$$

or

$$d_{min} \geq 1 - P_r \tag{7.12}$$

where P_r = maximum potential ratio and d_{min} = minimum distance from previously found clusters

Now, in the modified TSC-T-S fuzzy inference system, the two nearest clusters from both frequent and rare event groups (i.e. highest one from the frequent events and lowest one from the rare events) are accepted for developing fuzzy rules when

$$D_{min} \geq 1 - P_r \tag{7.13}$$

where D_{min} = minimum distance between frequent and rare even clusters. Here, maximum potential ratio is considered as accept ratio so as to accept most closely spaced clusters from two different groups.

Therefore, to verify the spacing between two cluster centers of two different groups the following check is applied:

$$\frac{(xf^{*}_{j\,Max\,f} - xf^{*}_{j\,Min\,r})}{Rf_a} \geq 1 - Accept\ ratio \quad \text{and} \quad \frac{(xr^{*}_{j\,Max\,f} - xr^{*}_{j\,Min\,r})}{Rr_a} \geq 1 - Accept\ ratio \tag{7.14}$$

If the above check is satisfied than the cluster centers of the entire data vector i.e. including both frequent and rare events of j^{th} data set are:

$$x^{*}_{j} = \lfloor xf^{*}_{j_f} \quad xr^{*}_{j_r} \rfloor \tag{7.15}$$

where x^{*}_{j} represents total C clusters in the data set, $xf^{*}_{j_f}$ represents total C_f clusters in the frequent events and, $xj^{*}_{j_r}$ represents total C_r clusters in the rare events. Therefore, the total clusters in the data set are defined as:

$$C = C_f + C_r \tag{7.16}$$

If the check defined by equation (16) is not satisfied than club the two closely spaced cluster center together and replace with a new cluster center defined as:

$$x^{*}_{j\,Revised} = \frac{(xf^{*}_{j\,Max\,f} - xr^{*}_{j\,Min\,r})}{2} \tag{7.17}$$

where, $x^{*}_{j\,\text{Revised}}$ is the revised cluster center and this reduces the closely spaced cluster centers and thus the number of rules in the fuzzy inference system. Therefore, the revised cluster centers in this case are:

$$x^{*}_{j} = \left\lfloor xf^{*}_{j_f\bullet} \quad xr^{*}_{j_r\bullet} \quad x^{*}_{j\,\text{Revised}} \right\rfloor \tag{7.18}$$

where, $xf^{*}_{j_f\bullet}$ are the cluster centers in frequent events excluding the highest cluster center and $xr^{*}_{j_r\bullet}$ are the cluster centers in rare events excluding the lowest cluster center.

Therefore, the total clusters are defined as:

$$C = (C^{*}_{f} + C^{*}_{r} - 1) \tag{7.19}$$

where $C^{*}_{f} = C_f - 1$ are revised clusters in the frequent events and, $C^{*}_{r} = C_r - 1$ are revised clusters in the rare events.

The above cluster centers defined by equation 17 and 20 reveals certain characteristics related to frequent and rare situations of the system to be modeled and can be reasonably used as the centers for the fuzzy rules' premise and antecedent membership function that describes the system behavior. To generate rules, the cluster centers (x^{*}_{j}) are used as the centers for the premise sets and the membership of input x_j to the j^{th} premise part of the i^{th} rule is defined by the Gaussian membership function:

$$\mu_{fij}(x_j) = e^{-\left(\frac{x_j - x^{*}_{fji}}{\frac{R_{fai}}{2}}\right)^2} \quad \text{when } i \in C_f \tag{7.20}$$

$$\mu_{rij}(x_j) = e^{-\left(\frac{x_j - x^{*}_{rji}}{\frac{R_{rai}}{2}}\right)^2} \quad \text{when } i \in C_r \tag{7.21}$$

where x_j is the j^{th} variable of the input data vector, x^{*}_{ji} is the i^{th} cluster center of the j^{th} input variable, R_{ai} is the cluster radius of the i^{th} cluster and i (= 1 … C) is the cluster radius index or number of rules. The shape of the Gaussian membership function defined by (eqn. 22 and 23) indicate that for every input vector a membership degree to each fuzzy set greater than zero is obtained and all the rules in the rule-base fires simultaneously. Therefore, this leads to the possibility of generating only a few rules for describing the accurate relationship between input and output.

The input membership function matrix of the TSC-T-S fuzzy model can be represented as:

$$\begin{bmatrix} \mu_{11} & \mu_{12} & \cdots & \mu_{1(Cf-1)} & \mu_{1R} & \mu_{12} & \cdots & \cdots & \mu_{1(Cr-1)} \\ \mu_{21} & \mu_{22} & \cdots & \mu_{2(Cf-1)} & \mu_{2R} & \mu_{22} & \cdots & \cdots & \mu_{2(Cr-1)} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ & & & & & & & & \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \mu_{(n-1)1} & \mu_{(n-1)2} & \cdots & \mu_{(n-1)(Cf-1)} & \mu_{(n-1)R} & \mu_{(n-1)2} & \cdots & \cdots & \mu_{(n-1)(Cr-1)} \\ \mu_{n1} & \mu_{n2} & \cdots & \mu_{n(Cf-1)} & \mu_{nR} & \mu_{n2} & \cdots & \cdots & \mu_{n(Cr-1)} \end{bmatrix} \quad (7.22)$$

7.6 TSC-T-S FUZZY MODEL

Fuzzy relational models can be regarded as an extension of linguistic models, which allow for different degrees of association between the antecedent and the consequent linguistic terms. A major distinction can be made between the linguistic model, which has fuzzy sets in both antecedents and consequents of the rules, and the T-S model, where the consequents are (crisp) functions of the input variables. Consider the identification of following unknown nonlinear hydrological system based on some available input-output data sets $x_k = [x_{1k}, x_{2k}, ...x_{nk}]^T$ and y_k (for $k = 1,....N$, and $N = N_f + N_r$), respectively:

$$y = f(x) \tag{7.23}$$

A model to describe the above unknown non linear system using a Takagi-Sugeno Fuzzy model (Takagi and Sugeno, 1985) for a n dimensional input space and single output consists of a set of rules R_i, $i = 1,...,C$ as given below:

Ri: if x_1 is μ_{i1} and if x_2 is μ_{i2} and ... and if x_n is μ_{in}

$$\text{THEN } y = f_i(x_1, x_2, ..., x_n) \tag{7.24}$$

where $x_1, x_2, ..., x_n$ are the antecedents and y is the consequent, μ_{i1}, μ_{i2}, ... μ_{in} are fuzzy sets and $f_i(x_1, x_2, ..., x_n)$ is a linear function of the form:

$$f_i(x_1, x_2, ..., x_n) = a_{0i} + a_{1i}x_1 + a_{2i}x_2 + ... + a_{ni}x_n \tag{7.25}$$

with a_{01}, a_{1i}, ... a_{ni} the parameters of the consequent part of rule R_i.

The total output of the proposed TSC-T-S fuzzy model of the nonlinear system represented by $C = C_f + C_r - 1$ cluster centers is computed by

$$y = \frac{\sum_{i=1}^{C_f - 1} \mu_i^f f_i(x_1, x_2, \ldots x_n) + \mu_{revised} f_i(x_1, x_2, \ldots x_n) + \sum_{i=2}^{C_r - 1} \mu_i^r f_i(x_1, x_2, \ldots x_n)}{\sum_{i=1}^{C_f - 1} \mu_i^f + \mu_{revised} + \sum_{i=2}^{C_r - 1} \mu_i^r} \tag{7.26}$$

Similarly, the total output of the proposed TSC-T-S fuzzy model of the nonlinear system represented by $C = C_f + C_r$ cluster centers is computed by

$$y = \frac{\sum_{i=1}^{C_f} \mu_i^f f_i(x_1, x_2, \ldots x_n) + \sum_{i=1}^{C_r} \mu_i^r f_i(x_1, x_2, \ldots x_n)}{\sum_{i=1}^{C_f} \mu_i^f + \sum_{i=1}^{C_r} \mu_i^r} \tag{7.27}$$

where $\mu_i \in [0,1]$ is the degree at which the antecedent of rule R_i holds.

For n dimensional input vector, the over all truth value of the i^{th} rule in the proposed TSC-T-S fuzzy model is defined by means of product operator:

$$\mu_i^f(x) = \prod_{j=1}^{n} \mu_{ij}^f(x_j) \text{ when } i \in C_f \tag{7.28}$$

$$\mu_i^r(x) = \prod_{j=1}^{n} \mu_{ij}^r(x_j) \text{ when } i \in C_r \tag{7.29}$$

where x_j is the j^{th} input variable in the n dimensional input vector, and μ_{ij}^f or μ_{ij}^r is the membership degree of x_j to the fuzzy set describing the j^{th} premise part of the i^{th} rule describing frequent or rare events.

Now the parameters ($a_i = [a_{i0}, a_{i1}, \ldots a_{iC}]$) of the consequent part of the proposed TSC-T-S fuzzy model output ($y = [y_1, y_2, \ldots y_N]^T$) given by equation (28) can be computed by global least square method by solving in following form:

$y = x.a$

or

$$\begin{bmatrix} y1 \\ y2 \\ . \\ . \\ y_N \end{bmatrix} = \begin{bmatrix} \psi^f_{11} & \psi^f_{11}.x_{11} & \cdots & \psi^f_{11}.x_{1n} & \psi^f_{1C_f} & \psi^f_{1C_f}.x_{11} & \cdots & \psi^f_{1C_f}.x_{1n} & \psi^r_{11} & \psi^r_{11}.x_{11} & \cdots & \psi^r_{11}.x_{1n} & \psi^r_{1Cr} & \psi^r_{1Cr}.x_{11} & \cdots & \psi^r_{1Cr}.x_{1n} \\ \psi^f_{21} & \psi^f_{21}.x_{21} & \cdots & \psi^f_{21}.x_{2n} & \psi^f_{2C_f} & \psi^f_{2C_f}.x_{21} & \cdots & \psi^f_{1C_f}.x_{1n} & \psi^f_{21} & \psi^r_{21}.x_{21} & \cdots & \psi^r_{11}.x_{1n} & \psi^f_{2C_r} & \psi^r_{2Cr}.x_{21} & \cdots & \psi^r_{1Cr}.x_{1n} \\ \cdots & \cdots & \cdots & \cdots & & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \psi^f_{N1} & \psi^f_{N1}.x_{N1} & \cdots & \psi^f_{N1}.x_{1n} & \psi^f_{NC_f} & \psi^f_{NC_f}.x_{N1} & \cdots & \psi^f_{1C_f}.x_{1n} & \psi^f_{N1} & \psi^r_{N1}.x_{N1} & \cdots & \psi^r_{11}.x_{1n} & \psi^f_{NC_r} & \psi^r_{NCr}.x_{N1} & \cdots & \psi^r_{1C_r}.x_{1n} \end{bmatrix}$$

$$\times \begin{bmatrix} a_{10} & a_{11} & a_{1n} & a_{20} & a_{21} & a_{2n} & a_{C0} & a_{C1} & a_{Cn} \end{bmatrix} \tag{7.30}$$

where

$$\psi^f_{ik}(x_k) = \frac{\mu^f_i(x_k)}{\sum_{i=1}^{k} \mu^f_i(x_k)} \text{ when } i \in C_f \tag{7.31}$$

$$\psi^r_{ik}(x_k) = \frac{\mu^r_i(x_k)}{\sum_{i=1}^{k} \mu^r_i(x_k)} \text{ when } i \in C_r \tag{7.32}$$

and $k = 1 \ldots N$; $i = 1 \ldots . C$ with N=number of data points and i = number of rules.

In the proposed fuzzy clustering model the threshold subtractive clustering assign a set of rules and antecedent membership functions for rare and frequent situations that models the data behavior. Than using global linear least square estimation each rules consequent equation (Equation 31) is determined. The advantage of this method is that it generates Gaussian membership functions (Eq. 22 and Eq. 23) for frequent and rare situations as fuzzy sets, which have, by nature, infinite support, therefore for every special input vector a membership degree to each fuzzy set greater than 0 is computed, and hence every rule in the rule-base fires. This leads to the possibility of generating only a couple of rules, describing the relationship between input and output channels accurate enough. Figure 7.1 illustrates the components of the proposed model and its data flow.

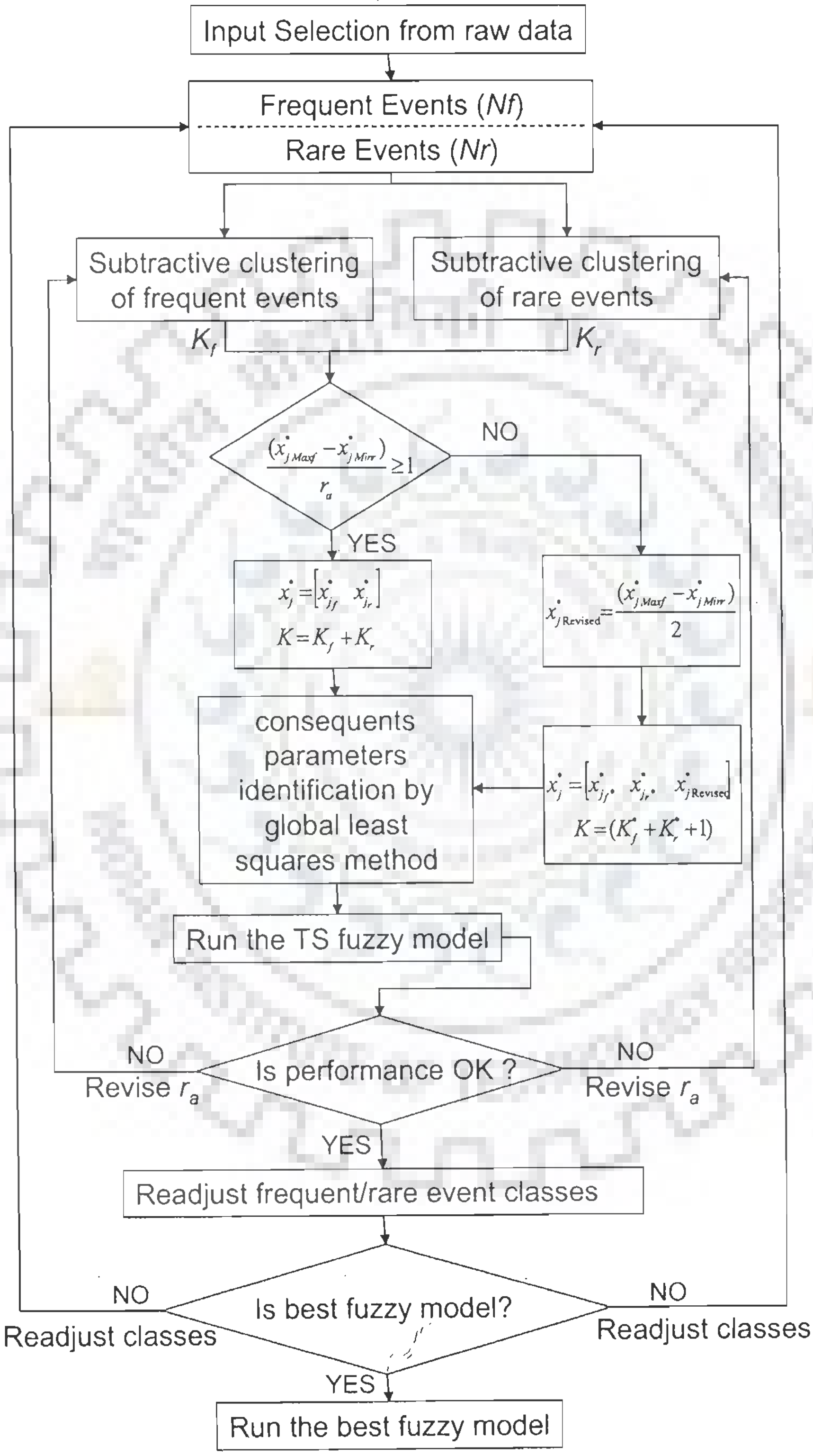

Figure 7.1: Flow Chart of the TSC-T-S Fuzzy Model Algorithm

7.7 STUDY AREA AND DATA USED

The developed model was tested and applied on the following data sets:

(1) A hypothetical hydrograph consisting of 140 values of discharge was considered to test the model. The data set consists of low discharge values as frequent events and high discharge values as rare event. The statistical properties of the hypothetical data set are presented in the Table 7.1.

(2) In the present study the upper Narmada basin upto Mandla G&D site covering the catchment area of 13120 sq km has been selected for flood forecasting (Figure 7.2). The hourly rainfall data for Jamtara, Dindori and Malankhand, hourly stage and daily discharge data at Mandla and Manot is available from 1991 to 1995. The hourly discharge values used in this study have been computed from hourly gauge data using the fuzzy logic based model as discussed in Chapter 4. For development of a real time flood-forecasting model at Mandla site, river discharge data and rainfall for the monsoon period have been used. Areal rainfall computed by Thiessen polygon method serves as the input to the forecasting model.

Table 7.1: Statistical properties of hypothetical data

	Frequent Events		Rare Events	
	Minimum Value	Maximum Value	Minimum Value	Maximum Value
Calibration Data	0.01	6.72	8.15	20.65
Validation Data	0.02	9.93	10.15	21.25

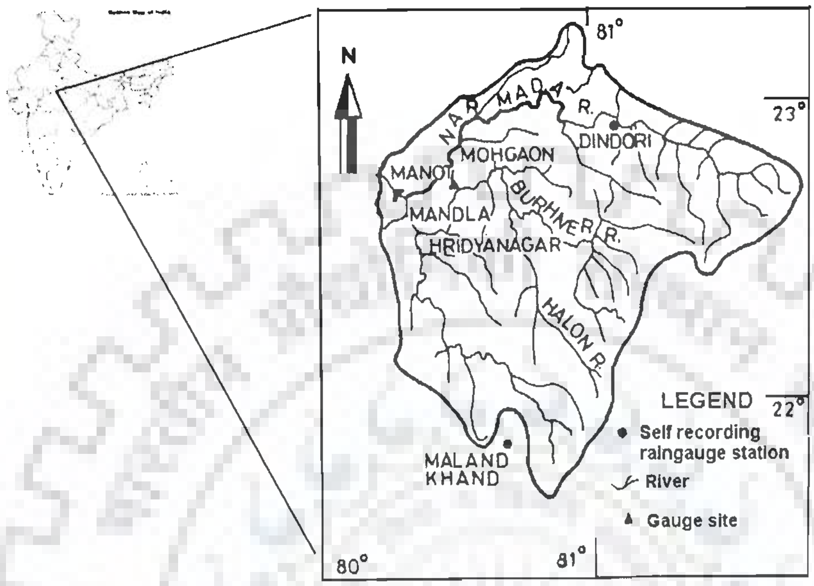

Figure 7.2: Index map of study area

7.8 MODEL INPUT SELECTION

The input vector is selected generally by trial and error method (Maier and Dandy, 2000). Determination of the number of antecedent rainfall and discharge values involves the computation of lags of rainfall and discharge values that have significant influence on the forecasted flow. These influencing values corresponding to different lags can be identified through statistical analysis of the data series by avoiding the trial and error procedure. The statistical parameters such as auto correlation function (ACF), partial auto correlation function (PACF) and cross correlation function (CCF) can be used for this purpose. Therefore, on the basis of PACF and CCF of the data series, the input vector have been selected for the flood forecasting model in the present study.

Auto Correlation Function (ACF) plot of river flow at Mandla reveals that the runoff series at Mandla is autoregressive (Figure 7.3). The Partial Auto Correlation

Function (PACF) of flow series at Mandla (Figure 7.3) with 95% confidence level gives potential antecedent runoff values that have influence on the runoff value at the current period. It can be seen from the Figure 7.3 that the runoff series up to 6 lags should be included in the input vector. Furthermore, cross correlation function (CCF) between the hourly runoff series at Mandla and average areal rainfall of the basin suggest the input rainfall vector to the fuzzy model. Similarly, CCF between the hourly runoff series at Mandla and Manot sites suggests the model input vector of flow series of Manot gauging site. The cross correlation between the spatially averaged rainfall and runoff at Mandla (Figure 7.4) indicates that the rainfall at 16, 17 and 18 lags influence the runoff. It is also evident from Figure 7.4 that the flow of Manot gauging site at 3 and 4 lags influence the runoff at Mandla. Thus, the following two models structures have been considered:

I. Model M:

Considering basin rainfall and antecedent discharge at Mandla gauging sites

$$Q_{Mandla,t} = f(R_{t-16}, R_{t-17}, R_{t-18}, Q_{Mandla,t-1}, Q_{Mandla,t-2}, Q_{Mandla,t-3}, Q_{Mandla,t-4}, Q_{Mandla,t-5} \text{ and } Q_{Mandla,t-6}). \quad (7.33)$$

II. Model MM:

Considering basin rainfall, antecedent discharge at Mandla and Manot gauging sites

$$Q_{Mandla,t} = f(R_{t-16}, R_{t-17}, R_{t-18}, Q_{Mandla,t-1}, Q_{Mandla,t-2}, Q_{Mandla,t-3}, Q_{Mandla,t-4}, Q_{Mandla,t-5} \text{ and } Q_{Mandla,t-6}, Q_{Manot,t-3}, Q_{Manot,t-4}). \quad (7.34)$$

where, $Q_{Mandla,t-1}$ is observed discharge of Mandla gauging site at t-1 hour, $Q_{Manot,t-3}$ is observed discharge of Manot gauging site at t-3 hour, R_{t-16} is spatially averaged rainfall values at t-16 hour, and t is lead time (hours).

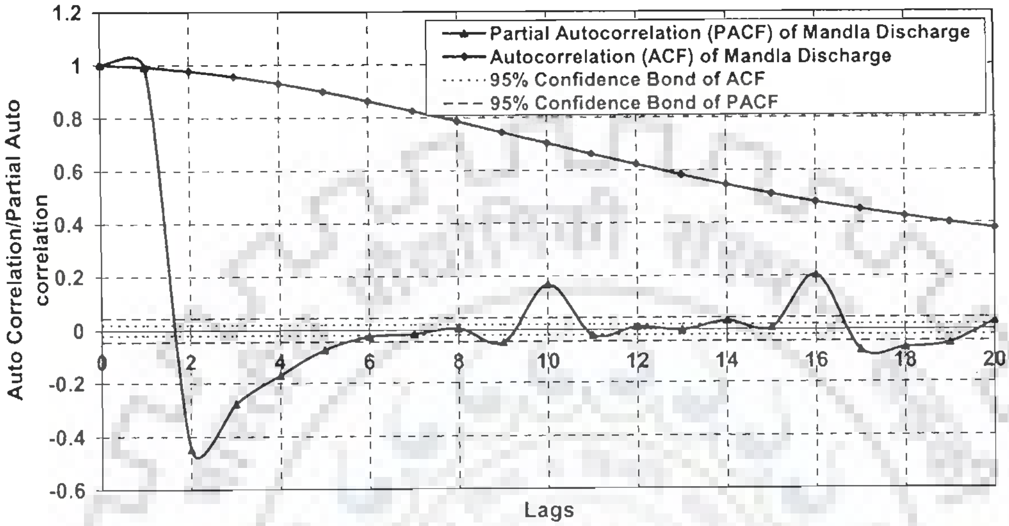

Figure 7.3: Auto-correlation and partial auto correlation of Discharge at Mandla

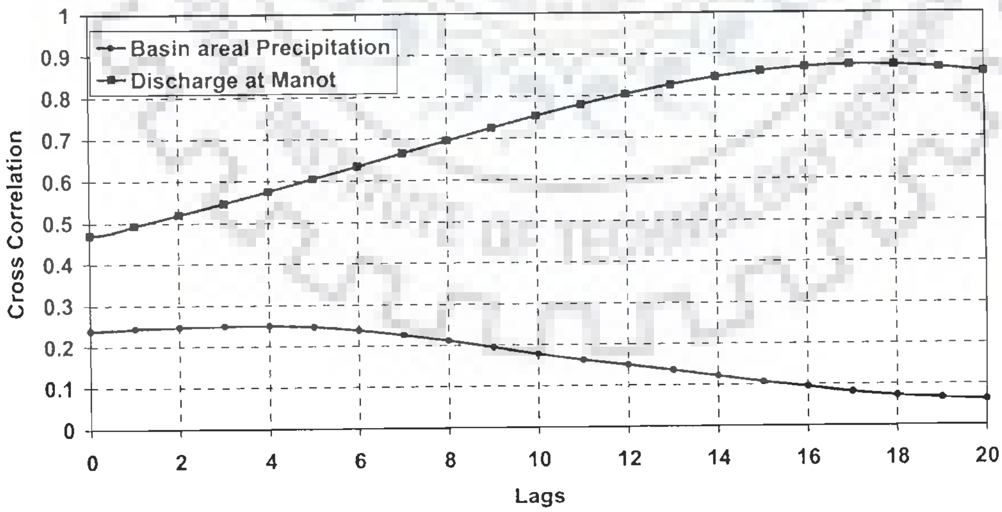

Figure 7.4: Cross correlation of Discharge at Mandla with areal precipitation and discharge at Manot

7.9 RESULTS AND DISCUSSION

7.9.1 ANN Model

The flood forecasting model has also been developed through a feed forward neural network with one hidden layer, considering the discharge as target variable to be forecasted. The feed forward hierarchical architecture is the most commonly used neural network structure (Maier and Dandy, 2000). As discussed in previous section and presented in Equations 7.33 and 7.34, 9 and 11 input variables have been identified for developing the real time flood forecasting models at Mandla site. The output layer has one neuron corresponding to the forecasted discharge at time t in the ANN architectures of 9-N-1and 11-N-1. For developing ANN model a sigmoid activation function was used for the hidden layer, and a linear transfer function was used for the output layer. Further, the optimal number of neuron (N) in the hidden layers have been identified using a trial and error procedure by varying the number of hidden neurons from 2 to 10 with 1 point on each successive increment. Further, the ANN model was trained using the training algorithm and procedure described in Chapter-4 and the optimal network architecture was selected based on the one with minimum root mean square error (RMSE). ANN structure consisting of 9 input neurons, 4 hidden neurons and 1 output neurons (9-4-1) and 11 input neurons, 4 hidden neurons and 1 output neurons (11-4-1) have been adopted as the best flood forecasting model structures for the models represented by Equations 7.33 and 7.44.

7.9.2 Fuzzy Model

For the development of subtractive clustering based TS fuzzy model, the procedure described in Chapter 4 has been applied. Further, the threshold subtractive clustering algorithm is employed together with the global least square method to identify T-S fuzzy model on the training data sets of both hypothetical and observed discharge data. A suitable transformation in the hydrologic series aids in improving the model performance (Sudheer et al., 2003). Before developing the model, logarithmic transformation as suggested by Nayak et al. (2005b) is applied to the data. The clustering partitions a data set into a number of groups such that the similarity within a group is larger than that among groups. Most similarity metrics are sensitive to the range of elements in the input vectors and may have an influence on the performance of the clustering algorithm (Babuska, 1998; Höppner et al., 1999). Therefore, the transformed data set is additionally standardized as:

$$x = \frac{x - \bar{x}}{\sigma} \tag{7.35}$$

where, $\bar{x}$ $(= \frac{1}{n}\sum_{i=1}^{n} x_i)$ is the mean and σ is the standard deviation of training data set. Further, the standardized data set has been normalized within the hypercube.

Total six parameters $(\eta, r_{af}, r_{ar}, \bar{\varepsilon}, \underline{\varepsilon}, \tau)$ influence the number of rules in the proposed threshold subtractive clustering approach. Values of $\eta = 1.5$, $\bar{\varepsilon} = 0.5$ and $\underline{\varepsilon} = 0.15$ (Chiu, 1994) are often used in subtractive clustering approach. The value of threshold parameter (τ) varies from 0 to 1. Value of $\tau = 0 \text{ or } 1$ indicate that the data set is considered as a singular series without dividing it in rare and frequent events. The subtractive clustering algorithm (Chiu, 1994) is a special case of the proposed threshold subtractive clustering algorithm when $\tau = 0 \text{ or } 1$ and $r_{af} = r_{ar}$. For the computation of the value of threshold parameter (τ), the training data set was sorted in ascending order. A plot of the data sorted in ascending order provides a basis for classification of data set into rare and frequent event and thus help in deciding the value of threshold parameter (τ). In order to find out optimum cluster centers and thus the optimum fuzzy model, the threshold subtractive clustering algorithm is initially used as subtractive clustering algorithm (considering $\tau = 0$ or 1 and $r_{af} = r_{ar}$) and the cluster radius was varied between 0.1 and 1 with steps of 0.02. These cluster centers and thus the Gaussian membership function obtained from training data set were used to compute consequent parameters through a linear least square method and a model was built. Evaluating the model by the global model performance indices such as root mean square error (RMSE) between the computed and observed discharge, the correlation coefficient and model efficiency (Nash and Sutcliffe, 1970), the optimal parameter combination of the model was sought. Once the optimization process is finished, the optimized membership functions for each input variable and consequent parameters are defined for an optimized T-S fuzzy model. This provides a conventional T-S fuzzy model (or SC-T-S fuzzy model).

For developing TSC-T-S fuzzy model, the graphically selected value of τ along with the value of $\eta = 1.5$, $\bar{\varepsilon} = 0.5$ and $\underline{\varepsilon} = 0.15$ were considered. For training the TSC-T-S fuzzy model the values of r_{ar} and r_{af} were varied with steps of 0.02 between 0.1 and 1 while, the value of other parameters (viz. $\eta, \bar{\varepsilon}, \underline{\varepsilon}$) were fixed. The number of rules obtained for the respective parameter values and a large influence is observed for r_{af} and r_{ar}. Further, smaller values of radius of influence of clusters (r_{ar} and r_{af}) results in model with higher number of rules.

Since the model subdivides the entire data set in two sets, a better representation of rare events is obtained through revised cluster centers. The hard boundary between frequent and rare events considered for independently clustering the data of two separate groups is removed and the cluster centers obtained for frequent and rare events are clubbed together. Further, the membership function is computed at each cluster center using equation 7.20 and 7.21. These membership function show an overlapping and therefore the input data falling in the frequent events have some membership in rare event and vis a vis the input data falling in rare event has membership in frequent event. The algorithm gives equal weights to rare and frequent events by independently computing the cluster centers in two different data sets. Therefore, it improves the performance of the model particularly for rare events and thus the overall modal performance also increases. Varying the value of τ in the steps of 0.1 on both lower and higher side ($\tau \pm 0.1$) and again computing the clusters and thus the T-S fuzzy model an optimal threshold value which provides a best fuzzy model can be obtained. The performance of the model may further be improved by considering an optimal combination (r_{af}, r_{ar}) of cluster radiuses for frequent and rare events. To achieve this optimal combination, values of r_{af} and r_{af} are varied in the steps of 0.02 to obtain a best combination of parameters that produces the TSC-T-S fuzzy model with best performance indices. Different values of cluster radius in rare and frequent events results in membership functions of different widths. This indicates more linguistic relevance of the model.

Further, using the methodology explained earlier, these cluster centers were used in consequent parameter computation. Training the model with different cluster radius and threshold values, an optimal combination of r_{af}, r_{ar} and τ which produces a best TSC-T-S fuzzy model is figured out. The process is repeated for each data set separately.

The model performance indices such as correlation coefficient, NS efficiency and RMSE indicate the over all model performance statistics. For describing the model performance throughout the calibration and validation period and to test the robustness of the developed model, performance evaluation criteria such as average absolute relative error (AARE) and threshold statistics (Jain and Ormsbee, 2002, Nayak et al., 2005a) have been employed in literature extensively. The AARE statistic provides overall performance index in term of absolute relative error between observed and predicted flow (absolute prediction error). While threshold statistic (TS) provides the distribution of absolute prediction error in terms of number of data points considered in calibration and validation. These statistics can be calculated using the following equations:

$$AARE = \frac{1}{n}\sum_{i=1}^{n}|\xi_i| \qquad (7.36)$$

in which $$\xi_j = \frac{Q_i^o - Q_j^p}{Q_j^o} \times 100 \qquad (7.37)$$

Where ξ_j = Relative error between observed and predicted flow in %, Q_i^o = observed flow and Q_j^p = predicted flow.

$$TS_j = \frac{y_j}{N} \times 100 \qquad (7.38)$$

where y_j is the number of stream flows (out of total N computed stream flows) for which absolute relative error between computed and observed flows is less than *j*%.

It is clear from the definition that higher values of TS and lower values of AARE would indicate better model. In flood forecasting, it is very important to know the performance of flow forecasting model in predicting higher magnitude flows. The above described performance criteria do not express the prediction ability of the model preciously from higher to low flow region. Therefore, it is felt to introduce herein a new model performance criteria termed as *peak percent threshold statistics* of prediction between top u% and l% data ($PPTS_{(l,u)}$). The term $PPTS_{(l,u)}$ is the average absolute relative error in prediction of flows lying in the band of top u% and l% data. For computation of the $PPTS_{(l,u)}$, the observed data are arranged in descending order and the following equation is used:

$$PPTS_{(l,u)} = \frac{1}{(k_l - k_u + 1)} \sum_{i=k_l}^{k_u} |\xi_i| \tag{7.39}$$

in which $k_l = \dfrac{l \times N}{100}$ and $k_u = \dfrac{u \times N}{100}$ (7.40)

where, l and u are respectively lower and higher limits in percentage, N is the number of data and ξ_i is the average relative error of the i^{th} data. This statistics can map the performance of the model in various magnitude ranges of the data. When the value of u=100%, the $PPTS_{(l,u)}$ can be represented as $PPTS_{(l,100)}$ or simply $PPTS_{(l)}$. Further, $PPTS_{(l)}$ indicates the peak percent threshold statistics of top l% data. Similarly, the same statistics can be used for evaluating the model performance in low flow modeling by smallest l% data from descending series.

7.9.3 Modeling Hypothetical Data Set

Compolo et. al. (1999) suggested that the capacity of a basin to respond to a perturbation is more accurate when recent discharge values are used. Results of the study carried out by Nayak et.al. (2005a) also verifies that flow forecasting model developed using discharge information of precious time steps provides predictions in good agreement with observed flows. Therefore, particularly in case of hypothetical data, forecasting models have been developed using the data of previous time steps so as to precisely verify the performance of proposed TSC-T-S fuzzy model. For deciding the number of previous time step data in the input structure, auto correlation analysis as suggested by Sudheer et al. (2002) has been carried out. The analysis suggested that input data of previous two time steps for hypothetical cases provide best autocorrelation. Using a sigmoid activation function for the hidden layer and a liner transfer function for the output layer, 2 input neurons, 3 hidden neurons and 1 output neurons were adopted as optimum network architecture for forecasting model. The three models ANN, SC-T-S fuzzy model and TSC-T-S fuzzy model developed using hypothetical data set were compared.

In flow forecasting the model performance for 1-step ahead forecast is generally for better then the forecasting of higher lead periods (Nayak et al., 2005a). Therefore, the performance of the proposed TSC-TS fuzzy model is checked through the 1-step ahead forecasts from the hypothetical data set. For the development of TSC-T-S fuzzy model, the value of τ has been computed by plotting the ascending series of hypothetical data as shown in Figure 7.5. From this Figure a threshold value has been chosen so as to classify

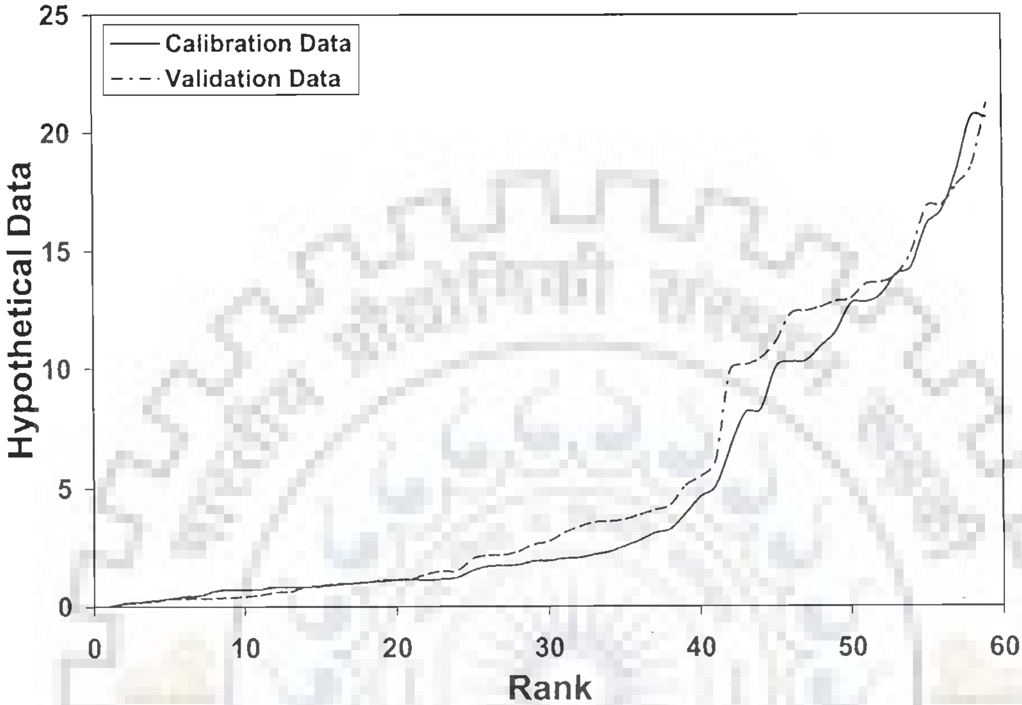

Figure 7.5: Plot of calibration and validation data set arranged in ascending order (Hypothetical data)

the training data set into frequent and rare events. Threshold parameter value for training data sets of hypothetical cases was chosen as 0.73 (44/60). Using the selected values of τ and optimal values of radius of influence of clusters for frequent and rare events, TSC-T-S fuzzy models have been developed. In order to verify the superiority of the proposed TSCTS fuzzy model, SC-T-S fuzzy model and ANN models were also developed for the hypothetical case. The performance indices of the models that provided best results both in calibration and validation are presented in Table 7.2.

The residual variance between observed and forecasted values is generally expressed by RMSE with optimal value equivalent to zero. The value of RMSE is found to vary considerably between 1.339 and 1.469 during calibration and validations of different models. The correlation, which measures the divergence of the actual observed values from forecasted values, is found to be constantly more than 0.96 for different models. It is evident that all the three models have comparable value of coefficient of correlation. The NS model efficiency which measures the capability of the model in

Table 7.2: Performance Indices of 1 h Lead Period Models (Hypothetical Data)

	Calibration Results			Validation Results		
	ANN	SC-T-S Fuzzy Model	TSC-T-S Fuzzy Model	ANN	SC-T-S Fuzzy Model	TSC-T-S Fuzzy Model
Correlation	0.9658	0.966	0.9702	0.9702	0.974	0.975
NS Eff	0.9327	0.943	0.944	0.9405	0.942	0.944
RMSE	1.433	1.419	1.339	1.469	1.443	1.441
AARE	193.4375	184.593	179.8274	121.0737	118.228	115.113
TS1	1.714	1.724	1.742	0	0.000	1.6949
TS2	3.414	3.448	3.4483	0	1.695	5.0847
TS5	6.8966	7.172	10.3448	11.8644	11.864	11.9
TS10	16.2414	17.069	18	27.8136	28.119	28.8136
TS20	36.2069	35.586	36.7069	43.7627	44.678	45.7627
TS50	56.8966	56.448	60.3448	65.7966	66.102	69.4915
PPTS(2)	24.0726	15.793	14.0816	11.2109	10.058	8.2063
PPTS(3)	15.4844	14.800	10.9169	17.1504	17.020	7.753
PPTS(5)	12.3779	11.600	9.5019	13.8144	13.531	8.3312
PPTS(10)	10.9704	11.800	10.1671	10.5463	10.324	10.09
PPTS(20)	10.0016	10.400	9.4581	9.2707	8.471	8.2592

predicting the runoff values away from the mean shows optimum efficiency equivalent to one when there is a perfect match between observed and estimated values. Perfectly zero value of the NS efficiency indicates that the model prediction is as good as no-knowledge model. While, negative value of NS efficiency is an indicator of the model worst than the no-knowledge model (Beven, 2000, Verniuwe, et al., 2005). The value of efficiency is found to be more than 93% with highest one obtained as 94.4% in case of TSC-T-S fuzzy model. The three global model efficiency criteria i.e. correlation coefficient, RMSE and efficiency indicates that the TSC-T-S fuzzy model provides better forecast in comparison to both ANN and SC-T-S fuzzy models.

When mapping the model performance for different error ranges through threshold statistics and AARE, consistently similar results were obtained from all the models. The value of AARE varies from 115.11 to 193.43 in hypothetical data modeling. The smaller values of AARE are obtained in case of TSC-T-S fuzzy model both for calibration and validation data sets. Furthermore, the values of threshold statistics computed from the forecasted flows obtained from different models are closely associated for higher errors. However, the numbers of data showing same range of error are slightly different for different models in case of smaller error ranges between computed and observed data. Another criteria i.e. PPTS statistics, proposed in this paper, clearly indicate the performance of different models in forecasting of high floods. Table 7.2 indicates that the PPTS value for TSC-T-S fuzzy model is always lower than the one obtained for SC-T-S and ANN models. The flow series forecasted through TSC-T-S fuzzy model reproduce the higher flow values more accurately in comparison to other two models.

Critical examination of all the performance indices revels that the TSC-T-S fuzzy model show betters performance in comparison to ANN and SC-T-S fuzzy models. Furthermore, both SC-T-S fuzzy model and TSC-T-S fuzzy models out performs corresponding ANN model. For management of floods, predication of peak floods is an important task. Performance of the models can be best compared through error in peak flow predication. Although the coefficient of correlation, NS-efficiency of TSC-T-S fuzzy model is slightly higher than the corresponding values obtained for SC-T-S fuzzy model. However, the slight improvement in PPTS indicates a significant impact on forecasting of higher magnitude flows. The value of PPTS(2), PPTS(3), PPTS(5), PPTS(10) and PPTS(20) indicated that the TSC-T-S fuzzy model shows a significant improvement in forecasting higher magnitude values. Figure 7.6 and 7.7 shows the calibration and validation results of hypothetical and forecasted hydrographs.

7.9.4 Modeling Observed Flow Data

7.9.4.1 Forecasting at very short time (1 hour lead time)

In case of observed flow data of Mandla Gauging site, the forecasting models (Equation 7.33 and Equation 7.44) have been calibrated and validated for six different data sets (Table 7.3) in order to verify the robustness of the forecasting models developed using data of different periods and lengths. In the first five cases (i.e. M8990 to M9394 and MM8990 to MM9394) two years of data were used for model calibration and one year of data for model validation and in the sixth case (M8994 or MM 8994), six years of data were used for calibration and one year of data for validation. Varying length for calibration period is also useful in verifying the effect of input data length on model development and performance. Furthermore, the input data were divided into two regimes, namely frequent and rare events by putting them in ascending order. It is observed that the flow data of the river Narmada at Mandla and Manot sites are composed of about 76% to 80% frequent events and 24% to 20% rare events during different selected periods. After the classification of input data set into two classes the value of τ is considered as 0.76 to 0.80 for different cases. Using these values of τ and

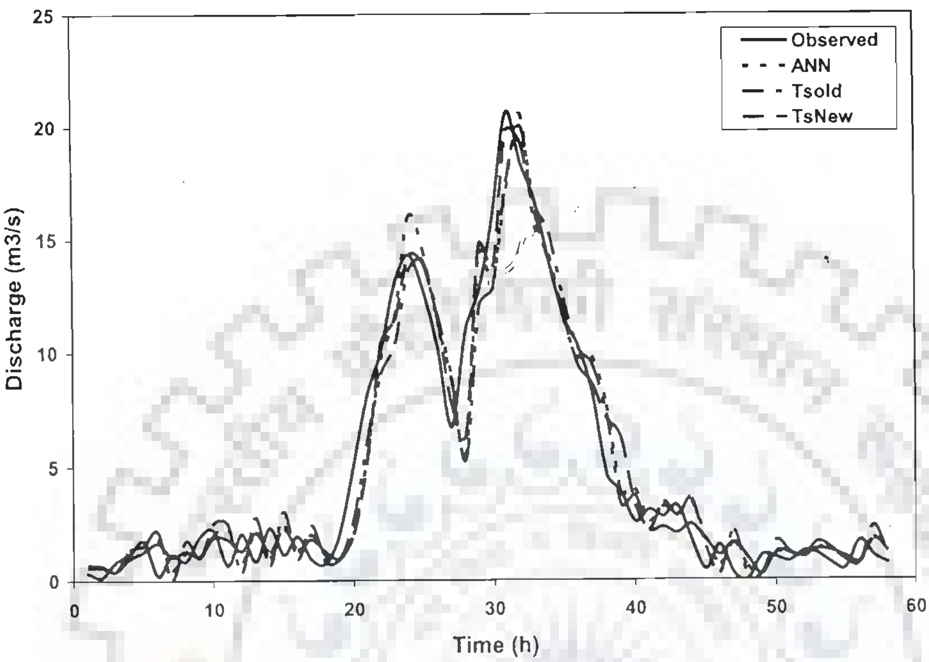

Figure 7.6: Comparison of hypothetical and forecasted hydrographs (Calibration result)

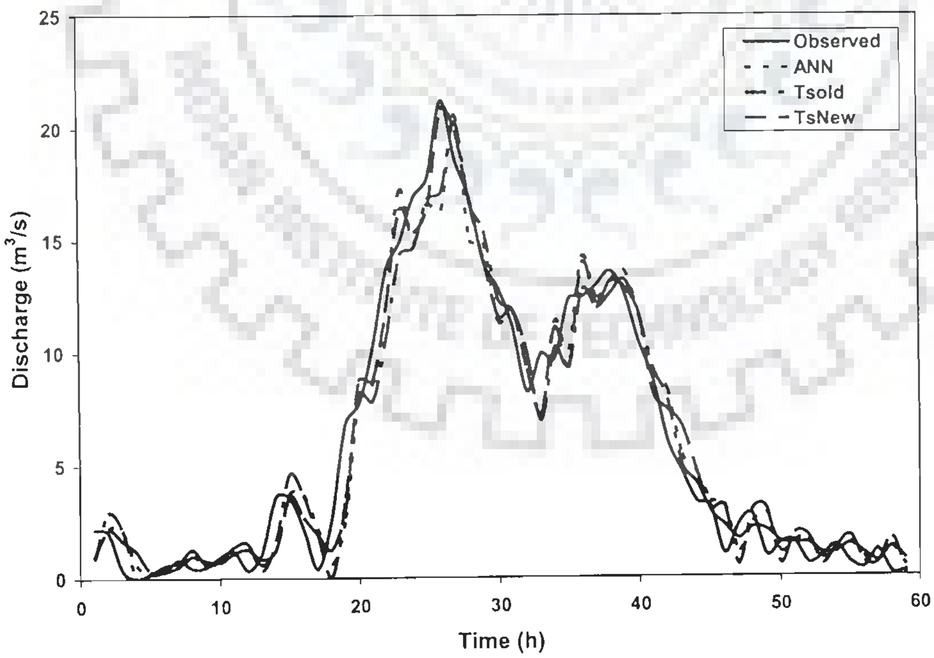

Figure 7.7: Comparison of hypothetical and forecasted hydrographs (Validation result)

Table 7.3: Statistical properties of the data selected for modeling

Model No.	Calibration period					Validation period			
	Rare events (%)	Period	Qmin	Qmax	SD	Period	Qmin	Qmax	SD
M8990/ MM8990	21	1989-90	8.86	2097.4	282.1	1991	5.76	4257.0	1051.6
M9091/ MM9091	23	1990-91	5.76	4257.0	792.8	1992	2.64	4354.5	513.6
M9192/ MM9192	24	1991-92	2.64	4354.5	513.6	1993	5.30	3379.3	350.5
M9293/ MM9293	24	1992-93	2.64	4354.5	436.7	1994	3.15	6330.4	944.1
M9394/ MM9394	24	1993-94	3.15	6330.4	735.4	1995	4.37	3730.4	417.3
M8994/ MM8994	25	1989-94	2.64	6330.0	677.4	1995	4.37	3730.4	417.3

varying radius of influences for frequent and rare events in between 0.1 to 0.9 with step size of 0.01, TSC-T-S fuzzy models were developed. Furthermore, using each data set ANN, SC-T-S fuzzy model and TSC-T-S fuzzy models were developed to predict river flows for 1 hour lead period. The values of performance indices of the models developed using two different model input structures (Equation 7.33 and Equation 7.34) considering the calibration period 93-94 and 89-94 and forecast of 1 hr lead period at Mandla site are presented in detail in Table 7.4 and Table 7.5. Further, the correlation coefficients for different models developed using six different data sets and two different input model structures (Models M and MM) are illustrated in Figure 7.8 and Figure 7.9. The plotted values of correlation coefficient indicate a definite improvement in forecasting of flow series through proposed model in comparison to SC-T-S fuzzy model and ANN model. The correlation coefficients of validation results of TSC-T-S fuzzy models M8990, M9091, M9192, M9293, M9394, M8994 are found to be 0.9905, 0.9915, 0.9910, 0.9921, 0.9915, 0.9905 and for models MM8990, MM9091, MM9192, MM9293, MM9394, MM8994 are found to be 0.9941, 0.9930, 0.9920, 0.993, 0.9927, 0.9926 respectively for one hour ahead forecast.

The RMSE value of SC-T-S fuzzy model is lower than ANN model in all the models developed using two different input structures and six different datasets. Further more, the TSC-T-S fuzzy model shows a further reduction in RMSE in comparison to SC-T-S fuzzy model as demonstrate by the model results shown in Table 7.4 and Table 7.5. The value of AARE and TS statistics which maps the performance of the models in terms of error, indicate that fuzzy models and in particular SC-T-S fuzzy model is better than ANN model in predicting more number of flow values accurately. Lower values of PPTS statistics and in general the values of PPTS(2), PPTS(3), PPTS(5) etc. indicate the capability of a model in forecasting higher flow values. The values of these statistics are presented in Table 7.4 and Table 7.5. The lower values of PPTS statistics (Table 7.4 and Table 7.5) confirms that the proposed TSC-T-S fuzzy model is capable in forecasting the higher flow values more accurately than the corresponding ANN and SC-T-S fuzzy models.

Table 7.4: Performance Indices of 1 hour Lead Models (Model M - Equation 7.34)

	M9394						M8994					
	Calibration			Validation			Calibration			Validation		
	TSC-T-S	SC-T-S	ANN	TSC-T-S	SC-T-S	ANN	TSC-T-S	SC-T-S	ANN	TSC-T-S	SC-T-S	ANN
Correlation	0.9911	0.9828	0.9760	0.9915	0.9830	0.9771	0.9901	0.9828	0.9732	0.9905	0.9840	0.9740
Efficiency	96.3102	95.8045	95.2321	96.5286	95.8888	95.6092	96.3721	95.6424	95.4762	96.4545	95.8153	95.5161
RMSE	88.731	90.452	95.447	88.689	89.919	94.749	84.002	84.452	85.539	83.830	84.931	85.429
AARE	3.789	3.924	4.102	3.756	3.803	4.061	3.623	3.663	3.928	3.546	3.595	3.842
TS1	46.280	45.525	45.503	49.316	47.832	47.219	49.021	45.924	44.731	49.125	47.733	45.805
TS2	54.123	53.633	52.164	55.115	54.030	53.627	56.549	53.723	52.679	56.668	53.801	52.730
TS5	78.481	76.749	73.263	80.784	79.542	76.778	82.531	81.912	80.997	82.620	82.057	80.312
TS10	93.318	91.227	90.193	94.083	92.610	92.020	93.631	92.457	91.552	93.884	92.741	90.953
TS20	96.746	95.206	94.761	98.598	97.689	97.509	99.104	97.224	96.233	99.293	98.379	97.555
TS50	99.071	98.414	97.110	96.684	99.056	99.836	98.354	97.812	96.564	99.083	99.121	98.734
PPTS(2)	3.181	3.421	6.684	3.310	3.246	3.563	2.801	2.983	3.457	2.842	3.035	3.593
PPTS(3)	5.415	5.844	6.717	4.913	5.750	6.648	3.481	3.544	4.327	3.537	3.630	4.450
PPTS(5)	8.937	9.621	9.992	8.877	9.454	9.897	7.902	7.772	7.903	7.976	7.881	8.124
PPTS(10)	6.221	6.742	7.102	6.019	6.527	6.909	6.104	6.256	6.667	6.335	6.392	6.719
PPTS(20)	5.896	5.637	6.704	4.866	5.444	5.569	5.003	5.312	5.497	5.078	5.375	5.581

Table 7.5: Performance Indices of 1- hour Lead Models (Model MM - Equation 7.33)

	M9394						M8994					
	Calibration			Validation			Calibration			Validation		
	TSC-T-S	SC-T-S	ANN	TSC-T-S	SC-T-S	ANN	TSC-T-S	SC-T-S	ANN	TSC-T-S	SC-T-S	ANN
Correlation	0.9931	0.9894	0.9834	0.9927	0.9874	0.9823	0.9927	0.9887	0.9819	0.9926	0.9882	0.9815
Efficiency	96.8500	96.5700	96.4800	96.5800	95.9700	95.6900	97.5000	97.1000	96.5000	96.7300	96.0200	95.5400
RMSE	83.324	84.721	89.962	88.123	88.552	93.578	80.283	82.455	85.534	82.127	83.726	84.323
AARE	3.567	3.782	4.040	3.544	3.880	4.139	5.501	5.577	6.073	3.582	3.669	3.915
TS1	47.221	46.389	46.167	49.832	48.660	48.110	50.538	45.956	45.532	49.265	47.870	45.840
TS2	56.548	56.429	56.253	55.474	54.840	53.670	58.534	56.181	55.945	57.512	54.910	53.600
TS5	83.869	83.385	81.228	82.736	80.240	76.842	84.325	83.620	82.982	82.820	82.210	81.130
TS10	93.729	93.671	92.789	94.225	93.290	92.181	94.137	93.327	93.270	94.397	93.420	91.740
TS20	98.069	97.954	97.156	98.867	97.890	97.793	99.392	97.418	97.200	99.330	98.530	98.330
TS50	99.442	99.213	98.575	99.171	99.710	99.861	99.082	99.065	99.057	99.610	99.520	99.230
PPTS(2)	3.162	3.419	6.563	3.205	3.121	3.516	2.618	2.815	3.261	2.833	3.022	3.573
PPTS(3)	5.085	5.067	5.794	4.832	5.579	6.249	3.367	3.388	4.151	3.527	3.614	4.426
PPTS(5)	5.079	5.095	6.403	8.241	9.188	9.415	7.647	7.504	7.634	7.952	7.846	8.079
PPTS(10)	6.128	6.292	6.751	5.920	6.212	6.233	5.511	5.651	6.089	6.316	6.363	6.683
PPTS(20)	5.434	5.485	6.036	4.722	4.969	5.216	4.110	4.536	4.685	5.063	5.351	5.551

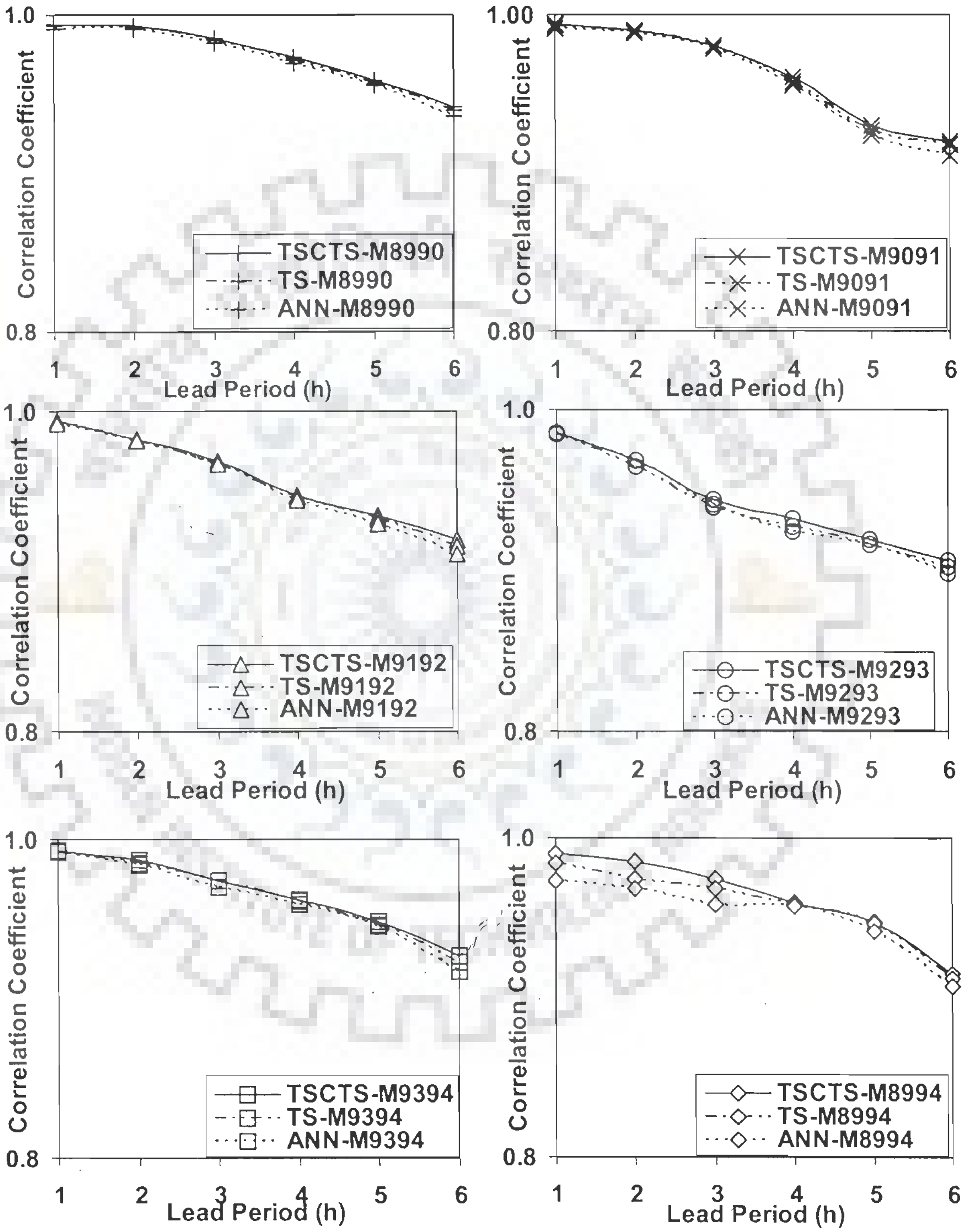

Figure 7.8: Variation of correlation coefficients along the forecast time horizon for different data sets of river Narmada at Mandla gauging site (Validation result-Model M)

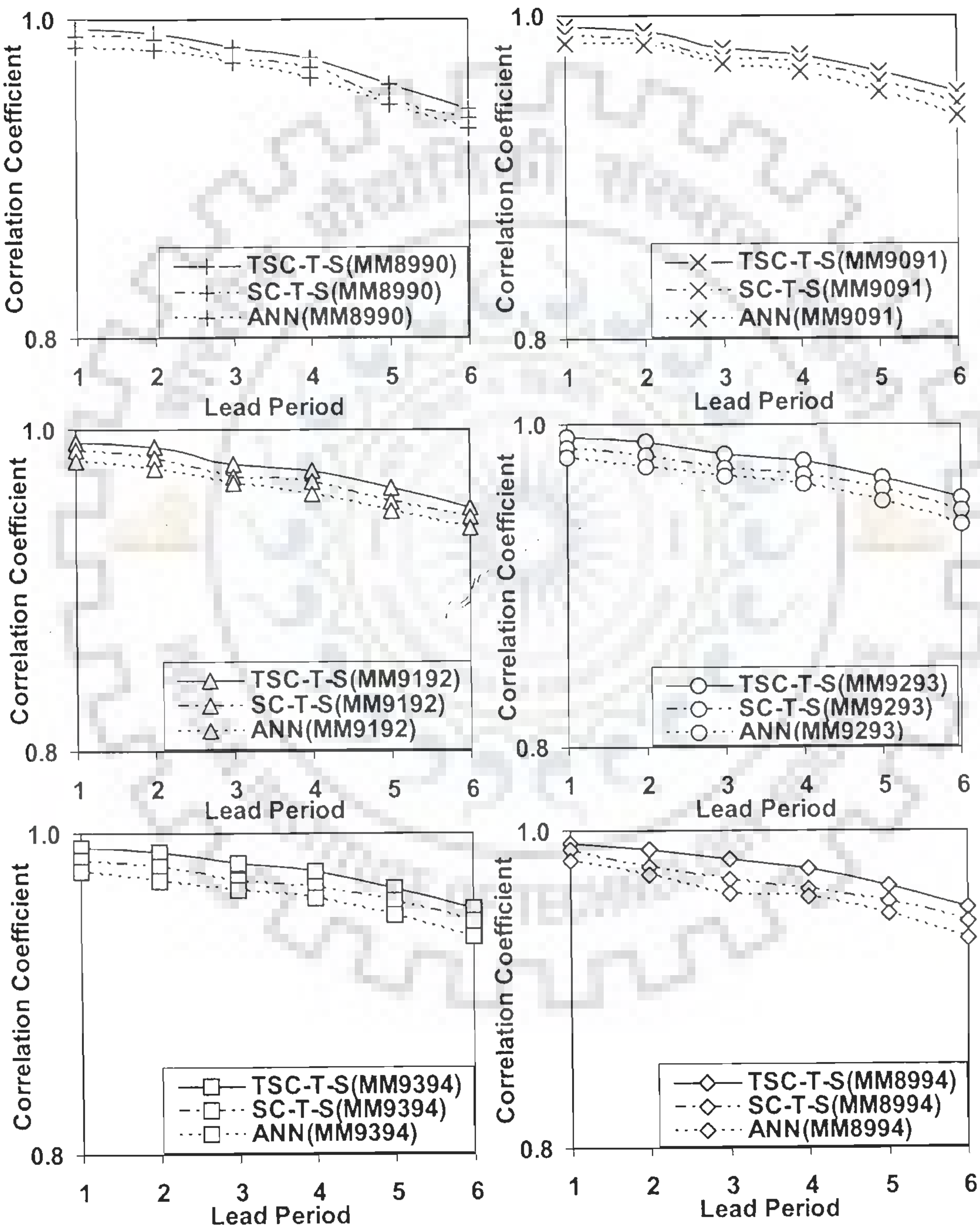

Figure 7.9: Variation of correlation coefficients along the forecast time horizon for different data sets of river Narmada at Mandla gauging site (Validation result-Model MM)

7.9.4.2 Forecasting at >1 hour lead time

The short term forecast for several hours provides a clear guide in project operation or a warning to people going to be affected by inundation or alert the teams for keeping a vigil on embankments and levees etc. along rivers. A forecasting model needs meteorological data from the catchment, river flow data in reaches or stretches of river at the analysis point at the earliest. It is understood that in case of forecasting of flow at high lead periods, generally the accuracy of flood forecasting decreases when forecasting time increases (Nayak et al., 2005a). For real time forecasting it is necessary to have a model that can operate within the adaptive mode (Wood and Connell, 1985). Forecasting at lead periods more than one hour (>1hr) can be more accurately modeled by adding more input information at previous time steps. In practice the discharge values of previous time steps (Equation 7.33 and Equation 7.34) are not readily available. Therefore, a simple recursive algorithm is used to obtain forecast for successive lead time. In this process known values of inputs were used to forecast Q_{t+1} at Mandla gauging site and thus in turn will serve to predict Q_{t+2}. This procedure is thus repeated until the computation of the spectrum of forecasted values ranging from Q_{t+1} to Q_{t+6} is obtained. Similarly, the model input represented by Equation 7.34 indicates that the forecasted values of Manot gauging sites (fore lead period 1 hr and 2hr) are required for forecasting discharge at Mandla gauging site at lead periods 5 hr and 6 hr. Therefore, the flow values of Manot site forecasted from the previous three flow values were supplied as an input to the model by incorporating a suitable subroutine in the flood forecasting model developed for Mandla gauging site. Using computed discharge as input to these models may cause the error to carry over from one step to another. However, such carry over errors may not have any significant effect due to higher accuracy of fuzzy and ANN models (Sudheer and Jain, 2003).

Results showing the performance statistics of all models at different lead periods are presented in Table 7.6 and Table 7.7. Further, the performance of the models in terms of correlation between the forecasted and observed values of flows is presented in Figure 7.8 and Figure 7.9. All the three models indicate reduction in correlation coefficient with increase in forecasting lead period. Further, it is apparent from these figures that the correlation statistic of TSC-T-S fuzzy model is superior to the other models at all lead periods.

The RMSE values with different lead times are presented in Figure 7.10 and Figure 7.11. It is depicted from Figure 7.10 and Figure 7.11 that the value of RMSE increases with forecasting lead period in all the models. However, it is evident that the rate of rise of RMSE with lead time is smaller in case of TSC-T-S fuzzy model. The TSC-T-S fuzzy model for M8994 forecasted the flows with a RMSE of 278.321 m^3/s at 6 hours, and the SC-T-S and ANN model forecasted the flows with RMSE of 284.98 and 292.385 m^3/s respectively. Similarly, the TSC-T-S fuzzy model for MM8994 forecasted the flows with a RMSE of 277.30 m^3/s at 6 hours, and the SC-T-S and ANN model forecasted the flows with RMSE of 283.977 and 290.000 m^3/s respectively.

Furthermore, the efficiency of the forecasting model along the all lead periods is improved when TSC-T-S fuzzy model is used (Figure 7.12 and Figure 7.13). The value of correlation coefficient and efficiency indicate a continuous falling trend. The rate of reduction of correlation coefficient and efficiency is highest in case of ANN model. However, the TSC-T-S fuzzy model indicates a comparatively lower rate of reduction of

Table 7.6: Performance Indices of >1 h Lead Models (Validation Results Model-M)

M8994	2 Hr			3 Hr			4 Hr			5 Hr			6 Hr		
	TSC-T-S	SC-T-S	ANN	TSC-T-S	SC-T-S	ANN	TSC-T-S	SC-T-S	ANN	TSC-T-S	SC-T-S	ANN	TSC-T-S	SC-T-S	ANN
Correlation	0.9854	0.9745	0.9690	0.9744	0.9687	0.9587	0.9598	0.9587	0.9575	0.9483	0.9466	0.9422	0.9157	0.9129	0.9082
Efficiency	91.2600	91.1900	90.9800	89.2200	89.0200	88.4400	86.5100	86.1400	85.3900	83.5800	83.1500	81.9100	78.6300	77.5600	76.6600
RMSE	115.770	117.300	122.141	152.420	152.645	155.239	191.864	196.270	208.334	236.264	238.350	242.760	278.321	284.980	292.385
AARE	5.485	5.555	5.724	7.373	9.441	9.709	11.673	12.254	12.811	12.453	14.974	15.586	18.369	18.562	19.669
TS1	25.780	25.260	24.070	23.230	22.790	21.350	10.090	8.910	6.790	8.240	7.240	6.050	5.370	4.640	4.480
TS2	37.420	37.220	36.360	33.360	32.460	32.300	18.570	18.450	14.270	14.130	13.790	13.130	11.130	10.790	10.100
TS5	61.610	61.500	61.390	57.830	57.760	54.780	36.970	36.960	35.140	29.680	29.690	28.450	24.540	24.480	23.530
TS10	84.990	84.120	82.560	72.420	72.010	71.600	62.550	62.110	61.670	59.630	58.750	58.320	42.920	42.650	40.740
TS20	94.200	94.150	94.280	88.790	88.770	87.130	83.380	83.320	81.690	77.910	77.700	77.820	71.750	71.530	71.140
TS50	99.260	99.210	99.260	97.520	97.330	97.380	96.600	96.190	95.290	94.830	94.810	94.160	92.900	92.730	92.190
PPTS(2)	6.120	6.630	7.040	8.560	9.330	11.050	11.760	12.560	13.130	14.180	15.790	16.790	17.200	18.180	18.940
PPTS(3)	6.810	7.660	8.380	10.770	11.680	13.130	14.680	14.770	16.970	18.370	20.900	23.450	23.360	25.190	26.610
PPTS(5)	15.320	15.870	16.280	23.270	24.060	24.170	28.200	30.040	31.790	31.620	34.140	37.600	38.140	38.440	39.110
PPTS(10)	11.540	11.670	11.510	16.940	17.380	17.910	22.090	22.680	24.780	25.980	26.690	28.300	29.420	30.610	31.720
PPTS(20)	9.260	9.310	9.280	14.310	14.490	14.540	19.260	19.250	20.810	22.940	23.080	23.170	26.400	26.580	27.180

Table 7.7: Performance Indices of >1 h Lead Models (Validation Results Model-MM)

M8994	2 Hr			3 Hr			4 Hr			5 Hr			6 Hr		
	TSC-T-S	SC-T-S	ANN	TSC-T-S	SC-T-S	ANN	TSC-T-S	SC-T-S	ANN	TSC-T-S	SC-T-S	ANN	TSC-T-S	SC-T-S	ANN
Correlation	0.9880	0.9770	0.9720	0.9820	0.9690	0.9610	0.9760	0.9640	0.9590	0.9660	0.9560	0.9480	0.9520	0.9430	0.9320
Efficiency	92.1590	91.5104	91.1919	90.0897	89.3313	88.6480	87.3560	86.4448	85.5860	84.4039	83.4451	82.1000	79.4016	77.8324	76.8333
RMSE	115.765	117.298	121.460	152.123	152.270	154.700	191.558	196.267	207.100	235.940	237.352	242.756	277.300	283.977	290.000
AARE	5.430	5.444	5.581	7.299	9.252	9.466	11.556	12.009	12.491	12.328	14.674	15.197	18.185	18.191	19.177
TS1	26.033	25.346	24.128	23.459	22.869	21.397	10.187	8.939	6.807	8.319	7.263	6.065	5.422	4.651	4.493
TS2	37.783	37.350	36.445	33.691	32.577	32.376	18.751	18.520	14.305	14.269	13.835	13.159	11.242	10.826	10.122
TS5	62.217	61.713	61.528	58.394	57.965	54.907	37.330	37.089	35.225	29.969	29.794	28.514	24.775	24.569	23.581
TS10	85.822	84.416	82.751	73.131	72.265	71.768	63.160	62.325	61.807	60.215	58.955	58.456	43.342	42.795	40.833
TS20	95.123	94.481	94.497	89.663	89.081	87.330	84.199	83.610	81.883	78.671	77.969	77.995	72.457	71.779	71.302
TS50	100.235	99.563	99.491	98.480	97.670	97.601	97.551	96.534	95.512	95.761	95.149	94.376	93.811	93.056	92.399
PPTS(2)	5.944	6.348	6.674	8.309	8.927	10.481	11.413	12.021	12.451	13.762	15.109	15.926	16.692	17.399	17.964
PPTS(3)	6.612	7.329	7.949	10.455	11.174	12.454	14.251	14.138	16.100	17.826	20.005	22.239	22.670	24.108	25.238
PPTS(5)	14.867	15.186	15.436	22.588	23.022	22.921	27.368	28.753	30.153	30.692	32.675	35.664	37.018	36.786	37.094
PPTS(10)	11.196	11.166	10.915	16.444	16.637	16.986	21.444	21.705	23.504	25.212	25.545	26.842	28.558	29.291	30.085
PPTS(20)	8.984	8.908	8.803	14.257	13.864	13.792	18.697	18.425	19.736	22.268	22.089	21.976	25.620	25.442	25.779

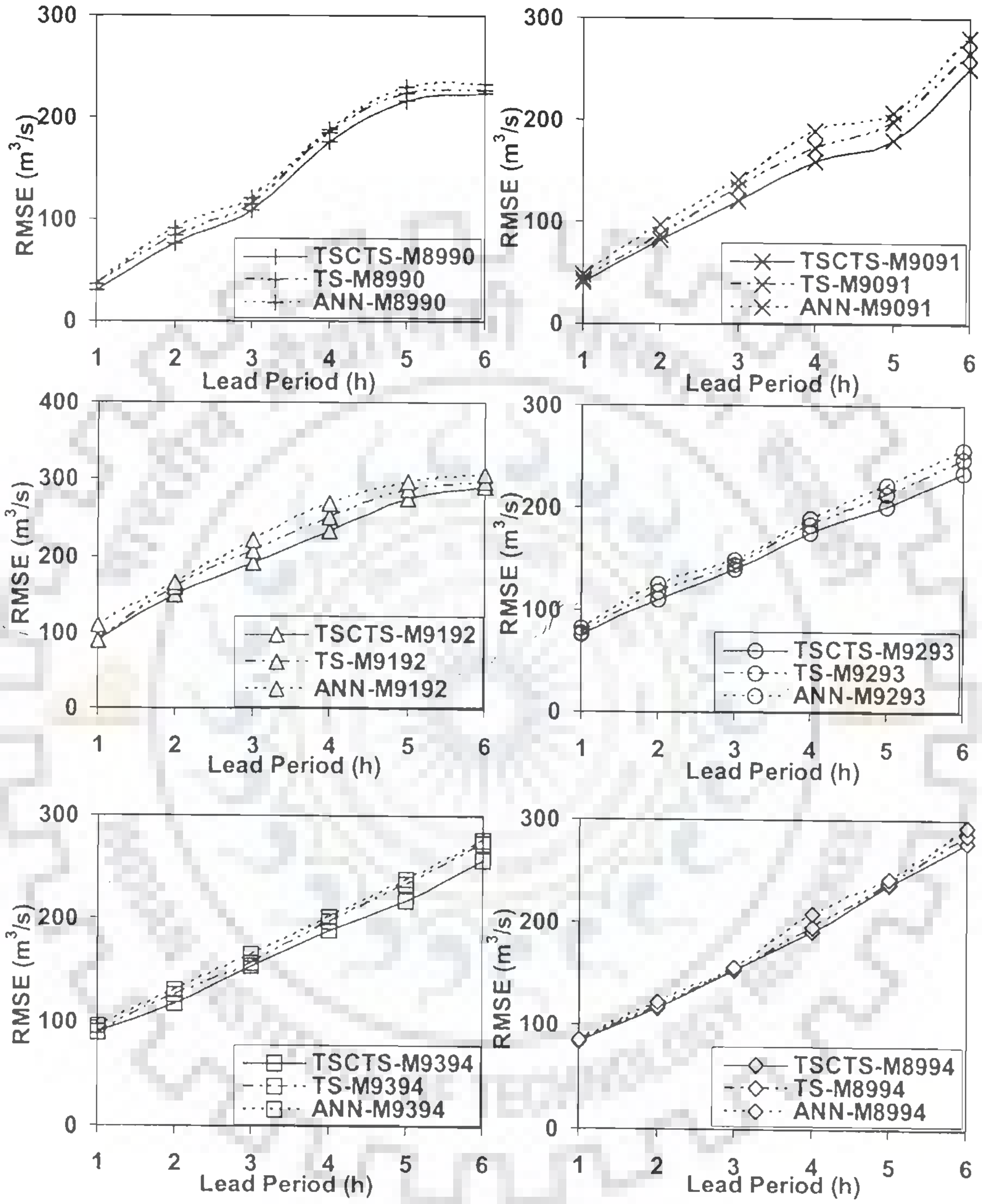

Figure 7.10: Variation of RMSE along the forecast time horizon for different data sets of river Narmada at Mandla gauging site (Validation result Model -M)

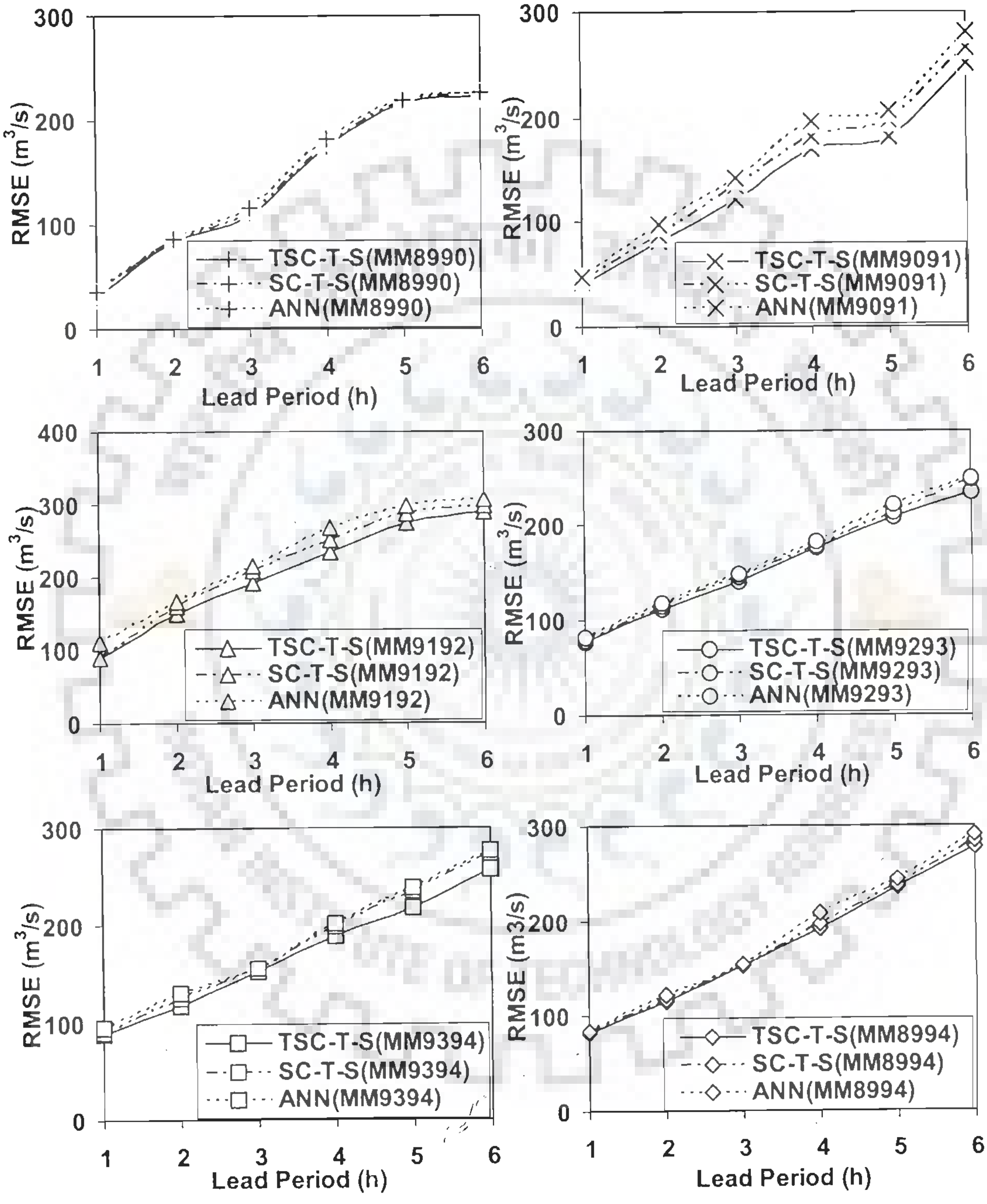

Figure 7.11: Variation of RMSE along the forecast time horizon for different data sets of river Narmada at Mandla gauging site (Validation result-Model -MM)

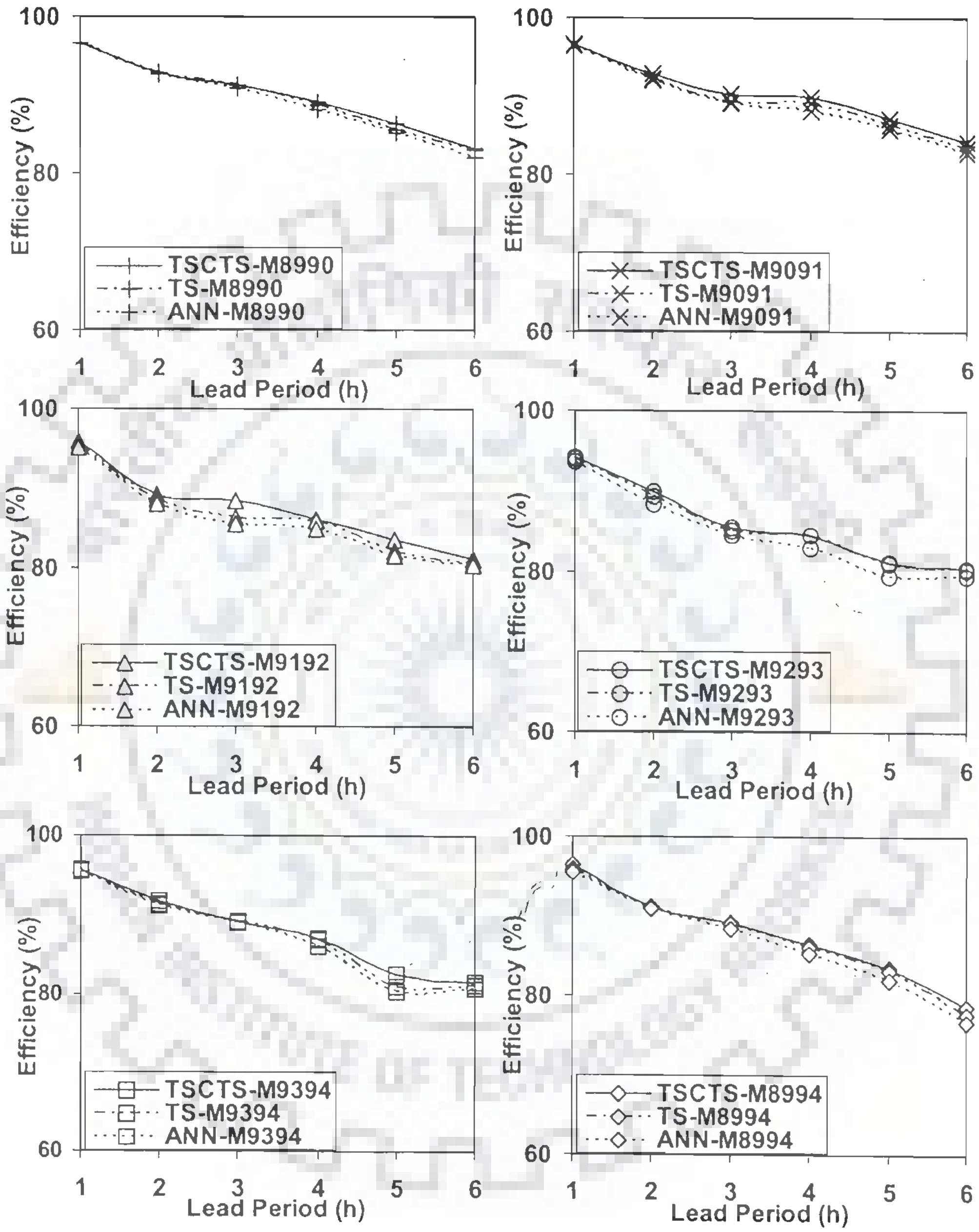

Figure 7.12: Variation of NS-Efficiency along the forecast time horizon for different data sets of river Narmada at Mandla gauging site (Validation result Model-M)

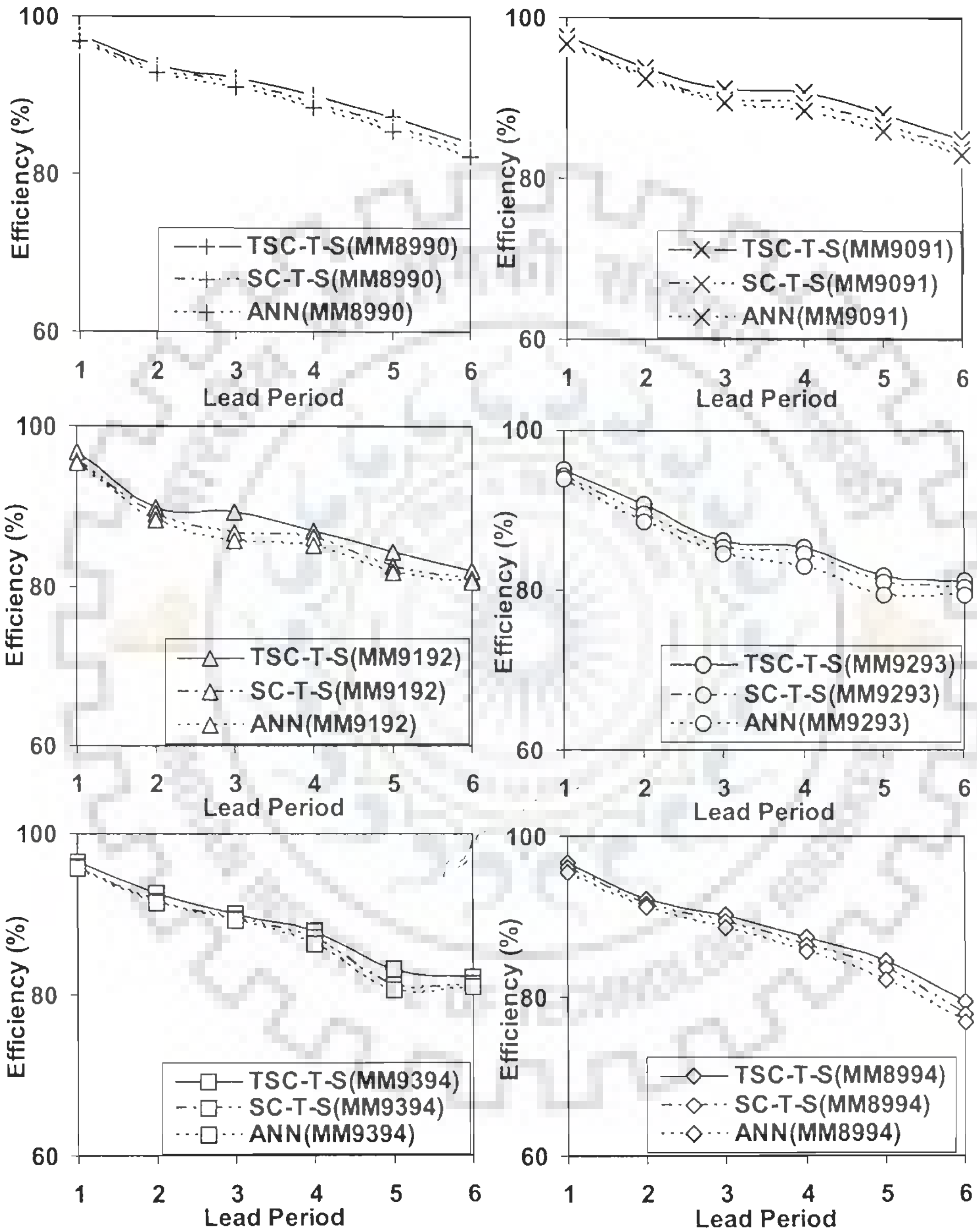

Figure 7.13: Variation of NS-Efficiency along the forecast time horizon for different data sets of river Narmada at Mandla gauging site (Validation result Model-MM)

both correlation coefficient and efficiency with lead period. Furthermore, it is also observed that the correlation and efficiency static is consistently in the same order during calibration and validation for TSC-T-S fuzzy model, which confirms a good generalization capability of the model.

Values of AARE and threshold statistics also indicate a reduction in prediction accuracy with increased lead period (Table 7.6 and Table 7.7). The TS statistics of the models indicates that less number of data can be accurately forecasted while increasing the forecasting lead period. These values indicate that all the models show comparable performance in terms of AARE for different lead periods, while the threshold statistics indicate that the number of data points falling under different error ranges is quite different for different models. The model validation results (Figure 7.14 and Figure 7.15) indicate that between 32% to 49% of flow values are predicted at 1 hr lead period by TSC-T-S fuzzy model with 1% error compared to 31.5% to 48.6% for SC-T-S fuzzy model and 24.12% and 48.1% for ANN. It is also depicted from the Figure 7.14 and Figure 7.15 that the number of flow values predicted at threshold statistics 1 (i.e. 1% error range) get drastically reduced when predicting the flow at higher lead periods. At higher threshold level i.e. at 20% (TS20) the difference in threshold statistics of 1 hr lead period and 6 hr lead period forecasts is small as compared to lower threshold statistics. The threshold statistics indicates the number of data points forecasted with desired value of accuracy. However, due to large variation in continuous river flow data series consisting of both high and low flow values, the TS statistics hardly provide any significant information about model performance.

The PPTS criterion discussed in the previous section was used to verify the model performance at high floods. For this purpose PPTS values for highest 2%, 3%, 5%, 10% and 20% flows have been computed. It is depicted from Figure 7.16 and Figure 7.17 that the PPTS reduces with the increase in lead period. Furthermore, the TSC-T-S fuzzy model illustrates its preeminence over other models in predicting high flow values. This can further be verified from the low numerical values of the PPTS statistics for TSC-T-S fuzzy model presented in Table 7.6 and Table 7.7. However, in other flow region all the models show comparably similar performance. The PPTS statistics indicates different patterns for different cases (M8990 to M8994 and MM 8990 to MM 8994). This indicates that in different data sets, variation in PPTS statistics is different and this can serve as an alternative criterion for critically selecting a suitable flood forecasting model.

It is also observed that the forecasting models developed using input structure represented by Equation 7.34 are superior than the one developed using input structure represented by Equation 7.33. This is due to inclusion of upstream discharge into the forecasting model has a direct impact on model performance. Furthermore, the models developed using long term data i.e. 1989-1994 (Model M8994 and MM8994) shows nearly average kind of model performance indices. However, models developed using small data lengths have varying model performance. It is also to be noted that in general the model developed from different data lengths show almost similar performance indices.

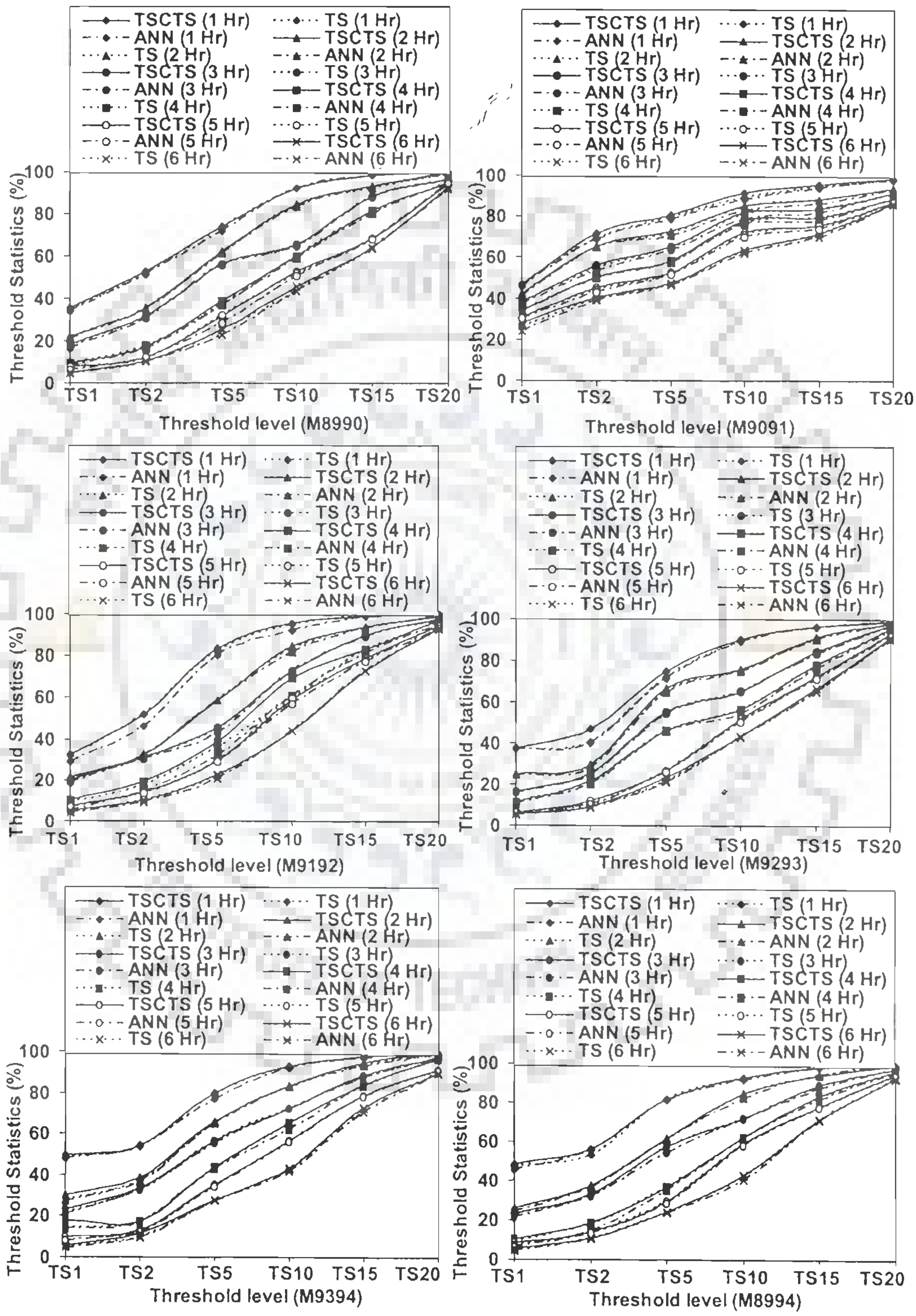

Figure 7.14: Variation of TS-statistics along the forecast time horizon for different data sets of river Narmada at Mandla gauging site (Validation result Model-M)

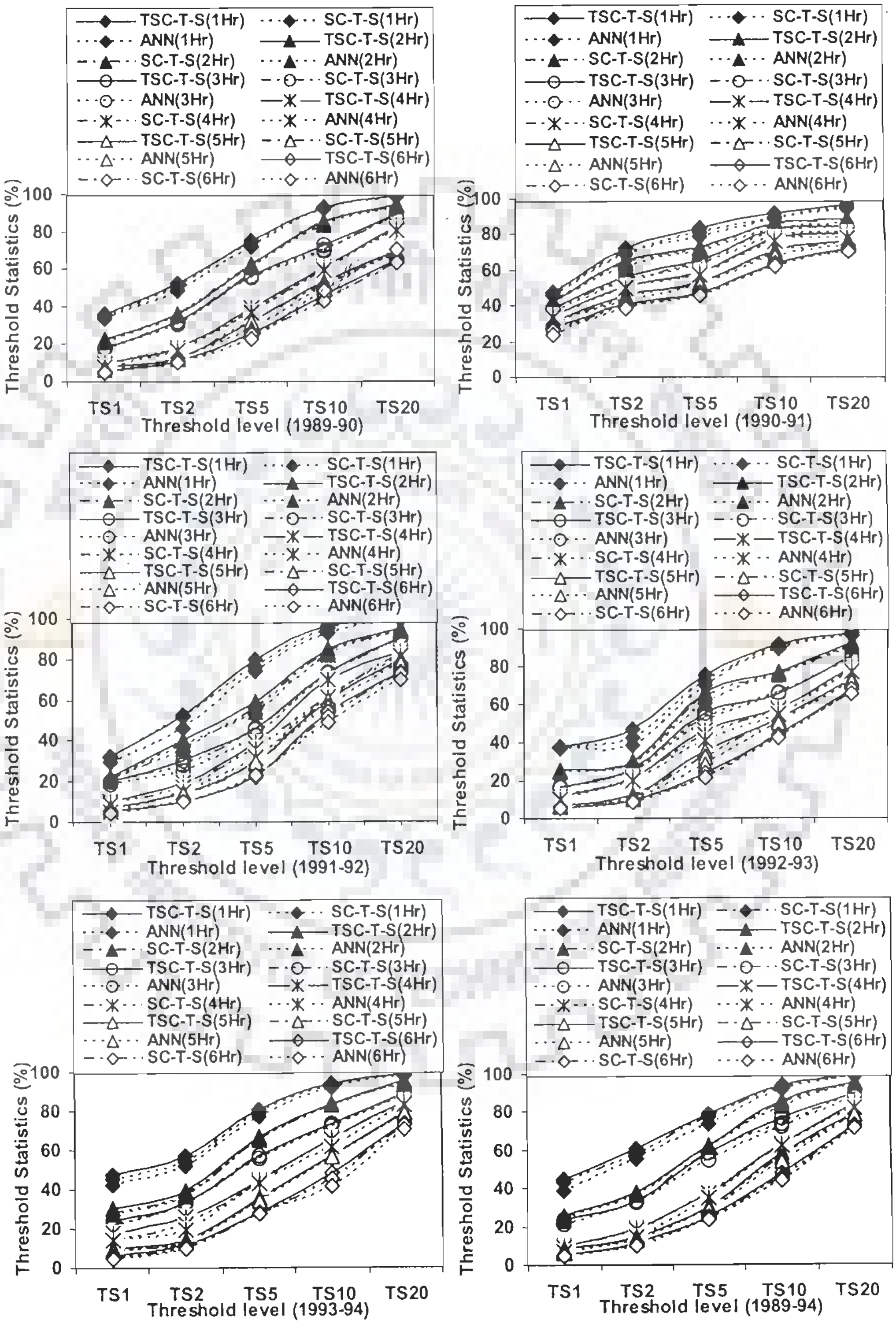

Figure 7.15: Variation of TS-statistics along the forecast time horizon for different data sets of river Narmada at Mandla gauging site (Validation result Model-MM)

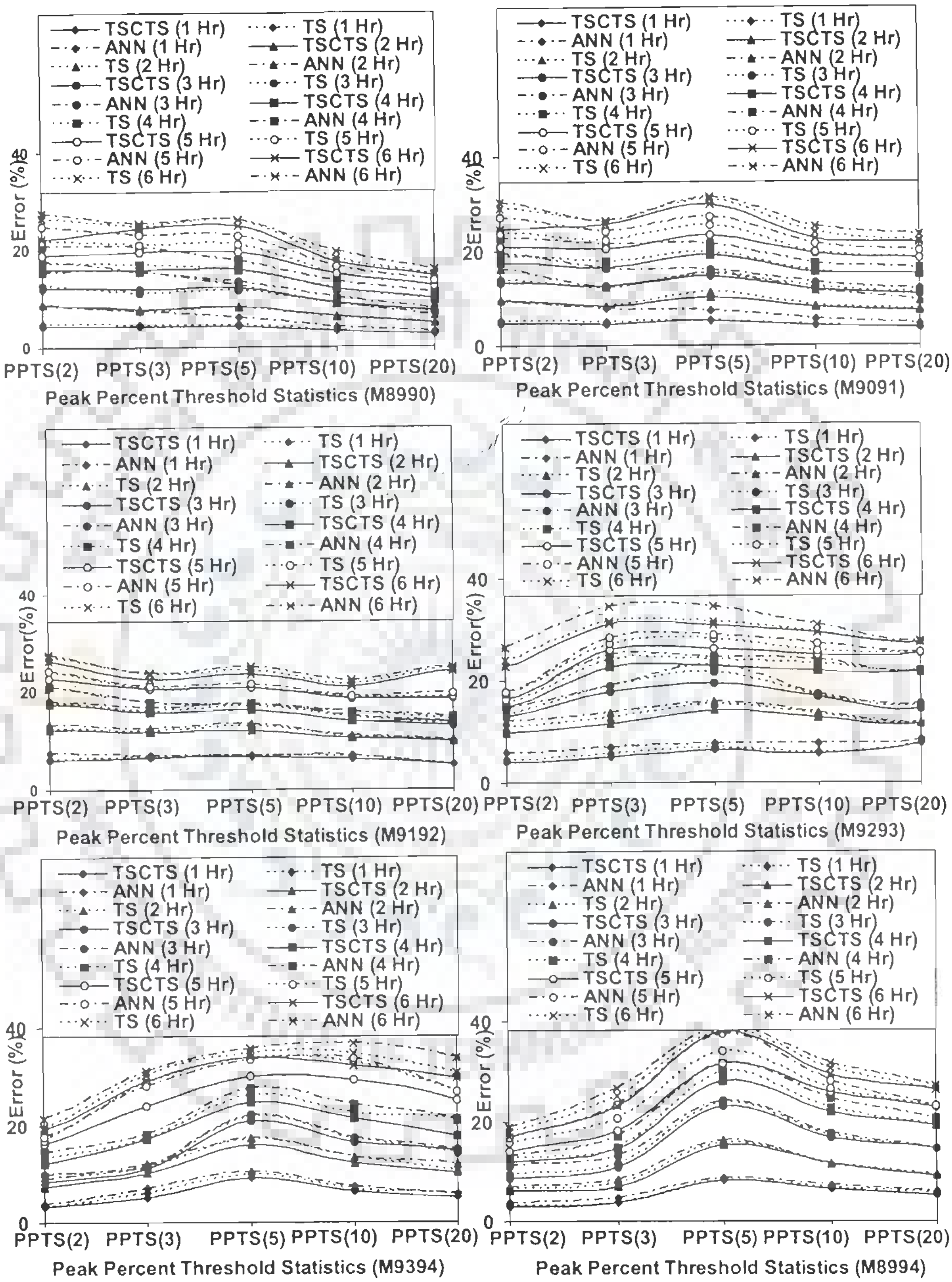

Figure 7.16: Variation of PPTS -statistics along the forecast time horizon for different data sets of river Narmada at Mandla gauging site (Validation result Model M)

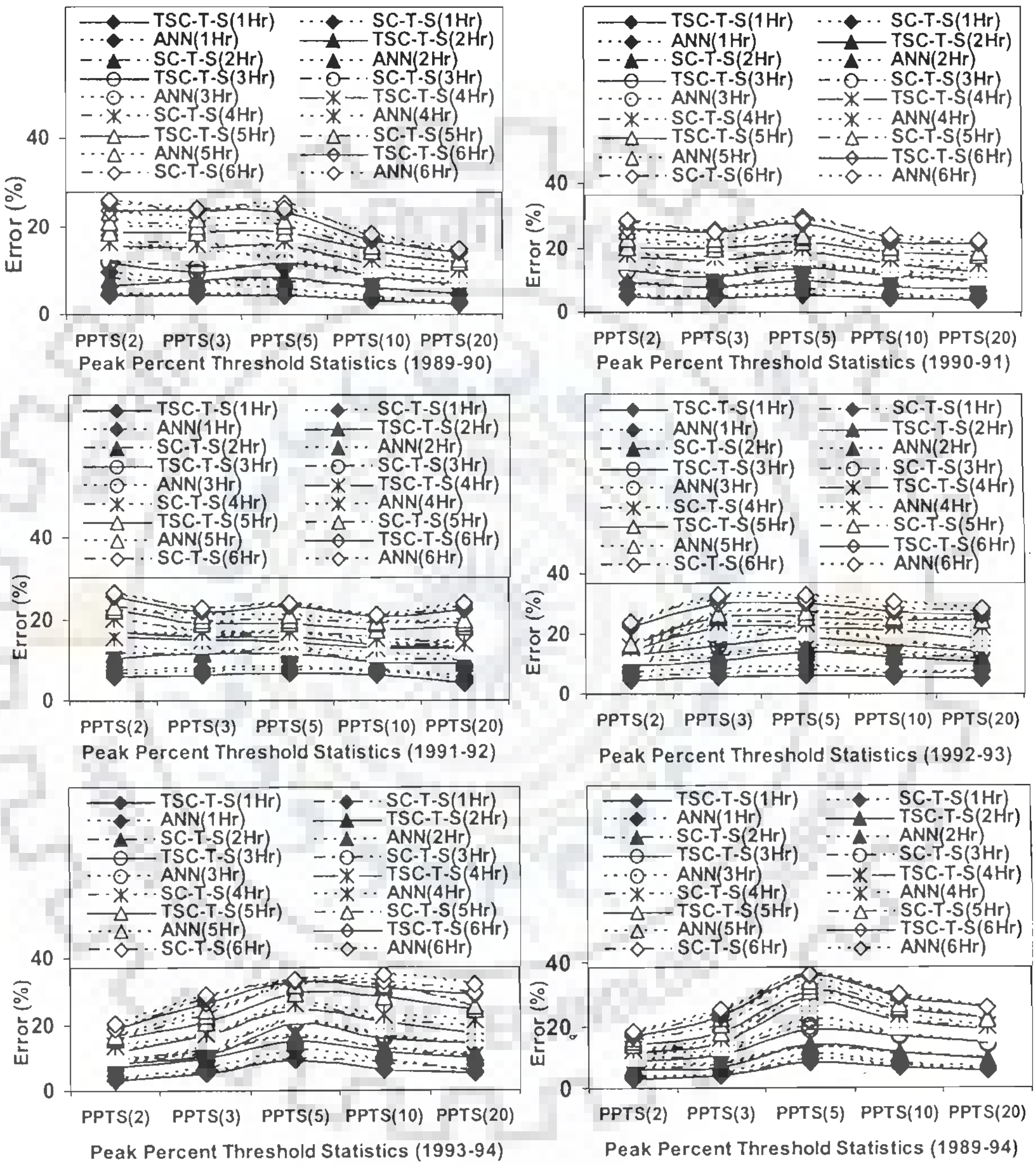

Figure 7.17: Variation of PPTS -statistics along the forecast time horizon for different data sets of river Narmada at Mandla gauging site (Validation result Model MM)

7.10 SUMMARY AND CONCLUSIONS

In order to improve the real time forecasting of floods, this study proposes a modified Takagi-Sugeno (T-S) fuzzy inference system termed as threshold subtractive clustering based Takagi-Sugeno (TSC-T-S) fuzzy inference system by introducing the concept of rare and frequent hydrological situations in fuzzy modeling system. The proposed modified fuzzy inference systems provide an option of analyzing and computing cluster centers and membership functions for two different hydrological situations generally encountered in real time flood forecasting. The methodology has been tested on hypothetical data set and than applied for flood forecasting using the hourly rainfall and river flow data of upper Narmada basin, Central India. The available rainfall-runoff data has been classified in frequent and rare events and suitable TSC-T-S fuzzy model structures have been suggested for better forecasting of river flows. The performance of the model during calibration and validation is evaluated by performance indices such as root mean square error (RMSE), model efficiency and coefficient of correlation (R). A new performance index termed as peak percent threshold statistics is proposed to evaluate the performance of flood forecasting model. The developed model has been tested for different lead periods using hourly rainfall and discharge data. Further, the proposed fuzzy model results have been compared with artificial neural network (ANN) and subtractive clustering based T-S fuzzy model (SC-T-S fuzzy model).

The proposed approach is a superset of the classical subtractive clustering based T-S fuzzy inference system (SC-T-S) and serves as a useful tool for developing flood forecasting models. A comparison with ANN and SC-T-S fuzzy models has shown a better performance of the proposed technique. Although all of the fuzzy and ANN based models performed almost equally well with both actual and hypothetical data sets, the advantage of the proposed fuzzy model is that they may forecast high flows more accurately, which is the most important task in flood forecasting. Practical application of the model takes only seconds for execution in Pentium processor based computer. Therefore, the proposed fuzzy algorithm enables and supports the creation and execution of real time flood forecasting model. Additional research could be carried out in order to establish the suitability of the proposed model in various regions.

CHAPTER 8

CONCLUSIONS AND SCOPE FOR FURTHER RESEARCH

8.1 CONCLUSIONS

The main results related to the firm objectives in which the thesis was organized are listed below:

A relationship between stages and corresponding measured discharges is usually derived using various graphical and analytical methods. Under certain conditions the discharge for a flood on a rising stage differs from that on the falling stage and this phenomenon is called hysteresis. Hysteresis is a hard non-linearity and complex to model. The satisfactory estimation of the discharge by the proposed fuzzy models from different data sets indicates that gauge-discharge modeling can reliably employ the fuzzy model. Comparison of fuzzy model with ANN and conventional curve fitting approaches indicate that the estimation of discharge from fuzzy model is more accurate both in case of actual observed data sets of various lengths and hypothetical data set.

Similarly, the gauge-discharge sediment relationship derived using fuzzy logic performs better than the ANN and regression method. The study suggests that the fuzzy model is able to capture the inherent nonlinearity in the river gauge, discharge and sediment relationship better than the other two. A comparative analysis of predictive ability of these models in different ranges of flow indicates that the fuzzy modeling approach is slightly better than the ANN.

A relationship of the rainfall-runoff process is one of the important relationships in water resources where an engineer needs this relationship to predict the future runoff values given the rainfall values. Because of fast development in the computing facility, in the later period of 20th century ANNs found there way in rainfall-runoff modeling. In the study various model structures have been tested for linear transfer function, ANN and fuzzy logic based models. The results of the study indicate that the ANN and fuzzy logic techniques are useful soft computing techniques in rainfall-runoff modeling. The results obtained from fuzzy logic based models were superior to other models.

The main potential areas of application of rainfall-runoff model is in short term real time forecasting of streamflows, where forecasts from such models form the basis of decisions pertaining to flood warning, flood control or river regulation. With this in view a new fuzzy modeling technique i.e. threshold subtractive clustering based Takagi-Sugeno model is proposed. The proposed approach is a superset of the classical subtractive clustering based T-S fuzzy inference system (SC-T-S) and serves as a useful tool for developing flood forecasting models. The proposed technique was first tested on hypothetical data sets. Further, detailed comparison of the forecasts made using ANN, SC-TS fuzzy model and TSC-TS fuzzy models indicates that the proposed method (TSC-T-S fuzzy model) which considers the rare and frequent hydrological situations in hydrological modeling is a better model. The results presented in this thesis are highly promising and suggest that fuzzy modeling is a more versatile and improved alternative to ANN approach. Furthermore, fuzzy logic algorithm has the ability to describe the knowledge in a descriptive human-like manner in the form of simple rules using linguistic variables.

8.2 SCOPE FOR FURTHER RESEARCH

The ANN and fuzzy logic methodology presented in this thesis can provide a promising solution to various hydrological modeling and forecasting problems. However, the analysis of the results reported in this work leave sufficient scope and opens new dimensions for further investigations, which could not be taken up owing to time constraint and are briefly presented as follows:

1) The gauge-discharge relationship is developed for different gauging sites of Narmada basin. The study can be further extended for other gauging sites in the same basin or in the other basins and studying the capability of these models in different channel controls.
2) The ANN and fuzzy model were developed to model hypothetical loop rating curves. However, it is always useful to develop a model for actual observed data sets showing the hysteresis.
3) The study related to development of gauge-discharge-sediment relationship can also be extended to other gauging sites of Narmada basin and other basins to establish the superiority of soft computing based models over conventional regression methods.
4) Rainfall-runoff modeling is one of the important areas of research. Similar studies should be carried out on basins located in different climatic and geographic regions to investigate the potential of the ANN and fuzzy rule based models. Further, more investigations are needed by introducing the other runoff producing hydrological variables and catchment characteristics in ANN and fuzzy rule based rainfall-runoff models.

5) Real time flood forecasting models using ANN, fuzzy rule based approaches and proposed threshold subtractive clustering based Takagi-Sugeno method have been tested on hypothetical and observed data base. The study can be further extended in different climatic and geographic regions and for different spatial scales.
6) Using data driven approach the desirable accuracy of identified fuzzy model can be increased substantially. However, in sacrificing a small amount of interpretability in fuzzy inference the model accuracy may be increased. A satisfactory tradeoff between model accuracy and interpretability may be a debatable issue and offers further research work.

REFERENCES

Abonyi, J., Babuska, R. and Szeifent, F. (2002) Modified Gath-Geva fuzzy clustering for identification of Takagi-Sugeno fuzzy models. IEEE Transactions on Systems Man Cybernetics, Part B, 32(5) 612-621.

Agarwal, A., Singh, J.K. and Ray, S. (2004) Artificial neural network rainfall-runoff modeling in varying domain. Institution of Engineers (India) Journal, 83, 166.172.

Agarwal, A. and Singh, R.D. (2004) Runoff modelling through back propagation artificial neural network with variable rainfall-runoff data. Water Resources Management, 18, 285-300.

Agarwal, A. Singh, R.D., Mishra, S.K and Bhunya, P.K. (2005) ANN based sediment yield models for Vamsadhara river basin (India). Water SA, 31(1), 95-100.

Anctil, F., Michel, C., Perrin, C. and Andréassian, V. (2004) A soil moisture index as an auxiliary ANN input for stream flow forecasting. Journal of Hydrology, 286(1-4), 155-167.

Angelov, P. (2004) An approach for fuzzy rule-base adaptation using on-line clustering. International Journal of Approximate Reasoning, 35(3), 275-289.

ASCE Task Committee on Application of Artificial Neural Networks in Hydrology (2000a) Artificial neural networks in hydrology. I: Preliminary concepts. Journal of Hydrologic Engineering, 5(2), 115-123.

ASCE Task Committee on Application of Artificial Neural Networks in Hydrology (2000b) Artificial neural networks in hydrology. II: Hydrologic applications. Journal of Hydrologic Engineering, 5(2), 124-137.

Asselman, N.E.M. (2000) Fitting and interpretation of sediment rating curves. Journal of Hydrology, 234, 228-248.

Atiya, A., El-Shoura, S., Shaheen, I. and El-Sherif, M. (1999) A comparison between neural network forecasting techniques case study: River flow forecasting, IEEE Transactions on Neural Network, 10(2), 402-409.

Babuška, R. (1998) Fuzzy modeling for control, International Series in Intelligent Technologies. Kluwer Academic Publishers, Boston, USA.

Babuška, R. (2001) Fuzzy and neural control DISC course lecture notes, Delft University of Technology, Delft, the Netherlands.

Baldwin, J.F. Lawry, J. and Martin, T.P. (1998) Mass assignment based induction of decision tree on wards. Proceedings of IPMU 1998, (1) 524-531.

Bardossy A. and Duckstein, L. (1992) Analysis of a Karstic aquifer management problem by fuzzy composite programming. Water Resources Bulletin 28(1), 63-73.

Bardossy, A. and Disse, M. (1993) Fuzzy rule based models for infiltration. Water Resources Research 29(2), 373-382.

Baruah, P. J., Tamura, M., Oki, K. and Nishimura, H. (2001) Neural network modelling of lake surface chlorophyll and sediment content from Landsat TM imagery. Proc. 22nd Asian Conference on Remote Sensing, 5-9 November 2001, Singapore.

Bergström, S. (1972) The HBV model – its structure and applications. Report RH No. 4, Swedish Meteorological and Hydrological Institute, Noorkoping, Sweden.

Bergström, S. and Forsman, A. (1973) Development of a conceptual deterministic rainfall-runoff model. Nordic Hydrology, Vol. 4, No. 3.

Bevan, K.J., Lamb, R, Quinn, P.F., Romanowicz, R. and Freer, J. (1995) TOPMODEL. in V.P. Singh (Ed). Computer models of watershed hydrology. Water Resources Publications, 627-668.

Beven, K.J. (2000) Rainfall-runoff modelling: The prime. J. Wiley & Sons, Chichester.

Bezdek, J.C. (1973) Fuzzy mathematics in pattern classification. PhD Thesis, Applied Math. Center Cornell University, Ithaca.

Bhattacharya, B. and Solomatine, D.P. (2005) Neural network and M5 model trees in modeling water level-discharge relationship. Journal of Neurocomputing, 63, 381-396.

Birikundavyi, S., Labi, R., Trung, H.T. and Rousselle, J. (2002) Performance of neural networks in daily streamflow forecasting. Journal of Hydrologic Engineering, 7(5) 392-398.

Bishop, C.M. (1994) Neural network and their applications. Review of Scientific Instruments, 65, 1803-1832.

Box, G.E.P. and Jenkins, G.M. (1976) Time series analysis: forecasting and control. Holden-Day, Oakland, CA.

Burn, D.H. and McBean, E.A. (1985) River flow forecasting model for Sturgeon River. Journal of Hydraulic Engineering, ASCE, 111(2), 316-333.

Campolo M, Andreussi, P. and Soldati, A. (1999) River flood forecasting with neural network model. Water Resources Research, 35(4), 1191-1197.

Chang, F.-J. and Chen, Y.-C. (2001) A counterpropagation fuzzy-neural network modelling approach to real time streamflow prediction. Journal of Hydrology, 245, 153-164.

Cheeseman, P. (1986) Probabilistic versus fuzzy reasoning. in Uncertainty in artificial intelligence. Eds. L.N. Kanal and L.F. Lemmer, Amsterdam, Elsevier Science Publishers, 1986, p. 85-102.

Chen, Y.H., Wang, W.-J. and Chiu, C.-H. (2000) New estimation method for the membership values in fuzzy set. Fuzzy Sets and Systems, 112, 521-525.

Chiu, S. (1994) Fuzzy model identification based on cluster estimation. Journal on Intelligent Fuzzy Systems, 2, 267-278.

Chiu, S. (1996) Method and software for extracting fuzzy classification rules by subtractive clustering, Fuzzy Information Proceeding Society, Biennial Conference of the North American, 461-465.

Chow, V.T., Maidment, D.R. and Mays, L.W. (1988) Applied hydrology, McGraw-Hill Book Company.

Cigizoglu, H.K. and Alp, M. (2006) Generalized regression neural network in modeling river sediment yield. Advances in Engineering Software 37, 63-68.

Cigizoglu, H.K. (2004) Estimation and forecasting of daily suspended sediment data by multi-layer perceptrons. Advances in Water Resources 27, 185-195.

Cigizoglu, H.K. and Kisi, O. (2006) Methods to improve the neural network performance in suspended sediment estimation. Journal of Hydrology, 317, 221-238.

Coppola, E.A., Duckstein, L. and Dvis, D. (2002) Fuzzy rule based methodology for estimating monthly groundwater recharge in a temperate watershed. Journal of Hydrologic Engineering 7(4), 326-335.

Daniel, T.M. (1991) Neural networks-applications in hydrology and water resources engineering. International Hydrology and Water Resources Symposium, Institution of Engineers, Perth, Australia, 797-802.

Dawson, C.W. and Wilby, R. (1998) An artificial neural network approach to rainfall-runoff modeling. Hydrological Sciences Journal, 43(1), 47-66.

Dawson, C.W. and Wilby, R. (2001) Hydrological modeling using artificial neural networks. Prog. Phys. Georg., 25 (1), 80-108.

De Vries, A. and Klavers, H. C. (1994) Riverine fluxes of pollutants: monitoring strategy first, calculation methods second. European Water Pollution Control, 4, 12-17.

DeGagne, M.P.J., Douglas, G.G., Hudson, H.R. and Simonovic, S.P. (1996) A decision support system for the analysis and use of stage-discharge rating curves. Journal of Hydrology, 184, 225-241.

Deka, P. and Chandramouli, V. (2003) A fuzzy neural network model for deriving the river stage-discharge relationship. Hydrological Science Journal, 48(2): 197-209.

Dooge, J.C.I. (1959) A general theory of the unit hydrograph.Journal of Geophysical Research, 64, 241–256.

Duan, N. (1983) Smearing estimate: a nonparametric retransformation method. Journal of American Society, 78, 605-610.

Dubois, D., Nguyen, H.T., Prade, H. and Sugeno, M. (1998) Introduction: the real contribution of fuzzy systems, in fuzzy systems: modeling and control. edited by H.T. Nguyen, M. Sugeno, Kluwer, Dordrecht, 1–17.

Elshorbagy, A., Simonovic, S.P. and Panu, U.S. (2000) Performance evaluation of artificial neural networks for runoff prediction. Journal of Hydrologic Engineering, 5(4), 424-433.

Faraway, J. and Chatfield, C. (1998) Time series forecasting with neural networks: a comparative study using the airline data. Applied Statistics, 47(2), 231-250.

Ferguson, R.I. (1986) River loads underestimated by rating curves. Water Resources Research, 22(1), 74-76.

Ferguson, R.I. (1987) Accuracy and precision of methods for estimating river loads. Earth Surface Processes and Landforms, 12, 95-104.

Fernando, A.K. and Jayawardena, A.W. (1998) Runoff forecasting using RBF networks with OLS algorithm. Journal of Hydrologic Engineering, ASCE, 3(3), 203-209.

Flood, I. and Kartam, N. (1994) Neural networks in civil engineering. I: Principles and understanding. Journal of Computing in Civil Engineering, 8(2), 131-148.

Fontane, D.G., Gates, T.K. and Moncada, E. (1997) Planning reservoir operations with imprecise objectives. Journal of Water Resources Planning and Management 123 (3), 154-168.

French, M., Krajewsi, W. F. and Cuykendall, R. R. (1992) Rainfall forecasting in space and time using a neural network. Journal of Hydrology, 137(1-4), 1-31.

Freeman, J.A. and Skapura, D.M. (1991) Neural networks algorithms, application and programming techniques, Addison-Wesley.

Gawne, K.D. and Simonovic, S.P. (1994) A computer based system of modeling the stage-discharge relationship in steady state conditions. Hydrological Sciences Journal, 39(5), 487-506.

Gorman, G. (1998) A review of fuzzy logic and its applications. http://www.it.nuigalway.ie/ Publications/TR/abstracts/gg.ps.gz.

Gupta, H. and Chakrapani, G.J. (2005) Temporal and spatial variations in water flow and sediment load in Narmada river basin, India: natural and man-made factors. Environmental Geology, 48, 579–589

Gustafson, D.E. and Kessel, W.C. (1979) Fuzzy clustering with a fuzzy covariance matrix. Proceeding of IEEE Transactions on Fuzzy Systems 1(3), 195-204.

Halff, A.H., Halff, H.M. and Azmoodeh, M. (1993) Predicting runoff from rainfall using neural networks, In Engineering Hydrology, Kuo CY (ed.). Proceedings of the Symposium sponsored by the Hydraulics Division of ASCE, San Francisco, CA, July 25-30, 1993. ASCE: New York, 760-765.

Han, D., Cluckie, I.D., Karbassioun, D., Lawry, J. and Krauskopf, B. (2002) River flow modelling using fuzzy decision trees, Water Resources Management, 16, 431-445.

Hecht-Nielsen, R. (1991) Neurocomputing, Addison-Wesley Publication Company, New York.

Hellendoorn, H. and D. Driankov (Eds.) (1997) Fuzzy model identification: selected approaches. Berlin, Germany: Springer.

Höppner, F., Klawonn, F., Kruse, R. and Runkler T. (1999) Fuzzy cluster analysis, Wiley, New York.

Hsu, K-L, Gupta, H.V. and Sorooshian S. (1995) Artificial neural network modeling of the rainfall-runoff process. Water Resources Research, 31(10), 2517-2530.

Hsu, Kuo-lin, Gupta, Hoshin V., Gao, Xiaogang, Sorooshian, S. and Imam, B. (2002) Self-organizing linear output map (SOLO): An artificial neural network suitable for hydrologic modeling and analysis, Water Resources Research, 38(12), 38-1.

Hundecha, Y., Bardossy, A. and Theisen, H.W. (2001) Development of a fuzzy logic-based rainfall-runoff model, Hydrologic Sciences Journal, 46(3), 363-376.

HYMOS (2001) WL delft hydraulics, M.H. Delft.

Imrie, C.E., Durucan, S. and Korre, A. (2000) River flow forecasting using artificial neural networks: generalization beyond the calibration range. Journal of Hydrology, 233, 138-153.

Jacquin, Alexandra P. and Shamseldin, Asaad Y. (2006) Development of rainfall--runoff models using Takagi--Sugeno fuzzy inference systems. Journal of Hydrology, 329(1-2), 154-173.

Jain, A. and Indurthy, S.K.V. P. (2003) Comparative analysis of event based rainfall-runoff modeling techniques-deterministic, statistical, and artificial neural networks. Journal of Hydrologic Engineering, 8(2), 93-98.

Jain, A. and Ormsbee, L.E. (2002) Short-term water demand forecast modeling techniques: Conventional methods versus AI, Journal of American Water Works Association. 94(7), 64-72

Jain, S.K. (2001) Development of integrated sediment rating curves using ANNs. Journal of Hydraulic Engineering, ASCE, 127(1), 30-37.

Jain, S.K. and Chalisgaonkar, D. (2000) Setting up stage discharge relations using ANN. Journal of Hydrologic Engineering, 5(4), 428-433.

Jain, A. and Srinivasulu S. (2004) Development of effective and efficient rainfall-runoff models using integration of deterministic, real-coded genetic algorithms and artificial neural network techniques. Water Resources Research, 40(4), W04302, doi:10.1029/2003WR002355.

Jang J.-S.R. (1993) ANFIS: Adaptive network based fuzzy inference systems. IEEE Transactions on Systems, Man and Cybernetics, 23(3), 665-685.

Jang J.-S.R. and Mizutani, E. (1996) Levenberg-Marquardt method for ANFIS learning. Proceedings of the International Joint Conference of the North American Fuzzy Information Processing Society Biannual Conference, Berkeley, California, 87-91.

Jang J.-S.R., Sun C.-T. and Mizutani, E. (2002) Neuro-fuzzy and soft computing. Prentice Hall of India Private Limited, New Delhi.

Jansoon, M. (1985) A comparison of detransformed logarithmic regression and power function regressions. Geografiska Annaler, 67A, 61-70.

Johnston, J. (1972) Econometric methods. McGraw Hill, Tokyo.

Karunanithi, N., Grenney, W.J., Whitley, D. and Bovee, K. (1994) Neural networks for river flow prediction. Journal of Computing in Civil Engineering, ASCE, 8(2), 210-220.

Kaynak, O. and Rudas, I. (1995) Soft computing methodologies and their fusion in mechatronicproducts. Computing and Control Engineering Journal, 6(2), 68-72.

Kindler, J. (1992) Rationalizing water requirements with aid of fuzzy allocation model. Journal of Water Resources Planning and Management, 118(3), 308-323.

Klir, G.J. and Yuan, B. (1995) Fuzzy sets and fuzzy logic –Theory and applications. Prentice-Hall, London.

Kisi, O. (2004a) Multi-layer perceptrons with Levenberg-Marquardt optimization algorithm for suspended sediment concentration prediction and estimation. Hydrological Sciences Journal, 49(6), 1025–1040.

Kisi, O. (2004b) Daily suspended sediment modeling using a fuzzy-differential evolution approach. Hydrological Sciences Journal, 49(1), 183–197.

Kisi, O. (2005) Suspended sediment estimation using neuro-fuzzy and neural network approaches. Hydrological Sciences Journal, 50(4), 683-696.

Kisi, O., Karahan, M.E. and Sen, Z. (2006) River suspended sediment modeling using fuzzy logic approach. Hydrological Processes, 20(20), 4351-4362.

Kreinovich, V., Nguyen H.T. and Yam, Y. (2000) Fuzzy systems are universal approximators for a smooth function and its derivatives. International Journal of Intelligent Systems, 15(6):565–574.

Krishnaiah, P. R. and Kanal, L. N. (1982) Classification, pattern recognition and reduction of dimensionality. Hand Book of Statistics, Vol. 2, North Holland, Amsterdam.

Lin, C.T. and Lee, C.S. G. (1996) Neural Fuzzy Systems: A Neuro-Fuzzy Synergism to Intelligent Systems, Prentice Hall.

Lin, B. and Namin, M. M. (2005) Modelling suspended sediment transport using an integrated numerical and ANNs model. Journal of Hydraulic Research, 43 (3), 302-310.

Lohani, A.K., Goel, N.K. and Bhatia, K.K.S. (2005a) Real time flood forecasting using fuzzy logic. Hydrological Perspectives for Sustainable Development, Volume I, Eds. M. Perumal, Allied Publishers Pvt. Ltd., New Delhi, 168-176.

Lohani, A.K., Goel, N.K.and Bhatia K.K.S. (2005b) Development of fuzzy logic based real time flood forecasting system for river Narmada in Central India. in International Conference on Innovation Advances and Implementation of Flood Forecasting Technology, ACTIF/Floodman/Flood Relief, October, 2005, Tromso, Norway, www.Actif.cc.net/conference2005/proceedings.

Lohani, A.K., Goel, N.K. and Bhatia, K.K.S. (2006) Takagi-Sugeno fuzzy inference system for modeling stage-discharge relationship. Journal of Hydrology, 331, 146-160.

Lohani, A.K., Goel, N.K. and Bhatia K.K.S. (2007) Reply to comments provided by Z. Sen on "Takagi–Sugeno fuzzy system for modeling stage-discharge relationship" by A.K. Lohani, N.K. Goel and K.K.S. Bhatia. Journal of Hydrology, *337*(1-2), 244-247.

Luchetta, A. and Manetti, S. (2003) A real time hydrological forecasting system using a fuzzy clustering approach. Computers & Geosciences, 29, 1111–1117.

Lundberg, A. (1982) Combination of a conceptual model and an autoregressive error model for improving short time forecasting. Nordic Hydrology, 233-246.

Mahabir, C., Hicks, F.E. and Fayek, A.R. (2003) Application of fuzzy logic to forecast seasonal runoff. Hydrologic Processes, 17, 3749-3762.

Maidment, D.R., ed. 1992. Handbook of Hydrology, McGraw-Hill, New York.

Maier, H.R. and Dandy, G.C. (2000) Neural networks for the prediction and forecasting of water resources variables: A review of modelling Issues and applications. Environmental Modelling & Software, 15, 101-124.

Malhotra, R. and Malhotra, D. (1999) Fuzzy systems and neuro-computing in credit approval. Journal of Lending & Credit Risk Management, Vol. 81 No.11, pp.24-7.

Mamdani, E.H. (1977) Application of fuzzy logic to approximate reasoning using linguistic systems. Fuzzy Sets and Systems, 26, 1182-1191.

Mamdani, E.H. and Assilian, S. (1975) An experiment in linguistic synthesis with a fuzzy logic controller. International Journal of Man-Machine Studies, 7(1), 1-13.

MathWorks (1994) The MathWorks MATLAB Digest. 2(5).

McCulloch, W.S. and Pitts, W. (1943) A logic calculus of the ideas immanent in nervous activity. Bulletin for Mathematical Biophysics, 5, 115-133.

Mehrotra, K., Mohan, C.K. and Ranka, S. (1997) Elements of artificial neural networks, Penram International Publishing (India), India.

Minns, A.W. and Hall, M.J. (1996) Artificial neural networks as rainfall runoff models. Hydrological Sciences Journal, 41(3), 399-418.

Minsky, M. and Papert, S. (1969) Perceptrons, An introduction to computational geometry. MIT press, expanded edition

Mujumdar, P.P. and Sasikumar, K. (1999) A fuzzy risk approach for seasonal water quality management of a river system, Journal of Water Resources Research, 38(1), 5-1-5-9.

Muzik, I. (1996) Lumped modeling and GIS in flood prediction. in Geographical Information Systems in Hydrology, V.P. Singh and M. Fiorentino, editors. Kluwer Academic Publishers.

Muzik, I. (1996) Flood modelling with GIS-derived distributed unit hydrographs. Hydrological Processes, 10(10), 1401-1409.

Nagy, H.M., Watanabe, B. and Hirano, M. (2002) Prediction of Sediment load concentration in rivers using artificial neural network model. Journal of Hydraulic Engineering, ASCE, 128(6), 588-595.

Nash, J.E. and Sutcliffe, J.V. (1970) River flow forecasting through conceptual models: 1. A discussion of principles. Journal of Hydrology, 10, 282-290.

Nayak, P. C., Sudheer, K. P. and Ramasastri, K. S. (2005a) Fuzzy computing based rainfall-runoff model for real time flood forecasting. Hydrologiccal Processes, doi:10.1002/hyp.5553, 19, 955– 968.

Nayak, P. C., Sudheer, K. P., Rangan, D.M. and K.S. Ramasastri (2005b) Short-term flood forecasting with a neurofuzzy model. Water Resources Research, 41, w 04004, doi:10,1029/2004WR003562.

Nielsen, S.A. and Hanseen, E. (1973) Numerical simulation of the rainfall-runoff processes on a daily basis. Nordic Hydrology, 5, 171-190.

Ozelkan, E.C. and Duckstein, L. (2001) Fuzzy conceptual rainfall-runoff models. Journal of Hydrology, 253(15) 41-68(28)

Panigrahi, D.P. and Mujumdar, P.P. (2000) Reservoir operation modeling with fuzzy logic. Water Resources Management, 14 (2), 89-109.

Pedrycz, W. (1984) An identification algorithm in fuzzy relational systems. Fuzzy Sets and Systems, 13, 153-167.

Phillips, J.M., Webb, B.W., Walling, D.E. and Leeks, G.J.L. (1999) Estimating the suspended sediment loads of rivers in the LOIS study area using infrequent samples. Hydrological Processes, 13, 1035-1050.

Ponce, V. M. and Hawkins, R. H. (1996) Runoff curve number: Has it reached maturity? Journal of Hydrologic Engineering, 1(1):11-19.

Raghuwanshi, N. S., Singh, R. and Reddy, L. S. (2006) Runoff and sediment yield modeling using artificial neural network. Hydrologic Engineering, ASCE, 11(1), 71-79.

Raman, H. and Sunilkumar, N. (1995) Multivariate modelling of water resources time series using artificial neural networks. Hydrological Sciences Journal, 40(2), 145-163.

Rajukar, M.P., Kothyari, U. C. and Chaube, U.C. (2004) Modelling of the daily rainfall-runoff relationship with artificial neural network. Journal of Hydrology, 285, 96-113.

Reznik, L. (1997) Fuzzy controllers. Newnes, Oxford, Copyright Leonid Reznik, 287pp; ISBN: 0 7506 3429 4.

Rodriguez-Iturbe, I. and Valdes, J.B. (1979) The geomorphologic structure of hydrologic response. Water Resource Research, 15(6), 1409-1420.

Rosenbaum, M. (2000) Harbours-Silting and Environmental Sedimentology (H-SENSE), Final Report, Department of Civil & Structural Engineering, The Nottingham Trent University, Nottingham, UK. http://hjs.geol.uib.no/HSense/

Ross, T. (1995), Fuzzy Logic with engineering applications. McGraw-Hill, New York.

Rumelhart, D. E., McLelland, J. L. and the PDP Research Group. (1986) Parallel distributed processing, explorations in the micro structure of cognition, vol. I: Foundations. MIT Press, Cambridge, Mass.

Sahoo, G.B. and Ray, C. (2006) Flow forecasting for a Hawaii stream using rating curves and neural networks. Journal of Hydrology, 317(1-2), 63-80.

Sahoo, B. Lohani, A. K. and Sahu, R.K. (2006) Fuzzy multiobjective and linear programming based management models for optimal land-water-crop system planning. Journal of Water Resources Management, Springer, 20, 931-948.

Sajikumar, S. and Thandaveswara, B.S. (1999) A non-linear rainfall-runoff model using an artificial neural network. Journal of Hydrology, 216, 32-55.

Samtani, B.K., Shete, D.T. and Shah, N.C. (2004) Sediment transport characteristics with special reference to transport parameter and flow parameter of Tapi river. International Conference on Hydraulic Engineering: Research and Practice, I.I.T. Roorkee.

Sasikumar, K. and Mujumdar, P.P. (1998) Fuzzy optimization model for water quality management of a river system. Journal of Water Resources Planning and Management, 124(2), 79-88.

See, L. and Openshaw, S. (1999) Applying soft computing approaches to river level forecasting. Hydrological Science Journal, 44(5). 763-778.

See. L. and Openshaw, S. (2000) A hybrid multi-model approach to river level forecasting. Hydrological Science Journal, 45 (4). 523-536.

Sen Z. (2001) Fuzzy Logic and Foundation. Bilge Kultur Sanat Publisher, Istanbul.

Sen, Z. and Altunkaynak, A. (2003) Fuzzy awakening in rainfall-runoff modeling. Nordic Hydrology, 35, 41-43.

Sikka, A. K. and Selvi, V. (2005) Experimental examination of rational runoff coefficient for small agricultural and forest watersheds in the Nilgiris, Agricultural Engineering Journal, The Institution of Engineers (India), Vol. 86.

Singh, K.P. and Durgunoglu, A. (1989) Developing accurate and reliable stream sediment yields. Sediment and The Environment, IAHS publication, Wallingford, 184 (Proceedings of the Baltimore symposium, May 1989), 193-199.

Singh, V.P. (1989) Hydrologic systems–rainfall-runoff modeling. vol. II, Prentice Hall Inc., Englewood Cliffs, New Jersey, USA.

Smith, J. and Eli, R. N. (1995) Neural network models of rainfall-runoff process. Journal of Water Resources Planning and Management, ASCE, 121(6), 499-508.

Solomatine, D. P. and Price, R. K. (2004) Innovative approaches to flood forecasting using data driven and hybrid modelling. Hydroinformatics Vol. 2 Proceedings of the 6th International Conference, Singapore, 21–24 June 2004.

Srinivasa Raju, K. and Duckstein, L. (2003) Multiobjective fuzzy linear programming for sustainable irrigation planning: an Indian case study. Journal of Soft Computing, 7(6), 412-418.

Stedinger, J. R. and Taylor, M. R. (1982) Synthetic streamflow generation 1. Model verification and validation, Water Resources Research, 18(4), 909-918.

Sudheer, K.P., Gosain, A.K. and Ramasastri, K.S. (2001) Selection of appropriate input vector to neural network based rainfall-runoff models: A statistical approach. International Conference on Civil Engineering, Bangalore, July 2001, 464-471.

Sudheer, K.P., Gosain, A.K. and Ramasastri, K.S. (2002) A data-driven algorithm for constructing artificial neural network rainfall runoff models. Hydrological Processes, 16, 1325–1330.

Sudheer, K.P. and Jain, S.K. (2003) Radial basis function neural network for modeling rating curves. Journal of Hydrologic Engineering, 8(3), 161-164.

Sudheer, K. P., Nayak, P. C. and Ramasastri K. S. (2003) Improving peak flow estimates in artificial neural network river flow models. Hydrological Processes, 17(3), 677– 686.

Sugeno, M. and Yasukawa, T. (1993) A fuzzy-logic based approach to qualitative modeling. IEEE Transactions on Fuzzy Systems, 1, 7-31.

Takagi, T. and Sugeno, M. (1985) Fuzzy identification of systems and its application to modeling and control. IEEE Transactions Systems, Man and Cybernetics, 15(1), 116-132.

Tawfik, M., Ibrahim, A. and Fahmy, H. (1997) Hysteresis sensitive neural network for modeling rating curves. Journal of Computing in Civil Engineering, 11(3), 206-211.

Tayfur, G. and Guldal, V. (2006) Artificial neural networks for estimating daily total suspended sediment in natural streams. Nordic Hydrology, 37(1), 69-79.

Tayfur, G. (2002) Artificial neural networks for sheet sediment transport. Hydrological Sciences Journal, 47(6), 879–892.

Tayfur, G. and Singh, V.P. (2003) Intelligence methods to predict discharge from event-based rainfall-runoff. Proceeding of the International Conference on Water and Environment, December 15-18, 2003, Bhopal, India

Thirumalaiah, K. and Deo, M.C. (1998a) Real-time flood forecasting using neural networks. Computer-Aided Civil and infrastructure Engineering, 13 (2), 101-111.

Thirumalaiah, K. and Deo, M.C. (1998b) River stage forecasting using artificial neural networks. Journal of Hydrologic Engineering, 3 (1). 26-32.

Thirumalaiah, K. and Deo, M.C. (2000) Hydrological forecasting using neural networks. Journal of Hydrologic Engineering, ASCE, 5 (2), 180-189.

Tokar, A.S. and Markus, M. (2000) Precipitation-runoff modeling using artificial neural networks and conceptual models. Journal of Hydrologic Engineering, ASCE, 5(2), 156-161.

Tokar, A.S. and Johnson, A. (1999) Rainfall-runoff modeling using artificial neural networks. Journal of Hydrologic Engineering, ASCE, 4(3), 232-239.

Tsukamoto, Y. (1979) An approach to fuzzy reasoning method. in Advances in Fuzzy Set Theory and Application, edited by M. M. Gupta, R. K. Ragade and R. R. Yager, pp. 137– 149, North-Holland, New York.

Uvo, C.B., Tölle, U. and Berndtsson, R. (2000) Forecasting discharge in Amazonia using artificial neural networks. International Journal of Climatology, 20(12), 1495 – 1507.

Van Der Tak, L.D. and Bras, R.L., 1990. Incorporating hillslope effects into the geomorphological instantaneous unite hydrograph. Water Resources Research, 26 (1), 2393–2400.

Van Dijk, A.I.J.M., Bruijnzeel, L.A., Vertessy, R.A. and Ruijter, J. (2005) Runoff and sediment generation on bench-terraced hillsides: measurements and up-scaling of a field based model. Hydrological Processes, 19, 1667-1685.

Vernieuwe, H., Georgieva, O., Baets, B.De., Pauwels, V.R.N., Verhoest, N.E.C. and Troch, F.P.De. (2005) Comparison of Data driven Takagi Sugeno models of rainfall discharge dynamics. Journal of Hydrology, 302, 173-186.

Vogel, R.M., Wilson, I. and Daly, C. (1999) Regional regression models of annual streamflow for the United States. Journal of Irrigation and Drainage Engineering, ASCE, 125(3), 148-157.

Walling, D.E. and Webb, B.W. (1988) The reliability of rating curve estimates of suspended sediment yield: Some further comments. Sediment Budgets, IAHS Publication. 174, Wallingford, U.K., 337-350.

Werbos, P.J. (1974) Beyond regression: new tools for prediction and analysis in the behavior sciences. PhD Thesis, Harvard University, Committee on Applied Mathematics.

Wood, E.F. and Connell, P.E. (1985) Real time forecasting, in Hydrologic forecasting. Edited by M.G. Andersons & T.P. Bust, John Willey & Sons Ltd.

Xiong, L., Shamseldin, A. and Connor, K. O' (2001) A non linear combination of the forecasts of rainfall-runoff models by the first order Takagi-Sugeno fuzzy system. Journal of Hydrology, 245, 196-217.

Yager, R.R. and Filev, D.P. (1994) Generation of fuzzy rules by mountain clustering. Journal of Intelligent and Fuzzy Systems, 2, 209-219.

Yakowitz, S.J. (1985) Markov flow models and the flood warning problem, Water Resources Research, 21, 81-88.

Yapo, P., Sorrooshian, S. and Gupta, V. (1993) A Markov chain flow model for flood forecasting. Water Resources Research, 29, 2427-2436.

Yi, S.Y. and Chung, M.J. (1993) Identification of fuzzy relational model and its application to control. Fuzzy Sets and Systems, 59, 25-33.

Yu, B. (2000) A systematic over estimation of flows. Journal of Hydrology, 233, 258-262.

Zadeh, L.A. (1965) Fuzzy Sets. Information and control, 8, 338-353.

Zadeh, L.A. (1973) Outline of a new approach to the analysis of complex systems and decision processes. IEEE Transactions on Systems, Man and Cybernetics, 1, 28-44.

Zadeh, L.A. (1994) Soft computing and fuzzy logic. Software, IEEE, 11(6), 48-56.

Zadeh, L.A. (1998) Some reflections on the anniversary of fuzzy sets and systems. Fuzzy Sets and Systems, 100, 5-7.

Zadeh, L.A., (1999) From computing with numbers to computing with words-from manipulation of measurements to manipulation of perceptions. IEEE Transactions on Circuits and Systems-I: Fundamental theory and applications, 45(1), 105-119.

Zealand, C.M., Burn, D.H. and Simonovic, S.P. (1999) Short term streamflow forecasting using artificial neural networks. Journal of Hydrology, 214, 32-48.

Zhang, B. and Govindaraju, R.S. (2000) Prediction of watershed runoff using Bayesian concepts and modular neural networks. Water Resources Research, 36(3), 753-762.

Zhu, M.-L. and Fujita, M. (1994) Comparisons between fuzzy reasoning and neural network methods to forecast runoff discharge. Journal of Hydroscience and Hydraulic Engineering, 12(2), 131-141.

Zimmermann, H.-J. (1996) Fuzzy set theory and its application. 3rd ed., Kluwer Academic Publishers, Boston.