FUZZY NEURAL NETWORK MODELING FOR HYDROLOGICAL STUDIES

A Thesis Submitted

For the award of the Degree of

DOCTOR OF PHILOSOPHY

BY

PARESH CHANDRA DEKA

to the

DEPARTMENT OF CIVIL ENGINEERING
INDIAN INSTITUTE OF TECHNOLOGY. GUWAHATI

JULY 2003

Dedicated to
Flood affected people

Certificate

It is certified that the work contained in the thesis entitled "FUZZY NEURAL NETWORK MODELING FOR HYDROLOGICAL STUDIES" by Paresh chandra Deka, Roll number 994702, a student in the department of Civil Engineering, Indian Institute of Technology Guwahati for the award of the degree of Doctor of Philosophy has been carried out under our supervision and that this work has not been submitted elsewhere for a degree.

Prime-Supervisor:
25/7/03
Dr.V Chandramouli
Assistant Professor
Civil Engg.Department
I. I.T.Guwahati-781039
July, 2003.

Co-Supervisor:
Anjan Dutta 25/7/03
Dr.Anjan Dutta
Associate Professor
Civil Engg.Department
I.I.T.Guwahati-781039
July, 2003.

ACKNOWLEDGEMENTS

I would like to place on record my deep sense of gratitude and sincere thanks to my thesis Prime-Supervisor **Dr.V.Chandramouli, Assistant Professor, Department of Civil Engineering** for his valuable guidance, suggestions and expert opinion for my research work. I also admire his patient explanation of the concepts and basic principles.

I also like to record sincere thanks and gratitude to my thesis Co-Supervisor, **Dr.Anjan Dutta, Associate Professor, Department of Civil Engineering** for his valuable suggestions, guidance and encouragement.

I am grateful to **Dr.S.Talukdar, Head of the department of Civil Engineering** for necessary facilities and support. I thank my **Doctoral committee members** for their useful suggestions.

I am thankful to **Water Resource Department, government of Assam** and **Brahmaputra Board, government of India**, for providing the necessary data during the research work.

My sincere thanks are also due to all the **Faculty members** of Hydraulics and Water Resources Engineering for their keen interest and suggestions.

I would like to record my sincere thanks to **Education Department**, Government of Assam, for according permission for undertaking research work at I.I.T, Guwahati.

I wish to thank **Er.R.Islam**, Superintending Engineer, Water Resource department, Government of Assam, for his kind cooperation during data collection.

I am grateful to **Er.P.Baishya** of Hydrology division, Water Resource department, Government of Assam, for his timely help and support for my research work.

I express my sincere thanks to the **staff members** of the Civil Engineering Department, I.I.T, Guwahati for their kind cooperation during my work.

I express my special thanks to my research colleagues **Er.R.Goswami, Er.J.Ahmed, Er.I.Gogoi, Er.A.Dutta and Er.B.Barman** for their kind support.

I wish to thank **those** who directly or indirectly helped me for smooth completion of the research work.

I have great pleasure in thanking my **family members** particularly my wife **Rumi** and my daughter **Fairyqueen** who took the pain for early completion of my research work at **I.I.T.**,Guwahati.

PARESH CHANDRA DEKA

ABSTRACT

Water resources related studies involve variables, which are highly random and uncertain in nature. Most hydrological variables exhibit a high degree of temporal and spatial variability. These studies are very essential to the mankind for providing a warning of the extreme flood or drought conditions and help to optimize the operation of systems like reservoirs and power plants etc. For better hydrological design, we need proper modeling of the system using these variables. Many approaches were suggested in the past. In this research study, a new modeling approach that uses artificial neural network and fuzzy logic concepts together is proposed for modeling hydrological problems.

Hybrid systems are designed to take advantage of the strengths of each system and avoid the limitations of each system. It is natural for neural networks to learn but it is cumbersome for a fuzzy system to learn. Hence a combination of the two would result in a rule- based system that can learn and adapt. Four different hydrological problems are modeled using the proposed fuzzy – neural network approach for examining the usefulness of it. Proposed hybrid system approach, which includes an artificial neural network modeling and fuzzy logic modeling is referred as FNN (fuzzy neural network) model.

FNN model is developed for deriving the stage-discharge relationship at various gauging stations of the main stem of river Brahmaputra with the objective of generating missing data to get continuous stage-discharge record for a long period. The performance of the proposed model is compared with a conventional model, a single neural network model, a modular neural network model by simulating the system.

Second stage is carried out for river flow prediction at downstream station by using upstream gauging station data. Six experiments are planned and performed in this study. The performance of fuzzy neural network model is compared with single neural network model.

An attempt is also made to derive general operating policies of a reservoir system using fuzzy neural network modeling approach from deterministic dynamic programming results for efficient reservoir operation. Two contrasting reservoir systems one in drought prone area (Aliyar) and another in surplus system (Pagladiya) in nature are considered in this study for assessing the ability of the developed models using three different experiments. The suitability of this approach in distributed flood routing is also examined by considering a small tributary of Brahmaputra river.

The usefulness of the proposed hybrid approach has been discussed and presented in detail.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF NOTATIONS

a, b	Coefficients used in linear regression
A	Fuzzy subset
b_1^j and b_2^k	Bias terms
D_t	Demand during time period t
dH/dt	Rate of change of stage
e_t	Evaporation rate during time period t
E	Residual error
E_t	Evaporation during time period t
$f_1(.)$ and $f_2(.)$	Activation function
G	Stage at site
G_o	Stage at which discharge is zero
H_t, H_{t-1}, H_{t-2}	Stage of river on current day, previous day and day before Yesterday
I_t	Inflow during time period t
$I_{t-1}, I_{t-2}, I_{t-3}$	Inflow during time period t-1,t-2 and t-3
k, i, l	The indices for the initial storage, inflow volume and final volume respectively
K	Storage capacity of the reservoir
K_j	Rank of residual error
l	Maximum limit of a fuzzy set
m	Lower limit of a fuzzy set
m	Number of inflow class intervals considered
n	Total number of periods remaining before reservoir operation terminates

N	=	Set size
O_{pk}	=	Output from kth mode of output layer of the network for Pth vector
p	=	Number of patterns
p_{ij}	=	Probability that inflow I_{jt+1} occurs in time period t+1,given a known inflow of I_{it} in period t
q	=	Number of neurons in output layer
Q	=	Discharge
Q_t, Q_{t-1}, Q_{t-2}	=	Discharge of river on current day, previous day and day before yesterday
Q_{It}, Q_{It-1}, Q_{It-2}	=	Discharge of river on current day, previous day and day before yesterday at gauging station I
Q_{IIt}	=	Discharge of river on day t at gauging station II
Q_{IIIt}	=	Discharge of river on day t at gauging station III
Q_{IVt}	=	Discharge of river on day t at gauging station IV
R_t	=	Release during time period t
St	=	Storage at the beginning of time period t
T	=	Number of fortnights
U	=	Universe of discourse
w_{ji}	=	Weights between j^{th} neuron in the output layer and i^{th} neuron in the hidden layer
W^0_{jk}	=	Connection weight between kth node of the input layer and Jth node of hidden layer
η, α	=	Learning rate and momentum factor
$\mu_A(x)$	=	Membership of x in fuzzy set A
μ_{cfs}	=	Truth function
x	=	The discharge at upstream station (input variable)
x_{pi}	=	Input to network for pth vector

y_j	=	Output from the neuron
y_j^t	=	Target output value
z	=	The discharge value at downstream station
Z_t	=	Objective function

LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
ARMAX	Auto regressive moving average with exogeneous variable
ARMA	Auto regressive moving average
BP-MLP	Backpropagation multiplayer perceptron
CFNN	Counterpropagation Fuzzy Neural Network
DP	Dynamic Programming
DPN model	Model which uses dynamic programming for optimizing Reservoir operation and neural network for deriving general operating policies from optimization results
DPFNN model	Model which uses dynamic programming for optimizing reservoir operation and fuzzy logic with neural network for deriving general operating policies from optimization results
FNN	Fuzzy Neural Network
FSDP	Fuzzy Stochastic Dynamic Programming
KWM	Kinematic wave modeling of Saint Venant equations
MNN	Modular Neural Network
MSE	Mean square error
MRE	Mean relative error
PMSE	Pooled mean squared error
SDP	Stochastic Dynamic Programming

CHAPTER 1

INTRODUCTION

1.1 WATER RESOURCES OF INDIA

India's economy and social structure is based on agriculture, which is based on the monsoon rains. Most of the rivers carry floods during the monsoon periods and dry or having low flow in the non-monsoon period. India is blessed with abundant land and water resources but the availability of water varies considerably with respect to time and space. Water resources development projects are vital for the development of the country like India where almost 50% populations are living below the poverty line. After independence, many projects were completed and made operational. But, at present, the stress is given to the efficient management of the water resources systems developed rather than construction of new projects due to the non-availability of sites, funds and ecological disturbances.

Planning for the development of water resources system is very complex in view of the competing demands for utilization. Water resources management systems have also to be considered as integral components of other complex systems covering the economy of the country as a whole. It is therefore, imperative that latest modern techniques of study and evaluation by adopting systems approach to the development of water resources are resorted to. Systems engineering is concerned with the decision making in relation to planning, design, construction or operation with variables which are associated with uncertainty, randomness and fuzzy in nature. In the recent past one of the important advancement made in the field of water resources systems engineering is the evolvement and application of optimization techniques for planning, design and management of complex water resources systems.

Quality data are essential for better assessment of the available and dependable natural water resources of river basins. It is also essential for comprehensive and coordinated planning for the optimum utilization of the water resources in the rivers, their tributaries for investigation and design of multipurpose river valley projects, for the development of irrigation, water supply and power projects, for flood control and mitigation, for navigation, pollution abatement etc. Most of the variables associated with hydrological systems such as precipitation, runoff from a catchment, base flow component, evaporation, etc. are highly random.

Many new methodologies are developed to model them closer to the reality. The current trend seems to be to model the data rather than the physical process. For modeling the data, the combination of Artificial neural network and Fuzzy logic are probably the most attractive technique among the researchers which is capable of handling imprecise, fuzzy, noisy and probabilistic information to solve complex problems in an efficient manner. Neural networks are inherently non-linear, highly parallel, robust and fault tolerant where as Fuzzy logic is capable of modeling vagueness, handling uncertainty, and supporting human type reasoning. They estimate a function without any mathematical model and learn from experience with sample data.

In literature, the use of fuzzy logic system concept and artificial neural network along with other methodologies are reported in solving many hydrological studies.

1.2 FUZZY SYSTEM

Fuzzy systems are defined by a number of fuzzy rules, a number of membership functions, and mechanisms to apply logical operators. They are suitable for situations where an exact model of a process is either impractical or very costly to build but an imprecise model based on the existing human expertise can do the job. In such situations, fuzzy systems are considered the best alternative, though they do not perform optimally. There are numerous successful applications of fuzzy systems in control and modeling. Uncertainties due to imprecision in objectives and model parameters in water resources problems have been modeled with fuzzy sets in some recent works. (Bardossy and Disse, 1993, Teegavarapu and Simonovic, 1999, Mujumdar and Sasikumar, 2002). Fuzzy sets are an aid in providing information in a more human comprehensible or natural form, and can handle uncertainties at various levels. The knowledge contained in fuzzy systems is transparent to the user.

1.3 ARTIFICIAL NEURAL NETWORK MODEL

The ANN approach is based on the highly interconnected structure of the brain cells. This approach is faster compared with its conventional compatriots, robust in noisy environments, flexible in the range of problems it can solve, and highly adaptive to the newer environments. Due to these established advantages, currently the ANN has numerous real world applications such as image processing, speech processing, robotics, and stock market predictions. There has been extensive research on its implementation in the system engineering related fields such as time series prediction, rule based control, rainfall-runoff modeling etc. In recent years, ANN methods have been successfully applied to many studies in the field of water resources engineering.

1.4 HYBRID SYSTEM-FUZZY NEURAL NETWORK MODEL

For complex systems, instead of a single technology, hybrid systems can easily satisfy all the requirements of the problem. In the quest for a solution to the problem at hand, it is natural to combine more than one technology to create hybrid systems. Hybrid systems are designed to take advantage of the strengths of each system and avoid the limitations of each system.

A fuzzy system adaptively infers and modifies its fuzzy associations from representative numerical samples. Neural networks, on the other hand, can blindly generate and refine fuzzy rules from training data. Both neural networks and fuzzy systems are dynamic, parallel processing systems that estimate input-output functions. Neural systems are treated in a numeric quantitative manner, whereas fuzzy systems are treated in a symbolic qualitative manner. It is natural for neural networks to learn but it is cumbersome for a fuzzy system to learn. Hence a combination of the two would result in a system that can learn and adapt.

The fuzzy neural network system, which is a judicious integration of the merits of neural networks and fuzzy approaches, enables one to build more intelligent decision making systems. This incorporates the generic advantages of artificial neural networks like massive parallelism, robustness, and learning in data-rich environments into the system. The modeling of imprecise and qualitative knowledge as well as the transmission of uncertainty is possible through the use of fuzzy logic. In systems where prior knowledge is available, what is known can be easily coded in rules and facts, but it is not a simple matter to encode prior knowledge in a neural network.

1.5 PLANNING THE PRESENT STUDY

For efficient prediction of river flow, an attempt has been made in this study to make use of a hybrid system approach which includes an artificial neural network modeling and fuzzy logic modeling referred as FNN (fuzzy neural network) model. The Brahmaputra river system located in Assam State, India is considered for this study.

The newly proposed FNN modeling is carried out for derivation of stage-discharge relationship at various gauging stations of the main stem of river Brahmaputra with the objective of generating missing data to get continuous stage-discharge record for a long period. For this purpose, a conventional model, an artificial neural network model, a modular neural network model and a fuzzy neural network model have been constructed and their performances are compared by simulating the system.

The hybrid modeling is carried out for river flow prediction at downstream station by knowing status of upstream gauging stations. Simulation studies also carried out to assess the performance of fuzzy neural network model and artificial neural network model. The suitability of the proposed approach in flood routing is also examined by considering a small drainage channel.

An attempt is also made with fuzzy neural network modeling approach for deriving general operating policies of a reservoir system for efficient reservoir operation. Two contrasting reservoir systems are considered in this study for assessing the ability of the developed models using different experiments.

1.6 OBJECTIVE OF THE PRESENT STUDY

The objectives of this study are to develop and investigate the applicability of the new hybrid system approach of fuzzy systems and neural network modeling in few hydrological problems. The objectives of this study are

(i) Building a combined (hybrid) approach using fuzzy systems and neural networks for hydrological studies.

Assessing the potential of Fuzzy Neural Network (FNN) model in deriving stage-discharge relationship, by comparing the model performance with traditional conventional methods and other neural network models.

(ii) Evaluating the applicability and potential of the hybrid approach of fuzzy neural network to river flow prediction at downstream gauging station using upstream station data and distributed flow routing problem.

(iii) Extending the use of FNN model to derive reservoir-operating rules for a single reservoir system using the dynamic programming optimization model results.

1.7 PRESENTATION OF THE WORK

The thesis is divided into 7 chapters. Fig 1.1 shows the organization of the thesis. First chapter gives a brief introduction and objectives of the research work carried out. In the second chapter the literature is reviewed in a detailed way covering relevant applications. The problem identification is also dealt in this chapter. In the third chapter, the methodologies are discussed in detail: Developing FNN model for deriving the stage discharge relationship is discussed in this chapter. The results are compared with other models. In the fourth chapter FNN modeling approach for river flow prediction is presented. Fifth chapter presents FNN modeling approach for deriving general operating policies of a reservoir system. In the sixth chapter, the applicability of proposed FNN modeling approach in flood routing is examined. Chapter seven gives the summary and conclusions of the present study.

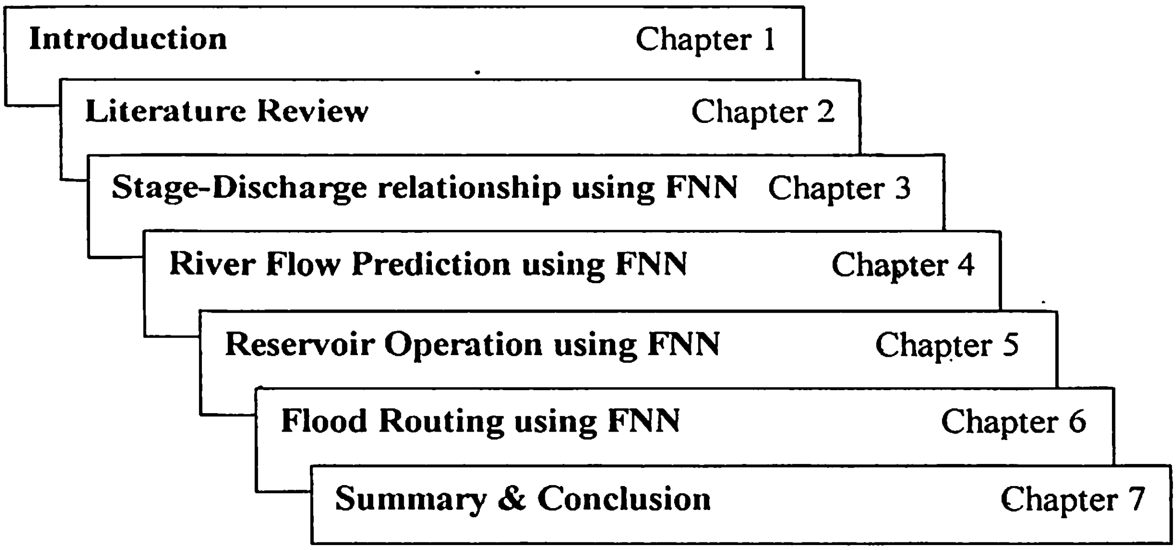

Fig.1.1 Presentation Format of the Thesis

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

A detailed review of literature is presented in this chapter in three sections. Applications of neural network model in water resources studies are presented in first section. In the second section, recent reviews of fuzzy logic application in water resources systems are presented. An overview of published literature on the applications of fuzzy neural network is reviewed in the third section.

2.2 ARTIFICIAL NEURAL NETWORK MODEL

An artificial neural network (ANN) is a parallel-distributed information processing system that has certain performance characteristics resembling biological neural networks of the human brain (Haykin, 1994). ANN consists of a number of interconnected computational elements called neurons that are arranged in a number of layers. The connection between each pair of neurons is called a link and is associated with a weight that is a numerical estimate of the connection strength. Every neuron in a layer receives and processes weighted inputs from neurons in the previous layer and transmits its output to neurons in the next layer. The weighted summation of the inputs to a neuron is converted to an output according to a transfer function (linear or sigmoidal function).

There are wide range of ANN architectures among which the three-layer feed forward architecture is widely used. In this network, there are two distinctive modes, training and testing modes. In the training mode, a training data set consisting input and output patterns are presented to the networks. The weights are found through an iterative process. The back-propagation learning algorithm is popularly used to find the weights such that the difference between the given outputs and the computed outputs by the network is sufficiently small. After the training, the network is tested with the testing data set (input variables only) to determine how accurately the network has simulated the input/output relationship.

ANN models are very robust and are able to deal with outliers and noisy or incomplete data. They are non-linear models and perform well even when limited data are available. ANNs are successfully used in hydrology related areas such as rainfall-runoff modeling, water quality, stream flow forecasting, water management policy, reservoir operations, precipitation forecasting etc.

In the past decade, many applications of ANN in water resources are reported in literature. Most of the applications used feed forward type neural networks for functional approximation problems. The combination of simplicity, interpolation, reasonably accurate prediction statistics, ability to provide conditional simulations and computational speed suggest that it can be a useful tool in water resources systems analysis. Various ANN applications found in literature are reviewed in this section.

2.2.1General introduction of ANN

McCulloch and Pitts (1943) outlined the first format model of elementary computing neurons. It was not widely adopted for the vacuum tube computing hardware description and the model never become technically significant during that decade.

Hebb (1949) first proposed a learning scheme for updating neuron's connection that we now refer to as the Hebbian learning rule. He stated that the information could be stored in connections. In 1960s, a new powerful learning rule called the Widro-Hoff learning rule was developed by Windrow and Hoff (1960,62). The rule minimized the summed square error during training involving pattern classification. The era of renaissance started with Hopfield's (1984) introduction of recurrent neural network architecture for associative memories.

Another revitalization of the field came from the publication of two volumes on parallel distributed processing edited by James Rumelhart and McClelland (1987). The new learning rules and other concepts introduced in this work had removed one of the most essential network training barriers that grounded the main stream efforts of the mid 1960s and it opened a new era for the once under-estimated computing potential of layered network. Lipmann (1987) introduced the use of neural network in functional approximation problems and discussed the merits of this procedure.

2.2.2 Applications of ANN in Water Resources System Studies

Rushid and Wong (1992) used pattern-matching capability of ANN to determine the aquifer parameter values from aquifer test data. In their study, neural network was trained to recognize patterns of normalized draw down data as input and the corresponding aquifer parameters as output. The results obtained were in good agreement with published results obtained using other techniques.

French et al. (1992) developed three-layered ANN to forecast rainfall intensity fields in space and time. They used back-propagation algorithm. After training with input patterns, the ANN was used to forecast rainfall using the current fields as input. Results showed that ANN was capable of learning the complex relationship describing the space-time evolution of rainfall. The ANN performance was compared with two other methods of short term forecasting, persistence and now casting. Now casting is a local weather forecasting with forecast lead-time up to 2 hours. This approach relied heavily on the timely use of current data in which remote sensing observations play a dominant role. They also concluded that the ability of the ANN to generalize the data not included in training depends on selecting a number of hidden nodes large enough to provide a means for storing higher order relationships necessary for adequately abstracting the process.

Tang and Fishwick (1993) studied the artificial neural network approach as a model for time series forecasting and compared it with the box Jenkins model.

Ranjithan et al. (1993) presented a screening approach, which used the pattern classification capability of neural network for ground water reclamation. They showed that this ground water management model could yield highly reliable remediation designs.

Rogers and Dowla (1994) proposed a new approach to the non-linear ground water management methodology, which optimized the aquifer remediation with the ANN.

Rizzo and Dougherty (1994) proposed a method called neural kriging for pattern completion based on the application of ANN and processing many operational objectives of the ordinary kriging approach. Kriging is an interpolating method of pattern completion that is widely used in the geo-hydrologic studies. Kriging leads to unbiased estimates of the field variable at a given point and the variance of the estimation error at that point. This network was described, implemented in a parallelising algorithm and applied to developed maps of discrete spatially distributed fields. A comparison with a reference field showed that the neural kriging network produced unbiased errors relative to sample bias and reproduced the variogram (graphical representation of variance in different lags) of a quantised random field with reasonable accuracy.

Saad et al. (1994) described a disaggregation procedure by training ANN. After training, this network gave the storage level of each reservoir of a system when supplied with the value of an aggregate storage level. The training was obtained by solving the deterministic operation problem of a large number of equally likely flow sequences. The training was done by back-propagation, and the minimization of quadratic error was computed by gradient method. The aggregated storage level was determined by stochastic dynamic programming (SDP) algorithm in which all hydroelectric reservoirs were aggregated to form one equivalent reservoir. A comparison with principal component analysis disaggregation technique with NN based technique was presented in this paper.

Smith and Eli (1995) used ANN to model rainfall runoff process. They used a 5 x 5 grid cell synthetic watershed to generate runoff from stochastically generated rainfall patterns. A back propagation algorithm was trained to predict the peak discharge and the time of peak resulting from single rainfall pattern. Various applications reported in literature revealed that ANN is a tool, which can perform in a better manner than the conventional statistical tools in function approximation problems.

In a preliminary study, Halff et al. (1993) designed a three-layer feed forward ANN using the observed rainfall hyetographs as inputs and hydrographs recorded by the U.S. Geological Survey (USGS) at Bellvue, Washington, as outputs. The authors decided to use five nodes in the hidden layer. A total of five storm events were considered. On a rotation basis, data from four storms were used for training, while data from the fifth storm were used for testing network performance. A sequence of 25 normalized 5 min. rainfalls was applied as inputs to predict the runoff.

Hjelmfelt and Wang (1993a-c) developed a neural network based on the unit hydrograph theory. Using linear superposition, a composite runoff hydrograph for a watershed was developed by appropriate summation of unit hydrograph ordinates and runoff excesses. To implement this in a neural network framework, the number of units in the inputs and hidden layer were kept as the same. The inputs to the ANN were sequences of rainfall. Instead of the threshold function, ramp transfer function corresponding to the rainfall Ø index was used for the hidden layer. The resulting network was shown to reproduce the unit hydrograph better than the one obtained through the standard gamma function representation.

In a later study, Hjelmfelt and Wang (1996) compared this method with a regular three-layered artificial network with back propagation. The authors concluded that a regular network could not reproduce the unit hydrograph very well and was more susceptible to noise than a network whose architecture was more suited for unit hydrograph computations.

In an application using two neural networks, Zhu et al. (1994) predicted upper and lower bounds on the flood hydrograph in Butter Creek, New York. Off-line predictions were made when present flood data were not available and estimates had to be based on rainfall data alone. On –line predictions were based on both rainfall and previous flood data.

The issue of enhancing the training speed using a three-layer network was addressed by Hsu et al. (1995) and Gupta et al. (1997). These studies advocated the linear least squares simplex algorithm, which partitions the weight space to implement a synthesis of two training strategies. Gupta et al. (1997) concluded that the linear least square simplex algorithm is a better training algorithm than back-propagation or conjugate gradient techniques.

Hsu et al. (1997) used a three layer feed forward ANN and recurrent ANN to model daily rainfall-runoff. They concluded that the feed-forward ANN needed a trial and error procedure to find the appropriate number of time delayed input variables to the model and also was not suitable to distributed watershed modeling. On the other hand, the recurrent ANN was able to provide a representation of the dynamic internal feedback loops in the system, eliminating the need for lagged inputs and resulting in a compact weight space. However, both ANNs performed equally well at runoff prediction.

Carriere (1996) developed a virtual runoff hydrograph system that employed a recurrent back-propagation artificial neural network to generate runoff hydrographs. A recurrent back-propagation network was utilized in which input layer feeds back to itself during training to capture time dependents in the series. The network consisted of seven input nodes, thirty-five nodes in hidden layer, and a single node in the output layer. The author concluded that the neural network could predict runoff hydrograph accurately, with good agreement between the observed and predicted values.

In a study by Minns and Hall (1996), data for network for training consisted of model results from one storm sequence, and two such sequences were generated for testing. A three-layer network with back-propagation was used. It was found that ANN performance was hardly influenced by level of non-linearity, with performance deteriorating only slightly for high levels of non-linearity. They pointed out the importance of standardization based on maximum and minimum values of inputs and outputs. Whenever the networks was required to predict "out of range" of the standardized values, the performance dropped significantly, suggesting that ANNs are not very good extrapolators.

Haykin (1994) showed that design of a supervised neural network might be pursued in a number of different ways. He viewed the back-propagation algorithm for the design of a multilayer perception (under supervision) as an application of stochastic approximation and the radial- basis function (RBF) networks as a curve-fitting problem in a high dimensional space. The author concluded that the learning for such networks was equivalent to finding a surface in a multidimensional space that provided a best fit to the training data, with the criterion for "best fit" was expressed in a statistical sense.

Mason et al. (1996) used radial basis function networks for accelerating the training procedure as compared with regular back-propagation techniques. The authors briefly discussed network architectures and compositions and tried five different forms of basis functions in their study. They concluded that, while radial based function networks did provide for faster training, such networks require the solution of a linear system of equations that may become ill conditioned specially if a large number of cluster centers are chosen.

Jayawardena and Fernando (1995, 1996) and Fernando and Jayawardena (1998) also used RBF methods for flood forecasting. They illustrated the application of (RBF) artificial neural networks using an orthogonal least squares algorithm (OLS) to model the rainfall-runoff process.

Shamseldin (1997) compared ANNs with a simple linear model, a season-based linear perturbation model, and a nearest neighbor linear perturbation model. The results suggested that the neural networks generally performed better than the other models during training and testing.

Tokar and Johnson (1999) reported that ANN models provided higher training and testing accuracy when compared with regression and simple conceptual models. Their target was to forecast daily runoff for the Little Patuxent River, Maryland, with daily precipitation, temperature, and snowmelt equivalent serving as inputs. It was found that the selection of training data has a large impact on accuracy of prediction. The authors trained and tested the ANN with wet, dry, and average year data, respectively, as well as combinations of these, in order to illustrate the impact of the training series on network performance. The ANN that was trained with wet and dry data had the highest prediction accuracy. The length of training record had a much smaller impact on network performance than the type of training data.

Dawson and Wilby (1998) used a three-layer back-propagation network to determine runoff over the catchments of the rivers Amber and Mole. ANN inputs were past flows and averages of past rainfall and flow values. The ANN output consisted of predicting future flows at 15 minutes interval up to a lead-time of six hours. When compared with actual flows, the ANNs appeared to overestimate low flows for the Mole river.

Bonafe et al. (1994) assessed the performance of a neural network in forecasting daily mean flow from the upper Tiber river basin in central Italy. The previous discharge, daily precipitation, daily mean temperature, total rainfall of the previous five days, and mean temperature over the previous ten days were selected as ANN inputs. They concluded that the ANN was able to yield much better performances than ARMA models.

Islam and Kothari (2000) reviewed and examined the utility of ANNs in characterizing, estimating, and predicting remotely sensed hydrologic processes and data from multiple sources. They studied two different types of ANN-recurrent n self-organizing networks in addition to multiplayer feed forward networks for spatial characterization of heterogeneous land surface processes.

Zhang and Govindaraju (2000) used modular neural networks for predicting monthly runoff for three medium sized watersheds in Kansas. They found that although singular neural networks tend to predict average events satisfactorily but they are not successful in predicting extreme events. The modular neural network architecture used here had one gating network and three expert networks to symbolically represent low, medium and high runoff events as runoff generation mechanisms are dominated by different physical processes for discharge events of differing magnitudes. Bayesian concepts were utilized in deriving training algorithm. Modular neural network showed improvement over ANN, which is directly dependent on the separability of the input space.

Thandaveswara and Sajikumar (2000) used ANNs for classification of river basins with a case study in India. They used ANN for clustering the basins on the basis of hydrological homogeneity. They carried out the study to check whether the classifications in the data hyperspace have any physical meaning or not. They also attempted to check whether the clustering with factors that affect runoff has any effect in runoff values of each cluster.

Burian et al. (2001) used ANN to perform rainfall disaggregation and found that the NN model can be applied effectively with various considerations like standardization of data, geographic location of training data, number of training iterations, number of hidden neurons. They concluded that data from rainfall gauging stations within several hundred kilometers of the station to be disaggregated were adequate for training the ANN rainfall disaggregation model.

2.2.3 Modeling stream flows

Stream flows are often treated as estimates of runoff from watershed. The papers that have directly dealt with streamflow itself, usually without involving precipitation as input are presented in this section. Prediction of a river flow or stream flow constitutes major input information in water resources planning and management. Such a prediction, if done on a continuous basis, would be helpful in many ways.

Kang et al. (1993) used ANNs and autoregressive moving average models to predict daily and hourly stream flows in the Pyung Chang River basin in Korea. Different three-layered ANN architectures were investigated. They concluded that ANNs are useful tools for forecasting stream flows.

Raman and Sunilkumar (1995) employed an ANN to model a multivariate water resource time series and compared the results with those obtained by traditional autoregressive moving average (ARMA) models. The objective was to synthesize monthly inflow data for two reservoir sites in the Bharathapuzha basin in south India. A three-layer feed forward ANN with back propagation was used in this study. The consecutive normalized inflows to the reservoir for two previous months were chosen as inputs. The output was normalized inflow for the current month. They concluded that the results obtained using the ANN compared well with those obtained using statistical models.

Karunanithi et al. (1994) used ANN in estimating stream flows at an ungauged site on the Huron River in Michigan. They compared ANN performance to an empirical two-station power law relationship that is based on log-transformation of the actual stream flow values. They used cascade-correlation algorithm so that the network architecture could be determined during training. They found that largest errors were associated with the highest stream flows. Neural networks were found to better predict these high events, while both methods predicted low stream flows fairly well. They stated that ANNs are capable of adapting their complexity to accommodate temporal changes in historical stream flow records. They claimed that ANNs are likely to be more robust when noisy data is present in the inputs.

Markus et al. (1995) used ANNs with the back-propagation algorithm to predict monthly stream flows at the Del Norte gauging station in the Southern Colorado. The inputs used were snow water equivalent alone, or snow water equivalent and temperature. They used periodic transfer functions (PTF) to predict stream flows based on similar inputs as an alternative form of prediction. They looked at forecast bias and root mean square error for assessing model performance. The results indicated that both ANNs and PTFs did a good job of predicting stream flows, and that including temperature as input improved model performance.

Poff et al. (1996) used ANNs to evaluate the changes in stream hydrograph from hypothetical climate change scenarios based on precipitation and temperature changes. The synthetic daily hydrograph was generated based on historic precipitation and temperature as inputs. They studied two streams in the northern United States under different climatological factors. Three classes of hydrological variables of interest were derived from ANN-generated stream flow output such as mean flow condition, high flow condition and low flow condition. The ecological implications of these changes for the two streams were discussed in terms of the hydrological variables.

Muttiah et al. (1997) also used the cascade-correlation algorithm in their efforts to predict two-year peak discharge from watersheds all over the continental United States. They investigated the possibility of a single model that could predict peak discharges from local to regional-sized watersheds. Network inputs consisted of the log of the drainage basin area, elevation, average slope, and average annual precipitation. The authors claim that ANNs showed some improvement over the standard regression techniques employed by the U.S. Geological Survey. Using input vector reduction techniques based on the cascade-correlation method, they concluded that drainage area and basin elevations could be used for predicting two-year peak discharges.

Liong et al. (2000) used ANN on flow forecasting in Dhaka, Bangladesh with very high degree of accuracy even for a seven lead day model. They found that it is important to determine the dominant model inputs, as these reduce the size of the network and consequently reduced the unnecessary data collection. They also analyzed the sensitivity of the inputs to verify the importance and found that the removal of the less sensitive inputs neurons insignificantly reduced the accuracy degree of the eight inputs neuron model.

Thirumalaiah and Deo (1998) selected a three-layer ANN for predicting flood stages for the city of Jagdalpur, India. The ANN was trained with back-propagation, conjugate gradient and the cascade-correlation algorithm, respectively. They found that the three training algorithms performed equally well in terms of predicting river stages. Back-propagation needed the most training epochs, and the cascade correlation needed the least. The ANNs predicted lower water levels accurately but generally underestimated the high water levels.

Thirumalaiah and Deo (2000) used ANN to real time forecasting of runoff and river stages at a gauging station in India. They concluded that flexible selection of the network architecture by the cascade-correlation training algorithm helped in reducing training time, which is an important factor in adaptive forecasting. They concluded that the excellent capability of the ANNs in qualitative decision making in hydrological forecasting as compared to multiple regression model.

Birikundavyi et al. (2000) used ANN for daily stream flow forecasting in the Mistanibi River, northeastern Quebec and found that ANN out perform the deterministic model PREVIS for up to a 5-day ahead forecasts. The results obtained with ANN were superior than classic auto-regressive model coupled with Kalman filter. They used previous days discharge, temperature, rainfall, and snowmelt days as inputs of the model.

Ichiyanagi et al. (1996) used linear function between input and output neurons to forecasting methods of time variation of the flow rate into a dam for a hydropower plant and found that prediction accuracy improved over sigmoidal function. They also found that linear function based neural network was able to forecast not only time variations of the flow rate displaying a single high and sharp peak but also once with multiple peaks. They attempted to forecast river flow rate following a fall of rain on the Hatanagi-Daiichi Dam, which feeds a hydropower plant located on the upper section of the Oi-River in central Japan.

The review on ANN applications indicates the merits and problems associated with ANN models. One of the major shortcomings of this approach is that the knowledge that is contained in the trained networks is difficult to interpret, because it is distributed across the connection weights in a complex manner. However, care must be taken not to present contradictory information to the ANN.

2.3 FUZZY LOGIC

Fuzzy logic is a superset of conventional (Boolean) logic that has been extended to handle imprecise data and the concept of partial truth. Lotfi A.Zadeh initiated fuzzy theory in 1965 with his seminal paper "Fuzzy Sets" (Zadeh, 1965). He developed the concept of "state", which forms the basis for modern control theory. In the early'60s, he thought that the classical control theory had put too much emphasis on precision and therefore could not handle the complex systems. As early as 1962, he wrote that to handle biological systems "we need a radically different kind of mathematics, the mathematics of fuzzy or cloudy quantities which are not describable in terms of probability distributions" (Zadeh, 1962). Later, he formalized the ideas into the paper "Fuzzy Sets". Fuzzy logic has been used for automatic control in more and more commercially available products such as cameras, where it is used for automatic focusing; and washing machines, which automatically adjust their washing cycles in response to the size of the load and how dirty the clothes are (Klir and Folger, 1998).

Fuzzy logic has been used in a number of water-resource applications but generally as a refinement to conventional optimization techniques in which the usual "crisp" or "hard" objective and some or all of the constraints are replaced by fuzzy ones (e.g., Parent and Duckstein, 1993; Kindler, 1993). The objective then can be formulated as maximizing the minimum membership value, which has the effect of balancing the degree to which the objective is attained with degrees to which the constraints have to be relaxed from their optimal values. In other applications, fuzzy membership functions are treated as utility curves for individual objectives with the overall objective of maximizing a weighted sum of these membership values (Gates et al., 1991; Heyder et al., 1991).

As suggested by name, fuzzy logic does not provide rigorous way for developing or combining fuzzy rules. As a result, there are many alternative way of doing so. Agsorn (1995) experimented with some of the more widely used alternatives, using as an example a simple nonlinear function of two variables, which made it possible to compare the results from the alternatives against the right answers (since these could be computed from the function). A relatively simple procedure was found to give best results, so it was adopted for this study.

Fuzzy logic has been successfully used in reservoir operation also as it is associated with imprecision and uncertainties.

Russell and Campbell (1996) developed reservoir-operating rules with fuzzy programming and found that it is a promising area but suffers from "curse of dimensionality". They found that it could be a useful supplement to other conventional optimization techniques.

A fuzzy rule based approach was adopted by Shrestha et al. (1996) to emulate reservoir operator's experience.

Fontane et al. (1997) used an implicit stochastic dynamic programming (SDP) formulation to derive operating rules with imprecise objectives; all operating objectives were considered as fuzzy sets, and preferences were described linguistically.

Esogbue and Kacprzyk (1998) presented a fuzzy criterion dynamic programming that sought to maximize the expected fuzzy criterion function representing the degree of satisfaction associated with the states of the system.

Tilament et al. (2001) developed a fuzzy explicit SDP (FSDP) approach with fuzzy operating objectives and a fuzzy intersection between immediate and future consequences associated with release decisions.

Dubrovin et al. (2002) developed a fuzzy rule based control model for multipurpose real-time reservoir operation and found that it is better to fulfill the new multipurpose operational objectives determined by the experts.

Tilament et al. (2002) developed a fuzzy stochastic dynamic program to solve multipurpose multi-reservoir operation problems for deriving optimal operating policies.

Conclusions from Agsorn's experiments (1995) and other studies (Campbell 1993;Tamaki 1994) were (a) The fuzzy system works best when the rules linking outputs to inputs can be accurately specified. (b) Sets of rules can be developed from operating data by the fuzzy inference method, but these are not quite as good as from accurate results. However, they can be improved by giving greater weight to inputs with larger membership functions and incorporating any insights from relevant theory and experience. (c) The system is robust in that some rules can be left out or can contain errors without seriously compromising performance. (d) Fuzzy logic programming is subject to the same "curse of dimensionality" as are other optimization techniques.

2.4 NEURO-FUZZY MODEL

During the past few years, fuzzy neural network (FNN) has emerged as one of the most active and fruitful areas of research in the fields of fuzzy logic and neural networks. It is concerned with the integration of the two fields in which significant advances have been made in the last decade. Several merger types of ANNs and fuzzy systems have been reported in the literature. They include various representations and architectures and therefore are suitable for different applications.

The concept of neuro-fuzzy systems has emerged as researchers have tried to combine the transparent, linguistic representation of a fuzzy system with the learning ability of an ANN (Brown and Harris, 1994).

A neuro-fuzzy system uses an ANN learning algorithm to determine its parameters (i.e. fuzzy sets and fuzzy rules) by processing data samples. Therefore, it can be trained to perform an input/output mapping, just as with an ANN, but with the additional benefit of being able to provide the set of rules on which the model is based The integration of neural and fuzzy systems leads to a symbiotic relationship in which fuzzy systems provide a powerful framework for expert knowledge representation, while neural networks provide learning capabilities and exceptional suitability for computationally efficient hardware implementations (Mitra and Hayashi, 2000).

There have been many attempts to synthesize Fuzzy Neural Network (FNN) model and according to their integration methodologies, two major categories of FNN can be identified. One is based on the fuzzification of conventional neural network model and the other is based on the implementation of conventional fuzzy systems using neural networks (Chung and Duan, 2000).

Methods proposed by Kosko (1992) and Jang (1993) are among many variations that combine neural networks and fuzzy system. Kosko (1992) used competitive networks to generate rules for fuzzy systems. Jang (1993) proposed a hybrid back-propagation/least square learning method to tune the parameters of a so-called adaptive network based fuzzy inference system.

Jang and Sun (1993) have shown that fuzzy systems are functionally equivalent to a class of radial basis function (RBF) networks, based on the similarity between the local receptive fields of the network and the membership functions of the fuzzy system.

Hayashi et al. (1993) fuzzified the delta rule for multiplayer perceptron (MLP) using fuzzy numbers at the input, output, and weight levels. But there were problems with the stopping rule.

Sayed and Razavi (2000) used a neuro-fuzzy approach for behaviour mode choice modeling to study the feasibility and advantages of the proposed approach. They showed that the capability of the proposed approach is similar or better than the conventional method and ANNs. They also observed that the approach used least amount of information in terms of the number of inputs.

In this research study, fuzzy neural network (FNN) modeling approach had been attempted to few hydrological studies by combining the efficiency of both the modeling approaches. This new approach is applied to derive stage discharge relationship, river flow prediction, flood routing and deriving general operating policies of a reservoir system. The problems considered here involve variables, which are by very nature, suitable for fuzzy modeling. For each case, the newly proposed modeling approach is compared with ANN models and other conventional models and the merits and other problems are explored in detail.

Using the better FNN modeling approach which defines the stage discharge relationship, the missing discharge informations for the considered major river flow gauging sites of Brahmaputra river are generated from stage values. With the flow data at four gauging sites, using fuzzy neural network approach, river flow prediction models are developed and their performances are examined.

The suitability of the proposed hybrid model is examined in flood routing by considering a small drainage channel. Also, an attempt has been made to derive general operating policies for a reservoir operation from optimization results using fuzzy neural network model. For this purpose, an upcoming reservoir called Pagladiya dam in Assam state and existing reservoir called Aliyar dam in Tamil Nadu, India are considered as a case studies.

CHAPTER 3

FUZZY NEURAL NETWORK MODEL FOR DERIVING STAGE-DISCHARGE RELATIONSHIP

3.1 ARTIFICIAL NEURAL NETWORK (ANN)

An interesting idea emerging from the vast pool of computer-based research is the possibility of emulating the processing mechanism of the brain. Although the biological unit still outperforms any man-made tool in terms of recognition, analysis, prediction, and particularly learning, the alluring success from the brain –simulation models has provided enough motivation for extended research. The ANN approach is based on the highly interconnected structure of the brain cells. This approach is faster compared with its conventional compatriots, robust in noisy environments, flexible in the range of problems it can solve, and highly adaptive to the newer environments. An ANN consists of a number of neurons that are arranged in an input layer, an output layer, and one or more hidden layers. The input neurons receive and process the input signals and sends the output to other neurons in the network where this process is continued. This type of network where information passes one way through the network is known as a feed forward network. A three-layer feed forward ANN along with a typical processing element, an activation function, and a threshold function embedded to its body as shown in Fig.3.1. The data passing through the connections from one neuron to another are manipulated by weights that control the strength of a passing signal. When these weights are modified, the data transferred through the network changes and the network output alters.

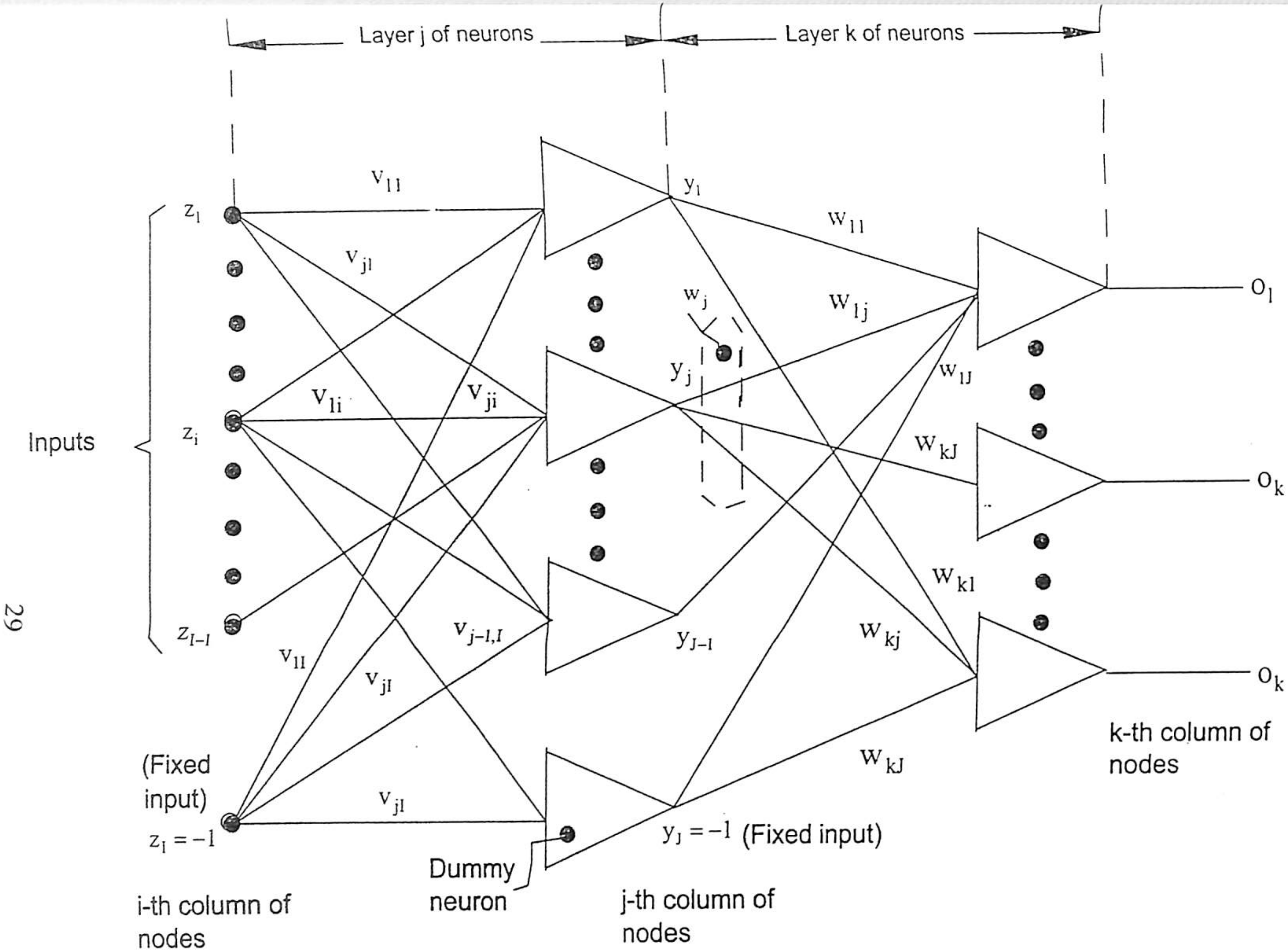

Fig.3.1.Layered feedforward neural network with two continuous perceptron layers

The weights are adjusted to obtain the desired response from an ANN. This process is called learning. Several learning examples are presented to the ANN, and when it has learned enough examples, it is considered to be trained. After the learning cycles, the weights are frozen. A data set that the ANN has not encountered before is presented to validate its performance. Depending on the outcome, either the ANN has to be re trained or it can be implemented for its designated use. Developing a neural network is unlike developing software because it is to be trained but not programmed. Rumelhart et al. (1986) give a lucid description of ANNs and their training aspects.

The multi-layer feed forward networks have been found to have the best performance with regard to input-output function approximation (Hsu et al. 1995). In hydrology, ANNs have been used for flow predictions, flow/pollution simulation, parameter identification, and to model complex non-linear input-output time series.

A feedforward error back propagation (BP) network may be adopted under a supervised learning mode; this is the most popular of the ANN architectures. Neurons in the input layer act as buffers through which input data are sent. The dummy neuron acts as a bias factor. The number of neurons in the hidden layer is decided after a rigorous course of training and testing. The sigmoidal function or linear function may be used for the activation function. The basic characteristics of the sigmoidal function are that it is continuous, differentiable everywhere, and is monotonically increasing. The output is always bound between 0 and 1 and the input to the function is not restricted. Using sigmoidal function, the output y_j from a neuron in the hidden layer becomes

$$y_j = f\left(\sum w_{ji} x_i\right) = \frac{1}{1 + e^{-\left(\sum w_{ji} x_i\right)}} \qquad (3.1)$$

Where

w_{ji} = the weight of the connection joining the j^{th} neuron in the hidden layer with the i^{th} neuron in the input layer,

x_i = the value of the i^{th} neuron in the preceding layer, and

y_j = the output from the j^{th} neuron in the layer under consideration.

The working principle of feed forward network is available elsewhere (Masters 1993). Mathematically, a three layer neural network with I input nodes, J hidden nodes in a hidden layer and K output nodes can be expressed as:

$$O_{Pk} = f_1\left(\sum_{j=1}^{L} w_{jk}^{o} f_2\left(\sum_{i=1}^{N} w_{ij}^{h} x_{Pi} + b_1^{j}\right) + b_2^{k}\right), \forall k \in 1,2,\ldots K \qquad (3.2)$$

Where

O_{Pk} = the output from the k^{th} node of the output layer of the network for the P^{th} vector (data point)

x_{Pi} = the input to the network for the P^{th} vector (data point)

w^{o}_{jk} = the connection weight between k^{th} node of the input layer and j^{th} node of the hidden layer

b^{j}_{1} and b^{k}_{2} = bias terms

$f_1(.)$ and $f_2(.)$ = activation functions.

3.1.2 Training of ANN

The generalized delta rule, popularly known as back propagation algorithm (Rumelhart et al. 1986), for training the network is embodied in the following steps:

(1) Start with an assumed set of weights. The initial weights are initialized with the help of a random number generator and they are very close to zero.

(2) Apply an input vector to the network and calculate the corresponding output values.

(3) Compare the actual outputs with the correct outputs and determine a measure of the error.

(4) Determine the amount by which each weight needs to be changed. In the BP algorithm, the weight associated with a neuron is adjusted by an amount proportional to the strength of the signal in the connection and the total measure of the error.

(5) Apply the corrections to the weights. The total error at the output layer is then reduced by redistributing this error backward through the hidden layers until the input layer is reached.

(6) Repeat the items 1-5 with all the training vectors until the error for all vectors in the training set is reduced to an acceptable value. In the steepest gradient descent algorithm, the weight update in iteration t is given by

$$\Delta w(t) = -\eta \frac{\partial E}{\partial w(t)} + \alpha \Delta w(t-1) \quad (3.3)$$

Where,

E = sum of squares of errors at output layer,

η= learning rate parameter, and

α = the momentum parameter.

For the flexibility of not forcing the response surface to pass through the origin, bias units are added in input and hidden layers, which are always given an input equal to 1. The error back propagation algorithm flow chart, which is used in this study, is given in Fig.3.2.

The ANN objective function surface is typically non-convex and contains multiple local optima. It has extensive regions that are insensitive to the variations in the network weights. This results in some major limitations of the BP algorithm. (a) These

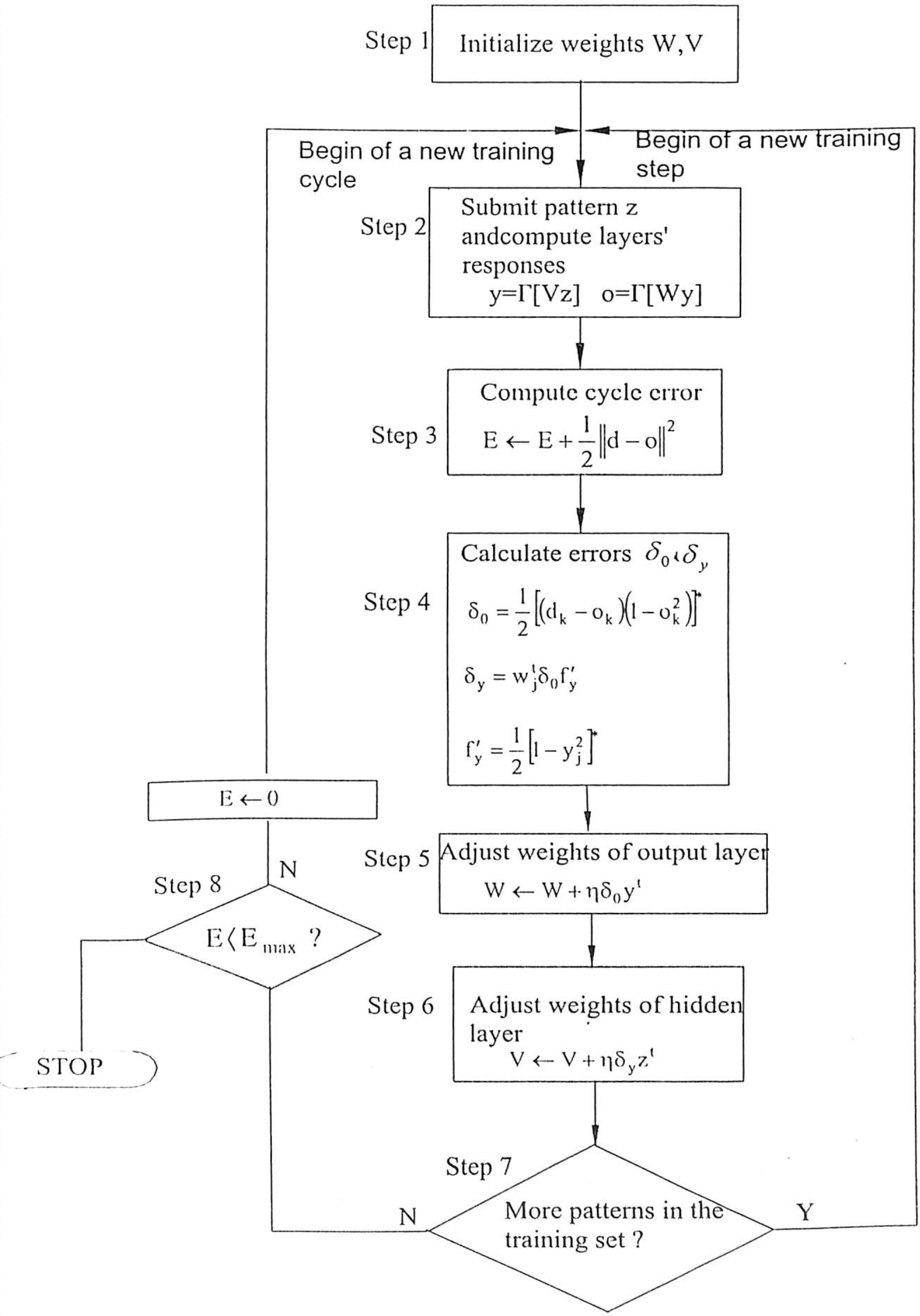

Fig.3.2.Error backpropagation training (algorithm flowchart)

network weights. This results in some major limitations of the BP algorithm. (a) These are easily trapped by local optima. (b) The convergence is a slow process. (c) The architecture is often ineffective, when searching weight spaces of high dimension. (d) Performance of a BP-ANN simulator is quite sensitive to the initial starting point.

The training of the data is carried out by monitoring the indices, namely mean square error (mse) and mean relative error (mre). These indices are defined as

1. Mean square error (mse)

$$mse = \frac{1}{pq}\sum_{q}\sum_{j=1}^{p}\left(y_j^{(t)} - y_j\right)^2 \tag{3.4}$$

2. Mean relative error (mre)

$$mre = \frac{1}{pq}\sum_{q}\sum_{j=1}^{p}\left|\frac{y_j^{(t)} - y_j}{y_j^{(t)}}\right| x100 \tag{3.5}$$

In which,

p = number of patterns used for training,

q = number of nodes in the output layer,

$y_j(t)$ = the target output pattern value (used for training) and

y_j = output from the neural network model.

The mse value indicates the goodness of fit at high output values and the mre value indicates the goodness of fit for moderate output values (Karunanithi et al. 1994). The number of neurons in the hidden layer, the number of hidden layers and the normalization factor for the data considered are decided after many trials by studying the performance of the ANN training indices.

3.1.3 Choosing Best Network

The network architecture, learning rate η and momentum factor α values are finalized after examining various combinations. The learning rate has a significant influence on the performance of the network. The learning rate indicates the rate of change of the weight vectors during training. If it is too large, oscillation of the weight vector results and the ANN model will remember only the training data. It means that the trained network will not be generalized for application to other data sets. On the other hand, if the learning rate is too small, the convergence will be very slow. Similarly a momentum factor α is used to accelerate the convergence. The momentum term determines the effect of previous weight changes on the present change in the weight space; this frees a solution trapped by local optima. Addition of momentum term sometimes results in faster training.

The number of neurons in the hidden layer in a multi-layered ANN is a subject to debate. Typically the generalization of prediction and accuracy of an application increases as the number of hidden neuron decreases; as the number of hidden neurons increases there is corresponding increase in the number of parameters describing the approximating function (Burian et al. 2001). When there is a large number of neurons in the hidden layer, the trained ANN is more specific to the training data.

For sigmoidal function, the output value from the network lies between 0 and 1. Hence normalization of the output data is required. The interconnecting weights are initialized by random numbers between –1 and +1.The weights are readjusted during training using the back-propagation algorithm for the given patterns.

The number of training iterations plays a significant role in predicting capabilities of the network. A training iteration is the process of showing a series of training data sets to the network and updating the weight matrix representing the connections between the neurons. Usually more training iterations are required if the relationship between inputs and outputs is complex. This needs more computing time. But there is a limit to the number of training iterations beyond which only marginal improvement in performance occurs; sometimes there is a decrease in performance.

The network architecture, learning rate, momentum factor, normalization factor, number of training iterations are decided for each case of different hydrological studies after different trials.

3.2 FUZZY SYSTEM MODEL

Fuzzy models are suitable for situations where the process involves imprecise and uncertain quantities. Fuzzy model are used to solve problems with imprecise parameters and insufficient information. Fuzzy sets are an aid in providing information in a more human comprehensible or natural form, and can handle uncertainties at various levels. In fuzzy systems, the knowledge can be captured in terms of rules and linguistic variables. The concepts and operational algorithms are given in many textbooks, for example Kosko (1992,1993), Klir and Folger (1998), McNeill and Thro (1994), Pedrycz (1993), and Zadeh and Kacprzyk (1992).

In fuzzy logic, variables are "fuzzified" through the use of membership functions that define the membership degree to fuzzy sets. A fuzzy subset A of a universe of discourse U is characterized by a membership function $\mu_A(x)$, which associates each element $x \in U$, a membership $\mu_A(x)$ in the interval [0,1] that represents the grade of membership in A (Sayed and Razavi, 2000). The three important components of a fuzzy set are given in Fig.3.3.

Generally, a small number of linguistic terms (e.g. HIGH, MEDIUM, LOW), referred to as fuzzy sets, are assigned to each variable (e.g., river discharge). These fuzzy sets overlap and cover the necessary range of variation for that variable. The key ideas are that fuzzy logic allows for something to be partly this and partly that, rather than having being either all this or all that; and that the degree of "belongingness" to a set or category can be described numerically by a membership number between 0 and 1. This transformation of real valued inputs into a degree of membership to a particular fuzzy set is called "fuzzification". Membership functions can be of different type of forms, including triangular, trapezoidal and Gaussian and B-spline functions (Brown and Harris, 1995). Even though fuzzy membership functions can take many forms, but simple straight-line functions are often preferred. Triangular functions with equal base width are the simplest possible and these are often selected for practical applications.

Fuzzy algorithms are formed by the union (use of the fuzzy OR operator) of individual fuzzy rules (Brown and Harris, 1994). The way in which the fuzzy operators (IF, THEN, AND, OR) are implemented can have a significant impact on model performance. Generally, truncation operators are used for this purpose (Zadeh, 1973). However, the use of algebraic operators has recently gained popularity (Wang and Mendel, 1992) as they produces smoother outputs (Brown and Harris, 1994). If a real valued output is required, a defuzzification process has to be carried out. This is generally achieved by either using a mean of maximums or a center of gravity defuzzification strategy (Brown and Harris, 1994).

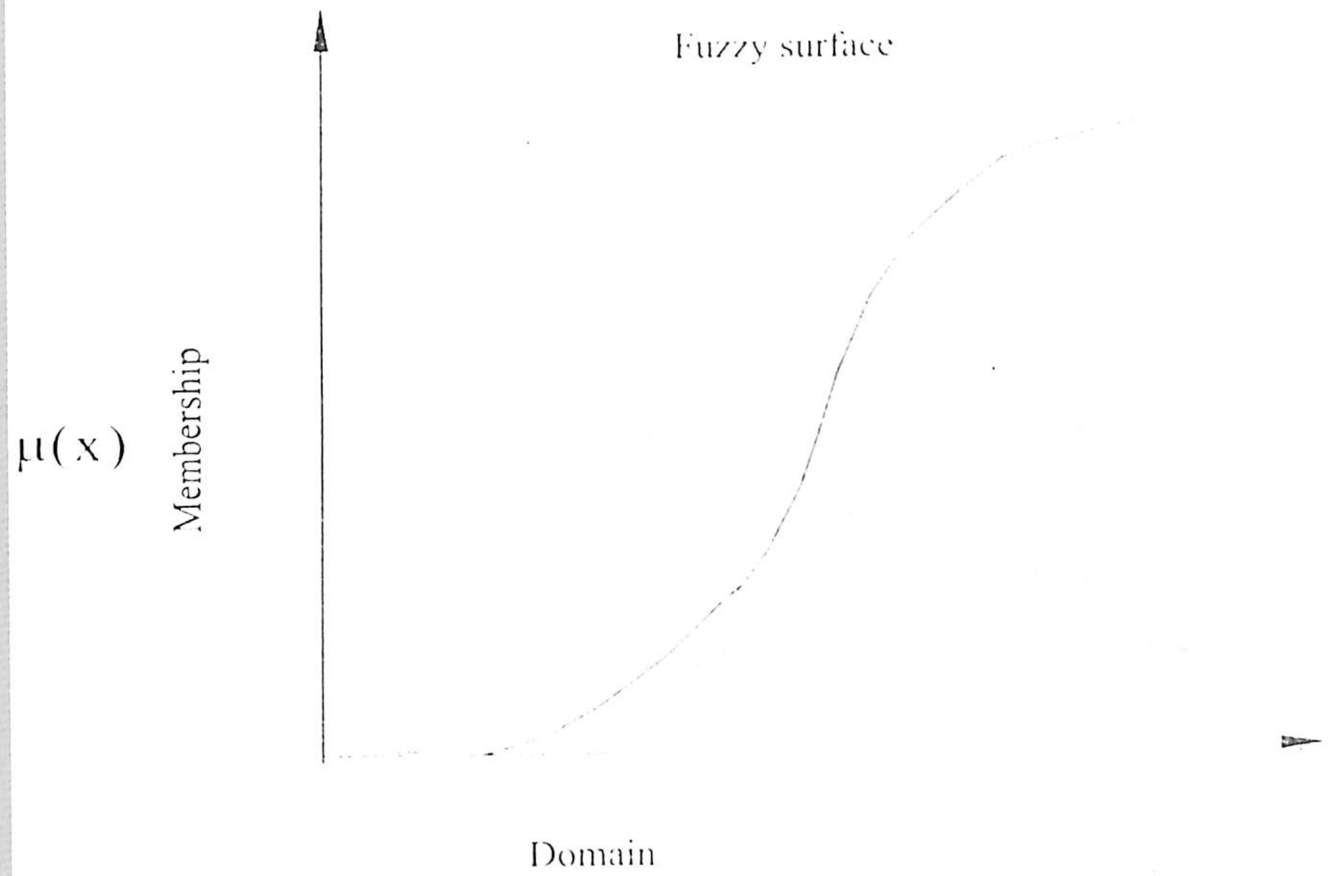

Fig.3.3.General structure of a fuzzy set

Fuzzy systems are defined by a number of fuzzy rules, a number of membership functions, and mechanisms to apply logical operators. Fuzzy rules can be of the following form:

" If the value of variable x is LARGE and variable y is MEDIUM then the variable z is SMALL." (3.6)

It is claimed that such rules more closely resembled the way we think than the more explicit mathematical rules. To model the thinking of a human expert, input variables are specified by category, such as "LARGE"; and fuzzy rules such as the one outlined in the preceding are developed on the basis of the expert's knowledge and experience. In the fuzzy inference method, sets of inputs data along with the corresponding outputs are provided to the fuzzy system and it "learns" how to transform a set of inputs to the corresponding set of outputs through a fuzzy associative mapping (FAM), sometimes called fuzzy associative memory (Kosko, 1992, 1993).

3.2.1 Fuzzy Compositional Rule of Inference

The simple mini-max method of fuzzy compositional rule of inference is used in this study.

Let us consider a rule

If x is VERY SMALL and y is MEDIUM then the output z is MODERATE (3.7)

First using the predicates, according to the mini – max method, the truth functions of the predicates are compared and minimum of it is considered.

$$\mu_{cfs} = \mathrm{Min}\,(\mu_{VS}(x_i),\ \mu_M\,(y_i)) \qquad (3.8)$$

Then the maximum of the truth functions of μ_{cfs} and μ_z will be considered for the next stage and used for truncating the output surface (Fig.3.4) i.e.

$$Max\ (Min\ (\mu_{VS}(x_i),\ \mu_M\ (y_i)),\ \mu_{MO}(Z)) \tag{3.9}$$

When more than one rule is fired then the final surface is decided by comparing the end result of both the rules. For example, let us consider the following rule base.

If x is VERY SMALL and y is MEDIUM, then the output z is MODERATE

If x is VERY SMALL and y is LARGE, then the output z is MODERATE

(3.10)

The output surface is truncated as (Fig.3.5).

$$Max\ \{Min\ (\mu_{VS}(x_i),\ \mu_M\ (y_i),\ \mu_{MO}(Z)),\ Min\ (\mu_{VS}(x_i),\ \mu_L\ (y_i),\ \mu_{MO}(Z))\} \tag{3.11}$$

A fuzzy logic system is more flexible and more transparent. Using the black box analogy, it is possible to open the lid, see how it works, and adjust it if necessary. The general fuzzy system modeling is given in Fig.3.6.

3.3 NEURO-FUZZY HYBRID MODEL

While neural networks are ideal for modeling known or unknown associations that exist between the input and output data, significant data cleaning and preprocessing are usually needed and the input data must be carefully prepared for the network to process. However, sometimes, training requires substantial time and resources. These difficulties restrict the widespread use of neural networks in many applications. In many decision-making systems, it is important to be able to explain the process by which the decision is made. In most of the cases, the development of ANN models were either described poorly or carried out incorrectly (ASCE task committee, 2000).

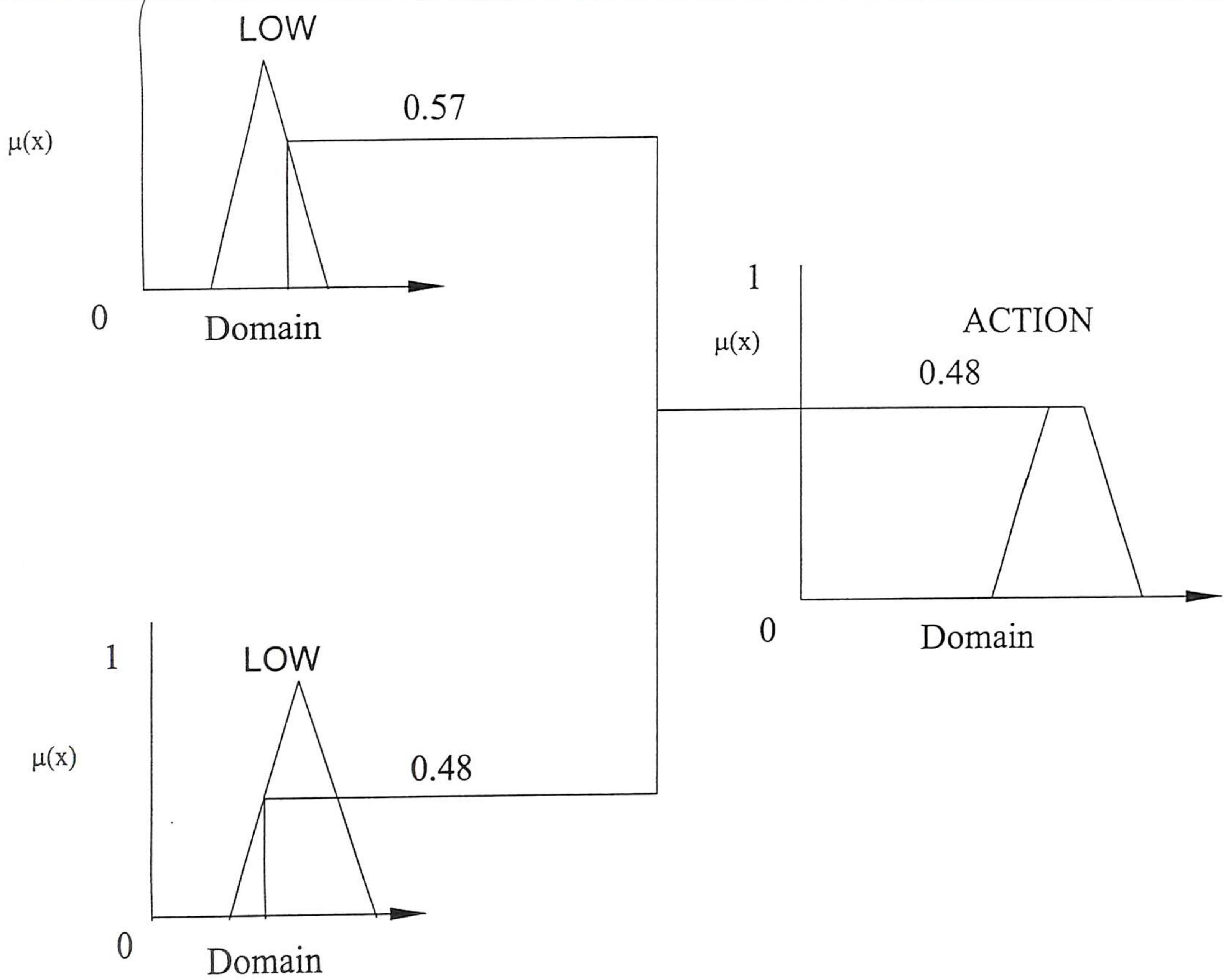

Fig.3.4.Truncating output surface

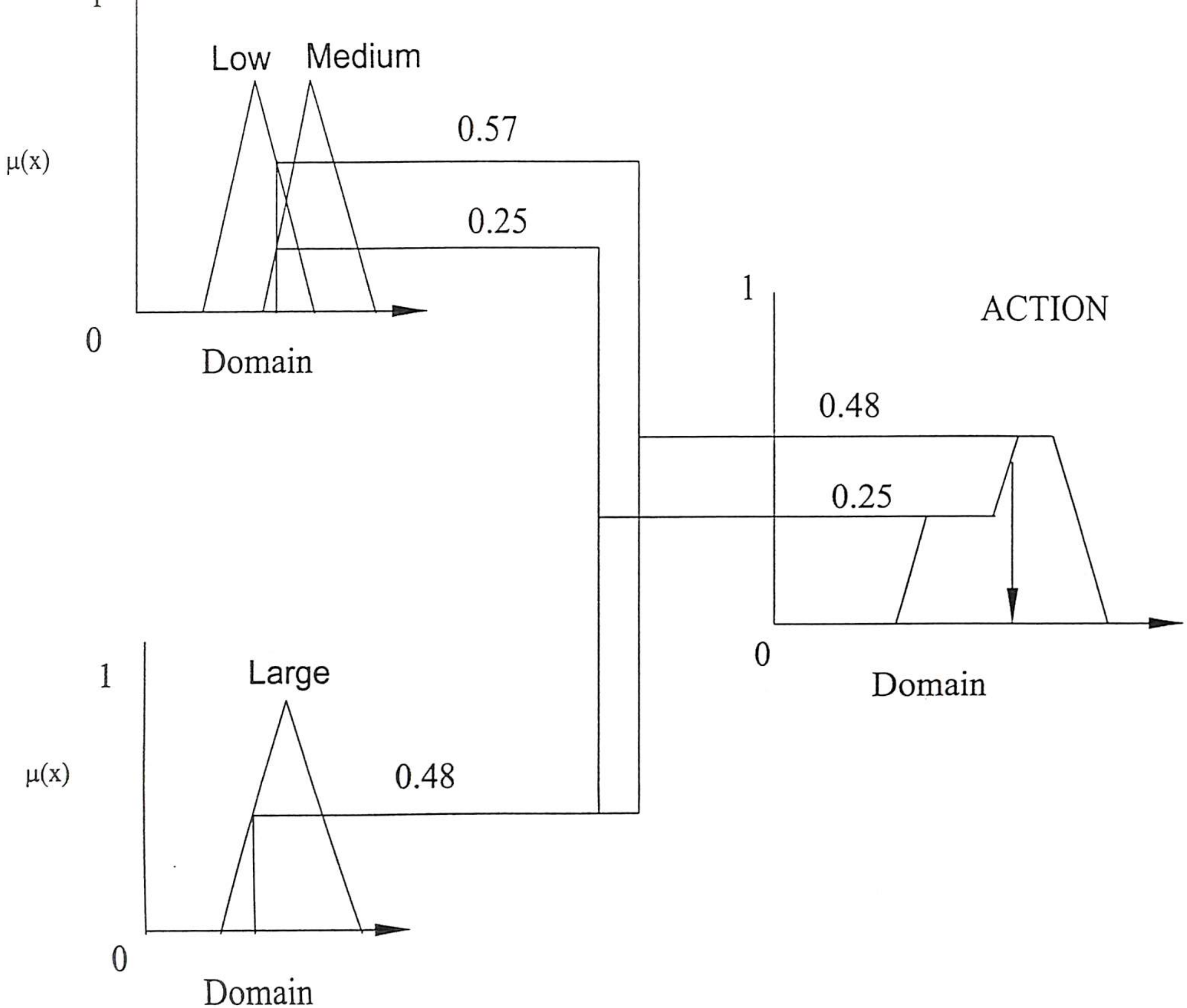

Fig.3.5.Minimum of membership function is to be considered

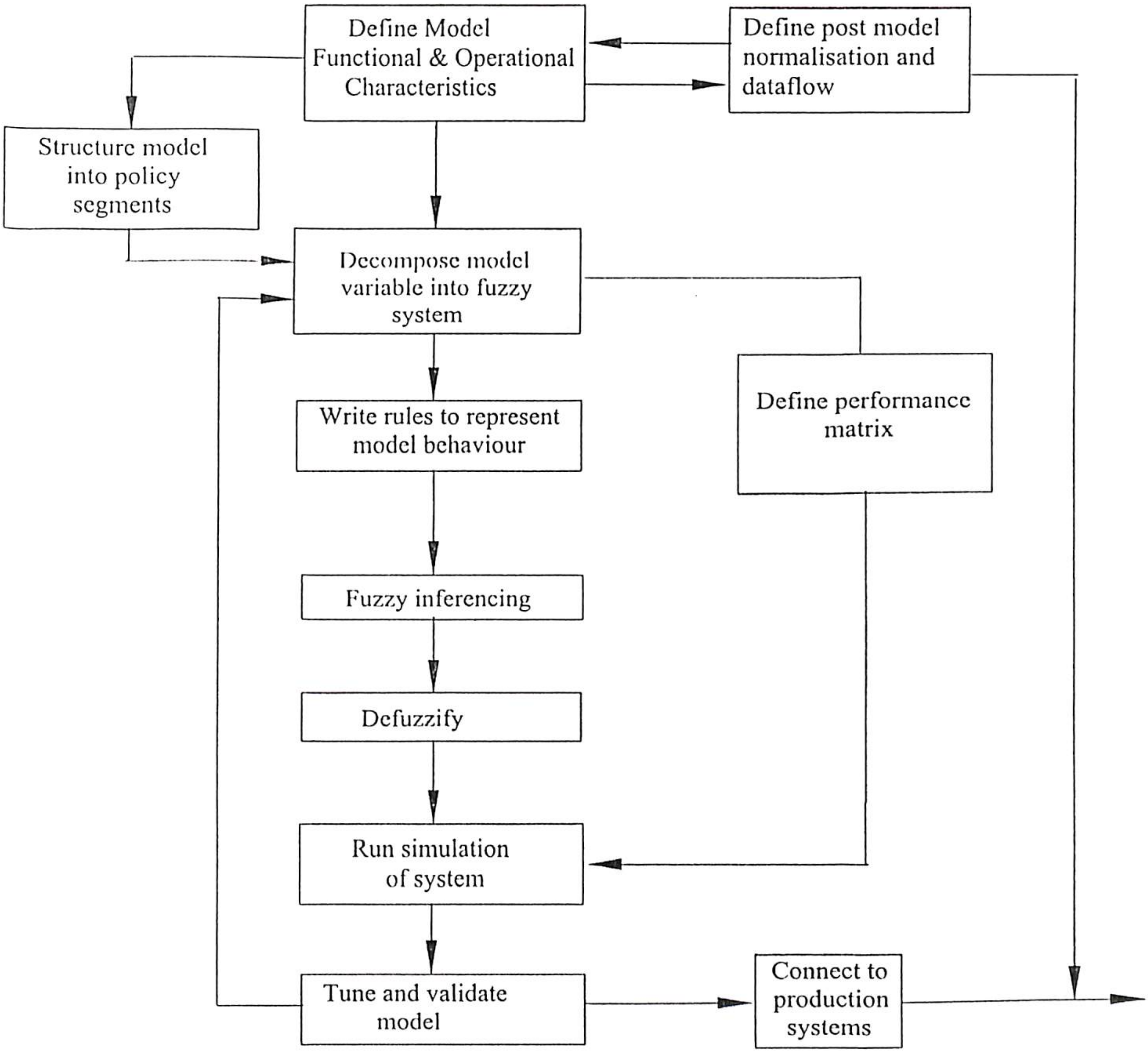

Fig.3.6.Fuzzy system development methodology

The main concept in fuzzy logic is to use unsharp boundaries of membership functions to describe the implicitly imprecise concepts in data representation. From this perspective, fuzzy logic is ideally suited for user interactions and data representation. Using the extension principle, most of the crisp operations can be readily adapted to fuzzy operations. In the crisp domain, models are made using regression or autoregressive-moving average representations. Likewise in the fuzzy domain, fuzzy models can also be made using fuzzy regression and fuzzy operators. Hence, fuzzy operations include both logical operations and numerical operations. Another useful feature of fuzzy logic is its ability to make inferences. Propositions are readily represented by fuzzy values. Since implication is also a fuzzy operator, approximate reasoning can be carried out naturally as fuzzy computations.

The concept of fuzzy logic clearly complements those of neural networks. The fuzzy logic provides knowledge from the data set but the neural network could not provide any knowledge to the user from the data set. Fuzzy logic can be used to model a system. Again, neural networks are suitable for modeling diverse type of systems. If there is prior knowledge about a system, fuzzy logic can easily convert the knowledge in terms of rules and relations. But it is difficult to preprogram a neural network with prior knowledge.

The proposed methodology is presented in the Fig.3.7. The algorithm uses artificial neural network model to derive the membership function for every fuzzy set created using the data (historical / generated) from other models or historical data. Proposed modeling approach is flexible and more specific. Different strategies have been adopted in developing the hybrid model for different studies and are presented in respective

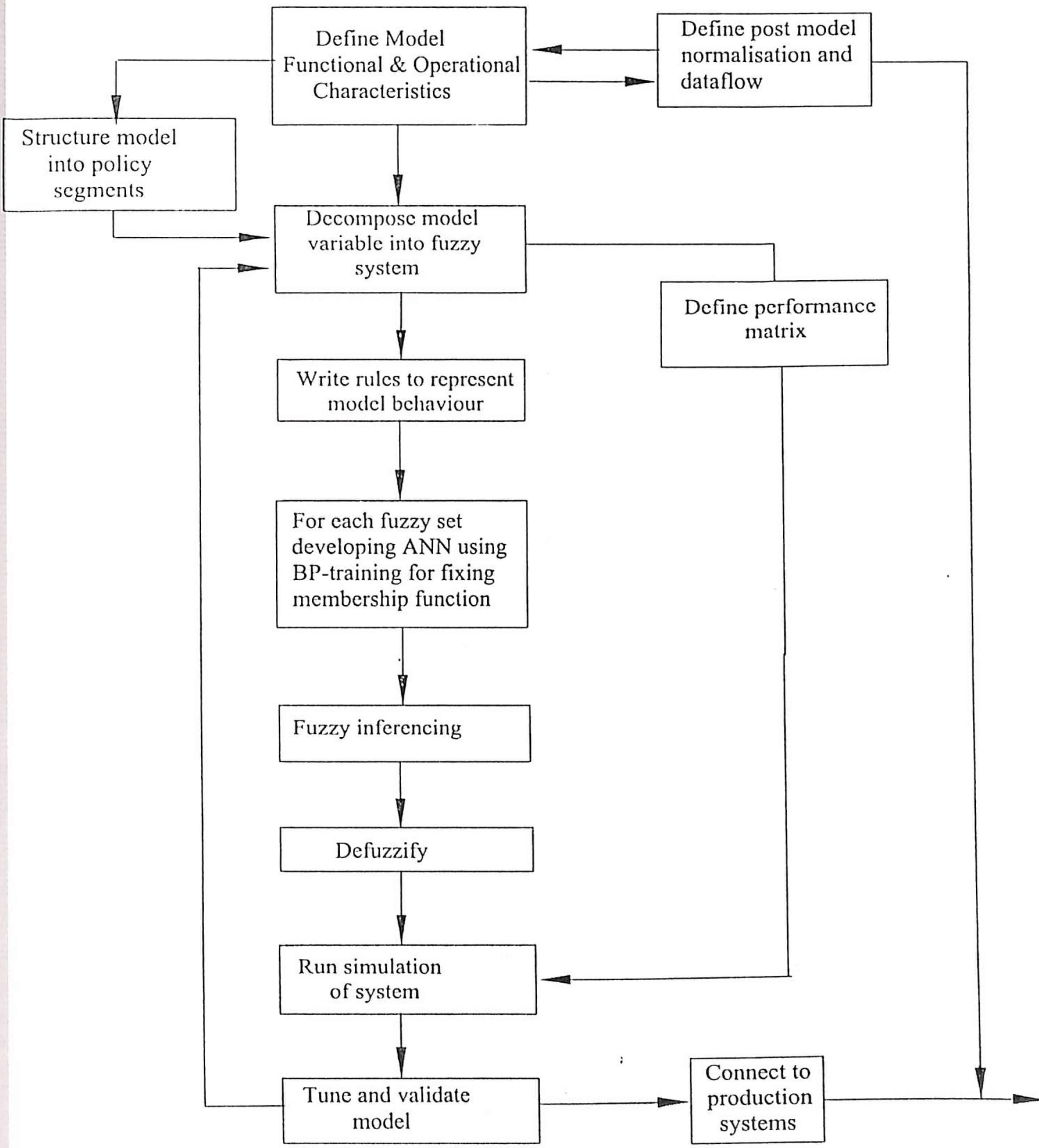

Fig.3.7.Proposed fuzzy system development methodology

chapters. The monotonic fuzzy implication or mini-max fuzzy composition rule of implication is used depending upon the number of rules that are fired.

In the proposed methodology, the following steps are followed in sequence:

1. Identifying the variables influencing the phenomenon and fuzzification of the inputs. This step involves a good assessment on the universe of discourse for each variable, creating fuzzy sets, fuzzy overlapping for adjacent fuzzy sets, etc.
2. Creating the rule base based on expert knowledge base
3. For each fuzzy set, from historical or synthesized data, training neural networks for finding membership function value. The problem of constructing a membership function is that of capturing the meaning of the linguistic terms employed in a particular application adequately and of assigning the meanings of associated operations to the linguistic terms.
4. Application of fuzzy operator and the fuzzy rule implication
5. Defuzzification
6. Simulation to verify the performance
7. Tuning if necessary

For every case study considered, the model development is very specific and according to the requirements, the model has been planned.

3.4 STAGE DISCHARGE RELATIONSHIP USING FUZZY NEURAL NETWORK MODEL

3.4.1 Introduction

For many hydrological analyses, streamflow monitoring on a regular basis is very essential basic information. In major rivers, the discharge estimation is very expensive and time consuming. The accuracy in the measurement of discharge is very essential and requires lot of skill. Thus the stage-discharge relationship has important bearing on correct assessment of discharge and the subsequent use of discharge data for water yield and hydrologic design. Hence in practical field, stage data is observed and from a stage discharge relationship (known as rating curve) the discharge is estimated. A rating curve is fitted using the simultaneous observations of the stage and discharge, often using a regression analysis. The process of establishing a rating curve is a mapping problem where stage is input variable and discharge is output variable. Such problem can be better addressed through a non-linear mapping approach. Unfortunately, for many applications the theory does not guide the model building process by suggesting the relevant input variables or the correct functional form. This difficulty makes it attractive to consider an "a theoretical" but flexible class of statistical models (Anders and Korn, 1999). ANN is powerful tool to relate sets of predictor variables (stage) to forecast variables (discharge) in non-linear ways.

Rating curves often exhibit hysteresis, with the stage-discharge relationship being different for rising and receding stages. The main limitations of conventional methods are problems associated with non-unique stage-discharge relations. It is caused by (1) Backwater effects (2) Hysteresis effect (loop rating curve) (3) Morphological changes: basically change in cross sectional area (4) Roughness changes: changes in channel bed material, changes in channel bed forms, vegetation growth, and bottom surface of ice cover.

Most of the gauging stations were selected so that the relationship between stage and discharge is expressed in a one valued curve or function and the hysteresis effect is not present. Very few locations satisfy this requirement. In other locations where looping stage discharge plot occur, the current practice requires the fitting of two separate relationships: one is for the rising phase and another for the falling phase. A single relationship is inadequate, while using two separate relationships leads to problems of separation.

Considering the Saint-Venant equations, when kinematic effects dominate the flow propagation, gravity and friction dominate over the other dynamic terms. It is only under these conditions that stage and discharge are uniquely related. This is usually the case of flood propagation in mountain rivers. Conversely, in flat rivers, besides gravity and friction, pressure becomes an important factor (Henderson, 1966). In flat rivers near a confluence with a river of similar size and flow, the convective acceleration terms becomes important to the dynamics of the flood propagation, even for a slowly rising flow, i.e. flow with negligible local acceleration. In this case, the rating curve cannot be represented as a one to one relation between stage and discharge. Instead, a third variable is to be used as an auxiliary variable for the rating. Two variables often used as auxiliary variables are the rate of change of stage at the rating station and the water stage at a nearby station along the stream (Kennedy, 1984). Use of the latter auxiliary variable is somewhat equivalent to including the water surface slope in the rating curve. Thus, using an estimate of the water slope as an auxiliary variable is a plausible approximation used in the hydrometry for correcting the rating to account for the hysteresis (Ansar and Gonzalez-Castro, 2002). Irrespective of the type of modeling, a closer look into the interrelation among the variables that govern the process may be the best tool for deciding what data should be included in the model.

Successful application of ANN in deriving the stage discharge relationship is reported in recent literature. Tawfik et al. (1997) used ANNs, with a saturating linear transfer function, to predict flow discharges at two locations over the Nile river using the stage, H, and the rate of change of stage, $\frac{dH}{dt}$, as network inputs. ANNs were shown to predict discharge without exhibiting the separation problem associated with a method that uses different regression relationships for the rising and receding portions based on when $\frac{dH}{dt}$ changes sign.

Jain and Chalisgaonkar (2000) established stage-discharge relationship using ANN with current stage as single input and current discharge as output. They also tried with more inputs like previous two days stages and discharges for predicting current day discharge as output. They found that better relationship could be possible with inclusion of stages as well as discharges of earlier days for current day discharge. They also found that the hysteresis effect could effectively be handled by the same mentioned network architecture with no partition of rising and falling data. They used hypothetical data to study the hysteresis effect. For stage discharge relationships, gauging site data of river Narmada and its tributary in India, were used.

Jain (2001) used neural networks for development of integrated sediment rating curves and found better than other conventional methods. He used current stage, previous stage, previous discharges, previous sediment concentrations as input variables for hysteresis effect considerations as these includes water surface slope as well as rate of change of the water surface slope. Sudheer and Jain (2003) used Radial Based Function (RBF) network for deriving stage-discharge relationship and found that it was better than back-propagation multi-layer perceptron (BP-MLP) network when there are situation of loop-rating curve. For high flow also, BP-MLP is inferior to RBF network.

In the study, the inclusion of terms for current, previous, one more previous period river stage data, and previous period discharge data for modeling indirectly incorporated the water surface slope as well as the rate of change of the water surface slope (Sudheer and Jain, 2003).

The unsteady flow effect leads to a loop curve, making the same stage representing two different discharge values in the rising and falling limbs of a flood wave and the relationship between stage and discharge is complex and fuzzy due to this hysteresis effect. Hence a fuzzy neural network modeling approach is attempted in this study to establish a better stage discharge relationship. A fuzzy neural network (FNN) is a neural network equipped with the capacity of handling fuzzy information, i.e., the input signals and / or connection weights and / or the outputs are fuzzy subsets or a set of membership values of fuzzy sets. In this study, the ANNs are trained using historical data to generate the fuzzy membership functions based on the input stage values. The performance of the suggested model is compared with simple ANN model, modularized ANN model and conventional model.

3.4.2 The system considered – A general description

The Brahmaputra river originates as Tsangpo, the source of which is at $31^0 30'$N and 82^0E in Tibet, in a great glacier mass in the Kailash range of the Himalayas to the east of the Mansarovar Lake (elevation 5300m) and flows through China, India, and Bangladesh for a total distance of 2880 km. before emptying in to the Bay of Bengal through a joint channel with the Ganga. The basin lies between latitudes $24^0 13'$ and $31^0 30'$ North and longitudes $82^0 00'$and $96^0\ 4'$ East. In Tibet, where it is called Tsangpo, the Brahmaputra flows eastward for 1100 km along the bottom of a longitudinal graben parallel to and about 160 km north of the Himalayas. At the extreme eastern end of its course in Tibet, the Tsangpo suddenly enters a deep narrow gorge at Pe (3500 m), which skirts around the Namcha Barwa peak (7755 m) and continued southward across the Himalayan ranges. The gradient of the river in the gorge section ranges from about 4.3m. to 16.8 m. per km. On entering India, the Tsangpo, now called Dihang, traverses 226 km. of mountainous course before debouching onto the Assam plain near Pasighat (elevation 155 m.). At the exit of the gorge the slope of the river is only 0.27 m. per km. Near Kobo, 52 km. south of Pasighat, two rivers (Dibang and Lohit) meet the Dihang, and the combined flow, called the Brahmaputra, moves westward thorough Assam for 720 km. until near Dhubri, where it swerves to the south and enters Bangladesh. The Brahmaputra has a gradient of 0.09-0.17 m./km. near Dibrugarh at the head of the valley and is further reduced to about 0.1m./km. near Guwahati (Pandu).

The Brahmaputra is the fourth largest river in the world in terms of average discharge at mouth, with a flow of 19,830 cumec. The hydrologic regime of the river responds to the seasonal rhythm of the monsoons and to the freeze-thaw cycle of the Himalayan snow. The rainy season (May to October) accounts for 82% of the mean annual flow at Pandu.The discharge is highly fluctuating. Discharge per unit drainage area in the Brahmaputra basin rivers is among the highest of major rivers of the world. At Pandu, the Brahmaputra yields 0.0306 cumec per sq.km and the mean annual flood discharge is 51,156 cumec.

The Brahmaputra is one of the most sediment-charged large rivers of the world. Among the largest rivers of the world, it is second only to the Yellow river in China in the amount of sediment transported per unit of drainage area.

The Brahmaputra valley is approximately 80 km. width in Assam. The total catchment area is 5,80,000 sq.km covering the full length from the source to the confluence of Bay of Bengal. The average width of the river is 5.46 km.

The average rainfall in the catchment is 2500 mm. due to the monsoon. More than 100 tributaries are available in the Brahmaputra river within Assam State. Out of which, 39 tributaries can be considered as major where 22 are north bank and 17 are south bank tributaries.

Flooding, bank erosion and drainage congestion are major problems of Assam during monsoon period. The problem varies from year to year and area to area. Flood in 3 to 4 waves is an annual feature that wipes out major chunk of the fruit of the people's labour. Area liable to floods in Assam and India as a whole as estimated by the National Flood Commission are 31.60 lakh hectares and 335.16 lakh hectares respectively. Assam thus account for 9.4% of the total flood prone area in India mainly because of Brahmaputra river and its tributaries. The main factors causing extensive floods are the adverse physiography of the region, heavy rainfall, excessive sediment due to frequent earthquakes and hill slides, reduction of forest coverage and encroachment of the riverine area due to population explosion. Major floods that have occurred in recent times are in 1954,1962,1966,1972,1977,1984,1988 and 1998 though floods of lesser magnitude occur almost every year.

The study area is shown in Fig.3.8. Out of four gauge discharge sites within Assam state, three gauging stations, namely Bessamara, Bhurbandha and Pandu (hereafter referred to as Gauging station I, Gauging station II and Gauging station III), are considered and daily stage discharge values for these stations are used for this research study. The daily flow data for these stations were collected from the Flood

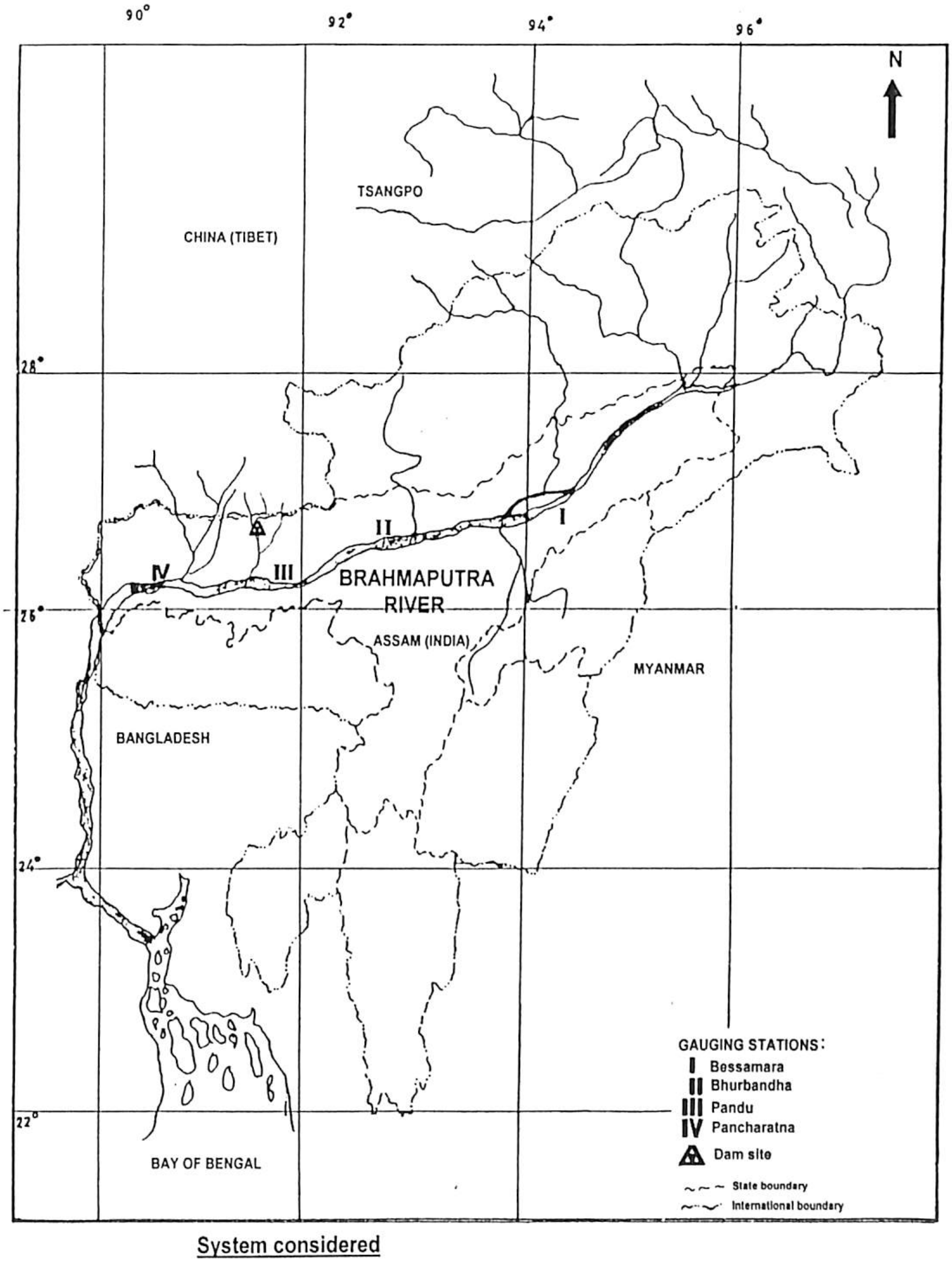

Fig.3.8 System considered- Brahmaputra River Basin

control department of Assam State (now Water Resources Department, Assam), India. The upstream gauging stations I and II are located at about 340 km and 150 km upstream of gauging station III respectively. The availability of data for different stations and the data considered for model training and testing are shown in Table 3.1.

For this research study, four models, namely a conventional curve-fitting model, a single neural network model, a modularized neural network model and a fuzzy neural network model, are considered for deriving the stage discharge relationship.

Table 3.1 Data availability, values of a and b for the conventional model and neural network architecture for different gauging stations considered

Sl. No	Gauging station	Data availability		Conventional model		NN architecture (Number of neurons)		
		Training	Testing	a	b	Input layer	Hidden layer	Output layer
1	**Gauging station I**							
	Experiment 1	1600	480	148.00	2.38	1	3	1
	Experiment 2	1600	257			4	4	1
2	**Gauging station II**							
	Experiment 1	1000	358	106.55	2.55	1	2	1
	Experiment 2	800	346			4	8	1
3	**Gauging station III**							
	Experiment 1	2500	891	127.68	2.45	1	3	1
	Experiment 2	2500	889			4	8	1

3.4.3 Conventional Model

Usually a functional relationship between stage and discharge is established with the help of field measurement and the relationship is expressed as a rating curve. Stream flow measurements are normally derived using the stage-discharge curve for transforming the record of stage into a record of discharge (Maidment, 1992). Normally a rating curve of the following form is used

$$Q = a(G - G_o)^b \tag{3.12}$$

Where Q = Discharge in m^3/s , G = River stage in m, G_o = River stage in m at which the discharge is nil and a, b = constants.

This type of relation is established by fitting a smooth curve between the stage and discharge records either by an ordinary or logarithmic scale. The stage for zero discharge is an unknown and its determination possesses some difficulties for major rivers. Sometimes iterations are performed with various values of G_o, and the value that gives the minimum sum of squares of errors for the model training data sequence is adopted. Depending on the channel behavior, two or more curves are also fitted to the data. A major limitation of this approach is that it is not able to consider the hysteresis effect (Fig.3.9).

In this study, G_o has been estimated from the observed data and the best values of a and b for the given range of stage are obtained by the least-squares error method (Table 3.1).

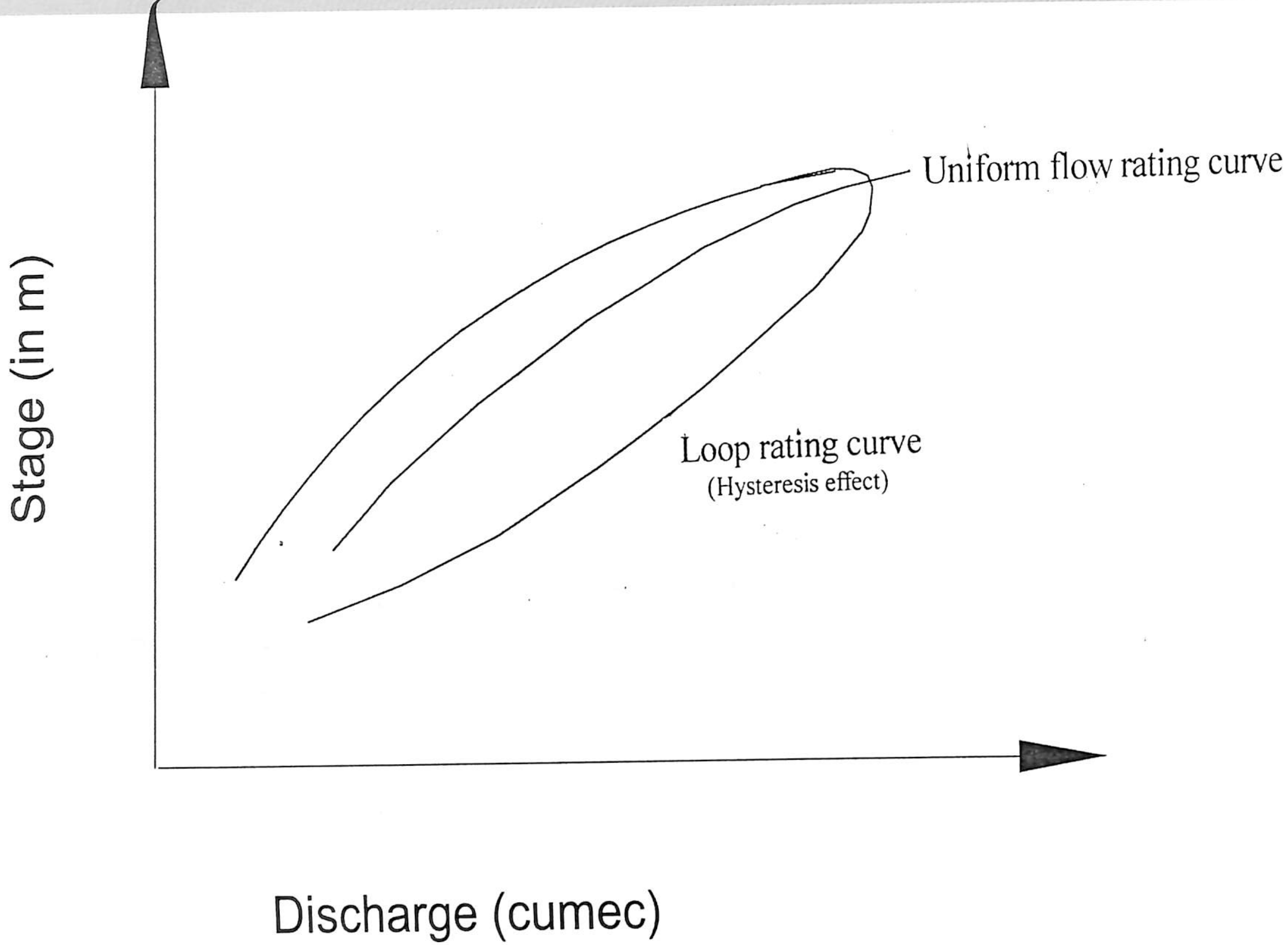

Fig.3.9.Conventional rating curve

3.4.4 Artificial Neural Network Model

As considerable amount of data about the studied process is available (as it is in the considered case), instead of the use of simplified "traditional" techniques such as a rating curve, using all the available data, a data driven ANN model is developed for deriving stage discharge relationship in this study. The single ANN model developed for this study is a feed forward neural network model. The training is carried out using the error back propagation algorithm (Rumelhart and McClelland, 1987). As the stage and discharge are time-dependent and very often they exhibit random fluctuations, their relationship is not always unique, one of the solutions is using more observations from several previous time steps and to build more complex ANN model. Two experiments on ANN models are developed in this research study. A single input and single output model (experiment 1) and four inputs and single output model (experiment 2) are used (Fig.3.10a, Fig.3.10b) after a detailed check of different combinations.

Mean Squared Error (mse) and Mean Relative Error (mre) indices are used in the analysis for proper training. Elshorbagy et al. (2000) introduced an index called the pooled mean square error (PMSE) and discussed the merits of this index. This index is also considered for comparing the performance of different models in this study. The number of neurons in the hidden layer, the number of hidden layers and the normalization factor for the data considered are decided after many trials by studying the performance of the ANN training indices. The details of different neural network models developed for the two experiments considered are listed in Table 3.1. The mse and mre indices for the conventional model for the three gauging stations considered are presented in Table 3.2 for training results. The Table 3.3 and Table 3.4 present the training results of experiment 1 and experiment 2 for ANN models.

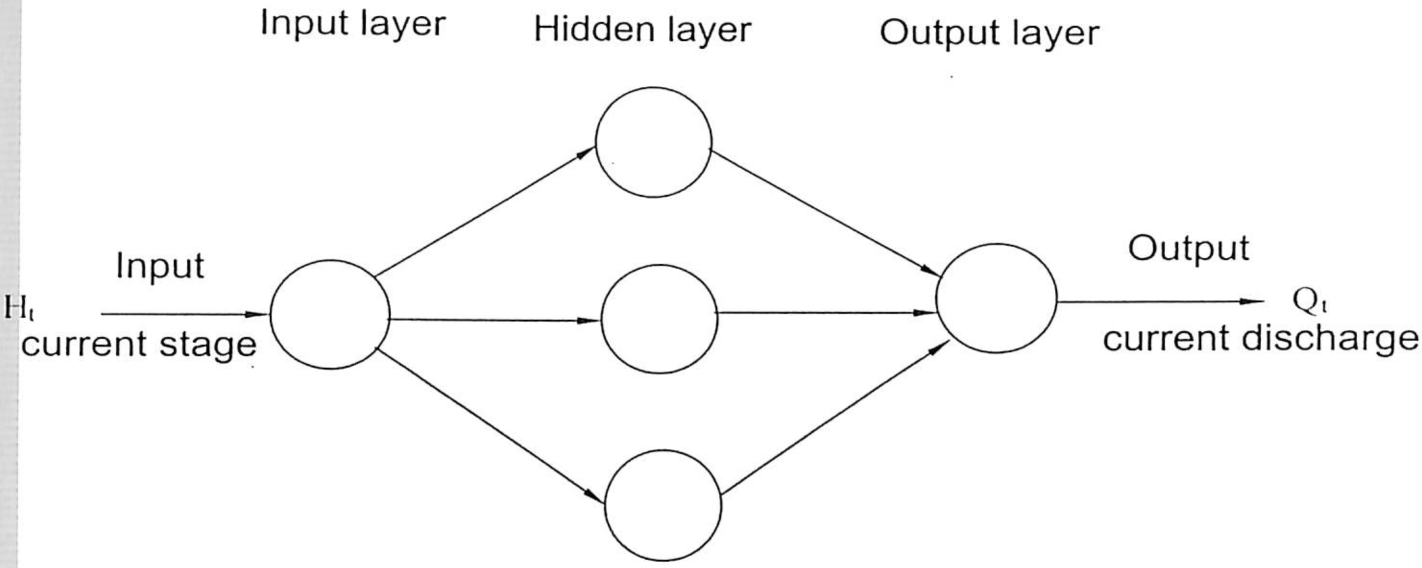

Fig.3.10a.ANN model (Expt.1)

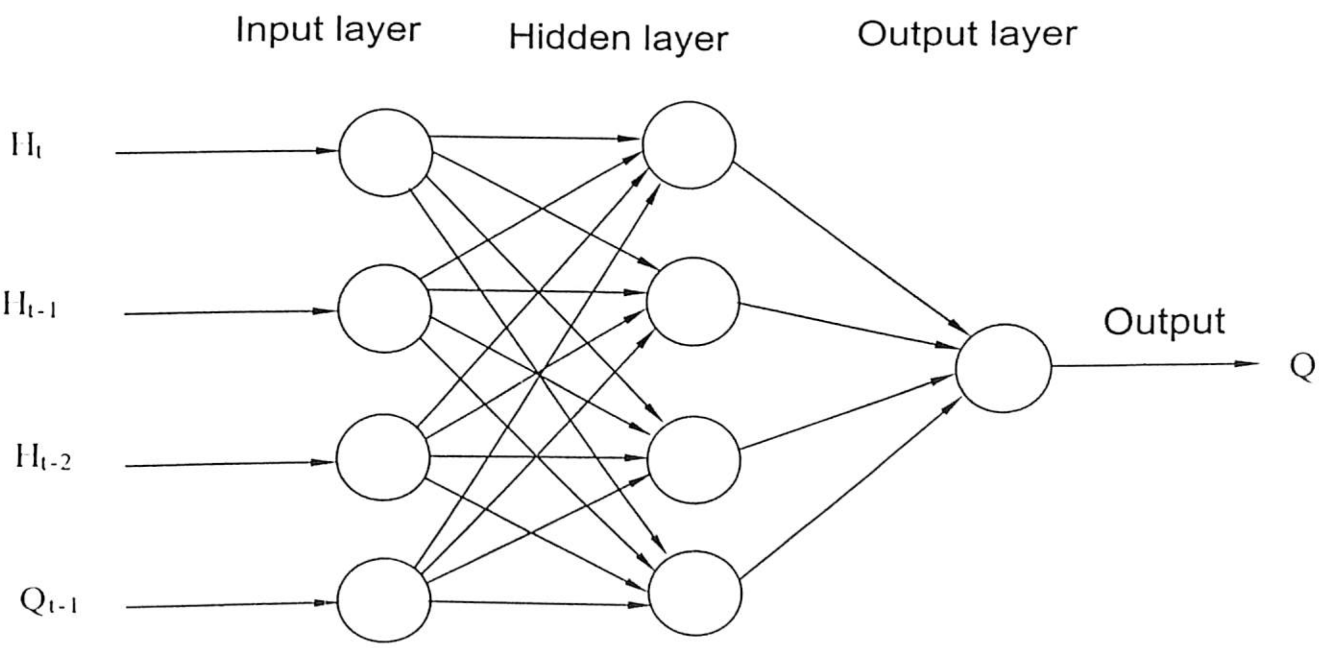

Fig.3.10b.ANN model (Expt.2)

Table 3.2 CONVENTIONAL MODEL (Training results) Expt.1

Sl. No	Gauging station	Training range (level in m)		Number of patterns	mse $x10^6(m^3/s)^2$	mre
		From	To			
1	I	80.03	87.80	1600	7.28	31.59
2	II	58.13	66.94	1000	10.09	30.34
3	III	40.79	49.95	2500	28.25	39.04

Table 3.3 ANN MODEL (Training results) Expt. 1

Sl.no	Gauging station	Training range (level in metre)		Number of patterns	mse $x10^6(m^3/s)^2$	mre
		From	To			
1	I	80.03	87.80	1600	6.06	26.74
2	II	58.13	66.94	1000	8.97	23.22
3	III	40.79	49.95	2500	7.99	17.34

Table 3.4 ANN MODEL (Training results) Expt. 2

Sl.no	Gauging station	Training range (level in metre)		Number of patterns	mse $x10^6(m^3/s)^2$	mre
		From	To			
1	I	80.03	87.80	1600	1.38	5.83
2	II	58.13	66.92	800	3.71	9.03
3	III	40.79	49.95	2500	5.78	5.56

3.4.5 Modularized Neural Network Model

For improving the performance of the neural network model, Zhang and Govindaraju (2000) suggested a modularized neural network approach for rainfall runoff modeling. They showed the advantages of segregating the patterns considered for training and organized the neural networks in a modular architecture to handle complex sets of rainfall-runoff data. They examined the performance of the modular networks in predicting runoff over three medium sized watersheds and showed that the modular networks as good alternatives for predicting runoff. A modularized neural network modeling approach is attempted in the present study for developing the stage discharge relationship (Fig.3.11).

In the modularized neural network (MNN) approach, the available patterns are segregated to small sub groups based on some criteria. After segregation, each sub group is trained with a neural network model. After completion of the training, with the help of

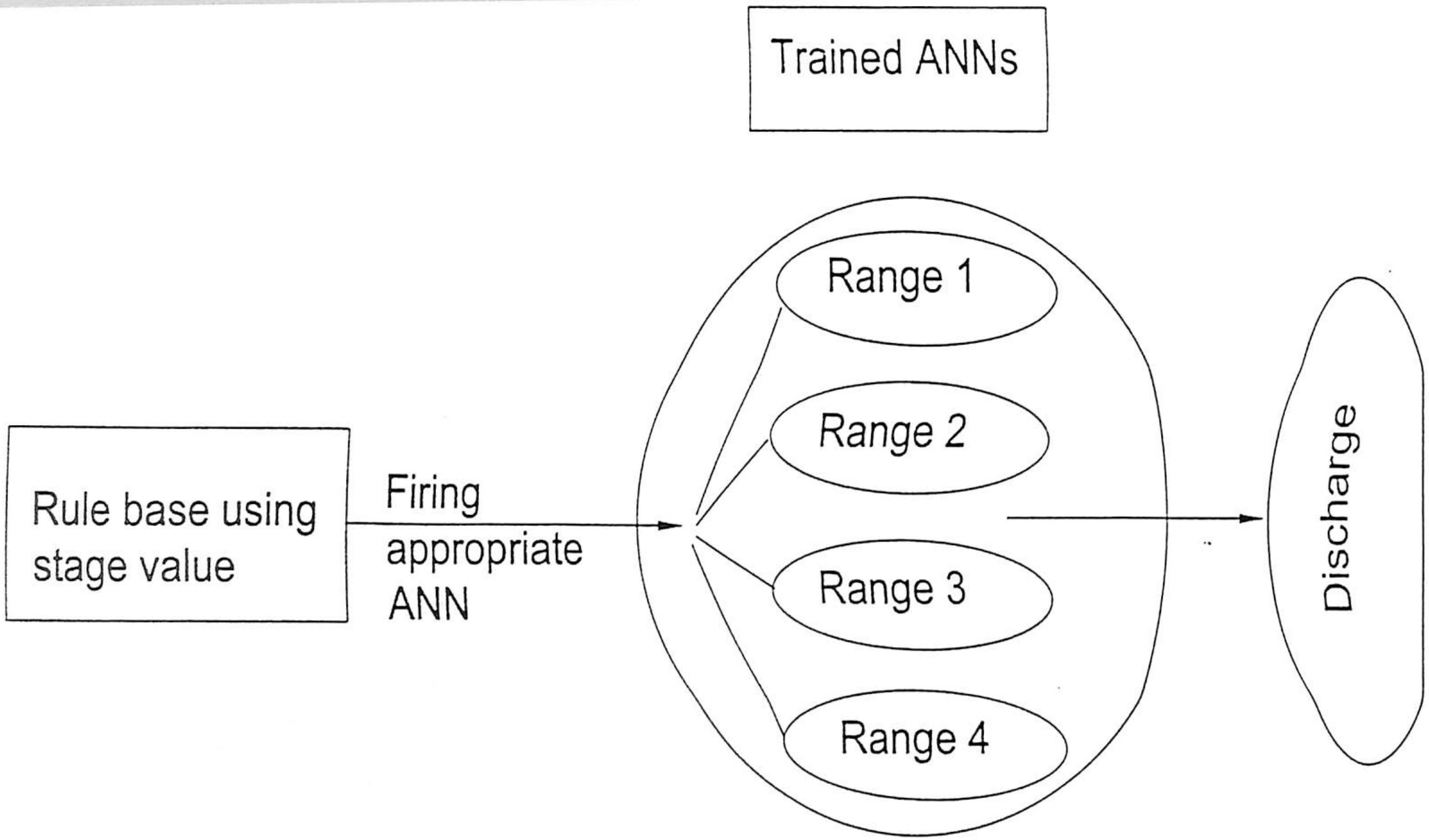

Fig.3.11.Modularized Neural Network model (MNN)

a rule base, which works on the criteria fixed for segregation, the appropriate neural network will be fired to obtain the final result. In the present case study, the available stage discharge data are segregated into four groups based on stage level, and each group is treated as a crisp set. In this approach, instead of a neural network model for the whole set of data, four neural network models, one for each group of data, are developed. The data range is fixed after examining the available patterns. Each set is used separately to train a neural network model. For the three gauging stations, for each group, the range of stage level (in m) and training results are given in the Table 3.5 and Table 3.6.

3.4.6 Fuzzy Neural Network Model

The unsteady flow effect leads to a loop curve, making the same stage representing two different discharge values in the rising and falling limbs of a flood wave and the relationship between stage and discharge is complex and fuzzy due to this hysteresis effect. Hence a fuzzy neural network modeling approach is attempted in this study to establish a better stage discharge relationship. In this study, the ANNs are trained using historical data to generate the fuzzy membership functions based on the input stage values.

In the fuzzification, the entire stage domain for a particular gauging station is assessed and the stage value is categorized into four fuzzy sets namely VERY LOW, LOW, MEDIUM and HIGH. Table 3.7 and Table 3.8 show the ranges of stage domain used for each fuzzy set. Similarly, the discharge domain is also categorized into four fuzzy sets namely VERY LOW, LOW, MEDIUM and LARGE. The overlapping of each fuzzy set is kept as 50 % of the previous set (if any) and 50 % of the subsequent set (if any).

Table 3.5 MNN MODEL (Training results) Expt.1

Sl.no	Gauging station		Training range (level in metre) From	To	No. of patterns	mse $x10^6(m^3/s)^2$	mre
1	I	Module I	80.03	81.09	400	0.66	28.93
		Module II	81.10	83.27	400	6.59	21.06
		ModuleIII	83.28	85.37	400	7.07	15.83
		ModuleIV	85.37	87.80	400	8.00	23.69
		Average performance				**5.51**	**22.37**
2	II	Module I	58.13	60.06	250	9.55	8.6
		Module II	60.07	61.76	250	3.35	31.52
		ModuleIII	61.76	64.26	250	13.67	27.50
		ModuleIV	64.26	66.94	250	17.83	15.67
		Average performance				**8.74**	**20.82**
3	III	Module I	40.79	41.91	625	3.66	32.60
		ModuleII	41.91	43.74	625	18.10	19.26
		ModuleIII	43.75	46.95	625	1.01	4.14
		ModuleIV	46.96	49.95	625	6.53	5.72
		Average performance				**7.33**	**15.43**

Table 3.6 MNN MODEL (Training results) Expt.2

Sl.no	Gauging station	Training range (level in metre)		No. of patterns	mse $x10^6(m^3/s)^2$	mre
		From	To			
1	I	80.03	80.98	400	0.02	4.56
		80.98	83.01	400	0.14	5.54
		83.01	85.20	400	0.53	5.98
		85.21	87.80	400	4.72	6.55
		Average performance			**1.35**	**5.66**
2	II	58.13	60.08	200	0.29	9.11
		60.08	61.64	200	0.96	7.17
		61.64	64.19	200	2.87	8.66
		64.19	66.92	200	7.77	9.22
		Average performance			**2.97**	**8.54**
3	III	40.79	41.92	625	0.03	2.26
		41.92	43.75	625	14.28	5.14
		43.75	46.96	625	2.15	6.45
		46.97	49.95	625	4.27	4.36
		Average performance			**5.18**	**4.55**

Table 3.7 FNN MODEL (Training results) Expt.1

Sl.no	Gauging station		Training range (level in metre) From	To	No. of patterns	mse $x10^6(m^3/s)^2$	mre
1	I	Module I	80.03	82.11	600	1.42	35.01
		Module II	80.71	84.23	800	5.08	38.35
		Module III	82.11	86.14	800	6.91	24.31
		Module IV	84.23	87.80	600	9.78	16.78
		Average performance				**5.83**	**29.00**
2	II	Module I	58.13	60.92	375	1.09	20.08
		Module II	59.52	63.15	500	6.41	44.03
		Module III	60.93	65.71	500	12.74	25.39
		Module IV	63.18	66.94	375	17.96	18.49
		Average performance				**9.55**	**28.09**
3	III	Module I	40.79	42.70	937	13.57	31.42
		Module II	41.42	45.39	1250	10.51	20.53
		Module III	42.70	46.95	1250	2.10	6.51
		Module IV	45.40	49.95	938	4.53	4.7
		Average performance				**7.48**	**15.46**

Table 3.8 FNN MODEL (Training results) Expt.2

Sl.no	Gauging station	Training range (level in metre)		No. of patterns	mse $x10^6(m^3/s)^2$	mre
		From	To			
1	I	80.03	81.90	600	0.06	5.49
		80.65	84.00	800	0.13	5.66
		81.90	86.06	800	0.46	5.02
		84.00	87.80	600	3.51	6.77
		Average performance			**0.94**	**5.68**
2	II	58.13	60.88	300	0.17	6.54
		59.54	62.76	400	0.64	6.50
		60.88	65.21	400	3.37	9.32
		62.76	66.92	300	7.73	10.74
		Average performance			**2.84**	**8.22**
3	III	40.79	42.71	937	9.37	4.72
		41.42	45.40	1250	7.54	5.55
		42.71	47.87	1250	1.89	4.82
		45.40	49.95	938	3.54	4.26
		Average performance			**5.46**	**4.88**

The historical data had been segregated based on stage value to different groups based on the ranges decided for each fuzzy set.

Mathematically, the membership function for every set is defined as:

$$\mu_A(x) = 0; \quad m > x, \; x > l \tag{3.13}$$

$$\mu_A(x) = \mathit{output} \text{ from trained neural network model if } m < x < l \tag{3.14}$$

Where m = the lower limit of a fuzzy set, l = the maximum limit for a fuzzy set and $\mu_A(x)$ = the membership function of a fuzzy set.

For each fuzzified grouping, namely VERY LOW, LOW, MEDIUM and HIGH, a separate neural network model is developed by training the segregated historical data to establish the membership function of each group (Fig.3.12) i.e. the fuzzy surface of each fuzzy set is developed using the trained neural network model.

The developed fuzzy surface for each fuzzy set is not a standard shape. This arbitrary shape is decided using the neural network. These fuzzy shapes are wavy matching behavior patterns that undulate over the domain. The membership function for each fuzzy set is established using ANN based on the observed stage discharge data using a neural network. Fig.3.13 shows the membership functions for the MEDIUM and HIGH fuzzy sets developed using the neural network.

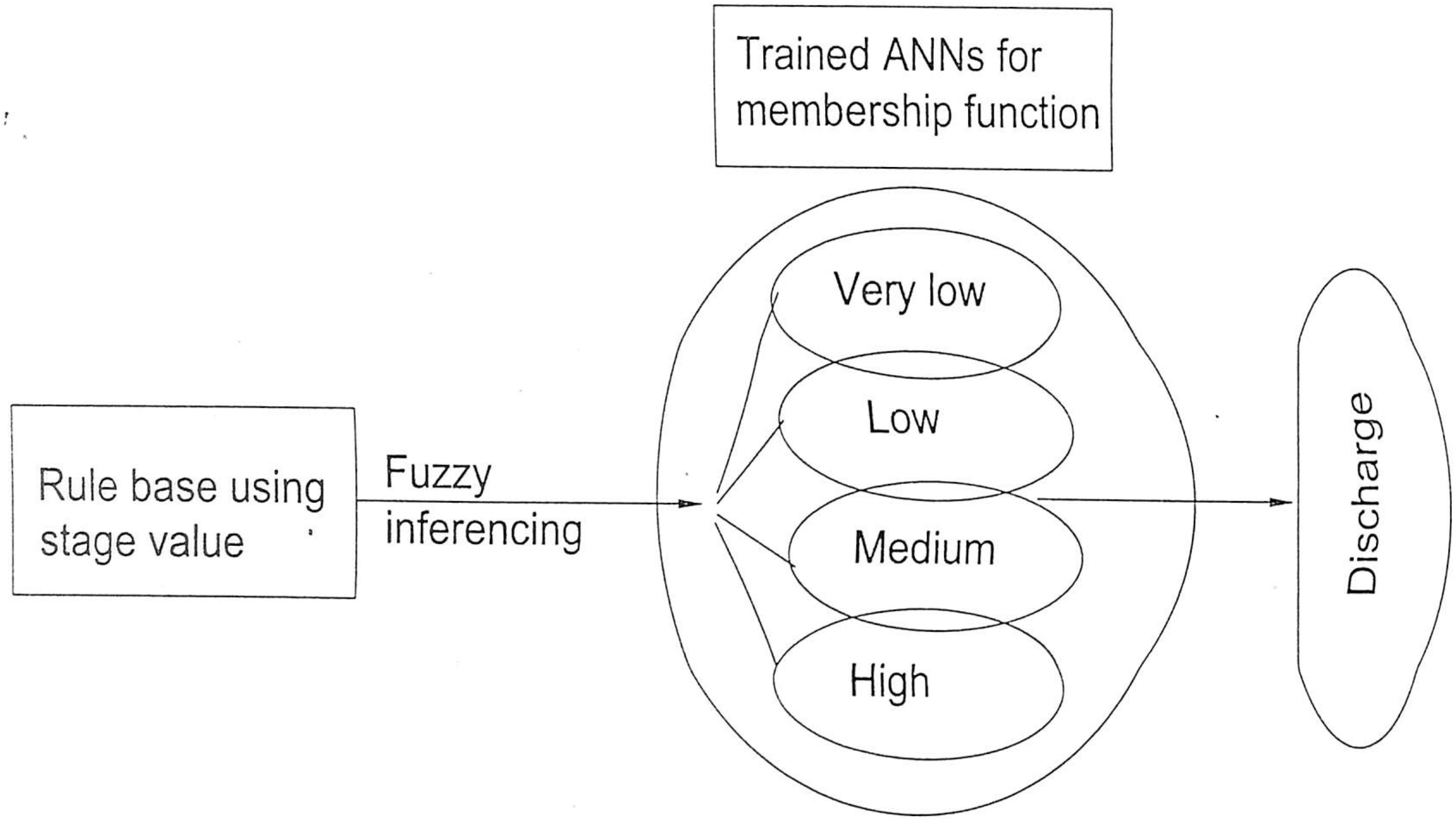

Fig.3.12.Fuzzy Neural Network model (FNN)

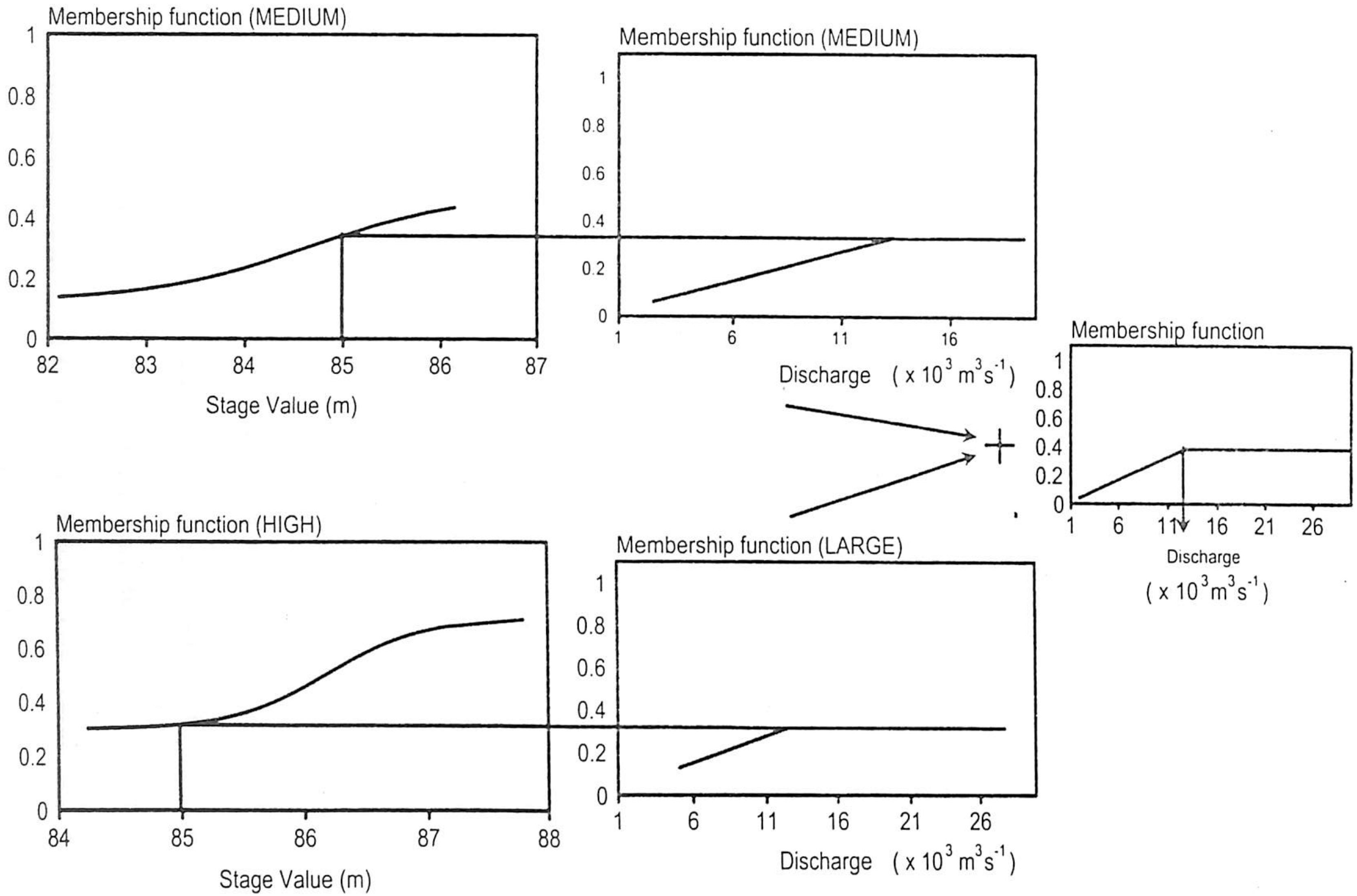

Fig.3.13.Fuzzy rules application using Min.-Max. Technique

Similarly, the membership function of the discharge data is given in Fig.3.14 for the LARGE fuzzy set. The neural network models, which has sigmoidal activation function in the output layer gives results in the range 0 to 1, due to the nature of the activation function. Hence, for training the neural network, the output data has to be normalized using a factor called normalization factor so that the results are comparable for error back propagation training. The membership function for the discharge data is derived based on the normalization factor used in the respective neural network model. This function is a straight line, increasing set with a slope equal to the normalization factor. The fuzzy associate memory developed for the fuzzy model has the following rules.

Rule 1: If the Stage is **VERY LOW** then the discharge is **VERY LOW**

Rule 2: If the Stage is **LOW** then the discharge is **LOW**

Rule 3: If the stage is **MEDIUM** then the discharge is **MEDIUM**

Rule 4: If the stage is **HIGH** then the discharge is **LARGE**

The fuzzy reasoning used here is the simple monotonic method, a basic fuzzy implication technique. Mathematically, For a simple proportional implication function,

$$If\ x\ is\ Y\ then\ z\ is\ W \tag{3.15}$$

$$z = f((x,Y),W) \tag{3.16}$$

Where x = the stage value, z = the discharge value, and Y and W are the fuzzy sets corresponding to the stage and discharge values. Under restricted set of circumstances, a fuzzy reasoning system can develop an expected value without going through the composition and decomposition. The value of the output is estimated directly from a corresponding truth membership grade in the antecedent fuzzy region

Fig.3.14a Membership function value for the discharge fuzzy set VERY LOW

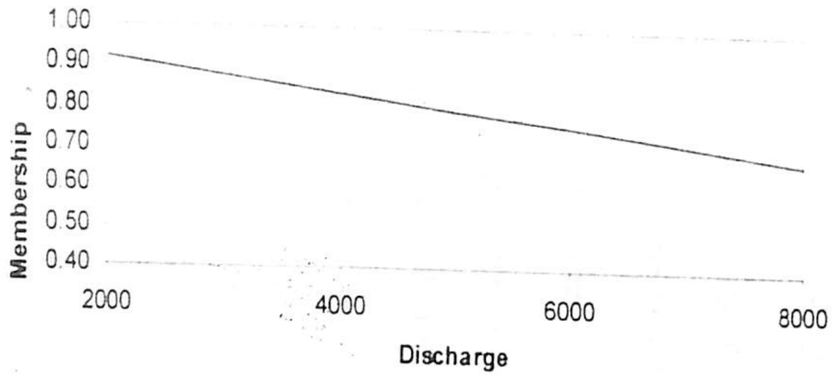

Fig.3.14b Membership function value for the discharge fuzzy set LOW

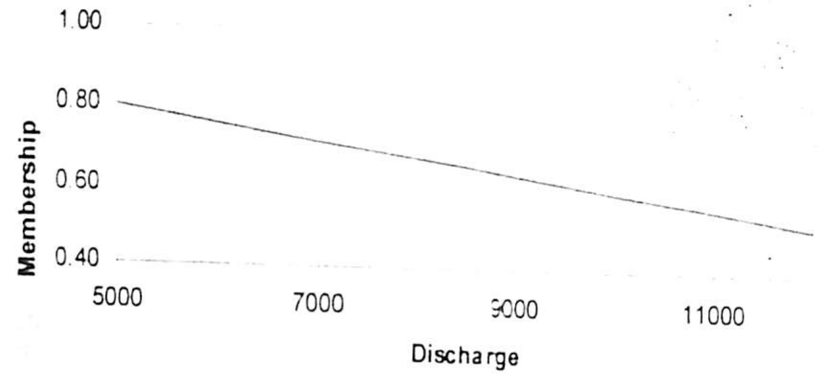

Fig.3.14c Membership function value for the discharge fuzzy set MEDIUM

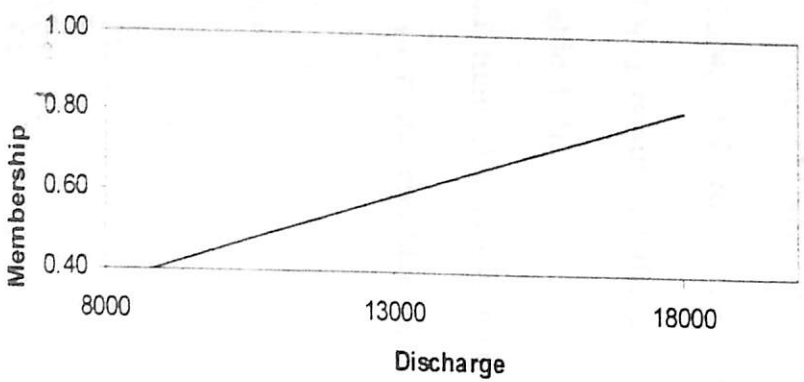

Fig.3.14d Membership function value for the discharge fuzzy set LARGE

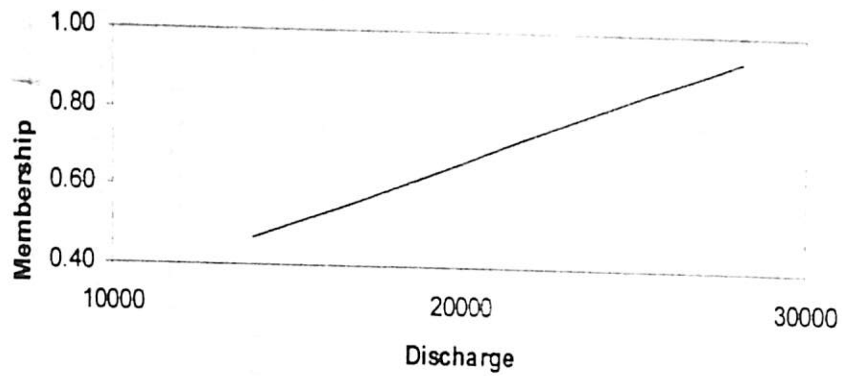

Fig.3.14.Membership function value for the discharge fuzzy set

Discharge in cumec

(Cox, 1994). This type of reasoning is followed when only one rule is fired and suitable for the stage level considered. On the other hand, if two rules are fired for a particular stage value, the Min-Max rule of implication is executed. The consequent fuzzy sets resulting from two rules will be producing an output fuzzy region by aggregation, which will be defuzzified to give the expected discharge value based on near edge of the support set defuzzification procedure (Fig.3.13).

3.4.7 Results and Discussion

The performances of different models considered are assessed using mse and mre indices for training and testing series. Conventional model is being used in experiment 1 only. In experiment 2, conventional model is not used because of four inputs as it is related to single input only. Training and testing data lengths are less in experiment 2 than experiment 1 due to the non-availability of continuous data. Patterns are selected in experiment 2 in such a way that the continuity exists among inputs and outputs.

The single ANN model, the Modularized ANN model (MNN) and the Fuzzy-Neural network model training results are given in Table 3.2 to Table 3.8 for both the experiments. Both the testing and the model training results of the conventional model are poorer than the other models (Table 3.2 and Table 3.9).

Neural network modeling is better suited than the conventional curve fitting method for functional approximation problems such as establishing stage discharge relationship (Jain and Chalisgaonkar, 2000).

Table 3.9 CONVENTIONAL MODEL (Testing results) Expt.1

Sl.no	Gauging station	No. of patterns	mse $x10^6(m^3/s)^2$	mre
1	I	480	4.08	28.77
2	II	358	38.45	64.62
3	III	891	11.34	24.86

The MNN model shows good improvement in the total mse and mre indices in the training data set relative to the single ANN model and conventional model (about 2 % to 20 % in the case of mse in both the experiments) as shown in Table 3.3 to Table 3.6. The performance of single ANN and MNN models in training are studied in detail by considering different modules for gauging station II data using experiment 1 and experiment 2. After the training, ANN trained results are divided into four modules as per same range training range adopted in case of MNN for comparison.

When the mse index is considered in each module, the MNN model is better than the ANN model in all the modules (Table 3.10). Hence, the overall mse index also shows that the MNN model is better than single ANN model.

Table 3.10 Module-wise Training Results for Gauging Station II

Model	mse $x10^6(m^3/s)^2$			
	Experiment 1		Experiment 2	
	Single NN model	MNN model	Single NN model	MNN model
Module I	0.32	0.09	0.32	0.29
Module II	3.45	3.35	2.15	0.96
Module III	13.89	13.67	4.44	2.87
Module IV	18.24	17.83	7.94	7.77

But, the MNN model performs poor in the testing. The mse and mre indices are high for MNN model for both the experiments and for all the gauging stations (Table 3.11, Table3.12, Table 3.13, Table 3.14, Table 3.15 and Table 3.16). For testing data, the mse results for different modules for both the experiments are given in Table 3.17. The single ANN model performs better in three modules and one module respectively in experiment 1 and experiment 2. But overall performance of MNN model is inferior. The MNN model suffers in the split zones. For example, consider the module I and module II split region, and module III and module IV split region (59.85 m to 60.10 m and 64.00 m to 64.50 m respectively). The MNN model shows poor performance than other models in these regions (Fig.3.15 and Fig.3.16). Due to this fact, the overall performance of the MNN model suffers. Hence it can be concluded that in the case of MNN, when the data are classified into four groups crisply, the knowledge captured from the four groups is

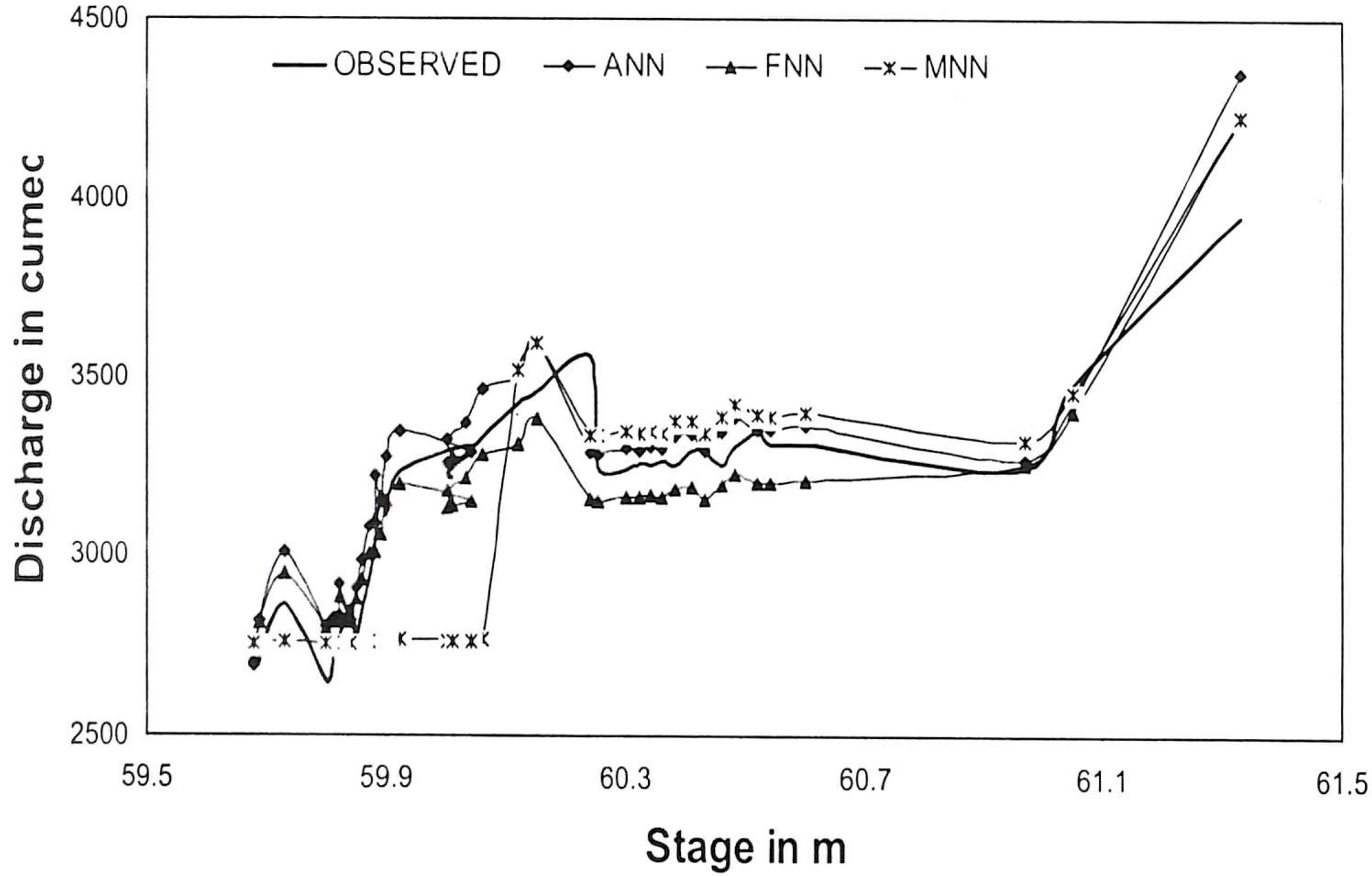

Fig.3.15.Performance of different models in the module I and module II split region

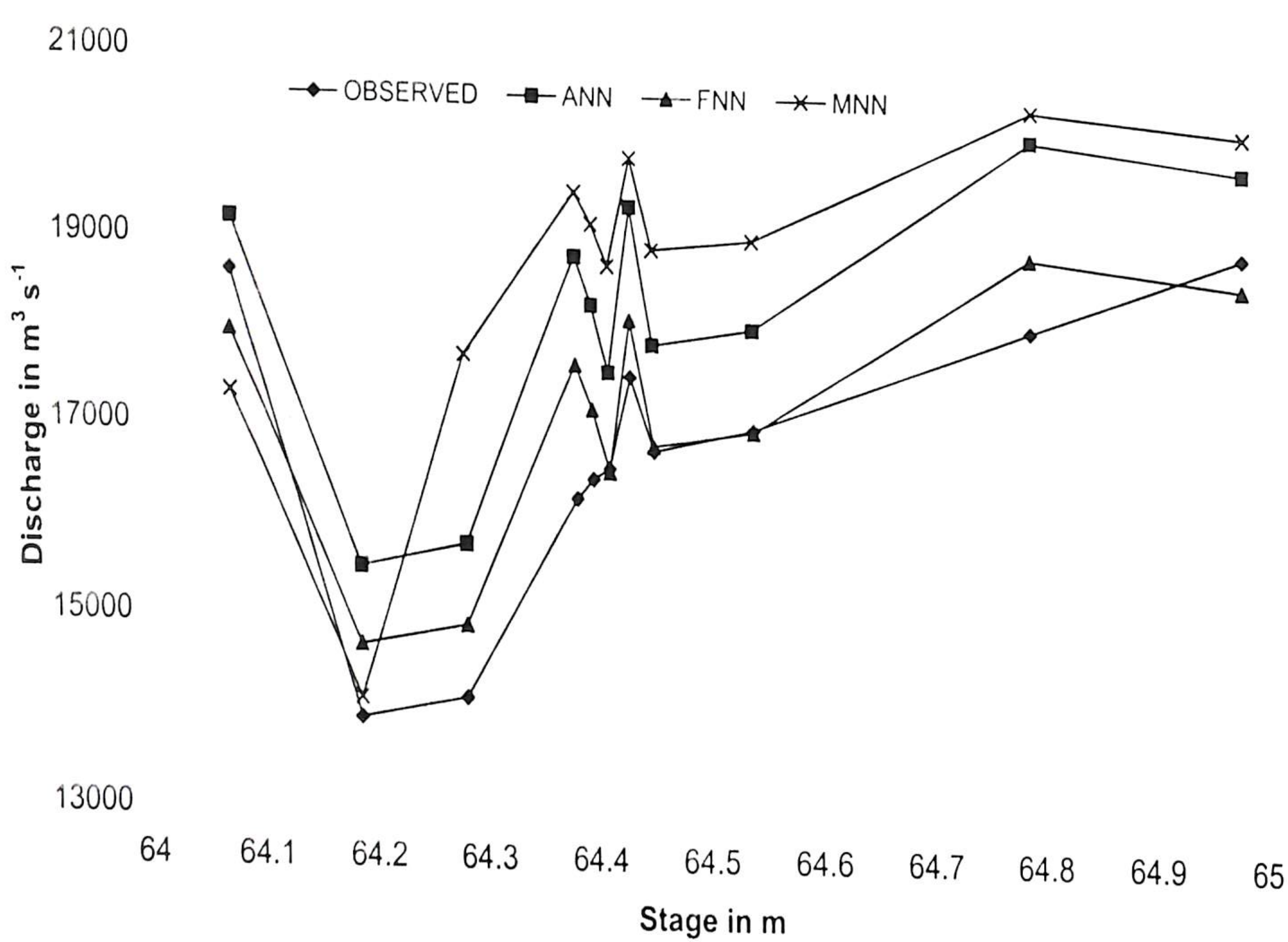

Fig.3.16. Performance of different models in the module III and module IV split region

not generalized properly. The discontinuity results due to the absence of knowledge about its neighboring regions. When all the four modules are used together, in testing, the performance of the MNN model suffers more in the split zones. The nature of the data is also very crucial for this performance. The modularized approach is very suitable for studies involving clustering the available information.

Table 3.11 GAUGING STATION I (Testing results) Expt.1

Sl.no	Model description	Testing range (level in metre)		No. of patterns	mse $x10^6(m^3/s)^2$	mre
		From	To			
1	MNN	80.03	87.80	480	2.65	18.00
2	FNN	80.03	87.80	480	2.64	15.15
3	ANN	80.03	87.80	480	2.20	12.07
4	Conventional	80.03	87.80	480	4.08	28.77

Table 3.12 GAUGING STATION II (Testing results) Expt.1

Sl.no	Model description	Testing range (level in metre)		No. of patterns	mse $x10^6(m^3/s)^2$	mre
		From	To			
1	MNN	58.13	66.94	358	32.19	58.66
2	FNN	58.13	66.94	358	27.88	49.84
3	ANN	58.13	66.94	358	29.29	58.62
4	Conventional	58.13	66.94	358	38.45	64.62

Table 3.13 GAUGING STATION III (Testing results) Expt.1

Sl.no	Model description	Testing range (level in metre)		No. of patterns	mse $x10^6(m^3/s)^2$	mre
		From	To			
1	MNN	40.79	49.95	891	6.36	20.17
2	FNN	40.79	49.95	891	4.93	15.33
3	ANN	40.79	49.95	891	5.95	20.36
4	Conventional	40.79	49.95	891	11.34	24.86

Table 3.14 GAUGING STATION I (Testing results) Expt.2

Sl.no	Model description	Testing range (level in metre)		No. of patterns	mse $x10^6(m^3/s)^2$	mre
		From	To			
1	MNN	80.03	87.80	257	3.84	8.65
2	FNN	80.03	87.80	257	2.27	5.83
3	ANN	80.03	87.80	257	2.86	5.87

Table 3.15 GAUGING STATION II (Testing results) Expt.2

Sl.no	Model description	Testing range (level in metre)		No. of patterns	mse $x10^6(m^3/s)^2$	mre
		From	To			
1	MNN	58.13	66.92	346	4.50	14.69
2	FNN	58.13	66.92	346	0.87	6.79
3	ANN	58.13	66.92	346	1.32	9.81

Table 3.16 GAUGING STATION III (Testing results) Expt.2

Sl.no	Model description	Testing range (level in metre)		No. of patterns	mse $x10^6(m^3/s)^2$	mre
		From	To			
1	MNN	40.79	49.95	889	2.24	5.37
2	FNN	40.79	49.95	889	1.75	3.83
3	ANN	40.79	49.95	889	1.84	4.75

Table 3.17 Module-wise Testing Results for Gauging Station II

Model	mse $x10^6(m^3/s)^2$					
	Experiment 1			Experiment 2		
	Single NN model	MNN model	FNN model	Single NN model	MNN model	FNN model
Module I	0.09	0.10	0.22	0.32	0.10	0.01
Module II	0.98	0.88	0.73	2.15	0.10	0.09
Module III	50.66	56.15	37.07	4.43	1.10	0.82
Module IV	77.35	84.93	85.75	7.94	12.88	1.86

But, in the case of FNN model, segregation of patterns is done by giving overlapping in the neighboring regions. Since the training is done by giving overlapping for each region, the discontinuity is avoided in the data. Hence for FNN model, the knowledge gathering during training is not affected as in the case of MNN model. Hence the FNN model performs better due to the training given with the overlapping data, which avoids discontinuity and also improves the performance of the FNN model.

Based on testing results, when we compare the performance of single ANN and FNN, the FNN performs better than ANN in all the cases except one case (about 6 % to 20 % better mse value than the single ANN) as shown in Table 3.11,Table 3.12,Table 3.13,Table 3.14,Table 3.15,and Table 3.16. Further, FNN model performs better in all modules for experiment 2 and in two modules in experiment 1 (Table 3.17).

Further, when the testing results of different models are compared for the experiment 2 (gauging station II), the hysteresis effect might be better represented by FNN model (Fig.3.17). The MNN model shows poor performance in the split zone (64.0 m to 65.0 m stage value) and not properly represents the hysteresis effect in this study. But the FNN model gives best performance in this zone also (Fig.3.17).

To assess the performance of the developed model without the previous day discharge, an attempt is also made with three inputs considering only stage values (current stage, one day earlier stage, two days earlier stage) and the current discharge as single output (experiment No.3). This study is done by considering the gauging station II. Here also, like other experiments, MNN model performance is better than ANN and FNN model during the training in terms of mse and mre (Table 3.18). But, FNN model performance is better than other models during testing (Table 3.19).

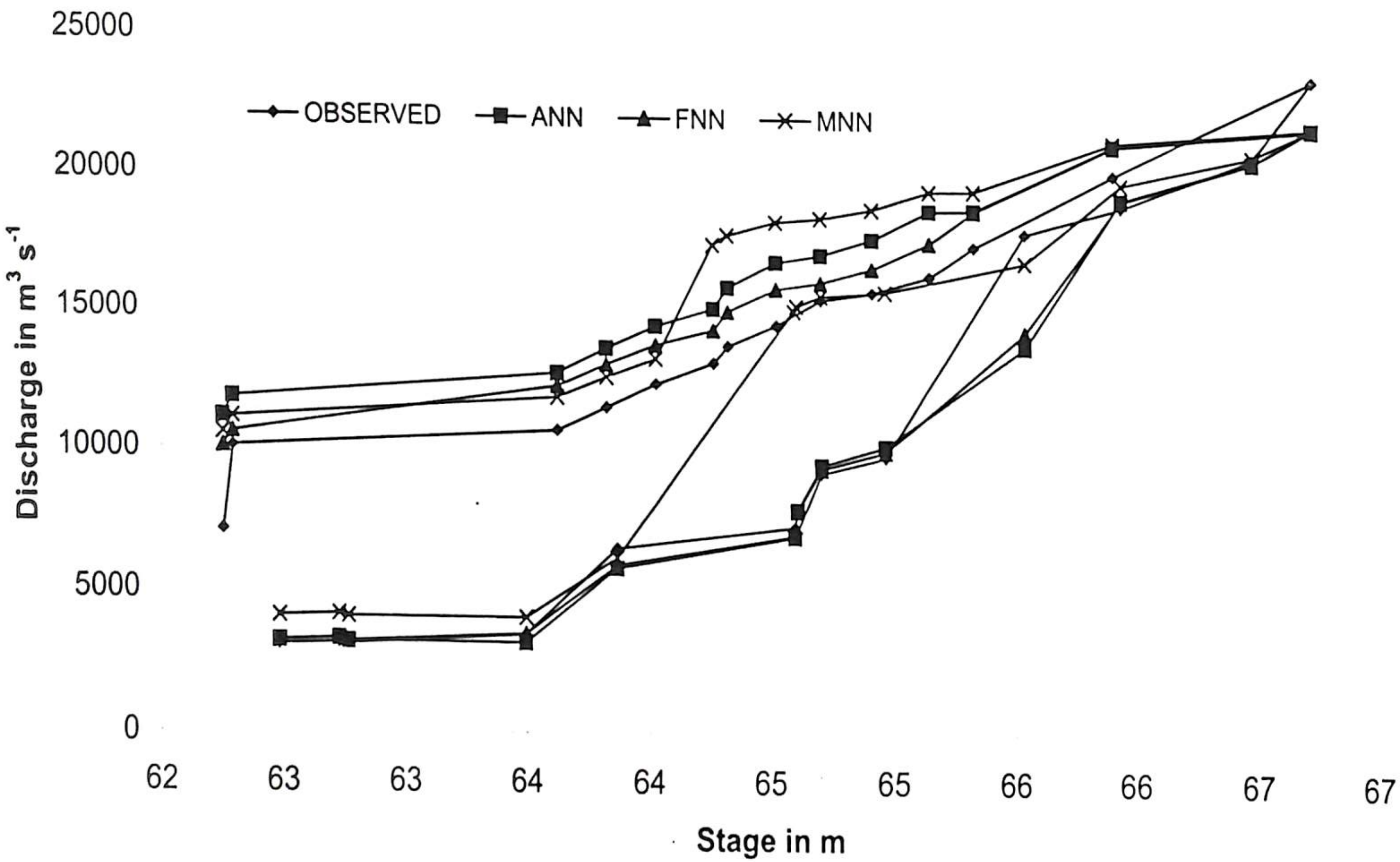

Fig.3.17. Comparing the results of different models-Hysteresis effect

Table 3.18 GAUGING STATION II (Training results) Expt.3

Sl. no	Model description		Training range (level in metre)		No. of patterns	mse $\times 10^6 (m^3/s)^2$	mre
			From	To			
1	MNN	Module I	58.13	60.08	200	0.30	9.22
		Module II	60.08	61.64	200	2.85	29.14
		Module III	61.64	64.19	200	9.86	23.54
		Module IV	64.19	66.92	200	14.60	13.57
					Average performance	**6.90**	**18.86**
2	FNN	Module I	58.13	60.88	300	0.96	18.88
		Module II	59.54	62.76	400	2.95	24.70
		Module III	60.88	65.21	400	10.32	22.91
		Module IV	62.76	66.92	300	14.96	16.98
					Average performance	**7.20**	**21.29**
3	ANN		58.13	66.92	800	**7.10**	**21.32**

Table 3.19 GAUGING STATION II (Testing results) Expt.3

Sl.no	Model description	Testing range (level in metre)		No. of patterns	mse $x10^6(m^3/s)^2$	mre
		From	To			
1	MNN	58.13	66.92	346	45.53	67.80
2	FNN	58.13	66.92	346	41.11	64.83
3	ANN	58.13	66.92	346	44.79	69.07

3.4.8 Discussions on the index PMSE

It is observed that in many research studies, using the mre to rank different models according to their performance is different to the ranking using mse. To overcome the difficulties in using mse and mre, a new statistical measure called the Pooled mean square error (PMSE) had been used which combines the effects of mse and mre (Elshorbagy et al. 2000). PMSE can also be used to increase the effect of the significant residuals that are above a predetermined threshold and to reduce the differential effect of the insignificant residuals that are below the predetermined threshold. For the calculation of the PMSE, a threshold value of 5% of the actual value is considered in this analysis.

The relative error of the outputs from the two models are pooled together to form one set, i.e. for example, the ANN and FNN model testing results are considered together in this estimation. The predicted values are given a rank of 1 if its relative error is ≤ 5%. The predicted values with relative errors more than the threshold 5% are ranked in a such a way that the highest residual is given the rank N, the next highest is rank N-1, and so on. Here N is the total number of data in one set (the ANN and FNN model testing results together). The PMSE is estimated as

$$PMSE = \frac{\sum_{j=1}^{N/2}\left(y_j^{(t)} - y_j\right)^2 .k_j}{\sum_{j=1}^{N} k_j} \tag{3.17}$$

Where N = set size and k_j = Rank of the residual error.

For this analysis, the gauging station II data are considered for experiment 2. The FNN model is performing better (Table 3.20). The complexity of the ranking process for different model performances using two indices, namely the mse and mre, is eased by the PMSE index.

Table 3.20 GAUGING STATION II (PMSE index) Expt.2

Sl. No	**Model**	**PMSE values** $x10^6(m^3/s)^2$
1	**ANN**	1.04
2	**FNN**	0.61

It is worth noting that for the gauging station II, the FNN model gives 34.45 % and 30.79 % improvement over the ANN model when we consider the mse and mre indices, respectively. For the same case, the FNN model shows 40 % of improvement over the ANN model when we consider PMSE index. It shows the better ability of the FNN model than other models in estimating the discharge closer to the observed value within the threshold of 5 % limit.

The research study shows the ability of the Fuzzy-Neural Network model in developing the stage discharge relationship. The FNN model has better predictive ability than the single ANN, modularized ANN and conventional models. The MNN model gives inferior results relative to the single ANN model and suffers due to data discontinuity even though the training of the MNN shows better values for the performance indicators. The FNN model is more flexible than the other models considered with more options of incorporating the fuzzy nature of the real world system.

CHAPTER 4

FUZZY-NEURAL NETWORK MODEL FOR RIVERFLOW PREDICTION

4.1 INTRODUCTION

In this chapter the applicability of fuzzy neural network modeling in river flow prediction is presented. To predict the river flow at downstream site using upstream flow data in the Brahmaputra river two models are developed. Four gauging stations flow data are used in the study for six different experiments, which has been done using different fuzzy inputs. Mainly the discharge at upstream sites, previous day discharge, discharge with two previous day lags are used for fuzzification in this study for developing FNN model. The rule base is generated for different experiments based on the availability of these combinations in the historical database. The performance of the fuzzy neural network model is analysed and compared with the artificial neural network model.

River flow predictions are useful in many ways. They provide a warning of the extreme flood or drought conditions and helped in optimizing the operation of water resource systems like reservoirs and hydropower plants. In many studies, streamflow prediction is an intermediate objective. Streamflows are often treated as estimation of runoff from the watershed.

Flows in streams and rivers are complex processes that are influenced by many factors such as the watershed topography, vegetation cover, soil types, channel characteristics, groundwater aquifers, precipitation distribution, snowmelt, rural and urban activities, and so on.

Many approaches have evolved over the last few decades to predict the streamflow in real time or in an on-line sense. They are deterministic as well as stochastic in nature, and include conceptual and statistical methods. These methods require considerable exogenous information that is time consuming and costly affairs. Also, they are subjected to certain assumptions. Often, these data are not available, which pose a great difficulty in model calibration. The occurrence of river flow, being uncertain, may not always be amenable to any specific modeling (Thirumalaiah and Deo, 1998).

The relatively recent hybrid technique combining fuzzy logic and artificial neural networks may therefore seem to be appropriate under these conditions because it produces model free computations as the output as a whole does not depend functionally on the input.

Kang et al. (1993) used artificial neural network (ANN) and auto regressive moving average models to predict daily and hourly streamflows in the Pyung Chang River basin in Korea. Different three layered ANN architectures were investigated and it was found that ANNs are useful tools for predicting streamflows. Karunanithi et al. (1994) compared the performance of ANN to an empirical two-station power law relationship that is based on log-transformation of the actual streamflow values. They estimated streamflow at an ungauged site on the Huron River in Michigan, based on data from United State Geological Survey stream gauging stations located 30 km. upstream and 20 km. downstream of the sampling site. They used cascade-correlation algorithm so that the network architecture could be determined during training. Neural networks were found to better predict high events, while both the methods predicted low streamflows fairly well.

Chang and Chen (2001) used stream flow and precipitation data of upstream of Da-Cha river in central Taiwan to evaluate the counterpropagation fuzzy- neural network (CFNN) rainfall-runoff model. They found that CFNN is reliable and better than auto regressive moving average with exogenous variable (ARMAX) model.

In this study, a new approach combining fuzzy logic and artificial neural network known as Fuzzy Neural Network (FNN) has been used for river flow prediction in the Brahmaputra River in the Assam state of India.

4.2 STUDY AREA

Four gauging stations namely Bessamara, Bhurbandha, Pandu and Pancharatna of the river Brahmaputra (hereafter referred to as Gauging station I, Gauging station II, Gauging station III and Gauging station IV), are considered and daily discharge values for these stations are used for this research study (Fig.3.8). The daily flow data for these stations were collected from the Flood control (now Water resource) department of Assam State, India. Six different experiments are attempted with different inputs for the study. Total 6939 patterns of flow data are available for the considered gauging stations. Out of that 5000 patterns are considered for training set and remaining 1939 patterns are used in the testing for the experiments 1,2,3, and 6. For experiment 4 and 5, testing patterns are 1937 and 1935 respectively. The upstream gauging stations I and II are located at about 340 km and 150 km upstream of gauging station III respectively. The Gauging station IV is located at about 150 km downstream of Gauging station III.

4.3 SINGLE ARTIFICIAL NEURAL NETWORK MODEL

The single ANN model developed for this study is a feed forward neural network model. The training is carried out using the error back propagation algorithm. The six experiments on ANN models are developed in this research study (Fig.4.1). A single input and single output model (Here after referred as experiment 1 and 2), two inputs and single output model (here after referred as experiment 3, 4, 5), three inputs and single output model (here after referred as experiment 6) are used after a detailed check of different combinations (Table 4.1). Monitoring the indices, Mean Square Error (mse) and Mean Relative Error (mre) the training of the neural network is done. This training involves training and cross validation. The number of neurons in the hidden layer, the number of hidden layers and the normalization factor for the data considered are decided after many trials by studying the performance of the ANN training indices. Two neurons are used in single hidden layer after examining many combinations. Normalization factors are kept as 10000 and 100000 for all the experiments.

4.4 FUZZY NEURAL NETWORK MODEL

A fuzzy neural network modeling approach is attempted in this study to predict discharge of a river. For each of the experiment performed, the discharges at different locations are used for fuzzification. The flow in the upstream reach is associated with various lateral inflow and outflow, which are difficult to estimate as it varies significantly with respect to time and space. This is uncertain and highly fuzzy in nature. In the experiment 1, current discharge of the gauging station I which is located at far from downstream is used as input for the single output of current discharge at the downstream gauging station III. The current discharge of the gauging station II is used

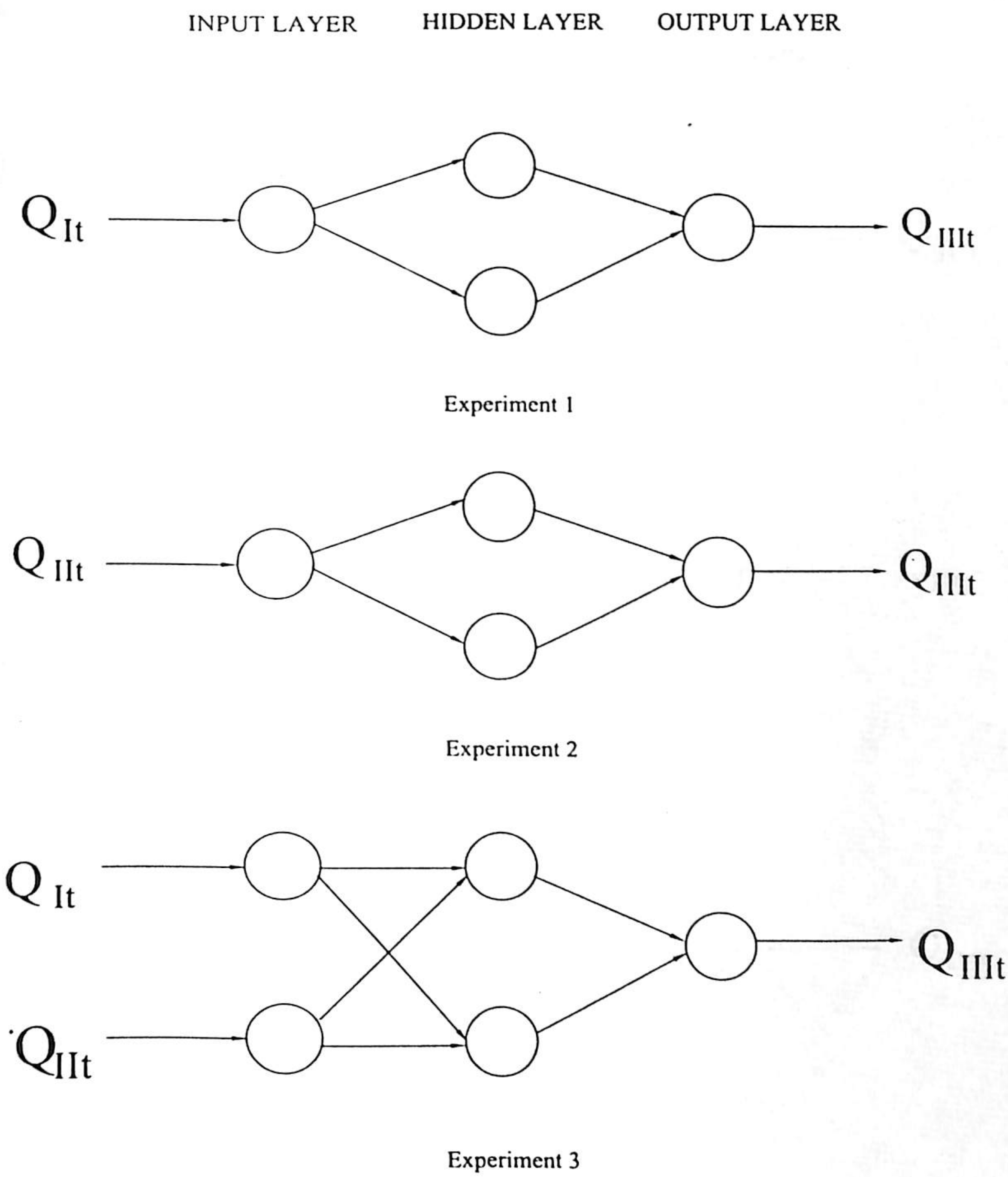

Fig.4.1. Experiments considered in the study

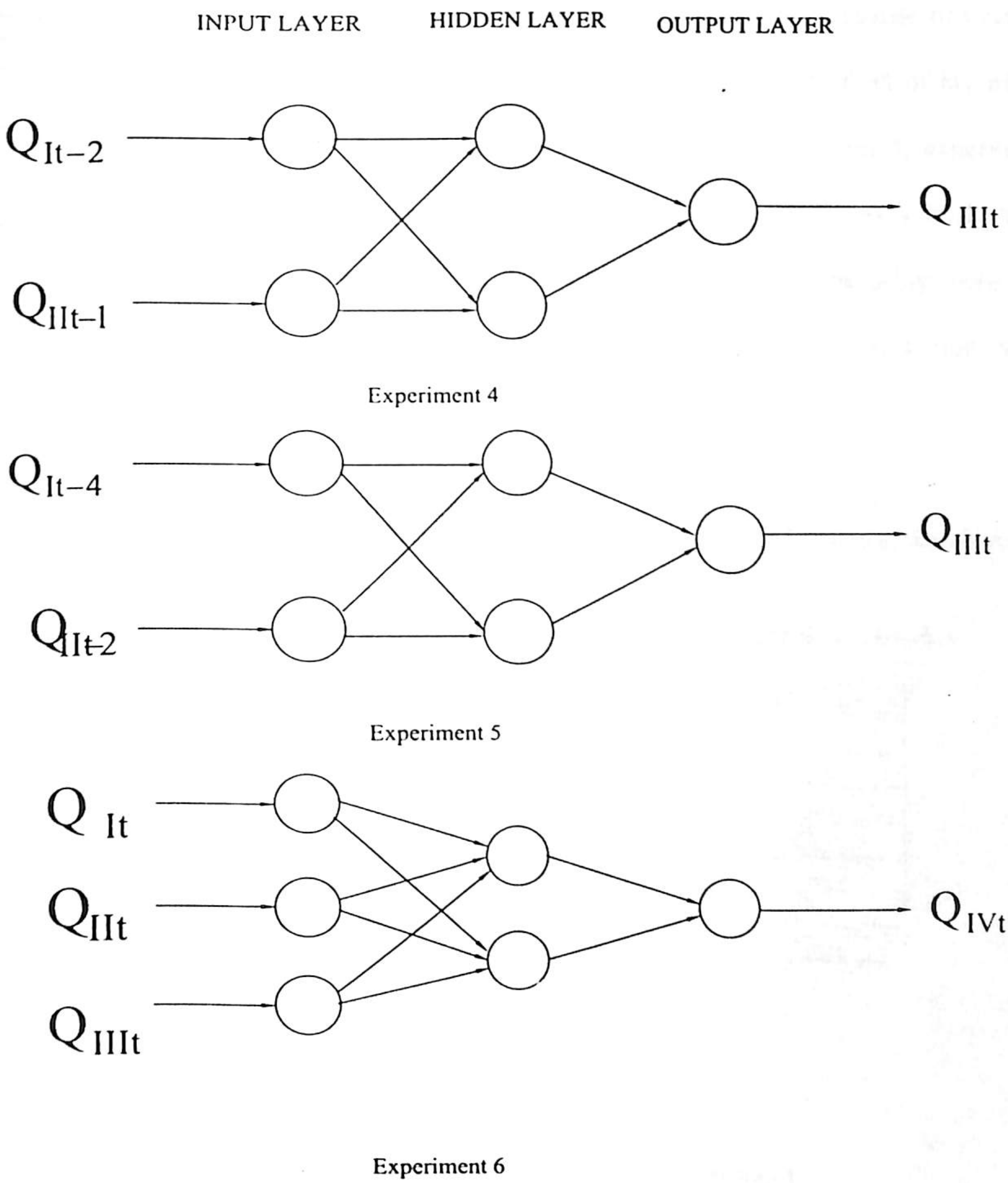

Fig.4.1. Experiments considered in the study

as input in the experiment 2 to examine the model behavior because of nearest station discharge value. Also, the travel time consideration and the effect of lag periods with more gauging station discharges are analysed in the experiment 3, experiment 4 and experiment 5 where current day, previous day and two earlier day's discharge data are used as inputs. The sensitivity of the model is also analysed by using more inputs like three gauging station discharges for the single output at downstream station IV.

4.4.1 FNN model for experiments 1 and 2

Table 4.1 shows different types of experiments tried in this research study.

Table 4.1 Model Description for different Experiments

Experiment No	Input	Output
1	$Q_{I\,t}$	$Q_{III\,t}$
2	$Q_{II\,t}$	$Q_{III\,t}$
3	$Q_{I\,t}$, $Q_{II\,t}$	$Q_{III\,t}$
4	$Q_{I\,t-2}$, $Q_{II\,t-1}$	$Q_{III\,t}$
5	$Q_{I\,t-4}$, $Q_{II\,t-2}$	$Q_{III\,t}$
6	$Q_{I\,t}$, $Q_{II\,t}$, $Q_{III\,t}$	$Q_{IV\,t}$

Here ,

$Q_{I\,t}$ = Discharge at gauging station I of a particular day t

$Q_{II\,t}$ = Discharge at gauging station II of a particular day t

$Q_{III\,t}$ = Discharge at gauging station III of a particular day t

$Q_{I\,t-2}$ = Two day's earlier discharge at gauging station I

$Q_{II\,t-1}$ = Previous day's discharge at gauging station II

$Q_{I\,t-4}$ = Four day's earlier discharge at gauging station I

$Q_{II\,t-2}$ = Two day's earlier discharge at gauging station II

$Q_{IV\,t}$ = Current day discharge at gauging station IV

In the fuzzification, for experiments 1 and 2, considering seasonal variation of flow, the entire discharge domain for a particular gauging station is categorized into four fuzzy sets namely VERY LOW, LOW, MEDIUM and HIGH. Table 4.2 shows the ranges of discharge domain used for each fuzzy set for experiments 1, 2, 3, 4, and 5.

Table 4.2 Zones for different fuzzy sets for Experiments 1, 2, 3, 4 and 5

Gauging station	Very Low (cumec)	Low (cumec)	Medium (cumec)	High (cumec)
I	< 5000	3000-10000	8000-28000	>25000
II	< 6000	4000-12000	10000-30000	>28000
III	< 10000	6000-20000	15000-40000	>35000

In this case also, the membership function for every set is defined as:

$$\mu_A(x) = 0; \quad m > x,\ x > l \tag{4.1}$$

$$\mu_A(x) = \mathit{output} \text{ from trained neural network model if } m < x < l \tag{4.2}$$

Where

m = the lower limit of a fuzzy set,

l = the maximum limit for a fuzzy set and

$\mu_A(x)$ = the membership function of a fuzzy set.

For each fuzzified grouping, namely VERY LOW, LOW, MEDIUM and HIGH, a separate neural network model is developed to establish the membership function of each group (Fig.4.2) i.e. the fuzzy surface of each fuzzy set is developed using the trained neural network model. The membership function for the discharge data is derived based on the normalization factor used in the respective neural network model. The fuzzy associate memory developed for the fuzzy model has the various rules, which are shown in Table 4.3a and Table 4.3b.

Table 4.3a Rule Base for Experiment 1

Rule number	Rules
1	IF flow is **VERY LOW** at upstream station I **then** flow is **VERY LOW** at downstream station III
2	IF flow is **VERY LOW** at upstream station I **then** flow is **LOW** at downstream station III
3	IF flow is **LOW** at upstream station I **then** flow is **LOW** at downstream station III
4	IF flow is **LOW** at upstream station I **then** flow is **MEDIUM** at downstream station III
5	IF flow is **MEDIUM** at upstream station I **then** flow is **MEDIUM** at downstream station III
6	IF flow is **MEDIUM** at upstream station I **then** flow is **HIGH** at downstream station III
7	IF flow is **HIGH** at upstream station I **then** flow is **HIGH** at downstream station III

Table 4.3b Rule Base for Experiment 2

Rule number	Rules
1	**IF** flow is **VERY LOW** at upstream station II **then** flow is **VERY LOW** at downstream station III
2	**IF** flow is **VERY LOW** at upstream station II **then** flow is **LOW** at downstream station III
3	**IF** flow is **LOW** at upstream station II **then** flow is **LOW** at downstream station III
4	**IF** flow is **LOW** at upstream station II **then** flow is **MEDIUM** at downstream station III
5	**IF** flow is **MEDIUM** at upstream station II **then** flow is **MEDIUM** at downstream station III
6	**IF** flow is **MEDIUM** at upstream station II **then** flow is **HIGH** at downstream station III
7	**IF** flow is **HIGH** at upstream station II **then** flow is **HIGH** at downstream station III

The fuzzy reasoning used here also is the simple monotonic method, a basic fuzzy implication technique.

$$\text{If } x \text{ is } Y \text{ then } z \text{ is } W \tag{4.3}$$

$$z = f((x, Y), W) \tag{4.4}$$

Where

x = the discharge at upstream station,

z = the discharge value at downstream station, and

Y and W = the fuzzy sets corresponding to the discharge values.

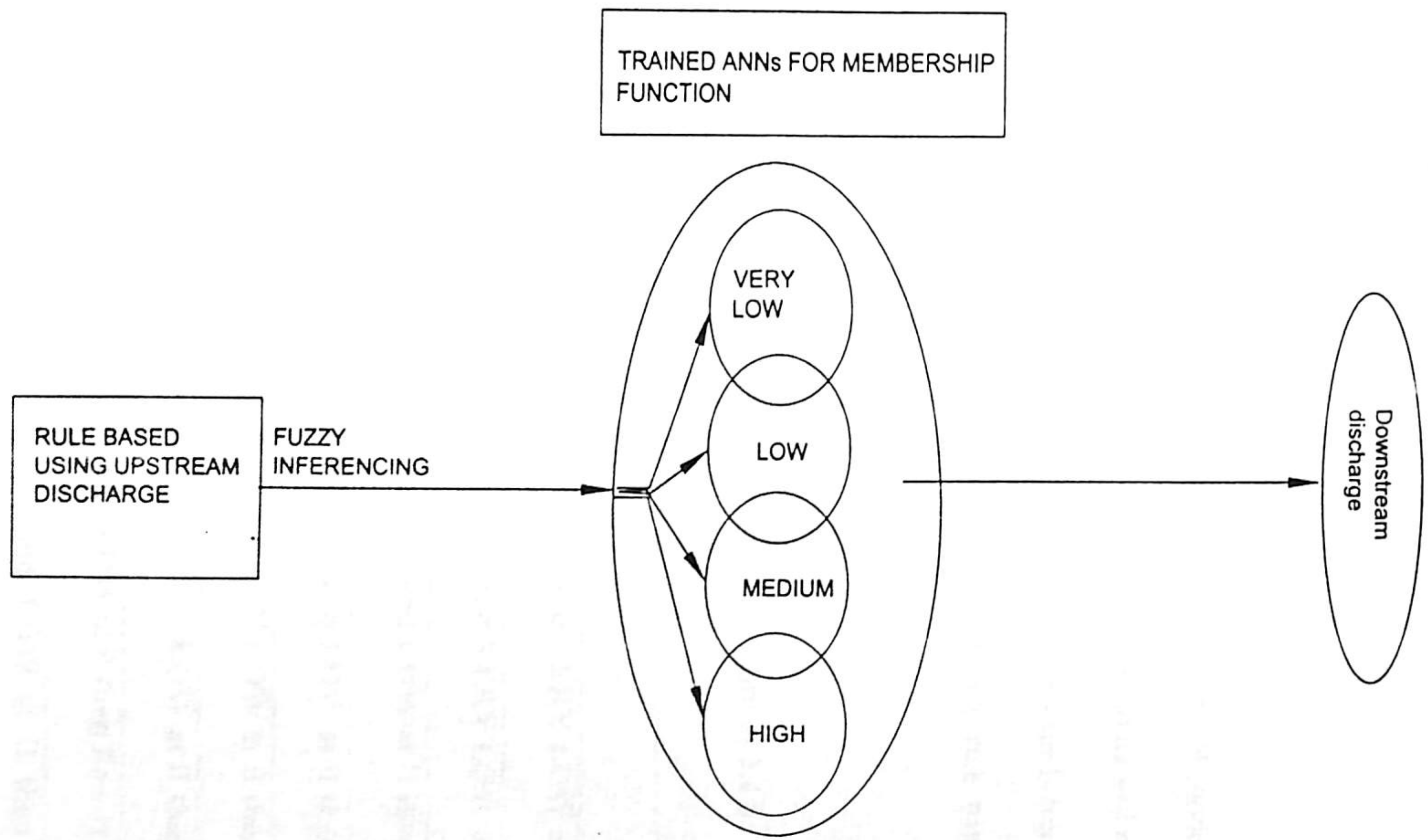

Fig.4.2. FNN model for Experiment 1,2,3,4 and 5

This type of reasoning is followed when only one rule is fired and suitable for the discharge considered. On the other hand, if two rules are fired for a particular discharge value, the Min-Max rule of implication is executed.

4.4.2 FNN model for Experiments 3, 4 and 5

In similar manner, for the experiments 3, 4 and 5, FNN models are developed with ANN for defining the membership function with two inputs and one output (Table 4.1). Experiments 4 and 5 are done with different lag periods for better analysis. Fig.4.2 shows the model development of these experiments. Fuzzy rule base used for these experiments are given in Table 4.4.

Table 4.4 Rule base for Experiment 3,4,5

Rule number	Rules
1	**IF** flow is **VERY LOW** at I **and VERY LOW** at II **then** flow is **VERY LOW** at III
2	**IF** flow is **VERY LOW** at I **and VERY LOW** at II **then** flow is **LOW** at III
3	**IF** flow is **VERY LOW** at I **and LOW** at II **then** flow is **VERY LOW** at III
4	**IF** flow is **VERY LOW** at I **and LOW** at II **then** flow is **LOW** at III
5	**IF** flow is **LOW** at I **and VERY LOW** at II **then** flow is **VERY LOW** at III
6	**IF** flow is **LOW** at I **and VERY LOW** at II **then** flow is **LOW** at III
7	**IF** flow is **LOW** at I **and LOW** at II **then** flow is **LOW** at III
8	**IF** flow is **LOW** at I **and LOW** at II **then** flow is **MEDIUM** at III

(Table 4.4 to be continued into next page)

(Table 4.4 continued)

9	IF flow is **LOW** at I **and** **MEDIUM** at II **then** flow is **LOW** at III
10	IF flow is **LOW** at I **and** **MEDIUM** at II **then** flow is **MEDIUM** at III
11	IF flow is **MEDIUM** at I **and** **LOW** at II **then** flow is **LOW** at III
12	IF flow is **MEDIUM** at I **and** **LOW** at II **then** flow is **MEDIUM** at III
13	IF flow is **MEDIUM** at I **and** **MEDIUM** at II **then** flow is **MEDIUM** at III
14	IF flow is **MEDIUM** at I **and** **MEDIUM** at II **then** flow is **HIGH** at III
15	IF flow is **MEDIUM** at I **and** **HIGH** at II **then** flow is **MEDIUM** at III
16	IF flow is **MEDIUM** at I **and** **HIGH** at II **then** flow is **HIGH** at III
17	IF flow is **HIGH** at I **and** **MEDIUM** at II **then** flow is **MEDIUM** at III
18	IF flow is **HIGH** at I **and** **MEDIUM** at II **then** flow is **HIGH** at III
19	IF flow is **HIGH** at I **and** **HIGH** at II **then** flow is **MEDIUM** at III
20	IF flow is **HIGH** at I **and** **HIGH** at II **then** flow is **HIGH** at III

Mathematically,

If x is Y And z is W Then p is Q (4.5)

Where x = discharge at gauging station I, z = discharge at gauging station II, p = discharge at gauging station III, and Y, W, Q are fuzzy sets corresponding to discharge values.

4.4.3 FNN model for Experiment 6

For the experiment 6, considering more seasonal variation of flow and more number of gauging sites, the entire discharge domain has been segregated into five categories namely VERY LOW, LOW, MEDIUM, HIGH and VERY HIGH (Fig.4.3).

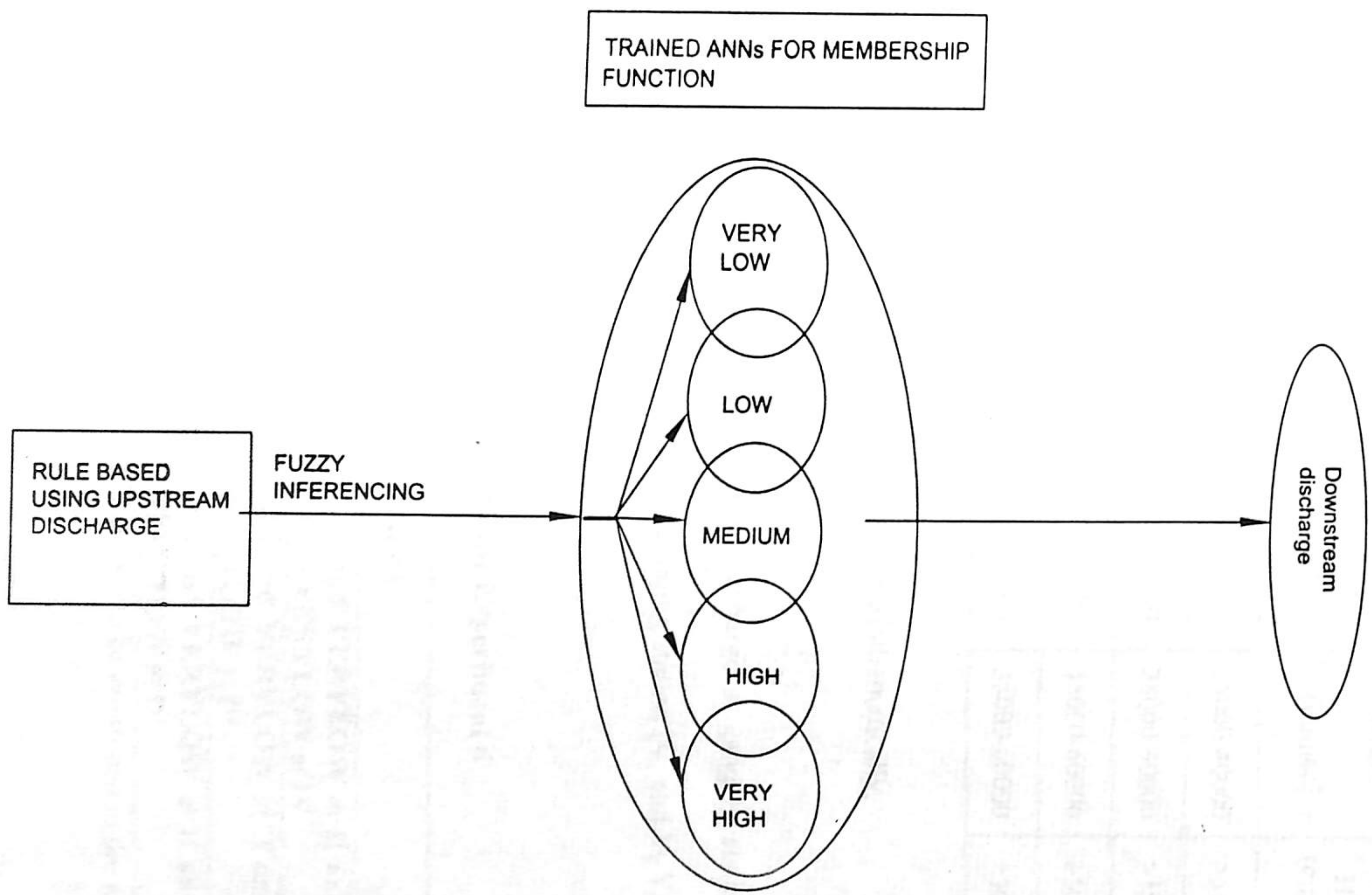

Fig.4.3. FNN model for Experiment 6

Table 4.5 shows the ranges of discharge domain used for each fuzzy set for experiment 6. For this experiment, the ANN model defining the membership function has three inputs and one output.

Table 4.5 Zones for different fuzzy sets for Experiment 6

Gauging station	Very Low (cumec)	Low (cumec)	Medium (cumec)	High (cumec)	Very High (cumec)
I	<5000	3000-10000	8000-28000	25000-40000	>35000
II	<6000	4000-12000	10000-30000	28000-40000	>35000
III	<10000	6000-20000	15000-40000	35000-60000	>50000
IV	<10000	6000-20000	15000-40000	35000-60000	>50000

Table 4.6 shows the fuzzy rules used for experiment 6.Mathematically,

If u is V And x is Y And z is W Then p is Q (4.6)

Where u = discharge at gauging station I, x = discharge at gauging station II, z = discharge at gauging station III, p = discharge at gauging station IV, and V, Y, W, Q are fuzzy sets corresponding to discharge values.

Table 4.6 Rule base for Experiment 6

Rule number	Rules
1	**IF** flow is **VERYLOW** at I **and VERYLOW** at II **and VERYLOW** at III **then** flow is **VERYLOW** at IV
2	**IF** flow is **VERYLOW** at I **and VERYLOW** at II **and VERYLOW** at III **then** flow is **LOW** at IV
3	**IF** flow is **VERYLOW** at I **and VERYLOW** at II **and LOW** at III **then** flow is **VERYLOW** at IV

(Table 4.6 to be continued to the next page)

(Table 4.6 continued)

4	**IF** flow is **VERYLOW** at I **and VERYLOW at II and LOW** at III **then** flow is **LOW** at IV
5	**IF** flow is **VERYLOW** at I **and LOW** at II **and VERY LOW** at III **then** flow is **VERYLOW** at IV
6	**IF** flow is **VERYLOW** at I **and LOW** at II **and VERY LOW** at III **then** flow is **LOW** at IV
7	**IF** flow is **VERYLOW** at I **and LOW** at II **and LOW** at III **then** flow is **VERYLOW** at IV
8	**IF** flow is **VERYLOW** at I **and LOW** at II **and LOW** at III **then** flow is **LOW** at IV
9	**IF** flow is **LOW** at I **and VERYLOW** at II **and VERY LOW** at III **then** flow is **VERYLOW** at IV
10	**IF** flow is **LOW** at I **and VERYLOW** at II **and VERY LOW** at III **then** flow is **LOW** at IV
11	**IF** flow is **LOW** at I **and VERYLOW** at II **and LOW** at III **then** flow is **VERYLOW** at IV
12	**IF** flow is **LOW** at I **and VERYLOW** at II **and LOW** at III **then** flow is **LOW** at IV
13	**IF** flow is **LOW** at I **and LOW** at II **and VERYLOW** at III **then** flow is **VERYLOW** at IV
14	**IF** flow is **LOW** at I **and LOW** at II **and VERYLOW** at III **then** flow is **LOW** at IV
15	**IF** flow is **LOW** at I **and LOW** at II **and LOW** at III **then** flow is **VERYLOW** at IV
16	**IF** flow is **LOW** at I **and LOW** at II **and LOW** at III **then** flow is **LOW** at IV
17	**IF** flow is **LOW at I and LOW** at II **and MEDIUM** at III **then** flow is **LOW** at IV
18	**IF** flow is **LOW** at I **and LOW** at II **and MEDIUM** at III **then** flow is **MEDIUM** at IV
19	**IF** flow is **LOW** at I **and MEDIUM** at II **and MEDIUM** at III **then** flow is **LOW** at IV
20	**IF** flow is **LOW** at I **and MEDIUM** at II **and** MEDIUM at III **then** flow is **MEDIUM** at IV
21	**IF** flow is **MEDIUM** at I **and VERY LOW** at II **and LOW** at III **then** flow is **VERYLOW** at IV
22	**IF** flow is **MEDIUM** at I **and VERY LOW** at II **and LOW** at III **then** flow is **LOW** at IV
23	**IF** flow is **MEDIUM** at I **and LOW** at II **and LOW** at III **then** flow is **LOW** at IV
24	**IF** flow is **MEDIUM** at I **and LOW** at II **and LOW** at III **then** flow is **MEDIUM** at IV

(Table 4.6 to be continued to next page)

(Table 4.6 continued)

25	**IF** flow is **MEDIUM** at I **and LOW** at II **and MEDIUM** at III **then** flow is **LOW** at IV
26	**IF** flow is **MEDIUM** at I **and LOW** at II **and MEDIUM** at III **then** flow is **MEDIUM** at IV
27	**IF** flow is **MEDIUM** at I **and MEDIUM** at II **and LOW** at III **then** flow is **LOW** at IV
28	**IF** flow is **MEDIUM** at I **and MEDIUM** at II **and LOW** at III **then** flow is **MEDIUM** at IV
29	**IF** flow is **MEDIUM** at I **and MEDIUM** at II **and MEDIUM** at III **then** flow is **LOW** at IV
30	**IF** flow is **MEDIUM** at I **and MEDIUM** at II **and MEDIUM** at III **THEN** flow is **MEDIUM** at IV
31	**IF** flow is **MEDIUM** at I **and HIGH** at II **and MEDIUM** at III **then** flow is **MEDIUM** at IV
32	**IF** flow is **MEDIUM** at I **and HIGH** at II **and MEDIUM** at III **then** flow is **HIGH** at IV
33	**IF** flow is **MEDIUM** at I **and HIGH** at II **and HIGH** at III **then** flow is **MEDIUM** at IV
34	**IF** flow is **MEDIUM** at I **and HIGH** at II **and HIGH** at III **then** flow is **HIGH** at IV
35	**IF** flow is **HIGH** at I **and MEDIUM** at II **and MEDIUM** at III **then** flow is **MEDIUM** at IV
36	**IF** flow is **HIGH** at I **and MEDIUM** at II **and MEDIUM** at III **then** flow is **HIGH** at IV
37	**IF** flow is **HIGH** at I **and HIGH** at II **and MEDIUM** at III **then** flow is **MEDIUM** at IV
38	**IF** flow is **HIGH** at I **and HIGH** at II **and MEDIUM** at III **then** flow is **HIGH** at IV
39	**IF** flow is **HIGH** at I **and HIGH** at II **and HIGH** at III **then** flow is **HIGH** at IV
40	**IF** flow is **HIGH** at I **and HIGH** at II **and HIGH** at III **then** flow is **VERY HIGH** at IV
41	**IF** flow is **VERY HIGH** at I **and HIGH** at II **and HIGH** at III **then** flow is **HIGH** at IV
42	**IF** flow is **VERY HIGH** at I **and HIGH** at II **and HIGH** at III **then** flow is **VERY HIGH** at IV

4.5 RESULTS AND DISCUSSION

The FNN and ANN models are compared based on mre and mse indices by considering training and testing patterns. For experiments 1 and 2, four fuzzy rules are used. During the critical periods (flood season), almost one-fourth of the rules make significant contributions to the model output. The rule base is generated for different experiments based on the availability of these combinations in the historical database. In this way, for the experiment 3, 4 and 5, significant rule combinations are 20 where as, the possible rule combinations are 64. Similarly, in the experiment 6, considered rule combinations are 42 only instead of possible rule combinations 256.

Sometimes rule combinations, which are not available in the training data sets, are encountered as an extra-ordinary case in the testing data set. In that case, the nearest rule combinations are considered. Again flow rate in the immediate upstream site of the considered site is more important than other upstream sites.

The model performances are assessed based on the validation results. The model building results are also used for assessing the better performance. The single ANN model, the Fuzzy-Neural network model training results are given in Table 4.7 and Table 4.8 for the experiment 1 and experiment 2 respectively. In both the experiments, only single input is used for different upstream gauging station discharge value for the same downstream output discharge. FNN is performing better than ANN in both the experiments.

Table 4.7 Training results for Experiment 1

Station-I Q_t	Station-II Q_t	Training		Number of patterns trained
		mre	mse x10^6	
Very Low	Very Low	29.50	3.74	1620
Very Low	Low	24.58	7.43	1342
Low	Low	19.20	7.93	1323
Low	Medium	16.53	15.59	500
Medium	Medium	14.98	27.08	1958
Medium	High	5.10	9.09	299
High	High	8.19	21.10	133
Average performance (FNN)		**26.75**	**15.50**	
Single ANN		**26.17**	**33.08**	**5000**

Table 4.8 Training results for Experiment 2

Station II Q_t	StationIII Q_t	Training		Number of patterns trained
		mre	mse x10^6	
Very Low	Very Low	28.39	3.63	1499
Very Low	Low	23.67	6.37	1342
Low	Low	18.71	7.45	1377
Low	Medium	15.54	16.10	737
Medium	Medium	14.98	29.73	1707
Medium	High	6.78	14.39	261
High	High	9.31	26.20	175
Average performance (FNN)		**19.80**	**13.38**	
Single ANN		**27.51**	**29.19**	**5000**

For the experiment 3,experiment 4 and experiment 5, model training results shows the lesser mse and mre value for FNN model than ANN model (Table 4.9, 4.10 and 4.11).

Table 4.9 Training results for Experiment 3

Station I Q_t	Station II Q_t	Station III Q_t	Training		Number of patterns trained
			mre	mse $x10^6$	
Very low	Very low	Very low	28.68	3.59	1465
Very low	Very low	Low	20.54	4.64	1093
Very low	Low	Very low	24.22	3.09	399
Very low	Low	Low	19.92	7.61	592
Low	Very low	Very low	22.43	3.06	340
Low	Very low	Low	18.59	5.93	653
Low	Low	Low	16.79	6.61	1096
Low	Low	Medium	13.77	10.11	409
Low	Medium	Low	13.04	5.88	161
Low	Medium	Medium	16.21	15.83	235
Medium	Low	Low	10.56	3.74	364
Medium	Low	Medium	14.94	16.89	440
Medium	Medium	Medium	14.89	31.34	1538
Medium	Medium	High	5.51	9.21	215
Medium	High	Medium	16.09	41.24	340
Medium	High	High	5.79	11.81	118
High	Medium	Medium	9.65	14.41	93
High	Medium	High	8.64	20.63	66
High	High	Medium	10.92	19.08	89
High	High	High	7.81	21.59	90
Average performance(FNN)			**18.31**	**11.35**	
Single ANN			**25.09**	**26.63**	**5000**

Table 4.10 Training results for Experiment 4

Station I Q_{t-2}	Station II Q_{t-1}	Station III Q_t	Training mre	Training mse $x10^6$	Number of patterns trained
Very low	Very low	Very low	28.72	3.61	1464
Very low	Very low	Low	20.76	4.75	1088
Very low	Low	Very low	24.28	3.07	397
Very low	Low	Low	20.35	7.81	585
Low	Very low	Very low	22.23	3.02	341
Low	Very low	Low	18.47	5.85	654
Low	Low	Low	16.96	6.73	1106
Low	Low	Medium	13.59	9.47	410
Low	Medium	Low	13.87	6.58	173
Low	Medium	Medium	15.11	13.45	233
Medium	Low	Low	10.31	3.61	366
Medium	Low	Medium	14.37	16.51	440
Medium	Medium	Medium	14.53	30.45	1551
Medium	Medium	High	4.67	6.40	203
Medium	High	Medium	15.39	37.79	343
Medium	High	High	5.68	10.99	112
High	Medium	Medium	10.32	16.77	77
High	Medium	High	6.07	13.38	80
High	High	Medium	11.37	20.30	88
High	High	High	6.40	14.51	103
Average performance (FNN)			**18.19**	**11.56**	
Single ANN			**24.76**	**24.84**	**5000**

Table 4.11 Training results for Experiment 5

Station I Q_{t-4}	Station II Q_{t-2}	Station III Q_t	Training		Number of patterns trained
			mre	mse $x10^6$	
Very low	Very low	Very low	28.74	3.61	1457
Very low	Very low	Low	20.83	4.96	1084
Very low	Low	Very low	23.87	2.99	398
Very low	Low	Low	21.08	8.39	581
Low	Very low	Very low	21.66	2.89	349
Low	Very low	Low	19.32	6.42	651
Low	Low	Low	17.63	7.05	1107
Low	Low	Medium	13.89	10.52	414
Low	Medium	Low	14.64	7.04	171
Low	Medium	Medium	14.78	13.10	231
Medium	Low	Low	11.11	4.16	375
Medium	Low	Medium	14.54	16.37	425
Medium	Medium	Medium	14.82	30.99	1533
Medium	Medium	High	5.25	7.35	219
Medium	High	Medium	15.35	38.44	346
Medium	High	High	5.38	9.48	115
High	Medium	Medium	10.89	17.74	82
High	Medium	High	8.96	22.24	74
High	High	Medium	11.34	19.44	92
High	High	High	7.83	22.51	90
Average performance (FNN)			**18.48**	**11.92**	
Single ANN			**25.01**	**25.86**	**5000**

Table 4.12 shows the model training results for the experiment 6 where three inputs are used for the single output. The model testing results for all the experiments are presented in the Table 4.13 for all the experiments. The study reveals that the Fuzzy-neural network model for river flow prediction is performing better than the single ANN model considered for all the experiments in general based on overall mse and mre values.

Table 4.12 Training results for Experiment 6

Station I Q_t	Station II Q_t	Station III Q_t	Station IV Q_t	Training mre	Training mse x10^6	Patterns trained
Very low	Very low	Very low	Very low	15.98	0.71	1459
Very low	Very low	Very low	Low	9.37	1.07	151
Very low	Very low	Low	Very low	16.48	1.03	1054
Very low	Very low	Low	Low	11.78	1.65	300
Very low	Low	Very low	Very low	14.46	1.19	381
Very low	Low	Very low	Low	14.01	2.12	130
Very low	Low	Low	Very low	15.48	1.48	465
Very low	Low	Low	Low	16.08	3.50	442
Low	Very low	Very low	Very low	15.06	1.02	335
Low	Very low	Very low	Low	9.68	1.20	142
Low	Very low	Low	Very low	16.28	1.57	543
Low	Very low	Low	Low	13.4	2.19	451
Low	Low	Very low	Very low	14.61	1.28	205
Low	Low	Very low	Low	12.33	1.85	137
Low	Low	Low	Very low	14.23	1.39	602
Low	Low	Low	Low	16.34	4.60	955
Low	Low	Medium	Low	15.92	6.06	345
Low	Low	Medium	Medium	9.67	6.20	178
Low	Medium	Medium	Low	16.96	7.87	129
Low	Medium	Medium	Medium	9.1	6.99	169
Medium	Very low	Low	Very low	10.66	0.89	39
Medium	Very low	Low	Low	10.84	1.84	66
Medium	Low	Low	Low	15.69	5.85	343
Medium	Low	Low	Medium	10.1	5.18	91
Medium	Low	Medium	Low	13.16	5.23	301
Medium	Low	Medium	Medium	10.87	9.90	273
Medium	Medium	Low	Low	16.31	6.74	229
Medium	Medium	Low	Medium	8.94	4.45	132
Medium	Medium	Medium	Low	11.82	4.90	256
Medium	Medium	Medium	Medium	8.53	9.80	1299
Medium	High	Medium	Medium	5.44	5.15	248
Medium	High	Medium	High	7.42	19.22	163
Medium	High	High	Medium	4.46	4.30	36
Medium	High	High	High	8.63	24.64	107
High	Medium	Medium	Medium	7.3	9.29	60
High	Medium	Medium	High	7.12	13.53	54
High	High	Medium	Medium	4.55	3.34	55

(Table 4.12 Continued in next page)

(Table 4.12 Continued)

High	High	Medium	High	8.67	22.05	54
High	High	High	High	8.73	25.14	74
High	High	High	Very high	5.37	20.94	24
Very high	High	High	High	1.87	0.81	7
Very high	High	High	Very high	3.58	5.67	3
Average performance (FNN)				**13.43**	**4.25**	
Single ANN				**16.36**	**15.23**	**5000**

Table 4.13 Testing results of all the Experiments considered

Sl. no	Description	ANN		FNN		Testing data
		mre	mse $x10^6$	mre	mse $x10^6$	
1	Expt.-1	28.33	38.37	23.78	22.91	1939
2	Expt.-2	22.41	35.05	21.02	29.78	1939
3	Expt.-3	23.60	29.01	20.68	22.27	1939
4	Expt.-4	22.49	27.03	20.63	21.65	1937
5	Expt.-5	21.92	27.95	20.68	23.30	1935
6	Expt.-6	19.43	13.06	19.47	11.92	1939

In experiment1, FNN is better than ANN by 40% in terms of mse and 16% in terms of mre in testing when compared with ANN. In experiment 2, FNN is better than ANN by 15% in terms of mse and 6% in terms of mre. In both the experiments 1 and 2,desired output was same with different inputs. Here only single input variable is used.

If we consider ANN models with different experiments, (for ANN of experiment 1 and ANN of experiment 3), the improvement in mse is 24% where as for FNN it is negligible. In these cases also desired outputs are same. This reveals that with lesser input variables FNN model gives better results. There is a significant improvement in the mse for ANN but FNN is good even with 1-1. ANN needs more input informations for better modeling.

In experiment 3, FNN is better than ANN by 23% in terms of mse and 12% in terms of mre where current informations of upstream sites are used. It is observed that lag period considerations are affecting FNN performance due to non-availability of RULE BASE in the case of experiment 4 and 5. By using one-day lag period or two day lag period data, the FNN model may perform still better if the rule base can be strengthened further.

In experiment 6, FNN is better than ANN by 9% in terms of mse, where three input variables are used.

The performance of FNN model are analysed for different seasons within a year. Fig. 4.4 shows the performance of ANN and FNN models in terms of mse for experiment 1 in the normal year 1999. The FNN is performing better (less mse) than ANN throughout the normal year considered. The performance of FNN model is either similar or better than ANN model in the year 1999 for the experiment 2 where nearest upstream discharge is used as input as shown in Fig.4.5. ANN is slightly predicting better than FNN in the medium flow zones, which is evident from experiment 2 results. In the Experiment 3, where two upstream stations discharges are used as inputs the predicting ability of FNN is suffered slightly in the medium flow zone as shown in Fig.4.6. The possible reason for this may be the large domain of medium flow. It is observed that almost 90% of testing data are in the overlapping zones. In the training data set, medium flow data dominating the set followed by very low and low flow data. The Fig.4.7 shows the predicting ability of FNN model during the high flood year of 1998 where FNN is closely following the observed flow in all the seasons. In the

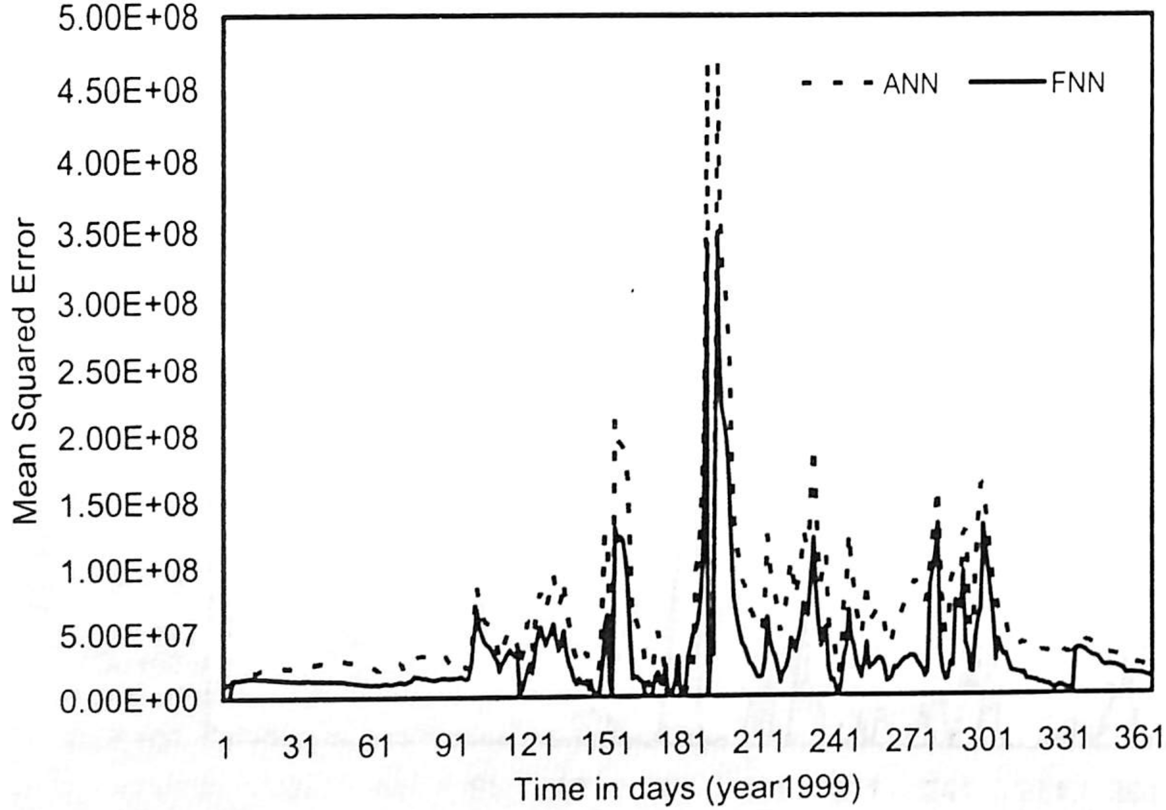

Fig.4.4. Mean squared error of ANN and FNN models (Expt.1)

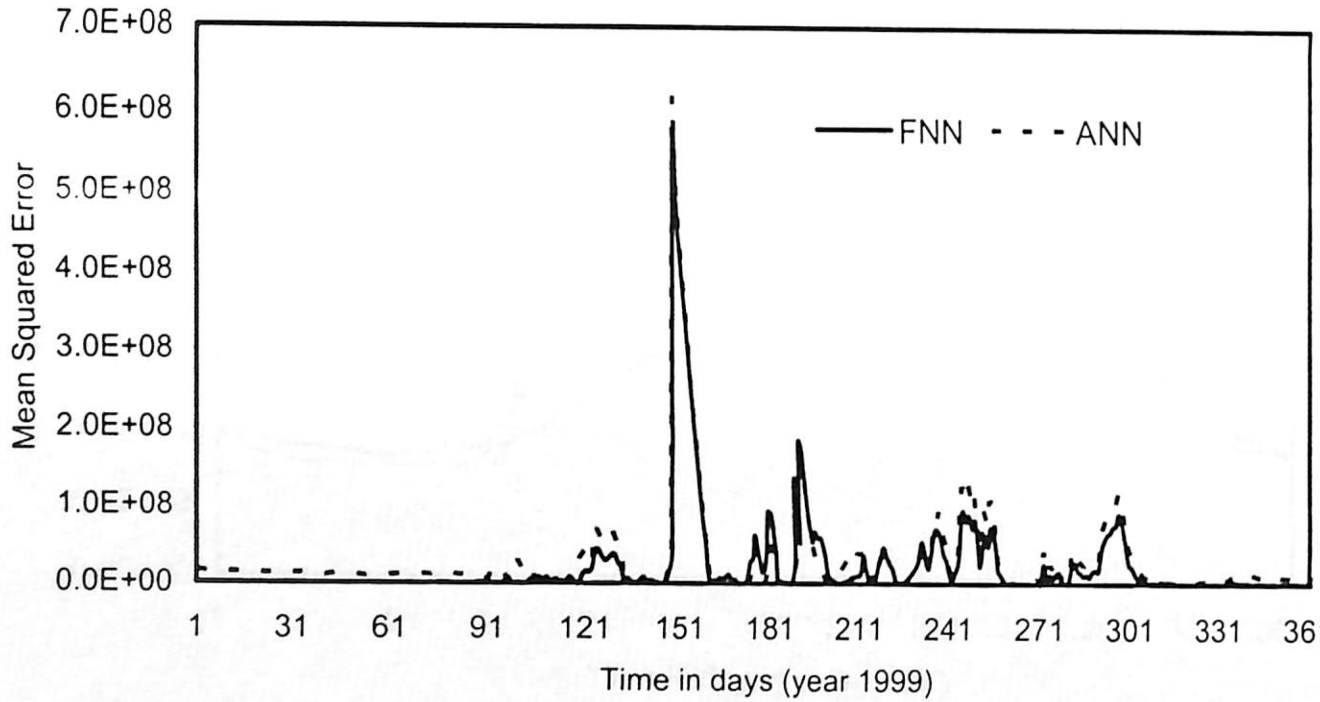

Fig.4.5. Mean squared error of ANN and FNN models (Expt.2)

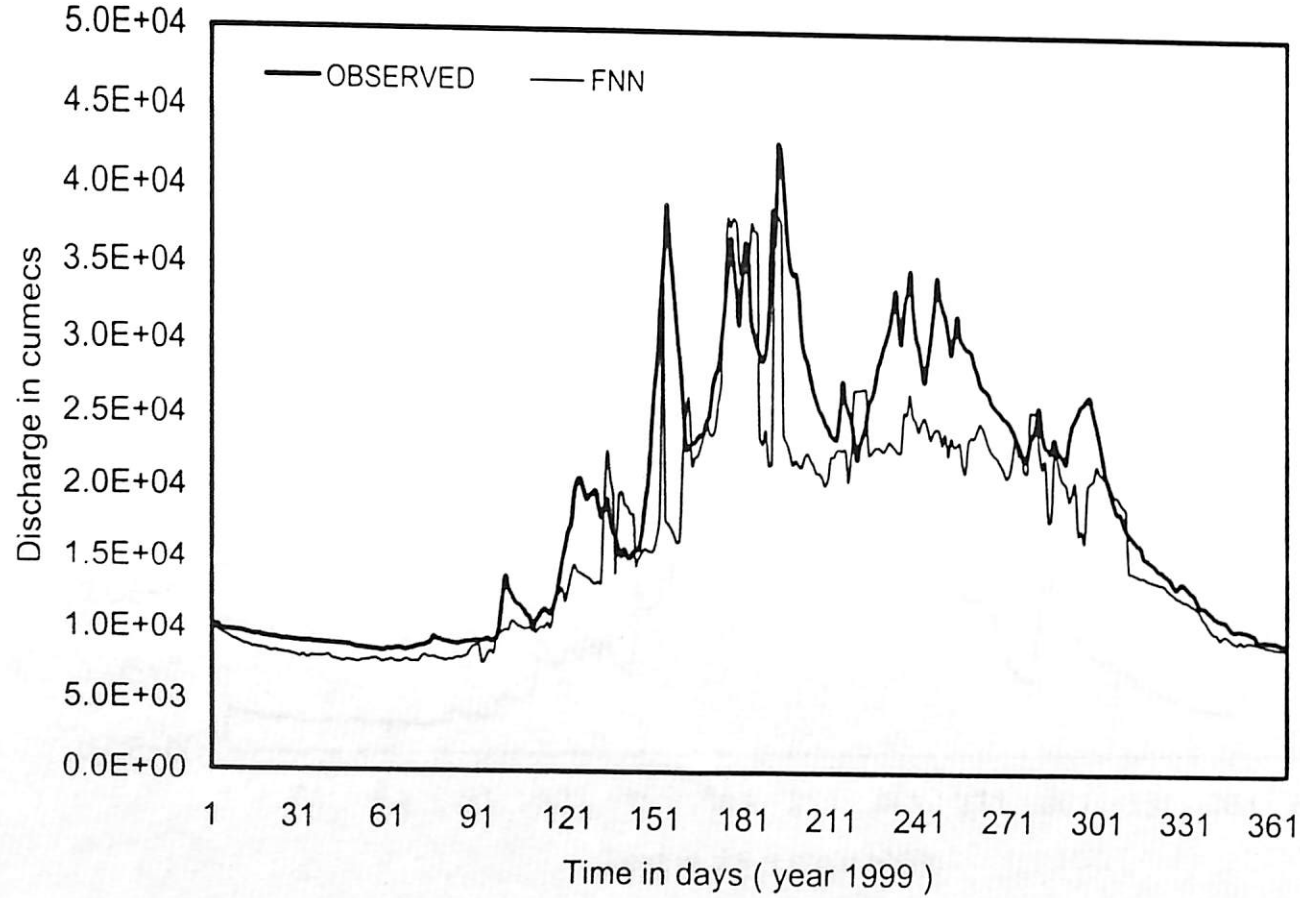

Fig.4.6. Model performance of FNN (Expt.3)

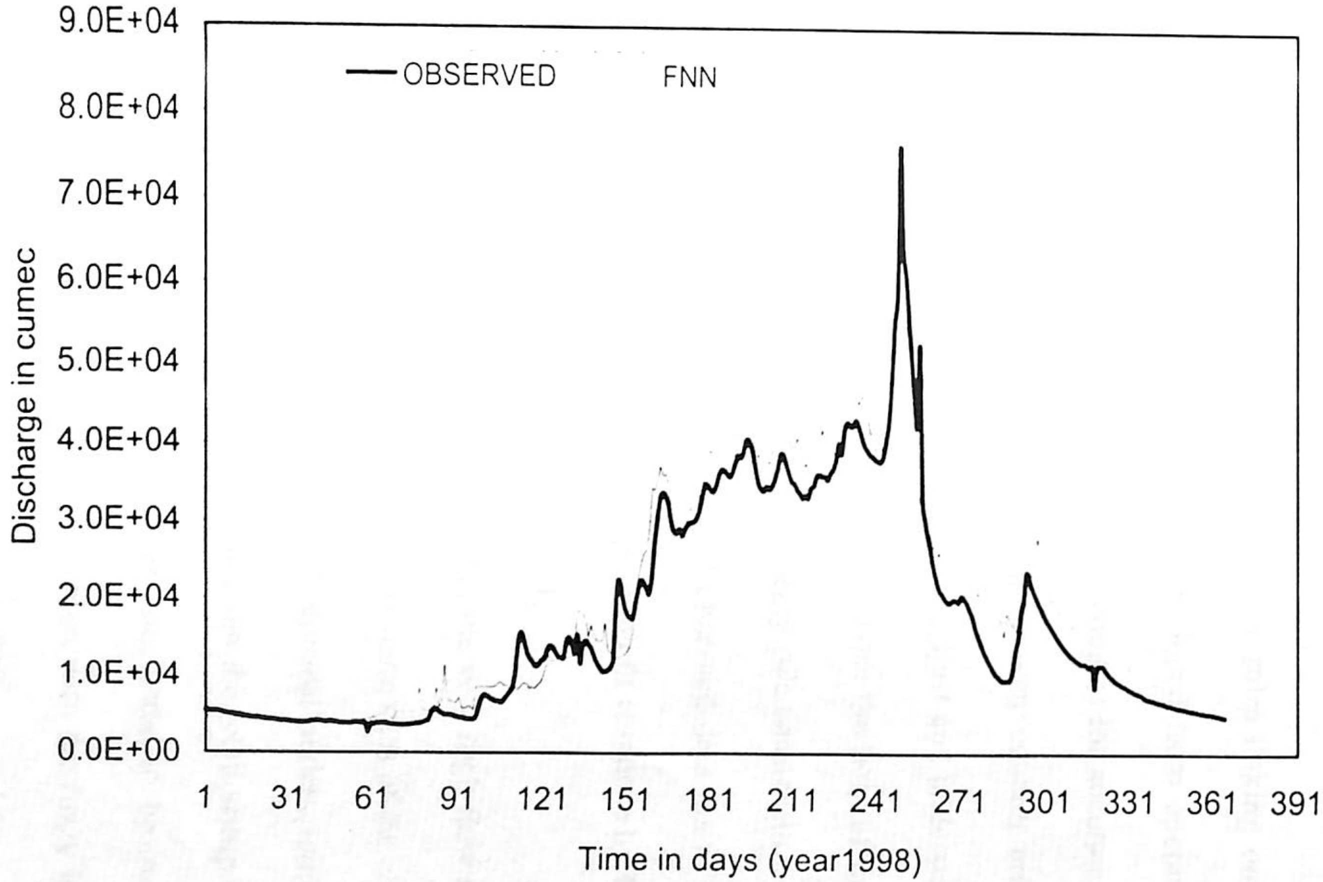

Fig.4.7. Model performance in high flood year(Expt.3)

experiment 6,where three upstream stations discharge data are used as inputs also shows the better performance of FNN model than ANN model (Fig.4.8).

Since the training data set contained extreme flow conditions, ANN is doing uniformly in all the zones, as there is no scope for extrapolation where ANN is weak in prediction.

The fuzzy system works best when the rules linking outputs to inputs can be accurately specified. Set of rules can be developed from operating data by the fuzzy inference method, but these are not quite as good as for accurate results. The system is robust in that some rules can be left out or can contain errors without seriously compromising performance. They are easy to adjust and understand. They can be fine-tuned in the light of operating experience or with the help of insights provided by an expert (Russell and Campbell, 1996). The fuzzy rule construction requires just a training set. The training set can be either a set of observed data (as in this study) or a set of outputs from a physical model. The computation of response by fuzzy rules is easy and requires very little time (Shrestha et.al, 1996).

The fuzzy rules obtained indicate that the very high flow most likely to occur at downstream site when there is high flow at upstream sites of the channel. Although these are in agreement with the current level of physical understanding of the system, the fuzzy rules do not provide any information about the relationship between the high flow and other environmental variables that are considered to be important (e.g., rainfall, watershed, lateral flow). The overlapping option with the fuzzy inferencing rules gives an advantage to this model. Furthermore, the FNN model also has more flexibilities associated with it in the form of fuzzy rule formulation, choosing different suitable architectures for each ANN for each fuzzy set, creating different fuzzy sets by experiment 6,where three upstream stations discharge data are used as inputs also shows the better performance of FNN model than ANN model (Fig.4.8).

Since the training data set contained extreme flow conditions, ANN is doing uniformly in all the zones, as there is no scope for extrapolation where ANN is weak in prediction.

The fuzzy system works best when the rules linking outputs to inputs can be accurately specified. Set of rules can be developed from operating data by the fuzzy inference method, but these are not quite as good as for accurate results. The system is robust in that some rules can be left out or can contain errors without seriously compromising performance. They are easy to adjust and understand. They can be fine-tuned in the light of operating experience or with the help of insights provided by an expert (Russell and Campbell, 1996). The fuzzy rule construction requires just a training set. The training set can be either a set of observed data (as in this study) or a set of outputs from a physical model. The computation of response by fuzzy rules is easy and requires very little time (Shrestha et.al, 1996).

The fuzzy rules obtained indicate that the very high flow most likely to occur at downstream site when there is high flow at upstream sites of the channel. Although these are in agreement with the current level of physical understanding of the system, the fuzzy rules do not provide any information about the relationship between the high flow and other environmental variables that are considered to be important (e.g., rainfall, watershed, lateral flow). The overlapping option with the fuzzy inferencing rules gives an advantage to this model. Furthermore, the FNN model also has more flexibilities associated with it in the form of fuzzy rule formulation, choosing different suitable architectures for each ANN for each fuzzy set, creating different fuzzy sets by

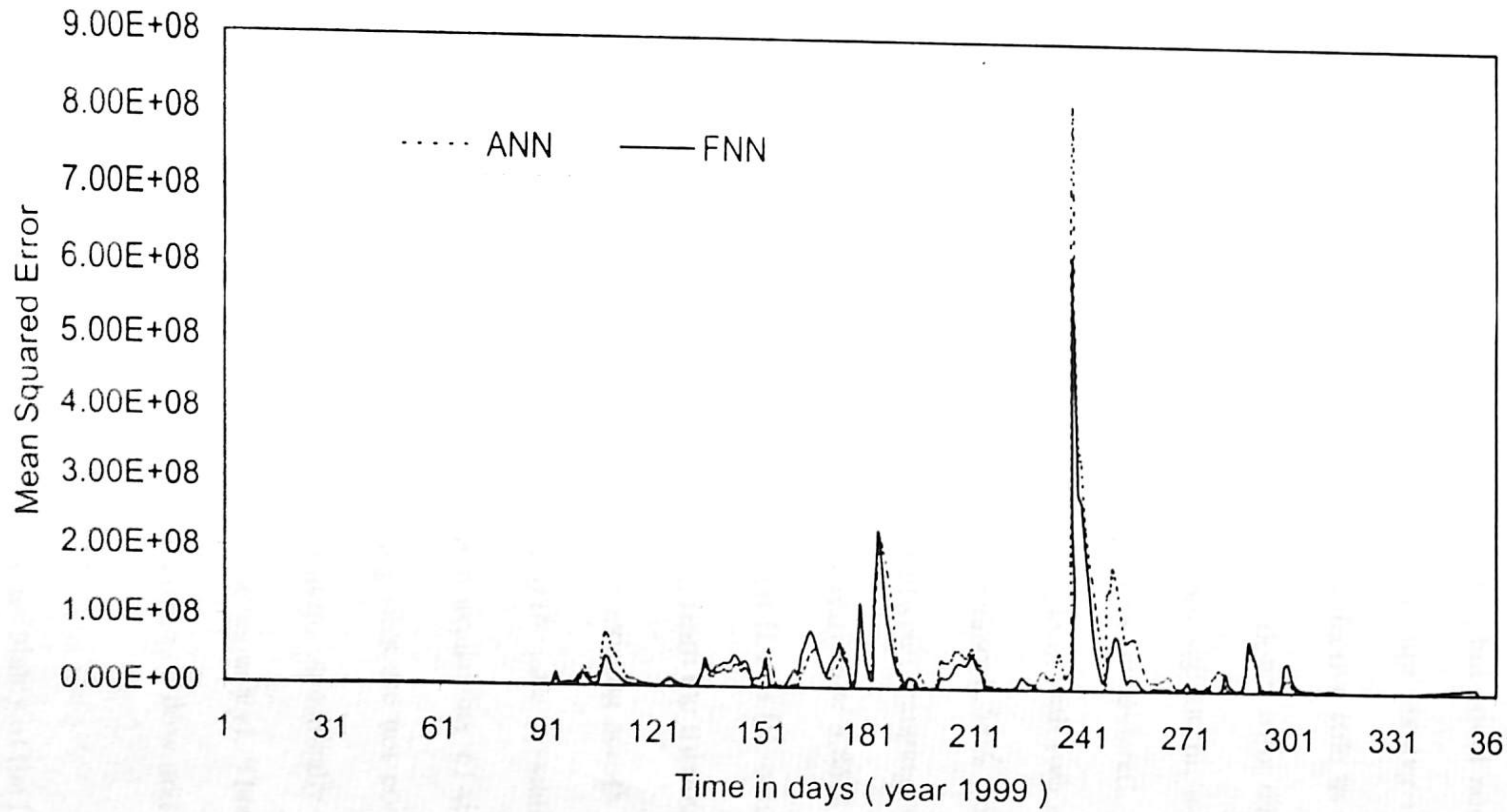

Fig.4.8. Mean squared error of ANN and FNN models (Expt.6)

considering suitable domains, etc. The FNN modeling fuzzification of the discharge data can be undertaken easily with the help of historical data and their statistics.

The FNN model is overall better, but could not capture fully expert thinking in exceptional circumstances. Also there are number of tributaries between various gauging sites, lateral flow has played effective role in efficient prediction. A careful assessment over this factor has been done with the available information. The contribution from those tributaries is not significant, as they are not exceeding 16% of the total flow between gauging sites considered. The main stem of the river Dihang carries 37% of total discharge along with two major contributors are Dibang (7.6%) and Lohit (9.5%) combining almost 54% which are joining the river at upstream of the gauging site I. Between gauging station II and I, two major tributaries Jia bharali and Subansiri contributes 5.84% and 10.66% respectively are joining the Brahmaputra river. Between II and III, contributions from the tributaries are around 10%. Similarly contribution from the tributaries between III and IV is less than 10%. There is no major structure existing across river Brahmaputra as of now and no water diversion is done between the gauging stations considered.

In this study, due to the non-availability of the data, the lateral inflow or outflow between the various gauging sites are not considered. As number of input increases, a fuzzy rule based system; specifically the number of rules also exponentially increases (curse of dimensionality). This limitation can be overcome by constructing more and more categories of flow and also rule base that should be used only under special circumstances.

The research study shows the better ability of the Fuzzy-Neural Network model in predicting river flow. FNN is flexible and easy to build . The transparency of the knowledge gained by FNN model is also an advantage. The proposed approach uses the least amount of information in terms of the number of inputs. The use of linguistic variables makes it relatively easy to interpret the rules and if necessary change them. Fuzzy rules are obtained in agreement with the physical understanding of the system. Fuzzy rule base can be constructed on the basis of expert knowledge or observed data. The seasonal variation is to be considered in the fuzzification phase. In addition to the use of absolute observed values, inclusion of season dependent relative values may increase the predicting ability of FNN, which is a future scope of study. This research study shows that the FNN approach has a great potential to be successfully applied to a wide range of hydrological problems.

CHAPTER 5

RESERVOIR OPERATION

5.1 INTRODUCTION

In this chapter the dynamic programming fuzzy neural network model (DPFNN model) developed for better reservoir operation is discussed. DPFNN model uses fuzzy logic and artificial neural network approach together to evolve a general operating policy from the results of deterministic dynamic programming optimization. The results of the DPFNN model are compared with the dynamic programming neural network model (DPN model) which uses the artificial neural network only to arrive at the general operating policy from the same deterministic dynamic programming optimization results. Two reservoir systems in India are considered for this study. One is the Pagladiya reservoir in Assam State, India, which is under construction and the other is Aliyar reservoir, which is operational in the Tamil Nadu State, India.

The reservoir system operation is complex in nature, as it has to incorporate all the input imprecision and uncertainties. Optimal use of available water in a reservoir for different purposes is attempted by many researchers using optimization and simulation methods. The output of the study, usually the optimal release should fulfill all the system requirements such as meeting various demands without violating the physical constraints of the system. An important system characteristic is that the ability of existing and proposed water resources systems to operate satisfactorily under the wide range of possible future demands and hydrologic conditions.

5.1.1 Literature review

Many approaches were attempted for reservoir operation studies in the past. They are presented in this section with the problem formulation.

Russell and Campbell (1996) stated that the fuzzy logic approach might provide a promising alternative to the methods used for reservoir operating modeling because the approach is more flexible and allows incorporation of expert opinion. This approach will facilitate the operators. The fuzzy rule based modeling of a reservoir operation is a simple approach which operates on an "IF-THEN" principle, where the "IF" is a vector of (fuzzy) explanatory variables such as inflow and "THEN" is a fuzzy consequences such as the actual release from dam. The construction of fuzzy rules also incorporates the experience of the reservoir operator, the "system expert" (Shrestha et al., 1996). Recently many research studies were reported using fuzzy hybrid models for reservoir operation studies too.

A fuzzy rule based approach was adopted by Shrestha et al. (1996) to emulate reservoir operator's experience. Shrestha et al. (1996) developed a fuzzy rule based model to derive operation rules for a multipurpose reservoir based on economic development criteria such as hydropower, municipal, irrigation, industrial, flood control, navigation and environmental criteria. They found that the fuzzy rule based model is easy to construct, apply and can be extended to complex system of reservoirs.

Russel and Campbell (1996) developed reservoir-operating rules with fuzzy programming and found that it is a promising area but suffers from "curse of dimensionality". They found that it could be a useful supplement to other conventional optimization techniques. Fontane et al. (1997) used an implicit SDP formulation to derive operating rules with imprecise objectives; all operating objectives were considered as fuzzy sets, and preferences were described linguistically.

Panigrahi and Mujumdar (2000) used fuzzy logic for reservoir operation for case study of the Malaprabha irrigation reservoir in Karnataka, India. Fuzzy rules had been derived from a simulated operation of the reservoir with a SDP operating policy with reservoir storage; inflow and demands are used as premises and the release as the consequences. They showed that fuzzy rule based reservoir operation is simpler than complex optimization procedure and the operators may feel more comfortable in using such models which is easy to develop. In this study, a fuzzy rule based reservoir operation model was developed for a single reservoir. Expert knowledge for framing the Fuzzy rules was derived from a deterministic dynamic programming (DP) model. The dynamic programming model was used here as an alternative to the expert knowledge that is generally available with experienced reservoir operators. The methodology for constructing the fuzzy rule base model was independent of the DP model.

Nagesh Kumar et al. (2001) developed a multi objective fuzzy linear programming model for reservoir operation. They considered irrigation and power generation as two objectives in their study. They studied Hirakud reservoir in Orissa state as case study using the proposed model. Linear membership functions were used to fuzzify the objective functions in that study.

Mohan and Raipure (1992) used a linear multiobjective programming model to derive the optimal releases for various purposes from a large-scale multi reservoir system consisting of five reservoirs in India. A trade-off analysis between the conflicting objectives of irrigation and hydropower generation was carried out in this work.

Esogbue and Kacprzyk (1998) presented a fuzzy criterion dynamic programming that sought to maximize the expected fuzzy criterion function representing the degree of satisfaction associated with the states of the system.

Dubrovin et al. (2002) developed a fuzzy rule based control model for multipurpose real-time reservoir operation and found that it is better to fulfill the new multipurpose operational objectives determined by the experts.

Tilament et al. (2002) developed a fuzzy stochastic dynamic program to solve multipurpose multi-reservoir operation problems for deriving optimal operating policies. The reservoir operation problem for the Mansour Eddahbi dam in Morocco was formulated as a classical stochastic dynamic programming (SDP) problem, where the objective function stresses energy maximization with particular volumes being released for irrigation and as a fuzzy stochastic dynamic programming (FSDP) problem, in which both hydropower generation and irrigation were considered as fuzzy constraints and aggregated by the weighting method. Despite major differences in the mathematical representation of operating objectives and constraints, they concluded that both formulations yielded similar measures of system performance.

5.2 PROBLEM FORMULATION

Artificial Neural Networks are also used successfully for single reservoir as well as multi-reservoir operation (Raman and Chandramouli, 1996; Jain et al., 1999; Chandramouli and Raman, 2001). While neural networks are ideal for modeling known or unknown associations that exist between the input and output data, significant data cleaning and preprocessing are usually needed. In other words, input data must be carefully prepared for the network to process. The more input data, the better the training results. The richer the input data, the more accurate is the model.

Simonovic (1992) had discussed the limitations of reservoir operation models. He also suggested some measures to make them more acceptable to the operators. Russell and Campbell (1996) also emphasized that due to the high degree of abstraction necessary for efficient application of optimization techniques, the applicability of most of the reservoir operation models is limited. The optimization models developed with uncertainty are more complex and the field operating personnel find it too difficult to use them. Further the results are very voluminous and hence interpreting them properly for day-to-day operation also becomes difficult.

Young (1967) derived general operating policies for reservoir operation from voluminous optimization results using regression procedure. Bhaskar and Whitlach (1980) analyzed a single multi purpose reservoir using backward DP algorithm to obtain optimal results. They made use of the procedure of deriving general operating policies from deterministic optimization as initiated by Young (1967).

Bhaskar and Whitlach (1980) considered a quadratic loss function and derived monthly policies by regressing optimal set of releases on the input and state variables. Karamouz and Houck (1982) also developed a general reservoir system operating rules by deterministic optimization and constructed a DPR model. The DPR model algorithm suggested by Karamouz and Houck (1982) had a deterministic dynamic program with a regression model for deriving operating policies from DP results.

Raman and Chandramouli (1996) developed a DPN model, which used neural network for deriving general operating policies from the deterministic dynamic programming optimization algorithm. Raman and Chandramouli (1996) derived rules from the optimization results using neural network approach for a single reservoir operation. They also compared the results to regression based models and showed that the DPN model gives improved performance than DPR model, stochastic dynamic programming model and standard operating policy for that particular case study.

Jain et al. (1999) found that ANN can be effectively used in reservoir operation and inflow prediction. They used time series modeling, optimization, system simulation and ANNs for the operation of a single, multipurpose reservoir. They examined the application potential of the ANN in attaining the reservoir operational objectives, compared with the conventional models. They found that the high flows are modeled better through the ANN, whereas low values are better predicted through the ARIMA model. The average monthly deviation for all of the individual years as well as for the entire period was less for the ANN model. For reservoir operation, the ANN model performance was the best in terms of hydropower generation and irrigation deficit.

Chandramouli and Raman (2001) developed DPN3 model for a three-reservoir system. In this study, from the optimization results of a three state variable DP, general operating policies were derived using neural network. They had shown the usefulness of ANN in deriving operating rules for a multi reservoir system. They compared the total performance of a multi reservoir system based on DPN3 model and single reservoir based DPN model operations. DPN3 model showed much improved results.

Chandramouli et al. (2002) developed a dynamic programming based neural network model for analyzing the water sharing between two reservoirs in a multi reservoir system catering for irrigation. They found that the DPN model gives very good performance compared to other models considered.

Cancelliere et al. (2002) used artificial neural networks for deriving irrigation reservoir operating rules and found that operating rules based on an optimization with constraints resembling real system operation criteria lead to a good performance both in normal and in drought periods, reducing maximum deficits and water spills.

Many variables associated with reservoir operation such as inflow to the system, base flow contribution, reservoir evaporation, demand, etc., can be expressed by fuzzy concept (Panigrahi and Mujumdar, 2000). In this study, an attempt is made to use the proposed fuzzy neural network hybrid model for deriving general operating policies from optimization results of a single objective single reservoir problem.

Two reservoir systems in India are considered for this study. Two models, namely a single neural network model and a fuzzy neural network model are developed for deriving reservoir release from deterministic DP results (DPN model and DPFNN model).

Planning reservoir operation is a dynamic multistage decision making problem in which the decision made at a given stage and state has an impact on the future of the system. System analysis, which involves use of optimization, simulation, and other decision-making techniques, is a set of powerful tools to solve reservoir operation problems. These techniques are increasingly being applied to real-life problems. A number of successful applications of optimization techniques to reservoir operation problems have been reported in the literature. Yeh (1985) also reviews the status of DP in reservoir optimization problems. Dynamic programming (DP) and its variants have been implemented to determine efficient operating policies for multipurpose, multi-reservoir systems. DP does not require any restriction on the shape of the objective function and can be extended to accommodate the stochastic nature of inflows, as well as the vagueness of some objectives and constraints. Yakowitz (1982) presented the main applications of DP in water resources problems such as reservoir operation, irrigation scheduling, and water quality control.

For multi purpose reservoir systems, both implicit and explicit stochastic problems have been formulated and solved. In the implicit scheme, the stochasticity is included by generating many equally likely sequences of inflows or by using forecasts, historical flow sequence or critical values of inflows. Then the optimization problem is solved in deterministic environment (deterministic dynamic programming). In the explicit scheme, the probabilistic structure of the inflows is incorporated directly into the optimization model (stochastic dynamic programming). In this study, a deterministic DP optimization is performed for deriving general operating policies of a reservoir.

5.3 SYSTEMS CONSIDERED

Pagladiya Dam

The system considered in this study is the proposed multipurpose dam across the perennial devastating river Pagladiya in the Nalbari district of Assam State in India. It is a north bank tributary originated from Bhutan hills. The hydrologic regime is characterized by significant variation in both monthly and annual flows. Rainfall in the monsoon period from April to September, are responsible for a large fraction of annual flow. The reservoir is expected to regulate the unstable stream flows of the river and to provide adequate water for irrigation as well as power generation.

Pagladiya dam site is located at about longitude 91°31′00″ East and latitude 26°31′30″ North. It is at 26 km north of Nalbari town. It has multipurpose objectives of irrigation, flood-control and hydropower generation. In this system, after power generation, flow from tailrace channel will be diverted into irrigation canals. Designed flood peak for flood protection is 1911 cumec. Designed flood storage requirement is 138 MCM. Table 5.1 shows the characteristics of the proposed reservoir. The dam site is shown in Fig.3.8.

Table 5.1 Salient features of the proposed reservoir

CHARACTERISTICS	QUANTITY
Storage capacity	473 MCM
Live storage	427 MCM
Dead storage	45.64 MCM
Maximum water level	91 M
Minimum pool elevation	76.85 M
Irrigation storage	267 MCM
Flood storage	160 MCM
Power plant capacity	5.50 MW
Maximum release	46.3 CUMEC
Annual average yield	939.16 MCM
Annual irrigation water requirement	65530 ha.m
Maximum discharge through spillway	2800 CUMEC
Full reservoir level	87.5 M

Data of 10 days inflows into the reservoir over a period of 32 years collected from the Brahmaputra Board were used in this study. The irrigation demands, evaporation losses are also obtained from the Board. For this reservoir system, 10 days time period backward DP model (3 time periods for each month) has been developed and the results are used for developing FNN model based reservoir operating policies.

Aliyar Dam

Aliyar reservoir (FRL +320.000 m) is constructed at the foothills in eastern slope of Anamalai hill range across Aliyar river in Tamil Nadu State, India. Aliyar river originates from northern slopes of Anamalai Hills and flows in a north-westerly direction for about 22.4 km before it enters the plain. This river is a tributary to Bharadhapuza river system. Storage capacity of this reservoir is 109 MCM. It has a catchment area of about 196.84 sq.km with an average annual rainfall of about 1200 mm. The fortnightly demand patterns with mandatory releases are given in Fig. 5.1. 27 years of fortnightly data are available for this reservoir system. For this system, a fortnightly time period backward DP model has been developed by considering 20 years of data. The rest of the data is used for comparing the performances of different models developed.

5.4 DP MODEL

Backward deterministic dynamic programming optimization technique is used to find the optimal reservoir releases. In this formulation inflow into the reservoir is considered as a known quantity. If we consider a reservoir with inflow as a known quantity, the aim of the reservoir operation is to find the optimal release to

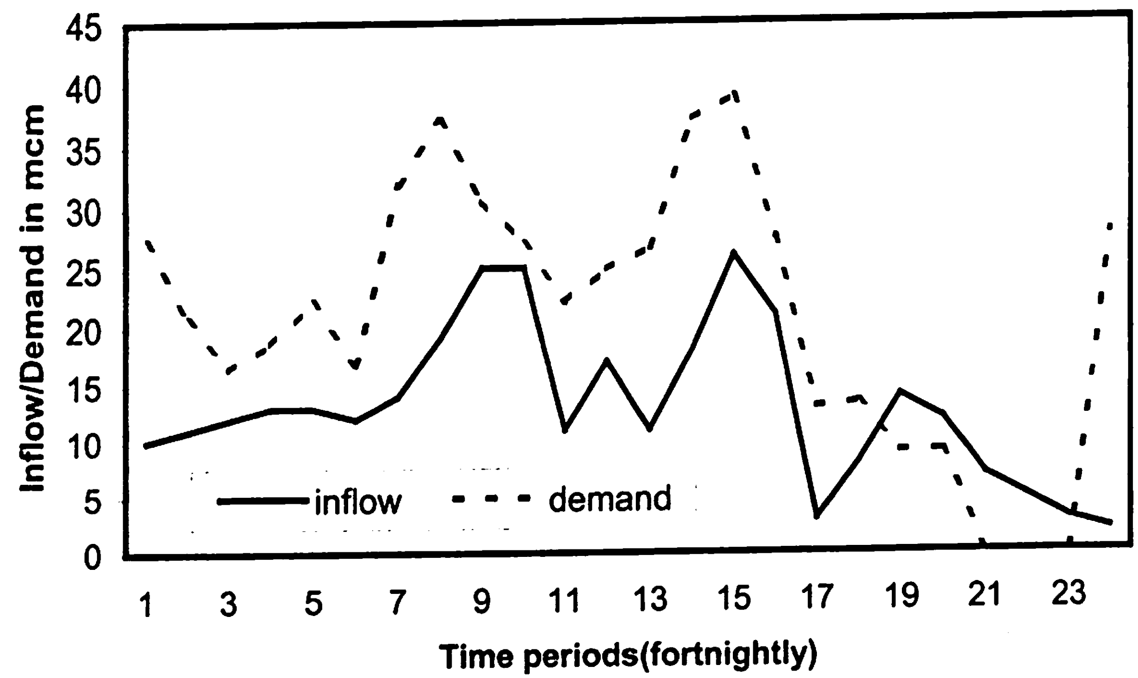

Fig.5.1.Inflow and Demand in a year (Aliyar)

maximize/minimize the given objective function. The objective function for the deterministic dynamic programming algorithm is the minimization of irrigation deficit

$$Z_t = \sum_{t}^{T} (D_t - R_t)^2 \tag{5.1}$$

Where

T= number of time periods;

R_t= release during time period t , D_t= demand during time period t .

i.e. the objective is to minimize the annual sum of squared deficit. The main advantage of this procedure is that it penalizes heavily when deviation is more. Further both negative and positive deviations are treated as same in penalization. The recursive equation for any time period t is

$$f_t^n(S_t) = \min_{R_t} \left[Z_t + f_{t+1}^{n-1}(S_t - I_t - R_t) \right] \tag{5.2}$$

subject to

$$
\begin{aligned}
&0.0 \le R_t \le R_{t\max} \\
&R_t \le S_t + I_t - E_t \\
&R_t \ge S_t + I_t - E_t - K \\
&S_{t\min} \le S_t \le S_{t\max} \\
&E_t = f(S_t, S_{t-1}, e_t)
\end{aligned}
$$

Where

S_t= storage at the beginning of time period t;

I_t= inflow during time period t;

K = storage capacity of the reservoir;

E_t = evaporation during time period t;

e_t = evaporation rate during time period t;

n = total number of periods remaining before reservoir operation terminates.

The decision making process occurs in stages. i.e. in different time periods. In each time period, a decision is to be made i.e. how much water is to be released so as to minimize the objective function. For each stage a recursive equation is constructed i.e. each of this equation represents a stage at which the decision is required (equation 5.2). The state variable considered here is the storage volume (S_t) (Fig. 5.2).

The decision variable is the optimal release (R_t) to be made at each stage. These recursive equations have to be solved in sequence.

5.4.1 Discussions

The DP model is solved for 18 years of historic data for Pagladiya reservoir system (T = 648 ten days period). Different discretization levels for the state variable are tried (2,5,10,15,20 Mm^3). Using different discretization for the state variable initial storage, optimal release for irrigation demand with mandatory release is estimated which are shown in Table 5.2. The same analysis is also performed for Aliyar reservoir. Based on both analyses, discretization 2 is adopted for all the analysis for both the reservoirs.

For Pagladiya dam, the computed optimal release using dynamic programming is closely following the demand in different time periods in a year, as the system is surplus in nature (Fig. 5.3). The irrigation demand in the monsoon period (April to September) varies between 19 MCM and 31 MCM with mild fluctuation except in the 3rd part of June (source: Brahmaputra Board Project Report).

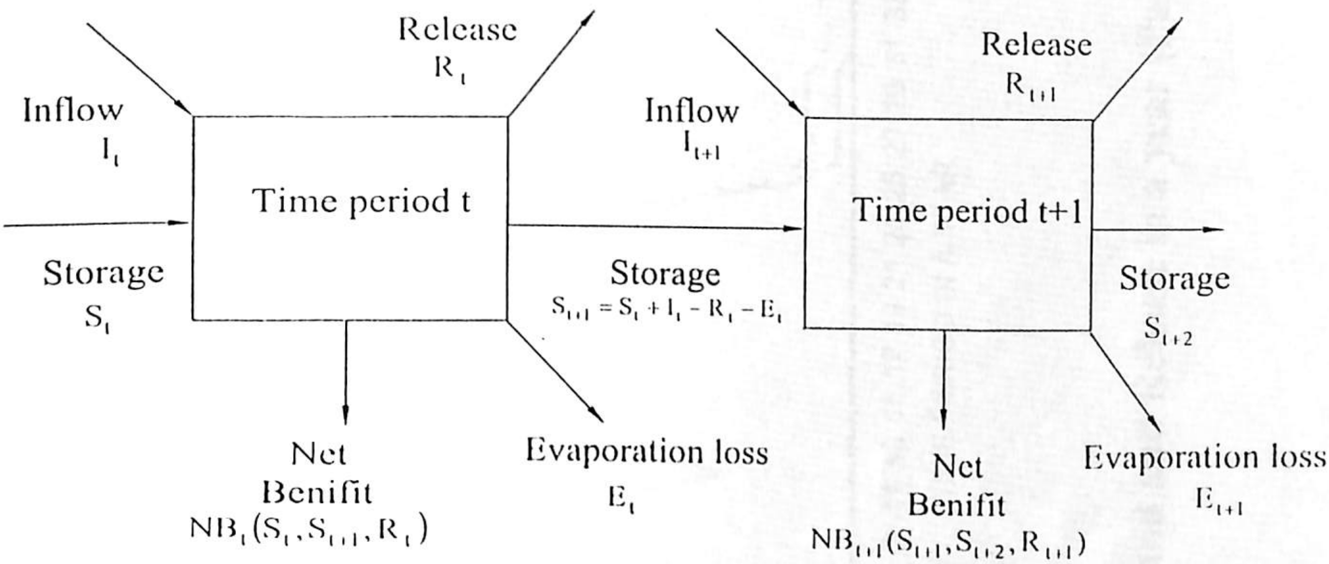

Fig.5.2.Reservoir operation problem

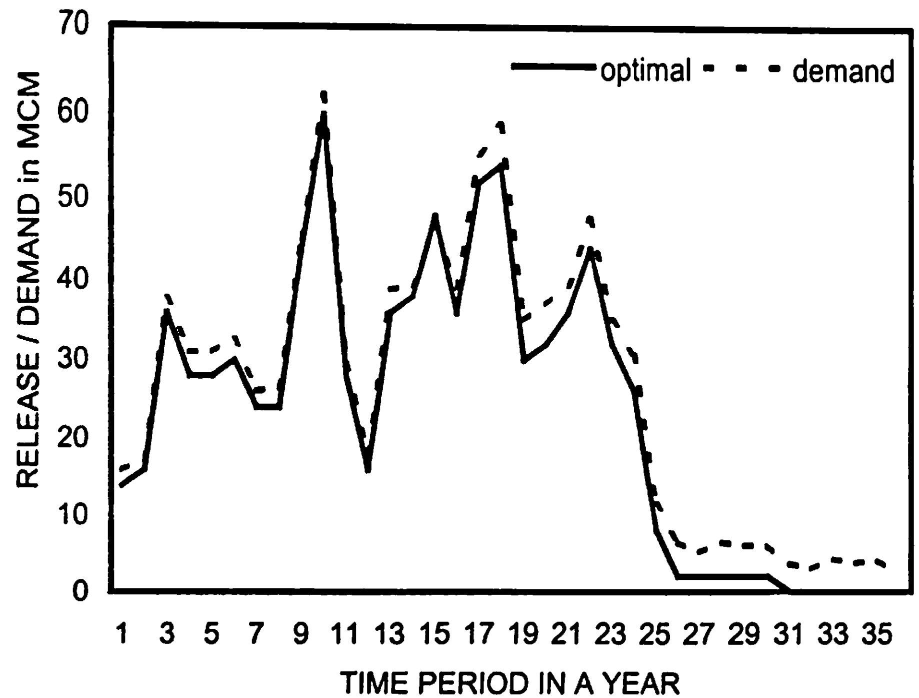

Fig.5.3.Demand and Release in a year (Pagladiya)

Table 5.2 Dynamic Programming optimization results (Pagladiya)

Discretization	Optimal release (MCM)	Squared deficit $(MCM)^2$	Spill (MCM)
2	15828	3433	8050
5	15743	4197	8123
10	14657	9074	8728
15	14376	12875	8309
20	12464	30141	9407

The total demand also includes the mandatory releases in the river channel for the riparian rights (20% of the normal inflow during that time period). The average basin rainfall varies between 150mm and 550mm per month in the same period with maximum vulnerable months as June to September for Pagladiya river system.

For Aliyar dam, the demand pattern is given in Fig. 5.1. Due to more command area and committed releases, the demand is much higher for this reservoir.

5.5 DPN MODEL DEVELOPMENT

The DP algorithm developed has provisions to print the results with different input combinations. After examining the available data, the following input variables are considered for DPN model in different experiments. Initial storage of the reservoir system at a particular time period, inflow into the reservoir at a particular time period, total demand of the reservoir system at a particular time period, inflow with lag 1, lag 2 and lag 3 time periods are used to develop DNN models in different experiments.

Three different experiments considered for the research study. First two experiments are presented in this section. The third experiment is presented in the subsequent section.

Experiment 1: The input variables inflow and initial storage at a particular time period and the output variable is optimal release during that time period.

Experiment 2: The input variables are current inflow, current initial storage and current demand and the output variable is current release.

The dynamic programming neural network model (DPN model) developed for this study, uses a feed forward neural network model for deriving general operating policies from the reservoir. The scheme adopted for DPN model development is given in Fig.5.4. Fig 5.5 shows the developed neural network model for experiment 2. The results of the DP optimization are printed in the required form of a particular experiment and using the generated patterns, DPN model is developed for different experiments. The training is carried out using the error back propagation algorithm. Sigmoidal activation functions are used in the considered neural network. The training is done by monitoring the performance index mean square error (mse) and mean relative error (mre). In this study, eight neurons are used in single hidden layer. For each experiment different DPN models are developed.

5.6 FUZZY NEURAL NETWORK MODEL

The fuzzy neural network modeling approach to find the general operating policy for the proposed reservoir is developed in a site-specific manner in this study. The results of the deterministic DP model and the field expert's opinion collected by field survey are used as the base for different FNN models created in this work. Three

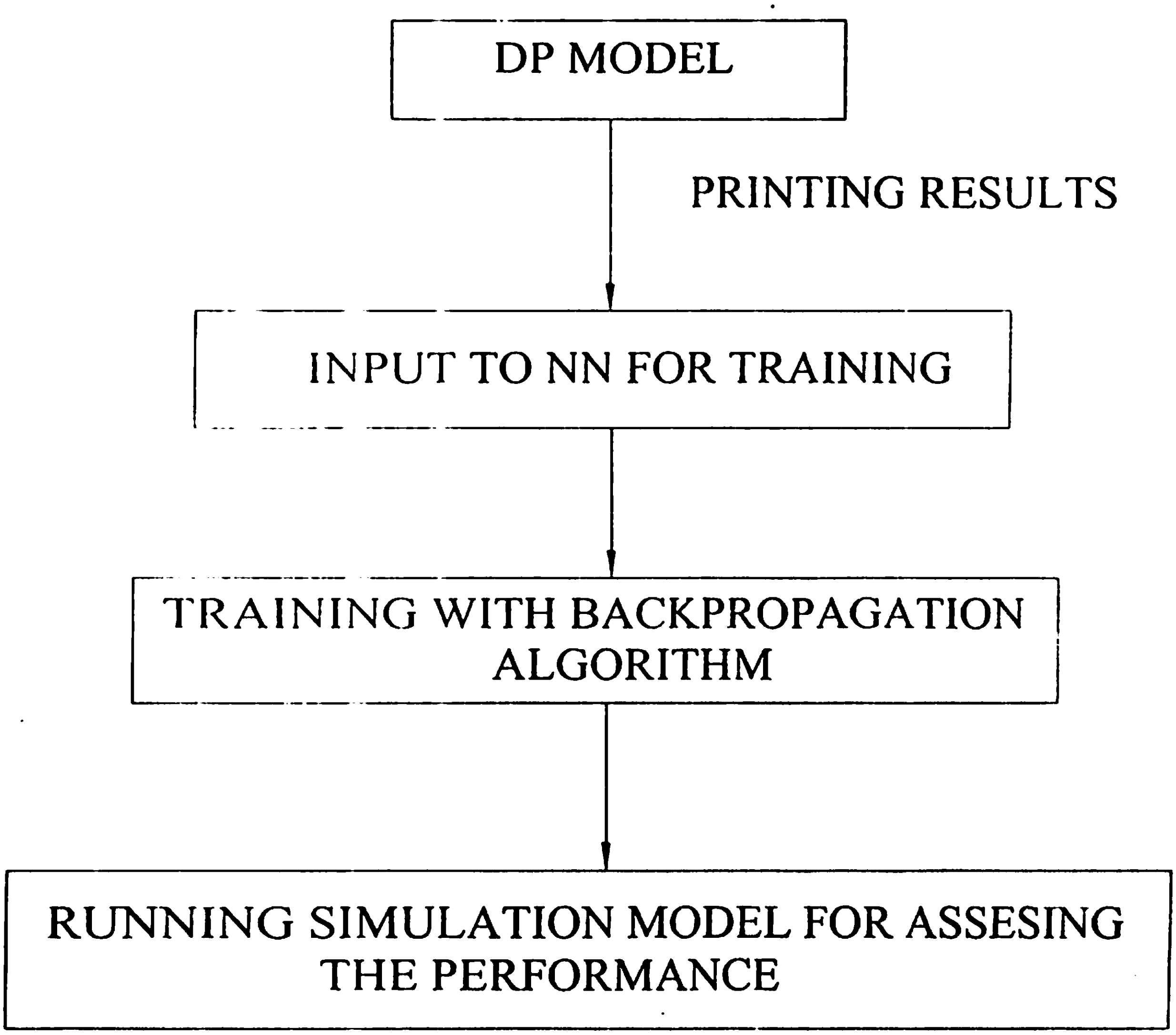

Fig.5.4.Scheme adopted for DPN model development

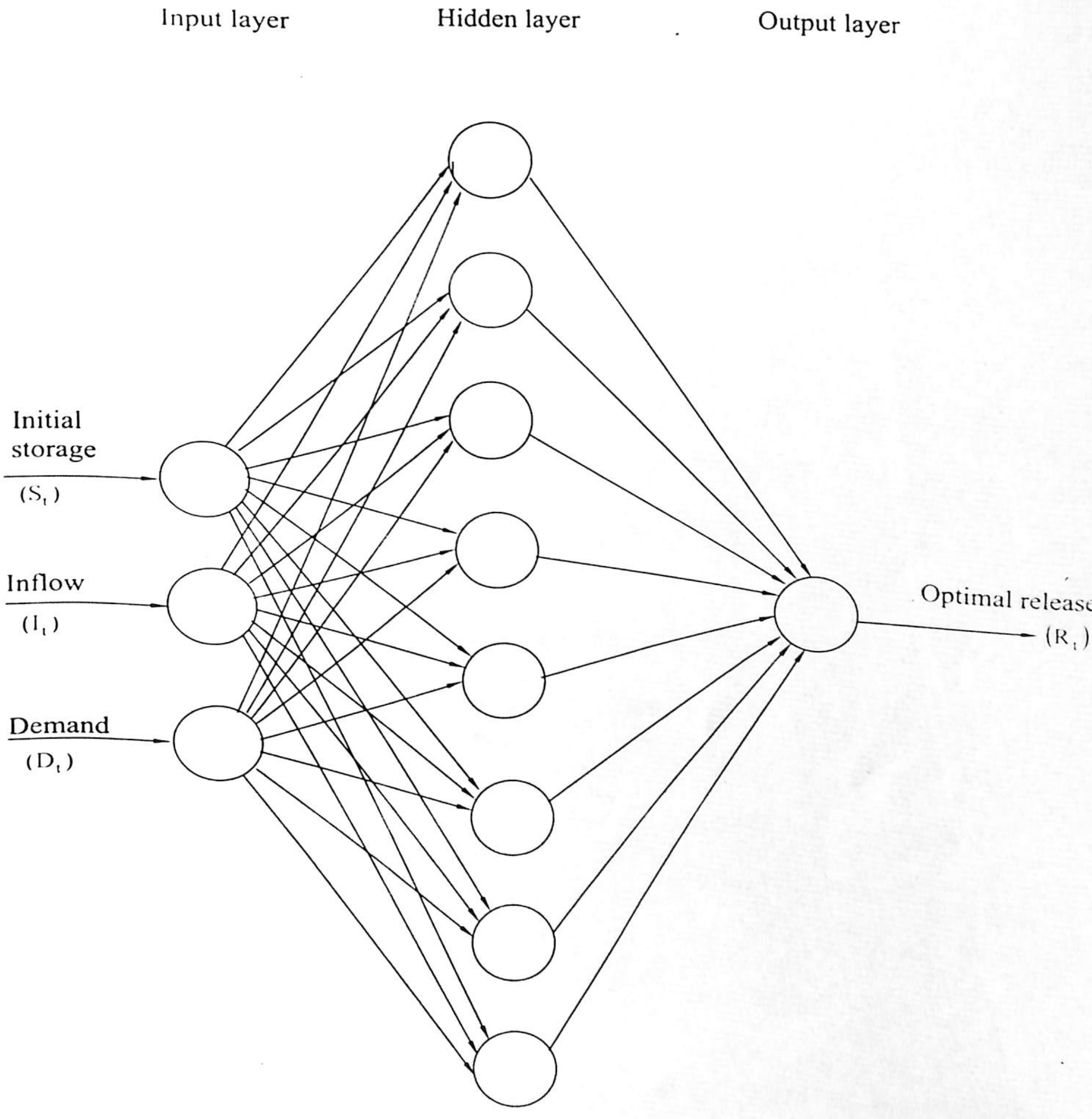

Fig.5.5.Developed neural network model (Expt.2)

different FNN models are developed for different experiments performed. After examining the available data, the following input variables are considered for fuzzification in different experiments. Initial storage of the reservoir system at a particular time period, inflow into the reservoir at a particular time period, total demand of the reservoir system at a particular time period, inflow with lag 1, lag 2 and lag 3 time periods are fuzzified to develop FNN models in different experiments.

For each experiment performed, the inputs considered for deriving general operating policy is divided into three fuzzy sets namely LOW, MEDIUM and HIGH respectively. The entire inflow domain, initial storage, demand and the total release are categorized into three fuzzy sets with necessary overlap. (Table 5.3 and Table 5.4)

Table 5.3 Domain for different fuzzy sets (Pagladiya reservoir)

Variables	LOW (MCM)	MEDIUM (MCM)	HIGH (MCM)
Inflow	0-100	50-150	>100
Initial Storage	0-200	100-300	>200
Demand	0-50	25-75	>50
Optimal Release	0-100	50-150	>100

The rule base is developed on the basis of both historical data and expert knowledge based on DP optimization results. The fuzzy associate memory developed for the fuzzy model has rules, which are shown in Table 5.5 for experiment 1.

Table 5.4 Domain for different fuzzy sets (Aliyar Reservoir)

Variables	LOW (MCM)	MEDIUM (MCM)	HIGH (MCM)
Inflow	0-20	10-30	20-75
Initial Storage	9-60	30-90	60-110
Demand	0-20	10-30	20-40
Optimal Release	0-20	10-30	20-40

Table 5.5 Fuzzy rule base formulated (Experiment No.1)

RULE NUMBER	RULES
1	IF Inflow is **LOW and** Initial storage is **LOW then** Release is **LOW**
2	IF Inflow is **LOW and** Initial storage is **MEDIUM then** Release is **LOW**
3	IF Inflow is **LOW and** Initial storage is **MEDIUM then** Release is **MEDIUM**
4	IF Inflow is **LOW and** Initial storage is **HIGH then** Release is **LOW**
5	IF Inflow is **LOW and** Initial storage is **HIGH then** Release is **MEDIUM**
6	IF Inflow is **MEDIUM and** Initial storage is **HIGH then** Release is **LOW**
7	IF Inflow is **MEDIUM and** Initial storage is **HIGH then** Release is **MEDIUM**

For each fuzzified grouping, namely LOW, MEDIUM and HIGH, a separate neural network model is developed to establish the membership function of each group i.e. the fuzzy surface of each fuzzy set is developed using the trained neural network model. As the neural network developed are having sigmoidal activation function, the output values are normalized. The results from DP optimization are segregated as per the domain values into groups and the training is done for each case. In this case too,

$$\mu_A(x) = 0; \quad m > x, \; x > l \tag{5.3}$$

$$\mu_A(x) = output \text{ from trained neural network model if } m < x < l \tag{5.4}$$

where

m = the lower limit of a fuzzy set,

l = the maximum limit for a fuzzy set and

$\mu_A(x)$ = the membership function of a fuzzy set. The developed fuzzy surface for each fuzzy set is not a standard shape. This arbitrary shape is decided using the neural network. The membership function for each fuzzy set is established based on the inputs considered in each experiment.

The membership function for the output variable optimal release is derived based on the normalization factor used in the respective neural network model. For the experiment 2, the rule base detail is given in Table 5.6. The patterns are available for all possible rule combinations from the DP results. Hence all the possible rules are used in this case. (27 rules).

Table.5.6 Fuzzy rule base formulated for Experiment 2

RULE NUMBER	RULES
1	IF Inflow is LOW and Demand is LOW then Release is LOW
2	IF Inflow is LOW and Demand is LOW then Release is MEDIUM
3	IF Inflow is LOW and Demand is LOW then Release is HIGH
4	IF Inflow is LOW and Demand is MEDIUM then Release is LOW
5	IF Inflow is LOW and Demand is MEDIUM then Release is MEDIUM
6	IF Inflow is LOW and Demand is MEDIUM then Release is HIGH
7	IF Inflow is LOW and Demand is HIGH then Release is LOW
8	IF Inflow is LOW and Demand is HIGH then Release is MEDIUM
9	IF Inflow is LOW and Demand is HIGH then Release is HIGH
10	IF Inflow is MEDIUM and Demand is LOW then Release is LOW
11	IF Inflow is MEDIUM and Demand is LOW then Release is MEDIUM
12	IF Inflow is MEDIUM and Demand is LOW then Release is HIGH
13	IF Inflow is MEDIUM and Demand is MEDIUM then Release is LOW
14	IF Inflow is MEDIUM and Demand is MEDIUM then Release is MEDIUM
15	IF Inflow is MEDIUM and Demand is MEDIUM then Release is HIGH
16	IF Inflow is MEDIUM and Demand is HIGH then Release is LOW
17	IF Inflow is MEDIUM and Demand is HIGH then Release is MEDIUM
18	IF Inflow is MEDIUM and Demand is HIGH then Release is HIGH

(Table 5.6 to be continued in the next page)

Table 5.6 continued

19	**IF** Inflow is **HIGH and** Demand is **LOW then** Release is **LOW**
20	**IF** Inflow is **HIGH and** Demand is **LOW then** Release is **MEDIUM**
21	**IF** Inflow is **HIGH and** Demand is **LOW then** Release is **HIGH**
22	**IF** Inflow is **HIGH and** Demand is **MEDIUM** then Release is **LOW**
23	**IF** Inflow is **HIGH and** Demand is **MEDIUM then** Release is **MEDIUM**
24	**IF** Inflow is **HIGH and** Demand is **MEDIUM then** Release is **HIGH**
25	**IF** Inflow is **HIGH and** Demand is **HIGH then** Release is **LOW**
26	**IF** Inflow is **HIGH and** Demand is **HIGH then** Release is **MEDIUM**
27	**IF** Inflow is **HIGH and** Demand is **HIGH then** Release is **HIGH**

For any experiment, the fuzzy reasoning used is the simple *monotonic method*, a basic fuzzy implication technique. This type of reasoning is followed when only one rule is fired and suitable for the inflow considered. If two rules are fired for a particular inflow value, the Min-Max rule of implication is executed. The consequent fuzzy region is restricted to the minimum of the predicate truth.

5.7 RESULTS AND DISCUSSIONS

The DPN model and DP-FNN model are compared using a simulation model based on the objective function. Both the models use the optimal release data from DP as base information for model development. Hence for both the reservoirs, for the validation series of 7 years, deterministic DP model is developed with same objective function and this original DP results for 7 years are used as benchmark for assessing the model performances.

In this discussion, the results of the simulation model, which operates based on the operating rules derived using DPN model and DPFNN model are compared. For every time period considered, DPN / DPFNN model gives optimal release based on some inputs provided to them. Based on mass balance, the final storage is computed in the simulation model. The final storage of previous time period becomes the initial storage for the subsequent period and the next period performance is assessed subsequently. As the total system performance depends on the operating policy, the objective function value resulting from different models are compared to assess the best model.

The Squared deficit and the spill for both the reservoirs from the dynamic programming optimization results are presented in Table 5.7.

Table5.7 Direct DP optimization results for validation series

Reservoir	Squared deficit $(MCM)^2$	Spill (MCM)
Pagladiya	5119	715
Aliyar	9374	12

5.7.1 Discussions on Experiment 1 and Experiment 2 for Pagladiya reservoir

Total squared deficit and spill for Pagladiya reservoir for two different experiments are presented in the Table 5.8. It is observed that the total squared deficit for DPFNN model is less than the DPN model by almost 50% in experiment 1 considering 7 years validation data.

The year wise squared deficit of DPFNN model and DPN model are shown in Fig.5.6 for the experiment 1. The DPFNN performed better than DPN model in all the years, which consists of normal years, water scarce years as well as water surplus years. Fig.5.7 shows the spill value for different years for the experiment 1 for both DPFNN and DPN model, which indicate the better performance of DPFNN model.

The efficiency of both the models are examined considering the within year performance for the experiment 1.The total number of nil deficit time periods are more in DPFNN model than DPN model as DPFNN is performing consistently better than DPN model which is shown in Fig.5.8.

Both the models considered are highly deviating from the DP optimization results (400%for DPFNN and 640% for DPN). The operating policies derived only using inflow and initial storage (i.e. Experiment 1) is not satisfactory.

The DPFNN model performance suffered in the experiment 2 where the squared deficit is almost two times than DPN model. Total spill for the DPFNN model is 40% less than the DPN model for the experiment 1. Spill also helps us to infer the quantity of water, which is wasted with out proper usage. The higher spill by DPFNN model in experiment 2 shows the inability of the operating policies developed by the considered model to use water effectively for irrigation.

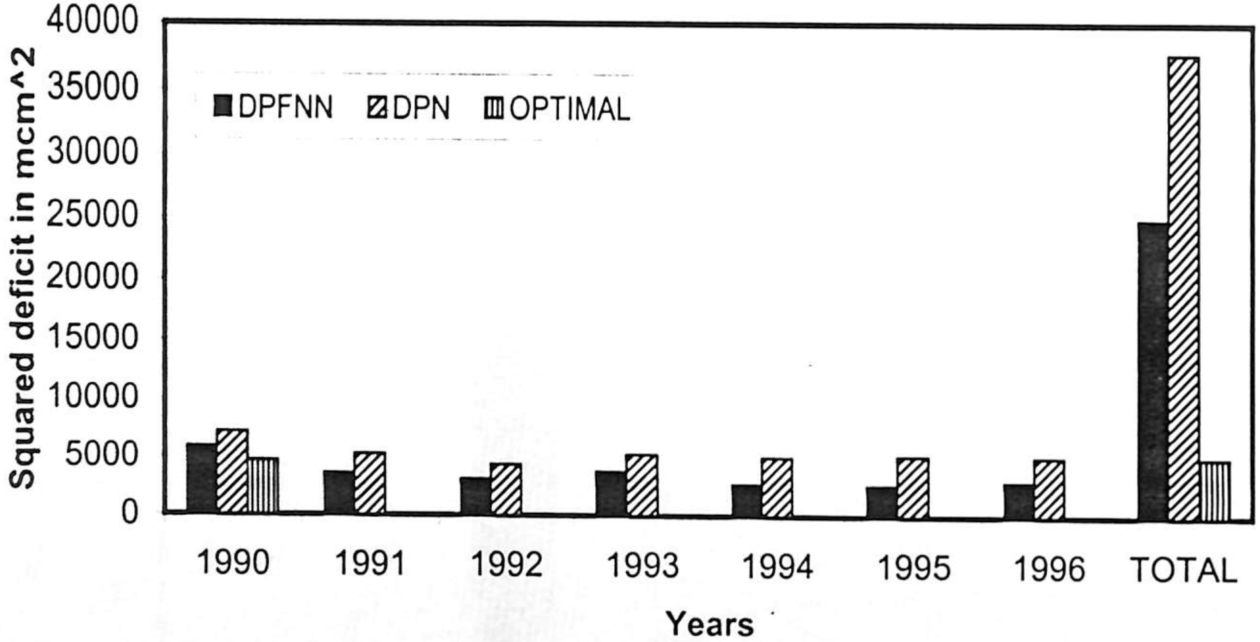

Fig.5.6. Year wise squared deficit for Expt.1 (Pagladiya)

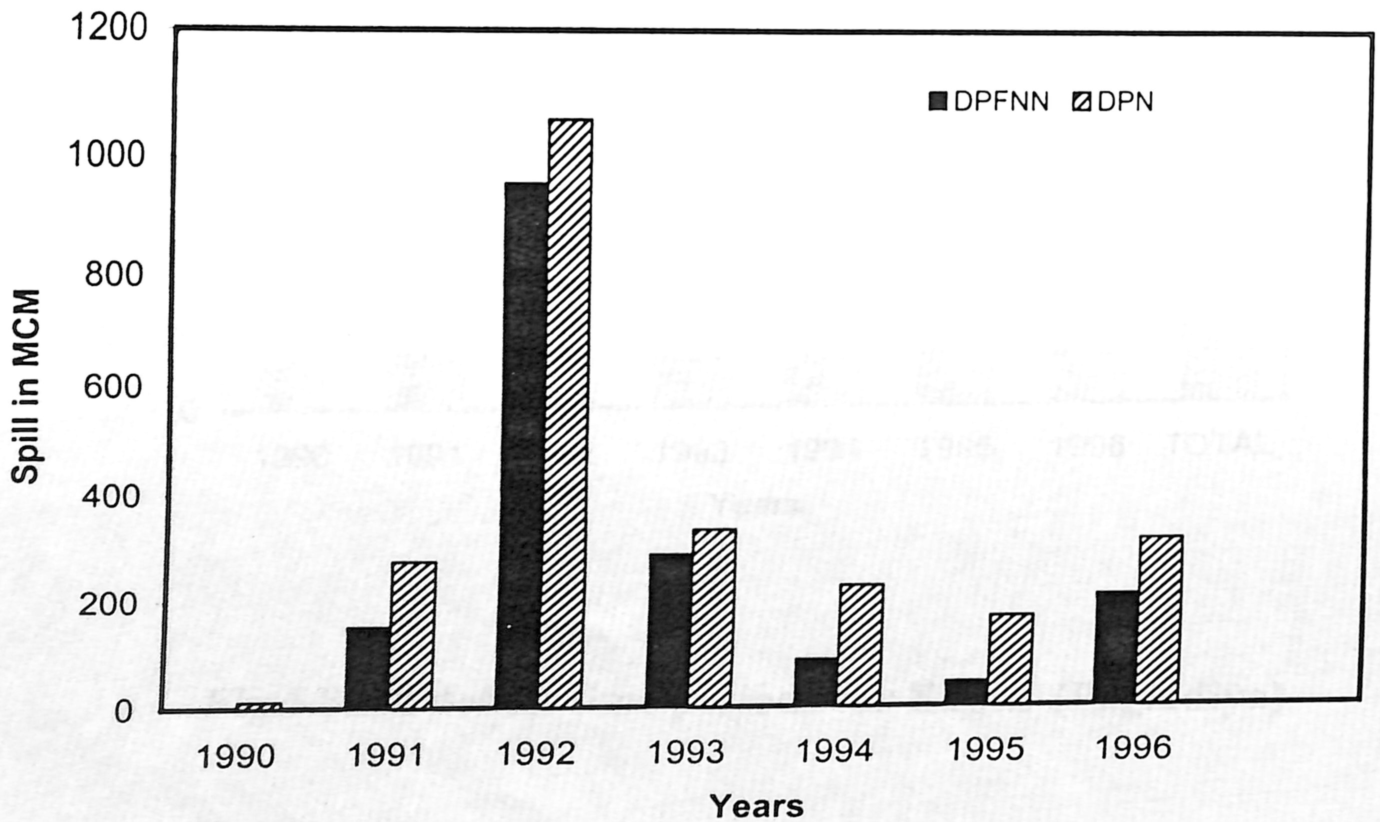

Fig.5.7. Year wise spill for Expt.1 (Pagladiya)

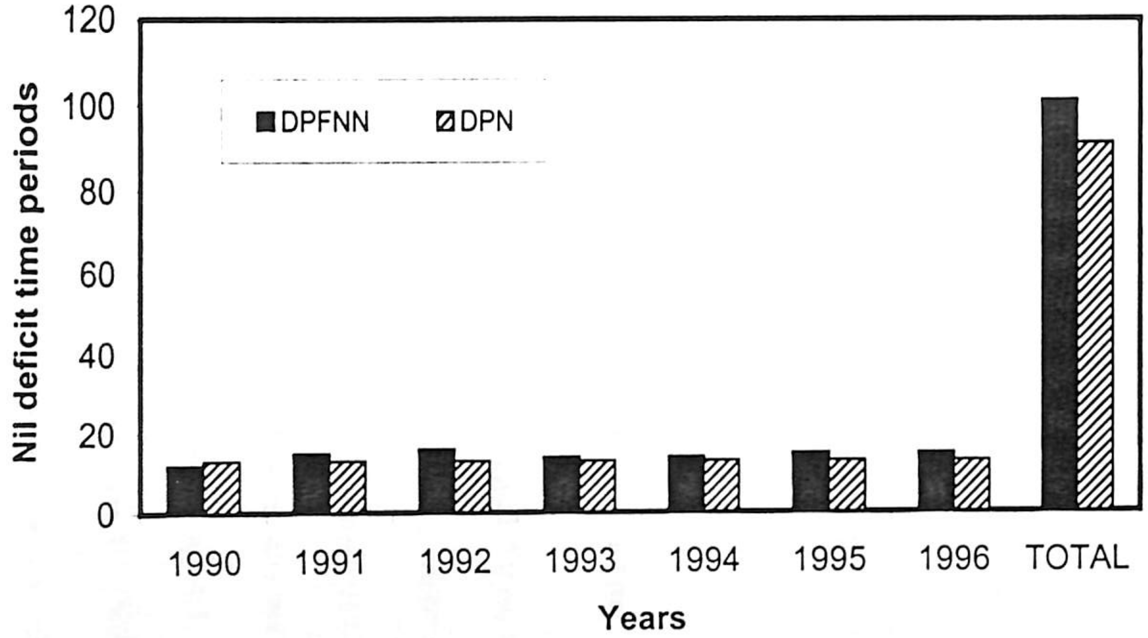

Fig.5.8.Nil deficit time periods for Expt.1 (Pagladiya)

But the performance of DPN and DPFNN models based on experiment 2 showed improvement over models based on experiment 1. (Fig. 5.9)

Table 5.8 Testing results for Pagladiya reservoir

Model	Experiment 1		Experiment 2	
	Squared deficit	Spill (MCM)	Squared deficit	Spill (MCM)
DPFNN	24983	1737	13894	1366
DPN	37760	2392	6471	874

5.7.2 Discussions on Experiment 1 and Experiment 2 for Aliyar reservoir

Another existing reservoir called Aliyar is considered for the analysis to examine the behavior of the proposed model in water scarce situation. Same experiments are conducted for this reservoir also. The total squared deficit and spill for the experiments 1 and 2 are shown in Table 5.9. The results are varying slightly for this reservoir. The objective function value for DPFNN model and DPN model are almost same. But DPFNN has more spills. Here also, the DPFNN model suffers by almost 12% than DPN model for the experiment 2 considering the squared deficit. But spill is less in DPFNN model than DPN model for the same experiment. In this system, DPFNN model does excess release and suffers in its performance.

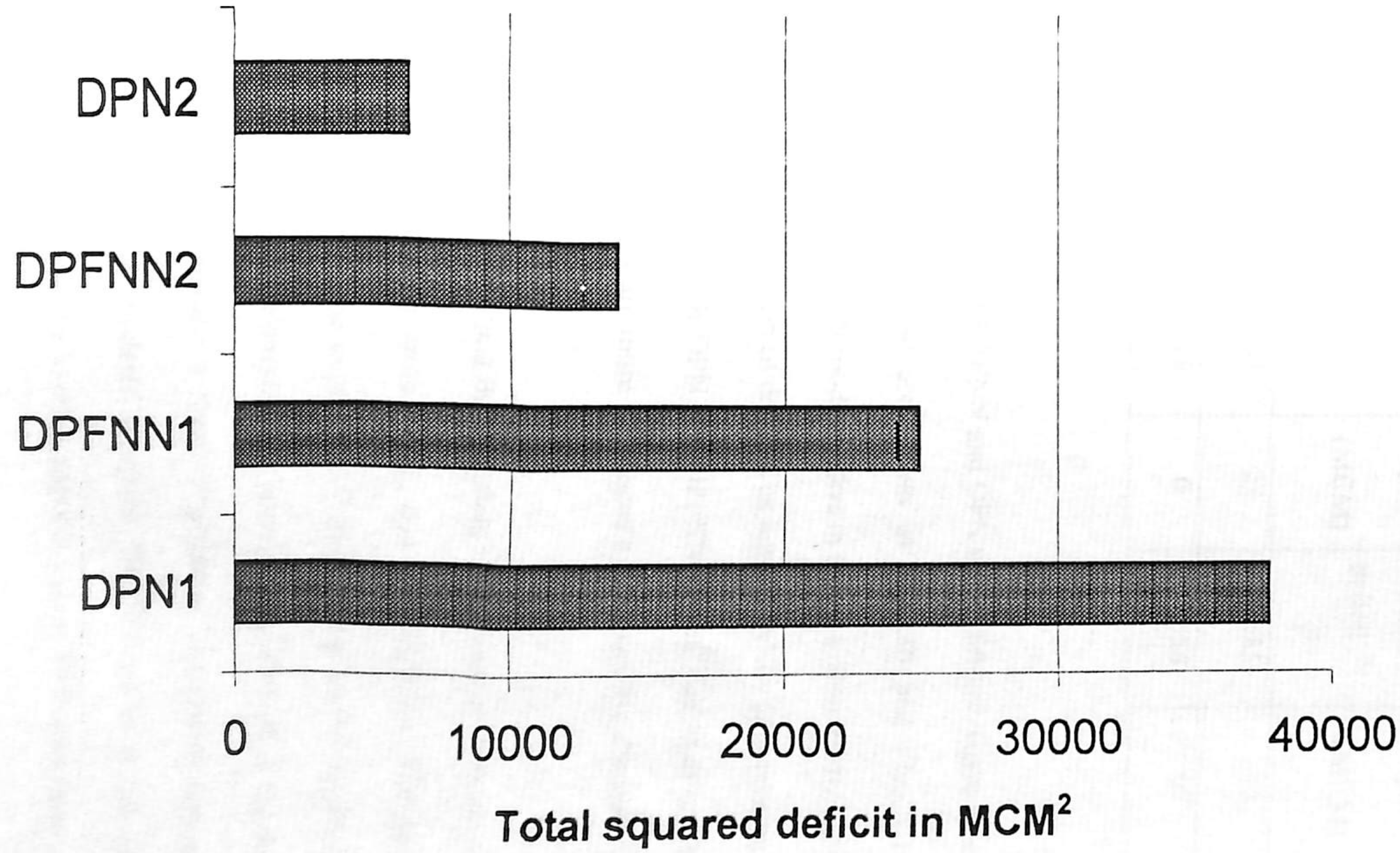

Fig.5.9.Total squared deficit of 7 year performance (Pagladiya)

Table 5.9 Model results for Aliyar reservoir

Model	Experiment 1		Experiment 2	
	Squared deficit	Spill (MCM)	Squared deficit	Spill (MCM)
DPFNN	17034	25	12185	13
DPN	17028	0	10554	97

The performance of DPFNN and DPN model for the Aliyar reservoir considering the objective function value are shown in Fig.5.10 and Fig. 5.11 year wise for experiments 1 and 2. DPFNN model suffers in the experiment 2 for all the 7 years.

Further, the exclusion of demand as input to ANN, (experiment 1), leads to more poor performances for both DPN and DPFNN model. Hence, it can be concluded that the model performances are more influenced by the variable demand during a particular time period.

It may be concluded that the modeling strategy adopted in the case of experiment 2 for DPFNN model need more tuning and simplification. The performance of the DPFNN model suffers in the experiment 2 may be due to the in-efficient rule base for the patterns considered. The overlapping criteria and the width of the domain base are to be suitably amended considering the field situation. The architecture used for different fuzzy sets are also to be modeled carefully. DPFNN model is not giving satisfactory performance in experiment 2 where all possible rule combinations are used.

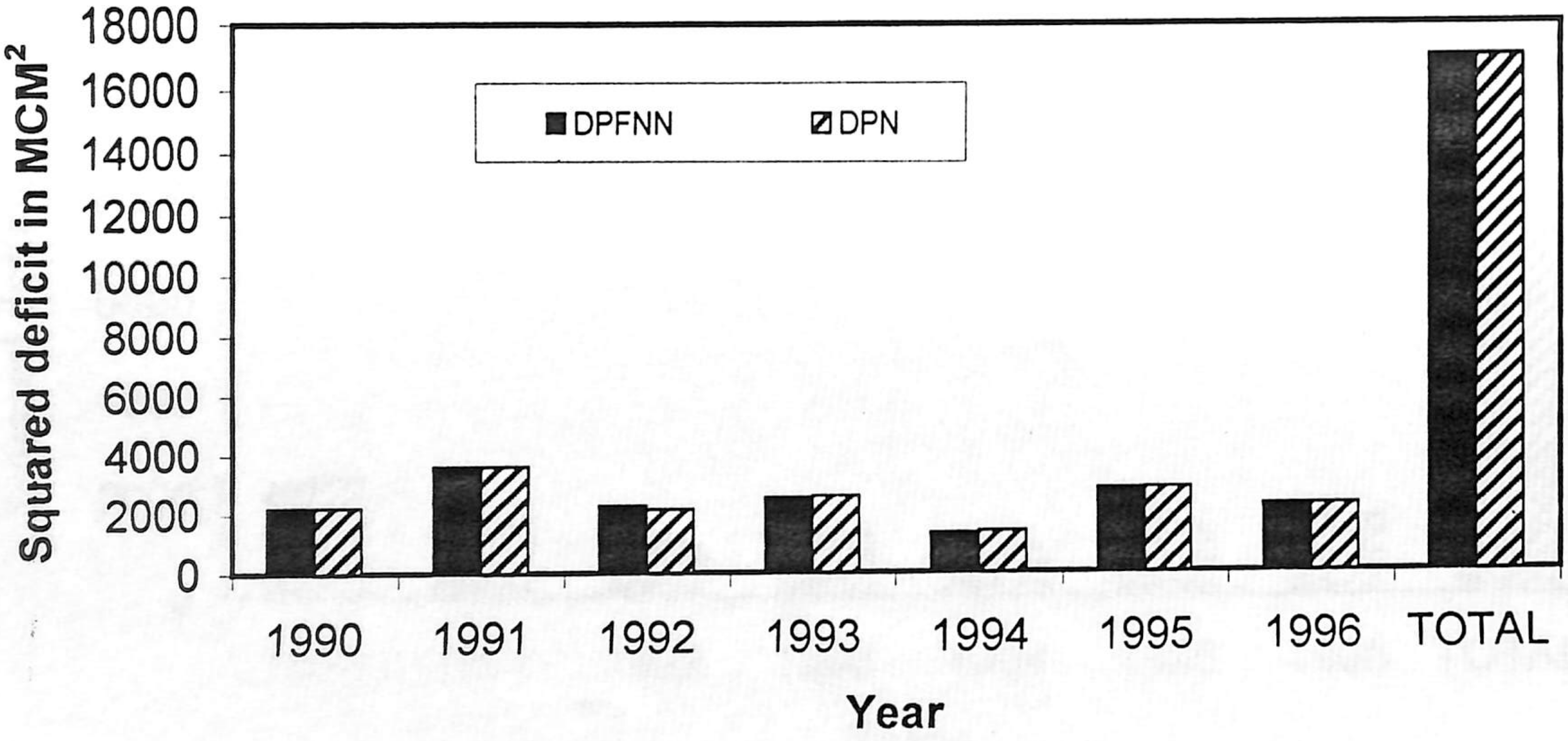

Fig.5.10. Year wise squared deficit for Expt.1 (Aliyar)

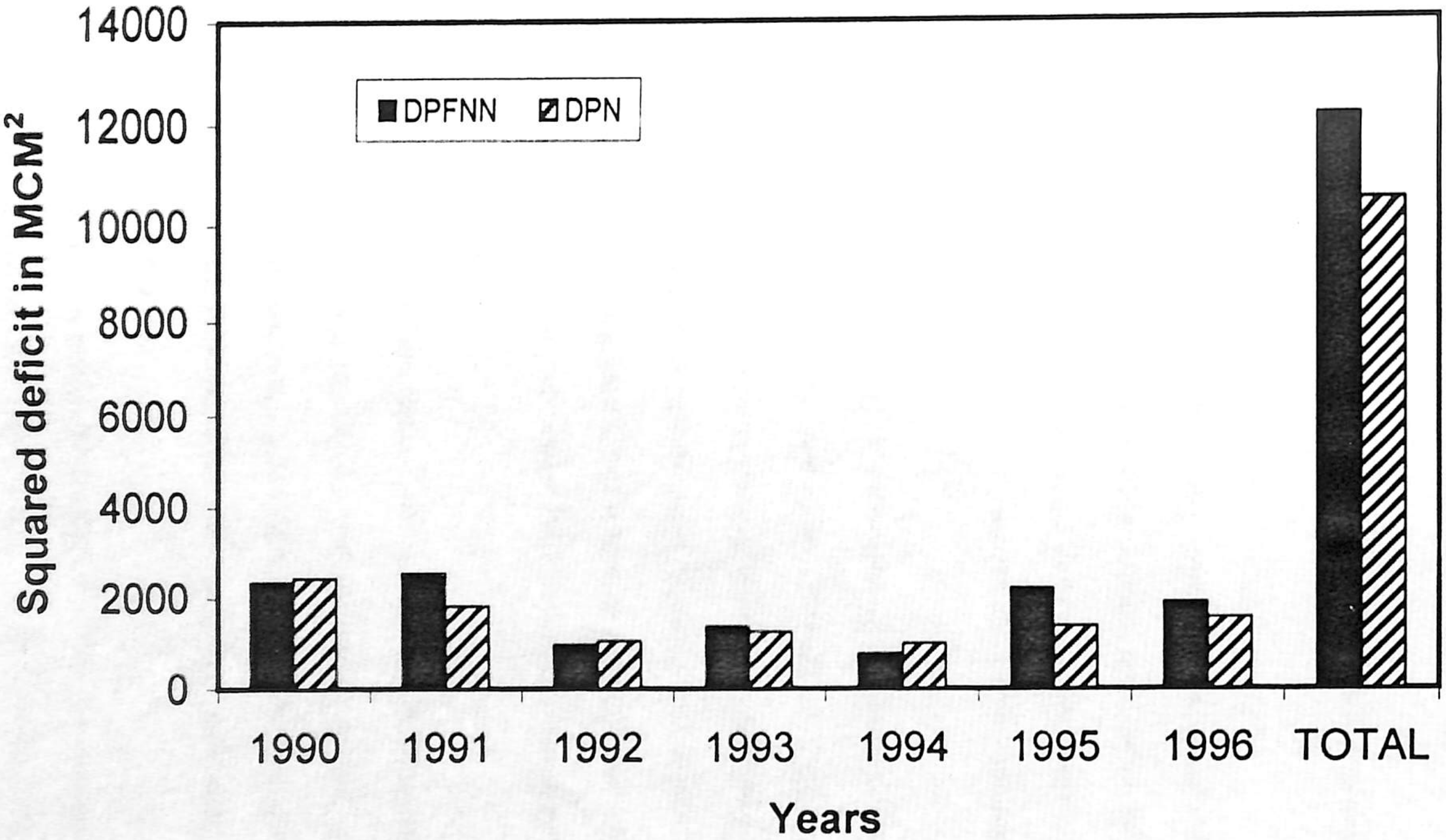

Fig.5.11.Squared deficit for Expt.2 (Aliyar)

5.7.3 Experiment 3

Based on the study experiences from experiment 1 & 2, experiment 3 is planned with slight modifications.

The deterministic optimization using regression and neural network methods attempt to capture the relationship between inputs and outputs. When the outputs are the control decisions and inputs are the state variables of the system, the problem is ill posed as control decisions are based on policies that are not known in advance (Simonovic, 1992).

Philbrick Jr. and Kitanidis (1999) discussed the limitations of the deterministic optimization applied to reservoir operations. Philbrick Jr. and Kitanidis (1999) demonstrated the contrasting control policies developed using deterministic optimization of inflow forecasts with control policies using stochastic optimization of probabilistic inflows. The DPR model suggested by Karamouz and Houck (1982) for obtaining the optimal release for a particular time period, the inflow during that period is used since it is a deterministic formulation.

As a continuation of that research, Raman and Chandramouli (1996) developed the neural network model and regression model for deriving general operating policies for a reservoir system. In that study, inflow during a particular time period was used as an input. In their study, the DPR model is based on a multiple linear regression form

$$R_t = aI_t + bS_t + c\,D_t + d \tag{5.5}$$

Where a, b, c and d are regression coefficients and D_t is the demand during the time period t. Similar to that, in DPN model too, I_t was an input to ANN model. In these models (both the DPR and DPN models) the variable inflow I_t during a time period is treated as a known quantity since it was a deterministic optimization.

In experiment 3, an attempt is made to develop operating policies, which needs the known data of previous time periods as input to decide about the decision variable using fuzzy neural network modeling.

In this experiment, the input variables are initial storage at a particular time period, inflow with lag 3 time periods, inflow with lag 2 time periods, inflow with lag 1 time period, demand during the considered time period and the output variable is optimal release during the considered time period. Hence from the deterministic optimization results, the operation rules are derived based on the inflow from previous three time periods and demand during that time period t, which can be estimated in advance. Hence the problem is not ill posed as in the earlier cases.

5.7.3.1 DPN model for experiment 3

This DPN model is built in as two-tier system. In the first phase, based on initial storage, the data are classified into three categories. For each case, a neural network is developed with inputs as inflow with lag 3 time periods, inflow with lag 2 time periods, inflow with lag 1 time period and the demand during the considered time period. After examining the initial storage during a particular time period, the operator will use an appropriate ANN to be fired. The division of data made for each storage class is crisp in nature.

5.7.3.2 DPFNN model for experiment 3

In the DPFNN model, the initial storage which is the state variable is not included as the input variable, but the initial storage is fuzzified into three fuzzy sets with overlapping namely, LOW, MEDIUM and HIGH. The whole patterns generated are classified into three groups as per the fuzzification adopted. Based on the historical data set optimization, the rule base is generated.

The neural network model is developed for the classified groups of these three fuzzy sets from optimization results. The neural network developed by considering the inflow from the catchment during time periods t-3, t-2 and t-1, demand during that time period (Fig.5.12).

The reservoir initial storage fuzzy sets membership functions are described using trained ANNs, which uses inflow from the catchment during time periods t-3, t-2 and t-1, and demand during that time period as inputs. The output optimal release is described by triangular membership function (Fig.5.13). The fuzzy inferencing is done using mini-max principle. The defuzzification is done based on near edge of the support set defuzification procedure.

Rule base :

If Initial storage is LOW, then optimal release is LOW

If Initial storage is MEDIUM, then the optimal release is LOW

If Initial storage is MEDIUM, then the optimal release is MEDIUM

If Initial storage is HIGH, then the optimal release is MEDIUM

If Initial storage is HIGH, then the optimal release is HIGH

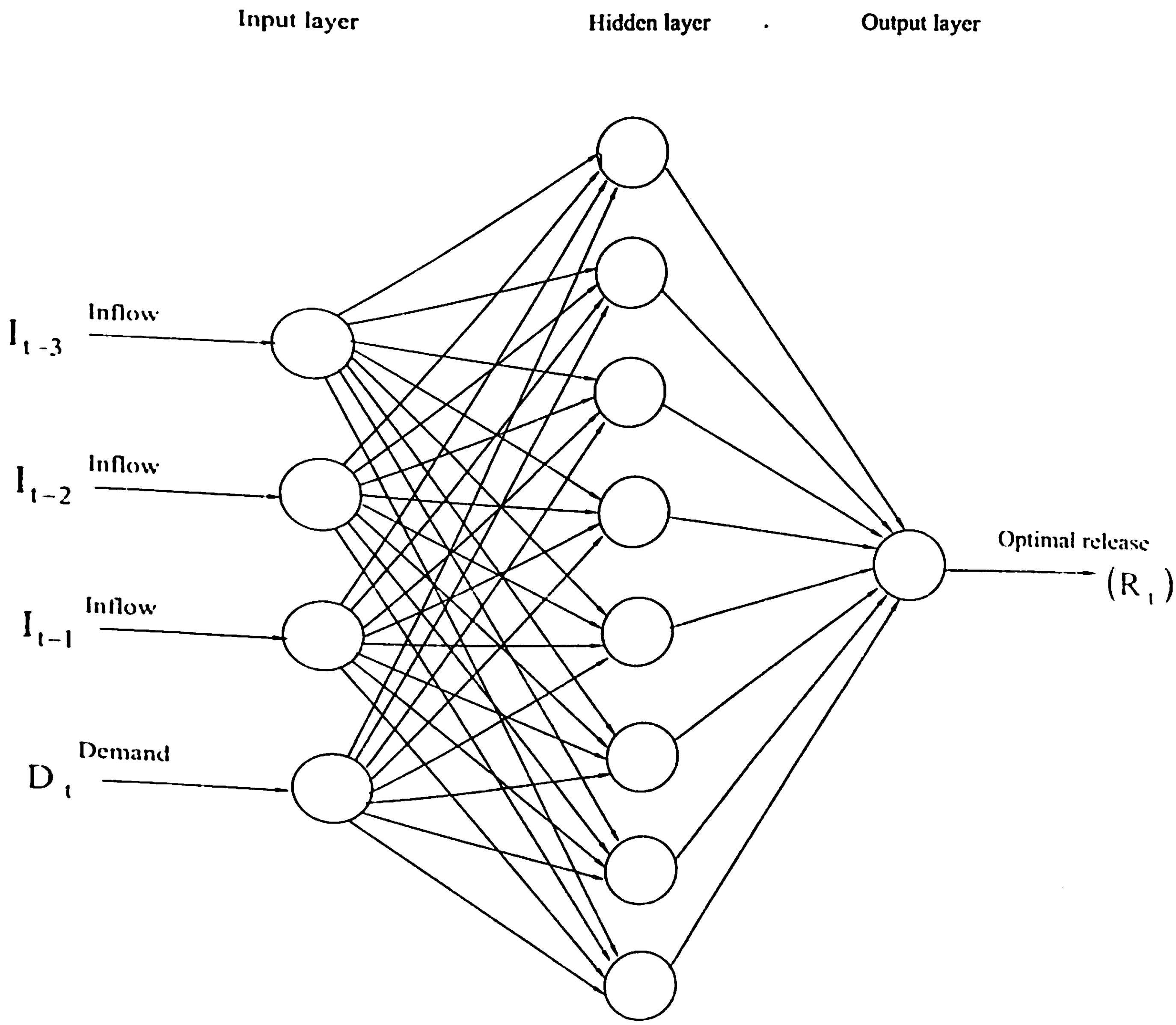

Fig.5.12. Neural network model for Expt.3

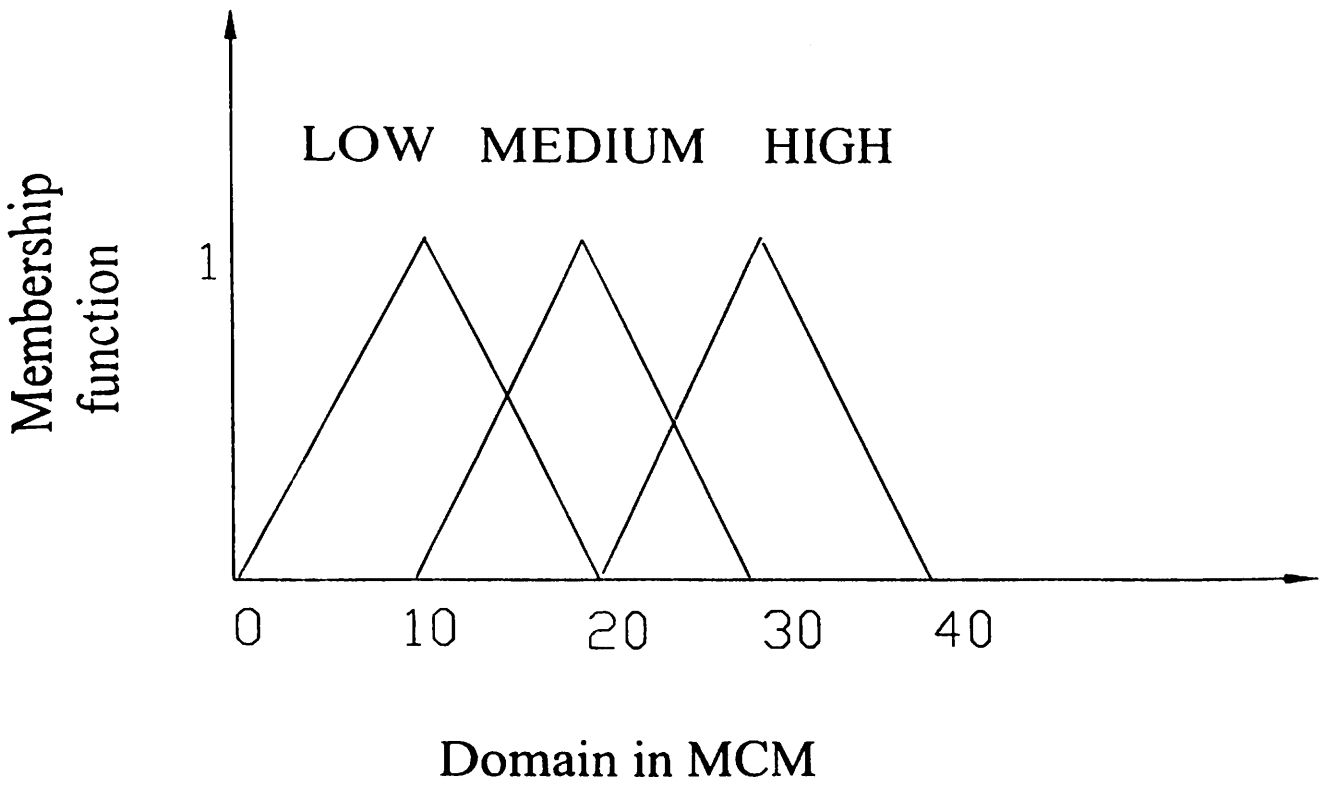

Fig.5.13. Triangular membership function for release (Aliyar)

Table 5.10 Model results for Experiment 3

Model	Pagladiya		Aliyar	
	Squared deficit	Spill (MCM)	Squared deficit	Spill (MCM)
DPFNN	6641	779	10451	64
DPN	6946	701	11560	85

In the case of experiment 3, for Pagladiya and Aliyar reservoirs, DPFNN model is performing better than DPN model. In the case of Aliyar reservoir, DPFNN model is carrying 11% less squared deficit than DPN model. The spill is less in DPFNN model compared to DPN model for the experiment 3. In the case of Pagladiya too, DPFNN model shows 4.5 % improvement in the total squared deficit value. The spill is more for DPFNN than DPN model. This is due to the system water availability. In the water scarce situation for Aliyar dam, operating policies of DPFNN model used more water effectively to improve the system performance. In more water available situation for Pagladiya reservoir, DPFNN model performance is better than DPN model but more water is spilled by DPFNN model due to the fact that it does more hedging.

5.7.3.3 Comparing DPFNN model of Experiment 3 with best performing DPN model of Experiment 2 for both the reservoirs

The DPFNN model of experiment 3 is better than DPN model of experiment 2 for Aliyar reservoir system. But for Pagladiya reservoir system, it is not so. The behaviour of the models in two contrasting nature of reservoirs are different. DPN model for Pagladiya reservoir (experiment 2) does more release and hence it meets the required demand (which results in lesser squared deficit)(Table 5.8). Since water availability is more, more release of DPN model (experiment 2) does not lead to sufferings in lean periods of the system. On the other hand, in a water scarce Aliyar system more release of DPN model (experiment 2) leads to sufferings in lean periods of the system and hence it is performing poorer when compared with DPFNN (Table 5.9). The practicability of using the experiment 3 model in field is high.

Advantage of fuzzy rule based system for reservoir operation is that by using linguistic statement like low initial storage, medium inflow and high release, the models are developed. The operators may find comfortable to use these models. Furthermore, the DP-FNN model also has more flexibilities associated with it in the form of fuzzy rule formulation, choosing different suitable architectures for each NN for each fuzzy set, creating different fuzzy sets by considering suitable domains, etc.

Formation of a fuzzy rule base for reservoir operation related to seasonal variation in both hydrological variables and operational targets. Snowmelt and rainfall play an important role in a hydrological year. Hence better performance may not be obtained with the same rules throughout the year. This leads to various kinds of rules required for different seasons. Sometimes rule combinations, which are not available in the training data sets, may be encountered as an extra ordinary case in the testing data set. In that case, the nearest rule combinations are considered though it affects the performance of the model.

The fuzzy rules obtained indicate that the high release from the dam most likely to occur when there is high inflow to the initial storage in the reservoir. Although these are in agreement with the current level of physical understanding of the system, the fuzzy rules do not provide any information about the relationship between the high inflow and other environmental variables that are considered to be important (e.g., rainfall, watershed, lateral flow).

The optimization models used in various reservoir operation studies are far too complex and data intensive to be of immediate use for actual operation. The fuzzy neural network model presented in this study, on the other hand, is mathematically simple and provides implementable, near optimal operating policies. Since the model is not mathematically complex, the technology transfer is expected to be more effective. It provides an opportunity for the reservoir operators to participate in formulating the rule base. In the present work, the fuzzy rules have been derived from a simulated operation of the reservoir with a deterministic DP operating policy. The DP model is used here only as an alternative to an expert who is presumed to have a good insight to provide the fuzzy rules for operations, and that the DP model itself is not essential for the approach presented here. The results presented here could be quite sensitive to the nature of the membership function and defuzzification methods. DP-FNN is flexible and easy to build.

CHAPTER 6

FUZZY NEURAL NETWORK APPROACH FOR FLOOD ROUTING

6.1 INTRODUCTION

Continuous forecasting of river flow can be made by indirect and direct methods. The indirect method initially involves prediction of runoff either through a rainfall-runoff model or by routing the flow observed at an upstream gauge to the desired location downstream. The routing techniques are more useful when the travel time is longer and the downstream flow is low or controlled. Very rarely, all the data necessary to apply a routing model to a length of channel or channel network is available. All the parameters and variables like rainfall in the catchment, catchment characteristics, influencing the inflow hydrograph, channel properties involves impreciseness or subjected to uncertainty. These quantities can be efficiently modeled by using fuzzy concepts. To examine the applicability of the fuzzy neural network modeling (FNN) for real time forecasting at different time periods and spaces along the channel, necessary data has been generated by using kinematic wave equation in the absence of field data for temporal as well as for spatial variation.

In this chapter, a kinematic wave equation model (KWM) is developed for a particular stretch of a small natural channel to generate the necessary data for the analysis, as it is difficult to obtain field data for any natural channel. Spatial and temporal variation of the flood wave is obtained for the stretch considered using the developed model. From the results of KWM, two models namely Fuzzy Neural Network model and Artificial Neural Network model have been developed to obtain continuous flow forecasting in the downstream sections of the channel and their performances are compared. The applicability of the FNN model for distributed flow routing has been demonstrated in the study. When we consider a long reach with a requirement of predicting at close spatial and temporal levels, the flood routing models will be huge and a field operator in the field will find it difficult to use them for practical applications. So in this study an attempt is made to develop the user-friendly fuzzy neural network model, which will be very easy for a field operator to use it in field with ease.

6.2 PROBLEM FORMULATION

The first attempt to numerically simulate the one-dimensional Saint Venant equations for flood routing problems was made by Stoker (1953) and Isaac-son (1954). In 1961, Preissmann provided the famous four-point box scheme. Since then, a variety of numerical techniques have been used to solve flood routing problems. These include the explicit characteristic models, the implicit finite difference models, and few attempts using the finite-element models.

The kinematic wave approximation includes the gravitational and frictional forces. In most natural open channels, the friction and bed slopes predominantly govern the movement of flood waves. The kinematic wave theory has been researched and reported extensively in hydrology literature since Lighthill and Whitham introduced it (Lighthill and Whitham, 1955). Growing environmental and ecological concerns have increased the role of the kinematic wave theory in describing and modeling environmental and hydrologic processes (Singh, 1996).

Hromadka and DeVries (1988) argued after a series of test varying the Δx and Δt that the use of the kinematic wave method for channel routing needs evaluation for use in hydrologic models unless guidelines are developed to control the arbitrary use of the kinematic wave in design studies. They added that kinematic wave programs needs internal checks to select Δx and Δt such that an accurate solution is achieved.

The kinematic wave equations, resulting from simplification of the Saint-Venant equations have many advantages. Among these are the possibility of analytical solutions for simple geometries and fewer boundary conditions as compared with the far more complex Saint-Venant equations.

Generally KWM do not need downstream boundary conditions but require only initial condition and upstream conditions. This implies that kinematic wave equation can only model discharge changes from upstream end but cannot account for downstream influences (Price, 1994). During application of kinematic equation, a uniform flow condition is usually assumed at downstream, provided no backwater effects (Akan and Yen, 1977). It is suitable when available data consists of observed upstream water depth on the reach. In addition to this, model requires far less computer time and storage than Saint-Venant equations. Hence it could be useful for rapidly calculating particular characteristics of a flood wave (Odai, 1999).

Most of the analysis of KWM is related to constant or time varying rainfall. Problems with spatial variation of rainfall or surface characteristics, such as roughness and slope, are still not well documented in the literature (Jaber and Mohtar, 2002). These are quantities for which there is often only semi quantitative informations available but cannot be expressed either with precise values or through statistical distributions. The usual mathematical tools cannot use information of this type because they do not take such uncertainties into account. Fuzzy neural network approach can solve the problem by transforming imprecise information into a formal statement of uncertainties to evaluate the way these uncertainties propagate to variables such as discharges and stages. In this way this problem is well suited for use in fuzzy neural network. Fig.6.1 shows the work plan for the analysis.

6.3 SYSTEM CONSIDERED

Ghoramara channel, a small north bank tributary of the Brahmaputra river, passing through the IIT Guwahati campus has been considered for the analysis. The channel is almost dry in the lean period but overflows during the rainy season. The average width of the channel is 6m and depth of the channel is 4m. No significant lateral flow exists for the reach considered. The collection of flow data has been carried out during the extreme lean period when average flow velocity was 0.25 m/s and average depth of flow was 0.15m in the middle of the river. Cross-sectional as well as longitudinal details have been collected by a detailed survey for a stretch of 600m in the channel (Fig.6.2). The longitudinal details such as riverbed level and bank level are collected at every 10m. interval. The cross section details such as bed level, depth of flow are taken at a space of 1.5m on either direction from the centerline of the river flow. The longitudinal bed slope as well as lateral bed slope is estimated from the measured data in the channel. The velocity of flow and the corresponding depth of flow are obtained for a whole day at an interval of one hour at inlet as well as at outlet section using area velocity flow meter sensor to obtain the inflow as well as outflow discharge

Fig.6.3 shows the model 4250 Area-Velocity Flow Meter used for flow measurement in this study. This equipment has a probe with two different sensor systems. By submerging it in the flow stream, mean velocity of flow and depth at which flow is measured can be read directly. It contains a pressure transducer to measure water

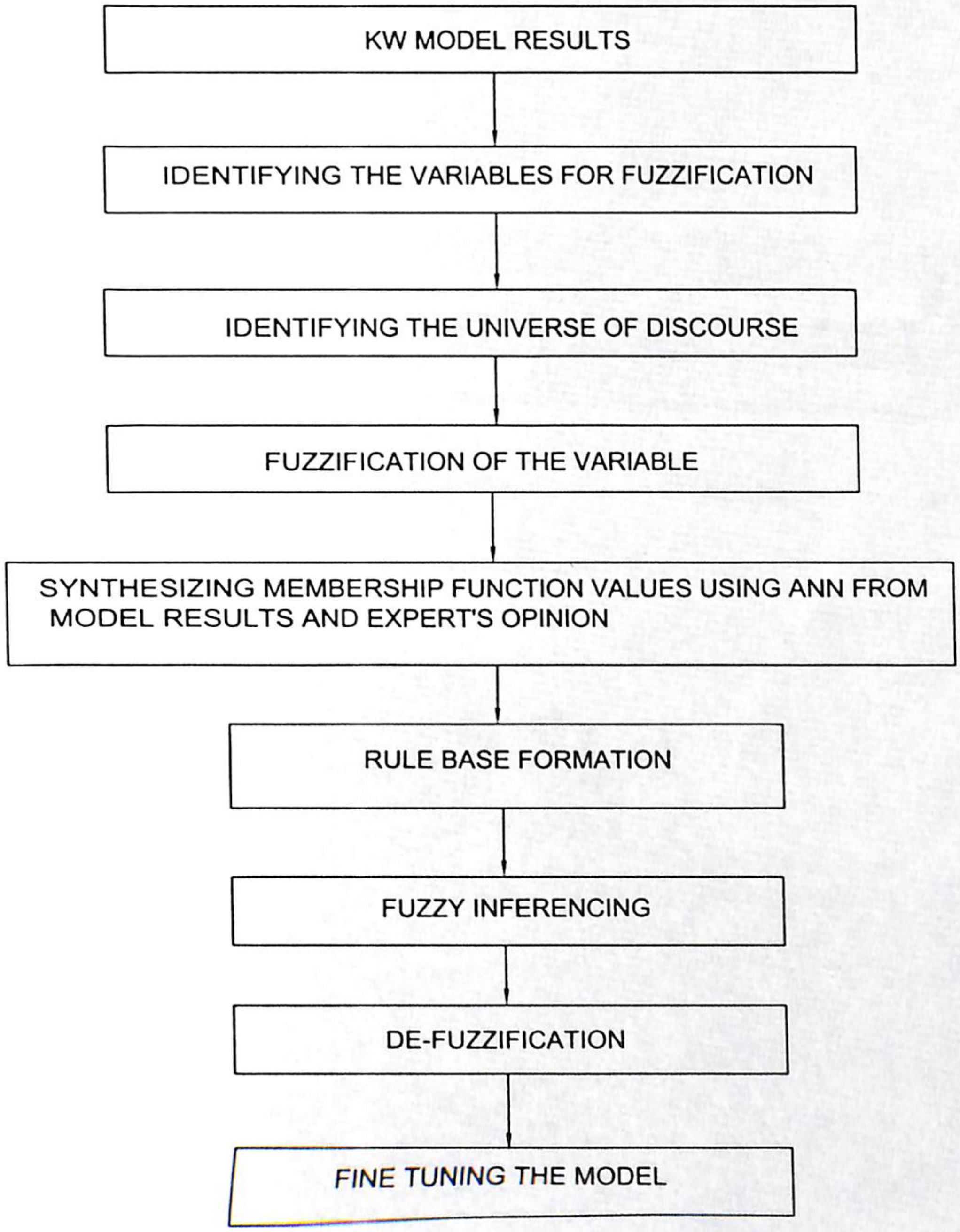

Fig.6.1. Work plan for the study

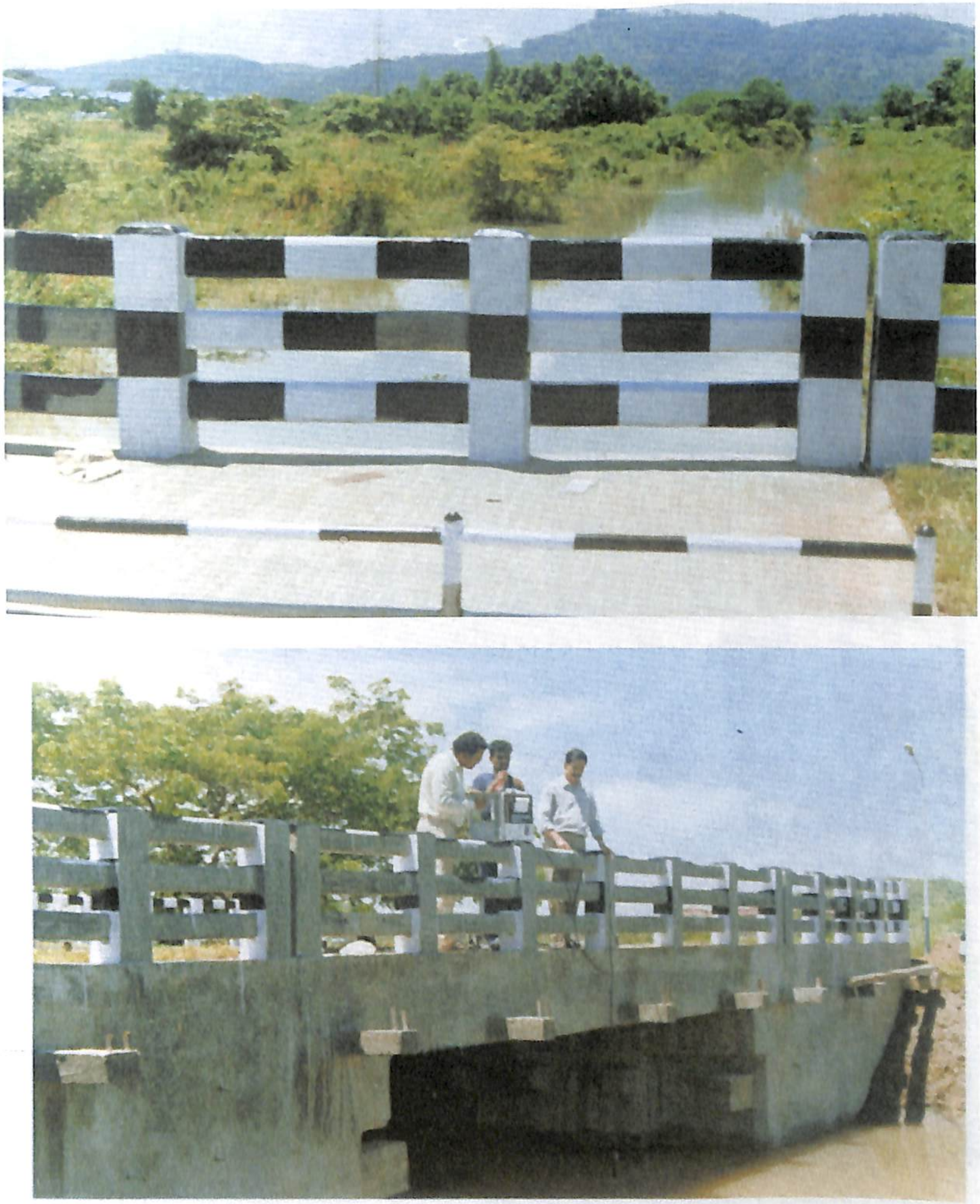

Fig.6.2. System considered and data collection process

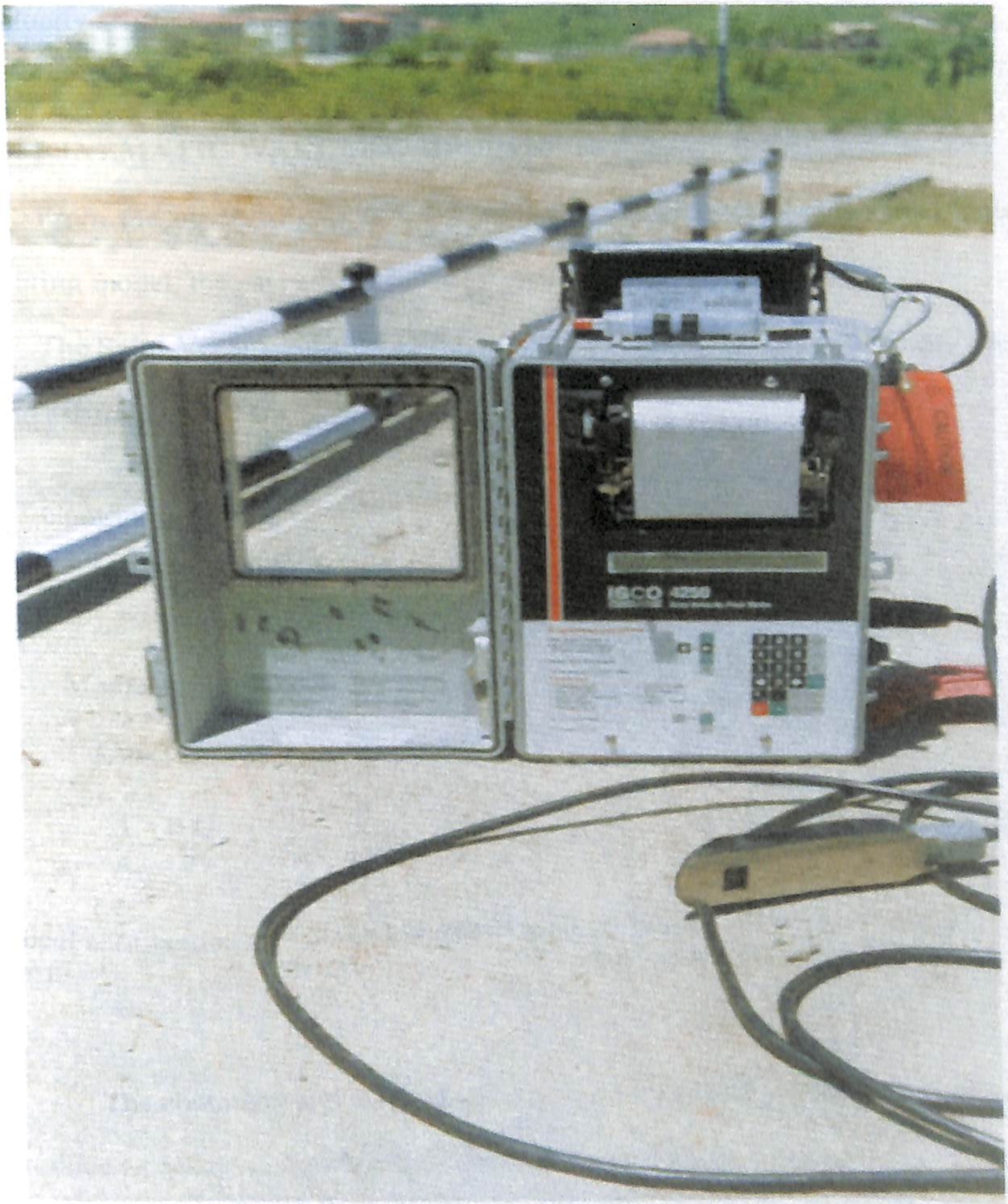

Fig.6.3. Area Velocity Flow Meter

depth and a pair of ultrasonic transducers to measure velocity. The working principle of velocity sensor is based on Doppler effect.

6.4 KINEMATIC WAVE MODEL

From the observed data of the channel on a particular day, using kinematic wave routing model, the data are generated for closer time and space domain.

The Saint-Venant equations (Neglecting lateral inflow, wind shear, and eddy losses, and assuming β=1) are:

Continuity equation

Conservation form $$\frac{\partial Q}{\partial x}+\frac{\partial A}{\partial t}=0 \tag{6.1}$$

Momentum equation

Conservation form

$$\frac{1}{A}\frac{\partial Q}{\partial t}+\frac{1}{A}\frac{\partial}{\partial x}\left(\frac{Q^2}{A}\right)+g\frac{\partial y}{\partial x}-g\left(S_0-S_f\right)=0 \tag{6.2}$$

Local acceleration term	Convective acceleration term	Pressure force term	Gravity force term	Friction force term

The continuity and momentum equations for the kinematic wave are combined to produce an equation with Q as the only dependent variable:

$$\frac{\partial Q}{\partial x}+\alpha\beta\, Q^{\beta-1}\frac{\partial Q}{\partial t}=q \tag{6.3}$$

The objective of the numerical solution is to solve eq. (6.3) for Q (x, t) at each point on the x-t grid, given the channel parameters α and β, the lateral inflow q (t), and the initial and boundary conditions. The purpose of the solution is to determine the outflow hydrograph Q (L, t). The numerical solution of the kinematic wave equation is more flexible than the analytical solution. It can more easily handle variation in the channel properties and the initial and boundary conditions.

The time and space derivatives of Q are approximated on the x-t grid as shown in Fig.6.4. The unknown value is Q_{i+1}^{j+1}. The values of Q on the j^{th} time line have been previously determined, and so has Q_i^{j+1}. It is solved by linear scheme. The backward difference method is used to set up the finite difference equations.

6.5 METHODOLOGY ADOPTED

As it was not possible in the field to have spatial data along the 600 m channel, using the KWM results these data are generated. FNN and ANN models are developed by keeping riverbed slope as independent fuzzy variable with other variables like roughness coefficient, width of channel and inflow at inlet.

The outflow at a distance of every 50m interval and time step of 10minutes has been computed for different bed slopes using the linear scheme of the one dimensional kinematic wave equation under the finite difference solution (Fig.6.4). The flow chart of the program has shown in Fig.6.5.

There are four inputs used in the computations. They are Inflow, Mannings coefficient N, bed slope S_o and channel width. For this study, Channel width and Manning's roughness coefficient are kept constant. The outflows are estimated for different bed slopes and different inflows. The other parameters can also be fuzzified for better analysis. But for the demonstrative purpose, only slope parameter is considered

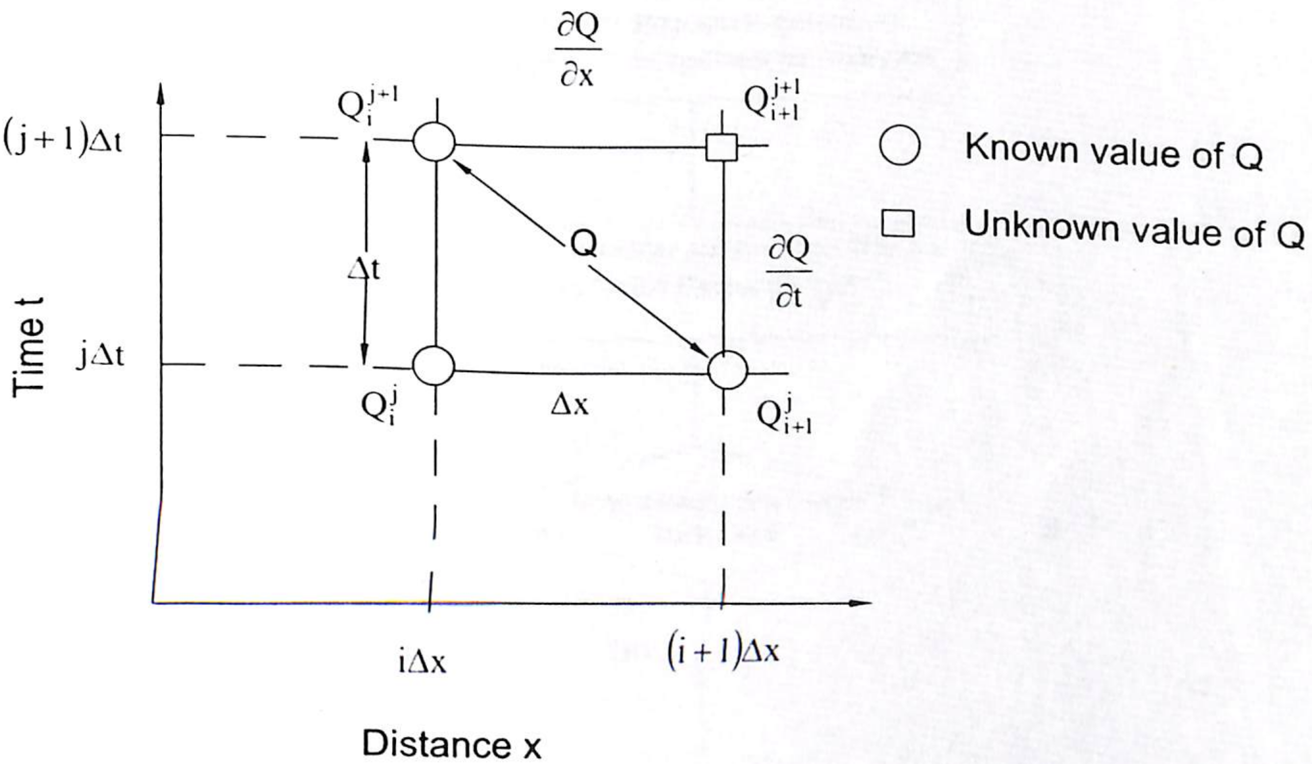

Fig.6.4. Finite difference box for solution of the linear kinematic wave computation

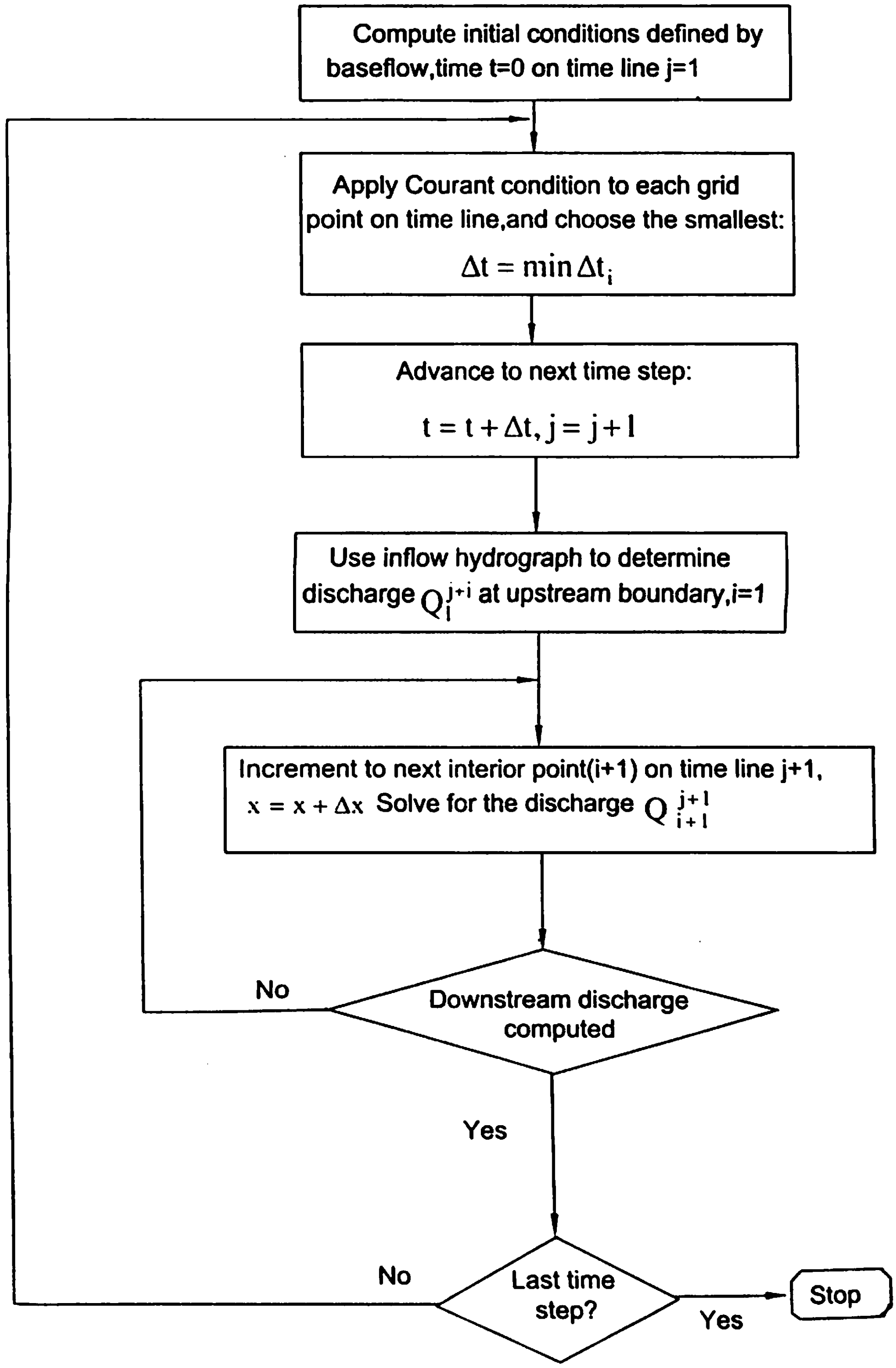

Fig.6.5. Flow chart for linear kinematic wave computation

for the fuzzification. The expert knowledge for framing the fuzzy rules is derived from the KW model results. The KWM results are used as an alternative to the historical field database. The methodology for building the fuzzy rule based model is independent of the KW model.

6.6 ARTIFICIAL NEURAL NETWORK MODEL (KW-ANN)

Out of total 288 patterns of data obtained from the KWM results, 198 patterns are used for training & cross validation and the remaining 90 patterns are used for model testing. Inflow, Mannings coefficient N, bed slope S_o and channel width are used as inputs and the output is outflow at various spaces. The training data consists patterns of extreme high and low bed slopes so as to learn the system behavior effectively. Mean square error and Mean relative error are used as performance indices in this study. ANN model is shown in the Fig.6.6.

6.7 FUZZY NEURAL NETWORK MODEL (KW-FNN)

Based on the bed slope, the whole training data has been segregated into various fuzzy sets that consist of overlapping of datasets. The inputs are fuzzified allowing the variation of bed slope only keeping other parameters constant. The various domains of slope and corresponding outflows are given in Table 6.1 and Table 6.2. Fig.6.1 shows the FNN model building procedure.

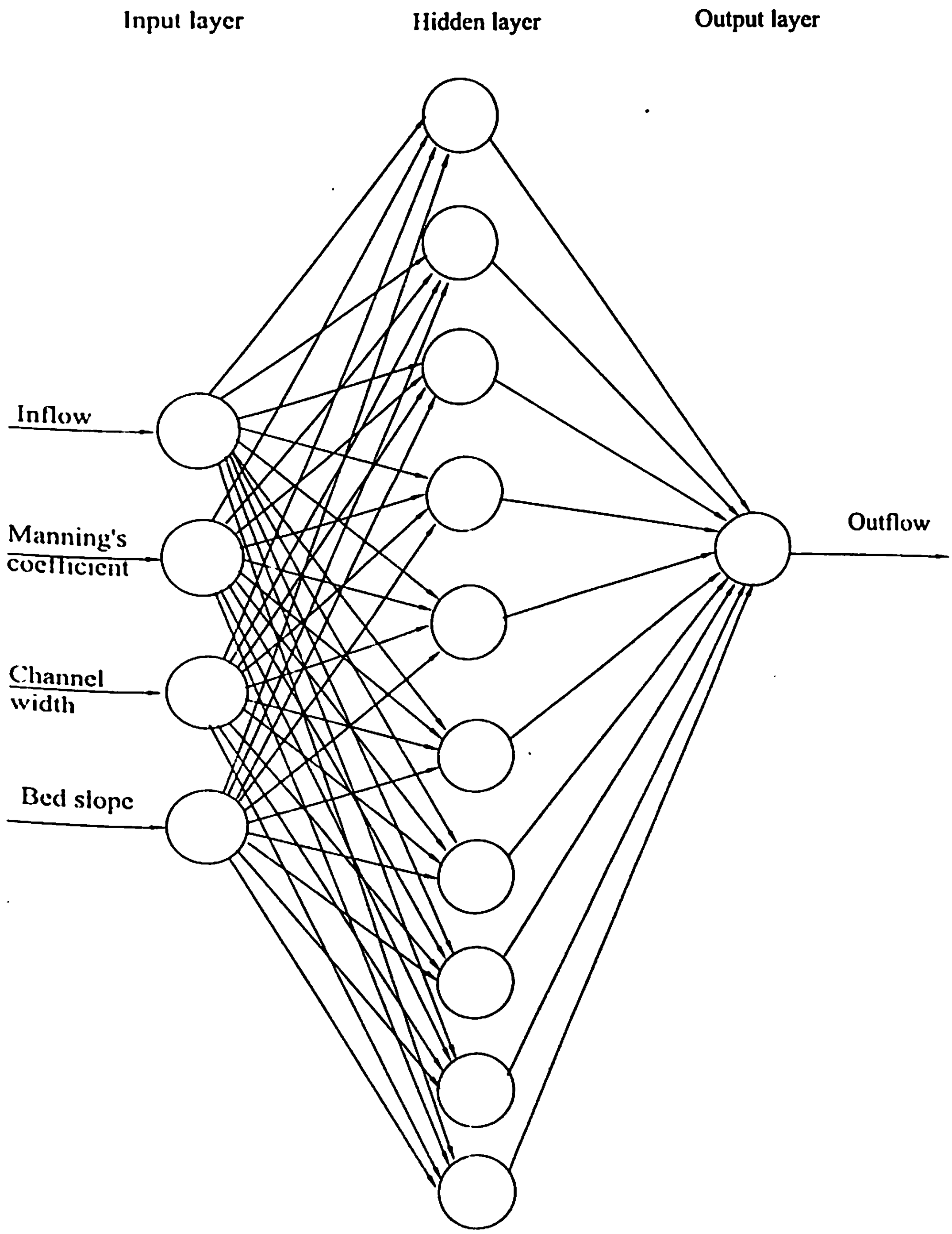

Fig.6.6. KW-ANN model

Table 6.1 Zones for different fuzzy sets for slope

SLOPE	VERY MILD	MILD	STEEP
DOMAIN	0.00-0.002	0.001-0.003	0.002-0.004

Table 6.2 Zones for different fuzzy sets for outflow

FLOW	LOW (cfs)	MEDIUM (cfs)	HIGH (cfs)
DOMAIN	20-30	25-35	30-40

Various rules have been formulated (Table 6.3). After construction of the fuzzy sets, every set has been trained using particular neural network architecture. For defuzzification, min-max principle has been used to get the crisp output.

Table 6.3 Rule Base for the Experiment

Rule number	Rules
1	**IF** river bed slope is **VERY MILD then** outflow is **LOW**
2	**IF** river bed slope is **VERY MILD then** outflow is **MEDIUM**
3	**IF** river bed slope is **MILD then** outflow is **MEDIUM**
4	**IF** river bed slope is **MILD then** outflow is **HIGH**
5	**IF** river bed slope is **STEEP then** outflow is **MEDIUM**
6	**IF** river bed slope is **STEEP then** outflow is **HIGH**

6.8 RESULTS AND DISCUSSION

All the training results in terms of mse and mre results are shown in Table 6.4. It is observed that the performance of the FNN model is better than ANN model considering the model building results (lower mse and mre value). When compared based on the model testing, FNN is performing better than the ANN model as shown in Table 6.5.

Table 6.4 Training results for the Experiment

Slope S_0	**Outflow Q_t**	**Training**		**Number of patterns trained**
		mre	**mse**	
Very Mild	Low	0.61	0.04	79
Very Mild	Medium	0.51	0.11	103
Mild	Medium	0.45	0.09	78
Mild	High	0.60	0.18	40
Steep	Medium	0.45	0.09	75
Steep	High	0.60	0.16	41
Average performance (FNN)		**0.52**	**0.10**	
Single ANN		**0.60**	**0.11**	**198**

Table 6.5 Testing results of the Experiment

ANN		**FNN**		**Testing data**
mre	**mse**	**mre**	**mse**	
5.28	2.56	3.60	1.78	90

The predictive ability of the FNN model are analysed considering the outflow at a space of 600m from the inlet section for different type of riverbed slopes. For very mild slope condition, the outflow produced by KWM and FNN are very close than the ANN model as shown in Fig.6.7. Better performance is observed considering the mild slope criteria (Fig.6.8). But, in case of steep slope criteria of the riverbed, the FNN model is performing almost similar to ANN model as shown in Fig.6.9. The performance of FNN suffers in the steep slope category because 90% of the field data is dominated by the very mild and mild slope criteria as the data collected during the extreme low flow condition.

The performance of the FNN model is also examined considering the measured outflow at different time periods of the particular day. The downstream discharge predicted by the FNN model is more close to the observed discharge compared to other model considered which shows the better ability of the FNN model than ANN model (Fig.6.10).

Fuzzy neural network modeling in flood routing performs better considering the natural channel. The ability of the FNN model by handling the uncertain and imprecise variables has been demonstrated. The model is simple and easy to build. The necessary data required for the model is very less. It also carries the ability to follow the temporal as well as the spatial variation of stream flow more closely than other model. It may be more effective in the real field situation when other routing models suffer due to insufficient information for the given system.

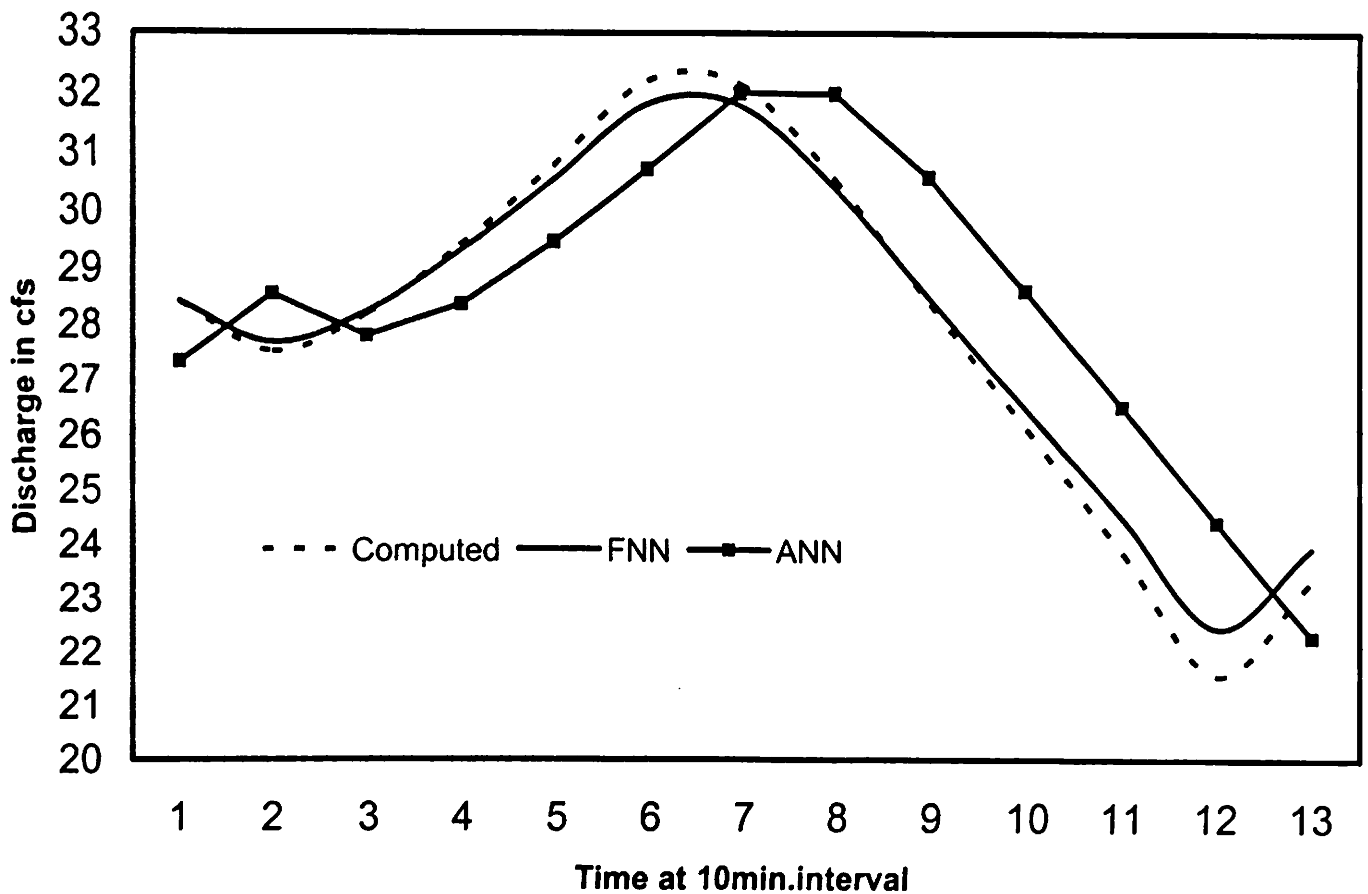

Fig.6.7. Model performance at 600m.downstream (verymild slope)

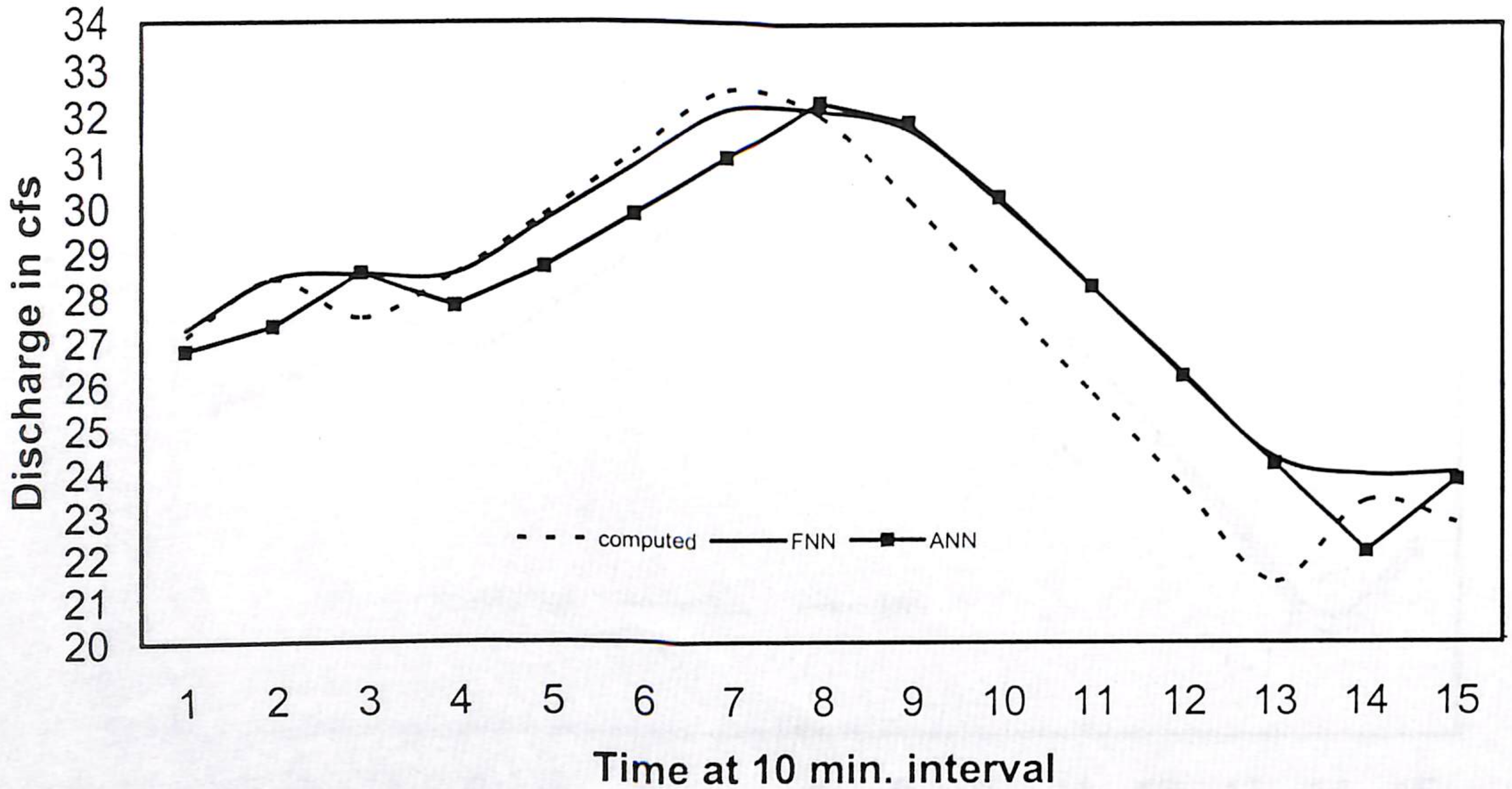

Fig.6.8. Model performance at 600m.downstream (mild slope)

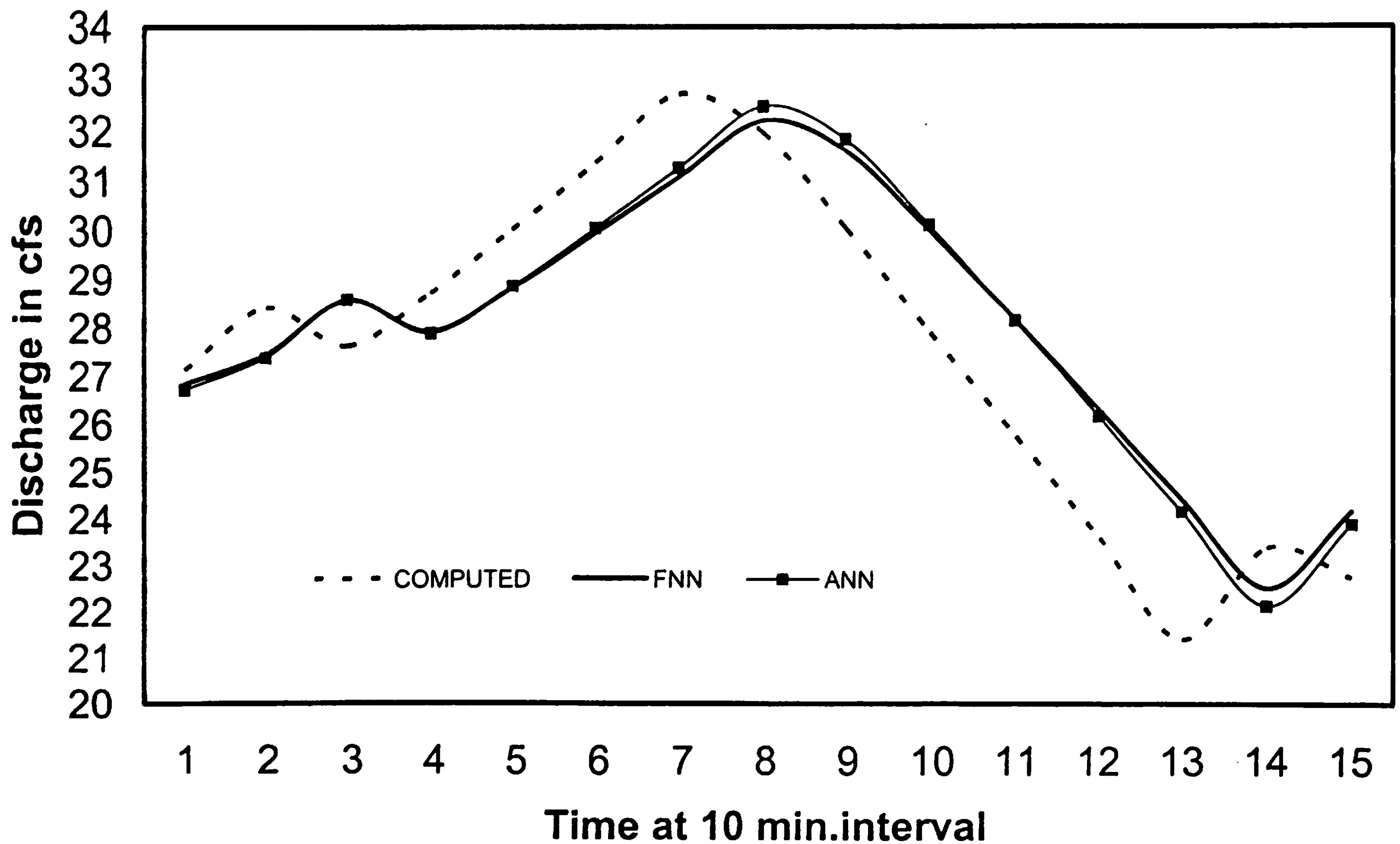

Fig.6.9. Model performance at 600m.downstream (steep slope)

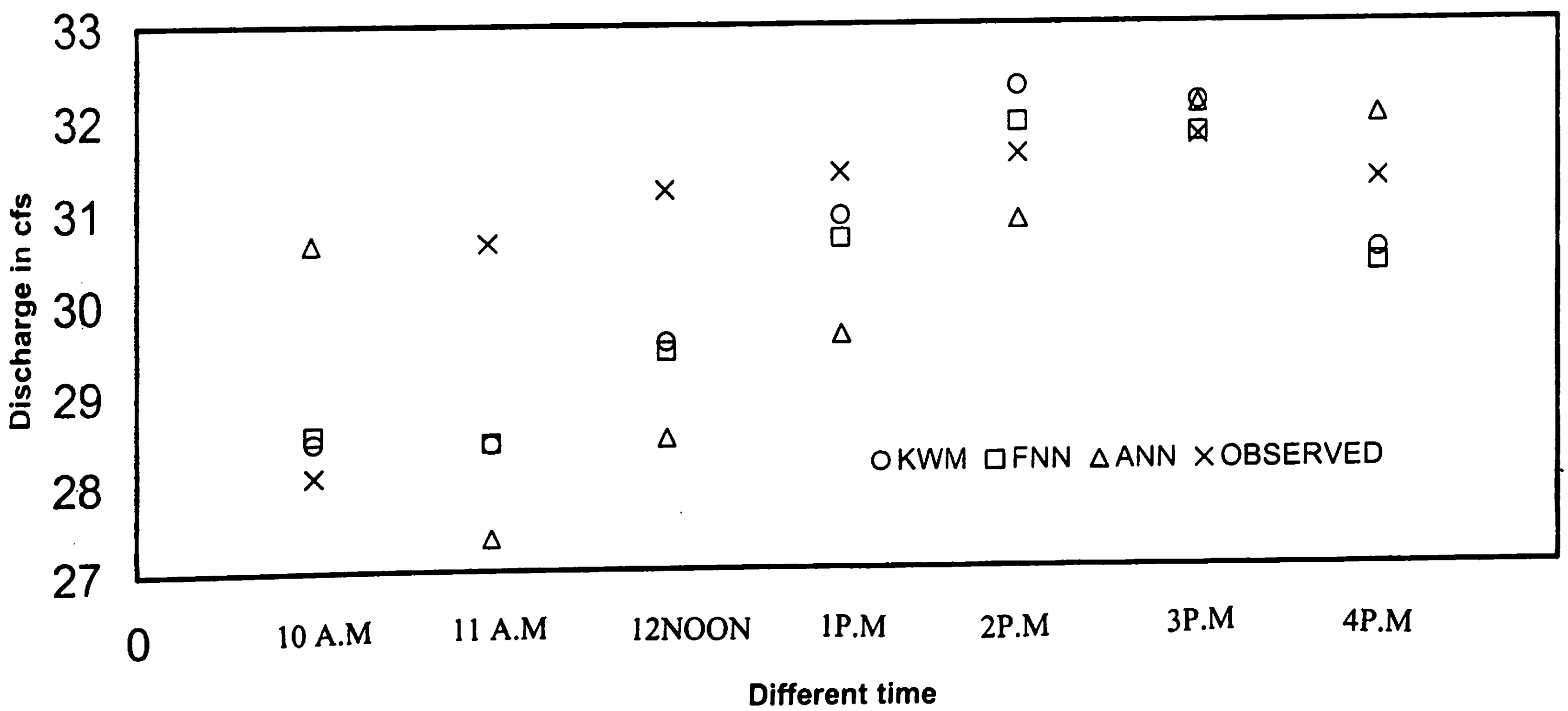

Fig.6.10. Model performance (different time)

CHAPTER 7

SUMMARY AND CONCLUSIONS

7.1 SUMMARY

A hybrid algorithm called Fuzzy Neural Network (FNN) model has been developed and presented in this study. The applicability of the proposed Fuzzy Neural Network model in four different hydrological problems is examined in this research work namely deriving stage discharge relationship, river flow prediction, deriving general operating policies for reservoir operation and distributed flow routing. The Brahmaputra river system located in Assam State, India is considered for this study. The proposed model can be developed and used very easily.

FNN model is developed for derivation of stage-discharge relationship at various gauging stations of the main stem of river Brahmaputra with the objective of generating missing data to get continuous stage-discharge record for a long period. For this, twenty years stage discharge data has been collected at four gauging sites. Out of available 20 years historical data, 13 years (1981-1993) flow data are used for model development and 6 years (1994-1999) flow data are used for verification. Mean squared error and mean relative error, are used as performance indices. Four different models namely a conventional model, a single neural network model (ANN), a modular neural network model (MNN) and a fuzzy neural network model (FNN) have been constructed at three gauging sites and their performances are compared by simulating the system. Three different experiments are performed.

Application of FNN model is extended for river flow prediction at downstream station by knowing status of upstream gauging stations. Simulation studies also carried out to assess the performance of fuzzy neural network model and single neural network model. Six different experiments are performed in the study. In first five experiments, 3 gauging stations in river Brahmaputra are considered and for experiment 6, 4 gauging stations are considered for analysis. Discharges in the upstream gauging stations with and without lag periods are used for fuzzification in developing the models.

An attempt is also made with fuzzy neural network model to derive general operating policies from deterministic dynamic programming for optimization results of single reservoir systems. Two contrasting single reservoir systems one in drought prone area (Aliyar) and another in surplus system (Pagladiya) in nature are considered in this study for assessing the ability of the developed models using three different experiments. For both the reservoirs, out of available data, 7 years of data are used for model validation of the single reservoir model. For the study, minimizing the sum of squared deficit is considered as the objective of optimization. A detailed analysis by comparing model building results, validation results, release, total spill in each model, drought and water surplus years performances have been carried out. Three different experiments of single reservoir systems are performed in this study to suggest suitable input variables.

The suitability of the proposed approach in flood routing is also examined by considering a small north bank tributary of the Brahmaputra river. Cross-sectional as well as longitudinal details have been collected by a detailed survey for a stretch of 600m in that channel. Depth of flow and corresponding flow velocity are also obtained for the stretch. Using the observed data, a kinematic wave equation (KWM) model is developed for generating the spatial and temporal data. From the results of KWM, the FNN and ANN models are developed. The usefulness of FNN model has been explored by comparing it with ANN model for flood routing all along the flow section.

7.2 CONCLUSIONS

From the above studies, the following conclusions are drawn. In general, the research study reveals that the proposed hybrid modeling gives improved results for different problems. The conclusions are presented case by case in this section.

I. Deriving stage-discharge relationship-

a) When Conventional, ANN, MNN, and FNN models are compared based on the performance indices, ANN, MNN, and FNN models perform better than conventional model.

b) When ANN, MNN, and FNN models are compared, ANN and FNN model performed better than MNN model. MNN model suffers in split regions due to data discontinuity.

c) FNN model performs better than ANN model in all the experiments. FNN model gives 2% to 20% improvement over ANN model. FNN performs better due to overlapping of data that provides continuity.

d) The hysteresis effect is better represented in the FNN model than other models. Firing of appropriate rules in the case specific situation is the advantage of FNN model.

II. River flow prediction-

a) FNN model showed better predicting ability than ANN model when compared using model building and testing results by considering different experiments.

b) Performance of FNN model is improved by 9% to 40% over ANN model in the various experiments. Performance of the FNN is slightly suffe... ...... more inputs are used.

c) The FNN prediction results are very close to the observed flow during the single input cases. In case of two or more input cases, FNN model performance is slightly deviated from the observed flow. But, FNN model is closely following the observed flow than ANN model considering the model testing results.

III. Reservoir operation-

Three different experiments are performed in deriving general operating policies of a reservoir system from deterministic DP optimization results. Based on the results, the following conclusions are derived.

a) Overall performance of DPFNN model is better than DPN model in terms of objective function value by 45 % to 50 % in experiment 1.

b) But DPFNN and DPN models based on experiment 1 are giving inferior results compared to Dynamic Programming optimization results.

c) DPN model performs better than DPFNN model when we consider Experiment 2. Adopting all possible rule combinations for DPFNN model is the possible cause of inferior performance.

d) In the case of simplified experiment 3, the DPFNN model performs better than DPN model for both reservoir systems. In this new approach, the problem is also not ill posed, as all the inputs to the models are known in advance to the user.

IV. Flood routing-

a) Based on performance indices, it can be inferred the FNN model performance is better than ANN model in terms of mse.

b) As the distances increases, FNN model shows better performance than ANN model for riverbed slope is verymild or mild and FNN model performance is almost similar to ANN model for steep slope condition of the riverbed.

FNN models are easy to build and simple to understand due to the transparency of knowledge associated with it. As per field personnel's interest, formation of rule base, decision about fuzzy sets and defuzzification strategy can easily be altered in the proposed algorithm. The use of linguistic variables make it relatively easy to interpret the rules and if necessary change them.

The overlapping option with the fuzzy inferencing rules gives an advantage to this model. Furthermore, the FNN model also has more flexibilities associated with it in the form of fuzzy rule formulation, choosing different suitable architectures for each ANN for each fuzzy set, creating different fuzzy sets by considering suitable domains, etc. The FNN modeling fuzzification of the discharge data can be undertaken easily with the help of historical data and their statistics. The FNN model is more flexible than the other models considered with more options of incorporating the fuzzy nature of the real world system.

7.3 FUTURE SCOPE OF STUDY

Fuzzy neural network approach is a promising area for various hydrological problems as observed in the study. For other hydrological problems, this approach can be effectively used to obtain more close behavior to the real field situation. More influencing variables can be included as fuzzy variables in different hydrological problems discussed in this study to improve the model performance. Different strategies in fuzzy modeling like defuzzification methods, membership functions and rule base formulation etc, are the areas showing good scope for extended research study in the proposed hybrid model.

From the hydrological or hydraulic point of view, the stage –discharge relation of gauging station I, II and III are related to each other. The dependence among the stations through an ANN approach may be another area for future research study.

REFERENCES

1. Agsorn, S. (1995)."Fuzzy logic in polder flood control operations in Bangkok." Phd thesis, University of British Columbia, Vancouver, Canada.

2. Akan, A.O. and Yen, B.C. (1977). "A nonlinear diffusion-wave model for unsteady open channel flow". *Proc.17th Congr.*vol.2, International Association for Hydraulic Research, Delft, The Netherlands, 181-190.

3. American Society of Civil Engineers Task Committee on Application of Artificial Neural Networks in Hydrology, (2000). Artificial neural networks in Hydrology, I Preliminary Concepts, *J. Hydrologic Engineering*, ASCE, 5(2), 115 -123.

4. American Society of Civil Engineers Task Committee on Application of Artificial Neural Networks in Hydrology, (2000). Artificial neural networks in Hydrology, II: Hydrologic applications, *J. Hydrologic Engineering*, ASCE, 5(2), 124 -137.

5. Anders, U., and Korn, O. (1999). "Model selection in neural networks". *Neural Networks*, 12,309-323.

6. Aziz, A., R.A., and Wong, K.F.V.A (1992). "Neural network approach to the determination of aquifer parameters." *Ground Water*, 30(2), 164-166.

7. Basheer, I.A., and Najjar, Y.M. (1995). "Designing and analyzing fixed bed adsorption systems with artificial neural networks." *J.Envir.Syst.*23 (3), 291-312.

8. Badiru, A.B and Cheung J.Y (2002). *Fuzzy Engineering Expert Systems With Neural Network Applications*. John Wiley & Sons, New York.

9. Birkundavyi, S., Labib, R., Trung, H.T., Rousselle, J. (2002). "Performa[nce of] neural networks in daily streamflow forecasting". *J. Hydrologic Engg.* ASCE, 7(5), 392-398.

10. Bowden, G.J., Maier, H.R., Dandy, G.C. (2002). "Optimal division of data for neural network models in water resources applications." *Water Resources Research*, 38(2), 2-1 to 2-11.

11. Bonafe, A., Galeati, G., and Sforna, M. (1994). "Neural networks for daily mean flow forecasting." Hydr.Engrg.Software V, w.R. Blain and K.L.Katsifarakis, eds.,Computational Mechanics Publications,Southampton,U.K.,1,131-138.

12. Brown, M. and Harris, C. (1994). *Neuro-fuzzy adaptive modeling and control.* Prentice-Hall, Englewood Cliffs, N.J., U.S.A.

13. Brown, M., and Harris, C. (1995)."A perspective and critique of adaptive neuro fuzzy systems used for modeling and control applications." *International Journal of Neural System*, 6(2), 197-220.

14. Burian, S.J., Durrans, S.R., Nix, S.J., Pitt, R.E. (2001). "Training artificial neural networks to perform rainfall disaggregation". *J.Hydrologic Engg.* ASCE, 6(1), 43-51.

15. Carpenter, W.C., and Barthelemy, J. -F. (1994). "Common misconceptions about neural networks as approximators." *J.Computing in Civ.Engrg.* ASCE,8(3), 345-358.

16. Campbell, P.F. (1993). "Applications of fuzzy set theory in reservoir operation". MASc thesis, University of British Columbia, Vancouver, Canada.

17. Carriere, P., Mohaghegh.S.and Gaskari, R. (1996). "Performance of a virtual runoff hydrograph system." *J.Water Resour.Plng.and Mgmt.*, ASCE, 122(6), 421-427.

18. Cancelliere, A., Giuliano, G., Ancarani, A., Rossi, G. (2002)." A Neural Net Approach For Deriving Irrigation Reservoir Operating Rules." *Water Resources Management*, 16, 71-88.

19. Chatfield, C. (1993). "Neural networks: forecasting breakthrough or passing fad." *Int.J forecasting*, 9,1-3.

20. Chandramouli, V., Kuppusamy, K.A., Manikandan, K. (2002)." Study On Water Sharing in a Multi-reservoir System Using a Dynamic Programming-Neural Network Model." *Water Resources Development*, 18(3), 425-438.

21. Chandramouli, V., Raman, H. (2001)."Multireservoir Modeling With Dynamic Programming And Neural Networks." *J.Water Resources Planning and Management*, ASCE, 127(2), 89-98.

22. Chung, F. L. and Duan, J. C (2000). " Multistage Fuzzy Neural Network modeling". *IEEE transactions on fuzzy systems*, 8(2), 125-142.

23. Chow, V.T., Maidment, D.R., Mays, L.W. (1988). *Applied Hydrology*, McGraw-Hill International Editions, Singapore.

24. Chang, F.J., and Chen, Y.C. (2001)."A counter propagation fuzzy-neural network modeling approach to real time streamflow prediction". *J.Hydrology*, Amsterdam, 245,153-164.

25. Clair, T.A., and Ehrman, J.M. (1998). "Using neural networks to assess the influence of changing seasonal climates in modifying discharge dissolved organic carbon, and nitrogen export in eastern Canadian rivers." *Water Resour.Res.*34 (3), 447-455.

26. Cox, E., (1994). *The Fuzzy systems hand book*, Academic Press Professional, USA.

27. Daniel, T.M.(1991). "Neural networks—applications in hydrology and resources engineering." *Proc., Int.Hydrol.and Water Resour. Symp.*, Institution of Engineers,Perth,Australia.

28. Dartus, D., Courivaud, J.M., and Dedecker, L. (1993). "Use of a neural net for the study of a flood wave propagation in an open channel." *J.Hydr.Res.*, Delft, The Netherland,31(2).

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

30. Dubrovin, T., Joima, A., Turunen, E., (2002)." Fuzzy Model For Real-Time Reservoir Operation." *J.of Water Resources Planning and Management*, ASCE, 128(1), 66-73.

31. Elshorbagy, A., Simonovic S. P. & Panu, U. S. (2000). " Performance evaluation of artificial neural networks for runoff prediction". *J. Hydrologic Engg.*, ASCE, 5(4), 424-427.

32. Esogbue, A., and Kacprzyk, J. (1998). " Fuzzy dynamic programming."*Decision Analysis, Operation Research and Statistics,* Handbook of Fuzzy Sets Series, Vol.5, Kluwer, Boston, 281-307.

33. Fernando, D.A.K., and Jayawardena, A.W. (1998). "Runoff forecasting using RBF networks with OLS algorithm." *J.Hydrologic Engrg.*, ASCE 3(3), 203-209.

34. Flood, I., and Kartam, N. (1994). "Neural Networks in civil engineering. I: Principles and understandings." *J.Computing in Civ.Engrg.*,ASCE,8(2),131-148.

35. Flood, I., and Kartam, N (1997). "systems." Artificial Neural Networks f Engrs.: Fundamentals and Applications. Kartam,I.Flood, and J.H.Garrett Jr.,eds.,ASCE,New York,19-43.

36. Fontane, D.G., Gates, T.K., and Moncada, E. (1997). "Planning reservoir operations with imprecise objectives." *J.Water Resources Planning and Management*, ASCE, 123(3), 154-163.

37. French, M.N., Krajewski, W.F., and Cuykendal, R.R. (1992). "Rainfall forecasting in space and time using a neural network" *J.Hydrology*, Amsterdam,137,1-37.

38. Garrett, J.H., et al. (1993). "Engineering applications of artificial neural networks."*J.Intel.Manuf.*,4,1-21.

39. Gates, T.K., Heyder, W.E., Fontane, D.G., and Salas, J.D. (1991). "Multicriterion strategic planning for improved irrigation delivery. I: Application." *J.Irrig. and Drain. Engr.*, ASCE, 117(6), 897-913.

40. Gupta, H.V., Ksu, K., and Sorooshian, S. (1997). "Superior training of artificial neural networks using weight-space partitioning."*Proc., IEEE Int.Conf.on Neural Networks,* Institute of Electrical and Electronics Engineers, New York.

41. Halff, A.H., Halff, H.M., and Azmoodeh, M. (1993). "Predicting runoff from rainfall using neural networks."*Proc., Engg.Hydrol.*,ASCE,New York,760-765.

42. Hashimoto, T., Stedinger, J.R, Loucks, D.P (1982). "Reliability, Resilency, and Vulnerability Criteria For Water Resource System Performance Evaluation."*Water Resources Research*, 18(1), 14-20.

43. Hayashi, Y., Buckly, J.J.and Czogala, E. (1993). "Fuzzy neural network wi signals and weights". *Int.J.Intell.Syst.*,vol.8(4),527-537.

44. Haykin, S. (1994). *Neural networks: a comprehensive foundation.* Mac-Millan, New York.

45. Henderson, F.M. (1966). "*Open Channel Flow*". Macmillan, New York.

46. Heyder, W.E., Gates, T.K., Fontane, D.G., and Salas, J.D. (1991). "Multicriterion strategic planning for improved irrigation delivery. II: Application." *J.Irrig. and Drain. Engrg.*, ASCE,117(6),914-934.

47. Hebb, D.O. (1949). *The organization behaviour, A neuropsychological Theory*, John Wiley, New York.

48. Hill, T., Marquez, L.Connor, M.O., and Remus, W. (1994). "Artificial neural networks for forecasting and decision making."*Int.J.Forecasting*, 10, 5-15.

49. Hjelmfelt, A.T., and Wang, M. (1993a). "Artificial neural networks as unit hydrograph applications."*Proc., Engg.Hydrol.*, ASCE,New York,754-759.

50. Hjelmfelt, A.T., and Wang, M. (1993b). "Runoff simulation using ANN."*Proc., 4th Int.Conf.in the Application of Artificial Intelligence to Civ.and Struct.Engg.*NN and Combinatorial optimization in Civ.and Struct.Engg.B.H.V.Topping and A.I.Khan, eds.,Civil-Comp Ltd.,Edinburgh,U.K.,517-522.

51. Hjelmfelt, A.T., and Wang, M. (1993c). "Runoff hydrograph estimation using artificial neural networks."*Proc., ASAE Conference*, American Society of Agricultural Engineers, St.Joseph, Mich.

52. Hjelmfelt, A.T., and Wang, M. (1996). "Predicting runoff using artificial neural networks."*Surface Water Hydrol.*, 233-244.

53. Hopfield, J.J. (1984). "Neurons with graded response have collective computational properties like those of two state neurons", *Proc. Of National Academic Sciences*.81: 3088-3092.

54. Hromadka, T.V., and DeVries, J.J. (1988). "Kinematic wave routing and computational error." *J. Hydraulic Engg.* ASCE, 114(2), 207-217.

55. Hsu, K., Gao, X., Sorooshian, S., and Gupta, H.V. (1997). "Precipitation estimation from remotely sensed information using artificial neural networks." *J.Appl.Meteorology*, 36(9), 1176-1190.

56. Hsu, K., Sorooshian, S., and Gupta, H.V. (1997). "Application of a recurrent neural network to rainfall-runoff modeling."*Proc., Aesthetics in the constructed Envir.*,ASCE,New York,68-73.

57. Hsu, K., Gao, X., Sorooshian, S., and Gupta, H.V. (1996). "An artificial neural network for rainfall estimation from satellite infrared imaginary."Applications of Remote Sensing in hydrol., *Proc.,3rd Int.Workshop*,NHRI Symp.No.17, NASA,Greenbelt,Md.

58. Hsu, K., Sorooshian, S., and Gupta, H.V. (1995). "Artificial neural network modeling of the rainfall-runoff process."*Water Resour.Res.*,31(10),2517-2530.

59. Hu, T. S., Lam, K. C. & Ng, S.T. (2001). " River flow time series prediction with a range dependent neural network". *Hydrological Sciences Journal, Oxford*, England, 46(5), 729-745.

60. Hundecha, Y., Bardossy, A. & Theisen, H. W. (2001). " Development of a fuzzy logic based rainfall-runoff model". *Hydrological Sciences Journal, Oxford*, England, 46(3), 363-376.

61. Hutton, P.H., Sandhu, N., and Chung, F.I. (1996). "Predicting THM formati[on] artificial neural networks."*Proc., North Am. Water and Envir. Conf.*,ASCE,New York,3557-3556.

62. Ichiyanagi, K., Kobayashi, H., Matsumura, T., Kito, Y. (1996). "Application of artificial neural network to forecasting methods of time variation of the flow rate into a dam for a hydro-power plant".*IEEE Transactions on neural network*,Vol.4,321-326.

63. Islam, S., and Kothari, R. (2000). " Artificial neural networks in remote sensing of hydrologic processes". *J.Hydrologic Engg.*ASCE, 5(2), 138-144.

64. Jain, S.K., Das, A., Srivastava, D.K. (1999)." Application of ANN for Reservoir Inflow Prediction and Operation." *J.of Water Resources Planning and Management*, ASCE, 125(5), 263-271.

65. Jain, A.K., and Mao, J. (1997). "Guest editorial: special issue on artificial neural networks and statistical pattern recognition."*IEEE Transac. On Neural Networks*,8(1), 1-3.

66. Jain, S. K. & Chalisgaonkar D. (2000). " Setting up stage-discharge relations using ANN". *J. Hydrologic Engg.*, ASCE, 5 (4), 428-433.

67. Jain, S.K. (2001). "Development of integrated sediment rating curves using ANNs". *J. Hydraulic Engg.* ASCE, 127(1), 30-37.

68. Jayawardena, A.W., and Fernando, D.A.K. (1995). "ANN in hydrometeorological modeling."*Proc., 4th Int.Conf.in the Application of Artificial Intelligence to Civ. And Struct.Engg.*, B.H.V .Topping and A.I.Khan,eds.,Civil – Comp,Ltd.,Edinburgh,U.K.,115-120.

69. Jaber,F.H., and Mohtar, R.H. (2002)."Dynamic time step for one-dimensional overland flow kinematic wave solution".*J.Hydrologic Engg.* ASCE,7(1),3-11.

70. Jayawardena, A.W., and Fernando, D.A.K. (1996). "Comparison of mul perceptron and radial basis function network as tools for flood forecasting."*Proc., North Am. Water and Envir.Conf.*,ASCE,New York,457-458.

71. Jang, J.S.R.and Sun, C.T. (1993). "Functional equivalence between radial basis function networks and fuzzy inference systems". *IEEE Trans.Neural Networks*, vol.4, 156-159.

72. Jang, J.R. (1993). "ANFIS: Adaptive-network-based fuzzy inference system". *IEEE Trans.Syst.,Man,Cybern.*,vol.23(3),665-685.

73. Johnson, V.M., and Rogers, L.L. (1995). "Location analysis in ground water remediation using NN."*Groundwater*, 33(5), 749-758.

74. Kang, K.W., Kim, J.H., Park, C.Y., and Ham, K.J. (1993). "Evaluation of hydrological forecasting system based on neural network model."*Proc., 25th congress of Int.Assoc.for Hydr.Res.,International Association for Hydraulic Research*,Delft,The Netherlands,257-264.

75. Kao, J.J. (1996). "Neural net for determining DEM-based model drainage pattern."*J.Irrig. and Drain.Engg.*, ASCE,122(2),112-121.

76. Karunanithi, N., Grenney, W. J., Whitley, D. & Bovee, K. (1994). " Neural networks for river flow prediction". *J. Computing in Civil Engg.*, ASCE, 8(2), 201-220.

77. Kennedy, E.J. (1984). "Discharge ratings at gauging stations". Techniques of water-resources investigations of the United States geological survey, Book 3.Chap.A10.

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

79. Klir, G.J., and Folger, T.A. (1988). *Fuzzy sets, uncertainty and information.* Prentice Hall, New York, N.Y.

80. Kojiri, T., Ito, K., and Sakakimo, S. (1994). "Rainfall estimation and real-time reservoir operation with neural network and fuzzy inference." Application of artificial intelligence in engineering, G.Rzevski, R.A.Adey, and D.W.Russel, eds., Computational Mechanics,Southampton,U.K.

81. Kosko, B. and Isaka, S. (1993). "*Fuzzy Logic*". Scientific American (July), 76-81.

82. Kosko, B.(1996). "*Neural Networks and Fuzzy Systems*". Prentice Hall of India (Original edition: Prentice Hall Inc., Englewood Cliffs, 1992).

83. Kuligowski, R.J., and Barros, A.P. (1998). "Experiments in short-term precipitation forecasting using artificial neural networks."*Monthly Weather Rev.*, 126(2), 470-482.

84. Lachtermacher, G., and Fuller, J.D.(1994). "Back propagation in hydrological time series forecasting." *Stochastic and statistical methods in hydrology and environmental engineering in time series analysis in hydrology and environmental engineering*, Vol.3, K.W.Hipel, et.al, eds., Kluwer,Dordrecht,The Netherlands,229-242.

85. Liong, S. Y., Lim, W. H., Paudyal, G.N. (2000). " River stage forecasting in Bangladesh: Neural network approach". *J.Computing in Civil Engg.*, ASCE, 14(1), 1-8.

86. Lighthill, M.J., and Whitham, G.B. (1955). "On kinematic waves. I: movement in long rivers". *Proc.R.Soc.London*, Ser.A, 229,281-316.

87. Lippman, R.P. (1987). An introduction to computing with neural nets. ASSP Magazine, Apr.4-21.

88. Loaiciga, H.A. (2002). "Reservoir Design and Operation with Variable Lake Hydrology." *J.Water Resources Planning and Management*, ASCE, 128(6), 399-405.

89. Lund, J.R. and Ferreira, I. (1996)."Operating Rule Optimization for Missouri River Reservoir System." *J.Water Resources Planning and Management*, ASCE, 122(4), 287-295.

90. Maier, H. R., and Dandy, G. C. (2000). " Neural networks for the prediction and forecasting of water resources variables: A review of modeling issues and applications". *Environmental Modeling and Software*, 15(1), 101-123.

91. Matahel Ansar, P.E.and Gonzalez-Castro, J.A. (2002). "Discussion of "Development of integrated sediment rating curves using ANNs" by S.K.Jain". *J.Hydraulic Engg*.ASCE, 128(9), 870-871.

92. Masters, T. (1993). "*Practical Neural Network Recipes in C++*". Academic Press, an Diego, A.

93. Mason, J.C., Price, R.K., and Tem"me, A. (1996). "A neural network model of rainfall-runoff using radial basis functions". *J.Hydr. Res*.Delft, The Netherlands, 34(4), 537-548.

94. Maidment, D.R., (1992). *Handbook of Hydrology*, McGraw Hill, New York, U.S.A.

95. Markus, M., Salas, J.D., and Shin, H.K. (1995). "Predicting streamflows b neural networks". *Proc., 1st Int.Conf.on Water Resources Engrg.*, ASCE,New York,1641-1646.

96. McCulloch, W.S., and Pitts, W.H. (1943). "A logical calculus of the ideas imminent in nervous activity". *Bulletin Mathematical Biophysics*, 5:113-115.

97. McNeill, F.M., and Thro, E. (1994). "Fuzzy logic: A practical approach". AP Professional, Boston, Mass.

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

99. Mitra, S. and Hayashi. Y. (2000). " Neuro-Fuzzy rule generation: Survey in soft computing framework". *IEEE Transactions on neural network*, 11(3), 748-768.

100. Moy, W., Cohon, J.L., ReVelle, C.S. (1986). "A Programming Model for Analysis of the Reliability, Resilence, and Vulnerability of a Water Supply Reservoir." *Water Resources Research*, 22(4), 489-498.

101. Mohan, S., and Raipure, D.M. (1992). "Multiobjective analysis of multi reservoir system". *J.of Water Resources Planning and Management*, ASCE, 118(4), 356-370.

102. Muttiah, R.S., Srinivasan, R., and Allen, P.M. (1997). "Prediction of two year peak stream discharges using neural networks."*J.Am.Water Resour.Assoc.*,33(3),625-630.

103. Nagesh kumar, D., Prasad, D.S.V., Raju, K.S. (2001). "Optimal reservoir operation using fuzzy approach."*Proc.International conference on Civil Engg.* (ICCE-2001), Bangalore, India, July23-25, Interline Publishing, Vol.II, 377-384.

104. Odai, S.N. (1999). "Nonlinear kinematic wave model for predicting open c flow rate". *J.Hydraulic Engg.*ASCE, 125(8), 886-889.

105. Panigrahi, D.P. and Mujumdar, P.P. (2000). "Reservoir Operation Modeling With Fuzzy Logic". *Water Resources Management*, 14, 89-109.

106. Parent, E., and Duckstein, L. (1993). *Proc.20th Anniversary Conf. Water Resource Plng. And Mgmt. Div.*, ASCE, New York, N.Y.

107. Pedrycz, W. (1993). "*Fuzzy Control and Fuzzy Systems*". 2nd ed. John Wiley and Sons, New York.

108. Poff, N.L., Tokar, S., and Johnson, P. (1996). "Stream hydrological and ecological responses to climate change assessed with an artificial neural network". Limnol. And Oceanog.,41(5),857-863.

109. Price, R.K. (1994). "Flood routing models". Computer modeling of free surface and pressurized flows, M.H.Chaudhry and L.W.Mays, eds. Kluwer Academic, Dordrecht, The Netherlands, 375-407.

110. Ranjithan, S., Eheart, J.W., and Garrett Jr., J.H. (1993)."Neural network based screening for ground water reclamation under uncertainty". *Water Resources Research*, 29(3), 563-574.

111. Raman, H. and Chandramouli, V. (1996)." Deriving a General Operating Policy For Reservoirs Using Neural Network." *J.of Water Resources Planning and Management*, ASCE, 122(5), 342-347.

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

113. Rajurkar, M. P., Kothyari, U. C. and Chaube, U. C. (2002). " Artificial networks for daily rainfall-runoff modeling". *Hydrological Sciences Journal, Oxford*, England, 47(6), 865-877.

114. Rizzo, M.D., and Dougherty, D.E. (1994). "Characterization of aquifer properties using artificial neural networks: Neural kirging". *Water Resources Research*, 30(2), 483-497.

115. Rogers, L.L., and Dowla, F.V. (1994). "Optimization of ground water remediation using artificial neural networks with parallel solute transport modeling". *Water Resources Research*, 30(2), 457-481

116. Rushid, A.A., and Wong, K.V. (1992). "A neural network approach to the determination of aquifer parameters". *Ground Water*, 30,164-166.

117. Rumelhart, D. & McClelland, J. L., (1987) *Parallel Distributed Processing: Explorations in the Microstructure of Cognition*, Vol. I and II, M.I.T.Press, Cambridge, M.A.

118. Rumelhart, D.E., Hinton, G.E, and Williams, R.J. (1986). "Learning internal representations by error propagation."*Parellel distributed processing*, Vol.1.MIT Press.Cambridge, Mass., 318-362.

119. Russell, S.O.and Campbell, P.F. (1996)."Reservoir Operating Rules With Fuzzy Programming." *J.of Water Resources Planning and Management*, ASCE, 122(3), 165-170.

120. Saad, M., Turgeon, A., Bigrs, P., and Duquette, R. (1994). "Learning disaggregation technique for the operation of long term hydro-electric power systems". *Water Resources Research*, 30(11), 3195-3202.

121. Sayed, T. and Razavi, A. (2000). " Comparison of neural and conv[illegible] approaches to mode choice analysis". *J.Computing in Civil Engineering*, ASCE, 14(1), 23-30.

122. See, L. and Openshaw, S. (2000). " A hybrid multi-model approach to river level forecasting". *Hydrological Sciences Journal, Oxford*, England, 45(4), 523-536.

123. See, L. and Openshaw, S. (1999). "Applying soft computing approaches to river level forecasting". *Hydrological Sciences Journal, Oxford*, England, 44(5), 763-778.

124. Shrestha, B.P., Duckstein, L., Stakhiv, E.Z. (1996)." Fuzzy Rule-Based Modeling of Reservoir Operation." *J.Water Resources Planning and Management*, ASCE, 122(4), 262-269.

125. Shi, J.J. (2000). "Reducing prediction error by transforming input data for neural networks". *J. Computing in Civil Engineering*, ASCE, 14(2), 119-116.

126. Shamseldin, A.Y. (1997). "Application of a neural network technique to rainfall-runoff modeling". *J. Hydrology*, Amsterdam, 199,272-294.

127. Simonovic, S.P., Venema, H.D., Burn, H.D. (1992)." Risk-based parameter selection for short-term reservoir operation."*J. Hydrology*, 131,269-291.

128. Singh V.P. (1996). *Kinematic wave modeling in water resources: surface water hydrology*, Wiley, New York.

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

130. Sudheer, K.P. and Jain, S.K. (2003). "Radial basis function neural network for modeling rating curves". *J. Hydrologic Engg.*, ASCE, 8 (3), 161-164.

131. [illegible] Ibrahim, A. and Fahmy, H. (1997)."Hysteresis sensitivity [illegible] for modelling rating curves." *J.Computing in Civil Engineering*, ASCE 11(3), 206-211.

132. Tamaki, R.D. (1994) "Real-time fuzzy logic control of combined sewer flows", M.A.Sc thesis, University of British Columbia, Vancouver, Canada.

133. Tang, Z. and Fishwick, P.A. (1993). "Feed forward neural nets as models for time series forecasting", *J.Comp.*,5(4),374-385.

134. Thirumalaiah, K., and Deo, M.C. (1998). " River stage forecasting using artificial neural networks." *J. Hydrologic Engineering*, ASCE, 3(1), 26-32.

135. Thandaveswara, B.S. and Sajikumar, N. (2000). "Classification of river basins using artificial neural network", *J. Hydrologic Engineering*, ASCE 5(3), 290-298.

136. Thirumalaiah, K., and Deo, M.C. (2000). " Hydrological forecasting using neural networks", *J. Hydrologic Engineering*, ASCE 5(2), 180-189.

137. Tilament, A., Fortemps, P., Vanclooster, M. (2002)." Effect of Averaging Operators in Fuzzy Optimization of Reservoir Operation." *Water Resources Management*, 16,1-22.

138. Tilament, A., P., Vanclooster, M., Duckstein, L., Persoons, E. (2002). "Comparison of fuzzy and nonfuzzy optimal reservoir operating policies". *J.of Water Resources Planning and Management*, ASCE, 128(6), 390-398.

139. Tilament, A., P., Persoons, E., Vanclooster, M. (2001). "Deriving efficient reservoir operating rules using flexible stochastic dynamic programming". *Proc., Ist Int.Conf.on Water Resources Management*, WIT Press, U.K.353-364.

140. Tokar, A.S., and Johnson, P.A. (1999). "Rainfall-runoff modeling using ar neural networks". *J. Hydrologic Engg.*, ASCE, 4 (3), 232-239.

141. Wang, L.X., and Mendel, J.M. (1992). " Fuzzy basis functions, universal approximation, and orthogonal least squares learning". *IEEE Trans. on Neural Networks*, 3(5), 807-814.

142. Windrow, B., and Hoff, M.E. (1960). "Adaptive switching circuits", *IRE, Western Electric Show and Convention Record*, Para 4(Aug.23): 96-104.

143. Xiong, L. and O'Connor, K.M. (2002). " Comparison of four updating models for real time river flow forecasting". *Hydrological Sciences Journal, Oxford, England*, 47(4), 621-639.

144. Yakowitz, S. (1982). "Dynamic Programming Applications in Water Resources." *Water Resources Research*, 18(4), 673-696.

145. Yeh, W.W-G.,(1985). "Reservoir Management and Operations Models: A state- of-the- art review." *Water Resources Research*, 21(12), 1797-1818.

146. Zadeh, L.A. (1962). "From circuit theory to systems theory," *Proc.* Institution of Radio Engineers, 50,856-865.

147. Zadeh, L.A. (1965). "Fuzzy sets." *Information and control*, 8, 338-353.

148. Zadeh, L.A. (1973). " Outline of a new approach to the analysis of complex systems and decision processes". IEEE *Trans. of Sys. Man and Cybernetics*, 3, 28-44.

149. Zadeh, L.A., and Kacprzyk, J., Eds. (1992). "*Fuzzy Logic for the Management of Uncertainty*."John Wiley and Sons, New York.

150. Zhang, B. and Govindaraju, R. S. (2000). " Prediction of watershed runoff using Bayesian concepts and modular neural networks". *Water Resourcs Research.*, 36(3), 753-762.

151. Zhu, M., Fujita, M., and Hashimoto, N. (1994). "Application of neural networks to runoff prediction". *Stochastic and statistical method in hydrology and environm ental engineering*, vol.3, K.W.Hipel et.al.eds., Kluwer,Dordrecht, The Netherlands,205-216.

152. Zurada, J.M. (1992). *Introduction to artificial neural systems*, West publishing Company, St.Paul, Minn, 1992.

Publications: Published, accepted and communicated

(Based on the research study)

1.Published in referred International Journal

Paresh Deka and V.Chandramouli, (2003) "A Fuzzy Neural Network Model for deriving the river stage-discharge relationship", *Hydrological Sciences Journal, Oxford*, England, vol.48 (2), 197-209.

2.Published in International Conference

Paresh Deka and V.Chandramouli (2002) "River flow prediction using fuzzy-neural network modeling", *Proceedings of International Conference IHAR*, August 2002 at National University, Singapore, Vol.II, 711-714.

3. Published in National Symposium

Paresh Deka and V.Chandramouli (2000) "Hydrological modeling of an urban Watershed - Guwahati city drainage - a case study", *Proceedings of Tenth National Symposium on Hydrology*, IAH, July 2000, New Delhi, 54-60.

4.Communicated

Paresh Deka and V.Chandramouli, (2002, September) "Fuzzy Neural Network model for river flow prediction" communicated to ASCE Journal of Hydrologic Engineering.

(Manuscript No.HE/2002/022564, dated 25/9/02).

Reviewer comments has come for the paper. The paper is revised and resubmitted.

Paresh Deka and V.Chandramouli, (2003, May) "Fuzzy Neural Network m[illegible]g for reservoir operation" communicated to International Journal of Water Resources Development, Mexico.

APPENDIX

(optimal architecture of various neural network models)

Figures are attached as the basis for deciding the network architecture of neural network model. These are Fig.A-1, Fig.A-2 and Fig.A-3.To obtain optimal network architecture, various trial and error procedures are adopted which are discussed in page 35.

Network architectures are different for various experiments that are based on input parameters and desired outputs. Number of sweeps, learning rate, momentum factor, number of neurons in hidden layer etc. are to be decided after various analysis and their performances.

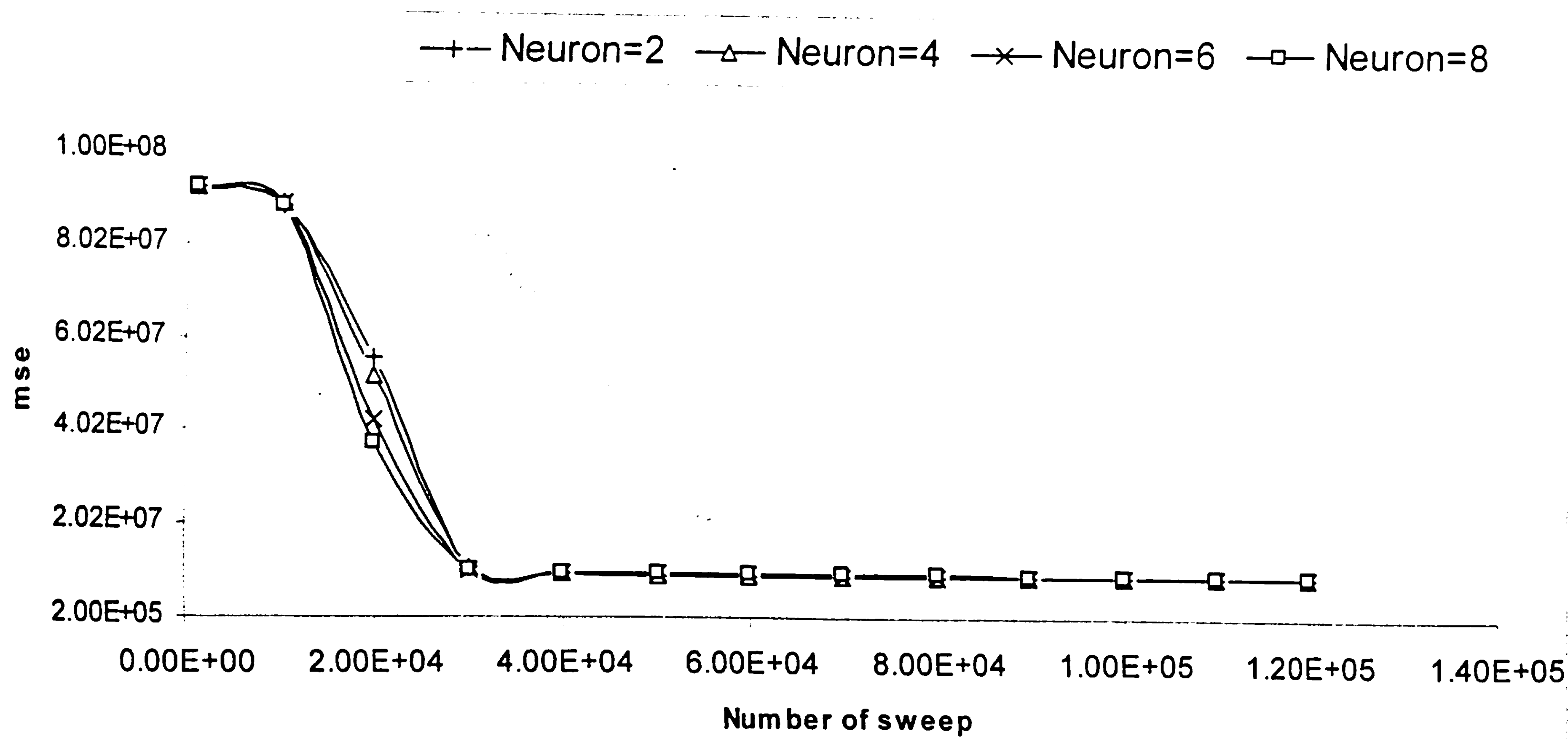

Fig.A-1 Variation of mse for different number of neurons in hidden layer(stage-discharge relationship -gauging station II,EXPT.1)

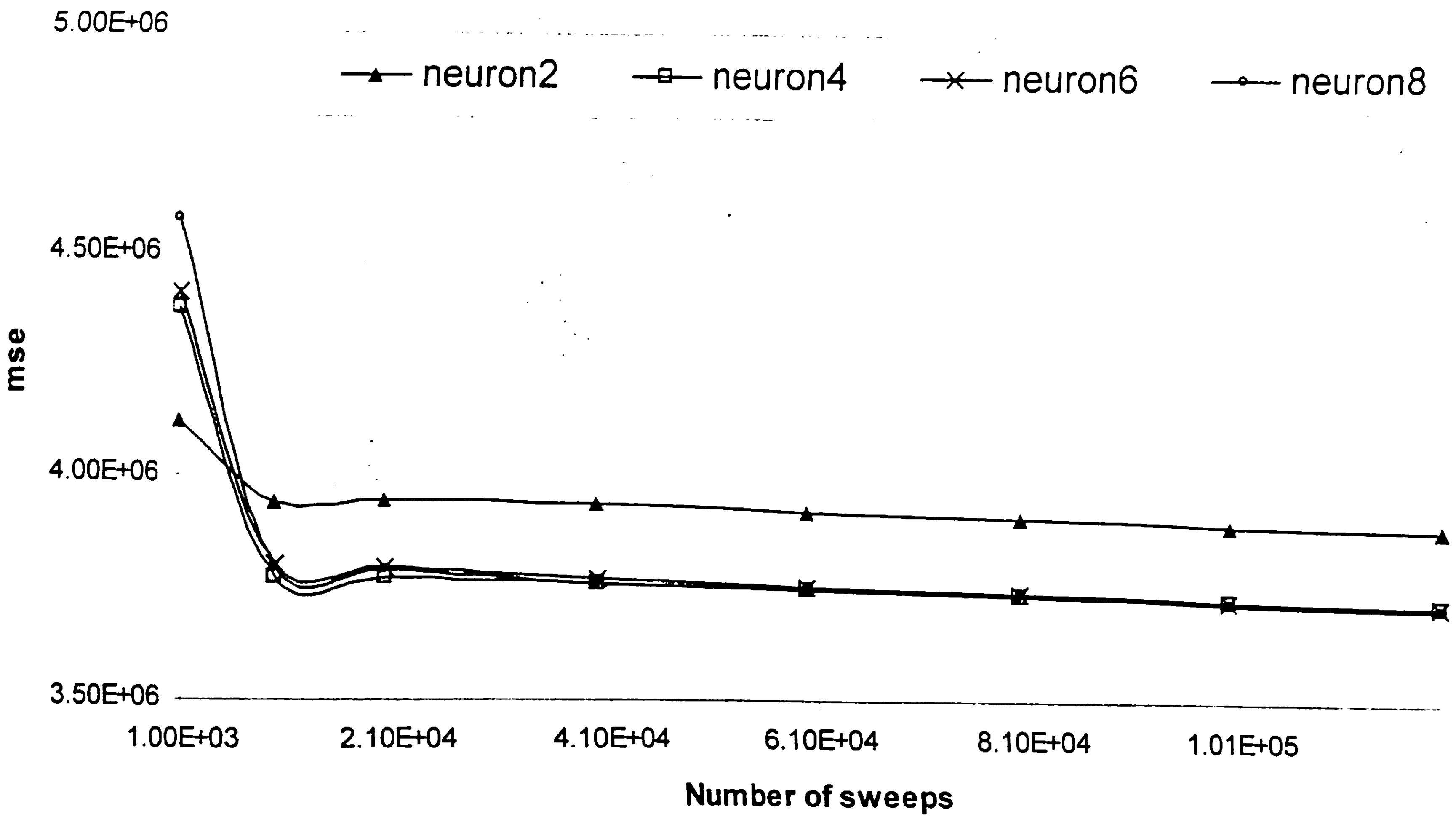

Fig.A-2 Variation of mse with different number of neurons in the hidden layer(Stage-discharge relationship,gauging stationII,Expt.2)

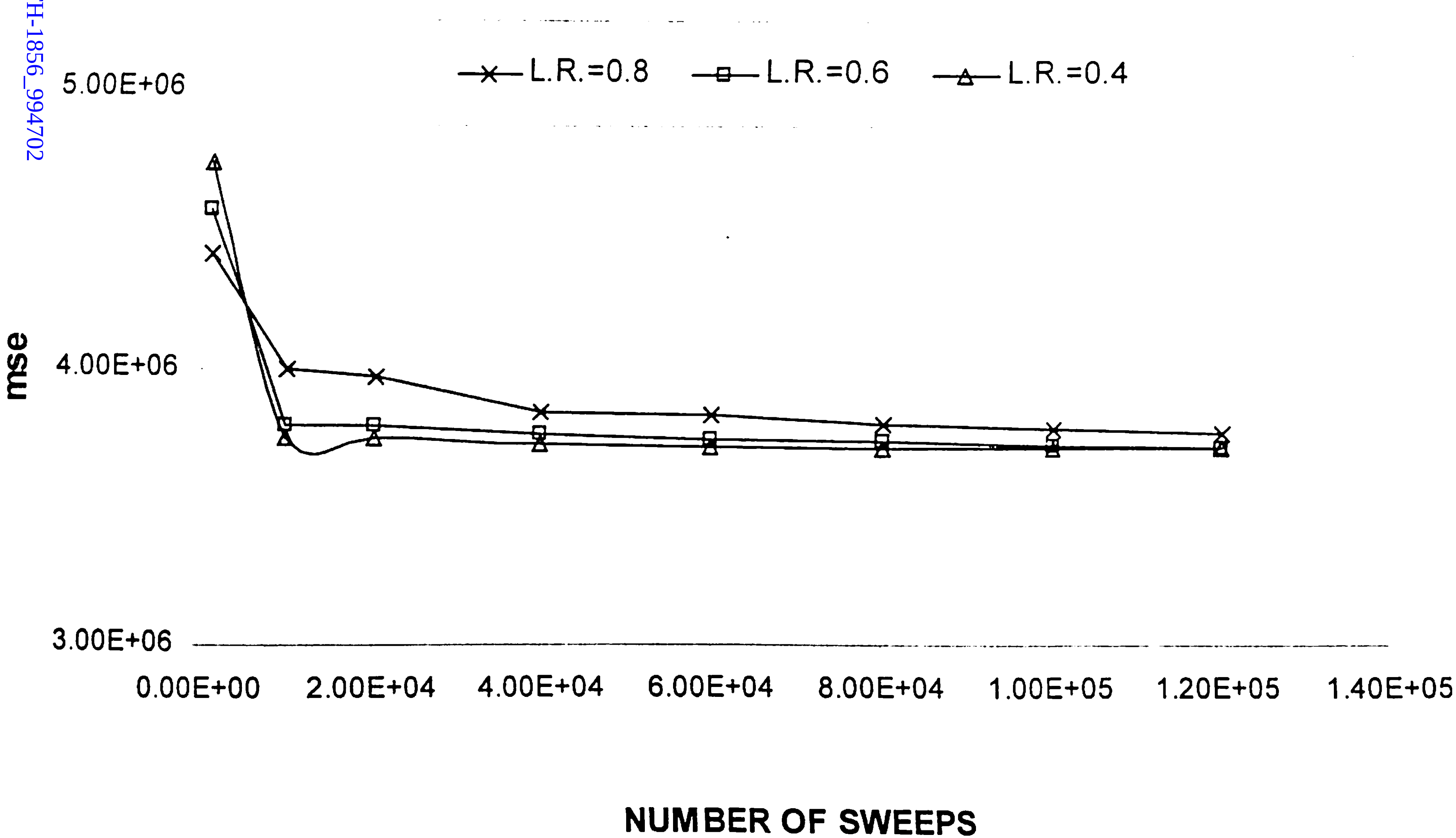

Fig.A-3 Performance of NN model for different learning rate(Stage-discharge relationship-Gauging station II,Expt.2)

CURRICULUM VITAE

1.NAME	Paresh Chandra Deka
2.DATE OF BIRTH	Ist May 1965.
3.EDUCATIONAL QUALIFICATION	
1988 Bachelor of Engineering (B.E)	
Institution	Regional Engineering College Silchar,Assam.
Specialization	Civil Engineering
Class	First class (Hons.)
1994 Master of Engineering (M.E)	
Institution	Assam Engineering College Guwahati,Assam.
Specialization	Watershed Management and Flood control
Class	First class
Doctor of Philosophy (Ph.D)	
Institution	Indian Institute of Technology Guwahati-781039
Date of Registration	2-08-1999.