ARTIFICIAL NEURAL NETWORK (ANN) BASED SPATIO TEMPORAL STUDIES FOR A TYPICAL REACH OF THE BRAHMAPUTRA

A DISSERTATION

submitted in partial fulfilment of the
requirements for the award of the degree
of
MASTER OF ENGINEERING
in
WATER RESOURCES DEVELOPMENT
(CIVIL)

By
T. S. PATIL

WATER RESOURCES DEVELOPMENT TRAINING CENTRE
UNIVERSITY OF ROORKEE
ROORKEE-247 667 (INDIA)

January, 2001

CANDIDATE'S DECLARATION

I hereby declare that the work presented in this dissertation entitled, **"ARTIFICIAL NEURAL NETWORK (ANN) BASED SPATIO TEMPORAL STUDIES FOR A TYPICAL REACH OF THE BRAHMAPUTRA"**, in partial fulfilment of the requirements for the award of Degree of Master of Engineering WRD (Civil) submitted in the Water Resources Development Training Centre, University of Roorkee, Roorkee, is an authentic record of my own work carried out since 16th July, 2000 to January, 2001 under the supervision of **Dr. Nayan Sharma**, Associate Professor, WRDTC, **Er. A.D. Pandey**, Assistant Professor, Department of Earthquake Engineering and **Dr. S.K. Ghosh**, Assistant Professor, Department of Civil Engineering, University of Roorkee, Roorkee, India.

The matter embodied in this dissertation has not been submitted by me for the award of any other degree.

Dated: January, 15th, 2001

Patil

(T.S. PATIL)

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

(ER. A.D. PANDEY)
Assistant Professor
Deptt. of Earthquake Engg.
University of Roorkee
Roorkee – 247667

(DR. NAYAN SHARMA)
Associate Professor,
W.R.D.T.C.
University of Roorkee
Roorkee - 247667

(DR. S.K. GHOSH)
Assistant Professor
Department of Civil Engineering
University of Roorkee
Roorkee – 247667

ACKNOWLEDGEMENT

I wish to express my deep sense of gratitude to **Dr. Nayan Sharma**, Associate Professor, Water Resources Development Training Centre, **Er A.D. Pandey**, Assistant Professor, Department of Earthquake Engineering, and **Dr. S.K. Ghosh**, Assistant Professor, Department of Civil Engineering, University of Roorkee for all the help and guidance provided by them during the preparation of this dissertation. The precious hours of interaction and the valuable suggestions given by them, really helped me in supplementing my thoughts in the right direction, to achieve the desired objective of completing the work in its present form. Working under their guidance will always remain a cherished experience in my memory.

I express my sincere gratitude to Prof. Devaduta Das, Director, WRDTC and Prof Gopal Chauhan, WRDTC for providing all the facilities required during the course of this work.

I also express my thanks to the staff of Computer Centre, WRDTC for providing the required computer facilities during the course of this study.

I wish to place on record my deep sense of gratitude to Shri A.D. Mohile, Ex-Chairman, Central Water Commission, New Delhi for giving me this opportunity to study this course. I also thank Sh. V.U. Koundanya, Secretary, Brahmaputra Board, Guwahati, and Sh. P.C. Hazarika, Chief Engineer, Flood Control Deptt, Govt of Assam, Guwahati for Supplying the precious data of Brahmaputra river for this study.

I would like to express my deepest gratitude to my Mother, Wife, and Children for their forbearance during this course.

I would like to thank all my batchmates and staff of WRDTC for their cooperation and valuable help extended to me during the study of this course.

Finally, my deep appreciation is due to Shri Lal Chand Goyal and Sri Manoj Gupta for all their help and co-operation in the computation work during this work.

Dated : January, 15th 2001
Roorkee

Patil
(T.S. PATIL)

CONTENTS

LIST OF TABLES

LIST OF ANNEXURES

LIST OF FIGURES

ABSTRACT

River Brahmaputra, the life line of North-East, is also the sorrow of many during high floods. Huge funds are being spent annually for the protection works at various locations, along the river Brahmaputra.

In order to train and provide access over the river at desired points, it is necessary to understand the fluvial dynamics of the river. River X-section is one of the important footprints which provide information regarding the river characteristics.

Even though, hydrographic surveys at defined X-sections at irregular time intervals are available, yet at any point of space and time, reliable information may not always be available in the required manner.

Spatio-Temporal analysis of morphological parameters with the help of latest technique of Artificial Neural Network would help in overcoming this deficiency to a large extent.

The advent of digital computers has seen the emergence of analytical tool in analysis and design of Civil Engineering Systems, which earlier seemed too complex or rigorous. At this stage Artificial intelligence technique - especially Artificial Neural Nets, or Neural Nets, are beginning to dominate most of the analytical and design aspects. The basic advantage in the use of Neural Nets being the capability of handling imprecise, imperfect and incomplete data while yet producing acceptable solutions.

In the present study the application of Neural Nets has been examined with specific reference to spatio-temporal analysis of morphological parameters in respect of Brahmaputra reach containing "Majuli Islands", the world's largest river island, where almost 1/3rd of it's total area has already been eroded by Brahmaputra. The main objective of the study can be enumerated as follows:

(1) To construct Neural Network model to correlate river X-section with respect to time.

(2) To study the river Shieft Pattern with reference to time using Neural Nets.

(3) To develop a functional Neural Net model to correlate X-sectional information with river Shi ft and top width patterns.

(4) Developing the Neural Nets to generate X-sections with reference to space and time using the hydrographic survey data and correlating the same with the latest available Satellite data.

It is also proposed to use the above spatio-temporal model to correlate it's findings with the latest available Satellite data of the river Brahmaputra, being utilized in an R&D project undertaken by WRDTC, U.O.R. Roorkee at the behest of MOWR, Govt. of India.

INTRODUCTION

1.1. GENERAL

The Brahmaputra is one of the largest rivers in the world. It passes through Tibet, India and Bangladesh before it's confluence with Bay of Bengal. The total watershed area is 5,80,000 sq.km of which 2,40,000 sq. km lies in India and Bhutan. The total length of Brahmaputra river is 2897 km out of which 1625 km is in Tibet, 918 km in India and 354 km in Bangladesh (Fig. 1.1). The width of the river ranges from 3 km to 20 km and at most of the places it is highly braided, as per report of Brahmaputra Board [1,3].

The river Brahmaputra is infamous for destruction caused by it's periodic flooding and drastic changes in it's course from time to time. The behaviour of the river is quite dynamic and erratic. It shifts it's course abruptly during monsoon season causing erosion and deposition at various locations leading to immense loss of property. The erratic and dynamic nature of the river can be easily understood from it's behaviour at 'Majuli', the world's largest river island, where almost 1/3rd of it's total area has already been eroded by the Brahmaputra as per R&D project report of WRDTC [9].

The study of river morphological features like stream bed profile is helpful in calibration and testing of river models and can be used for planning engineering activities such as road networks, site locations of bridges and other river hydraulic

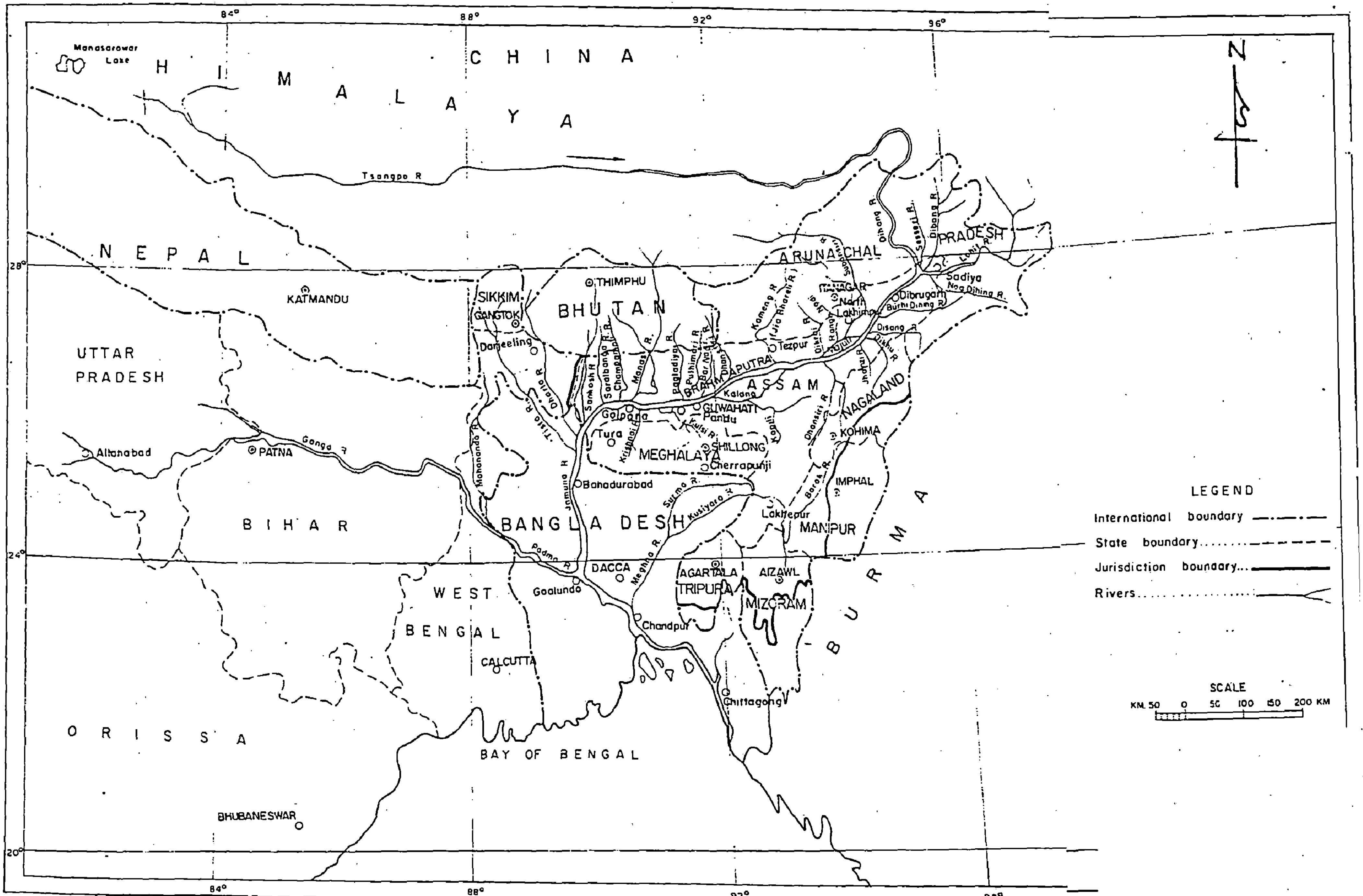


FIG 1·1 INDEX PLAN OF BRAHMAPUTRA

structures such as barrages, sluices, levee etc. Changes in stream bed profile over a reasonably long period of time can be an indicator of the future trends the river is likely to adopt, and this information has an important bearing on the stability of the above stated engineering activities.

1.2 DEFINITION OF THE STUDY

The study of river morphology attempts to describe and explain typical features of the rivers. These features are formed as a result of complex dynamics of flow over a mobile bed. Almost in all cases, the river bed profiles have irregular shape and size. The complexity of representing this information mathematically increases, where the sections are moderately or heavily braided as in the case of river Brahmaputra. In such situations, the fluvial land form comprising river sections undergo changes in time and space. Analysis of this phenomenon is not a simple process and require extensive input from field. The analysis has to reasonably account for variation in space and time. such an analytical procedure is known as spatio-temporal analysis.

A river being a dynamic body, it's morphology can be idealized by adopting a spatio-temporal analytical procedure. Even though hydrographic surveys at defined X-sections at irregular time interval are available, yet at any point of space and time, reliable information may not always be available in required manner.

Spatio-temporal analysis of morphological parameters with the help of latest technique of Artificial Neural Network (ANN) may help in overcoming this deficiency to a large extent.

1.3 OBJECTIVE OF THE STUDY

The main objective of the study are as follows:

1. To construct Neural Network Model to correlate river X-section with respect to time.
2. To study the river shift pattern with respect to time using Neural Nets.
3. To develop a functional Neural Net model to correlate X-sectional information with river shift and top width patterns.

REVIEW OF LITERATURE AND PREVIOUS STUDIES ON THE SUBJECT

2.1 INTRODUCTION

River Brahmaputra, the life line of North – East is also the sorrow of many during high floods. Huge funds are being spent annually for the protection works at various locations, along the river Brahmaputra.

In order to train and provide access over the river at desired points, it is necessary to understand the fluvial dynamics of the river. River x-section is one of the important foot prints which provide information regarding the river characteristics. This information can be used effectively in planning and designing any river training measures or any river hydraulic structures [9].

It would therefore be worthwhile to take a review of studies done on the subject at International and National level on the fluvial dynamics of the river.

2.2 INTERNATIONAL STATUS

Practically, very little work for modelling the Brahmaputra river has been done at international level till now. Throne et al (1990) and C.S. Bristow et al (1990) have presented a study on the Bangladesh portion of the river Brahmaputra. The above study pertains to the parametric analysis of hydrographic-data without spatio-temporal processing of the data for developing mathematical functions of the morphological features.

Furthermore, most of the river morphological studies carried out already as reported in the literature involve non braided rivers of the world. Thus river morphological studies for a large braided alluvial river like Brahmaputra will call for a treatment on a different footing from the study and research stand point, in view of it's multiple channel river configuration.

2.3 NATIONAL STATUS

At the national level, study and research work for modelling morphological behaviour of Brahmaputra by incorporating the complexities of each changing channel geometry is still awaiting it's due attention from the research workers in a comprehensive way.

The Brahmaputra river over the years has been the focus of many people, due to it's rapidly shifting nature and havoc caused during flood. Suffering caused by the flood of the river led to establishment of Brahmaputra Flood Control Department by the Govt. of Assam and the Brahmaputra Board by the Govt. of India for formation and execution of strategic overall plan for water management including the preparation of master plan for training the Brahmaputra river based on a thorough understanding of all aspects of the river and it's catchment.

A study on the Brahmaputra river was carried out by WAPCOS through a team of renowned engineers like Sri S.Y. Chitale, Prof. R.J.Garde, Sri N.K. Sarma and others (1980) to identify the basic morphological parameters of the river Brahamputra in Assam. Their study was pertaining to shoal formation in the river bed, river meandering bed movement, river behaviour under special condition and other hydrological aspects of the river.

Dr. Nayan Sharma, Associate Professor of WRDTC, University of Roorkee and presently Principal Investigator of MOWR R&D projects on Brahmaputra river, formulated new braiding indices to describe braiding phenomenon and fluvial land form pattern in quantitative terms. Further, Sharma (1997) also studied the behavioural pattern of the Brahmaputra and developed certain functional relationship among the braid indicators for a highly braided river such as Brahmaputra. Singh (1995) in his unpublished M.E. Dissertation under the guidance of Sri A.D. Pandey, Department of Earthquake Engineering, University of Roorkee, Roorkee used the normalised data of the measured cross-section and utilised shape function in spatial as well as temporal direction simulating intermediate cross-section profile and validated the same.

Issar (1995) in his unpublished M.E. Dissertation, under the guidance of Dr. S.K. Ghosh, attempted to identify the navigation problems in Brahmaputra river by analysing satellite derived maps and hydrological data.

Other notable studies on the river Brahmaputra have been carried out by Bhagawati (1990), Kalita (1992), Hussain (1992), and Murthy on the morphological study of the river Brahmaputra and use of remote sensing data at different stretches of river.

Lahiri (1998) studied on spatial characteristics of drainage geometry of Brahmaputra river and it's tributaries based on visual interpretation of IRS-1B imagery (on 1:2,50,000 scale) and topographic maps of different period.

2.4 CONCLUSIONS

The works enumerated above deal with only the present status of the river and the analysis of it's causes. However, the present study which involves spatio-temporal analysis explores into an important area of morphology for any instance of time and space using Artificial Neural Network technique. Till now hardly any large scale river valley projects have been taken up in the Brahmaputra basin for control of flood, stabilization of river morphology and harnessing the large water resources for the economic development of North – East region of India. As and when planning and implementation of any such large projects are considered, there will be imperative need to use a predictive model, as designed to be developed in the present study, for generating the probable future trend of the river behaviour, and hence the need of such a spatio-temporal model is eminent.

NEURAL NETWORK APPROACH

3.1 INTRODUCTION TO NEURAL NETWORK

A view has emerged during past few years that computing based on models inspired by our understanding of the structure and function of biological neural Network (Brain) may hold the key to success of solving intelligent (natural) tasks by machines. The new field is called 'Artificial neural Network'. Computing model inspired by biological neural network may provide new directions to solve problems arising in natural tasks. In particular, the neural network would extract relevant features from the input data and perform a pattern recognition task by learning from examples without explicitly stating the rules for performing the task, (Yegnarayana, 1999).

The problems that are addressed by the Neural Networks are intractable or cumbersome with traditional methods. These new computing architectures inspired by the structure of the brain are radically different from the computers that are widely used today. Neural Networks are massively parallel systems that rely on dense arrangements of interconnections and surprisingly simple processors.

Artificial neural network take their name from the networks of nerve cells in the brain. Although a great deal of biological detail is eliminated in these computing models, the artificial neural networks retain enough of the structure observed in the brain to provide insight into how biological neural processing may work. Thus, these models contribute to a paramount scientific challenge - the brain understanding itself.

3.2 ARTIFICIAL NEURAL NETWORK (ANN) - AN OVERVIEW

3.2.1 ANN, a branch of Artificial Intelligence

Artificial neural networks (ANN) is a branch of Artificial Intelligence (AI). AI can be defined as a field of study concerned with designing and programming of machines to accomplish tasks that people accomplish using their intelligence. AI also attempts to understand how human beings think.

The AI distinguishes itself from other computer science and systems engineering disciplines, by approaching problem from relatively heuristic point of view (viz. By Thumbrule and in an Interpolative way).

Though AI has much in common with other computer science disciplines, it differs from conventional computer science areas in following aspects.

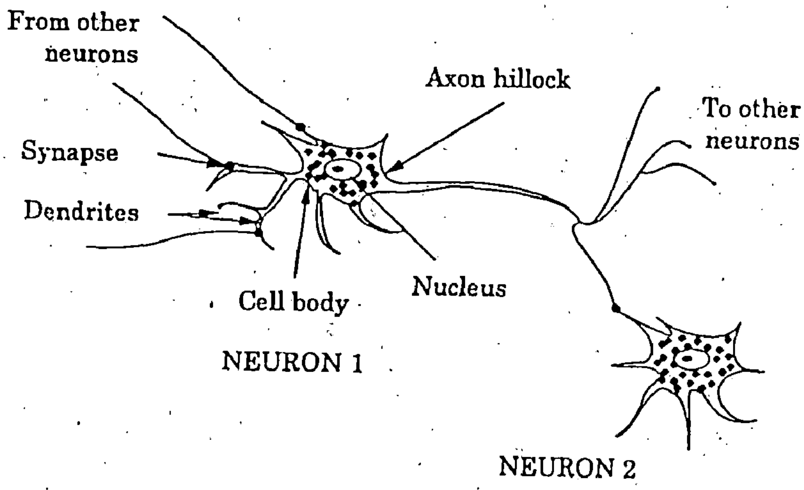
1. It's view point is plausible and logical reasoning, instead of qualitative calculations.
2. Subject matter (mental activity - very knowledge - intensive).
3. Tolerance for errors and imprecise or incomplete data.
4. Symbolic manipulation (e.g. pattern recognition) instead of numeric orientation.
5. Evolutionary design principles i.e. non-procedural, anticipating addition and changes.
6. Knowledge based design i.e. learns from experience etc.
7. Inference and deduction i.e. has a line of reasoning and can explain itself.
8. Heuristic or approximate problem-solving approach.

Application of AI is in the as diversified field as: Games & puzzles (chess, rubic cube etc.); Expert systems, eg. Use of computers for advice & Consultant-decision support in the field of Finance, Industry, and Military - command and control etc; Artificial neural network (ANN), natural language processing (NLP), Robotics (Intelligent machines), computer vision - analysing visual information such as satellite imageries etc. (Patridge D. et al, 1990).

3.2.2 A.N.N. - The Basic Structure

Neural Networks are responsible for making significant advances in the traditional AI fields of speech and visual recognition. Investment managers are creating investment models to better manage money and improved profits. Marketing professionals are employing neural network to accurately target products to potential customers. Geologists can increase their probability of striking oil. Lenders use neural networks to determine the credit risk of loan applicants. Scientists and engineers use them to model and predict complex phenomena such as liquefaction potential of soil, simulating the analysis of R.C.C. grid structure in structural engineering, computation of mode choice analysis in transport engineering, prediction of critical slip surface and minimum factor of safety of a complex slope at a site. The variety of problems that can be solved effectively by neural networks is virtually endless.

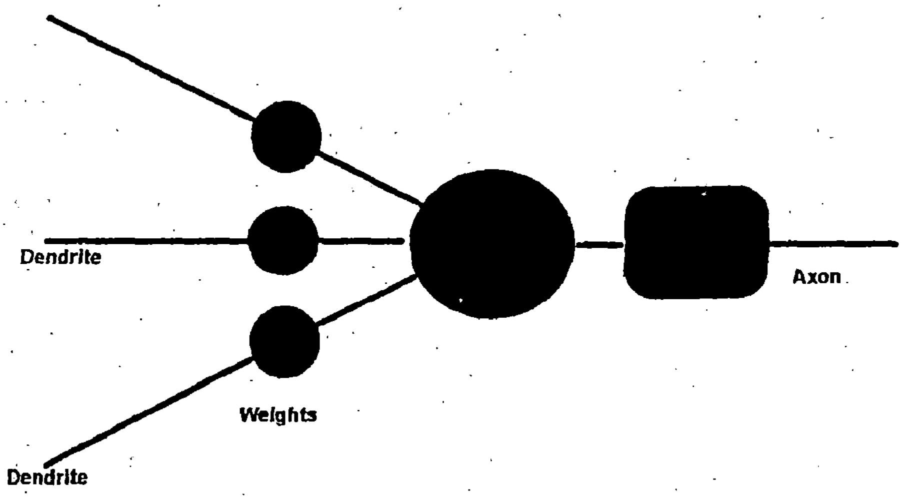
A human brain continually receives input signals from many sources and processes them to create the appropriate output response. Our brains have billions of neurons ($\approx 10^{11}$ neurons) that are interconnected by 10^{15} interconnections called Dendrites, (Fig. 3.1) to create an elaborate neural networks (Yeg Narayana, 1999). These networks execute millions of necessary functions needed to sustain normal life.



Schematic diagram of a typical neuron or nerve cell.

Neuron

The neuron model used by Neural Planner is shown below. Its functionality is considerably simpler than that of real neurons but it is suitable for use as the basic element in an artificial neural network.



The dendrites are the inputs to the neuron and the axon is the output. The terms dendrites and axons are not usually used with the artificial neuron and they are only included here so that comparisons can be made with real neurons.

FIG3·1 Biological & Artificial Neuron.

For some years now, researchers have been developing models, both in hardware and software, that imitate a brain's cerebral activity in an effort to produce an ultimate form of artificial intelligence.

Back propagation model: The back propagation model, however, is largely responsible for changing this trend. It is an extremely effective learning tool that can be applied to wide variety of problems. Back propagation related models require supervised training. This means they must be trained using a set of training data where known solutions are supplied.

Training of neural network is essentially carried out through the presentation of a series of example patterns of associated input and output values. The most commonly used learning system and the one adopted in the present study, is back propagation model.

Back propagation type neural networks processes information in interconnecting processing elements, known as neurons or neurodes or nodes (Fig. 3.1). These nodes are organized into groups known as layers. There are three distinct type of layers in a back propagation neural network (Pandey A.D. et al, 1999).

i. The input layer

ii. The hidden layer or layers, and

iii. The output layer

A network consists of one input layer, one or more hidden layers and one output layer. Connection exists between the nodes of adjacent layers to relay the output signals from one layer to the next. Fully connected network occur when all nodes in each layer receive connection from all nodes in each proceeding layer. Information enters a network through the nodes of the input layer. The input layer nodes are unique in that their sole purpose is to distribute the input information to the next processing layer, i.e. the first hidden layer. The hidden and output layer nodes process all incoming signals by applying factors to them, known as weights. Fig. 3.2 shows the architecture of a typical neural network consisting of three layers of interconnected neurodes. All inputs to a node are weighted, combined and then processed through a transfer function that controls the strength of signal relayed through the node's output connections. The transfer function serves to normalize a node's output strength between 0 and 1. There are generally three types of transfer functions, the sigmoid function, the Binary and Ramp functions (Fig. 3.3). Network processing continues through each node and layer until the network's response is obtained at the output layer. Here sigmoidal transfer function is used.

During training, the network's response at the output layer is compared to a supplied set of known answers to the output layer, known as training targets. The errors are determined and back propagated through the network in an attempt to improve the network's response. The nodal weight factors are adjusted by amounts determined by the training algorithm. Training of the neural network is carried out iteratively until the average sum squared errors over all training patterns are minimized. The iterative procedure of processing inputs through the network, determining the errors and back propagating the errors through the network to adjust the weights constitute the learning process. One training iteration is complete when all supplied training cases have been processed through the network. The training algorithms adjust the weights in an attempt to drive the networks response error (average sum squared error) to a minimum [5].

Two factors are used to control the training algorithm's adjustment of the weights. They are the learning rate coefficient 'η' and the momentum factor 'α'. The learning rate determines the amount that each weight will change during each learning cycle, and the momentum factor determines the amount that each weight will change relative to the change in the previous learning cycle. If the learning rate is too fast, i.e. 'η' is too large, network training can become unstable. If 'η' is too small, the network will learn at a very slow pace. The momentum factor 'α' has a smaller influence on learning speed, but it can influence training stability and promote faster learning for most networks. In this present study the learning rate as 0.15 and the momentum factor as 0.35 has been arrived at by trial & error.

On satisfactory completion of the training phase, verification of the performance of neural network is then carried out using data patterns that were not included in the training set, however these should be in the same range of training data patterns. This is often called as testing phase. This determines the quality of predictions in comparison to the desired outputs.

On completion of satisfactory tests, the network is ready for interrogation for the desired values of inputs provided these are with in the range of training parameters. During interrogation mode, the network processing ends at the output layer.

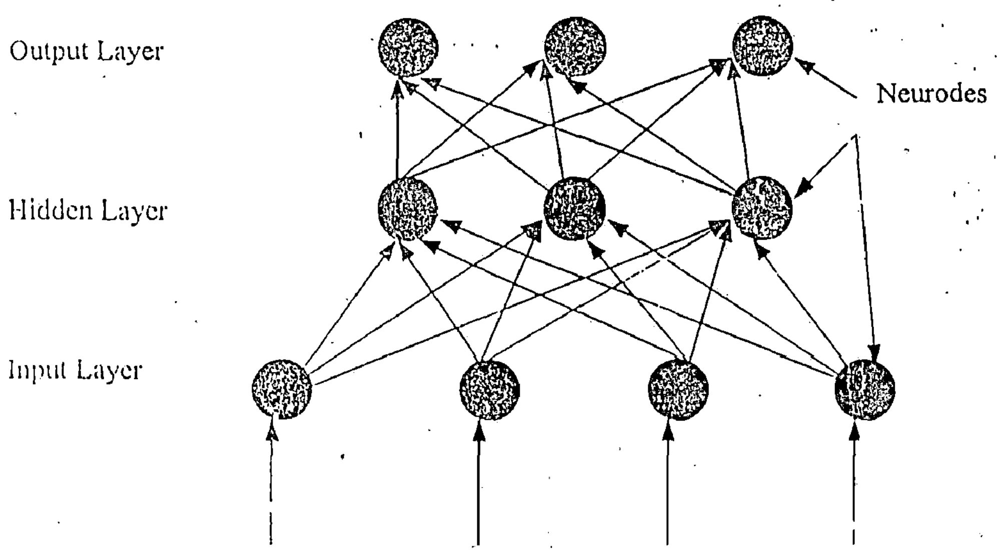


Fig. 3.2 Typical Neural-Network Architecture

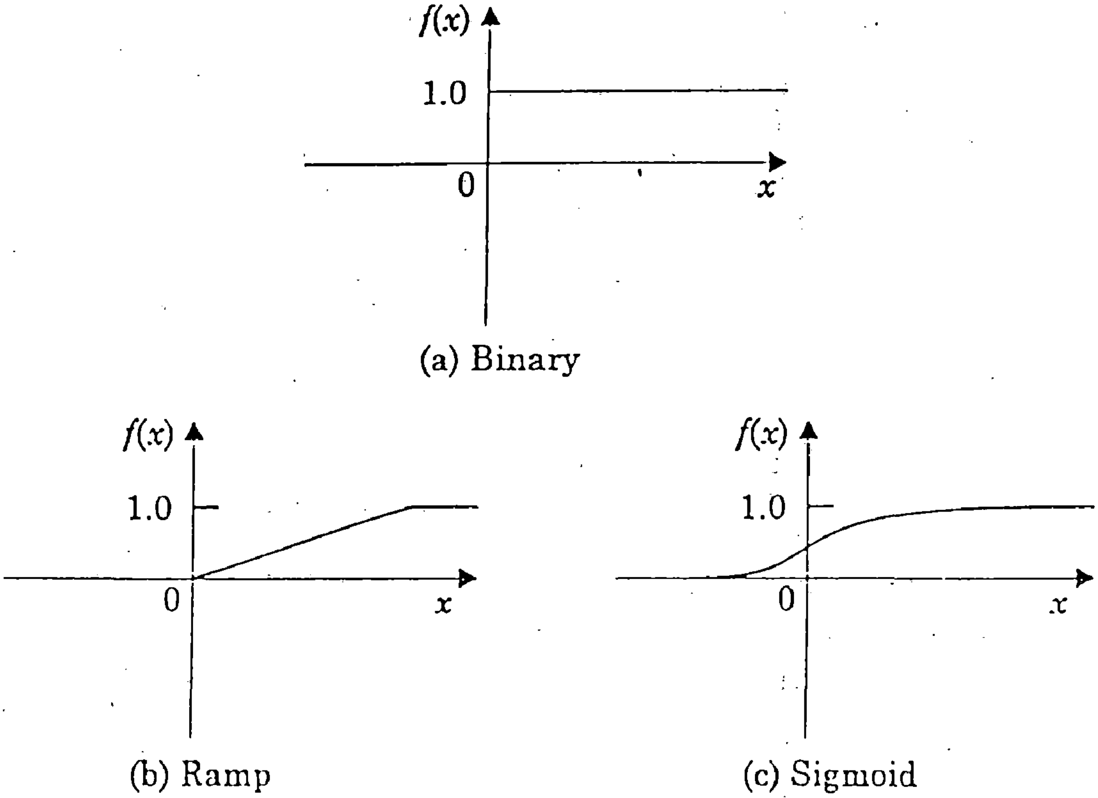


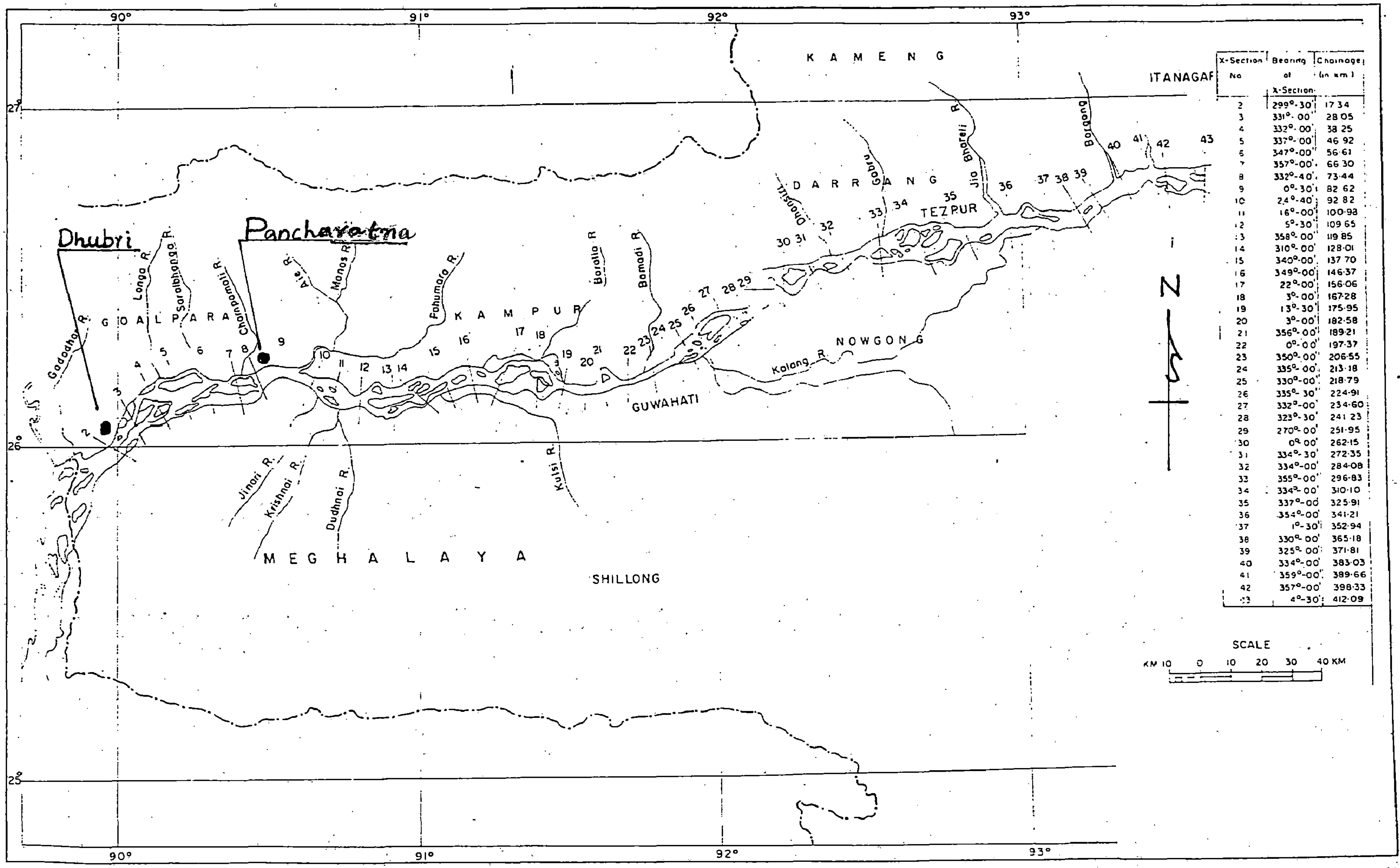
Figure 3.3 Some nonlinear functions.

LAYOUT OF THE MODEL AND DATA PROCESSING

4.1 DATA COLLECTION

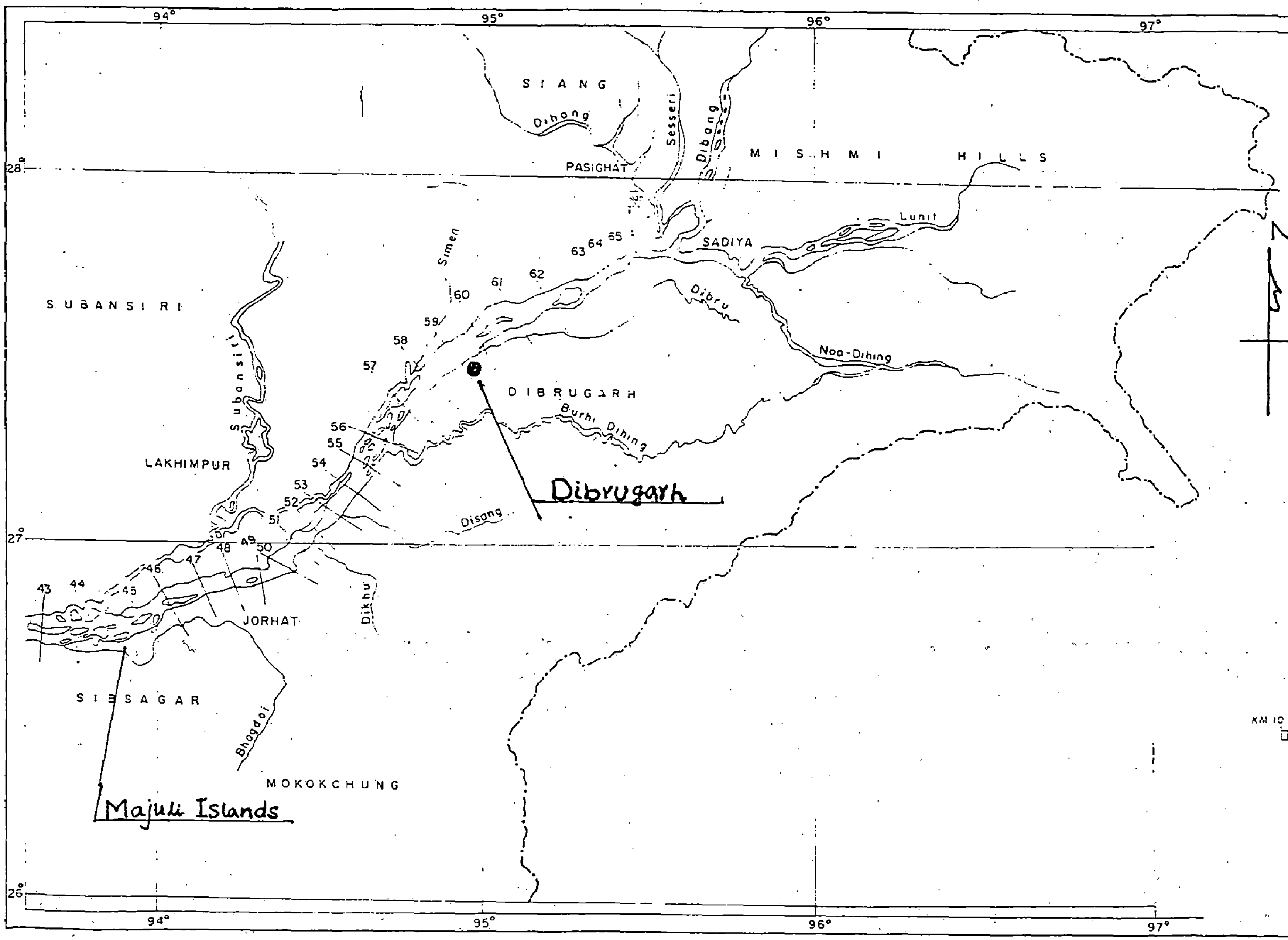
In order to study the Spatio-temporal river morphological behaviour of the river Brahmaputra with special emphasis on the river reach in the vicinity of 'Majuli Islands' hydrographic survey data at different cross sections from Dibrugarh (27°3' N, 94°55' E) to Dhubri (26°01'N, 90° E), (Fig. 4.1 a & b) was collected by contacting Assam Flood Control Division, Brahmaputra Board, Central Water Commission with considerable efforts and time. As river Brahmaputra is an international river, it's data is restricted in nature and special efforts were required to collect the data from aforementioned agencies.

For the convenience of hydrographic survey etc. Brahmaputra river has been divided into different cross sections which are numbered from 1 to 65, 1 falling in Bangladesh near the mouth of the river. The C/S in India starts from 2 (Dhubri) near the international Border between India and Bangladesh and extends upto C/S No. 65 near Dibrugarh. These C/S were decided during the British era, depending on topography and accessibility of the river. 'Majuli Islands' fall within the reach from cross-sections 44 (km-423.31) to cross-section 54 (km 522.27) (Fig. 4.1b).



X-Section No	Bearing of X-Section	Chainage (in km)
2	299°-30'	17 34
3	331°-00'	28 05
4	332°-00'	38 25
5	337°-00'	46 92
6	347°-00'	56·61
7	357°-00'	66 30
8	332°-40'	73·44
9	0°-30'	82 62
10	24°-40'	92 82
11	16°-00'	100·98
12	5°-30'	109 65
13	358°-00'	119 85
14	310°-00'	128·01
15	340°-00'	137 70
16	349°-00'	146·37
17	22°-00'	156·06
18	3°-00'	167·28
19	13°-30'	175·95
20	3°-00'	182·58
21	356°-00'	189·21
22	0°-00'	197·37
23	350°-00'	206·55
24	335°-00'	213·18
25	330°-00'	218·79
26	335°-30'	224·91
27	332°-00'	234·60
28	323°-30'	241 23
29	270°-00'	251·95
30	0°-00'	262·15
31	334°-30'	272·35
32	334°-00'	284·08
33	355°-00'	296·83
34	334°-00'	310·10
35	337°-00	325·91
36	354°-00'	341·21
37	1°-30'	352·94
38	330°-00'	365·18
39	325°-00'	371·81
40	334°-00'	383·03
41	359°-00'	389·66
42	357°-00'	398·33
43	4°-30'	412·09

Fig 4·1a Map Showing CS 2 to CS 43



X-Section No	Bearing of X-Section	Chainage (in km)
44	357°-00	423 31
45	347°-00	439 63
46	330°-30'	453 91
47	336°-00'	465 13
48	342°-00'	474·82
49	350°-30	483·49
50	296°-00'	490 63
51	315°- 00'	498 80
52	315°- 00'	505 94
53	301°- 00'	513 08
54	307° 00'	522 77
55	302°-30'	531·95
56	290°-00'	541·13
57	315°- 30'	558 98
58	312°- 00'	570·20
59	314°- 30'	579·38
60	332°- 30	589·07
61	331°-00'	601 82
62	330°-30'	613 04
63	338°-00'	626 30
64	324°-00'	634 46
55	322°-00'	640 07

Fig 4·1b Map Showing CS45 to CS65

Following data was collected for the purpose of present study:

i. C/s 2 to C/s 65 for the years 1957, 71, 77, 81, 88 and available cross sections for the years between 1988 to 1997.

ii. Ten daily average discharge of river Brahmaputra for 1981/82, 1988/89 to 1998/99 at G&D site at Pancharatna (Km No 75) (Fig. 4.1a).

iii. Ten daily average stage data at Pancharatna from 1987/88 to 1998/99.

iv. Monthwise daily average sediment concentration for years 1988/89 to 1996/97 at Pancharatna.

In addition to above data, data as available in the river Atlas of Brahmaputra Board was utilized, wherever necessary and feasible, for the years prior to 1988.

4.2 TOPOLOGY OF THE MODEL

The main purpose of the present study is to obtain x-section details with respect to time and space. It is therefore necessary to choose the input and output parameters in such a way as to accomplish this task easily.

4.2.1 Input Layer

The input variables used in the neural network are four, as follows (Fig. 4.2)

(a) Chainage along the river Brahmaputra starting from CS2 (km 17.34) upto CS65 (km 640.07)

(b) Year starting from 1957 when the earliest data is available and upto 2010, the year upto which predictions are attempted to be made.

(c) Month

(d) Day.

The cross section available in the data are taken as available on Ist January of that year. The purpose of choosing these variables for the input is to enable interrogation of the fully trained model for any chainage between CS 2 (km. 17.34) and CS 65 (km 640.07) for any year, month and day between 1957 and 2010.

As already stated, the sole purpose of input layer is to distribute input data values to the first hidden layer. The number of nodes in the input layer will be equal to number of input data values in the model (Fig. 4.2). The total number of input neurons considered for training, testing and interrogating the model are four.

4.2.2 The Output Layer

The Number of output neurodes depends upon the number of output variables. As stated above the main purpose in the study is to get the x-section point at various points of time and space. The cross sections available in the raw data are in the form of reduced distance (RD) from left bank, and elevation (RL) of river bed at this RD for a particular cross section as per figure below. Each cross section has varying number of such surveyed points depending upon top width (TW) of the river at that x-section.

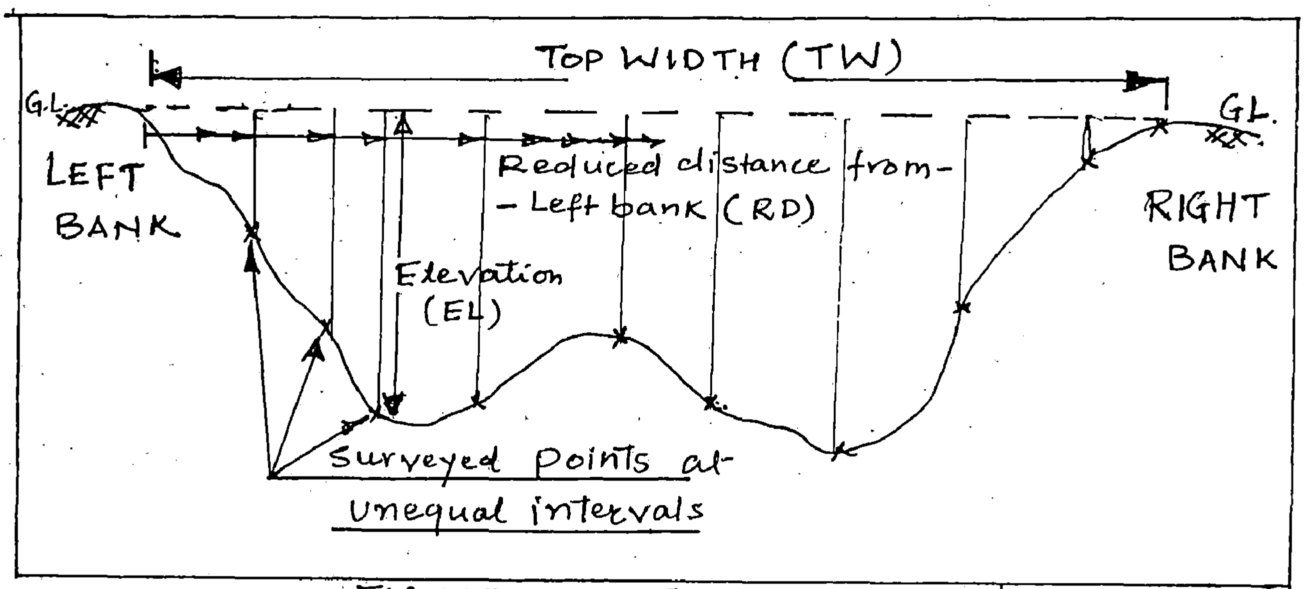


FIG : Typical Surveyed X-Section

However, for a particular model the neural network must have a fixed number of neurodes at the outer layer. In order to match the number of neurodes in outer layer of network with the number of surveyed points in a x-section, it is necessary to normalize the surveyed points in the cross section to a fixed number. In this study the cross section is normalized for 25 equispaced points, so that each point can be represented by one output neurode. Here normalization of the cross section into 25 equispaced points means, dividing the top width (TW) into 25 equal intervals and interpolating the river bed elevation at each of these points by making use of the surveyed data, as per fig. below.

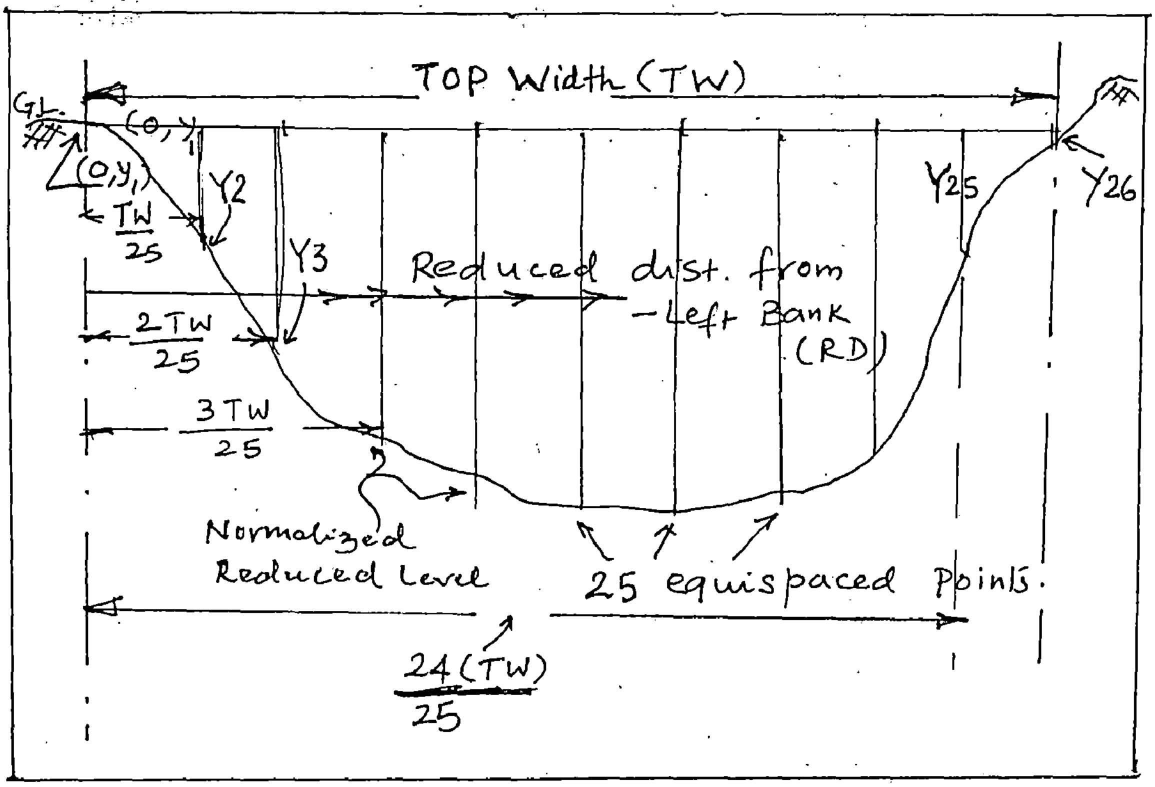


Fig. Typical Normalized X-Section

The normalization is accomplished through Langrange's, interpolation function, for which a computer software, Normal. F, has been used (Annexure 4.1). There are sub-routine functions which are to be called to accomplish the task. The block diagram of the programe is given at fig 4.3.

The normalization of data, i.e. generation of 25 equispacecd points alongwith appropriate river bed elevation is the essential part of the output layer, as the number of output neurons in the training set has to be constant throughout. Thus each neuron in the output layer from 1 to 26, represents the coordinate, $(0,y_1)$, $(TW/25, y_2)$, $(2TW/25, y_3)$, $(3TW/25, y_4)$...(TW,y_{26}), respectively, where TW is the width of river and is represented by 28th neuron, while y_1, $y_{2\ldots26}$ are the normalized river bed elevation represented by first 26 neurons. The 27th neuron in the output layer represents discharge Q in m^3/s as observed on 1st January of input year at Pancharatna site (Fig. 4.2).

4.2.3 The Hidden Processing Structure

Choosing the number of hidden layers and the number of hidden nodes in each layer is not an easy task. Currently there is no thumb rule for determining the optimal number of neurodes in the hidden layer or the number of hidden layers, except through experimentation. Many factors play a part in determining what the optimal configuration should be. These factors include the quantity of training patterns, the number of input and output nodes, and the relationships between the input and output

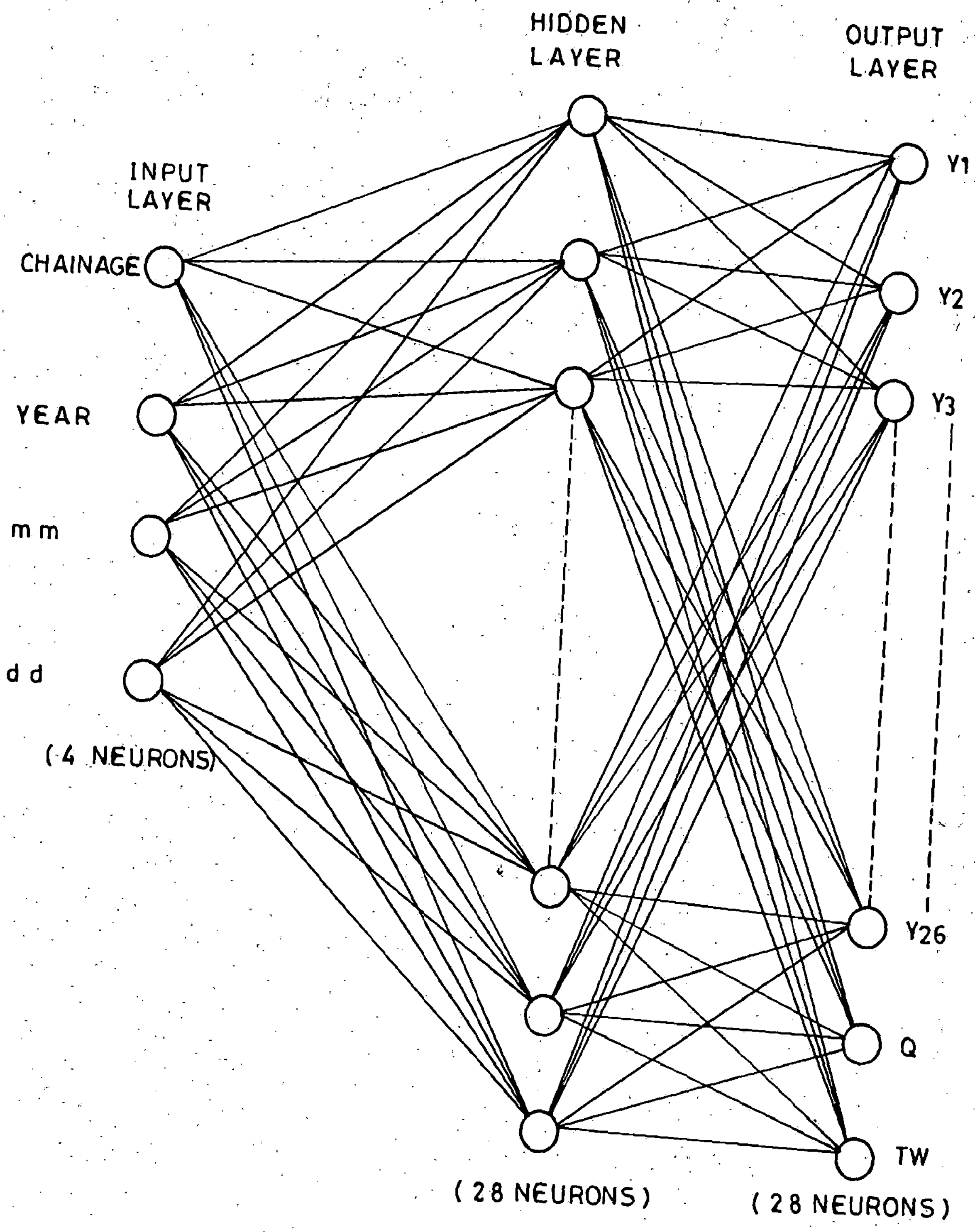
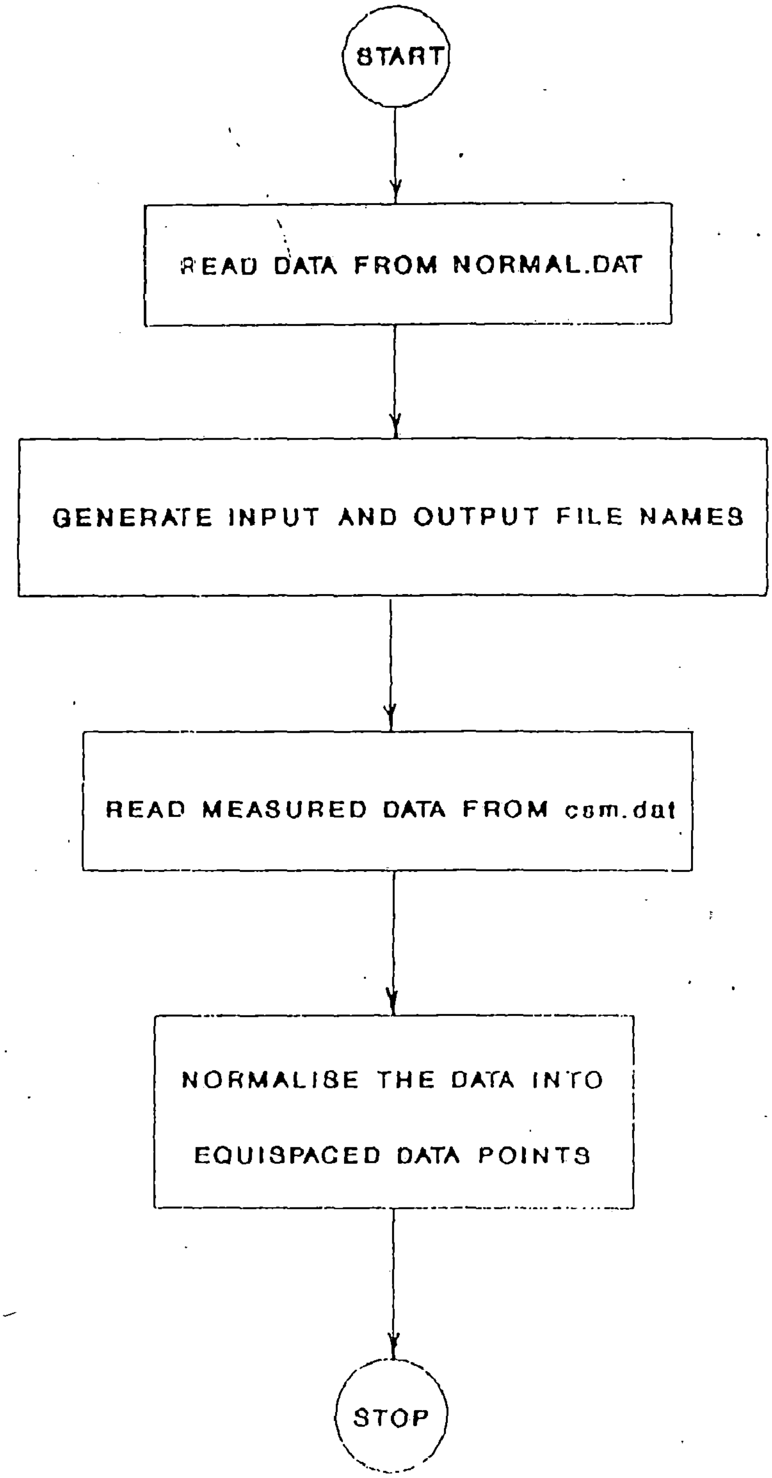


FIG. 4.2 NETWORK TOPOLOGY

FIG. 4.3

BLOCK DIAGRAM OF NORMAL.F



data. When a network's hidden processing structure is too large and complex for the model being developed, the network may tend to memorize input and output sets rather than learn relationships between them. Such a network may train well but test poorly. Also network training time will significantly increase when a network is unnecessarily large and complex. In the present study one hidden layer is considered for the model and the number of hidden neurons arrived at, by trial and error, are twenty eight.

4.3 THE TRANSFER FUNCTION

A node's transfer functions serves the purpose of controlling the output signal strength for the node, except for the input layer which uses the inputs themselves. These functions set the output signal strength between 0 and 1. The input to the transfer function is the dot product of all the node's input signals and the node's weight vector. The sigmoid transfer function is the most widely used function for back propagation neural networks, which is also used in this study. The sigmoidal function acts like an output gate that can be opened (1) or closed (0). Since the function is continuous, it is also possible for the gate to be partially opened, i.e. somewhere between 0 and 1. Models incorporating sigmoid transfer functions usually exhibit better generalization in the learning process and often yield more accurate models, but may also require longer training time [5].

4.4 TRAINING OF THE NEURAL NETWORK

All the neural network analysis for this study were carried out by using the Neural Planner 4.10. Neural Planner is a window based neural network system. It allows to produce multilayered neural network using a simple graphical editor or create a standard three layer networks from training file. There are also facilities for producing training, testing and interrogating files in the Neural Planner. The Neural Planner can learn from training files, self test itself using testing files and allow for interrogation by interrogating files.

4.4.1 The Training Data

A total of 338 sets of data with cross section from 2 to 65, with different actually observed values of discharge, and top width, for the years 1957 to 1997 have been processed. Among the 338 of data sets 318 data sets have been used for training and the rest 20 cases have been used for testing. The training, testing and interrogation data is stored in the networks '.tti' file (training, testing, interrogation file). Neural planner has the facility of feeding the training, testing and interrogation data to the Neural Network through '.tti' file either manually or through a Notepad, provided the data is presented in a desired format as given in the Neural Planner. In this study the training, testing and interrogation data has been fed to the networks '.tti' file (fin_25.tti) through the notepad. After the network is fully trained, the results which are stored in the network's Interrogation Section (npr file) can be retrieved as the output.

The full details of actual data used for training and testing can not be reproduced in this dissertation as this data is restricted in nature.

To account for future predictions, fictitious data, close to some assumed data for the year 2005 for cross section No. 2 and for the year 2010, for cross section No. 65 have been inducted into training file. It may be mentioned here that instead of fictitious data, only a question mark (?) can also be entered against the relevant output in the training file. ANN is capable of forming suitable patterns connecting input and output data from training file and is capable of correcting the fictitious values so fed in. The fictitious data is fed in only to allow increase in the range for interrogating of the network for future predictions.

Some processing of the data is usually required before presenting the input patterns to the neural network. This usually involves scaling or normalization (this is different from normalization used in section 4.2.2 for generating equidistant points across a C/S) of the input patterns to values in the range 0-1. This is necessary because the sigmoid transfer function modulates the output to values between 0 and 1. Normalization of the data can be as simple as either dividing the value by the maximum value or by subtracting the minimum value and then dividing the resultant value by the range, which is the maximum value minus the minimum value. The input patterns for both the training and testing phase were prepared and the normalization was done automatically by the neural network planner.

All the neural network analysis, for this study, were carried out with the learning rate $\eta = 0.15$, and the momentum factor $\alpha' = 0.35$. These optimal values of learning rate and momentum factors were determined through trial and error. Training of the neural network was carried out until the average sum squared errors over all the training patterns were minimized, with number of cycles run equal to 18600 in the testing phase. Once the neural network has been trained, the spatio-temporal analysis for any reach of the river including in the vicinity of "Majuli Island" between C/S 44 to C/S 54 for the years between 1957 and 2010 has been carried out, by providing relevant values of chainage year, month, day in the input layer of the network, by using interrogating file section, and seeking the output in the interrogating file.

The result of some such interrogations especially in the vicinity of 'Majuli Island' are given in Table 4.2 and Table 4.3. The result of all the interrogation cases upto year 2010 are reproduced at Table 4.4. The discussions on the results so obtained including the validity and reliability of the results obtained are discussed in Chapter 5.

Table 4.1 Typical Normalized X-Section

CROSS SECTION NO.= 2
FOR THE YEAR 1957 TOP WIDTH= 11887.000
FOR THE YEAR 1971 TOP WIDTH= 9700.000
FOR THE YEAR 1977 TOP WIDTH= 12479.000
FOR THE YEAR 1981 TOP WIDTH= 12500.000
FOR THE YEAR 1988 TOP WIDTH= 13200.000

1957		1971		1977		1981		1988	
.0	26.35	.0	28.90	.0	29.80	.0	30.77	.0	31.36
475.5	26.13	388.0	28.88	499.2	28.35	500.0	30.77	528.0	27.46
951.0	26.28	776.0	28.87	998.3	24.03	1000.0	30.77	1056.0	27.40
1426.4	25.87	1164.0	26.20	1497.5	22.11	1500.0	24.85	1584.0	28.08
1901.9	26.08	1552.0	23.58	1996.6	25.48	2000.0	27.04	2112.0	26.61
2377.4	26.17	1940.0	27.60	2495.8	26.00	2500.0	14.16	2640.0	18.81
2852.9	26.14	2328.0	27.98	2995.0	26.48	3000.0	28.22	3168.0	19.85
3328.4	25.65	2716.0	27.47	3494.1	26.01	3500.0	27.59	3696.0	17.76
3803.8	25.29	3104.0	24.45	3993.3	23.86	4000.0	27.72	4224.0	16.24
4279.3	26.48	3492.0	25.39	4492.4	18.49	4500.0	28.96	4752.0	18.82
4754.8	26.37	3880.0	27.83	4991.6	20.04	5000.0	28.59	5280.0	27.41
5230.3	26.48	4268.0	27.02	5490.8	23.20	5500.0	19.68	5808.0	27.55
5705.8	26.27	4656.0	23.01	5989.9	23.39	6000.0	27.77	6336.0	26.94
6181.2	26.58	5044.0	26.80	6489.1	24.33	6500.0	27.00	6864.0	28.09
6656.7	27.36	5432.0	26.39	6988.2	19.75	7000.0	25.72	7392.0	23.35
7132.2	27.38	5820.0	26.08	7487.4	25.98	7500.0	23.50	7920.0	27.97
7607.7	24.33	6208.0	25.35	7986.6	23.47	8000.0	13.80	8448.0	27.41
8083.2	22.40	6596.0	18.90	8485.7	19.71	8500.0	11.73	8976.0	27.98
8558.6	14.90	6984.0	20.75	8984.9	17.84	9000.0	25.56	9504.0	28.02
9034.1	11.38	7372.0	23.15	9484.0	11.08	9500.0	24.32	10032.0	22.43
9509.6	27.17	7760.0	25.01	9983.2	24.41	10000.0	28.63	10560.0	22.89
9985.1	26.52	8148.0	20.57	10482.4	27.38	10500.0	28.65	11088.0	17.54
10460.6	25.68	8536.0	8.78	10981.5	26.85	11000.0	27.18	11616.0	23.29
10936.0	25.80	8924.0	11.84	11480.7	26.96	11500.0	27.35	12144.0	27.91
11411.5	25.58	9312.0	19.68	11979.8	26.57	12000.0	28.91	12672.0	28.93
11887.0	25.29	9700.0	29.10	12479.0	27.50	12500.0	28.28	13200.0	28.96

CROSS SECTION NO.= 3
FOR THE YEAR 1957 TOP WIDTH= 6968.000
FOR THE YEAR 1971 TOP WIDTH= 9850.000
FOR THE YEAR 1977 TOP WIDTH= 14920.000
FOR THE YEAR 1981 TOP WIDTH= 15475.000
FOR THE YEAR 1988 TOP WIDTH= 13268.000

1957		1971		1977		1981		1988	
.0	33.64	.0	31.91	.0	33.00	.0	33.04	.0	29.04
278.7	30.24	394.0	31.91	596.8	32.38	619.0	25.28	530.7	30.18
557.4	27.53	788.0	31.91	1193.6	26.08	1238.0	26.44	1061.4	23.48
836.2	19.02	1182.0	31.91	1790.4	24.35	1857.0	17.51	1592.2	30.02
1114.9	17.88	1576.0	31.91	2387.2	30.10	2476.0	25.10	2122.9	30.21
1393.6	21.66	1970.0	31.91	2984.0	30.21	3095.0	30.59	2653.6	29.94
1672.3	27.79	2364.0	31.91	3580.8	29.27	3714.0	29.61	3184.3	31.05
1951.0	29.33	2758.0	31.86	4177.6	29.86	4333.0	25.01	3715.0	30.91
2229.8	29.02	3152.0	31.09	4774.4	25.93	4952.0	23.91	4245.8	29.69
2508.5	30.21	3546.0	31.48	5371.2	25.41	5571.0	14.86	4776.5	28.92
2787.2	31.09	3940.0	31.24	5968.0	25.95	6190.0	27.27	5307.2	28.66
3065.9	30.03	4334.0	29.37	6564.8	24.92	6809.0	30.38	5837.9	28.48
3344.6	30.23	4728.0	28.79	7161.6	21.18	7428.0	27.75	6368.6	20.67
3623.4	30.45	5122.0	29.23	7758.4	27.65	8047.0	27.84	6899.4	22.36
3902.1	30.21	5516.0	29.18	8355.2	26.82	8666.0	29.45	7430.1	19.96
4180.8	27.76	5910.0	24.10	8952.0	27.42	9285.0	29.50	7960.8	28.81
4459.5	26.85	6304.0	21.56	9548.8	28.43	9904.0	29.24	8491.5	30.37
4738.2	27.29	6698.0	26.50	10145.6	27.75	10523.0	28.72	9022.2	30.76
5017.0	27.92	7092.0	19.22	10742.4	28.51	11142.0	28.75	9553.0	30.17
5295.7	27.74	7486.0	20.79	11339.2	28.67	11761.0	24.14	10083.7	19.28
5574.4	26.79	7880.0	21.89	11936.0	28.05	12380.0	28.72	10614.4	17.21
5853.1	28.87	8274.0	29.02	12532.8	28.40	12999.0	27.97	11145.1	29.26
6131.8	24.92	8668.0	27.46	13129.6	22.18	13618.0	28.26	11675.8	28.85
6410.6	25.08	9062.0	27.19	13726.4	30.29	14237.0	30.08	12206.6	24.18
6689.3	26.43	9456.0	30.02	14323.2	29.60	14856.0	29.49	12737.3	30.84
6968.0	27.09	9850.0	27.00	14920.0	29.42	15475.0	23.50	13268.0	30.72

Table 4.2

GENERATED SPATIAL SERIES FOR YEAR 1998 FOR REACH BETWEEN CS 46 TO CS 47. (OUTPUT OF fin _25.npr)

Neuron No.	C S 46, at 453.91km TW = 14500m R. L.	Km 457 TW = 14496m R. L.	Km 462 TW = 14491 R. L.	C S 47 at 465.13 km TW = 14488 R. L.
1	78.8	79.4	80.4	81
2	82.3	82.7	83.5	83.9
3	76.8	77.4	78.4	79
4	75.6	76.1	76.98	77.31
5	79.8	80.4	81.38	81.9
6	81.7	82.3	83.2	83.8
7	79.6	80	80.56	81.3
8	74.4	74.9	75.78	76.3
9	69.8	70.4	71.27	71.83
10	73.0	73.6	74.57	75.17
11	81.6	82	82.85	83.35
12	80.5	81.23	82.33	83.02
13	75.1	75.6	76.46	76.98
14	76.8	76.65	77.54	78
15	69.7	70.4	71.4	72.11
16	78.9	79.6	80.6	81.29
17	79.6	80.1	81	81.53
18	78	78.5	79.4	79.89
19	75.8	76.3	77.18	77.7
20	76.5	77	77.9	78.5
21	73.6	74.3	75.4	76
22	74.3	74.9	75.9	76.5
23	78.8	79.3	80.2	80.7
24	81.0	81.6	82.4	82.8
25	74.15	74.8	75.8	76.5
26	79.5	80.1	81.0	81.6

Table 4.3

GENERATED TEMPORAL SERIES FOR CS 47@ Ch. 465-13 FOR YEARS 1995, 96 , 98, 2000. (OUTPUT OF fin _25.npr)

Neuron No.	1995 TW = 14385m R. L. (m)	1996 TW = 14430 R. L. (m)	1998 TW = 14488 R. L. (m)	2000 TW =14523 m R. L. (m)
1	81.7	81.5	81	80.4
2	83.5	83.6	83.9	84.4
3	79	79.0	79	79
4	77.6	77.60	77.5	77.4
5	82.2	82.11	81.9	81.8
6	83.9	83.95	83.8	83.6
7	81.4	81.43	81.3	81.2
8	76.3	76.3	76.3	76.4
9	71.7	71.7	71.8	71.1
10	75.3	75.29	75.2	75
11	83.4	83.4	83.3	83.2
12	83.13	83.1	83	82.9
13	76.19	76.9	77	77
14	77.7	77.8	78	78.5
15	72	72	81.3	80.9
16	81.6	81.55	81.3	80.9
17	81.5	81.5	81.5	81.5
18	80	79.9	79.9	79.8
19	77.8	78.77	78.5	78.3
20	78.8	78.77	78.5	78.3
21	75.9	75.9	76.0	76.2
22	76.7	76.6	76.52	76.4
23	80.8	80.7	80.7	80.6
24	82.8	82.8	82.8	82.9
25	76.5	76.5	76.5	76.6
26	81.5	81.57	81.65	81.79

Table 4.4

Spatio-Temporal Generated Series Upto Year 2010

fin_25.npr

Case Name	Chainage	Year	mm	dd	Y1	Y2	Y3	Y4	Y5	Y6	Y7	Y8	Y9	Y10	Y11	Y12	Y13	Y14	Y15	Y16	Y17	Y18	Y19	Y20	Y21	Y22	Y23	Y24	Y25	Y26	Q	TW
PRED1	465	2001	1	1	81	80	79	82	82	84	81	76	76	77	77	78	76	77	78	79	78	78	78	78	80	78	78	76	79	79	7167	13935
PRED2	465	2003	1	1	81	80	79	82	83	84	81	76	76	77	77	78	76	78	78	79	78	78	78	79	80	79	79	77	79	79	7179	14009
PRED3	465	2005	1	1	81	80	79	83	84	85	81	76	76	77	76	79	77	78	79	79	78	78	78	79	81	79	80	77	79	79	7186	14099
PRED4	465	2007	1	1	81	80	80	84	84	85	81	76	76	77	76	79	77	78	79	79	78	78	78	80	81	80	80	77	80	79	7191	14205
PRED5	465	2009	1	1	81	80	80	84	85	86	82	77	76	77	76	79	77	79	79	79	79	77	78	80	82	81	81	78	80	79	7195	14324
PRED6	465	2010	1	1	81	80	80	84	85	86	82	77	76	77	76	79	77	79	79	80	79	77	78	80	82	81	81	78	80	79	7196	14387
PRED7	454	2001	1	1	79	78	77	80	80	82	79	74	75	76	75	76	74	75	76	77	76	76	76	76	78	77	76	74	77	78	7165	13925
PRED8	454	2003	1	1	79	78	77	80	81	82	79	74	75	76	75	76	74	76	77	77	76	76	76	77	79	77	77	75	77	77	7177	14004
PRED9	454	2005	1	1	79	78	77	81	82	83	79	75	74	75	75	77	75	76	77	77	76	76	76	77	79	78	78	75	78	77	7185	14098
PRED10	454	2007	1	1	79	78	78	81	82	83	80	75	74	75	74	77	75	76	77	77	77	76	76	78	80	78	78	76	78	77	7191	14208
PRED11	454	2009	1	1	79	78	78	82	83	84	80	75	74	75	74	77	75	76	77	77	77	75	76	78	80	79	79	76	78	77	7194	14329
PRED12	454	2010	1	1	79	78	78	82	83	84	80	75	74	75	74	77	75	[illegible]	77	78	77	75	76	78	80	79	79	76	78	77	7195	14394
PRED13	454	2003	1	1	79	78	77	80	81	82	79	74	75	76	75	76	74	76	77	77	76	76	76	77	79	77	77	75	77	77	7177	14004
PRED14	457	2001	1	1	80	79	77	80	81	82	80	75	75	76	75	77	75	76	77	77	76	76	77	77	79	77	77	75	78	78	7165	13929
PRED15	457	2010	1	1	80	79	79	83	84	85	80	75	75	75	75	77	75	77	78	78	77	76	77	79	81	79	80	77	78	78	7195	14394
PRED16	461	2001	1	1	80	79	78	81	82	83	80	75	76	77	76	78	76	77	77	78	77	77	77	77	79	78	78	75	78	79	7166	13933
PRED17	461	2010	1	1	81	80	79	84	85	85	81	76	75	76	75	78	76	78	79	79	78	77	77	80	81	80	81	77	79	78	7196	14391
VALID1	138	1997	12	31	40	35	36	36	35	35	35	35	35	33	33	35	34	34	34	36	37	35	34	35	37	35	37	36	36	39	6216	12716

Table 4.4 (cont'd)

VALID2		138	1993	1	1	41	35	39	39	37	36	36	37
	35	32	34	35	35	34	35	38	38	36	35	38	39
	37	38	38	37	41	6911	11345						
O200	390	1987	12	31	72	72	72	72	72	73	74	71	71
	71	69	70	69	68	70	70	70	69	70	71	70	68
	68	69	75	72	4053	12761							
P1	189	1982	1	1	48	44	46	46	44	45	45	43	43
	42	41	43	43	42	43	45	45	45	43	45	45	43
	44	44	45	47	5224	10320							
P2	189	1983	1	1	48	44	46	46	44	45	45	43	43
	42	41	43	43	41	43	45	45	45	43	45	45	43
	44	44	44	47	5479	10522							
P3	189	1984	1	1	48	43	45	46	44	45	45	43	43
	41	41	43	43	41	43	45	45	45	43	45	45	43
	44	44	44	47	5733	10711							
P4	189	1985	1	1	47	43	45	46	44	44	44	43	42
	41	41	42	43	41	43	45	45	44	43	45	45	43
	44	44	44	47	5970	10884							
P5	189	1986	1	1	47	43	45	46	44	44	44	43	42
	41	41	42	42	41	42	45	45	44	43	45	45	43
	44	44	44	47	6181	11041							
P6	189	1987	1	1	47	43	45	46	44	44	44	43	42
	40	40	42	42	41	42	45	45	44	43	45	45	43
	44	44	44	47	6359	11182							
P7	189	1987	12	31	47	44	45	45	44	44	46	43	44
	45	42	43	43	41	43	44	44	46	44	44	44	43
	44	44	46	47	4029	10926							
P8	183	1975	1	1	47	44	45	46	43	44	44	41	42
	43	41	43	44	42	43	44	43	45	43	43	43	41
	42	43	44	46	4372	8816							
P9	180	1987	12	31	46	43	44	43	42	43	44	41	43
	43	40	42	41	40	41	43	43	44	42	43	43	42
	43	43	44	46	4028	10827							
P10	193	1987	12	31	48	45	46	45	44	45	46	43	45
	45	42	44	43	42	43	45	45	46	44	45	45	43
	45	44	46	48	4030	10967							
M1	454	1971	1	1	79	79	79	79	79	79	81	78	77
	78	78	77	76	76	77	77	76	77	79	79	77	76
	76	77	82	80	5057	12121							
M2	454	1977	1	1	79	78	78	78	78	79	81	77	77
	78	77	77	75	75	76	77	76	77	78	78	77	76
	75	76	81	80	4507	12858							
M3	454	1981	1	1	79	78	77	78	78	79	80	77	76
	77	77	76	75	75	76	77	76	77	78	77	77	76
	75	75	80	80	5166	13360							
M4	454	1987	12	31	79	79	80	81	81	81	81	79	78
	79	77	78	78	77	78	78	77	77	78	80	78	77
	77	78	83	80	4066	13182							
M5	465	1981	1	1	81	80	79	79	79	81	82	78	78
	79	78	78	76	76	77	78	77	78	79	79	78	77
	76	76	81	81	5148	13460							
M6	465	1987	12	31	81	81	82	82	82	83	83	80	79
	80	79	80	79	79	80	80	79	79	80	82	80	79
	79	80	84	81	4070	13236							
M7	532	1977	1	1	93	92	91	91	92	92	94	91	91
	92	91	91	90	90	91	92	90	92	92	92	90	90
	89	90	94	94	4458	13285							

Table 4.4 (cont'd)

M8	532	1981	1	1	93	92	91	91	92	93	93	91	91
	92	91	91	90	90	91	92	90	91	92	92	90	90
	89	90	94	93	5067	13663							
M9	532	1987	12	31	93	94	94	95	94	94	94	92	92
	94	93	94	93	93	93	93	92	94	94	94	93	92
	93	93	96	94	4103	13272							
IM1	454	1973	1	1	79	79	78	78	78	79	81	78	77
	78	77	77	76	76	77	77	76	77	79	79	77	76
	75	76	81	80	4563	12307							
IM2	454	1975	1	1	79	78	78	78	78	79	81	78	77
	78	77	77	76	75	76	77	76	77	79	79	77	76
	75	76	81	80	4438	12566							
IM3	454	1979	1	1	79	78	77	78	78	79	80	77	77
	78	77	77	75	75	76	77	76	77	78	78	77	76
	75	75	80	80	4747	13134							
IM4	454	1983	1	1	79	78	77	77	78	79	80	76	76
	77	76	76	74	75	76	77	76	76	77	77	77	75
	75	75	79	79	5692	13524							
IM5	454	1985	1	1	79	78	77	77	78	79	80	76	76
	77	76	76	74	74	76	77	76	76	77	77	77	75
	75	74	79	79	6181	13631							
IM6	465	1983	1	1	81	80	78	79	79	81	81	78	78
	79	78	78	76	76	77	78	77	78	79	79	78	77
	76	76	81	81	5674	13613							
IM7	465	1985	1	1	81	80	78	79	79	81	81	77	77
	78	78	78	76	76	77	78	77	78	79	78	78	77
	76	76	80	81	6170	13708							
IM8	457	1981	1	1	80	79	78	78	78	80	81	77	77
	78	77	77	75	75	76	77	76	77	78	78	77	76
	75	75	80	80	5161	13389							
IM9	457	1987	12	31	80	80	81	81	81	82	81	79	78
	79	78	79	78	78	79	78	78	78	79	80	79	77
	78	78	83	80	4067	13198							
IM10	462	1981	1	1	80	79	78	79	79	80	81	78	77
	78	78	78	76	76	77	78	77	78	79	79	78	77
	76	76	81	81	5153	13433							
IM11	462	1987	12	31	80	81	82	82	82	82	82	80	79
	80	78	79	79	78	79	79	78	79	79	81	80	78
	79	79	84	81	4069	13222							
I1	440	1984	1	1	78	77	75	76	76	78	78	74	74
	75	74	75	73	73	74	75	74	74	75	75	75	74
	73	73	77	78	5968	13466							
I2	454	1984	1	1	79	78	77	77	78	79	80	76	76
	77	76	76	74	75	76	77	76	76	77	77	77	75
	75	74	79	79	5949	13584							
I3	465	1984	1	1	81	80	78	79	79	81	81	78	78
	78	78	78	76	76	77	78	77	78	79	78	78	77
	76	76	81	81	5934	13667							
I4	475	1984	1	1	82	81	80	80	81	82	83	79	79
	80	79	79	77	78	79	80	79	79	80	80	79	78
	78	77	82	82	5922	13729							
I5	483	1984	1	1	83	82	81	82	82	83	84	80	80
	81	81	81	79	79	80	81	80	81	82	81	81	80
	79	79	83	83	5912	13776							
I6	491	1985	1	1	85	84	82	83	84	85	85	81	81
	82	82	82	80	80	81	83	81	82	83	82	82	81
	80	80	84	84	6149	13834							

Table 4.4 (cont'd)

I7	499	1986	1	1	86	85	83	84	85	86	86	83	83
	84	83	83	82	82	83	84	83	83	84	84	83	82
	82	82	86	86	6358	13865							
I8	506	1987	1	1	88	87	85	86	87	88	88	84	84
	85	84	85	83	84	85	86	84	85	86	85	85	84
	83	83	87	87	6538	13867							
I9	513	1987	1	1	89	88	86	88	88	89	89	86	86
	87	86	87	85	85	86	87	86	87	87	87	86	85
	85	85	88	88	6540	13854							
I10	523	1979	1	1	91	90	89	89	90	90	92	89	89
	89	89	89	88	87	89	90	88	89	90	90	88	88
	87	88	92	91	4675	13536							
I11	491	1986	1	1	85	84	82	83	84	85	85	81	81
	82	82	82	80	80	81	83	81	82	83	82	82	81
	80	80	84	84	6361	13850							
I12	491	1987	1	1	85	84	82	83	84	85	85	81	81
	82	82	82	80	80	82	83	81	82	83	82	82	81
	80	80	84	84	6537	13858							
I13	491	1978	1	1	84	84	83	83	83	84	86	83	82
	83	82	82	81	81	82	83	81	82	84	84	82	81
	80	81	86	85	4567	13328							
I14	491	1979	1	1	84	84	83	83	83	84	86	83	82
	83	82	82	81	81	82	83	81	82	83	84	82	81
	80	81	86	85	4702	13447							
I15	491	1987	1	1	85	84	82	83	84	85	85	81	81
	82	82	82	80	80	82	83	81	82	83	82	82	81
	80	80	84	84	6537	13858							
I16	440	1965	1	1	78	77	78	77	78	78	79	76	75
	76	76	75	75	75	76	75	74	75	77	78	76	76
	76	76	80	78	7051	11835							
I17	454	1968	1	1	79	79	79	79	79	80	81	78	77
	78	77	77	77	76	77	77	76	77	79	79	77	77
	77	77	82	80	6467	11993							
I18	465	1980	1	1	81	80	79	79	79	81	82	78	78
	79	78	78	76	76	77	79	78	78	79	79	78	77
	76	77	82	81	4919	13360							
I19	475	1967	1	1	82	81	82	81	82	82	83	80	79
	81	80	79	80	79	80	80	79	80	81	82	80	80
	79	80	84	82	6764	12155							
I20	483	1978	1	1	83	82	82	82	82	83	85	82	81
	82	81	81	80	79	80	82	80	81	82	82	80	80
	79	80	85	84	4574	13277							

RESULTS

5.1 VALIDATION OF RESULTS

After training and testing of the Neural Network, the network has been interrogated for different cross sections spread over different years.

The validation of the results, the spatio-temporal behaviour of the river at these sections are discussed as follows.

The cross section number 55 at km 531.93 in the vicinity of 'Majuli Islands' has been chosen for the validation purpose. The cross section at this chainage was generated by interrogating the network for this location for the year 1977 by first including the actual data for the year 1977 and then excluding this data from the training file.

The cross section so obtained was compared with the actual cross section of the river for this year and was found to be reasonably in agreement, showing a similar trend over the width (Fig. 5.1).

To compare the sensitivity of the network due to incomplete data, the network was again trained and tested by excluding the actual data for this cross section for the year 1977, and forcing the network to forget the earlier learnt patterns (by selecting "forget learning" menu). The result of cross section output showed that there is no appreciable change in the cross section generated earlier, showing that Neural Network

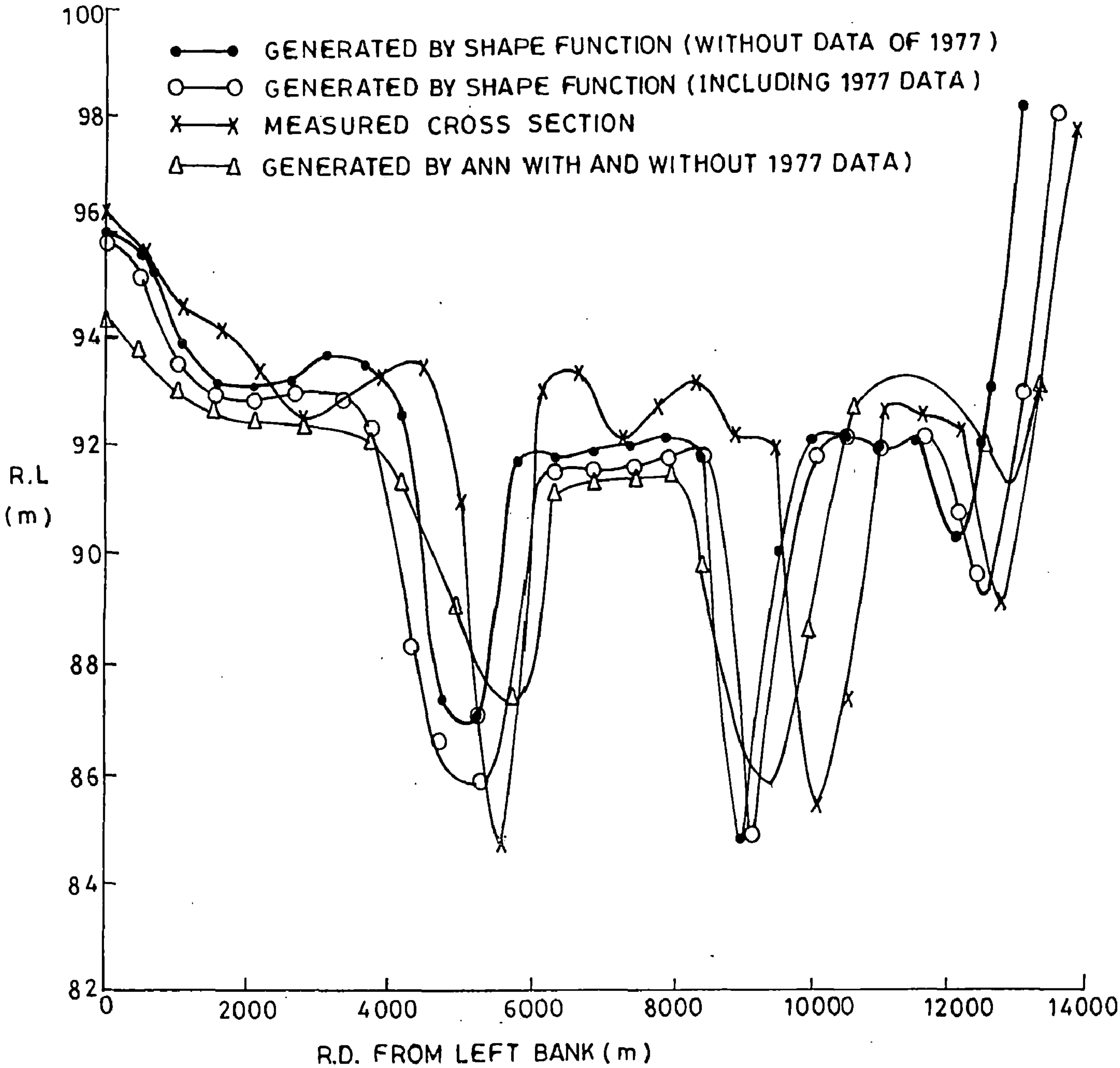


FIG. 5·1 SENSITIVITY ANALYSIS: CROSS SECTION No. 55 AT KM 531·93 is insensitive to incomplete data. In the same graph (Fig. 5.1), results of generating the cross section no. 55 for the year 1977, by a statistical method, [7] using shape function has been shown for two cases. In the first case the actual data for 1977 is used along with other years-available data (i.e. 1957,71,81 & 88). In the second case, data of 1977 is excluded and cross section no. 55 is generated.

The result shows that the statistical method is quite sensitive to the quality of data available, as seen from the difference in the two cross sections generated, although the trend has remained unaltered.

For further validation of the network, another cross section, viz cross section number 15 at chainage 137.7 km has been generated for the years 1998 and 1993 and results are shown in fig. 5.2. It can be seen that results of generated cross section and actual measured cross section are in good agreement. Also in fig 5.3 comparison of generated cross section number 47, for the year 1981 in the vicinity of Majuli island and the actul measured cross section No. 47 for the year 1981 shows good resemblance and similar trends.

5.2 RESULTS OF SPATIO-TEMPORAL STUDIES

Spatio- temporal studies are done to study the changes in profile for any intermediate location and for any intermediate year between the years of survey. In addition, in the present study, attempt to study the behavior of the river beyond the year 2000 are also made.

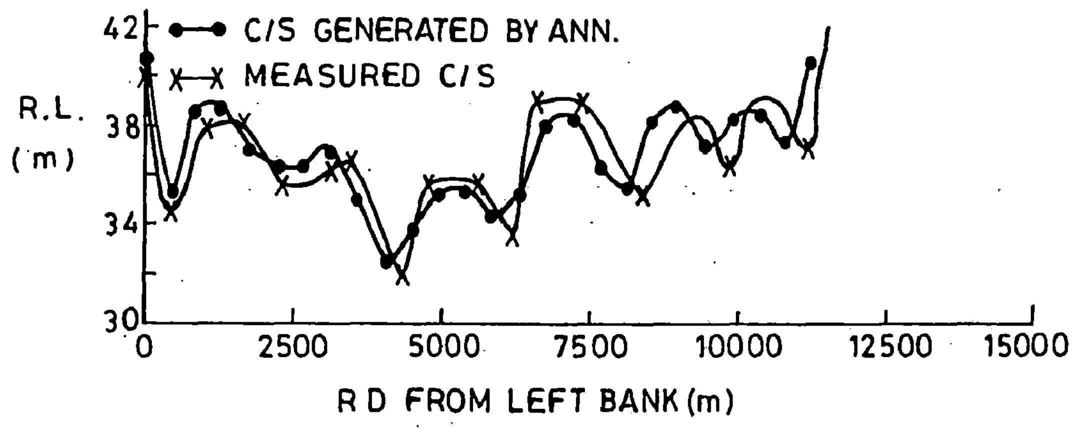
Spatial series between the cross section 46 and cross section 47 for the year 1998 have been generated with the help of trained network and the results are indicated in the graphs (Fig. 5.4). The study helps in knowing the cross sectional pattern at the intermediate chainages, where actual surveyed cross sections are not available. The study also indicates shift of thalweg, changes in the width of the river etc. It can be seen from graph at Fig. 5.4 that generated CS 46 and CS 47 for the year 1998 resemble with actual x-section and have similar trend.

It is however observed from the generated spatial series that there is no appreciable change in cross sectional pattern between section 46 and 47, for the year 1998, accepting that river longitudinal slopes can be conviniently obtained for the shorter reaches of the river. These results can be verified from the satellite imageries for the intermediate cross sections.

Temporal series for the cross section No-47 for the years 1995,96,98 have also been generated by interrogating the trained net-work. In addition this cross section has been also predicted for the years 2001, 3,5,7,9 and 10. The results are shown in the graphs (Fig. 5.5, 5.6).

The perusal of these figures would indicate marked morphological changes in the cross section over the years by observing formation of new channels, deepening of existing channels, indicating erosion and deposition taking place over the years, as observed below. It can be observed from Fig. 5.5 that generated CS 47 for year 1998 resembles with actual c/s and has similar trends.

C/S No. 15 YEAR 1998



C/S No. 15 YEAR 1993

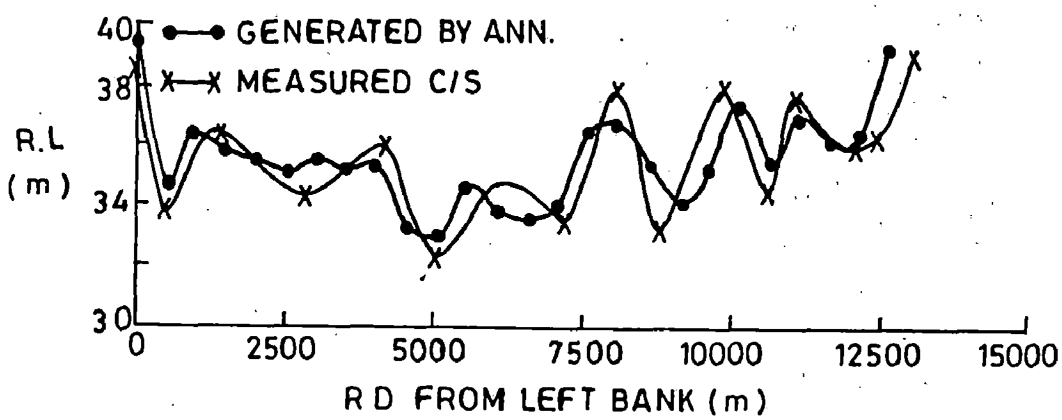


FIG. 5·2 VALIDATION

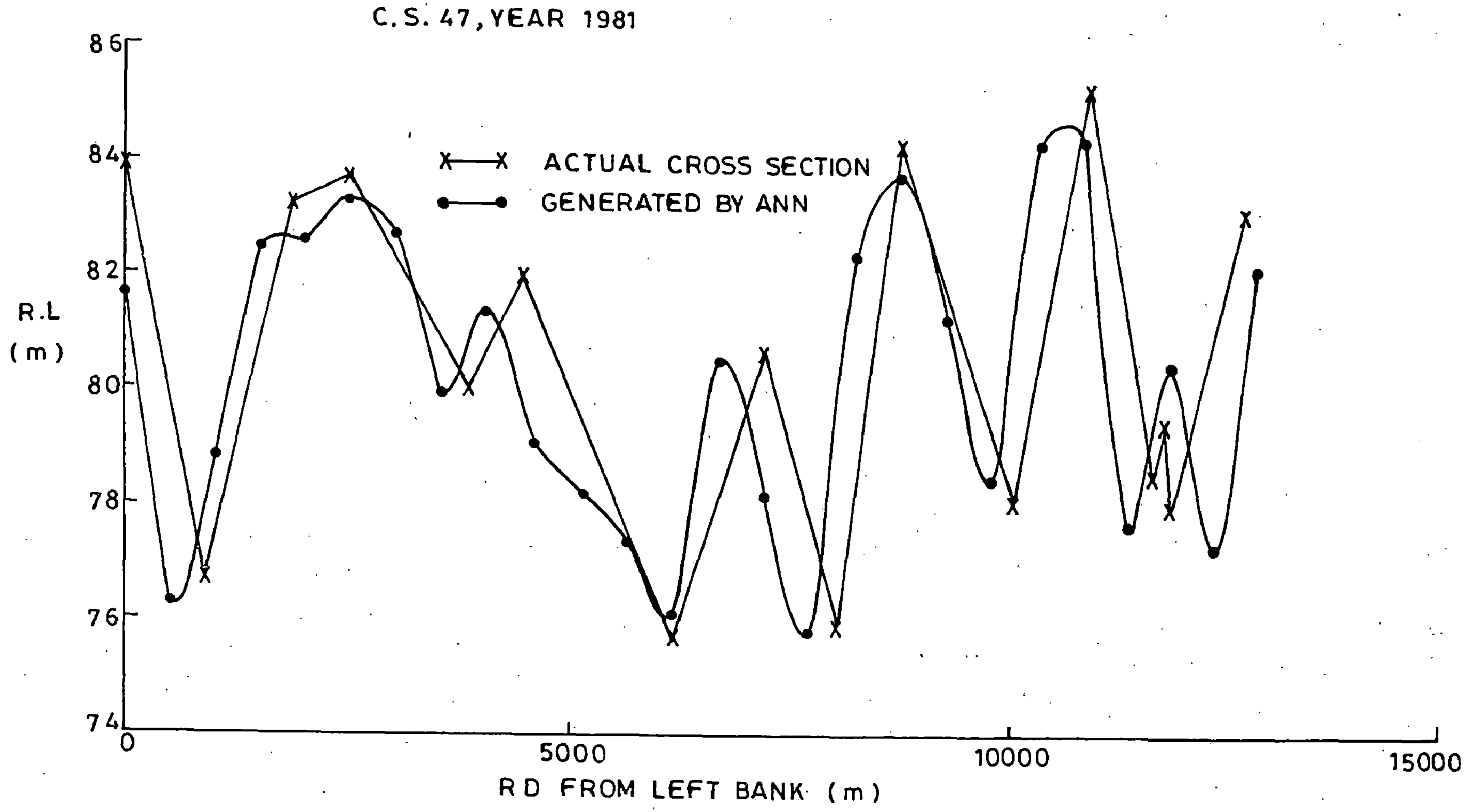


FIG. 5·3 VALIDATION

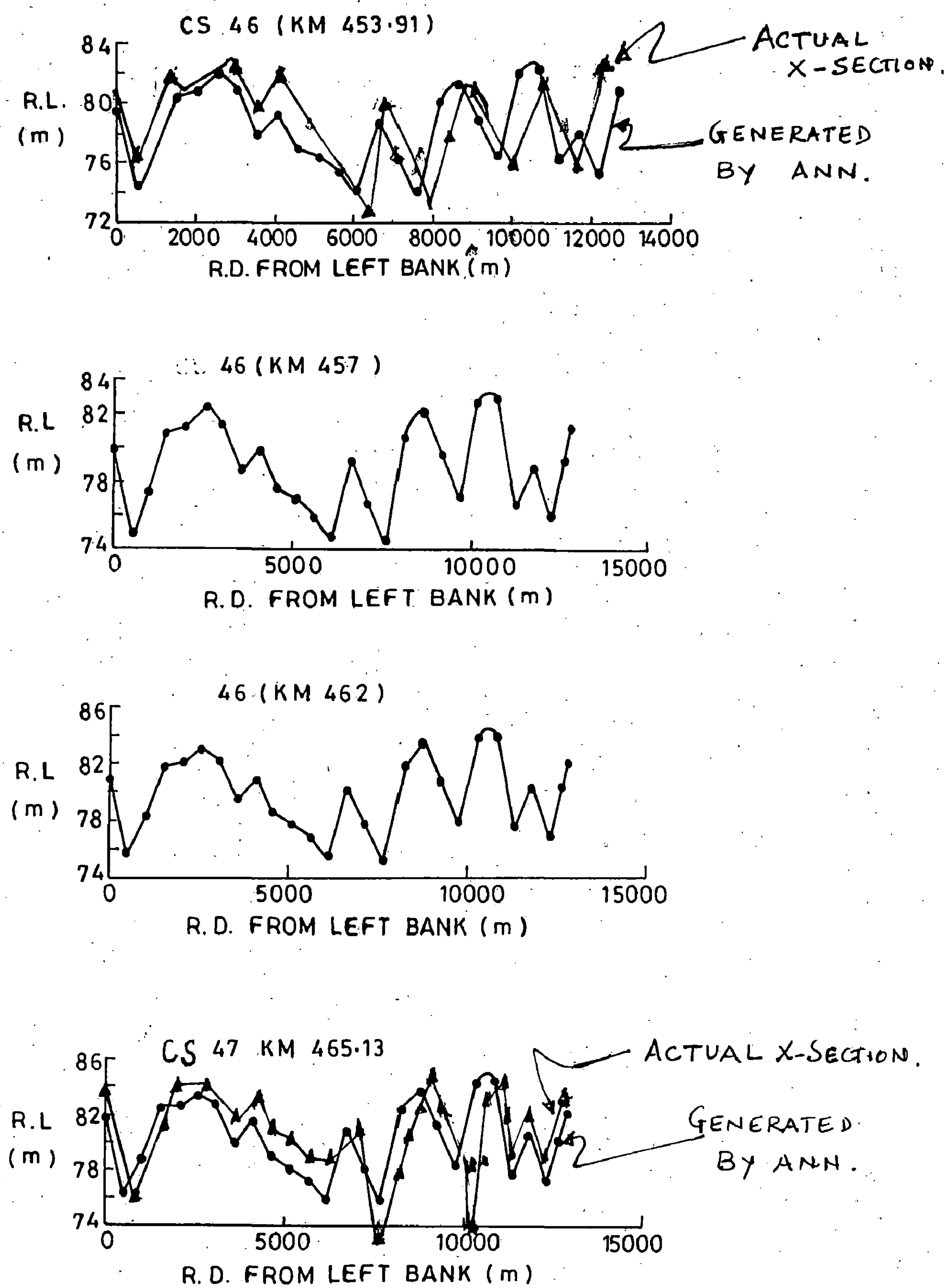
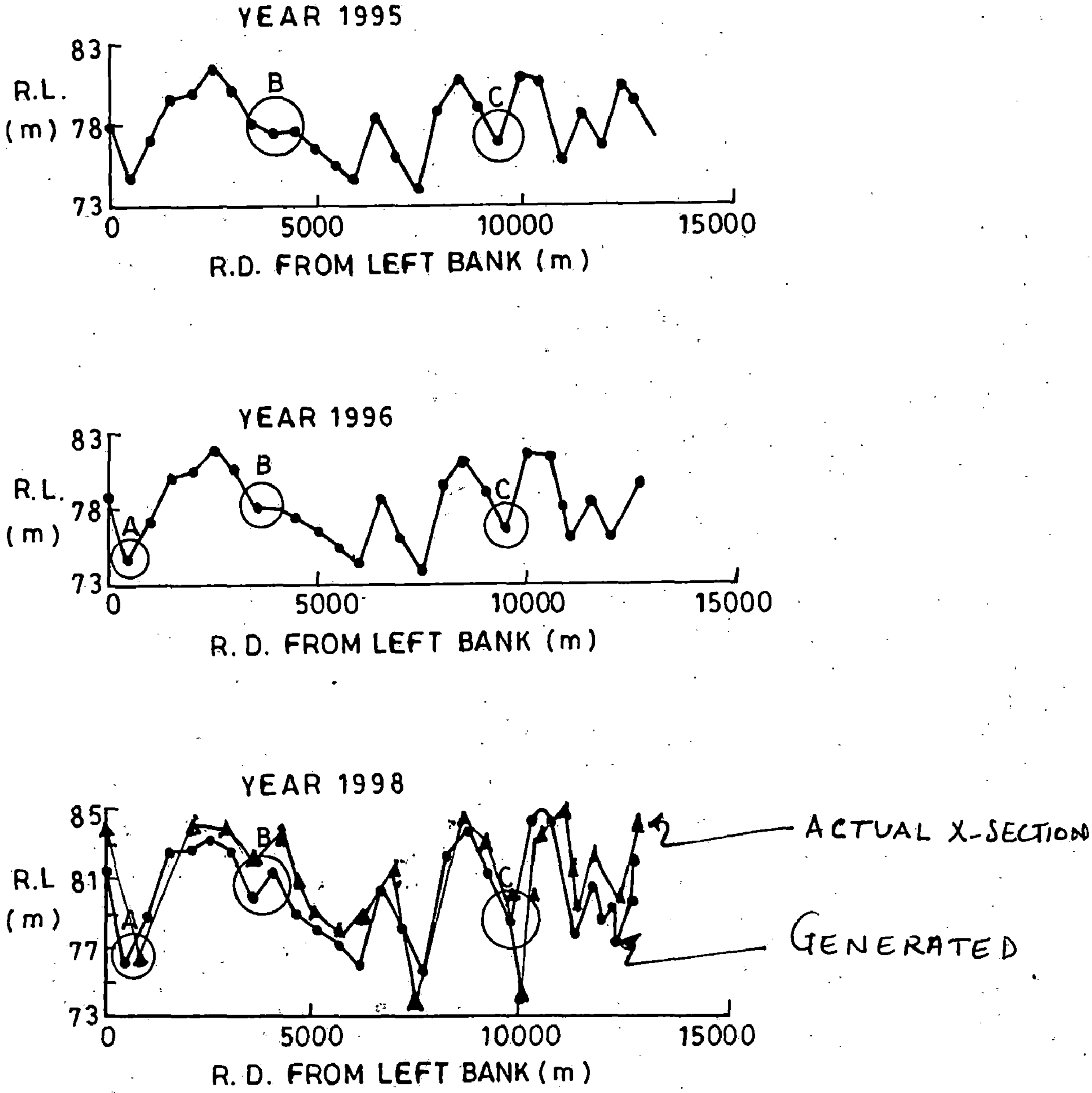
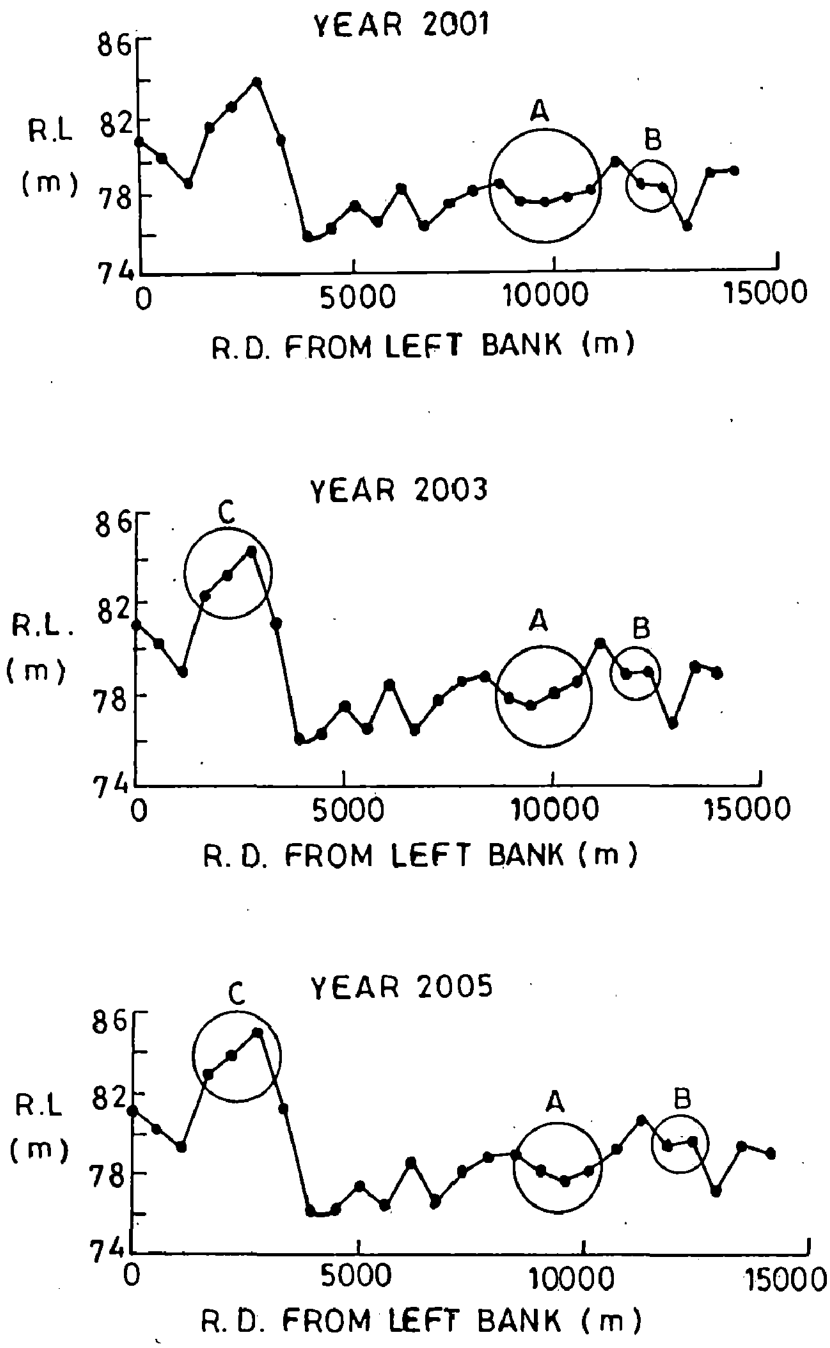


FIG.5·4 SPATIAL SERIES (YEAR 1998, C/S 46 TO C/S 47)



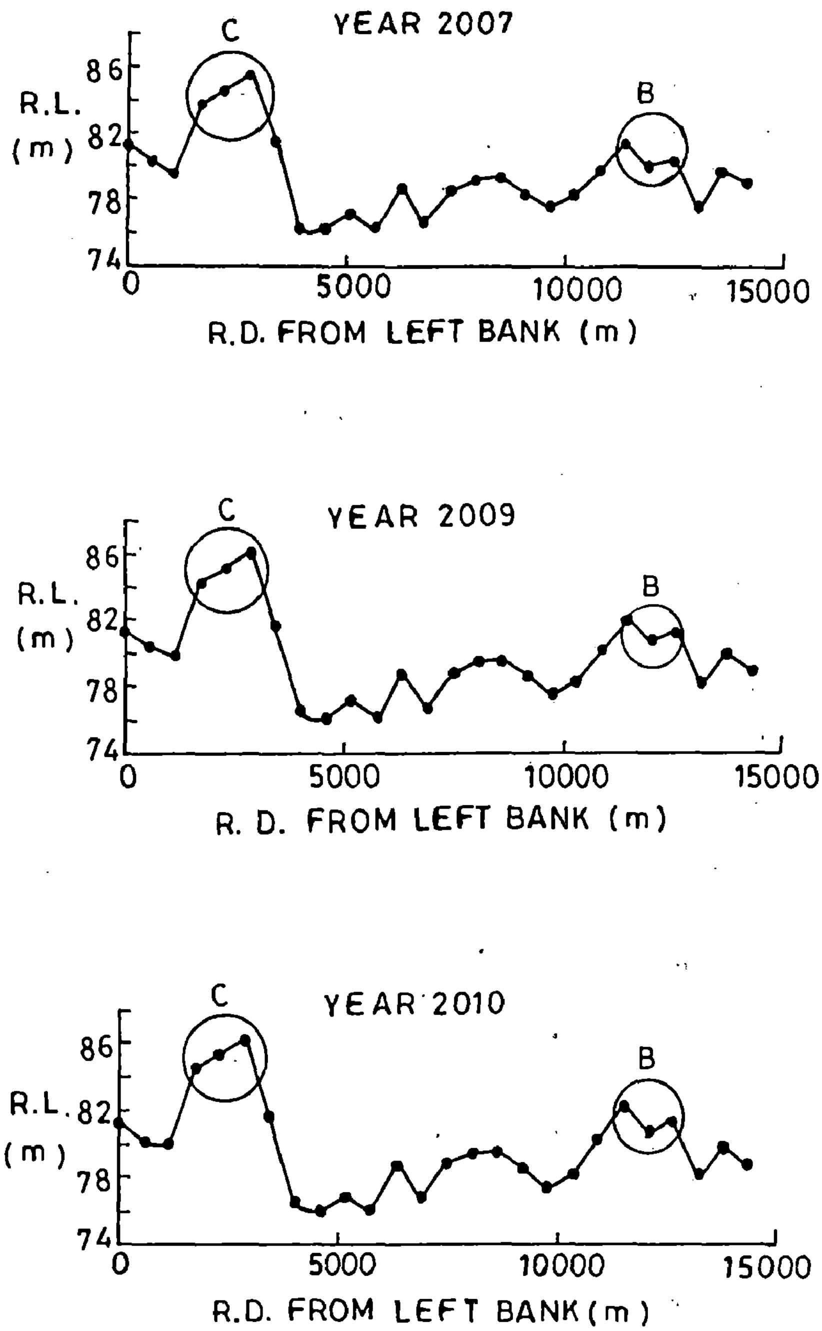
A — DEEPENING OF CHANNEL
B — FORMATION OF NEW CHANNEL
C — CHANGE IN CHANNEL GEOMETRY

FIG.5·5 GENERATED TEMPORAL SERIES
(C/S 47 @ KM 465·13)



A — CHANGE IN CHANNEL PROFILE

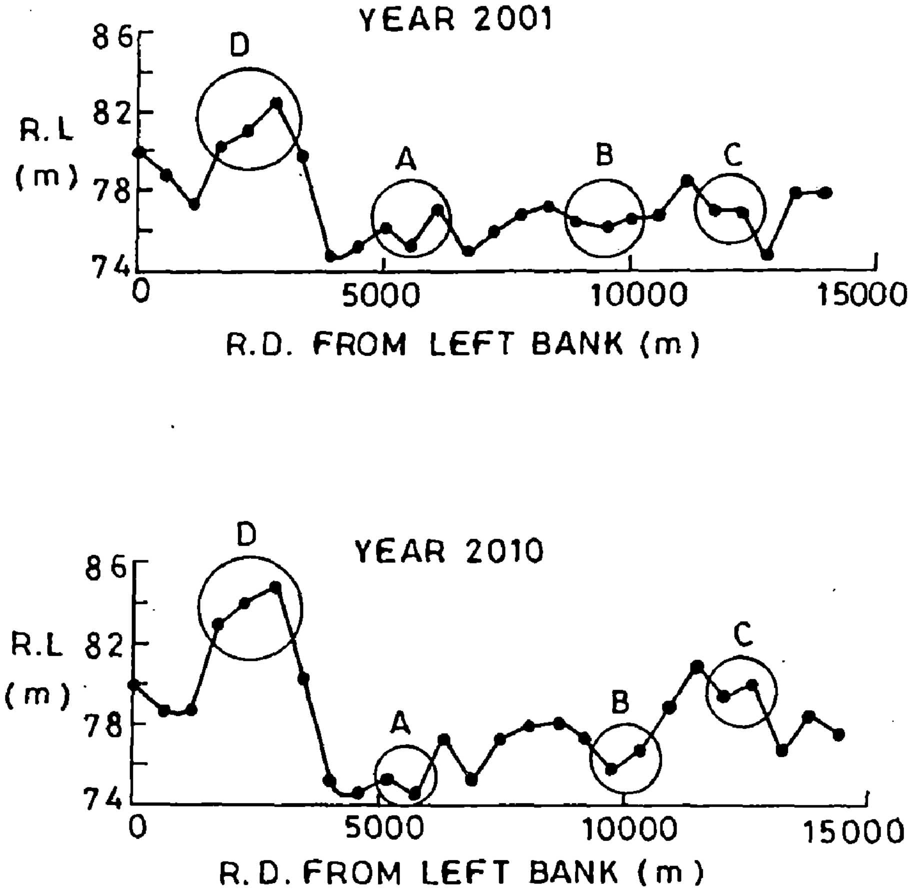
FIG. 5·6 PREDICTED CROSS SECTION No. 47 (KM 465·13) (TEMPORAL SERIES)



B — GRADUAL CHANGE IN CHANNEL GEOMETRY

C — GRADUAL CHANGE IN BANK PROFILE

FIG. 5·6 Contd.........



A —— CHANNEL DEEPENING
B —— CHANNEL FORMATION
C —— CHANNEL FORMATION
D —— CHANGE IN BANK PROFILE

FIG. 5-7 TEMPORAL SERIES FOR CS @ 457 KM
(BETWEEN CS 46 AND 47)

5.3 OBSERVATIONS

The Neural Network has been trained using the hydrographic data for the years 1957, 71, 77, 81, 88 and 1997 for cross section from 2 to cross section 65. The networks capability of predicting the future morphological changes in the river has also been extended by using fictitious data for the year 2005 (for c/s 2) and for the year 2010 (for c/s 65). Thus now Network is capable of predicting detailed of cross section at any chinage of the river upto the year 2010.

As an illustration, the cross section No. 47 at km 465.13 has been chosen and a temporal series for the year 2001, 2003, 2005, 2007, 2009 and 2010 has been generated (Fig. 5.6.).

The prediction indicates that there are changes in Bank profile on the left bank at RD 2000 m to 3000 m as shown at portions indicated at C in the (Fig. 5.6). Also there is likelihood of formation of channel at point B, shown at RD of 12000 km from left bank. Another intermediate cross section at chinage 457 km between CS 46 and CS 47 at Fig. 5.7 for the year 2001 shows clear indication of channel formation at point B (RD 9500 m) and C (RD 12000 m) where heavy erosion is likely. Erosion can also be observed at point A (RD 6000) and a likely hood of channel formation.

A point D, (RD 2000 m) in Fig. 5.7, there is likelihood of deposition and erosion and change in bank geometry to the extent of 6.0 m between years 2001 and 2010.

The changes in the Brahmaputra river in the vicinity of 'Majuli Island', which are covered from CS 44 to 54, are intense as shown by the study. The details in these changes can also be obtained by interrogating the trained Neural Network on month to month basis also, as the input allows for such an interrogation.

The comparison of results of generated temporal and spatial series indicate that temporal series show more sensitiveness to the morphological changes compared to the changes shown by spatial series.

DISCUSSIONS

The present study has established that Artificial Neural Network is a powerful tool that can be deployed in the field of river Engineering for not only simulating the river cross section profile between the known cross sections but can also be used to forecast the morphological pattern of the river in future, the importance of which needs no further emphasization.

The river behavior is a complex phenomenon and cannot be predicted accurately by present analytical and statstical methods, due to number of simplifying assumptions made, which have a direct bearing on the quality of the result.

In the application of the 'Artificial Neural Network' to such complex problems no such assumptions are required to the made, but the network learns by 'examples' by forming patterns with the use of known input and outputs. Further the network can tolerate insufficient or inaccurate data, as shown and experienced during this study. This property of the neural network makes it an ideal tool for it's application in river engineering, where the data available is seldom sufficient or of high degree of accuracy.

Neverthless, it has been experienced during this study that Network takes a sufficiently long time to formulate and learn the patterns for a complex phenomenon like river engineering and related morphological study. A number of combinations of 'learning rate' and 'momentum' have to be tried by trial and error method especially during testing period. It is also important the manner in which the data is arranged to be fed in the input 'neurodes', whether in a chronological (temporal) manner or in a spatial manner.

It may be pointed out here that other models having 50 normalized points in the cross section or even 100 normalized points in the cross section can be experimented with. It is possible that the network may be able to learn more accurately (though slowly) to form the patterns.

Further different combinations of input variables such as sediment concentration, discharge, stage also could be tried in different models to have the best combination for the output results. Due to limitations in time and absence of adequate data these innovations could not be tried during the study.

In view of the above some limitations on the quality of output is bound to result, when the network has to be trained in a given or limited period of time.

It has been observed during the study that although the network has generally performed satisfactorily some outputs are not within a reasonable accuracy due to limitations discussed above. The netwoks efficency can be still improved by adopting innovative methods for training the network's, examining number of combinations of input and output, increasing neurodes in output - layer by increasing number of normalized points in a cross-section and by giving sufficient time for learning and testing phases.

Never the less, the study has shown it's usefulness in it's application to morphological study of complex river behaviour especially that of river Brah maputra, which is considered to be most braided and erratic, in it's behaviour.

SUMMARY, CONCLUSIONS & SCOPE FOR FURTHER STUDIES

7.1 SUMMARY

This work has been undertaken for the first time to showcase the use of 'Artificial Neural Network' in a complex river behavioural phenomenon such as that of Brahamaputra river.

The input data used for constructing the network comprised of river cross sections from 2 to 65 for the available years from 1957 to 1997, in a length of 640 km from Indo-Bangladesh Border to Dibrugarh.

The reach analysed was that in the vicinity of 'Majuli Island' which is infamous for constant erosion, deposition, and morphological changes.

A Spatio-temporal study of the typical reach in the vicinity of Majuli Island was made by using the trained network. The results generated by the network are obseved to be in general agreement with the actual. The results generated in the intermediate sections can be verified by use of satellite imageries.

7.2 CONCLUSIONS

Based on the work done and results obtained, the following conclusions emerge

i) Artificial Neural Network is a powerful tool and has good potential to solve complex river behavioural problems, especially in the highly braided rivers like Brahamaputra, even with the use of insufficient and inaccurate data.

ii) ANN can be used not only to interpolate the cross sections in between surveyed cross section, both with respect to time & space but can also be used to predict the cross section and morphological behaviour of a river for the future. This is by far the most important property of the network, which needs more investigation and innovative study.

Innovative methods for training the network, examining different combinations of input and outputs needs to be investigated for such a highly complex network, to enable to learn accurately and fast.

7.3 SCOPE FOR FUTURE STUDIES

1) The neural network forms different learning patterns in different environments. Innovations in this respect can be achieved by trial and error method which require longer time periods. In such scenario it is possible to adopt different options for data input and changes in topology of the network, increase in the number of neurodes in the output layer by increasing number of normalized points in a cross-section to say 50, 75 or 100, to arrive at highly efficient network through trial and error. Satellite data will aid to validate the procedure of the nerural network.

2) The Neural Network, thus trained, will be capable of very accurately predicting the morphological changes in the river cross-section and river course which can serve as guideline for taking precautionary measures in advance, by the concerned Agencies/departments.

REFERENCES

1. Brahmaputra Board, Ministry of Water Resources, (1986), *"Atlas of the Brahmaputra Basin"*, Vol. I.
2. Brahmaputra Board, Ministry of Water Resources, (1986), *"Atlas of Brahmaputra Basin"*, Vol. II.
3. Brahmaputra Board, Ministry of Water Resources, (1995), *"Master Plan of Brahmaputra Basin, Part-1 (Main Stem)"*.
4. Garde R.J. and K.G. Ranga Raju (1995), *"Mechanics of Sediment Transportation and Alluvial Stream Problem"*, New Age International Publishers Ltd., New Delhi.
5. Pandey A.D., D.K. Gupta et al (1999), *"Neural Nets for Evaluation of Liquefaction Potential"*, A Paper submitted at South-Asian Countries Conference on Challenges to Architects and Civil Engineers during Twenty-First Century, April 7-9, 1999, Kathmandu, Nepal.
6. Partridge D. and Wilks Y. (1990), *"The Foundations of Artificial Intelligence"*, Edited by Derek Partridge & Yorick Wilks, Published by Press Syndicate of the University of Cambridge, Cambridge.
7. Singh G.P. (1995), *"Spatio – Temporal Idealization of Typical Cross Sections of a Large Braided Alluvial River"*, Unpublished Dissertation Report of M.E. (WRD), WRDTC, University of Roorkee, Roorkee, India.
8. Varma G.S. (1999), *"Application of Neural Networks in Seismic Soil Slope Stability Analysis"*, Unpublished Dissertation Report of M.E. Earthquake Engineering, Department of Earthquake Engineering, University of Roorkee, roorkee.
9. Water Resources Development Training Centre (2000), *"River Morphology Studies of Brahmaputra with Remote Sensing"*, R&D Project No. BP 98001 of WRDTC, University of Roorkee, Roorkee.
10. Yegnarayana B. (1999), *"Artificial Neural networks"*, Prentice Hall of India Private Limited, New Delhi.

Annexure 4.1

NORMAL.F

```
/***********************************************************************
        PROGRAM FOR OBTAINING NORMALISED DATA AT EACH CROSS-SECTION
***********************************************************************/
//      Normalisation of observed data into eqispaced data at
//      desired number of points
#include<stdio.h>
#include<conio.h>
#include<math.h>

        int count;

main()
{
        int count,i,j,ii,k,l,m,n,nn,nw,np,nyr[6],jj,kk,mm,dd;
        float x[250],y[250],xs[250],xx[30][5],yy[30][5],tw,x1,x2,ch[70],Q[6];
        void  interp();

//      x,y     measured co-ordinates of the cross-section
//      xs      scaled  values for interval -1 and 1
//      xx,yy   normalised values of x,y
//      m       number of years for which data are available
//      n       number of locations where x-sections have been measured
//      nn      number of normalised data points for each cross-section
//      np      number of points input
//      nw      number of points in interpolating window
//              =2 for linear interpolation
        FILE *fp,*fp1,*ft;
        fp1=fopen("chain.dat","r");
        fp=fopen("xsec.dat", "r");
        ft=fopen("res1.dat","w");
        for(kk=2;kk<=65;kk++)
        {
        fscanf(fp1,"%f",&ch[kk]);
        }

        fprintf(ft,"[LABELS]\t[Chainage]\t[Year]\t[mm]\t[dd]\t[Y1]\t[Y2]");
        fprintf(ft,"\t[Y3]\t[Y4]\t[Y5]\t[Y6]\t[Y7]\t[Y8]\t[Y9]\t[Y10]\t");
        fprintf(ft,"[Y11]\t[Y12]\t[Y13]\t[Y14]\t[Y15]\t[Y16]\t[Y17]\t");
        fprintf(ft,"[Y18]\t[Y19]\t[Y20]\t[Y21]\t[Y22]\t[Y23]\t[Y24]\t");
        fprintf(ft,"[Y25]\t[Y26]\t[Q]\t[TW]\n[END]");
        fprintf(ft,"\n\n[TESTING]\t>\t\t>\t>\t>\t<\t<\t<\t<\t<\t<\t<");
        fprintf(ft,"\t<\t<\t<\t<\t<\t<\t<\t<\t<\t<\t<\t<\t<\t<\t<\t<");
        fprintf(ft,"\t<\t<\n");
        fprintf(ft,"[dummy]\t\t0\t\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t");
        fprintf(ft,"0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t");
        fprintf(ft,"0\t0\n[END]");
        fprintf(ft,"\n\n[TRAINING]\t>\t\t>\t>\t>\t<\t<\t<\t<\t<\t<\t<");
        fprintf(ft,"\t<\t<\t<\t<\t<\t<\t<\t<\t<\t<\t<\t<\t<\t<\t<\t<\t<\t<\n");
        fscanf(fp,"%d %d %d %d",&nw,&m,&n,&nn);
        count=0;
        for(ii=2;ii<=n;ii++)
        {

          for(k=1;k<=m;k++)
          {
            fscanf(fp,"%d",&np);
            for(i=1;i<=np;i++)
            fscanf(fp,"%f%f",&x[i],&y[i]);
            count=count+1;
//      transform to limits between -1 and +1

        if(k==5)
        {
        [illegible]
        [illegible]
        [illegible]
```

```
{ mm=1;
  dd=1;
  }

  x1=x[1];
  x2=x[np];
  tw=x2-x1;
  Q[1]=7200;
  Q[2]=5000;
  Q[3]=4400;
  Q[4]=5000;
  Q[5]=4000;
  nyr[1]=1957;
  nyr[2]=1971;
  nyr[3]=1977;
  nyr[4]=1981;
  nyr[5]=1987;

  fprintf(ft,"[D%d]\t\t%.2f\t\t%d\t%d\t%d\t",count,ch[ii],nyr[k],mm,dd);
  for(i=1;i<=np;i++)
  xs[i]=(2*x[i]-(x1+x2))/(x2-x1);

//  interpolate the polynomial at normalized values of x

  interp(np,nn,nw,xs,y,tw,k,xx,yy);

      for(i=1;i<=nn+1;i++)
        {
  fprintf(ft,"%.2f\t",yy[i][k]);
//  printf("%d\t%d\t%f\t",i,k,yy[i][k]);
        }
  fprintf(ft,"%.2f\t%.2f\n",Q[k],tw);
  }
  }
  fprintf(ft,"[END]\n\n");
  fprintf(ft,"\n[INTERROGATING]\t>\t\t>\t>\t>\t<\t<\t<\t<\t<\t<\t<\t<");
  fprintf(ft,"\t<\t<\t<\t<\t<\t<\t<\t<\t<\t<\t<\t<\t<\t<\t<\t<\t<\t<\t<\n");
  fprintf(ft,"[dummy]\t\t0\t\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t");
  fprintf(ft,"0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\n[END]\n\n\n");
  fprintf(ft,"[LIMITS]\t>\t\t>\t>\t>\t<\t<\t<\t<\t<\t<\t<\t<\t<\t<");
  fprintf(ft,"\t<\t<\t<\t<\t<\t<\t<\t<\t<\t<\t<\t<\t<\t<\t<\n");
  fprintf(ft,"[Highs]\t\t0\t\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t");
  fprintf(ft,"0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\n");
  fprintf(ft,"[Lows]\t\t0\t\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t");
  fprintf(ft,"0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\t0\n[END]");


  return(0);

  }
//  ************************************************
//  subroutine interp(np,nn,nw,xs,y,tw,k,xx,yy)
//  ************************************************

//  lagrangian interpolation using moving window
//  for computing normalised value of x & y
   void interp(np,nn,nw,xs,y,tw,k,xx,yy)
    float xs[250],y[250],tw,xx[30][5],yy[30][5];
    int np,nn,nw,k;
  {
  float delx,a,b,c,p,axi,axj,xxx;
  int i,j,l,nwm,ns,ne,nwmid;
  delx=2.0/nn;
  nwm=(nw/2)+0.999999;
  ns=1;
  ne=ns+nw-1;
  nwmid=ns+nwm;
     for(l=1;l<=nn+1;l++)
     {
          xxx=-1+(l-1)*delx;
          c=0;
```

```
if(ne<np)
{
    A:
    if(xxx>xs[nwmid])
    {
        ns=ns+1;
        ne=ns+nw-1;
        nwmid=ns+nwm;
        goto A;
    }
}
for(i=ns;i<=ne;i++)
{
    axi=xs[i];
    p=1;
    for(j=ns;j<=ne;j++)
    {
        if(i==j)
            goto B;
        else
        {
            axj=xs[j];
            a=(xxx-axj)/(axi-axj);
            p=p*a;
        }
        B:
    }
    b=p*y[i];
    c=b+c;
    //        printf("%d\t%f\t",i,y[i]);
}
yy[l][k]=c;
xx[l][k]=(xxx*tw+tw)/2;

}

}

/**************************************************************
                    END OF PROGRAM
**************************************************************/
```