STUDY OF STAGE-DISCHARGE RELATIONSHIP USING ARTIFICIAL NEURAL NETWORK

A DISSERTATION

submitted in partial fulfillment of the
requirements for the award of the degree
of
MASTER OF ENGINEERING
in
WATER RESOURCES DEVELOPMENT

By

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CANDIDATE'S DECLARATION

I hereby declare that the work which is presented in this Dissertation entitled **"STUDY OF STAGE-DISCHARGE RELATIONSHIP USING ARTIFICIAL NEURAL NETWORK"** in partial fulfilment of the requirement for the award of the degree of MASTER OF ENGINEERING in WATER RESOURCES DEVELOPMENT (Civil) submitted in Water Resources Development Training Centre, University of Roorkee, Roorkee, is a record of my own work carried out during the period from July, 2000 to January, 2001 under supervision of **Dr. S.K. Jain,** 'F', NIH, Roorkee and **Dr. U.C. Chaube**, Professor, WRDTC, University of Roorkee, Roorkee, India.

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

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

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Dated : January ,2001 **(TAPAS RANJAN PATTNAIK)**

CONTENTS

LIST OF THE TABLES

LIST OF FIGURES

SYNOPSIS

The management of any river valley project greatly depends on the accurate assessment of water availability so that its yield can be properly optimized. Therefore the measurement of discharge of any gauging site plays a paramount importance. The discharge records are studied for a variety of applications. We are very often interested in annual peak discharge with a given return period, maximum probable floods, low flow for drought management/ control and also for assessment of hydropower potential.

The measurement of discharge is an expensive affair. Therefore the conventional technique is to obtain a continuous record of river stage. From the observed stage and discharge, a rating curve correlating stage and discharge is established. The subsequent procedure consists of reading discharge (Q) corresponding to measured stage (G) from G-Q relation. One of major limitation in the rating curve is that it does not take into account the hysterisis effect .

Secondly the proper assessment of volume of sediment transported by a river is of vital interest due to its importance in design and management of water resources project. The conventional method of quantifying the sediment is from sediment rating curve which is plot of sediment concentration versus discharge.

But with emergence of powerful computational tool, attempts have been made to develop a technique that does not require algorithm or role development but can have strong predictive capability without physics being explicitly involved. Artificial Neural Networks (ANNs) is answer to this. ANNs is in the recent decade has gained a remarkable popularity because of its ability to properly deal with non linear multivariate problems in hydrological analysis.

The attempt has been in the present study to establish a relation between stage-discharge and sediment concentration and discharge using Artificial Neural Networks and to verify the effectiveness of ANNs results in comparison to the conventional techniques.

INTRODUCTION

1.1 GENERAL

Water is a precious gift of nature. It not only serves as a vital substance for human existence but also plays an important role in advancing the civilization. Therefore it has become the prime objective of our planners for proper preservation and optimal utilization of this scarce resource.

A hydrological system is one of natural complexities. Its outcome, observed data, expressed in time series, usually has a non-linear character. But with the advancement of computational techniques, such non-linear, multivariate problems can be effectively handled with simpler approaches offered through 'conceptual' and black-box solutions. The Artificial Neural Networks (ANNs) is one such tools which emulate the parallel distributed processing of the human nervous system. The application of ANNs to water resources problems is rapidly gaining popularity due to their immense power and potential in mapping of non-linear system data. It is a tool, which does not involve any physical law, on the other hand it is able to capture knowledge within a data set. Statistical solutions require a prior information about data structure produced by a system. But on the contrary, ANN is able to solve the problems without any prior assumptions. As long as enough data is available a neural network will extract any regularities or pattern that may exist and use it to form a relationship.

The accurate assessment of availability, demand and deficit of water in every river valley project carries a great deal of significance for the reason that any sort of erroneous assessment may lead to its failure. Secondly the discharge measurement plays a significant role in flood forecasting. The flood forecasting is a process of estimating the future stages of flows and their time sequence at selected places along the river. The estimates and predictions consist of maximum discharge and time duration of crest of a hydrograh.

1.2 OBJECTIVES OF THE STUDY

The conventional practice of estimating stream flow is by establishing stage-discharge relationship using a set of observed data. The measurement of discharge is an expensive affair. It is, therefore, the practice to draw a rating curve relating the observed stage and discharge data. The next step is to record the stage in the field and read the corresponding discharge from the rating curve. The major limitation in this process is that the stage-discharge relationship does not take into account the hysterisis effect.

The present study attempts to establish stage-discharge relationship through Artificial Neural Networks. The objective is to compare result with other conventional technique and to verify the potentiality of ANNs.

In addition to stage-discharge, correct estimation of sediment volume being carried by a river is very important for many water resources projects. The conventional technique for estimating the sediment is from the sediment-rating curve. The relationship is established by regression analysis. But this methodology does not provide accurate results. The study aims at predicting the sediment through Artificial Neural Networks and to observe whether results show any improvement over the conventional approach.

ARTIFICIAL NEURAL NETWORK

2.1 GENERAL

Most of the hydrological processes are non-linear and for their analysis we require mapping and modeling of data. Traditionally such type of mapping is usually performed by statistical tools such as multi-regression, curve fitting etc. however when underlying physical laws are unknown or precisely not known, it is rather difficult to model the phenomenon adequately. Attempts have been made to develop a technique that does not require algorithm or rule development and thus reduce the complexity of software. This is possible through an emerging powerful tool, the Artificial Neural Networks. Not only this is an ideal tool for input-output mapping, but also the problems involving non-linear multi variate type can be effectively handled by ANN.

Artificial Neural Networks is a parallel distributed information processing system. The very theme of computing system is borrowed from the analogy of biological neural network. In day-to-day life many tasks involving intelligence or pattern recognition are extremely difficult to assess, but appears to perform very easily by human brains. The brains have the ability to recognise the objects surrounding them and can make sense out of the visual informations. The highly sophisticated human brains, which contain more than 100 billions of interconnected neurons, are able to learn quickly from experience and is generally superior to any existing machine in tasks involving recognition, learning and control. The main difference between brains and machine intelligence comes from the fact that brains perceive everything as a pattern, whereas for a machine every thing is data.

2.2 BIOLOGICAL NEURAL NETWORK

A typical neuron is composed of a cell body, a tubular axon. The axon is essentially a long, thin tube that splits into branches terminating in little end bulbs that almost touches the dendrites of other cells. The small gap between an end bulb and a dendrite is called a synapse across which information is propagated. So the dendrites serve as receptors for signals from other neurons whereas the purpose of axon is transmission of the generated neural activity to other nerve cells. Transmission of the signal across the synaptic gap is mostly effected by chemical activity.

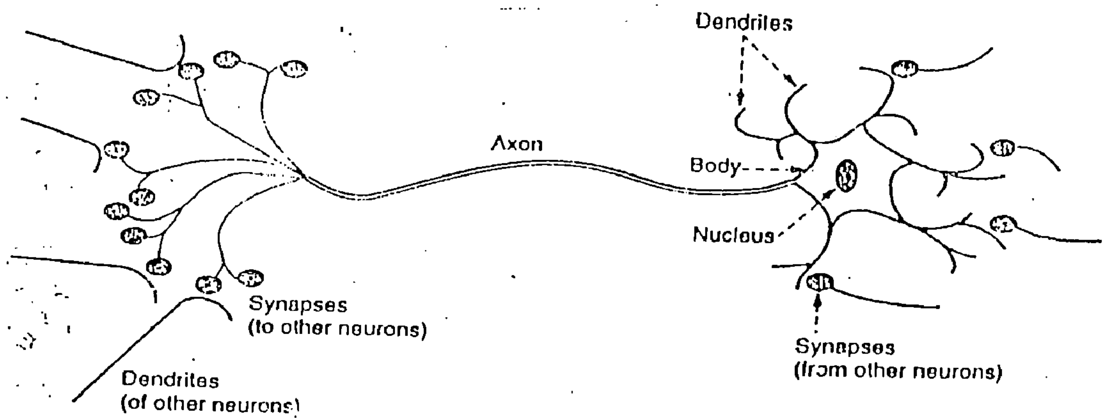


Figure 2.1: Schematic view of the biological neuron

2.3 ARTIFICIAL NEURAL MODELS

An Artificial neural model is a highly simplified model of biological neural model. The neural network consists of a number layers. Each layer contains many single elements called nodes, cells or neurons where the information processing occurs.

All the layers are interconnected i.e. each node is connected to every unit in the previous and next layers through connection links. Each connection link has an associated weight that represents its connection strength. Information passes from input to output side.

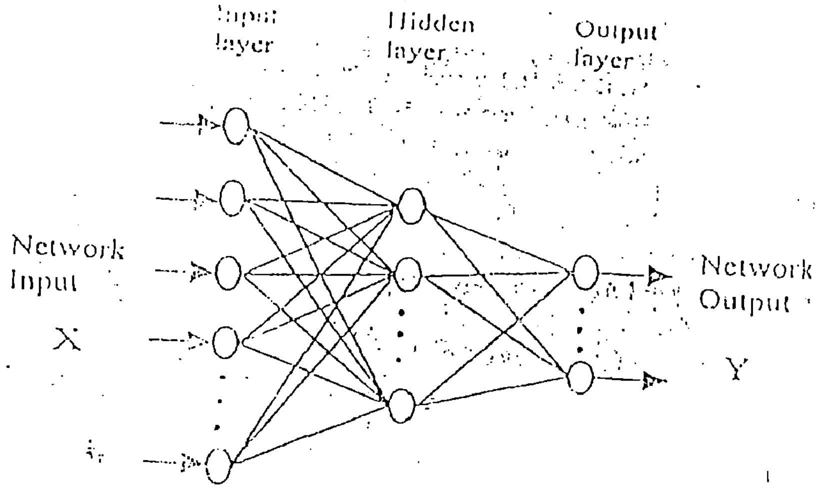


Figure 2.2 : A typical 3- layer Neural Network

When the signals are received by a node, it multiplies every input by the weight, sums the product and passes the sum through a transfer function to produce the result.

The figure 2.3 represents a typical j^{th} node of a network which receives input variables. The inputs to such a node may come from the outputs of other nodes or an input vector $X = (x_1, \ldots\ldots, x_i, \ldots\ldots, x_n)$. The sequence of of weights leading to the node form a weight vector $W_j = (W_{1j}, \ldots\ldots W_{ij}, \ldots\ldots, W_{nj})$, where W_{ij} represent the connection weight from the i^{th} node in the preceding layer to this node. The output of node j, y_j, is obtained by computing the value of function f with respect to inner product of vector X and W_j minus b_j, where b_j is the threshold value, also called the bias, associated with this node. The output of node j, y_j is computed with the following equation.

$$y_j = f(XW_j - b_j)$$

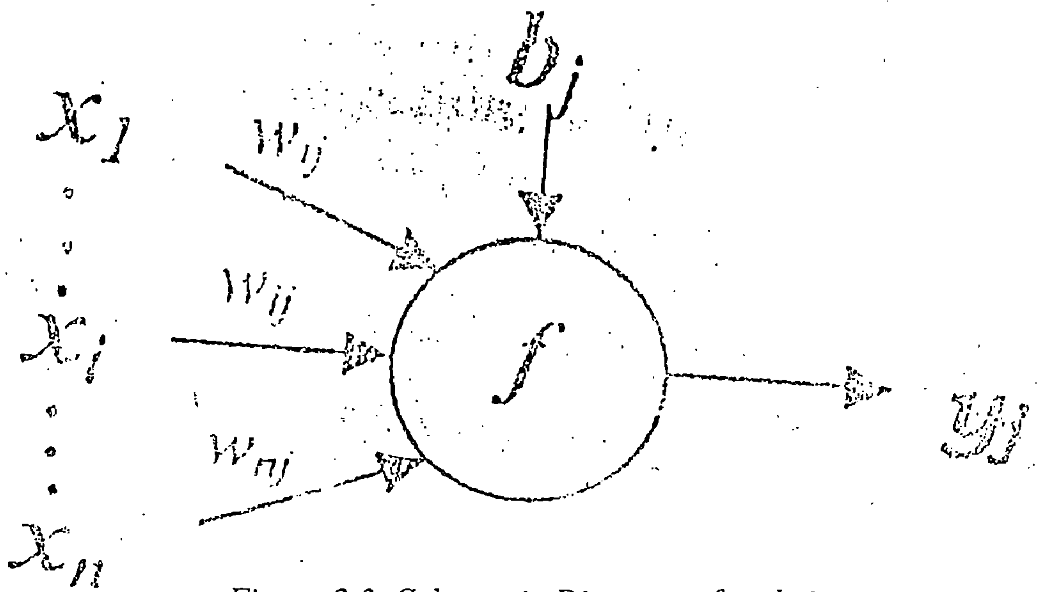


Figure 2.3: Schematic Diagram of node j

Where 'f' is the activation function. It implies that the propagation of output from one node to the other occurs by a transfer function called activation function. There are number of activation functions used in neural network. But most common among them is sigmoid function.

Sigmoid function: This is the most popular node function used in neural nets. It is usually a steadily increasing S-shaped curve. This function is continuous, differentiable everywhere. The advantage of this function is that its smoothness makes it easy to devise learning algorithms and understand the behaviour of large networks whose nodes compute such function. The output y_j from the j^{th} node in a layer is

$$y_j = f(S_j) = \frac{1}{[1 + \exp(-S_j)]}$$

where $S_j = \Sigma\, W_{ji}\, X_i$

W_{ji} = weight of the connection joining the j^{th} neuron in a layer with the i^{th} neuron in the pervious layer.

X_i = value of the i^{th} neuron in the previous layer.

Due to the nature of sigmoid function, the input to function S_j can vary $\pm \infty$ and the output y_j is always bounded between 0 to 1. Therefore it is essential to normalize the data i.e to convert to range {0,1} all the input values before passing them into a neural network. This scaling down of input-output quantities helps in smoothening the solution space and average out some of the noise effects. However, there is some danger of losing information through this procedure. For data normalization, the procedure is

$$N_i = \{(R_i - Min_i)/(Max_i - Min_i)\}$$

Due to the output range of the sigmoid function, all values must be denormalized to provide meaningful result. This can be achieved by simply reversing the normalization algorithm used on the input units. List of some of other functions used in ANN are given below:

(i) Step function

(ii) Ramp function

(iii) Gaussian function

(iv) Piecewise linear function.

2.4 NEURAL NET ARCHITECTURE

A single node is insufficient for many practical problems and therefore the networks with a large number of nodes are frequently used. The way nodes are connected determines how computations proceed. Some of the commonly used network architectures are discussed below:

(1) Fully Connected networks:

In this structure every node is connected to every node and these connections may be either excitatory (positive weights), inhibitory (negative weights) or irrelevant (almost zero weights). Because of the large number of parameters, such type of neural network is seldom used. In this network with 'n' nodes, there are n^2 weights.

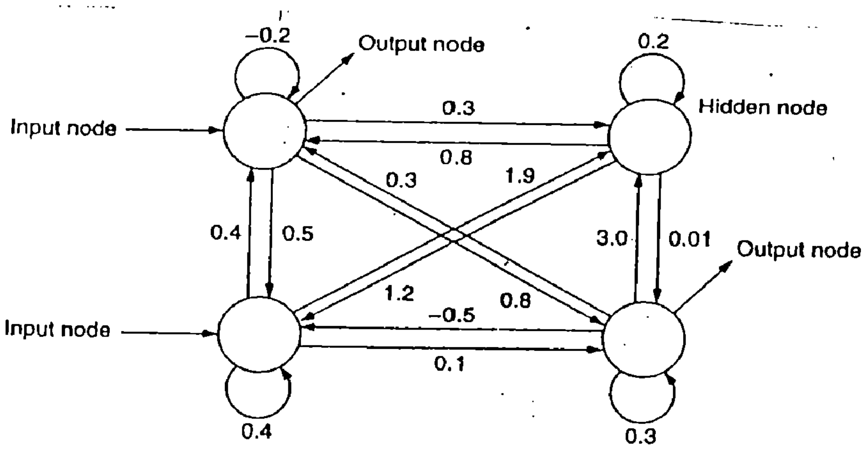


Figure 2.4: A Fully Connected network

(2) Layered Networks:

These are networks in which nodes are partitioned into subsets called layers, with no connections that lead from layer j to layer k.

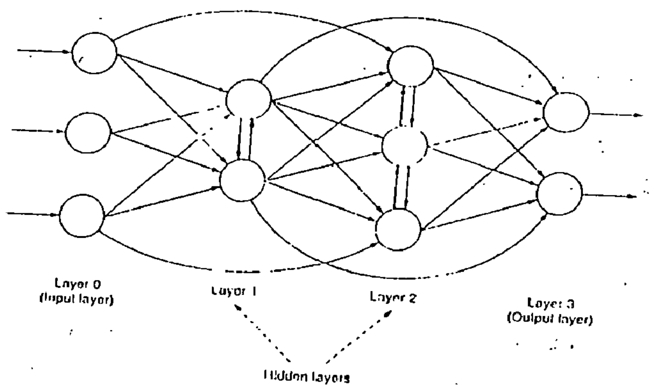


Figure 2.5: A Layered networks

(3) Feed-forward Networks

It is the most commonly used neural net architecture. Here the information passes in one way (forward). It has an input layer, an output layer and one or more hidden layers in between input and output layers. The input layer neurons receive the input variables. This layer is transparent and possesses all the quantities that influence the output. The nodes in input layer are not computational. They simply broadcast the data over the connections to the hidden nodes. Each connection is associated with a weight. The strength of signal passing from one neuron to the other depends on weights of interconnection. When the weights are modified, the data transferred through network changes and network output alters. All the connections are "feed forward" that is they allow the information transfer only from a layer to the next consecutive layers. A network may contain one or more hidden layers; of course there is no fixed rules as how many units should be included in the hidden layer. It is rather determined through trial and error procedure.

2.5 TRAINING NEURAL NETWORKS

It is presumed that ANN does not have prior knowledge about the problem. Therefore it is required to train the network. The objective of training is to minimize the difference between target output and network output. At the beginning of training the weights are initialized either with a set of random values or based on some previous experience. Next the weights are systematically changed by learning process in such a manner that the target output is as close as the network output. Many learning examples are repeatedly presented to the network, and the process is terminated when this difference is less than a specified value. At this stage, the ANN is considered trained.

It has been observed that an insufficient data set leads to poor learning. The more data we provide to the network, the more improved results we expect from it. The ANN has an in-built mechanism of growing wiser with a set of input variables. The number of samples required for training a network is not predetermined. Rather it is decided on the basis of trial and error. Of course these issues are complex because there is considerable dependence on the specific problem being attacked using a neural network. To ensure a good approximation, Carpenter and Bartherleng stated that the number of data pairs used for training should be equal to or greater than the number of parameters (weights) in the network. Sometimes with too large a sample, the network may perform very well over the data set used for training, but it may not be much powerful for the testing data. Neural learning is considered to be successful only if the system can perform well on the data sets for which it is not trained.

2.6 CROSS TRAINING

As stated earlier, sometimes when the network is exposed to more data, it may lead to over-training. The reason for which the over-training occurs in the network is that in the process of trying to learn the underlying rule, network has started trying to fit the noise component of the data as well. In over-training the network memorizes the individual examples, rather than trends in data set as a whole. When this happens the network performs very well over the data set used for training, but shows poor predictive capabilities when supplied with data other than the training patterns. To prevent this kind of over-fitting, a cross training procedure is usually recommended. The goal of this procedure is to stop training, when the network begins to over-train. The second portion of the data is reserved for this purpose. After the adjustment of network parameters, the network is used to find the error for this data set. Initially, the errors for both the training and cross training data set go down. After an optimal amount of training has been achieved, the errors for the training set continue to decrease, but those associated with cross training data set begin to rise. This is an indication that further training will likely result in network over-fitting the training data. The process of training is stopped at this time and the current set of weights and thresholds are assumed to be optimal values.

There are several learning algorithms for ANN. A few of such popular algorithms have been discussed below.

2.7 LEARNING ALGORITHM:

There are several learning algorithms of ANN. A few a such popular algorithms have been discussed below.

2.7.1 Back Propagation Algorithm

This is a widely adopted algorithm to adjust the inter connection weights during training. It is based on generalized delta rule learning procedure and involves the presentation of a set of pairs of input and output patterns. The actual result is subtracted from the target result to find the output layer errors. The error at the output layer is then redistributed backwards through the hidden layers until the input layer is reached. If output vector.

$Y_p = (y_1, y_2, \text{-----}\ y_p)$ and target vector $T_p = (t_1, t_2, \text{----}, t_p)$, the objective is to minimize the cumulative error of the network.

$$\text{Error} = \sum_{p=1}^{P} \text{Err}\left(Y_p T_p\right)$$

P = number of training pattern

p = { 1, 2, 3, ------- P}.

The function Err should be non-negative and should be small if Y_p is close to T_p (otherwise large). An error measure is obtained by examining the difference $e_{p,j} = |Y_{p,j}-T_{p,j}|$ between the jth components of the actual and target output vectors. Our goal is to find out a set of weights that minimize.

$$\text{Sum square Error} = \sum^{p}\sum^{k} (Y_p - T_p)^2$$

or mean squared Error (MSE) = $\frac{1}{P}\sum^{P}\sum^{k} (Y_p-T_p)^2$. Therefore, the back propagation algorithm is a generalization of the least mean squared algorithm that modifies network weights to minimize the mean squared error between desired and actual outputs of the network.

For minimization of error, gradient descent technique is adopted. The error is propagated through the network to each node and accordingly the connection weights are adjusted in a direction that corresponds to the negative gradient of an error measure. It is based on the following equation :

$$\Delta W_{ij}(n) = -\eta * \frac{\partial E}{\partial W_{ij}} + \alpha * \Delta W_{ij}(n-1)$$

where ΔW_{ij} (n) & ΔW_{ij}(n-1) = weight *increments between* i & j *during nth*, (n-1)*th pass.*

α = momentum factor which can speed up the training in very flat region of error surface and help prevent oscillation in weights.

η = learning rate which is used to control the chance of avoiding the training process being trapped in a local minima instead of global minima.

$\frac{\partial E}{\partial W_{ij}}$ = Negative gradient of error.

As discussed above the BP involves two steps. First step is the forward pass in which the effect of input is passed forward through the network to outer layer. After the error is computed, a second step starts backward through network. The errors at the outer layer is propagated back towards the inner layer with weights are modified as per gradient descent technique.

2.7.1.1 Limitation of back propagation learning

(i) the major drawback of this algorithm is that, the solution often follows a zig-zag path while trying to reach a minimum error position, which may slow down the training process.

(ii) It is also possible for the training process to be trapped in local minima despite the use of a learning rate.

2.7.1.2 Setting of parameter values

Following are important parameters which are required to decide during training of networks.

(1) Initialization of Weights

Training is generally commenced with randomly chosen initial weight values. Typically the weights chosen are small (between – 1.0 and 1.0 or – 0.5 to + 0.5). Because larger weight magnitudes may drive the output layer to saturation, requiring large amounts of training time to emerge from the saturated state. This phenomenon results from the behaviour of the sigmoid function.

(2) Choice of Learning Rate

Weight vector changes in back propagation are proportional to the negative gradient of error $\left(\Delta_p W_{ij} \alpha - \frac{\partial E_p}{\partial W_{ij}}\right)$. This guideline determines the relative changes that must occur in different weights when a training sample is presented. The magnitude of change depends on the appropriate choice of the learning rate 'η'. A large value of 'η' will lead to rapid learning but weight may then oscillate, while low values imply slow learning. The right value of 'η' will depend on the application. Generally the values between 0.1 and 0.9 are used.

(3) Momentum

Back-propagation leads the weights in a neural network to a local minimum of the MSE, possibly substantially different from global minimum that corresponds to the best choice of weights. This problem can be particularly bothersome if the "error surface" (plotting MSE against network weights) is highly uneven and jagged with a large number of local minima.

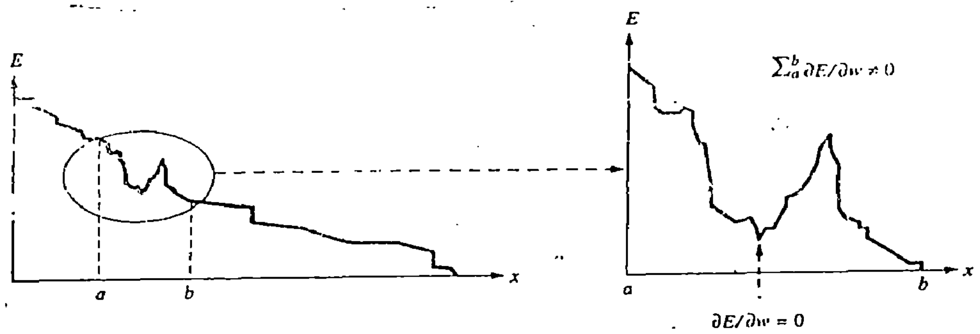


Fig. 2.6 : Graph of Jagged Error Surface

(4) **Number of hidden layers and nodes :**

It is determined by trial and error method.

(5) **Number of Samples**

The Number of the samples needed for good training depends on the several factors. A rule of thumb, obtained from related statistical problems, is to have at least five to ten times as many training samples as the number of weights to be trained.

2.7.2 Linear Least Square Simplex (LLSSIM) Algorithm

One of the major drawback in the backpropagation algorithms is that they are easily trapped by local optima. This finding prompted to develop an algorithm for training three-layer-feed forward ANNs that is more effective and efficient than BP. One such algorithm is called LLSSIM, used the combination of MSE and multi-start simplex optimization. It was developed by Hsu, & H.V. Gupta (1995) It partitions the weight space to implement the above two training strategies. The input hidden layer weights are estimated using a multi start simplex non-linear optimization algorithm. While the hidden output layer weights are estimated using optimal linear least square estimation. The non-linear portion of the search is thereby confined to a smaller dimensional space, resulting in acceleration of the training process. The simplex search involves multi-starts that are initiated randomly in the search space, and the probability of finding local minima is virtually eliminated.

2.7.3 Cascade Correlation Algorithm

Fahlman and Lebiere (1990) proposed the cascade correlation algorithm that allows a network structure to develop according to the requirements of a problem.

Unlike other approaches it starts with a minimal network without any hidden nodes and grows during the training by adding new hidden units one by one. This is referred as cascade architecture development. First the output nodes are trained to minimize the total output error. Then a new node is inserted and connected to every output node and all previous hidden nodes. The new node is trained to correlate with the output error. The addition of new hidden nodes is continued until maximum correlation between the hidden nodes and error is attained.

2.7.4 Radial Basis Functions

Sometimes in practice we encounter problems where samples of two class are clustered together as shown in figure below.

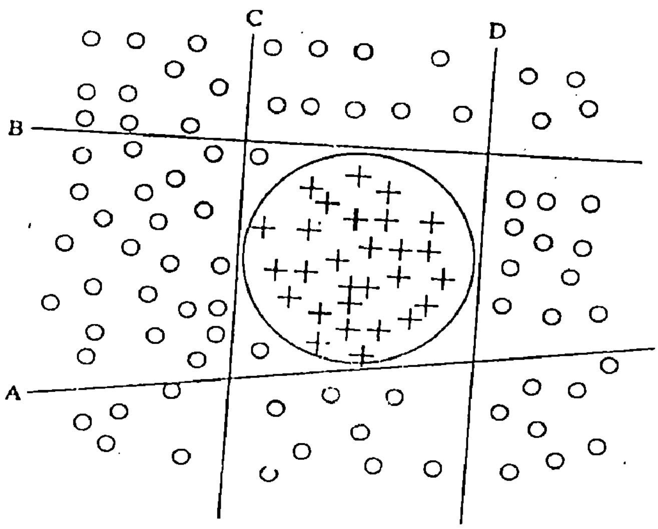


Fig 2.7 Two class problem with a single cluster

With a traditional feed-forward network using sigmoid functions, perhaps four or five hidden nodes may be required for this problem. On the other hand, only one node would be sufficient to discriminate between two classes if we could use a node function that approximates the circle. This concept leads to evolve a new algorithm known as Radial

Basis function. This network consists of a single hidden layer feed-forward network with sigmoid function with non-linear units, followed by an output layer with linear units. This hidden layer consists of a number of nodes and a weight vector (μ) which is called a "centre". If the input vector is 'i' the Standard Euclidean distance i.e. $u = \|\mu\text{-}i\|$ is used to measure how far an input vector is from the centre. For each node, the Euclidean distance between the centre and the input vector of the network input is computed and transformed by a non-linear function that determines the output of the node, in the hidden layer.

2.8 VALIDATION

After the training is complete, the ANN performance is validated. The weights are collected from the training module to test the network and monitor its performance of test samples in terms of MES criterion.

2.9 STRENGTH AND LIMITATION OF ANN

2.9.1 Advantage

The following are some of reasons for which ANNs have become an attractive computational tool :

(i) They are able to recognize the relation between input and output variables without explicit physical consideration.

(ii) They work well even when the training sets contain noise and measurement errors. Very often, in hydrology, the problems are too ill-defined for meaningful analysis using physically – based methods. The presence of noise in the input-outputs is handled by ANN effectively without severe loss of accuracy.

(iii) Non-linear nature of its activation function helps in solving non-linear, multi-variate type problem.

2.9.2 Limitation

(i) Success of an ANN application depends on the quality and quantity of data available. This requirement cannot be easily met.

(ii) Secondly, ANN is having lack of physical concepts and relations. This is the reason for skeptical attitude for methodology.

(iii) The choice of network architecture, training algorithm and definition of error are usually determined by user's past experience and preference, rather than the physical aspects of the problem.

2.10 APPLICATION OF ANN

Because of its efficiency in handling effectively with non-linear models, ANN has been applied successfully in a wide range of areas in hydrology. ANNs have been adopted in rainfall – runoff modeling, stream flow forecasting , groundwater modeling, precipitation forecasting, reservoir operation. Also the ANNs have found applications in such diverse areas as neurophysiology, physics, biomedical Engineering, Electrical Engineering.

LITERATURE REVIEW

3.1 GENERAL

The broad field of modern water management can be described as one of the most interesting research areas concerning modeling techniques and prediction systems. The emergence of powerful computational tools in recent decade has helped researchers to evolve mechanism that extract the relationship between input output of a process, without the physics being explicitly provided. That is why simple approaches offered through 'conceptual' and 'black-box' solutions are fast becoming attractive alternatives. The ANN is one such new strategy that gained popularity in recent years for its ability to emulate the pattern recognition capacity of human brain and nervous system.

About fifty-seven years ago (1943) McCulloch and Pitts proposed new a idea i.e. Artificial Neural Networks using biological neuron. Landahl, McCulloch and Pitts recommended that many arithmetic and logical operations could be implemented using neuron models.

In 1949, Donald Hebb et. al proposed a learning scheme for adjusting connection weights based on pre and post-synaptic values of the variables. Hebb's law became a fundamental learning rule in neural networks literature. In 1974, a new algorithim was proposed by Werbos (1974) and largely ignored by the scientific community until the 1980's. Parker (1985) and LeCun (1985) rediscovered it, but its modern specification was provided and popularized by Rumelhart (1986). Since this procedure employs a gradient search strategy, its performance it quite sensitive to initial starting point as observed by Wasserman(1989). The solution may be easily trapped by local optima. This findings prompted to develop a different algorithm. Hsu et. al (1995) introduced a new algorithm, viz. LLSSIM to train a three layer feed forward network. It has been found to reliably obtain the global or near global solution of the problem. Hsu et. al (1995) observed that ANN model approach provides a better representation of rainfall-runoff model for a medium sized basin when compared to the ARMAX (Auto-regressive Moving average with exterior inputs).

3.2 APPLICATION

Motivated by successful applications in modeling nonlinear system behavior in a wide range of areas, ANNs have been widely applied in hydrology and hydraulics. Chan and Tsang (1992) compared the multi regression and ANN approaches to model snow-water equivalent, and observed that ANN yields better result.

Raman and Sunil Kumar (1995) investigated the use of ANN for synthetic inflow generation and compared model performance with that of a multi variate auto regressive (ARMA) model, proposed by Box and Jenkins (1976).

Carriere et. al (1996) designed a virtual runoff hydrograph system based on ANN by training a recurrent back propagation neural network. They obtained good correlation between the observed and predicted data.

Chang and Noguchi (1996) demonstrated the fact that adopting neural network model to rainfall runoff modeling, parameters relating to catchment can be avoided in the input and virtually, no parameter inside the model need to be calibrated manually.

Raman and Chandramauli (1996) derived reservoir operating polices by a neural network procedure (DPN model) and by using a multi linear regression procedure (DPR model) from DP algorithm. They compared the performance of each during the validation period taking last three years of historic data. They demonstrated the fact that DP algorithm based on DPN model provided better performance than the other models.

Dawson and Wilby (1998) while using ANN for river flow forecasting have given an overview of ANNs, their training and data standardization. Based on the results of an application study, they have highlighted the ability of ANN to cope with missing data and to learn from the event currently being forecast in real-time. They have also emphasised the need for thorough investigation into the relationship between the training period-length and hydrological realism of the ANN forecast.

3.3 REVIEW RELATED TO PRESENT STUDY

The accurate measurement of stream flow is an important aspect in Water Resources management. The conventional practice is to establish stage-discharge relationship through rating curve (Maidment, 1992). Based on measurements made of middle Mississippi river during 1993 flood, Westphal et.al (1999) noted that the stage-discharge relations for rating curves are not single valued. This is the major drawback in conventional approach as it does not take into account hysterisis effect which gives a loop rating curve.

Jain and Chalisgonkar (2000) studied the mapping of stage through ANN. The daily gauge and discharge of Kolar river at Satrana gauging site and of Narmada river at Jamatara site were adopted for study. The coefficient of correlation and sum of squares of errors for training and testing data were computed for ANN models and the curve fitting approach. It is observed that when more and more informations were supplemented to input layer, mapping by ANN improved rapidly than curve fitting. Furthermore, for a hypothetical data set of a loop rating curve (hysterisis effect), ANN could achieve an almost perfect match.

In water resources planning, the volume of sediment transported by a river is of vital importance. McBean and Al-Nassri (1998) studied that sediment load is no way related with discharge. They recommended to correlate sediment concentration to obtain meaningful results. Jain (2001) established an integrated stage-discharge-sediment concentration relation using ANN approach. The data of two gauging sites, viz. Chester, Thebes on Mississippi river were used to compare the performance of ANN and the conventional curve-fitting approach. For both of the data sets, the ANN results are much closer to the observed values than the conventional technique.

STUDY OF STAGE – DISCHARGE, SEDIMENT USING RATING CURVE

4.1 GENERAL

The first and foremost requisite for planning water resources development is the accurate assessment of stream flow which is the most important basic data for hydrologic studies. The precipitation, evaporation, evapotranspiration etc. are difficult to measure exactly, since those are dependent upon several physical and climatic factors (temp., humidity, soil moisture, geology, topography etc.). Interestingly stream flow is the only part of the hydrologic cycle that can be measured accurately.

4.2 METHODS OF DISCHARGE MEASUREMENT

There are various methods for discharge measurement.

4.2.1 Indirect Method

Discharge measuring structures : Flow measurement structures are constructed in channels in an effort to ensure a constant stage – discharge relationship resulting in accurate discharge measurement without the use of velocity measurement. The discharge through such structures can be obtained from equations or tables relating the discharge to the water surface elevation adjacent to or within the structure. Therefore only field measurements required for the purpose are stage measurements.

4.2.2 Direct Method

4.2.2.1 Area – Velocity Method

Most common method of measuring the discharge in large streams consists in measuring flow velocities at a number of points in flow C.S. and the product of the average flow velocity and flow area gives the desired discharge.

4.2.2.2 Area – Slope Method

During flood, it is extremely difficult to predict the time of flood peak and also stations are inaccessible for recording stage. Under these circumstances water surface is determined by flood marks and discharge is calculated by using the formula :

$$Q = \frac{1}{n} * A * R^{2/3} * S^{1/2}$$

Where,

n = Manning's rugosity.

R = hydraulic mean depth

S = Water surface slope.

4.2.2.3 Radio-Tracer Method

In this method a known quantity of tracer substance is introduced into water and the concentration is measured after it has become dissipated uniformly in water. An analysis of water then gives the degree of dilution and hence the discharge rate.

4.3 RATING CURVE

The direct measurement of discharge is a time-consuming and costly procedure. Therefore, a correlation between stage and discharge expressed in form of a curve on graph or a rating curve or a mathematical equation is called a stage – discharge curve or a rating curve or rating equation. This relationship of stage and discharge is established through a series of careful measurement. Normal shape of the stage discharge curve drawn on an ordinary graph paper is parabolic. Any abnormality in shape of the curve is an indication of variation in the characteristics of river.

A sudden flattening of the parabolic curve at bankful stage is caused on account of river bank spills which drastically reduce the rate of water level with increased discharge. Therefore the development of stage-discharge relationship carries utmost importance. Once the stage discharge relationship is established , the subsequent procedure consists of measuring the stage and reading the discharge from stage discharge relationship.

4.4 RAPID RISE AND FALL OF STAGE (UNSTEADY FLOW)

When a flood wave passes a gauging station in the advancing portion of the wave the approach velocities are larger than in steady flow at corresponding stage. Thus for the same stage more discharge than in a steady uniform flow occurs. In the retreating phase of the flood wave, the converse situation occurs with reduced approach velocities giving lower discharges than in an equivalent steady flow case. Thus the stage discharge relationship for an unsteady flow will not be a single-valued relationship as in steady flow but it will be a looped curve. It may be noted that at the same stage, more discharge passes through the river during rising stages than in falling ones.

Steady flow in a river reach is characterized by a single rating curve, known as normal rating curve. Normally the rating curve has the form as follows :

$$Q = C_r (G-a)^{\beta}$$

Where,

Q = Stream discharge.

G =Gauge height (stage)

a = A constant that represents, the gauging reading corresponding to zero discharge.

C_r, β are rating curve parameters

Single rating curve developed from unsteady stage and discharge measurements using least – squares approach may also be considered as normal rating curve, assuming that equal number of stage and corresponding discharge measurements, both in the rising and falling stages of flood wave, have been used in the development of rating curve.

During rising stage, discharge is underestimated by the single valued (normal) rating curve. This will lead to under estimation of yield and design capacities of spillway, channel etc.; leading to underutilization of water and risk of structural failure. Therefore storage designed on the basis of such series would be under sized storage and would spill more frequently.

During falling stage, discharge is overestimated by single valued (normal) rating curve. This will lead to overestimation of yield, design capacities of spillway and other structures. The storage capacities of spillway and other structures designed on such dependable yield would remain oversized and would not be filled for large number of years.

Flood forecasting studies carried out on the basis of discharge obtained by converting stage to discharge using single valued (normal) rating curve would lead to error in forecasted peak and its time at a downstream location.

Variation in inflow hydrograph due to hysterisis nature of stage-discharge curve during rising stage and receding stage of a flood at gauging site, as compared to discharge measured traditionally on the basis of single valued rating curve may significantly alter the nature and magnitude of routed hydrograph at the d/s reach, where flood forecasting is required to be done.

4.5 SEDIMENT RATING CURVE

The accurate assessment of volume of sediment transported by a river commands a great deal of importance in design and management of water resources project. The conventional approach to calculate the sediment is from sediment rating curve.

A sediment rating curve is a relationship between sediment and river discharge. On extensive research it was revealed that the relationship between sediment load and the discharge gives the misleading results. Later on it was recommended to correlate sediment concentration with discharge. Therefore sediment rating curve is a relationship between the sediment concentration and river discharges. The relationship is basically a non-linear mapping problem and is usually established by regression analysis. The curve is generally expressed in the form of a power equation which is of the form

$$S = cQ^d$$

Where,

S = suspended sediment concentration (mg/l)

Q = discharge in m^3/sec.

'C' and 'd' are constants.

4.5.1 Limitation

The estimation of sediment being transported is a two-step procedure. First step is to estimate the discharge which is not measured very frequently. The measured stage data are used the estimate the discharge from discharge rating curve. The second step is to estimate sedimentation concentration from the sediment rating curve. Clearly, the errors from the Ist step will be carried over to the second step, thereby augmenting the error in estimation of sediment.

STUDY AREA, DATA AVAILABILITY AND PROCESSING

The proposed ANN approach requires uninterrupted time-series data pertaining to river stage, discharge and sediment concentration at a gauging station. The time series should be of sufficient length to obtain stable estimates of the parameters. The gauging site chosen for the study is on river Krishna at Vijayawarda.

5.1 OVERVIEW OF KRISHNA BASIN

The river Krishna is the second largest river in peninsular India. The river rises in the Mahadev range of Western Ghats near Mahabeleswar at an altitude of about 1337 m above mean sea level and about 64 km from Arabian sea. After traversing a distance of about 1400 kms, the river joins the Bay of Bengal in Andhra Pradesh. The river in its course, covers the states Maharashtra, Karnataka and Andhra Pradesh. The Krishna basin extends over an area of 258948 km^2, nearly 8% of the total geographical area of the country.

It lies between latitude 13° 07′ N and 19° 20′ N and longitude 73° 22° N and 81° 10′ E. It is roughly triangular in shape with its base along the Western ghats and apex at Vijayawada. The percentage of areas of basin in the states of Andhra Pradesh, Karnataka and Maharashtra are 29.4, 43.8, 26.8 respectively. The principal tributories of the river are the Ghataprabha, the Malaprabha, the Bhima, the Tungabhadra, the Musi, the Palleruand the Meneru. The basin is agriculturally well developed. Since the early 1850s, major irrigation works have been undertaken in the basin. About 86% of surface water potential of the basin has been put to beneficial use so far. Nagarjunasagar, one of the earliest multi-purpose, project taken up in the basin provides for irrigation of an area of 0.9 million ha. Upstream of Nagarjunasagar is Shisailam for an irrigated area of 0.2 million ha. Krishna is an interstate river and each of the basin–states has been allocated a certain share of the total water available in the basin.

5.2 DATA AVAILABILITY

For Vijayawada gauging station, the daily time series of river stage, discharge and sediment concentration for three years (1982-83, 83-84, 84-85) were collected from hydrological observations and flood forecasting organization (South) Hyderabad. On the dates when depth of flow was shallow (below 0.30 mtrs) and discharge was very low, the sediment load was expected to be negligible and hence presumed nil.

5.3 DATA PROCESSING

Before applying any data set to neural networks, it is pre-requisite to examine the consistency of data set. It can be ascertained by determining the coefficient of correlation. The coefficients of correlation between two variables, say x and y, whose n pairs are available, can be calculated by

$$\text{Correlation} = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2 \sum_{i=1}^{n} (y_i - \bar{y})^2}}$$

Where, the bar denotes the mean of the variable.

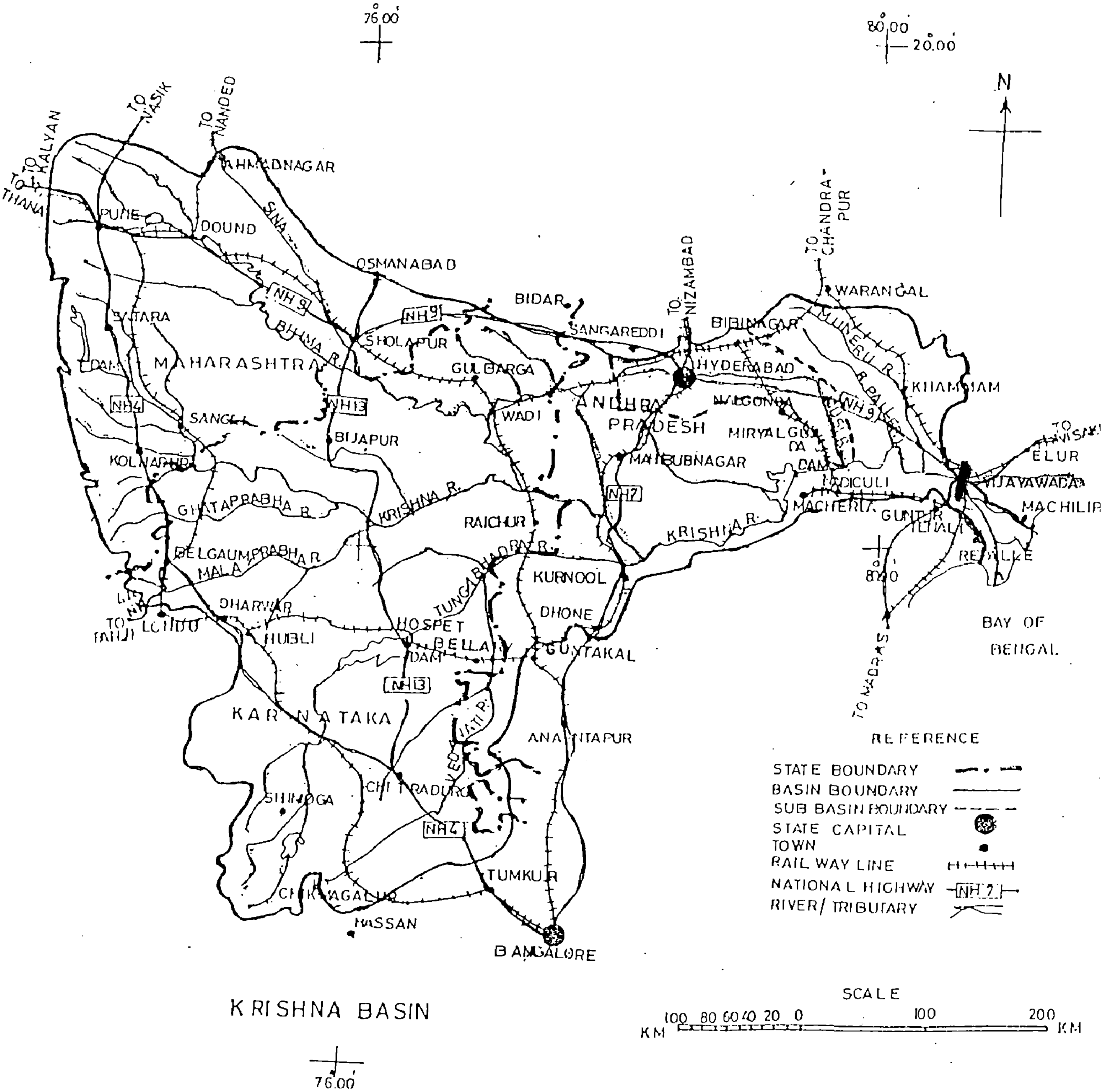
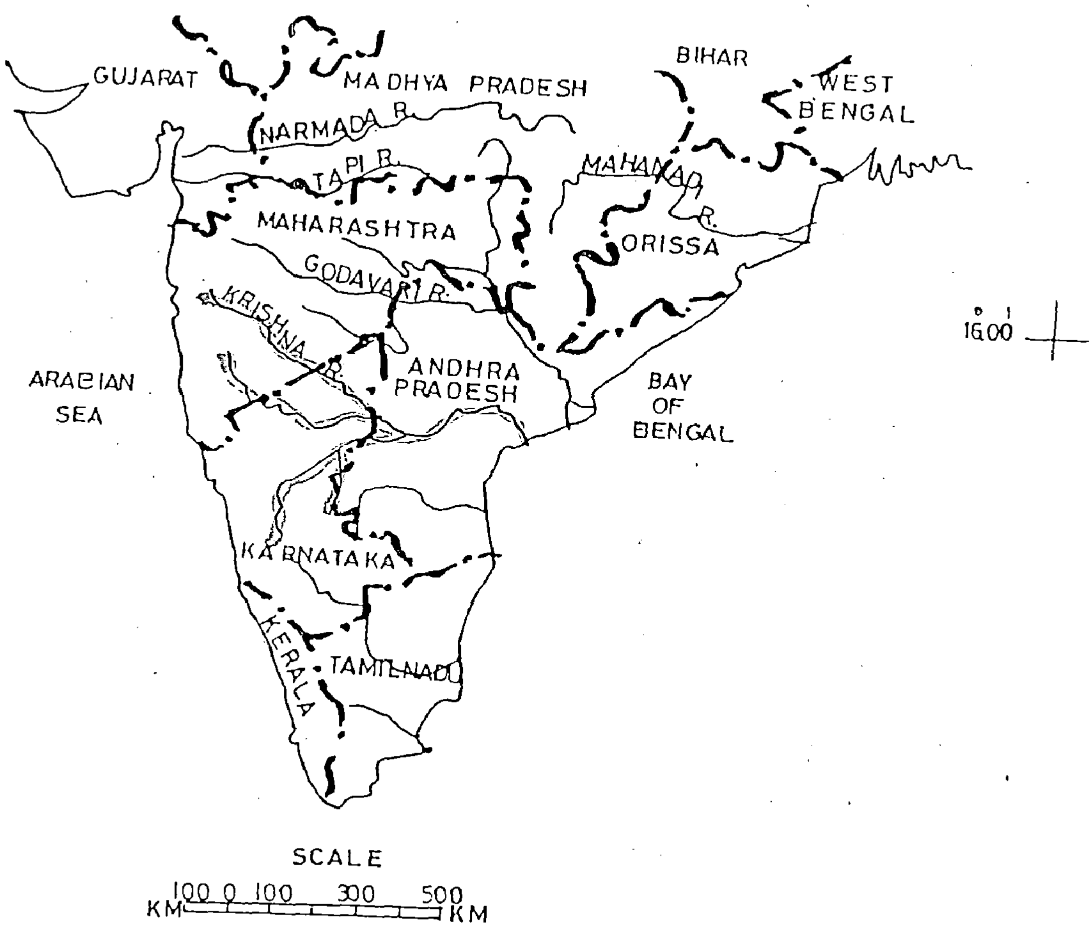


Fig. 5.1: Index map of Krishna Basin



INDIAN PENINSULA

Fig. 5.2: Index map showing Krishna river

For Vijayawada gauging site, out of the available data of three years, the first two years data (i.e. 1982-83 & 1984) are chosen for calibration and third year data (i.e. 1984-85) is chosen for validation. The coefficient of correlation among the stage, discharge, and sediment. Concentration for the calibration and validation data are given in Table 5.1.

Table 5.1
Correlation matrix for stage, Discharge, and sediment concentration Data, Vijayawada site

Correlation variable	Stage (1)	Discharge (2)	Sediment concentration (3)
(a) Calibration Period			
Stage	1	0.9087	0.4608
Discharge	0.9087	1	0.6829
Sediment concentration	0.4608	0.6829	1
(b) Validation Period			
Stage	1	0.9227	0.6144
Discharge	0.9227	1	0.7563
Sediment concentration	0.6145	0.7563	1

5.4 OVERVIEW OF BAITARANI BASIN

Another site at Anandapur on river Baitarani was chosen for the study. It has a catchment area of 8570 sq.km. The combined basin of Brahmani and Baitarani extends over an area of 51822 sq. km., nearly 1.7% of total geographical area of country. The independent drainage area of Baitarani is 12879 sq.k. The basin lies in the states of Madhya Pradesh, Orissa and Bihar. Irrigation has been practised in the basin from historical times. During the plan period, important project completed in the basin is Salandi project. Anandpur Barrage which is also an important project is under completion. The ultimate irrigation potential from the existing and ongoing has been assessed as 0.72 Mha. As against this, the potential created amounts to 0.24 Mha. The basin has adequate water which needs to be developed for beneficial use by storage projects and ground water exploitation.

5.5 DATA AVAILABILITY

For Anandapur gauging site, the daily time series of river stage, discharge for three year (1984-85, 1985-86 and 1986-87) were collected from Godavari Mahanadi Circle, Central Water Commission (CWC). The data were processed and consistency was checked in accordance with the procedures mentioned earlier.

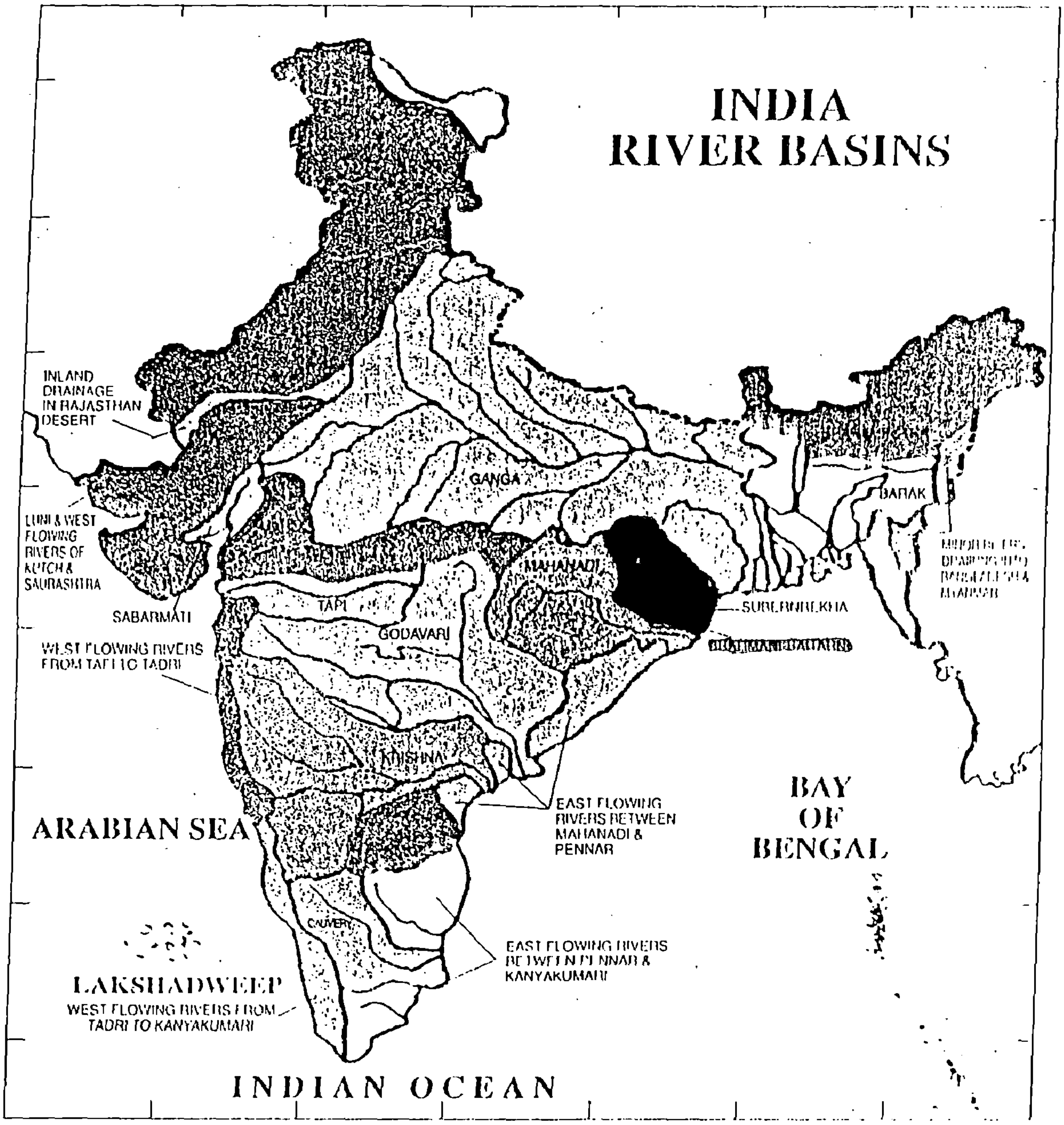


Fig. 5.3: Index map showing Baitarani Basin and the river

RESULT AND ANALYSIS

VIJAYAWADA SITE ON RIVER KRISHNA

6.1 NORMALIZATION

Before the training process carried out, the data sets were normalized to the range 0 and 1. However, to avoid output signal saturation that can sometimes be encountered in ANN applications, the data were normalized to the range of 0 to 0.95.

6.2 INPUT AND OUTPUT NEURONS

For the data set, a three layer network was trained. For better mapping of input and output data, stage and discharge of two previous time periods were used. In the present study, following combinations of input variables were presented to networks:

a) Input node consisting of H_t.

b) Input nodes consisting of H_t and H_{t-1}

c) Input nodes consisting of H_t and Q_{t-1}

d) Input nodes consisting of H_t, H_{t-1} and Q_{t-1}

e) Input nodes consisting of H_t, H_{t-1} and H_{t-2}

f) Input nodes consisting of H_t, H_{t-1}, H_{t-2} and Q_{t-1}

g) Input nodes consisting of H_t, H_{t-1}, H_{t-2}, Q_{t-1} and Q_{t-2}

In each case the output node had only one neuron, i.e., the discharge 'Q_t'

6.3 NETWORK TRAINING

The LLSSIM algorithm developed by Hsu, Gupta and Sorooshian (1995) was used in the study. The software for LLSSIM was made available by Prof. H. V. Gupta. The input data for LLSSIM was prepared according to guidelines of the software. Here while choosing the initial structure, the number of the hidden nodes was kept to one. As the training process progressed, the hidden nodes are automatically added one at a time by LLSSIM, till the structure yields minimum error. For each combination of inputs, the number of nodes in the hidden layer which gave the minimum sum of square error (SSE) was found out. After the training was over, the weights were saved and used to test the network performance. The best structure was chosen based on SSE and coefficient of correlation criteria. Table 6.1 shows the results while mapping stage/ discharge for Vijayawada site. Here the best structure was found to be (1-5-1) i.e. present stage is the only variable in the input node. The SSE and coefficient of correlation were computed for the curve fitting approach also and results are given in Table 6.1. Figure 6.1 to 6.4 indicate the graph for predicated and actual discharge of training and testing period.

Table 6.1
Sum of square errors and coefficient of correlation for ANN models and conventional procedure- Training and Testing data for Vijayawada Site.

ANN model inputs	ANN structure	Training data		Testing data	
		SSE	Coeff. Of correlation	SSE	Coeff. Of correlation
H_t	1-5-1	0.2044×10^8	0.998	0.2438×10^7	0.993
H_t, H_{t-1}	2-5-1	0.3067×10^8	0.996	0.2438×10^7	0.987
H_t, Q_{t-1}	2-4-1	0.4330×10^8	0.994	0.2870×10^7	0.990
H_t, H_{t-1} & Q_{t-1}	3-5-1	0.4052×10^8	0.996	0.1105×10^8	0.985
H_t, H_{t-1} & H_{t-2}	3-6-1	0.4448×10^8	0.994	0.2490×10^7	0.965
H_t,H_{t-1} H_{t-2} & Q_{t-1}	4-5-1	0.8293×10^8	0.988	0.6218×10^7	0.923
H_t, H_{t-1} H_{t-2} Q_{t-1} & Q_{t-2}	5-4-1	0.9044×10^8	0.988	0.1457×10^8	0.953
Curve fitting		0.7632×10^9	0.909	0.2954×10^8	0.923

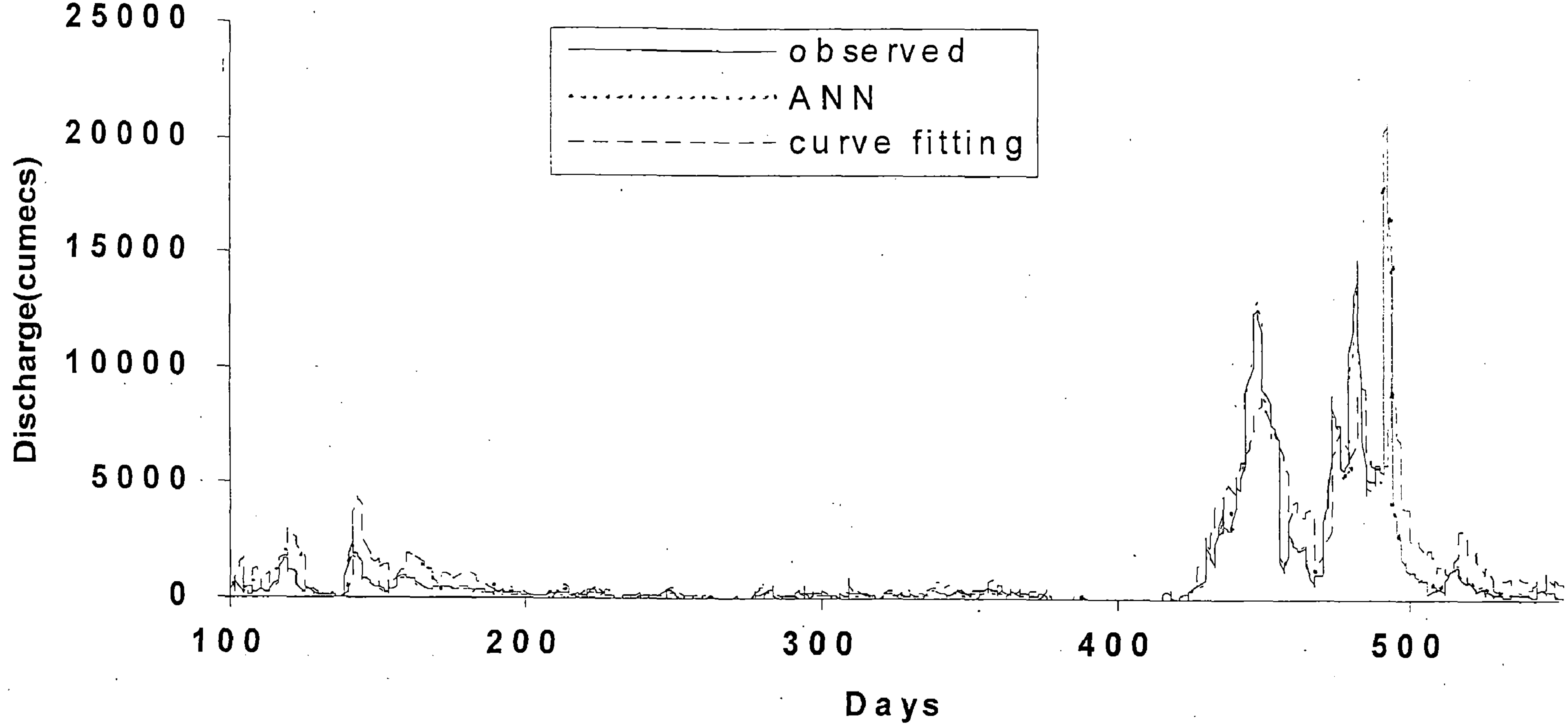


Fig 6.1:Observed & computed (conventional & ANN techniques) discharge for Vijayawada site – Training period

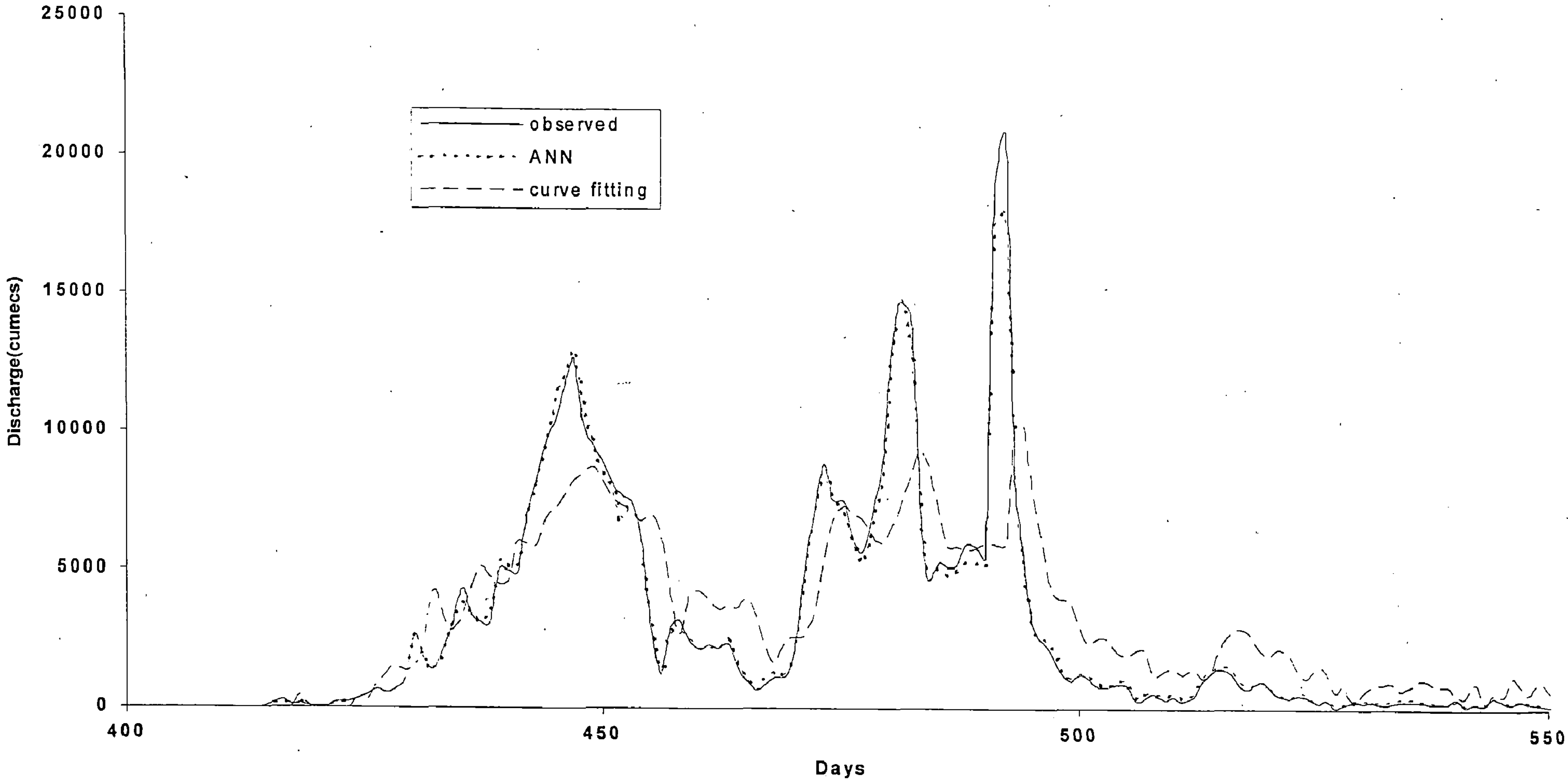


Fig 6.2: observed & computed (conventional &ANN techniques) discharge showing peak for Vijayawada site – Training period

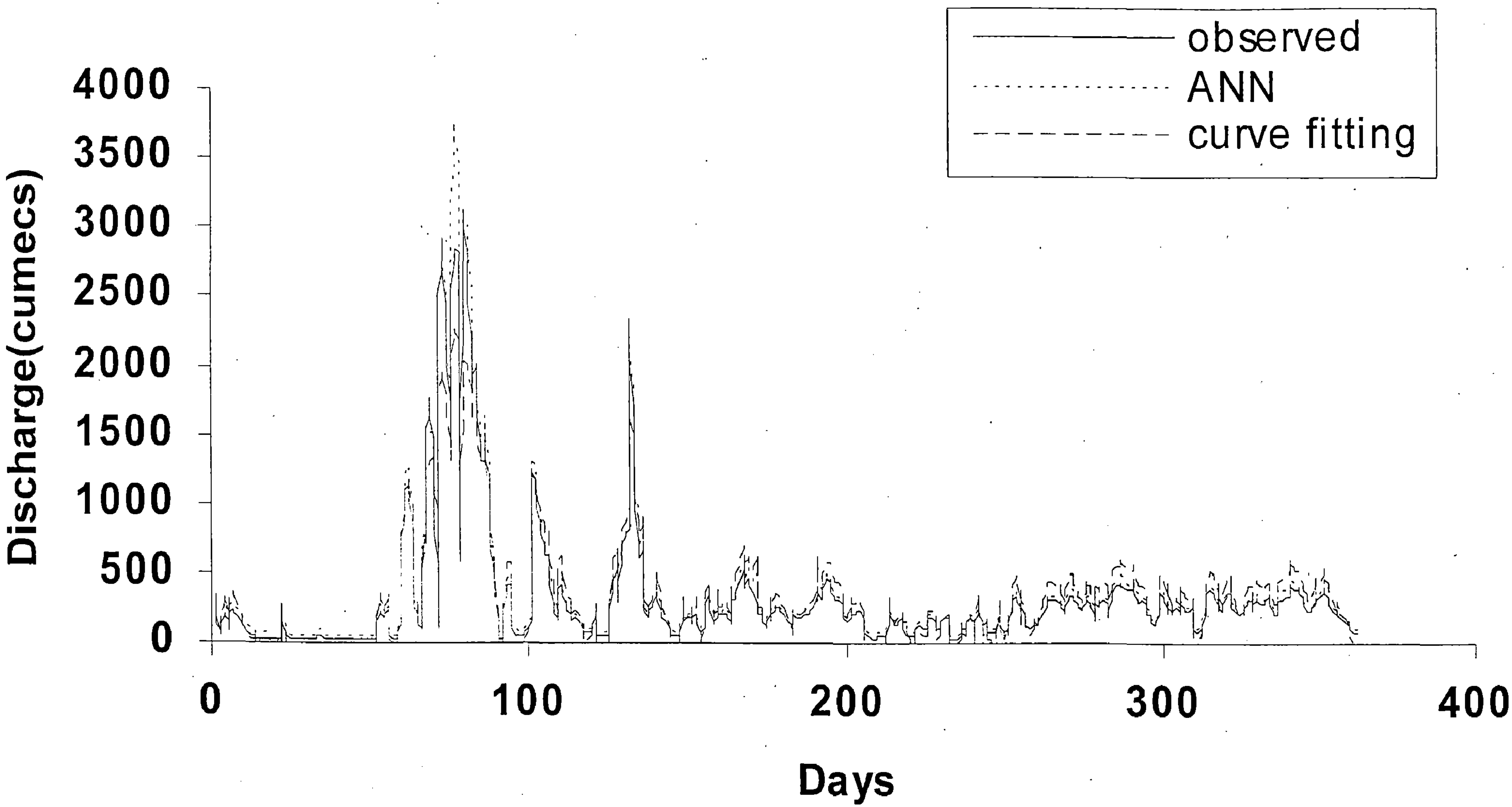


Fig 6.3: Observed & computed (conventional & ANN techniques) discharge for Vijayawada site – Testing period

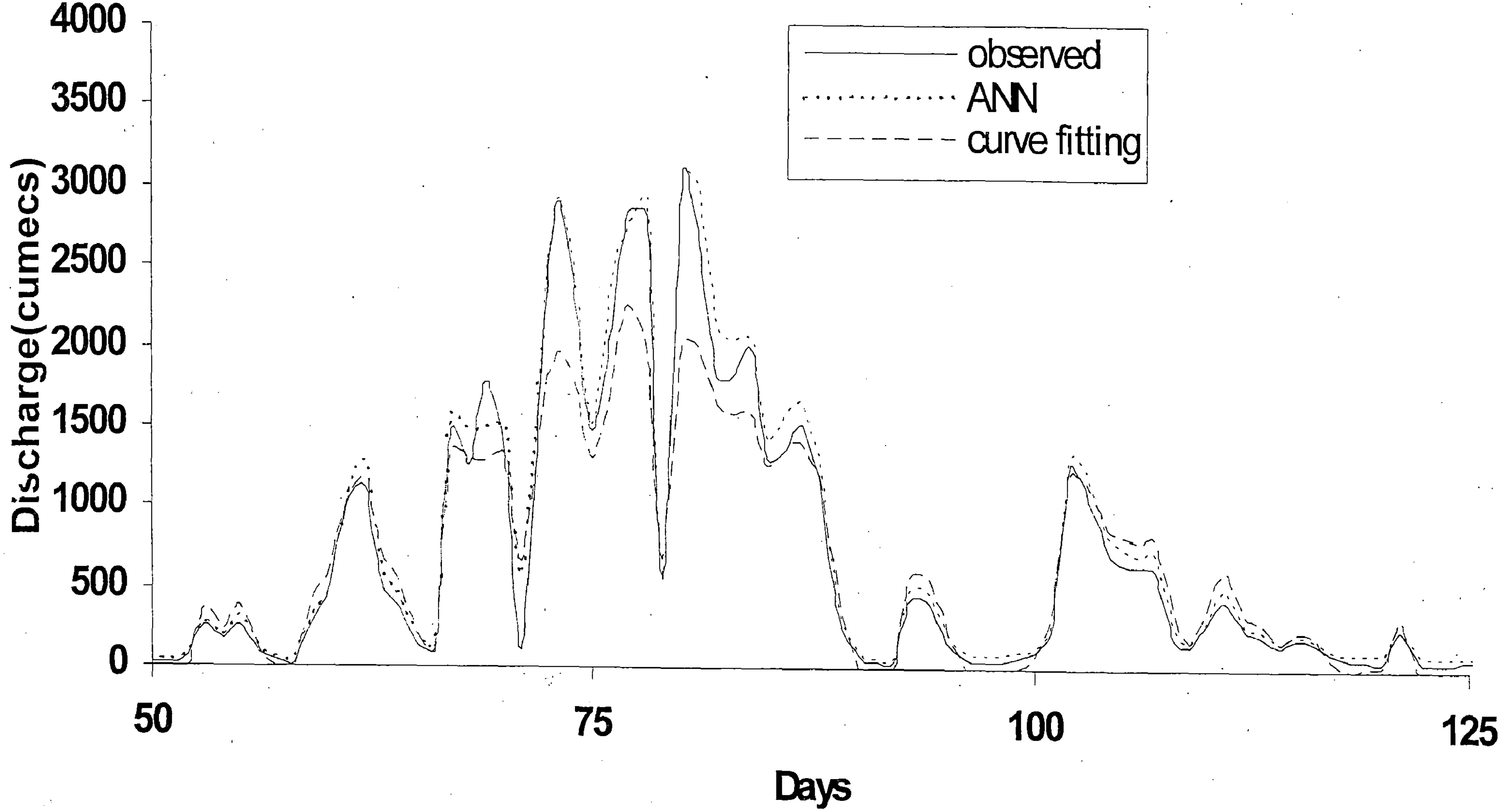


Fig 6.4: observed & computed (conventional & ANN techniques) discharge showing peak for Vijayawada site - Testing period

6.3.1 Analysis

From table 6.1, it is observed that SSE for ANNs is smaller and coefficient of correlation is higher than the curve fitting approach for both calibration and validation period. Fig. 6.2 & 6.4 shows that the ANNs almost matches the peak. But in case of conventional approach the peak is underestimated both for training and testing period. This clearly indicates that high flood discharge during unsteady flow is quite accurately assessed through ANN techniques.

Impact of Additional Input Variable

In the second attempts the rate of rise of stage was included as an additional input variable. The network was trained with rate of rise of stage, stage, and discharge to see whether this additional information improves the network results. Hence the structure (5-5-1) was found to be the best structure. The Multi-linear regression (**MLR**) model was used to compare the outcome of ANN model. In MLR model, slopes m_1, m_2, m_3 ...... m_n (where n is the number of variables) were obtained for each of the variables $x_1, x_2, x_3, \ldots$ x_n. The model is given below:

$$Y_e = m_1.x_1 + m_2.\,x_2 + m_3.x_3 + \ldots + m_n.\,x_n + b$$

Where Y_e = estimated discharge, b = constant.

The SSE and coefficient of correlation for both ANNs model and MLR model have been shown in table 6.2

Table 6.2

Sum of square of errors and coefficient of correlation for ANNs models and conventional procedure – Training and testing data for Vijayawada site

ANN model inputs	ANN structure	Training data		Testing data	
		SSE	Coeff. Of correlation	SSE	Coeff. Of correlation
R_t & H_t	2-3-1	0.2845×10^9	0.988	0.1017×10^8	0.955
R_{t-1}, R_t & H_t	3-5-1	0.2013×10^9	0.971	0.3025×10^9	0.536
R_{t-1}, R_t H_{t-1} & H_t	4-5-1	0.5849×10^8	0.992	0.2823×10^8	0.899
R_{t-1}, R_t H_{t-1}, H_t & Q_{t-1}	**5-5-1**	**0.5217×10^8**	**0.993**	**0.4645×10^7**	**0.975**
R_{t-2}, R_{t-1}, R_t H_t, H_{t-1} & Q_{t-1}	6-4-1	0.1629×10^9	0.980	0.3798×10^8	0.862
R_{t-2}, R_{t-1}, R_t H_t, H_{t-1}, H_{t-2} & Q_{t-1}	7-4-1	0.2024×10^9	0.971	0.1682×10^8	0.908
R_{t-2}, R_{t-1}, R_t H_t, H_{t-1} H_{t-2} Q_{t-1} & Q_{t-2}	8-3-1	0.2595×10^9	0.964	0.1404×10^8	0.909
Multi-linear regression		0.2266×10^9	0.967	0.7646×10^7	0.950

6.4.1 Analysis

It is observed that when the network is trained with an additional information, i.e., rate of rise of stage, the networks prove effective in comparison to the conventional technique. But while comparing the results with the previous case where the stage was mapped with discharge only, the results did not show any improvement. Therefore it can be concluded that for a large catchment situated in flat terrain as reflected by the current data set, the rate of rise of stage is not of much account in determining discharge. Furthermore, the daily stage, discharge data have been used in the present analysis. Therefore the rate of rise of stage obtained in an interval of 24 hrs may not carry that much significance in improving the network output.

6.5 ASSESSMENT OF SEDIMENT CONCENTRATION

For assessment of sediment concentration, a three layer network was trained. The input variables constituting stage, discharge, sediment concentration of different combinations were tried. In the present study, the following combinations of input data were chosen.

a) H_t, H_{t-1} , Q_{t-1} and S_{t-1}

b) H_t, H_{t-1}, H_{t-2}, Q_{t-1} and S_{t-1}

c) H_t, H_{t-1}, H_{t-2}, Q_{t-1} Q_{t-2} and S_{t-1}

d) H_t, H_{t-1}, H_{t-2}, Q_{t-1} ,Q_{t-2} ,S_{t-1} and S_{t-2}

e) H_t, H_{t-1}, Q_{t-1} ,Q_{t-2} ,S_{t-1} and S_{t-2}

f) H_t, H_{t-1}, H_{t-2}, Q_{t-1} ,Q_{t-2} ,S_{t-1} and S_{t-2}.

Here the output layer has two neurons, one for discharge Q_t and other for sediment concentration S_t.

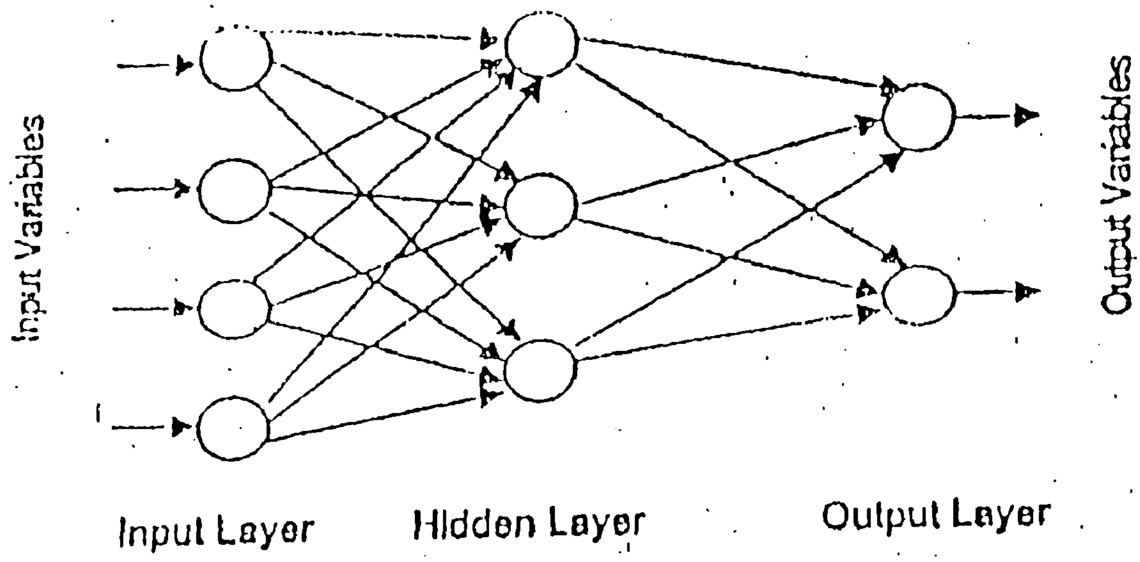


Figure 6.5: A typical three layer feed forward ANN for discharge and sediment concentration.

The data of stage, discharge, sediment concentration for the year (1982-83) were chosen for calibration and data for year 1983-84 were chosen for validation. The coefficient of correlation and SSE were evaluated for every combination. The configuration (6-4-2) gave the best combination of coefficient of correlation and SSE and hence was selected as the best structure. The same was compared with curve fitting.

The results are shown in table 6.3. Fig. 6.6 to 6.9 show observed and predicted discharge and sediment concentration for training and testing period.

6.5.1 Analysis

The table 6.3 shows the SSE and coefficient of correlation for ANNs and curve fitting. For both calibration period and validation period the ANN estimate gives better result for both discharge and sediment concentration. But for validation period, the sediment concentration from curve fitting estimate shows slight improvement over the ANN estimate. The graph shows that in curve fitting approach, one of the peaks in overestimated and one of peaks in ANN underestimated. Otherwise rest of the curve for ANN approach matches very closely with observed curve in comparison to the conventional technique.

ANANDAPUR SITE ON RIVER BAITARANI

6.6 NORMALIZATION

The data sets available for year 1984-85, 1985-86, 1986-87 were normalized.

Table 6.3

SSE and coefficient of correlation for ANN techniques and curve fitting – Training and testing data of Vijayawada site.

ANN model inputs	ANN Structure	Training data				Testing data			
		Discharge		Sediment		Discharge		Sediment	
		SSE	correl.	SSE	correl.	SSE	Correl.	SSE	Correl.
H_{t-1} H_t Q_{t-1} & S_{t-1}	4-3 -2	0.2101×10^7	0.997×10^6	0.3725×10^6	0.599	0.1712×10^9	0.974	0.9905×10^7	0.730
H_{t-2}, H_{t-1}, H_t Q_{t-1}, & S_{t-1}	5-4 -2	0.693×10^7	0.989	0.3164×10^6	0.691	0.7471×10^9	0.886	0.1141×10^8	0.485
H_{t-2} H_{t-1}, H_t Q_{t-2}, Q_{t-1}& S_{t-1}	6-10-2	0.3536×10^8	0.944	0.3731×10^6	0.560	0.5564×10^9	0.908	0.1105×10^8	0.490
H_{t-2}, H_{t-1}, H_t Q_{t-2}, Q_{t-1}, S_{t-2}, S_{t-1}	7-3-2	0.8457×10^7	0.989	0.2707×10^6	0.740	0.9360×10^9	0.809	1144×10^8	0.448
H_t, H_{t-1}, Q_{t-2}, Q_{t-1}, S_{t-2}& S_{t-1}	6-4-2	0.1074×10^8	0.984	0.3210×10^6	0.662	0.6459×10^9	0.916	0.7869×10^7	0.730
Curve fitting		0.4783×10^8	0.921	0.5643×10^6	0.5587	0.8054×10^9	0.8609	0.6487×10^7	0.760

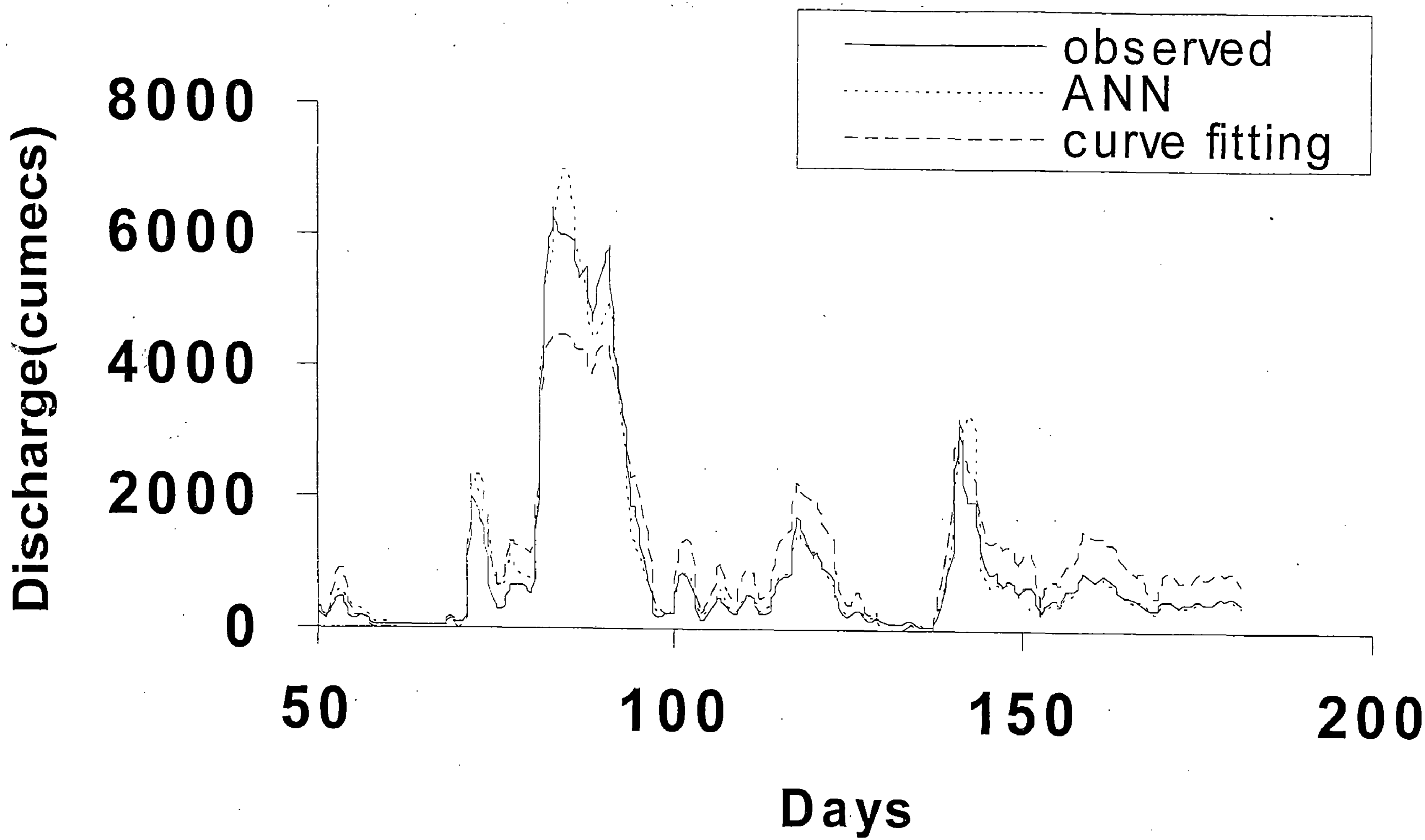


Fig 6.6 : Observed & computed Discharge - Training period for Vijayawada site (stage, discharge, sediment conc.)

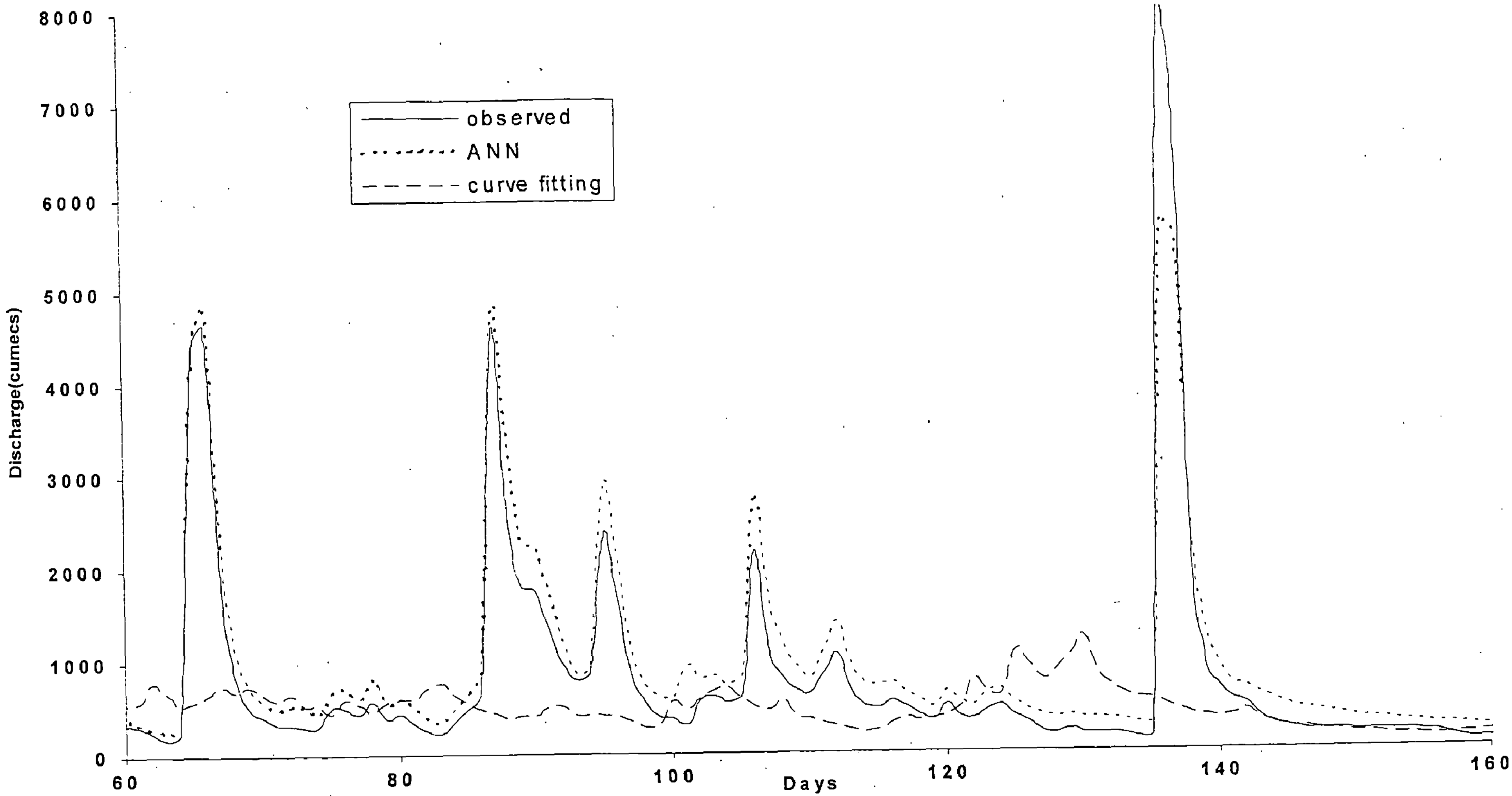


Fig 6.7: Observed & computed discharge – Testing period for Vijayawada site (stage,discharge,sediment conc.)

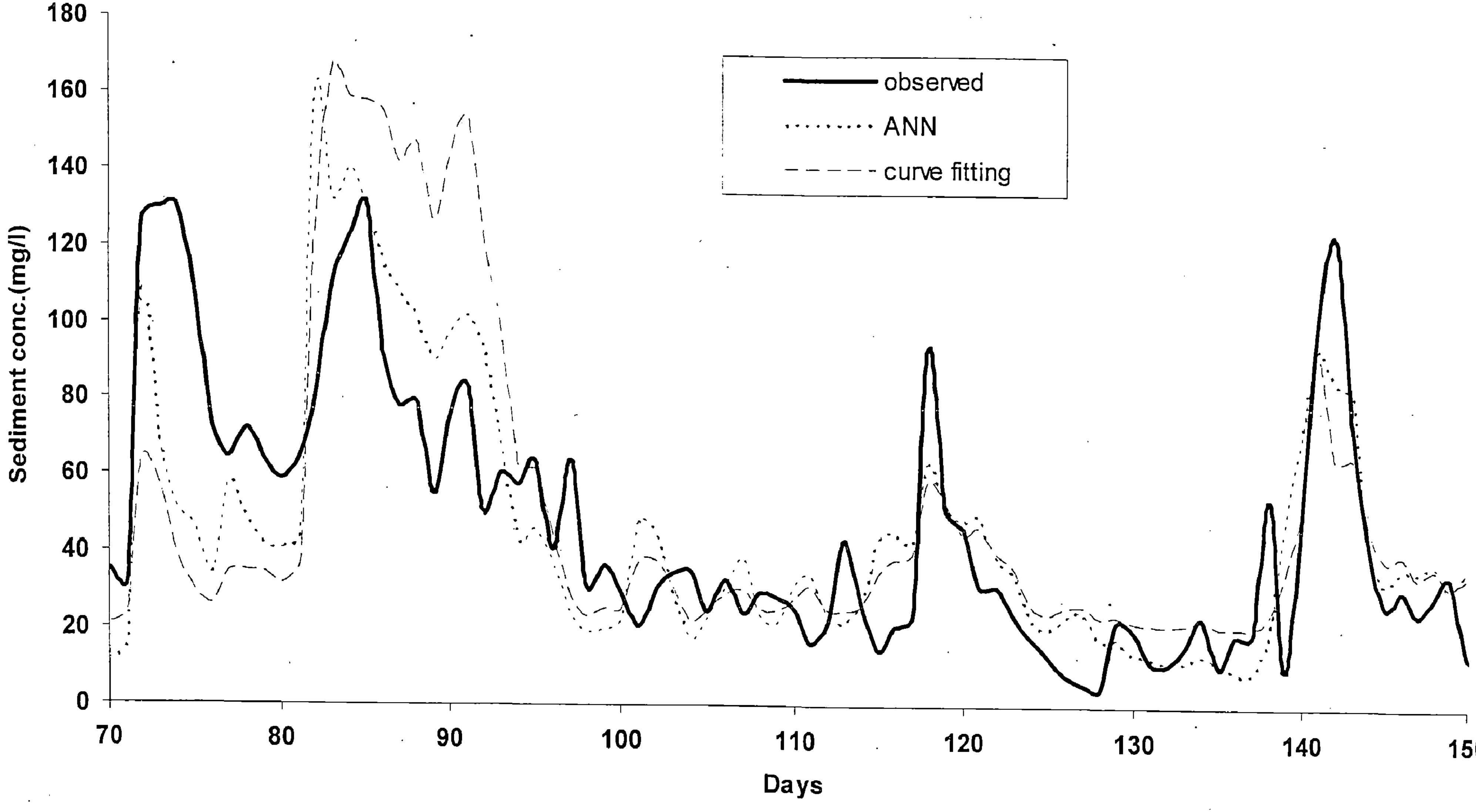


Fig 6.8: Observed & computed sediment conc. For Vijayawada site – Training period

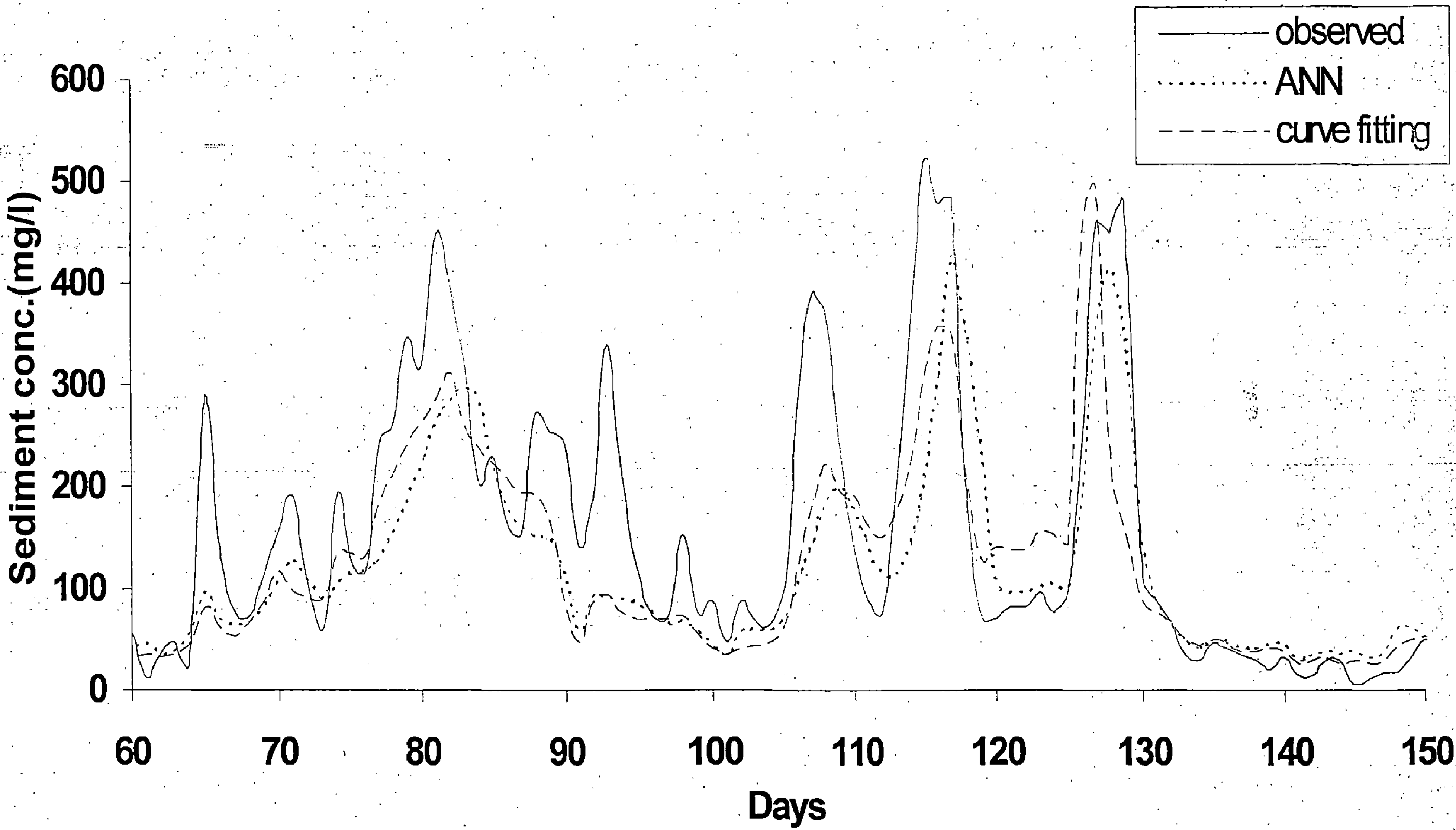


Fig 6.9: Observed & computed sediment conc. For Vijayawada site – Testing period

6.7 TRAINING THE NETWORK

A three layer feed forward network was trained with BP algorithm development by Rumelhart et.al.(1986). The input data for BP algorithm was prepared according to guidelines. In the trial networks, the number of hidden layer neurons was varied between 1 to 12. Each time SSE and coefficient of correlation were recorded.

The stage was mapped with discharge taking 1984-85, data sets for calibration and 1985-86 data sets for validation. The results were compared with curve fitting. Table 6.4 Shows the results for ANN and conventional techniques.

Table 6.4

Sum of square errors and coefficient of correlation for ANN models and conventional procedure- Training and Testing data for Anandpur Site.

ANN model inputs	ANN structure	Training data		Testing data	
		SSE	Coeff. Of correlation	SSE	Coeff. Of correlation
H_t	**1-10-1**	**0.2561×10^7**	**0.993**	**0.1539×10^8**	**0.970**
H_t, H_{t-1}	2-7-1	0.1847×10^8	0.911	0.9376×10^8	0.836
H_t, H_{t-1}, Q_{t-1}	3-4-1	0.1443×10^8	0.914	0.7961×10^8	0.842
H_t,H_{t-1} H_{t-2} & Q_{t-1}	4-2-1	0.1798×10^8	0.914	0.8638×10^8	0.844
H_t, H_{t-1} H_{t-2} Q_{t-1} & Q_{t-2}	5-4-1	0.1230×10^8	0.919	0.7308×10^8	0.839
Curve fitting		0.1862×10^8	0.870	0.8972×10^8	0.807

6.7.1 Analysis

After training the network, it is observed SSE and coefficient of correlation for ANN yield better results than curve fitting with BP algorithm. The network produces the best structure while mapping current stage with current discharge. The stage, discharge of the previous time periods does not carry much significance improving the network output.

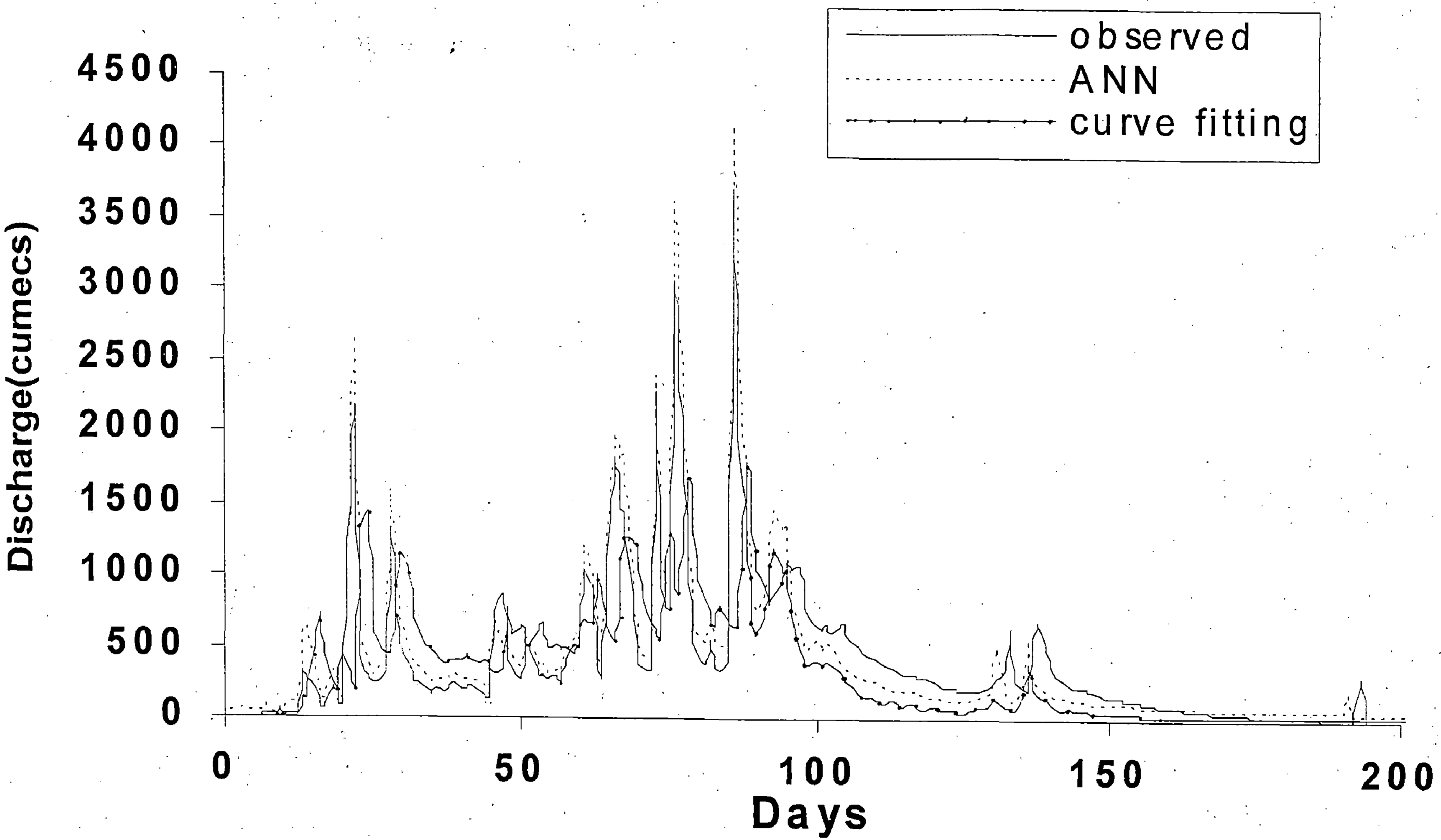


Fig 6.10: Observed & computed (conventional & ANN techniques) Discharge for Anandapur site – Training period

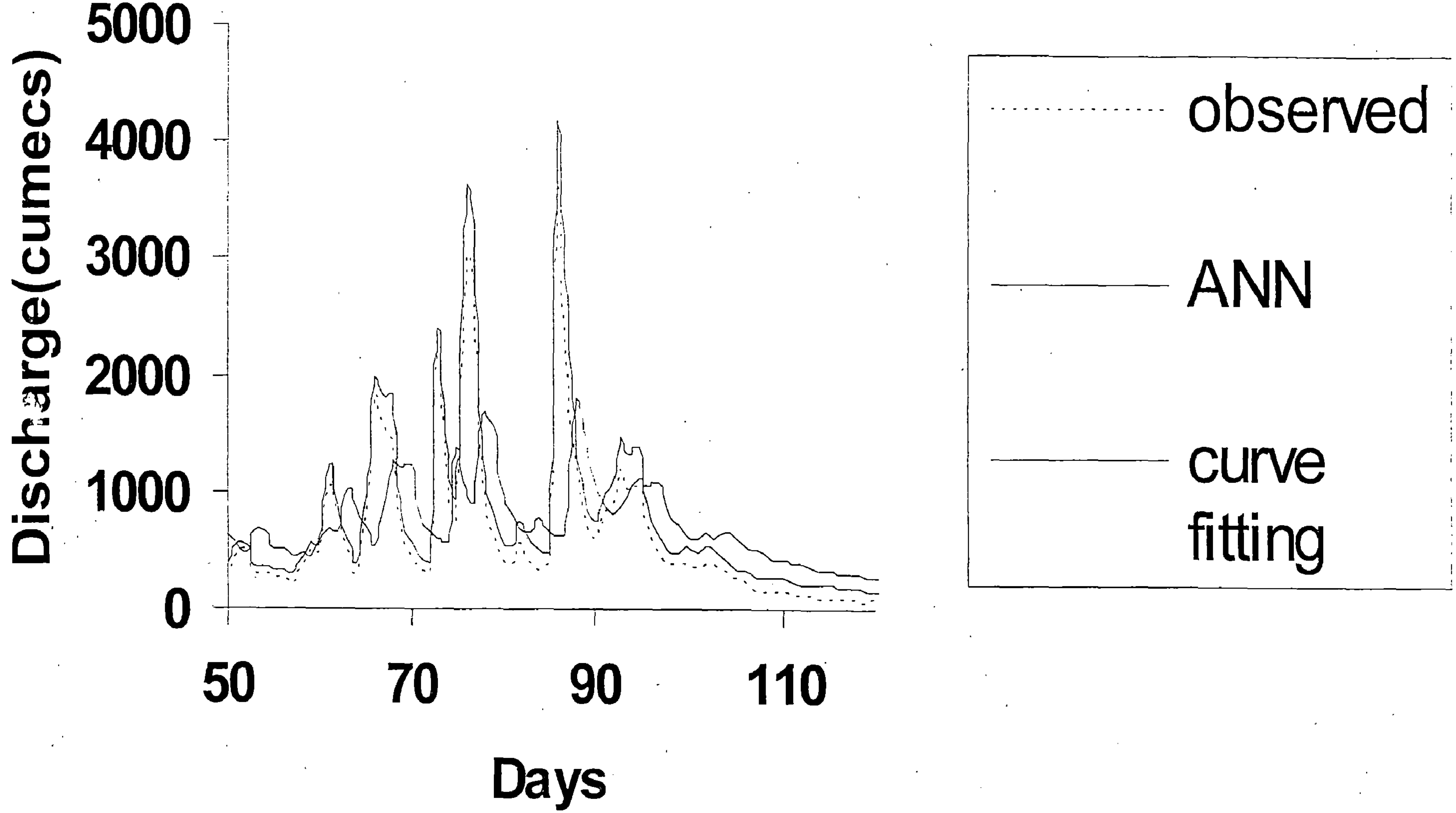


Fig 6.11: Observed & computed (conventional & ANN techniques) discharge showing peak for Anandapur sute – Training period

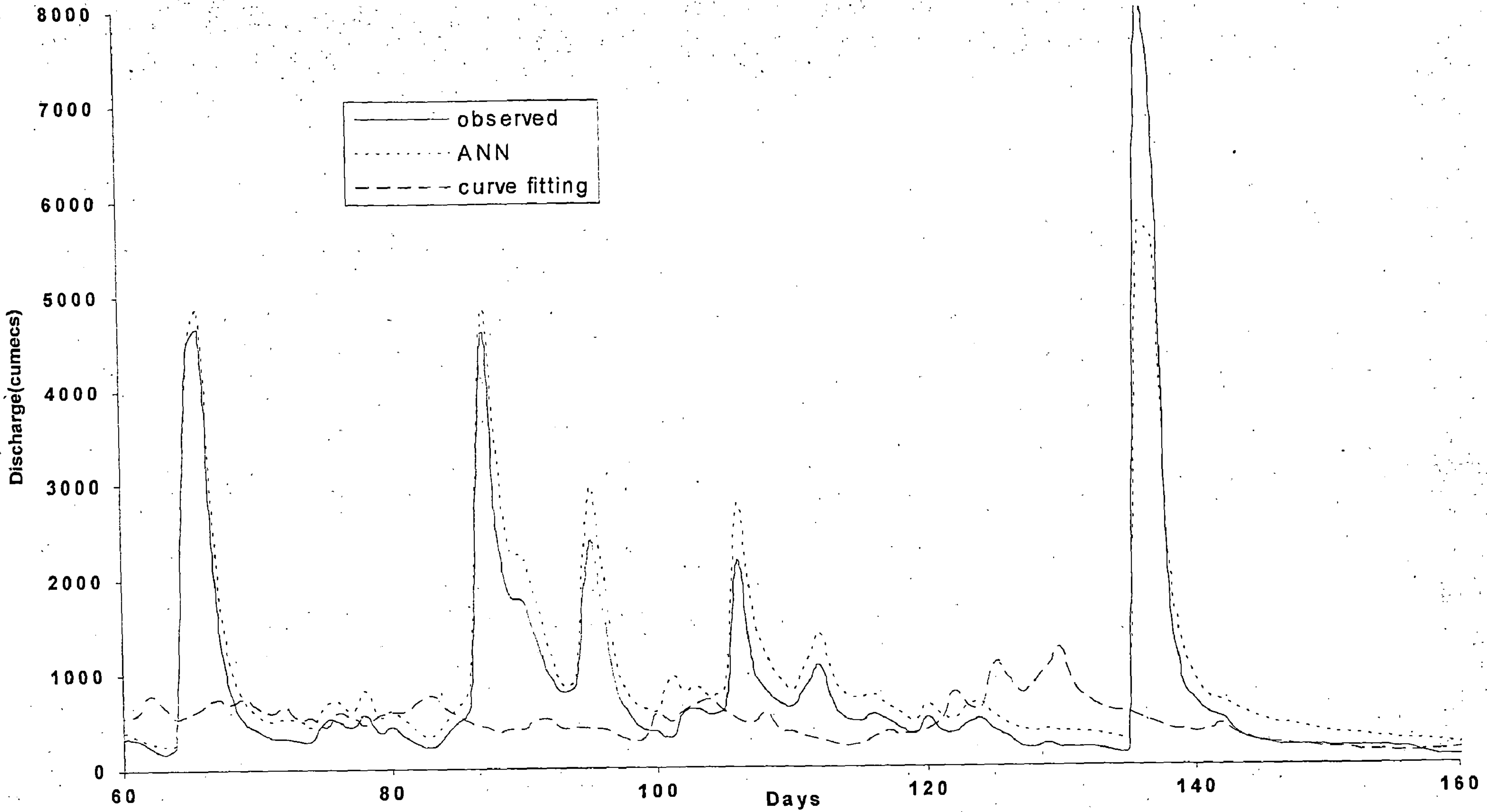


Fig 6.12: Observed & computed (conventional & ANN techniques) Discharge for Anandapur site – Testing period

CONCLUSION

In this dissertation work, the stage-discharge relation and sediment-discharge relation were set up through Artificial Neural Networks for Vijayawada gauging site on river Krishna and the LLSSIM algorithm was used. The data for another gauging site situated at Anandapur river Baitarani were chosen to map the stage-discharge through BP algorithm.

Conclusions derived from the above study are given below.

(i) ANN approach is much superior to conventional curve fitting, multi linear regression approach for establishing stage-discharge relation.

(ii) For a gauging site situated in flat terrain, the additional information like rate of rise of stage as an input variable does not improve the network results. The rate of rise of stage in an interval of 24 hrs does not prove to be an additional information for strengthening the network.

(iii) For establishing the stage-discharge-sediment concentration ANN approach yields better performance than the conventional technique.

(iv) In both LLSSIM and BP algorithms, while extracting the relationship between stage and discharge, the current stage is better mapped with current discharge

(v) While presenting the network the rate of rise of stage as an additional information for mapping stage and discharge relationship and also while assessing the sediment concentration, the inputs of previous time periods substantially help in refining the output of network.

RECOMMENDATION:

(i) Further study is required to verify the network output for the mapping of stage discharge with rate of rise of stage on hourly basis as an additional input .

(ii) The network performance is also required to study for providing cross sectional area at various stage as an additional information in the input layer.

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