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APPLICATION OF ARTIFICIAL NEURAL NETWORKS (ANN) IN RESERVOIR OPERATION

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PREFACE

The development of the economy of a country depends on its development of water resources. In India, many major and medium reservoirs have been constructed to meet the fast growing demands such as irrigation, hydropower generation, drinking water supply, and industrial water supply. Water resources systems are complex and need systematic study to arrive at optimal planning and management decisions. Many mathematical models are developed to make optimal releases from existing storage structures. Generally mathematical models are classified into simulation model, optimization model and the combination of these two models. The concepts inherent in the simulation approach are easier to understand and communicate than the other modeling concepts. But simulation modeling is time consuming to find optimal or near optimal releases. In recent years, the application of artificial neural networks in water resources system analysis is increasing. An ANN can represent any arbitrary function given sufficient complexity of the trained network.

In this report, two different neural network models were developed for Dharoi reservoir, Gujarat: one for flood control operation and the other for conservation operation. Feed forward structure was used to model the ANN. The networks were trained by back propagation algorithm. The floods of 10 July 1977, 22 June 1980 and 23 July 1982 were used to evaluate the trained neural network for flood control operation. The data set with actual release for 10 daily duration was considered for training and evaluating the ANN model for conservation operation. The data set with simulated release for monthly duration was also used to model the ANN and the results of this model was compared with the ANN model with actual release. The results are presented in tabular and graphical forms.

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ABSTRACT

Reservoirs, the most important elements of complex water resources systems, are constructed for spatial and temporal redistribution of water in quantity and quality. Ever increasing water demands and the difficulties associated with building new surface storage facilities envisage more efficient operation of existing reservoirs such as, improved coordination of reservoir operations and the effective use of streamflow and demand forecasts. Systems analysis has proved to be a potential tool in the planning and management of the available water resources. Reservoir system management practices and associated modelling and analysis methods involve allocating storage capacity and streamflow between multiple uses and users. The models developed to provide operating rules for reservoirs are classified as simulation models, optimization models and combination of these two models. Simulation models are used to study the reservoir system with different operating rules whereas optimization models are used to optimize the operation by considering the inflows, demands, reservoir characteristics, evaporation rates, etc., as constraints. Simulation models can also provide near optimized releases by repeated runs of different operating policies.

In recent years, Artificial Neural Networks (ANN) are increasingly being used to predict water resource variables. An ANN can represent any arbitrary nonlinear function given sufficient complexity of the trained network. Feed forward networks are generally used in ANN models. This type of ANN consists of three types of layers, namely an input layer, hidden layer(s) and an output layer. The input layer consists of number of neurons (for example, reservoir storage and inflow) on which depends the output neurons (for example, release). Generally sigmoid function is applied as activation function to provide the output. These networks are trained mostly by back propagation algorithm. The input and output neuron values are normalized between 0 and 1 before the training.

In the present study, two different neural network models were developed for Dharoi Reservoir, Gujarat: one for flood control operation and the other for conservation operation. Seven different combinations of input variables were trained for both flood control and conservation operation. The coefficient of correlation and the sum of squared errors for different network structures were compared and the combination, which gave the highest coefficient of correlation and small sum of squared errors, was selected.

The floods of 10 July 1977, 22 June 1980 and 23 July 1982 were used to evaluate the trained neural network for flood control operation. The floods were moderated as per the policy adopted in the training of the neural network and the end reservoir storage in all three floods were below revised HFL (193.60 m). So the trained neural network model can be used effectively to moderate the floods.

Two neural network models were developed for conservation operation: one with actual release for 10 daily duration and other with simulated release for monthly duration. The coefficient of correlation and the sum of squared errors were 0.609 and 5242 for neural network model with actual release for the evaluation data set. The coefficient of correlation and the sum of squared errors were 0.934 and 2134 for neural network model with simulated release for the evaluation data set. The neural network trained with the simulated release can be used to decide the release from the reservoir for conservation purposes.

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INTRODUCTION

Efficient water resources development and management is necessary for any country for its economic growth. The public needs and objectives and numerous factors affecting water resources management change over time. Population explosion and economic growth increases the water demand for various uses such as drinking and industrial water supply, irrigation, hydroelectric power generation, recreation, etc. In India more than 80 percent of rainfall occurs in the four monsoon months from June to September. More than 3000 major and medium multipurpose reservoir projects have already been constructed in India to regulate the streamflow for various uses. These storage structures are to be operated effectively and efficiently to meet the various demands to the maximum possible extent.

The operating policy is a set of rules for determining the quantities of water to be stored or released or withdrawn from a reservoir or system of several reservoirs under various conditions. Reservoir operators frequently follow traditional policies that prescribe reservoir releases based on limited criteria such as current storage levels, season, and demands. Operating policies can be derived using system techniques such as simulation, optimization and combination of these two. A simulation model is a representation of a system, which is used to analyze the behavior of the system under a given set of conditions. Identification of optimal policies using simulation is a difficult task when possible control policies are numerous. Repeated runs of simulation models with different possible operating policies can give near optimal releases. But optimization methods may be used to identify the optimal operating policies efficiently and accurately and the effort and risk of trial and error method in simulation models can be avoided.

A variety of generalized reservoir system simulation models like HEC-5, the Basin Runoff and Streamflow Simulation (BRASS), SWD (USACE Southwestern Division), the Streamflow Synthesis and Reservoir Regulation (SSARR), the Hydro System Seasonal Regulation (HYSSR), the Hydropower System Regulation Analysis (HYSIS), the Reservoir Operating Quality Routing Program (RESOP-II), MITSIM, the Water Right Analysis Program (TAMUWRAP), Interactive River System Simulation Program (IRIS) and, optimization models like HYDROSIM, MONITOR-I, REZES have been reported in the literature (Wurbs, 1993). It is difficult to develop generalized simulation and optimization models due to the inherent complexity present in every reservoir system. A Software package developed at NIH, known as Software for Reservoir Analysis (SRA), includes a generalized Multipurpose Multireservoir Simulation model (Jain et al, 1997). This module is fairly generalized but may require some modifications according to specific reservoir system details. It has been used to develop near optimal operation policies for Sabarmati river system, Bargi and Tawa Reservoirs (Jain et al, 1997, Jain et al, 1996, and Senthil Kumar et al, 1997).

In recent years, Artificial Neural Networks are being increasingly used to model hydrological processes due to their capability to represent any arbitrary nonlinear function given sufficient complexity of the trained networks. Some of the cited examples from the literature are rainfall-runoff modeling, rainfall prediction, flood forecasting, water quality modeling, ground water modeling, development of water management policy, and reservoir operation studies. (Maier et al, 2000; Raman et al, 1996; Jain et al, 1999).

1.1 The scope of this report

The scope of this report is to develop two neural network models for Dharoi Reservoir, Gujarat: one for flood control operation and the other for conservation operation. Feed forward ANN model structure has been used. Back propagation algorithm has been used to train the combinations.

This report consists of five chapters. The chapter two briefly presents the theory behind the Artificial Neural Networks, Artificial Neuron models, Neural Net Architectures, training of neural networks, the evaluation methods of trained networks and the application of neural networks in the field of hydrology. The chapter three describes the Sabarmati River Basin and the Dharoi reservoir. The chapter four presents the application of ANN to Dharoi reservoir for flood control and conservation operation. The chapter five gives the conclusions of the study.

CHAPTER 2

ARTIFICIAL NEURAL NETWORKS (ANN) AND THEIR APPLICATIONS

2.1 Introduction

The neural network of an animal is part of its nervous system, containing a large number of interconnected neurons (nerve cells). **Artificial Neural Networks** refer to computing systems whose central theme is borrowed from the analogy of biological neural networks. Artificial neural networks are also referred to as "neural nets", "artificial neural systems", "parallel distributed processing systems", and "connectionist systems." The biological unit outperforms any man made tool in terms of recognition, analysis, prediction, and particularly learning. ANN approach is faster compared with its conventional compatriots, robust in noisy environments, flexible in the range of problems it can solve, and highly adaptive to the newer environments. Due to these established advantages, currently the ANN has numerous real world applications such as image processing, speech processing, robotics, and stock market predictions. There has been extensive research on its implementation in the system engineering related fields such as, time series prediction, rule-based control, and rainfall-runoff modeling. Each of the following advantages of a neural network can be usefully exploited in constructing models of the water resource processes (Thirumalaiah et al, 1998):

a. Neural networks are useful when the underlying problem is either poorly defined or not clearly understood.
b. Their application does not require knowledge of the underlying process beforehand.
c. They are advantageous when specific solutions do not exist to the problem posed.
d. Neural networks are most suitable for dynamic forecasting problems because the weights involved can be updated when fresh observations are made available.
e. A small amount of errors in the input does not produce significant change in the output because of distributed processing.
f. They save on data storage requirements because it is not necessary to keep all past data in memory.
g. They do not require any exogenous input other than a set of input-output vectors for training purpose.

2.2 Artificial Neuron Models

An ANN consists of a number of neurons that are arranged in an input layer, an output layer, and one or more hidden layers. The input neurons receive and process the input signals and send the output to other neurons in the network where this process is continued. This type of network where information passes one way through the network is known as a feed forward network. The textbook written by Mehrotra et al (1997) can be referred for more types of neural networks. A three-layer feed forward ANN is shown in Fig. 1a.

The number of input nodes, N, and the number of output nodes, M, in an ANN are dependent on the problem to which the network is being applied. Unfortunately, there are no fixed rules as to how many nodes should be included in the hidden layer. If there are too few nodes in the hidden layer the network may have difficulty generalizing to problems it has never encountered before. On the other hand, if there are too many nodes in the hidden layer, the network may take an unacceptably long time to learn anything of any value.

Fig. 1b provides a closer look at an individual neuron (in the hidden and output layers). Each neuron, j, has a number of input arcs, x_1 to x_n. Associated with each arc, i, is a weight, w_{ij}, which represents a factor by which any values passing into the neuron are multiplied. A neuron, j, sums the values of all inputs according to the following equation:

$$S_j = \sum_{i=1}^{N} w_{ij} x_j + w_{oj}$$

In the above equation an additional term, w_{oj}, called a *bias*, has been included. An activation function is applied to the value S_j, to provide the final output from the neuron. This activation function can be linear, discrete, or some other continuous distribution function. However, in order to use the back-propagation algorithm to train a network, this function must have the property of being everywhere differentiable. The sigmoid function satisfies this criterion and is the function generally used in most feed forward neural network applications. This function is represented by:

$$f(x) = \frac{1}{1 + e^{-x}}$$

2.3 Training of Neural Networks

A network learns by adjusting the biases and weights that link its neurons. However, before training can begin, a network's weights and biases must be set to small random values. A practical rule of thumb is to set the weights and biases to random values in the range ($-2/\Omega$, $2/\Omega$) for a neuron with Ω inputs. If initial random weights are not limited to this kind of range, network learning may be slow as extreme initial positioning on the sigmoid function can restrict the extent to which weight changes are made by the training algorithm (Dawson et al, 1998).

Once a network has been initialized with preliminary weights and biases, the network is then trained by providing it with a number of examples (training pairs from the calibration set) which show the network how it is expected to behave. Each training pair has a particular input value (several, if there is more than one input node) and an expected output that the network should generate based on that input. The network is thus presented with this calibration data repeatedly (a specified number of epochs) until it is able to match its outputs with those that are expected (or closely enough to be acceptable). The way in which this training occurs is through the use of a training algorithm called back-propagation. This algorithm is currently the most common approach to train feed forward ANN (Dawson et al, 1998).

The basis of the back-propagation algorithm is that a training pair is selected from the training set and applied to the network. The network calculates the output, which should be based on the inputs provided in this training pair. The resultant outputs from the network are then compared with the expected outputs identified by the training pair. The weights and biases of each neuron are then adjusted by a factor based on the derivative of the sigmoid function, the differences between the expected network outputs and the actual outputs (the error), and the actual neuron outputs. Through these adjustments it is possible to improve the results that the network generates, and thus the network is seen to *learn*. How much each neuron's weights and bias are adjusted in the back-propagation algorithm also depends on a *learning parameter* - a single factor by which all adjustments are multiplied. A large learning parameter can mean that training oscillates from one poor extreme result to another, whilst a small learning parameter can lead to a situation where the network does not learn anything and is caught in a local minimum, unable to take a bold step to reach a more accurate set of weights. Fig. 1c provides an example where only one weight is adjusted in order to reduce a network's error.

W_1 in Fig. 1c highlights the concept of local minima in which a network can become trapped during training if the learning parameter is too small. In this case the adjustment cannot lift the weight over the "hills" on either side of W_1 and the network stabilizes with this error. Ideally the network would like to stabilize at W_2 but unless the learning parameter is increased this is impossible. One way around this problem is to use a variation of the back-propagation algorithm, where the learning parameter is dynamically adjusted or, alternatively, retraining the network from scratch starting with a different set of initial weights and biases that may, by chance, be closer to W_2 to start with. Obviously, it takes more than one iteration of the back-propagation algorithm for a network to learn. In addition, a network must also be shown all the training pairs that are available, otherwise it will learn only one input and output combination and will not be able to generalize.

Many new algorithms have been introduced to improve the BP-ANN performance and to counteract the problems mentioned in the above paragraph. The problems of local optima and slow convergence can be over-come by adding momentum and noise terms. The momentum term determines the effect of previous weight changes on the present change in the weight space; this frees a solution trapped by local optima. Adding a momentum term sometimes results in much faster training. The addition of noise is another approach to break out of local minima. In this, a random number is added to each component of the input vector as it is applied to the network. Provision should be made in the simulator to send the noise to input patterns within a desired range. To counter the ineffective architecture and the sensitivity of BP-ANN to initial starting point, an initial randomized weight space should be adopted. This helps in breaking the symmetry. In case the convergence is slow or found to be locked up, the weight matrix should be broken and a new initial weight matrix, randomized with desired range should be given. This process should be continued until convergence is visible during the use of the simulator. The existing input pattern should be shuffled and resent to the simulator to counter the input pattern sensitivity of the BP algorithm effectively. The training cycles should be decided on the basis of faster convergence compared with others, including the one that restrains the patterns exactly between 0 and 1. Minns and Hall (1996) have emphasized the importance of the correct standardization factors. They mentioned that the choice of standardization ranges significantly influences the performance of the ANN, and they have cautioned that the ANN should not be used for extrapolation.

2.4 The standardization of Input data

Due to the nature of the sigmoid function used in the back-propagation algorithm, it is prudent to standardize (i.e. convert to the range (0, 1)) all input values before passing them into a neural network. Without this standardization, large values input into an ANN would require extremely small weighting factors to be applied. This can cause a number of problems:

1. Due to inaccuracies introduced by floating point calculations on microcomputers, one should avoid using the very small weighting values that would be required.
2. Without using extremely small initial weights, changes made by the back-propagation algorithm would be insignificantly small, and training would be very sluggish, as the gradient of the sigmoid function at extreme values would be approximately zero. It is this gradient that is used in the adjustment of weights and biases in an ANN during training.

Due to the output range of the sigmoid function, all values leaving an ANN are automatically output in a standardized format. These output values must be "destandardized" to provide meaningful results. This can be achieved by simply reversing the standardization algorithm used on the input nodes. This requires care when one handles real life data, as one must standardize all the data involved as well as decide on the optimum way to achieve this.

There are two ways to approach data standardization: the values are standardized with respect to the range of all values; and the values are standardized with respect to the sum of squares of all values.

For example, for input values, these calculations are performed as follows:

$$N_i = \frac{R_i - Min_i}{Max_i - Min_i}$$

$$N_i = \frac{R_i}{\sqrt{SS_i}}$$

where R_i is the real value applied to node i; N_i is the subsequent standardized value calculated for node i; Min_i is the minimum value of all values applied to node i; Max_i is the maximum value of all values applied to node i; SS_i is the sum of squares of all values applied to node i. There are no fixed rules as to which approach should be used in particular circumstances and there has been very little research on the subject (Dawson et al, 1998).

2.5 Evaluation of Networks

In order to train and test artificial neural networks, it is necessary to have two sets of training data-a calibration set and a validation set. Having trained a network with calibration data the accuracy of the results obtained from that network can be assessed by comparing its responses with the validation set. The comparison can be made using the sum of squared error (SSE) calculated as follows:

$$SSE = \sum_{p=1}^{N} (T_p - O_p)^2$$

where T_p = target value for the pth pattern; O_p = ANN output value for the pth pattern; and N = total number of patterns. The comparison can also be made by the coefficient of correlation between the target and output values of the validation set as follows:

$$r = \sum_{p=1}^{N} \frac{(T_p - \overline{T})(O_p - \overline{O})}{\sqrt{(T_p - \overline{T})^2 (O_p - \overline{O})^2}}$$

where T and O are mean of target and output values of the validation set.

2.6 Uses of Neural Networks

The tasks performed using Neural Networks can be classified as supervised and unsupervised learning. In supervised learning, a teacher is available to indicate whether a system is performing correctly, or to indicate a desired response, or to validate the acceptability of a system's response, or to indicate the amount of error in system performance. In unsupervised learning, no teacher is available and learning must rely on guidance obtained heuristically by the system examining different sample data or the environment. The example of supervised learning is provided by classification problems whereas clustering provides an example of unsupervised learning.

The neural networks approach can be used in classification, clustering, vector quantification, pattern association, function approximation, forecasting and control applications.

Neural Networks have been used to classify samples i.e., map input patterns to different classes. For instance, each output node can stand for one class. An input pattern is determined to belong to class i if the ith output node computes a higher value than all other output nodes when that input pattern is fed into the network. In some networks, an additional constraint is that the magnitude of that output node must exceed a minimal threshold, say 0.5.

In clustering problems, all that is available is a set of samples and distance relationships that can be derived from the sample descriptions. For example, flowers may be clustered using features such as color and number of petals.

Neural Networks have been used for compressing voluminous input data into a small number of weight vectors associated with nodes in the networks. Vector quantification is the process of dividing up space into several connected regions, a task similar to clustering.

In pattern association, another important task that can be performed by Neural Networks, the presentation of an input sample should trigger the generation of a specific output pattern.

Function approximation is the task of learning or constructing a function that generates approximately the same outputs from input vectors as the process being modeled, based on available training data.

There are many real life problems in which future events must be predicted on the basis of past history. Neural networks can be used to forecast the future events. In forecasting problems, it is important to consider both short term and long term predictions.

Control addresses the task of determining the values for input variables in order to achieve desired values for output variables. This is also a function approximation problem, for which feed forward, recurrent and some specialized networks have been used. Adaptive control techniques have been developed for systems subject to large variations in parameter values, environmental conditions, and signal inputs. Neural networks can be employed in adaptive control systems to provide fast response without requiring human intervention.

2.7 The applications of Artificial Neural Networks

The concept of the artificial neurons was first introduced by McCulloch and Pitts (Maier and Dandy, 2000) in 1943. They used this concept in biophysics. From then onwards it has been effectively used in the areas of finance, power generation, medicine, water resources and environmental science for prediction and forecast. Many studies are reported in the literature on the application of Artificial Neural Networks in the field of water resources. About 43 works related to forecasting of streamflow, river stage, rainfall, water table fluctuation, algal concentration, pH concentration, and salinity are reported in the review paper of Maier and Dandy (2000). Application of ANN to reservoir operation studies is reported only in two technical papers in the journals. Some of the technical papers related to streamflow forecasting and reservoir operation studies are briefly described as in the following paragraphs.

Dawson and Wilby (1998) used artificial neural network approach to rainfall-runoff modelling. They applied it for two flood prone catchments in UK using real hydrometric data. They compared the performance of ANN with conventional flood forecasting systems. They used multilayered feed forward network structure to model the flood forecasting system and back propagation algorithm for training the network combinations. They explained the capability of ANN, the general structure used for the modelling, training of the structures, standardization of the data before training and the method to evaluate the network performance. They concluded that from the validation simulations that there is considerable scope for the development of a fully operational ANN flood forecasting system.

Jain, Das and Srivastava (1999) used artificial neural network for reservoir inflow prediction and the operation for Upper Indravati Multipurpose project, Orissa. They developed two ANNs to model the reservoir inflows and to map the operation policy. Feed forward structure was used for ANN model. Back propagation algorithm was used for training the neural networks. An auotregressive integrated moving average time series model was constructed to fit the monthly inflow series. They found that ANN was suitable to predict high flows and auotregressive integrated moving average time series model was suitable to predict low flows. The optimal releases were derived using nonlinear regression by relating inflow, storage and demand. They concluded that ANN was a powerful tool for input-output mapping and can be used effectively for reservoir inflow forecasting and operation.

Kao (1996) used artificial neural networks to determine the drainage pattern from DEM data. They compared the results with other seven methods. Feed forward structure was used to model the ANN. Back propagation algorithm was used for training the neural network model. They applied this model to a subwatershed located on Chin-Mei Creek, Taipei County, Taiwan. They found that results obtained using neural network method are superior than the results obtained by the drainage network method, which was performed better than other seven methods.

Maier and Dandy (2000) reviewed the works done in the application of artificial neural networks to predict and forecast water resources variables. They outlined the steps to be followed in the development of such ANN models. A review of 43 papers in the prediction and forecasting of water resources variables were considered for laying down the procedure to model the ANN structure. They found that almost in all papers, feed-forward networks were used to model ANN and majorities of these networks were trained by back propagation algorithm. They concluded that ANNs were being used increasingly for the prediction and forecasting of a number of water resources variables, including rainfall, flow, water level and various water quality parameters. They also pointed that in all the papers, the modelling theory was explained poorly.

Maier and Dandy (1999) used six methods to optimize the connection weights of feed forward ANN. Those were the generalized delta (GD) rule, the normalized cumulative delta (NCD) rule, the delta bar delta (DBD) algorithm, the extended delta bar delta (EDBD) algorithm, the quickprop (QP) algorithm, and the maxprop (MP) algorithm. They applied all these methods to forecast the salinity in the river Murray Bridge, South Australia. They concluded that any impact different learning rules have on training speed is masked by the effect of epoch size and the number of hidden nodes required for optimal model performance.

Raman and Sunilkumar (1995) used artificial neural network for the synthesis of inflows to two reservoirs Mangalam and Pothundy located in the Bharathapuzha, Kerala. Real observations were used to train and test the feed forward networks. Feed forward structure was used to model the

ANN. They used back propagation algorithm to train the data set. They remarked that the neural network provided a very good fit with the data. They compared the results of ANN model with autoregressive model. They concluded that ANN model could be used to model the water resource time series in place of multivariate modelling.

Raman and Chandramouli (1996) used artificial neural networks for deriving better operating policy for the Aliyar Dam in Tamil Nadu. They used feed forward structure to model the ANN. Back propagation algorithm was used for training the neural networks. They derived the operating policies using three models, dynamic programming (DP) model, stochastic dynamic programming model (SDP) and standard operating policy (SOP). General operating policies were derived using neural network model (DPN) from the DP model. They compared the results of ANN with regression model (DPR). They concluded that the neural network procedure based on the dynamic programming algorithm provided better performance than the other models. They remarked also that the neural network approach could allow more complex modelling than the regression procedure and this approach was able to produce a suitable degree of nonlinear components with the required complexity to match the considered patterns as closely as possible.

Thirumalaiah and Deo (1998) used artificial neural networks in real time forecasting of water levels at a given site continuously throughout the year based on the same levels at some upstream gauging station and/or using the stage time history recorded at the same site. They used feed forward structure to model the river stage forecasting system. The network was trained by three algorithms namely, error back propagation, cascade correlation, and conjugate gradient. They compared the results with each other. The trained networks were verified with untrained data. They concluded that the continuous forecasting of a river stage in real time sense was possible through the use of neural networks.

Yang et al (1997) developed an artificial neural network (ANN) model to simulate fluctuations in midspan water table depths and drain outflows as influenced by daily rainfall and potential evapotranspiration rates. The model was developed using field observations of water table depths from 1991 to 1993 and drain outflows from 1991 to 1994 made at an agricultural field in Ottawa. They used feed back procedure first for ANN model and they introduced lag procedure to improve the simulation results. The training was done by back propagation algorithm. They concluded that it is highly desirable in ANN modelling to have a training data set that includes both general and extreme conditions. Otherwise the model performance may not be very satisfactory.

Zealand, Burn and Simonovic (1999) used the artificial neural networks to forecast the short-term streamflow. They explored the possibility of using ANN over the conventional methods for the forecasting of the flood. They examined the size of input data and the number, and the size of the hidden layers of ANNs. Feed forward structure of the ANN was used in the forecasting of streamflow. The sigmoidal function was used as activation function in this study. Back propagation algorithm was used for the training of the network. The trained ANN had been applied to Winnipeg River System (catchment area 20000 km^2) in Northwest Ontario, Canada. From the results they concluded that ANN approach might provide a superior alternative to the time-series approach for developing input-output simulations and forecasting models in situations that do not require modelling of the internal structure of the watershed.

It is observed from the literature that the majority of the studies using ANN technique are in the field of streamflow and rainfall forecasting. Few studies have been concentrated in reservoir operation, forecasting of salinity, derivation of drainage pattern, and water table fluctuation. In most of the studies, feed forward structure and the back propagation algorithm have been used to design and train the ANN models respectively. On the basis of the literature review, it has been decided to design the ANN model with three layered feed forward structure and to use back propagation algorithm to train the designed ANN model structure in this study.

CHAPTER 3

DESCRIPTION OF THE STUDY AREA

3.1 The Sabarmati River Basin

The river Sabarmati is one of the major west flowing rivers of India. The river rises in the Aravalli range at north latitude 24°40' and east longitude 73°20' in the Rajasthan state at an elevation of 762 m near the popular shrine of Amba Bhavani and further flowing through the Gujarat state, outfalls into the Gulf of Cambay. The drainage basin of the river extends over an area of 21,085 sq. km and lies between longitude 71°55' E to 73°49' E and latitude 22°15' N to 24°54' N. The basin drains a part of the Rajasthan state and parts of Sabarkantha, Ahmedabad, Banaskantha, Mehsana, Surendranagar and Kaira districts of Gujarat state.

The length of the basin is about 300 km and it is about 105 km wide. The topography of the Sabarmati basin can be considered to be hilly in the early reaches up to the Dharoi dam after which, the river flows mostly in plains.

3.2 The Sabarmati River System

The Sabarmati river is one of the four main rivers which traverse the alluvial plains of Gujarat. After traversing a course of about 48 km in the Rajasthan state, the river enters the Gujarat state. At the 51st km of its run, the Wakal river joins it from the left near the village Ghonpankhari. Flowing in a generally southwest direction among the jungle covered hills, at the 67th km of its run, the Sei river joins it from the right near Mhauri. At about 103 km from the source, the Harnav river joins it from the left which enters directly in the Dharoi reservoir. Emerging from the dam, it travels through the alluvial plains of Gujarat. At about 170 km from its source, it is joined by the Hathmati river from the left. Continuing to flow southwestward, the river passes through the Ahmedabad city, about 165 km downstream of the Dharoi dam. Further 65 km downstream, another tributary, the Watrak joins the river Sabarmati from the left. Flowing for a further distance of 68 km, the river outfalls into the Gulf of Cambay in the Arabian sea.

On the Sei river, a diversion dam has been constructed in the Rajasthan state and one such diversion dam has also been proposed on the river Wakal. On the Harnav river, a storage dam as well as a diversion weir have been constructed. On the Hathmati river, a reservoir, a pick up weir and a canal system have been constructed for providing irrigation. The river Guhai meets the river

Hathmati between the dam and the weir. Across the river Guhai, a storage dam has been constructed near Khandhol. Downstream of the Ahmedabad city, a barrage namely, Wasna barrage has been constructed across the river Sabarmati for diverting water for irrigation and water supply. An index map of the basin is given in Fig. 2.

3.3 The Climate in the Sabarmati Basin

The Sabarmati basin experiences four distinct seasons. The winter season begins in December and is over by the end of February. During this period, light rainfall occasionally occurs. The summer season begins from March and ends about mid June. Sometimes, thunderstorms occur during this period. The monsoon sets in by the middle of June and continues till the end of September. During this period, about 95% of the total annual average rainfall occur. Heavy showers generally occur in association with monsoon depression from the Bay of Bengal and the Arabian Sea. The Sabarmati river sometimes sends down very heavy floods and some of these have caused devastation in Ahmedabad and villages in the downstream, destroyed crops, carried away cattle, changed the course of the delta channels and filled up harbour with silt. The highest known floods have occurred in 1875, 1941, 1950 and 1973.

The upper reaches of the basin receive an average annual rainfall of over 900 mm. In contrast, the lower reaches receive only about 650 mm. The average annual rainfall, for whole of the catchment, is about 785 mm.

3.4 The Physical Characteristics of Dharoi Dam

Dharoi reservoir is a multipurpose reservoir located about 165 km upstream of the city of Ahmadabad, Gujarat and it is the major flood controlling structure in Sabarmati basin. The other purposes of this reservoir are irrigation, domestic water supply to Ahmadabad and Gandhinagar cities and hydroelectric power generation.

The most important structure located in the Sabarmati basin is the Dharoi dam. This dam is located in district Mehsana, taluka Kheralu, village Dharoi, about 103 km from the source of the river. The latitude and longitude of the dam is 24°00' N and 72°52' E respectively. The dam was completed in the year 1976. The total catchment area at the dam site is 5540 sq.km. and the live and dead storage capacities of the reservoir (as per revised capacity plan after 50 years) are 775.89 and 131.99 M Cum respectively.

Upstream of the Dharoi dam, there is a gauging site on the river Sabarmati at Kheroj. The inflow forecast for the Dharoi dam is issued when the discharge of the order of 567 cumec (20000 cusec) or more is expected to enter the reservoir at any time. The Dharoi reservoir moderates the inflow in the space provided between FRL (189.59 m) and (HFL 193.60 m) to protect the downstream area from flooding. The safe carrying capacity of river downstream of the dam is 14160 cumec (5 lakh cusec).

3.5 The Operational Purposes of the Dharoi Dam

The purposes of the reservoir are (i) to moderate the incoming floods so that the controlled discharge at the Ahmedabad city does not exceed 14160 cumec (5 lakh cusec) up to the inflow rate of 21665 cumec (7.65 lakh cusec). The restricted outflow should be allowed up to 16992 cumec (6 lakh cusec) if the inflow rate increases. (ii) to meet water supply requirements for the cities of Ahmedabad and Gandhinagar. (iii) irrigation requirements for the command area (iv) hydroelectric power generation. The power plants at the dam site have not yet been installed.

CHAPTER 4

APPLICATION OF ANN TO DHAROI RESERVOIR FOR FLOOD CONTROL AND CONSERVATION OPERATION

4.1 Data used for the study

The river Sabarmati has experienced heavy floods in the past. The peak of the design flood for the Dharoi reservoir is 27180 cumec while the volume of the design flood hydrograph is 3095.26 M Cum. The available storage space between FRL (189.59 m) and HFL (193.60 m) for flood moderation is 491.16 M Cum. The main industrial cities that are located on the banks of the Sabarmati river are Gandhinagar and Ahmedabad. The safe channel capacity of the Sabarmati river at Ahmedabad is 14160 cumec (5.0 lakh cusec). The Dharoi reservoir is to be operated so that the total flow in the river at Ahmedabad, including the flow from the catchment downstream of Dharoi, does not exceed 14160 cumec. One constraint on the release from the spillways is that the discharge should not exceed 16992 cumec.

The Dharoi reservoir is to be operated for flood control as soon as the level in the reservoir exceeds the full reservoir level. In the Sabarmati System studies (1997), the methodology of simulation was adopted for deriving the optimal policy for flood regulation. Various policies of the flood regulation were tried using various scenarios of safe channel capacity and different conditions in the reservoir. An exhaustive flood control simulation of the reservoir was carried out using the design flood hydrograph. The results of simulation were intercompared. The policy which best met the objectives was finally recommended for adoption. The ordinates of PMF hydrograph are presented in Table 1.

The operation policy for the reservoir when PMF hydrograph is input, the safe carrying capacity of downstream channel is 9000 cumec, maximum spillway release capacity is 14900 cumec, only 90 percent gates are operational and beginning reservoir storage is 829.415 M Cum was available. This was used to train the neural network model for flood control operation.

In the above-mentioned policy, the following conditions were considered.

a) the maximum release through the spillway is restricted to channel capacity (9000 cumec).

b) the total release is restricted to either the release capacity of the spillway or the assumed maximum spillway release whichever is minimum if the inflow is greater than the restricted maximum spillway capacity (16992 cumec) till the reservoir level reaches to emergency level (191.00 m).

a) the total release is restricted to the channel capacity (9000 cumec) till the reservoir level reaches to the bottom level (189.59 m) of the flood control zone.

The data used for developing neural network model for flood control operation is presented in Table 2.

The actual release from the reservoir for irrigation and drinking water supply, reservoir storage and inflow for 10 daily duration from 1976 to 1999 have been considered to model the conservation operation. This data were collected from the project authority. The 10 daily demands have been taken from final report of consultancy project of the Sabarmati System Studies(1997). The data with actual release used for developing the neural network model for conservation operation is presented in Table 3.

4.2 Development and training of ANN

The learning algorithm adopted for the network was of a supervisory mode, batch-processing type, based on the generalized delta rule proposed by Rumelhart et al. (1986). The adjustment of the interconnection weights during training employs the error BP algorithm. In the BP algorithm, the weight associated with a neuron is adjusted by an amount proportional to the strength of the signal in the connection and the total measure of the error. The total error at the output layer is then reduced by redistributing this error backward through the hidden layers until the input layer is reached. This process continues for the number of prescribed sweeps or until a prescribed error tolerance is reached. The computer program for the training of the neural network was readily available and the same has been used for training the network structure for flood control and conservation operation. As mentioned by Dawson et al (1998) different combinations are to be considered to make the network learning more generalized.

4.2.1 Flood Control Operation

Using the data for flood control operation, the combination of inflow(t) and reservoir storage(t) as input neurons and total release(t) as output neuron was considered for the initial training. A program was written to prepare the training data (standardized) which vary from 0 to 1. This combination was trained with error tolerance (the difference between the targeted and expected values), learning parameter, the number of cycles for learning and the neurons in the hidden layer as 0.01, 0.1, 100 and 2 respectively. Then the summation of weights multiplied by the input values was passed through the activation function to get the expected value from the trained network. These expected values were denormalised (destandardized) to match with the targeted values. The match was checked by the sum of squared errors and the coefficient of correlation. In the training of the above-mentioned combination, the number of cycles were increased in steps upto 5000 and it was found that the convergence was static for these number of cycles. So 5000 was selected as a constant value for the number of cycles and was used for the training of other combinations. For this initial combination, the sum of squared error of targeted and expected values was very high (808610000) and coefficient of correlation was low (0.850). Then the network was trained with the decreased values of error tolerance and increased values of the learning parameter. The learning parameter and the error tolerance were fixed with low sum of squared errors and high coefficient of correlation. The neurons in the hidden layer were increased from minimum to the number from where the coefficient of correlation decreases. The number of neurons, which gave highest coefficient of correlation, was selected for this combination. It was observed that convergence for this combination was achieved with the error tolerance, the learning parameter, the number of cycles and neurons in the hidden layer as 0.001, 0.1, 5000 and 5 respectively. The sum of squared error was 685139600 and the coefficient of correlation was 0.911. It was noticed during training that the rate of convergence was fast in initial sweeps, but after some additional sweeps, it was either static or was very slow. To get the optimized weights for the neural network model, the following combinations of inputs were tried as described above:

a) inflow(t-1), inflow(t) and reservoir storage(t);
b) total release(t-1), inflow(t) and reservoir storage (t);
c) inflow(t-1), total release(t-1), inflow(t) and reservoir storage(t);
d) inflow(t-2), inflow(t-1), inflow(t) and reservoir storage(t);
e) inflow(t-2), inflow(t-1), total release(t-1), inflow(t) and reservoir storage(t);

f) inflow(t-2), inflow(t-1), total release(t-2), total release(t-1) inflow(t) and reservoir storage(t).

In all cases the output neuron was total release(t).

Table 4 shows the results of the training for different combinations for flood control operation. It was noticed that the best convergence was achieved for the combination of total release(t-1), inflow(t) and reservoir storage (t) as input neurons, total release(t) as output neuron with the error tolerance, the learning parameter, the number of cycles and neurons in the hidden layer as 0.001, 0.4, 5000 and 3 respectively. The sum of squared error was 96978130 and the coefficient of correlation was 0.983. Then the weights for this best trained structure were freezed to evaluate the trained network for the flood control operation. The optimal weights for this best trained network structure are presented in Table 5.

4.2.2 Conservation Operation

The combination of inflow(t), reservoir storage(t) and total demand(t) (irrigation and drinking water supply) as input neurons, total release (t) (irrigation and drinking water supply) as output neuron was considered for conservation operation with the error tolerance, the learning parameter, the number of cycles and neurons in the hidden layer as 0.01, 0.1, 5000 and 2 respectively. For this initial combination, the sum of squared error of targeted and expected values was high (41517) and the coefficient of correlation was low (0.522). Then the network was trained with the decreased values of error tolerance, increased values of the learning parameter, the number of cycles and the neurons in the hidden layer as explained in the previous section. It was observed that convergence for this combination was achieved with the error tolerance, the learning parameter, the number of cycles and neurons in the hidden layer as 0.001, 0.7, 5000 and 4 respectively. The sum of squared error was 37499 and the coefficient of correlation was 0.585. From the results of initial training, it was decided to train the network with different combinations as mentioned below to get the better neural network structure. The following are the different combinations of inputs to the neural network structure.

a) inflow(t-1), inflow(t), reservoir storage(t) and total demand(t);
b) total release(t-1), inflow(t), reservoir storage (t) and total demand(t);
c) inflow(t-1), total release(t-1), inflow(t) reservoir storage(t) and total demand(t);

d) inflow(t-2), inflow(t-1), inflow(t) reservoir storage(t) and total demand(t);

e) inflow(t-2), inflow(t-1), total release(t-1), inflow(t) reservoir storage(t) and total demand(t);

f) inflow(t-2), inflow(t-1), total release(t-2), total release(t-1) inflow(t) reservoir storage(t) and total demand(t).

In all cases the output neuron was total release(t).

The Table 6 shows the results of the training for different combinations for conservation operation. It was observed that the best convergence was achieved for the combination of inflow(t-2), inflow(t-1), total release(t-2), total release(t-1) inflow(t) reservoir storage(t) and total demand(t) as input neurons, total release (t) as output neuron with the error tolerance, the learning parameter, the number of cycles and neurons in the hidden layer as 0.001, 0.6 , 5000 and 9 respectively. The sum of squared error was 23133 and the coefficient of correlation was 0.748. Comparing the above ANN combination with the combination of total release(t-1), inflow(t), storage(t) and demand(t) as input neurons and total release(t) as output neuron, the improvement over the coefficient of correlation and the sum of squared errors was less. This combination was considered finally for the simulation of evaluation data set. So the weights for this structure were freezed to evaluate the trained network for the conservation operation. The optimal weights for this best trained network structure are presented in Table 7.

4.3 Evaluation of the trained ANN combinations

4.3.1 Flood Control Operation

After the training was over, the weights were collected from the training module of the BP simulator to test the neural network for both flood control and conservation operation. The three floods, 10 July 1977, 22 June 1980 and 23 July 1982 were selected for the model validation from the observed data. All the three floods are presented in Table 8. The initial storage was considered as 829.415 M Cum, which corresponds to the beginning level of the flood control zone, for simulating the floods through the trained neural network model. In all the three floods the previous period release was considered as 0. It was observed from the simulation results that the total releases through spillway for 30 minutes interval were made according to the specified policy (channel capacity - 9000 cumec; assumed maximum spillway release - 14900 cumec; 90 percent gate operational). The results of validation for all three floods are presented in the Table 9, 10 and 11. These results are represented graphically in the Fig. 3, 4, and 5.

4.3.2 Conservation Operation

The data set from January 1996 upto October 1999 was used for the evaluation of the trained neural network for the conservation operation. The validation data for the conservation operation is presented in Table 12. This data set was used to simulate the total release through the trained neural network structure with the optimized weights collected from the BP simulator. The coefficient of correlation for validation data set through the trained ANN was 0.609 and the sum of squared errors was 5242. The results of validation for conservation operation with actual release are presented in Fig. 6.

4.4 Discussion of results of ANN simulations

4.4.1 Flood Control Operation

From the ANN simulation for the flood of 10 July 1977 with the storage corresponding to beginning level of flood control zone as initial storage (829.415 M Cum), it was observed that the release was not equal to the channel capacity (9000 Cumec) in the beginning of the flood as assumed in the simulation of flood control operation policy. This is due to the limitation of ANN model in recognizing the rising or falling limb of the inflow hydrograph. The base of the design flood hydrograph (86 hours) is much higher than the base of floods (19 hours for 10 July 1977, 14 hours for 22 June 1980 and 24 hours for 23 July 1982). The total release made through ANN for the whole flood duration was lower than the inflow except the flood 23 July 1982. This is due to the low inflow (less than 566.4 Cumec) in many intervals for whole duration of the flood 23 July 1982. For the flood 10 July 1977, the total inflow was 71.392 MCum and the total release was 52.588 MCum. For the flood 22 June 1980, the total inflow was 76.457 MCum and the total release was 57.005 MCum. For the flood 23 July 1982, the total inflow was 46.469 MCum and the total release was 59.911 MCum. The difference between the total inflow and total release in all three floods was very small compared the space (491.16 MCum) available between FRL (189.59 m) and HFL (193.60 m). Is clearly seen from the release pattern through ANN model for all the three floods that high release was maintained after the peak of the inflow to create space in the reservoir for receiving the flood in future. The end storage at the end of the flood was higher than the full reservoir capacity (829.415 M Cum) except the flood 23 July 1982. In the training data set, the end storage at the end of the flood was less than full reservoir level, but the volume stored in the reservoir at the end of flood regulation was less than revised HFL storage (1400.006 M Cum) in all the cases of floods considered for network evaluation.

So it is observed that the Neural Network trained with the combination of Release(t-1), inflow(t) and reservoir storage(t) as input neurons, release(t) as output neuron with the storage corresponding to the beginning level of flood zone (829.415 M Cum) as initial storage can properly moderate the releases from the reservoir during severe floods. Hence this ANN model can be used for operation of the reservoir.

4.4.2 Conservation Operation

The optimized weights from the training of several combinations for the conservation operation were collected from the BP simulator. The combination of total release(t-1) inflow(t), reservoir storage(t) and total demand(t) as input neurons, total release (t) as output neuron was considered as the best network for the conservation operation as discussed in the section 4.2.2. The data used for the training of the ANN model was not representing the release pattern according to the demand. This gave poor correlation for the training data set. The validation data set from January 1996 to October 1999 was used to decide the release for irrigation and drinking water supply using the best-trained neural network. The coefficient of correlation for the validation data was 0.609 and the sum of squared errors was 5242. In all the data sets, the release was more than the demand. This was main factor, which gave very poor correlation between the targeted and calculated release. This indicates that the training data set of actual release was not suitable.

It was decided to train another ANN for conservation operation taking the simulated values of monthly release and reservoir storage with monthly historical inflow from 1967 to 1994 (Sabarmati System Studies, 1997). The simulated values of releases are "near optimal" values derived by the rule curve method using the simulation model developed at Water Resources Systems Division, NIH, Roorkee. The demands for the period from 1967 to 1994 have been taken from the Final Report of Sabarmati System Studies (1997) as supplied by the project authority. The releases were optimized through the simulation model by fine tuning the rule curves. The data set from 1967 to 1990 was used for calibrating the ANN model and the data set from 1991 to 1994 was used for the validation of trained neural network. The data for calibration and validation of

ANN model are presented in Table 13 and 14. As mentioned earlier, different combinations of input neurons and simulated release as output neurons were tried with different possible values of error tolerance, learning parameter, cycles and neurons in hidden layer. The results of the ANN training for conservation operation with simulated release are presented in Table 15. The best convergence was achieved for the combination of inflow(t-2), inflow(t-1), release(t-2), release(t-1), inflow(t), reservoir storage(t), demand(t) as input neurons and release(t) as output neuron with error tolerance, learning parameter, number of cycles and number hidden layers as 0.001 , 0.5, 5000 and 8 respectively. But the improvement over the result of combination of release(t-1), inflow(t), reservoir storage(t), demand(t) as input neurons and release(t) as output neuron with the above combination was less. So this combination was considered finally for the simulation of the evaluation data set. The weights for this combination were frozen and were used to simulate the release from 1991 to 1994. The optimal weights for this best combination are presented in Table 16. The coefficient of correlation and the sum of squared errors were 0.934 and 2134. The ANN model with simulated release for conservation operation was better correlated than the model with the actual release. So the ANN model developed with simulated release can be used effectively to decide the release from the reservoir for conservation operation.

CHAPTER 5

CONCLUSIONS

The neural network procedure to determine the releases from the reservoir for flood control and conservation operation was developed for Dharoi dam on Sabarmati in this study. Three layered feed-forward neural network structures were used. Back propagation algorithm was used to train the ANN models.

The operation policy for the reservoir when PMF hydrograph is input, the safe carrying capacity of downstream channel is 9000 cumec, maximum spillway release capacity is 14900 cumec, only 90 percent gates are operational and beginning reservoir storage is 829.415 M Cum was available. The training data set for the ANN model for flood control operation was prepared from this operation policy. For the ANN model for conservation operation, the data of actual release, inflow, demand for irrigation and drinking water supply, and beginning reservoir storage from June 1976 to December 1995 for 10 daily duration were used as training data set and the data from January 1996 to October 1999 were used as validation data set.

Seven different combinations of input data for both flood control and conservation operation were developed and trained by BP simulator with different error tolerance, learning parameter, number of cycles and number of hidden layers. The following observations were made from the training and the validation results.

1. The combination of total release(t-1), inflow(t) and reservoir storage(t) as input neurons, and total release(t) as output neuron was found to be the best for flood control operation. The coefficient of correlation between the input release to the ANN model and the release calculated by the same was 0.983 for this combination.
2. The best-trained ANN model regulated the high floods considered (10 July 1977, 22 June 1980, and 23 July 1982) for evaluation according to the allowable spillway capacity (14900 cumec) and channel capacity (9000 cumec).
3. The end storage at the end of flood regulation was less than storage at the HFL (193.60 m) in all floods considered for the evaluation of neural network model for the flood control operation.

4. The combination of total release(t-1) inflow(t) reservoir capacity(t) and total demand(t) as input neurons, total release (t) as output neuron was the best neural network model for the conservation operation.
5. The validation result for conservation operation with actual release indicated that the target values were poorly correlated to the ANN modeled values. The coefficient of correlation between the target values and the ANN modeled values was 0.609 for this validation set.

Another ANN model was developed with the monthly data of simulated release, inflow, demand for irrigation and drinking water supply, and beginning reservoir storage. The data from 1967 to 1990 were used for training and the data from 1991 to 1994 were used for the validation. The coefficient of correlation between the target values and the ANN modeled values for calibration and validation were 0.914 and 0.934 respectively.

It is concluded from the above observations that the neural network models can be successfully used as a simple tool to decide the release from a reservoir. The ANNs are good in learning the underlying pattern.

REFERENCES

1. Dawson,C.W., and Wilby,R. (1998). "An artificial neural network approach to rainfall-runoff modelling". *Hydrological Sciences Journal*, 43(1), 47-66.
2. French, M. N., Krajewski, W. F., and Cuykendall, R. R. (1992). "Rainfall forecasting in space and time using a neural network". *Journal of Hydrology*, 137(1-4), 1-31.
3. Hsu, K-L., Gupta, H.V., and Sorooshian, S. (1995). "Artificial neural network modeling of the rainfall-runoff process". *Water Resources Research*, 31(10), 2517-2530.
4. Jain, S.K., Goel, M.K., Senthil kumar, A.R., and Agarwal, P.K. (1996). "Multiobjective Optimization of Operation of a Dam". TR(BR)-143, National Institute of Hydrology, Roorkee, India.
5. Jain, S.K., Chalisgaonkar, D., and Goel, M.K. (1997). "Software for Reservoir Analysis (SRA)". UM-1/96-97, National Institute of Hydrology, Roorkee, India.
6. Jain, S.K., Das, A., and Srivastava, D.K. (1999). "Application of ANN for Reservoir Inflow Prediction and Operation". *Journal of Water Resources Planning and Management*, ASCE, 125(5), 263-271.
7. Jain, S.K., and Chalisgaonkar, D. (2000). "On Setting up Stage-discharge Relations using ANN", *Journal of Hydrologic Engineering*, ASCE, 5(4) , 428-433.
8. Kao, J-J. (1996). "Neural Net for Determining DEM-Based Model Drainage Pattern". *Journal of Irrigation and Drainage Engineering*, ASCE, 122 (2), 112-121.
9. Karunanithi,N., Grenney,W.J., Whitley,D., and Bovee,K. (1994). "Neural networks for river flow prediction." *J. Comp. in Civ. Engrg.*, ASCE, 8(2), 210-220.
10. Maier, H.R., and Dandy, G.C. (1999). "Empirical Comparison of Various Methods for Training Feed-Forward Neural Networks for salinity Forecasting". *Water Resources Research*, 35 (8), 2591-2596.
11. Maier, H.R., and Dandy, G.C. (2000). "Neural Networks for the Prediction and Forecasting of Water Resources Variables: A Review of Modelling Issues and Applications". *Environmental Modelling & Software*, 15, 101-124.
12. Mehrotra, K., Mohan, C.K., and Ranka, S. (1997). Elements of Artificial Neural Networks, Penram International Publishing (India), India.
13. Minns, A.W., and Hall, M.J. (1996). "Artificial Neural Networks as rainfall runoff models". *Hydrological Sciences Journal*, 41(3), 399-418.

14. Raman, H., and Sunilkumar,N. (1995). "Multivariate modelling of Water Resources time series using Artificial Neural Networks". *Hydrological Sciences Journal*. 40(2), 145-163.

15. Raman, H., and Chandramauli,V. (1996). "Deriving a general operating policy for reservoirs using Neural Network". *Journal of Water Resources Planning and Management*, ASCE, 122(5), 342-347.

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

17. Sabarmati System Studies - Final Report - Vol. I & II. (1997), National Institute of Hydrology, Roorkee, India.

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

19. Senthil kumar, A.R., Jain, S.K., Goel, M.K., and Neema, R.K. (1997). "Development of Operation Policy for Tawa Dam". CS(AR)-18/96-97, National Institute of Hydrology, Roorkee, India.

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

21. Thirumalaiah, K., and Deo, M.C. (1998). "River Stage Forecasting using Artificial Neural Networks". *Journal of Hydrologic Engineering*, ASCE, 3 (1), 26-32.

22. Wurbs, R.A. (1993). "Reservoir-System Simulation and Optimization Models". *Journal of Water Resources Planning and Management*, ASCE, 119(4), 455-472.

23. Yang, C-C., Prasher, S.O., Lacroix, R., Sreekanth, S., Patni, N.K., and Masse, L. (1997). "Artificial Neural Network Model for Subsurface-Drained Farmlands". *Journal of Irrigation and Drainage Engineering*, ASCE, 123 (4), 285-292.

24. Zealand, C.M., Burn, D.H., and Simonovic, S.P. (1999). "Short Term Streamflow Forecasting using Artificial Neural Networks". *Journal of Hydrology*, 214, 32-48.

SALIENT FEATURES FOR DHAROI DAM

GENERAL	
Location	Village – Dharoi, Taluka - Kheralu District- Mehsana, State - Gujarat
Latitude	24° 00' 00" N
Longitude	72° 52' 00" E
River	Sabarmati
Year of completion	1976
Purpose	Water supply, Irrigation, Flood control & Hydropower generation
HYDROLOGY	
Total Area of catchment at dam site	5540 sq. km.
Mean annual rainfall in the catchment	633 mm
Maximum probable flood	27176 Cumec
Maximum observed flood on 2.9.1973	14158 Cumec
DAM DATA	
Water Spread Area at F.R.L.	107.45 sq. km.
F.R.L.	189.59 m
H.F.L.	193.60 m
Dead storage level	175.87 m
R.L. of top of Dam	195.07 m
Gross storage capacity at F.R.L.	907.88 MCum
Live storage capacity at F.R.L.	775.89 MCum
Dead storage capacity	131.99 MCum
SPILLWAY DETAILS	
Discharge capacity at H.F.L.	21982 Cumec
Spillway restricted release	16992 Cumec
HEAD REGULATORS	
Sill levels	170.69 m (water supply) 175.87 m (irrigation) 171.91 m (river penstock) 175.57 m (canal penstock)

Table 1 The Design Flood (P.M.F.) Hydrograph for Dharoi Dam

TIME (Hour)	P.M.F. ORDINATES (Cumec)	TIME (Hour)	P.M.F. ORDINATES (Cumec)
0	566.41	44	23102.24
2	854.72	46	26187.76
4	1568.98	48	27180.12
6	2514.02	50	26113.85
8	3438.12	52	23965.73
10	4337.86	54	21500.71
12	5189.46	56	18990.37
14	6000.57	58	16425.38
16	6746.53	60	13922.40
18	7414.61	62	11504.96
20	7981.87	64	9310.96
22	8452.56	66	7436.99
24	8848.77	68	5883.32
26	9162.28	70	4683.09
28	9576.04	72	3701.22
30	10231.96	74	2884.17
32	11034.55	76	2159.44
34	12020.11	78	1559.05
36	13231.95	80	1062.59
38	14825.54	82	730.10
40	17065.99	84	598.70
42	19758.99	86	566.41

Table 2 The data for the training of Flood Control Neural Network (30 minutes interval)

S.No.	Inflow (Cumec)	Ini-stor (MCum)	Tot-rel (Cumec)	S.No.	Inflow (Cumec)	Ini-stor (MCum)	Tot-rel (Cumec)
1	566.4	829.4150	9000.0	44	8334.9	560.6361	7203.7
2	638.5	814.2238	9000.0	45	8452.6	562.6641	7241.4
3	710.6	799.1624	9000.0	46	8551.6	564.8359	7281.4
4	782.6	784.2309	9000.0	47	8650.7	567.1142	7323.2
5	854.7	769.4293	9000.0	48	8749.7	569.4954	7366.9
6	1040.8	754.7576	9000.0	49	8848.8	571.9762	7412.3
7	1226.8	740.4209	9000.0	50	8927.1	574.5536	7459.0
8	1412.9	726.4193	9000.0	51	9005.5	577.1878	7506.9
9	1599.0	712.7527	9000.0	52	9083.9	579.8770	7555.6
10	1827.7	699.4212	9000.0	53	9162.3	582.6195	7605.3
11	2056.5	686.5016	9000.0	54	9265.7	585.4137	7656.3
12	2285.3	673.9939	9000.0	55	9369.2	588.3021	7709.0
13	2514.0	661.8981	8898.0	56	9472.6	591.2819	7763.3
14	2745.0	650.3977	8698.6	57	9576.0	594.3501	7819.2
15	2976.1	639.6723	8512.9	58	9740.0	597.5040	7877.5
16	3207.1	629.6969	8340.5	59	9904.0	600.8479	7939.2
17	3438.1	620.4480	8180.9	60	10068.0	604.3759	8004.2
18	3663.1	611.9023	8033.6	61	10232.0	608.0821	8072.3
19	3888.0	604.0267	7898.1	62	10432.6	611.9609	8144.0
20	4112.9	596.7998	7774.2	63	10633.3	616.0716	8219.9
21	4337.9	590.2011	7661.3	64	10833.9	620.4070	8299.7
22	4550.8	584.2106	7558.9	65	11034.5	624.9598	8383.3
23	4763.7	578.7875	7466.6	66	11280.9	629.7232	8471.4
24	4976.6	573.9140	7383.9	67	11527.3	634.7714	8564.5
25	5189.5	569.5725	7310.7	68	11773.7	640.0956	8662.5
26	5392.2	565.7460	7246.4	69	12020.1	645.6866	8765.3
27	5595.0	562.4003	7190.6	70	12323.1	651.5363	8873.4
28	5797.8	559.5201	7143.0	71	12626.0	657.7365	8987.8
29	6000.6	557.0906	7103.4	72	12929.0	664.2761	9000.0
30	6187.1	555.0975	7085.8	73	13232.0	671.3389	9000.0
31	6373.5	553.4717	7056.6	74	13630.3	678.9471	9000.0
32	6560.0	552.2341	7034.4	75	14028.7	687.2723	9000.0
33	6746.5	551.3723	7018.9	76	14427.1	696.3146	9000.0
34	6913.5	550.8739	7010.0	77	14825.5	706.0738	9000.0
35	7080.6	550.6923	7006.7	78	15385.7	716.5500	9000.0
36	7247.6	550.8171	7008.9	79	15945.8	728.0344	9000.0
37	7414.6	551.2386	7016.5	80	16505.9	740.5268	9000.0
38	7556.4	551.9471	7029.2	81	17066.0	754.0273	10755.8
39	7698.2	552.8880	7046.1	82	17739.2	765.3754	10957.9
40	7840.1	554.0538	7067.0	83	18412.5	777.5715	11164.1
41	7981.9	555.4371	7091.9	84	19085.7	790.6082	11383.9
42	8099.5	557.0310	7136.2	85	19759.0	804.4609	11616.8
43	8217.2	558.7568	7168.6	86	20594.8	819.1061	11865.6

Table 2 The data for the training of Flood Control Neural Network (30 minutes interval) - contd.

S.No.	Inflow (Cumec)	Ini-stor (MCum)	Tot-rel (Cumec)	S.No.	Inflow (Cumec)	Ini-stor (MCum)	Tot-rel (Cumec)
87	21430.6	834.8079	12142.9	131	8374.0	1255.7550	14900.0
88	22266.4	851.5149	12440.0	132	7905.5	1243.9940	14900.0
89	23102.2	869.1914	12753.6	133	7437.0	1231.3900	14900.0
90	23873.6	887.8076	13082.3	134	7048.6	1217.9430	14900.0
91	24645.0	907.2207	13423.6	135	6660.1	1203.7970	14900.0
92	25416.4	927.4076	13771.4	136	6271.7	1188.9520	14900.0
93	26187.8	948.3569	14124.2	137	5883.3	1173.4080	14900.0
94	26435.8	970.0594	14481.4	138	5583.3	1157.1650	14900.0
95	26683.9	991.5654	14835.5	139	5283.2	1140.3820	14900.0
96	26932.0	1012.8810	14900.0	140	4983.1	1123.0590	14900.0
97	27180.1	1034.5260	14900.0	141	4683.1	1105.1950	14900.0
98	26913.6	1056.6180	14900.0	142	4437.6	1086.7920	14900.0
99	26647.0	1078.2300	14900.0	143	4192.2	1067.9470	14900.0
100	26380.4	1099.3620	14900.0	144	3946.7	1048.6610	14900.0
101	26113.8	1120.0140	14900.0	145	3701.2	1028.9320	14900.0
102	25576.8	1140.1860	14900.0	146	3497.0	1008.7620	14771.1
103	25039.8	1159.3910	14900.0	147	3292.7	988.4568	9000.0
104	24502.8	1177.6290	14900.0	148	3088.4	978.1717	9000.0
105	23965.7	1194.9010	14900.0	149	2884.2	967.5190	9000.0
106	23349.5	1211.2060	14900.0	150	2703.0	956.4986	9000.0
107	22733.2	1226.4010	14900.0	151	2521.8	945.1523	9000.0
108	22117.0	1240.4870	14900.0	152	2340.6	933.4798	9000.0
109	21500.7	1253.4640	14900.0	153	2159.4	921.4814	9000.0
110	20873.1	1265.3320	14900.0	154	2009.3	909.1568	9000.0
111	20245.5	1276.0700	14900.0	155	1859.3	896.5623	9000.0
112	19617.9	1285.6780	14900.0	156	1709.2	883.6976	9000.0
113	18990.4	1294.1560	14900.0	157	1559.1	870.5629	9000.0
114	18349.1	1301.5050	14900.0	158	1434.9	857.1581	9000.0
115	17707.9	1307.6990	14900.0	159	1310.8	843.5300	9000.0
116	17066.6	1312.7390	14900.0	160	1186.7	829.6786	9000.0
117	16425.4	1316.6250	14900.0	161	1062.6	815.6039	1062.6
118	15799.6	1319.3560	14900.0	162	979.5	815.5932	979.5
119	15173.9	1320.9610	14900.0	163	896.3	815.5825	896.3
120	14548.1	1321.4400	14900.0	164	813.2	815.5718	813.2
121	13922.4	1320.7930	14900.0	165	730.1	815.5611	730.1
122	13318.0	1319.0190	14900.0	166	697.3	815.5504	697.3
123	12713.7	1316.1570	14900.0	167	664.4	815.5398	664.4
124	12109.3	1312.2080	14900.0	168	631.5	815.5291	631.5
125	11505.0	1307.1700	14900.0	169	598.7	815.5184	598.7
126	10956.5	1301.0450	14900.0	170	590.6	815.5077	590.6
127	10408.0	1293.9330	14900.0	171	582.5	815.4970	582.5
128	9859.5	1285.8330	14900.0	172	574.5	815.4863	574.5
129	9311.0	1276.7460	14900.0	173	566.4	815.4756	566.4
130	8842.5	1266.6720	14900.0				

Table 3 The data for the training of ANN for Conservation Operation with actual release

S.No.	Inflow (MCum)	Ini-stor (MCum)	Demand (MCum)	Tot-rel (MCum)	S.No.	Inflow (MCum)	Ini-stor (MCum)	Demand (MCum)	Tot-rel (MCum)
1	306.694	193.090	1.380	1.380	60	1.836	83.392	8.870	9.109
2	330.578	221.294	1.380	1.380	61	0.733	75.633	8.563	6.603
3	269.194	234.489	1.380	1.380	62	0.883	69.092	8.563	2.661
4	245.406	232.649	6.597	6.597	63	0.416	66.883	8.563	1.261
5	187.485	254.339	6.597	6.597	64	0.356	65.326	8.850	2.382
6	133.389	220.416	6.597	6.597	65	0.333	62.636	8.850	1.818
7	69.040	214.299	10.363	19.005	66	0.124	60.710	8.850	1.319
8	13.392	206.088	10.363	43.978	67	0.376	58.983	9.633	0.830
9	11.870	194.506	10.363	18.416	68	8.333	58.275	9.633	1.486
10	11.446	182.614	20.150	15.268	69	2.860	65.043	9.633	3.381
11	5.496	177.516	20.150	13.856	70	28.788	64.335	6.820	4.833
12	11.521	170.437	20.150	17.552	71	50.698	88.291	6.820	3.267
13	8.019	164.406	16.397	13.626	72	60.484	135.721	6.820	0.000
14	5.496	158.799	16.397	12.405	73	14.409	196.205	1.380	12.937
15	3.014	151.890	16.397	13.037	74	28.659	197.678	1.380	9.433
16	3.794	138.609	20.327	12.378	75	165.000	216.253	1.380	0.000
17	3.133	129.973	20.327	11.564	76	131.304	361.254	6.597	0.000
18	1.662	119.382	20.327	11.868	77	33.172	512.558	6.597	15.559
19	1.966	107.858	18.947	4.549	78	12.084	530.171	6.597	14.972
20	4.077	105.253	18.947	10.562	79	17.148	526.546	10.363	16.440
21	2.252	98.145	18.947	7.264	80	3.646	527.254	10.363	24.465
22	2.904	93.133	8.870	9.936	81	3.465	504.544	10.363	26.910
23	1.042	83.675	8.870	4.655	82	2.662	477.757	20.150	24.465
24	2.766	78.069	8.870	6.086	83	7.603	454.396	20.150	12.305
25	1.829	74.699	8.563	6.665	84	1.848	448.279	20.150	19.067
26	1.957	69.658	8.563	4.767	85	2.597	427.070	16.397	12.185
27	0.365	66.176	8.563	2.915	86	1.452	406.371	16.397	19.068
28	1.745	63.287	8.850	2.283	87	0.843	384.086	16.397	21.745
29	1.898	62.749	8.850	2.181	88	0.352	359.337	20.327	24.207
30	21.008	62.466	8.850	5.406	89	1.220	332.295	20.327	21.423
31	1.916	78.068	9.633	7.461	90	2.158	307.461	20.327	23.168
32	4.951	71.641	9.633	3.113	91	3.457	286.450	18.947	21.057
33	96.008	72.122	9.633	4.473	92	0.700	266.798	18.947	21.118
34	329.169	163.415	6.820	6.820	93	0.578	243.154	18.947	16.827
35	363.723	243.522	6.820	6.820	94	0.250	226.079	8.870	18.436
36	371.444	226.844	6.820	6.820	95	0.897	203.822	8.870	17.305
37	328.824	228.968	1.380	1.380	96	0.077	185.162	8.870	15.933
38	172.284	232.592	1.380	1.380	97	0.000	166.558	8.563	13.700
39	211.346	217.216	1.380	1.380	98	0.376	149.341	8.563	8.158
40	306.888	230.185	6.597	6.597	99	0.520	140.025	8.563	3.302
41	176.830	232.224	6.597	6.597	100	0.000	135.862	8.850	4.893
42	108.074	218.264	6.597	6.597	101	0.007	128.868	8.850	4.893
43	64.908	213.535	10.363	10.363	102	0.157	121.789	8.850	5.382
44	19.776	209.656	10.363	10.973	103	0.497	113.521	9.633	4.893
45	9.044	204.162	10.363	13.394	104	0.675	107.348	9.633	4.893
46	7.181	198.640	20.150	15.223	105	31.090	101.996	9.633	4.404
47	6.055	190.259	20.150	12.046	106	0.092	128.472	6.820	1.957
48	3.586	183.179	20.150	12.040	107	30.608	125.640	6.820	1.957
49	5.359	171.853	16.397	9.690	108	7.930	153.589	6.820	5.382
50	2.778	166.558	16.397	7.216	109	123.597	156.137	1.380	1.467
51	3.194	161.149	16.397	8.495	110	96.191	278.267	1.380	0.000
52	1.667	155.401	20.327	9.090	111	23.468	374.458	1.380	4.893
53	0.449	147.869	20.327	8.698	112	5.544	393.034	6.597	11.009
54	1.337	138.807	20.327	9.771	113	2.480	387.569	6.597	16.194
55	0.113	129.491	18.947	9.095	114	1.626	371.626	6.597	13.804
56	0.000	119.580	18.947	9.021	115	0.604	357.241	10.363	18.911
57	1.280	108.622	18.947	7.196	116	0.442	336.712	10.363	9.474
58	1.599	101.656	8.870	9.055	117	1.173	322.667	10.363	8.145
59	0.205	94.152	8.870	8.757	118	0.322	313.209	20.150	10.810

Table 3 The data for the training of ANN for Conservation Operation with actual release - contd.

S.No.	Inflow (MCum)	Ini-stor (MCum)	Demand (MCum)	Tot-rel (MCum)	S.No.	Inflow (MCum)	Ini-stor (MCum)	Demand (MCum)	Tot-rel (MCum)
119	8.394	307.886	20.150	0.514	176	0.000	467.365	9.633	16.036
120	18.555	315.446	20.150	0.234	177	39.475	448.308	9.633	14.948
121	0.490	333.767	16.397	0.543	178	35.452	470.111	6.820	13.211
122	0.638	333.286	16.397	0.702	179	34.404	490.726	6.820	0.000
123	1.819	332.804	16.397	2.006	180	17.543	525.130	6.820	14.679
124	0.536	332.295	20.327	1.683	181	8.236	527.254	1.380	20.551
125	0.179	325.499	20.327	1.794	182	148.174	511.822	1.380	4.893
126	0.180	320.855	20.327	1.987	183	41.475	655.104	1.380	11.743
127	0.984	316.324	18.947	2.139	184	14.679	684.836	6.597	14.679
128	0.503	314.540	18.947	1.766	185	8.766	684.836	6.597	23.853
129	0.547	311.426	18.947	1.597	186	34.046	669.545	6.597	24.508
130	0.183	307.886	8.870	2.173	187	3.263	678.040	10.363	15.033
131	0.000	304.261	8.870	1.950	188	1.359	665.298	10.363	15.243
132	0.226	300.212	8.870	2.540	189	2.621	647.458	10.363	16.280
133	0.000	296.191	8.563	2.584	190	6.510	632.111	20.150	9.908
134	0.019	292.320	8.563	3.925	191	1.806	628.713	20.150	4.775
135	0.000	284.440	8.563	4.966	192	0.586	622.766	20.150	5.262
136	0.114	277.984	8.850	6.136	193	0.903	616.112	16.397	3.227
137	0.000	266.798	8.850	6.793	194	0.000	610.448	16.397	6.122
138	0.478	253.659	8.850	10.642	195	0.802	602.350	16.397	10.626
139	0.617	239.869	9.633	12.232	196	1.525	591.051	20.327	11.241
140	10.751	225.315	9.633	8.318	197	0.751	578.904	20.327	10.517
141	338.976	225.315	9.633	9.633	198	2.303	564.632	20.327	10.861
142	170.624	444.655	6.820	6.820	199	1.708	553.107	18.947	10.814
143	6.881	472.858	6.820	0.000	200	1.122	542.715	18.947	10.248
144	179.510	479.739	6.820	13.456	201	1.095	530.907	18.947	6.021
145	208.931	632.111	1.380	2.446	202	0.509	522.044	8.870	7.874
146	57.062	838.595	1.380	1.380	203	0.440	510.378	8.870	5.000
147	225.467	848.194	1.380	2.446	204	0.676	503.185	8.870	7.231
148	34.525	865.666	6.597	6.597	205	0.298	494.860	8.563	11.033
149	9.091	790.295	6.597	12.310	206	1.115	481.268	8.563	11.497
150	2.365	786.294	6.597	15.423	207	1.850	469.432	8.563	11.497
151	0.479	771.626	10.363	18.761	208	6.448	458.473	8.850	7.166
152	18.658	748.548	10.363	13.173	209	1.332	456.180	8.850	1.784
153	0.045	729.888	10.363	10.602	210	0.384	454.367	8.850	8.151
154	0.016	715.390	20.150	3.622	211	0.000	444.060	9.633	9.736
155	1.700	706.498	20.150	7.804	212	1.180	430.723	9.633	5.401
156	0.550	696.729	20.150	5.628	213	3.273	422.823	9.633	10.911
157	3.450	681.438	16.397	5.773	214	1.280	413.393	6.820	14.679
158	1.724	678.040	16.397	5.602	215	23.150	397.281	6.820	10.764
159	1.858	671.244	16.397	3.770	216	115.544	409.429	6.820	5.138
160	1.905	665.298	20.327	2.789	217	4.276	519.835	1.380	5.749
161	1.100	662.749	20.327	6.603	218	116.365	517.655	1.380	11.254
162	0.819	652.583	20.327	8.671	219	36.150	622.766	1.380	14.006
163	0.845	641.512	18.947	7.815	220	6.630	644.910	6.597	16.563
164	0.207	630.298	18.947	7.458	221	4.146	633.809	6.597	24.954
165	0.181	619.368	18.947	6.713	222	1.888	611.269	6.597	35.560
166	0.744	609.769	8.870	8.085	223	2.228	571.626	10.363	36.024
167	0.013	598.329	8.870	7.336	224	0.184	531.643	10.363	29.796
168	0.000	587.031	8.870	8.391	225	0.587	496.219	10.363	16.128
169	0.000	574.090	8.563	9.109	226	9.316	474.246	20.150	6.293
170	0.000	556.902	8.563	9.905	227	1.222	473.538	20.150	1.712
171	0.000	541.101	8.563	9.013	228	0.989	471.471	20.150	6.140
172	0.202	525.017	8.850	8.378	229	0.555	464.618	16.397	7.460
173	0.193	571.822	8.850	8.415	230	0.754	456.180	16.397	9.712
174	0.000	498.258	8.850	9.418	231	0.734	445.278	16.397	10.898
175	0.390	479.796	9.633	8.791	232	0.419	433.130	20.327	6.311

Table 3 The data for the training of ANN for Conservation Operation with actual release - contd.

S.No.	Inflow (MCum)	Ini-stor (MCum)	Demand (MCum)	Tot-rel (MCum)	S.No.	Inflow (MCum)	Ini-stor (MCum)	Demand (MCum)	Tot-rel (MCum)
233	0.244	424.040	20.327	5.812	291	73.486	838.793	1.380	1.380
234	3.473	416.083	20.327	14.672	292	53.628	873.481	6.597	6.597
235	0.000	401.529	18.947	14.589	293	55.310	877.842	6.597	6.597
236	1.050	384.086	18.947	11.824	294	33.862	883.392	6.597	6.597
237	0.938	371.060	18.947	10.359	295	15.452	877.842	10.363	10.363
238	1.476	360.894	8.870	15.374	296	6.593	865.298	10.363	13.149
239	1.175	345.660	8.870	14.826	297	2.066	842.814	10.363	13.113
240	1.634	330.850	8.870	16.648	298	0.554	829.732	20.150	21.347
241	2.400	313.209	8.563	12.673	299	0.615	803.709	20.150	21.765
242	1.882	301.005	8.563	14.462	300	0.647	777.375	20.150	21.183
243	2.681	290.103	8.563	12.606	301	0.500	752.428	16.397	24.498
244	0.368	279.399	8.850	13.299	302	0.716	724.989	16.397	23.268
245	0.612	259.436	8.850	14.732	303	2.009	698.711	16.397	26.398
246	0.808	241.682	8.850	14.758	304	0.710	670.196	20.327	22.923
247	0.649	224.692	9.633	13.847	305	0.511	645.957	20.327	20.944
248	0.889	209.316	9.633	11.927	306	0.297	623.531	20.327	26.636
249	16.743	196.063	9.633	7.710	307	0.000	595.299	18.947	21.722
250	259.493	204.474	6.820	0.058	308	0.417	569.078	18.947	22.843
251	48.478	463.230	6.820	0.000	309	0.582	540.478	18.947	20.015
252	157.412	510.349	6.820	0.000	310	1.180	517.570	8.870	19.045
253	251.542	667.761	1.380	1.380	311	0.438	497.125	8.870	23.130
254	280.914	783.972	1.380	1.380	312	0.914	467.931	8.870	21.142
255	76.810	779.187	1.380	1.380	313	0.084	443.409	8.563	20.354
256	52.328	792.864	6.597	6.597	314	0.000	419.368	8.563	23.163
257	35.519	813.761	6.597	6.597	315	0.343	389.154	8.563	21.628
258	27.123	842.814	6.597	6.597	316	0.000	360.781	8.850	22.649
259	45.834	860.201	10.363	10.363	317	0.278	333.965	8.850	22.346
260	42.217	875.633	10.363	10.363	318	0.029	307.942	8.850	20.072
261	2.354	870.423	10.363	1.335	319	1.793	285.346	9.633	13.634
262	2.144	871.442	20.150	5.221	320	0.000	271.329	9.633	12.280
263	4.577	865.298	20.150	10.272	321	0.000	253.263	9.633	11.009
264	2.598	855.075	20.150	16.473	322	0.106	239.671	6.820	11.009
265	1.338	837.774	16.397	16.052	323	63.919	227.438	6.820	9.258
266	2.744	819.113	16.397	16.669	324	9.369	281.098	6.820	3.904
267	2.390	802.718	16.397	18.505	325	161.199	286.563	1.380	11.121
268	3.454	782.981	20.327	16.274	326	32.400	436.641	1.380	10.200
269	1.334	764.236	20.327	16.271	327	17.172	458.841	1.380	27.054
270	1.429	747.019	20.327	18.332	328	7.843	448.959	6.597	24.465
271	0.769	727.821	18.947	16.208	329	2.773	432.337	6.597	14.200
272	1.416	710.491	18.947	16.424	330	1.240	419.368	6.597	17.922
273	0.164	692.566	18.947	17.467	331	52.856	400.254	10.363	19.414
274	0.806	673.594	8.870	15.224	332	6.206	431.742	10.363	3.295
275	0.780	658.048	8.870	18.437	333	1.840	434.178	10.363	0.146
276	1.232	636.471	8.870	19.466	334	0.000	435.571	20.150	3.445
277	0.017	614.271	8.563	15.172	335	0.000	430.015	20.150	6.958
278	0.000	594.534	8.563	13.884	336	0.141	419.991	20.150	18.734
279	0.192	574.798	8.563	16.446	337	0.099	397.168	16.397	6.134
280	0.082	550.814	8.850	18.290	338	0.562	387.908	16.397	16.494
281	0.055	527.169	8.850	21.062	339	0.184	369.361	16.397	14.161
282	0.000	499.192	8.850	21.647	340	0.028	351.238	20.327	3.455
283	0.160	469.231	9.633	19.542	341	1.099	345.745	20.327	15.292
284	1.902	445.872	9.633	12.944	342	0.183	327.226	20.327	10.232
285	0.412	430.581	9.633	4.758	343	0.176	310.632	18.947	6.652
286	54.704	421.832	6.820	6.616	344	0.000	303.412	18.947	10.936
287	4.002	469.885	6.820	8.425	345	0.000	289.452	18.947	8.776
288	10.846	463.995	6.820	20.894	346	0.000	279.937	8.870	11.317
289	304.856	453.291	1.380	11.381	347	0.000	265.977	8.870	4.281
290	205.640	743.904	1.380	1.380	348	0.041	260.625	8.870	4.709

Table 3 The data for the training of ANN for Conservation Operation with actual release - contd.

S.No.	Inflow (MCum)	Ini-stor (MCum)	Demand (MCum)	Tot-rel (MCum)	S.No.	Inflow (MCum)	Ini-stor (MCum)	Demand (MCum)	Tot-rel (MCum)
349	0.000	254.084	8.563	11.317	406	0.000	126.800	20.150	0.000
350	0.000	239.643	8.563	8.261	407	0.000	125.190	20.150	0.000
351	0.000	227.438	8.563	15.684	408	0.000	123.570	20.150	0.000
352	0.000	208.693	8.850	6.299	409	0.000	121.850	16.397	0.000
353	0.000	199.518	8.850	20.832	410	0.370	120.120	16.397	0.000
354	0.000	175.336	8.850	6.687	411	0.000	119.440	16.397	0.000
355	0.000	164.800	9.633	4.900	412	0.000	118.280	20.327	0.000
356	0.000	157.120	9.633	4.820	413	0.000	117.290	20.327	0.000
357	15.610	150.900	9.633	0.690	414	0.000	116.610	20.327	0.000
358	2.720	165.020	6.820	0.000	415	0.000	115.870	18.947	0.000
359	0.000	167.740	6.820	3.500	416	0.000	115.190	18.947	0.000
360	43.460	162.020	6.820	7.240	417	0.000	114.620	18.947	0.000
361	29.650	196.710	1.380	3.120	418	0.000	113.630	8.870	0.000
362	30.840	223.240	1.380	0.000	419	0.000	112.050	8.870	0.000
363	11.130	254.080	1.380	3.510	420	0.000	110.860	8.870	0.000
364	1.460	261.700	6.597	2.290	421	0.000	109.160	8.563	0.000
365	0.550	259.540	6.597	1.830	422	0.980	107.550	8.563	6.850
366	0.240	256.150	6.597	1.950	423	0.460	99.840	8.563	12.380
367	0.000	252.440	10.363	2.930	424	0.110	84.470	8.850	9.840
368	0.000	248.330	10.363	2.930	425	0.000	73.140	8.850	5.280
369	0.000	243.210	10.363	3.710	426	0.000	66.200	8.850	2.810
370	0.000	237.060	20.150	2.930	427	0.000	61.500	9.633	0.800
371	0.000	231.510	20.150	2.930	428	8.380	59.800	9.633	0.000
372	0.000	225.710	20.150	2.930	429	0.740	67.190	9.633	0.000
373	0.000	220.840	16.397	2.930	430	21.520	66.740	6.820	0.000
374	0.000	215.370	16.397	2.930	431	50.940	87.750	6.820	0.000
375	0.000	210.670	16.397	3.220	432	110.570	138.160	6.820	0.000
376	0.000	205.320	20.327	3.790	433	438.630	248.680	1.380	0.000
377	0.000	200.020	20.327	2.930	434	30.800	687.050	1.380	0.000
378	0.000	195.070	20.327	3.220	435	50.680	715.640	1.380	3.670
379	0.000	190.370	18.947	2.930	436	7.840	759.820	6.597	29.760
380	0.000	186.150	18.947	3.140	437	4.800	731.980	6.597	23.200
381	0.000	181.820	18.947	2.630	438	36.070	707.230	6.597	0.220
382	0.000	178.220	8.870	3.850	439	11.090	740.790	10.363	21.600
383	0.000	172.870	8.870	4.280	440	1.150	725.470	10.363	32.220
384	0.000	167.030	8.870	4.700	441	0.470	688.860	10.363	15.540
385	0.000	160.610	8.563	4.840	442	0.000	665.300	20.150	10.370
386	0.000	153.100	8.563	4.890	443	0.000	648.980	20.150	6.210
387	0.000	147.020	8.563	4.890	444	0.000	638.080	20.150	15.220
388	0.000	140.590	8.850	5.960	445	0.000	617.950	16.397	13.320
389	0.000	131.250	8.850	5.870	446	0.000	600.680	16.397	16.940
390	0.000	122.270	8.850	7.370	447	0.000	579.500	16.397	12.430
391	0.000	110.090	9.633	6.110	448	0.000	562.820	20.327	18.850
392	1.100	101.510	9.633	6.110	449	0.000	540.420	20.327	12.950
393	3.900	95.870	9.633	5.440	450	0.000	524.420	20.327	17.200
394	2.270	94.010	6.820	2.780	451	0.000	503.360	18.947	16.050
395	6.900	92.700	6.820	0.040	452	0.000	483.960	18.947	17.360
396	0.670	99.440	6.820	0.000	453	0.000	462.810	18.947	15.600
397	0.450	98.900	1.380	0.000	454	0.000	444.150	8.870	17.740
398	12.540	98.730	1.380	0.000	455	0.000	422.710	8.870	18.420
399	27.380	110.430	1.380	0.000	456	0.000	400.140	8.870	9.920
400	0.500	136.850	6.597	0.000	457	0.000	386.240	8.563	12.900
401	0.000	136.420	6.597	0.000	458	0.000	368.800	8.563	13.290
402	0.000	134.700	6.597	0.000	459	0.000	351.320	8.563	17.650
403	0.000	132.880	10.363	0.000	460	0.000	329.180	8.850	16.170
404	0.000	130.850	10.363	0.000	461	0.000	308.370	8.850	15.340
405	0.000	128.750	10.363	0.000	462	0.000	287.270	8.850	12.720

Table 3 The data for the training of ANN for Conservation Operation with actual release - contd.

S.No.	Inflow (MCum)	Ini-stor (MCum)	Demand (MCum)	Tot-rel (MCum)	S.No.	Inflow (MCum)	Ini-stor (MCum)	Demand (MCum)	Tot-rel (MCum)
463	0.000	268.830	9.633	25.060	522	0.000	757.157	20.327	18.493
464	0.000	239.590	9.633	14.880	523	0.000	735.409	18.947	11.739
465	0.000	222.000	9.633	7.340	524	0.000	720.515	18.947	21.692
466	54.960	211.780	6.820	1.270	525	0.000	695.597	18.947	13.171
467	6.260	266.740	6.820	0.000	526	0.000	679.031	8.870	19.130
468	17.580	273.000	6.820	0.000	527	0.000	655.982	8.870	14.686
469	0.970	290.580	1.380	0.000	528	0.000	636.302	8.870	16.359
470	2.490	291.550	1.380	8.300	529	0.000	613.025	8.563	19.047
471	164.370	294.040	1.380	0.100	530	0.000	588.843	8.563	15.046
472	54.480	458.410	6.597	0.000	531	0.000	567.747	8.563	18.796
473	17.540	512.890	6.597	26.620	532	0.000	542.432	8.850	21.009
474	17.550	500.550	6.597	26.930	533	0.000	516.437	8.850	18.090
475	2.420	488.370	10.363	27.230	534	0.000	493.416	8.850	21.723
476	0.000	466.080	10.363	21.580	535	0.000	464.476	9.633	4.736
477	0.000	434.540	10.363	13.610	536	3.098	447.317	9.633	7.340
478	0.000	417.130	20.150	10.380	537	0.000	438.057	9.633	8.074
479	0.000	402.940	20.150	20.900	538	0.000	423.814	6.820	5.765
480	0.000	377.940	20.150	14.480	539	53.386	411.978	6.820	5.861
481	0.000	359.680	16.397	12.750	540	326.074	456.356	6.820	0.000
482	0.000	343.620	16.397	17.810	541	59.312	782.019	1.380	0.000
483	0.000	321.360	16.397	15.450	542	18.399	839.351	1.380	4.322
484	0.000	301.460	20.327	14.160	543	58.797	849.667	1.380	24.466
485	0.000	284.440	20.327	11.660	544	91.530	879.513	6.597	7.177
486	0.000	270.250	20.327	19.750	545	21.600	900.495	6.597	25.832
487	0.000	247.430	18.947	9.410	546	5.539	885.516	6.597	46.218
488	0.000	235.480	18.947	12.340	547	2.623	836.104	10.363	35.029
489	0.640	221.120	18.947	8.760	548	0.500	797.678	10.363	41.095
490	0.000	211.640	8.870	8.620	549	0.000	751.012	10.363	35.259
491	0.000	201.190	8.870	7.270	550	0.000	707.773	20.150	5.840
492	0.000	191.670	8.870	7.400	551	0.000	697.154	20.150	24.024
493	0.000	181.930	8.563	6.730	552	0.000	668.951	20.150	24.276
494	0.000	172.670	8.563	6.730	553	0.000	638.879	16.397	14.117
495	0.000	162.820	8.563	6.730	554	0.000	622.058	16.397	26.244
496	0.000	152.200	8.850	6.720	555	0.000	593.034	16.397	12.816
497	0.000	141.530	8.850	6.730	556	0.000	576.780	20.327	20.298
498	0.000	131.620	8.850	7.410	557	0.000	553.702	20.327	16.117
499	0.000	119.640	9.633	6.730	558	0.000	532.663	20.327	22.928
500	5.730	109.080	9.633	6.730	559	0.000	504.035	18.947	14.973
501	0.120	104.400	9.633	6.730	560	0.000	485.856	18.947	19.745
502	225.500	95.540	6.820	2.820	561	0.000	462.806	18.947	17.402
503	20.410	317.740	6.820	0.000	562	0.000	441.568	8.870	20.599
504	13.140	336.280	6.820	2.450	563	0.000	418.434	8.870	15.396
505	141.380	343.960	1.380	0.000	564	0.000	399.773	8.870	23.445
506	98.410	484.380	1.380	0.000	565	0.000	371.909	8.563	10.464
507	254.810	581.200	1.380	0.000	566	0.000	357.412	8.563	23.596
508	279.370	835.450	6.597	6.597	567	0.000	329.322	8.563	20.865
509	134.990	896.500	6.597	6.597	568	0.000	302.081	8.850	17.898
510	116.530	899.840	6.597	6.597	569	0.000	278.777	8.850	24.139
511	58.320	903.810	10.363	10.363	570	0.000	248.676	8.850	13.906
512	39.890	906.810	10.363	10.363	571	0.000	228.600	9.633	18.271
513	14.910	907.830	10.363	17.320	572	0.000	206.031	9.633	13.124
514	4.320	894.520	20.150	15.140	573	0.000	188.503	9.633	8.188
515	1.830	880.190	20.150	6.990	574	0.000	177.545	6.820	5.637
516	0.940	871.190	20.150	16.020	575	26.594	169.078	6.820	5.754
517	0.000	852.130	16.397	11.474	576	289.953	188.248	6.820	3.700
518	0.000	834.801	16.397	8.964	577	134.429	474.133	1.380	0.000
519	0.000	822.879	16.397	24.871	578	264.862	607.784	1.380	0.000
520	0.000	794.449	20.327	11.254	579	92.214	870.536	1.380	3.985
521	0.000	779.640	20.327	19.440	580	855.756	890.160	6.597	6.597

Table 3 The data for the training of ANN for Conservation Operation with actual release - contd.

S.No.	Inflow (MCum)	Ini-stor (MCum)	Demand (MCum)	Tot-rel (MCum)	S.No.	Inflow (MCum)	Ini-stor (MCum)	Demand (MCum)	Tot-rel (MCum)
581	294.825	885.176	6.597	6.597	641	0.000	170.636	8.850	14.347
582	123.109	905.819	6.597	6.597	642	0.000	152.060	8.850	10.478
583	53.590	907.829	10.363	10.363	643	0.000	138.440	9.633	6.799
584	23.364	906.838	10.363	28.312	644	12.436	129.378	9.633	7.696
585	6.923	894.520	10.363	31.050	645	39.446	132.890	9.633	6.728
586	0.724	865.015	20.150	18.416	646	68.065	163.641	6.820	3.344
587	0.503	842.871	20.150	17.600	647	141.434	228.146	6.820	1.590
588	0.143	814.494	20.150	14.431	648	144.506	367.662	6.820	0.000
589	0.000	796.517	16.397	21.652	649	272.582	511.114	1.380	0.000
590	0.000	771.372	16.397	28.359	650	364.365	783.491	1.380	1.380
591	0.000	738.805	16.397	25.690	651	447.578	899.164	1.380	1.380
592	0.000	708.566	20.327	21.344	652	413.717	894.521	6.597	6.597
593	0.000	684.723	20.327	19.408	653	266.530	894.832	6.597	6.597
594	0.000	662.976	20.327	25.415	654	115.603	899.844	6.597	6.597
595	0.000	633.980	18.947	19.063	655	51.214	904.828	10.363	10.363
596	0.000	612.771	18.947	18.756	656	33.464	907.829	10.363	10.363
597	3.419	590.344	18.947	21.496	657	25.567	907.829	10.363	31.283
598	0.122	570.126	8.870	14.556	658	9.557	892.850	20.150	11.113
599	0.000	552.513	8.870	16.792	659	3.854	887.838	20.150	24.248
600	0.000	530.653	8.870	23.418	660	3.415	864.392	20.150	26.876
601	0.000	502.676	8.563	20.087	661	4.117	837.717	16.397	12.193
602	0.000	478.748	8.563	22.027	662	2.770	827.722	16.397	21.029
603	0.000	451.933	8.563	24.905	663	0.000	806.286	16.397	29.099
604	0.000	420.869	8.850	22.415	664	1.658	773.410	20.327	7.772
605	0.000	393.289	8.850	22.480	665	2.298	765.142	20.327	14.402
606	0.000	364.802	8.850	24.185	666	1.444	751.012	20.327	29.758
607	0.000	334.362	9.633	11.869	667	2.015	719.722	18.947	23.319
608	19.184	317.995	9.633	8.081	668	1.386	695.851	18.947	28.157
609	12.549	325.640	9.633	8.073	669	0.000	665.553	18.947	23.977
610	285.199	326.830	6.820	4.572	670	0.474	637.349	8.870	26.082
611	576.102	606.116	6.820	6.820	671	0.000	609.344	8.870	17.877
612	99.273	803.624	6.820	6.820	672	0.000	586.889	8.870	22.422
613	28.979	864.080	1.380	1.380	673	0.000	556.987	8.563	18.826
614	23.342	872.065	1.380	1.380	674	0.000	531.983	8.563	21.730
615	17.000	860.710	1.380	6.842	675	0.000	505.139	8.563	26.035
616	8.350	819.029	6.597	12.614	676	0.000	473.085	8.850	24.003
617	21.652	775.789	6.597	8.118	677	0.000	443.607	8.850	19.588
618	30.799	743.055	6.597	6.597	678	0.000	419.000	8.850	27.314
619	10.452	735.410	10.363	10.363	679	0.000	384.510	9.633	15.083
620	2.878	718.080	10.363	10.363	680	13.891	363.840	9.633	9.673
621	10.001	685.516	10.363	25.458	681	1.527	362.707	9.633	9.419
622	0.581	665.552	20.150	19.721	682	0.000	350.191	6.820	6.565
623	0.511	643.551	20.150	13.841	683	11.421	338.666	6.820	6.116
624	0.000	627.240	20.150	27.383	684	130.788	342.347	6.820	3.257
625	0.000	593.798	16.397	23.820	685	34.193	469.318	1.380	0.459
626	0.000	562.848	16.397	18.213	686	12.234	500.977	1.380	6.973
627	0.000	536.882	16.397	25.914	687	42.853	502.676	1.380	7.584
628	0.000	504.459	20.327	24.041	688	31.197	535.098	6.597	5.504
629	0.861	475.180	20.327	12.287	689	12.888	558.375	6.597	11.437
630	0.000	462.183	20.327	29.204	690	2.040	554.863	6.597	53.090
631	0.000	429.931	18.947	22.343	691	1.003	498.032	10.363	41.638
632	0.000	404.587	18.947	18.885	692	4.334	452.669	10.363	17.273
633	0.000	381.934	18.947	24.137	693	1.183	436.217	10.363	7.340
634	0.000	353.731	8.870	23.405	694	0.000	425.655	20.150	5.668
635	0.000	325.640	8.870	22.865	695	0.000	416.990	20.150	25.646
636	0.000	295.653	8.870	16.617	696	0.000	386.436	20.150	21.773
637	0.000	275.407	8.563	20.396	697	0.000	358.544	16.397	6.932
638	0.000	250.771	8.563	21.348	698	0.000	348.294	15.397	6.116
639	0.000	223.503	8.563	21.652	699	0.000	338.978	16.397	27.525
640	0.000	195.866	8.850	19.848					

Table 4 Results of ANN Training for Flood Control Operation

Input Combinations	Error Tolerance	Learning Parameter	Neurons in the hidden layer	Coefficient of Correlation	Sum of Squared errors
I(t), S(t)	0.001	0.1	5	0.911	685139600
I(t-1), I(t), S(t)	0.001	0.6	6	0.942	471706600
R(t-1), I(t), S(t)	0.001	0.4	3	0.983	96978130
I(t-1), R(t-1), I(t), S(t)	0.001	0.4	5	0.983	98336400
I(t-2), I(t-1), I(t), S(t)	0.001	0.4	3	0.944	441974900
I(t-2), I(t-1), R(t-1), I(t), S(t)	0.001	0.4	6	0.983	97377320
I(t-2), I(t-1), R(t-2), R(t-1), I(t), S(t)	0.001	0.4	6	0.983	98720400

THE NUMBER OF CYCLES - 5000
THE OUTPUT NEURON – R(t)

Table 5 Optimal Weights of Various Layers in the Designed ANN for Flood Control Operation

Layer/Node	Weights received at node		
	N1	N2	N3
Input/1 Input/2 Input/3	-8.572548 -6.665743 0.034579	-5.179861 0.786027 -0.614580	-0.936499 1.805451 -0.148473
Hidden1/1 Hidden1/2 Hidden1/3	-5.344691 -6.638442 1.142521		

Table 6 Results of ANN Training for Conservation Operation with Actual Release

Input Combinations	Error Tolerance	Learning Parameter	Neurons in the hidden layer	Coefficient of Correlation	Sum of Squared errors
I(t), S(t), D(t)	0.001	0.7	4	0.585	37499
I(t-1), I(t), S(t), D(t)	0.001	0.8	5	0.611	35505
R(t-1), I(t), S(t), D(t)	0.001	0.6	3	0.738	23705
I(t-1), R(t-1), I(t), S(t), D(t)	0.001	0.6	5	0.737	24037
I(t-2), I(t-1), I(t), S(t), D(t)	0.001	0.8	4	0.624	39167
I(t-2), I(t-1), R(t-1), I(t), S(t), D(t)	0.001	0.6	6	0.733	24372
I(t-2), I(t-1), R(t-2), R(t-1), I(t), S(t), D(t)	0.001	0.6	9	0.748	23133

THE NUMBER OF CYCLES – 5000
THE OUTPUT NEURON – R(t)

Table 7 Optimal Weights of Various Layers in the Designed ANN for Conservation Operation with Actual Release

Layer/Node	Weights received at node		
	N1	N2	N3
Input/1	-17.581366	-12.324131	1.164717
Input/2	0.573094	5.462986	4.419679
Input/3	-3.860137	0.636012	-5.259532
Input/4	-1.139029	2.686011	-0.337221
Hidden1/1	-12.332870		
Hidden1/2	-6.144305		
Hidden1/3	6.514290		

Table 8 Validation Data for the Trained ANN for Flood Control Operation

Time (30 minutes)	10 July 1977 Flood (Cumec)	22 June 1980 Flood (Cumec)	23 July 1982 Flood (Cumec)
1	532.000	644.000	224.000
2	546.000	1778.000	168.000
3	168.000	2912.000	112.000
4	952.000	1652.000	112.000
5	1344.000	392.000	112.000
6	1176.000	518.000	112.000
7	1008.000	644.000	112.000
8	784.000	1162.000	112.000
9	560.000	1680.000	112.000
10	476.000	952.000	140.000
11	392.000	224.000	168.000
12	420.000	224.000	196.000
13	448.000	224.000	224.000
14	392.000	3808.000	168.000
15	336.000	7392.000	112.000
16	1344.000	5936.000	140.000
17	2352.000	4480.000	168.000
18	2212.000	2828.000	140.000
19	2072.000	1176.000	112.000
20	3108.000	1036.000	98.000
21	4144.000	896.000	84.000
22	2800.000	728.000	98.000
23	1456.000	560.000	112.000
24	1330.000	336.000	532.000
25	1204.000	112.000	952.000
26	1204.000	98.000	952.000
27	1204.000	84.000	952.000
28	938.000		2492.000
29	672.000		4032.000
30	476.000		2576.000
31	280.000		1120.000
32	462.000		1008.000
33	644.000		896.000
34	630.000		798.000
35	616.000		700.000
36	532.000		686.000
37	448.000		672.000
38			756.000
39			840.000
40			700.000
41			560.000
42			378.000
43			196.000
44			210.000
45			224.000
46			224.000
47			224.000

Table 9 Validation Results for the Trained ANN for 10th July 1977 Flood

Time (30 minutes)	Beginning Storage (MCum)	Inflow (Cumec)	Release (Cumec)	End Storage (MCum)
1	829.415	532.000	671.666	829.164
2	829.164	546.000	675.908	828.930
3	828.930	168.000	644.656	828.072
4	828.072	952.000	720.365	828.489
5	828.489	1344.000	778.085	829.507
6	829.507	1176.000	752.106	830.270
7	830.270	1008.000	728.388	830.774
8	830.774	784.000	700.884	830.923
9	830.923	560.000	677.441	830.712
10	830.712	476.000	669.526	830.364
11	830.364	392.000	662.147	829.877
12	829.877	420.000	664.494	829.437
13	829.437	448.000	666.931	829.043
14	829.043	392.000	662.091	828.557
15	828.557	336.000	657.416	827.979
16	827.979	1344.000	777.550	828.998
17	828.998	2352.000	1016.707	831.402
18	831.402	2212.000	977.692	833.623
19	833.623	2072.000	937.847	835.664
20	835.665	3108.000	1322.391	838.879
21	838.879	4144.000	1990.530	842.755
22	842.755	2800.000	1207.203	845.622
23	845.622	1456.000	802.966	846.798
24	846.798	1330.000	777.647	847.792
25	847.792	1204.000	757.443	848.596
26	848.596	1204.000	757.346	849.400
27	849.400	1204.000	757.396	850.204
28	850.204	938.000	720.413	850.595
29	850.595	672.000	689.558	850.564
30	850.564	476.000	670.313	850.214
31	850.214	280.000	653.690	849.541
32	849.541	462.000	668.862	849.169
33	849.169	644.000	686.350	849.093
34	849.093	630.000	685.005	848.994
35	848.994	616.000	683.584	848.872
36	848.872	532.000	675.401	848.614
37	848.614	448.000	667.672	848.218

Table 10 Validation Results for the Trained ANN for 22nd June 1980 Flood

Time (30 minutes)	Beginning Storage (MCum)	Inflow (Cumec)	Release (Cumec)	End Storage (MCum)
1	829.415	644.000	682.354	829.346
2	829.345	1778.000	861.688	830.995
3	830.995	2912.000	1229.150	834.024
4	834.024	1652.000	840.635	835.485
5	835.485	392.000	663.010	834.997
6	834.997	518.000	673.467	834.717
7	834.717	644.000	685.768	834.642
8	834.642	1162.000	749.695	835.384
9	835.384	1680.000	841.784	836.893
10	836.893	952.000	722.011	837.307
11	837.307	224.000	649.174	836.542
12	836.542	224.000	648.894	835.777
13	835.777	224.000	648.870	835.012
14	835.012	3808.000	1718.092	838.774
15	838.774	7392.000	5990.687	841.296
16	841.296	5936.000	4255.091	844.322
17	844.322	4480.000	2421.312	848.028
18	848.028	2828.000	1229.579	850.905
19	850.905	1176.000	756.643	851.659
20	851.659	1036.000	733.338	852.204
21	852.204	896.000	715.133	852.530
22	852.530	728.000	695.595	852.588
23	852.588	560.000	678.271	852.375
24	852.375	336.000	658.274	851.795
25	851.795	112.000	641.314	850.842
26	850.842	98.000	640.269	849.866
27	849.866	84.000	639.286	848.866

Table 11 Validation Results for the Trained ANN for 23rd July 1982 Flood

Time (30 minutes)	Beginning Storage (MCum)	Inflow (Cumec)	Release (Cumec)	End Storage (MCum)
1	829.415	224.000	646.421	828.655
2	828.655	168.000	644.548	827.797
3	827.770	112.000	640.591	826.845
4	826.845	112.000	640.551	825.894
5	825.894	112.000	640.524	824.942
6	824.943	112.000	640.497	823.991
7	823.991	112.000	640.471	823.040
8	823.040	112.000	640.444	822.089
9	822.089	112.000	640.417	821.138
10	821.138	140.000	642.328	820.234
11	820.234	168.000	644.287	819.376
12	819.376	196.000	646.289	818.566
13	818.566	224.000	648.333	817.802
14	817.802	168.000	644.236	816.945
15	816.945	112.000	640.284	815.994
16	815.994	140.000	642.180	815.090
17	815.090	168.000	644.136	814.233
18	814.233	140.000	642.142	813.329
19	813.329	112.000	640.176	812.378
20	812.378	98.000	639.192	811.404
21	811.404	84.000	638.220	810.406
22	810.406	98.000	639.131	809.432
23	809.432	112.000	640.057	808.482
24	808.482	532.000	673.657	808.227
25	808.227	952.000	719.514	808.645
26	808.645	952.000	719.810	809.063
27	809.063	952.000	719.833	809.481
28	809.481	2492.000	1059.519	812.060
29	812.060	4032.000	1886.420	815.922
30	815.922	2576.000	1111.247	818.558
31	818.558	1120.000	745.563	819.232
32	819.232	1008.000	727.752	819.737
33	819.737	896.000	713.477	820.065
34	820.065	798.000	701.892	820.238
35	820.238	700.000	691.103	820.254
36	820.254	686.000	689.578	820.248
37	820.248	672.000	688.113	820.219
38	820.219	756.000	697.072	820.325
39	820.325	840.000	706.652	820.565
40	820.565	700.000	691.141	820.581
41	820.581	560.000	676.991	820.370
42	820.370	378.000	660.655	819.862
43	819.862	196.000	646.359	819.051
44	819.051	210.000	647.312	818.264
45	818.264	224.000	648.328	817.500
46	817.450	224.000	648.308	816.736
47	816.736	224.000	648.284	815.972

Table 12 Validation Data for ANN for Conservation Operation with actual release

S.No.	Inflow (MCum)	Ini-stor (MCum)	Demand (MCum)	Tot-rel (MCum)	S.No.	Inflow (MCum)	Ini-stor (MCum)	Demand (MCum)	Tot-rel (MCum)
1	0.000	307.913	20.327	7.298	36	0.000	268.158	16.397	8.894
2	0.000	294.549	20.327	6.116	37	0.000	257.568	20.327	5.709
3	0.000	287.017	20.327	7.340	38	0.000	250.658	20.327	10.538
4	0.000	276.653	18.947	6.606	39	0.000	238.595	20.327	9.215
5	0.000	267.903	18.947	6.483	40	0.000	227.495	18.947	6.605
6	0.000	258.417	18.947	7.686	41	0.000	219.652	18.947	7.340
7	0.000	247.940	8.870	7.707	42	0.000	210.760	18.947	6.606
8	0.000	237.916	8.870	8.563	43	0.000	202.775	8.870	6.606
9	0.000	225.825	8.870	10.275	44	0.000	193.940	8.870	7.340
10	0.000	211.270	8.563	7.707	45	0.000	183.576	8.870	9.368
11	0.000	200.000	8.563	8.563	46	0.000	170.636	8.563	7.610
12	0.000	187.201	8.563	9.419	47	0.000	160.612	8.563	7.339
13	0.000	173.835	8.850	7.707	48	0.000	149.172	8.563	8.379
14	0.000	161.574	8.850	8.562	49	0.000	136.599	8.850	7.375
15	0.000	148.266	8.850	10.276	50	0.000	126.348	8.850	7.340
16	0.000	133.880	9.633	7.707	51	0.483	114.257	8.850	9.480
17	15.531	121.420	9.633	8.563	52	0.000	99.391	9.633	5.606
18	5.105	126.547	9.633	9.419	53	2.188	91.604	9.633	5.800
19	1.508	119.751	6.820	5.505	54	223.729	85.374	9.633	3.323
20	30.854	112.842	6.820	6.116	55	1.233	303.554	6.820	0.000
21	84.559	136.061	6.820	1.865	56	6.838	302.308	6.820	0.000
22	38.134	218.179	1.380	0.000	57	51.793	307.008	6.820	0.000
23	17.712	255.840	1.380	0.000	58	74.381	357.412	1.380	0.000
24	20.820	272.207	1.380	0.000	59	12.375	430.837	1.380	0.000
25	36.663	291.094	6.597	0.000	60	87.369	440.832	1.380	1.804
26	83.881	326.377	6.597	0.000	61	22.811	524.904	6.597	0.000
27	18.897	408.098	6.597	0.000	62	90.513	544.868	6.597	8.838
28	6.149	423.276	10.363	14.970	63	37.119	625.145	6.597	46.240
29	2.104	406.994	10.363	16.097	64	18.370	611.808	10.363	35.781
30	0.178	354.382	10.363	21.816	65	11.662	591.562	10.363	17.499
31	0.000	310.803	20.150	6.453	66	9.148	582.699	10.363	10.421
32	0.000	302.081	20.150	6.116	67	1.160	577.516	20.150	14.128
33	0.000	294.662	20.150	8.869	68	0.000	561.206	20.150	25.297
34	0.000	284.327	16.397	5.505	69	0.000	532.210	20.150	14.714
35	0.000	277.644	16.397	7.946	70	0.000	513.776	16.397	11.893

Table 12 Validation Data for ANN for Conservation Operation with actual release - Contd.

S.No.	Inflow (MCum)	Ini-stor (MCum)	Demand (MCum)	Tot-rel (MCum)	S.No.	Inflow (MCum)	Ini-stor (MCum)	Demand (MCum)	Tot-rel (MCum)
71	0.000	499.306	16.397	24.531	105	0.360	340.223	20.150	17.401
72	0.000	470.990	16.397	16.098	106	0.000	319.807	16.397	25.499
73	0.000	451.366	20.327	17.400	107	0.000	292.057	16.397	15.015
74	0.000	431.941	20.327	25.749	108	0.000	274.673	16.397	14.864
75	0.000	403.285	20.327	12.572	109	0.000	257.171	20.327	21.723
76	0.000	387.371	18.947	25.601	110	0.000	233.809	20.327	11.820
77	0.000	359.507	18.947	16.065	111	0.000	220.246	20.327	12.772
78	0.000	340.762	18.947	20.926	112	0.000	205.691	18.947	22.548
79	0.000	317.457	8.870	18.797	113	0.000	181.877	18.947	11.219
80	0.000	296.390	8.870	9.490	114	0.000	169.021	18.947	7.016
81	0.000	284.440	8.870	22.449	115	0.000	160.611	8.870	8.155
82	0.000	258.417	8.563	10.055	116	0.000	151.040	8.870	8.318
83	0.000	244.485	8.563	15.673	117	0.000	141.328	8.870	8.807
84	0.000	223.701	8.563	19.744	118	0.000	130.822	8.563	7.044
85	0.000	196.942	8.850	7.707	119	0.000	122.412	8.563	8.562
86	0.000	185.219	8.850	8.563	120	0.000	112.275	8.563	9.419
87	0.000	172.533	8.850	10.275	121	0.000	100.920	8.850	7.708
88	0.155	158.828	9.633	7.600	122	0.000	91.320	8.850	8.563
89	1.915	105.677	9.633	7.340	123	0.000	80.475	8.850	10.275
90	18.608	98.655	9.633	8.033	124	0.000	67.676	9.633	7.706
91	33.634	107.150	6.820	2.574	125	0.344	58.587	9.633	8.562
92	26.663	137.732	6.820	0.000	126	12.760	49.299	9.633	0.000
93	7.512	163.387	6.820	0.000	127	2.813	58.926	6.820	0.000
94	12.001	168.823	1.380	1.019	128	0.924	61.135	6.820	0.000
95	6.727	178.819	1.380	2.854	129	12.394	61.503	6.820	0.000
96	20.608	181.396	1.380	0.000	130	4.394	73.283	1.380	0.000
97	4.818	200.226	6.597	0.000	131	2.061	77.332	1.380	0.000
98	60.651	203.681	6.597	0.000	132	0.733	78.833	1.380	0.000
99	36.161	263.259	6.597	0.000	133	0.000	78.691	6.597	0.000
100	11.165	297.890	10.363	1.223	134	1.183	77.955	6.597	0.000
101	41.405	305.281	10.363	6.901	135	12.710	78.380	6.597	0.000
102	16.017	338.524	10.363	6.274	136	8.977	90.273	10.363	0.000
103	5.845	346.113	20.150	4.475	137	2.908	98.881	10.363	0.000
104	3.152	345.915	20.150	6.477	138	0.167	101.373	10.363	0.000

Table 13 The Data for training of ANN for Conservation Operation with Simulated Release

S.No.	Inflow (MCum)	Ini-stor (MCum)	Demand (MCum)	Tot-rel (MCum)	S.No.	Inflow (MCum)	Ini-stor (MCum)	Demand (MCum)	Tot-rel (MCum)
1	13.540	215.740	28.900	28.900	47	0.500	553.210	25.690	25.690
2	333.770	192.660	20.460	20.460	48	0.230	509.530	26.550	26.550
3	172.360	497.790	4.140	4.140	49	56.660	461.310	28.900	28.900
4	265.460	653.620	19.790	19.790	50	182.090	473.950	20.460	20.460
5	45.290	829.410	31.090	31.090	51	93.920	623.640	4.140	4.140
6	12.310	827.530	60.450	60.450	52	36.900	699.710	19.790	19.790
7	14.300	763.710	49.200	49.190	53	9.920	702.520	31.090	31.090
8	6.840	713.930	60.980	60.980	54	2.590	667.280	60.450	60.450
9	3.720	646.920	56.840	56.840	55	1.760	596.180	49.200	49.190
10	1.920	581.870	26.620	26.610	56	0.320	536.500	60.980	60.980
11	1.060	542.080	25.690	25.690	57	0.760	465.550	56.840	56.840
12	0.770	499.220	26.550	26.550	58	0.440	400.250	26.620	26.610
13	0.460	451.870	28.900	28.900	59	0.330	362.790	25.690	25.690
14	245.240	409.260	20.460	20.460	60	0.170	324.130	26.550	26.550
15	670.500	622.680	4.140	4.140	61	34.160	282.470	28.900	28.900
16	21.940	829.410	19.790	19.790	62	91.990	277.570	20.460	20.460
17	5.990	815.560	31.090	31.090	63	61.360	341.360	4.140	4.140
18	2.660	774.790	60.450	60.450	64	11.600	389.760	19.790	14.840
19	1.770	702.130	49.200	49.190	65	0.980	377.390	31.090	0.000
20	0.470	640.850	60.980	60.980	66	0.530	369.410	60.450	18.350
21	0.890	568.540	56.840	56.840	67	0.520	342.950	49.200	18.960
22	0.860	501.780	26.620	26.610	68	0.400	316.340	60.980	18.960
23	0.500	462.500	25.690	25.690	69	0.000	290.730	56.840	20.550
24	0.270	421.220	26.550	26.550	70	0.320	263.650	26.620	26.610
25	4.750	376.130	28.900	28.900	71	0.230	229.430	25.690	25.690
26	81.740	339.670	20.460	20.460	72	0.140	195.090	26.550	26.550
27	55.610	392.120	4.140	4.140	73	17.100	159.130	28.900	22.020
28	33.440	433.920	19.790	19.790	74	113.360	148.280	20.460	20.460
29	2.600	437.500	31.090	23.320	75	800.350	236.080	4.140	4.140
30	0.560	406.950	60.450	32.460	76	2107.320	829.410	19.790	19.790
31	0.270	365.860	49.200	18.960	77	191.920	829.420	31.090	31.090
32	0.240	338.600	60.980	18.960	78	47.110	829.410	60.450	60.450
33	2.620	312.430	56.840	20.550	79	20.400	800.160	49.200	49.190
34	0.320	287.510	26.620	26.610	80	11.030	755.930	60.980	60.980
35	0.100	252.620	25.690	25.690	81	6.900	692.490	56.840	56.840
36	0.730	217.340	26.550	26.550	82	3.930	629.950	26.620	26.610
37	50.460	180.880	28.900	28.900	83	2.110	591.250	25.690	25.690
38	238.970	195.250	20.460	20.460	84	5.580	548.250	26.550	26.550
39	341.360	406.370	4.140	4.140	85	2.110	504.030	28.900	28.900
40	449.850	731.420	19.790	19.790	86	43.790	461.750	20.460	20.460
41	74.780	829.410	31.090	31.090	87	76.910	474.420	4.140	4.140
42	26.830	829.410	60.450	60.450	88	12.760	535.920	19.790	19.790
43	15.510	780.010	49.200	49.190	89	10.840	517.260	31.090	23.320
44	3.880	731.200	60.980	60.980	90	2.120	493.480	60.450	49.930
45	2.110	661.010	56.840	56.840	91	0.880	435.090	49.200	41.640
46	0.980	594.160	26.620	26.610	92	0.670	384.720	60.980	49.470

Table 13 The Data for training of ANN for Conservation Operation with Simulated Release - contd.

S.No.	Inflow (MCum)	Ini-stor (MCum)	Demand (MCum)	Tot-rel (MCum)	S.No.	Inflow (MCum)	Ini-stor (MCum)	Demand (MCum)	Tot-rel (MCum)
93	0.300	327.960	56.840	21.700	139	4.420	753.330	49.200	49.190
94	0.370	299.320	26.620	26.610	140	4.280	693.900	60.980	60.980
95	0.270	264.150	25.690	25.690	141	2.500	624.630	56.840	56.840
96	0.240	228.630	26.550	26.550	142	1.160	558.680	26.620	26.610
97	125.550	191.190	28.900	28.900	143	0.000	518.570	25.690	25.690
98	316.900	279.130	20.460	20.460	144	0.000	475.270	26.550	26.550
99	398.220	565.880	4.140	4.140	145	47.760	428.010	28.900	28.900
100	531.110	829.410	19.790	19.790	146	41.100	432.700	20.460	20.460
101	124.070	829.410	31.090	31.090	147	275.360	443.220	4.140	4.140
102	19.060	829.410	60.450	60.450	148	15.080	702.170	19.790	19.790
103	7.830	772.290	49.200	49.190	149	0.000	683.280	31.090	31.090
104	5.090	715.970	60.980	60.980	150	45.670	638.500	60.450	60.450
105	4.390	647.190	56.840	56.840	151	11.550	610.580	49.200	49.190
106	1.400	582.800	26.620	26.610	152	8.310	560.400	60.980	60.980
107	0.660	542.470	25.690	25.690	153	6.050	497.010	56.840	56.840
108	0.120	499.210	26.550	26.550	154	1.130	436.440	26.620	26.610
109	11.110	451.220	28.900	28.900	155	2.700	398.870	25.690	25.690
110	170.610	419.140	20.460	20.460	156	0.420	361.540	26.550	26.550
111	818.260	558.340	4.140	4.140	157	513.590	318.700	28.900	28.900
112	526.530	829.410	19.790	19.790	158	319.800	743.080	20.460	20.460
113	83.630	829.410	31.090	31.090	159	430.790	792.470	4.140	4.140
114	24.720	829.410	60.450	60.450	160	52.260	829.410	19.790	19.790
115	6.310	777.910	49.200	49.190	161	2.120	829.410	31.090	31.090
116	3.620	720.000	60.980	60.980	162	3.640	784.630	60.450	60.450
117	8.040	649.710	56.840	56.840	163	17.120	712.800	49.200	49.190
118	6.190	588.910	26.620	26.610	164	0.000	666.600	60.980	60.980
119	4.290	553.220	25.690	25.690	165	5.210	593.460	56.840	56.840
120	20.880	513.280	26.550	26.550	166	4.100	530.630	26.620	26.610
121	112.270	485.220	28.900	28.900	167	3.950	493.970	25.690	25.690
122	997.120	552.280	20.460	20.460	168	0.000	455.210	26.550	26.550
123	653.990	792.470	4.140	4.140	169	63.260	408.650	28.900	28.900
124	572.830	829.410	19.790	19.790	170	84.300	429.140	20.460	20.460
125	103.060	829.410	31.090	31.090	171	190.960	482.540	4.140	4.140
126	41.980	829.410	60.450	60.450	172	59.770	657.090	19.790	19.790
127	44.330	795.060	49.200	49.190	173	20.290	683.240	31.090	31.090
128	14.160	774.660	60.980	60.980	174	23.000	658.590	60.450	60.450
129	21.590	714.080	56.840	56.840	175	7.210	607.870	49.200	49.190
130	7.590	665.830	26.620	26.610	176	7.030	553.420	60.980	60.980
131	11.220	630.080	25.690	25.690	177	3.160	488.860	56.840	56.840
132	40.570	595.140	26.550	26.550	178	2.750	425.560	26.620	26.610
133	12.020	568.720	28.900	28.900	179	0.000	389.830	25.690	25.690
134	140.070	534.780	20.460	20.460	180	3.190	350.090	26.550	26.550
135	250.940	641.810	4.140	4.140	181	5.900	310.380	28.900	28.900
136	129.230	829.410	19.790	19.790	182	133.320	276.800	20.460	20.460
137	24.450	829.410	31.090	31.090	183	151.360	381.560	4.140	4.140
138	22.430	806.810	60.450	60.450	184	12.400	518.480	19.790	19.790

Table 13 The Data for training of ANN for Conservation Operation with Simulated Release - contd.

S.No.	Inflow (MCum)	Ini-stor (MCum)	Demand (MCum)	Tot-rel (MCum)	S.No.	Inflow (MCum)	Ini-stor (MCum)	Demand (MCum)	Tot-rel (MCum)
185	0.000	499.730	31.090	23.320	231	69.340	260.260	4.140	4.140
186	21.700	465.500	60.450	49.930	232	2.340	318.120	19.790	0.000
187	8.060	427.010	49.200	41.640	233	0.630	312.550	31.090	0.000
188	7.660	383.900	60.980	50.470	234	0.000	305.390	60.450	18.350
189	9.800	333.100	56.840	36.290	235	0.000	279.600	49.200	18.960
190	11.430	299.320	26.620	26.610	236	0.000	253.780	60.980	18.960
191	18.370	275.060	25.690	25.690	237	0.540	229.040	56.840	20.550
192	31.110	256.930	26.550	26.550	238	0.080	203.780	26.620	26.550
193	149.030	248.420	28.900	28.900	239	0.630	171.070	25.690	25.690
194	299.900	357.820	20.460	20.460	240	0.000	139.340	26.550	26.550
195	556.100	626.340	4.140	4.140	241	5.610	106.100	28.900	22.020
196	117.390	829.410	19.790	19.790	242	9.120	85.910	20.460	18.960
197	46.780	829.410	31.090	31.090	243	36.800	73.780	4.140	0.000
198	42.560	829.010	60.450	60.450	244	0.540	108.020	19.790	0.000
199	15.900	795.240	49.200	49.190	245	0.000	105.640	31.090	0.000
200	0.860	746.600	60.980	60.980	246	0.000	102.790	60.450	18.350
201	1.300	673.200	56.840	56.840	247	0.270	81.870	49.200	18.960
202	15.210	605.370	26.620	26.610	248	0.190	61.070	60.980	15.370
203	13.320	578.300	25.690	25.690	249	0.360	44.330	56.840	0.000
204	2.800	546.690	26.550	26.550	250	0.000	43.290	26.620	0.000
205	6.020	499.790	28.900	28.900	251	0.270	41.450	25.690	0.000
206	90.120	461.460	20.460	20.460	252	0.000	39.420	26.550	0.000
207	580.730	520.090	4.140	4.140	253	7.870	36.620	28.900	0.000
208	157.170	829.410	19.790	19.790	254	167.190	42.450	20.460	18.960
209	30.190	829.410	31.090	31.090	255	476.670	187.410	4.140	4.140
210	2.750	812.520	60.450	60.450	256	43.490	650.640	19.790	19.790
211	7.780	739.430	49.200	49.190	257	10.050	660.730	31.090	31.090
212	9.600	683.550	60.980	60.980	258	0.190	626.270	60.450	60.450
213	7.840	619.700	56.840	56.840	259	0.000	553.400	49.200	49.190
214	13.350	559.120	26.620	26.610	260	0.540	492.640	60.980	60.980
215	2.590	531.080	25.690	25.690	261	0.190	422.570	56.840	56.840
216	0.000	490.010	26.550	26.550	262	0.000	357.410	26.620	26.610
217	2.480	442.220	28.900	28.900	263	0.540	320.460	25.690	25.690
218	85.500	401.850	20.460	20.460	264	2.180	283.280	26.550	26.550
219	185.230	456.930	4.140	4.140	265	0.000	245.310	28.900	28.900
220	14.750	626.210	19.790	19.790	266	92.700	207.970	20.460	20.460
221	62.350	608.150	31.090	31.090	267	165.910	273.930	4.140	4.140
222	0.560	626.390	60.450	60.450	268	84.640	427.230	19.790	19.790
223	2.140	553.890	49.200	49.190	269	2.620	481.680	31.090	23.320
224	9.980	495.240	60.980	60.980	270	0.000	450.360	60.450	49.930
225	4.280	434.490	56.840	56.840	271	0.000	390.630	49.200	38.030
226	2.830	373.190	26.620	26.610	272	0.000	343.750	60.980	18.960
227	0.000	338.690	25.690	25.690	273	0.900	317.270	56.840	20.550
228	8.040	300.400	26.550	26.550	274	0.000	290.560	26.620	26.610
229	15.460	267.400	28.900	28.900	275	0.000	255.270	25.690	25.690
230	42.680	244.580	20.460	20.460	276	0.000	219.790	26.550	26.550

Table 14 Validation Data for ANN for Conservation Operation with Simulated Release

S.No.	Inflow (MCum)	Ini-stor (MCum)	Demand (MCum)	Tot-rel (MCum)	S.No.	Inflow (MCum)	Ini-stor (MCum)	Demand (MCum)	Tot-rel (MCum)
1	0.000	255.270	25.690	25.690	26	0.000	424.060	26.550	26.550
2	0.000	219.790	26.550	26.550	27	0.000	378.600	28.900	28.900
3	2.990	182.510	28.900	24.390	28	286.210	337.380	20.460	20.460
4	235.080	154.620	20.460	20.460	29	444.400	592.650	4.140	4.140
5	453.250	362.760	4.140	4.140	30	1151.610	829.410	19.790	19.790
6	486.890	799.620	19.790	19.790	31	75.840	829.420	31.090	31.090
7	104.420	829.410	31.090	31.090	32	1.240	829.410	60.450	60.450
8	7.140	829.410	60.450	60.450	33	0.000	754.590	49.200	49.190
9	6.420	760.450	49.200	49.190	34	0.000	690.760	60.980	60.980
10	2.800	702.890	60.980	60.980	35	0.000	617.280	56.840	56.840
11	3.160	632.030	56.840	56.840	36	0.000	548.940	26.620	26.610
12	1.450	566.620	26.620	26.610	37	0.000	507.880	25.690	25.690
13	1.180	526.660	25.690	25.690	38	0.000	464.850	26.550	26.550
14	3.710	484.310	26.550	26.550	39	28.690	417.950	28.900	28.900
15	2.800	440.370	28.900	28.900	40	868.500	404.070	20.460	20.460
16	343.100	400.360	20.460	20.460	41	62.680	792.470	4.140	4.140
17	123.450	711.050	4.140	4.140	42	54.980	829.410	19.790	19.790
18	107.300	815.170	19.790	19.790	43	21.090	829.410	31.090	31.090
19	2.820	829.410	31.090	31.090	44	0.990	803.480	60.450	60.450
20	0.000	785.320	60.450	60.450	45	0.000	728.760	49.200	49.190
21	0.000	709.880	49.200	49.190	46	0.000	665.320	60.980	60.980
22	0.000	646.720	60.980	60.980	47	3.090	592.200	56.840	56.840
23	0.000	573.870	56.840	56.840	48	0.110	527.290	26.620	26.610
24	0.000	506.140	26.620	26.610	49	0.000	486.750	25.690	25.690
25	0.000	465.930	25.690	25.690	50	0.000	444.300	26.550	26.550

Table 15 Results of ANN Training for Conservation Operation with Simulated Release

Input Combinations	Error Tolerance	Learning Parameter	Neurons in the hidden layer	Coefficient of Correlation	Sum of Squared errors
I(t), S(t), D(t)	0.001	0.5	5	0.899	15876
I(t-1), I(t), S(t), D(t)	0.001	0.5	5	0.899	15728
R(t-1), I(t), S(t), D(t)	0.001	0.5	6	0.914	13532
I(t-1), R(t-1), I(t), S(t), D(t)	0.001	0.5	6	0.915	13460
I(t-2), I(t-1), I(t), S(t), D(t)	0.001	0.5	5	0.903	15232
I(t-2), I(t-1), R(t-1), I(t), S(t), D(t)	0.001	0.5	8	0.915	13321
I(t-2), I(t-1), R(t-2), R(t-1), I(t), S(t), D(t)	0.001	0.5	8	0.915	13203

THE NUMBER OF CYCLES – 5000
THE OUTPUT NEURON – R(t)

Table 16 Optimal Weights of Various Layers in the Designed ANN for Conservation Operation with Simulated Release

Layer/Node	Weights received at node					
	N1	N2	N3	N4	N5	N6
Input/1	0.314287	-2.055679	-2.420723	-4.417418	1.840281	-2.822798
Input/2	0.602184	-1.201905	-1.019794	1.766065	1.456036	3.789593
Input/3	-0.995797	-1.462713	-2.207310	0.448456	-0.375398	-0.017736
Input/4	0.067294	-4.053555	-4.460369	-8.209265	4.902446	-4.496866
Hidden1/1	1.259822					
Hidden1/2	-4.152955					
Hidden1/3	-4.492891					
Hidden1/4	-7.318473					
Hidden1/5	7.071802					
Hidden1/6	-3.711504					

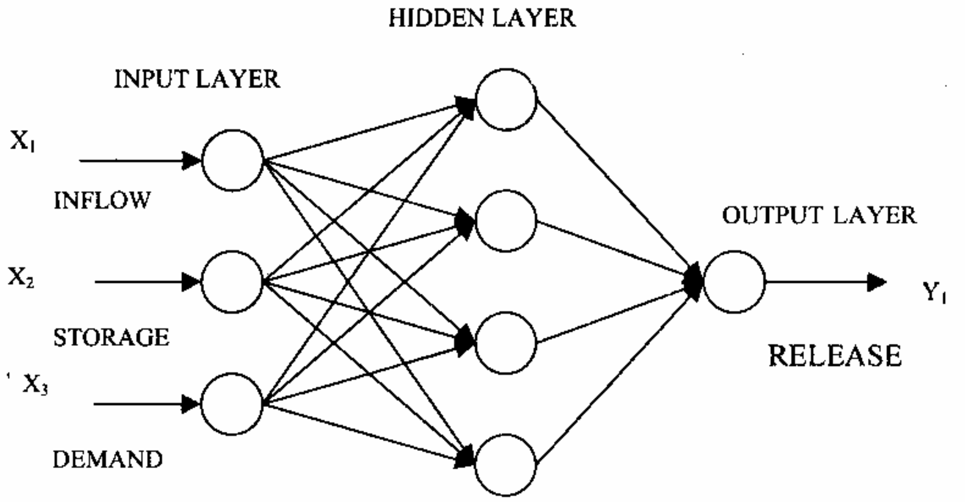

Fig. 1a Three Layer Feed Forward ANN Topology

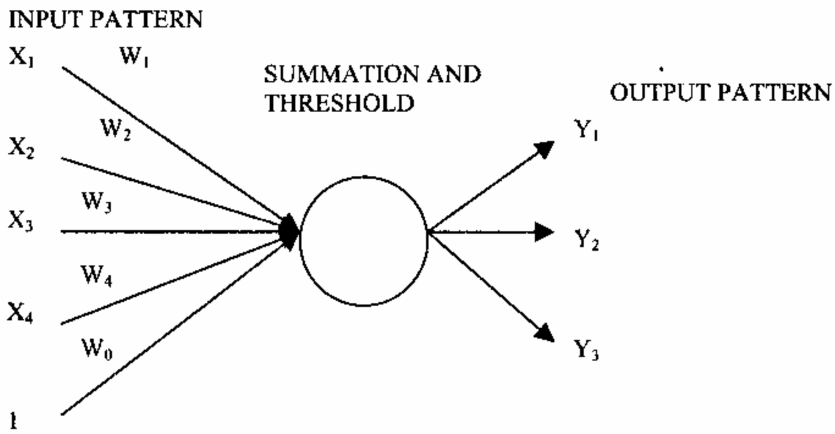

Fig. 1b Processing Element of ANN

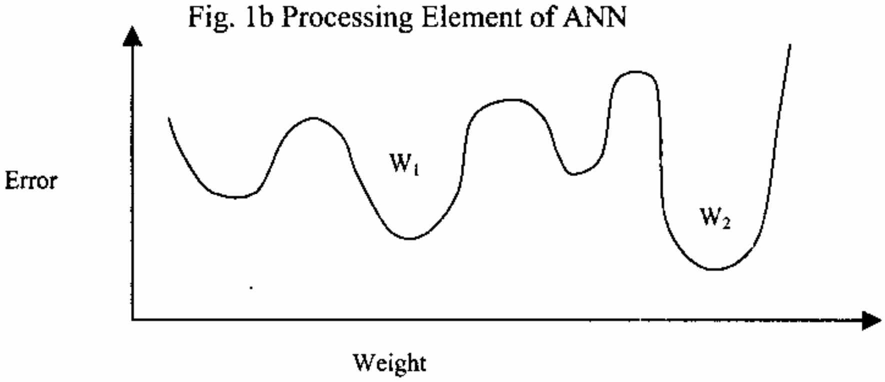

Fig. 1c Function showing weight Vs Error

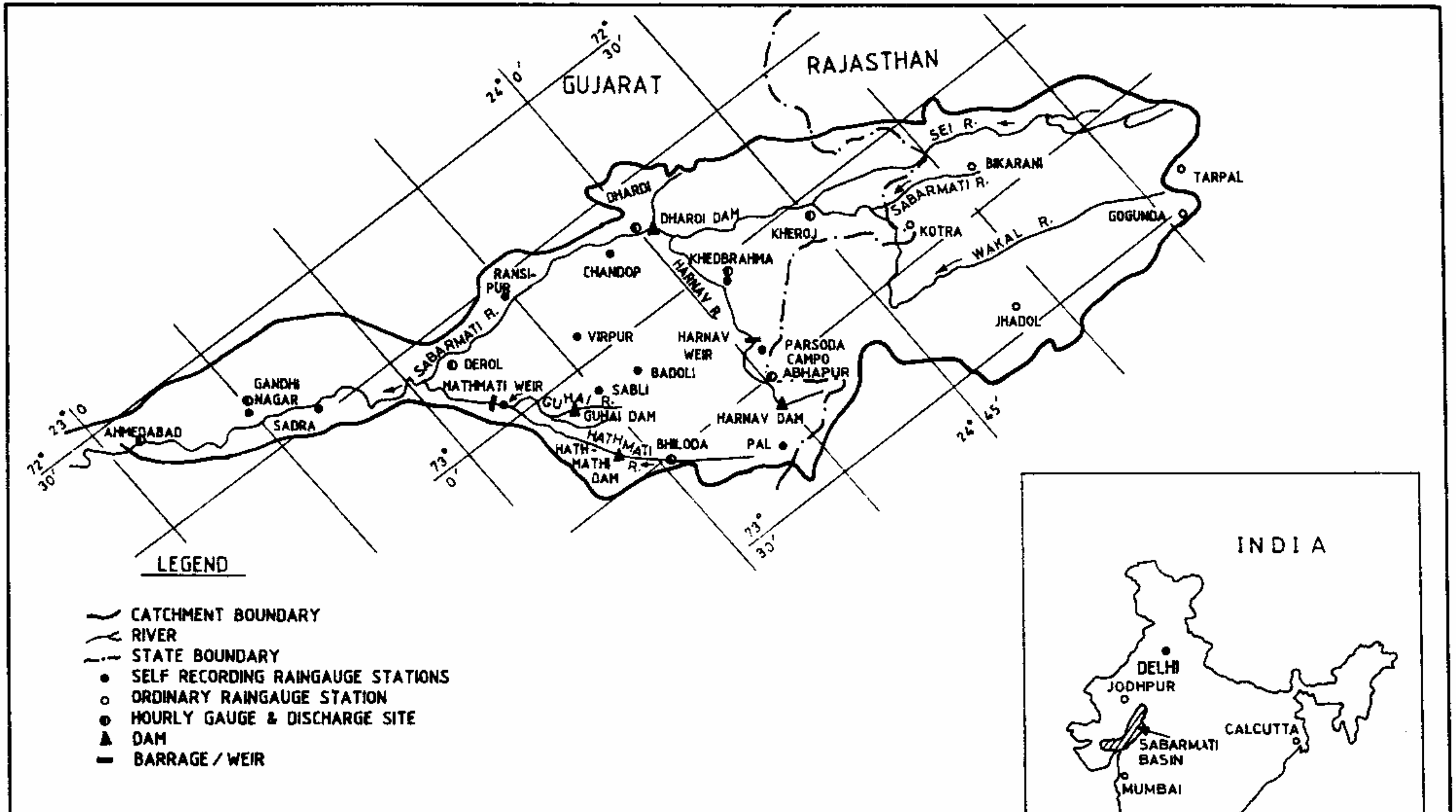

FIG. 2 INDEX MAP OF SABARMATI BASIN (INDIA)

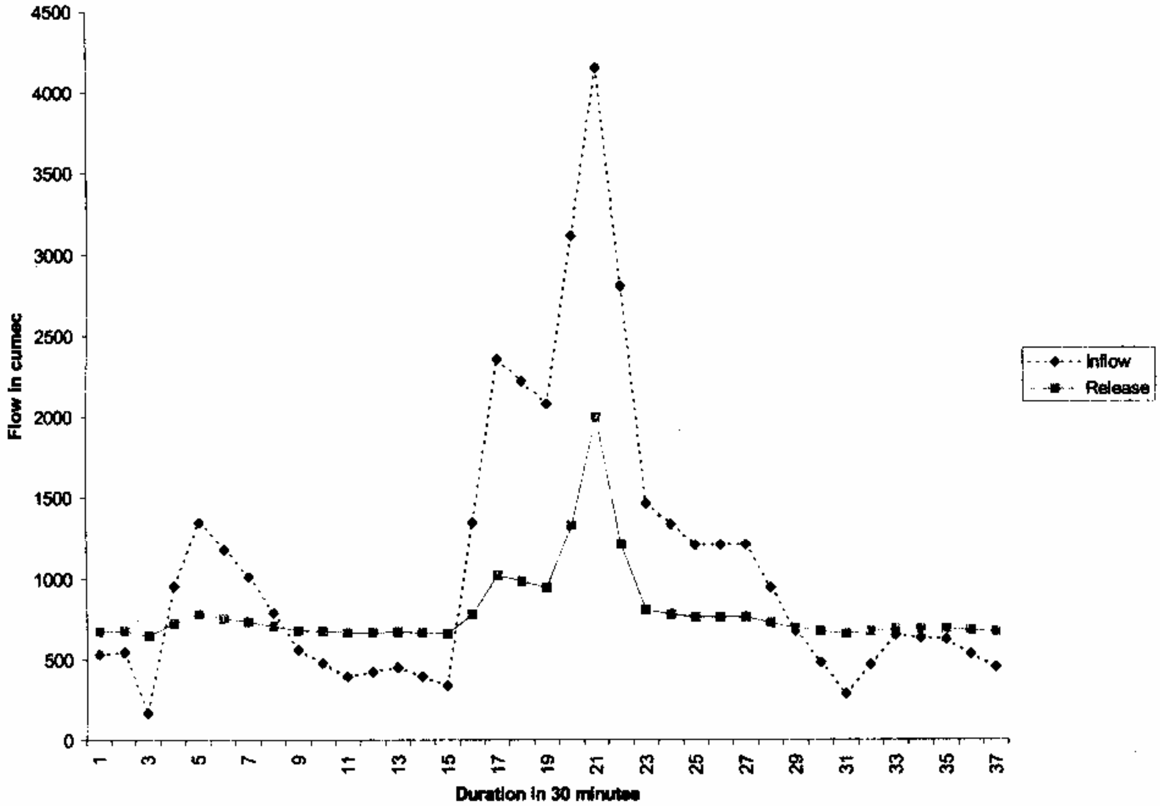

Fig. 3 Regulated Release through ANN for the flood 10th July 1977

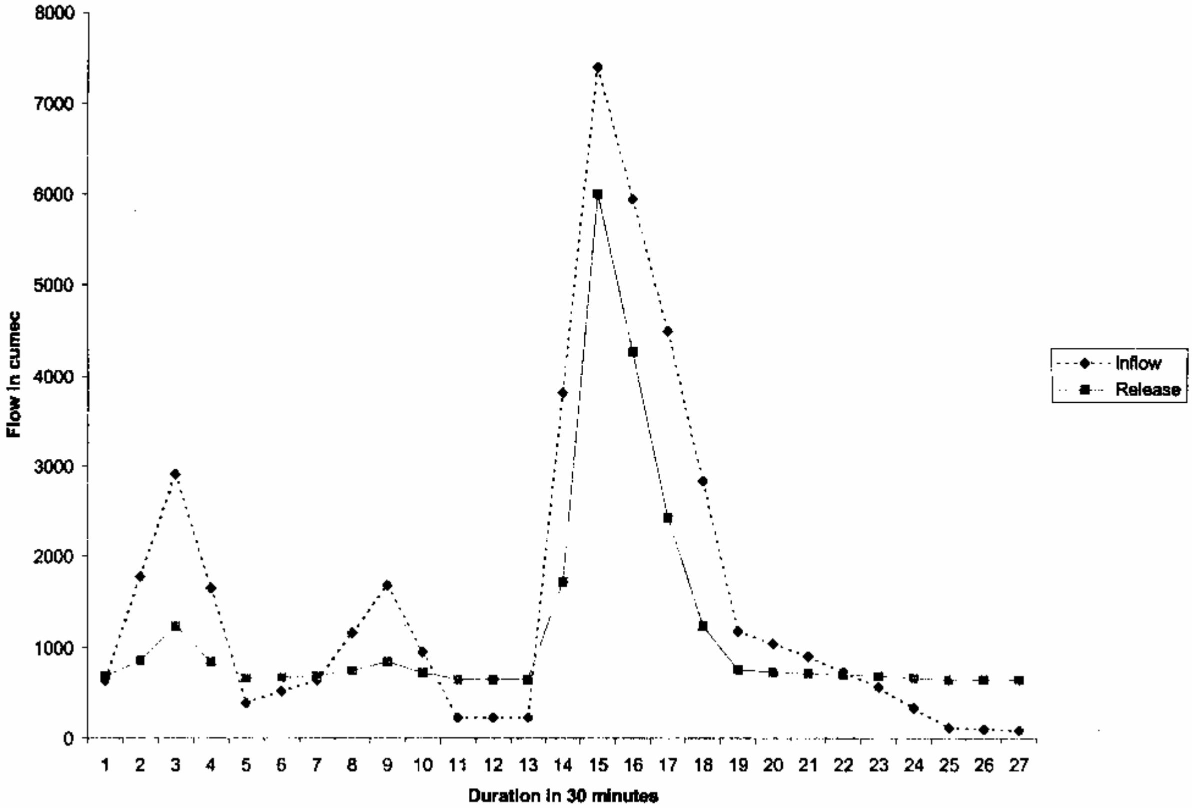

Fig. 4 Regulated Release through ANN for the flood 22nd June 1980

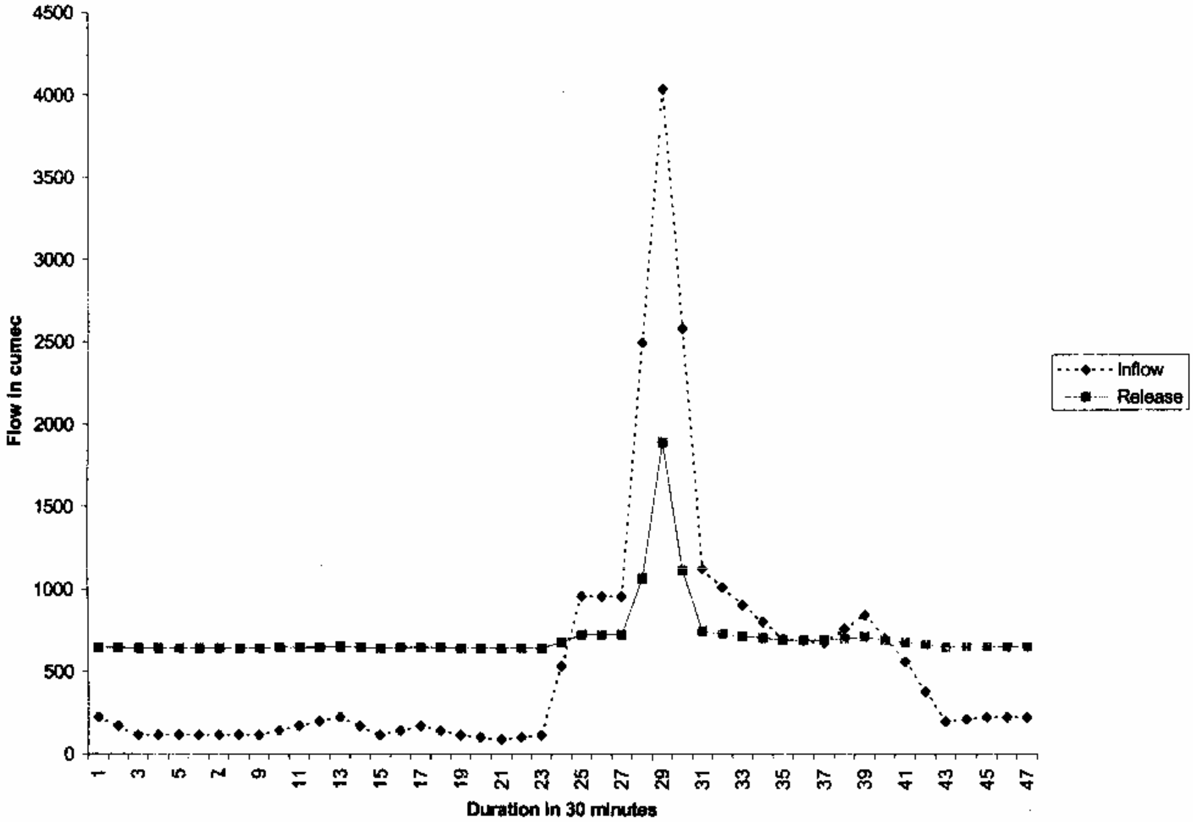

Fig. 5 Regulated Release through ANN for the flood 23rd July 1982

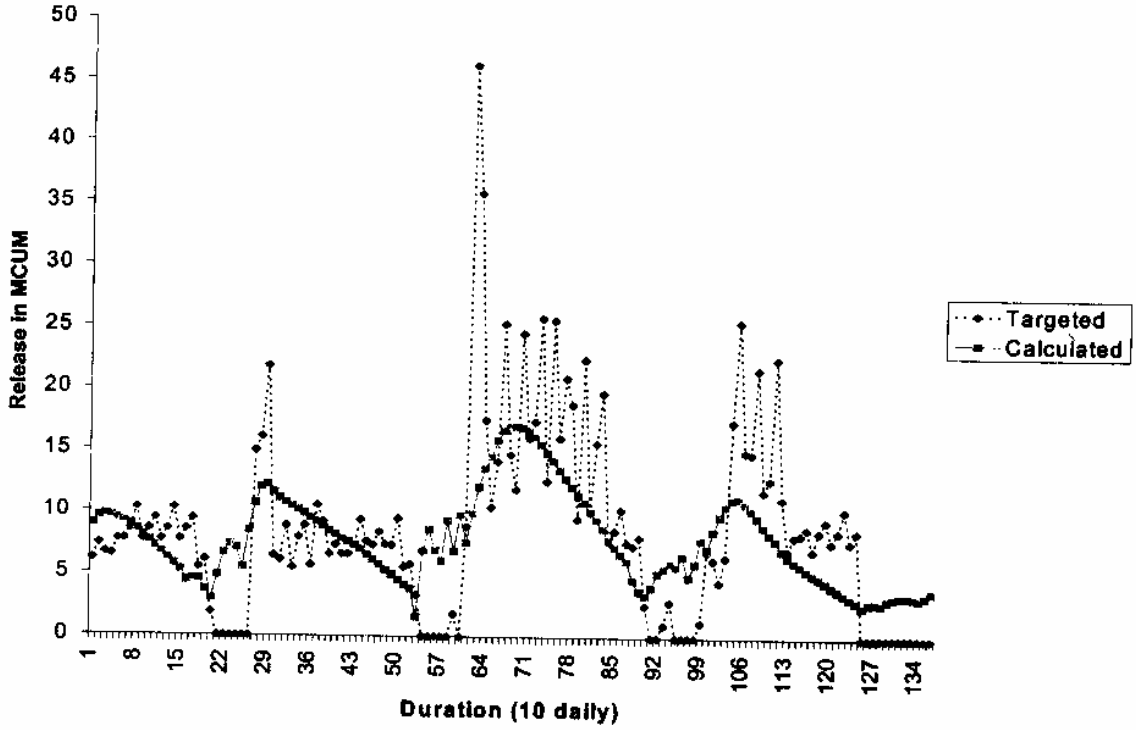

Fig. 6 Validation Results of ANN for Conservation Operation with Actual Release

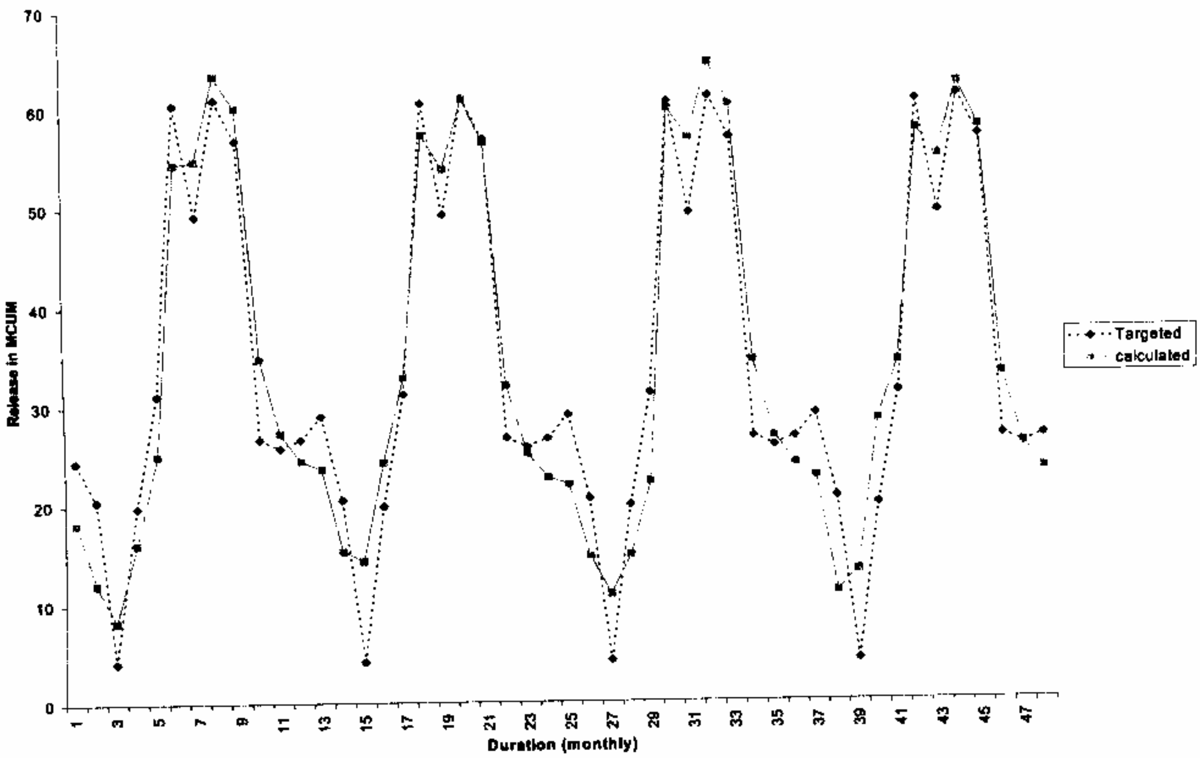

Fig. 7 Validation Results of ANN for Conservation Operation with Simulated Release

Head	:	Dr S K Jain
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Scientific Staff	:	Sh P K Agarwal