Application of Neuro-Genetic Algorithm to Determine Reservoir Response in Different Hydrologic Adversaries

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Abstract: The hydrologic adversaries like high magnitude storms, extreme dryness, aridity, more than normal demand for water etc. often cause a huge stress on the storage structures such as reservoirs and check dams. This stress implies a lot of adverse effects on the adjacent population. One of the major causes of floods and droughts were due to the mis-management of stored water during hydrologic adversaries. The present study tries to estimate the distribution of the surplus water in the case of hydrologic adversaries. In this regard, two years of daily discharge data of one of the reservoirs, Panchet, of the river Damodar was randomly selected and grouped into six categories based on their magnitude. Three neural models were built. One out of the three was selected due to better performance validating criteria. The behaviour of the inputs in the case of hydrologic abnormality was configured with respect to the available historical records and applied to the selected model. The output would give the magnitude of surplus in the case of the pre-configured hydrologic adversaries. According to the results, the Panchet reservoir could not mitigate the stress created due to the applied hydrologic adversaries. The study was conducted with a single reservoir and one major hydrologic pattern of the decade. A more detailed study with the help of this approach could further improve the model estimation.

Keywords: neuro-genetic models; reservoir response; hydrologic uncertainities; multireservoir river basin

The decision support system (DSS) of a reservoir controles the amount of water supplied to different sectors like industry, domestic sector, agriculture etc. The risk from such decisions becomes more pronounced during severe hydrologic conditions such as a high demand in dry conditions, a low demand in wet conditions, an abnormal inflow, an excessive evaporation due to extremely dry climate, etc. The reservoirs become highly stressed during such adverse conditions and the reservoir management can avoid or induce at that time severe damages. Coulibaly *et al.* (2005) suggested a combined model approach to improve the forecast of the reservoir inflow and found that different approaches will work better for different watersheds, lead times, and types of events. This conclusion was supported by WMO (1992), Singh (1995), Singh and Woolhiser (2002), etc. One day ahead stream-flow forecasting by multiple-layer perceptron (MLP) networks at a daily time step was studied for 47 watersheds by Anctil and Rat (2005). Karaboga *et al.* (2004) proposed a control method based on fuzzy logic for the real-time operation of spillway gates of a reservoir during any flood of any magnitude up to the probable maximum flood. Ahmed and Sarma (2005) determined the efficiency of neuro-modelling algorithms on generation of synthetic stream flow. Majumder *et al.* (2007) proposed the pattern for maximum water use for the River Damodar catchments with the help of back propagation neural networks.

India's irrigation development in this century, and particularly after the independence, consists of many large storage based systems. However, in the pre-British period in India, there were practically no large reservoir projects. Even in the British period, a few storage structures were built only at the beginning of this century. Post-independence India, however, has seen more than 60% of irrigation budgets going for Major and Medium (M & M) projects. India, with a geographical area of 3.3 million square kilometers, experiences extremes of climate. The annual average rainfall in the country is about 1170 mm, which is equivalent to nearly 4000 mm. India's irrigated agriculture sector has been fundamental to India's economic development and poverty alleviation. Some 28% of India's Gross Domestic Product (GDP) and 67% of employment are based on agriculture. Agriculture is the primary source of livelihood in rural areas, which account for 75% of India's population and 80% of its poor. And, in turn, irrigation is the base for about 56%, possibly more, of total agricultural output. The rapid expansion of irrigation and drainage infrastructure has been one of India's major achievements (Lahiri-Dutt 2000).

The present study tries to estimate the impact of hydrologic adversaries on the selected reservoir operation. The reservoir surplus was used to show the impact on the reservoir operation. Reservoir inflow and outflow along with the water supplied in different sectors were treated as the input. The pattern was encoded in three neural models and these models were used to estimate the surplus for the conditions observed in the periods of hydrological extremities.

Study area

In this context, in the present study was selected the Panchet reservoir of the river Damodar, a multi-reservoir network which is controlled by Damodar Valley Corporation (DVC). DVC was India's first river development project and second large-scale river project of the last century after the Tennessee Valley Authority (TVA) in USA. The British administrator, W.W. Hunter, in his Statistical Account of Bengal described Damodar floods as "rainwater rushing off the hills through innumerable channels into the river bed with such great force and suddenness that the water rose to form a gigantic head wave of great breadth and sometimes rising up to 1.5 metres in height". The uncontrolled part of the catchment, comprising about 3200 km^2, extends from below Maithon and Panchet dams to Durgapur Barrage for about 60 km had faced many high intensity storms and plays a major role in the agricultural development of the area. The construction of additional dams in the upper reaches (i.e. above Panchet and Mithon) contributes significantly to the runoff. The problem of the distribution of stored water is always pronounced in DVC catchment. When there is enough storage, the supplied water is adequate but in the case of adverse conditions, i.e. when the storage becomes too high or low, the distribution of the surplus water becomes the main cause of hydrologic devastations (Lahiri-Dutt 2000). A brief description of the DVC catchment is given next.

Description of the river basin

The Damodar river which lies between the latitudes 23°30'N and 24°19'N and longitudes 85°31'E and 87°21'E, originates from the Palamu Hills of Chota Nagpur at an elevation of about 610 m above the mean sea level. It flows in south easterly direction, entering the deltaic plains below Raniganj in Burdwan district of West Bengal, India. Near Burdwan, the river abruptly changes its course to southerly direction and joins the Hoogli river about 48 km below Kolkata. The slope of the river bed during the first 241 km is about 1.89 m/km. During the next 161 km it is about 0.57 m/km, followed by about 0.19 m/km in subsequent 145 km. The river is fed by six streams of which the principal tributary, the Barakar, joins it where the river Damodar emerges from the Palamu Hills. The four main multipurpose reservoirs are located at Tilaiya, Konar, Maithon, Panchet, and Barrage at Durgapur was commissioned during 1953–1959. Another tributary, the Khudia, whose catchment is intercepted neither by Maithon nor Panchet reservoirs, joins the Damodar near its confluence with the Barakar. In the plains, the river splits into several channels and ultimately joins the rivers Roopnarayan & Hoogli. The total length of the river is about 541 km. The total catchment area of the river is 28 015 km^2 of which 10 985 km^2 lies under Panchet (Konar – 997 km^2, Tenughat – 4500 km^2, and Panchet 5488 km^2) and 6293 km^2 under Maithon (Tilaiya – 984 km^2, and Maithon – 5309 km^2).

Climate of the river basin

Moderate winters and hot and humid summers characterise the climate of the area. The mean annual rainfall in different catchments of the Da-

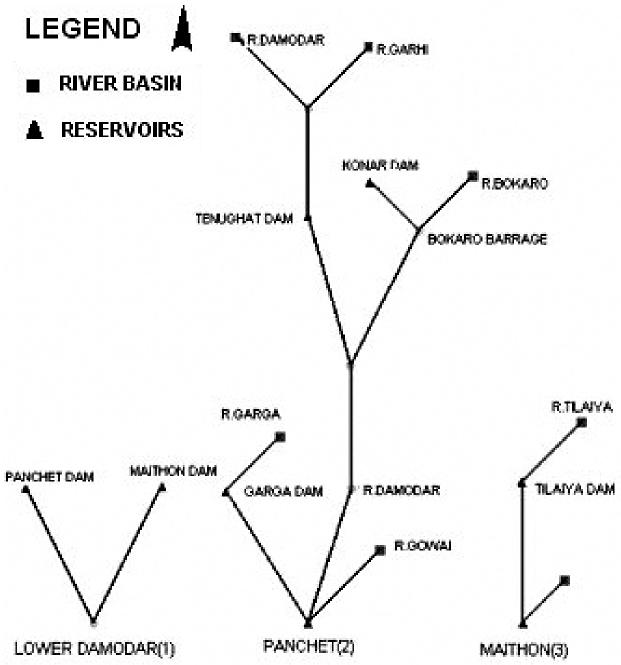

Figure 1a. Schematic diagram of hydrologic modeling tree of river Damodar

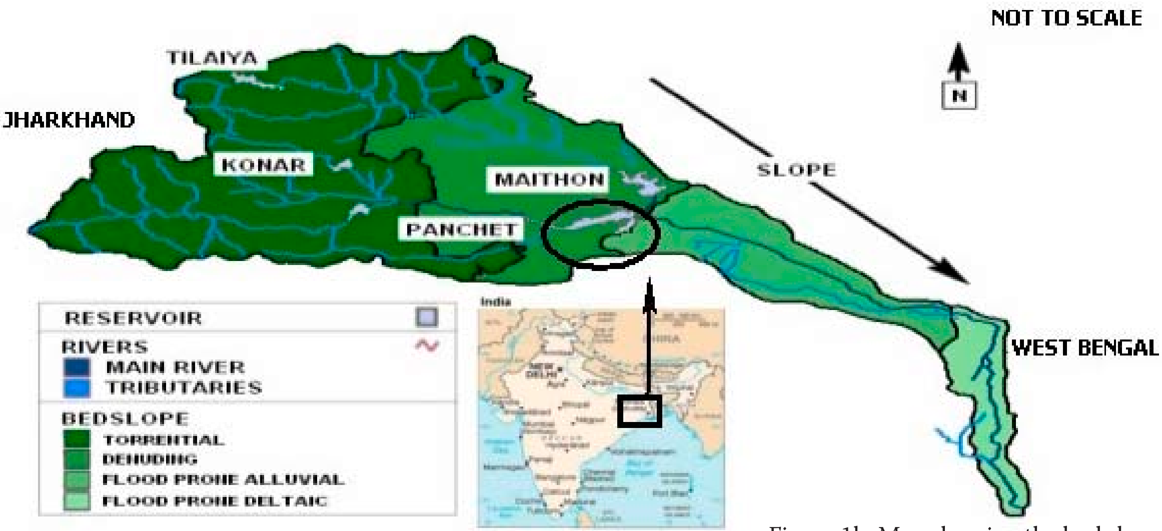

Figure 1b. Map showing the bed slope variation of the river basin

modar valley is 126 cm in Barakar, 127.2 cm in Damodar, and 132.9 cm in the lower valley. 82% of the mean annual rainfall occurs during the four monsoon months from June to September. The mean daily temperature varies from 40°C to below 20°C in winters. The rainfall in this area during the monsoon season is mainly due to the passage of depressions and low pressure over and near the area and the active monsoon conditions due to the accentuation of the seasonal trough.

Geo-morphology

The upper portion of the catchment consists of rough, hilly regions, whereas the lower portion is of flat deltaic plane, nature.

Figure 1a shows the network diagram of the River Damodar catchment in three parts. 1st part depicts the connectivity between the Panchet and Maithon sub-catchment with Durgapur Barrage. 2nd and 3rd part demonstrates the hydrologic modeling tree for the two (Panchet and Maithon) sub-catchment. In Figure 1b the Torrential bed slope represents deciduous forest, high slope and semi-pervious soil class. Denuding bed slope represents medium slope, non-arable land type with a soil class not conducive for agriculture. Flood-prone alluvial and deltaic bed slope represents flood prone regions of the basin with clayey and silty-loam soil.

The Panchet reservoir considered in the study falls within the Denuding (D) bed slope region.

Control structures

DVC has a network of four dams – Tilaiya and Maithon on the river Barakar, Panchet on the river Damodar, and Konar on the river Konar. Besides, Durgapur barrage and canal network, handed over to Government of West Bengal in 1964, remained a part of the total system of water management. Four multipurpose dams were constructed during the period of 1948 to 1959, namely Maithon, Panchet, Tilaiya, and Konar reservoirs. Out of these four reservoirs, the first three are used for hydropower generation. Konar is used only for agricultural purposes of the adjacent area. Though the water supplied for hydropower generation is allowed to return back to the reservoir, a small percentage of water gets diverted or evaporated. Panchet has a capability of 80 MW of power generation and a part of the supplied water is used up for this purpose (Roy *et al.* 2004).

Objective

The objective of the present study is to estimate the distribution of the surplus water in the case of various hydrologic adversaries. The study helps to identify whether or not the impact of the adversaries could be mitigated by a reservoir. In this regard, two years of daily discharge data of one of the reservoirs of the DVC system was randomly selected and grouped into six categories based on their magnitude of discharge. Three neural models were built. One of the three models was selected because it showed the most consistent validation performance. The behaviour of the inputs in the case of hydrologic abnormality was configured with respect to the available historical records (CWC 2005) and applied to the selected model. The output would give the magnitude of surplus in the case of the pre-configured hydrologic adversaries. According to the results, the Panchet reservoir would be in high stress when the applied hydrologic adversaries should happen in reality.

Data description

Daily reservoir discharge data, i.e. inflow, outflow, reservoir storage, and water supply data, i.e. water used for irrigation, industry, and domestic use of Panchet reservoir for the year 1997–1998, were considered as the input and water surplus, calculated with the help of water supply dataset was considered for output. The water surplus of the reservoir was calculated using the formula prescribed by Majumder *et al.* (2007).

The correlation coefficient of the output data series with the input data sets were –0.74, –0.76, –0.74, 0.04, 0.58, 0.47, and 0.04, respectively, for water used in domestic, industrial, and hydropower sectors; storage, inflow, and outflow. The mean values for the output and input data series were found to be equal to 49.44 and 1.54, 13.58, 26.34, 270.18, 14.74, 15.15, 142.48, respectively, for the surplus and water used in domestic, industrial, and hydropower sectors; storage, inflow, outflow, and water level. The output data series were found to be platykurtic (–1.54) and kurtosis of the input datasets were derived as 6.01, 0.80, –0.93, 683.95, 8.38, 21.32, and 683.95, respectively, for water used in domestic, industrial, and hydropower sectors; storage, inflow, outflow, and water level.

The variation of the output data series was 43.71 whereas that of the input data series were 1.74, 14.66, 28.01, 906.25, 24.48, 28.36, and 477.90, respectively, for water used in domestic, industrial, and hydropower sectors; storage, inflow, outflow, and water level data series.

According to the correlation measurements, the water use was found to be inversely related to the water surplus whereas the inflow, outflow, and level were found to be positively correlated with the output, although this relationship was not very pronounced. The central tendency measurements were found to be highly varied for the water level and storage. Other input data sets and the output showed moderate variations.

The output data series after clusterisation showed a standard deviation and mean value equal to 15.05 and 32.37 units, respectively.

METHODOLOGY

Artificial neural network

An artificial neural network (ANN) is a flexible mathematical structure that is capable of identifying complex nonlinear relationships between the input and output data sets. The ANN model of a physical system can be considered with n input neurons (x_1, x_2...x_n), h hidden neurons (z_1, z_2.... z_n), and m output neurons (y_1, y_2...y_n). Let t_j be the bias for neuron z_j and f_k for neuron y_k. Let w_{ij} be the weight of the connection from neuron x_i to z_j and beta the weight of the connection z_j to y_k. The function that ANN calculates is:

$$y_k = g_A\ (\Sigma z_i b_{jk} + f_k)\ \dots\ (j = 1 - h) \quad (1)$$

In which,

$$z_j = f_A\ (\Sigma x_i w_{ij} + t_j)\ \dots\ (i = 1 - n) \quad (2)$$

where:

g_A, f_A – activation functions (Sudheer 2005)

The development of an artificial neural network, as prescribed by ASCE (2000a) follows the following basic rules,

(1) Information must be processed at many single elements called nodes.
(2) Signals are passed between nodes through connection links and each link has an associated weight that represents its connection strength.
(3) Each of the nodes applies a non-linear transformation called activation function to its net input to determine its output signal.

The numbers of neurons contained in the input and output layers are determined by the number of input and output variables of a given system. The size or number of neurons of a hidden layer is an important consideration when solving the problems using multilayer feed-forward networks. If there are fewer neurons within the hidden layer, there may not be enough opportunity for the neural network to capture the intricate relationships between the indicator parameters and computed output parameters. Too many hidden layer neurons not only require a large computational time for accurate training, but may also result in overtraining. A neural network is said to be "over-trained" when the network focuses on the characteristics of the individual data points rather than just capturing the general patterns present in the entire training set. The network building procedure is divided into 3 phases which are described further.

Network building procedure

Selection of network topology

Neural networks can be of different types, like feed forward, radial basis function, time lag delay etc. The type of the network is selected with respect to the knowledge of the input and output parameters and their relationship. Once the type of network is selected, the selection of network topology is the next concern. Trial and error method is generally used for this purpose but many studies now prefer the application of genetic algorithm (Ahmed & Sarma 2005). Genetic algorithms (GA) are search algorithms based on the mechanics of natural genetic and natural selection. The basic elements of natural genetics – reproduction, crossover, and mutation – are used in the genetic search procedure. A GA can be considered to consist of the following steps (Burn & Yulianti 2001):

(1) Select an initial population of strings.
(2) Evaluate the fitness of each string.
(3) Select strings from the current population to mate.
(4) Perform crossover (mating) for the selected strings.
(5) Perform mutation for selected string elements.
(6) Repeat steps 2–5 for the required number of generations.

Genetic algorithm is a robust method of searching the optimum solution to complex problems like the selection of optimal network topology where it is difficult or impossible to test for optimality. The basics of GA have already been discussed by many authors like Wang (1991), Wardlaw & Sharif (1999), Ahmed and Sarma (2005). Hence, the details of the basic procedures of GA are not focused on in the present literature.

Training phase

To encapsulate the desired input-output relationship, the weights are adjusted and applied to the network until the desired error is achieved. This is called as "training the network". There is innumerable number of "training the network" algorithms, among which back-propagation (ASCE 2000b) is mostly preferred. In the present study, Batch Back Propagation (BBP), Incremental Back Propagation (IBP), and Levenberg-Marquardt (LM), each of them derived from the basic back-propagation algorithms, are used as the training algorithm in this present study.

BBP is an advanced variant of Back Propagation where the network weights update takes place once per iteration.

IBP is a variation of the Back Propagation where the network weights are updated after presenting each case from the training subset, rather than once per iteration. This is an originally invented variant of back propagation and sometimes referred to as Standard Back Propagation.

LM (Kisi 2007) is an advanced non-linear optimisation algorithm. It is the fastest algorithm available for multi-layer perceptrons. However, it has the following restrictions:

It can only be used on networks with a single output unit.

It can only be used with small networks (a few hundred weights) because its memory requirements are proportional to the square of the number of weights in the network.

Testing phase

After training is completed, some portion of the available historical dataset is fed to the trained network and the known output is estimated out of them. The estimated values are compared with the target output to compute the mean square error (MSE). If the value of MSE is less than 1%, the network is said to be sufficiently trained and ready for the estimation. The dataset is also used for cross-validation to prevent over-training during the training phase (Sudheer 2005).

In the present study, the IBP, BBP, and LM algorithms are used to train the model. The best model was selected with the help of the performance validation criteria as explained in the next section.

Evaluation of the network

The accuracy of the results obtained from the network is assessed by comparing its response with the validation set. The commonly used evaluation criteria include the correct classification rate (CCR), correlation coefficient (R) and Standard Deviation (SD) (Bhatt *et al.* 2007).

$$\mathrm{CCR} = ((Tpc - Opc)/Tpc) \times 100 \tag{3}$$

$$R = [\sum_1^n((Tp - Tm)(Op - Om))/(\sum_1^n(Tp - Tm)^2 \sum_1^n(Op - Om)^2)^{½}] \tag{4}$$

$$\mathrm{SD} = \frac{\sum_1^n (Tn - Tn)^2}{n} \tag{5}$$

where:

Tpc – group of the actual dataset
Opc – estimated group
Tp – target group for the p^{th} pattern
Op – estimated group for the p^{th} pattern
Tm, Om – mean target and estimated groups, respectively, and n is the total number of patterns.

CCR is used in the classification tasks as a qualitative characteristic. This rate is calculated by dividing the number of correctly recognised records by the total number of records. CCR is measured in relative units or in percents. R is the degree of correlation between two variables. In the present study, the actual and predicted data series were grouped. That is why Spearman's Formula for Rank Correlation (Das 1991) was used to measure the relationship between the two data series. SD is the measure of deviation of the estimated value from the target output. As both of the data series were in a composite condition, the SD for the present study is calculated with the help of the formula given next:

$$\sigma_{T_p} = \sqrt{\frac{\sum fT^2{}_p}{N}} - \sqrt{\left(\frac{\sum fT_p}{N}\right)^2} \tag{6}$$

where:

σ_{T_p} – denotes SD
fT – group frequency
N – total number of data in the series

The same formula is calculated for *Op*. (Das 1991) (Eq. (6)). The SD for the actual and predicted series is found out by dividing SD of the actual series and SD of the predicted series. A perfect match between the observed data and model simulations is obtained when SD approaches 0.0.

RESULT AND DISCUSSION

Model development

Three neural models were developed from the reservoir dataset within the selected time scale, among which the model with the smallestt MSE, highest R, and minimum SD was selected for the simulation work.

The input and output parameters were taken as explained in the following paragraph.

The objective of the study was to estimate the impact of dry and wet hydrologic conditions on the Panchet reservoir. The surplus water of any reservoir represents the available water after fulfilling the necessary demands. The amount of water also determines the hydrologic stress of a reservoir. A high surplus implies that the reservoir is in an unstressed condition. The opposite reveals the stressfulness of the same. Hence, as the output it was taken the amount of water used in domestic, industrial, hydropower sectors with reservoir storage, inflow; outflow, and water level were taken as the input. Hydrological data set of two years was collected from the maintenance authority of the reservoir and daily data of all the parameters were fed into the neural models.

The time scale is one of the major constraints of any estimation problem. In the present study,

Table 1. Summary table showing optimum artificial neural network (ANN) model's architecture and ANN internal parameters

Network name	IBP	BBP	LM
Network topology			
Network type	feed-forward fully connected network	feed-forward fully connected network	feed-forward fully connected network
No. of inputs	7	7	7
No. of hidden layers	2	1	1
Hidden units in the 1st hidden layer	1	1	1
Hidden units in the 2nd hidden layer	2	0	0
No. of outputs	1	1	1
Connection weight	10	8	8
All the topology was created using genetic algorithms with following parameters			
Population size	40	40	40
No. of generations	60	60	60
Network size penalty	6	5	6
Crossover rate	0.8	0.8	0.8
Mutation rate	0.2	0.2	0.2
Training algorithm and parameters			
Training algorithm	Incremental back propagation	Batch back propagation	Levenberg-Marquardt
Training iteration	2	3	2
Stop training conditions			
CCR on training subset must be achieved	98	98	98
Maximum allowed number of iterations	100 000	100 000	100 000
Training & testing results			
Training stop reason	Generalisation loss became too high	Generalisation loss became too high	Error reduction became too low
Average CCR (training)	90.14	79.68	91.55
Average MSE (testing)	93.16	82.91	67.52
Performance validating criteria			
CCR	90.97	80.57	87.68
R	0.83	0.89	0.92
SD	1.07	0.81	0.05

IBP – Incremental Back Propagation , BBP – Batch Back Propagation, LM – Levenberg-Marquardt, MSE – mean square error, CCR – correct classification rate, R – correlation coefficient, SD – standard deviation.

the time scale was not ignored but hydrologic conditions and reservoir response to such conditions were given more weightage. The response of the Panchet reservoir was observed for two consecutive years and its response was analysed for the hydrologic conditions that were prevalent in the selected time span. The entire data set was ranked in an ascending way with respect to the magnitude and categorised with the help of the rules explained in the next paragraph. Neural network is a universal classifier (Hassoun 1995). It can estimate clustered dataset with more ef-

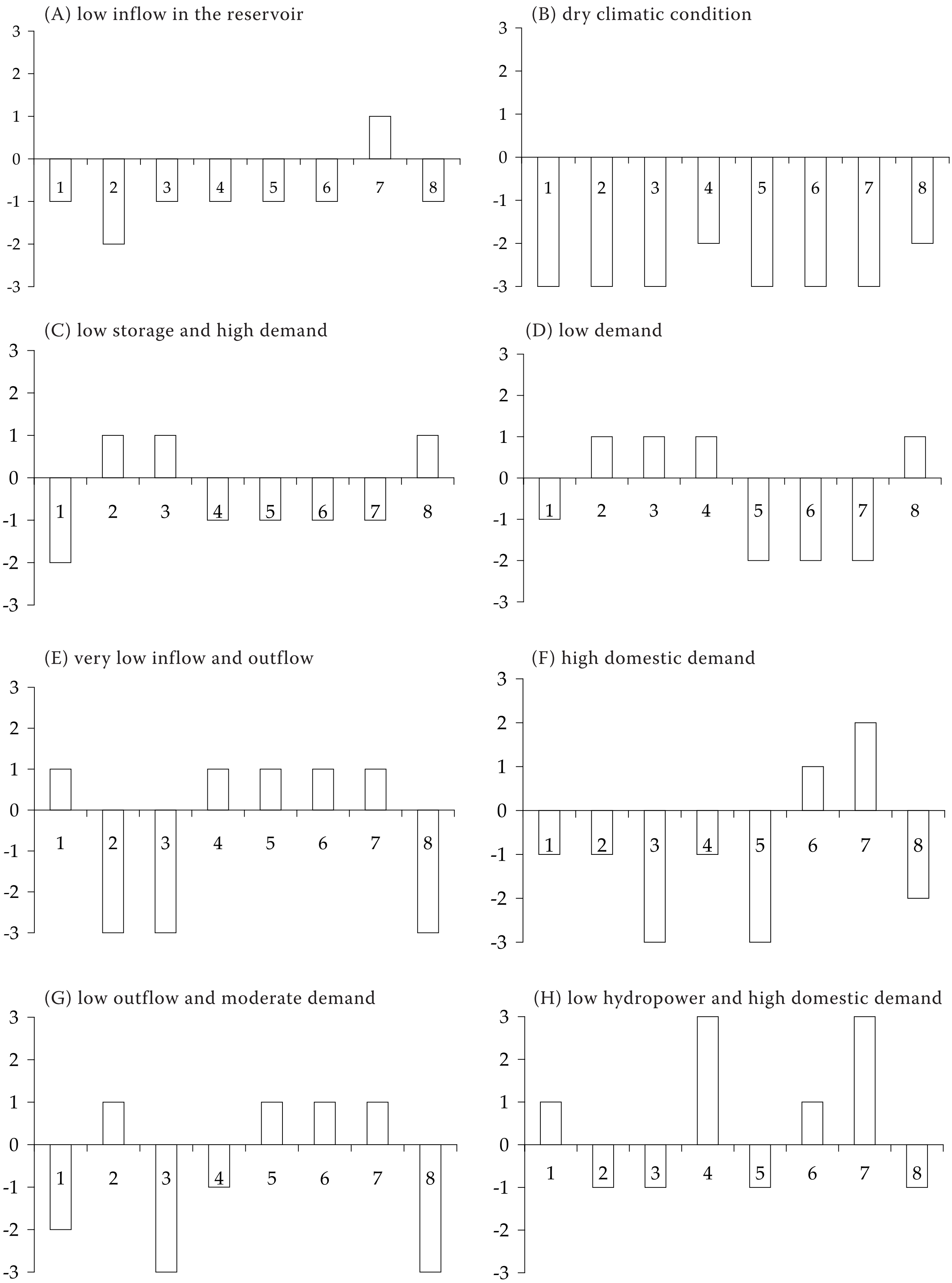

Figure 2. Figure showing the reservoir surplus for different hydrologic conditions as found from the historical data set

Table 2. Table showing the values represented in Figure 2

Value in the curve	Category/Parameter
X axis	Parameter
1	reservoir level (input)
2	reservoir inflow (input)
3	reservoir outflow (input)
4	reservoir storage (input)
5	water used for hydropower(input)
6	water used for industrial sector (input)
7	water used for domestic sector (input)
8	reservoir surplus (output)
Y axis	category
3	P
2	MP
1	LP
−1	LT
−2	MT
−3	T

P – peak, MP – mid-peak; LP – low-peak; LT – low trough; MT – mid-trough; T - trough

ficiency than any other model. As every neural model follows a binary system of encoding, the accuracy of the neural model increases if clustered dataset is used.

As unstable dataset is defined such dataset which separates maximum or minimum from others. These datasets help to determine the threshholds of the entire data set. To be more precise, each peak and each trough borders the stability of the data set. And if the categorisation of the data set is done with respect to the stability of the parameters, the output is said to be a more accurate representation of the problem (Parasuraman & Elshorbagy 2007).

The rules by which the dataset was classified are given next:

(1) If the rank of the data is below 5, then the data is clustered into group P (peak).

(2) If the rank of the data is below 15 but greater than 5, then the data is clustered into group MP (mid-peak).

(3) If the rank of the data is below 250 but greater than 15, then the data is clustered into group LP (low-peak).

Table 3. Table showing reservoir surplus under dry and wet hydrologic adversaries

Condition	Reservoir level	Reservoir inflow	Reservoir outflow	Reservoir storage	Water used for hydropower	Water used for industrial	Water used for domestic	Reservoir surplus
Dry	MP	T	T	P	T	T	T	MT
	T	T	T	MP	T	T	T	MT
	T	T	T	T	T	T	T	MT
	T	T	T	T	T	P	T	MT
	MT	T	T	T	T	MP	MT	MT
	MT	T	T	T	T	MP	P	MT
	MT	T	T	T	P	P	P	T
Wet	P	P	T	T	T	P	P	MT
	P	P	T	T	T	T	T	T
	P	P	T	P	T	T	T	MT
	P	P	P	P	T	T	T	MT
	P	P	P	MP	T	P	T	MT
	P	P	P	MP	T	P	P	MT
	MP	MP	MP	MP	P	T	P	T
	MP	MP	MP	MP	P	P	P	T
	T	T	T	T	P	P	P	T
	P	P	P	T	P	P	P	T
	P	P	P	T	T	P	P	MT
	P	P	P	P	T	P	P	MT
	P	P	P	P	P	P	P	T

P – peak, MP – mid-peak; LP – low-peak; LT – low trough; MT – mid-trough; T - trough

(4) If the rank of the data is below 500 but greater than 250, then the data is clustered into group LT (low trough).

(5) If the rank of the data is below 550 but greater than 500, then the data is clustered into group MT (mid-trough).

(6) If the rank of the data is greater than 550 then the data is clustered into group T (trough).

The minimum and maximum ranks were 1 and 731, respectively; as total 730 data were applied to the neural models to train the same.

68.18% of the clustered data set was used for training and 15.91% each of the same dataset were used for cross validation and testing purposes. Table 1 shows the MSE and absolute error after training and testing datasets. The model architecture and connection weight are also shown.

The network topology was selected the genetic algorithm and IBP, BP, and LM were used as the training algorithms to find the optimum result. The average CCR after training with LM algorithm was found to be 91.55% which is by 114.89% and 100.63% greater than BP and IBP networks, respectively. The average CCR after testing for LM was 67.52, i.e. 0.81 and 0.72 times the CCR achieved with IBP and BP, respectively.

The predicted results from LM achieved a CCR of 87.68% which was 1.08 times and 0.96 times the CCR found from BP and IBP networks. The CCR of IBP was greater than that of LM but IBP was found to be 110.84% less associated than LM which had 92% positive association with the target data series. LM had 5% deviation whereas IBP and BP had 107% and 81% deviation, respectively. The connection weight of LM was also 0.8 times smaller than that of IBP. According to the performance validation criteria and connection weight of the networks, LM was selected as the best model out of the three even if the CCR of IBP was greater than that of LM. As the connection weight is directly related to the amount of data required for training that network, the requirement of heavier data is not conducive for the simulation.

The selected model was applied to estimate the surplus water of a reservoir with respect to dry and wet hydrologic adversaries. Figure 2 (a–h) depicts the surplus of the reservoir due to the reservoir inflow and outflow, water use, and reservoir level in dry and wet climatic conditions as found from the historical dataset. *X* axis denotes the input and output whereas *Y* axis depicts the grouped data set. The table represents the input and output values.

The hydrologic adversaries were created by changing the input category. The adversaries were divided into two groups. The first group represents the stresses in a dry hydrologic conditions and next group represents the stresses that comes with wet hydrologic conditions. Incase of both of the adversaries the reservoir surplus becomes very low or low. That concludes that the reservoir will be in a huge negative stress in the case of various hydrologic adversaries (Table 3). This was eminent in the result given in the last row of the table where all the inputs were grouped into the maximum but still the surplus shows a low value. The observations of the results also conclude that there is some specific impact of water use on surplus which is natural. This help to verify the practicality of the model. Even when the reservoir inflow and outflow were high and the demands were low, the surplus still falls into the lowest group. Thus from the results it could be clearly concluded that the reservoir would be in stress for both dry and wet hydrologic adversaries.

CONCLUSION

The present study tried to modulate the distribution of the surplus water in the case of various dry and wet hydrologic adversaries to identify whether or not the impact of the adversaries could be mitigated by the present reservoir network. In this regard, two years of daily discharge data of one of the reservoir in the DVC system was randomly selected, ranked ascendingly based on their magnitude, and grouped into six categories. Three neural models were built. One was selected with respect to the better performance validating criteria. The behaviour of the inputs in the case of hydrologic adversaries were then configured and applied to the selected model. The output would give the magnitude of surplus in the case of these pre-configured hydrologic adversaries. According to the results, the reservoir would be in high stress when such hydrologic adversaries should happen in reality. The present study has shown an approach to predicting reservoir response to hydrologic stress on a single reservoir. The same study can be applied on multi-reservoir basins which can show the integrated response of the total basin. Neural models are data dependant. Hence, it is important to apply an appropriate amount of data to train the model, so that the desired types of patterns can be learned.

The present study can be improved if separated models are developed for separate seasons. The same can be done for different types of storms observed in the basin.

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