I J C T A, 9(20), 2016, pp. 377-384

Assessment of Memory based Artificial Neural Networks in Stream Flow Simulations

Shyama Debbarma* and Parthasarathi Choudhury**

ABSTRACT

Water resources management of a river basin requires adequate information of its sub-basins. Different flow modelling techniques have been applied to extract essential information of flow of a river system, which is required in planning, management and operation of water resources of a region. Artificial neural networks(ANN) is one such techniques, which have been used extensively in various aspect of water resources management. This paper present the applicability of memory based ANN in four different models in flow modelling of Dholai (Rukni) river, Assam, India. Daily precipitation and discharge data of Dholai(Rukini) river have been used to evaluate the performances of the selected ANN models. The data covers a period from 2000-2005. Results indicated that Gamma memory neural network(GMNN) model outperformed other ANN models while Tanh transfer function and Levenberg-Marquardt learning rule is employed. It also performed best in simulating major flood events of the test data series dominating other chosen ANN models. Hence, GMNN model can be used as an alternative technique for modelling of stream flows. Inferences drawn here would be useful to readers and policy makers.

Keywords: Simulation; Jordon-Elman, gamma memory; TDNN; laguarre; flow

1. INTRODUCTION

The severity of major floods contributes significantly to increased attention toward the investigation of different flow modeling techniques and hence increases their prediction accuracy. Flood modeling follows largely two major modeling approaches: conceptual (phenomenological) modeling, which retains some of the physical laws in their mathematical formulation, and black-box modeling, which relies heavily on an input-output description of the conceptual models. Black-box models attracted to hydrologist and modelers due to the cost effectiveness and large amount of data required for the conceptual models. Black-box models includes linear and non-linear statistical method and artificial neural networks. Artificial neural networks proved to be better than other linear and nonlinear models due to its ability to capture the temporal features of time series problem. Adoption of memory based neural networks such as gamma, time delay and laguarre memory made it more popular than the other static ANN models. In fact, these memory based neural networks are popularly utilized in various fields [1, 2, 3,4,5,6]. The intent here is to focus on the applicability of ANNs in water resources management aspect. Moreover, improvement in the ability of ANN modeling techniques in flood prediction could help those affected by the flood. The present study aims to analyze the performances of four memory based neural network models in simulating daily mean discharge of Dholai (Rukni) river located in Assam, India. Dholai river is tributary of Barak river basin. The selected ANN models are Jordon-Elman network(JEN), Gamma memory neural network(GMNN), Time delay neural network(TDNN) and Laguarre memory neural network(LMNN). The model performances are measured in terms of training min MSE; CV min MSE; testing MSE; NMSE; MAE; Min Abs Error; Max Abs Error; and r respectively.

* Department of Civil Engineering National Institute of Technology, Silchar, Assam, India, *Email: shyamadebbarma@gmail.com*

** Department of Civil Engineering National Institute of Technology, Silchar, Assam, India, *Email- pschou@yahoo.com*

The rest of the paper is organized as follows. Proposed embedding and extraction algorithms are explained in section II. Experimental results are presented in section III. Concluding remarks are given in section IV.

2. STUDY AREA AND DATA

The ANN model are applied to predict the daily flows of the Dholai river located in Assam, India. Dholai river is a tributary of Barak river in North-East India(Figure 1). Daily mean flow data from 2000-2005 are availed from CWC Shillong and corresponding daily mean precipitation data from RMC, Guwahati. Daily precipitation data for future time series are downscaled using suitable downscaling techniques and kept ready for prediction purpose covering a period of 2016-2045.

3. METHODOLOGY

Four memory based ANN models are chosen in the present study which are Jordon-Elman network(JEN), Gamma memory neural network(GMNN), Time delay neural network(TDNN) and Laguarre memory neural network(LMNN). The last three models are the associated models of time lagged recurrent neural network(TLRN). All the models are described as follows:

3.1. Jordon-Elman network(JEN)

Jordan and Elman networks(JEN) is an extended form of the multilayer perceptron with context units, which are processing elements (PEs) that remembers past activity. Context units provide the network with the ability to extract temporal information from the data. JEN provides four basic topologies, differing by the layers that feeds the context units. The first configuration feeds the context units with the input samples, giving an integrated past of the input (memory traces). A second configuration generate memory traces from the first hidden layer (as proposed by Elman). A third possibility is to utilize the past of the last hidden layer activations as input to the context units. The final choice is to utilize the past of the output layer to generate the memory traces, as proposed by Jordan.

Figure 1: Map of Dholai river basin.

The context units remember the past of their inputs using what has been called a recency gradient, that is the unit forgets the past with an exponential decay. It means that events that just happened are stronger than the ones that have occurred in the further past. The context units control the forgetting factor through the Time constant, ranging from 0 to 1. A value of 1 is useless, which means that all of the past is factored in while a value of zero means that only the present time is factored in or no self-recurrent connection. A value closer to 1 means the longer the memory depth and the slower the forgetting factor. Context units are required when learning patterns over time. In the Elman network, the output of the hidden neurons from the previous time step are copied to the context units (Figure 2). In the Jordan network, the outputs of the network are copied to the context units. Further, the context units are locally recurrent. The local recurrences decrease the values by time constant (a multiplicative constant) as they are fed back. This constant determines the memory depth.

The context units can be treated as input units, as if they were obtained from an external source. As the recurrent connections contained in the context units are fixed, network training is done by static backpropagation. The JEN models are advantageous over the previous neural models that can only solve static problems[7,8]. Temporal problems are ones where the current outputs are affected the previous value of the input series. The Jordan and Elman networks can solve time series problems by adapting information over time using recurrent connections. But, both of these nets are constrained in their ability to handle time. The time constant of the Jordan network is fixed and often difficult to set optimally for a given problem. Moreover, the past is always exponentially attenuated, which may not be very representative of the problem.

3.2. Time lagged recurrent network(TLRN)

Time lagged recurrent network(TLRNs) are MLPs coupled with short term memory structures that are locally recurrent. TLRN is an appropriate model especially for processing temporal (time-varying) problems which includes time series prediction, temporal pattern recognition and system identification. The training algorithm used with TLRNs is more advanced than standard backpropagation.

TLRN has three memory structures namely, TDNN; Gamma; and Laguarre memories. The TDNN memory structure is simply a cascade of ideal delays or a delay of one sample. The gamma memory is a cascade of leaky integrators. Laguarre memory is a little more advanced than the other two memories.

In focused topology, the memory kernels connected to the input layer only. Hence, only the past of the input is remembered. If the focused switch is not set, the hidden layers' PEs will also be equipped with

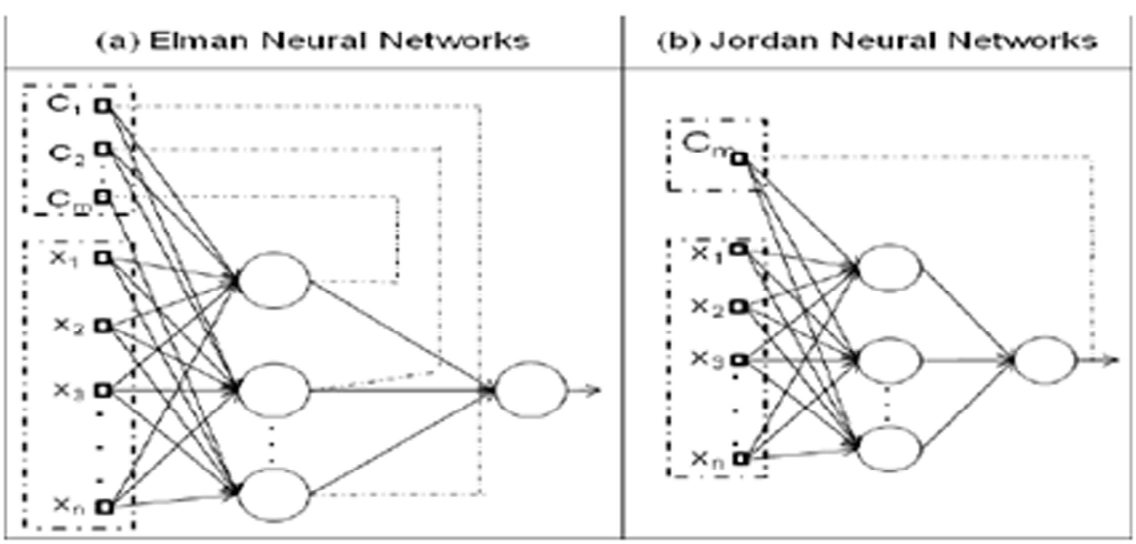


Figure 2: Block diagrams of Jordan and Elman neural models

memory kernels. The depth in samples parameter (D) is used to estimate the number of taps (T) in the memory structures of the network. The number of taps within the input memory layer is dependent on the type of memory structure used. For the TDNN memory, the number of input taps T is equal to the depth D. The formula for the other two memory types is $T=2D/3$. The number of taps for the memory structures at hidden layer n is computed (for all memory types) by the formula $Tn=T/2*n$. This is only used as a starting point for the memory depth, since the depth will be adapted by the network. Key advantages of TLRNs are the smaller network topology required to learn temporal problems as compared to MLPs; their low sensitivity to noise; an adaptive memory depth for best duration to represent the input signal's past. TLRNs has some disadvantages too. The recurrent adaptation of the weights is nonlinear, so the training can get caught in local minima. Another disadvantage is that straight backpropagation cannot be used for training. The backpropagation through time (BPTT) algorithm is quite complex and requires a lot of memory.

Three models were developed from TLRNs using memories such as gamma memory neural network(GMNN); Laguarre memory neural network(LMNN) and Time delay neural network(TDNN). Detailed information of these models are available in[1,2,9,10]. Block diagrams of these three TLRN models are shown in Figure3-Figure5 present.

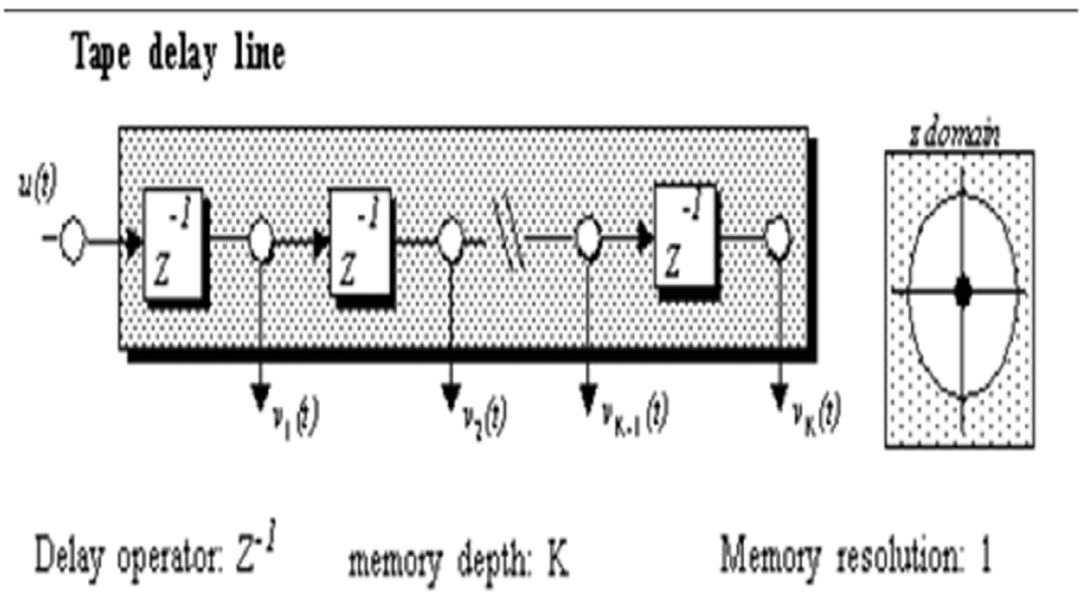


Figure 3: Block diagrams of TLRN

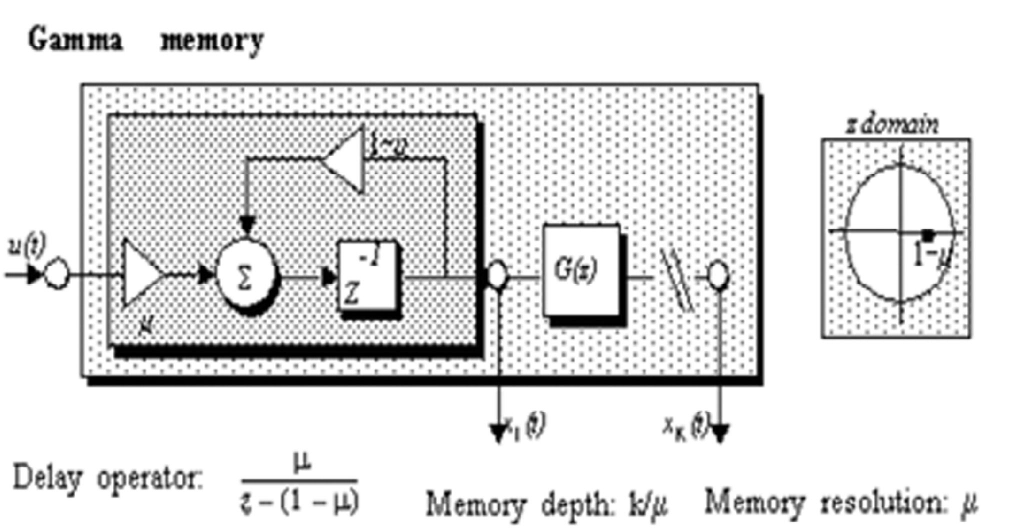
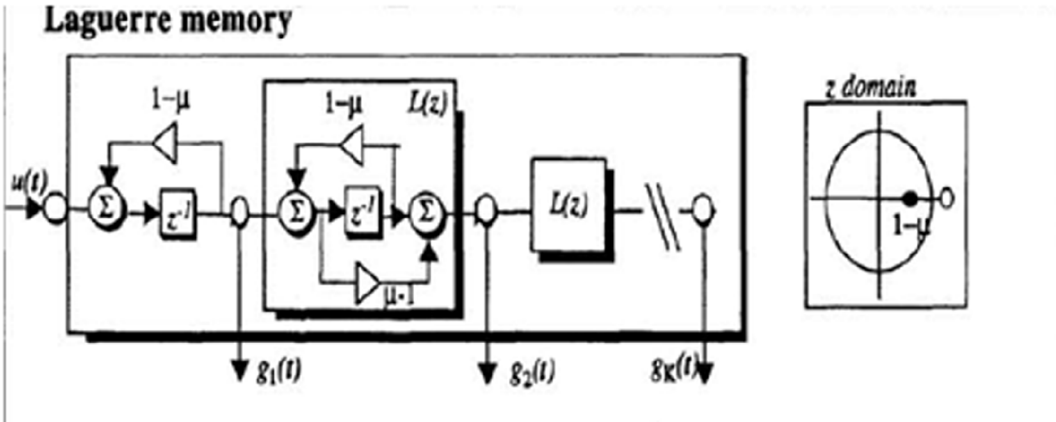


Figure 4: Block diagrams of GMNN



$$\frac{\mu}{z-(1-\mu)} \quad ; \quad \frac{z-(1-\mu)^{-1}}{z-(1-\mu)}$$

Figure 5: Block diagrams of LMNN

4. RESULTS AND DISCUSSIONS

Four memory based neural network models are developed using NeuroSolution-5 software namely, Jordon-Elman network(JEN); Gamma memory neural network(GMNN), Time delay neural network(TDNN); and Laguarre memory neural network(LMNN). These models are trained and tested several times with various sets of network parameter such as transfer functions; learning rules; sample depth; hidden layers; and processing elements with daily observed precipitation data as input and daily observed discharge as output to the networks. The daily mean precipitation and discharge data are the data of Dholai (Rukni) river basin. The training and validation data considered here covers a period of 5 (2000-2005) years, out of which first 60% data are considered for training, next 15% data are considered for cross-validation and remaining 25% data are considered for testing the models. Upon adjustment of different parameters of each network structure during the calibration, the best performing network structures are achieved with Tanh transfer function and Levenberg-Marquardt learning rule for all the neural network models. The model performances are measured in terms of training min MSE; CV min MSE; testing MSE; NMSE; MAE; Min Abs Error; Max Abs Error; and r respectively. The training and testing results for all the ANN models are shown in Table 1. The results indicated that GMNN model dominated other models followed by JEN model. The minimum mean squared errors for training, cross-validation and testing results are 0.018, 0.011 and 551.71 respectively. Test results also indicated that GMNN model outperformed in other parameters such NMSE; MAE; Min Abs Error; Max Abs Error; RMSE and r respectively. A hydrograph of observed and best models discharge output is generated for the test series for comparing the performance of the best model(GMNN) with respect to the observed discharge(Figure 6).

Table 1
Training and test results of all the ANN models

Sl.	*Model*	*Training results*		*Testing results*						
No.	*Name*	*Training Min MSE*	*CV Min MSE*	*MSE*	*NMSE*	*MAE*	*Min Abs Error*	*Max Abs Error*	*r*	*RMSE*
1	JEN	0.018	0.013	675.14	0.37	16.99	0.020	100.14	0.797	25.98
2	TDNN	0.011	0.014	749.41	0.41	18.31	0.003	116.16	0.777	27.37
3	LMNN	0.024	0.015	1041.05	0.57	17.98	0.001	182.96	0.724	32.26
4	GMNN	0.018	0.011	551.71	0.30	14.71	0.050	113.06	0.848	23.48

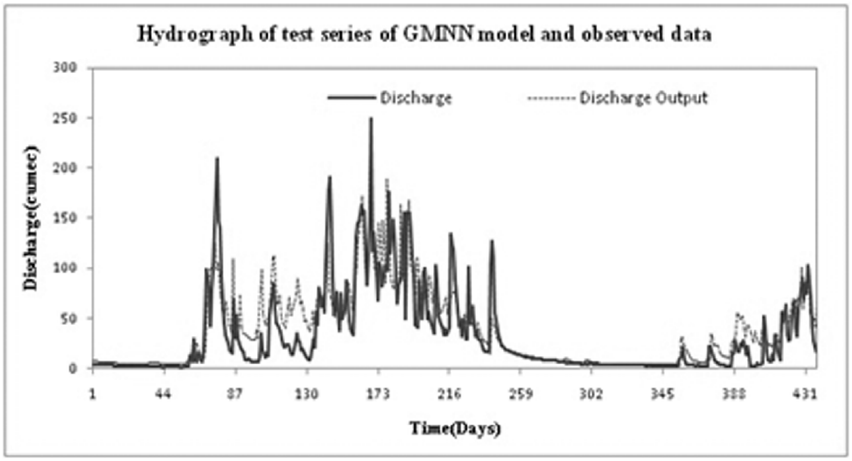


Figure 6: Hydrograph of test series of GMNN model and observed data

To assess the accuracy of the ANN models, the model output data are analyzed in simulating major events of test series. The severe events of test data series are selected as most severe day, mean of five severe events and mean of ten severe events respectively. These flood events are analyzed in terms of percentage error with respect to the observed events. From the analysis, it is found that the minimum percentage error is achieved by GMNN model dominating other models in all the cases with minimum error as 0.57%, 13.17% and 14.42 for most severe day, mean of five severe events and mean of ten severe events respectively. The analysis results are shown in Table 2. Fig. 7- Fig. 9 are presented to show the variations in the actual mean values of the selected events of all the models with respect to the observed values. GMNN model simulated the daily mean observed discharge better than other models. Overall, GMNN model proved to be an effective tool in river flow modeling.

Table 2
Percentage mean error of various flood events

Events	*Percentage errors of various events*			
	JEN	*TDNN*	*LMNN*	*GMNN*
Most severe event error	28.99	35.28	31.39	0.57
Mean of five severe events error	39.39	36.62	37.32	13.17
Mean of ten severe events error	39.71	35.50	34.39	14.42

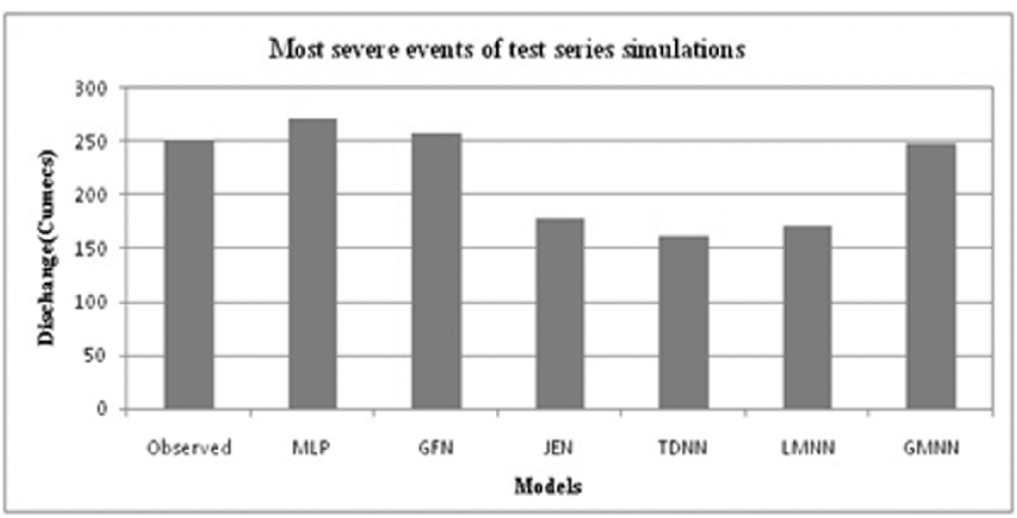


Figure 7: Model wise simulation of most severe event.

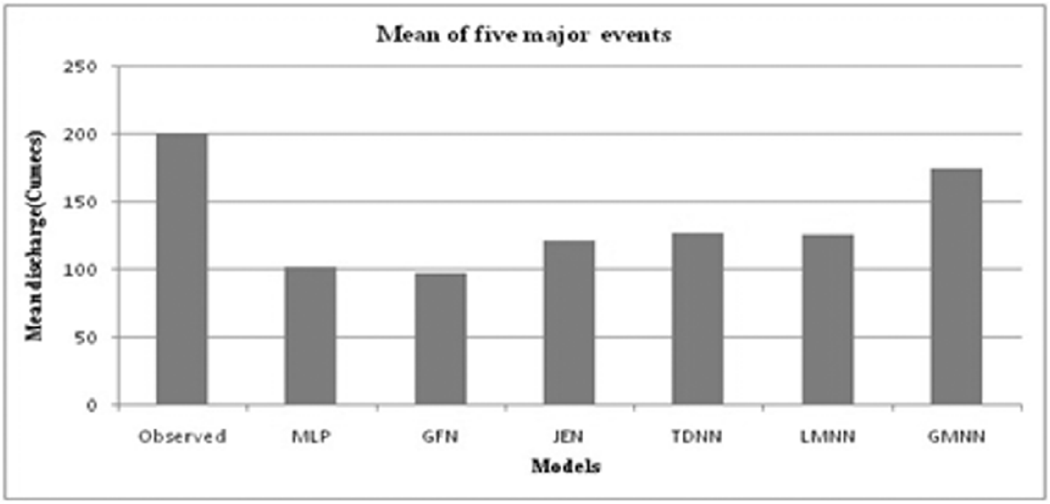


Figure 8: Model wise simulation of mean of five severe events.

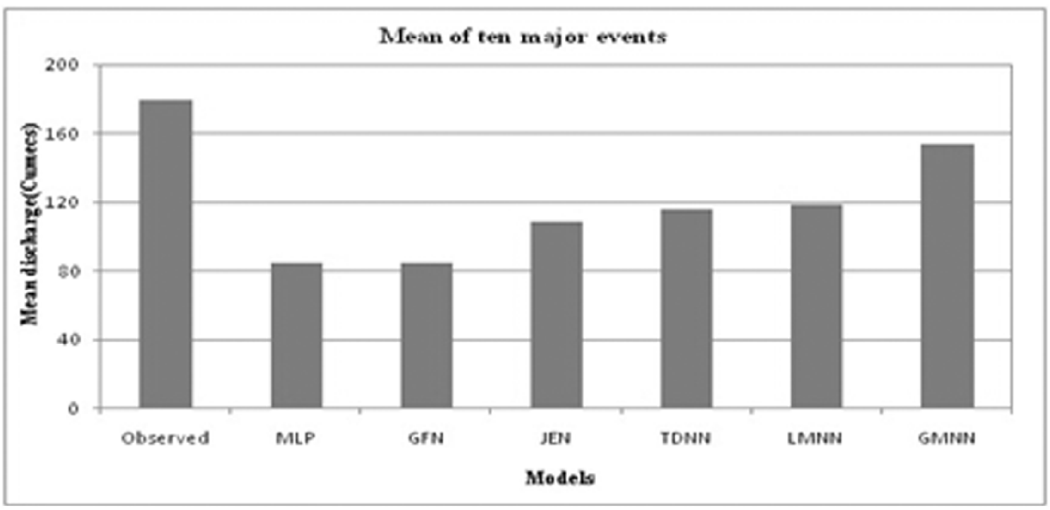


Figure 9: Model wise simulation of ten most severe events.

4. CONCLUSION

This paper aimed to analyze the performance of four different memory based ANN models in simulating daily river discharge of Dholai(Rukni) river. The ANN models includes memory in its network topology. Important features of all the selected neural network modelling techniques and basic concepts were introduced. The simulation ability of all the ANN models with the observed mean daily data for test data series were compared. Simulation models such as GMNN model performed better than other selected ANN models. The model performances are accessed in terms of training min MSE; CV min MSE; testing MSE; NMSE; MAE; Min Abs Error; Max Abs Error; RMSE and r respectively. The model performances are also studied using model output data in simulating major events of test series with respect to corresponding observed data. The severe events of test data series are selected as most severe day, mean of five severe events and mean of ten severe events respectively. From the analysis, it is found that the GMNN model dominated other models in all the cases.

The area of neural networks is large and scopes for future research exist in many aspects.. Overall, GMNN model proved to be an efficient tool among the other chosen ANN models and information derived from the present study would be useful in planning, management and operation of the selected river and its main river.

REFERENCES

[1] Dibike, Y. B., and Coulibaly, P., 2006, “Temporal neural networks for downscaling climate variability and extremes”, Neural Networks, 19, pp.135–144.

[2] Choudhury, P., and Roy, P., 2015, “Forecasting Concurrent Flows in a River System Using ANNs”, J. Hydrol. Eng., 20-8, pp. 1-7.

[3] French, M. N., Krajewski, W. F., and Cuykendall, R. R., 1992, Rainfall forecasting in space and time using a neural network,” J. Hydro., Amsterdam, 137, pp. 1–31.

[4] Hsu, K. L., Gupta, H. V., and Sorooshian, S., 1995, “Artificial neural network modeling of the rainfall-runoff process,” Water Resour. Res.,31(10), pp. 2517–2530.

[5] 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), pp. 201–220.

[6] Zealand, C. M., Burn, D. H., and Simonovic, S. P.,1999 “Short term stream-flow forecasting using artificial neural networks,” J. Hydro., Amsterdam,214, pp. 32–48.

[7] Pham, D.T., and Karaboga, D., 1999, “Training Elman and Jordan networks for system identification using genetic algorithms,” Artificial Intelligence in Engineering, 13, pp. 107–117.

[8] Liou, C. Y., Huang, J. C., and Yang, W. C., 2008, “Modeling word perception using the Elman network,” Neurocomputing, 71, pp.3150– 3157.

[9] Kisi, O., 2007, “Streamflow forecasting using different artificial neural network algorithms,” ASCE J. of Hydrol. Eng.,7(12-5), pp. 532-539.

[10] Principe, J. C., Hsu, H. H., and Kuo, J. M., “Analysis of Short Term Memories for Neural Networks,” pp. 1011-1018.