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RIVER REACHES FLOOD FLOW PREDICTION USING PRNN MODELS

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ABSTRACT

An experiment on predicting flood flows at different upstream and a down stream section of a river network applying partial recurrent neural networks (PRNN) with and without memory structure attached to the input layer is presented. Performance of PRNN having TDNN memory, Gamma memory, and Laguarre memory attached to the input layer have been investigated in the study. The models are applied to forecast flood flows at four different locations in Tar basin, USA. Results obtained indicates that though there may be difficulties in training a partially recurrent network having no memory the model performs better in forecasting multiple flows over a basin.

KEYWORDS: PRNN, Gamma Memory, River Network

INTRODUCTION

Flood flow prediction with adequate lead time is essential to provide time for taking safety measures and evacuation of population being endangered by the imminent flood disaster. Artificial Neural Network (ANN) is a powerful computational tool having capabilities of capturing underlying characteristics of a physical process from the data set. ANN models can extract relationships between the input(s) and output(s) efficiently but, the model can not explain underlying physics governing the problem. Some of the earliest application of ANN in hydrology has been reported by Daniel (1991). Application of static ANNs in modeling hydrologic time series can be found in the works of Hsu et al.(1993,1995), Zhu et al.(1994), Smith and Eli(1995), Thirumalaiah and Deo (1998), Sajikumar and Thandaveswara(1999), Zeeland et al.(1999),Sudheer et al.(2002), Chou et al.(2005),Deka and Chandramoulli(2005), Shrestha et al.(2005), Alvisi et al.(2006), Raiand Mathur (2007), Kisi(2004,2007,2008). The ASCE task committee (2000) on application of ANNs in hydrology, while summarizing the application of ANN in different areas of hydrology opined that ANN may be suitable for the problems of estimation and prediction in hydrology because of its strong capacity to identify the underlying nonlinear relationship of a physical process. Application of ANN in areas of hydrology shows that mostly static ANN models have been employed to describe hydrologic problems. Maier and Dandy (2000) reviewed 43 papers dealing with prediction and forecasting of water resources variables and reported that all but only two papers used static MLP networks. MLPs and other static ANN models apply only input output matching to describe a physical process. Flood flow being a non-linear time varying hydrologic process the flow parameters changes continuously with time and the variation characteristics for a reach is contained in the data set collected systematically over time. Temporal variations in input and output of a system can be modeled with an ANN using a Time Delay Neural Network (TDNN). A TDNN is essentially equivalent to using an MLP with multiple past samples as input. In recent past Hsu et al(1997), Anmala et al.(2000), Dibike et al.(1999), Coulibaly et al.(2001), Diamantopoulou et al.(2006),Wang et al.(2009) applied different types of recurrent ANN models to incorporate temporal dimensions for a hydrologic problem and the results are encouraging. Most of the ANN based flood forecasting models available in the literature is capable of providing forecast at

a single location and do notpossess forecast updating capability. This limits applicability of the models in real time applications.

During flood, flow at upstream and downstream stations change continuously with time. Flood flow in a river system is characterized by coherent evolution of inflow(s), outflow(s) and storages in the river reach and indicate existence of a relationship among concurrent flows at the bounding sections.

A partially recurrent neural network (PRNN) possesses recurrent structure connecting the first hidden layer to itself through a recurrent connection and also adds a feed forward connection, through a bypass synapse, from the input axon to the layer after the first hidden layer. In the case of PRNN, the recurrent structure acts as a state for the feed forward structure and has infinite memory depth. On the other hand a time lagged Recurrent Neural Network (TLRN) has adaptable memory depth with an effective upper limit. This paper investigates applicability of PRNN models with and without memory attached to the input layer for predicting concurrent flood flows at multiple locations in a river system. The present study shows a PRNN model having infinite memory depth may face difficulties during training but can provide better results in forecasting multiple flows.

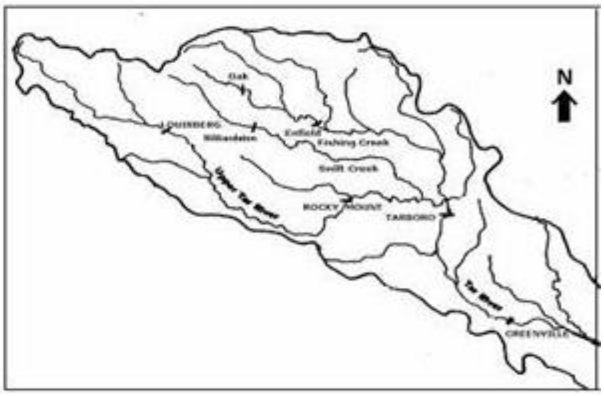


Figure 1: Map of the Study Area in Tar River Basin

STUDY AREA

The proposed flood forecasting model formulations is demonstrated for the Tar-Pamlico River basin in North Carolina (NC), USA. Figure 1 shows the map of the study area. Major tributaries of the Tar River main stem include Cokey Swamp, and Fishing, Swift and Sandy Creeks. In the Upper Tar river basin, tributary flow from Swift Creek, Fishing and Little fish Creeks contribute to the flow at Tarboro, NC. This study uses present flow information available at Tarboro (Q_4) and its three upstream gauge sites, at Rocky Mount (Q_1), Hilliardston (Q_2), and Enfield (Q_3) to predict future flows at these stations.

PARTIAL RECURRENT NEURAL NETWORK (PRNN)

A Partially recurrent neural network feedbacks the first hidden layer to itself through recurrent synapse connection via a context unit. The context unit represents a type of short term memory operated by a delay operator. In addition to feedback the network also adds a feed forward connection from input axon to the layer after the first hidden layer through a synapse bypassing recurrency. The recurrent connection in the hidden layer allows the network to detect and generate time varying pattern of the dynamic system. The output of the hidden nodes at time t which are stored in the context units are fed back as additional inputs at time (t+1), effectively treating the recurrent structure act as a state for the feed forward structure.

In addition to recurrent connection in the hidden layer memory can be attached with the input layer of a fully / partially recurrent network. Three types of memory structure can be found in the literature these are: TDNN, Gamma and Laguarre memory. TDNN is a multi channel tapped delay line with ideal delay and the memory is generated by a time delay unit. A TDNN has fixed memory depth with highest resolution, $\mu = 1$ while, Gamma and Laguarre has adaptable memory depth. Adaptable memory depth allows deciding best duration for an input's past.

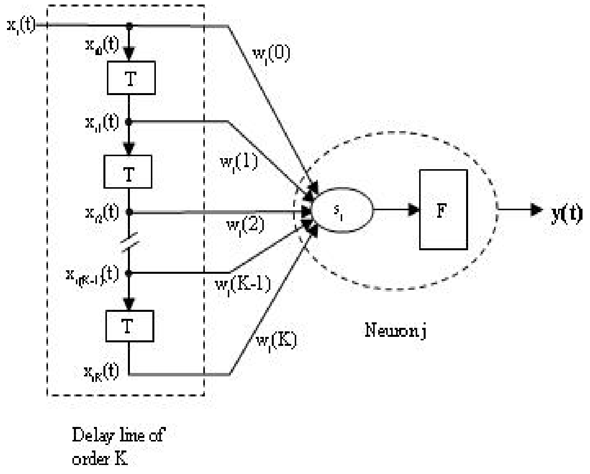


Figure 2: Single Neuron with Delay Line of Order K

For a single neuron, i at the input layer shown in Figure 2 for any given input $x_i(t)$, the TDNN delay operator, T yields the past values given by, $x_{ik}(t) = x_i(t-k), k = 0,1,2,3,....... K$.

Gamma memory (GM) cascades self recurrent connections with local feedback. The memory generated by the time delay unit has a adaptable parameter μ which can control the memory depth, d. For the neuron, i shown in Figure 2 when the input layer is attached with gamma memory the delay is a dispersive delay line of order K, generated by delay unit operator, T. There exists a trade-off between memory depth and resolution parameter μ. For a K^{th} order structure the memory depth $d = \dfrac{K}{\mu}$.

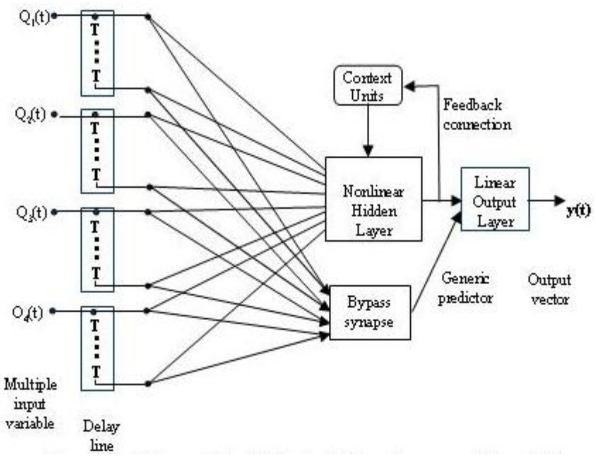


Figure 3: Partial Recurrent Neural Network with Focused Memory Used for Prediction of Flow at Multiple Sections

For a number of tap used in the memory structure resolution parameter μ can be optimized using a performance criterion. Since for a number of taps in the memory element best compromise between resolution and the memory depth can be achieved, a GM can decide duration that best represents an input's past. For any given input $x_i(t)$ to a neuron i in the input layer, the value for the first tap $x_{i0}(t) = x_i(t)$ and delay operator yields the past value of $x_{ik}(t)$, given by $x_{ik}(t) = (1-\mu)x_{ik}(t-1) + \mu x_{i,k-1}(t-1), k = 1,.....K$ and are stored in the taps. Figure 3 shows the PRNN model with the memory attached to the input layer used in this case.

Laguarre memory (LM) is based on the Laguarre function and has same properties as that of gamma memory. Similar to the GM the resolution parameter is used to control memory depth for a number of taps used in the memory element.

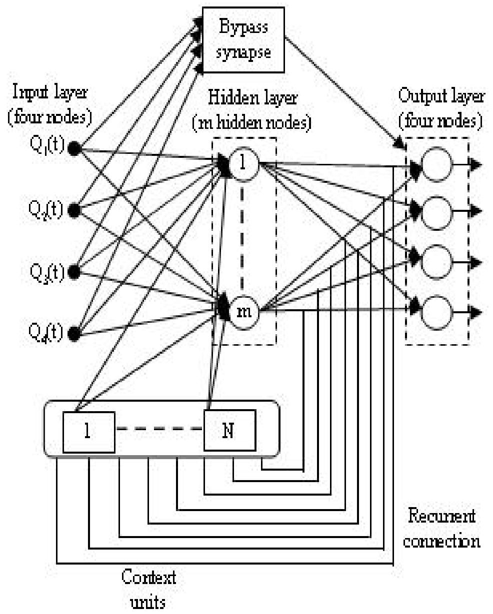


Figure 4: Partial Recunent Neural Network without Attaching Memory to the Input Layer (PRNN)

Four different PRNN models are used in present study to forecast river flows at multiple sections in a river network. The models used are (i) partially recurrent neural network with focused Gamma memory (PRNNG), (ii) partially recurrent neural network with focused Laguarre memory (PRNNL), (iii) partially recurrent neural network with focused TDNN memory (PRNNTD) and (iv) partially recurrent neural network with no memory (PRNN).

NETWORK DESIGN FOR PREDICTION

The computational complexity of a network and its generalization capabilities directly depends on network topology. A larger-than-necessary networks tend to over fit the training data leading to poor generalization performance, while on the other hand a smaller-than-necessary network faces difficulty in learning the training data. The common method of trial and error is used to design the network.

In each case of network design, a large number of networks differing in number of hidden nodes and memory depth are trained and the smallest one that learns the training data with best generalization performance is selected. Table 1 shows the architectural description of the focused PRNN models with TDNN, Gamma Memory and Laguarre memory used in the study and without memory to the input layer.

Table 1: Architectural Description of PRNN with the Selected Memories Fed into Input Layer and without Any Memory to the Input Layer

Model	Memory Order (K)	Model Architecture (p-m-n)
PRNNG	K = 1	08 – 4 - 4
PRNNTD	K = 2	12 – 3 - 4
PRNNL	K = 1	08 – 3 - 4
PRNN	Without memory	04 – 3 - 4

p = No of input nodes; m = No of hidden nodes; n = No of output nodes

Back propagation through time (BPTT) algorithm was used to train the PRNN networks.

RESULTS

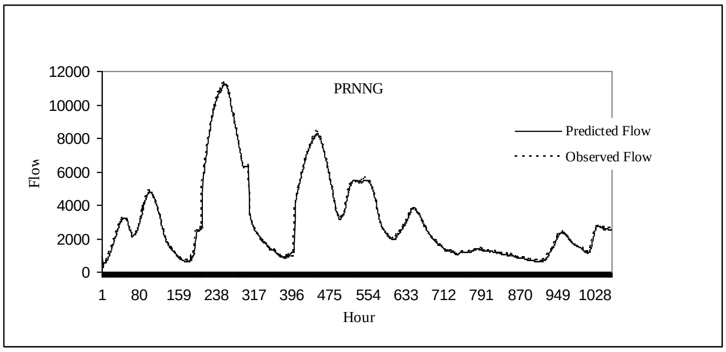
To evaluate the model performances in forecasting flows at multiple sections performance indices like root mean square error (RMSE), coefficient of efficiency, (CE) and correlation coefficient, (r) are used. The model performances indices for a forecasting step of 2 hours are summarized in Table 2. Figure 5 shows observed and predicted flow for Tarboro obtained using the PRNN models. The results given in the Figure 5 and in Table 2 indicate that focused PRNN without memory to the input layer performs better almost in all counts considered in the study.

CONCLUSIONS

Flood flow prediction at three upstream and a down stream section of a river network using partial recurrent neural networks with and without memory attached to the input layer is accomplished. Flow prediction at different stations are obtained using partially recurrent neural networks attached with three different memories namely, TDNN memory, Gamma memory, and Laguarre memory at to the input layer. The models are applied to forecast flood flows in Tar basin, USA. Results obtained indicates that though there may be difficulties in training a partially recurrent network having no memory attached to the network, the model performs better in forecasting multiple flows over a basin.

Table 2: Comparative Performance of ANN Models in Terms of RMSE (m^3/s), CE and r

Gauging Station	Model	RMSE	CE	r	Gauging Station	Model	RMSE	CE	r
Rocky Mount	PRNNG	62.48	0.9970	0.9990	Hilliardston	PRNNG	42.02	0.9968	0.9983
	PRNNTD	205.71	0.9760	0.9885		PRNNTD	188.34	0.9422	0.9753
	PRNNL	72.55	0.9972	0.9989		PRNNL	47.46	0.9960	0.9980
	PRNN	60.33	0.9975	0.9991		PRNN	41.63	0.9969	0.9986
Enfield	PRNNG	15.16	0.9893	0.9936	Tarboro	PRNNG	94.94	0.9950	0.9993
	PRNNTD	67.02	0.9533	0.9823		PRNNTD	373.89	0.9783	0.9893
	PRNNL	18.72	0.9964	0.9982		PRNNL	94.01	0.9986	0.9993
	PRNN	15.46	0.9987	0.9978		PRNN	75.88	0.9989	0.9995



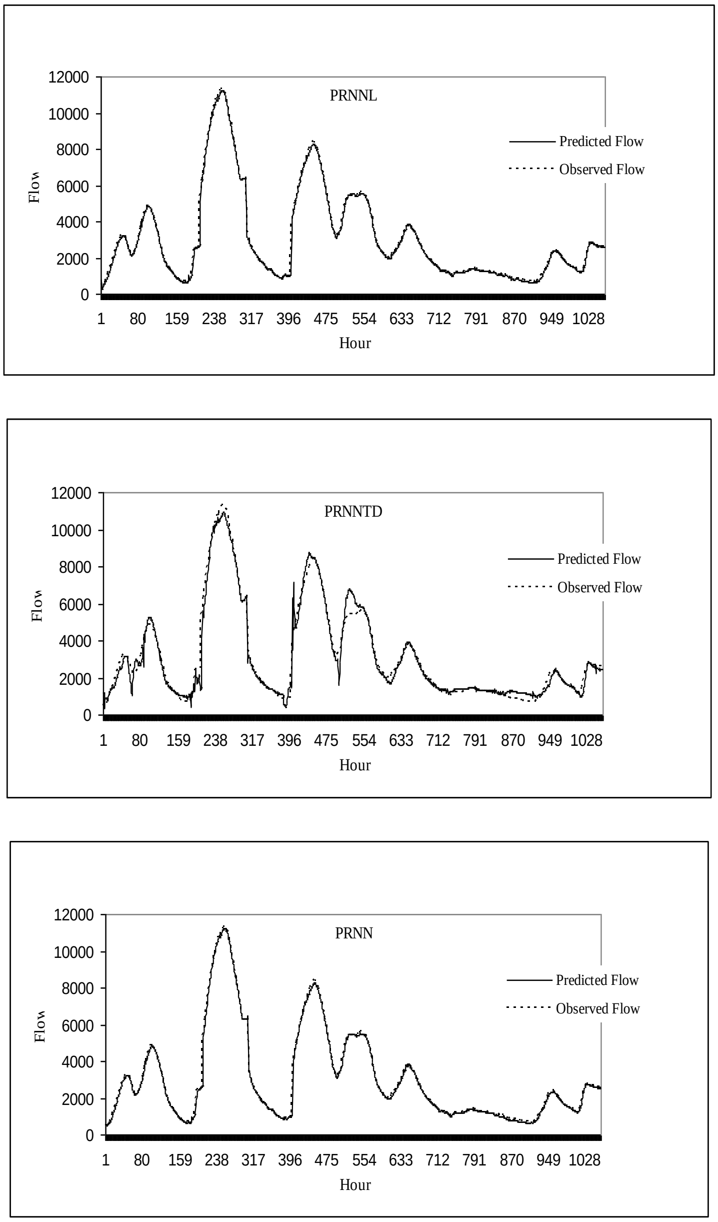


Figure 5: Flow Forecasts Obtained for Tarboro Using Different PRNN Modes

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