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Geomorphology-based Time-lagged Recurrent Neural Networks for Runoff Forecasting

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Abstract

Artificial Neural Networks have been widely used to develop effective runoff-forecasting models. An overwhelming majority of networks are static in nature and also developed without incorporating geomorphologic information of the watershed. The objective of this study is to develop an efficient dynamic neural network model which also accounts for morphometric characteristics of the catchment. The model developed using Time-Lagged Recurrent Neural Networks (TLRNs) is used to estimate runoff for river Dikrong, a tributary of river Brahmaputra in India. Comparisons with traditional static models, with and without integration of geomorphologic data, reveal the proposed model to be a promising tool in operational hydrology.

Keywords: *rainfall-runoff modelling, artificial neural networks, Time-Lagged Recurrent Neural Network (TLRN), gamma memory*

1. Introduction

Accurate forecasting of runoff is an important aspect in water resources planning and management. Ability of a model to provide accurate forecasts with sufficient lead times becomes extremely important in case of catastrophic flood events to avoid destruction of property and loss of human lives. But the highly non-linear rainfall-runoff relationship and a high degree of spatial and temporal variability in the process makes the modelling process a very complicated task. Over the years, considerable researches have been carried out in this field and hydrologists have proposed numerous rainfall-runoff models to address these issues. Some of the significant contributions are unit hydrograph theory, SCS curve number method, application of regression analysis and artificial neural networks in rainfall runoff modelling etc. The currently used models in hydrology may be classified into three categories-conceptual based models, geomorphology based models and empirical relations. Conceptual models are based on the conceptual representations of the physical flow processes over the entire watershed. Though these models lead to a better understanding of the underlying processes of hydrological systems, their requirement of large amount of data (land use, land cover, soil types, *etc*.) for calibration, and associated time for model building renders them undesirable in operational hydrology. Quite often, especially in developing countries, these data are not available or sometime it is difficult to obtain these data due to various reasons. As a result, many times these models are not suitable for practical field problems. Geomorphology based models link the hydrological response of a river basin to its morphometric characteristics. In their pioneering study, Rodriguez-Iturbe and Valdes (1979) showed that watershed characteristics may be coupled with a linear model structure for routing surface runoff through the stream network. On the other hand, empirical models are based on system analysis or "black-box" approach that tries to establish a direct mapping between the historical records of inputs (rainfall, humidity, *etc*) and outputs (runoff) without regard to the system dynamics.

In the last two decades, Artificial Neural Networks (ANN) have found widespread usage in forecasting of water resources variables as documented in several studies (ASCE Task Committee, 2000; Govindaraju and Rao, 2000). But despite their popularity, several papers (ASCE Task Committee, 2000; Gupta *et al*., 2000; Hsu *et al*., 1997; Zhang and Govindaraju, 2000) have advocated a more cautious approach than simply using ANN as a black-box model to map input-output relationships. Integration of physical principles has been identified as an important criterion for ANN to emerge as a universally accepted simulation tool. Very few studies till now have attempted to integrate geomorphologic information with the ANN model. Most of them rely heavily on the GIUH theory which have various limitations for filed applications. Also, majority of ANN are static in nature and hence incapable of temporal processing. Apart from this, the models are also developed using a lump modelling approach which does not consider the spatial variability of rainfall over a

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watershed. In this study, we have presented a new method of developing a runoff-forecasting model considering morphometric parameters of the watershed and their special variability.

2. Artificial Neural Networks

Artificial neural networks are classified as black-box models that have been widely used in flood forecasting (Wright *et al*., 2002; Chau *et al*., 2005), stream flow prediction (Zealand *et al*., 1999; Kisi, 2007), rainfall-runoff modelling (Tokar and Johnson, 1999; Thurumalaiah and Deo, 2000) and water level prediction (Huang *et al*., 2003; Alvisi *et al*., 2006). The general architecture and working of ANN is easily available in existing literature and has not been discussed in this paper. A detailed treatment of the structure and operation of ANN is available in Fausett (1994) and Haykin (1999).

Most of the ANN models that we come across in the existing literature are of static nature relying on the Multilayer Perceptron network (MLP) to learn relationships. MLP is a static and memory less network that characterises unidirectional flow without any memory element or recursion. Their simplicity and ability to transform input data into desired response has made it a popular pattern-classification tool. In their paper, Maier and Dandy (2000) reviewed 43 papers dealing with prediction and forecasting of water resource variables out of which all but two papers used MLP networks and 36 of them employed the backpropagation algorithm and only one used a recurrent neural network (Chow and Cho, 1997). But quite often static MLPs yield sub-optimal solutions due to several limitations like getting trapped in local minima, large number of epochs, over-fitting of data and computational time. Being mere static classifiers, they lack the ability to investigate the temporal dimension of data and cannot intuitively learn from previous states of the system. This is very important in case of hydrological systems since the present response of a hydrologic system is intrinsically dependent on their previous states. In order to encode temporal characteristics in static MLP, commonly a sliding window of input sequences is considered (Jain *et al*., 1999; Coulibaly *et al*., 2000). This approach consists of selecting a fixed number of past items relevant to the current system response, providing the network with a form of static memory. But the inability of this approach to decode temporal patterns with arbitrary time intervals makes it unsuitable for situations that require high prediction efficiency.

3. Geomorphology-based ANNs

It is widely accepted that hydrological response of a river basin is related to its geomorphological characteristics and this relationship can be expressed through empirical relations (Horton, 1945; Strahler 1957). The integration of geomorphologic properties with ANN architecture will be able to overcome a major criticism against ANNs, which is the lack of fundamental physical principles in its implementation. Gautam *et al*. (2000) developed ANN models for predicting stream runoff using soil moisture data for Tono area of Central Japan. Zhang and Govindaraju (2003) found many similarities between the geometric nature of channel network and the parallel-connectionist mechanism of ANNs and developed a Geomorphology-based ANN (GANN) for prediction of runoff over watersheds. Flow path probabilities were computed using geomorphologic parameters such as bifurcation ratio, area ratio, channel length and slope ratio, required for the development of a Geomorphologic Instantaneous Unit Hydrograph (GIUH). A three-layered ANN was implemented with rainfall excesses from the current time-step and previous time-steps as input, path probabilities as connection weights between the hidden and output layers and the number of nodes in hidden layer equal to the number of paths. Unlike the GIUH theory, this architecture did not assume the nature of travel-time distribution or spatial and temporal constancy of surface water velocity, which is a disadvantage of GIUH theory. The GANN was utilised to estimate runoff hydrographs from several storms over two Indiana watersheds. The encouraging results obtained have made GANNs a promising tool in runoff forecasting. Yitian and Gu (2003) developed a flow and sediment prediction ANN model by using the actual river network to design the ANN architecture. The model was applied to model daily discharges and annual sediment discharges in the Jingjiang reach of the Yangtze River and Dongting Lake, China. The results have validated the usefulness of ANN in modelling complex network of rivers and show the possibility of integrating fundamental physical principles into a data-driven modelling technique and has also shown the use of a natural system for ANN construction. Sarangi *et al*. (2005) empirically associated several geomorphological parameters with measured rainfall and runoff measurements and used as input to a three-layered backpropagation feed-forward network. Results indicated superior performance of ANN due to this integration of watershed information. Apart from the literature reviewed above, not much research has been done in developing an effective modelling tool by incorporating watershed information into network architecture.

4. Proposed Methodology

As is evident from the literature review that the ANN based models lack the power of temporal processing of a hydrologic time series which exhibit interesting patterns over time. Also, the absence of physical concepts and relations has been a major area of concern for proponents of this methodology. On the other hand, Geomorphology based ANN developed till now, even though yielding better results are difficult to develop due to their dependence on GIUH theory which limits its usability in operational hydrology. Also, most of the models adopted the lump modelling approach which does not account for the spatial variation of rainfall over a watershed. It assumes uniform distribution of rainfall over a catchment and uses the average rainfall for developing the rainfall-runoff model. Chen and Adams (2006) showed that for catchments having significant spatial variability of rainfall and geomorphological characteristics, lump model may not be adequate to compute catchment runoff.

In order to overcome the drawbacks like static network structure, lack of physical concepts and lumped approach, a new methodology has been proposed in this paper combining a Dynamic Neural Network like TLRN and semi-distributed approach for integrating morphometric information. To the best knowledge of the authors, no study has been conducted that combines the watershed information with historical rainfall-runoff data as well as employs a dynamic neural network to model their relationship. The proposed approach eliminates the necessity of assuming spatial consistency of rainfall and lack of physical principles in ANNs by adopting a semi-distributed approach of incorporating geomorphological information. Also, employing a dynamic neural network like TLRN means the network is capable of learning temporal variations from dataset. For comparative purposes, performance of models trained by static feed-forward models with lump and distributed approach are also provided.

5. Focussed TLRNs

TLRNs are MLPs with locally recurrent connections and short-term memory structures that can learn temporal variations from the dataset. TLRNs are considered state-of-the-art in nonlinear time series prediction. Though many different TLRNs designs are available, the general architecture of a TLRN is given by adding a feedback loop to a static network which introduces "short- term" memory in the network. Network size of TLRNs is lower than MLPs that use extra inputs to represent the past state of the system, though its memory requirement is comparatively higher. Focussed TLRN implies that only the processing elements of the input layer are equipped with memory kernels and the past values of the input are stored for learning temporal patterns.

In most dynamic models, tapped delay lines are used to feed delayed values of inputs or outputs or both to the input of the network. (Narendra, 1991). In this paper, the most studied TLRN network, Gamma model (De Vries and Principe, 1992), is used to obtain forecasts instead of tapped delay lines. Eq. (1) and Eq. (2) defines the output of each tap of a discrete gamma memory structure (Motter and Principe, 1994).

$$X_o(t) = X(t) \tag{1}$$

$$X_K(t) = (1-\mu)\,X_k(t-1) + \mu\,X_{k-1}(t-1);\ k = 1,\ldots,K \tag{2}$$

As is evident from Fig. 1, when $\mu = 1$, the gamma memory becomes a tapped delay line. The advantage of using gamma memory is that it provides an adaptive memory structure with a controllable memory. Using the gamma parameter μ an optimal compromise between depth (D) and resolution (R) may be achieved during training. Here, memory depth (D) refers to how far into the past the memory stores information, and resolution (R) refers to the degree to which information regarding the input is stored. Eq. (3) gives the order (K) of gamma memory which is the

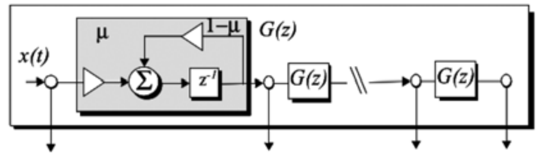

Fig. 1. Gamma Memory

product of resolution and depth.

$$K = D * R \tag{3}$$

For a Kth order Gamma memory, the memory depth (D) is approximated by (K/μ) and memory resolution (R) is μ.

The applicability of different types of recurrent neural networks incorporating the temporal dimension of hydrologic time series can be found in the works of several researchers. Dibike *et al*. (1999) employed different ANN architectures for developing numerical-hydraulic models, including a Recurrent Neural Network (RNN). Anmala *et al*. (2000) reported the superior performance of RNN over feed-forward networks for predicting monthly runoff. Xue and Dibike (2001) found the TLRN topology to be very suitable for flood forecasting purposes. Coulibaly *et al*. (2001) employed a tIme Delay Recurrent Neural Network (TDRNN) as a combination of TDNN and RNN networks for multivariate reservoir inflow forecasting. Kote and Jothiprakash (2008) used time lagged recurrent networks for river level prediction. Hussain *et al*. (2008) reported that TLRN shows faster convergence in time series data prediction than the backpropagation learning algorithm. The superior performance of TLRN over the standard back-propagation for time series data prediction was also found in the studies of Badjate and Dudul (2009) and Kale and Dudul (2009). Wang *et al*. (2009) investigated the accuracy of a TLRN model for forecasting suspended sediment load occurring episodically during the storm events in Kaoping River basin located in southern Taiwan. The models showed good performance in suspended sediment load forecasting when using only water discharge variable as the network input.

5.1 Backpropagation Though Time (BPTT) Learning Algorithm

A classic definition of learning is given by Mendel and McLaren (1970) and later adapted by Haykin (1999): "*Learning is a process by which the free parameters of a neural network are adapted through a process of stimulation by the environment in which the network is embedded. The type of learning is determined by the manner in which the parameter changes take place*". For TLRN, a dynamic learning algorithm like Backpropagation Through Time (BPTT) is adopted which is suitable for temporal problems and more advanced than standard backpropagation. Instead of a one-to-one mapping between static input and static output, BPTT maps a batch of inputs to a batch of outputs. BPTT captures the temporal signature of the data by training over a trajectory of the input space. It computes the instantaneous gradients over the trajectory and sums its effect over time (Williams and Peng, 1990). A single exemplar using this training methodology is completed two steps,

1. Computation of network error over the entire trajectory during forward pass.
2. Computation of the gradients and sensitivities at the end of the trajectory during backward pass for a fixed number of samples.

A comprehensive discussion of BPTT is available in Haykin (1999).

6. Geomorphologic Parameters

The integration of watershed information in the proposed ANN methodology here is achieved through several geomorphologic parameters.

6.1 Drainage Density (D_d)

It is defined as the total length of the channels in a catchment divided by the area of the catchment. Catchment with permeable sub-soil parameters and dense vegetation cover has low drainage density. As drainage density represents resistance to flow, the catchment response will be directly proportional to the drainage density.

6.2 Elongation Ratio (R_l)

It is defined as the ratio of the diameter of a circle whose area is equal to the basin area to the maximum length of the basin. Low value of elongation ratio indicates smaller time of concentration which will lead to quick catchment response.

6.3 Relief Ratio (Rr)

It is the difference in elevation between the stream source and mouth to the length of the stream. It gives the average drop in elevation per unit length of the stream. High value of relief ratio means quick catchment response.

6.4 Weighted Factor

The catchment response is directly proportional to area of the catchment (A), drainage density (D_d), relief ratio (Rr) and inversely proportional to the elongation ratio (R_l). A weighting factor is calculated representing the contribution of rainfall in a sub-catchment on catchment response.

$$w_i = \frac{v_i}{\Sigma_i^I v_i} \tag{4}$$

Where i is the number of sub-catchments and,

$$v_i = \frac{(A_i D_{d_i} R_{r_i})}{R_{l_i}} \tag{5}$$

The weighting factor defined above can be used to calculate the contribution of the catchment towards runoff.

7. Model Formulation

Appropriate design of neural network architecture is an important issue as a sub-optimal design may lead to problems ranging from poor learning to over fitting of data. We resort to the commonly used trial-and-error procedure to arrive at the best network design. A large number of networks for each model, differing only in the number of hidden neurons are tested and the one with smallest network size that learns the data is selected as optimal design.

The semi-distributed models couple historical rainfall-runoff data with geomorphologic information of the dataset using the weighted factor given in Eq. (4). On the other hand, the lump models use the rainfall-runoff records as inputs with no explicit integration of morphometric properties. Out of the two models each in semi-distributed and lump approach, one is trained by a dynamic neural network called TLRN powered by BPTT algorithm while the other is trained by a static feed-forward model with backpropagation algorithm. A total of four models are developed in this study: TLRN model with distributed approach (TLRND), feed-forward model with distributed approach (FFD), TLRN model with lumped approach (TLRNL) and feed-forward model with lumped approach (FFL). The architectural description of the various models is given in Table 1.

The optimal number of hidden nodes for the TLRND and FFD model is found to be seven and eight respectively while fifteen and eight neurons are found appropriate for the TLRNL and FFL model respectively.

In order to avoid data over fitting, Shahin *et al*. (2002) suggested to divide the data into three sets. Daily concurrent measurements of rainfall and runoff over 1277 days are available, out of which, following this recommendation, 50% of the dataset was randomly used for training, 25% for testing and 25% for cross-validation of the TLRN models. The feed-forward models used 250 records for testing, 250 for cross-validation and the rest for training. The training records are used to train the neural network by the process of error minimization. Cross validation leads to better generalization of the network and avoids overtraining. Finally, the testing phase shows the overall performance of the network by introducing previously unseen samples as inputs.

The models developed by semi-distributed approach accounts for the spatial variability of rainfall. Using Thiessen polygon method, the catchment area is divided into number of sub-divisions equal to the number of rain-gauge stations. The intersection of the Thiessen polygon boundary and streamline is considered as the outlet for that sub-catchment. Spatial uniformity over a sub-catchment is assumed for rainfall recorded by a rain gauge station. Digital Elevation Model (DEM) data from the freely available 90-m global SRTM (Shuttle Radar Topographic Mission) dataset was used for delineating the watersheds and extracting geomorphologic information using Watershed Modeling System

Table 1. Architecture of Different ANN Models

Model	Memory Order (k)	Model Architecture (p-m-n)
TLRND	2 (Adaptive)	15-7-1
FFD	1 (Static)	10-15-1
TLRNL	2 (Adaptive)	15-6-1
FFL	1 (Static)	4-8-1

(WMS 8.2). Contribution from each sub-catchment is calculated using the weighted factor given by Eq. 4. These derived records are used as inputs to the network with several periods used as input vectors. The input-output mapping for the semi-distributed models trained by TLRN and feed forward neural network is given by Eqs. (3) and (4) respectively.

$$Q(t) = f(w_i p_i(t), Q(t)), \quad i = 1, 2, \ldots, I \tag{6}$$

$$Q(t) = f(w_i p_i(t), w_i p_i(t-1), \ldots, Q(t-1),), \; i = 1, 2, \ldots, I \tag{7}$$

The lump modelling approach considers the areal average rainfall of the whole catchment. The input-output relationship of the two models employing the lumped approach may be written as Eq. (8) for TLRN model and Eq. (9) for feed forward model.

$$Q(t) = f(p_a(t), Q(t)), \; i = 1, 2, \ldots, I \tag{8}$$

$$Q(t) = f(p_a(t), p_a(t-1), Q(t-1)), \; i = 1, 2, \ldots, I \tag{9}$$

Where $Q(t)$ is the discharge and $p_i(t)$ is the rainfall at time t for watershed i, w_i is the weighting factor for i^{th} catchment and p_a is the average rainfall for the whole catchment using Thiessen polygon method.

The TLRN model developed in this paper uses the widely studied gamma model trained by BPTT algorithm. The static ANN model developed in the present study is single-hidden layer feed forward model with backpropagation learning algorithm. In both the models, sigmoidal transfer function is used for the neurons in the hidden layer and pure linear transfer function is used in the output layer. The numbers of hidden nodes in all models are fixed using trial-and-error and the one that yields the best performance with smallest network is selected.

8. Performance Criteria

Several statistical measures were employed to evaluate the accuracy of the models as there is no universally suitable and unique test (Yapo *et al*., 1998; Legates and McCabe, 1999).

8.1 Root Mean Square Error (RMSE)

It is one of the most commonly-used statistics which measures the difference between estimated and model-predicted values. A RMSE value closer to zero indicates better model performance.

$$RMSE = \sqrt{\frac{\Sigma(Q_{obs} - Q_{est})^2}{N}} \tag{10}$$

where, Q_{obs}, Q_{est}, are the observed and estimated runoff values.

8.2 Coefficient of Correlation (R)

Coefficient of correlation is a measure of goodness of fit that represents the degree of co-linearity between observed and estimated values of network output. Its value ranges from -1 (perfect negative correlation) to 1 (perfect positive correlation). Coefficient of correlation is expressed as:

$$R = \frac{\Sigma(Q_{obs} - avgQ_{obs})(Q_{est} - avgQ_{est})}{\sqrt{\Sigma(Q_{obs} - avgQ_{obs})^2}\sqrt{\Sigma(Q_{est} - avgQ_{est})^2}} \tag{11}$$

where, Q_{obs}, $avgQ_{obs}$, Q_{est}, $avgQ_{est}$ are the observed, average observed, estimated and average estimated runoff values.

8.3 Nash-Sutcliffe Efficiency (E)

Proposed by Nash and Sutcliffe (1970), value of E ranges from 1 (perfect fit) to -∞. However, as the difference between estimated and observed values in this normalised statistic is calculated as squares, larger values tend to be overestimated while smaller values get neglected (Legates and McCabe, 1999). The E may be expressed as:

$$E = 1 - \frac{\Sigma(Q_{obs} - Q_{est})^2}{\Sigma(Q_{obs} - avgQ_{obs})^2} \tag{12}$$

8.4 Threshold Statistics (TS_x)

It is defined as the ratio of the number of data points estimated for which Absolute Relative Error (ARE) is less than x% (denoted by n_x) to the total number of data points estimated (N). The TS statistic represents the error distribution in predicting flows and ARE levels of 5, 10, 20, 30, 40, 50 and 70% are used in this study. Higher the TS_x value, the better is the model performance.

$$TS_x = \frac{n_x}{N} \tag{13}$$

$$ARE = \frac{\Sigma \frac{Q_{est} - Q_{obs}}{Q_{obs}}}{N} \tag{14}$$

8.5 Average Absolute Relative Error (AARE)

A lower AARE value means better predictive capability of the model. The AARE can be expressed as:

$$AARE = \frac{\Sigma \left| \frac{Q_{est} - Q_{obs}}{Q_{obs}} \right|}{N} \tag{15}$$

The effectiveness, *i.e.* the predictive capability of the model is indicated by TSx and AARE statistics while R, RMSE and E are used to evaluate the efficiency of the model. Efficiency of a model refers to its ability to simulate the non-linear rainfall-runoff relationship.

9. Study Area

The proposed methodology is employed to model the rainfall-runoff data recorded for the Dikrong river catchment (Fig. 2). Situated in Northeastern part of India, it has a catchment area of 824.23 km^2 with the outlet situated at Papumpare district of Arunachal Pradesh (27°14'13'-93°48'56"). Rainfall records are sourced from four rain gauge stations located within the catchment. They are Hoz, Ompuli, Sagalee and Laporang. After dividing using Thiessen polygon method, the sub-catchments of Hoz, Ompuli, Sagalee and Laporang were found to spread over areas of 181.13 km^2, 146.84 km^2, 217.43 km^2 and 278.83 km^2 respectively. The Dikrong catchment has dense forests and

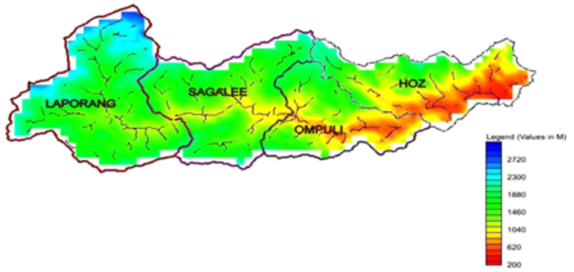

Fig. 2. Schematic Map of the Dikrong Catchment

permeable sub-soil materials which is reflected in the low value of drainage density (0.36 km/km^2). The elevation of Dikrong catchment ranges from the highest of 2890 m to the lowest of 210m. The relief ratio is 0.045, while among the sub-catchments, it is highest for Laporang (0.095).

10. Results and Discussion

The effectiveness, efficiency and field applicability of the proposed geomorphology-based dynamic neural network model is evaluated by utilizing the rainfall-runoff records for the Dikrong catchment. Different statistical measures are used to evaluate the performance of the models vis-à-vis R, AARE, RMSE, E and TSx. In this study, the available dataset was divided into three datasets: training, cross validation and testing. The training data is used to fix the network parameters by the process of training. The validation data set is used in order to avoid over fitting of the network. The performance of the trained network is then tested using the testing data set. Out of 1277 concurrent measurements, 25% was used for cross validation in order to avoid over training and facilitate network generalisation. Table 2 shows the values of the different statistics for two geomorphology based models with a semi-distributed approach, one gamma-TLRN model (TLRND) and another feed forward model (FFD) during the testing phase. Similarly, Table 3 shows the comparative performance of two models with a lumped approach and no integration of morphometric characteristics – One Gamma-TLRN model (TLRNL) and another feed forward model (FFL) during testing phase.

Performance statistics clearly indicate that the TLRN model with gamma memory and semi-distributed approach of integrating geomorphologic information (TLRND) performs far better than all the other models, including the widely-used feed forward model with lump-modelling approach (FFL). The TLRN model with lump modelling approach (TLRNL) performs better than both the feed forward models, distributed (FFD) and lump (FFL). While all the models yield satisfactory forecasts with R value of above 0.90, the TLRND outperforms other models.

Between the two distributed models, FFD yields prediction with AARE value of 26.4%. The corresponding value for TLRND model is 14.5% which represents an 82.07% improvement over the FFD model. The TS_5 statistics during testing phase are 18.73% for TLRND and 18.60% for FFD. This translates into a relative achievement of 0.70% for TLRND model over FFD model. The ability of the models to learn the input-output relationship or efficiency can be evaluated on the basis of R, RMSE and E statistic. All three statistics show the superior performance of TLRND model over FFD model. E value for TLRND and FFD model is 0.950 and 0.847 respectively, which is a 12.16% improvement. The coefficient of correlation (R) shows an improvement of 5.62% in the testing phase with values of 0.977 for TLRND and 0.925 for FFD. The RMSE value also improves by 101.62% for TLRND over the FFD model. The RMSE value for the TLRND is 27.18 and that for the FFD is 54.80 respectively. Thus, the performance of the TLRND model is significantly better than FFD model.

The AARE values at testing phase for the lump models are 0.228 for TLRNL and 0.332 for FFL. Thus, the effectiveness of TLRNL model is improved by 45.61%. The TS_5 values are 19.51 for TLRNL and 13.80 for FFL representing an improvement of 41.38% for TLRNL model over FFL. Similarly, the TLRNL model is more efficient then FFL model when compared on the basis of R, RMSE and E statistic. The R value for TLRNL and FFL model is 0.935 and 0.921 respectively. There is a modest 1.52% improvement of efficiency for the TLRNL model over FFL model. The TLRNL model yields predictions with RMSE value of 43.70 with the corresponding value of 55.20 for FFL model, which is a 26.3% improvement. The E statistic also improves by 0.36% for TLRNL model with the value being 0.848 for TLRNL model and 0.845 for FFL model.

The results indicate that dynamic networks like TLRN, both with and without integration of morphometric properties, are superior to traditional feed forward models in runoff forecasting.

Table 2. Comparative Performance of ANN Models with Semi-Distributed Approach

Model	R	AARE	RMSE	E	TS*x*						
					5%	10%	20%	30%	40%	50%	70%
TLRND	0.977	0.145	27.18	0.950	18.73	45.61	83.77	89.34	93.80	96.47	98.04
FFD	0.925	0.264	54.80	0.847	18.60	36.00	57.60	73.40	80.20	85.40	92.80

Table 3. Comparative Performance of ANN Models with Lumped Approach

Model	R	AARE	RMSE	E	TSx						
					5%	10%	20%	30%	40%	50%	70%
TLRNL	0.935	0.228	43.70	0.848	19.51	38.56	59.09	71.32	78.21	83.15	96.94
FFL	0.921	0.332	55.20	0.845	13.80	28.40	49.00	60.40	67.40	76.00	91.20

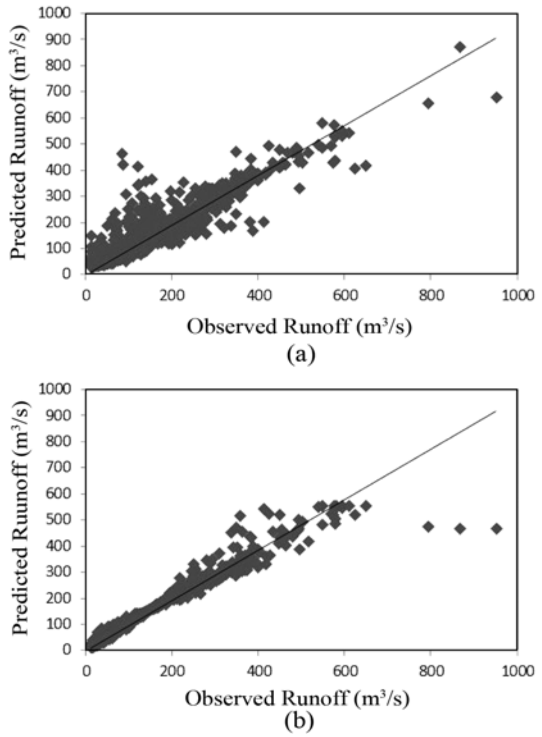

Fig. 3. Scatter Plot of Observed vs Predicted Runoff Forecasts of the TLRND Model using: (a) TLRNL Model, (b) TLRND Model

To further analyse the prediction performance, scatter plot of the two best models, TLRND and TLRNL, are presented by Fig. 3(a) and Fig. 3(b). Larger deviation from the ideal or 45º line indicates lesser prediction accuracy. The scatter plot of TLRND model falls close to the ideal or 45º line, whereas the TLRNL plot exhibits greater deviation from the ideal line. This clearly indicates that the TLRND model gives more accurate predictions in runoff-forecasting than all the other models including the TLRNL model.

11. Conclusions

In this paper, an ANN-based runoff-forecasting model has been proposed that combines the advantages of dynamic neural network, integration of geomorphologic information, and adaptation of a semi-distributed modelling approach. The simple method adopted in this study by combining the morphometric properties of a watershed gives better predicting capabilities in comparison to models developed without geomorphological parameters. Comparison with various models clearly indicates that the distributed Time Lagged Recurrent Neural Network (TLRND) model demonstrates significant improvement over all the other models. The model proposed in this paper can be a reliable and effective prediction tool in runoff forecasting leading to better management of hydro-systems. As a general rule, dynamic neural networks outperformed the traditional static networks and integration of geomorphologic information led to further improvement in prediction efficiency.

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