IMPORTANCE OF INPUT PARAMETER SELECTION FOR SYNTHETIC STREAMFLOW GENERATION OF DIFFERENT TIME STEP USING ANN TECHNIQUES

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Abstract: Streamflow time series is gaining importance in planning, management and operation of water resources system day by day. In order to plan a system in an optimal way, especially when sufficient historical data are not available, the only choice left is to generate synthetic streamflow. Artificial Neural Network (ANN) has been successfully used in the past for streamflow forecasting and monthly synthetic streamflow generation. The capability of ANN to generate synthetic series of river discharge averaged over different time steps with limited data has been investigated in the present study. While an ANN model with certain input parameters can generate a monthly averaged streamflow series efficiently, it fails to generate a series of smaller time steps with the same accuracy. The scope of improving efficiency of ANN in generating synthetic streamflow by using different combinations of input data has been analyzed. The developed models have been assessed through their application in the river Subansiri in India. Efficiency of the ANN models has been evaluated by comparing ANN generated series with the historical series and the series generated by Thomas-Fiering model on the basis of three statistical parameters- periodical mean, periodical standard deviation and skewness of the series. The results reveal that the periodical mean of the series generated by both Thomas –Fiering and ANN models is in good agreement with that of the historical series. However, periodical standard deviation and skewness coefficient of the series generated by Thomas–Fiering model are inferior to that of the series generated by ANN.

1 INTRODUCTION

Proper planning, efficient management and optimal operation of the water resources system is an utmost need of the recent time. Earlier, water resources planners used to handle planning and management with the only available historical hydrological records. Those approaches have a limitation that they do not have a futuristic aspect in their planning because of insufficiency of long series of future data. As a result, synthetically generated time series is gaining high importance among researchers which has lead to the development of several models for the generation of time series. Forecasting of streamflows is of vital importance for flood caution, operation of flood-control-purposed reservoir, determination of river water potential, production of hydroelectric energy, allocation of domestic and irrigation water in drought seasons, and navigation planning in rivers (Bayazıt, 1988). Conventional time series models such as Thomas-Fiering model (Thomas and Fiering, 1962), autoregressive moving average (ARMA) models, auto-regressive integrated moving average (ARIMA), autoregressive moving average with exogenous inputs (ARMAX) and (Box and Jenkins, 1976) have been applied by many researches in their studies, as they predict reasonably accurate results. But the traditional methods suffer from the limitation of being linear and stationary. Hence, new technologies and algorithms have come up as powerful tools for modeling several problems related to water resources engineering. ANN is one of them. ANN has been used successfully to solve different kinds of hydrological problems (ASCE, 2000). Particularly, the ANN approaches when applied to hydrologic time series modeling and forecasting have shown better performance than the classical techniques (Govindaraju and Rao, 2000).

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Ahmed and Sarma (2007) presented ANN model for generating synthetic streamflow series of the river Pagladia, Assam in India. Comparing different models they found that the ANN model is the best in generating synthetic streamflow series for the Pagldia Project. Wen and Lee (1998) presented a neural-network based multiobjective optimization of water quality management for river basin planning and water quality control for the Tou-Chen River Basin in Taiwan. Chandramouli and Raman (2001) developed a dynamic programming based neural network model for optimal multi reservoir operation Parambikulam Aliyar Project. Chandramouli and Deka (2005) introduced a decision support model (DSM) based on ANN for optimal operation of a reservoir in south India. Diamantopoulou et al. (2006) developed three layer cascade correlation artificial neural network (CCANN) models for the prediction of monthly values of some water quality parameters in rivers Axios and Strymon, at a station near the Greek Bulgarian borders. Yurekli et al. (2004) used Thomas-Fiering and ARIMA models for the daily maximum stream flow. Srinivasulu and Jain (2006) presented a study on different training methods available for the training of multi-layer perceptron (MLP) network for modeling rainfall-runoff process. Treiber and Schultz (1976) generated sreamflow data on monthly and daily basis using Thomas-Fiering model and the Karlsruhe model type A for computing reservoir capacity. Zealand et al. (1999) investigated the utility of ANN for short term forecasting of streamflow. Birikundavyi et al. (2002) investigated the performance of ANN methods in prediction of daily streamflows. They showed that ANN method yielded better results than ARMA models. Kumar et al. (2004) employed recurrent neural network (RNN) model in streamflows forecasting. Stedinger and Taylor (1982) presented that streamflow construction and simulation is a process of verification that a stochastic streamflow model reproduces those statistics which by design it should reproduce.

In the present study an attempt has been made to evaluate the efficiency of ANN model to generate synthetic series of streamflow rate averaged over different time steps with varying input parameters. The ANN generated outputs are compared with conventional Thomas-Fiering model and historical streamflow of the Lower Subansiri Hydroelectric Project (LSHEP).

1.1 Study Area

This project is located on the Assam-Arunachal boarder near North Lakhimpur town of Assam as shown in Fig.1. The project area lies in the Lower Subansiri District of Arunachal Pradesh and Dhemaji District of Assam, India. River Subansiri originates from the south of the Po Rom peak (Mount Pororu) at an elevation of 5059 m in the Tibetan Himalaya. After flowing for 190 km through Tibet, it enters India. It continues its journey through the Himalayas of India for 200 km and enters the plains of Assam through a gorge near Gerukamukh. The Subansiri is the largest tributary of the Brahmaputra. Its total length up to the confluence of Brahmaputra River is 520 km. Its drainage area up to its confluence of the River Brahmaputra is 37, 000 Sq.km. The river maintains almost a stable course in the hilly terrain but becomes unstable as soon as it enters the alluvial plains of Assam.

2 SYNTHETIC STREAM FLOW GENERATION

The basic assumption in synthetic streamflow generation is that the streamflow population can be described by stationary stochastic process. Hence synthetic streamflow may be generated by fitting statistical model. In the following sections two different methods viz. Thomas-Fiering and ANN for synthetic sreamflow generation are discussed.

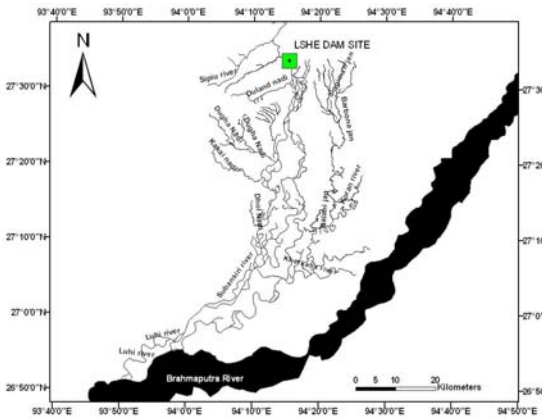

Figure 1: Location of the LSHE dam site.

2.1 Thomas-Fiering Model

Thomas Firings method is widely used for the generation of synthetic streamflow. It is a Markov Chain model which describes that there is a definite dependence between the flow of present time step and that of previous time step. For applying Thomas Firings method input data is generally transformed by using different methods like log transformation, power transformation and Box-Cox transformation (Box-Cox, 1962) to have the input data in a normal distribution. In this study log transformation method is adopted to transfer the historical data. Raman and Sunil Kumar (1995) and Salas et al. (1985) used the same method for the transformation of data in their studies and found it to be quite efficient. Maass et al. (1970) presented that log transformed data has the advantage of eliminating the occurrence of negative flows while generating synthetic streamflow. The recursive equation of Thomas Fiering model used for the study is give below:

$$q_{p+1,t} = q_{av,p+1} + r_{p,p+1}(\sigma_{p+1}/\sigma_p)(q_{p,t} - q_{av,p}) + \sigma_{p+1}(1 - r_{p,p+1}^2)^{1/2}\zeta_{p,t} \quad (1)$$

where, p = period which may be 10 days or month; t= year; $q_{av,p}$ = mean of the historical streamflow series for period p(current period t); $q_{av,p+1}$ = mean of the historical streamflow series for period $p+1$(next period); σ_p and σ_{p+1} = standard deviation of historical series of period p and $p+1$ respectively; $r_{p,p+1}$ = correlation between period p and $p+1$ of historical series; $\xi_{p,t}$ = independent standard normal random variable; $q_{p+1,t}$ = logarithmic predicted value of period $p+1$ for particular t. The $q_{p+1,\ t}$ values thus generated are then transformed to periodical flow by using the following relationship;

$$Q_{p+1,t} = \exp(q_{p+1,t})$$

Using the above model 100 years synthetic steramflow series is generated for the LSHE project of different time step.

2.2 Artificial Neural Network (ANN)

Application of ANN is gaining popularity in different fields. It has been efficiently applied to solve many problems of water resources and hydrology. The neural networks are composed of simple elements operating in parallel. These elements are analogous to biological nervous systems. Neurons arranged in a group are called layers. The neurons in a layer are connected to the adjacent layer by the means of weights; the network function is determined largely by the connections between elements. But in the same layer, these neurons do not have any connection. A neural network can be trained to perform a particular function by adjusting the values of the connections (weights) between elements. Generally, neural networks are adjusted, or trained, in order to achieve a particular target for a give output. Feed forward neural network is used in the present study. The network has one input layer with some neurons where input data is fed to the network, one or more hidden layer(s) where data is processed and one output layer from where results are produced for the given input. The training process involves giving known input and target to the network and adjusting internal parameters viz. weight and biases based on the performance measure and other network parameters.

2.2.1 Parameters of Network Selection

Selection of network involves rigorous trial and error procedures. Mean Square Error (MSE) and Mean Relative Error (MRE) are two indices which have been used for the performance measure of the network. As MSE and MRE are good measures for indicating the goodness of fit at high and moderate output values respectively (Karunanithi et al., 1994).

$$MSE = \frac{1}{2}\sum_{q}\sum_{j=1}^{p}(y_j^{(t)} - y_j)^2 \quad (2)$$

$$MRE = \frac{1}{pq}\sum_{q}\sum_{j=1}^{p}\left(\frac{\left|y_j^{(t)} - y_j\right|}{y_j^{(t)}}\right)100 \quad (3)$$

where, $y_j^{(t)}$ = standardized target value for pattern j, y_j = output response from the network for pattern j, p = total number of training pattern; q = number of output nodes.

Besides the network architecture, momentum factor and learning rate are also important network parameters, used to evaluate the network performance. The network architecture is decided based on the MRE value as MRE gives more realistic idea about the predicted output. Therefore, it plays an important role in network selection. The value of learning rate η and momentum factor α is decided after evaluating different combinations. The learning rate is highly influential for the convergence of training. If it is too high, then search may miss a valley in the error surface, on the other hand if it is too small, the convergence will be very slow (Chandramouli and Raman, 2001). A momentum factor, α, is generally used to accelerate the convergence (Ahmed and Sarma, 2007). An iterative procedure in combination of different learning rate and moment factor is adopted to finalize the number of neurons in the hidden layer. Burian et al. 2001 stated that typically the generalization of prediction and accuracy of an application increase as the number of hidden neurons decreases; as the number of hidden neurons increases, there is a corresponding increase in the number of parameters describing the approximating functions. Hence the ANN network becomes more specific to the training data as the neurons in the hidden layer increases. Generally, in ANN application the numbers of neurons in the hidden layer are decided after trial and error for a particular application. The trial for this study is started with three neurons in the hidden layer and the network is studied up to a model with 20 neurons in the hidden layer. The activation function used for this work is sigmoid. This function generally takes the normalized input and target. Therefore normalization of the data is essential. The inputs and targets patterns are normalized so that the values fall in the range of [-1, 1]. The expression used for the same is given below;

$$p_n = 2\left(\frac{p - \min_p}{\max_p - \min_p}\right) - 1 \tag{4}$$

The tan-sigmoid function is also used for the output in order to achieve the output values in range of -1 to 1. The obtained output is then un-normalized to get the predicted target value in the same unit. The expression for the output of un-normalization is;

$$p = 0.5(p_n + 1)(\max_p - \min_p) + \min_p \tag{5}$$

where, p_n is normalized input, p is actual input min_p is minimum value of input vector, max_p is maximum value of the input vector.

2.2.2 ANN Model for Synthetic Streamflow Generation

In the present study, three layer feed-forward neural networks is selected. The tan-sigmoid transfer function is used in hidden layer and output layer which generate the output value ranging from 0 to 1. The illustrative neural network architecture is shown in Fig. 2 which is developed on monthly basis. Inflow data of the six years (2002-2007) for the LSHE project has been used in this study, out of which, 4 years data is used for the training of the network and 3 years overlapped data are used for the testing of the network. Since, there are 12 periods for monthly series, the value of the mean, standard deviation, average time rate of change of discharge in different periods of the series (gradient), maximum and minimum value of historical flow repeats after each 12 period for the particular generation. The same is followed for each time step. The most common and popular multi-layer network used in training algorithm- Back Propagation (BP) (Rumelhart et al., 1986 and Hagan et al., 1996) is adopted in this study.

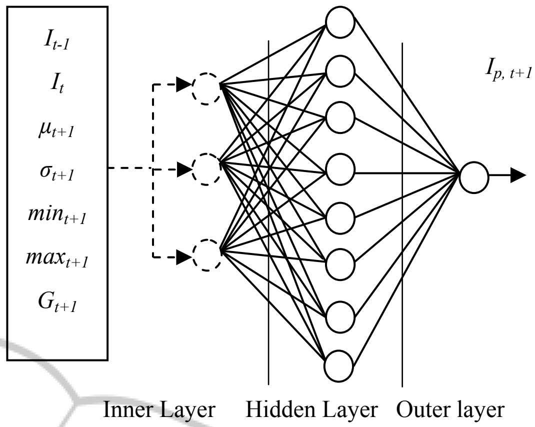

Figure 2: ANN architecture for synthetic streamflow generation.

It is found that a model working well for a monthly streamflow series does not perform well for a series having smaller time step discretization such as ten daily, eight daily, six daily. Therefore it was decided to attempt different model for different time step discretization.

Nonlinearity of streamflow series increases with decrease in the length of time step over which the values are averaged. Therefore different models having different number of input parameters have been tried to obtain the best possible model for a particular time step length. Different models have been tried in this study by using different combinations of input parameter from the following set of input parameters; streamflow of current period (I_t), streamflow of previous period (I_{t-1}), mean (μ_{t+1}) and standard deviation (σ_{t+1}) of historical streamflow of next period, minimum value of inflow from the given historical record (min_{t+1}) and maximum value of inflow from the given historical record (max_{t+1}), average time rate of change of discharge of the series (G_{t+1}). A total of seven different combinations of input parameters were tried. Nomenclature followed for the ANN model of different time step is: ANN (time step) DI, where ANN stands for Artificial Neural Network, D represent day and I (can varies from 1 to 7) represents a particular trial combinations of the input parameters. Thus ANN10D1 represent 10 daily ANN model with 1st input parameter combination.

Training was initially carried out for 2500 iterations but it was found that there was no significant improvement in MSE value after 2000 iteration, rather the time requires to train the network was increasing, hence the network is trained up to 2200 epochs. The MRE value for the testing and training was found separately and network is selected considering the lowest MRE and MSE values for the particular number of neurons in hidden layer. In this study, the best model has been decided by varying numbers of neurons in hidden layer from 3 to 10. For each network different combinations of learning rate η = 0.00, 0.01, 0.02, 0.04, 0.05, 0.07, 0.09, 0.1, 0.2, 0.3, 0.5, 0.7 and 0.9 and momentum factor α = 0.01, 0.02, 0.04, 0.05, 0.07, 0.09, 0.1, 0.2, 0.3, 0.5, 0.7 and 0.9 have been tried for the final selection of model.

The best value for learning rate η and momentum factor α was found after extensive trial of different combination of η and α. Table-1 present the best ANN models selected for different time step.

2.2.3 Streamflow Generation Model

In this study, after trained and tested network was simulated to generate the series of synthetic streamflow, it was found that after several iterations the network produces the repeated streamflow series. This may be occurring because of the difference between actual target values and predicted target values which leads to the residual series while training and testing. The statistical analysis of residual series shows that, it can be adequately modeled as normally distributed and crosscorrelated series with zero mean and unit standard deviation (Ochoa-Rivera et al., 2007). Therefore, it is very important to introduce random component in the streamflow generation model to prevent the network from generating repetitious sequence of streamflow. A small random component calculated on the basis of the standard deviation of the observed streamflow is added to the output produced by the network (Ahmed and Sarma, 2007). Thus repetitive generations of streamflow were handled by introducing a random component $\xi_t\sigma_t$ in the model. Where, ξ_t is an independent standard normal random variable with mean zero and variance unity, σ_t is the standard deviation of observed streamflow of the corresponding month. Synthetic streamflow series of hundred years are generated by feeding the known value of inflow of previous period, inflow of current period, periodical mean of the historical flow of next period and periodical standard deviation of the historical flow of next period, maximum and minimum of historic flow of next period and average time rate of change of discharge in different periods of the series (gradient) of flow. The output of the model will be the predicted inflow of the succeeding period and it will serve as input for the next iteration. If negative flow occurs during synthetic streamflow generation, would be replaced by the minimum value of the historic flow for the particular period (Ahmed and Sarma 2007).

3 RESULTS AND DISCUSSION

Hundred years' synthetic streamflow series has been generated using Thomas-Fiering model and ANN-based models for different combinations of inputs. The results are compared with the observed

Table 1: Different ANN models selected on the basis of different parameters.

ANN Model for Different Time Step	Best Input Parameters	Number of Neurons in hidden Layer	Learning Rate	Momentum Factor	Training		Testing		Skewness of the Series		
					MSE	MRE	MSE	MRE	Actual	Thomas Fiering	ANN
ANN30 D1	I_t, μ_{t+1} and σ_{t+1}	8	0.05	0.05	0.0288	39.6045	0.0636	40.5137	1.3584	1.7089	1.4308
ANN10 D1	I_t μ_{t+1} and σ_{t+1}	3	0.05	0.50	0.0405	28.2546	0.0580	41.4286	0.9685	1.1984	1.0925
ANN08 D1	I_t, μ_{t+1} and σ_{t+1}	10	0.04	0.02	0.0323	19.3615	0.0426	30.5810	1.3443	2.1950	1.6550
ANN06 D3	I_t, μ_{t+1}, σ_{t+1} and G_{t+1}	8	0.09	0.90	0.0292	19.8986	0.0392	31.6238	1.3548	2.0833	1.9310

Inflow of present time step (I_t), Mean of the historical series (μ_{t+1}) of next period, Standard deviation of historical series (σ_{t+1}) of next period,
Minimum value of inflow from the given historical record (min_{t+1}),
Maximum value of inflow from the given historical record (max_{t+1}) and
Average time rate of change of discharge of the series (G_{t+1})

streamflow series of six years (2002-2007) on the basis of statistical parameters; periodical mean, periodical standard deviation and skewness of the generated and actual observed series and presented in Table 1. The best ANN model for each of the different time discretization has been selected based on the extensive trial carried out with several combinations of input parameters. The Table 1 gives the information of each of those models along with the corresponding parameter for which they are working best. Several trails has been made to work out the best ANN model for different time step discretization by considering different numbers of hidden neurons and input parameters. 8 neurons in hidden layer, momentum factor $\alpha = 0.05$ and learning rate $\eta = 0.05$ was found to be the best for monthly streamflow generation. Streamflow generated by ANN series though generates slightly higher value in case of periodical mean, periodical standard deviation of the generated series is quite close to the actual series. The skewness value of the series generated by ANN30D1 is found closer to the skewness value of actual series in comparison to that of the Thomas-Fiering model.

In case of the ten daily ANN models, ANN10D1 is found best. It has 3 neurons in hidden layer (Table 1) with $\alpha = 0.5$ and $\eta = 0.05$. It was observed that both ANN generated series and Thomas-Fiering model generated series are in good agreement with the actual series in respect of periodical mean. In respect of standard deviations and skewness of the series, ANN10D1 outperform the Thomas-Fiering model.

The ANN08D1 having 10 neurons in hidden layer, $\alpha= 0.02$ and $\eta = 0.04$ is performing better among others ANN models for eight daily time step. Periodical mean of the ANN generated series has been found to give slightly lower values in the pre-monsoon period and slightly higher value in the dry period as compared to actual series, but it follows quite well to the observed series in case of periodical standard deviation. As observed in the previous cases regarding Thomas-Fiering model, here also it can capture the periodical mean very well but it fails to capture the periodical standard deviation. The skewness coefficient of the entire series generated by ANN08D1 is relatively close to skewness value of the actual streamflow series as compared to the skewness value of the series generated by Thomas-Fiering model.

For six daily time step discretization the ANN06D3 model having four input parameter (Table 1), 8 neurons in hidden layer, $\alpha = 0.9$ and $\eta = 0.09$ found to be the most efficient as compared to others. The results reveals that though the periodical mean of the series generated by Thomas–Fierings methods follows good except for the period during second seasonal peak i.e. during months of August and September, the series generated by ANN predicts relatively low values during pre monsoon period. On the other hand the periodical standard deviation of series generated by ANN is in close agreement with the actual series while the series generated by Thomas-Fiering model gives very high values. Moreover, the skewness value of the whole series generated by Thomas Fiering is also found higher than the skewness of the actual series as compared to ANN (Table 1).

4 CONCLUSIONS

The performance of the ANN based model for the synthetic streamflow generation of the LSHE project with the limited data set has been investigated and its comparison is made with the Thomas-Fiering model considering some statistical parameters viz. (i) periodical mean, (ii) periodical standard deviation and (iii) skewness coefficient of the series. The influence of the time step discretization and selection of input parameters on the synthetic generation of streamflow has been evaluated using both the above said methods. Different models based on input variables and network parameters have been tried and the best model for each time step discretization has been evaluated using above said three statistical measures. The selection of input parameters plays an important role in the streamflow generation. It has been found from the result that the input parameters which have been working well for higher time step discretization models did not work well for the cases of smaller time step discretization. As the models ANN30D, ANN10D and ANN08D found better with three input parameters i.e. It, $\mu t+1$ and $\sigma t+1$ while for ANN06D: It, $\mu t+1$, $\sigma t+1$ and Gt+1; were performing better as compared to three input parameters. Table 1 presents the best model, their input variables and the network parameters.

The results of the study depict that: though periodical mean of the series generated by Thomas-Fiering follows well to the periodical mean of observed series as compared to the ANN model in most of the time discretizations, it gives quite high values in case of periodical standard deviation as compare to the ANN generated series.. The skewness of the series generated by Thomas-Fiering and ANN models are compared, the skewness of the ANN generated series is found closer to the skewness of the observed streamflow series for each of these time step discretizations. Out the three performance criteria; (i) periodical mean, (ii) periodical standard deviation and (iii) skewness coefficient of the series, ANN was found to be performing quite well for the periodical standard deviation and skewness coefficient of the series, while its performance for periodical mean, was also found satisfactory and within acceptable limit. Based on the above analysis, ANN can be regarded as a competitive alternative method of computing synthetic streamflow series having potential of better performance as compared to Thomas-Fiering model.

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