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Research Paper

COMPARATIVE STUDY OF STREAM FLOW PREDICTION MODELS

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Stream flow prediction is required to provide the information of various problems related to the design and effective operation of river balancing system. The evaluation of natural and technical science over the past centuries has been closely related to experimental studies and modeling of natural resources. Methods to continuously predict water levels at a site along a river are generally its model based. Hydrologist has relied on individual techniques such as determinates, stochastic, conceptual or black box type to model the complex, uncertain rainfall and consecutive water levels. These techniques provide reasonable accuracy in modeling and prediction of stream flow. River Wainganga has been subjected to water level rise during 2004-2005 and, consequently, the low-laying areas along the bank are in undated, giving problems to local inhabitants, irrigation activities and people properly. Another river Bagh has been connecting to the said river the problem of flood arises more. Therefore predicting water levels has started to attract the attention of the researchers. How this local problem get solved or minimized? An attempt has been made to use the conventional method such as Autoregressive model, more deterministic approach through multi-Linear Regression model and Artificial Neural Network which is capable of identifying complex non-linear relationship between input and output data without attempting to reach understanding into the nature of the process. The performances of these approaches were compared and the best possible result amongst them is the key point of this study.

Keywords: Artificial neural network, Runoff, River, Auto-regressive, Multi-linear regression

INTRODUCTION

Water is not lost in undergoing various processes of hydrological cycle namely, evaporation, condensation, rainfall, stream flow etc., but gets converted from one form to another was known during the Vedic period. Prediction of rainfall quantity in advance by observation of natural phenomenon is illustrated Puranas, Vrahatsamhita (550A.D.), Meghmala (900A.D.), and reference of rain gauges is available in Arthshashtra of Kautilya (400B.C.) and Astadhyali of Panini (700 BC). The quantity of rainfall in various parts of India was also known to Kautilya. It means ancient books also reflect the

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importance and the high stage of development of water resources and hydrology in ancient India.

Stream flow predictions for a particular section are required in order to do the attentiveness against the un-avoidable situation when the water level rises. The situation may cause due to improper operation and lack of co-ordination between the human beings who are directly or otherwise indirectly involved in the process of controlling the hydraulic structures. Such stream flow predictions are invariably based on observation of rainfall on the upper catchment, often supplemented by rainfall the intervening catchment. The quantities of water prediction are obtained in real time, by using a model to transform the input functions of time. These can be upgraded, modified considering the errors observed in previous prediction up to the time of making the forthcoming prediction. It has a wide spectrum of applicability for the recent and future planning field and the important factor in the sustainable management of water resources. The huge amount of water in the rainy season destructs the mind as well as path of the rivers. If a river flows with its peak discharge, another river meet at a certain point with full of discharge, then what will happen and Up to what extent?

The proper balance is needed to minimize the losses related with the human beings as well as other all formal and informal barriers. To overcome the cause effective modeling must be adopted. This can be sorted out by using the best possible, efficient and effective water resources system. Various types of models being used to solve the above said problem, these can be broadly grouped as deterministic models, stochastic or statically models, neural network based model, conceptual or lumped parameters or simplified physical model and distributed physical models. Of these, some are data dependence and some requires physical information about the systems as in the case of conceptual model.

Morocho and Hart (1964) connected upon the growth of two distinct approaches to the problem of establishing the relationship between rainfall and stream flow which they referred to as physical hydrology and system investigation. The former term was used to describe investing into the behaviour of interdependence between hydrological processes, the long term objective being a complete synthesis of the hydrological cycle. The progress achieved with this approach has materially assisted with the development of hydrological model that are both physically based and spatially distributed.

The ANN is advantageous because even if the exact relationship between sets of input and output data is unknown but is acknowledged to exist, the network can be trained to learn that relationship, required on a prior knowledge of catchment characteristics. In the hydrological context, the input pattern consist of rainfall depths and the output the discharges at the catchment outlet. Since the contributions from different parts of the catchment arrive at the outlet of different times, the variations in the discharge output may be considered to be determined by rainfall depths at both the concurrent and previous time intervals. Preliminary work (Hall and Mines, 1993) has indicated that the number of antecedent rainfall ordinates required is broadly related to the lag time of the drainage area. Since the ANN relates the pattern of inputs to the pattern of output, volume continuity is not a constraint.

AIM OF STUDY

The aims of this study are to develop prediction models as a tool to predict the flows, are as under.

- To develop AR model for conventional approach for runoff based lead time runoff prediction of Wainganga sub basin under Godavari basin.
- To develop MLR model for deterministic approach for runoff based lead time runoff prediction of said basin.
- To develop ANN model for runoff based lead time runoff prediction for same basin.
- To study the effect of input patterns on runoff prediction.
- To carry out performance evaluation of developed models using different performance criteria.
- Comparison of above developed models.

HYDROLOGICAL MODEL CLASSIFICATION

Hydrological models are commonly classified as physical models and abstract models. Physical models include scale models like hydraulic models of a spillway, analog models which use another physical system having properties similar to those of the real system. Abstract models shows the system in mathematical form. The system operation is described by a set of equations &logical statements. A mathematical model can also be transformed to a computer programme describing an algorithm for the system. Almost all useful hydrological models are in fact implemented as computer programmes.

The models are classified according to three important criteria such as, a) Randomness (deterministic or stochastic), b) Spatial variation (lumped or distributed), and c) Time variability (time- dependent, time independent).The simplest type of model will be a deterministic lumped time-independent model. The most complex type of model would be a stochastic model with space variation in three dimensions and with time variation.

LINEAR REGRESSION MODELS

Regression is the procedure of establishing relationship between two variables, referred to as the response variable "y" (dependent variable), & the explanatory variable "x" (independent variable). Simple Linear Regression Models referred to as the linearity of the variables associated with the problem. Regression is performed in order to, i) Learn something about the relationship between the two variables, ii) Remove a portion of the variation in one variable in order to gain a better understanding of some other, more interesting portion of the variation, and iii) predict values of one variable for which data are available.

MULTIPLE LINEAR REGRESSIONS (MLR)

MLR is the extension of Simple Linear Regression to the case of multiple explanatory variables. MLR is the procedure of establishing relationship between a dependent variable "y"& set of independent variables x_1, x_2, x_3...xn, governing a phenomenon. In hydrological application, runoff is considered to be dependent on rainfall at different stations; runoff at a particular station depends on runoff at upstream gauging stations, runoff at current time step & previous time step as independent variables with runoff at future time step as dependent variable etc.

STOCHASTIC MODELS

In order to evaluate a new sophisticated model can be applied to approximate the relationship between a set of inputs and a set of outputs, it is necessary to compare the predictive capabilities of new model with the existing approaches. The comparison of models is usually accomplished by testing all the models of interest on a data set from the same watershed.

There are varies regression models like Auto Regressive {AR (p)}, Auto Regressive Moving Average {ARMA (p,q)}and Auto Regressive Integrated Moving Average {ARIMA (p,d,q)} based on their p,q and d. Since the data available for the present study is non- stationary, the basic requirement to develop the AR and ARMA models could not be satisfied. The ARIMA time series analysis uses lags and shifts in the historical data to uncover patterns (e.g. moving averages, seasonality) and predict the future values. The ARIMA model was first developed in the late 60s but it was systemized by Box and Jenkins (1976). ARIMA is more complex to use than other statistical prediction techniques but quite powerful and flexible.

ARTIFICIAL NEURAL NETWORK

The human brain contains billions of interconnected neurons. Due to the structure in which the neurons are arranged and operate, humans are able to quickly recognize patterns and process data. An ANN is a simplified mathematical representation of this biological neural network. It has the ability to learn from examples, recognize a pattern in the data, adapt solutions over time, and process information rapidly.

Rumelhart *et al*. (1986) first introduced back propagation algorithm based on gradient descent search optimization. It is particularly useful as pattern-recognition tools for generalization of input-output relationships. The most common application in water resources includes those for rainfall runoff relationships and stream flow prediction.

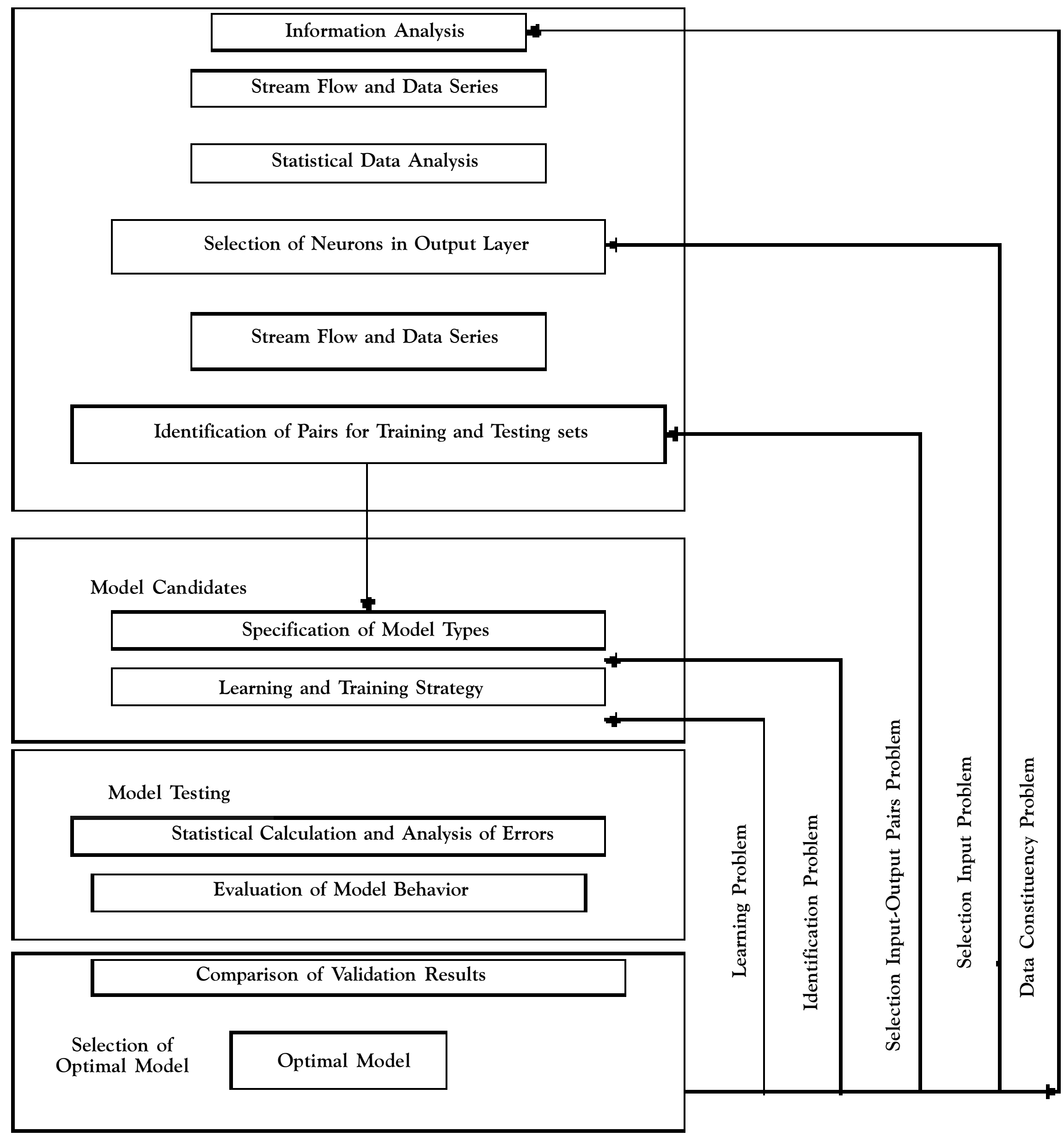
ANNs are structured is intimately linked with the learning algorithm used to train the network. A typical ANN consists of a classifying neural network is by the number of layers: single (Hopfield nets), bi-layer (Adaptive Resonance nets) and multi-layer (most back propagation nets). ANNs can also be categorized based on the direction of information flow and processing. In a Feed Forward Network, the nodes are generally arranged in layers, starting from a first input layer and ending at the final output layer. There can be several hidden layers, with each layer having one or more neurons. Information passes from the input to the output side. The neurons in one layer are connected to those in the next, but not to those in the same layer. Thus, the output of a neuron in a layer is dependent only on the outputs it receives from previous layers and the corresponding weights. On the other hand, in a recurrent or feedback ANN, is vice-versa. This is generally achieved by recycling previous network outputs as current inputs, thus allowing for feedback. Sometimes, lateral connections are used where neurons within a layer are also connected. ANN formulation stages are tabulated in “Figure .1”.

STUDY AREA AND DATA PREPARATION

General

The present study emphasizes on runoff-based runoff prediction for Wainganga River sub-basin under Godawari basin. Strom information is obtained from Keolari gauging station. Multiple Linear Regression (MLR), Autoregressive (AR)

Figure 1: Stages in ANN Formulation



and Artificial Neural Network (ANN) models were used for runoff-based runoff prediction.

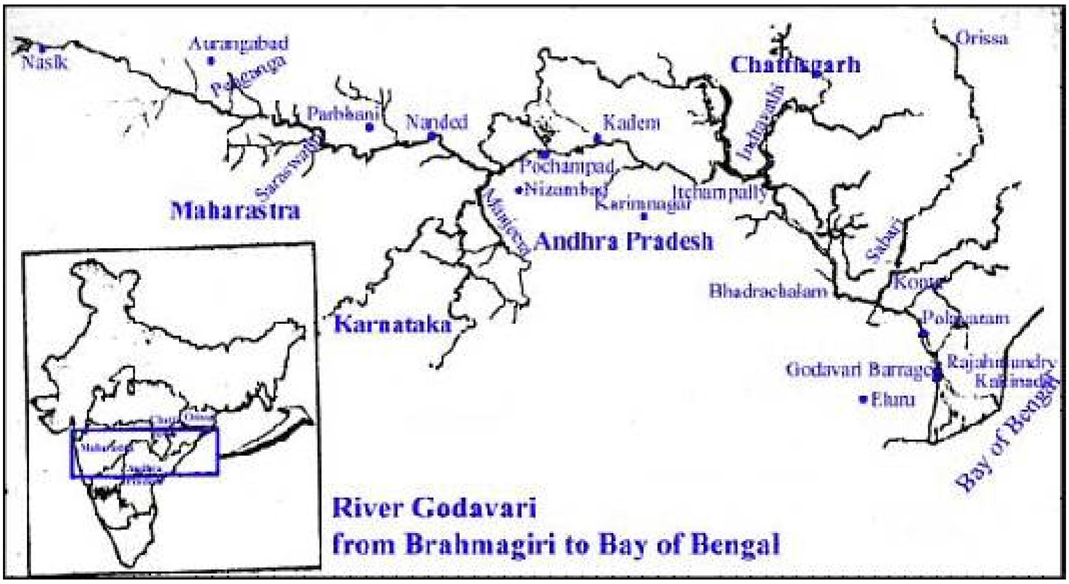
DETAILING OF RIVER BASINS

Wainganga River sub-basin under Godavari basin was taken for runoff based runoff forecasting. Storm values are collected from Keolari gauging station on Wainganga River. Figures 2 and 3 shows the map of Godavari basin and selected area respectively.

Wainganga is a river of India, which originates about 12 km. from Mundara village of Seoni district in the southern slopes of the Satpura Range of MP and flows south through MP and Maharashtra in a very widening course of approximately 360 miles. After joining the Wardha, the united stream, known as the Pranahita, ultimately falls into the River Godavari. The River has developed extensive flood plains with sweeping graceful meanders & low alluvial flats and meander terraces. It has high banks 10 to 15 m on either side. Wainganga River receives numerous tributaries on either bank and drains the western, central and eastern regions of Chandrapur, Gadchiroli and Nagpur districts. The chief tributaries of the Wainganga are Bagh, Garhavi, Khobragadi, Kathani and Potphondi on the western bank and Andhari on the eastern bank.

Figure 2: Godawari Basin

Figure 3: Map Showing Selected Area



Data Collection

Hourly runoff values 424 storms are available out of which 16 storms were collected from Waingang α sub-basin. Thirteen storms were used for estimation/training purpose and the last three storms were used for validation/testing purpose. In this, all 890 hourly runoff data were used for estimation/training and the last 116 data were used for validation/testing with different models. The data were obtained from the (CWC), Nagpur.

Data Preparation

The aim is to carry out runoff based flow prediction using deterministic, stochastic and ANN approaches. Input-Output data patterns used in different models for one to five-hour lead-time prediction study are described in the following section.

Lead Time Prediction

Hourly runoff values of different individual storms of Wainganga River sub-basin were taken for lead-time flow prediction purpose. One, two, three, four and five hours' ahead prediction of runoff is carried out using Multiple Linear Regression (MLR), Autoregressive modeling (AR) & Artificial Neural Network (ANN). The effect of dependence of past runoff values on flow prediction are attempted with: i) Constant input runoff values and varying corresponding output runoff value and ii) Varying input runoff values and corresponding constant output runoff value.

Table 1 shows the input-output pattern which are used in MLR, AR and ANN models of flow prediction for Wainganga River sub-basin. "Table 2" shows the input-output pattern for different lead-time predictions which are used in MLR, AR and ANN models of flow prediction for Bagh River sub-basin.

Table 1: Output Pattern for Different Lead-Time Runoff Prediction

S. No.	Inputs/Independents	Lead Time	No. of Inputs/Independents	Output/Dependent
1.	Q_{t-1}, Q_{t-2}, Q_{t-3}, Q_{t-4} and Q_{t-5}	1 hr.	5	Q_t
2.	Q_{t-1}, Q_{t-2}, Q_{t-3}, Q_{t-4} and Q_{t-5}	2 hr.	5	Q_{t+1}
3.	Q_{t-1}, Q_{t-2}, Q_{t-3}, Q_{t-4} and Q_{t-5}	3 hr.	5	Q_{t+2}
4.	Q_{t-1}, Q_{t-2}, Q_{t-3}, Q_{t-4} and Q_{t-5}	4 hr.	5	Q_{t+3}
5.	Q_{t-1}, Q_{t-2}, Q_{t-3}, Q_{t-4} and Q_{t-5}	5 hr.	5	Q_{t+4}

Table 2: Input-Output Pattern for One Hour Ahead Runoff Prediction

S. No.	Inputs/Independents	Lead Time	No. of Inputs/Independents	Output/Dependent
1.	Qt-1	1 hr.	1	Qt
2.	Qt-1 and Qt-2	1 hr.	2	Qt
3.	Qt-1, Qt-2 and Qt-3	1 hr.	3	Qt
4.	Qt-1, Qt-2, Qt-3 and Qt-4	1 hr.	4	Qt
5.	Qt-1, Qt-2, Qt-3, Qt-4 and Qt-5	1 hr.	5	Qt

MODEL DEVELOPMENT

Wainganga Sub-Basin

The main aim of the present research work is to carry out runoff based flow prediction using three different prediction approaches such as Deterministic, Stochastic and ANNs. Three different models like Multiple Linear Regression (MLR), Autoregressive (AR) and Artificial Neural Network (ANN) were developed for flow-prediction of Wainganga River sub-basin under Godavari basin.

Multiple Linear Regression Model

Multiple Linear Regression model with different input-output patterns of two and three hour lead-time/warning time runoff prediction for Wainganga River is shown in "Table 3".

Table 3: Multiple Linear Regression Model Description: Wainganga Sub-Basin

Sr. No.	Inputs / Independents	Output/ Dependent	Description / formulation of the model	Coefficients
1.	$Q_{t-1}, Q_{t-2}, Q_{t-3}, Q_{t-4}$ and Q_{t-5}	Q_{t+1}	$Q_{t+1} = \begin{cases} a + b_1Q_{t-1} + b_2Q_{t-2} + b_3Q_{t-3} \\ + b_4Q_{t-4} + b_5Q_{t-5} + e \end{cases}$	b_1, b_2, b_3, b_4, b_5
2.	$Q_{t-1}, Q_{t-2}, Q_{t-3}, Q_{t-4}$ and Q_{t-5}	Q_{t+2}	$Q_{t+2} = \begin{cases} a + b_1Q_{t-1} + b_2Q_{t-2} + b_3Q_{t-3} \\ + b_4Q_{t-4} + b_5Q_{t-5} + e \end{cases}$	b_1, b_2, b_3, b_4, b_5

Where Q_{t-1}; Q_{t-2}, Qt_{-3}, Qt_{-4} and Q_t-5 are runoff values at time one to five hour and Q_{t+1} and Q_{t+2} are runoff values at time seven and eight hour respectively.

AUTO REGRESSIVE MODEL (AR)

Auto Regressive Model with different input-output patterns of two and three hour lead-time flow prediction for Wainganga River is shown in Table 4.

Where y_{t-1}, y_{t-2}, y_{t-3}, y_{t-4} and y_{t-5} are runoff values at time one to five hour and y_{t+1} and y_{t+2} are runoff values at time seven and eight hour respectively.

Table 4: Autoregressive Model Description: Wainganga Sub-Basin

Sr. No.	Inputs / Independents	Output/ Dependent	Model Description / Formulation	Coefficients
1.	$y_{t-1}, y_{t-2}, y_{t-3}, y_{t-4}$ and y_{t-5}	y_{t+1}	$y_{t+1} = \begin{cases} \phi_1 y_{t-1} + \phi_2 y_{t-2} + \phi_3 y_{t-3} \\ + \phi_4 y_{t-4} + \phi_5 y_{t-5} + e_t \end{cases}$	$\phi_1, \phi_2, \phi_3, \phi_4, \phi_5$
2.	$y_{t-1}, y_{t-2}, y_{t-3}, y_{t-4}$ and y_{t-5}	y_{t+2}	$y_{t+2} = \begin{cases} \phi_1 y_{t-1} + \phi_2 y_{t-2} + \phi_3 y_{t-3} \\ + \phi_4 y_{t-4} + \phi_5 y_{t-5} + e_t \end{cases}$	$\phi_1, \phi_2, \phi_3, \phi_4, \phi_5$

ARTIFICIAL NEURAL NETWORK MODEL (ANN)

ANN with different input-output patterns of two and three hour lead-time prediction for Wainganga River is shown in Figures 4 and 5 respectively.

Figure 4: Training/Testing Pattern for Two Hour Ahead Forecasting

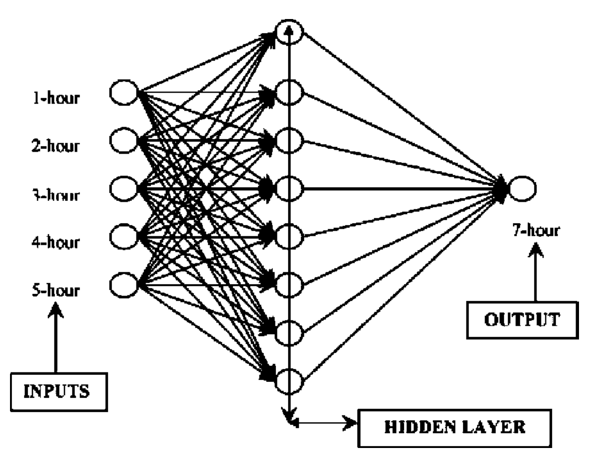
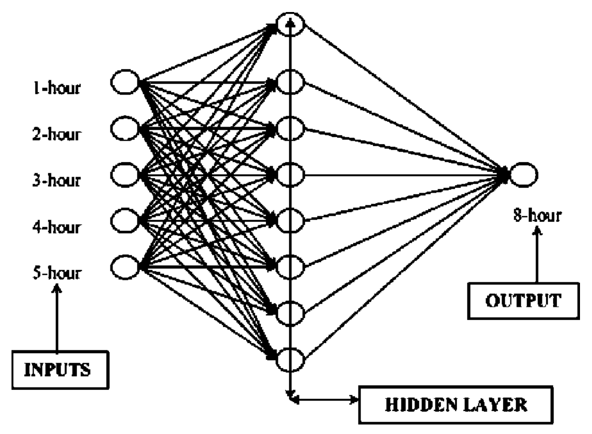


Figure 5: Training/Testing Pattern for Three Hour Ahead Forecasting



ANNs configuration, parameters and activation functions used in the model for Wainganga River sub-basin are given in Tables 5, 6 and 7 respectively.

Table 5: ANNs Configuration		
Layer	No. of Layers	No. of Neurons in a Layer
Input	1	5
Hidden	1	8
Output	1	1

Table 6: ANNS Parameters	
Parameter	Parameter Value
Learning Rate	0.1
Momentum factor	0.1

Table 7: ANNs Functions	
Function Type	Function Used
Network Type	Feed Forward
Learning Function	Back propagation With momentum
Update Function	Topological Order
Weights	Randomize

MODELS APPLICATION

Multiple Linear Regressions

Three important approaches like Deterministic, Stochastic and Artificial Neural Network were considered. Models such as Multiple Linear Regression, Auto Regression and Feed Forward Neural Network were developed for the flow prediction using hourly runoff values collected from Keolari gauging station on Wainganga River sub-basin under Godavari basin. One, two, three, four and five hours' ahead prediction of Waingangasub basin was carried out using MLR, AR and ANNs. A well-known spread-sheet EXCEL was used for MLR model. Regression analysis option available in data analysis tools option was explored. MLR coefficients and constant are listed in Table 8.

PERFORMANCE STATISTICS

The performance of developed model can be evaluated with different performance statistics like Mean Square Error (MSE), Efficiency Index (EI), Mean absolute deviation (MAD), Coefficient of Correlation (R) and Coefficient of Determination (R^2). Table 9 shows performance statistics of MLR models for different lead-time prediction. From the table, it is found that the value of MSE and MAD increases while Efficiency Index and coefficient of correlation decreases with increase in lead-time prediction. A consistent trend is observed in the different performance statistics parameters, which clearly indicates that one and two hour lead-time prediction gives better predicts than 3, 4 and 5 hour lead-time for MLR models.

AUTO REGRESSIVE MODEL (AR)

AR modeling can be performed with some of the well-known statistical packages providing facility

Table 8: MLR Coefficients and Constant: Wainganga Sub-Basin						
Lead Time	b_1	b_2	b_3	b_4	B_5	Constant
1-Hour	–0.00750	0.005180	0.20408	–0.17235	0.853446	30.179
2-Hour	–0.15873	0.128288	0.15214	0.088789	0.555063	60.593
3-Hour	–0.12755	–0.04846	0.21831	0.082495	0.561105	81.0432
4-Hour	–0.03795	–0.09137	0.05609	0.130349	0.558766	98.745
5-Hour	–0.03807	–0.00124	0.01225	–0.031291	0.604362	116.362

for Time Series Analysis and prediction for using EXCEL or writing source code in C or MATLAB.

PERFORMANCE STATISTICS

Table 10 shows performance statistics of AR models for different lead-time prediction. From the table, it is found that the values of MSE, MAD, EI and coefficient of correlation are not consistent, due to inherent random variation in sequential runoff values.

ARTIFICIAL NEURAL NETWORK MODEL (ANN)

Well-known public domain software, SNNS for neural network simulation was used for developing ANN model. Validation was carried out for one to five hour ahead prediction using Feed Forward Back Propagation Algorithm. In absence of an appropriate mathematical form of the model as in previous two cases, testing of runoff data was carried out using weight and bias values stored for the trained network. Different learning/ transfer function was used to map the output of a particular layer. Weights and biases were stored in the network and the same network weights and biases were used for the prediction/validation of sequential runoff inputs. One hour and two hour lead-time prediction shows good result with the observed runoff. It was observed that developed ANN model for three to five hour' ahead forecasting yields were reasonably poor correlation with the observed runoff.

PERFORMANCE STATISTICS

Table 11 shows performance statistics of ANNs models for different lead-time prediction. From the table, it is found that the value of MSE and MAD increases while Efficiency Index and coefficient of correlation decreases with increase in lead-time prediction.

Table 9: Performance Statistics of MLR Model

Lead Time	MSE	EI	MAD	R	R2
1-Hour	0.002517	0.9140	0.0278	0.9604	0.9220
2-Hour	0.007591	0.7315	0.0527	0.8893	0.7910
3-Hour	0.010198	0.6071	0.0588	0.8350	0.6973
4-Hour	0.011742	0.4725	0.0618	0.7973	0.6356
5-Hour	0.011773	0.4288	0.0624	0.7857	0.6171

Table 10: Performance Statistics: AR Model

Lead Time	MSE	EI	MAD	R	R2
1-Hour	0.001445	0.9407	0.0290	0.9795	0.9590
2-Hour	0.005125	0.8180	0.0492	0.9250	0.8562
3-Hour	0.002858	0.8895	0.0353	0.9518	0.9054
4-Hour	0.003132	0.8595	0.0306	0.9306	0.8657
5-Hour	0.003234	0.8430	0.00351	0.9220	0.8494

Table 11: Performance Statistics: ANN Model

Lead Time	MSE	EI	MAD	R	R2
1-hr.	0.001440	0.9510	0.0210	0.9751	0.9471
2-hr.	0.004055	0.8566	0.0393	0.9263	0.8530
3-hr.	0.006950	0.7321	0.0513	0.8589	0.7369
4-hr.	0.009954	0.5528	0.0580	0.8004	0.6406
5-hr.	0.007721	0.6252	0.0568	0.7921	0.6270

RESULTS AND DISCUSSION

The study inclined in the way of comparison of Deterministic, Stochastic and Black-box methods for stream flow prediction. Multiple Linear Regression, Auto Regression and Feed Forward Artificial Neural Network Models were developed for the flow prediction using hourly runoff values collected from two different gauging stations on Wainganga River sub-basin under Godavari basin. Table 12 shows the performance statistics comparison of said models.

Table 12: Performance Statistics Comparison of MLR, AR and ANN Models

Model	MSE	EI	MAD	R	R^2
1-hr ahead prediction					
MLR	0.002517	0.9140	0.0278	0.9604	0.9220
AR	0.001445	0.9407	0.0290	0.9795	0.9590
ANN	0.001440	0.9510	0.0210	0.9751	0.9471
2-hr ahead prediction					
MLR	0.007591	0.7315	0.0527	0.8893	0.7910
AR	0.005125	0.8180	0.0492	0.9250	0.8562
ANN	0.004055	0.8566	0.0393	0.9263	0.8530
3-hr ahead prediction					
MLR	0.010198	0.6071	0.0588	0.8350	0.6973
AR	0.002858	0.8895	0.0353	0.9518	0.9054
ANN	0.006950	0.7321	0.0513	0.8589	0.7369
4-hr ahead prediction					
MLR	0.011742	0.4725	0.0618	0.7973	0.6356
AR	0.003132	0.8595	0.0306	0.9306	0.8657
ANN	0.009954	0.5528	0.0580	0.8004	0.6406
5-hr ahead prediction					
MLR	0.011773	0.4288	0.0624	0.7857	0.6171
AR	0.003234	0.8430	0.00351	0.9220	0.8494
ANN	0.007721	0.6252	0.0568	0.7921	0.6270

CONCLUSION

One to five hours ahead prediction of Wainganga river flow is carried out using MLR, AR and ANN. After analysis, it is observed that AR Model gave satisfactory results compared to MR and ANN. Prediction accuracy decreases as lead-time increases in all these three models except for four hour ahead prediction. ANN model is found to be better in simulation and prediction the flow characteristics under consideration compared to MLR and AR models for one hour ahead prediction. However, AR models produce better predicting results compared to MLR and ANN. With rigorous exercise on different aspects such as selection of an appropriate transfer function best suit to the data, number of hidden layers, number of neurons in each hidden layers, number of epochs, ANN models can lead to much better prediction.

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