Comparison of Rainfall-Runoff Model Using ANN and MLR

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Abstract : Rainfall and surface runoff are the driving forces of all hydrology studies and designs. Rainfall-runoff relationship is non-linear, a complex which based on many factors like forest cover, evaporation rate, wind speed etc. In present practice, Artificial Neural Network (ANN) and Multi Linear Regression (MLR) techniques are used to find out one day ahead runoff in Amba river basin located at Maharashtra, India. ANN is simple cushy technique and it considers only the antecedent rainfall and runoff data as input variables. The inner system which control the conversion will converted into ANN weights. The architecture of the network is find, weights are evaluated so as to characterize the coveted output by a learning process in which the ANN is trained to obtain the expected results. Also, we construct MLR equations to prognosis runoff values and compare with performance evaluation criteria of Coefficient correlation (R), Mean Square Error (MSE), Root Mean Square Error (RMSE) and hydrograph analysis. It is found that the ANN can forecast runoff perfectly, with good relation in find values. The daily stream flow hydrograph shows that ANN expected peak values are underestimated while MLR predicted values are overestimated on a river basin.

Keywords: ANN, Multi Linear Regression.

I. INTRODUCTION

Rainfall and equivalent runoff are most crucial hydrological processes, so it is depend on the local physiographic, biotic and climatically elements. Rainfall on a catchment is the precipitation from the atmosphere to surface of earth in liquid form or (rain). Runoff of a catchment area in any mere interval is the total quantity of water draining into a reservoir or into a stream in that interval, which can be explicit as a millimeter of water over a catchment area or the total volume of water in cubic meter. Water available in a specific time at a specific location in a specific area in a river basin can be find out on basis of the rainfall-runoff regression model. The important factors of a hydrological model are precipitation, infiltration, stream flow, interception, evaporation, transpiration, variability in time and space. If the rainfall durability overreaches the infiltration rate then the runoff starts suddenly. Physiography of the local area suddenly create effects to the rainfall and the generated runoff from the catchment. The characteristics, i.e. wind velocity, temperature, annual rainfall and relative humidity also affect the rainfall-runoff relation in the basin.

II. LITERATURE SURVEY

A. Artificial Neural Network

ANN is the best selection techniques to modeling non-planar complex rainfall runoff phenomenon. Tokaret al. [1] used ANN for modeling daily runoff as a function of daily snowmelt, temperature, and precipitation. The study proved that ANN gives better accuracy which compared with conceptual and regression models. The study also proved that for obtaining sufficiently reliable predictions, the data should characteristic of the watershed and the climatic conditions. Rajurkaret al.[2] employed the daily rainfall and runoff data of Narmada catchment for the development of a model for transforming rainfall into runoff. A linear multi-point single output model (MISO) has been effectively used for deriving the response function relating rainfall to runoff. MISO model predicted runoff is then improved with help of neural network. This paper proved that combination of MISO and ANN forms better accuracy than non-linear and linear MISO models. K.P.Sudheeret al.[3] employed two neural network models viz., ANN-RD and ANN-TD for determining best rainfall-runoff simulation. This paper discusses the issue of peak flow prediction by ANN river flow models and presents an appropriate statistical procedure to address the problem. Wilbyet al.[4] developed evaporation, precipitation and discharge data for progressing neural network and important runoff model. Various practical's are conducted with successively decreasing the amount of information, to determine the extent to which networks can safely assimilate the hydrological processes. The study proved that a neural network with seven input nodes and three hidden nodes were able to considered the behavior of the conceptual model. The correlation analysis proved two hidden nodes corresponded to the quick flow and base flow elements the third one node represented the seasonal difference in the soil moisture shortage. Riadet al.[5] developed rainfall-runoff data at the Aghbalou station for constructing rainfall-runoff model by using ANN. Input parameters for ANN model, rainfall and runoff for the previous seven days with the rainfall expected for the day. The overall rainfall-runoff data of last seven years were divided into two parts. The data of six years composed the training data and the data for one year was used for testing the trained ANN. The capacity of ANN was defined with multiple linear regression (MLR) model. The values of ANN are found in relation with observed results. The study proved that ANN is having a good capacity of modeling complex non-linear hydrological processes. Jeonget al. [6] employed models viz., ensemble neural network (ENN) and single neural network (SNN) for giving best rainfall-runoff simulation. The practice proved that ENN provided the least root mean square error (RMSE) and therefore performed efficiently than SNN. ENN compared with existing rainfall-runoff simulation model TANK based on certain probabilistic accuracy measures, ENN outperformed the TANK model in most of the test cases. Abrahartet al. [7] gives the applicability of neural networks for modelling non-planar rainfall-runoff relationships. The neural network modelling gives better results for developing non-planar change and can be helpful to obtain datasets. Kaltehet al. [8] produced rainfall-runoff model by using ANN and differentiate the Garson's algorithm, Neural Interpretation Diagram, and randomization approach. The study gives that ANN not only effectively learns the complex processes but also capable an understanding about the complex relationships between the processes. Solaimaniet al. [9] employed three different training algorithms for producing ANN models for prophecy rainfall. Efficiencies of Levenberg-Marquardt, conjugate gradient, and gradient descent training algorithms were compared. Monthly climatic, hydrometric data were used to development of the ANN model. The study showed that by combining computational efficiency with input nodes that describe the hydro-climatologic variables, an improvement in ANN prediction can be achieved. ShreenivasLondheet al.[10] employed three data-driven techniques, namely artificial neural networks (ANN), genetic programming (GP) and model trees (MT) to forecast river flow one day ahead at two stations in the Narmada catchment of India. All the models performed practically well as far as accuracy of forecast is concerned. It given that the ANN and MT methods performed almost equally well, but GP performed better. R. B. Magar et al.[11] developed and compared MLR models and ARIMA models using time-series lumped rainfall data derived from the Koyna watershed in Maharashtra, India to predict the inflow. Lumped rainfall data was derived using each station time series and Thies sen polygon method. They concluded that both the MLR and ARIMA models performed equally well for sufficiently longer rainfall data. Machado et al.[12] used three ANN models prepared on monthly rainfall-runoff compared with the monthly time scale conceptual model IPHMEN. Back-propagation algorithm was used for training the ANN. The IPHMEN conceptual model was compared educated ANN during calibration and validation phases. IPHMEN model provided anomaly results with big deviation flows. This practice proved that the trained ANN has better potential for accurately predicting the observed flows. Chen et al.[13] employed the rainfall-runoff model for typhoon using ANN. The study proved that regression analysis is suitable for slight variation in data. But for substantial variation in data, ANN provided a promising method. ANN showed to be easy and flexible to perform evaluation tool for the complex hydrological phenomenon. R. B. Magar et al. [14] shows the development and case study of Nash IUH for the Koyna in Maharashtra, India. The moments (MOM) are used for estimation of parameters. IUH useful for predicting the flood into the reservoir for a given rainfall. The important direct runoff hydrograph (DRH) estimated from IUH derived is compared with the observed DRH and found to be in good agreement with each other. Phukoetphimet al.[15] developed different three types viz., neural interpretation diagram, Garson's algorithm, and sensitivity analysis to understand the contribution of input variables and knowledge extraction approaches to neural network modelling of rainfall-runoff relationships.

Multi Linear Regression

MLR is the simplest, statistical and well-developed representation of the time-invariant relationship between an input function and corresponding output function. MLR models are considered as benchmark in reservoir inflow forecasting. M. H. Diskinet al.[16],outlined three model as an interpretation of the regression equation for the relationship between annual rainfall and annual runoff from watersheds. The elements can be find out by the usual least square equations if the runoff data do not include zero or near zero values. For semiarid watersheds in which runoff may be zero for some years, a special procedure is proposed for evaluating the parameters. The procedure seeks the minimum of an objective function defined as the sum of squared deviations between observed data and prediction line defined by the regression model. Robert Hirsch et al. [17], highlights on several procedures use for reconstruction streamflow records for sites where no record or only a short record exists. The methods gives drainage area ratio , use of monthly means and standard deviations based on regional streamflow-basin characteristics models and two different methods of using the cross-correlation of flow records. The analysis suggest that important estimates of flow and reservoir yields may be made without any at-site measurements provide that good regional information transfer models are available. Robert Hirsch et al. [18], demonstrated three methods of fitting straight lines to data and their purpose are discussed and contrasted in terms of their applicability in various water resources contexts such as ordinary least square, least normal square and the linear of organic correlation. Keith Loague et al.[19],used a set of model performance calculations for three events-based rainfall-runoff models for small upland catchments. The models include a regression model, a unit hydrograph model, and a quasi-physically based model. The results show the unit hydrograph model and the quasi-physically based model have little forecasting power whereas regression model is marginally better. Driver N.E. et al. [20], proposed linear regression model for the estimation of storm-runoff loads and volumes from physical, land-use, and climatic characteristics of urban watersheds throughout the United States. The use of these models is to estimate storm-runoff loads and volumes at gauged and ungauged urban watersheds. The most accurate models were those forthe more arid western United States, and the least accurate models were those for areas that had large quantities of mean annual rainfall. F.H.S. Chew, et al. [21], invented six rainfall-runoff approaches simple polynomial equation, simple process equation, simple time-series equation, complex time-series model, simple conceptual model and complex conceptual model are compared with the models used to simulate daily, monthly and annual flows in eight unregulated catchments. H. Raman et al. [22], the comparative study between the traditional approach and data driven approach in synthetic hydrology has been done. JagadeeshAnmala et al. [23], demonstrated artificial neural network (ANN) for predicting runoff over three medium sized watersheds in Kansas. The performance of ANN's possessing architecture and neural network were evaluated by comparing with an empirical model and it was found that ANN provides a better result than the empirical model. Jain A et al. [24], studied the comparative analysis of technique based on deterministic (unit hydrograph theory), statistical (regression analysis) and artificial neural networks (ANN) for better representation of an event based rainfall-runoff process. K.W.Chau et al. [25], used empirical planar regression model as a benchmark for comparing the capacity of Genetic algorithm based artificial neural network (ANN-GA) and the adaptive-network-based fuzzy inference system (ANFIS) for flood forecasting in a channel reach of the Yangtze river in china when cautious treatment is made to avoid overfitting, both hybrid algorithm produces better accuracy in performance than the linear regression model. Oli G.B. Sveinsson et al. [26],investigate the capacity of various models and process for prophecy aggregated May-July stream flow for the Chur chill full basin on the Quebec-Labrador Peninsula is compared. The models like autoregressive, autoregressive with exogenous and planar model are used and comparative study is made between them.

III. STUDY AREA

In this practice runoff model and rainfall- runoff model to prophecy runoff one day ahead were produced at three rain gauge stations namely, Tuksai, Pali, and Salinde in Amba river basin. The river Amba came in the Sahyadri ranges at an altitude of 822 meters at 3.20kms south of village Khandala at Rajmachi in Borghat of Tal. Maval Dist. Pune. Then traveling by 78.17kms and flowing towards west. This river meets Dharmatar Creek near village Dherand of Tal. Alibag Dist. Raigad at 0.00 meters level and then merges in the Arabian Sea. The Amba came into the minute area of Dist. Pune and Raigad of Maharashtra. Rainfall variation in Amba basin ranges from 4323mm to 1450mm with an average of 2769mm. Amba basin is in a humid climate. The metrological data from 1990 to 2011 the minimum average temperature observed at these stations was 20.58°C and maximum average temperature 33.94°C. Fig. 1 shows Index map of Amba basin which explains location of rain gauge and gauge discharge stations.

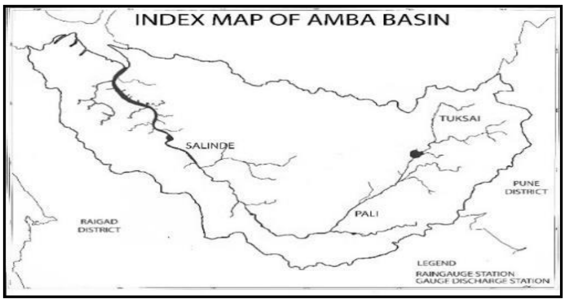

Figure. 1 Index Map Of Ambabasin(Source :Maharastra Irrigation Department, Karmali)

The stations namely Tuksai, Pali and Salinde situated on a tributary of Amba River were taken for the present study. It was therefore decided to develop five separate models for the five monsoon months of June, July, August, September and October at Tuksai, Pali, and Salinde to forecast discharge one day in advance. The models will hereafter be called as TkJune, TkJuly, TkAug, TkSept and TkOct for Tuksai station, PJune, PJuly, PAug, PSept and POct for Pali station and SdJune, SdJuly, SdAug, SdSept and SdOct for Salinde station.

IV. METHODOLGY

A. Data transformation

Luk et al (2000) gives that networks trained on transformed data can give best performance. A logarithmic conversion has been pre-owned to bring the observed data to near normal distribution. Transformation is performed on every result variable independently using the following eqn. 1) and eqn. 2) respectively.

$$\mathbf{Z_{p.t.} = a\log_{10}\left(P_{obs(t)} + b\right)......1)}$$

$$\mathbf{Z_{q.t.} = a\log_{10}\left(Q_{obs(t)} + b\right).......2)}$$

The predicted results were then back-transformed using the following eqn. 3).

$$\mathbf{Q_{pred(t)} = 10^{Z_{qt}/a} - b \;....3)}$$

Where, $\mathbf{Z_{p.t.}}, \mathbf{Z_{q.t.}}$ are the transformed values of the rainfall, runoff during time period 't', a and b are arbitrary constant assumed as 0.5 and 1 respectively.

B. Model formulation using ANN

The total data categorized in education, testing and validation phase from which 70% data was considered for training, 15% data was considered for testing and validation purpose. All calculations for training, testing and validation performance were carried out using Neural fitting tool box provided in the MATLAB software. The ANN is developed for three different phases in the most general sense. The first is the training phase and the second and third are the validation and testing phase. ANNs have the ability to perform with a better quantity of observation from the patterns on which they are educated. Several methods do exist to train. The successful and extensively used training algorithms is multi-layered perceptron (MLP). A simple ANN can be seen in fig. 2. The functional relationship for rainfall-runoff model can be stated as

$$\mathbf{Q_{t+1} = f(Q_t, Q_{t-1}, Q_{t-n}, R_t, R_{t-1}, R_{t-n})}$$

Where, R and Q denotes rainfall and discharge flowing through the river respectively.

The Ann is operated using back-propagation training algorithm in this study. Back-propagation network is having a layered structure with an input, output, and hidden layers. The modified systemis continue in the output layer,

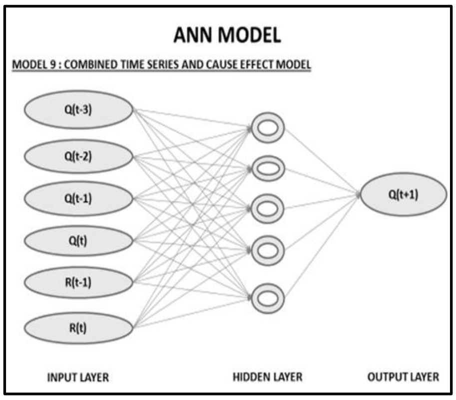

Fig. 2 Typical structure of ANN model

where the error between the network outputs and expected targets is calculated and then propagated back to the network through a learning mechanism. The tansig and purelin transfer function were used in the hidden and output layers respectively. The generalized delta rule is an extensively used learning mechanism in back-propagation neural network. The implementation of such algorithm update the network weights in the direction, in which the performance function decreases most rapidly. The number of neurons in the hidden layer was decided by trial and error. The data division was kept the same, to compare results with the ANN and MLR models. The ANN model is tested and the output are compared by means of the correlation coefficient (R), root mean square error (RMSE) and mean square error (MSE).

C. Model formulation using MLR

MLR is the expansion of simple linear regression to the case of multiple explanatory variables. MLR is the procedure of establishing relationship between a dependent variables Y and set of independent variables $X_1, X_2, X_3 \dots X_n$, governing a phenomenon. In MLR, the operation is a linear equation, i.e., Straight-line in the form. Eqn. 3) shows simplified MLR equation which explains that dependent and independent elements.

$$\mathbf{Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \ldots.3)}$$

Where,Y = Dependent variable,β_0 = Constant or intercept, β = Slope for X1, X1 = First independent variable, n = Number of independent variables, β_n = Slope coefficient for Xn, Xn= nth independent variable.In these work, one-day ahead runoff variable is taken as dependent variable whereas runoff at a current time step, previous time steps similarly rainfall at a current time step, the previous time steps are taken as an independent variable. Popular spreadsheet Microsoft Excel provide comprehensive statistical program packages, which include a regression tool.

D. Evaluation of model performance

The developed models were evaluated for their accuracy by employing statistical parameters like correlation coefficient (R), root mean squared error (RMSE), mean squared error (MSE) along with the hydrographs and scatter plots between the models predicted and observed discharge values. The error measures are explained below:

1. Correlation coefficient (R):

This is a number between -1.0 and +1.0, which measures the degree to which two variables are planar related. If there is a perfect linear relationship with a positive slope between the two variables, the correlation coefficient is equal to 1. The measure, however, is very intensive to derive from larger observations. Eqn. 4) denotes Karl Pearson's correlation coefficient between observed and predicted discharge.

$$\mathbf{R = \frac{\sum_{i=1}^{N} t_i p_i}{\sqrt{\sum_{i=1}^{n} t_i^2}\sqrt{\sum_{i=1}^{n} p_i^2}} \ \ldots\ldots 4)}$$

R is correlation coefficient, N is the number of training data samples,$t_i = T_i - \overline{T}$, $p_i = P_i - \overline{P}$,T_i and P_i are the target and predicted values for i = 1..., N respectively,$\overline{T}$ and $\overline{P}$ are the mean values of the target and predicted data set respectively.

2. Root Mean Square Error (RMSE)

This measure gives an overall agreement between the observed and modeled datasets. It has no upper bound with zero as the value for a perfect model. This measure is good for iteratively arrived at predictions and gives only an overall picture of errors. Eqn. 5) shows RMSE between observed and predicted values

$$\mathbf{RMSE = \sqrt{\left(\frac{1}{N}\sum_{i=1}^{N}(T_i - P_i)^2\right)} \ \ldots 5)}$$

4.4.3 Mean Square Error (MSE) :

The ability of the ANN-predicted values to match measured data is calculated by the Mean Square Error (MSE). Eqn. 6) denotes MSE between the target and predicted values.

$$\mathbf{MSE} = \left(\frac{1}{N}\sum_{i=1}^{N}(T_i - P_i)^2\right) \qquad \text{...6)}$$

Overall the ANN results are more important if R, MSE, and RMSE are near to 1, 0 and 0, respectively.

V. RESULTS AND DISCUSSIONS

A. Results of ANN and MLR

Tables 1 shows correlation coefficient between the observed and predicted discharge values for all the models developed using ANN and MLR.It was found that correlation coefficient R is greater than 0.9 have a significant impact on one-day advance runoff prediction. Out of total 105 models, we are selected 15 models which have higher values of R, lower values of RMSE and MSE on Tuksai, Pali and Salinde gauge discharge stations for June, July, August, September and October months on Amba river basin. It was found that correlation coefficient R having non-significant value as compared to ANN.

Table 2 explains performance criteria for Pali station for month of August.

SR. NO.	MODEL NAME	MODEL PARAMTERS	R (ANN)	R(MLR)
1	TkJune	Qt-1, Qt, Rt	0.9414	0.9112
2	TkJuly	Qt-1, Qt, Rt	0.9333	0.9227
3	TkAug	Qt-2, Qt-1, Qt, Rt-1, Rt	0.9329	0.9154
4	TkSep	Qt-1, Qt, Rt-1, Rt	0.9342	0.9259
5	TkOct	Qt-1, Qt, Rt	0.9085	0.8624
6	PJune	Qt-3, Qt-2, Qt-1, Qt, Rt-1, Rt	0.9190	0.7321
7	PJuly	Qt-3, Qt-2, Qt-1, Qt, Rt-1, Rt	0.9322	0.7406
8	PAug	Qt-1, Qt, Rt	0.9156	0.9024
9	PSep	Qt-3, Qt-2, Qt-1, Qt, Rt-1, Rt	0.9224	0.9025
10	POct	Qt-3, Qt-2, Qt-1, Qt, Rt-1, Rt	0.9552	0.9429
11	SdJune	Qt-3, Qt-2, Qt-1, Qt	0.9015	0.7511
12	SdJuly	Qt-3, Qt-2, Qt-1, Qt	0.9373	0.8902
13	SdAug	Qt-3, Qt-2, Qt-1, Qt	0.9028	0.8706
14	SdSep	Qt-3, Qt-2, Qt-1, Qt	0.9035	0.8523
15	SdOct	Qt-3, Qt-2, Qt-1, Qt	0.9340	0.8683

Table 2 Performance Criteria(Station – Pali, Month – August)

MODEL NAME (PAug4)	R	MSE	RMSE
ANN	0.9156	0.007	0.0875
MLR	0.9024	0.090	0.0950

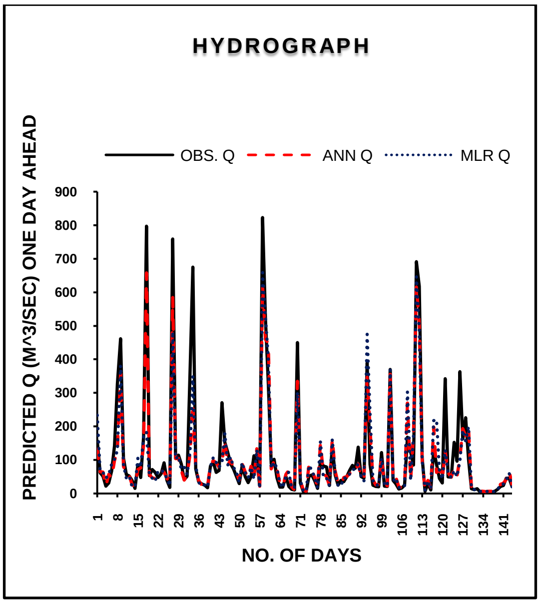

Fig. 3 Hydrograph (testing) for PAug4 IDEAL to DIFFER ANN and MLR

The selected model for August month on Pali gauge discharge station shows that 3 input parameters (Qt-1, Qt, Rt) and 1 output (Qt+1). Fig. 3 explains that, due to non-linear behaviour input parameters, low flows and medium flows are predicted reasonably accurate, high inflows are underpredicted by using ANN and MLR. From the hydrographs, it can be observed that both ANN and MLR hydrograph follows the pattern of the identified graph of rising limb and recession limb with very less variation. The direction of rainfall, the peak inflow is slightly under-predicted in ANN and MLR, but within the limit of < 20% of observed peak. Therefore, we found out that both ANN and MLR performs well for predicting one day ahead discharge. But MLR does not perform very well to exactly match observed flow. Therefore, we select ANN hydrograph is better than MLR hydrograph for one-day advance discharge.

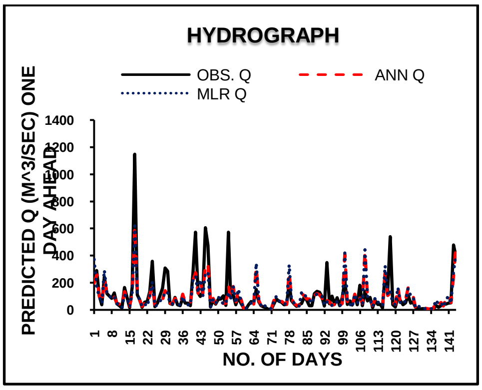

Fig. 4Hydrograph (validation) for PAug4 Model to compare ANN and MLR

Fig. 4 explains that ANN exactly underpredicts discharge (620.54 m3/sec) up to the observed value (1147.981 m3/sec) on one day ahead. Due to non-linear behaviour input parameters, low flows and medium flows are predicted reasonably accurate, high inflows are underpredicted by using ANN and MLR. From the hydrographs, it can be observed that both ANN and MLR hydrograph follows the pattern of the observed hydrograph of rising limb and recession limb with very less variation. Due to leaf shape of the catchment and direction of rainfall, the peak inflow is slightly under-predicted in ANN and MLR, but within the limit of < 20% of observed peak. Therefore, we conclude that both ANN and MLR performs well for predicting one day ahead discharge. But MLR does not perform very well to exactly match observed flow. Therefore, we select ANN hydrograph is better than MLR hydrograph for one-day advance discharge.

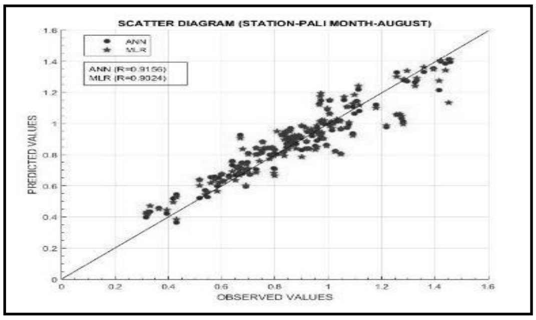

Fig. 5Scatter Plot (testing) for PAug4 Model to compare ANN and MLR

In scatter diagram (Fig. 5), the band is rising from left to right then it indicates positive correlation. The blue and red band indicates that impact of correlation analysis. The blue data points are more nearer to 45 degrees line compared with red data points. Therefore, it concluded that ANN have ahigher degree of accuracy for prediction. From above discussions, we conclude that ANN hydrograph performs very well in testing as well as validation for predicting one day ahead discharge. ANN model underpredicts or exactly predicts observed discharge for low flows, medium flows and peak flows. Also, due to leaf shape of the catchment, rainfall intensity is non-linear. Therefore, ANN is useful for non-linear, complex, dynamic behaviour of the rainfall-runoff mechanism.

VI. CONCLUSIONS

Nine ANN models each are developed on Tuksai, Pali, and three ANN models are constructed on Salinde gauge discharge stations with various inputs parameters for June to October months for predicting one-day ahead discharge. Also, constructs the same number of multi linear equations on above gauge discharge stations. Hence, total 210 models are used in this report to predict one-day ahead discharge. Initially, only antecedent stream flow values are used to predict runoff, later on, antecedent rainfall was also added as inputs, which show the improvement in the models. And if there is increasing no. of input parameters, increases R-value, decreases MSE and RMSE. Because ANN is black box model, we did not know what exactly going to the model. We train the model repeatedly and find out the optimum solution for prediction one-day advance discharge. However, we cannot predict exact value of discharge; it may be under predicts or over-predicts over observed discharges. The ANN models have been identified as a robust model in modelling the rainfall-runoff relationship. It can model accurately the storm hydrograph for single-storm and multiple-storm events. Clearly, ANN application to model the daily stream flow hydrograph was good. This is time for the ANN to become a priority tools to overcome the problem of flow hydrograph prediction. The performance standards like correlation coefficient, Mean Square Error, Root Mean Square Error, hydrographs and scatter plots helps to select best models amongst ANN and MLR. From above data analysis, ANN is more superior to MLR.

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