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A Neural Network Approach To Real Time Rainfall Estimation

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Abstract— **Rainfall estimation from a watershed is of utmost importance for various hydraulic and hydrologic purposes like flood discharges, flow depths and other flood chracteristics (Jorge 2000). Operationally, rainfall estimation in real time on a 3-hourly timescale is potentially of great benefit for various hydrological forecasting purposes in a basin. In the present study, the aim is to analyze the temporal variations of rainfall using regression and ANN models. In the present study, rainfall estimation of Sutlej sub-watershed Himachal Pradesh which is located in districts of H.P having average elevation of 1400 m and spread over an area of 15802 km^2 approximately is done using ANN and regression models. The basin hydrology features like flow accumulation, stream flow direction, watershed etc. have been extracted using SRTM DEM. An attempt has been made to use Trophical Rainfall Measuring Mission (TRMM) data procured from USGS website, as an input to an Artificial Neural Network (ANN) model during this study. Input parameters (Air temperature, Wind Speed, Air pressure, and Specific humidity) effects on rainfall have also been studied and correlation among these parameters has been analyzed. It has been observed that precipitation is heavily dependent on specific humidity and air temperature for the study area. Further, Multiple Linear Regression (MLR) model and ANN models have also been compared and to check the performance of rainfall prediction. Two different algorithms of ANN i.e. Stochastic Gradient Descent (SGD) and Multiple Layer Perceptron (MLP) have been used for rainfall estimation. The RMSE has been observed as 7.46 for SGD (ANN) whereas 8.87 and 9.8 for MLP (ANN) and MLR model respectively. Thus, the results obtained shows that the rainfall may be predicted better with the ANN model than the regression model.**

Keywords: Rainfall, Watershed, Regression, ANN, SGD, MLR, MLP

I. INTRODUCTION

The rainfall constitutes the available water resources on land and is vital for human. Short- term extreme rainfall leads to flood while long time no rainfall cause the drought. Therefore, rainfall is an important parameter in determining of water budget, drought analysis and planning of water resources. The latest developments in artificial intelligence provide an alternative approach to estimate rainfall. Many investigations have been run by various researchers to check the applicability of artificial neural networks (ANN) to various problems in the meteorological and hydrological areas such as short term stream flow, evaporation, solar radiation, rainfall-runoff, wind speed and rainfall estimation[16]. The effects of temporal variation have been investigated on short-term rainfall forecasting and it has been proved that the ANNs provide much accurate predictions. The results of various studies shows that the ANN models provides a good fit with the actual data and a high applicability in prediction of extreme precipitation[15]. Some studies have trained ANNs to recognize the historical rainfall patterns for new rainstorm events recorded from a number of rain gauges in catchment for reproduction of relevant patterns. Real-time monitoring of rainfall is vital to allow timely responses to potential disasters. Real-time monitoring of rainfall for rainfall amounts at 3-hourly intervals in the past has been regarded as an appropriate temporal resolution. Agricultural applications such as monitoring gaps in the growing season can also be dealt by daily estimates. Rainfall monitoring from satellite data is an attractive alternative as it has the capability for good spatial coverage, is relatively inexpensive to access and is readily available in real time. A new approach has been reported based on the application of an artificial neural network (ANN) to a combination of USGS website data[6]. The method described may in principle be used for different time periods such as daily scale, monthly scale or yearly scale but as the most readily available data for validation and calibration are 3-hourly observations, during this study also, the present study has been focused on a 3-hourly timescale.

Important Parameters

Four input parameters have been considered for rainfall estimation i.e. Air pressure, Air temperature, Wind speed and Specific humidity.

Air Pressure- The weight of air molecules pressing down the earth is known as air pressure. Change in air molecule pressure is experienced moving upward into the atmosphere from the sea level. The weight of atmosphere on a particular area pushing downwards is indicated by low and high pressure readings. At low pressures, the air rises freely into the atmosphere where it condenses and cools. The clouds are formed around dust particles due to condensation of ice crystals and water droplets in the sky. Condensation of water vapours takes place and they fall as rain. Without low pressure, much of the air and the water vapor within it wouldn't reach a high enough altitude to condense, so it wouldn't rain. If there is no low pressure, much of the air consisting of water vapours doesn't reach a suitable altitude for condensation, so it wouldn't rain. This is the reason that the areas of low pressure often face rains. Steady and long rain is not what always happens as the rain comes down in varying intensities. The occurrence of steady and long rains happens because of the location of the low pressure system related to a warm front. When the moist and warm air enters the low pressure area and starts getting pulled up ahead of the warm front over the mass of cool air, longer and steadier rainfall or snow are experienced.

Air Temperature- The measure of how hot or cold air is known as air temperature. It is one of the most common weather parameter. Specifically, the energy of motion or kinetic energy of the gases that makes up air is represented by air temperature. The air temperature increases on quick movement of gas molecules. Water vapours concentration present in the atmosphere decides the rainfall volume in a heavy shower. The chances of heavy showers increase at higher temperatures as more water vapour may be present in the atmosphere. Time scale from several minutes to hours and days can be responsible for change in properties of rain shower. Different processes in the atmosphere are the reason for creation of various types of rainfall. At elevated temperatures, the intensification of convective precipitation happens quickly especially at temperatures ranging 12-20 degree Celsius.

Specific Humidity- The mass of water vapour in a unit mass of moist air is known as specific humidity. It is expressed as Kg of vapour/ Kg of air. The specific humidity can be considered as extremely useful quantity in water resources. Moreover, with the change in the pressure or temperature of a body of air, the specific humidity doesn't changes until the moisture is either added or taken away from it(Some indices of humidity are sensitive to the temperature and pressure). Due to this stability of specific humidity, it can be used as an identifying property of a moving air mass. With increasing temperatures, there is a rapid increase in specific humidity of saturated air and the chances of precipitation increases at higher temperatures when the humidity is more in the air.

Wind Speed- The moving of air from high to low pressure due to changes in temperature represents a fundamental atmospheric quantity known as wind speed. Note that due to earth's rotation, wind direction is almost parallel to isobars. Many operations such as aviation, weather forecasting and maritime operations are effected by wind speed. The precipitation is effected by wind speed in a way that the rainfall intensity decreases and rainfall loss rate increases with increase in the wind speed.

Rainfall Estimation

Temperature, Pressure, Wind Speed and Humidity are the crucial input parameters to rainfall prediction models, statistical characterization of extreme rainfall frequency and validation of satellite remote sensing algorithms. The rainfall product development has been discussed in the next chapters, and the practical and theoretical requirements of validating new advanced technologies and rainfall. A discussion has been done on rainfall estimation which includes uncertainty of rainfall estimates. The major challenge in hydrologic applications is the validation of rainfall products for broader utilization of products. The most important instrument for studying the hydrological cycle is temporal distributed modeling, concerning future changes in climate as well as its present state and land use. Results from such simulations are relevant particularly for the fields of hydropower, water resources and natural hazards. The development of hydrological modeling system has been done to the conditions in mountaineous environments with their highly variable climatic and environmental conditions and implements a process-oriented approach.

Disadvantages of Conventional Techniques

Principally, estimation of gap of data by conventional methods such as differentials, mean, sampling methods, extrapolation and interpolation and proportional is time consuming and a many times associated with error. The reason for the attempt of researchers to develop a black box model such as ANN is the need for long-term historical information, natural uncertainty and non-linearity of a stochastic process such as precipitation and complexity of physical-based methods. When data is insufficient and accurate prediction is more important than conceiving the physics of a problem, black box models could be a good option. Black box models can be a good option when accurate prediction is more important rather than conceiving the physics of a problem and data is insufficient.

ANN in Hydrology

Artificial Neural network falls under soft computing tools category like fuzzy logic or ARIMA (Auto Regressive Integrated Moving Average), Genetic Algorithm in which a model is trained to attain outputs. Computing systems such as artificial neural networks (ANN) are inspired by biological neural networks but are not identical to them. These kinds of systems can consider examples for learning to perform tasks without getting programmed with any of the task specific rules.

A collection of connected nodes or units known as artificial neurons develop base of ANN, which loosely model the neurons in a biological brain. A signal from one artificial neuron to another can be transmitted in each connection just like synapses in animal brain. One artificial neuron receives and processes a signal and then signals it to connected artificial neurons. Warren created A computational model was created by McCulloch and Walter Pitts (1943) for neural networks based on algorithms and mathematics known as threshold logic. Pavement of way in research of neural networks splitting into two different approaches was done by this model. The first one focuses on application of neural networks in artificial intelligence and the other one focusing on biological processes in brain. This led to work on nervous networks and how they can be linked to finite automata. Generally, physical processes based models may need mathematical equations for solving the problem which requires high demand of data and sometimes it may be required to estimate the input parameters. Therefore, the effect of these parameters appears normally in the model output and determination of these parameters is based on modeler's judgement subjectively(Sen, 2009).

In this step, selection of a training algorithm and determination of the ANN architecture is involved. While retaining a compact and simple structure, model yielding the best performance in minimizing error may be considered as optimal architecture. There was no presence of any unified theory which determines an optimal ANN architecture. Often, similar results can be obtained by more than one ANN. Different output and input nodes are dependent on problems. The flexibility lies in selecting the number of hidden layers and in assigning the number of nodes to each of these layers. The optimal architecture is generally decided by

applying the trial and error method. The most efficient and best method to find the optimal architecture is back propagation algorithm. There are three major factors on which the potential of feed-forward artificial neural networks can be attributed:
(1) No explicit mathematical equation is required for multilayered feed forward neural networks for relating output and inputs.
(2) Any continuous function can be approximated with any arbitrary number of ReLU hidden nodes of a single layer feed forward network.
(3) A single hidden layer feed forward network of some m' ReLU nodes receives a squared error of 0, whereas a set of some m' basis functions receives a squared error of 0, where the dimension of the input is d.
Point 2 is representing the existence of theorem capable in establishing the feed forward ANN whereas the computational superiority of feed forward network is represented by points 1 and 3. However, it does not allow the number of hidden nodes to be used in a given situation for a systematic determination. The performance of a network is influenced significantly by the number of hidden layer neurons, too many nodes over fitting the training data whereas the network approximates poorly with too few nodes. The feed forward network uses lateral connections in a controlled assignment of role in the hidden layer neurons starting with the fringe nodes and leaving unsupervised nodes in the center of the hidden layer. Due to the presence of functionally similar neurons in the hidden layer center, like soft weight sharing, the behaviour of network is like a growing algorithm without the explicit need of adding hidden units consequently. This localized weight sharing algorithm helps in a determination of number of hidden layer neurons systematically required for a given learning task.

II. STUDY AREA

The present study has been undertaken on Sutlej river sub-basin. West of Lake Rakshastal in Tibet is the source of the Sutlej. Sutlej is an ephemeral stream that descends from the Rakshastal Lake. Outlet point is marked at Bhakra dam situated in Bilaspur district of Himachal Pradesh in northern India. The 90km long reservoir created by the bhakra dam is spread over an area of 168.35 square km. The present Sutlej River sub-basin lies in Western Himalayas and is bounded by latitude 30^0 54' N to 31^0 48' N and longitude 76^0 12' E to 78^0 00' E. The extracted watershed has an average elevation of 1400m and drains a total area of approximately 15802 km^2. The spread of Sutlej sub-basin is mainly in district Rampur, Bilaspur and few parts of Shimla.

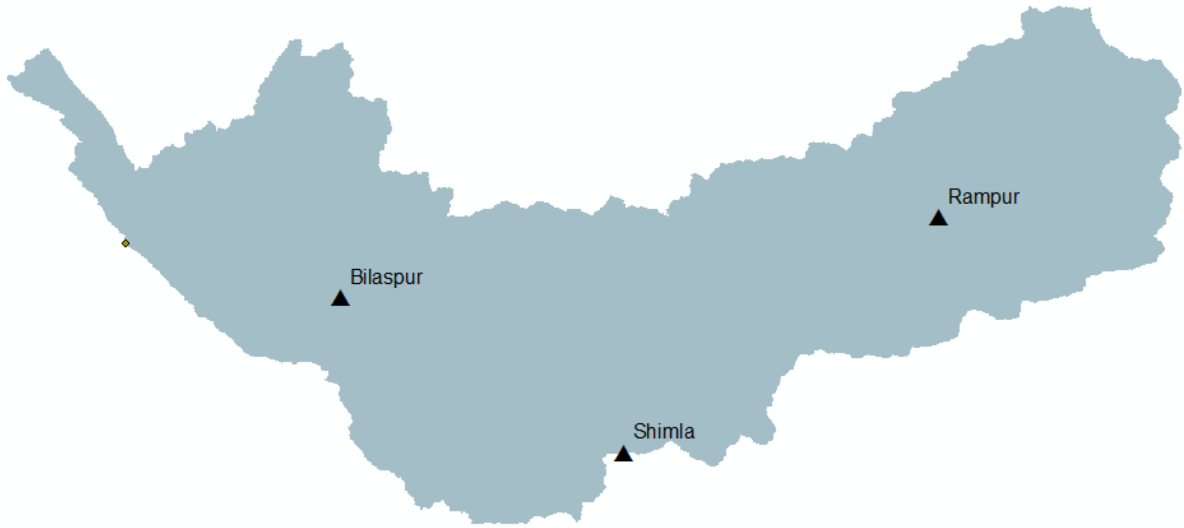

Figure 1 A Typical Sutlej sub-basin

III. OBJECTIVES OF THE STUDY

The next chapter discusses about the numerous studies and research gap involved in hydrological modelling using statistical methods and ANN (Artificial Neural Networks). Following objectives have been formulated in present study using various research gaps:

- To analyze the relation between dependent and independent variables.
- To estimate rainfall at watershed outlet using Regression method and ANN.
- To quantify errors in rainfall estimations.

IV. METHODOLOGY

Artificial Neural Networks Model

The general form of an ANN is a "black box" model which is of a type that is regularly used to model high-dimensional and non-linear data. However, most ANNs are used to solve problems of prediction for particular system, as opposed to formal model-building or growth of underlying knowledge of how the system works. Excitement stems from the point that these networks are efforts to model abilities of human brain which have approximately ten billion neurons acting at the same time. Neurons, basic computational unit of brain, are highly interconnected, with a typical neuron being connected to several thousand other neurons. As opposed to this, ANNs rarely have more than a few hundred or a few thousand neurons. So, networks comparable to a human brain in complexity are still far beyond the capability of the fastest, most highly parallel computers in existence. ANNs are well suited for problems in which solutions require knowledge that is specified with difficulty but for which enough data should be available. In this sense, they can be treated as one of the non-linear non-parametric multivariate statistical methods. Universal functional approximations are done by ANN. It has been shown that any continuous function can be approximated by an ANN to any desired degree of accuracy. ANN is a feed forward network with multiple layers as shown in Figure 3. The ANN with a back-propagation algorithm is a neural network structure that takes the input to the network and multiplies it on the connections by the weights between nodes or neurons, summing up their products before passing them from a threshold function for producing an output. The back-propagation algorithm works by minimizing the error between the target (actual) and the output by propagating back the error into the network. According to the size of the initial error, the weights between the neurons on each of the connections are changed. A new output and error are produced when the input data is fed forward again. The process is repeated till an acceptable minimized error is obtained. A transfer function is used by each of the neuron and is entirely connected to nodes on the next layer. Once an acceptable value of error is achieved, the training process is halted. The resulting model is therefore a function that is an internal depiction of the output in terms of the inputs at that point.

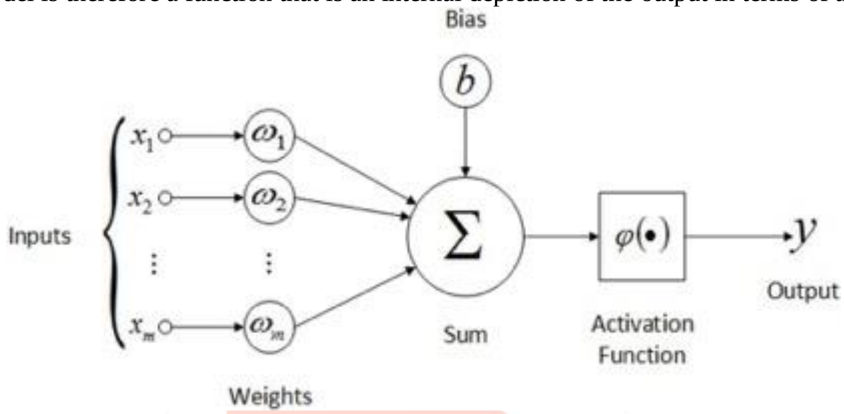

Figure 2 ANN Structure

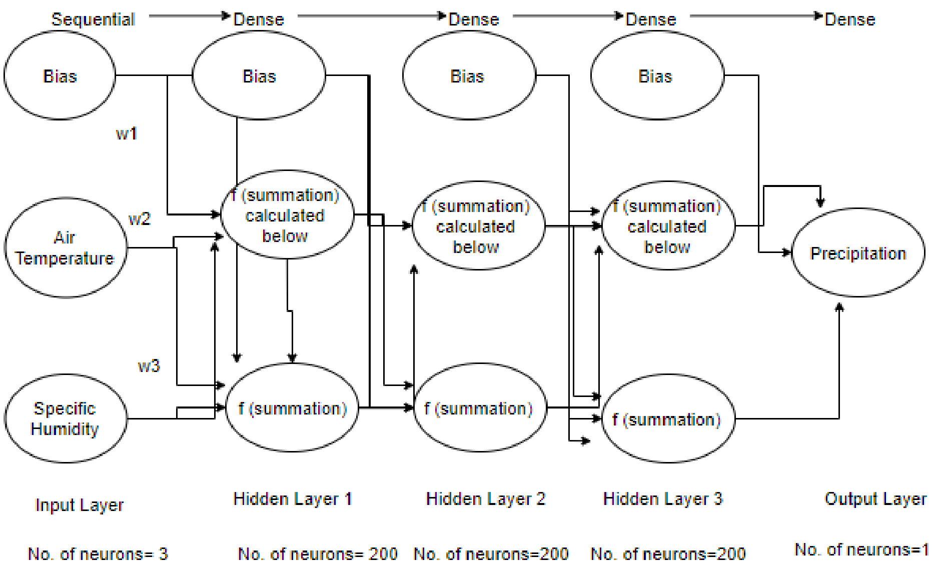

Figure 3 Flow chart of ANN model

Multiple Linear Regression Model

Multiple linear regression models are the model that assesses the connection between multiple independent variables and a dependent variable. The mathematical illustration of multiple linear regression is:

$$Y = aX_1 + bX_2 + c + \varepsilon$$

Where:

Y – Output variable i.e. precipitation

X_1, X_2 – input variables i.e. air temperature and specific humidity

c – Intercept

a, b – slopes

ε – Residual (error)

The same conditions are followed by multiple linear regressions as the simple linear models. However, in multiple linear analysis, as there are different independent variables on one hand, another mandatory condition is also needed to be fulfilled for the model i.e. non-collinearity. There should be minimum correlation between the independent variables. It becomes difficult to assess the correct relationship between the independent and dependent variables when the independent variables are highly correlated.

Model Evaluation

Many analytical methods have been proposed for the inter-comparison and evaluation of different models, which can be assessed in terms of numerical computations and graphical representation. The graphical performance criteria involve a scatter and linear plot of the predicted and observed weather parameters for testing and training data sets for all the models.

The numerical performance criterion involves:

Root Mean Square Error (RMSE)

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}((\hat{y}i - yi))^2}$$

RMSE is always greater than 0, and closer the values to 0 better the model performance.

Mean Square Error (Loss)

$$MSE = \frac{1}{N}\sum_{i=1}^{N}((\hat{y}i - yi))^2$$

MSE is always greater than 0, and closer the value to 0, better the model performance.

To calculate the above evaluation parameters, 50 iterations (epochs) were run in model.

RESULTS AND DISCUSSIONS

Analysis of Rainfall Estimation

1000 random values has been picked up for all the three independent variables (Air temperature, Wind speed, Air pressure and Specific humidity) and have been plotted against dependent variable(Precipitation).The scatter plots are as follows:

Air Pressure- Effect of Air pressure against Precipitation has been almost similar as studied during the research. As the Air pressure falls, the precipitation has been heavy and intense during those time periods. Therefore, it has been concluded from the analysis that precipitation is inversely proportional to air pressure.

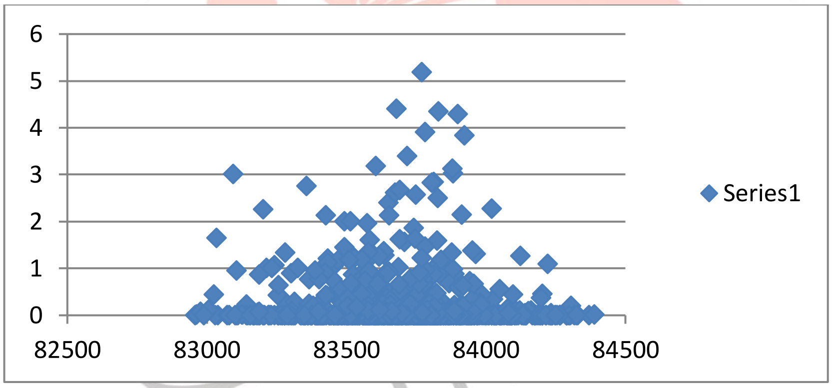

Figure 4 Precipitation v/s Air Pressure

Air Temperature- It has been realized that at higher temperatures, due to increase in water vapours, rainfall has been intense at those times. Therefore, Precipitation is directly proportional to Air Temperature.

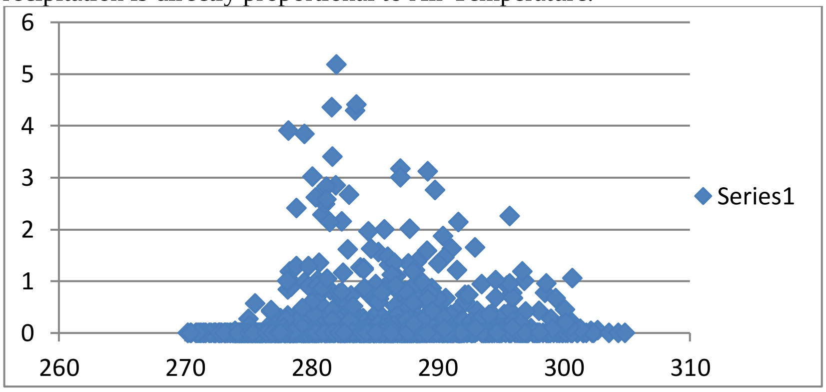

Figure 5 Precipitation v/s Air Temperature

Specific Humidity- When the Specific Humidity existed higher in air, the chances of rainfall and the intensity of rainfall have been higher for those entries. Therefore, it has been concluded that Precipitation is directly proportional to Specific Humidity.

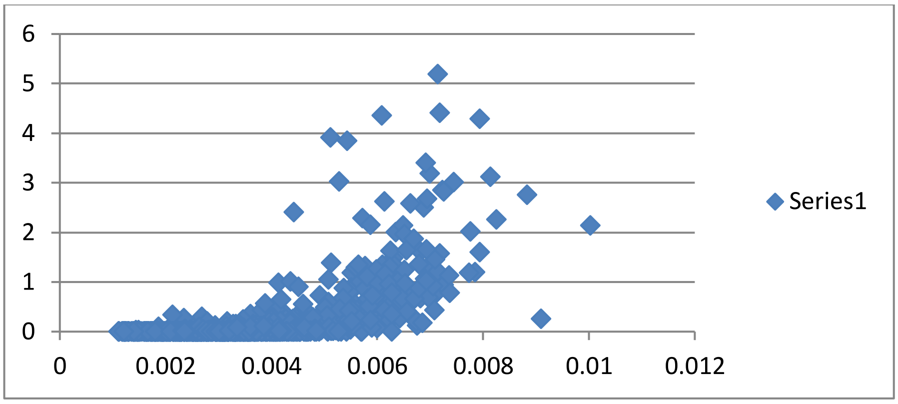

Figure 6 Precipitation v/s Specific Humidity

Wind Speed- When the wind speed varied with time and plotted against precipitation, no predictable relation between wind speed and precipitation has been appreciated. So, no relation between wind speed and precipitation has been concluded.

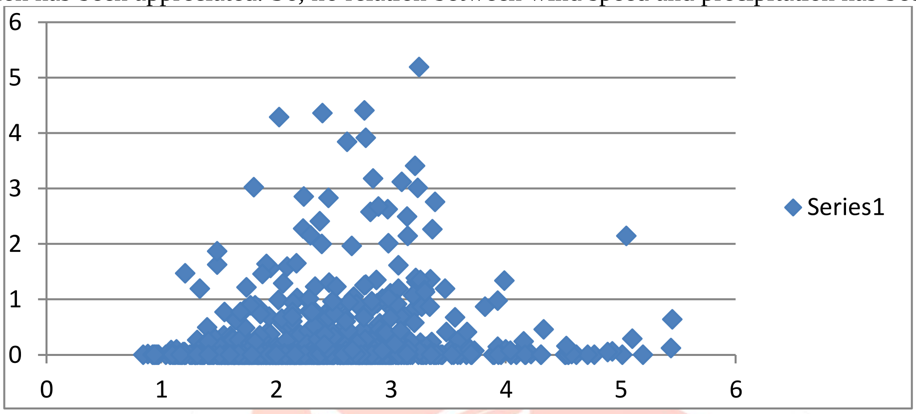

Figure 7 Precipitation v/s Wind Speed

Pearson Similarity

As discussed in the previous chapter, pearson similarity method has been used which is the most common method for finding the correlation between input variables i.e. wind speed, specific humidity, air temperature, air pressure and output variable i.e. precipitation. The correlation has been found using python language in jupyter notebook.

The pearson coefficient for air temperature, wind speed, specific humidity and air pressure has been calculated with respect to precipitation, the values came out to be:

Air temperature- 0.229522
Air pressure - -0.212204
Specific humidity- 0.476789
Wind speed- -0.028155

From this analysis, it has been concluded that the output variable i.e. precipitation is more related to Air temperature and Specific humidity rather than Air pressure and Wind speed. So, the further results and model implementation have been calculated and run on the basis of two variables which were Air temperature and Specific humidity.

ANN performance

The performance of ANN has been examined on the basis of statistical parameters i.e. RMSE and loss. The learning adopted has been unsupervised learning. The total iterations or epochs run were 50 epochs. During each epoch, it is very clear from Figure 8 and Figure 9 that the loss and RMSE kept decreasing for training data and the minimum RMSE and loss came for the 50th epoch.

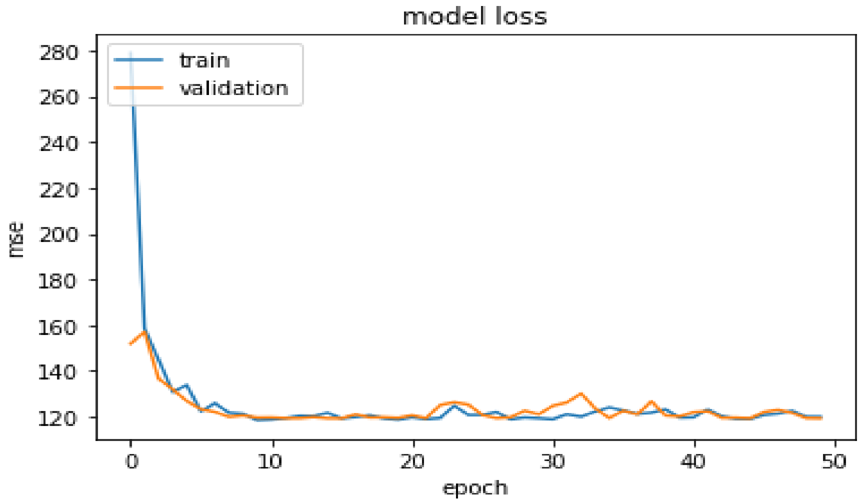

Figure 8 Loss v/s epoch

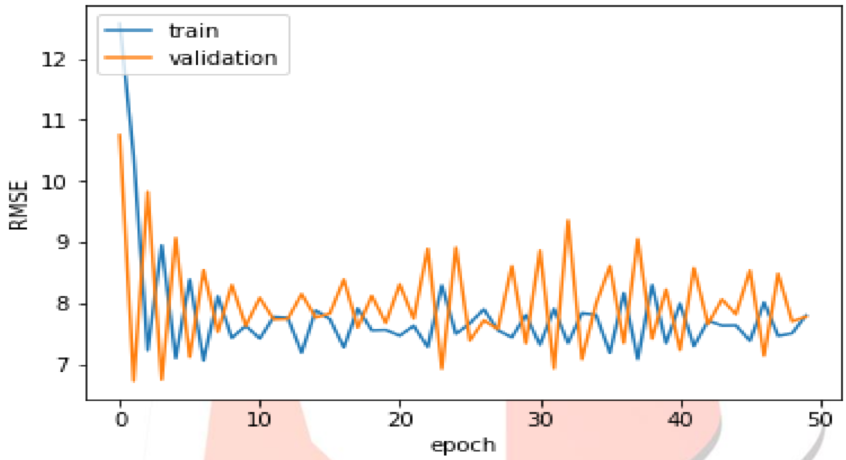

Figure 9 RMSE v/s Epoch

Epoch	Training Loss	Training RMSE	Validation Loss	Validation RMSE
1	135.90	8.08	124.82	7.01
2	124.60	7.77	122.47	7.19
3	121.10	7.64	134.36	9.66
4	123.22	7.61	119.42	7.75
5	120.76	7.58	120.26	8.23
6	120.52	7.59	120.09	8.19
7	121.00	7.61	120.15	8.21
8	125.83	7.65	120.46	8.27
9	125.07	7.85	123.69	7.09
10	121.29	7.58	119.71	7.61
11	120.53	7.63	122.66	8.61
12	119.14	7.55	120.63	8.31
13	118.98	7.52	119.62	8.05
14	120.40	7.59	120.03	8.18
15	120.17	7.54	119.47	7.98
16	120.09	7.54	123.58	8.72
17	119.66	7.56	120.18	8.21
18	120.58	7.64	121.48	7.30
19	120.58	7.46	119.92	8.15
20	119.20	7.53	124.95	8.87
21	1222.38	7.76	122.92	7.15
22	119.76	7.45	119.58	8.03
23	119.10	7.58	122.56	7.18
24	119.18	7.62	119.83	7.57
25	119.56	7.53	119.37	7.83
26	118.97	7.45	120.24	8.23

27	119.91	7.68	119.63	8.05
28	123.02	7.70	120.00	7.23
29	121.73	7.46	119.42	7.75
30	120.00	7.57	120.39	8.26
31	119.01	7.67	120.45	7.44
32	119.77	7.51	119.37	7.83
33	118.96	7.60	121.24	7.33
34	120.14	7.65	119.49	7.70
35	119.45	7.53	119.88	8.14
36	119.62	7.56	119.92	7.55
37	118.92	7.46	122.94	8.64
38	120.04	7.52	124.57	8.83
39	121.35	7.70	120.28	7.47
40	119.81	7.60	120.10	7.51
41	119.86	7.52	121.94	8.51
42	119.93	7.60	119.68	8.07
43	120.68	7.58	122.68	7.17
44	119.28	7.59	120.33	7.46
45	119.54	7.48	121.66	8.47
46	119.60	7.53	124.59	8.83
47	120.87	7.76	119.69	7.62
48	120.11	7.51	119.37	7.86
49	120.52	7.56	119.97	7.54
50	118.8	7.46	122.40	8.57

Table 1 Values of RMSE and Loss for training and validation data

Fifty epochs were run and the minimum error values for validation data came for the 50th epoch in which RMSE came out to be 7.46 and MSE came out to be 118.8.

Comparison of actual and predicted data

Stochastic Gradient Technique

The values of precipitation have been estimated by stochastic gradient technique and the plot of actual v/s predicted values for rainfall is shown in Figure 10.

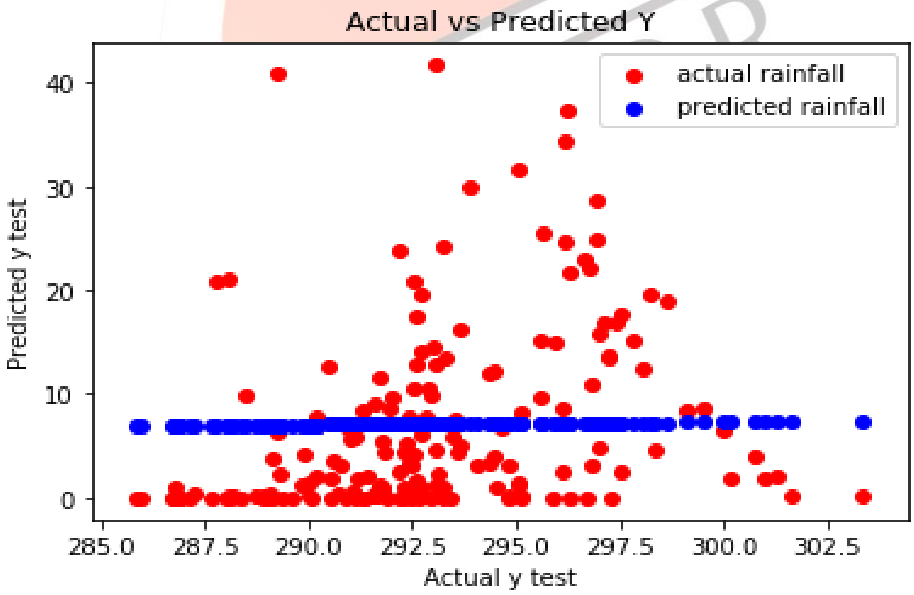

Figure 10 Snapshot of predicted v/s actual precipitation by stochastic gradient descent technique (ANN)

Multiple Layer Perceptron Technique

The values of precipitation have been estimated by MLR technique and the plot of actual v/s predicted values for rainfall is shown in Figure 11.

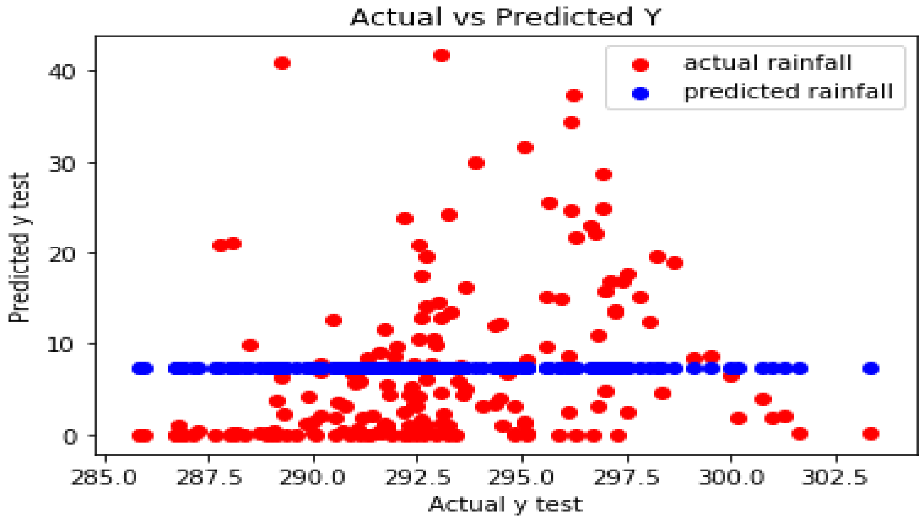

Figure 11 Snapshot of predicted v/s actual precipitation by Multiple Layer Perceptron (ANN)

Multiple Linear Regression Model

The values of precipitation have been estimated by Linear Regression model and the plot of actual v/s predicted values for rainfall is shown in Figure 12.

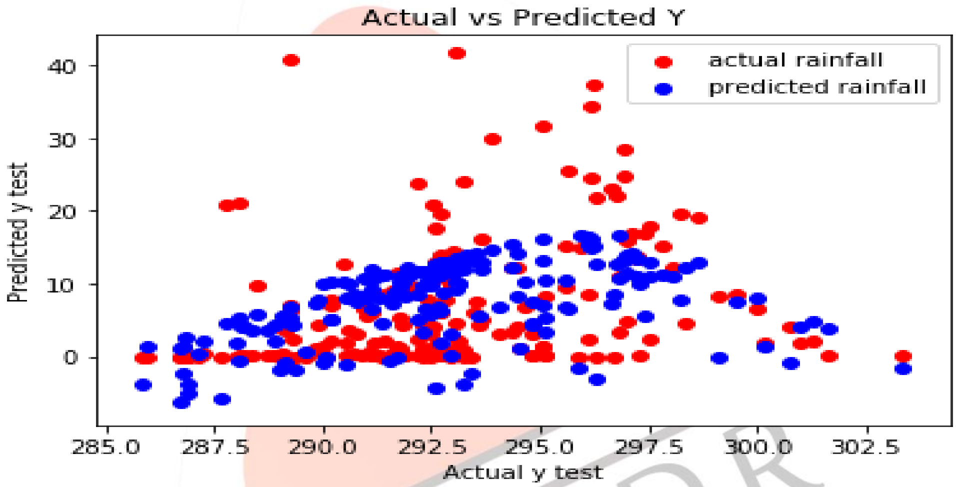

Figure 12 Snapshot of predicted v/s actual precipitation by Multiple Linear Regression

VII. CONCLUSION

In the present study, ANN model with stochastic gradient technique has been developed for validation and testing of rainfall with predicted rainfall for Sutlej sub-basin of Rampur, Shimla and Bilaspur of Himachal Pradesh, India. 20 percent data has been used for testing, 65 percent for training the model and 15 percent has been used for validation process. Further, the observed 3-hourly rainfall values have been collected from Giovanni (USGS) with Bhakra dam as outlet point. The following broad conclusions that can be drawn from the present study are as:

i. The development of ANN has provided significant results. After the model of watershed generated, it was found out that the result matches observation. The methodology adopted in this study allowed us to determine the hydrological parameters and verify the geometry of the watershed. This study reveals that the use of geographical information system (GIS) and the ANN model proves to be an easy and accurate way of modelling hydrological processes and must be encouraged in the field of water resources engineering and management.

ii. When using such an approach, a sound knowledge of the underlying physical processes is not pre-requisite. Only knowledge of the factors that influence a process and a qualitative relationship between the cause and the effect is required.

iii. In hydrological sciences, almost each field trip to a site is a rather different case study from other sites although they may be geographically close to each other. Catchment chracteristics also plays an important role in ANN modelling. ANN model with stochastic gradient technique can be used with various input parameters to give better predictions for rainfall. ANN with multiple layer perceptron or multiple linear regression cannot be fully valid for the description of the hydrological phenomenon concerned.

iv. The performance of ANN with stochastic gradient descent rule has been found to be satisfactory as the RMSE with SGD rule (ANN) has been 7.46 whereas 8.87 and 9.8 for MLP (ANN) and MLR respectively for regression predictions.

v. Further in the field of water resources, ANN with SGD technique can lead to attain solutions related to irrigation, crop pattern and draughts faced. It's a robust technique which solves and improves the existing models and processes.

Future Scope

On the basis of performance evaluation, ANN with SGD can be applied for rainfall prediction for the study of watershed, the ANN modelling and control may be viewed as a step towards a rapprochement between conventional and precise analytical approach and human-like decision making. Although probabilistic and statistical methods have been used for many years too in hydrology but the stochastic method has given additional dimension to problem solving. Further by generating different sets of data for various input variables using satellite observations can lead in use of ANN with SGD in hydrology very extensively.

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