River Runoff Forecasting Model Using Time lagged Artificial Neural Network

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Abstract— In this paper Narmada river, of subtropical region in India is chosen for flood forecast modeling with Artificial neural network. The modeling methods were mainly focused to forecast magnitudes of river runoff (trend and magnitude) for future time intervals. The Time Lagged Neural Network (TLNN) models are designed with two types of data set. In the first type of TLNN design the output layer is fed only by the runoff values that is univariate data set where only the past runoff values of 5, 5 and 10 years are taken into consideration (univariate input). While in second types of TLNN design the output is made dependent of two (multivariate) input layers of rainfall and the runoff. In this paper the prediction of river runoff found flourishing and relevant through ANN methods particularly in case of subtropical Indian rivers, which are mainly having monsoon dependent runoff.

Keywords: Rainfall, Runoff, Forecasting, Artificial Neural Network, Time Lagged Neural Network

I. INTRODUCTION

Nature has given us its various resources in different forms. Sometimes these resources come to human being in a silent manner and sometimes they come with a great manifestation. The water which is a main component of natural resources comes to us in a variety of forms. Among these forms the flood is always presenting the new challenges to human civilization. It is observed that rain fall and related flood showing a very fluctuated and intense behavior day by day.

An extreme natural event only becomes a disaster when it has an impact on human settlements and activities. Therefore, there is both a strong social and natural science component to floods. A flood May cause innumerable problems such as loss of agricultural produce, water logging, erosion of land, health hazards and loss of human lives. The Indian sub-continent, due to its unique geo-climatic conditions has been traditionally very sensitive to natural disasters [1]. In recent past, India has a yearly expenditure of 1534 Crore for flood control during 1998-2011 [2].

The devastating flood situation is one of the main concerns of the entire world today. Earlier the flood forecasting system were depending upon the speculative analysis executed by experienced engineers of the same field. With the time the discrete numerical models came into operation which were included in the creative work field of universities and researchers [3]-[5]. The circumstances presented to humanity in this way always indicate the need for efforts of separate and new flood management policies, which are a major means of dealing with natural disasters.

In the current scenario too, many recent major floods constantly alert us to the increasing requirements to anticipate and deal with the disaster. The quantitative forecast of the trend of disasters and the effective way of dealing with them is the main pillar of disaster management today. Systematically dealing with flood-like situations and abundant availability of cheap security measures are the main permanent elements in the management related to natural disasters. Taking care of environmental balance in the means of management is also becoming very important. need of systematic approaches [6]-[9].

In the context of India, with a very wide terrain and different geographical conditions, the rainfall amount between 50 - 200 CM has been observed. Despite so many variations, the rain here seems to follow a fixed trend and behavior in almost every specific area. The areas of the highest rainfall are the Western Ghats as well as the North East and Meghalaya Hills, Assam, West Bengal and the western slopes of the eastern Himalayas are considered where it is about 200 cm or more. Areas of moderately heavy rainfall include Gujarat, southern Tamil Nadu, north-eastern Peninsular, Western Ghats, eastern Maharashtra, Madhya Pradesh, Orissa and the southern parts of the central Ganges Valley where rainfall of about 100-200 cm is observed. Areas of low rainfall are considered to have an average rainfall of 50–100 cm with the upper Ganges Valley, eastern Rajasthan, Punjab, southern plateau of Karnataka, Andhra Pradesh and Tamil Nadu. Similarly, areas with low rainfall are considered to be the northern part of the Deccan plateau along with Kashmir, western Rajasthan, Punjab where the rainfall average is less than 50 cm. Some of the important features of rainfall trends are seen in this region due to the specific geographical conditions of India's borders and the effect of rainy winds etc. In North India, rainfall decreases towards the west and on the other hand in peninsular India, except Tamil Nadu, it decreases towards the east [10].

In line with this specific rainfall spread of country, the India Meteorological Department IMD Pune has constructed a rainfall time series of 36 meteorological sub-divisions using 1476 rain gauge stations, including hilly areas.

It is found that average southwest monsoon rainfall contributes 75.2% of annual rainfall and pre-monsoon rainfall contributes most (9%) to annual rainfall. Similarly, the contribution of winter monsoon (4.8%) and post monsoon (11%) in annual rainfall.

II. METHODOLOGY

The effective implementation of flood management system requires the reliability combined with the availability of concerned data as it is non-trivial in nature [12]. The weaknesses of the physically based and statistical models stated above boost the involvements of machine learning

(ML) concepts in flood forecasting approaches [13]. In this research aim is to develop an integrated modelling framework which will enable us to select the best suited model for forecasting the river runoff. In order to achieve the research pursuit in the study 10 years rainfall and runoff data of two river from subtropical (Narmada at Handia basin) region have been taken for the forecasting model development. The performance of the modelling system is evaluated by comparing the model predictions with results of the runoff observations at onsite gauge stations. The following figure 1, displays the modeling framework to have a vivid understanding of the research methodology carried out.

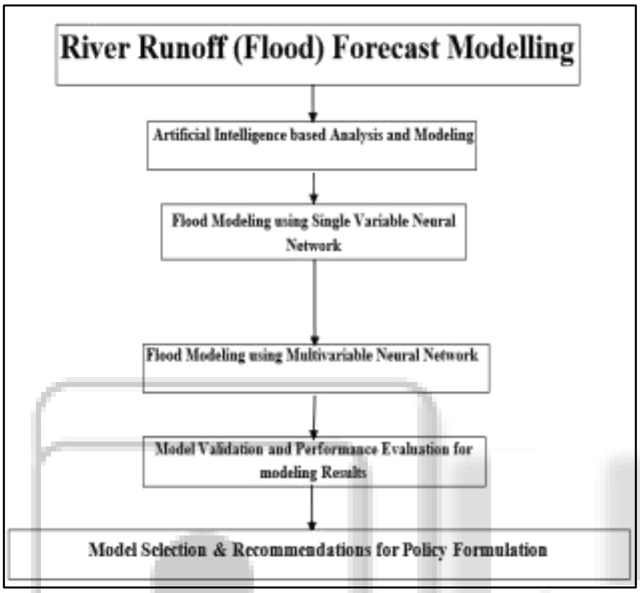

Fig. 1: Conceptual Framework of Computational Modeling for River Flow Forecasting

In order to achieve the targets of the conceptual figure of research methodology the following computational works are requisite to be carried out after the collection of the native and raw rainfall and runoff data.

1) Preprocessing and descriptive statistical analysis: This exercise is required so as to check its accuracy and usefulness to achieve the goal.
2) Development of Neural Network Model (Univariate and Multivariate).
3) Statistical performance evaluation and comparison of above modeling outputs from the actual observed data to assure the accuracy and efficiency of the work.

Backpropagation is a common method for training a neural network. For training process, Bayesian regularization is used for minimizing a linear combination of squared errors and weights.

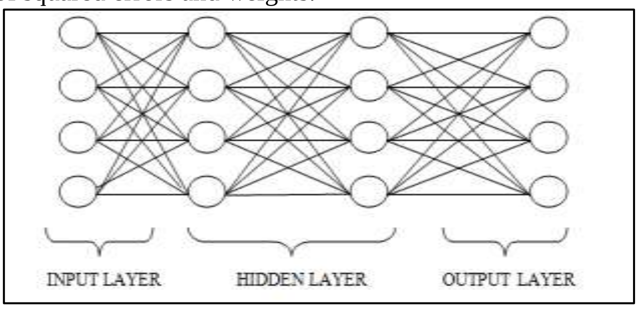

Fig. 2: Neural Network Architecture

Back Propagation neural network example is explained in figure 2. The network is composed of two inputs, two hidden neurons, two output neurons. Additionally, the hidden and output neurons will include a bias. In back propagation neural network currently predicts weights and biases. To predict weight and bias, data are inserted and forwarded though the entire network. The total net input to each hidden layer neuron is the total net input using an activation function, then repeat the process with the output layer neurons. So, the total net input for h_1 as equation (i):

$$\mathrm{net}_{h_1} = w_1 * i_1 + w_2 * i_2 + b_1 * 1 \qquad \text{(i)}$$

Then sum of layer to get the output of h_1

$$\mathrm{out}_{h_1} = \frac{1}{1 + e^{-\mathrm{neth}_1}} \qquad \text{(ii)}$$

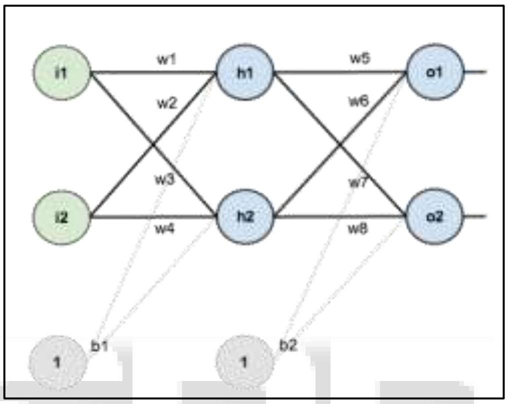

Fig. 3: Back Propagation Neural Network

Further carrying out the same process for h2 in figure 3. Then process is repeated for the output layer neurons, using the output from the hidden layer neurons as inputs. Here's the output for o_1 as in equation (iii):

$$\mathrm{net}_{o_1} = w_5 * \mathrm{out}_{h_1} + w_6 * \mathrm{out}_{h_2} + b_2 * 1 \qquad \text{(iii)}$$

And carrying out the same process for o_2. Then error is calculated for each output neuron using the squared error function and sum them to get the total error as in equation (x):

$$E_{\mathrm{total}} = \sum \frac{1}{2}(\mathrm{target} - \mathrm{output})^2 \qquad \text{(iv)}$$

The working of the neural network is focused towards adjusting the weights associated with entire network in order to reach the target data values, for minimizing the error between output and target values.

For this proposed model a neural network-based estimator is designed for channel estimation and equalization. Neuro-Estimator architecture have three layers include input layer, hidden layer and output layer. The received noisy data is sent to the input layer of the neural network and this data is feed forwarded to hidden layer and output of the hidden layer is computed as in equation (v):

$$\mathrm{net}_j^h = \sum I_i W_{ij}\,, j = 1,2, \ldots \ldots n \qquad \text{(v)}$$

where I_i is input data of ith units, w_{ij} is input-to-hidden layer weights. Then hidden layer output is obtained by activation function. This output of the hidden layer is forwarded to the final output layer of the network. In output layer, the final neural network output is computed as:

$$net_o^k = \sum O_j^h w_{jk} \quad \text{(vi)}$$

where O_j^h is the input to the output layer coming from hidden layer and w_{jk} is hidden-to-output layer weights. However, Output layer output expressed as:

$$O_k^o = f(net_k^o) \quad \text{(vii)}$$

where O_k^o is output layer output of kth units. In training process, the back-propagation learning algorithm is based on Bayesian training function. Bayesian training function minimizes a linear combination of squared errors and weights. It also modifies the linear combination so that at the end of training the network has good generalization qualities.

III. RESULT ANALYSIS

In this research the Time Lagged Neural Network modeling is designed in two segments (2002-06, 2010-14) with univariant training dataset (runoff) as well as multivariant dataset (rainfall runoff) of 5 years, 5 years and 10 years respectively. Further the forecast is obtained for lag L=0, L=1 & L=2, i.e. for the same month (L=0) and for one- & two-months advance (L=1 and L=2) runoff forecasting. The TLNN models are designed with two types of data set. In the first type of TLNN design the output layer is fed only by the runoff values that is univariate data set where only the past runoff values of 5, 5 and 10 years are taken into consideration (univariate input). While in second types of TLNN design the output is made dependent of two (multivariate) input layers of rainfall and the runoff i.e. the multivariate input data sets are used in which both rainfall and contemporaneous runoff values of 5, 5 and 10 years are devised. In this analysis, continuous data contains rainfall and runoff data from year 2005-06 and 2013-14. Thus, the forecast results are obtained as detailed in the table below:

TLNN Model Type	Dataset Type	Input Data Duration	Training Year	Forecast Intervals	Input	Output	Total Forecasts
Univariate	(2002-2006), (2010-2014)	5	2002-2006	L=0	Runoff	Runoff	2005-06
		5	2010-2014	L=1			2013-14
		10	2002-2014	L=2			2013-14
Multivariate	(2002-2006), (2010-2014)	5	2002-2006	L=0	Rainfall and Runoff	Runoff	2005-06
		5	2010-2014	L=1			2013-14
		10	2002-2014	L=2			2013-14

Table 1: TLNN Design Scheme for Runoff Forecasting

A. *Multivariant TLRNN modelling for Discontinuous Data (2010-2014)*

In this analysis, five-year multivariant data is taken from discontinuous dataset of 2002-14. Three analysis is performed using five years are used for training (2002-2006), five-year training (2010-2014) and finally 10 year training (2002-2014) are used.

Model Details		L=0	L=1	L=2
Maximum Range	OBS	21385		
	PRED	21151	20752	20418
Standard Deviation	OBS	4294		
	PRED	4246	4174	4110
Skewness	OBS	4.1056		
	PRED	4.0927	4.073	4.0489
Kurtosis	OBS	19.3559		
	PRED	19.2748	19.1485	18.9962
Mean Absolute Deviation	OBS	2187		
	PRED	2170	2149	2132
Performance Measures	CC	1	0.99	0.99
	CD	0.9874	0.9692	0.9516
	wR^2	0.7900	0.7753	0.7613
	E	0.999	0.9990	0.9975
	d	1	0.9997	0.9993
	Erel	0.9975	0.9955	0.808
	drel	0.9995	0.9989	0.955
	FB	0.0122	0.0312	0.0485
	MG	1.01	1.03	1.04
	VG	1	1	1

Table 2: Statistical Properties and Performance Measures for Multivariant Discontinuous Data (2005-2006)

Year Set	2002-2006		
Testing Year	2005-06		
	L=0	L=1	L=2
MBE	10.875	27.4583	47.0417
MAE	19.2916666	29.125	48.875
RMSE	21.7782383	34.6536	60.7142
NMSE	0.01827908	0.02582	0.22506
SD	1270.58434	1270.6	1280.13
SKW	1.52207100	1.52905	1.52384
KUR	3.57763731	3.58223	3.58942
AME	40	64	116
PD	6	31	16
PEP	0.15591057	0.80554	0.41576
MARE	0.0870779	0.11293	0.271
MRE	0.0946641	0.14627	-0.0947
MSRE	0.0420186	0.05661	1.85255
RVE	0.0121694	0.03073	0.05264
MPE	0.0008995	0.00136	0.00228
RAE	0.01112916	0.0281	0.04814
PI	0.77268982	0.8991	0.20379
VE	0.98768058	0.9683	0.94443
MSLE	0.026	0.0372	0.611
MDPE	4.50870367	8.30949	9.12534
FREQ	2.16025832	2.426259	2.791403

Table 3: Runoff Forecasting for Multivariant Discontinuous Data (2002-2006)

Model Details		L=0	L=1	L=2
Maximum Range	OBS	5976.96		
	PRED	5961.44	5994.96	5894.04
Standard	OBS	1549.854		

Deviation	PRED	1547.59	1548.091	1530.882
Skewness	OBS	2.277152		
	PRED	2.267226	2.278998	2.267896
Kurtosis	OBS	7.064865		
	PRED	7.012743	7.109182	7.014652
Mean Absolute Deviation	OBS	1021.212		
	PRED	1020.42	1025.381	1007.32
Performance Measures	CC	0.9999	0.999	0.9998
	CD	0.987	0.97	0.971
	wR^2	0.790	0.781	0.777
	E	0.999	0.9992	0.998
	d	0.999	0.9998	0.999
	Erel	0.999	0.979	0.9972
	drel	0.9998	0.994	0.9993
	FB	0.0104	0.034	0.0392
	MG	1.0104	1.03	1.0400
	VG	1.00	1.001	1.0015

Table 4: Statistical Properties and Performance Measures for Multivariant Discontinuous Data (2013-14)

Year Set	2010-2014		
Testing Year	2013-14		
	L=0	L=1	L=2
MBE	8.875	29.3333	49.4167
MAE	15.625	31.8333	51.5833
RMSE	19.14092474	36.6481	63.7345
NMSE	0.017905382	0.08674	0.50751
SD	1554.177475	1544.49	1553.16
SKW	2.28413607	2.28256	2.29012
KUR	7.08479748	7.11472	7.15101
AME	36	66	118
PD	9	26	4
PEP	0.149725503	0.43254	0.06654
MARE	0.090796076	0.2031	0.39743
MRE	0.052624691	0.41385	0.84261
MSRE	0.029313025	0.73573	7.40692
RVE	0.010130402	0.03348	0.05641
MPE	0.000743134	0.00151	0.00245
RAE	0.008690653	0.02872	0.04839
PI	0.78516652	0.02846	-9.9397
VE	0.989765923	0.96536	0.94022
MSLE	0.0219	0.20	0.23
MDPE	4.696177028	14.7144	12.9758
FREQ	2.091658255	2.460441	2.825489

Table 5: Runoff Forecasting for Multivariant Discontinuous Data (2010-2014)

Year Set	2002-2014		
Testing Year	2013-14		
	L=0	L=1	L=2
MBE	10.29166	23.9167	47.5
MAE	12.95833	26.75	50.5
RMSE	17.59142	33.2941	66.8961
NMSE	0.054067	0.18729	0.36188
SD	1551.792	1555.95	1542.32
SKW	2.275660	2.26267	2.30705
KUR	7.070094	7.02983	7.25509
AME	38	60	117
PD	2	2	8
PEP	0.0332723	0.03327	0.13309
MARE	0.12571473	0.25873	0.31582
MRE	0.267867049	3.03849	-2.6886
MSRE	0.562670383	202.776	201.785
RVE	0.011747461	0.0273	0.05422
MPE	0.000616306	0.00127	0.0024
RAE	0.010077894	0.02342	0.04651
PI	-0.01527883	-2.6848	-8.984
VE	0.988112896	0.97193	0.94267
MSLE	0.142	0.4	0.044
MDPE	4.402564301	11.4234	9.65089
FREQ	2.047977933	2.402105	2.859895

Table 6: Runoff Forecasting for Multivariant Discontinuous Data (2002-2014)

B. Univariant TLRNN modelling for Discontinuous Data (2010-2014)

Five-year data is taken from discontinuous dataset of 2002-14. Three analysis is performed using univariant data of five years are used for training (2002-2006), five-year training (2010-2014) and finally 10-year training (2002-2014) are used.

Model Details		L=0	L=1	L=2
Maximum Range	OBS	3787.28		
	PRED	3795.28	3776.28	3791.44
Standard Deviation	OBS	1270		
	PRED	1270.785	1272.343	1281.51
Skewness	OBS	1.522429		
	PRED	1.51709	1.515503	1.525254
Kurtosis	OBS	3.564943		
	PRED	3.544271	3.547816	3.57013
Mean Absolute Deviation	OBS	977.1627		
	PRED	978.535	981.9752	986.3052
Performance Measures	CC	0.999926	0.999798	0.999574
	CD	0.986	0.974054	0.961565
	wR2	0.7888	0.779243	0.769252
	E	0.999706	0.999	0.997807
	d	0.999927	0.99975	0.999457
	Erel	0.982076	0.907703	0.673315
	drel	0.995705	0.979011	0.931414
	FB	0.016928	0.034482	0.050537
	MG	1.017072	1.035087	1.051847
	VG	1.000287	1.00119	1.002558

Table 7: Statistical Properties and Performance Measures for Univariant Discontinuous Data (2005-06)

Year Set	2002-2006		
Testing Year	2005-06		
	L=0	L=1	L=2
MBE	15	30.2917	44.7917
MAE	17.6666666	31.9583	46.7917
RMSE	21.3229141	39.3219	59.0081
NMSE	0.01744939	0.03819	0.13129
SD	1270.78549	1272.34	1282.02
SKW	1.51709035	1.5155	1.52438
KUR	3.54427095	3.54782	3.56875
AME	38	70	117
PD	17	27	48

PEP	0.44174661	0.7016	1.24728
MARE	0.08073948	0.13774	0.22544
MRE	0.09582338	0.19201	0.09992
MSRE	0.03965365	0.09142	3.69077
RVE	0.01678551	0.0339	0.05012
MPE	0.00082373	0.00149	0.00218
RAE	0.01535056	0.031	0.04584
PI	0.93459261	-0.8092	-2.527
VE	0.98292792	0.96491	0.94723
MSLE	0.0256	0.0574	0.055
MDPE	3.53426215	12.5426	9.90177
FREQ	2.14887740	2.504139	2.771583

Table 8: Runoff Forecasting for Univariant Discontinuous Data (2002-2006)

Model Details		L=0	L=1	L=2
Maximum Range	OBS	5976.96		
	PRED	5961.4	5994.9	5894.0
Standard Deviation	OBS	1549.85		
	PRED	1547.5	1548.0	1530.8
Skewness	OBS	2.27		
	PRED	2.2672	2.2789	2.2678
Kurtosis	OBS	7.064		
	PRED	7.0127	7.1091	7.0146
Mean Absolute Deviation	OBS	1021.21		
	PRED	1020.4	1025.3	1007.3
Performance Measures	CC	0.9999	0.9998	0.9998
	CD	0.9879	0.9767	0.9716
	wR^2	0.790	0.7813	0.7773
	E	0.9998	0.9992	0.9989
	d	0.9999	0.9998	0.9997
	Erel	0.9993	0.9793	0.9972
	drel	0.9998	0.9949	0.9993
	FB	0.0104	0.0344	0.0392
	MG	1.0104	1.0350	1.0400
	VG	1.0001	1.0011	1.0015

Table 9: Statistical Properties and Performance Measures for Univariant Discontinuous Data (2013-14)

Year Set	2002-2014		
Testing Year	2013-14		
	L=0	L=1	L=2
MBE	9.083333333	31.2083	65.75
MAE	18.75	33.875	70.4167
RMSE	20.99007702	41.8863	44.0677
NMSE	0.036624386	0.20967	0.13838
SD	1547.590308	1548.97	1548.97
SKW	2.267226222	2.27723	2.27723
KUR	7.012742612	7.10305	7.10305
AME	40	70	110
PD	31	12	12
PEP	0.515721178	0.19963	0.19963
MARE	0.127426218	0.26916	0.23503
MRE	0.120878832	0.91246	0.35175
MSRE	0.108738138	8.21925	2.1029
RVE	0.010368204	0.03562	0.07505
MPE	0.000891761	0.00161	0.00335
RAE	0.008894659	0.03056	0.06438
PI	0.771110398	-1.1085	0.02101
VE	0.98952317	0.96306	0.92218
MSLE	0.0582	0.1942	0.549
MDPE	9.345794393	9.13951	11.54
FREQ	2.140442216	2.544005	2.576499

Table 10: Runoff Forecasting for Univariant Discontinuous Data (2002-2014)

C. Comparative Multivariant Analysis for Data (2002-14) for Lag 0, 1 and 2

Lag 0 forecasts are near about actual run-off for all conditions. Forecasts at lag 1 and 2 are over predictive or high runoff events as compared to actual values. However, TLRNN model with lag=2 can efficiently be used for prewarning even 2 months before about the occurrence of major runoff / flood. In this section, comparative multivariant analysis is performed for 2005, 2006, 2013 and 2014 with lag=0, lag=1 and lag=2. Below figure 4 shows the predictive and actual values for the year 2005-06 with 5 years training dataset (2002-2006). Similarly, figure 5 shows the predictive and actual values for the year 2013-14 with 10 years training dataset (2002-2014).

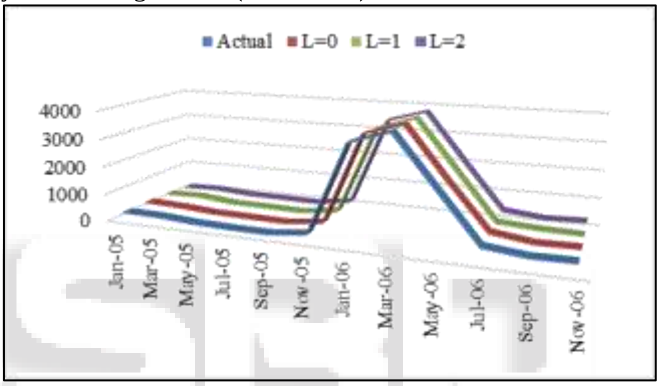

Fig. 4: Multivariant Actual Vs Predicted Run-off Prediction for 2005-06

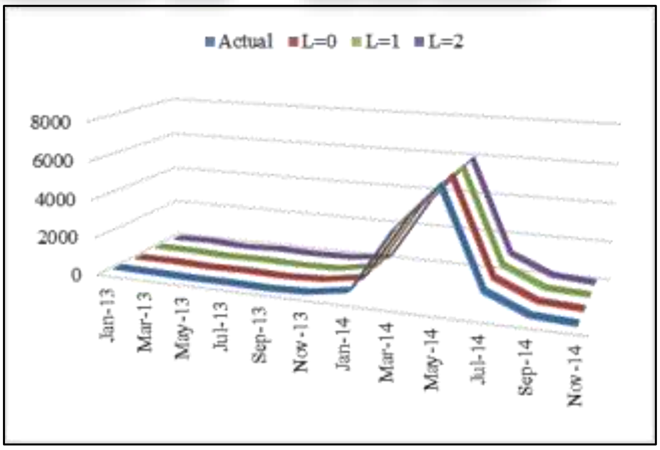

Fig. 5: Multivariant Actual Vs Predicted Run-off Prediction for 2013-14

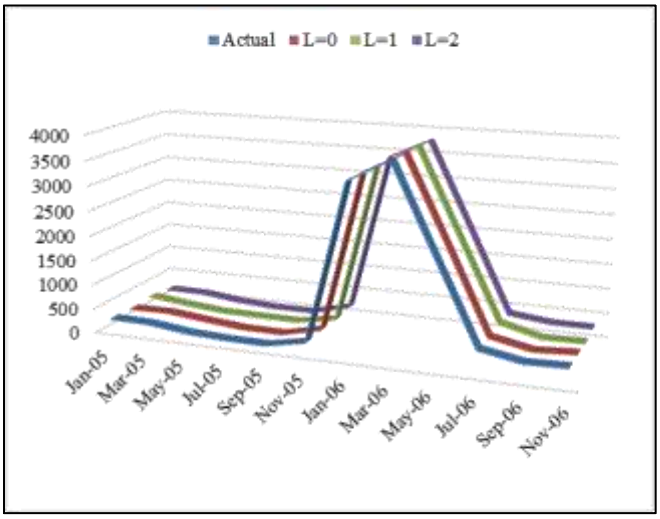

Fig. 6: Univariant Actual Vs Predicted Run-off Prediction for 2005-06

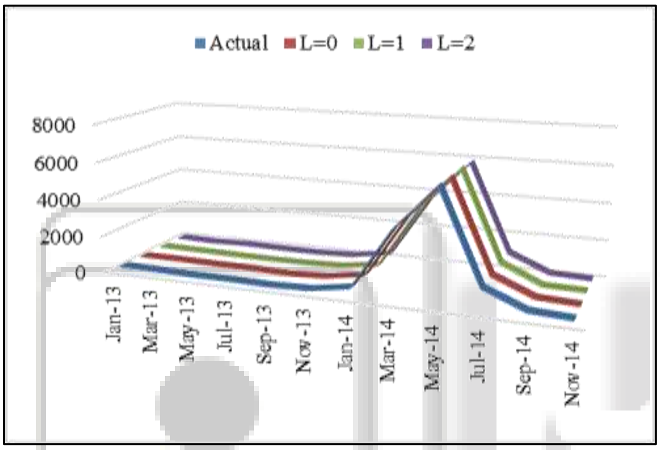

Fig. 7: Univariant Actual Vs Predicted Run-off Prediction for 2013-14

IV. CONCLUSION

In this paper a computational framework for the forecasting of monthly river runoff based on different hydrological patterns and conditions has been proposed. Rainfall and Runoff data of subtropical regions namely Narmada used for the simulation model development. The forecasts have been developed using two different types of datasets i.e. with the past data of runoff only and with the association of past data of rainfall and runoff. As observed and forecasted runoff are the major input to frame models and the rainfall is considered the major source of uncertainty (referred to as precipitation uncertainty). The computational techniques do not incorporate process details in rainfall - runoff phenomenon, the comparison of forecasting results and computational ease is the way to judge their performance.

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