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RESEARCH ARTICLE

CLIMATE PREDICTION USING DETERMINISTIC ANN MODEL.

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Abstract

The ANN based models are most imperative and demanding for climate prediction. Back-Propagation Neural Network is an appropriate methodology in identification of parameters for long-term rainfall data. Presented BPN model is best to identify climatic parameter for prediction as well as forecast rainfall. Forecasting of rainfall over vindhya region has been analyzed through developed BPN model. The observed long period average (LPA) is 956.74 for 45 years data time series of vindhya region. It is observed that the MAD (6.09) is less than the SD (14.37) during the testing period. Correlation coefficient of training period is 0.89 and for testing period is 0.95. The performance of the model is accurately observed.

Introduction:-

IMD's operational model is appropriate for long range forecast of monsoon rainfall over whole central India. However it is unsuccessful in case of long range forecast (LRF) over a very smaller vindhya region which is allocated in central India. The IMD's operational model is based on statistical power regression analysis which uses few global dynamic parameters (i.e., predictors). It is concluded that impact of global parameters (i.e., independent) on the monsoon rainfall (i.e., dependent) over the smaller region is irrelevant. Identification of physically connected global meteorological parameters for monsoon rainfall over smaller region is also extremely difficult. Thus, only alternate solution is deterministic forecast[1]. The ANN techniques are sufficiently suitable in identification of internal dynamics of chaotic time series data. Thus, BPN model in deterministic forecast is used in this study.

The model is operated for LRF of monsoon rainfall over vindhya region for testing period. This study concentrates on the performance of efficiency of BPN model and it is observed that this model is efficient enough for LRF of monsoon rainfall over smaller geographical region like district with higher level of accuracy[2]. The advantage of this study is that, it has been evaluated and concluded that BPN is sufficiently suitable for identification of internal dynamics of high dynamic monsoon rainfall[3]. The model performed well both in training and independent periods [4]. In many other cases BPN is found to be fit for prediction of other climate activities. On the basis of humidity, dew point and pressure in India, Sahai et al and Sawaitul et al [5,6], have used the back propagation neural network model for predicting the rainfall.

In this study, the BPN is used in deterministic forecast for long-range monsoon rainfall for India. The impact of variance in learning rate and momentum factor in the model is also studied.

Data preprocessing:-

The developed model use time series (X_i) from the year 1970 to 2014 have been constructed for vindhya region. Since, transfer function sigmoid axon is used in the BPN model. The output of sigmoid axon has in close interval 0 to 1. Therefore, model data time series is normalized and obtained new normalized data time series (R_i). Data time series (x_i) for the first 35 years (1970–2004) are used for developing the model. Remaining 10 years (2005–2014) data time series (xi) is used to test the model independently for its acceptance.

Data Normalization and Splitting:-

Data Input:-

Data entry type: Imported from ExcelSheet

Data series name 1:	Year	Actual and Normalized Data Series: 45 Years
Data series name 2:	Rainfall	Number of Training Samples : 35 Years
Units :	mm.	Number of Testing Samples : 10 Years

Splitting (training and testing dataset) :

Table 1 : Training data set (1970-2004) and Testing dataset (2005-2014)

Training Dataset			
Year	**Normalized value of Rainfall (mm)**	**Year**	**Normalized value of Rainfall (mm)**
1970	0.591377	1987	0.598493
1971	0.669092	1988	0.597744
1972	0.631464	1989	0.537075
1973	0.579184	1990	0.63936
1974	0.573279	1991	0.58904
1975	0.632964	1992	0.532094
1976	0.57478	1993	0.581387
1977	0.643612	1994	0.591428
1978	0.651737	1995	0.622093
1979	0.509426	1996	0.610391
1980	0.662376	1997	0.505437
1981	0.600177	1998	0.564736
1982	0.629964	1999	0.636996
1983	0.55652	2000	0.570264
1984	0.605711	2001	0.639425
1985	0.594553	2002	0.594851
1986	0.578683		
Testing Dataset			
Year	**Normalized value of Rainfall (mm)**		
2005	0.589176		
2006	0.543197		
2007	0.539526		
2008	0.568055		
2009	0.517473		
2010	0.551524		
2011	0.614916		
2012	0.625406		
2013	0.64168		
2014	0.611216		

Table 2: Statistics of training dataset and testing dataset

Statistics of Data	Training Dataset	Testing Dataset
Min (x_i) of Rainfall	506.6	556.6
Max (x_i) of Rainfall	1498.0	1268.8
Mean value (x_i)	977.0942857142855	885.4799999999999
Standard Deviation (x_i)	244.88219489818215	241.67858269472973
% of Mean(x_i)	25.06228912383474	27.293511168488248
Minimum normalized value (r_i)	0.5054374937643421	0.5174729874428113
Maximum normalized value (r_i)	0.6690921228304405	0.6416799190400463
Mean value (r_i)	0.5956103832774173	0.5802169069399181
Standard Deviation (r_i)	0.0402430487455586	0.04517710183161851
% of Mean (r_i)	6.756606311010968	7.7862436084263615

Initial Variables of BPN:-

Table 3: Initial values of BPN variables.

A. Weights in hidden layer V(i,j); i=10, j=2		B. Biases in hidden layer Vo(j); j=2		B. Weights in output layer W(j); j=2	
V(i,1)	**V(i,2)**	**Vo(1)**	**Vo(2)**	**W(1)**	**W(2)**
0.889864	0.253677	0.390054	0.694807	0.546431	0.356959
0.931142	0.094606				
0.149762	0.079962				
0.83213	0.575017				
0.214287	0.651923				
0.41332	0.629334				
0.444514	0.933841				
0.881214	0.437617				
0.174556	0.732116				
0.435148	0.175127				

Selection of parameters (recommended by this model):-

Table 4: BPN parameter setup values.

Model recommendation:
Momentum factor: 0.2382
Note : This recommendation is given by desired epochs 7000000, number of iteration 5, number of input vector (n) 10, number of neurons in hidden layer (p) 2.
Number of input vectors (n): 10
Number of neurons in hidden layer (p): 2
Learning rate: 0.1151
Momentum factor: 0.2382

Table 5: Optimized MSE.

Epoch count	MSE
1	1.63289262934093E–01
100	1.67082747834919E–03
1000	1.67029292416874E–03
10000	1.65516581866368E–03
7000000	1.33629916609829E–03

The architecture of deterministic forecast is shown in Table 3.The initial trainable weights including biases of the network initialized by the random values between 0 and 1 are shown in Table 6. Error (MSE) minimizing process called epochs during the training period. After 7000000 epochs the MSE minimized up to 1.33629916609829E–03. During the training process, it has been observed that the MSE optimized regularly after each epoch. The epoch is a parallel process which minimizes the MSE as depicted in Table 5. The training started with initial set of weights between 0 and 1 MSE = 1.63289262934093E–01, at beginning stage epochs MSE minimized to its lowest point. Continue the minimizing process and finally after 7000000 epochs the MSE minimized to its lowest point 1.33629916609829E–03.

Optimum Variables of BPN: Optimized weights and biases for Desired Epochs = 7000000 and MSE = 0.0013592475951864345

Table 6: Optimum values of BPN variables.

A. Weights in hidden layer V[i][j], s.t., i=1..10 & j=1..2		B. Updated weights V0[i], s.t., i=2		C. Updated weights W[i], s.t., i=2	
V(i,1)	**V(i,2)**	**Vo(1)**	**Vo(2)**	**W(1)**	**W(2)**
0.887308	0.251494	0.390054	0.694807	0.546431	0.356959
0.928574	0.092413				
0.147197	0.077776				
0.829497	0.572786				
0.211762	0.649765				
0.41081	0.627184				
0.441937	0.931653				
0.878659	0.435436				
0.171959	0.729914				
0.43251	0.172895				
Bias in output layer: 1.95E-05		LPA = 956.74			

The performance of the model in training period as well as for the testing period is shown in figure 1 & 2. The actual and predicted values are well correlated.

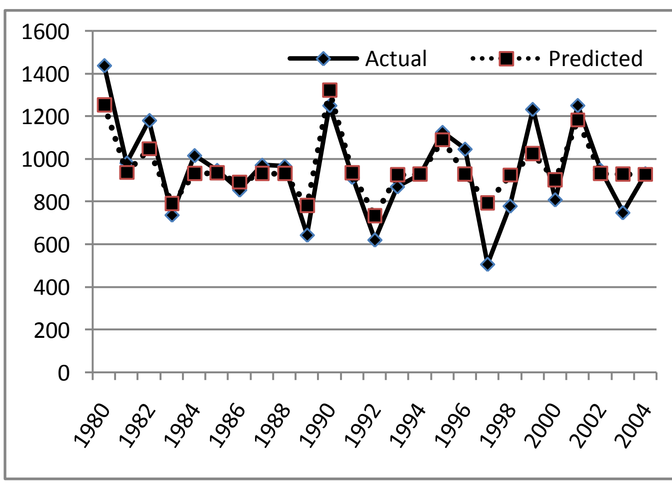

Fig.1: Performance in Training Period.

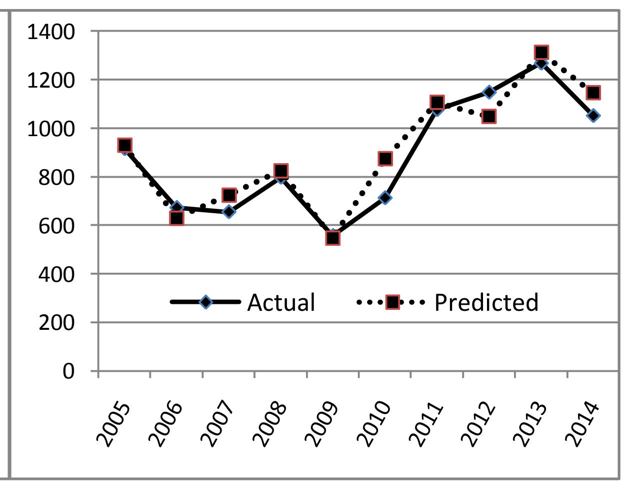

Fig.2: Performance in Testing Period.

Result and Discussion:-
The performance of the model in training period as well as for the testing period is shown in figure 1 & 2. The actual and predicted values are well correlated. This study produces results with high accuracy. In order to check the performance of BPN during the testing period with new data, it was tested with the 10 years (2005–2014) of the test data. The performance of BPN model during the testing period (2005–2014) and training period (1970-2004) is illustrated in Table-1. This detail reflects the efficiency of the BPN model in prediction. The statistics of the performance of the BPN in training as well as in testing period is illustrated in table-2.

Table 7: Output of BPN Model.

Statistical data of Training Period	
Mean :	948.19
Mean Absolute Deviation(MAD) :	58.3376000000
SD(% of LPA) :	14.3726402307
MAD(% of LPA) :	6.0975395614
Statistical data of Testing Period	
Mean :	885.48
Mean Absolute Deviation(MAD) :	34.6760000000
SD(% of LPA) :	7.2942647798
MAD(% of LPA) :	3.6243911617
Model Acceptance Decision:	
MAD(% of mean) = 6.09753956142734 is less and less than half of the SD(% of mean)= 14.3726402306542	
Result:- Model Accepted.	

The obtained results are illustrated in Table-7. Long period average (LPA) observed as 956.74 for 45 years data time series of vindhya region. It is observed that the MAD (6.09) is less than the SD (14.37) during the testing period. Correlation coefficient of training period is 0.89 and for testing period is 0.95. The result reflects the efficiency of the model.

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