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BPN model for long-range forecast of monsoon rainfall over a very small geographical region and its verification for 2012

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New operational long range forecasting model of India Meteorological Department (IMD) is statistical in nature, which has many inherent limitations. The correlation between monsoon rainfall and its predictors can never be perfect. It may suffer epochal changes and there may be a cross correlations among predictors. It is almost impossible to identify appropriate predictors of monsoon rainfall over a smaller region like district or division as well. Thus, attempts to forecast monsoon rainfall over a small geographical region like district through this current IMD's operational model become inaccurate. It is found that Back Propagation Neural Network (BPN) is skilled enough to identify the internal dynamics of chaotic data time series and sufficiently suitable to predict future value by past recorded data time series. Thus a BPN model in deterministic forecast has been developed for a long range forecast (LRF) of monsoon rainfall over smaller Indian geographical region. Our study area, Ambikapur is located at 23° 07′ 23″ N, 83° 11′ 39″ E, an average elevation of 623 meters (i.e., 2078 feet) and Total Geographical Area (TGA) is 15 733 km^2. Performance of the model during the development period (1951–2007) has been found excellent. The performance during the testing period (2008–2011) has also been found good except for the years of 2009 and 2010. The model has also been verified independently and operated for the year 2012. The deviation between actual and predicted monsoon rainfall in Long Period Average (% of LPA) for this year is found 2.7% only. These facts exhibit the efficacy of the proposed model.

Keywords: meteorology, long-range forecast, monsoon rainfall, neural network, back-propagation, deterministic

1. Introduction

LRF of weather (especially monsoon rainfall) over very smaller region is one of the most important and challenging operational tasks carried out by meteorological services all over the world. It is a complicated procedure that includes multiple specialized fields of expertise. Researchers have separated weather forecasting methodologies into two main branches in terms of numerical modeling and scientific processing of meteorological data. The most widespread techniques used for rainfall forecasting are the numerical and statistical methods. Even though researches in these fields have conducted for a long time, but success of these models are rarely visible because the rainfall data time series shows chaotic behavior. Due to the chaotic nature, finding out the best and perfect predictors become very difficult (Basu and Andharia, 1992). The accuracy of models is dependent upon the initial conditions that are inherently incomplete. These systems are not able to produce satisfactory results in local and short-term cases. The performances, however, are poor for LRF of monsoon rainfall even for the larger spatial scale and particularly, for the Indian region. IMD has been using statistical models for predicting monsoon rainfall. But those statistical models have inherent limitations such as the statistical models are not useful to study the highly nonlinear relationships between monsoon rainfall and its predictors. And it will never be possible to get different sets of regional and global predictors to explain the variability of the two neighboring regions having distinguished rainfall features. However, Guhathakurta (1998) has found these statistical models to be successful in those years of normal monsoon rainfall and failed surprisingly during the extreme monsoon years like 2002 and 2004. Also Rajeevan (2000; 2004) and Thapliyal et al. (1992) have found that the statistical models have many inherent limitations. Guhathakurta et al. (1999) have also observed that the correlations between monsoon rainfall and the predictors can never be perfect. Krishnamurthy et al. (2002) and Sahai et al. (2002) have found that attempts to forecast monsoon rainfall as well as climate parameters through statistical technique over smaller areas like a district, or monsoon periods such as a July, monsoon (June–September), have become unsuccessful as correlations fall drastically. Guhathakurta (2006) has observed that the weather prediction over high-resolution geographical regions is very complicated, especially in case of prediction of various weather phenomena over smaller scale geographical region such as district. It is very difficult and challenging task to identify appropriate parameters / predictors. In such situation the deterministic forecast system is proved to be an efficient methodology for forecasting the internal dynamics of highly non-linear chaotic data time series. In support of the same experiment of deterministic BPN model, we have gone through several past literatures, Geetha and Selvaraj (2011) have predicted monthly monsoon rainfall for Chennai, India by using BPN model. The model performed well both in training and independent periods. 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 as predictors, Vamsidhar et al. (2010) have used the BPN model for predicting the rainfall. In the training they have obtained 99.79% of accuracy and 94.28% in testing. From these results they have concluded that rainfall can predicted in future using the same method. Sawaitul et al. (2012) have also done an experiment on forecasting future weather and they have concluded that the Back Propagation algorithm can also be applied on the weather forecasting data. Artificial Neural Networks (ANNs) are capable of modeling a weather forecast system. The ANN based signal processing approach for weather forecasting is capable of yielding good results and can be considered as an alternative to traditional meteorological approaches.

After a comprehensive literature review of around thirty years it has been concluded that the major architectures of ANN; BPN, and Redial Basis Function Network (RBFN) are sufficiently suitable to predict weather phenomenon. In the comparative study among various ANN techniques, BPN and RBFN are found as appropriate solutions for prediction of various scientific/business applications. However, model needs appropriate predictors as input to observe output. As we have already discussed that identification of predictors is almost a temporal timidity. The correlations between smaller region's monsoon rainfall and its predictors can never be perfect. They may undergo epochal changes and there may be cross-correlations between the parameters. Attempts to forecast monsoon rainfall over smaller areas like a district become unsuccessful as correlations falls drastically. The only way to do this is through dynamical atmospheric general circulation models with specified boundary conditions and varying initial conditions. As of today, globally, dynamical models do not have the required efficacy to accurately simulate the salient features of the mean monsoon and its variability. They are further hampered by the lack of data in the oceanic regions important to the monsoon. Routine outputs of dynamical models run by a few global prediction centers are available, but India-specific dynamical models need to be developed in order to achieve the type of accuracy demanded by Indian users. In the mean time, empirical/statistical methods will need to be developed and refined for generating long-range predictions of monsoon rainfall. In an intense survey of the literatures it has been found that meteorologists believe that deterministic forecasting method is one of the useful techniques for predicting rainfall especially when the identification of physically connected predictors is very difficult. Thus, in this contribution, BPN model is used in deterministic long-range forecast of monsoon rainfall over a very smaller geographical region is presented through this paper. A finite-dimensional dynamical system is a system whose state at any instant can be completely characterize by a set of scalar observations $x_1, x_2, \ldots, x_n$. This set is of course fixed and must always characterize the system throughout its evolution. The evolutionary history of the system is then given by time series $x_1(t), x_2(t), \ldots, x_n(t)$; these function of time trace out a trajectory in n-dimensional phase space. A dynamical system is deterministic if its evolution is completely determined by its current state and past history.

In this study, the BPN is used in deterministic long-range forecast of monsoon rainfall over Ambikapur region (geographically as depicted in the following Fig. 1). The region is geographically located at 23° 07′ 23″ N, 83° 11′ 39″ E. It has

Figure 1. Ambikapur region, geographically located at 23° 07′ 23″ N latitude, 83° 11′ 39″ E longitude. (Source: Google map)

an average elevation of 623 meters (i.e., 2078 feet) and total geographical area (TGA) is 15 733 km^2. The model is developed and tested successfully. And finally it is verified independently for current year 2012. The performance of the model during the development, testing period and its verification is found excellent is presented through this paper.

The paper is organized in various sections, wherein, section II, discussed data collection and preprocessing of meteorological data as per the requirement of the model, section III discussed architecture of BPN model, results and discussions is discussed in section IV, and finally concluded the paper in section V.

2. Data description and preprocessing

Total Monsoon Rainfall (TMRF) time series (X_i) from the year 1951 to 2012 have been constructed for Ambikapur region of Chhattisgarh, India. Since, transfer function sigmoid axon is used in the BPN model (as discussed in next section III). The output of sigmoid axon has in close interval 0 to 1. Therefore, TMRF data time series is normalized by using following equation1 and obtained new normalized TMRF data time series (R_i). The equation 2 is used to de-normalize thereafter for actual representation x_i. Data time series (x_i) for the first 57 years

(1951–2007) are used for developing the model. Remaining 5 years (2008–2012) data time series (x_i) is used to test the model independently for its acceptance. And finally model is verified and operated for the year of 2012.

$$R_i = \frac{x + \min(x_i)}{x_i + \max(x_i)} \tag{1}$$

$$x_i = \frac{\min(x_i) - R_i \max(x_i)}{(R_i - 1)} \tag{2}$$

3. About BPN model

The BPN model in deterministic forecast is illustrated in Fig. 2, where eleven input vectors (x_1, …, x_{11}) in input layer are used to input past eleven years rainfall data time series, three neurons in hidden layer (z_1, …, z_3) and one neuron in output unit are used to observe 12th year TMRF data. The entire model parameters and their justifications are given in the following Tab. 1. Thus a total of 40 trainable weights including biases have been used in the network. Output target value for the network is actual 12th year TMRF data.

It has been found that MAD (% of mean) between actual and model predicted value is directly proportional to number of hidden neuron (p). As a result, three neurons in hidden layer have been selected and it provides most desirable result. Output target value for the network is actual data to be predicted. The

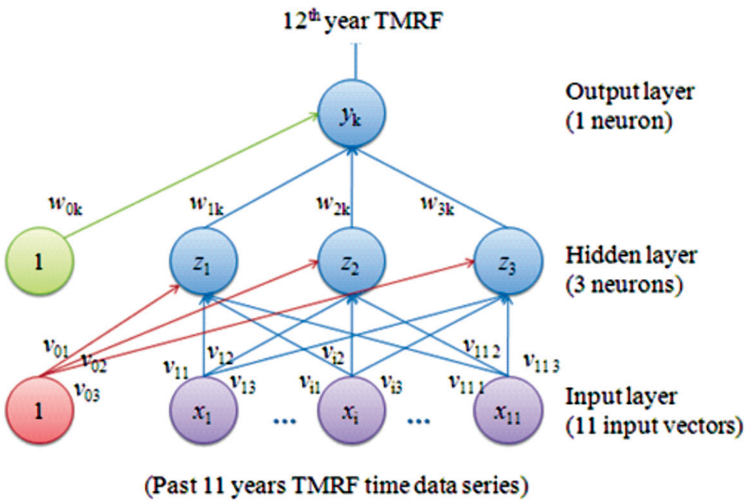

Figure 2. BPN in deterministic forecast.

Table 1. Parameters of BPN model.

Sl. No.	Parameter(s)	Value	Justification
1.	Number of layer	3	This network has input layer at the bottom, one hidden layer at the middle, and one output layer at the top. Here n = 11input vectors at the input layer (i.e. x_1, x_2, …, x_{11}), p = 3 neurons in hidden layer (i.e., z_1, z_2, z_3) and one neuron (y_k) in output unit.
2.	Number of hidden layer	1	Phillip (2003) observed that one hidden layer is sufficient, using two hidden layer rarely improves the model, and it may introduce a greater risk of converging to a local minima (M_L).
3.	Number of neurons in hidden layer	3	It has been identified that the three neuron in hidden layer and eleven input vectors provided satisfactory result for all meteorological data, and increase in number of neurons in hidden layer increases Mean Absolute Deviation (MAD) between actual and predicted value. (Karmakar et al*.*, 2009; 2012).
4.	Number of input vector (x_is) ‘n’	11	Karmakar et al. (2009) have found for all cases, the MAD is inversely proportional to ‘n’. In this case, n = 11 is found appropriate. An experimental result is depicted in the Fig. 3 (a) and (b). Wherein, MSE is least when n = 11. However, the value of ‘n’ is depending on internal dynamics of time series.
5.	Learning rate (α)	0.3	It is found that, a high learning rate ‘α’ leads to rapid learning but the weights may oscillate, while a lower learning rate leads to slower learning (Kumar, 2007).
6.	Momentum factor (μ)	0.9	Various experiments have done by choosing momentum factors between 0 and 1 in this study. It is found, momentum factor 0.9 in the weight update formula, the convergence was faster. The main purpose of the momentum is to accelerate the convergence of error propagation algorithm during the training period.
7.	Initial weights (v_{ij}s & w_{ij}s)	11×3+3+3+1 = 40 normalized values assigned as initial weights	It is found that, if initial weight is too large the initial input signals to each hidden or output unit will fall in the saturation region where the derivative of sigmoid has very small value (f(network) = 0). If initial weights are too small, the network output to a hidden or output unit will approach zero, which then causes extremely slow learning. To get the best result the initial weights (and biases) are set to random number between 0 and 1.

Table 1. Continued.

Sl. No.	Parameter(s)	Value	Justification
8.	Number of biases in hidden layer and values	3 and random values within close interval [0, 1]	The initial weights (bias) can be done randomly and moreover there is a specific approach. The faster learning of a BPN can be obtained by using Nguyen-Widrow (NW) initialization. Kumar (2007) has found this method is designed to improve the learning ability of the hidden units.
9.	Number of biases in output layer and value	1 (since one output unit is used) and random values within close interval [0, 1].	Kumar (2007) has found this method is designed to improve the learning ability of the output units.
10.	Transfer function	Sigmoid $f(x) = \dfrac{1}{1+e^{-\delta x+n}}$	The neurons output is obtained as $f(x_j)$ where f is a transfer function typically the sigmoid function is used. The output of the neuron will be in close interval [0, 1] as shown in the Fig. 4.
11.	MSE level	MSE = 4.99180426869658000E–04	Rumelhart et al. (1986) first introduced BPN based on gradient descent method (Kumar, 2007). Being a gradient descent method, it minimizes the mean square error (MSE) of the output computed by the network during the feed-forward and back-propagation process.
12.	Number of epochs	1500000 epochs	It has been observed that 1500000 epochs found best fitted to train the network. After this point MSE is exhibiting an increasing trend and is considered as over training of the network.
13.	Learning algorithm	Delta learning rule, Rumelhart et al. (1986)	$\Delta V_{jk} = \alpha\, \delta_j\, x_i$ is the generalized delta rule used in BPN during training the network
14.	Local minima (M_L)	After 500000 epochs the MSE minimized up to 9.15076092085467E–04 as depicted in the Fig. 5.	M_L is called local minima. After this point the MSE's are shown a constant trend. Generally in this point, a scientist often stops the training process for their specific applications. This is the only grounds of poor performance of the BPN model.
15.	Global minima (M_G)	After 1500000 epochs the MSE minimized up to 4.99180426869658E–04 as depicted in the Fig. 5.	M_G This point is termed global minima which is maximum trained network point. In this point the maximum performance of BPN model may achieve.

neurons output is obtained as $f(x_j)$ where f is a transfer function typically the sigmoid axon is used i.e.

$$f(x) = \frac{1}{1+e^{-\delta x+n}}$$

Where δ determines the slope and η is the threshold. In the proposed model $\delta = 1$, $\eta = 0$, the output of the neuron will be in close interval [0, 1] as shown in

Fig. 4. Learning rate $a = 0.3$ is used. It is found that, $a = 0.3$ is suitable for almost all of the cases and in this study. Momentum factor $\mu = 0.9$ is used.

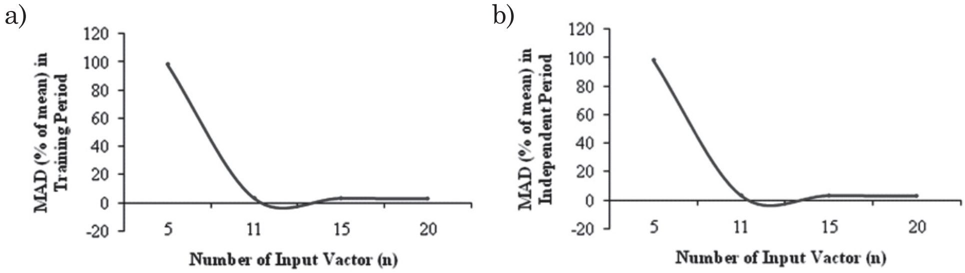

Figure 3. Relation between n and MAD (% of mean): (*a*) in independent period and (*b*) in training period.

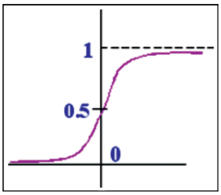

Figure 4. Output of sigmoid axon.

Rumelhart et al. (1986) first introduced BPN based on gradient descent method (Kumar, 2007) used to train the model. Being a gradient descent method, it minimizes the Mean Square Error (MSE) between actual and predicted values by updating weights and biases of the model during the feed-forward and back-propagation process. This process called training of the model. In this study, BPN is trained by supervised learning method. Supervised training is the process of providing the network with a series of sample inputs and comparing the output with the expected response. It is found that during the training process the convergence of MSE was faster when $a = 0.3$ and $\mu = 0.9$. After the training process the model is accepted by comparing Mean Absolute Deviation (MAD) between actual and predicted values and Standard Deviation (SD) of actual data time series. As the model acceptance hypothesis is MAD ≤ (½ of SD).

$$MAD = \left| \frac{1}{n} \sum_{i=1}^{n} (x_i - p_i) \right| \qquad SD = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (X_i - m)^2}$$

where p_is are predicted values and '*m*' is mean value.

Table 2. Framework of BPN model in deterministic forecast.

BPN	α	Neuron in hidden layer (p)	Input vector (n)	Trainable weights (w_i)	Target (y_k)
In deterministic forecast	0.3	03	Past 11 years TMRF	40 (including biases)	12^{th} year TMRF

The framework of deterministic forecast is shown in Tab. 2. The initial trainable weights including biases of the network initialized by the random values between 0 and 1 are shown in Tab. 3. Error (MSE) minimizing process called epochs during the training period. After 1500000 epochs the MSE minimized up to 4.99180426869658E–4 which is marked as M_G (Global minima) in the graph (as depicted in the Fig. 5). On this point the optimized weights are shown in Tab. 4.

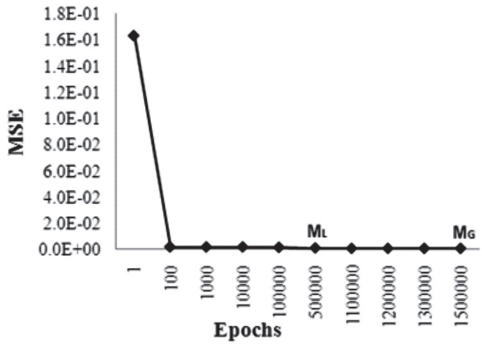

Figure 5. Minimizing MSE.

During the training process it has been observed that the MSE optimized regularly after each epoch, as the epoch is a parallel process which minimizes the MSE as depicted in Tab. 5. The training started with initial set of weights between 0 and 1 at point 'P' where MSE = 1.63289262934093E–01, after 5,00000 epochs MSE minimized to its local lowest point called M_L. In this point often scientists are stops their experiment. As we discussed this point is not final point. We continue the minimizing process and finally after 1500000 epochs the MSE minimized to its lowest point 4.99180426869658E–04 marked as M_G global minima or maximum trained network point as shown as Fig. 5. During the literature review various authors are clearly declared that, obtaining global minima is almost difficult or temporal nervousness. However, it is obtained in this study. Note that a Java based simulator is developed for the training process. For accuracy and better performance, double data types are used. As it is resultant data from the Java simulator are presented in this section.

Table 3. Initial weights.

	$V_{i=1\ \text{to}\ 11;\ j=1\ \text{to}\ 3}$	
0.280800521373748	0.168759763240814	0.044127523899078
0.472349166870117	0.809812307357788	0.855300962924957
0.119313240051269	0.312592983245849	0.731210827827453
0.923533260822296	0.312689185142517	0.295242071151733
0.313810527324676	0.941224575042724	0.792520821094512
0.007087528705597	0.538136720657348	0.904589712619781
0.512941122055053	0.947724163532257	0.393840074539184
0.071080148220062	0.571404635906219	0.451620757579803
0.040320515632629	0.674218833446502	0.487735211849212
0.353351771831512	0.232466399669647	0.005873143672943
0.984928369522094	0.470367133617401	0.641462087631225
	Initial hidden biases V_{0i}; i = 1 to 3	
0.5814671516418457	0.5955716967582703	0.21110987663269043
	Initial output bias W_0	
	0.5	

Table 4. Optimized weights after 1500000 epochs.

	$V_{i=1\ \text{to}\ 11;\ j=1\ \text{to}\ 3}$	
13.212680441	–3.043977842	–14.397325147
12.839138110	6.880667764	–3.267866395
–18.220808470	–11.208725106	–7.818172624
–1.665566401	3.380170693	9.262771717
6.007453047	2.824425500	–0.613637485
–13.113640093	–5.893302749	2.576067728
–5.373775965	–6.117592000	–3.119470042
–4.065856516	–5.748926243	–5.717660860
1.752119801	2.226165188	4.205130417
–5.860865432	–3.593515579	–2.458649507
9.387518936	14.261855302	20.131087700
	Updated hidden biases V_{0i}; i = 1 to 3	
0.000105201421449794	0.000101529553254394	0.000024046052091308
	Updated output bias W_0	
	0.000167955628075041	

Table 5. Optimized MSE.

Epoch count	MSE
1	1.63289262934093E–01
100	1.67082747834919E–03
1000	1.67029292416874E–03
10000	1.65516581866368E–03
100000	1.33629916609829E–03
500000	9.15076092085467E–04
1100000	5.75971925301642E–04
1200000	5.63477906270142E–04
1300000	5.43576724081598E–04
1500000	4.99180426869658E–04

4. Results and discussions

The performance of the model is evaluated by comparing SD and MAD between actual and model forecasted values and the value of Correlation Coefficient (CC) between actual and model forecasted values. As we discussed above if MAD is less than and half of SD then we can accept the model. In these performance criteria, the performance of the BPN model during training as well as testing period is found excellent. The model trained with 57 years (1951–2007) training dataset. The performance of the training period has shown a very high compatibility between the actual and predicted rainfall except for the year 1994. The MAD (i.e., 2.84) is found less than and half of the SD, i.e., 7.31. The CC between the actual and predicted values was very high i.e., 0.88. The results of development/training period are given in Tab. 6 and depicted in the Fig. 6.

In order to check the performance of BPN during the testing/independent period with new data, it was tested with the 5 years (2008–2012) of the test data. Once again the BPN has shaped up a fantastic performance except for the year 2009 and 2010. Since the actual rainfall in the year 2009 and 2010 was exceptionally very low thus the model shows high deviation between actual and predicted rainfall for those years. The performance of BPN model during the testing period (2008–2012) is illustrated in Tab. 7. This detail reflects the efficiency of the BPN model in forecasting. Thus an operational independent verification of the model for current year 2012 has been done. The obtained results are illustrated in Tab. 7 and Fig. 6. Except the year 2009 and 2010, it is observed that the MAD (i.e., 7.1) is less than the SD (i.e., 10.1) during the testing period. And the CC is 0.73. These facts also explain the efficacy of the model during the testing period and independent verification. The statistics of the performance of the BPN in training as well as in independent period is illustrated in Tabs. 7 to 9.

The meteorologists are uses forecasting results in the qualitative indication term known as long period average (LPA). The result also calculated in this term as given in the Tabs. 7 and 8 and Fig. 6. The actual % of LPA of TMRF (1951–2011) in this region is 97.1. And the predicted value is 94.4. Deviation is found only 2.7 (% of LPA). Therefore, TMRF over this region is 97.1–2.7 (in % of LPA) has been forecasted.

Table 6. Performance of the BPN in development period (1962–2011).

Year	De-normalized data (in mm)		Rainfall (in % of LPA)	
	Actual	Predicted	Actual	Predicted
1962	952.3	928.3	78.2	76.3
1963	1089.6	1105.7	89.5	90.8
1964	1523.4	1253.0	125.2	103.0
1965	1226.0	1449.5	100.7	119.1
1966	815.4	863.7	67.0	71.0
1967	1081.4	1127.2	88.9	92.6
1968	914.8	1039.6	75.2	85.4
1969	1193.3	1206.2	98.0	99.1
1970	906.0	827.1	74.4	68.0
1971	1773.5	1751.2	145.7	143.9
1972	1188.6	1267.9	97.7	104.2
1973	1153.4	1213.8	94.8	99.7
1974	919.4	988.4	75.5	81.2
1975	1534.6	1592.5	126.1	130.8
1976	1604.3	1416.5	131.8	116.4
1977	1674.0	1590.4	137.5	130.7
1978	1103.4	1353.7	90.7	111.2
1979	1020.1	1111.1	83.8	91.3
1980	936.9	951.5	77.0	78.2
1981	1106.9	1221.2	90.9	100.3
1982	1303.2	1329.4	107.1	109.2
1983	1254.8	975.6	103.1	80.2
1984	1184.4	1085.0	97.3	89.1

Table 6. Continued.

Year	De-normalized data (in mm)		Rainfall (in % of LPA)	
	Actual	Predicted	Actual	Predicted
1985	1231.7	1018.4	101.2	83.7
1986	1257.8	1187.5	103.3	97.6
1987	1540.0	1621.6	126.5	133.2
1991	1645.6	1334.2	135.2	109.6
1992	1190.7	1401.2	97.8	115.1
1993	1236.6	1219.9	101.6	100.2
1994	2092.8	1498.5	171.9	123.1
1995	1146.7	1095.5	94.2	90.0
1996	1619.7	1514.9	133.1	124.5
1997	1139.4	1250.8	93.6	102.8
1998	1049.3	1048.7	86.2	86.2
1999	1229.5	1582.1	101.0	130.0
2000	1236.0	1218.0	101.6	100.1
2001	1820.5	1787.9	149.6	146.9
2002	1086.0	1078.1	89.2	88.6
2003	1240.6	1106.6	101.9	90.9
2004	858.4	803.8	70.5	66.0
2005	952.7	872.8	78.3	71.7
2006	1066.3	1010.6	87.6	83.0
2007	1046.8	945.8	86.0	77.7

Table 7. Testing for years 2008 –2012.

Year	De-normalized rainfall data (in mm)		Rainfall (in % of LPA)	
	Actual	Predicted	Actual	Predicted
2008	1358.4	1139.2	111.6	93.6
*2009	603.2	1271.1	49.6	104.4
*2010	649.7	1345.6	53.4	110.6
2011	1445.5	1412.0	118.8	116.0
2012	1181.8	1148.9	97.1	94.4

Table 8. Performance of the BPN in training and independent period.

Training period (1951–2007)			Independent period (2008–2012)		
SD (% of mean)	MAD (% of mean)	CC	SD (% of mean)	MAD (% of mean)	CC
7.306	2.841	0.88	8.8	7.8	0.7

Table 9. Performance of the BPN in independent period except the year 2009 and 2010.

Independent period (2008, 2011 and 2012)		
SD (% of mean)	MAD (% of mean)	CC
10.1	7.1	0.73

Table 10. Comparative analysis of results of BPN in deterministic forecast and IMD's model.

Year	BPN in deterministic forecast (for Ambikapur in % of LPA)		IMD's model (For Central India in % of LPA)	
	Actual	Predicted	Actual	Predicted
2012	97.1	(97.1±2.7) = 94.4	96	96±8

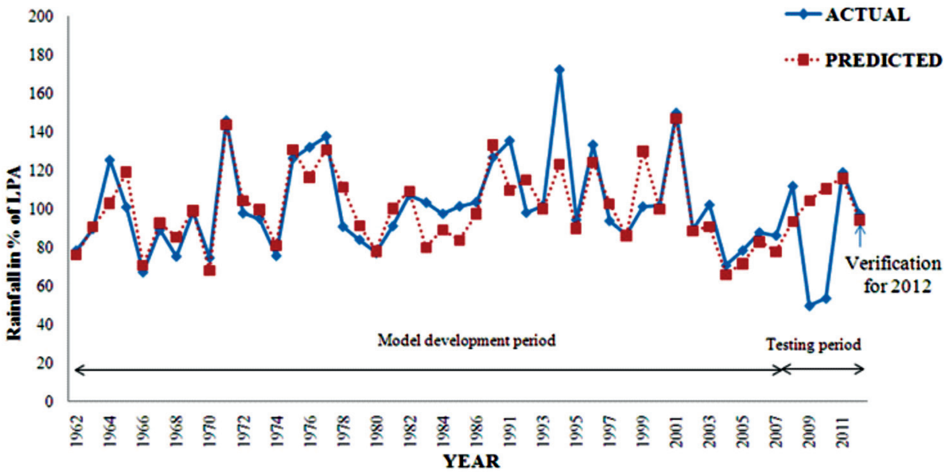

Figure 6. Performance of the BPN in development period (1951–2007) and testing for 2008–2012 and verification for 2012.

Forecasted advisory of IMD's operational model over whole central India is given in following Tab. 10 (Press release of IMD Pune, 2013).It is clear that actual rainfall (in % of LPA) over whole central India is 96 however, for the region Ambikapur is 97.1. Thus again it is concluded that IMD's advisory for the year 2012 i.e., 96±8 (in % of LPA) is not applicable for this region. Here, deviation 8 (in % of LPA) is also enormous. Thus, it does not match with the actual rainfall of Ambikapur region for 2012. In other hand, forecasted value by BPN model in deterministic forecast provided excellent result 94.4 (% of LPA) with only deviation 2.7 (% of LPA).

5. Conclusions

IMD's operational model is appropriate for LRF of monsoon rainfall over whole Central India. However it is unsuccessful in case of LRF over a very smaller region like Ambikapur 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). These similar parameters are not useful for prediction over this region. 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. 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.

In this article, the details of development and testing of BPN model in deterministic forecast has been discussed and applied in LRF of monsoon rainfall over a very smaller geographical region. As a very smaller region Ambikapur (TGA 15 733 km^2), India, was in under study. The model is operated for LRF of monsoon rainfall over this region for 2012. The model proved to be accurate in 2012. For this year, the model forecasted 94.4 (% of LPA) with the deviation of 2.7 (% of LPA). However, IMDs model based on global parameters forecasted for Central India is 96 (% of LPA) with the deviation of 8 (% of LPA). Thus, BPN model is better evaluated over the IMDs model. This experiment 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. 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. Disadvantage is that, it required many training effort some time it may be temporal nervousness, possibly over fitting during the training process.

This experiment produces results with high accuracy thus BPN can be further applied to forecast various weather phenomenon however it required perfect observations to design BPN parameters like, learning rate, momentum factor, initial weights, neurons in hidden layer, number of input vectors, number of hidden layers, transfer function, training cycles (i.e., epochs), etc. There is no automatic way to select these parameters, and if incorrect values are specified the convergence may be exceedingly slow, or it may not converge at all. Finally it has been concluded that BPN model has adequate efficiency to LRF of monsoon rainfall over a smaller region. It has capacity to learn internal variability of monsoon rainfall data time series itself. It may have ability to overcome the challenges of meteorological services all over the world especially monsoon rainfall over a very smaller region.

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SAŽETAK

BNP model za dugoročnu prognozu monsunske oborine nad vrlo malim zemljopisnim područjem i njegova verifikacija za 2012. godinu

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Novi operativni dugoročni prognostički model Indijskog meteorološkog odsjeka (IMD) statistički je model te stoga sadrži određena ograničenja. Korelacija između monsunske oborine i njezinih prediktora nikada ne može biti savršena. Ona može biti pod utjecajem stoljetnih promjena, a mogu postojati i poprečne korelacije među samim prediktorima. Gotovo je nemoguće odrediti odgovarajuće prediktore monsunske oborine nad malim zemljopisnim područjem. Stoga su pokušaji prognoze monsunske oborine nad malim zemljopisnim područjem trenutnim operativnim modelom u IMDu neprecizni. Pokazuje se da neuralna mreža s propagacijom unatrag (BNP) zadovoljavajuće uspješno identificira internu dinamiku kaotičnih vremenskih nizova podataka te je prikladna za prognozu budućih vrijednosti na temelju vremenskog niza izmjerenih podataka. Stoga je razvijen deterministički BNP model za dugoročnu prognozu (LRF) monsunske oborine iznad manjeg indijskog područja. Područje istraživanja je Ambikapur koje se nalazi na 23° 07′ 23″ N zemljopisne širine i 83° 11′ 39″ E zemljopisne dužine, na prosječnoj nadmorskoj visini od 623 metra (2078 stopa) s ukupnom zemljopisnom površinom (TGA) od 15733 km^2. Uspješnost modela tijekom razvojnog razdoblja (1951.–2007.) bila je izvrsna. Njegova uspješnost tijekom testnog razdoblja (2008.–2011.) je također bila dobra izuzev za 2009. i 2010. godinu. Model je također nezavisno verificiran i primijenjen za 2012. godinu. Odstupanje između izmjerene i prognozirane monsunske oborine u usporedbi s dugogodišnjim srednjakom (% od LPAa) za tu je godinu iznosi samo 2,7%. Ove činjenice ukazuju na učinkovitost predloženog modela.

Ključne riječi: meteorologija, dugoročna prognoza, monsunska oborina, neuralne mreže, propagacija unatrag, deterministički

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