Utilization of Intrinsic mode functions and multivariate regression analysis for forecasting monsoonal rainfall of Nagaland, Manipur, Mizoram and Tripura

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The South West Monsoon rainfall data of the meteorological subdivision containing Nagaland, Manipur, Mizoram and Tripurais shown to be decomposable into six empirical time series, namely, intrinsic mode functions. This helps one to identify the first empirical mode as a nonlinear part and the remaining as the linear part of the data. The nonlinear part is handled by neural network based Generalized Regression Neural Network based technique whereas the linear part is modeled through regression technique. It is found that the proposed model explains around 75% of inter annual variability. The model is efficient in statistical forecasting of rainfall as verified. The statistical forecast of the subdivision for the year of 2013 is 93.10 cm whereas the actual data is 88.71.

PACS numbers:

I. INTRODUCTION

The summer monsoon or called the southwest monsoon (SWM) is the substantial component of annual rainfall in India. The rainfall during June, July, August and September is the SWM rainfall on a yearly basis. The economy and agriculture is vastly dependent on SWM rainfall and its characteristics for different regions of India As a case study, we undertake the analysis of SWM rainfall of the subdivision No.6 consisting of the states Nagaland, Manipur, Mizoram and Tripura (NMMT). The location of NMMT is presented in Fig. 1.

Efforts are made from earlier times to understand the connections between SWM and other global phenomena namely El Nino (EN), southern oscillation (SO) and sunspot cycle. This raises the question whether the quantum of rainfall for the season can be forecast keeping in view the regularity with which the monsoon season appears. In the past, this issue has been addressed in two different ways. In the first approach, rainfall is thought to be the effect of other antecedent meteorological parameters. The works of Gowariker et al. (1989), Thapliyal (1990), and Sahai et al. (2003) may be mentioned in this connection. The model of Sahai et al. (2003) linked global SST data with Indian monsoon seasonal data appears to be a successful one. In the second approach, rainfall time series is supposed to carry the images of all causes in itself. In this connection Sahai et al. (2000), Iyenger and Raghukant (2003) may be mentioned where even though causes are not known; but with sufficiently large data series rainfall is modeled as replicating past data with the help of Greens function.

Some studies elaborate the periods latent in the data with the help of Fourier analysis such as Campbel et al. (1983), Narashima and Kailash (2001), Sukhla and Paolino (1983). The hidden periodicity such as sunspot cycle, QBO, El-Nino is predominant in their study. The periodicity of 3, 5.8, 11.6, 20.8 etc along with oscillatory trends are the important features of their studies. However, transitions of the knowledge to efficiently in the forecast are not possible. The approach of Iyenger (1991), Iyenger and Basak (1994) for decomposition of the SWM rainfall into principal components are also very much relevant for understanding the periodicity of the rainfall.

The present paper studies the forecasting of SWM rainfall of NMMT with the above points in the background. A new representation of the data series, in terms of a finite number of empirical time series as Intrinsic Mode Functions (IMFs) is presented. These time series are simpler than the original data for modeling and forecasting.

II. EMPIRICAL MODES

The time series of the SWM rainfall data series is now decomposed into finite number of empirical mode, namely, Intrinsic Mode Function (IMF) as per Huang et al. (1998). An IMF is a data derived function such that, in its interval of definition the number of zeros and extrema are either equal or differ at most by one. Further, at any point, the meanvalue of the local positive and negative envelopes of the IMF would be zero.

Each IMF so obtained is a narrowband time series with an identifiable central period around which the oscillations take place. The amplitude and period of IMFs are hierarchical as the number of IMFs. The amplitude and period also provide a physical basis, for relating monsoon rainfall with other meteorological parameters that show similar character of periods as a particular IMF. As a study, the present papers study a North-East subdivision of Indian rainfall time series and decompose the observed data into their basic IMFs. The SWM rainfall series of NMMT the data exhibit six modes of temporal variation. The last mode always corresponds to the climatic average remaining almost constant.

The traditional method of investigating rainfall data has depended on models of stationary random processes

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US ISSN: 2689-9957
website:https://ajamc.smartsociety.org/

with Gaussian properties. Application of the corresponding statistical tests to verify the auto-correlation or power spectral density functions of SWM data leads to the result that signals, if any, in these data are very weak (Iyenger 1991). The non-Gaussianness of SWM data prevents the data to be modeled in terms of a linear time series. On the other hand, the particular form of the nonlinear model to be used is not quite obvious. Previously (Iyengar and Raghukanth, 2003) it has been demonstrated that a nonlinear model with variable frequency harmonic terms can be effectively used to explain about 60% of the IAV. This would indicate that the basic data which is not a white noise should carry the decomposed IMFs as signals. The first IMF exhibits highest-frequency mode and is strongly non-Gaussian. The other hierarchical IMFs are progressively less random.

TABLE I: SWM rainfall data (18711990).

Region	Area(Sq. km)	m_R(cm)	σ_R(cm)	Skewness	Kurtosis
NMMT	255,511 sq. km	125.4	26.4	-0.5670	2.9574

NMMT: Nagaland, Manipur, Mizoram and Tripura

III. RAINFALL DATA

The area rainfall data of NMMT are collected from the website www.tropmet.res.in of Indian Institute of Tropical Meteorology (IITM), Pune. The SWM rainfall data which is the sum of the monthly values of June, July, August and Septemberare selected for detailed study. Some basic statistics of the data such as the climatic normal (mR) and climatic deviation about the normal (R) are presented in Table 1.

FIG. 1: Meteorological subdivision of Nagaland, Manipur, Mizoram and Tripura (NMMT).

IV. INTRINSIC MODE FUNCTIONS

The method of extraction of IMFs is briefly described below with reference to the data series of NMMT. Following Huang et al. (1998), at every time step the average of the positive (E) and negative (E) envelopes are found. This average $m_0(t)$ which is the bias of the data about the zero level, is subtracted from the raw data to get $R_1(t) = R(t)m_0(t)$. This new time series is further processed as in the previous step to get $R_2(t) = R_1(t) - m_1(t)$. This process is repeated m times till the sieved data Rm(t) is centered symmetrically such that with every zero only one peak or valley occurs. Such an $R_m(t)$ (uptp 6 in our case) is the first intrinsic mode denoted as IMF_1. In Fig. 2, IMF_1 of the NMMT series is extracted after six iterations. To extract the second IMF, the first IMF is subtracted from the original data and the process is repeated. On similar lines IMF_3, IMF_4,, IMF_6 are hierarchically extracted until the sieved data shows no oscillations. A long-term climate trends, center-line drifts, long period non-stationary features come out as the sixth IMF. For the time series of Fig. 2-7, six IMFs of SWM rainfall are presented. It is observed that the last IMF is invariably positive and is a mode slowly varying around the long-term average. This may be thought of as the normal or climatic component about which the IAV of the monsoon rainfall appears. This IAV itself can be decomposed into five dynamic modes each evolving around specific frequency or period.

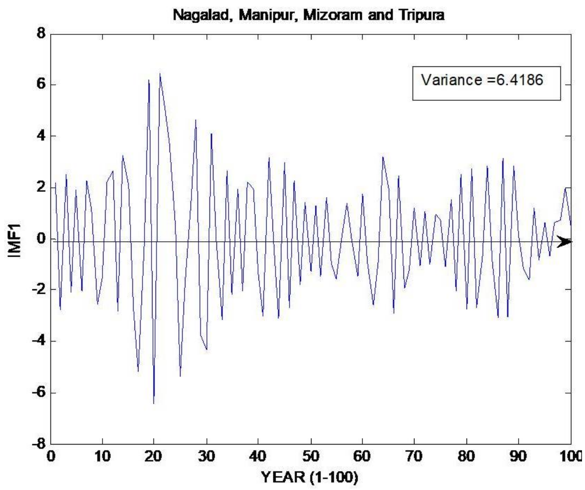

FIG. 2: First Intrinsic Mode Function (IMF_1) of SWM rainfall of NMMT.

The contribution of the corresponding IMFs is found on the basis of time averaging is shown to indicate the relative contribution of an IMF to the total variability of the rainfall. It is easily observed that all IMFs exhibit slowly varying amplitudes and frequencies (Fig. 2-7) indicating a narrow band processes with well-defined Hilbert transforms. However, even without such a representation the dominant period of oscillation can be found

TABLE II: Central period of the IMF's in years and % variance contributed.

	IMF 1		IMF 2		IMF 3		IMF 4		IMF 5	
	T	IAV%	T	IAV%	T	IAV%	T	IAV%	T	IAV%
NMMT	2.76	42.22	4.76	18.61	18.46	10.23	35-40	3.64	Not detectable	20.56

NMMT: Nagaland, Manipur, Mizoram and Tripura

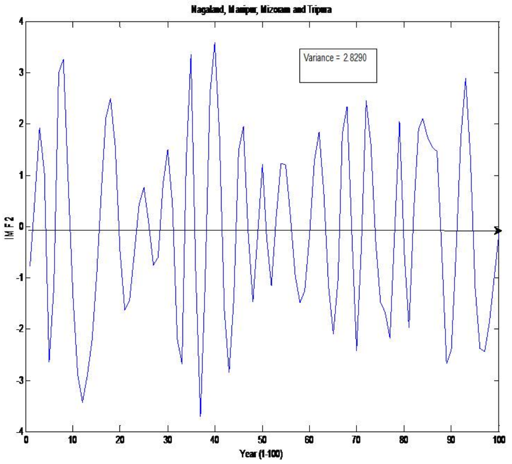

FIG. 3: Second Intrinsic Mode Function (IMF_2) of SWM rainfall of NMMT

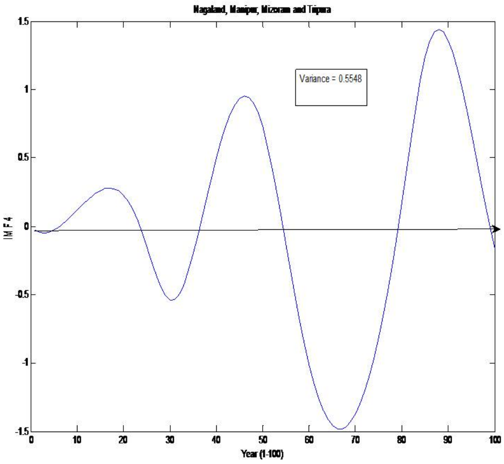

FIG. 5: Fourth Intrinsic Mode Function (IMF_4) of SWM rainfall of NMMT.

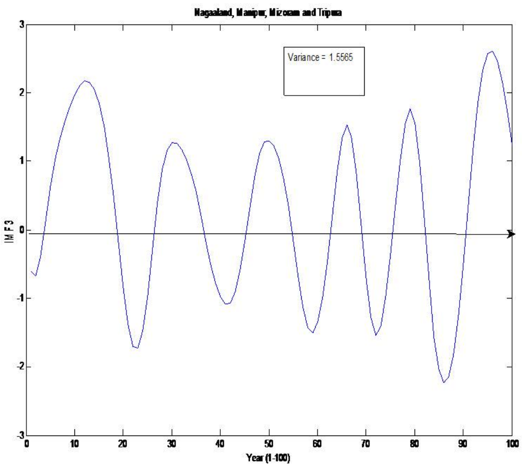

FIG. 4: Third Intrinsic Mode Function (IMF_3) of SWM rainfall of NMMT.

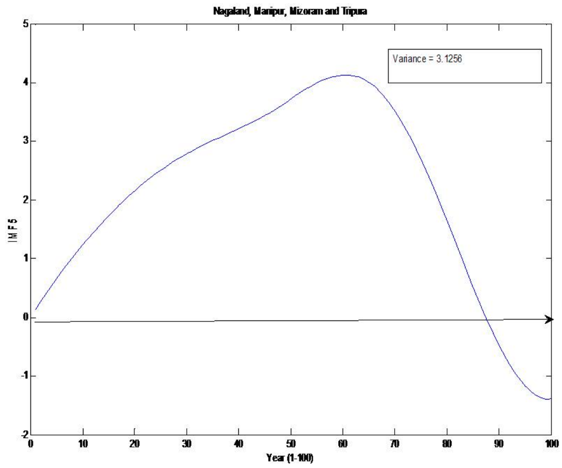

FIG. 6: Fifth Intrinsic Mode Function (IMF_5) of SWM rainfall of NMMT.

by counting the zeros and the extrema in an IMF. In Table 2, the central period along with the contribution of each IMF to IAV percentage is listed. It is observed that IMF1 is a predominant mode with an average period of 2.76 years contributing to 42.2% of IAV. IMF_2 is second most important mode with a dominant period of 4.46 years. These two modes are closely connected with the quasi-biennial oscillation (QBO) and El NioSouthern Os-

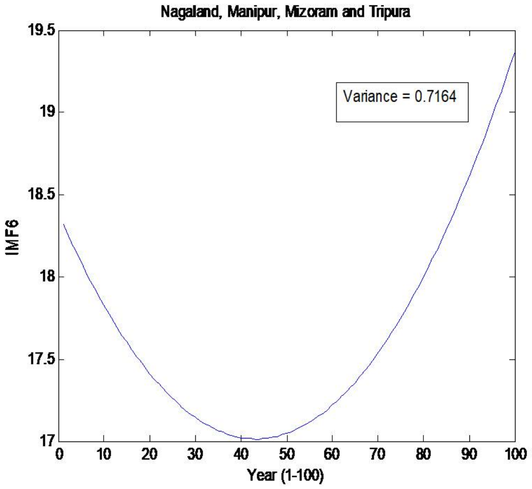

FIG. 7: Sixth Intrinsic Mode Function (IMF_6) of SWM rainfall of NMMT.

cillation (ENSO) phenomenon. In the same way, IMF_3 can be associated with the sunspot cycle of about 12-18 years approximately sunspot cycle (Bhalme and Jadav, 1984). The central period of IMF4 is about 30 years, which can be related to tidal forcing (Campbell et al., 1983). The fifth IMF shows an elongated period of the order of 60 year last component, which is the residue, as per Huang et al. (1998), is here taken as the slowly varying climate mode. This way, IMF_6 is here identified as the deterministic long-term behavior. It may be mentioned here that wavelet analysis of monsoon rainfall data by Narasimha and Kailas (2001) indicated the presence of six quasi-cycles (modes) at nearly the same average periods obtained here. The present study has been able to identify the time histories of the embedded modes also in the form of various IMFs. The representation obtained for any of the data series is of the type $R(t) = \sum IMF_i(t)$. The sum of the IMFs leads to the original data; the error between the sum of the six IMFs data series has an average value of 10^{-4} .

V. IMF STATISTICS

For understanding the statistical relation between the IMFs and the data, one has to construct the correlation matrix of the time series. In Table 3, the correlation matrix (6x6) of the NMMT SWM data and the six variable IMFs is shown. It is understood that correlation values between the data and the IMF are statistically significant and hence are phenomenically meaningful. Further, among themselves the IMFs are statistically uncorrelated or orthogonal. Thus, we can expect the sum of the variances of the IMFs to be nearly equal to the total variance of the data. However, due to sample size effects and round off errors there can be small differences between the two-variance figures. For example, the sum of the variances of the IMFs of NMMT adds up to 70.5, whereas the data variance is 71.7.

TABLE III: Correlation matrix of IMFs and Data SWM rainfall NMMT.

	Data	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6
Data	1.0000	0.8019*	0.1177	0.250*	0.1678*	0.1910	0.1011
IMF1		1.0000	0.1365	-0.0244	0.0055	-0.0086	-0.0264
IMF2			1.0000	-0.1688	0.0192	0.0060	0.0133
IMF3				1.0000	-0.0123	0.2101	-0.1341
IMF4					1.0000	0.1081	-0.0113
IMF5						1.0000	0.1812
IMF6							1.0000

*Significant at 5%.

VI. FORECASTING STRATEGY

The possibility of statistical forecasting of SWM rainfall incorporating the IAV is now converted to IMF series through the IMFs. The first IMF carries the higher frequency of the information and hence is expected to be much more random than others. One way of describing uncertainty in rainfall is through the probability density function of the data (Iyenger, 1991). It is known that rainfall, as a random variable is nonGaussian. This is true of the data studied here (Table 1) even though, being the sum of several individual variables, the seasonal data has a tendency towards being Gaussian. Thus, the signals of the original SWM rainfall series are converted to the oscillations signal of IMFs.

There is great interest among the agriculture, industrial and policy-making sectors in India to know in advance how the monsoon in a particular year behaves as far as rainfall is concerned. Thus, considerable literature exists on the various strategies adopted by the India Meteorology Department (IMD) in producing a long range forecast for the All India seasonal rainfall (Rajeevan et al., 2000; Rajeevan, 2001). Forecasting may be seen as extending the data series by one step. This exercise, for simple functions with an analytic form can be easily carried out by Talyors series expansion. However, rainfall data is highly erratic and no simple function can be fitted to the whole data series. Hence, the approaches taken have been statistical whether explicitly stated to be so or not. The decomposition of data into IMFs presents another approach for forecasting Indian monsoon rainfall. It is clear that one can attempt modeling and forecasting the IMFs.

For accurate forecasting, one has to work with accurate values of R_js or IMFs. This difficulty can be overcome by recognizing that except for the first IMF, others can be modeled through linear regression on their own past values. In fact for purposes of forecasting it is found easier to handle the data Rj as consisting of a nonlinear part and a linear part. The first IMF1j represents the nonlinear part, where as $y_j = (R_j - IMF_{1j})$, (j =1, 2, 3, ... , n - 1) represents the linear part of the data. The stationarity of this part has also been verified by the standard run test on decadal variance value yj associated with NMMT, with N = 13, there are seven runs about the median value of the decadal variance. For the remaining data, in the order listed in Table 1, the runs are [6, 7, 8, 8, 5, 6, 8] implying that the variance remains constant in time and hence stationarity accepted since the tabulated runs at 5% significance level are between 4 and 11. With this in view, the representation for the linear part avoiding yn, is chosen as

$$y_{n+1} = C_1 R_n + C_2 y_{n-1} + C_3 y_{n-2} + C_4 y_{n-3} + C_5 y_{n-4} + C_6 \quad (1)$$

It is found that the equation (1) provides an excellent fit for the linear part with the data base. The regression coefficients are found the series of 1871-1990 the database The regression coefficients are found from the data series of 18711990, such that IMF_1 and y_j are available for the period 1872 to 1990. The regression coefficients and the resulting standard deviation of the error σ_R are presented in Table 4. In each case, the correlation coefficient (CC) between the actual data and fitted value as per the above equation is also presented in the table. In all the cases, the correlation is highly significant, indicating the appropriateness of identifying y_j as the linear part of monsoon rainfall.

The first IMF that accounts for most of IAV of monsoon rainfall is non-Gaussian and non-linear process. In the case unstructured complex problem, the Generalized Regression Neural Network (GRNN) an improved version of Neural Network class of technology based on nonparametric regression, suggested by (Spect, 2002) is applied.

VII. GENERALISED REGRESSION NETWORKS ARCHITECTURE CONNECTED TO NON LINEAR IMF_1

A. ARCHITECTUE OF GRNN

A GRNN model contains two hidden layers, pattern neurons and summation neurons. The calculations performed in each pattern neuron of GRNN are $exp(-D_j^2/2\sigma^2)$, D_j being the distance between training sample and being smoothness parameter, the normal distribution is considered at each training sample. The signals of the pattern neuron, going into the Denominator neuron are weighted with corresponding values of the training samples Y_j. The weights on the signals going into the Numerator are one. Each sample from the training data influences every point that is being predicted by GRNN.

The author (Spect 2002) showed that GRNN works for modeling and extending regression, prediction, classification and function approximation. The idea is that every training sample will represent mean to a radial basis neuron. After several trials with number of previous values of IMF_1, a GRNN with hidden layer is utilized as shown in Figure 12.

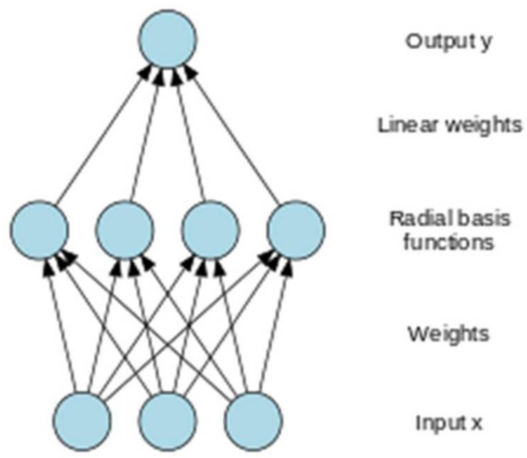

FIG. 8: General Regression Neural Network with Radial Basis Functions.

B. RESULTS OF IMF_1 WITH GRNN

The computation has been done using MATLAB toolbox on GRNN algorithms, with 1871-2000 as the training period. With the help of antecedent IMF1 values, the GRNN model is capable of predicting IMF1 for the year (n +1). In Table 5, the standard deviation $\sigma_y(e)$ of the errors is constructed on the training period data is shown along with the correlation coefficient (CC) between the actual IMF_1 and the GRNN results. It is observed that GRNN is quite versatile in capturing the latent nonlinear structure evidenced by the high correlation (0.8062) between the actual and simulated IMF1 values. An advantage of this approach is that the error in the model can also be characterized statistically.

VIII. FORECASTING

The successful modeling of IMF_{1j} and y_j can be extended by one year, to make a forecast of the next year rainfall value. Firstly, for y_{n+1} and then for $IMF_{1,n+1}$ is computed from the models mentioned above. The sum of the two values produces a forecast for R_{n+1}. Here, the performance of the forecast strategy is investigated by considering for the period (19912013), that was deliberately left out of the modeling exercise. The quality of modeling R_j in the training period (18751990) and the efficiency of one-step-ahead forecasting in the testing period (19912013) are presented in Table 6.

The sample forecast is an expected value and may be slightly deviate from the actual observation. In Table 7,

TABLE IV: Regression coefficients of Equation (1).

Region	C_1	C_2	C_3	C_4	C_5	C_6	σ_y	CC
NMMT	**0.05252003**	**-0.000227877**	**-0.0109865721**	**0.0489769**	**-0.032434821**	**18.9298859**	**2.2458**	**0.766585886**

NMMT: Nagaland, Manipur, Mizoram and Tripura

TABLE V: Statistics of GRNN model for IMF: training period (18712000).

Region	$\sigma_y(e)$	Correlation Coefficient (CC)
NMMT	2.8545	0.9255

NMMT: Nagaland, Manipur, Mizoram and Tripura

detailed numerical results on the independent forecasts are presented. Fig. 13 elaborates the actual rainfall data and predicted rainfall data for testing period (1991-2013).

It is evidenced that the present strategy for forecasting SWM rainfall one year ahead, works well within *certain limits*. It may be noted that the sample and actual data is 0.89, which is sufficiently high. In verifying the ability of the model for the forecasting, 19912013, the model parameters are kept constant all through the thirteen years there by relaxing the constrains for forecasting exercise, the model parameter have to be updated, every year before forecast. It is observed that even under the less than ideal condition, the forecasts produced by the model are good enough. For a sample size of N = 23 (1991 - 2013), the correlation coefficient (CCf) in the test period has to be at least 0.6 to be taken as significant. It is found from Table 6 that CCf is well above 0.6.

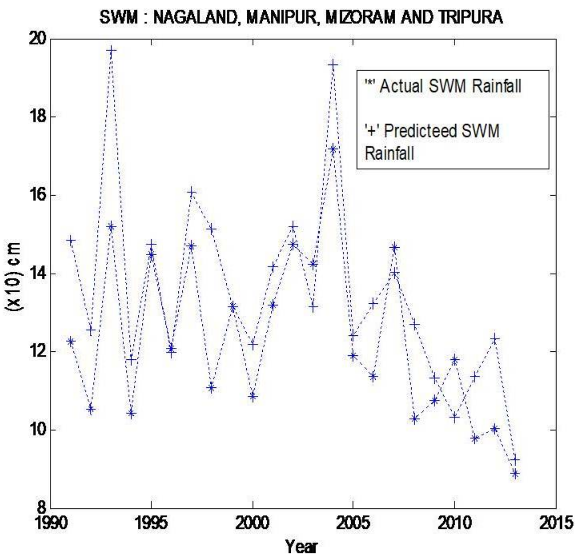

FIG. 9: The actual SWM rainfall and Predicted SWM rainfall of NMMT for the testing period (1991-2013).

IX. PERFORMANCE OF THE MODEL

To verify the performance of the model proposed, three statistical parameters are chosen. The first two are the Root Mean Square Error (RMSE) and the correlation coefficient (CC_m) between the given data and the simulated values out of the model. A statistic called Performance Parameter [4], namely, $PPm = 1(\sigma_m^2)/(\sigma_d^2)$, where σ_m^2 is the mean square error and σ_d^2 is the actual data variance, has also been extracted. In a perfect model, m2 will be zero and both CC_m and PP_m would tend towards unity. Table 6 indicates that the efficiency of the present model is good for testing period and correlation coefficient between forecasted forecast is an expected value and hence may not precisely match with the actual observation.

X. DISCUSSION

IAV of monsoon rainfall of NMMT has been investigated in this paper with a valuable perspective and points out some interesting feature. It is identified that the seasonal SWM rainfall time series of NMMT can be decomposed into six statistically almost uncorrelated modes; the summation of which gives back the original data. The sixth mode is identified easily associated with the climatic variation persistent over the total data base. The remaining five empirical modes (IMFs) are narrow band random processes, with well defined central periods, connected to certain well defined meteorological phenomenon. The first IMF which accounts for the highest variability is strongly nonGaussian and can be successfully predicted using GRNN techniques. The remaining part of the rainfall after removing the first IMF is agreeable for a linear multiple regressive representation. With two decided separate representations; a methodology has been developed to forecast rainfall. However, the analysis does not account for other variability, namely, intra annual, inter seasonal or intra seasonal variability present in the monsoon rainfall. The forecast of SWM rainfall for NMMT for the year 2012 and 2013 are123.18 cm and 93.10 cm respectively corresponding to the actual SWM rainfall of 100.18 cm 88.71cm, which are within one standard deviation of mean rainfall. Among the first five IMFs, it has been seen that first three IMFs contributed nearly 90% of the variability. It may be interpreted that if those are simultaneously negative, the chances of drought

TABLE VI: Performance of the modeling and forecasting strategy.

Region	Modeling period (1872–1990)			Forecasting period (1991–2013)		
	$\sigma_m(e)$	CC_m	PP_m	$\sigma_f(e)$	CC_f	PP_f
NMMT	3.29	0.89	0.83	3.04	0.91	0.82

NMMT: Nagaland, Manipur, Mizoram and Tripura

TABLE VII: Independent test forecasting.

	NMMT	
Year	Actual(x10)cm	Forecast(x10) cm
1991	12.2671	14.9124
1992	10.5481	12.5204
1993	15.1873	19.8251
1994	10.4138	11.8652
1995	14.4094	14.8132
1996	12.0621	12.1012
1997	14.6991	16.0112
1998	11.0602	15.2662
1999	13.1517	13.2021
2000	10.8651	12.0822
2001	13.1962	14.1038
2002	14.7192	15.1280
2003	14.2221	12.9866
2004	17.1950	18.4192
2005	11.8962	12.3821
2006	11.3524	13.0012
2007	14.6562	14.3221
2008	10.2941	12.3802
2009	10.7382	11.2110
2010	11.7873	10.4522
2011	9.7655	11.6122
2012	10.018	12.3182
2013	8.8710	9.3102

NMMT: Nagaland, Manipur, Mizoram and Tripura

are high. For flood like situation those are highly positive which are in agreement with (Iyenger and Raghukant, 2003).

XI. CONCLUSION

IAV of NMMT has been investigated with an innovative point of view in the current paper. It is established that SWM rainfall time series, sampled annually, is decomposed into six statistically orthogonal modes; sum of the modes gives back original data to an accurate level. Sixth mode is associated with the overall climatic variation whilst the remaining five empirical modes are associated with narrow-band random processes having specified central periods and are connected to important meteorological phenomenon parameters. The approach that that first mode IMF1 accounting for highest variability, is strongly non-Gaussian and is modeled by GRNN technique; whereas the remaining part of the rainfall is amenable for linear auto-regressive representation is an interesting approach. The combination of two techniques amenable to forecasting exercise of the rainfall prediction is developed for NMMT. The particular approach is general enough and efforts are on to include the analysis in other regions of India.

Acknowledgement

The author sincerely thanks National Data Centre ADGM (R) Pune for providing SWM rainfall data of the Gangetic plains of West Bengal, India.

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