Advances in Adaptive Data Analysis
Vol. 2, No. 1 (2010) 81–96

FORECASTING THE AIR TRAFFIC FOR NORTH-EAST INDIAN CITIES

C. MALLIKARJUNA

Department of Civil Engineering
Indian Institute of Technology, Guwahati, Assam, India
c.mallikarjana@iitg.ernet.in

S. T. G. RAGHU KANTH

Department of Civil Engineering
Indian Institute of Technology, Madras, Chennai, India
raghukanth@iitm.ac.in

In this article, a new strategy for modeling and forecasting the air traffic data series is presented. The empirical mode decomposition technique is used to decompose the monthly air traffic time series into finite number of intrinsic modes. This helps in identifying the last empirical mode as a trend and the summation of remaining modes as the fluctuation in the data. The fluctuation part is handled by artificial neural network (ANN) techniques, whereas the trend is amenable for modeling through simple regression concepts. It is found that the proposed model explains 46–89% of the variability of five air traffic time series considered here. The model is efficient in statistical forecasting of air traffic as verified on an independent subset of the data series.

Keywords: India air traffic; time series; empirical mode decomposition; artificial neural network.

1. Introduction

North eastern region of India (NERI) with an area of 263,179 sq. km. consists of seven states namely Assam, Meghalaya, Tripura, Mizoram, Manipur, Arunachal Pradesh, and Nagaland. As per the Directorate of Economics and Statistics of NERI, the population density in this region is 148 persons/sq.km., which is about 47% of the total country's average density. Except the state of Assam, this region of India predominantly consists of hilly terrain which poses a major challenge in providing basic transport infrastructures such as roadways and railways. Moreover, this region is poorly connected with the rest of the country due to its geographical location. In view of these difficulties associated with roadways and railways, recently the Indian government has started investing huge money in this region to build the airport infrastructure. This has led to the development of five major airports located at Guwahati, Agartala, Imphal, Shillong, Silchar, and Dibrugarh

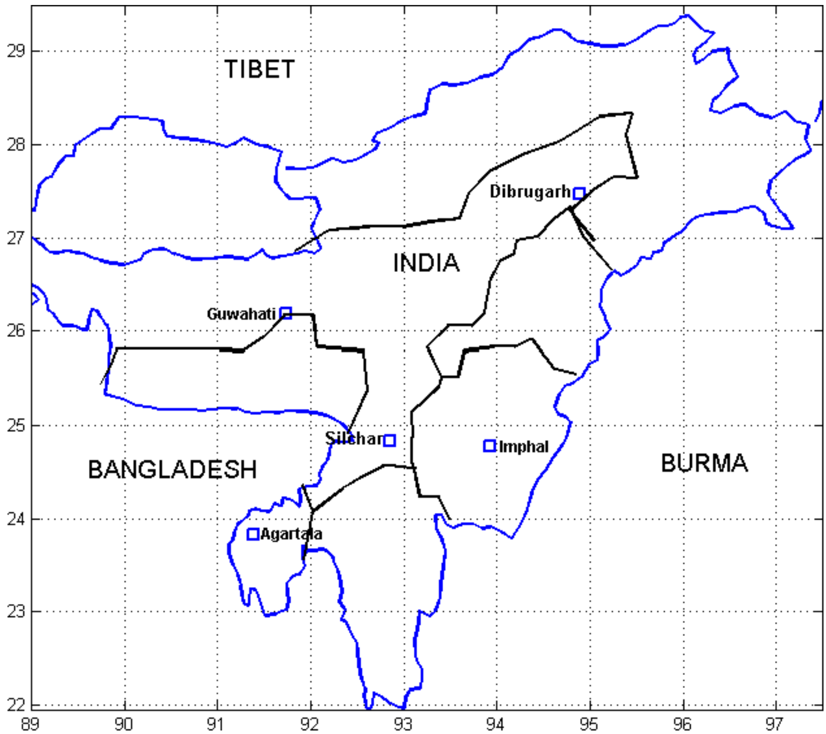

Fig. 1. Geographic location of the five airports considered in the present study.

cities in NERI (Fig. 1). In the year 2005–2006, a total of 34,036 aircraft movements were noticed in this region. This increased to 42,009 in 2006–2007, which is about 23.4% increase in aircraft movement. The passenger traffic has also increased by 40.2% in NERI region, during this period. Currently, the average number of scheduled flights operated per week between NERI and rest of India is about 226. Based on the monthly air traffic, these five airports lie in the top 45 airports in India.

Due to this tremendous increase in both aircraft and passenger traffic, several non-operational airports are being upgraded to the operational level in NERI. Due to this demand, the infrastructure in the existing and proposed new airports is being developed in this region. This demands forecasting of both passenger and aircraft at these airports, which is the key input to provide adequate infrastructure. There have been several studies in the past for modeling and forecasting the air traffic data. Karlaftis *et al.* (1996) studied different airport-specific travel demand models for understanding possible limitations in forecasting accuracy. Statistical data describing air travel demand patterns for two major international airports, the Frankfurt and Miami international airports, have been used to demonstrate the effectiveness of the proposed models. It was found that simple models with few independent variables perform as good as more complicated and costly models and external factors have a pronounced effect on air travel demand. Strand (1999) emphasized the need for incorporating both local and non-local motive forces in airport-specific forecasting techniques. Place-specific area characteristics and forces are important in the sense that they create major differences in the relative traffic potential between airports. Bhadra (2003) analyzed the effect of local factors such as economic and demographic characteristics on origin and destination travel in the United States. Local characteristics are more significant in origin and destination travel pattern than national information such as Gross Domestic Product. Bhadra (2008), in another work, analyzed the structure and dynamics of the origin and destination of core air travel market demand using quarterly time series data. An empirical framework is proposed that formalizes the relationship between passenger flow and average fares, income of communities, and distance between communities.

In the Indian context, there were few works on modeling the air travel demand for some of the major airports. Sen (1985) analyzed monthly revenue passenger-kilometers flown by Indian airlines from Apr. 1976 to Dec. 1980 for possible trends which are later used for short-term forecasting. He has also analyzed the effect of possible fare changes on the revenue passenger-kilometers. Rengaraju and Arasan (1992) developed city-pair air travel demand model for modeling domestic air travel between 40 city pairs. In this process, air travel demand was related a vector of socioeconomic variables and a vector of transport system variables.

Several analytical models are available to forecast the air traffic. Most of these techniques are applicable if the air traffic has attained saturation levels. Not only the five airports considered in the present study but all the major Indian airports are handling increasing air traffic and this upward trend is not going to reach saturation levels in the coming decade. This renders most of the analytical models less relevant and empirical approaches seem to be better alternative. It has been observed from the literature [Bhadra (2003); Karlaftis *et al.* (1996)] that personal consumption expenditure and per capita gross domestic product are the major factors which are influencing air passenger traffic. It can also be found that in addition to the econometric variables, location specific variables are also found to be significantly influencing the air traffic.

An attempt is made in this paper to forecast the air traffic for five major airports in NERI. Monthly air traffic data corresponding to these five airports have been utilized in developing the model. Due to the non-availability of econometric variable data for NERI, nonlinear auto regressive models are used for modeling and forecasting the air traffic data. Based on empirical mode decomposition technique [Huang *et al.* (1998)], the nonstationary trend at these five airports is extracted from the air traffic data. The obtained trend is modeled using simple regression models. The remaining part of the data is modeled by using artifical neural network (ANN). The passenger traffic forecasting models are developed separately for the five airports. The proposed models are also validated by using the data not included in the modeling period. It is found that the developed model is efficient in forecasting the air traffic with reasonable accuracy.

2. Air Traffic Data

Monthly air traffic data for all the major airports in India are available with Airports Authority of India (Traffic News, Airports Authority of India). Air traffic data for Guwahati (26°10′N, 91°46′E), Imphal (24°49′N, 93°57′E), Silchar (24°49′N, 92°48′E), Agartala (23°30′N, 91°^{12}′E), and Dibrugarh (27°28′N, 94°54′E) which are the major cities in NERI, are available from the year 2002 onwards till May 2007. These traffic data indicate the total monthly air traffic handled by an airport including incoming and outgoing traffic. The location of these five airports in northeast India is shown in Fig. 1. Among the five airports considered for this study, Guwahati airport is handling over 100,000 passengers a month. Entry of low-cost carriers such as Air Deccan (in the year 2003) and the consistently increasing National Gross Domestic Product have been resulted in significant raise in the air traffic. Air traffic growth in all the five cities, except Dibrugarh–Imphal and Dibrugarh–Silchar, is highly correlated and the same can be seen in Table 1.

3. Empirical Mode Composition

The most popular method for analyzing data series is the Fourier-based spectral analysis which uses sine and cosine functions as the basis. But the major limitation on the use of Fast Fourier Transform (FFT) is that the data must be linear and temporally stationary. Unfortunately, air traffic data of four airports as shown in Figs. 2(a)–2(e) are nonlinear and nonstationary that is improper to be analyzed by FFT method. Air traffic data are inherently nonstationary in developing countries due to the fact that the number of people traveling by Air is increasing as the per capita income is increasing. In such situations, Fourier analysis can yield distorted and incomplete information on the nature of the air traffic data. The only way to represent the physics of nonlinear and nonstationary processes is through adaptive basis functions. To extract these basis functions a new technique called empirical mode decomposition (EMD) has been proposed by Huang *et al.* (1998), with which any complicated data set can be decomposed into a finite and often small number of intrinsic mode functions (IMFs). The extracted IMFs are complete, adaptive,

Table 1. Correlation between air traffic data in NERI.

City	Guwahati	Agartala	Imphal	Dibrugarh	Silchar
Guwahati	1	0.94	0.91	0.85	0.85
Agartala		1	0.90	0.80	0.87
Imphal			1	0.68	0.92
Dibrugarh				1	0.63
Silchar					1

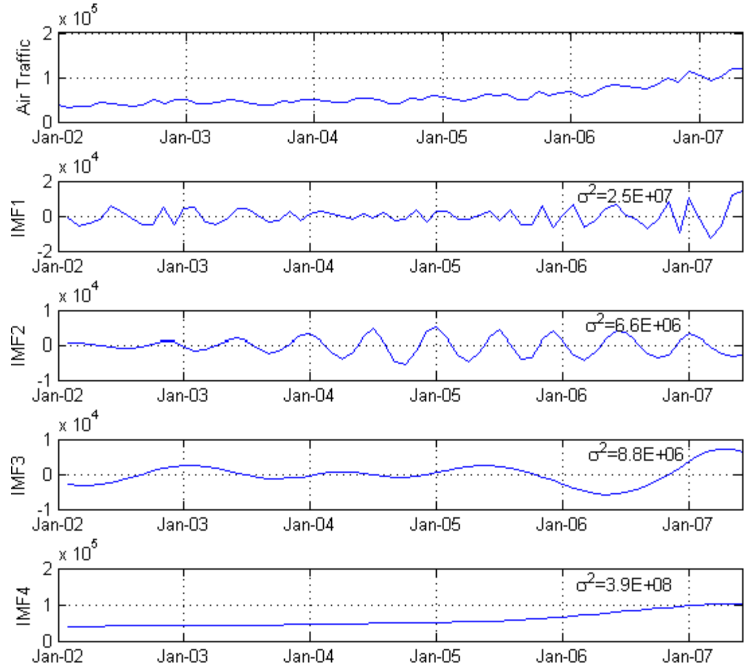

Fig. 2a. IMFs of Guwahati air traffic.

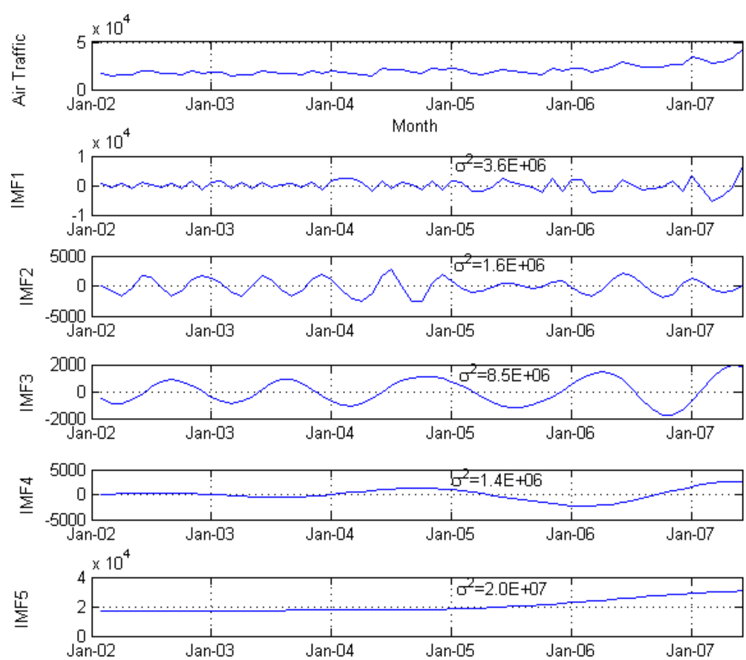

Fig. 2b. IMFs of Agartla air traffic.

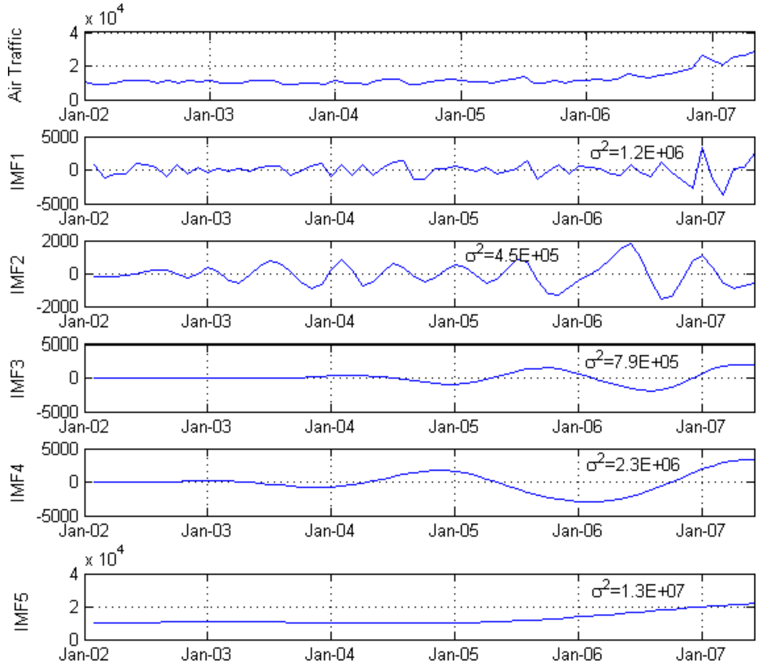

Fig. 2c. IMFs of Imphal air traffic.

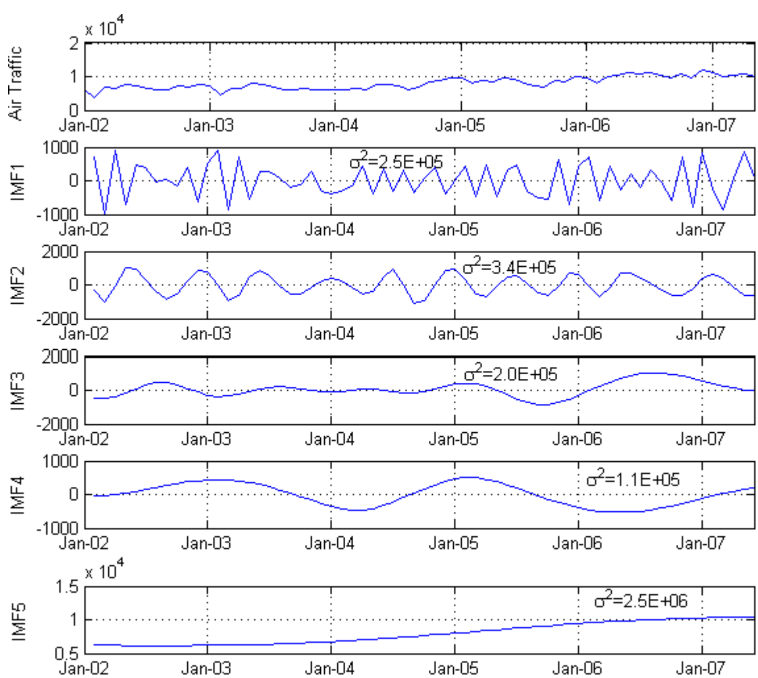

Fig. 2d. IMFs of Dibrugarh air traffic.

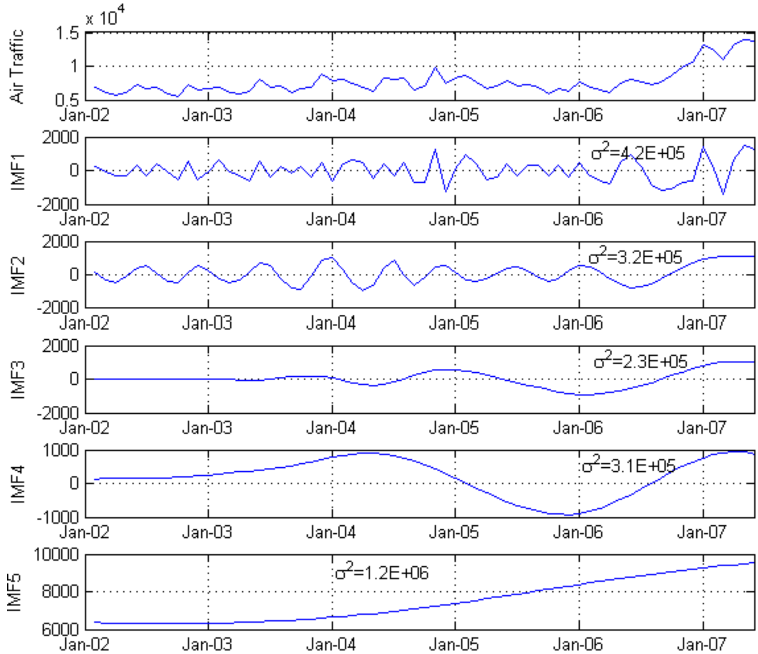

Fig. 2e. IMFs of Silchar air traffic.

and almost orthogonal. Due to its ability in faithfully characterizing nonlinear and nonstationary data, EMD is widely used in analyzing various observational data such as blood-pressure variation, rainfall, ocean waves, system identification, and earthquake acceleration time histories [Iyengar and Raghukanth (2005); Huang and Attoh-Okine (2005)]. The theory and application of EMD for extracting the IMFs has been discussed in detail by Huang *et al.* (1998). Briefly, the method of extraction of IMFs is described below.

(1) Identify the consecutive peaks and consecutive valleys of the given data time series, $R(t)$ and construct the lower and upper envelopes by cubic splines.
(2) At every time step, determine the average of the positive (E^+) and negative (E^-) envelopes as

$$m_0(t) = (E^+(t) + E^-(t))/2. \tag{1}$$

(3) Subtract the average $m_0(t)$ which is the bias of the data about the zero level from the raw data to get

$$R_1(t) = R(t) - m_0(t). \tag{2}$$

(4) Treating $R_1(t)$ as the signal, this new time series is further processed from step 1 to get

$$R_2(t) = R_1(t) - m_1(t). \tag{3}$$

(5) Repeat the process m times till the sieved data $R_m(t)$ is centered symmetrically such that with every zero only one peak or valley occurs. Such an $R_m(t)$ is the first intrinsic mode denoted as IMF_1.
(6) To extract the second IMF, subtract IMF_1 from the original data and repeat the sifting process from Step 1 by treating R-IMF_1 as the original data series.
(7) On similar lines extract IMF_3, $\mathrm{IMF}_4, \ldots$ until the sieved data show no oscillations or are an IMF by itself.

The number of extrema decreases with the hierarchical extraction of IMFs from the data. Thus, long-term trends, centerline drifts, and long-period nonstationary features come out as the last IMF. For the air traffic data of Guwahati, four IMFs can be extracted. Air traffic for other NERI cities can be decomposed into five IMFs. These are shown in Figs. 2(a)–2(e). 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 trend about which the air traffic oscillates. With EMD, the variability of air traffic data is decomposed into five dynamic modes each evolving around a specific frequency or period. In all the figures, the variance of the basic data series, and that of the IMFs found by time averaging, is shown to indicate the relative contribution of an IMF to the total variability of the air traffic (Table 2). It is easily observed that all IMFs exhibit slowly varying amplitudes and frequencies. Hence, these are narrow band processes with well-defined Hilbert transforms. However, even without such a representation the dominant period of oscillation can be found by counting the zeros and the extrema in an IMF. The percentage of variance explained by each IMF, or the contribution of each IMF to total variance of the air traffic is also presented in Table 2. It is observed that air traffic for Guwahati exhibits last IMF which characterizes the trend in the data to be the predominant mode contributing to 89.2% of the inter-monthly variability. Similarly, the last IMF is also the major mode in the remaining four airports with contribution to the variance of the data in between 30% and 72%. Except for Imphal and Diburgarh, IMF_1 is the second most important mode in all the cases. The period of IMF_1 in all the cases varies in between 3 and 3.6. The second IMF oscillates around 6.5–7.2 months. The central period of IMF_3 is about 13–21.67 months. For Imphal, IMF_4 and for Dibrugarh, IMF_2 is the second most important mode contributing to the variability of the data. The last component, which is the residue, is here taken as the slowly varying mode resulting due to the growth in per

Table 2. Variance observed in air traffic data and contribution of IMFs.

City	IMF_1		IMF_2		IMF_3		IMF_4		IMF_5	
	Period	%Variance	Period	%Variance	Period	%Variance	Period	%Variance	Period	%Variance
Guwahati	3.61	5.29	6.5	1.40	16.25	1.86	65.00	82.45	—	—
Agartala	2.95	12.68	6.5	5.63	13.00	2.99	21.67	4.93	65.50	70.42
Imphal	3.25	5.80	7.22	2.17	21.67	3.82	32.50	11.11	65.00	62.80
Dibrugarh	2.71	7.29	6.50	9.91	13.00	5.83	21.67	3.21	65.00	72.89
Silchar	3.10	11.02	6.50	8.40	21.67	6.04	32.50	8.14	65.00	31.50

Table 3. Correlation matrix of Guwahati IMFs.

	Data	IMF_1	IMF_2	IMF_3	IMF_4
Data	1.0000	0.3458	0.0498	0.3591	0.9537
IMF_1		1.0000	0.0871	0.0902	0.1032
IMF_2			1.0000	−0.0980	−0.0825
IMF_3				1.0000	0.2351
IMF_4					1.0000

capita income. 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 $R(t) = \sum \mathrm{IMF}_i(t)$. In all the five cases the sum of the IMFs leads to the original data, as can be easily verified. For example, the error between the sum of the four IMFs and the Guwahati air traffic data series has an average value of 10^{-12} with a standard deviation of 10^{-11}.

3.1. *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 (5×5) correlation matrix of the Guwahati air traffic data and the four variable IMFs are shown. It is immediately clear that, except for IMF_2 correlation values between the data and the IMFs are statistically significant and hence are physically meaningful. Further, among themselves the IMFs are statistically uncorrelated or orthogonal. Thus, one 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. In this case, the sum of the variances of the IMFs of Guwahati air traffic adds up to 4.73E+08, whereas the data variance is also 4.31E+08. The first IMF carries the higher frequency end of the information and hence is expected to be more random than others.

4. Forecasting Strategy

The recent unprecedented growth in air traffic and the resulting air congestion necessitates the study of air traffic demand forecasting. Forecasting may be seen as extending the data series by one time step. This exercise, for simple functions with an analytic form can be easily carried out by Talyor's series expansion. However, air traffic data are 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 air traffic. It is clear that one can attempt modeling and forecasting the IMFs which are simpler, instead of the original data. The sum of the predicted values of IMFs, leads to a forecast for the air traffic. However, difficulties arise in finding IMFs at the end of a record. This is because the envelope on both the sides at a point is not defined without the subsequent data point. Use of a mirror image of the past data for the next value, as suggested by Huang *et al.* (1998), would not be acceptable in a forecasting exercise. Thus, if the data R_j are given for $j = 1, 2, \ldots, n$, IMF_1 can be accurately found only for $j = 2, \ldots, (n-1)$. As the distance between extrema increases with higher IMFs, extrapolation errors propagate into the signal and distort the temporal structure of the higher IMFs at the end points. Hence, for forecasting the value of R_{n+1} one has to work without accurate nth values of IMFs. This difficulty can be overcome by recognizing that except for the first IMFs, the last IMF which characterizes the trend in the data can be modeled through linear regression with time. In fact for purposes of forecasting it is found easier to handle the data R as consisting of a fluctuation part (Y) and a trend part (X). The last IMF represents the trend part, whereas $Y = (R - X)$, represents the fluctuation part of the data.

4.1. *Modeling the trend*

Air traffic growth that has been started in early 2000s is yet to reach saturation levels. The air traffic data used in the present study includes some initial data which belong to the period during which there was no considerable growth in the air traffic. This can be observed from the data for Guwahati city, as shown in Fig. 2(a). Similar trend has been observed for the other four cities. Keeping this in mind, IMFs are utilized in extracting the nonstationary trend of air traffic. Trend represented by the last IMF for Guwahati air traffic data is shown in Fig. 2(a). In case of Dibrugarh and Silchar, data related to the last two IMFs have been utilized in representing the observed trend. This trend has been modeled utilizing the combination of linear and power functions as shown below.

$$X_j = at + be^{nt} + c, \tag{4}$$

where, t is the time; a, b, n, and c are constants in the regression. It is found that in all the five cases, this equation provides an excellent fit for the linear part of the database. The regression coefficients are found from the data series of 1–50 months. The regression coefficients and the resulting standard deviation of the error $\sigma_X(\varepsilon)$ 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 this table. In all the cases, the correlation is highly significant, indicating the appropriateness of identifying X_j as the trend part of air traffic data.

Table 4. Regression coefficients of trend part (X).

City	a	b	n	c	σ	CC
Guwahati	239.5	231.3	0.085	3.833E+4	4.89E+04	0.98
Agartala	−1626	4.643E+05	0.004	−4.53E+05	1.79E+04	0.99
Imphal	101	3013	0.001	4560	1.04E+04	0.59
Dibrugarh	64.63	3513	−19.45	5616	7.32E+03	0.95
Silchar	25.65	6.55E+05	−15.27	6475	7.14E+03	0.94

4.2. *Artificial neural network (ANN) model for fluctuation part*

It has been pointed out that all IMFs except the last one characterize the fluctuations in air traffic data is perhaps the outcome of a complex nonlinear process. It is not apparent from the time series of IMFs what type of nonlinear model would be appropriate. In such unstructured problems, it has been pointed out by Eisner and Tsonis (1992) that ANN approach can provide efficient working models. These authors have showed that ANN works for modeling and extending the chaotic trajectories of the Lorenz equation. Hsieh and Tang (1998) have highlighted the fact that ANN provides variational data assimilation models, which can be viewed as extensions of linear statistical models. Here, after several trials an ANN model with one hidden layer as shown in Fig. 3, depending on past five steps of data is chosen for Y_j. There are in total 15 parameters to be found in this model, which are found using the MATLAB toolbox on ANN algorithms, with first 50 months as the training period. For verifying the use of the model in forecasting, in any month the fluctuation value (Y_j) is taken as the difference between the observed R_j and X_j of Eq. (4). With the help of five antecedent Y values, the ANN model is capable of predicting Y for the year $n+1$. In Table 5, the standard deviation (σ_a) of the error in hind casting, conducted on the training period data, is shown along with

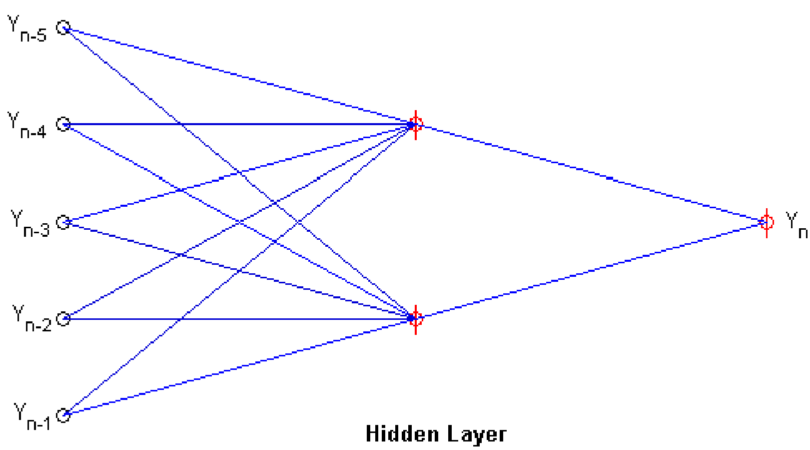

Fig. 3. ANN model for the fluctuation part (Y) of the air traffic data.

Table 5. Statistics of ANN model for fluctuation part (Y).

City	σ	CC
Guwahati	6.1E+03	0.53
Agartala	3.9E+03	0.90
Imphal	2.4E+03	0.64
Dibrugarh	1.1E+03	0.59
Silchar	1.1E+03	0.51

the correlation coefficient (CC) between the actual IMFs and the ANN results. It is observed that the ANN methodology is quite versatile in capturing the embedded nonlinear structure as evidenced by the correlation between the actual data and simulated values. An advantage of this approach is that the error in the model can also be characterized statistically.

5. Forecasting

The successful modeling of X_j and Y_j can be exploited to extend the data by one month, to make a forecast of the next month air traffic value as a random variable with a standard deviation much less than the random deviation. This will have to be done in two steps, following the procedure described above, first for last IMF (X_{n+1}) and then for Y_{n+1}. The sum of the two values produces a forecast for R_{n+1}, with a definable sample probability distribution. Here, the robustness of the forecasting strategy is investigated by considering all the five data sets for the period of 15 months, which was deliberately kept out of the modeling exercise. The quality of modeling R_j in the training period (1–50 months) and the efficiency of one-step-ahead forecasting in the testing period (51–65 months) are presented in Table 6. This table indicates that uniformly, in all cases except Dibrugarh, the present strategy for forecasting air traffic one month ahead works well within certain limits. For all the five cities the modeling and forecasting results are shown graphically also in Figs. 4(a)–4(e). The sample forecast is an expected value and hence need not precisely match with the actual observation. To verify the robustness of the model proposed, two statistical parameters have been chosen. The first one is correlation coefficient CC_m between the given data and the values simulated out of the model. The second statistic called performance parameter, $\mathrm{PP}_m = 1 - \sigma_m^2/\sigma_d^2$, where σ_m^2 is the mean square error and σ_d^2 is the actual data variance, has also been found. In a perfect model, both CC_m and PP_m will tend toward unity. Table 6 demonstrates that the efficiency of the present model is excellent in all the cases. For verifying the ability of the model to independently forecast air traffic one month ahead, the last 15-month data have been used as the testing period. The model parameters are held constant all through the 15 months, which represent conditions more stringent than necessary. This is so since in a real-forecasting exercise, the model parameters

Table 6. Performance of modeling and forecasting strategy.

City	Modeling period (Jan. 2002–Feb. 2006)		Forecasting period (Mar. 2006–May 2007)	
	CC	PP	CC	PP
Guwahati	0.95	0.89	0.95	0.88
Agartala	0.76	0.56	0.88	0.75
Imphal	0.61	0.46	0.85	0.70
Dibrugarh	0.84	0.81	0.41	−0.08
Silchar	0.74	0.64	0.93	0.58

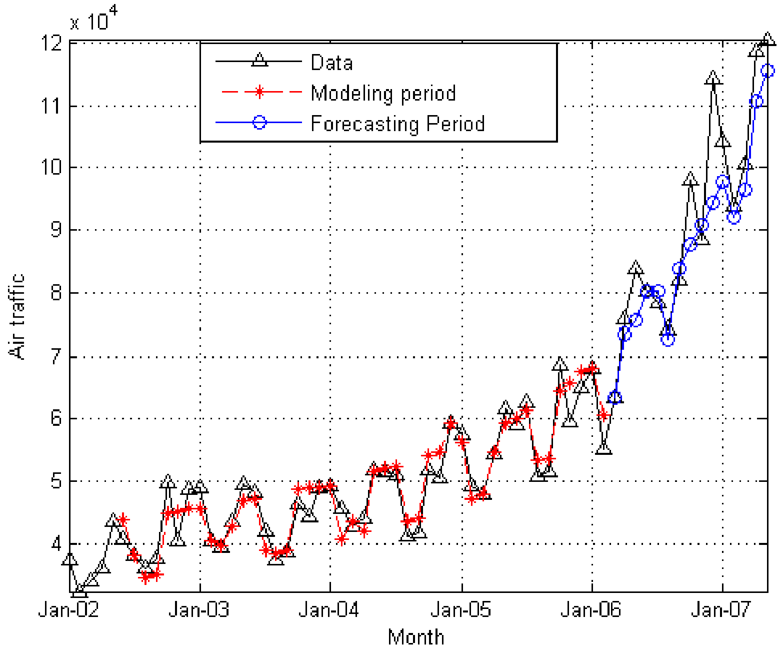

Fig. 4a. Comparison of air traffic data for Guwahati.

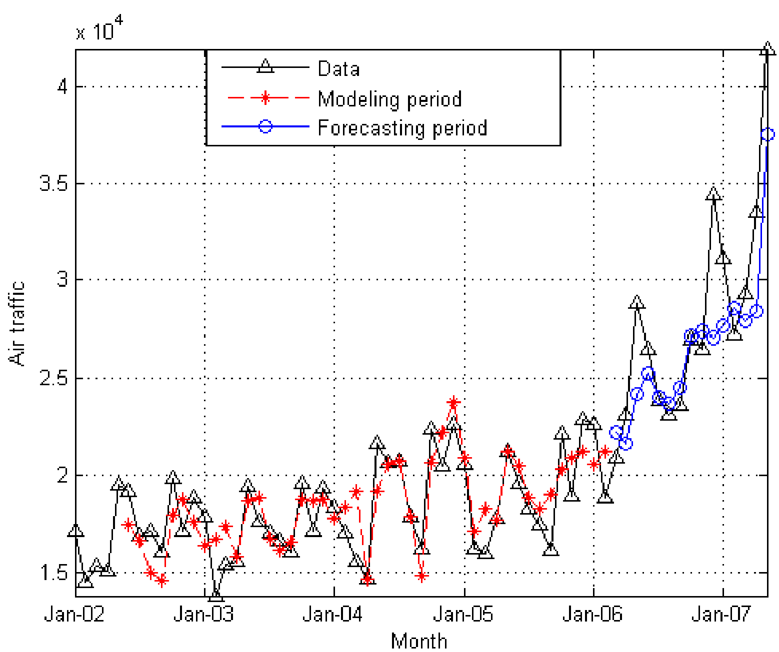

Fig. 4b. Comparison of air traffic data for Agartala.

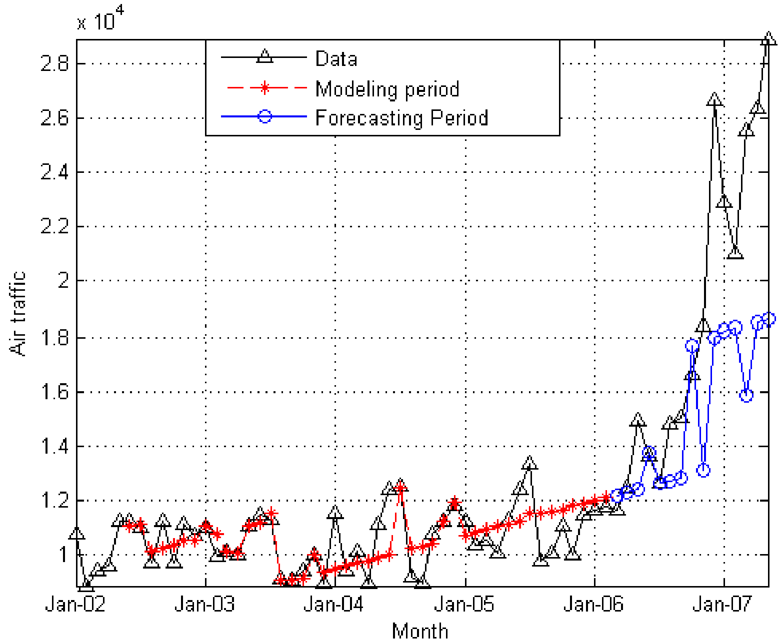

Fig. 4c. Comparison of air traffic data for Imphal.

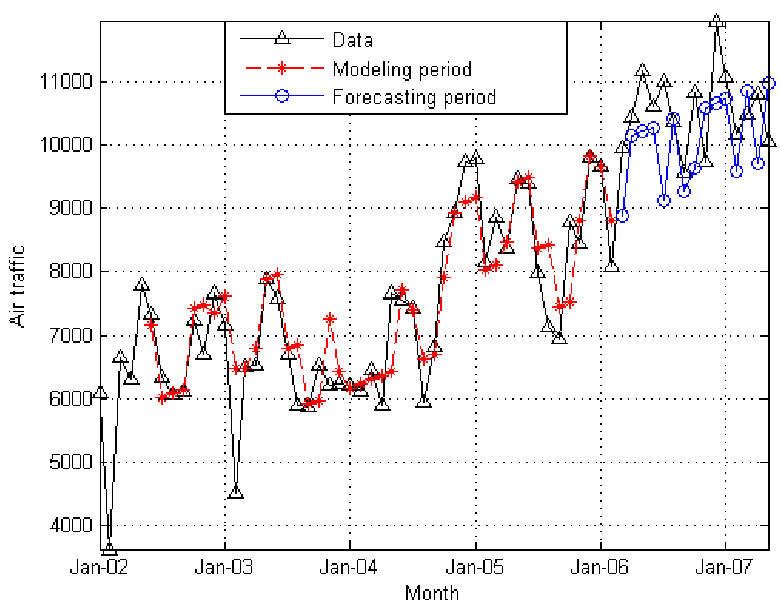

Fig. 4d. Comparison of air traffic data for Dibrugarh.

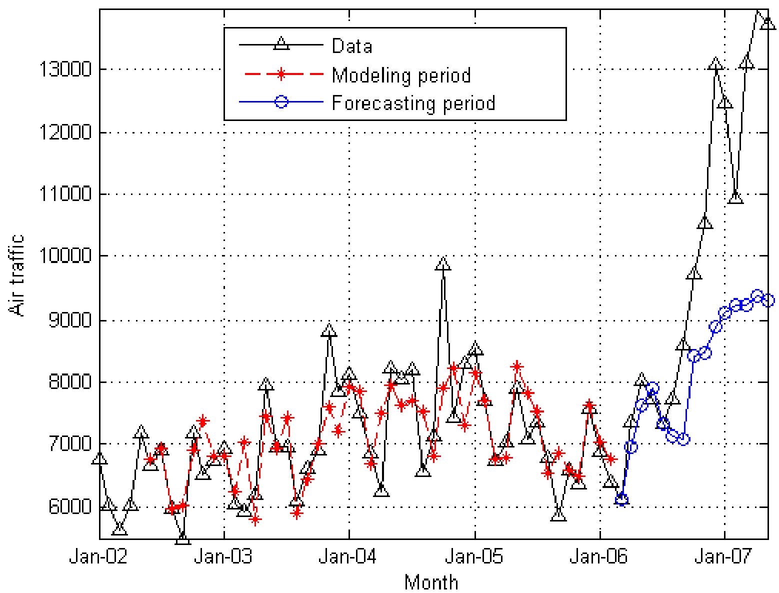

Fig. 4e. Comparison of air traffic data for Silchar.

can be updated, every time before giving a forecast. It is observed that even under this less than ideal condition, the forecasts produced by the model are good. For a sample size of $N = 15$, the correlation coefficient (CC_f) in the test period has to be at least 0.5 to be taken as significant. It is found from Table 6 that the forecasting skill is well beyond this threshold level, in all the cases except Dibrugarh.

6. Summary and Conclusions

A novel approach for investigating and forecasting the variability of air traffic of NERI has been presented here. The empirical mode decomposition of the time series data of five different cities, in terms of IMFs, brings out some interesting features of air traffic data. The first is the possibility of interpreting the air traffic for a given month as the sum of four to five independent modes. The contribution of the last mode to the variance of the total traffic is in between 31% and 82%. The part of the data after removing last IMF characterizes the fluctuation in the data and it has been represented in terms of a nonlinear model. Since it is not obvious what type of nonlinear model has to be used for fluctuation part, after several trials, an ANN model with five input nodes and a single hidden layer with two nodes has been found to be suitable. The trend part of the data which has been represented by the last IMF is modeled empirically using a combination of linear and power functions. Air traffic data from Jan. 2002 to Feb. 2006 has been used for modeling purpose and the remaining data has been used for validation purpose. From the performance indices it has been found that in both modeling and forecasting periods, proposed methodology is able to predict the air traffic reasonably. Proposed models could explain 46–89% of the variability of five air traffic data series used in this study. Except in case of Dibrugarh air traffic data, the proposed models' performance during the forecasting period has been found to be good. Considering the multiplicity of factors that are influencing the air traffic demand and non-availability of the same, the proposed methodology could be used for forecasting the short-term air traffic for other major airports in the developing countries.

References

Bhadra, D. (2003). Demand for air travel in the United States: Bottom-up econometric estimation and implications for forecasts by origin and destination pairs. *J. Air Transport.*, **8**, 2: 19–56.

Bhdra, D. (2008). Structure and Dynamics of core US air travel markets: A basic empirical analysis of domestic passenger demand. *J. Air Transport Manag.*, **14**, 1: 27–39.

Eisner, J. B. and Tsonis, A. A. (1992). Nonlinear prediction, chaos and Noise. *Bull. Amer. Meteorol. Soc.*, **73**, 1: 49–60.

Huang, N. E. and Attoh-Okine, N. O. (2005). *The Hilbert–Huang Transform in Engineering*, Taylor and Francis.

Huang, N. E., Shen, Z., Long, S. R., Wu, C. M., Shih, H. H., Zheng, Q., Yen, N. C., Tung, C. C. and Liu, H. H. (1998). The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. *Proc. R. Soc. London, A* **454**: 903–995.

Iyengar, R. N. and Raghu Kanth, S. T. G. (2005). Intrinsic mode functions and a strategy for forecasting Indian monsoon rainfall. *Meteorol. Atmos. Phys.*, **90**, 1–2: 17–36.

Karlaftis, G. M., Zografos, K. G., Papastavrou, J. D. and Charnes, J. M. (1996). Methodological framework air-travel demand forecasting. *J. Transport. Eng., ASCE*, **122**, 2: 96–104.

Rengaraju, V. R. and Arasan, V. T. (1992). Modeling for air travel demand. *J. Transport. Eng., ASCE*, **118**, 3: 371–380.

Sen, A. (1985). Examining air travel demand using time series data. *J. Transport. Eng., ASCE*, **111**, 2: 155–161.

Strand, S. (1999). Airport-specific traffic forecasts: The resultant of local and non-local forces. *J. Transport Geogr.*, **7**, 1: 17–29.

Traffic News, Airports Authority of India, web: www.airportsindia.org.in, Accessed in January, 2008.