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Predictability of temperature and pressure for issuing aircraft take-off forecast over Madras airport

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सार — वायुयान के निर्धारित प्रस्थान से कम से कम 3 घंटे पहले धरातल के तापमान और वायु दाब से संबंधित कुछ हद तक उपयुक्त पूर्वानुमान प्राप्त हो जाने से वायुयान के कर्मचारियों को यात्रियों और सामान के लिए अनुकूलतम योजना बनाने में सहायता मिलती है। मद्रास हवाई अड्डे पर तापमान और वायु दाब के पूर्वानुमान के लिए मकरीडाकिस और व्हीलराइट (1978) द्वारा बताए गए सामान्यकृत अनुकूलतम फिल्टर (ए. एफ.) एलगारिथम की विधि का प्रयोग किया गया है और इस पूर्वानुमान क्षमता की तुलना सततावृति, स्वतः समाश्रयी प्रक्रिया और अन्य सांख्यिकीय तकनीकों की विधि के द्वारा प्राप्त किए गए पूर्वानुमानों से की गई। इन परिवर्तनीय कारकों की प्रावस्था समष्टि की गति रेखाओं से उत्पन्न आकर्षणों के आयामों का आंकलन सहसंबंध आंशिक आयामों वाले ग्रासबर्गर और प्रोकेशिया (1983) एलगारिथम के प्रयोग द्वारा किया गया है ताकि इन परिवर्तनीय कारकों के प्रतिरूपण के लिए आवश्यक प्रागुक्तिता तथा प्राचलों की न्यूनतम और अधिकतम संख्या का पता लगाया जा सके।

ABSTRACT. Forecasting surface temperature and pressure to a reasonable degree of accuracy atleast 3 hours ahead of the scheduled departure of an aircraft helps the aircrew to make the optimum planning for the payload and cargo load. The method of generalised Adaptive Filter (AF) algorithm as suggested by Makridakis and Wheelright (1978) has been used to forecast temperature and pressure over Madras airport and the forecast efficiency is compared with that obtained through method of persistency, auto regressive processes and other statistical techniques. The dimensions of attractors of the phase space trajectories of these variables have been estimated using the Grassberger and Procaccia (1983) algorithm of correlation fractal dimension with a view to find out the predictability of these variables and the minimum and maximum number of parameters needed for modelling these variables.

Key words — Adaptive filtering, Autoregressive process, Dimensionality, Persistency, Fractal dimension, Take-off forecast, Screening regression.

1. Introduction

The dynamics and the physical/complex processes causing the variability of the weather parameters in time and space pose challenges to the meteorologist to predict the weather elements such as temperature and pressure within specified/allowable error limits. The take-off forecast comprising of temperature and pressure needs to be issued atleast 3 hours ahead of the expected time of departure of an aircraft to enable the aircrew for making a cost effective planning of optimum payload and cargo load. It is a matter of fact that departure of the actual temperature from the forecast value by more than 2°C (specifically on the +ve side) at the time of take-off may cause unloading of few tonnes of cargo and in some cases the passenger loads too (Daya Kishan, 1979; De and Mazumdar, 1997), as the higher temperature warrants higher engine efficiency which will be achieved by expending more fuel and/or reducing the load of the aircraft to obtain sufficient lift (IMD, 1974). Hence forecasting the temperature (pressure) within an absolute error of 1°C (1 hPa) is highly desirable for the safe and efficient aircraft operations. International Civil Aviation Organisation (ICAO, 1995) has prescribed the operationally desirable frequency of accuracy of forecast as the forecast temperature (pressure) should be within ±1°C (±1 hPa) from the actual value in atleast 90% of the cases.

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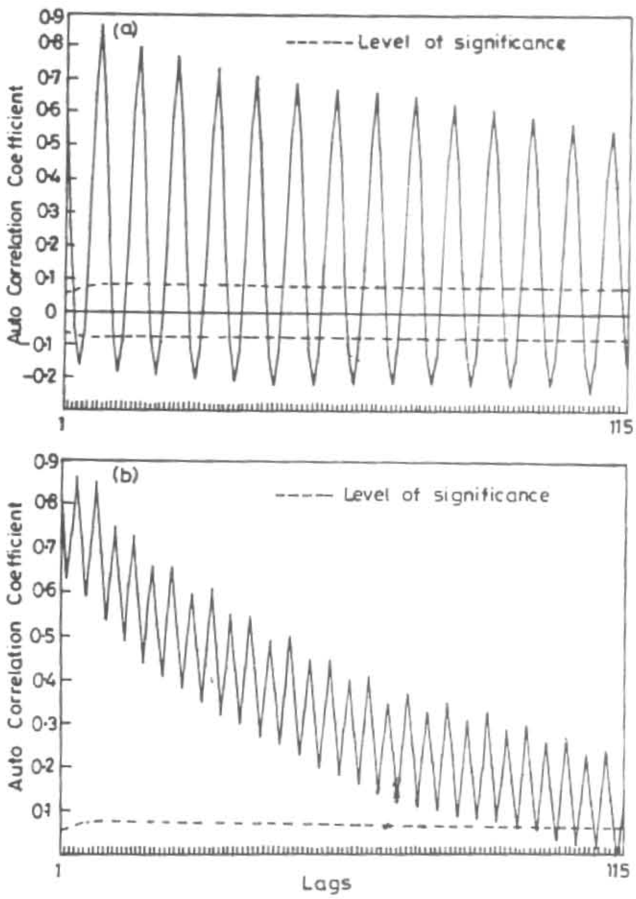
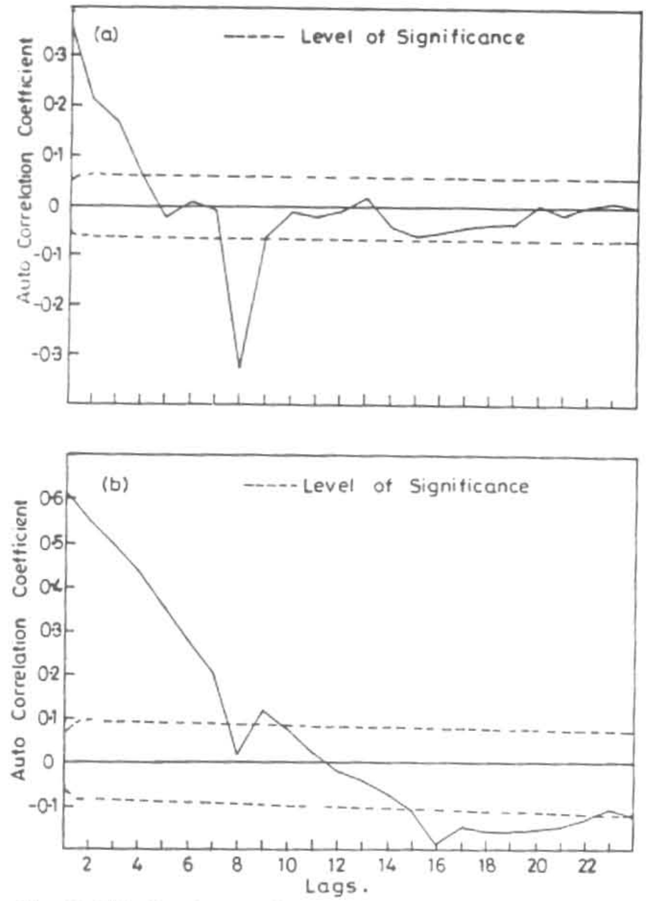


Figs. 1(a&b). Correlogram of (a) temperature and (b) pressure series of auxiliary synoptic hours recorded over Madras airport during October-December 1984-88



Figs. 2(a&b). Correlogram of standardised and seasonal differenced (a) temperature and (b) pressure series of auxiliary synoptic hours recorded over Madras airport during October - December 1984-88

As numerical weather prediction models (NWP) normally run at every 12 hours and the data assimilation and execution of the model usually take three to four hours, the first output will be available only after three to four hours after initial data time. For many aviation applications this duration is a quite long and model-dependent statistical guidance is not very responsive to nowcasting (WHO, 1992). In the absence of a foolproof model to forecast temperature and pressure in a very short time scale (*i.e.*, 3 hours ahead), the operational forecast of these parameters are issued by the meteorologist, as a matter of routine, on climatology and persistency basis. In this paper, an attempt has been made to work out the percentage efficiency of the forecasting skill based on the method of persistency for the forecast periods 0000, 0300, 0600, ..., 2100 UTC. Alternatively, forecasting these parameters employing autoregressive schemes, screening regression and the generalised adaptive filtering have also been attempted and the results of various methods are compared. The dimensionality of the phase space trajectories of these data series were also found out as per the Grassberger and Procaccia algorithm with a view to ascertain as to whether the predictability of these parameters can be deterministic or otherwise.

Since the weather parameters exhibit significant inter seasonal variability besides intra seasonal, to address the forecasting problem, the data have been considered season-wise. For this purpose, the classifications adopted by India Meteorological Department (IMD), *viz.*,

Winter — January and February

Pre-Monsoon — March to May

Monsoon — June to September

Post-monsoon — October to December

have been considered. As the predictability of weather parameters over Madras is quite a challenging task during the extremely pulsatory northeast monsoon (October to December) season, special emphasis is made for this season and the suitability of techniques applied for this season have been explored to the other season also subsequently. We organise this paper in the following manner — section 2 contains the data used in this study, section 3 the correlogram analysis of the timeseries, section 4 the methodology and computation and section 5 the results and conclusion.

2. Data

The 3 hourly auxiliary synoptic data of all the meteorological parameters of observation (in the standard code format) for the period 1984 to 1988 recorded by the Meenambakkam airport meteorological office, Madras have been used. The above data was obtained from the National Data Centre, Pune. Some of the missing data were copied from the records maintained at the climatological section of Regional Meteorological Centre, Madras and wherever it was also not feasible, the same were supplied with the climatological mean values.

3. Correlogram analysis of three hourly surface temperature and pressure for October to December

In order to ascertain as to whether some signal exists within the timeseries itself, auto correlation coefficients (ACC) have been computed upto 300 lags separately for temperature and pressure for the 5 years period. Since the data confine to 3 months period, *viz.*, October - December and they are separated by years, the auto covariances are computed for each year separately and finally composited to get the ACCs. The ACCs show seasonality (lag 8) besides high degree of persistency, as the lags are almost continuously significant upto 114 in the case of temperature and 112 in the case of pressure. Fig. 1 shows a plot of ACCs of both the series. The mean and standard deviation at sub-periods, *viz.*, 0000, 0300, 0600, ..., 2100 UTC are calculated and they are presented in Table 1.

The variability of mean and standard deviation at subperiods could be the cause for non-stationarity of the series. In order to achieve stationarity, the series have been standardised (departure from mean at each sub-period is divided by the respective standard deviation at each sub-period) and the ACCs computed. Now the ACCs have almost dropped to zero after lag 34.

However the significant spikes at seasonal and fractional multiple of seasonal lags still persists. Hence the series have been seasonal differenced (length of seasonality = 8), ACCs computed for the standardised and seasonal differenced series and the correlogram is depicted in Fig. 2.

TABLE 1

Mean and standard deviation of temperature and pressure recorded over Madras airport during October-December 1984-88 at 0000, 0300, 0600, ..., 2100 UTC

Time	Temperature(°C)		Pressure (hPa)	
(in UTC)	Mean	Std. Deviation	Mean	Std. Deviation
0000	23.58	1.77	1008.70	2.99
0300	25.78	1.89	1010.87	2.65
0600	28.88	2.18	1009.99	2.70
0900	29.06	2.39	1007.39	2.92
1200	27.36	1.79	1007.87	2.84
1500	25.68	1.73	1010.03	2.67
1800	24.77	1.75	1009.97	2.50
2100	24.04	1.76	1008.36	2.58

TABLE 2

Forecast efficiency through the method of persistency in forecasting temperature and pressure within an absolute error of 1°C and 1 hPa over Madras airport during 1984-88

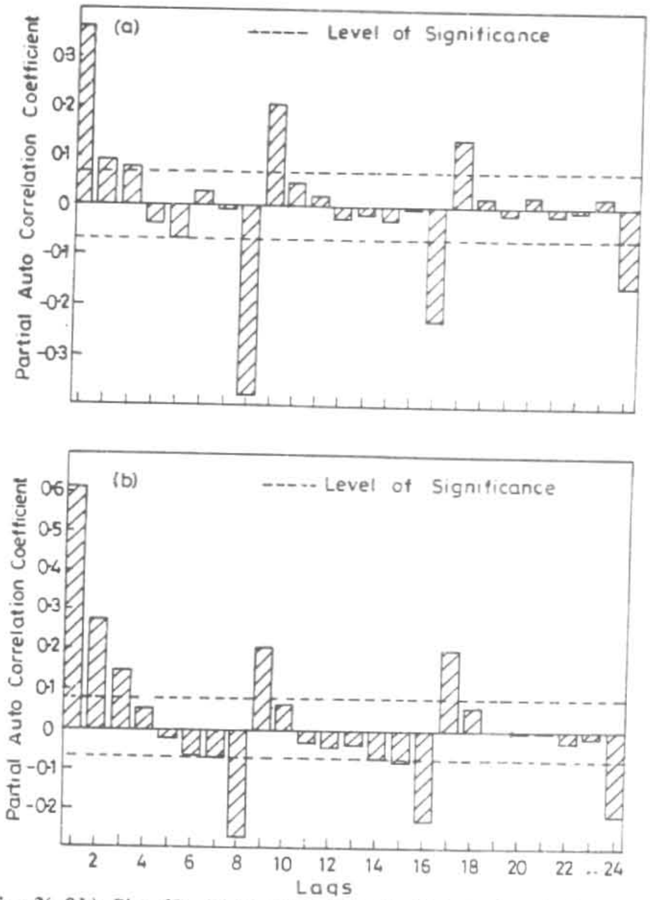
Season	% efficiency in forecasting	
	Temperature	Pressure
Winter	77.6	70.3
Pre-monsoon	77.3	62.7
Monsoon	51.2	66.1
Post-monsoon	68.5	65.5

The series were further first differenced and lag 4 differenced (*i.e.*, at fractional multiple of seasonality) to ascertain the vanishing of stray significant spikes seen at Fig. 2. But the results were not encouraging. As such without complicating the series with further differencing operations, it is concluded that the stray significant spikes (lag 8 in respect of temperature and lags 16 to 21 in respect of pressure) out of 300 lags of ACCs computed from 3680 data points could be due to environmental (observational) noise also. As such the standardised and seasonal differenced series now can be considered as stationary since the ACCs dropped to zero quickly (exponentially) which is a requisite condition for employing the Box - Jenkins ARIMA model (Alan Pankratz, 1983). Similar operations were carried out for other seasons also and the results confirmed the necessity of standardisation and seasonal differencing to bring the series to stationarity which is a pre-requisite for univariate modelling.

4. Methodology and computation

4.1. *Method of persistency*

As the surface temperature and pressure manifest daily cycle (which is revealed by significant ACC at seasonal lag 8), the method of persistency (foreshadowing temperature



Figs. 3(a&b). Plot of Partial Auto Correlation Coefficients of standardised and seasonal differenced (a) temperature and (b) pressure series over Madras airport during October-December 1984- 88

and pressure based on the observed values at the same time period of the previous day) is normally used by operational meteorologist after applying some corrections based on the trend of the current day observed values. The efficacy of this method in predicting temperature and pressure within an absolute error of 1°C and 1 hPa respectively during 1984 to 1988 is summarised in Table 2. As expected, the efficiency in predicting temperature and pressure during winter was better than the other seasons presumably due to minimum convection and associated precipitation during this season. However the desired standard of efficiency as set by ICAO could not be met through this method in any season.

4.2. *Auto Regressive (AR)/Moving Average (MA) process*

The partial auto correlation coefficients (PACC) have been computed upto lag 24 for the standardised and seasonal differenced temperature and pressure series separately to identify the AR/MA process and they are shown in Fig. 3. Here again, the stray (spurious) significant spikes of PACCs were seen at lags 16, 17 in respect of temperature and 14 to 17 in the case of pressure. The significant spikes at lags 1,2,3,8 and 9 suggest that the auto regressive(AR) process of order 3 can be used to forecast the temperature and pressure respectively. However, the significant spikes at lags 8 and 9 (though the intervening spikes at lags 4 to 7 are insignificant) preempted us to try AR(8) and AR(9) processes also. Since the PACCs did not drop to zero quickly and the ACCs have discrete significant spikes, especially in the case of pressure, the MA process has not been attempted. Marquardt's compromise method of estimating the AR coefficients (Alan Pankratz, 1983) has been used. Analysis of ACCs of residuals conform that the models were adequate. As the improvement in efficiency between AR(2) and AR(3) so also between AR(8) and AR(9) was not appreciable and the forecasting model should be parsimonious, results of AR(2) and AR(8) have been tabulated in Table 3. Since the desired standard of efficiency of forecast as set by the ICAO could not be achieved in this method, an alternative approach, *viz.*, Winters' three parameter exponential smoothing (Winters, 1960) to smooth for trend, seasonality and

TABLE 3

Frequencies of the absolute error in forecasting the temperature within 1° C and the pressure within 1 hPa over Madras during October to December 1988 by using the auto regressive (AR) process

Absolute error	Temperature		Pressure	
	AR(2) model	AR(8) model	AR(2) model	AR(8) model
≤0.25	150	136	155	169
0.251-0.5	148	134	168	150
0.501-0.75	112	104	128	135
0.751-1.0	86	85	106	103
≤1.00	496	459	557	557
	(68.3%)	(63.7%)	(76.7%)	(77.4%)
≥ 1.00	230	261	169	163
Total	726	720	726	720

TABLE 4

Results of Winters' three parameter exponential smoothing in forecasting surface temperature at Madras airport during 1988

Season	Best values of coefficients			RMSE (°C)	% efficiency
Winter	0.359	0.159	0.299	1.328	65.25
Pre-monsoon	0.360	0.160	0.300	1.366	60.99
Monsoon	0.310	0.120	0.260	1.726	54.54
Post-monsoon	0.280	0.100	0.230	1.527	52.06

TABLE 5

Comparison of forecast efficiency of adaptive filtering (AF) method with the method persistency in predicting pressure (within an error ±1 hPa) over Madras airport during October - December 1988

Particulars	Time (UTC)							
	0000	0300	0600	0900	1200	1500	1800	2100
Method of persistency	68.1	65.9	63.7	47.3	53.8	60.4	69.2	69.2
Order of AF	2	2	2	2	2	2	2	8
AF model efficiency	72.5	80.2	92.3	98.9	98.9	93.4	97.8	86.8
AF model RMSE	0.92	0.82	0.56	0.52	0.61	0.74	0.77	0.69
AF test period RMSE	0.99	0.76	0.60	0.44	0.45	0.48	0.43	0.67
Standard deviation	1.77	1.89	2.18	2.39	1.78	1.73	1.75	1.76

TABLE 6

Comparison of forecast efficiency of adaptive filtering (AF) method with the method persistency in predicting temperature (within an error of ±1 °C) over Madras during October - December 1988

Particulars	Time (UTC)							
	0000	0300	0600	0900	1200	1500	1800	2100
Method of persistency	70.3	63.7	69.2	67.0	76.9	67.0	75.5	72.5
Order of AF	2	8	8	8	8	8	8	9
Efficiency of AF model	80.2	68.1	59.3	68.1	82.4	69.2	82.4	93.1
AF model RMSE	0.83	0.96	1.34	1.39	0.96	0.89	0.87	0.84
AF test period RMSE	0.83	1.05	1.30	1.08	0.80	1.02	0.76	0.87
Standard deviation	2.99	2.64	2.92	2.92	2.84	2.67	2.50	2.58

stationarity was attempted. The method is described in the next section.

4.3. *Winters' three parameter exponential smoothing*

Winters' scheme is based on three equations, *viz.*,

$$S_t = \alpha \frac{X_t}{I_{t-L}} + (1-\alpha)(S_{t-1} + b_{t-1})$$

$$b_t = \gamma (S_t - S_{t-1}) + (1-\gamma) b_{t-1}$$

$$I_t = \beta \frac{X_t}{S_t} + (1-\beta) I_{t-L}$$

where $\{X_t\}$ is the time series considered.

S_t is the smoothed value of the series that does not include seasonality,

L is the length of seasonality (in the present study L = 8 which is nothing but the daily cycle of weather parameter as 8 lags of 3 hours duration constitute a day),

b_t accounts for trend smoothing and

I_t is the seasonal adjustment factor.

The coefficients α, β, γ are to be obtained through iterative search so as to minimize the root mean squared error (RMSE). Data pertaining to 1984 to 1987 were used for developing the model coefficients and that of 1988 was used for verification. The best values of α, β, γ and the efficiency in forecasting temperature within the error limit desired have been tabulated in Table 4. The results of this method were rather inferior to those of the method of persistency and AR processes (our findings on the applicability of this method to meteorological variables/supremacy of AR process over this method corroborates the earlier finding by Reid (1971) as furnished in Kendall, 1973). As such this method was not tried for the pressure series. Hence another method, *viz.*, the method of generalised adaptive filtering was tried. The method is briefly outlined here.

4.4. *Method of generalised adaptive filtering (AF)*

The time series $\{X_t\}$ can be modelled as

$$X_t = \sum_{i=1}^{p} \phi_i X_{t-i} + e_t$$

where p is the order of the process, e_t is the residual error and ϕ_i *s* are estimated such that the e_t is the minimum. The ϕ_i *s* are estimated through non-linear least square method using the method of steepest descent algorithm to cause for the reduction in the Mean Squared Error (MSE). The method starts with the initial values of ϕ_i (i = 1,2,3, ..., p) and by repeatedly applying the recurrence relation $\phi'_i = \phi_i + 2Ke_t X_{t-i}$ where ϕ'_i is the newly adapted parameter and K is the learning constant which speeds up the adaptation. The itera-

TABLE 7

Results of forward screening regression analysis for forecasting temperature over Madras during October - December 1988

Variables used in the equation	Beta coefficients	Std. error of coefficients	'*T*' value	Probability of exceeding '*T*' limits
Temp. lag 8	0.823313	0.017164	47.968*	0.000005
R.H. lag 1	-0.283184	0.040855	-6.931*	0.00001
U lag 1	-1.777773	0.613076	-2.900#	0.0038
Constant term	7.403983	0.692213	10.696*	0.00001

* - significant even beyond 0.001% level,

\# - significant at 0.1% level,

R.H. - Relative Humidity; *U* - *U* component of the wind direction.

iterations will be stopped at a desirable stage of reduction in MSE say the new MSE is no better than the previous MSE by 0.0001 or so. The theoretical basis of this algorithm, the computational procedure and the efficiency of the method of steepest descent guarenting convergence have been described in the celebrated papers of Wilde and Beighter (1964), Widrow (1966) and Wheelright and Makridakis (1973).

The attractive feature of the adaptive filtering is that its parameters (coefficients) automatically get adjusted as and when a new data is made available and for this reason the AF can be considered as a subset of artificial neural network which recognises the changing pattern of the series. Also the stationarity is not the stringent requirement for AF technique.The value of K within the limits $0 < K \leq 1 / (\sum_{1}^{p} X_t^2)_{max}$ guarantees convergence, according to widrow (1966). Values of K outside this limit may also work, but the convergence will be very slow and the result may be sub-optimal. Makridakis and Wheelright (*loc. cit*) have shown that the upper limit of K is governed by the inequality $K \leq 1/p$ where p is the order of the process. Hence, we have chosen the upper limit of K as 0.5 ($K \leq 1/2$) to conform the AF(2) process and the lower limit was selected based on the value of inverse of sums of squares of maximum values in each series separately corresponding to the order of AF process (p). However, in any case, the values of X_t need to be standardised, *viz.*, $X_t^* = (X_t / \sqrt{\sum_{1}^{p} X_{t-i}^2})$ to ensure uniform convergence that is independent of data set fluctuations since the future values of X_t may be larger than that of those observed previously.

The value of the learning constant K has been varied from 0.00001 to 0.50 in steps of 0.001 to find out that value of K which gives the minimum MSE of the model. We found that K = 0.0015 is the best choice of the learning constant. The modelling was done for the data pertaining to 1984-1987 and validation of the model was done for the year 1988 for the order of processes varying from 2 to 9. Table 5 lists the forecasting efficiency of the adaptive filtering method in forecasting the pressure. For comparison, the method of persistency (forecasting of pressure based on the pressure value of the previous day at the same time of observation) has been made, as this method is by and large followed by the operational forecasters after applying small corrections depending on other synoptic/climatological considerations. The AF model and test period RMSEs are very much comparable with the original standard deviation suggesting that the skill of AF model is very good. It can also be seen that the AF (2) / AF (8) processes not only performed better than the method of persistency and AR process but also meets the desired standard of operational efficiency set by ICAO.

However, the forecast of temperature based on AF(8) process (which has performed well in comparison to other AF processes ranging from 2 to 9) did not fully meet the target fixed by ICAO though its performance was far better than the persistence (see Table 6). The stability of the filtering coefficients were obtained in less than 100 iterations and that too in AF (2) process itself in the case of pressure but the number of iterations went up as high as 3000 in the processes ranging from AF(2) to AF(9) in the case of temperature. One of the reasons for the slow convergence of the temperature model might be that the daily range of temperature varies so widely due to the persistent low/medium clouds covering more than half the sky and their dissipation due to precipitation was also not uniform in the northeast monsoon period (the daily range of pressure value is far less than that of temperature). The pulsatory behaviour of northeast monsoon rainfall had already been well established by many research workers.

Though the AF model and test period RMSEs are lower than that of the original standard deviation conforming the suitability of the models identified, the forecast efficiencies are far below the ICAO standard at 0300, 0600, 0900 and 1500 UTC. Nevertheless, the models performed better than

TABLE 8

Performance of adaptive filter algorithm in forecasting temperature (within ± 1 °C error limit) and pressure (within ± 1 hPa error limit) at Madras airport during 1988

Time	Temperature				Pressure			
(UTC)	AF(p)	S.D	RMSE	Pers AF efficiency(%)	AF(p)	S.D	RMSE	Pers AF efficiency (%)
				Winter				
0000	2	1.51	1.14	86.2	2	2.32	0.55	91.4
0300	3	1.39	0.65	86.2	3	2.26	0.50	86.2
0600	8	1.51	0.74	81.0	2	2.19	0.38	98.3
0900	8	1.51	0.46	94.8	2	2.31	0.37	96.5
1200	9	1.07	0.36	96.6	2	2.48	0.42	98.3
1500	9	1.06	0.44	94.8	2	2.49	0.34	98.3
1800	8	1.38	0.61	86.2	2	2.25	0.42	93.1
2100	9	1.38	0.54	93.1	9	2.24	0.35	100.0
				Pre-monsoon				
0000	3	2.17	0.91	81.1	3	3.23	0.88	76.7
0300	3	2.20	1.03	77.8	3	3.09	1.02	84.4
0600	8	2.51	1.72	66.7	2	3.37	0.66	85.5
0900	8	2.78	1.91	60.0	3	3.39	0.64	92.2
1200	8	2.09	1.33	78.9	2	3.24	0.54	94.4
1500	8	1.83	0.80	83.3	2	3.45	0.80	91.1
1800	2	2.02	0.54	93.3	2	3.32	0.59	93.3
2100	9	2.13	0.66	84.4	9	3.10	0.56	88.9
				Monsoon				
0000	3	1.66	1.15	73.3	3	2.46	0.91	83.3
0300	3	1.92	1.23	66.7	3	2.41	0.93	78.3
0600	8	2.35	1.60	66.7	2	1.76	0.62	95.0
0900	2	2.70	2.07	52.5	2	2.19	0.78	88.3
1200	8	2.48	2.18	46.7	2	2.39	0.65	92.5
1500	8	1.79	1.15	71.7	3	2.13	0.74	85.0
1800	3	1.74	1.12	78.3	2	1.96	0.67	95.0
2100	8	1.74	1.02	80.0	9	2.06	0.76	90.8

TABLE 9

Results of dimensionality analyses of standardised and seasonal differenced three hourly temperature and pressure series at Madras during 1984-88

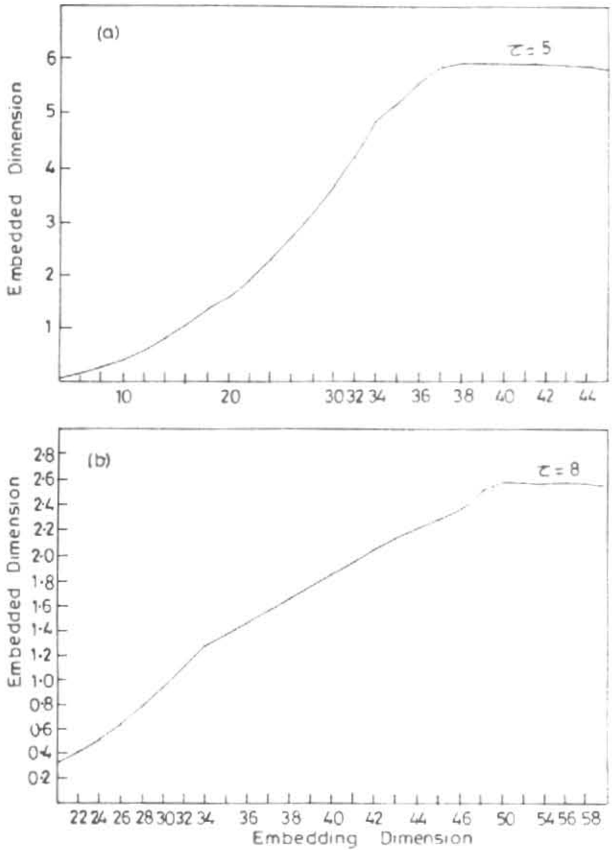
Season	No. of data points	Time shift	Temperature		Time Shift	Pressure	
			S.D.	F.D.		S.D.	F.D.
Winter	2376	5	35	4.492	8	46	1.179
Pre-monsoon	3680	5	66	3.836	8	57	3.543
Monsoon	4880	7	36	7.230	8	42	3.980
Post-monsoon	3680	5	38	5.934	8	52	2.590

S.D. = The dimension at which saturation is attained (upper bound of the number of parameters needed for modelling)
F.D. = Fractal dimension or the saturating dimension (lower bound of the number of parameters needed for modelling)

the method of persistency which is normally followed by forecasters in view of operational urgency and other statistical models attempted.

4.5. *Screening regression*

The problem of forecasting temperature was then attempted based on multivariate analysis as the univariate method could not yield the expected level of accuracy. The predictors selected were wind direction and speed (its *U* and *V* components), pressure and relative humidity (RH) all were of one time lag (in the present study one time lag is 3 hours as we utilise the auxiliary synoptic hours data), temperature of time lag 8 (*i.e.*, corresponding temperature of previous day, analogous to persistency, as it has very high



Figs. 4(a&b). Plot of embedded dimension *Vs* embedding dimension of standardised and seasonal differenced (a) temperature and (b) pressure series over Madras airport during October-December 1984-88

correlation coefficient significant even at 0.1% level). The method of forward screening was resorted to on the data pertaining to 1984-87 as the developmental period. Choosing temperature of lag 8, RH of lag 1 and wind direction of lag 1 as the potential predictors, the validation of the prediction equation was done for the year 1988.

The multiple correlation coefficient after including these variables in the predicting equation is 0.87791. The analysis of variance reveals the F value as 1077.96 which is very highly significant as the probability of exceeding this F value is 0.00001, in other words this is significant even beyond 0.001% level of significance. The results of screening regression analysis are summarised in Table 7. The percentage efficiency was 71.5% [which is slightly better than the AR process efficiency (68.3%) but lower than AF process (74.5%)] which again is lower than the desired goal, *viz.*, atleast in 90% of the cases the absolute error of the forecast should be less than 1°C. Considering the simplicity and parsimony as the criteria for a good model, we ultimately concluded that the AF processes may be used for forecasting temperature and pressure over Madras airport.

4.6. *Results of AF models for winter, pre-monsoon and monsoon seasons*

Data of 1984-87 of the other seasons were subjected to AF processes on the lines similar to those mentioned in section 4.4. The best orders of AF that ensured minimum MSE and their efficiencies in predicting temperature and pressure within the error limit prescribed are furnished in Table 8. The efficiency obtained through the method of persistency at different time periods are also furnished in Table 8 for comparison. The AF processes have almost met the ICAO target in predicting pressure in all seasons while the efficiency in some improvement is still needed in predicting temperature during 0300 to 0900 UTC in all except winter season. Nevertheless, it is evident that the AF models perform far better than the other forecasting methods.

4.7. *Dimensionality analysis*

As the predictability of temperature in all these methods, *viz.*, persistency, univariate and multivariate techniques did not fully meet the objectives, it was considered necessary to do the dimensionality analysis to find out as to whether the attractors of the phase space trajectories are randomly chaotic or deterministic. The correlation fractal dimension algorithm suggested by Grassberger and Procaccia (1983) which has been freely used by many research workers (Bhattacharya *et al.*, 1995; *Sangeet* Chatterjee and Mustafa Yilmaz, 1995; Satyan, 1988; Sujit Basu and Andharia, 1992) is used in this study also.

Since the ACC upto lags 114 were significant (in respect of October to December), but the computation of embedded dimension requires that the data points should be independent, it is absolutely essential to have the timeshift (τ) as 115 which is very high and the number of coordinates in phase space will be considerably reduced. As such, we utilized the standardised and seasonal differenced temperature and pressure series since the lag 5 in respect of temperature and lag 8 in respect of pressure are insignificant and the series are almost stationary (as can be seen from Fig. 2). Moreover, due care has been taken in transforming the data into phase space trajectory coordinates with timeshift 5 and 8 (for temperature and pressure respectively) so that trial end data coordinate of one year does not mix with the front end data coordinate of the next year while computing the Euclidean distance between the phase space trajectory coordinates; in other words, as the data are separated by an yearly interval, the Euclidean distance computation between coordinates of phase space were resorted to individual years and finally composited to get the embedded dimension. The saturation of the embedded dimension in both the cases are very slow and a plot of embedded dimension with embedding dimension is shown in Fig. 4.

The fractal dimension of the strange attractors of the temperature series is 5.93 and the saturation has been reached in an embedding dimension of 38, whereas the fractal dimension of pressure series is 2.58 and the saturating embedding dimension is 52. From this dimensionality, it can be inferred that a minimum of 6 parameters are necessary with an upperbound of 38 parameters are needed for modelling the temperature and the minimum and maximum number of parameters required for modelling the pressure are 3 and 52. Though the methods discussed so far employ the number of parameters between this lower and upperbound, further analysis on the combination of various parameters need to be carried out to meet the standard of accuracy of operational forecast. However keeping in view of the parsimony and operational feasibility, AF(8) and AF(9) processes for forecasting the temperature and AF(2) and AF(8) for pressure over Madras airport may be followed as these models have efficiency better than persistency and with a small desk calculator the forecast can be issued in no matter of time by utilising the recent past data of the same station. The results of the dimensionality analysis are summarised in Table 9. The minimum number of data points (N) required for computing the dimensionality (D) as laid in Ruelle (1990), *viz.*, $2 \log_{10} N > D$ is totally satisfied by the length of the series considered.

5. Results and conclusions

(*i*) The adaptive filtering technique can be used to forecast temperature and pressure over Madras airport as its efficiency is better than other statistical method and it almost meets the target set by ICAO on operationally desirable accuracy of forecast.

(*ii*) The dimensionality analyses reveal that the attractor dimensions are fractal and the phase space trajectories are deterministic chaos suggesting that the modelling is feasible. Since it warrants high number of parameters that would be sufficient for modelling, further analysis need to be conducted.

6. Scope for future work

The forecasting of temperature based on dynamical parameters such as temperature advection from the nearby source, insolation and radiation etc by considering data of adjacent stations is being attempted. Also the suitability frontier regression model employing the maximum likelihood estimating procedure is also being explored.

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