

## Multi layer perceptron model in pattern recognition of surface parameters during pre-monsoon thunderstorm

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**सार** - इस शोध-पत्र में कोलकाता ( $22^{\circ} 32'$ ,  $88^{\circ} 20'$ ) में मानसून ऋतु से पूर्व की तड़ित झंझाओं की घटनाओं के पूर्वानुमान से संबंधित धरातल के प्राचलों के पैटर्न का पता लगाने के लिए बहुसतही पर्सेप्ट्रान तथा फ्यूजी तर्क-वितर्क की अवधारणा का उपयोग किया गया है।

इनसे प्राप्त हुए परिणामों से यह पता चला है कि तड़ित झंझाओं के दिनों में फ्यूजी बहुसतही पर्सेप्ट्रान (एफ.एम.एल.पी.) निदर्श के मानों से धरातल के तापमान में उल्लेखनीय रूप से उतार-चढ़ाव आता है जबकि गैर-तड़ित झंझाओं के दिनों में एफ.एम.एल.पी. के निदर्श का धरातल के तापमान के साथ सही मेल पाया जाता है।

इनसे प्राप्त हुए परिणामों से यह भी पता चला है कि कोई भी निश्चित पैटर्न धरातल के ओस बिन्दु तापमान और धरातल के अवदाब के लिए उपलब्ध नहीं करवाया जा सकता है जो इन तूफानों की घटनाओं का पूर्वानुमान लगाने में सहायक हो सके।

**ABSTRACT.** The concept of Multi Layer Perceptron and Fuzzy logic is introduced in this paper to recognize the pattern of surface parameters pertaining to forecast the occurrence of pre-monsoon thunderstorms over Kolkata ( $22^{\circ} 32'$ ,  $88^{\circ} 20'$ ).

The results reveal that surface temperature fluctuates significantly from Fuzzy Multi Layer Perceptron (FMLP) model values on thunderstorm days whereas on non-thunderstorm days FMLP model fits well with the surface temperature.

The results further indicate that no definite pattern could be made available with surface dew point temperature and surface pressure that can help in forecasting the occurrence of these storms.

**Key words** – Multi Layer Perceptron, Fuzzy logic, Pattern recognition, Pre-monsoon thunderstorms, Forecast.

### 1. Introduction

Pre-monsoon thunderstorm, locally known as Nor'wester, is a type of severe local storm which occurs over northeastern part of India during the period (March-May), when the wind flow pattern in the lower levels is in rapid transition from winter to southwest monsoon circulation with upper levels still maintaining the westerly flow of the winter. The prediction of the occurrence of these storms is of great concern to the atmospheric scientists of India because of the devastating nature

leading, occasionally, to tremendous hazards. Basic phenomenon associated with severe local storm is thunderstorm, which in turn is associated with cumulus convection. It is a link between the turbulent flow in the lower levels to laminar flow in the free atmosphere. It, thus, involves, among other things, the physical processes that take place in the lower level for exchange of heat, momentum and mass as well as the microphysics of the cloud formation above the condensation level. The triggering of such storms, therefore, depends upon the nature of the surface parameters. Traditionally

meteorological measurements made at the earth's surface are called the surface observations. These surface measurements or surface observations are principally used for synoptic analysis to define the state of the atmosphere and the position of the development of the weather system at the surface. The recorded measurements used by the forecasters to prepare surface weather maps have included pressure, temperature, dew point temperature, wind speed and wind direction etc. These surface parameters are observed at least every three hourly, at 0000 UTC, 0300 UTC, 0600 UTC and so on. Based on the observations of the surface parameters many investigations were undertaken and performed to forecast the occurrence of pre-monsoon thunderstorms over northeastern part of India. Normand (1921) studied the wet bulb process in thunderstorm cloud and identified the air mass thunderstorm. Sohoni (1928) investigated sharp change in surface parameters with the passage of thunder squalls and possible interaction with the environment at various levels. Sen (1931) observed the influence of orography in vergence field causing moisture flow. Koteswaran and Srinivasan (1958) suggested coupling of low level and upper level features. Raisarkar (1953) observed that thermodynamic structure of the atmosphere over Calcutta got modified due to the advection of temperature changes. Desai and Rao (1954) had given primary importance to the low level features.

The present study although concerns the analysis of the surface parameters during the occurrence of pre-monsoon thunderstorms, but the approach is different, having an aroma of newness. In the current paper the concept of multi layer perceptron model with fuzzy logic is being introduced to visualize its potential in forecasting the occurrence of pre-monsoon thunderstorm over Kolkata by recognizing the pattern of the surface parameters. The multi-layer perceptron model developed here have been used in recognizing the pattern of some parameters on the basis of a given set of inputs. The orientation of the pattern of a particular parameter can help in the prediction of the event in future. The most important feature of this model is its adaptive nature, where learning by example can solve a problem. This feature makes it very appealing in application domain where there is little or incomplete understanding of the problem to be solved, but training data is readily available.

**2. Methodology**

*2.1. Architecture of the model*

The classical Perceptron represents a whole network for the solution of certain pattern recognition problems. The essential innovation of Perceptron model is to

introduce numerical weights and a special interconnection pattern between inputs and outputs (Rosenblatt, 1961). A simple Perceptron is a computing unit with certain threshold, such that 'n' real inputs  $X_1, X_2, X_3, \dots, X_n$  through edges with weights  $W_1, W_2, W_3, \dots, W_n$  lead to an output '1' if  $\sum W_i X_i \geq \theta$  and an output '0' if  $\sum W_i X_i < \theta$ , where ' $\theta$ ' is the threshold. Perceptron of zero threshold is more convenient to deal with (Rojas, 1996). This corresponds to linear separations that are forced to pass through the origin of the input space. In general, a multi layer perceptron consists of a lowermost input layer, any number of hidden layers and an output layer at the top. In a network, the total input received by neuron 'j' in (h+1) layers is defined as;

$$X_j^{h+1} = \sum_i Y_i^h W_{ji}^h - \theta_j^{h+1} \tag{1}$$

where

$Y_i^h$  – state of the  $i^{\text{th}}$  neuron in the preceding  $h^{\text{th}}$  layer,

$W_{ji}^h$  – weight of the connection between  $i^{\text{th}}$  neuron  $h^{\text{th}}$  layer and  $j^{\text{th}}$  neuron  $(h + 1)^{\text{th}}$  layer,

$\theta_j^{h+1}$  – threshold of  $j^{\text{th}}$  neuron in  $(h + 1)$  layer.

For convenience, the threshold ' $\theta$ ' is taken to be zero. Equation (1), thus, modifies to;

$$X_j^{h+1} = \sum_i Y_i^h W_{ji}^h \tag{2}$$

where

$$Y_i^h = \begin{cases} [1 / \{1 + \exp(-X_j^h)\}] & \text{for } h > 0 \\ X_j^0 & \text{for } h = 0 \end{cases} \tag{3}$$

$W_{ji}^h$  is set to small random values within  $[-0.5, 0.5]$  (Pal *et al.*, 1999).

A fuzzy multi layer perceptron can be designed with the help of interval valued fuzzy sets (Kwon *et al.*, 1994) containing the following elements;

(i) *Input vector*

$$X_p^0 = (X_{p1}^0, X_{p2}^0, X_{p3}^0, \dots, X_{pn}^0) \tag{4}$$

Where

$$X_{pi}^0 = (X_{pi}^{OL}, X_{pi}^{OU}) \quad (5)$$

$$i = 1(1)n$$

$OL$  – lower bound of the interval

$OU$  – upper bound of the interval.

(ii) Operations at the input ( $h = 0$ ) as well as hidden and output layers ( $h > 0$ );

$$Y_{pi}^h = X_{pi}^h; \quad i = 1(1)n \quad (6)$$

Where,

$$X_{pk}^h = \sum_i Y_{pi}^{h-1} W_{ki}^{h-1} + \theta_k^h; \quad k = 1, 2, 3, \dots, m^n \quad (7)$$

and  $m^n$  – number of hidden nodes in 'h' layer.

## 2.2. Learning rule of the model

To describe the learning rule of the model, for sake of simplicity, the output of the hidden layer is taken as a  $J$ -dimensional real-valued vector

$$Z = (z_0, z_1, z_2, \dots, z_j)^T$$

The vector  $Z$  supplies the input for the output layer of  $L$  units. This output layer generates an  $L$  - dimensional vector  $y$  in response to the input vector  $x$  which, when the network is fully trained, becomes identical to a desired output vector  $d$  associated with  $x$ . For simplicity,  $Y_i^h, s$  defined in equation (3), are denoted by  $f_h(\text{net})$ . The connection weights are then adjusted to minimize the error function (Rumelhart *et al.*, 1986b) over the training set

$$E = (1/2) \sum_{l=1}^L (d_l - y_l)^2 \quad (8)$$

Using delta rule (Hassoun, 1999), the weights are updated as;

$$\Delta \omega_{ij} = \omega_{ij}^{\text{new}} - \omega_{ij}^c = (-) \rho_0 (\partial E / \partial \omega_{ij}) \quad (9)$$

$$\Delta \omega_{ji} = \omega_{ji}^{\text{new}} - \omega_{ji}^c = (-) \rho_h (\partial E / \partial \omega_{ji}) \quad (10)$$

where

$\omega_{lj}$  – input layer weights

$\omega_{ji}$  – hidden layer weights

$\omega_{lj}^{\text{new}}, \omega_{ji}^{\text{new}}$  – updated (new) weights

$\omega_{lj}^c, \omega_{ji}^c$  – current weights

$\rho_0, \rho_h$  – small positive values.

$$j = 1, 2, 3, \dots, J$$

$$l = 1, 2, 3, \dots, L$$

$$i = 1, 2, 3, \dots, N$$

Now,

$$\frac{\partial E}{\partial \omega_{ji}} = \left( \frac{\partial E}{\partial Z_j} \right) \left[ \frac{\partial Z_j}{\partial (\text{net}_j)} \right] \left[ \frac{\partial (\text{net}_j)}{\partial \omega_{ji}} \right] \quad (11)$$

With

$$\frac{\partial (\text{net}_j)}{\partial \omega_{ji}} = x_i \quad (12)$$

$$\frac{\partial Z_j}{\partial (\text{net}_j)} = f'_h(\text{net}_j) \quad (13)$$

$$\begin{aligned} \frac{\partial E}{\partial Z_j} &= \frac{\partial}{\partial Z_j} \left\{ (1/2) \sum_{l=1}^L [d_l - f_0(\text{net}_l)]^2 \right\} \\ &= (-) \sum_{l=1}^L (d_l - y_l) f'_0(\text{net}_l) \omega_{lj} \end{aligned} \quad (14)$$

Thus,

$$\Delta \omega_{ji} = \rho_h \left[ \sum_{l=1}^L (d_l - y_l) f'_0(\text{net}_l) \omega_{lj} \right] f'_h(\text{net}_j) x_i \quad (15)$$

Small positive constants  $\rho_0$  and  $\rho_h$  are initially set to some value less than 1 (one) and then they are made to

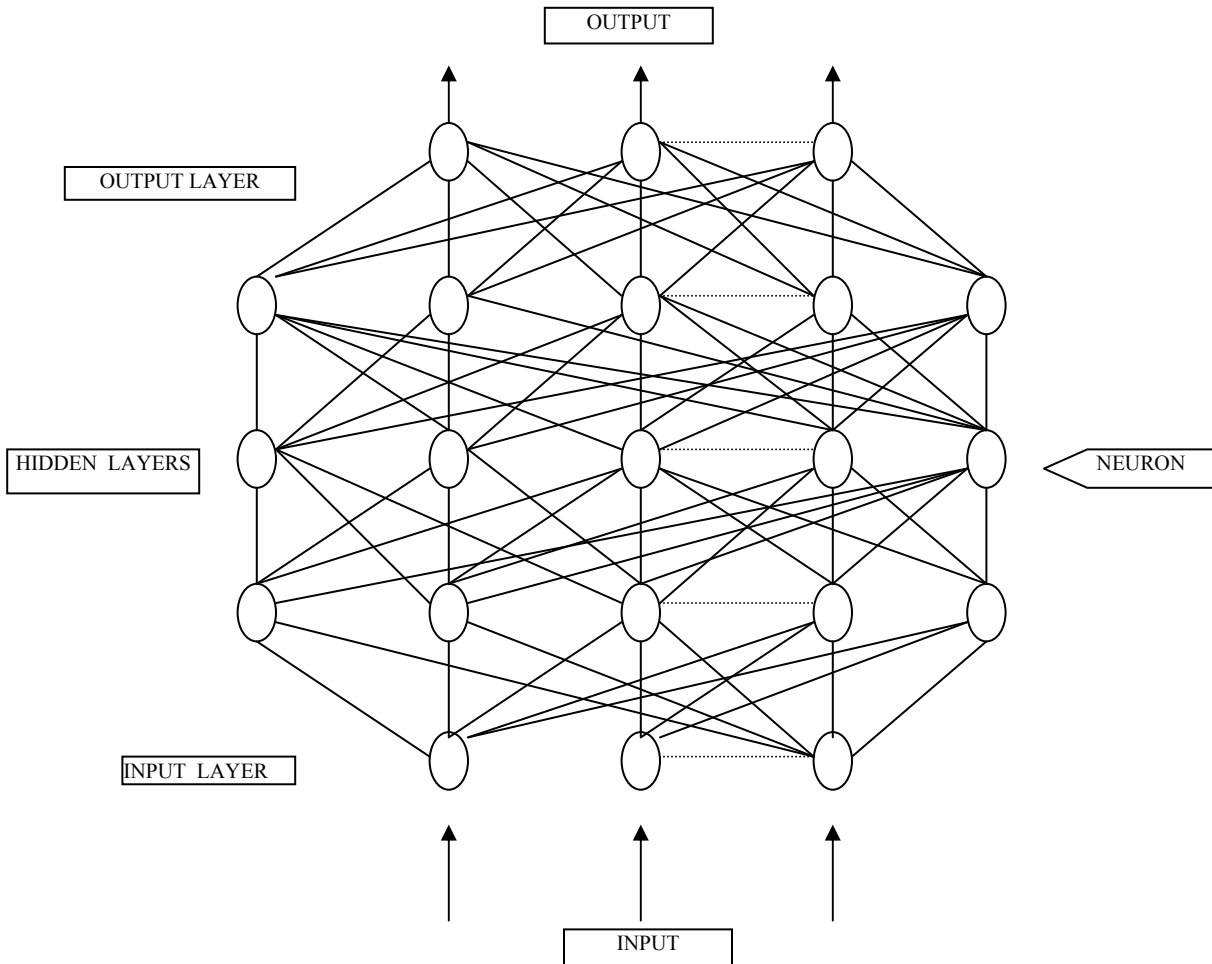


Fig. 1. Schematic representation of multi layer perceptron with three hidden layers

evolve themselves to make the network converge to a desired output ( Chan and Fallside, 1987).

Ultimate error signal is

$$(d_j - y_j) = \sum_{i=1}^L (d_i - y_i) f'_0(\text{net}_i) \omega_{ij} \quad (16)$$

The procedure of learning stops when the error becomes sufficiently small. The acceptable range of error will vary according to the nature of the input patterns. The training can be done with different number of nodes and different error will be generated.

### 3. Results and discussion

A multi layer perceptron model with fuzzy logic having zero threshold is designed in this paper to

recognize the pattern of surface temperature, surface dew point temperature and surface pressure over Kolkata during the pre-monsoon month (April, 1997) (Figs. 2, 3, & 4). The thunderstorms that occur in April are less in number but severe in nature, which can be depicted from the climatological chart. Prediction of such storms is more difficult. This is the reason why the month of April has been chosen for the study. The values of the parameters recorded upto 1200 UTC are considered to be the predictor whereas the values of these parameters for 1500 UTC and 1800 UTC are to be predicted.

The components of the input vectors have been constructed as  $X_{p(T)}$ ,  $X_{p(T_d)}$ ,  $X_{p(P)}$  using fuzzy logic. The modes of the distributions of average temperature ( $T$ ), average dew point temperature ( $T_d$ ) and average pressure ( $P$ ) have been computed using ten years data of pre-monsoon thunderstorms over Kolkata.

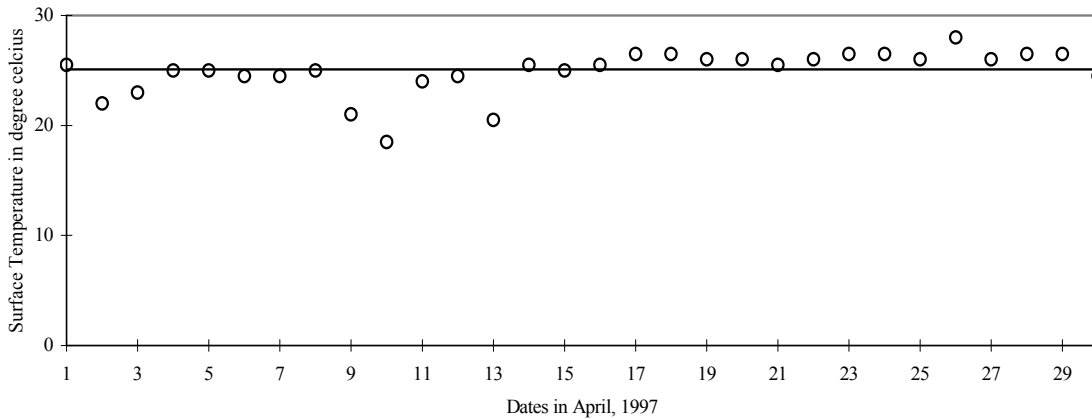


Fig. 2. Pattern of average surface temperature from observation (dots) as well as from fuzzy MLP Model (line) over Kolkata

The proposition tested in this problem is as follows;

$P$  : The value of the parameters ( $T$ ,  $T_d$  or  $P$ ) is very close to the mode is very true.

The membership function is defined as;

$$\mu(x) = (1/2) \times (x + M) M^{-2}$$

where

$$x \in [15,40] \text{ for } T$$

$$x \in [10,35] \text{ for } T_d$$

$$x \in [600,1300] \text{ for } P$$

and

$M$  – Mode of distribution.

Membership values for each parameter are computed for each day of April 1997 upto 1200 UTC. The entry with maximum membership value has been taken as the upper bound and entry with minimum membership value has been taken as the lower bound of the components of the input vectors.

Thus, the input vectors with these parameters are;

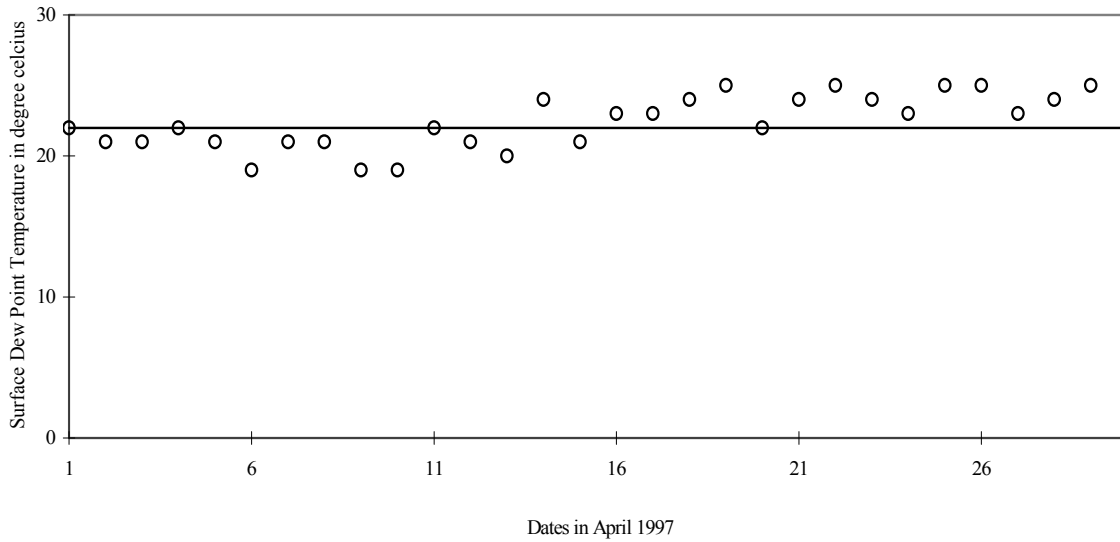
$$X_{p(T)}^0 = \{[23,32], [23,30], [22,29], [22,30], [24,31], [23,32], [22,31], [23,33], [22,32], [20,31],$$

$$[19,30], [21,31], [22,33], [21,31], [23,32], [22,32], [23,34], [25,35], [25,35], [25,35], [26,34], [26,34], [26,32], [25,32], [26,33], [24,31], [25,32], [26,34], [25,33], [27,35]\}$$

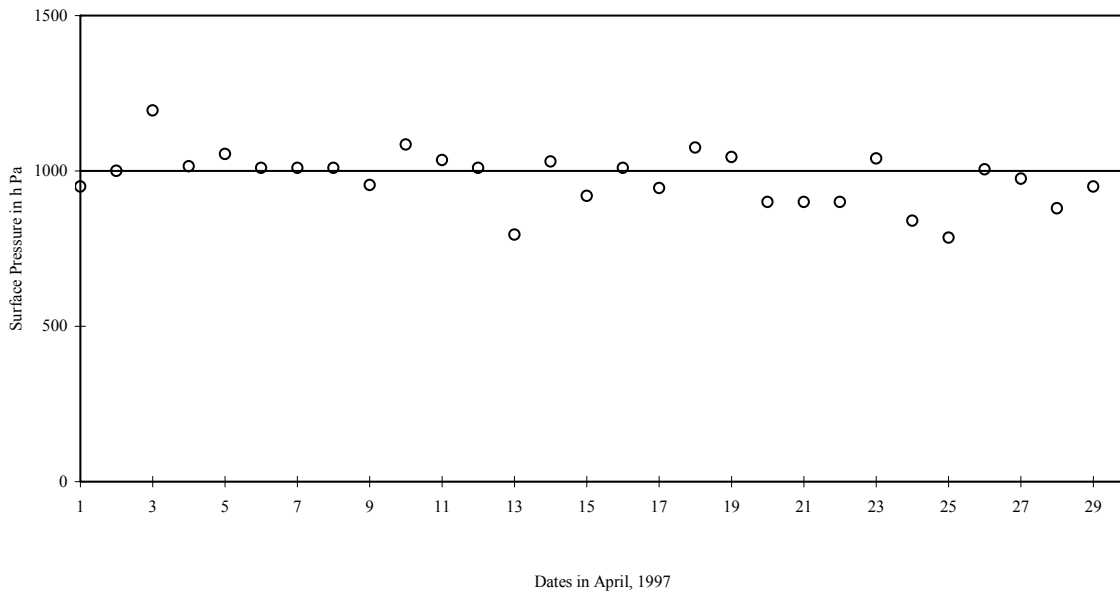
$$X_{p(T_d)}^0 = \{[21,23], [20,22], [19,21], [19,21], [16,21], [13,21], [18,22], [19,26], [20,24], [18,22], [18,22], [20,23], [21,25], [20,25], [20,25], [21,26], [20,23], [23,26], [10,25], [18,24], [23,24], [19,25], [21,25], [22,25], [24,25], [18,23], [23,24], [21,24], [21,25], [23,26]\}$$

$$X_{p(P)}^0 = \{[690,1090], [850,1100], [990,1150], [820,1320], [850,1350], [1010,1090], [1010,1010], [1010,1010], [580,1010], [810,1280], [1010,1200], [450,940], [730,1090], [680,1140], [670,1030], [720,1050], [850,1130], [830,1200], [700,1060], [1040,1090], [630,1030], [850,1150], [580,1030], [520,940], [720,1060], [780,1170], [600,1010], [850,1010], [720,1210]\}$$

The perceptrons are designed in such a way that they contain three layers (Fig. 1). In course of designing the MLP model for the aforesaid parameters, the connection weight  $[-0.2, 0.2] \subset [-0.5, 0.5]$  is taken for reaching the hidden layer and the connection weight  $[-0.32, 0.5]$  is taken for reaching the output layer. The only parameter



**Fig. 3.** Pattern of average surface dew point temperature from observation (dots) as well as from fuzzy MLP Model (line) over Kolkata



**Fig. 4.** Pattern of average surface pressure from observation (dots) as well as from fuzzy MLP Model (line) over Kolkata

that varies is the number of nodes in the hidden layer. In this paper the numbers of nodes in the hidden layer are;

42 for surface temperature

36 for surface dew point temperature

16 for surface pressure.

The configuration of nodes in a hidden layer is somewhat arbitrary (James and Tag, 1994) that depends upon the nature of the chosen problem. During training the set, the interval algebra (Pal and Mitra., 1999) is used

whenever required. After learning by example, the pattern of average temperature, average dew point temperature, and average pressure for 1500 GMT and 1800 GMT is recognized as follows;

$$Y_{p(T)}^2 = [24.2, 26] \text{ in degree Celsius}$$

$$Y_{p(Td)}^2 = [20.88, 22.32] \text{ in degree Celsius}$$

$$Y_{p(P)}^2 = [928, 992] \text{ in hPa}$$

A definite pattern of surface parameters could be recognized from Figs. 2,3 and 4. Fig 2 shows that the observed surface temperature is less than the model output from 2 April to 14 April whereas the observed values become greater than the model output from 15 April and onwards. The figure also indicates that FMLP model is a very good fit to surface temperature for the days having no thunderstorm. But, for the disturbed days, having thunderstorm activity, the observed values significantly fluctuate from the FMLP model output. Thus, if the surface temperature of any UTC is known then, using the proposed model, the surface temperature of future UTC's can be predicted for the days having no thunderstorm activity. Further, viewing the fluctuating pattern of the surface temperatures it is possible to predict the occurrence of pre-monsoon thunderstorms.

Fig. 3 shows that the observed surface dew point temperature is less than the model output from 2 April to 14 April whereas these values become greater than the model output from 15 April and onwards. The figure offers no definite information regarding the occurrence of thunderstorm.

Fig. 4 shows that the observed surface pressure is greater than the model output from 2 April to 14 April whereas these values become less than the model output from 15 April and onwards. The figure offers no definite information regarding the occurrence of thunderstorm.

The pattern of the surface parameters reveals that, among the other parameters, surface temperature represents a predictive index for the occurrence of pre-monsoon thunderstorm over Kolkata.

It is also apparent from the figures that after 15 April the surface temperature and surface dew point temperature increases whereas the surface pressure decreases over Kolkata. Thus, after 15 April the frequency of convective activity may increase. Probably this is the reason why number of thunderstorms is more in May than in April over this area.

#### 4. Conclusions

The results of the present study show that the pattern of surface temperature obtained using multi layer perceptron model with Fuzzy logic represents the dominating parameter in forecasting the occurrence of pre-monsoon thunderstorm over Kolkata.

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