Radial Basis Function Network for Hourly Surface Temperature Prediction

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***Abstract*— Surface temperature is one of the most important factors in forecasting the likelihood occurrence of a thunderstorm. Accurate forecasting of thunderstorms is critical for a large range of users in the community. This paper utilizes Radial Basis Function Network (RBFN) model for the prediction of hourly temperature 24 h in advance. The test results show that RBFN model is very promising in forecasting the 24 h advance hourly temperature with satisfactory mean absolute error (MAE) and correlation coefficient (CC).**

Keywords — Radial Basis Function Networks; surface temperature; forecasting; ; thunderstorm.

I. INTRODUCTION

Severe thunderstorms frequently occur over the eastern and north-eastern states of India during the pre-monsoon months of April and May. These months are characterized by hot and humid conditions and hence these conditions are conducive for thunderstorm formation. The most intense thunderstorms as well as the highest number of thunderstorms occur over the states of West Bengal and Orissa. These severe thunderstorms associated with thunder, squall lines, lightning, torrential rain, and hail cause extensive loss in agriculture, damage to property, and also loss of life. The highest numbers of aviation hazards are reported during occurrence of these thunderstorms [1]. Forecasting thunderstorm is one of the most difficult tasks in weather prediction, due to their rather small spatial and temporal extension and the inherent non-linearity of their dynamics and physics [2]. Accurate location specific and timely predictions are required to avoid loss of lives and property. Surface temperature is one of the most important factors in forecasting the likelihood occurrence of a thunderstorm.

Artificial neural networks (ANNs) are trainable self-adaptive systems that can "learn" to solve complex problems from a set of examples and generalize the "acquired knowledge" to solve unforeseen problems as in weather prediction [3]. ANNs, there exists the capability to extract the relationship between the inputs and outputs of a process, without the physics being explicitly provided [4]. The use of a neural network has shown a great deal of promise in accomplishing the goal of predicting surface temperature with high accuracy [5-6]. There are several types of models available for ANN application, but the Multilayer Perceptron Network (MLPN) trained with the Back-propagation (BP) algorithm is the most used one. Other types of neural networks are Radial Basis Function Networks (RBFN), Functional Link Networks, Kohonen networks, Recurrent Networks and Hybrid Networks etc. [7]. The RBFN is a popular alternative to the MLPN. Fernando and Jayawardena [8] reported that RBFN is found to perform better than MLPN trained with BP algorithm. Park and Sandberg [9] proved that RBFN with one hidden layer are capable of universal approximation. However, the application of RBFN neural networks to weather forecasting problems still rare, but recently it is getting more attention due to its advantages over MLPN.

In this paper, experiments are conducted with RBFN model to predict severe thunderstorms that occurred over Kolkata (22.52ºN, 88.37ºE) using thunderstorm affected meteorological parameters. The geographical location of the study area is given in Figure 1. The performance of RBFN model is evaluated using predicted hourly surface temperature during thunderstorm days. The accuracy of the predictions was evaluated by the correlation coefficient (CC) and the mean absolute error (MAE) between the measured and predicted values. The goal of this study is to use RBFN to predict hourly surface temperature 24 h ahead using prior weather data as inputs during pre-monsoon season. This study is presented in the following manner. Section 2 presents data and methodology. The results and discussions are described in Section 3 and the conclusions in Section 4.

Fig. 1. The geographical location of the study area.

II. DATA AND METHODOLOGY

RBFN is a non-linear layered feed forward networks used as a universal approximator. The RBFN is capable of implementing arbitrary non-linear transformations of the input space. This learning is equivalent to finding a surface in a multidimensional space that provides a best fit to the training data. RBFNs contain a single hidden layer of processing elements (PEs). This layer uses gaussian transfer functions, rather than the standard sigmoidal functions employed by MLPs. The centers and widths of the gaussians are set by unsupervised learning rules, and supervised learning is applied to the output layer. These networks tend to learn much faster than MLPNs [10].

RBFN have the advantage of not suffering from local minima in the same way as MLPN. This is because the only parameters that are adjusted in the learning process are the linear mapping from hidden layer to output layer. Linearity ensures that the error surface is quadratic and therefore has a single easily found minimum. In regression problems this can be found in one matrix operation. In classification problems the fixed non-linearity introduced by the sigmoid output function is most efficiently dealt with using iteratively re-weighted least squares. RBFNs are typically trained in a maximum likelihood framework by maximizing the probability (minimizing the error) of the data under the model [11].

This study evaluates the utility of RBFN model for estimating hourly surface temperature. Major numbers of thunderstorms are occurred over Kolkata in April and May. Thus the hourly meteorological data sets of these two months are selected for training and testing. The hourly mean sea level pressure, relative humidity, and wind speed of 3 years (April and May 2007 to 2009) collected from the India meteorological department (IMD) of Kolkata, were used for this study. The other additional input parameters for each model are month, day and hour of the observation. Neural networks generally provide improved performance with the normalized data. All the weather data sets were therefore transformed into values between −1 and 1 through dividing the difference of actual and minimum values by the difference of maximum and minimum values. At the end of each algorithm, outputs were denormalized into the original data format for achieving the desired result.

A three-layer structure (one input layer, one hidden layer, and one output layer) was selected with the Gaussian activation function was chosen for the hidden layer, and linear function for the output layer. The chosen weather data were divided into two randomly selected groups, the training group, corresponding to 67% of the patterns, and the test group, corresponding to 33% of patterns, so that the generalization capacity of network could be checked after training phase. The performance of the RBFN model to derive thunderstorm forecast 24 h ahead is evaluated using predicted hourly surface temperature during two thunderstorm days of May 2009 (May 3 and 15, 2009). The accuracy of the predictions was evaluated by CC and MAE between the measured and predicted values.

III. RESULTS AND DISCUSSION

The surface parameters play a significant role in the genesis whereas the strength of the upper air pull is required to assess the growth of the thunderstorm [12]. The greater the density differences between air masses (temperature and humidity) the greater the atmospheric instabilities that develop, and the greater the intensity of these thunderstorms [13]. Recent studies show a high positive correlation between surface temperature and lightning activity [14]. The hourly temperatures on the surface are useful tool in forecasting the likelihood occurrence of a thunderstorm [15]. Meteorologists warn that a sudden drop in temperature during the day indicate for thunderstorm [13].

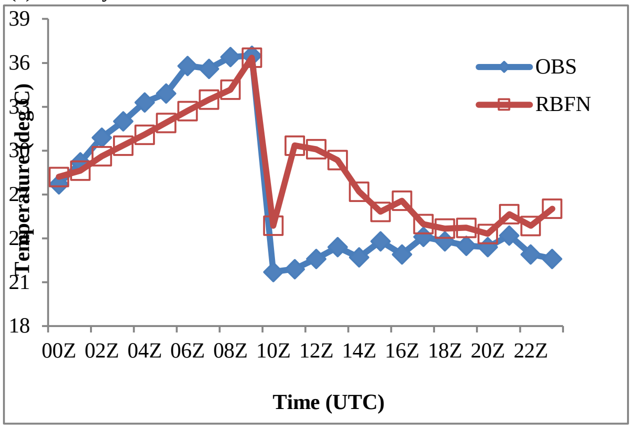
Figure 2 shows the inter-comparison of observed and RBFN model predicted diurnal variation of surface temperature (ºC) over Kolkata valid for 3 May 2009 and 15 May 2009. From the figures, it is clearly see that the observed data show a sudden drop in temperature in all thunderstorm days. The RBFN model captured the sudden temperature drop during the thunderstorm hour for both cases. For the first case (Figure 2a), the observed temperature showed a sudden drop of 14ºC from 36ºC to 22ºC at 10 UTC. The RBFN model prediction showed a drop from 36ºC to 24ºC (12ºC) at 10 UTC. In the second thunderstorm case (Figure 2b), observed temperature showed a drop from 30ºC to 24ºC (6ºC) at 13 UTC, whereas RBFN model showed a drop from 31ºC to 26ºC (5ºC) at 13 UTC. From these analyses, we can observe that RBFN model captured the sudden temperature fall during thunderstorm hour with almost same drop in intensity.

A statistical analysis based on MAE, and CC is performed for comparisons between the predicted and observed temperature for 3 May 2009 and 15 May 2009 (Table 1). The MAE measures the level of agreement between the forecast and the observations for continuous variables. The results indicated that, the RBFN model has less prediction error during these thunderstorm days. Another verification method used for this study is correlation coefficient. It measures the strength of the linear relationship between the forecasts and observations. A correlation greater than 0.8 is generally described as strong, whereas a correlation less than 0.5 is generally described as weak. From the table we can clearly see that RBFN model predicted values are strongly correlated with observation during these thunderstorm days.

TABLE 1. Performance comparison of RBFN predictions for hourly temperature during thunderstorm days

DATES	MAE	CC
3-May-09	2.5	0.84
15-May-09	1.1	0.96
AVERAGE	1.8	0.90

(a) 3 May 2009



(b) 15 May 2009

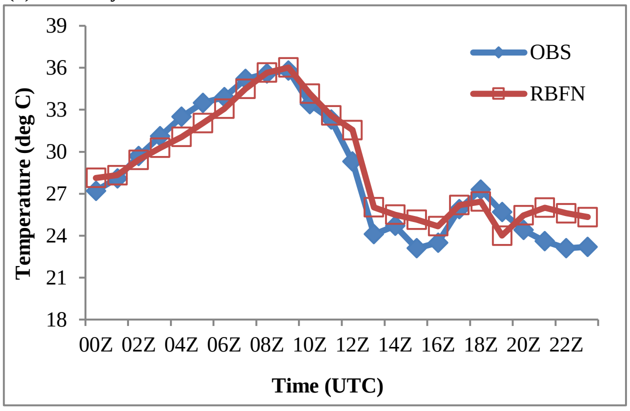


Fig. 2. Comparison of RBFN model predicted hourly surface temperature with observation on (a) 3 May 2009 (b) 15 May 2009.

In this paper, an efficient method for the forecasting of hourly surface temperature 24 h in advance during thunderstorm days is presented. RBFN model was used as a function approximator to predict the surface temperature on severe thunderstorms days that occurred over Kolkata on 3 May 2009 and 15 May 2009 and validated the model results with observation. A statistical analysis based on MAE and CC is also performed for comparison among predicted and observed data. After analyzing the results, we can conclude that the RBFN model has well predicted the hourly temperature in terms of sudden fall of temperature and intensity during thunderstorm hours. The results of these analyses demonstrated the capability of RBFN model in prediction of severe thunderstorm events over eastern Indian region.

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REFERENCES

[1] A. J. Litta, U. C. Mohanty, S. Das, and S.M. Idicula, “Numerical simulation of severe local storms over East India using WRF-NMM mesoscale model,” Atmospheric Research, vol. 116, pp.161–184, 2012.

[2] I. Orlanski, “A rational subdivision of scales for atmospheric processes,” Bulletin of the American Meteorological Society, vol. 56, pp. 527–530, 1975.

[3] C. M. Bishop, “Neural Networks for Pattern Recognition,” Oxford University Press, Oxford, UK, 1995.

[4] J. M. Zurada, “Introduction to artificial neural systems.” West Publishing Company, Saint Paul, Minnesota, 1992.

[5] I. Maqsood, M. R. Khan and A. Abraham, “An ensemble of neural networks for weather forecasting,” Neural Comput. & Applic., vol. 13, pp. 113-122, 2004.

[6] Mohsen Hayati, and Zahra Mohebi, “Application of Artificial Neural Networks for Temperature Forecasting,” International Journal of Engineering and Applied Sciences, vol.4, No.3, pp. 164-168, 2008.

[7] Leorrey Marquee, Marcus O’ Connor and William Remus, “Artificial Neural Network Models for Forecasting and Decision Making,” International Journal of Forecasting, vol. 10, Issue 1, 1994.

[8] Fernando, D. A. K., and Jayawardena, A. W. “Runoff forecasting using RBF networks with OLS algorithm.” J. Hydrol. Engrg., ASCE, 3(3), pp. 203–209, 1998.

[9] Park, J. and Sandberg, I. W. “Approximation and radial basis function networks.” Neural Computation, vol. 5, pp. 305–316, 1993.

[10] Orr, M. J., “Regularization in the selection of radial basis function centers”, Neural Computation, vol. 7, pp. 606-623, 1995.

[11] J. Park, I. W. Sandberg, “Universal approximation using radial basis function,” Neural Comput., pp. 246–257, 1991.

[12] Asnani, G. C., “Tropical Meteorology (Revised Edition).” vol. II. Sindh Colony: Audh, Pune, 2006.

[13] Price, C., “Global thunderstorm activity, Sprites. In: M. Fullekrug et al. (eds.) Sprites,” Elves and Intense Lightning Discharges, pp. 85-99, 2006.

[14] William, E. R., “Lightning and climate: A review,” Atmos. Res., vol. 76, pp. 272-287, 2005.

[15] Lopez, L., Garcia-Ortega and E., Sanchez, J. L., “A short-term forecast model for hail.” Atmospheric Research, vol. 83, pp. 176-184, 2007.