NOWCASTING OF SEVERE STORMS AT A STATION BY USING THE SOFT COMPUTING TECHNIQUES TO THE RADAR IMAGERY

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I. INTRODUCTION

The severe storms pose a great threat to lives and property of man kind. An accurate rain nowcast from weather radar can identify the potential for heavy rain and possibility for flash flooding (Vieux and Bedient '1998). By virtue of higher temporal sampling of the precipitating systems, the radar based observations pose a good candidate to deal with the nowcasting problems. The nowcasting of rainfall from radar involves the identification of precipitating systems, its evolution and movement. The conventional short term forecast of both position and size is based on a weighted linear fit to the storm history data (Rinehart, and Garvey 1978, Dixon and Winner 1993). The use of artificial neural network (ANN) has been recognized as a promising way of making prediction on time series data. This method is non parametric where it does not required the assumption of any form of model equations. The main features of ANN is its ability to map input data to output data to any degree of non linearity. Many researchers have utilized this technique to predict the rainfall by using the data from various platforms such as model output (Kuligowski and Barros, 1998), satellite (Rivolta et al. 2006), and radar (Denceux and Rizand, 1995)

II. PRESENTATION OF RESEARCH

The main objective of the present work is to develop a soft computing based methodology to nowcast the severe rain situations over a station with the help of Doppler Weather Radar (DWR) imageries. The main advantage of using the DWR observations is that the ambiguous reflectivity images due to anomalous propagation can be discarded with the help of radial velocity measurements. For the present study the DWR facility at Satish Dhavan Space Center, Shriharikota (13.66 °N & 80.23 °E), India is utilized. For this purpose, the reflectivity (dBZ) imageries of DWR are utilized. The storm structures are identified with the threshold values of reflectivity factor ≥ 40 dBZ. The block diagram of the proposed methodology is shown in Figure (1). The main components of the proposed methodology are (a) the morphological analysis of precipitating structures in the DWR imageries (b) matching of the two successive imageries at t and t + Δt time interval (c) tracking of the precipitating structures and (d) training of the extracted input/output image features for the nowcasting of rain by using the ANN technique.

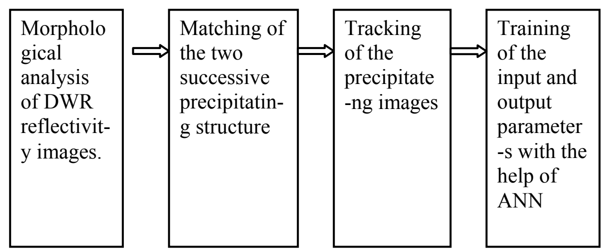

Fig 1: Block diagram of methodology of nowcasting of severe rain

The inputs from the radar imageries are provided to the ANN at $T_{(0)}$, $T_{(0+1/2)}$ and $T_{(0+1)}$ hrs and the nowcasting is carried out with 2 hrs lead time at T $_{(0+3)}$ hrs. The architecture of the ANN is shown in figure 2. which consists of one input layer (15 nodes), two hidden layer (with 35 and 25 nodes and one output layer (with 01 node).

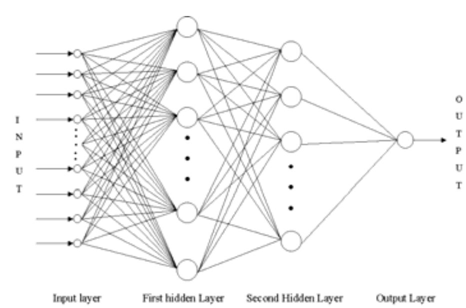

Figure2: Architecture of ANN

The following 15 input parameters are selected for the ANN network:
(1). Area (km^2) of precipitating system for reflectivity ≥20 dBZ at T_0, (2). Area (km^2)of precipitating system of reflectivity ≥ 40dBZ at T_0, (3). Line of Sight Distance (km)

between system and target station at T_0 for the system ≥ 20 dBZ, (4). Ratio of the change of area for ≥ 20 dBZ during T_0 to $T_{0+1/2}$ (5). Ratio of the change of area for ≥ 40dBZ during T_0 to $T_{0+1/2,}$ (6). Ratio of the change of distance of the system with respect to target station during T_0 to $T_{0+1/2}$ for the system ≥ 20 dBZ (7). Deviation of the system from line of sight during T_0 to $T_{0+1/2}$ for the system ≥ 20 dBZ (8). Velocity of the system during T_0 to $T_{0+1/2}$ for the system ≥ 20 dBZ (9). Correlation between the images during T_0 to $T_{0+1/2}$ for the system ≥ 20 dBZ (10). Ratio of the change of area of ≥ 20dBZ during $T_{0+1/2}$ to T_{0+1} (11). Ratio of the change of area of ≥ 40dBZ during $T_{0+1/2}$ to T_{0+1} (12). Ratio of the change of distance of the system with respect to target station during $T_{0+1/2}$ to T_{0+1} for the system ≥ 20 dBZ (13). Deviation of the system from line of sight during $T_{0+1/2}$ to T_{0+1} for the system ≥ 20 dBZ (14). Velocity of the system during $T_{0+1/2}$ to T_{0+1} for the system ≥ 20 dBZ (15). Correlation between the images during $T_{0+1/2}$ to $T_{0+1\,=}$ for the system ≥ 20 dBZ The output parameter is rain intensity as observed from the radar imageries (for reflectivity ≥ 40 dBZ)

The image analysis and training of the ANN is carried out on MATLAB platform. The results obtained from the soft computing approach are also compared with the results obtained from linear multiple regression methods.

III . RESULTS AND CONCLUSIONS

The results from the training of ANN in terms of matching and mismatching of the ANN output with the observed values are presented in Table -1.

Metho-dology	Training/ Validation	Case	Match	Mismatch
ANN	Training	Yes Rain	89%	11%
	Validation	Yes Rain	77%	23 %
Linear Regres sion	Training	Yes Rain	62%	38%
	Validation	Yes Rain	55%	45%

Table1: Statistics of the Training and Validation experiments

The statistics of matching/mismatching is found out for YES-RAIN situations . Overall it is observed that the results are better for training data set compared to validation data set (Table -1). Further the same input/output data set is utilized to estimate the coefficients for the linear multiple regression in the following form i.e. $Y = \sum c_i x_i$, where x_i is the i^{th} input and c_i is the i^{th} coefficient. The index i is from 1 to 15. Similar types of statistics are also obtained from the conventional linear multiple regression analysis and is presented in Table 1. Overall nature of the statistics is same as observed from the ANN. But the accuracy is better for ANN methodology compared to linear multiple regression analysis. Comparatively, reasonably good results are obtained by soft computing method and there is significant improvement by the proposed methodology compared to linear multivariable regression method.

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