Nowcasting of Yes/No rain situations at a station using soft computing technique to the radar imagery

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A soft computing model for nowcasting of Yes/No rain situations, with a lead time of 2 h, is developed over DWR station at Satish Dhawan Space Centre (SDSD), Shriharikota (13.66°N, 80.23°E) using Doppler weather radar (DWR) reflectivity imageries. Primarily, precipitating systems of mesoscale, i.e. meso-gamma (2-20 km), meso-beta (20-200 km) and meso-alpha (200-2000 km) are considered for the present study. The main components of soft computing approach are: analysis of two-dimensional reflectivity imageries from DWR and utilization of artificial neural network (ANN) for training of input/output data. About 15 input and one output parameters are extracted from radar imageries. The image analysis and training of ANN are carried out on MATLAB platform. After training of ANN, 91 and 77% results are matched with the observed values for No rain and Yes rain situations, respectively. The probability of detection (POD) for the nowcasting of Yes/No rain situations is found to be 0.84. The significant improvement in the nowcasting of Yes/No rain situations is observed by the developed methodology as compared to linear multivariable regression method. The POD of Yes/No rain for other two locations, namely Chennai (12.99°N, 80.18°E) and Tiruvallur (13.09°N, 79.57°E) are found to be 0.81 and 0.77, respectively. Overall, reasonably good results are obtained by the newly developed soft computing model.

Keywords: Doppler weather radar (DWR), Image processing, Artificial neural network (ANN), Multilayer perception, Rain nowcasting

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1 Introduction

An accurate rain nowcast from weather radar can identify the potential for heavy rain and possibility for flash flood¹. 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.

For the identification of precipitating systems, Crane² developed a method in which, for a given plan position indicator (PPI), two-dimensional cells are identified as regions around local maxima in the reflectivity field. These cells are then grouped into ‘volume cells’ through the vertical association of cells in successive PPIs. Rosenfeld³ used a reflectivity threshold to represent a storm and then identified cells within the storm as regions around local maxima. Dixon & Weiner⁴ identified different storm situations with different reflectivity threshold criteria, e.g. for individual convective cell, the contagious area ≥ 40 dBZ, for convective storms ≥ 30 dBZ and mesoscale convective complexes ≥ 25 dBZ. Johnson et al.⁵ identified the storm cells, if it has a maximum reflectivity of at least 30 dBZ, with an area of 5 km². They considered the storms as separate one if the storm structures are separated by local minima at least 10 dBZ lower than the maxima reflectivity within the storm area.

⁵Retired
The conventional short term forecast for position and size is based on a weighted linear fit to the storm history data\textsuperscript{2-4,6-8}. Most of the nowcasting techniques, broadly, can be divided into two approaches. One approach is to find the best possible fit between two different maps of radar data of two-dimensional field that were obtained within a certain time interval\textsuperscript{9}. This radar based approach relied on the statistical comparison of the rain field in two successive images using cross correlation function\textsuperscript{6}. The cross correlation coefficient is calculated for different displaced superposition of two images and its maximum indicates most probable displacement. Forecast is obtained by linear extrapolation of displacement vector applied to whole images\textsuperscript{6}. Although this simple technique performs quite well in frontal situations, characterized by large rainfall area with uniform advection, but it suffers from severe limitations during convective situations, where multiple rain cells may have different directions and speeds of motions. Another approach of nowcasting techniques is to track and forecast the area and the mass centroids of the precipitating systems that are assumed to represent individual convective storms or convective cells\textsuperscript{9,10}. It is a more structured approach which usually consists of four steps: (i) echo definition; (ii) echo description by features; (iii) echo matching; and (iv) forecast by vector extrapolation.

Browning \textit{et al}.\textsuperscript{9} developed the quantitative forecasting of frontal rain for hourly rainfall with a lead time of 6 h using linear extrapolation technique. The study was carried out using the composite picture from four weather radars. They pointed out that factors such as development and decay of the rainfall systems, which lead to the breakdown of the basic assumption, underlying the linear extrapolation approach, accounted for about a quarter of the errors in the forecast. Roberts & Wilson\textsuperscript{11} developed the microburst nowcasting method with a lead time of 10 min by using single and multiple Doppler radars. They identified the microburst signature by rapidly decaying reflectivity core, increasing radial convergence within clouds and reflectivity notches. Through a simple linear regression analysis on digital radar data, Doneaud \textit{et al}.\textsuperscript{12} demonstrated that correlation between total rain volume and area time integral of echo area (≥ 20 dBZ) is strongest. Dixon & Wiener\textsuperscript{4} developed a methodology, known as Thunderstorm Identification, Tracking, Analysis and Nowcasting (TITAN), for the real time automated identification, tracking and short term forecasting of thunderstorm based on volume scan weather radar data. They utilized 10 radar derived parameters for this purpose. Li \textit{et al}.\textsuperscript{13} developed the methodology for the nowcasting of motion and growth of precipitation with radar over a complex orography. They upgraded the Tracking Radar Echo by Correlation (TREC) methodology\textsuperscript{8} with a new methodology by the name Continuity of TREC vectors (COTREC). In this method, they incorporated the growth and decay of radar echoes. Johnson \textit{et al}.\textsuperscript{5} developed the Storm Cell Identification and Tracking (SCIT) algorithm with 16 radar reflectivity derived parameters. This algorithm identified the storm, calculated its characteristics with 16 reflectivity parameters and tracked storm movements. MacKeen \textit{et al}.\textsuperscript{14} examined these 16 parameters with respect to storm life time. The detailed review of the status of the nowcasting of convective precipitation up to the year 1998 is done by Wilson \textit{et al}\textsuperscript{15}. Germann & Zawadzki\textsuperscript{16,17} used the Eulerian and Lagrangian persistence of continental scale radar patterns to produce the probabilistic forecast of precipitation rates. Li & Lal\textsuperscript{18} developed the quantitative precipitation forecast algorithm based on the TREC with a lead time of 3 h.

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 require the assumption of any form of model equations. The main feature of ANN is its ability to map input data to output data to any degree of non-linearity. The ANN exhibit the capacity to learn and to represent highly non-linear function. Many researchers have utilized ANN technique to predict the rainfall by using data from various platform such as model output\textsuperscript{19,20}, satellite\textsuperscript{21}, radar\textsuperscript{22-24} and combination of these platforms\textsuperscript{25,26}. French \textit{et al}.\textsuperscript{22} utilized three layer back propagation network, which received the last radar imagery as an input and is trained to predict the rainfall field with 1 h lead time. The target field is generated by the mathematical rainfall simulation model. Denceux & Rizand\textsuperscript{23} developed an approach for the analysis of weather radar data for short range rainfall forecasting based on neural network model. In their approach, each image in a sequence is approximated using a modified radial basis function.
network trained by a competitive mechanism. The nowcasting of rain field is performed by analyzing the time series of weight values. Chow & Cho24 developed a rain nowcasting methodology. It deals with the extraction of information from radar imageries and past records of rainfall by using the recurrent sigma pi neural network model. By using the neural network based approach, Tomassetti et al.27 investigated the possibility of short term prediction of rain rate from radar observations with a lead time of 15 to 45 min. The developed technique uses a simple multilayer network whose input layer is provided with a rain rate of 9 or 25 adjacent pixel of radar rain rate estimation map, while the goal is to predict rain rate of central pixels at further time steps. The result from the proposed methodology is found to be reasonably accurate and good results are obtained using a simple feed forward architecture. They further pointed out that performance is improved if short sequences of frames are used to train the network. Due to the installation of the state-of-the-art Doppler Weather Radar (DWR) at various stations in India and its immense potential in detecting the precipitating systems, the necessity for the development of radar based rain nowcasting model is realized. The present work is a collective step in this direction.

The main objective of the present work is to develop a soft computing based model to nowcast the Yes/No rain situations over a station with the help of DWR imageries. The main advantage of using DWR observations is that 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 Dhawan Space Center, Shriharikota (13.66°N, 80.23°E), India is utilized.

2 DWR system and Rain estimation

The DWR, utilized for the present study, is installed at Satish Dhawan Space Centre (SDSC), Shriharikota (13.66°N, 80.23°E). The SDSC is situated at the coast of Bay of Bengal (Fig. 1). The utilized DWR operates at S-band (2.8 GHz frequency). DWR consists of a high power coherent transmitter which transmits the signal as a pencil beam with 1° beam width and very low side lobe levels. It is steerable in azimuth and elevation directions. A state-of-the-art digital signal processor extracts three essential base products, viz. reflectivity (Z), mean radial velocity (V), spectral width (σ) of hydrometeors spectra, from the log/linear channels of the receiver. For the present study, the two-dimensional reflectivity imageries at 0.5° elevation angle are utilized. The DWR station receives maximum rainfall during north-east monsoon period (October-December) as compared to south-west monsoon period (June-September). For the present study, DWR observations during north-east monsoon period are utilized. The dates of the observations and their start and end time are provided in Table 1.

At the very outset, the reflectivity imageries of DWR are validated with the ground truth observations. The comparison of rain estimation (by reflectivity imageries of DWR) with rain gauge measurements was carried out during 1-9 November 2006. The rain accumulated at eight stations around DWR was utilized. The names and locations of these stations are listed in Table 1.

<table>
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<th>Time, hrs UT</th>
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</tr>
<tr>
<td>25 October 2006</td>
<td>18:30 - 22:30</td>
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<td>00:00 - 08:00</td>
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<td>21:30 - 24:00</td>
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<tr>
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<td>00:00 - 13:00</td>
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<tr>
<td>27 October 2006</td>
<td>19:00 - 23:00</td>
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<td>28 October 2006</td>
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<td>30 October 2006</td>
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<td>6 November 2006</td>
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</tr>
<tr>
<td>5 November 2004</td>
<td>18:00 - 23:30</td>
</tr>
</tbody>
</table>

Table 1—Rain events considered for the present study

Fig. 1—Location and reliable aerial coverage of DWR
stations are provided in Table 2. These rain gauges were tipping bucket types. Each station recorded hourly rain fall accumulation. The rain rate from the DWR is calculated by using the relations during stratiform and convective rain, respectively\(^{28}\). These relations are developed with the help of rain drop size distribution observations by Joss Waldvogel Disdrometer (JWD) near the radar site. The scatter plot for DWR vs rain gauge measured rain fall intensity for one hour integration time is shown in Fig. 2. The linear fit is carried out to the scatter plot. The best fit equation along with error statistics in terms of root mean square error (rmse) and bias are provided in the figure panel. The slope value of the best fit linear equations is ~ 0.70, which indicates that toward the higher rain intensity regimes the DWR observations are underestimating the rain accumulation compared to rain gauge measurements. This error and biasing may be attributed to the different sampling volume and temporal resolution of these two systems. The rain gauge measurements are essentially point measurements whereas the radar observations are area integral. Overall there is good agreement between these two measurements.

3 Methodology for rain nowcasting model and Data preparation

The soft computing technique to DWR reflectivity imageries is used to develop the nowcasting model for Yes/No rain situations. The block diagram of the proposed model is shown in Fig. 3. The main components of the proposed model are: (a) morphological analysis of precipitating systems in the DWR imageries; (b) matching of the two successive imageries at t and t+\(\Delta t\) time interval; (c) tracking the reflectivity imageries of the precipitating systems; and (d) training of the extracted input/output image features for the nowcasting of rain by using the ANN technique.

The selection of input parameters for ANN are decided on the basis of physical understanding of the concept of “Approaching the Destination”. The particular concept consists of various components such as: (i) coordinates of the objects and its line of sight (LOS) distance from the destination; (ii) matching the images at successive time intervals; (iii) velocity vector (speed and direction) of the object; (iv) displacement of the object; and (v) decay and growth of the object. The moving objects can be identified and tracked by knowing these parameters at different intervals of time. On the basis of the adopted concept, primarily the coordinates of the precipitating systems, its area and LOS distance with destination are calculated at T0, T0+1/2 and T0+1 hrs and thereafter, velocity vector, change in area, correlation coefficient for the successive images are calculated from T0 to T0+1/2 and T0+1/2 to T0+1 hrs. On the basis of these considerations, total 15 parameters are identified for the input to the ANN. The input parameters are provided in Table 3. 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 2h lead time at T(0+3) hrs.

For the present study, primarily the precipitating systems are considered at mesoscale level, i.e. meso-gamma (2-20 km), meso-beta (20-200 km) and meso-alpha (200-2000 km) (ref. 29). Therefore, the precipitating systems are of different nature in their origin and characteristics. The given systems are characterized by its total area (\(\geq 20\) dBZ) and the area of the convective portion (\(\geq 40\) dBZ), if any, with in the system. The total area of the precipitating

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Table 2—Location of the automatic weather stations

<table>
<thead>
<tr>
<th>Station name</th>
<th>Latitude</th>
<th>Longitude</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chinna- Semavaram</td>
<td>13.33°N</td>
<td>80.19°E</td>
</tr>
<tr>
<td>Ponneri</td>
<td>13.26°N</td>
<td>80.26°E</td>
</tr>
<tr>
<td>Vellammal</td>
<td>13.14°N</td>
<td>80.19°E</td>
</tr>
<tr>
<td>Uttukotta</td>
<td>13.33°N</td>
<td>79.90°E</td>
</tr>
<tr>
<td>Kuduvalli</td>
<td>13.21°N</td>
<td>80.05°E</td>
</tr>
<tr>
<td>Poondi</td>
<td>13.20°N</td>
<td>79.87°E</td>
</tr>
<tr>
<td>Cholavaram</td>
<td>13.23°N</td>
<td>80.03°E</td>
</tr>
<tr>
<td>Annappa</td>
<td>13.35°N</td>
<td>80.09°E</td>
</tr>
</tbody>
</table>

y=0.69*x-0.022
rms=1.77
bias=1.11

Fig. 2—Scatter plot for DWR vs AWS rain rates (for one hr integration time)
systems and the area of the convective portions with in the system vary in the range 500-22000 km$^2$ and 100-2000 km$^2$, respectively. The precipitating systems with larger convective portions are mainly the cases of squall line and mesoscale complexes.

3.1 Extraction of morphological features of precipitating systems from DWR reflectivity imageries

The image analysis of the radar reflectivity imageries are carried out with the help of image processing tool box of MATLAB. For feature extraction from the reflectivity imageries, the area of each precipitating structure, its centroids at successive time steps are estimated. The movements of the systems are studied with the help of their centroids.

3.1.1 Area of the precipitating systems

The present approach is first to detect the total number of precipitating systems in a given radar imagery and then to estimate the area of each system. The precipitating system identification technique is applied to the radar data in the radar coordinate system of range, azimuth, and elevation. In a reflectivity imagery, two contiguous regions are identified separately through a binary image with the given reflectivity thresholds, i.e. $Z \geq 20$ dBZ and $Z \geq 40$ dBZ. The pixel values above these thresholds are converted to 1 and below the assigned threshold it is 0. The area of each precipitating systems for these two threshold levels are estimated by using the 8-bit connectivity component algorithm in binary image$^{30}$. The schematic diagram for 8-bit connectivity with 8 neighbors is shown in Fig. 4. In this diagram a pixel ‘p’ at coordinates (x, y) has eight neighbors, which are denoted by $N_8(q)$. Two pixels ‘p’ and ‘q’ are said to be 8 adjacent if $p \in N_8(q)$. Morphological processing starts at the peaks in the marker image and spread throughout the rest of the image based on the connectivity of the pixels. The connectivity is defined as which pixels are connected to other pixels. It means if two adjoining pixels are 1, then they are part of the same object regardless of whether they are connected along the horizontal, vertical, or diagonal direction. The area is a measure of the size of the foreground of the image. The area is the number of pixels in the image multiplied by their pixel resolution. The area of each of the precipitating structure is calculated by the expression:

$$A_n = \sum I_i W_i$$

…(1)
where, $l_i$ is the value of the $i$th pixel; $W$, the average radar pixel resolution (0.56 km$^2$); and $n$, the number of precipitating system in a given reflectivity imagery.

### 3.1.2 Centroid of the precipitating systems

For a shape represented by a region $R$ containing $N$ pixels, the center of mass is calculated by the expression:

$$
- \frac{m}{N} = \frac{1}{N} \sum_{(m,n) \in R} m,
$$

$$
- \frac{n}{N} = \frac{1}{N} \sum_{(m,n) \in R} n
$$

where, $m$ and $n$, are the latitude and longitude coordinates of the pixels in a region $R$.

### 3.2 Matching of the same precipitating systems during the successive time interval

For matching the two precipitating systems at two successive time steps in the next radar imagery, the total number of precipitating systems are found out within a region of 60 km radius by assuming that the maximum speed of the precipitating structure will be $\sim$ 60 km hr$^{-1}$ (ref. 4). Within the assigned circle, the correlation coefficient is found between the different systems and the initial system by using the expression:

$$
\sqrt{\left( \frac{X_{0+i} - X_{\text{station}}}{X_{0+i} - X_{\text{station}}} \right)^2 + \left( \frac{Y_{0+i} - Y_{\text{station}}}{Y_{0+i} - Y_{\text{station}}} \right)^2 }
$$

... (4a)

where, $i$, is the index with the values of 0, $\frac{1}{2}$ and 1.

Similarly, the line of sight (LOS) distance between the rain systems at two successive time steps is calculated with the help of estimated centroids of each system by using the expression:

$$
\Delta S = \sqrt{\left( X_2 - X_1 \right)^2 + \left( Y_2 - Y_1 \right)^2 }
$$

... (4b)

where, $(X_1, Y_1)$ and $(X_2, Y_2)$, are the centroids of the systems at $T_{(0)}$ and $T_{(0+1/2)}$ hrs or $T_{(0+1/2)}$ and $T_{(0+1)}$ hrs, respectively.

### 3.3 Tracking of the precipitating system at successive time intervals

The tracking of the individual precipitating system is carried out by estimating the line of sight (LOS) distance, velocity, displacement and growth/decay of the precipitating systems using the following steps:

#### 3.3.1 Line of sight (LOS) distance

The line of sight distance (LOS) between the system centroid and station coordinates are estimated by using the expression:

$$
\frac{\sqrt{\sum (A_{mn} - \bar{A}) \sum (B_{mn} - \bar{B})}}{\sqrt{\sum (A_{mn} - \bar{A})^2 \sum (B_{mn} - \bar{B})^2}}
$$

... (3)

where $\bar{A} = \text{mean2}(A)$, and $\bar{B} = \text{mean2}(B)$.

Here, $A$ and $B$ are matrices of same size of the 1st and 2nd imagery. After estimating the correlation of the different sets of two systems, the systems which ever is having the maximum correlation with the first one is identified as successive system.

### 3.3.2 Velocity of the precipitating systems

First, the LOS distance traveled by the system during $T_0$ to $T_{0+1/2}$ ($\Delta T_1$) and $T_{0+1/2}$ to $T_{0+1}$ ($\Delta T_2$) is calculated. Then, the velocity of the precipitating systems is calculated by using the equation:

$$
V = \frac{\Delta S}{\Delta T}
$$

... (5)

### 3.3.3 Displacement of the precipitating system

If $OC_1$ and $OC_2$ are the line of sight distance of the centroid of the precipitating system from the target station at two successive time steps, i.e. $t$ and $t + \Delta t$, respectively then, the change of position of the centroid at time interval $\Delta t$ is represented by the ratio $OC_1$ and $OC_2$:

$$
OC = \frac{OC_1}{OC_2}
$$

... (6)

According to this expression if $OC > 1$, it indicates that the displaced precipitating system is nearer to the target station compared to original position. Further, if $OC < 1$, it indicates that the displaced precipitating...
system is farther to the target station compared to original position. Further, it is to be noted that even if $OC > 1$, it may not approach towards the target. To ensure that it is really moving towards the target station, the deviation from the line of sight is also computed from the expression:

$$D = | (OC_1 - OC_2) - C_1 C_2 |$$

...(7)

where, $C_1 C_2$, is the distance between the centroid of two precipitating systems.

For this expression, if the value of $D$ is 0, it indicates that the system is exactly moving towards the target station. The increase of $D$ value indicates more deviation from the line of sight, which may not reach to the target station inspite of $OC > 1$.

### 3.3.4 Growth and decay of the precipitating systems

The growth and decay of the precipitating systems during $T(0) - T(0+1/2) \text{ hrs}$ or $T(0+1/2) - T(0+1) \text{ hrs}$ are estimated in three steps: (i) match the images of the same precipitating systems at two successive time intervals; (ii) estimate the area of the same precipitating systems at two successive time intervals; and (iii) find the ratio of the area at two successive time intervals. After identifying the two successive images of the same systems, the area of each system at two successive time intervals, i.e. $A_1$ and $A_2$ are estimated. For the estimated areas, if the ratio $A_1/A_2 < 1$, then it is considered as growth of the system and if $A_1/A_2 > 1$, it is identified as decay of the systems. Further, for $A_1/A_2 \approx 1$, it is considered as no growth or decay of the precipitating system.

### 3.4 Training for input/output parameters of ANN for rain nowcasting

ANN technique is applied for rain nowcasting over a station with a lead time of 2 h. For the training of ANN Multi Layer Perceptron (MLP) architecture is utilized\(^1\). The ANN is highly interconnected, interactive data processing unit. Nodes of each layer are connected by weights, which change with the output error according to the gradient descent rule. Each of the input is multiplied by an initialized weight matrix, which gives responses at each of the hidden nodes. These responses are then multiplied by a transfer function. Transfer function utilized in the present architecture is a sigmoid function of the form:

$$F(s) = 1/[1+\exp(-s)]$$

...(8)

The simplest implementation of back propagation is the learning and updates of the network weights and biases in the direction in which the performance function decreases more rapidly (the negative gradient). Weights are updated as

$$w_{ik} = w_{ik}^{t-1} - \eta \frac{\partial E_k}{\partial w_{ik}}$$

...(9)

where, $w_{ik}^{t}$, is the new updated weight at $t^{th}$ iteration; $w_{ik}^{t-1}$, the weight at $(t-1)^{th}$ iteration; $E_k$, the error at the output node (k); and $\eta$, the learning rate.

The MLP is trained using 15 parameters retrieved from reflectivity imageries as input and the Yes/No rain situations after two hours as output. The output is in binary mode, i.e. 1 for Yes rain and 0 for No rain. The total numbers of considered data points are ~1000. Whole dataset is divided into two parts where 3/4 of the data is utilized for the training purpose and 1/4 is considered for validation. For the training of input/output features of MLP network, Levenberg-Marquardt algorithm is used in MATLAB environment. The main advantage of using this algorithm is that it converges quickly as compared to most of the other training algorithms. It can train any network as long as its weight, net input and transfer functions have derivative functions. Various networks are trained with different hidden layers. The optimum MLP neural network architecture is shown in Fig. 5. It consists of input layer with 15 nodes, two hidden layers with 35 and 25 nodes, respectively and output layer with one node.

### 4 Results

#### 4.1 A case study of the morphological feature extraction and movements of the precipitating systems

On 26 October 2006, typical movement of the precipitating systems at different instances of time as
observed from the DWR imageries are shown in Figs 6 (a-d). The radar imageries are presented at 0100, 0200, 0800 and 0900 hrs UT, respectively. The system is moving towards the radar site. For the identified individual systems, the total areas of the precipitating systems along with their centroids are estimated at different instances of time with the threshold value of reflectivity $\geq 20$ and $\geq 40$ dBZ, respectively. The morphological parameters of the precipitating systems as estimated from the reflectivity imageries at various stages are presented in Table 4. The percentage of fractional area of the convective portion $[(A_{\text{Convective}}/A_{\text{Total}}) \times 100]$ at the four stages are found to be 1.48, 0.60, 6.73 and 3.75%, respectively. It indicates that at 0100 and 0200 hrs UT, the system is at a very initial stage of its formation; at 0800 hrs UT it is in mature stages and after that it is at dissipation stage. By virtue of $A_1/A_2 > 1$, it is also noticed that the there is overall growth for the total system ($\geq 20$ dBZ), whereas for the convective portion there is decay during these two time intervals, where $A_1/A_2$ is found to be $<1$. The correlation between two images during the mature stages is found to be more as compared to initial stages. At 0100 hrs UT, the distance of the center of the first system from the radar site is $\sim 222$ km. The ratio of the change of distance of the rain system during these periods is found to be $>1$ indicating that rain system is approaching toward the station. Further, by virtue of low value of $D$ (0.73), it is also observed that initially during 0100 - 0200 hrs UT, the deviation of the centroid of

<table>
<thead>
<tr>
<th>Time, hrs UT</th>
<th>Area of total system ($\geq 20$ dBZ), km²</th>
<th>Area of convective system ($\geq 40$ dBZ), km²</th>
<th>Centre of the system Latitude</th>
<th>Centre of the system Longitude</th>
<th>LOS distance from target ($\geq 20$ dBZ), km</th>
<th>Ratio of change of distance for the system ($\geq 20$ dBZ)</th>
<th>Deviation from Velocity for the Correlation for line of sight ($\geq 20$ dBZ), km/s</th>
<th>Correlation for the system ($\geq 20$ dBZ)</th>
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<td>0100</td>
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<td>48</td>
<td>80.22</td>
<td>11.68</td>
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<tr>
<td>0200</td>
<td>6004</td>
<td>36</td>
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<td>11.86</td>
<td>204</td>
<td>0.71</td>
<td>1.24</td>
<td>3.34</td>
</tr>
</tbody>
</table>

Fig. 6—Radar reflectivity imageries at: (a) 0100; (b) 0200; (c) 0800; and (d) 0900 hrs UT on 26 October 2006

Table 4—Estimated parameters from radar imageries of the precipitating systems at different instance of time
the rain systems from the line of sight is not very significant but during the later period, 0800 - 0900 hrs UT when the precipitating system nearly reached the target station, there is significant deviation of the centroid of the rain system. But inspite of this significant deviation, the station experienced the rain. It is attributed to the growth of the precipitating systems as indicated by the increase in area during 0900 hrs UT (19918 km²). The average velocity of the moving system during the whole period is found to be \( \sim 4.0 \text{ m/s} \). The correlation between two imageries during the mature stage is found to be more as compared to initial stage.

4.2 Results from the training of ANN and its validation

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 5. The statistics of matching/mismatching for No rain and Yes rain situations are found out separately. Overall, it is observed that for both the situations the results are better for training data set as compared to validation data set. Moreover, the matching statistics is better for the nowcasting of No rain situations compared to Yes rain situations.

In the context of these results, it is important to mention that the dominant cause of the poor forecasting is the decay and growth of the precipitating systems during the forecast period. The mismatching of No rain situation is generally considered due to the rapid growth of new systems, whereas mismatching of the Yes rain situation is due to the rapid decay of the systems during the nowcast period. The relatively better nowcasting of the “No rain” situations compared to “Yes rain” situations may be attributed to the lesser probability of the development of new precipitating system as compared to greater probability of the dissipation of the systems during the nowcast period. Further, the same input/output data set is utilized to estimate the coefficients for the linear multiple regression in form

\[ Y = \sum c_i x_i, \text{ where, } x_i \text{ is the } i^{th} \text{ input; and } c_i \text{ the } i^{th} \text{ coefficient. The index } i \text{ is from 1 to 15. Similar types of statistics are also obtained from the conventional linear multiple regression analysis and is presented in Table 5. Overall nature of the statistics is same as observed from the ANN. But the accuracy is better for ANN methodology as compared to linear multiple regression analysis.}

The validation of the developed methodology during real situations is carried out on 25 and 29 October 2006. On 29 October validation is for Yes rain situation and on 25 October, it is for No rain situations. The sequence of the input radar images on 29 October at 1400, 1430 and 1500 hrs UT are shown in Figs 7 (a, b and c), respectively and the image corresponds to predicted Yes rain situation which is shown at 1700 hrs UT [Fig. 7(d)]. Similarly, the sequence of the input radar images on 25 October at 1000, 1300 and 2000 hrs UT are shown in Figs 7 (e, f and g), respectively and the image corresponds to predicted No rain situation which is shown at 0400 hrs UT [Fig. 7(h)]. It is observed that in both the situations, the developed ANN methodology of rain nowcasting is performing reasonably well.

As DWR data of other stations are not available, therefore, testing of the developed algorithm at other DWR stations could not be carried out. But nevertheless, with DWR data of Shriharikota the algorithm is tested at other locations within the domain of the DWR range, i.e. 200 km of radius for the optimum measurements. For this purpose, two location one at Chennai (12.99°N, 80.18°E) and other at Tiruvallur (13.09°N, 79.57°E) are considered. To test the algorithm all the parameters are calculated with respect to space coordinates of these two locations. Thereafter, the prepared input matrices with respect to these two locations are multiplied with the updated weight matrices to get the output results. For these two stations, the results are provided in Table 6. It is observed that though percentage of match for No rain situations is reduced marginally as compared to Shriharikota but the percentage of Yes rain situation is nearly same at Shriharikota. Overall, the percentage statistics at all the three stations are reasonably well.

<table>
<thead>
<tr>
<th>S. No.</th>
<th>Name of the station</th>
<th>Cases</th>
<th>Match, %</th>
<th>Mismatch, %</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Chennai</td>
<td>No rain</td>
<td>82</td>
<td>18</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(12.99°N, 80.18°E)</td>
<td>Yes rain</td>
<td>80</td>
</tr>
<tr>
<td>2.</td>
<td>Tiruvallur</td>
<td>No rain</td>
<td>79</td>
<td>21</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(13.09°N, 79.57°E)</td>
<td>Yes rain</td>
<td>76</td>
</tr>
</tbody>
</table>
As the code of the other models are not available, therefore, the results of the present model is tried to compare with other method in a indirect way. The nowcasting model, known as Thunderstorm Identification Tracking Analysis and Nowcasting (TITAN), is used to nowcast the thunderstorms ($\geq 30$ dBZ) with a lead time of 30 min (ref. 4). However, in the present study, the nowcasting is carried out with a lead time of 2 h by taking into account the precipitating systems of $\geq 20$ dBZ, which may consists of convective core of higher dBZ within the system. Nevertheless, the results of the present work are discussed in context with the results from TITAN by using the probability of detection (POD: $N_{\text{success}} / N_{\text{success}} + N_{\text{failure}}$) approach, where, $N_{\text{success}}$ and $N_{\text{failure}}$ are number of cases of success and failure. The success is the situation when both the truth and nowcast conditions (Yes rain/ No rain) are same and failure implied to the situation when the truth and nowcast conditions are not same. The POD for the nowcast of Yes / No rain with a lead time of 2 h for Shriharikota, Chennai and Tiruvallur stations are found to be 0.84, 0.81 and 0.77, respectively. Dixon & Wiener$^4$ reported that POD for the thunderstorm nowcast, for volume–by-volume analysis and track by track analysis is 0.42 and 0.59, respectively. The higher POD by the present developed methodology is expected because of the larger precipitating systems are taken into account, whereas TITAN is primarily used for smaller precipitating systems at thunderstorm scale.

5 Summary and Conclusion

In the present work, a soft computing model is developed to nowcast the Yes/No rain situations at a station with a lead time of 2 h. For this purpose, 15 input parameters from radar imageries are provided to the ANN. A reasonably good agreement is observed between the predicted and observed values. The results from the ANN are found to be better as compared to linear multiple regression technique. The advantage of utilizing the DWR is that it can discriminate the anomalous propagation and therefore, avoiding the ambiguous precipitating systems. The developed model presents the nowcasting of the rain at station due to a selected individual rain cell in the radar reflectivity imagery. For the composite result at the point location due to all the identified cells in the radar imagery the final nowcast should be made by taking into account all the identified precipitating systems through the logic “OR” operation. Though the present model is developed for the localized point location but it can be further extend to nowcast the rain field.

Fig. 7— (i) Input imageries at: (a) $T_0$, (b) $T_0+1/2$, and (c) $T_0+1$ hrs UT; and output imagery at: (d) $T_0+3$ hrs UT on 29 October 2006 (ii) Input imageries at: (e) $T_0$, (f) $T_0+1/2$, and (g) $T_0+1$ hrs UT; and output imagery at: (h) $T_0+3$ hrs UT on 25 October 2006
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References