Adaptive neuro-fuzzy inference system to estimate the predictability of visibility during fog over Delhi, India

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Abstract
In the present research it was attempted to estimate the predictability of visibility during fog over the airport of the most polluted city Delhi (28° 38’ N, 77° 12’ E), India, with an adaptive neuro-fuzzy inference system (ANFIS). The investigation started with the evaluation of fuzzy membership to categorize the data into different ranges. The output variables of fuzzy membership are used as the input in the multilayer perceptron model of artificial neural networks. In this hybrid computing system, the ANFIS was trained with the data from 2000 to 2010 for estimating the predictability of visibility during fog over Delhi airport. The results show that the ANFIS provides minimum forecast errors (9.09%) with 12 hr lead time in comparison to other neural network models and the existing forecast models. The results were validated with observations from 2011 to 2015. The coupled model ANFIS shows minimum error in visibility forecasting during fog over Delhi airport with validation from observations as well. The study therefore suggests that the ANFIS may be adopted as an alternative operational model for forecasting visibility during fog with 90.91% accuracy for a 12 hr lead time.

KEYWORDS
ANFIS, fog, forecast, fuzzy, GRNN, MLP, MLR, RBFN, visibility

1 | INTRODUCTION

Fog forecasting during winter months has become essential in recent times especially over airports to avoid aviation hazards. The loss of visibility during fog causes loss of life and property which has become comparable to high impact weather events (Gultepe and Milbrandt, 2007). Due to severe disruption of commercial airfield operations, particularly at Delhi airport (Figure 1), forecasting visibility has become a crucial issue (Ghude, 2017). The proximity of the Himalayan region makes Delhi susceptible to cold waves during the winter resulting in the beginning of the fog season which starts in November and attains a peak in January with average temperatures varying between 12 and 13°C (Roy Bhowmik et al., 2004; Gera et al., 2013). The prevailing synoptic condition has been demonstrated for the onset as well as the formation of fog by low wind speed and persistent subsidence of high pressure over the region with a northerly and north-westerly zonal advection supporting cold air advection over the locale. The boundary layer is inflated by...
northerly and northwesterly advection leading to a net decrease in temperature. The moisture incursion and high concentrations of pollutants caused by land surface processes and emission sources in the Indo-Gangetic plains favour and accelerate the persistence of foggy conditions for extended periods (Ghude, 2017). Elevated inversion layers are observed during the winter months. The association between the occurrence of fog and the incursion of cold waves due to the passage of western disturbances during winter has been observed by Gera et al. (2013). The western disturbance is likely to approach the western Himalayan region. The wind over Delhi and the National Capital Region blows from a southwesterly direction (Chaudhuri et al., 2015a,b). Detailed studies including the magnitude and consequences of fog in weather forecasting have been carried out by many scientists (Willett, 1928; Roach et al., 1976; Charlton and Park, 1984; Meyer et al., 1986; Gulottie and Milbrandt, 2007; Chaudhuri et al., 2009; 2015; Dutta and Chaudhuri, 2015; and many others). The evaluation of visibility is made as per the norm at the regional Indira Gandhi International (IGI) airport and archived at the Regional Meteorological Centre, New Delhi. The daily data of visibility at 1 hr temporal resolution used in the present study are collected from the Regional Meteorological Centre, New Delhi. The investigation made by Schalkwyk and Dyson (2013) on fog assessment at Cape Town International Airport, South Africa, for 1997–2010 was referred to in the present work. Loss to aviation economy due to winter fog in New Delhi during 2011–2016 has been estimated by Kulkarni et al. (2019), where stable and clear atmospheric conditions, lower surface temperatures, an ample moisture supply and a strong low-level inversion persisting for most of the night usually facilitates the formation of dense fog during winter in Delhi. In addition, an analogue dynamical model for forecasting fog-induced visibility over Delhi has been evaluated. The validation was carried out against hourly visibility data recorded at IGI airport over Delhi during the winter months (December and January) for the period 2009–2012 (Goswami and Sarkar, 2016). The concept of fuzzy logic was introduced by Zadeh in 1965 to represent data and information possessing non-statistical uncertainties. The use of linguistic variables and flexibility in the method are introduced through fuzzy logic (Murtha, 1995; Pokrovsky et al., 2002; Chaudhuri, 2011; Chaudhuri and Middey, 2012 and many others). The method of artificial neural networks, on the other hand, is observed to have potential in atmospheric as well as oceanic studies in pattern recognition, classification and prediction (Bose and Liang, 1995; Gardner and Dorling, 1998; Hsieh and Tang, 1998; Haykin, 1999; Bodri and Cermak, 2000; Maqsood et al., 2005; Chaudhuri, 2006; 2010; and many others). Artificial neural network models have been developed to predict the visibility during fog over three major cities of India, Kolkata, Delhi and Bangaluru (Chaudhuri et al., 2015). To overcome the difficulty of nonlinear relationships in a geophysical system, the coupled systems of fuzzy membership followed by artificial neural networks have been widely executed in various areas. Chaudhuri and Middey (2011) developed an adaptive neuro-fuzzy inference system (ANFIS) to forecast the peak gust speed associated with thunderstorms during the pre-monsoon season.
(April–May) over Kolkata, India. Duong et al. (2013) studied a conjunct space cluster-based ANFIS and applied it for the seasonal forecast of tropical cyclones making landfall along the Vietnam coast with high accuracy. The ANFIS is used in long-range forecasting of all India summer monsoon rainfall (Chaudhuri et al., 2016). Chaudhuri et al. (2018) implemented the Sugeno ANFIS for forecasting the seismic moment of large earthquakes over the Indo-Himalayan region.

An attempt is made in the present study to identify the best model for forecasting the visibility during fog using pressure, relative humidity, temperature, dew point temperature, wind speed and direction as input and visibility as the target output. The ANFIS is implemented to achieve the target. To check the accuracy of the ANFIS, different neural network models are used and compared with statistical and existing forecast models.

2 | DATA AND METHODOLOGY

2.1 | Data

The data of surface parameters were collected for the months of November to February during the period from 2000 to 2015 over Delhi (28° 38’ N, 77° 12’ E), India, from IGI airport, Delhi, archived at the Regional Meteorological Centre, New Delhi. The input variables for training and testing the ANFIS models were temperature, dew point temperature, relative humidity, pressure, wind speed and direction, whereas the target output was the horizontal visibility during fog. The data were collected at 1 hr temporal resolution.

2.2 | Methodology

To achieve the target output, statistical and soft computing methods were implemented.

2.2.1 | Statistical method

Box-whisker plots
Box–whisker plots are graphical representations which include minimum value, first (lower) quartile, median, third (upper) quartile and the maximum value. Outliers are also indicated on a box plot. The implication of a box–whisker plot plays a significant role in research methodology and data analysis to display the variability in the dataset. The box–whisker plot represents a pictorial synopsis of the dataset used in the study for analysis including the central tendency, dispersion, asymmetry and extremes, arrived at through percentile rank analysis and the plotting of maximum and minimum dataset values. Besides, it provides an effective way of identifying asymmetrical attributes in the dataset by measuring the central tendency and the spread free from the assumption of a normal distribution. The box–whisker plot is useful to identify the variation and variability in the parameters (Banacos, 2011; Chaudhuri and Middey, 2014, Chaudhuri et al., 2015).

Multiple linear regression equation
Multiple linear regression is the most common form of linear regression analysis. It is used to explain the relationship between one continuous dependent variable and two or more independent variables which can be continuous or categorical (Yu, 2014; Ceyhun et al, 2016). Many scientists have used the multiple linear regression approach for probabilistic computation of the value of the target output (Courville and Thompson, 2001; Zientek et al., 2008; Nimon et al., 2010; Das and Chaudhuri, 2014).

A multiple linear regression equation was formulated for forecasting the visibility during fog over Delhi, India:

\[ Y = a_1X_1 + a_2X_2 + a_3X_3 + a_4X_4 + a_5X_5 + C \]

where \(X_1, X_2, ..., X_6\) are the input parameters: \(X_1\), temperature (°C); \(X_2\), dew point temperature (°C); \(X_3\), surface pressure (hPa); \(X_4\), relative humidity (%); \(X_5\), visibility (km); \(Y\), visibility in fog.

Multiple linear regression equations were formulated after analysing the data for the different categories of fog:

\[ Y = (0.190)X_1 + (0.06)X_2 + (0.25)X_3 + (1.01)X_4 + (0.99)X_5 + (-0.104) \]

2.2.2 | Soft computing approach

Fuzzy membership
The fuzzy logic is observed to be very helpful in modeling approach because of its strength and self-control in processing imprecise data. The conceptual approach of fuzzy logic can allow the complexity of a problem to be solved. The nonlinear functions of arbitrary complexity (Zadeh, 1965) can be resolved without any difficulties. A fuzzy system can be developed to match any set of input–output data. In the present study the trapezoidal function was used to categorize the input as well as the output variables (Chaudhuri and Middey, 2011).
Artificial neural network

Artificial intelligence is useful for functional prediction and system modelling where the physical processes are not understood or are highly complex. The multilayer perceptron (MLP) is a well accepted neural net in practice (Gardner and Dorling, 1998; Chaudhuri and Middey, 2011) (Figure 2). In this regard the back propagation algorithm is used to train the feedforward network of interconnected neurons. The back propagation algorithm works by iteratively changing the interconnecting weights of the network so that the prevailing error between the observed value and the model output can be minimized with accuracy. Mathematically this can be expressed as:

\[ y = \left( \sum_{i=1}^{n} \omega_i x_i + b \right) = (w^T x + b) \]

where \( w \) is the vector of weights, \( x \) denotes the vector of inputs, \( b \) is the bias and \( T \) is the activation function.

The radial basis function neural network (RBFN) is another successfully implemented category of neural network. The architecture of the RBFN considered in this study comprised a three-layer neural network with one input layer, one hidden layer and one output layer, where each hidden unit implements a radial activation function (Figure 3). In the present study, the Gaussian activation function was used for the RBFN:

\[ \Phi_j(X) = -\left( (X-\mu_j)^T \sum (X-\mu_j)^{-1} \right) \]

for \( j = 1, \ldots, L \), where \( L \) represents the number of hidden units and \( X \) is the input matrix. \( \mu_j \) and \( \Sigma_j \) are the mean and covariance matrix of the \( j \)th Gaussian function. The

**FIGURE 2** Architecture of the multilayer perceptron model for forecasting visibility during fog over Delhi airport with 12 hr lead time

**FIGURE 3** Architecture of the radial basis function neural network model for forecasting visibility during fog over Delhi airport with 12 hr lead time
output layer implements a weighted sum of the hidden units output as:

$$\Psi_k(X) = \sum_{j=1}^{L} \lambda_{jk} \Phi_j(X)$$

for \( k = 1, ..., M \), where \( M \) is the number of output units and \( \lambda_{jk} \) are the output weights. The output of the radial basis function is limited to the interval \((0, 1)\) by the sigmoid function given by:

$$Y_k(X) = \frac{1}{1 + \exp[-\Psi_k(X)]}$$

There is no requirement for an iterative training procedure as back propagation in the generalized regression neural network (GRNN) which is based on kernel regression networks (Hannan et al., 2010; Cigizoglu and Alp, 2005, Celikoglu and Cigizoglu, 2007). The structure of the GRNN includes one input layer, a pattern layer, a summation layer and an output layer (Figure 4). In addition, it is consistent that, as the training set size becomes large, the estimation error approaches zero (Chaudhuri et al., 2015):

$$Y_i = \frac{\sum_{i=1}^{n} y_i \exp[-D(x, x_i)]}{\sum_{i=1}^{n} \exp[-D(x, x_i)]}$$
D(x, x_i) = \sum_{k=1}^{m} \left( \frac{x_i - x_{ik}}{\sigma} \right)^2

Adaptive neuro-fuzzy inference system (ANFIS)

The acronym ANFIS is derived from adaptive neuro-fuzzy inference system. To build an ANFIS model first a fuzzy inference system is developed by computing the membership functions by means of a trapezoidal curve followed by a back propagation algorithm. This method offers a process for artificial modelling to gather information about a dataset to calculate the membership function to learn the given input and output parameters. The learning method works like that of neural networks.

The trapezoidal curve is a function of a vector x and depends on four scalar parameters a, b, c and d:
The architecture of the ANFIS model is given in Figure 5.

Graphical representation:

Figure 7: Variability in (a) wind direction and (b) wind direction over Delhi airport at 12 hr prior to the formation of fog.

The predicted and actual values of the parameters are denoted by $Y_{dp}$ and $Y_{da}$ respectively.

4 | Results and Discussion

As stated earlier, the data on temperature, dew point temperature, surface pressure, relative humidity, visibility, wind speed and direction were collected. Box-whisker plots of the parameters were drawn to find their variability during fog over Delhi (Figure 6). The temperature was observed to vary between 3 and 25°C over Delhi during the period. However, the maximum variability in temperature was observed to be confined within 9.49 and 23.97°C. The dew point temperature was observed to have maximum variability within the range 4.87–11.00°C. The maximum variability of relative humidity was observed to be within 48.42% and 96.85%. The surface pressure varied between 1,014.00 and 1,020.00 hPa with maximum variability within 1,014.49 and 1,018.14 hPa. The maximum variability of visibility during fog was observed to be within 0.60 and 2.82 km. The variability of wind speed and direction is shown in

\[
f(x,a,b,c,d) = \begin{cases} 0 & x < a \\ \frac{x-a}{b-a} & a \leq x < b \\ 1 & b \leq x \leq c \\ \frac{d-x}{d-c} & c \leq x \leq d \\ 0 & x \geq d \end{cases}
\]
pie charts during fog over Delhi. The wind was observed to remain mostly calm at 12 hr before the formation of fog. However, most of the wind was observed to approach from the southwest direction to Delhi airport at 12 hr before the formation of fog (Figure 7).

The fuzzy membership functions of the parameters were estimated. The parameters were classified into three categories (low, medium and high) for precise forecasts. The temperatures between 2 and 10°C were categorized in the low range, between 10.2 and 18°C in the medium range and between 18.2 and 26°C in the high range. Similarly, the ranges of dew point temperature were categorized in the low, medium and high ranges as 0–6°C, 6.2–12°C and 12.2–18°C respectively. Likewise, the pressure was categorized as low, medium and high for 1,000–1,010 hPa, 1,010.2–1,020 hPa and 1,020.2–1,030 hPa respectively. The relative humidity was categorized similarly using fuzzy membership functions to low, medium and high categories within 25% to 50%, 50.5% to 75% and 75.5% to 100% respectively. The horizontal visibility was categorized from 0 to 1.5 km as low, 1.6 to 2.9 km as medium and 3.0 to 4.5 km as high (Figure 8).
The outputs of the fuzzy memberships of the parameters were arranged to prepare the input matrix of the MLP model. Three architectures of MLP models were used in the present study. The first model had one input layer, one hidden layer with one node and one output layer (MLP1), the second model consisted of one input layer, two hidden layers with two nodes in each and one output layer (MLP2) and the third model comprised one input layer, three hidden layers with three hidden nodes in each and one output layer (MLP3). The coupling of the fuzzy output with MLP1 leads to the coupled model ANFIS 1, and similarly for ANFIS 2 and ANFIS 3 (Chaudhuri and Middey, 2011; Chaudhuri et al., 2016).

The results show that the low range of visibility during fog is predicted by ANFIS 3 with minimum forecast error in comparison to ANFIS 1 and ANFIS 2 (Figure 9a).

### Table 1 Comparison of the present study with other existing models

| SL no. | Models | Objective | Forecast errors |
|--------|--------|-----------|-----------------|
| 1      | Forecast with artificial neural network model (ANN) (Fabbian and Dear, 2006) | Prediction of fog at Canberra international airport applying the ANN model | Error perturbation (%), 15 |
| 2      | Real time forecast (Jenamani and Tyagi, 2012) | Evaluation of skill scores of real time fog forecasting system, various fog model performances at IGI airport during 2008–2011 and future prospects | MAE, 18.3 |
| 3      | Forecast with decision tree method (Wantuch, 2001) | Visibility and fog forecasting based on decision tree method | PE, 35 |
| 4      | Forecasting the visibility during fog over Delhi airport with 12 hr lead time (present study) | ANFIS model | PE, 9.09 MAE, 2.78 RMSE, 4.96 |

**Figure 9** The estimated forecast error in predicting the visibility during fog over Delhi airport using the ANFIS 1, ANFIS 2 and ANFIS 3 models for low, medium and high ranges

**Figure 10** The forecast errors generated by different models in forecasting the visibility during fog over Delhi airport using surface parameters with 12 hr lead time during the training period
**FIGURE 11** Variability in the input parameter temperature from 1 to 12 hr prior to the formation of fog

**FIGURE 12** Variability in the input parameter dew point temperature from 1 to 12 hr prior to the formation of fog

**FIGURE 13** Variability in the input parameter relative humidity from 1 to 12 hr prior to the formation of fog

**FIGURE 14** Variability in the input parameter surface pressure from 1 to 12 hr prior to the formation of fog
The values of PE, MAE and RMSE were estimated with ANFIS 3. The study shows that, in forecasting the low range of visibility during fog, the values of forecast errors in terms of PE, MAE and RMSE are 9.390%, 2.203% and 4.719%. The performance of the ANFIS 3 model in forecasting the visibility during fog within the medium range was estimated (Figure 9b). It was found that, in forecasting the medium range of visibility during fog, the values of forecast error in terms of PE, MAE and RMSE are 7.989%, 2.853% and 4.921% respectively. The PE, MAE and RMSE in forecasting a high range of visibility during fog were estimated with the ANFIS 3 model as 8.371%, 2.807% and 4.192% respectively. The results thus show that the values of forecast error are minimum for forecasting a high range of visibility as per the categorization through the fuzzy membership function. Further, the ANFIS 3 model shows minimum error in comparison to the ANFIS 2 and ANFIS 1 models (Figure 9c). The skill of the ANFIS coupled model was also estimated by comparing with existing models (Table 1).

The forecast of visibility during fog using the ANFIS models was compared with the MLP, the RBFN, the GRNN model and multiple linear regression. The different errors in terms of PE, MAE and RMSE were
evaluated. The results show that the ANFIS model has minimum error in predicting visibility during fog. The values of PE, MAE and RMSE are 9.09%, 2.78% and 4.96% respectively with the ANFIS. However, PE, MAE and RMSE in forecasting the visibility during fog using the MLP model are 15.13%, 6.65% and 13.45% respectively. Further, using the RBFN model, the PE, MAE and RMSE in forecasting the visibility during fog are 29.33%, 7.71% and 15.15%. It is observed that the GRNN shows higher values of the forecast error in forecasting visibility during fog over Delhi airport. A statistical model was used in terms of multiple linear regressions to assess the visibility during fog over Delhi and also shows higher error in comparison to the ANFIS (Figure 10).

The study shows that the error in predicting the visibility during fog is less with the ANFIS coupled model than with other models with 12 hr lead time. The coupled model run is made with 1 hr intervals to identify the lead time for the best forecast. The box–whisker plots show the variability of the input and output parameters over Delhi airport at 1 hr intervals (Figures 11–15). The skill of the present coupled model was assessed by computing the PE, MAE and RMSE with 1 to 12 hr lead time (Figure 16). The figure shows that the PE is 3.66% in forecasting the visibility with 1 hr lead time while it becomes 9.09% with 12 hr lead time. The same finding is observed considering the MAE and RMSE. It is evident from the results that the errors in forecasting increase with increasing lead time. The errors generated by the different models in forecasting the visibility during fog over Delhi airport with 12 hr lead time during the testing and validation periods show that the ANFIS performs better than the other models (Figure 17). The errors in forecasting visibility during fog over Delhi airport using the ANFIS model with 1–12 hr lead time during the validation period were estimated (Figure 18). The error in forecasting visibility during fair weather and during passage of a weather system using the ANFIS model with 12 hr lead time was estimated (Figure 19). The results show that the percentage error is less during passage of a weather system than during fair weather.

5 CONCLUSION

From the perspective of aviation safety the forecasting of visibility during fog is an absolute necessity. An adaptive neuro-fuzzy inference system (ANFIS) has been developed to forecast the near surface visibility during fog over the airport of Delhi. The coupled model ANFIS shows minimum forecast error (9.09%) with 12 hr lead time in comparison with other neural network models. The skill of the coupled model was checked by comparing with other existing models (Table 1). The result of the study further shows that the forecast error is 3.07% with 1 hr lead time and the error increases with increasing lead time. Fog is a micro-scale phenomenon and thus the forecast of visibility during fog with the ANFIS over Delhi airport with 12 hr lead time is pragmatic for aviation safety. The model may thus be suggested as an alternative option for operational forecasting of near surface visibility during fog over Delhi airport.

ACKNOWLEDGEMENT

The corresponding author thanks the DST, GOI, for providing the opportunity to work for CCP.

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**How to cite this article**: Goswami S, Chaudhuri S, Das D, Sarkar I, Basu D. Adaptive neuro-fuzzy inference system to estimate the predictability of visibility during fog over Delhi, India. *Meteorol Appl*. 2020;27:e1900. [https://doi.org/10.1002/met.1900](https://doi.org/10.1002/met.1900)