METEOROLOGICAL APPLICATIONS
Meteorol. Appl. **22**: 563–575 (2015)
Published online 15 December 2014 in Wiley Online Library
(wileyonlinelibrary.com) DOI: 10.1002/met.1488

Track and intensity forecast of tropical cyclones over the North Indian Ocean with multilayer feed forward neural nets

Sutapa Chaudhuri,* Debashree Dutta, Sayantika Goswami and Anirban Middey
Department of Atmospheric Sciences, University of Calcutta, India

ABSTRACT: Precise forecasting of the track and intensity of tropical cyclones remains one of the top priorities for the meteorological community. In the present study multilayer feed forward neural nets with different architectures are developed to identify the best neural net for forecasting the track and intensity of tropical cyclones over the North Indian Ocean (NIO) with 6, 12 and 24 h lead time. Forecast errors are estimated with each neural net. The result reveals that the neural net architecture 1 (NNA 1) with 10 input layers, 2 hidden layers, 5 hidden nodes and 2 output layers provides the best forecast for both the track and the intensity of the tropical cyclones over NIO. Two cyclones of the same category in Saffir Simpson Hurricane Scale, namely Nargis and Phet, that occurred over the Bay of Bengal and the Arabian Sea of the NIO basin are considered in the present study for validation. The result reveals that the prediction errors (%) with NNA 1 model in estimating the intensity of the cyclones Nargis and Phet during the validation are 3.37, 8.29 and 9.74 as well as 6.38, 11.26 and 18.72 with 6, 12 and 24 h lead time, respectively. The mean track errors for 6, 12 and 24 h forecasts are observed to be 45, 69 and 89 km for cyclone Nargis and 54, 87 and 98 km for cyclone Phet. NNA 1 model is observed to perform better than NNA 2 and NNA 3 models and the existing numerical models.

KEY WORDS multilayer feed forward neural net; forecast; track; intensity; tropical cyclones; NIO

Received 1 June 2014; Revised 4 November 2014; Accepted 6 November 2014

1. Introduction

Weather forecasts and warnings are the most important services required by the government and industry in protecting life, property, environment and daily activities. Tropical cyclones are one of the most devastating and destructive natural disasters. The loss of life and property, and the human suffering caused by tropical cyclones in the coastal areas of various parts of the Earth are well known. Indian coasts are also observed to be significantly vulnerable and susceptible to tropical cyclones. The northern part of the Bay of Bengal is known for its potential to generate dangerous storms with high surges (Chaudhuri and De Sarkar, 2008). 8 out of 10 recorded cases of very heavy loss of life (ranging from about 40 000 to well over 200 000) in the world due to tropical cyclones have been observed in the Bay of Bengal and the Arabian Sea of the North Indian Ocean (NIO) (WMO, 2010).

Forecasting the track and intensity of tropical cyclones with precise accuracy and adequate lead time is a prime responsibility of the meteorological community across the globe. Forecast lead time of tropical cyclones may be divided into two distinct periods for the community response and meteorological view point: the medium range forecast, beyond 24 h and up to 72 h, and the short range forecast, up to 24 h (Leslie *et al.*, 1992).

The medium range forecast provides planning and guidance advice and opportunity to develop local community awareness of potential threat whereas the short range forecast becomes very important as the cyclones approach the coast (Bengtsson, 1989). Most communities require a 12–24 h forecast to respond to a tropical cyclone warning with industrial shut down and evacuation and at least a 12 h forecast before landfall for civil defence authorities to prepare for the storm hazards. The forecast with <12 h lead time falls under short range forecast (Wilson and Sarrazin, 1989). Nowcasting (0–6 h) is a developing subject area for high-impact weather forecasting. It blends observations and model forecasts that are often more accurate than the simple extrapolation techniques used in the past.

Intensity forecast involves not only climatology and persistence of the trend over the entire timescale together with some empirical and pattern recognition approaches (Leslie *et al.*, 1992) but also many dynamic modelling techniques, which are discussed in the later sections of this article.

1.1. Background

1.1.1. *Statistical dynamic techniques*

The first statistical guidance used by the US National Hurricane Center was the Hurricane Analog Technique (Neumann and Hope, 1972). The tropical cyclone motion forecast for 24 h is dominated by climatology and persistence, especially for the low-latitude areas (Neumann and Pelissier, 1981; Keenan, 1982; Elsberry *et al.*, 1988). Dynamic and statistical–dynamic techniques, which incorporate forecast changes in the large timescale flow, are most effective at longer time scales.

Two major causes of errors may therefore be identified in short-term forecasts, which are the initial analysis errors that degrade the persistence forecast (Jarrell *et al.*, 1978; Neumann, 1981) and sharp changes of intensity or motion that cannot be captured by persistence or climatological techniques. Keenan (1982) has shown that the intensity forecast based on a combination of synoptic reasoning and the Dvorak technique provided no advantage relative to the persistence technique. Wang and

* Correspondence: S. Chaudhuri, Department of Atmospheric Sciences, University of Calcutta, 51/2, Hazra Road, Kolkata 700019, West Bengal, India. E-mail: chaudhuri_sutapa@yahoo.com

Neumann (1985) used the transitional probabilities for tropical cyclone track prediction. Chaudhuri *et al.* (2012) estimated the predictability of severe tropical cyclones over the NIO by observing the features of cyclonic depression with a condition-decision support system of rough set theory (Chaudhuri, 2008). Recently, Singh *et al.* (2011) used the advanced research (ARW) Weather Research and Forecast model (WRF) with 3D variational data assimilation (3DVar) system to investigate the impact of satellite data assimilation on the track and intensity forecast of tropical cyclones over the NIO. It was observed that the Quick Scatterometer (QuikSCAT) near surface winds and Special Sensor Microwave/Imager (SSM/I) derived from total precipitable water (TPW) have a positive impact on track forecasting. Singh *et al.* (2012) simulated a cyclone track over the NIO using the Lagrangian advection model. The study revealed that the mean track errors for 12, 24 and 36 h forecast of cyclone Gonu are 58, 84 and 111 km, respectively, while those of cyclone Sidr are 53, 100 and 95 km, respectively. Osuri *et al.* (2012) found that WRF-ARW produced better forecast of cyclone track for 48 h with track error of 119 km over the NIO. The outcome was also compared with the results of the operational centers such as the National Center for Environmental Protection (NCEP), the European Centre for Medium range Weather Forecast (ECMWF), the United Kingdom Met Office (UKMO), the India Meteorological Department (IMD) and the National Center for Medium Range Weather Forecast (NCMRWF).

1.1.2. Neural network techniques

The artificial neural network (ANN) method has shown potential in oceanic and atmospheric sciences (Hsieh and Tang, 1998). ANN has been used to solve many real-world problems through pattern matching, classification and prediction (Gardner and Dorling, 1999; Chaudhuri, 2006). Bodri and Cermak (2000) developed an ANN model using 38 year rainfall data to predict monthly and yearly precipitation levels for multiple sites in the Czech Republic. The tropical cyclone pattern identification system using neural oscillatory elastic graph matching model (NOEGM) and the tropical cyclone track mining system using hybrid radial basis function (HRBF) network have been developed by Lee and Liu (2000). The model shows improvement of 30 and 18%, respectively, over the existing numerical model forecast of tropical cyclone pattern and track. Maqsood *et al.* (2004) used an ensemble of ANN to provide 24 h predictions of air temperature, wind speed and humidity at the Regina Airport in Canada. The superiority of neural network classifier technique over linear discriminant analysis (LDA) in the framework of a statistical model for forecasting tropical cyclogenesis was provided by Hennon *et al.* (2005). The performance of the neural network model during the 1998–2001 Atlantic hurricane seasons showed better results with a neural network classifier than the LDA for 6–48 h probabilistic forecast. Wedge *et al.* (2005) developed an ANN model for the prediction of waves spilling over sea walls using the sea conditions and wall properties as inputs. Lee (2009) predicted typhoon storm surge in Taiwan using the back propagation neural network (BPNN) model. The inputs for the BPNN model were wind speed, wind direction, atmospheric pressure and values of astronomical tides. The root mean square error (RMSE) in the forecast was observed to vary between 0.03 and 0.38. Chaudhuri (2010) developed an ANN model to forecast severe thunderstorms using convective energies as input. Chaudhuri and Middey (2011) developed an adaptive neuro fuzzy inference system to forecast the peak wind speed associated with severe thunderstorms. Roy and Kovordányi (2012) have explained the utility of the ANN technique in tropical cyclone track forecasting.

The present study is aimed at forecasting the track and intensity of tropical cyclones over the NIO with multilayer feed forward neural network models having different architectures with 6, 12 and 24 h lead times. The records and data of tropical cyclones that occurred over the NIO from 2002 to 2010 are considered to develop the ANN models. The input matrices are prepared with the data of 10 parameters: central pressure (hPa), pressure drop (hPa), sea surface temperature (SST) (°C), cloud top temperature (CTT; K), cloud optical depth (COD), aerosol optical depth, T number, cloud coverage, cloud water path (CWP) and cloud top pressure (hPa) collected at 6, 12 and 24 h before the occurrence of the tropical cyclones. The targets are the track and intensity of the cyclones. The tropical cyclones Nargis, reported in 2008 over the Bay of Bengal, and Phet, reported in 2010 over the Arabian Sea, are considered for validation of the model's forecasting capability. These cyclones are chosen for validation because both are of Saffir Simpson Hurricane Scale but the origins of the cyclones are different.

Cyclone Nargis was reported to be a very severe cyclonic storm of category 4 and was one of the worst natural disasters in the recorded history of Burma. The cyclone made landfall in Burma on 2 May 2008, causing catastrophic destruction and at least 13 800 fatalities. Around 5500 people were reported to be missing and a large area of Bangladesh, Burma, India and Sri Lanka was affected by the cyclone. Damage was estimated to be over US $1 billion, which made it one of the most damaging cyclones ever recorded in this basin (Pattanaik and Rama Rao, 2009; Ford, 2010). Cyclone Phet was also of category 4 and occurred in 2010 over the NIO. Damage due to Phet was estimated to exceed US $78 million, with a total of 44 fatalities (Gutro, 2010).

2. Materials and methods

2.1. The data

The dataset considered for the present study includes the records of tropical cyclones reported over the Bay of Bengal and the Arabian Sea of the NIO.

- The SST data were collected from the National Oceanic and Atmospheric Administration (NOAA) site (http://www.esrl.noaa.gov/psd/data/gridded/data.noaa.oisst.v2.highres.html) within $0.5° \times 0.5°$ grid resolution over the global grid of $720° \times 360°$. NOAA high resolution SST data (Reynolds *et al.*, 2007) provided by the NOAA/Oceanic and Atmospheric Research (OAR)/Earth System Research Laboratory (ESRL) Physical Sciences Division, Boulder, Colorado, USA, were collected from http://www.esrl.noaa.gov/psd/.
- The data of CTT (K), COD, aerosol optical depth, cloud coverage, CWP (gm^{-2}) and cloud top pressure (hPa) were collected from the Moderate Resolution Imaging Spectro-radiometer (MODIS) satellite within $1° \times 1°$ global grid.
- The meteorological data of central pressure (hPa) (it is a measurement of pressure at the sea level), T number, maximum sustained surface wind (kn) and pressure drop (hPa) were collected from the IMD for the period 2002–2010. The central pressure is a point value representing the minimum sea level pressure associated with the tropical cyclone. The T number is a measure of intensity derived from pattern matching of satellite imagery. The Dvorak technique (Dvorak, 1975) is a method using enhanced infrared and/or visible satellite imagery to quantitatively estimate the intensity of a tropical

system. Using the pattern formed by the clouds of a tropical cyclone, expected systematic development, and a series of rules, an intensity analysis and forecast can be made. The pressure drop can be expressed as the difference between the central pressure and the environmental pressure (Pradhan *et al.*, 2012). The pressure drop data were collected from the IMD with 3 h intervals.

The SST is the water temperature close to the surface of the ocean which is an important parameter for cyclogenesis. The CTT is the atmospheric temperature at the level of the cloud top; the COD is the measure of attenuation of the light passing through the atmosphere due to the scattering and absorption by cloud droplets; aerosol optical depth (AOD) represents the degree to which aerosols prevent the transmission of light by absorption or scattering of light; cloud coverage is the portion of the sky cover which is attributed to clouds; CWP is the columnar amount of liquid water in the cloud and represents the atmospheric pressure at the level of the cloud top. The data and records of tropical cyclones over the NIO from 2002 to 2005 are used to prepare the models whereas the data and records from 2006 to 2010 are used for testing the models. Two significant tropical cyclones Nargis and Phet that occurred over the NIO are considered for validation with observation. Phet was reported to be a very severe cyclonic storm that developed over the Arabian Sea and turned into a tropical cyclone on 31 May 2010. Its first landfall was in the Oman Desert attaining its peak intensity on June 4. It turned its direction to northeast and made landfall as a deep depression at Thatta, Pakistan, in the evening of 6 June 2010.

2.2. The methodology

Multilayer feed forward network models are developed in the present study with different architectures to identify the best model for forecasting the track and intensity of tropical cyclones over the NIO. The ANN method is an information processing paradigm or mathematical model that is inspired by the way in which biological nervous systems process information. It is composed of a number of highly interconnected processing elements or artificial neurons working in unison to solve specific problems. An ANN is generally configured for a specific application, such as data classification, pattern recognition or prediction through a learning process (Bose and Liang, 1996; Haykin, 1999).

The basic processing elements of neural networks are called artificial neurons, or simply neurons or nodes. In a simplified mathematical model of the neuron, the effects of the synapses are represented by connection weights that modulate the effect of the associated input signals, and the non-linear characteristic exhibited by neurons is represented by a transfer function. The neuron impulse is then computed as the weighted sum of the input signals and transformed by the transfer function. The learning capability of an artificial neuron is achieved by adjusting the weights in accordance with the chosen learning algorithm. A typical feed forward ANN consists of three or more interconnected layers of nodes, which are the input layer, one or more hidden intermediate layers and an output layer. ANN can have various forms; however the most common is the feed forward network architecture. In this configuration, different numeric inputs to the network are passed forward from an input layer, through one or more hidden layers to an output layer (Grimes *et al.*, 2003; Shank *et al.*, 2008; Chaudhuri, 2010). The data pass through a network and are modelled according to weight adjustment on each connecting link. At each neuron, the values of its inputs are combined and an appropriate transfer function is applied. The transfer functions commonly used are either sigmoid or hyperbolic tangent. A neuron then produces an output which is passed on to the next neuron it is linked to or out of the network. Thus, for a given

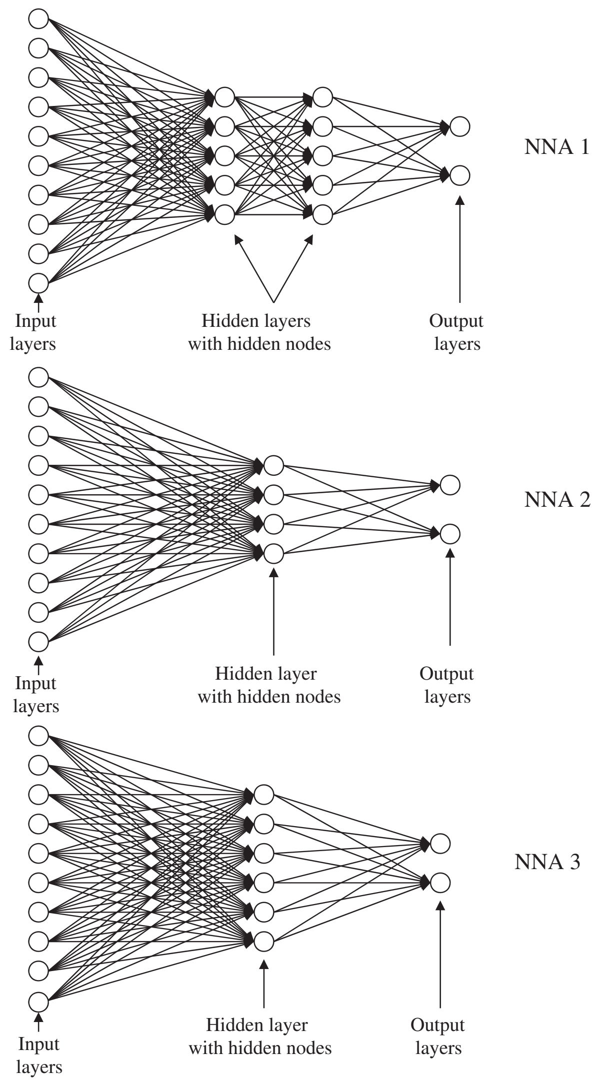


Figure 1. The figure represents the multilayer feed forward neural net architecture 1 (NNA 1), neural net architecture 2 (NNA 2) and neural net architecture 3 (NNA 3).

Table 1. Correlation matrix between 24 h advance (N1) input values and intensity (MSWS) output parameters on current day (N) associated with tropical cyclones over NIO (2002–2010).

Inputs on day N1	Output (MSWS in kn) on day N
CP (hPa)	−0.91
MSWS (kn)	0.79
PD (hPa)	0.95
SST (°C)	0.02
T number	0.97
CTT	0.83
CWP	0.43
AOD	0.28
COD	0.39
CC	0.72

AOD = aerosol optical depth, CC = cloud cover, COD = cloud optical depth, CP = central pressure, CTT = cloud top temperature, CWP = cloud water path, MSWS = maximum sustained wind speed, PD = pressure drop, SST = sea surface temperature.

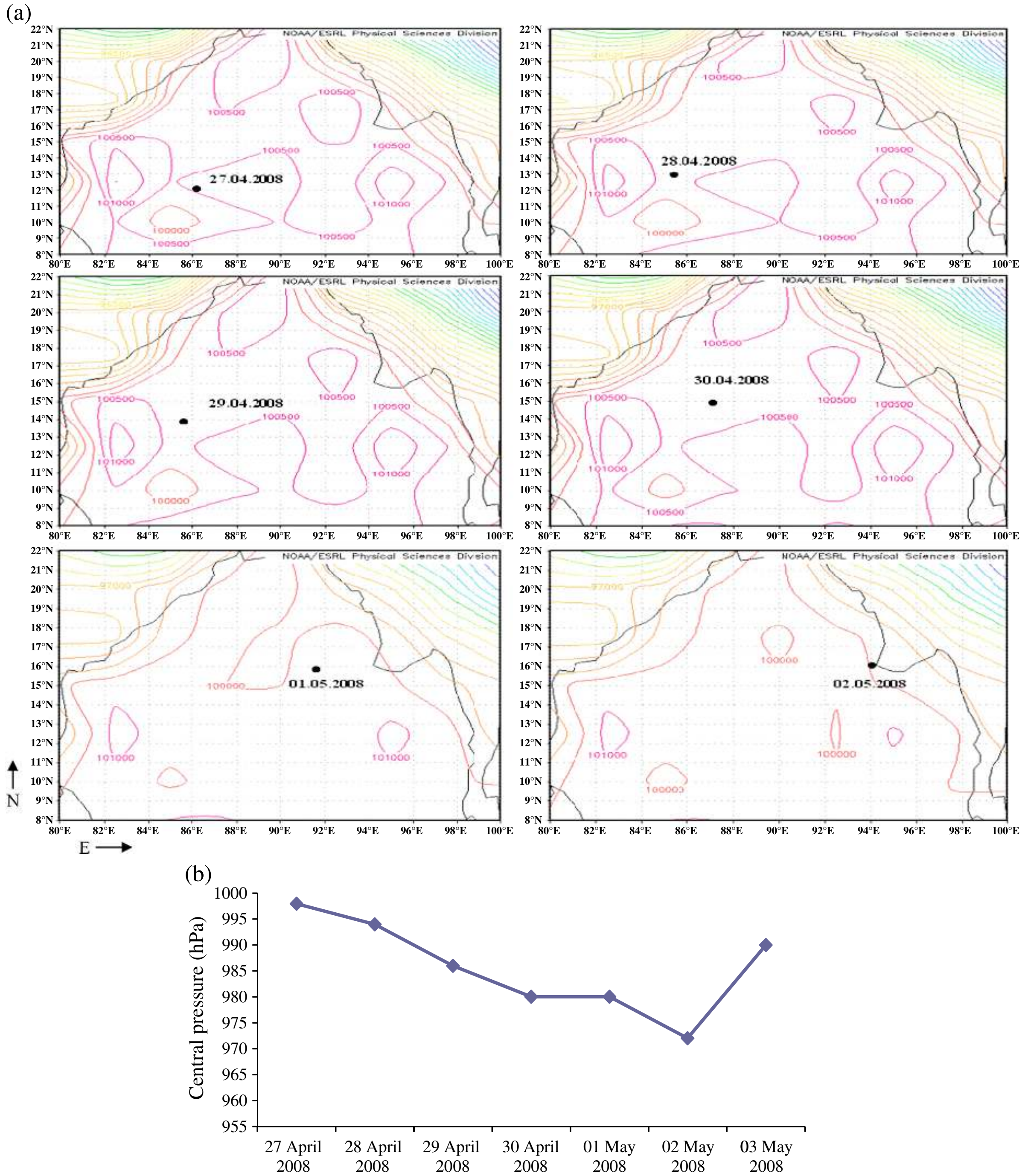


Figure 2. (a) The spatial variation of the central pressure associated with cyclone Nargis where the black dot represents the eye of the cyclone. Selected area: 80 ° to 100 ° E and 8 ° to 22 ° N and (b) temporal variation of the central pressure (hPa) associated with cyclone Nargis (27 April 2008 to 3 May 2008).

set of inputs to a neural network, a particular output response is obtained. A network can be trained to respond in different ways to different inputs by adjusting the weights linking its neurons together and thus a functional mapping is produced to a set of predictands from a set of predictors.

The interval activity of the neuron can be expressed as:

$$v_k = \sum_{j=1}^{p} w_{kj} x_j \tag{1}$$

Each neuron k receives incoming signals from every neuron j in the previous layer. Each incoming signal (x_j) is associated with a weight (w_k). The net input v_k to neuron k is a sum of the incoming signal times the weight. The net input, v_k equals the sum of the weight times the input signal for all the inputs to the neuron j from neuron k starting at output of neuron $j = 1$ and ending at $j = n$.

The activation function acts as a squashing function, such that the output of a neuron in a network lies between certain values (usually 0 and 1, or −1 and 1) (Pal and Mitra, 1999). In general, there are three types of activation function (φ). Firstly, the threshold function takes on a value of 0 if the summed input is less than a certain threshold value (v), and the value

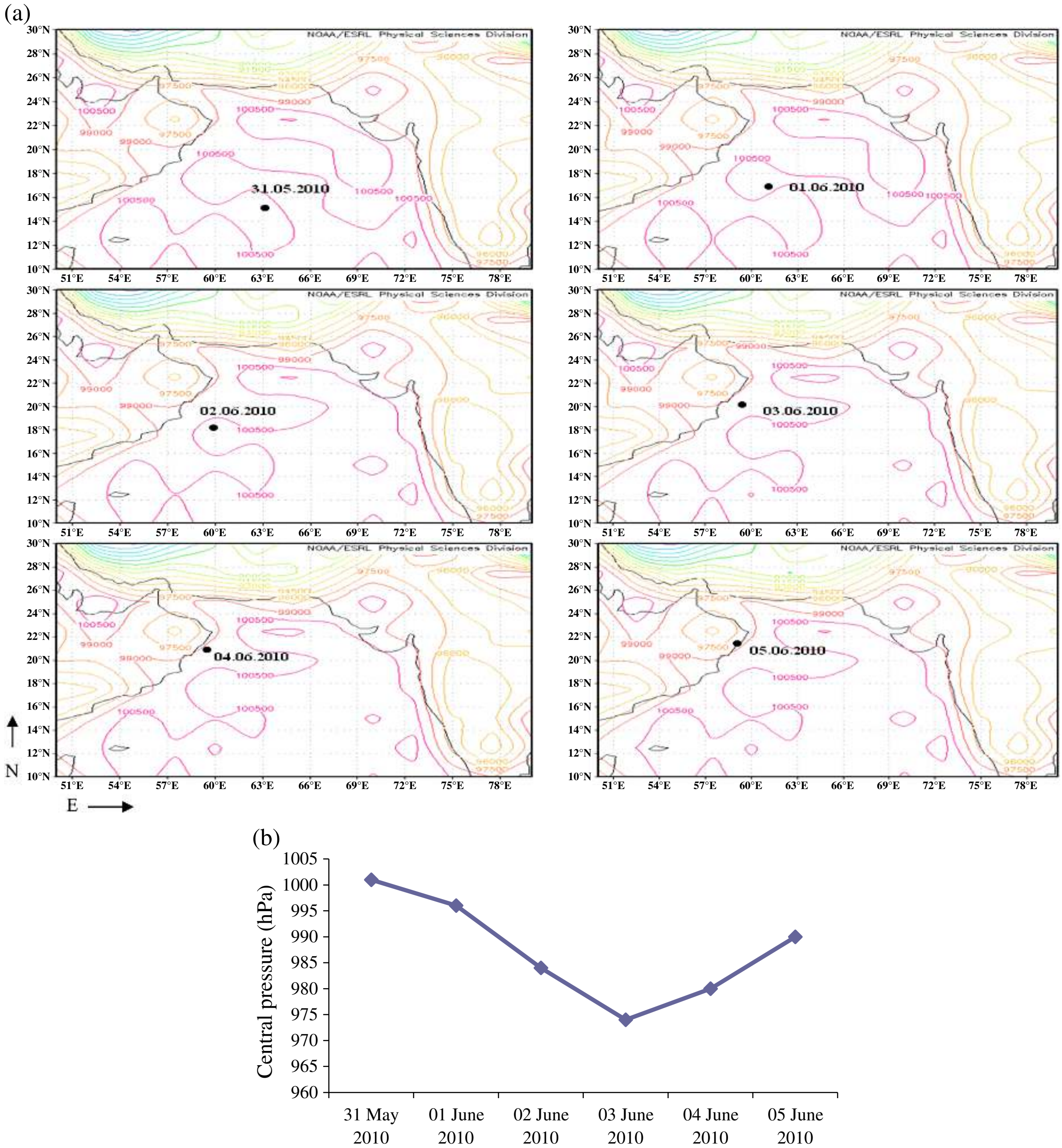


Figure 3. (a) The spatial variation of the central pressure associated with cyclone Phet, where the black dot represents the eye of the cyclone. Selected area: 50° to 80° E and 10° to 30° N and (b) the temporal variation of the central pressure (hPa) associated with cyclone Phet (31 May 2010 to 5 June 2010).

1 if the summed input is greater than or equal to the threshold value:

$$\varphi(v) = \begin{cases} 1 & \text{if} \quad v \geq 0 \\ 0 & \text{if} \quad v < 0 \end{cases} \tag{2}$$

Secondly, the piecewise linear function which can take on the value of 0 or 1, can also take on values in between depending on the amplification factor in a certain region of linear operation:

$$\varphi(v) = \begin{cases} 1 & v \geq 1/2 \\ v & -1/2 \quad > v > 1/2 \\ 0 & v \leq -1/2 \end{cases} \tag{3}$$

Thirdly, the sigmoid function can range between 0 and 1; however, sometimes it is helpful to use the −1 to 1 range also. Sigmoid function refers to the special case of the logistic function and can be defined as:

$$S(t) = \frac{1}{1 + e^{-t}} \tag{4}$$

The example of the sigmoid function is the hyperbolic tangent function:

$$\varphi(v) = \tan h\left(\frac{v}{2}\right) = \frac{1 - \exp(-v)}{1 + \exp(-v)} \tag{5}$$

Log sigmoid function is represented mathematically as:

$$\sigma(t) = \frac{1}{1 + e^{-\beta t}} \tag{6}$$

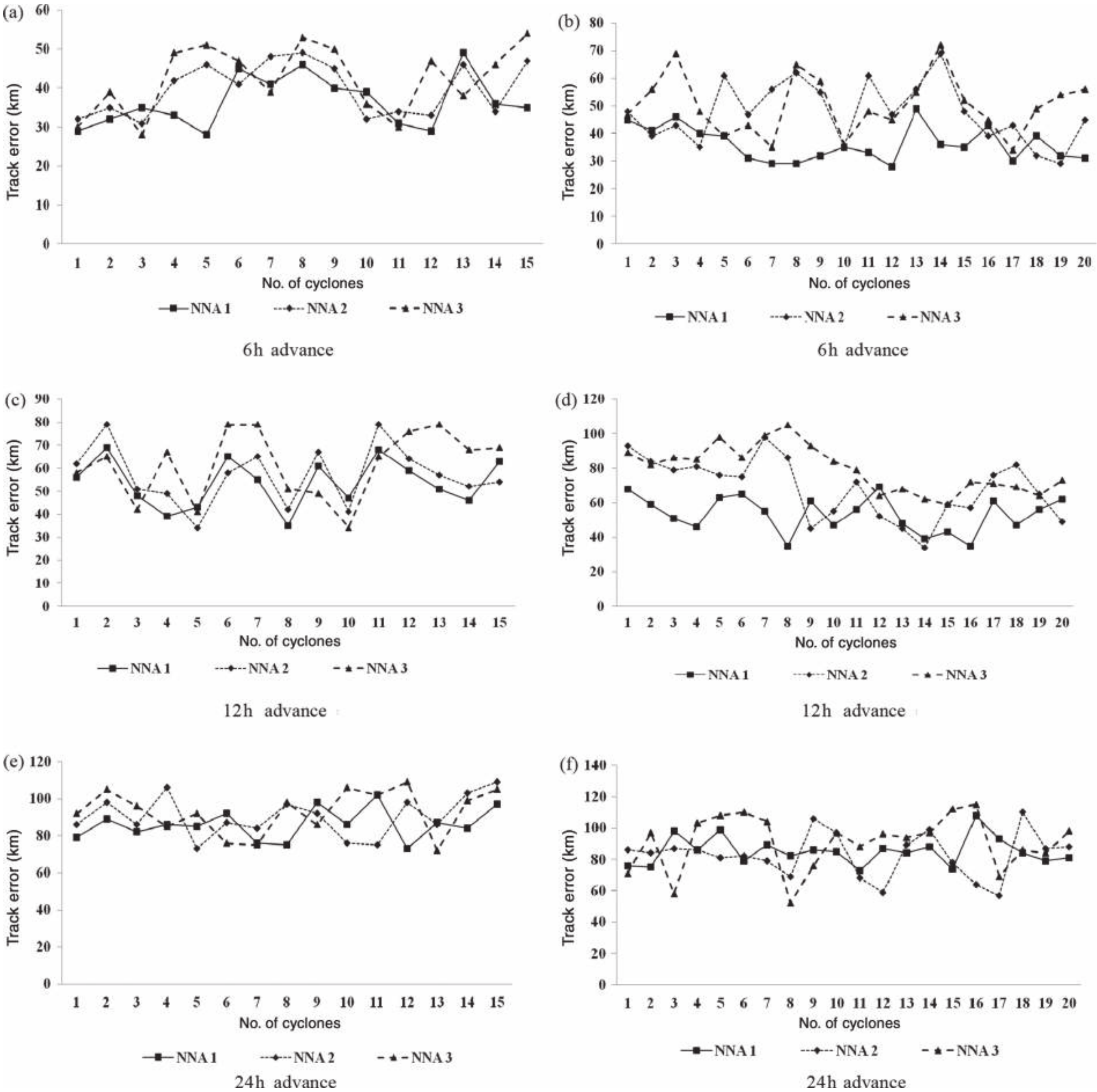


Figure 4. The mean track error (km) for 6, 12 and 24 h forecast during training (a), (c) and (e) and testing (b), (d) and (f) of neural network models having different architectures NNA 1, NNA 2 and NNA 3.

where β is the slope parameter and t is the time step, and

$$a = \log \operatorname{sig}(n) \tag{7}$$

where a is the output of the ANN model and n is the sum of the weighted inputs from the previous layer. The ANN output is in the range of 0–1. In Equation (7), $a \rightarrow 1$ as $n \rightarrow \infty$ and $\alpha \rightarrow 0$ as $n \rightarrow \infty$. The target values are preset at 0.1 and 0.9 respectively, instead of 0 and 1 in order to prevent the value of n from moving to one extreme (towards $+\infty$ or $-\infty$). The log sigmoid function is considered in the present study.

The multilayer perceptron (MLP) is perhaps the most popular neural network architecture (NNA) in use in recent times (Gardner and Dorling, 1998; Chaudhuri and Middey, 2011). It is a feed forward network of interconnected neurons usually trained using the error BP algorithm (Cerdeña *et al.*, 2007). The BP algorithm works by iteratively changing the interconnecting weights of the network such that the overall error that exists between the observation and model forecast is reduced. Mathematically this can be expressed as:

$$y = \varphi\left(\sum_{i=1}^{n} \omega_i x_i + b\right) = \varphi\left(w^T x + b\right) \tag{8}$$

where w is the vector of weights, x denotes the vector of inputs, b is the bias and φ is the activation function.

The quality of prediction is obtained from the performance of the test set of data. The overall prediction error (PE) is measured as (Perez and Reyes, 2001):

$$\mathrm{PE} = \frac{\left\langle \left| Y_{\mathrm{dP}} - Y_{\mathrm{dA}} \right| \right\rangle}{\left\langle Y_{\mathrm{dA}} \right\rangle} \tag{9}$$

where $\langle\rangle$ implies the average over the whole test set. The predicted and actual values of the parameters are denoted by Y_{dP} and Y_{dA}, respectively.

The predictive model is considered to be good if the PE is sufficiently small, that is, close to 0. The model with minimum PE is identified as the best prediction model.

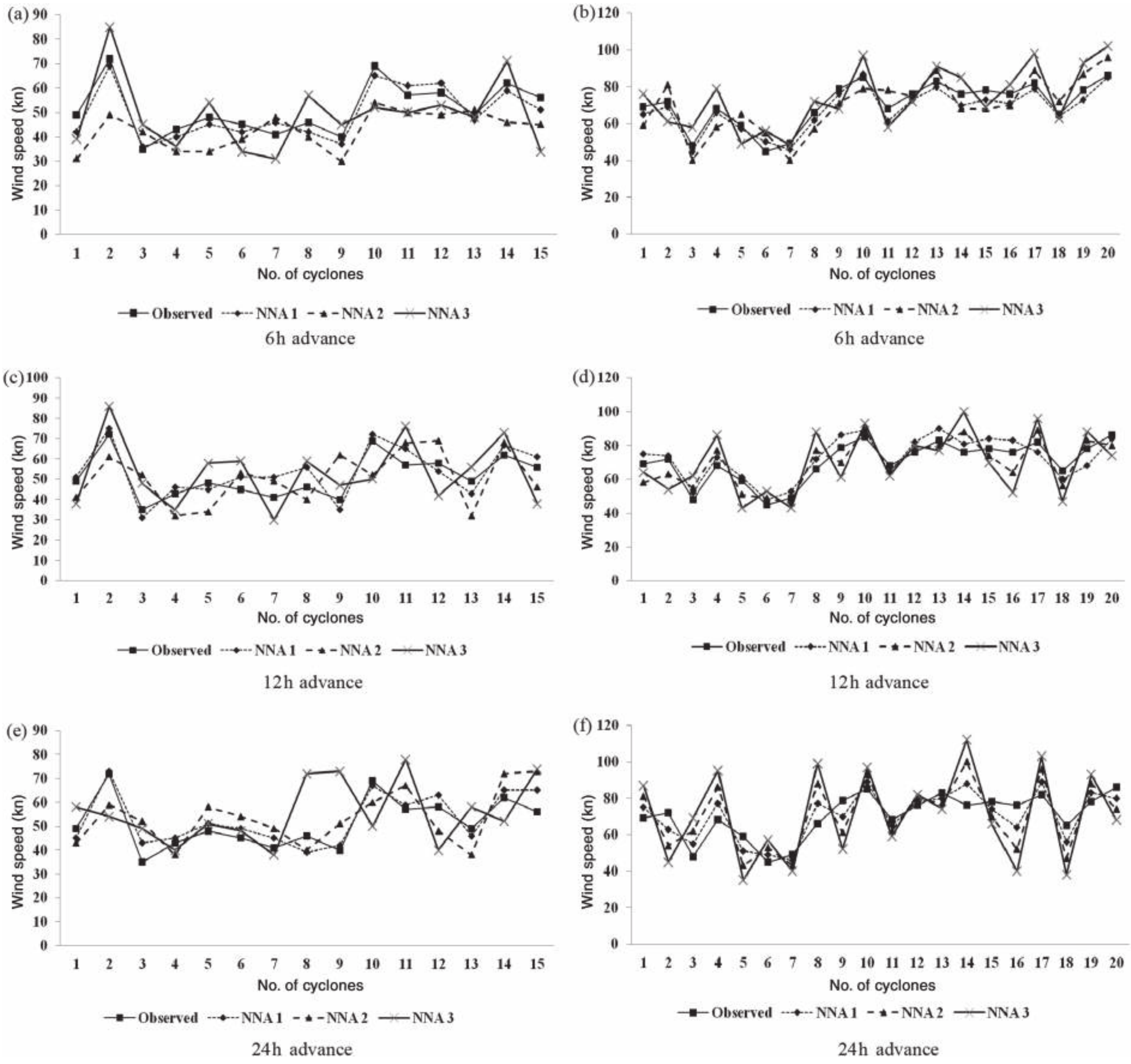


Figure 5. The tropical cyclone intensity in terms of wind speed (kn) for 6, 12 and 24 h forecast during training (a), (c) and (e) and testing (b), (d) and (f) of neural network models having different architectures NNA 1, NNA 2 and NNA 3.

The RMSE and mean absolute error (MAE) are computed for testing the accuracy of the prediction:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_{\mathrm{dA}} - Y_{\mathrm{dP}}\right)^{2}} \tag{10}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|Y_{\mathrm{dP}} - Y_{\mathrm{dA}}\right| \tag{11}$$

3. Implementation procedure

At the outset, the collected data during the period from 2002 to 2010 are separated into two parts, 2002 to 2005 and 2006 to 2010. The data from 2002 to 2005 are analysed to prepare the input matrix to train the multilayer feed forward neural nets for forecasting the target output of the track and intensity of tropical cyclones over the NIO. The data from 2006 to 2010 are used to test the neural nets in forecasting the target output of the track and intensity of tropical cyclones over the NIO. The input matrices are prepared with the data of 10 parameters: central pressure (hPa), pressure drop (hPa), SST (°C), CTT (°K), COD, aerosol optical depth, T number, cloud coverage, CWP and cloud-top pressure (hPa) collected at 6, 12 and 24 h before the occurrence of the tropical cyclones. The output is the track and intensity of tropical cyclones over the NIO. Each tropical cyclone has a typical 5–7 day life span (depression to landfall). The ANN set up was made using 10 input and 2 output systems. For a typical 5 day tropical cyclone episode with 3 h data, there are 24/3 = 8 time points available of which 8 × 5 = 40 data points for each input/output pair appears. Total number of 400 (40 × 10) input and 80 (40 × 2) output will be presented for a 5 day episode. Only non-MODIS parameters change in 3 h intervals but the MODIS parameter entries will change on a daily basis, that is, for a whole day, MODIS parameters will be constant. Cloud parameters such as CTT (°K), COD, aerosol optical depth, cloud coverage, CWP have unique impact on the track and intensity of tropical cyclones. In case of tropical storms, differences among forecasts occur much earlier in terms of cloud cover (CC) and deep convective activity than they do in terms of deepening and track (Chaboureau *et al.*, 2012). Dvorak technique is used for analysing intensity with satellite

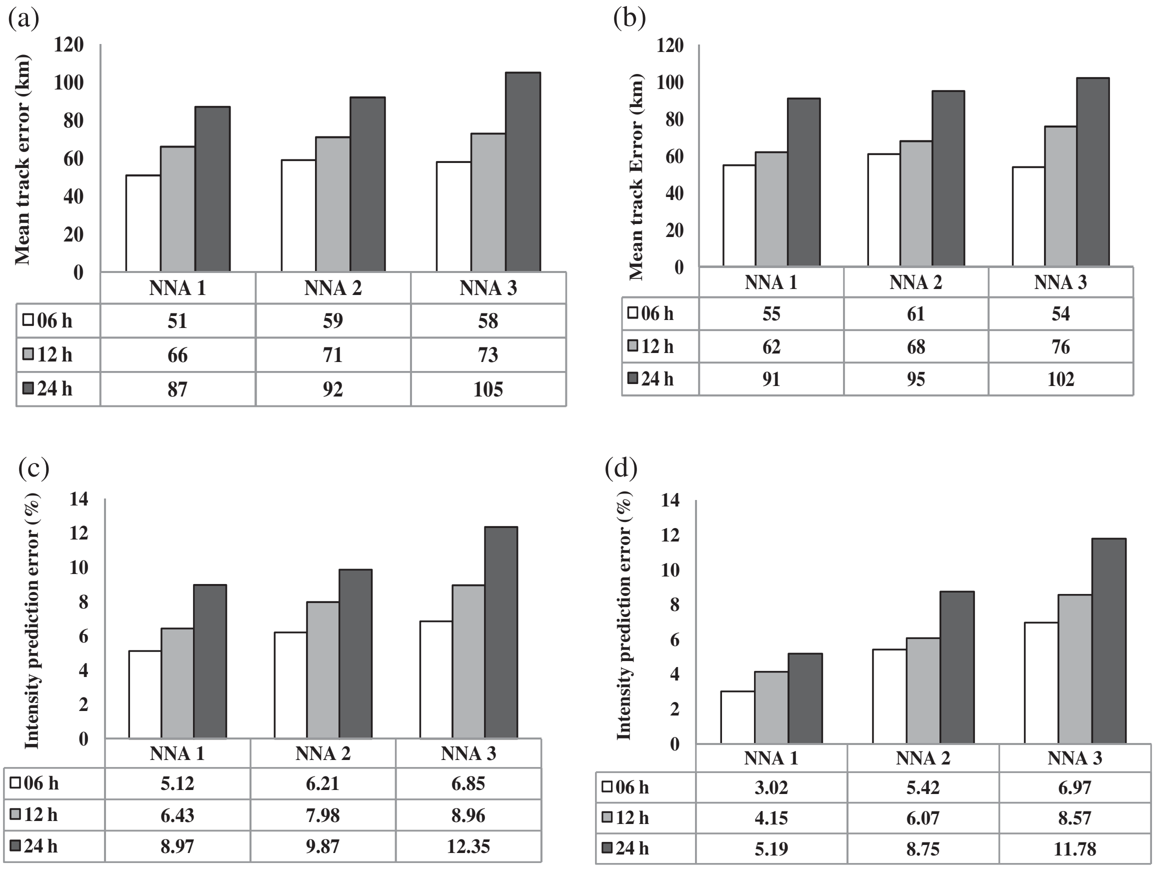


Figure 6. The figures show the errors during training and testing of the neural network model of different architectures for mean track error (a and b) and error in intensity prediction (c and d) of tropical cyclones over North Indian Ocean (NIO) with 6, 12 and 24 h lead time.

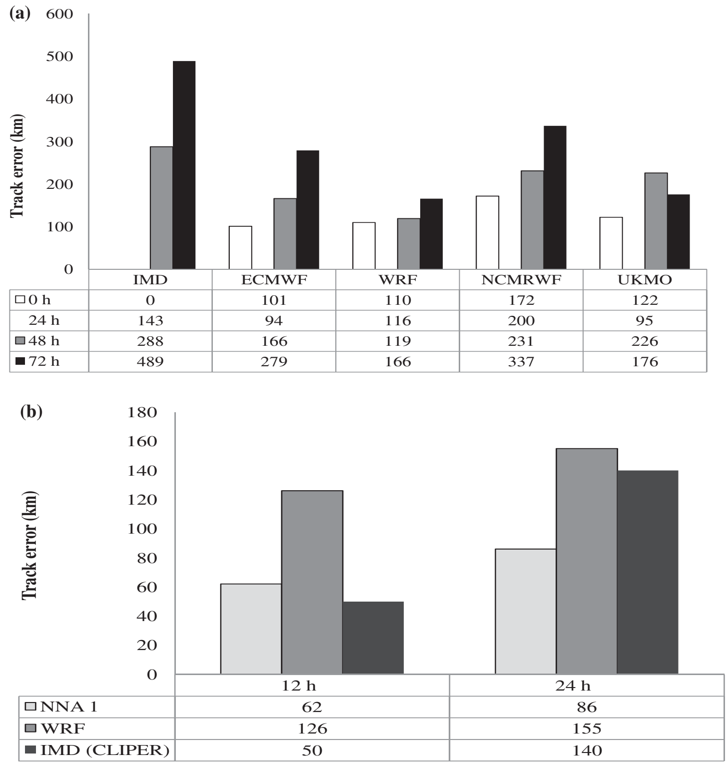
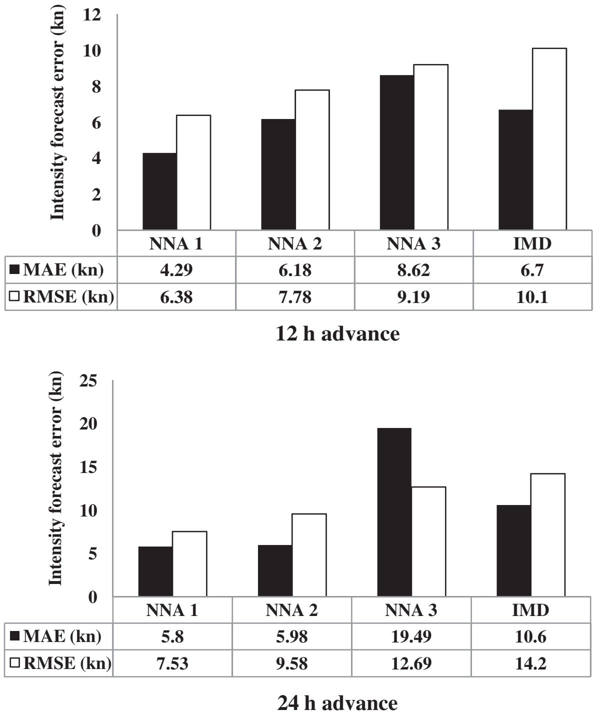


Figure 7. The diagrams show (a) the mean track errors (km) with WRF model and models of other operational forecasting centers for tropical cyclones of North Indian Ocean (NIO) (see Osuri *et al.*, 2012) and (b) the comparison of the mean track errors (km) with neural network architecture (NNA) 1, WRF and India Meteorological Department (IMD) (CLIPER) models for tropical cyclones of the NIO.

imagery (Dvorak, 1975) that adopts both visible and infrared cloud feature measurements. All the input values are reduced to a point value by taking the centre value. All the input parameters are standardized before they are fed into the neural network.

The correlations between 24 h before (N1) input with present day's (N) maximum sustained wind speed (MSWS) (output) reveals the potential of inputs for forecasting the target output (Table 1). The high wind speeds associated with storms, leading to high AOD may be due to sea salt over oceans and dust over continents (Lehahn *et al.*, 2010). Recently, Middey and Chaudhuri (2012) have observed a correlation of the order 0.85 between suspended particulate matter and AOD over tropical stations. Storms often produce high clouds with high coverage. The correlations of other parameters such as central pressure (hPa), pressure drop (hPa), SST (°C) are shown in Table 1. It is observed that the intensity as *per* MSWS is strongly but negatively correlated with central pressure, whereas it is positively and strongly correlated with the previous day's pressure drop (0.97) and T number (0.95). It is evident that continuous pressure drop in the previous day assures increased intensity of the cyclonic system in the coming hours. However, MSWS is positively but weakly correlated with SST. The previous day's (24 h before) CC and CTT show good correlations (0.72 and 0.83, respectively) with present day's cyclone intensity (i.e. MSWS). This is obvious because both CC and CTT positively influence the strength of tropical cyclones. More CC and high CTT leads to huge horizontal and vertical cloud growth resulting from severe convective activity. However, other parameters like AOD, COD and CWP have small value correlations (0.28, 0.39 and 0.43, respectively) with MSWS. The multilayer feed forward neural nets are comprised of three architectures, neural net architecture 1 (NNA 1), neural net architecture 2 (NNA 2) and neural net architecture 3 (NNA 3) (Figure 1). NNA 1 is prepared with 10 input layers, 2 hidden layers, 5 hidden nodes and 2 output layers. NNA 2 is prepared with 10 input layers, 1 hidden layer, 4 hidden nodes and 2 output layers. NNA 3 is prepared with 10 input layers, 1 hidden layer, 6 hidden nodes and 2 output layers.



	NNA 1	NNA 2	NNA 3	IMD
■ MAE (kn)	4.29	6.18	8.62	6.7
□ RMSE (kn)	6.38	7.78	9.19	10.1

	NNA 1	NNA 2	NNA 3	IMD
■ MAE (kn)	5.8	5.98	19.49	10.6
□ RMSE (kn)	7.53	9.58	12.69	14.2

Figure 8. The mean absolute error (MAE) and root mean square error (RMSE) of intensity forecast (in kn) of tropical cyclones over North Indian Ocean (NIO) using neural network architectures (NNAs) and comparison with India Meteorological Department's (IMD's) forecast results (see Mahapatra *et al.*, 2013) with 12 and 24 h lead time.

Number of hidden layers in practical problem does not exceed two. The main difficulty comes up during number of node selection in hidden layers (Heaton, 2008). There are many guideline

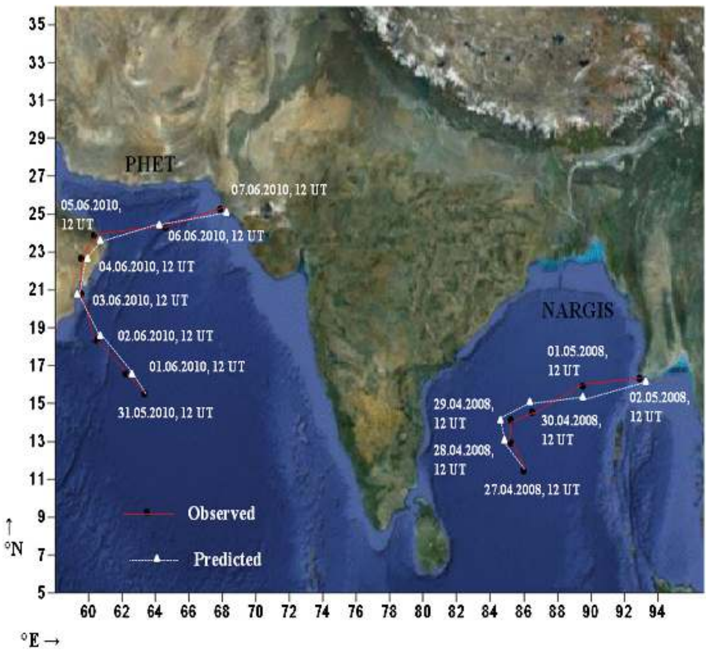
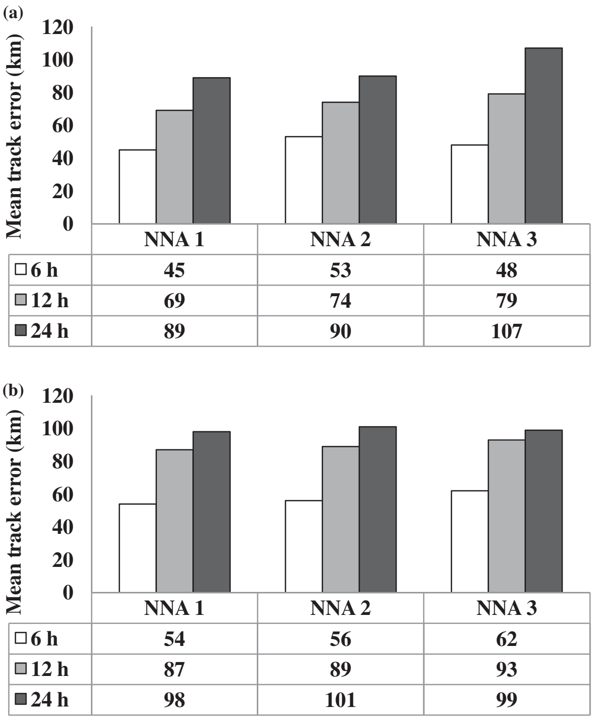


Figure 9. Observed and neural network architecture (NNA) 1 predicted track of tropical cyclones (Nargis and Phet) of North Indian Ocean (NIO) with 24 h lead time.



(a)

	NNA 1	NNA 2	NNA 3
6 h	45	53	48
12 h	69	74	79
24 h	89	90	107

(b)

	NNA 1	NNA 2	NNA 3
6 h	54	56	62
12 h	87	89	93
24 h	98	101	99

Figure 10. Mean track error values (in km) for multilayer feed forward neural nets with different architectures (NNA 1, NNA 2 and NNA 3) during validation in estimating the track of the cyclone (a) Nargis and (b) Phet with 6, 12 and 24 h lead time.

methods for determining the correct number of neurons to use in the hidden layers, such as:

- the number of hidden neurons should be between the sizes of the input and the output layers;
- the number of hidden neurons should be two-third the size of the input layer, plus the size of the output layer;
- the number of hidden neurons should be less than twice the size of the input layer.

These three rules provide a starting point for consideration. Ultimately, the selection of architecture for the neural network will come down to trial and error.

More than three networks have been tested but the performances of the selected three are found to be satisfactory.

4. Results and discussion

The result reveals that the NNA 1 provides the best forecast with minimum PE with 6, 12 and 24 h lead time. The most accurate forecast is provided by the NNA 1 model with 6 h lead time. The PE is observed to increase with increase in lead time.

Two tropical cyclones, Nargis and Phet reported to develop over the Bay of Bengal and the Arabian Sea of the NIO basin are considered in the present study for validation.

The characteristics of both the cyclones are analysed prior to implementation of the models in order to estimate the forecast skill during validation. Some noticeable characteristics are observed for both the cyclones during comparative analyses. The spatial variation of the sea level pressure (hPa) associated with the cyclones Nargis and Phet as evident from NCEP/NCAR (National Center for Atmospheric Research) reanalysis images are shown in Figures 2(a) and 3(a), respectively, where the black dot represents the eye of the cyclone. The temporal variation in the central pressure is observed for both the cyclones (Figures 2(b) and 3(b)). The minimum central pressure for cyclone Phet is observed on the 4th day whereas for cyclone Nargis the minimum central pressure is observed on the 6th day after genesis.

Different architectures of the multilayer feed forward neural network models are then executed for validation in estimating the track and intensities of cyclones Nargis and Phet. Fifteen tropical cyclones during the period from 2002 to 2005 are trained with multilayer feed forward neural network models (NNA 1, NNA 2 and NNA 3) for 6, 12 and 24 h forecast, whereas 20 tropical cyclones during the period from 2006 to 2010 are considered for testing the models. The forecast of track (km) and intensity (kn) with 6, 12 and 24 h lead time during training and testing of the models are shown in Figures 4 and 5. The track forecast during training and testing with NNA 1 model shows more consistency than other two neural net models, NNA 2 and NNA 3 (Figure 4). However, as the lead time increases, the error was found to increase. The NNA 1 model is also observed to perform better than the other two neural net models for intensity forecast (Figure 5). The mean errors in track (km) and intensity (kn) forecast during training and testing of the models are evaluated (Figure 6). The PEs are computed for each cyclone for specific lead times 6, 12 and 24 h and then averaged for all cyclones. There is no indication of overfitting of the models as evident from the comparable error values during both training and testing stages. The results reveal the superiority of the NNA 1 model over the other two network models, NNA 2 and NNA 3. The NNA 1 model shows mean track errors of 51, 66 and 87 km during training and 55, 62 and 91 km during testing for 6, 12 and 24 h forecast of track. The consistency is also maintained by the NNA 1 model for the intensity forecast. The PE for 6, 12 and 24 h forecasts of intensity are 5.12, 6.43 and 8.97% during training and 3.02, 4.15 and 5.19% during testing of the NNA 1 model.

Osuri *et al.* (2012) have compared WRF simulated tropical cyclone tracks on a real-time basis with other operational track forecasts provided by IMD (Quasi Lagrangian Model, QLM), NCMRWF (T254L64 global model), ECMWF and UKMO over the NIO (Figure 7(a)). Four tropical cyclones were considered for the comparative study: Nargis, Rashmi, Khaimuk and Nisha, which occurred in 2008. The performance of the NNA 1 model is compared with the existing best numerical models for track and intensity forecast of tropical cyclones over the NIO in recent times (Figure 7(b)). The 24 h forecast of mean track by the NNA 1 model is observed to be better than the existing models (Figure 7(a) and (b)).

The error in forecasting the intensity of tropical cyclones during the period 2002 to 2010 with the NNA 1 model is estimated. The MAE is observed to be 4.29 and 5.8 kn and RMSE values are observed to be 6.38 and 7.53 kn for 12 and 24 h forecast respectively (Figure 8(a) and (b)). The results are compared with the intensity forecast provided by IMD (Mahapatra *et al.*, 2013) which shows MAE values to be 6.7 and 10.6 kn and RMSE values to be 10.1 and 14.2 kn for 12 and 24 h forecast respectively, showing that NNA 1 provides better prediction than the existing models (Figure 8(b)).

The neural net models, once trained and tested, are implemented for validation by considering two severe tropical cyclones, Nargis and Phet (Figure 9). The observed and predicted track with 24 h lead time by NNA 1 is estimated (Figure 10). The mean track errors for 6, 12 and 24 h forecasts are found to be 45, 69 and 89 km, respectively, for cyclone Nargis and 54, 87 and 98 km, respectively, for cyclone Phet.

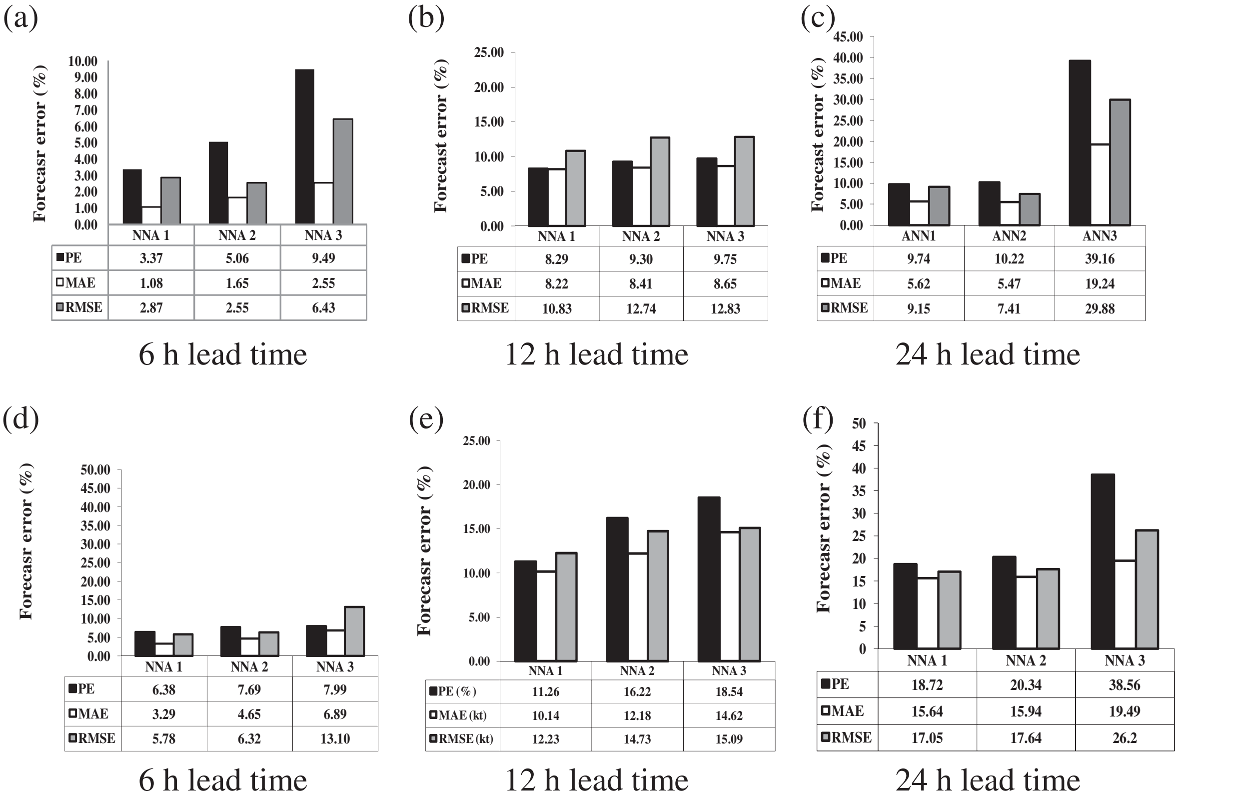


Figure 11. The error matrices with multilayer feed forward neural nets with different architectures (NNA 1, NNA 2 and NNA 3) during validation in estimating the intensity of the cyclone Nargis with 6, 12 and 24 h lead time (a)–(c) and tropical cyclone Phet with 6, 12 and 24 h lead time (d)–(f).

The errors (%) in predicting the intensity of tropical cyclones with multilayer feed forward neural nets of different architectures during validation with 6, 12 and 24 h lead time are computed (Figure 11). The result shows that the forecast errors (PE, MAE, RMSE) with the NNA 1 model in estimating the intensity of cyclone Nargis during validation are 3.37%, 1.08 kn, 2.87 kn (for 6 h lead time), 8.29%, 2.04 kn, 3.75 kn (for 12 h lead time), and 9.74%, 5.62 kn, 9.15 kn (for 24 h lead time) (Figure 11(a)–(c)). The forecast errors (PE, MAE, RMSE) with NNA 1 in estimating the intensity of cyclone Phet during validation are 6.38%, 3.29 kn, 5.78 kn (for 6 h lead time), 11.26%, 10.14 kn, 12.23 kn (for 12 h lead time) and 18.72%, 15.64 kn, 17.05 kn (for 24 h lead time) (Figure 11(d)–(f)). Predicting the track and intensity of both the cyclones Nargis and Phet by using other neural net models, NNA 2 and NNA 3, shows more errors than NNA 1 (Figure 11).

5. Conclusion

Using a single forecasting technique across all ocean basins is questioned for reliable performance because the geographical and climatological characteristics of the various cyclone formation basins are not similar (Roy and Kovordányi, 2012). Thus, the cyclones of North Indian Ocean (NIO) alone are considered in the present study. The availability of Moderate Resolution Imaging Spectro-radiometer (MODIS) terra/aqua and NASA satellite data along with the conventional meteorological data and the user-friendly computational technique of artificial neural network led to identification of the best neural net among multilayer feed forward neural nets for forecasting the track and intensity of tropical cyclones over the NIO. The performances of the models are checked by validating the track and intensity of two significant cyclones of the same category that prevailed over the NIO in the years 2008 and 2010. The neural net architecture 1 (NNA 1) is identified as the best neural net for forecasting the track and intensity of the cyclones over the NIO and is also comparable with other existing numerical models. The important findings of the research can be summarized as below:

- track and intensity of tropical cyclones over NIO can be well assessed using neural network models at least 24 h in advance with accuracy levels comparable with existing numerical model output;
- NNA 1 is more capable than NNA 2 and NNA 3 in forecasting both the track and intensity of NIO cyclones, and,
- the increase in the hidden layers of the neural net increases the forecast accuracy whereas the forecast accuracy is not affected by the increase or decrease of the hidden nodes of the neural net.

In the present study, the model is validated with two cyclones, and its performance is encouraging. The model will be tried for real-time forecast of other cyclones over the NIO and if the performance is observed to provide similar results then the operational organizations can be requested to use the same as an additional model along with the conventional ones for track and intensity forecasting of tropical cyclones over the NIO.

Real-time forecasts of developing tropical cyclones anywhere in the world are based on numerical weather prediction and ensemble technologies. However, the associated damage due to tropical cyclones especially over the coastal regions is subjected to the understanding of various disciplines, for example communications, hydrometeorology, geography, socioeconomic structure of the regions (basins), and administrative promptness. Though the cyclones, Nargis and Phet, are of category 4 and their official forecasts (Saito *et al.*, 2010; Haggag and Badry, 2012) are of comparable accuracy, the damages associated with them were very different. The associated number of deaths and destruction vary from basin to basin and relating the real-time forecast with coastal vulnerability (Brakenridge *et al.*, 2012) is therefore another spectrum of research.

Acknowledgements

The authors thank the India Meteorological Department (IMD), Govt. of India for providing the necessary data for the research. The authors acknowledge NCEP/NCAR, MODIS and NOAA for the analyses and data. The authors gratefully acknowledge the comments and suggestion of the Editor, Dr P. J. A. Burt and the anonymous reviewers, which helped to improve the clarity of the present study.

References

Bengtsson L. 1989. Medium-range forecasting – an introduction. *Meteorol. Atmos. Phys.* **40**: 1–2.

Bodri L, Cermak V. 2000. Prediction of extreme precipitation using a neural network: application to summer flood occurrence in Moravia. *Adv. Eng. Softw.* **31**: 311–321.

Bose NK, Liang P. 1996. Neural network fundamentals with graphs, algorithms, and applications. McGraw-Hill, Inc.: Hightstown, NJ.

Brakenridge GR, Syvitskil JPM, Overeem I, Higgins SA, Kettner AJ, Stewart-Moore JA, et al. 2012. Global mapping of storm surges and the assessment of coastal vulnerability. *Nat. Hazards* **66**(3): 1295–1312, DOI: 10.1007/s11069-012-0317-z.

Cerdeña A, Albano G, Juan CP. 2007. Remote sensing of water cloud parameters using neural networks. *J. Atmos. Oceanic Technol.* **24**: 52–63.

Chaboureau JP, Nuissier O, Claud C. 2012. Verification of ensemble forecasts of Mediterranean high-impact weather events against satellite observations. *Nat. Hazards Earth Syst. Sci.* **12**: 2449–2462.

Chaudhuri S. 2006. Artificial neural network model to forecast maximum wind speed associated with severe thunderstorms. *Vatabaran* **30**(1): 14–19.

Chaudhuri S. 2008. Preferred type of cloud in the genesis of severe thunderstorms – a soft computing approach. *Atmos. Res.* **88**: 149–156.

Chaudhuri S. 2010. Convective energies in forecasting severe thunderstorms with one hidden layer neural net and variable learning rate back propagation algorithm. *Asia-Pacific J. Atmos. Sci.* **46**(2): 173–183.

Chaudhuri S, De Sarkar A. 2008. Monthly frequency distribution of severe tropical cyclones a statistical approach. *Asian J. Water Environ. Pollut.* **5**(1): 1–6.

Chaudhuri S, Middey A. 2011. Adaptive neuro-fuzzy inference system to forecast peak gust speed during thunderstorms. *Meteorol. Atmos. Phys.* **114**: 139–149.

Chaudhuri S, Middey A, Goswami S, Banerjee S. 2012. Appraisal of the prevalence of severe tropical storms over Indian Ocean by screening the features of tropical depressions. *Nat. Hazards* **61**(2): 745–756.

Dvorak V. 1975. Tropical cyclone intensity analysis and forecasting from satellite meteorology. *Mon. Weather Rev.* **103**: 420–430.

Elsberry RL, Weniger EL, Meanor DH. 1988. A statistical tropical cyclone intensity forecast technique incorporating environmental wind and vertical wind shear information. *Mon. Weather Rev.* **116**: 2142–2154.

Ford S. 2010. Is the failure to respond appropriately to a natural disaster a crime against humanity? The responsibility to protect and individual criminal responsibility in the aftermath of cyclone Nargis. *Denver J. Int. Law Policy* **38**: 227.

Gardner MW, Dorling SR. 1998. Artificial neural networks (the multilayer perceptron) – a review of applications in the atmospheric sciences. *Atmos. Environ.* **32**: 2627–2636.

Gardner M, Dorling S. 1999. Neural network modeling and prediction of hourly NOx and NO_2 concentrations in urban air in London. *Atmos. Environ.* **33**: 709–719.

Grimes DIF, Coppola E, Verdecchia M, Visconti G. 2003. A neural network approach to real-time rainfall estimation for Africa using satellite data. *J. Hydrometeorol.* **4**: 1119–1133.

Gutro R. 2010. Tropical cyclone Phet threatens the Indian and Pakistani coastlines, NASA/Goddard Space Flight Center, 443-858-1779.

Haggag M, Badry H. 2012. Hydrometeorological modeling study of tropical cyclone PHET in the Arabian Sea in 2010. *Atmos. Clim. Sci.* **2**: 174–190.

Haykin S. 1999. Neural networks: a comprehensive foundation (2nd ed.). Prentice Hall: Upper Saddle River, NJ.

Heaton J. 2008. *Introduction to Neural Networks for Java*, 2nd edn. Heaton Research Inc.: Chesterfield, MO.

Hennon CC, Marzban C, Hobgood JS. 2005. Improving tropical cyclogenesis statistical model forecasts through the application of a neural network classifier. *Weather Forecast.* **20**: 1073–1083.

Hsieh WW, Tang B. 1998. Applying neural network models to prediction and data analysis in meteorology and oceanography. *Bull. Am. Meteorol. Soc.* **79**(9): 1855–1870.

Jarrell JD, Samson B, Donald SN. 1978. An analysis of western north pacific tropical cyclone forecast errors. *Mon. Weather Rev.* **106**: 925–937.

Keenan TD. 1982. A diagnostic study of tropical cyclone forecasting in Australia. *Aust. Meteorol. Mag.* **27**: 249–258.

Lee TL. 2009. Prediction of typhoon storm surge using artificial neural network. *Adv. Eng. Softw.* **40**: 1200–1206.

Lee RT, Liu JK. 2000. Tropical cyclone identification and tracking system using integrated neural oscillatory elastic graph matching and hybrid RBF network track mining techniques. *IEEE Trans. Neural Netw.* **11**(3): 680–689.

Lehahn Y, Koren I, Boss E, Ben-Ami Y, Altaratz O. 2010. Estimating the maritime component of aerosol optical depth and its dependency on surface wind speed using MODIS and QuikSCAT data. *Atmos. Chem. Phys. Discuss.* **10**: 1983–2003, DOI: 10.5194/acpd-10-1983-2010.

Leslie LM, Hess GD, Holland GJ, Morison RP. 1992. Predicting changes in intensity of tropical cyclones using Marcov chain technique. *Aust. Meteorol. Mag.* **40**: 41–46.

Maqsood I, Khan MR, Abraham A. 2004. An ensemble of neural networks for weather forecasting. *Neural Comput. Appl.* **13**: 112–122.

Middey A, Chaudhuri S. 2012. The reciprocal relation between lightning and pollution and their impact over Kolkata, India. *Environ. Sci. Pollut. Res.* **20**: 3133–3139, DOI: 10.1007/s11356-012-1219-z.

Mohapatra M, Bandyopadhyay BK, Nayak DP. 2013. Evaluation of operational tropical cyclone intensity forecasts over north Indian Ocean issued by India Meteorological Department. *Nat. Hazards* **122**: 589–601, DOI: 10.1007/s11069-013-0624-z.

Neumann CJ. 1981. Trends in forecasting the tracks of Atlantic tropical cyclones. *Bull. Am. Meteorol. Soc.* **62**: 1473–1485.

Neumann CJ, Hope JR. 1972. Performance analysis of the HURRAN Tropical cyclone forecast system. *Mon. Weather Rev.* **100**(4): 245–255.

Neumann CJ, Pelissier JM. 1981. An analysis of Atlantic tropical cyclone forecast errors, 1970–1979. *Mon. Weather Rev.* **109**: 1248–1266.

Osuri KK, Mohanty UC, Routray A, Kulkarni MA, Mahapatra M. 2012. Customization of WRF-ARW model with physical parameterization schemes for the simulation of tropical cyclones over North Indian Ocean. *Nat. Hazards* **63**: 1337–1359, DOI: 10.1007/s11069-011-9862-0.

Pal SK, Mitra S. 1999. Neuro-fuzzy pattern recognition: methods in soft computing. John Wiley & Sons, Inc.: Hoboken, NJ.

Pattanaik DR, Rama Rao YV. 2009. Track prediction of very severe cyclone 'Nargis' using high resolution weather research forecasting (WRF) model. *J. Earth Syst. Sci.* **118**(4): 309–329.

Perez P, Reyes J. 2001. Prediction of particulate air pollution using neural network techniques. *Neural Comput. Appl.* **10**: 165–171.

Pradhan D, Mitra A, De UK. 2012. Estimation of pressure drop and storm surge height associated to tropical cyclone using Doppler velocity. *Indian J. Radio Space Phys.* **41**: 348–358.

Reynolds RW, Smith TM, Chunying L, Chelton DB, Casey KS, Schlax MG. 2007. Daily high-resolution-blended analyses for sea surface temperature. *J. Clim.* **20**: 5473–5496.

Roy C, Kovordányi R. 2012. Tropical cyclone track forecasting techniques: a review. *Atmos. Res.* **104–105**: 40–69.

Saito K, Kuroda T, Kunii M. 2010. Numerical simulation of Myanmar cyclone Nargis and the associated storm surge part II: ensemble prediction. *J. Meteorol. Res. Jpn.* **88**(3): 547–570.

Shank DB, Hoogenboom G, Mc Clendon RW. 2008. Dewpoint temperature prediction using artificial neural networks. *J. Appl. Meteorol. Climatol.* **47**: 1757–1769.

Singh SK, Kishtawal CM, Pal PK. 2012. Track prediction of Indian Ocean cyclones using Lagrangian advection model. *Nat. Hazards* **62**: 745–778, DOI: 10.1007/s11069-012-0121-9.

Singh R, Kishtawal CM, Pal PK, Joshi PC. 2011. Assimilation of the multisatellite data into the WRF model for track and intensity simulation of the Indian Ocean tropical cyclones. *Meteorol. Atmos. Phys.* **111**: 103–119, DOI: 10.1007/s00703-011-0127-y.

Wang J, Neumann CJ. 1985. A Markov – type analog model for prediction of typhoon motion in northwestern Pacific. *Sci. Sin. B* **28**: 517–526.

Wedge D, Ingram D, McLean D, Mingham C, Bandar Z. 2005. A global–local artificial neural network with application to wave overtopping prediction. In *Artificial Neural Networks: Formal Models and Their Applications – ICANN 2005*. Springer: London; 109–114.

Wilson LJ, Sarrazin R. 1989. A classical-REEP short-range forecast procedure. *Weather Forecast.* **4**: 502–516.

WMO. 2010. Tropical cyclone operational plan for the Bay of Bengal and the Arabian Sea. Technical Report No. TCP-21, World Meteorological Organization, Geneva, Switzerland.