Maximum Sustained Wind Prediction of Storm Surge in Bay of Bengal

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Abstract

Most of the countries around the Bay of Bengal are threatened by storm surges associated with severe tropical cyclones. The destruction along the coastal regions of India, Bangladesh, and Myanmar are serious due to the storm surge. To mitigate the impacts of tropical storm, the prediction of storm surge need to be accurate. Traditional process-based numerical models have the limitation of high computational demands to make timely forecast and deterministic numerical models are strongly dependent on accurate meteorological input to predict storm surge. In this work, a Multilayer perceptron (MLP) and a Radial Basic Function Network (RBFN) used to predict the maximum sustained wind speed in knots (VMAX) of storm in coastal areas of Bay of Bengal. The ANN network model provides fast, real-time storm surge estimates at Bay of Bengal. Simulated and historical storm data are collected for model training and testing, respectively. North India Ocean Best Track Data from Joint Typhoon Warning Center (JTWC) used to perform experiments. The result of MLP is predicted VMAX value closer than in RBFN prediction.

Keywords: *Artificial Neural Network, storm surge, JTWC*

1. Introduction

Storm surge is an abnormal rise of water generated by a storm, over and above the predicted astronomical tide [1]. Figure1 shows the storm surge. In recent history, the notable coastal flooding disasters led to tropical cyclones. Total water level rises by the changes of atmospheric pressure and extreme wind stress in storm surge. Nowadays, numerical storm surge models such as SLOSH, ADCIRC, and general process-based hydrodynamic and transport models such as FVCOM, ROMS and Delft3D have been applied to predict storm surge. The numerical models are normally based on the two-dimensional or three-dimensional shallow water NavierStokes equations. In this paper, we predict the maximum sustained wind speed defined by the Joint Typhoon Warning Center by using multilayer-perceptron and radial basis function network in ANN.

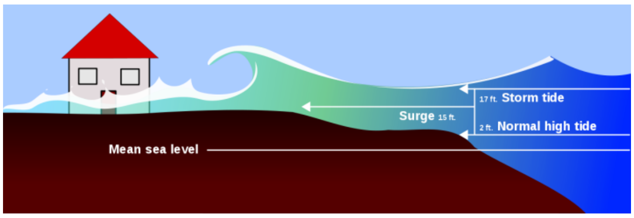

Figure 1. Storm Surge [1]

2. Related Works

Lee [4] developed a back propagation neural network model combined with harmonic analysis to predict the storm surge and surge deviation in Taiwan. Data from Suao Harbor station used and the capability of the ANN model in storm surge forecasting are compared two numerical methods, FEMA and MIKE 21 model and the results showed the capability of the ANN model in storm surge forecasting.

De Oliveira et al. [5] applied a neural network model to predict coastal sea level variations related to meteorological events along the southeastern coast of Brazil. They used the pressure, wind values and tide gauge time series as inputs to the model to analyze the relationship between these variables and the storm surge event, and showed that the model can be efficient in predicting the non-tidal residuals and effectively complement the standard harmonic analysis model.

Seung-Woo Kim et al.[6] used combination of ANN and moving average. For the ANN, they used six hurricane parameters input and one target output, storm surge. One hidden layer has numbers of neuron (16 ~ 25). They used 446 tropical storms as synthetic because they have no historical hurricane data and tested on historical hurricanes Katrina and Gustav and demonstrated R from 0.917 to 0.996.

Hoonshin Jung and Himangshu S. Das [7] used to estimate hurricane central pressure CP and Radius to Maximum Winds (R_{Max}) in 130 tropical storms with ANN. The neural network model tested four historical hurricanes - Dennis (2005), Katrina (2005), Rita (2005), and Gustav (2008).

Anton Bezuglova, Brian Blantonb, Reinaldo Santiago[8] described ANN with two hidden layers and multiple outputs by using TensorFlow library (opensource) and also compared the performance of the NN model and other models on synthetic and real hurricane data.

S.K.Dube [2] described the input parameters (including characteristics and coastal geometry wind stress and seabed friction and information of astronomical tides) for the model and highlighted the activity of surge prediction in India. To validate the model, three scenarios are described.

A.W.Jayawardena [9] described the comparison between the accuracy of predictions in RBF model using k-means clustering and MLP with error back propagation method. In this paper represented their RBF network model required less trial and error, time and effort than MLP with BP approach.

Hadi Memarian [10] represented comparison the predictive performance of the Multi-Layer Perceptron (MLP) and the Radial Basis Function (RBF) neural networks in prediction of suspended discharge at the Hulu Langat watershed using time series of daily water discharge as the input data and showed MLP is more traceable fluctuations in daily sediment load than the RBF network.

In Gayathri R [11] estimated the storm surge and onshore inundation by using numerical Advanced Circulation (ADCIRC) model with Aila storm. And model computed the maximum surge and net water level elevations and this study were aimed to understand storm surge and inundation characteristics along vulnerable coastal locations.

3. Study Area and Available Data

Bay of Bengal is largest bay in the world but relatively shallow embayment of the northeastern Indian Ocean, occupying an area of about 839,000 square miles (2,173,000 square km). It lies roughly between latitudes 5° and 22° N and longitudes 80° and 90° E. It is bordered by Sri Lanka and India to the west, Bangladesh to the north, and Myanmar (Burma) and the northern part of the Malay Peninsula to the east as shown in Figure2. Storms appear three or more times in Bay of Bengal every year. In this paper, we collected historical storm surge data from Joint Typhoon Warning Center (JTWC). We used 514 instances for training and 173 instances for testing about storms from 2000 to 2005.

Figure 2. Area of Bay of Bengal

4. Architecture of neural networks

In neural network, each of input variables is normalized. In the MLP (multi-layer perceptron), input units or hidden units are combined with linear combination function. The linear combination of input units created hidden units and output units modeled as a function of linear combinations of hidden units. In this paper, suppose storm data is represented by a vector x of parameters, the vector y represents storm maximum wind. For two layer feed-forward network:

$$f(x) = W_h * h + b_h$$

$$h = \sigma(W_i * x + b_i)$$

where h is the output of the hidden layer, and W_h, W_i are weight matrices and b_h, b_i are biases for the hidden and input layers respectively. $\sigma(.\ )$ is a nonlinear function and is typically a hyperbolic tangent or a sigmoid function:

$$\sigma_{tanh}(x) = \frac{2e^{-1} - 1}{2e^{-x} + 1}$$

$$\sigma_{sigmoid}(x) = \frac{1}{1+e^{-x}}$$

Neural network model can be represented three components: input layer, hidden layer and output layer (Figure 3). The neural network includes regression and classification methods. For regression, this model has one output unit, and, for k-class classification, there are k output units in the output layer.

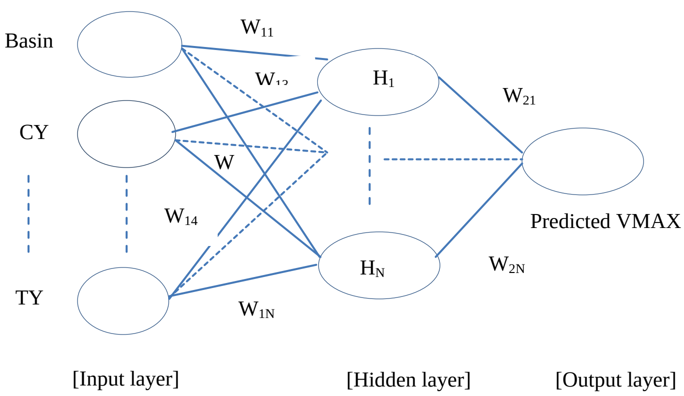

Figure 3. Feed-Forward Architecture of ANN

5. Radial Basis Function Network (RBFN)

Radial Basis Function Network is an artificial neural network and is built by considering the basis function as a neuronal activation function and the w_{kp} parameters as weights. The output of RBFN is:

$$y_k(x) = \widetilde{W}\,\tilde{\varphi}(x),$$

Where $\tilde{\varphi}^T \equiv (\varphi_0 \ldots.. \varphi_k)$ and $\widetilde{W}$ holds both weights and bias. If the basis functions are of Gaussian type:

$$\varphi_j(x) = \exp[-\frac{(x-\mu_j)^T \sum_j^{-1}(x-\mu_j)}{2}]$$

where $\sum j$ is a covariant symmetrical matrix.

In the form of a two layer network where the hidden neurons have the basis functions as activation function. The weight matrix from input to hidden layer is $\breve{1}$ and the output layers have the identity activation function. In this paper, we used Gaussian basis function. The basis function associated with bias is the constant function $\varphi_0(x) = 1$.

6. System Overview

In this section, the overview of the system is presented as shown in Figure 4.

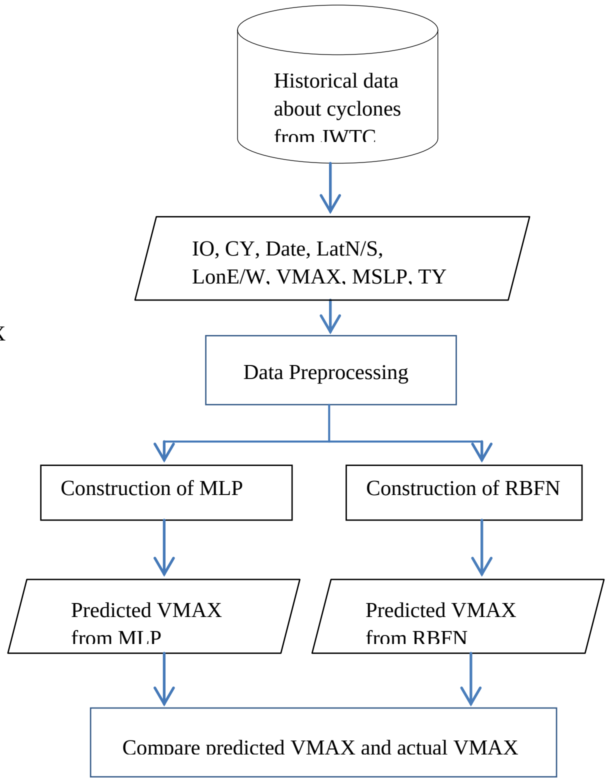

Figure 4. System Overview

The historical data (locations of basin, annual cyclone number, warning date and time, acronym for each objective technique, forecast period, latitude and longitude, maximum sustained wind speed in knots and minimum sea level pressure,….) are collected from Joint Typhoon Warning Center. We use data preprocessing (e.g. discretize, normalize, standardize) to improve the performance and accuracy. In this system, we use normalization. And normalized results are classified by using classification methods. We construct multilayer perceptron and radial basis function network by using classification methods. In construction Multilayer perceptron, we use one input layer, one hidden layer and one output layer. In input layer, 12 input data and 8 hidden data in hidden layer and one output data (predicted wind speed) in output layer. Activation Function is sigmoid function and change learning rate and momentum. In construction Radial Basis Function Network, we use Gaussian basis function as activation function and a k-means clustering method, clusteringSeed is used to pass on to K-means. And numClusters is used for K-Means to generate. Finally, we compare the predicted results from two methods.

7. Experimental Results

In this section, we trained 514 instances and 12 attributes (IO, CY, Date, TECH, TAU (forecast period), LatN/S, LonE/W, VMax, MSLP, TY (type of cyclones) (21 storms) in Bay of Bengal from 2000 to 2004 and tested 173 instances (6 storms from 2005) and 12 attributes (IO, CY, Date, TECH, TAU (forecast period), LatN/S, LonE/W, VMax, MSLP, TY (type of cyclones) for two methods. In this study, six models with sigmoid function, one hidden layer and hidden 8 neurons are developed for MLP. MLP1, MLP2 and MLP3 are developed using learning rate (L) is 0.3, 0.4 and 0.5 respectively and momentum (M) is 0.2. MLP4, MLP5 and MLP6 are developed using learning rate is 0.3 and momentum is 0.3, 0.4 and 0.5 respectively. And RBFN are developed with four models- RBFN1, RBFN2, RBFN3 and RBFN4. RBFN1 and RBFN2 are developed using numCluster (B) (The number of clusters for K-Means to generate) is 2 and clusteringSeed(S) (The random seed to pass on to K-means) is 1, 2 respectively. RBFN 3 and RBFN4 are developed using numCluster is 3 and clusteringSeed is 1, 2 respectively.

The prediction performances of the considered models are evaluated using two evaluation parameters namely, mean absolute error (MAE) and root mean squared error (RMSE) as shown in Table 1 for MLP models and Table 2 for RBFN.

$$MAE = \sum_{i=1}^{n} \frac{Y_i - \bar{Y}_i}{n}$$

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(Y_i - \bar{Y}_i)^2}{n}}$$

Where Y_i is the actual data and $\bar{Y}_i$ is predicted data and n is the number of data.

Table 1. Training and testing results of MLP

	Epochs=500		Mean Absolute Error (MAE)	Root Mean Squared Error (RSME)
MLP	L=0.3, M=0.2	Training	0.0414	0.0618
	MLP1	Testing	0.8054	0.9071
	L=0.4, M=0.2	Training	0.123	0.1574
	MLP2	Testing	0.2779	0.3478
	L=0.5,M=0.2	**Training**	**0.0854**	**0.1042**
	MLP3	**Testing**	**0.206**	**0.2568**
	L=0.3,M=0.3	Training	0.037	0.061
	MLP4	Testing	0.7345	0.83
	L=0.3,M=0.4	Training	0.0918	0.1268
	MLP5	Testing	0.9355	1.2061
	L=0.3,M=0.5	Training	0.927	0.1285
	MLP6	Testing	1.0304	1.3056

Table 2. Training and testing results of RBFN

			Mean Absolute Error (MAE)	Root Mean Squared Error (RSME)
RBFN	B=2,S=1	Training	0.1192	0.16
	RBFN1	Testing	0.2424	0.3263
	B=2,S=2	Training	0.1193	0.16
	RBFN2	Testing	0.2425	0.3265
	B=3,S=1	Training	0.1175	0.1573
	RBFN3	Testing	0.2624	0.3482
	B=3,S=2	**Training**	**0.1593**	**0.1593**
	RBFN4	**Testing**	**0.2336**	**0.3101**

For Table 1, MLP3 is developed using learning rate is 0.5 and momentum is 0.2; having MAE and RMSE; 0.0854 and 0.1042 for training and 0.206 and 0.2568 for testing. i.e MLP3 gives better result with same input and difference parameters. For Table 2, RBFN4 is developed using numCluster is 3 and clusteringSeed is 2; having MAE and RMSE; 0.1179 and 0.1593 for training and 0.2336 and 0.3101 for testing. i.e RBFN4 gives better result with same input and difference parameters. For comparison the prediction results from MLP and RBFN, we choose the MLP3 and RBFN3. In prediction of wind speed, we suppose MLP and MLP3 are the same and RBFN and RBFN3 are the same. From the comparison of MLP and RBFN which have been used in this study and Figure 5 appears with the best results for this study. From Figure 5, the capability of the ANN in predicting the wind speed using multilayer perceptron is much better than when using radial basis function network. This is because multilayer perceptron comprises of one or more hidden layer and can change activation function.

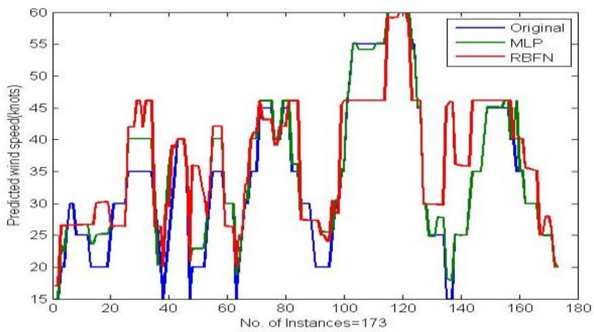

Figure 5. Comparison results of original wind speed, MLP wind speed and RBFN wind speed

8. Conclusion

In this paper, we predicted the maximum wind speed of storms by using two neural methods such as multilayer perceptron and radial basic function network. In comparison between two methods, the predicted wind speed of multilayer perceptron is closer to the original wind speed than the predicted wind speed of radial basis function network. In future, we predict the storm surge directions (LatN/S and LonE/W), maximum wind speed, mean sea level pressure, rainfall and related storm surges as input and the storm directions (LatN/S and LonE/W), peak surge of the storm as output by using multilayer perceptron.

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