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Trend Analysis and Mapping of Severe Cyclonic Storms in Bay of Bengal using ANN and Exponential Smoothing

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***Abstract* – History is evident of the destruction caused by tropical cyclones. Researchers in past have tried to analyze the trends in the annual occurrence of these tropical cyclones so as to forecast their occurrence in upcoming years. However, the variation in the frequency of severe cyclonic storms (tropical cyclones of higher intensity) has a random nature. Hence, conventional statistical techniques prove to be incapable of analyzing the trends. In this paper, a unique Artificial Neural Network (ANN) based technique is proposed to analyze the trends in frequency of severe cyclonic storms in the region of Bay of Bengal. The proposed ANN based technique makes use of invertible nature of exponential smoothing to enhance the learning process. In the proposed technique, ANN is trained using smoothed target data and the output of ANN is inverse-smoothed to obtain the forecast. The ANN based method maps the data much better than conventional statistical methods and gives a fairly accurate forecast which will help to mitigate horrific effects of tropical cyclones.**

***Index Terms* – Artificial Neural Networks, Exponential Smoothing, Tropical Cyclones, Severe Cyclonic Storms, Forecasting, Cyclone Mitigation.**

I. INTRODUCTION

Tropical cyclone systems are one of the most powerful and destructive meteorological systems on Earth. On an average, approximately 86 tropical cyclones form every year [1]. Low pressure systems may develop into tropical cyclones over the warm tropical and subtropical waters under basic favorable meteorological conditions such as diverging winds aloft, converging winds at base, light to relaxed vertical wind shears and enhanced mid tropospheric moisture. During landfall, they cause devastation due to heavy rains, storm surges, strong winds and gale [2].

It was observed that 8 out of 10 events in which heavy loss of life due to tropical cyclones was reported, took place in Bay of Bengal and Arabian Sea. Out of 8 catastrophic events reported, 5 were in Bangladesh and 3 were in India [3]. The devastation was unduly larger because of the terrain in northern part of Bay of Bengal which amplified the severe effects of cyclones. Tropical cyclone "Bhola" (3 - 13 November 1970) in Bay of Bengal caused an estimated death toll of 3 - 5 lakh and affected around 4.7 million people mostly in Bangladesh [4]. The numbers indicate that this was perhaps the deadliest tropical cyclone ever recorded. Hence, among the tropical cyclone basins in the world, Bay of Bengal has been chosen in this paper for analysis.

Artificial Neural Networks (ANNs) are learning algorithms that are inspired from neural network in brain. ANN is a powerful and popular tool to map random data appropriately [5]. In this paper a novel ANN based technique has been proposed to analyze tropical cyclone frequency trend. The proposed technique makes use of exponential smoothing to enhance the mapping process. Exhaustive literature survey has revealed that none of the researchers have yet reported this technique in the domain of long term cyclone frequency forecasting.

II. OVERALL TREND

Since 1996, many researchers have analyzed the trends in tropical cyclone frequency using various statistical techniques which are discussed in [6-9]. These statistical techniques are mostly based on linear regression and reveal a generalized decreasing trend in the frequencies of tropical cyclones. It can be seen from figure 1 that the data is fairly random in nature. Since a line is insufficient and incapable of mapping such random and nonlinear trends, these statistical techniques cannot be used to forecast tropical cyclone frequencies for upcoming years.

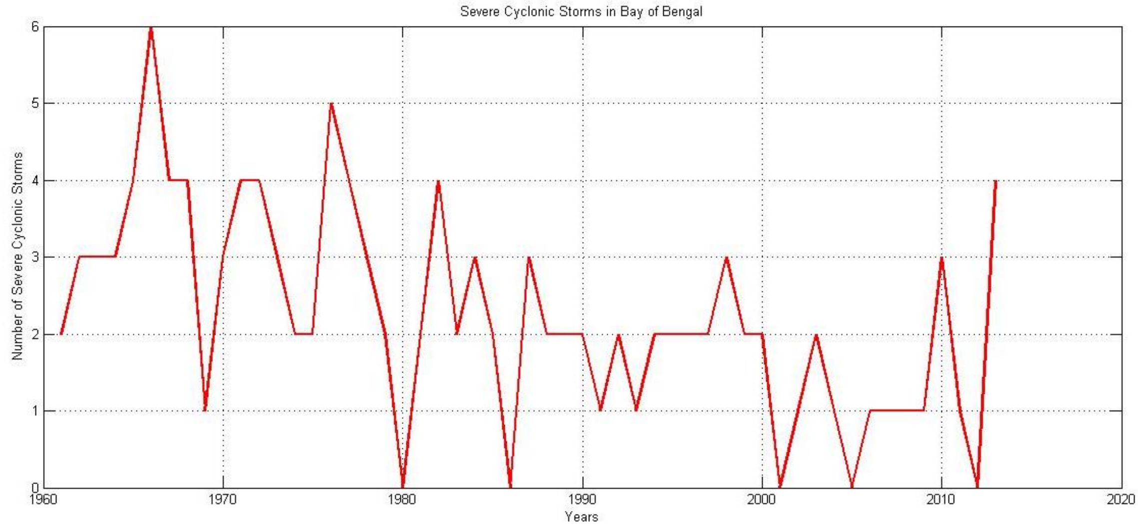

Figure 1: Frequency of Severe Cyclonic Storms in Bay of Bengal

Figure 2 shows comparison between the trend generated by statistical linear regression by [9] and the trend generated by ANN based method. The ANN which was used to obtain this trend was a Layer-Recurrent Neural Network with 1 hidden layer having 25 hidden neurons. The number of hidden neurons was determined by the expression proposed in [10]. Levenberg-Marquardt algorithm was used for training and tan-sigmoid as activation function.

The ANN based regression indicates an increasing trend from year 2007 in contrast to a generalized decreasing trend as proposed by majority of researchers.

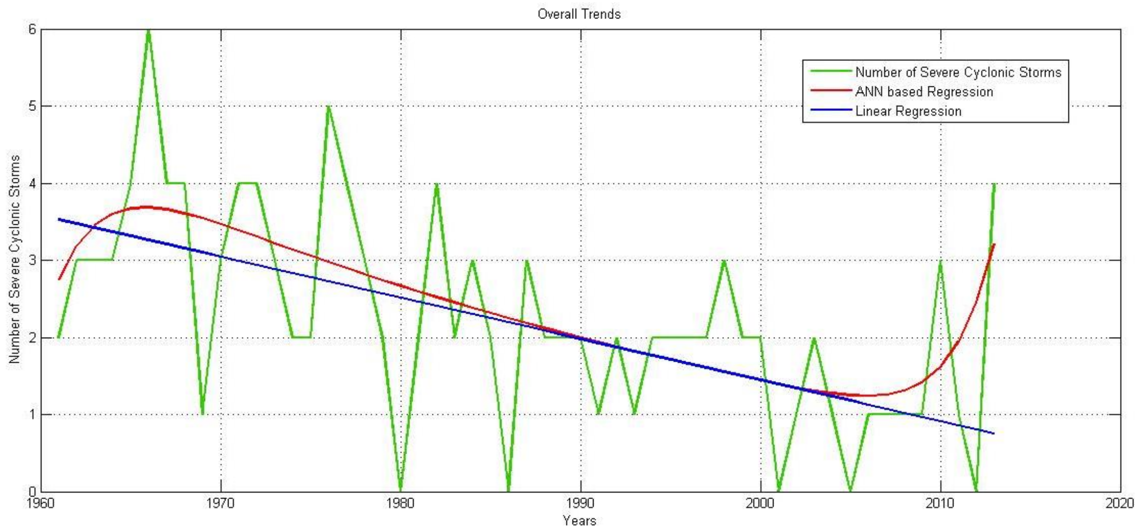

Figure 2: Comparison of trends

III. Exponential Smoothing

Exponential Smoothing is a well-known technique commonly used in financial forecasting and inventory management. The method isolates important trends/patterns from a noisy or random data. Exponential smoothing is a procedure which makes continuous revision of a forecast considering recent experiences [11]. Exponential smoothing tries to smooth out the data by mapping the original data into a forecast domain using equations (1) and (2).

$$S_0 = X_0 \qquad (1)$$
$$S_{T+1} = \alpha * X_T + (1 - \alpha) * S_T \qquad (2)$$

In above equations, S_T is the forecasted value of X_T (actual value) at time instance "T". This mapping or transformation of domain is invertible in nature.

Single Exponential Smoothing is invertible in nature. A sample dataset was used to confirm this property. Table 1 shows that the original dataset was reproduced by consecutive smoothing and inverse-smoothing. Equations (3) and (4) were used to inverse-smooth the data.

$$D_0 = S_0 \tag{3}$$
$$D_{T+1} = \frac{S_{T+1}}{\alpha} - \frac{S_{T}*(1-\alpha)}{\alpha} \tag{4}$$

In above equations D_T is the inverse-smoothed data corresponding to time instance "T" and rest notations have same meaning as in previous equations.

Table 1: Invertible nature of exponential smoothing (α = 0.2)

Dataset	Smoothed Data	Inverse-smoothed Data
1	1.0000	1.0000
2	1.0000	2.0000
3	1.2000	3.0000
4	1.5600	4.0000
5	2.0480	5.0000
6	2.6384	6.0000
7	3.3107	7.0000
8	4.0486	8.0000
9	4.8389	9.0000
10	5.6711	10.0000

IV. PROPOSED TECHNIQUE

It can be clearly seen from figure 1 that the data is random in nature and has rapid and sharp changes. This kind of data, if not preprocessed, becomes difficult for ANN to map. Preprocessing can be done using exponential smoothing to smooth out the data. It was observed that the ANN successfully maps this smoothed data. However, the output of ANN in this case would give smoothed values instead of "actual" ones. To obtain the "actual" values, the smoothed output values should be inverse-smoothed.

This smoothing and consecutive inverse-smoothing is analogous to Laplace Transform. Laplace transform is commonly used for analyzing electrical circuits. Electrical circuits are complicated and hence difficult to analyze in time domain. Hence electrical engineers transform or map these circuits into a different domain using Laplace transform (corresponding to smoothing). It becomes computationally easy to analyze these circuits in the transformed domain. After analyzing they are converted back to time domain using inverse Laplace transform (corresponding to inverse-smoothing).

The proposed technique works is following steps:

Step 1: Smoothing of data which is to be used as target, using equations (1) and (2).
Step 2: Training of ANN with smoothed data as target. This step is depicted in figure 3.
Step 3: Providing the input data to ANN corresponding to which forecast is required.
Step 4: Inverse-smoothing of output using equations (3) and (4). This step is depicted in figure 4.

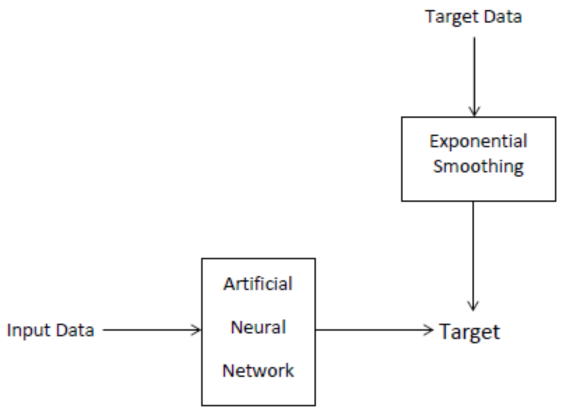

Figure 3: Block diagram of proposed technique (during training)

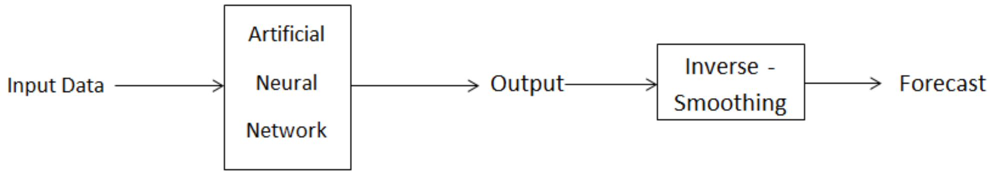

Figure 4: Block Diagram of proposed technique (during forecasting)

V. DATASET

The dataset used in this paper was obtained from India Meteorological Department's (IMD) Cyclone e-Atlas. The Cyclone e-Atlas consists of tracks and details of depressions, cyclonic storms and severe cyclonic storms spanning North Indian Ocean (NIO) over the period of 1891 to 2014. The data for Bay of Bengal has been used in this paper. Severe cyclonic storms have been chosen over cyclonic storms for analysis due to their higher intensity and magnitude of damage. IMD classifies any low pressure system in the NIO on the basis of its maximum sustained 3 minutes surface winds. Currently different techniques of estimation of winds associated with low pressure systems are used using radars, coastal observatory, ships or buoys and satellites [12]. Maximum sustained 3 minutes surface winds for severe cyclonic storm category is between 48-63 knots (89-117 Km/hr).

The launch of Television and Infrared Observational Satellite (TRIOS – 1) in 1960 was a foundation stone in usage of satellite for detection of "Tropical Cyclones". Hence the period is divided into pre-satellite era (1891-1960) and satellite era (1960 onwards) [8]. To ensure better estimates, the data used in this paper ranges from 1964 – 2013 in which 111 severe cyclonic storms have been recorded.

VI. TESTING AND RESULTS

The proposed technique was implemented and tested using MATLAB. The ANN was created using standard MATLAB toolbox for neural networks. The training dataset included years (1964-2008) as input and the number of severe cyclonic storms corresponding to years 1964-2008 as output. The ANN used had 2 hidden layers with 50 hidden neurons each. At present there is no formal way of determining the best suited architecture for neural networks [13]. It has been suggested in [14] to start with a single hidden layer and to add an extra layer if the results are not acceptable. The topology of ANN used for this particular problem was selected after exhaustive searching and testing. As suggested in [15], the number of neurons was kept same for both the hidden layers. Back-propagation algorithm was used for learning and Levenberg-Marquardt algorithm was used for training with tan-sigmoid as activation function. The smoothing factor (α) for exponential smoothing and inverse-smoothing was 0.2. As the smoothed data is to be inverse-smoothed later, the choice of α is insignificant. The result of mapping during training period is shown in figure 5. On the basis of this training, the values corresponding to years 2009 to 2013 are predicted which are then compared with actual values in table 2.

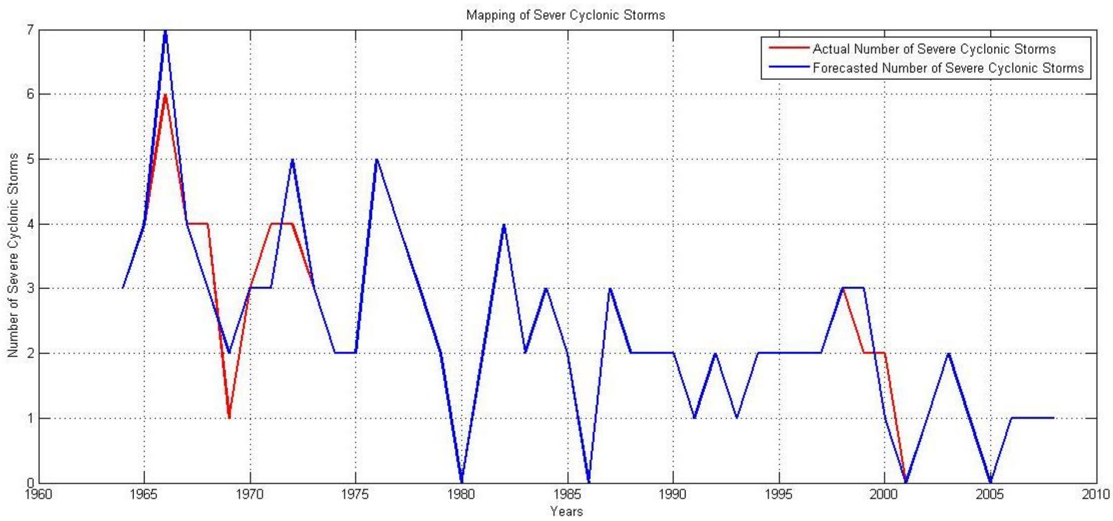

Figure 5: Mapping of data during training

Table 2: Results

Year	Actual Number	Forecasted Number	Round –off values
2009	1	1.0783	1
2010	3	3.2211	3
2011	1	1.1378	1
2012	0	0.9352	1
2013	4	3.8384	4

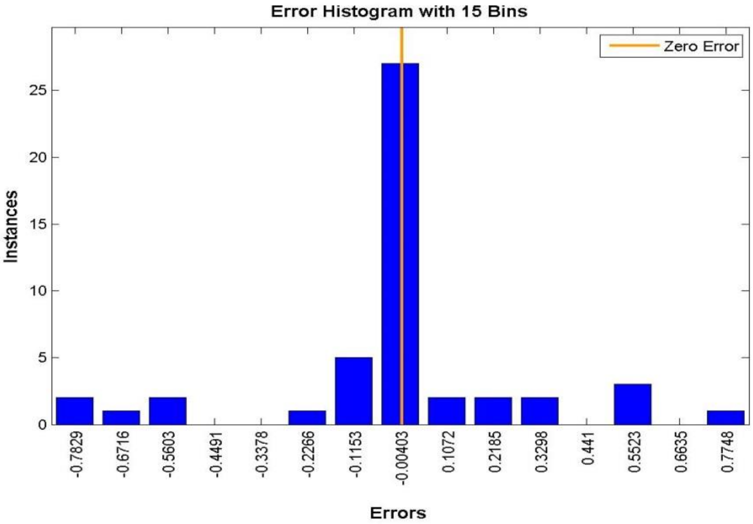

Figure 6: Error histogram

VII. Conclusion

The error histogram in figure 6 shows the accuracy of training and table 2 shows the accuracy of the proposed technique. As it has been shown in the previous section that statistical linear regression method is incapable of analyzing such random data, ANN based techniques were used. It was observed that exponential smoothing enhanced ANN mapping. The forecasted results thus obtained fairly agree with the actual observations. Based on this, the cyclone mitigation policy and the action plans can be designed accordingly. Disaster management in the countries surrounding Bay of Bengal (India, Bangladesh, Myanmar and Sri Lanka) can be improved if the frequency of severe cyclonic storms in upcoming years is precisely known.

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