LONG TERM OCEAN WAVE FORECASTING

A DISSERTATION

Submitted in partial fulfillment of the requirements for the award of the degree

of

MASTER OF TECHNOLOGY

in

WATER RESOURCES DEVELOPMENT

(CIVIL)

By

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CANDIDATE'S DECLARATION

I hereby certify that work which is being presented in the dissertation entitled "LONG TERM OCEAN WAVE FORECASTING" is in partial fulfillment of the requirement for the award of the degree of master of technology and submitted to the Department of Water Resources Development and Management (WRD&M), Indian Institute of Technology, Roorkee. This is an authentic record of my own work carried out at CW&PRS, Pune, during the period from August, 2009 to September, 2010 under the supervision and guidance of Dr. M.L. Kansal, Prof., Water Resources Development & Management, Indian Institute of Technology, Roorkee-247667, and Dr. J. D. Agrawal, Senior Research Officer, CW&PRS, Pune.

The matter presented in this dissertation has not been submitted by me for the award of any other degree.

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Certified that the dissertation titled "**LONG TERM OCEAN WAVE FORECASTING**", which is being submitted by Shri Bal Krishna in partial fulfilment of the requirement for the award of Degree of Master of Technology in Department of Water Resources Development and Management (WRD&M), Indian Institute of Technology, Roorkee, is a record of student's own work carried out by him at CW&PRS, Pune under my supervision and guidance. The matter included in this dissertation has not been submitted for the award of any other Degree.

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LIST OF SYMBOLS

Symbol	Discription
U_g	:Geostrophic wind speed
Δp	:Atmospheric pressure difference
ρ_a	:Air density
f	:Coriolis parameter
ω	:Angular velocity
ϕ	:Latitude in degree
Δn	:Isobar spacing measured in degrees latitude
U_{10}	:Surface wind speed or wind speed at 10m elevation above msl
R_g	:Multiplying factor
U_A	:Adjusted wind-stress factor
U^*	:Friction velocity between air-sea interface
C_D	:Drag coefficient
F_e	:Effective Fetch in Kilometers
F_i	:Fetch distance in kilometres along the direction i
α_i	:Angle (°) between the wind direction and the direction i
t_{min}	:Minimum Wind duration blowing over the fetch
F	:Fetch in Kilometers
H_s	:Significant wave height
F_{min}	:Minimum fetch length
g	:Accelaration due to gravity
$\bar{x}$	:Mean

σ	:Standard deviation:
R	:Correlation coefficient
N	:Number of data points
Y_T	:Transformed probability axis i.e. Reduced Variate for T year return period
X_T	:Transformed wave height
P	:Probability of Non-Exceedance
Q	:Probability of Exceedance = 1-P
Q_g	: Gumbel's Probability of Exceedance
Q_w	: Wiebull's Probability of Exceedance
α, β	:Weibull and Gumbel parameter
γ	:Lower limit of H i.e. threshold value in a peak over threshold data set
C_1, C_2	:Unbiased plotting position
G	:Gumbel Reduced Variate
W	:Wiebull Reduced Variate
Z	:Log-Normal Reduced Variate

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ABSTRACT

Knowledge of magnitude as well as behavior of wind waves is esséntial in the entire planning, design, construction, operation and maintenance related activities carried out in the whole ocean area including harbour, coastal and offshore regions. The requirement for each activity however may vary. For example design exercises require prediction of wave heights over a period of 100 years, as against planning and construction related works which call for forecasting of wave heights as well as that of their behavior for a short period of a few hours or so.

The most important factors for establishing design wave for a coast are the long-term storm data and storm wave modelling. In this study, the authors have applied various deep-water parametric storm wave prediction models like SMB(Sverdrup-Munk-Bretschneider), Wilson and CEM(Coastal Engineering manual Model,U.S.Army,2006) including artificial neural network to a 115-year period of historical severe storms. The wave heights for each storm were hindcasted and the wave heights which were significant to the respective coasts were extrapolated to long term using Gumbel, Weibull and Log-Normal distributions. Assuming, no theoretical justification is available as to which distribution is to be used (Burcharth and Liu, 1994). The average of these three distributions for specified return periods were taken as a design wave height. The results of the offshore design wave height (m) predicted for both the locations, are represented in the following Table.

Table: Predicted Extreme Wave Height (m) for Various Return

Return Period	25	50	75	100	150
Off Mumbai	12.6	14.2	15	15.7	16.2
Off Pondicherry	18.9	21.2	22.4	23.5	24.7

The studies on the applicability of ANN to the problem of wave prediction indicated that the appropriate trained network could provide satisfactory results.

The methodology adopted in this study for storm wave hindcasting seems to be realistic for practicing of coastal engineers; however, it fails to reproduce the exact directivity of the wind waves in cyclonic situations because the gradient wind has not been taken into account. Long-term prediction of design events is often statistical and is based on using the probability of non-exceedence or exceedence; return period and the associated encounter probability to assess risks. Thus, a clear understanding of this subject is required in order to make correct decisions to optimize the design wave height and to avoid natural hazard associated with the failures of important projects; especially, in the dynamic environment of the ocean.

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INTRODUCTION

1.1. General

Offshore industries such as shipping, oil and gas, fishery etc. have paramount importance to the economy of a maritime country like India. Timely information and reliable forecast of ocean parameters will be benefiting to these billion worth industry together with millions of coastal population who mainly depend upon fishing for their livelihood. Thus forecasting of an ocean state is the need of our country.

Rapidly increasing maritime activities, both commercial and scientific have made man to move far beyond the coastal waters. International trade and demand for resources have progressively increased its dependence on sea. India has a coastline measuring over 7500km of which about 3000km stretch is on the west coast; about 2700km on the east coast and the remaining includes the coastline of Lakshadweep and Andaman Group of Island. Several storms occur on the east and west coast of India every year, particularly during the periods from April to June and October to January, due to typical meteorological condition in the oceans. The frequency of cyclone is low on west coast (about 2 per year) whereas on the east coast the cyclones are more frequent (about 5 per year). India's investment in maritime activities involving transport, fishing and exploration is increasing every year and is of vital national interest. The technical success and economic performance of these activities are dependent on the reliability of the assessment of environmental parameters, which determine the design of maritime structures.

Structural engineers need an estimate of the likely severest conditions to be experienced by the structures. The usual parameter chosen to describe such conditions is N year return value of the wave height, where N year return value is defined as that which is exceeded on average once every N years. Return value is a statistical parameter, and the engineer in his design has to allow for the possibility of wave greater than say the 100-year return value, or even of several such waves occurring within a few years. Nevertheless, the concept of return value as a design criterion has proved useful, and the extreme wave condition, which a coastal or offshore structure is designed to survive are called design wave conditions. These conditions are usually expressed in terms of wave characteristics as a function of occurrence probability. The method usually employed to estimate the N years return value of wave height is to fit some specified probability distribution to the few years data and to extrapolate to a probability of occurrence of once in N years.

Establishing the extreme wave heights for different return periods for different types of marine structures is very essential for their safe and economic design. A lack of this information will result either in an unsafe or an over designed (and hence uneconomical) structure. Hence, it is essential to correctly predict the design wave heights for different return periods.

In order to cope with the hazards associated with heavy sea states extreme event statistics are needed which in turn require homogeneous and long observational records. Unfortunately, such information is hardly available, either due to incomplete observational records or even due to a complete lack of observational data. In such cases hindcasts obtained from numerical models have become a frequently used tool as they may provide at least the best possible guess of the environmental conditions that may have been observed at given time and location. Therefore, hindcasts are often considered to be a substitute reality.

Prediction of waves from the knowledge of generating wind is difficult to model by using deterministic equations. Exact mathematical equations to this content are difficult to derive and hence empirical as well as statistical methods are often adopted. The results may suffer from high uncertainty and low reliability. As an alternative an Artificial Neural Network (ANN) models have been applied successfully to storm prediction problems. The main feature of the neural networks is that it models a random input with the corresponding random output and their application does not require knowledge of the underlying physical process as a precondition. It establishes the relationships between inputs and outputs based on learning processes.

Recent use of neural networks has shown its potential usefulness in ocean wave predictions.

1.2. Scope of the study

The main objective of this study is to propose a technique for the long-term ocean wave forecasting at a given oceanic location. The scope of works includes:

1. Survey of historical meteorological data over a period of typically 100 years or longer, to identify the most severe storms responsible for extremes;
2. Storm Wave hindcasting using SBM (Sverdrup-Munk-Bretschneider), Wilson, CEM (Coastal Engineering manual,2006), and ANN models.
3. Analysis of above models and
4. Extreme Wave analysis which provides estimates of design wave associated with specified return periods

The reported studies involve hindcast of extreme wave heights at two Indian coastal locations namely off Pondicherry on East and off Mumbai on the West side of the Indian coastline as shown in Fig. 1.1. These locations are highly explored and exploited for various marine infrastructure developments.

1.3 Organization of Work

This study is organized as follows:

Chapter 1:This chapter included brief introduction of wave forecasting with scope of study. The necessity of long term wave forecasting is highlighted

Chapter 2: In this chapter wave climate, available sources of wave data and suitability of wave data for the reported studies have been described.

Chapter 3: This chapter provides review of the literature of different wave forecasting techniques. Some of the literature based on an ANN which is one of the wave forecasting technique, has been presented herein.

Chapter 4: The basic principle of ocean wave is described in this chapter with emphasize given on storm wave generation and growth. The wind field computations required for the recognition of storm conditions are also briefly discussed in this chapter.

Chapter 5: Different approaches for hind casting of wave heights through various parametric and ANN model are elaborated in this chapter.

Chapter 6:This chapter include data analysis and calculation of wave height for the storm wave using parametric and ANN models. The results obtained are also discussed.

Chapter 7: The various distribution models for the extreme wave analysis have been briefed. The hindcasted wave height results obtained from chapter 6 have been applied to the distribution models for the extreme wave analysis and the results obtained from the same have been discussed.

Chapter 8: In this chapter conclusion of the wave hindcasting, ANN and extreme wave analysis through distribution models have been presented. Future scope of study also have been discussed here.

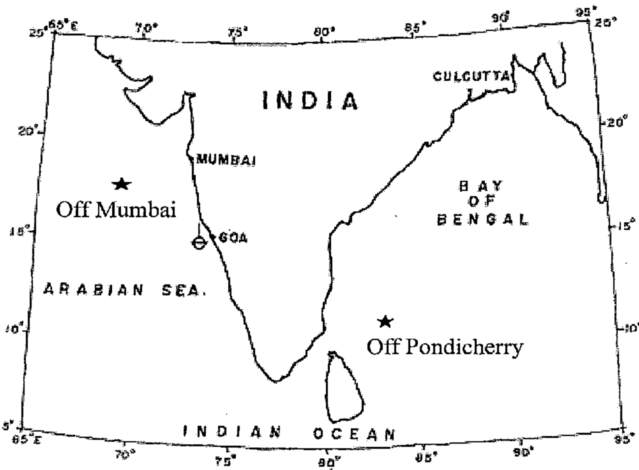


Fig 1.1: Indian Coastline Showing Locations of the Study Area

WAVE CLIMATE AND SOURCE OF WAVE DATA

2.1 Wave Climate

Wave climate refers to the general condition of sea-state at a particular location. The main elements of wave climate in the offshore design are the significant wave height (Hs). Normally, significant wave height is used as design wave height. It is not economically feasible to design any marine structures for the maximum wave height that is likely to impact upon the structure. So, a reasonable wave height for design is employed. A significant wave height is the average height of the highest one third of the waves during a given time period. For the sake of uniformity the term wave height is used instead of significant wave height in this thesis.

A wave statistics is classified as wave climate statistics (short-term and medium-term) and extreme wave statistics (long term) (Goda, 1990). The wave climate statistics deals with statistical properties of individual waves within short time duration, whereas long-term statistics deals with the extreme wave conditions. The wave climate statistics is important for operational aspects of maritime structures while the extreme wave statistics is required for estimating design wave conditions. Wave data of several years without significant gaps are the standard requirement for wave climate analysis whereas the data of several decades are requirement of extreme wave statistics. The determination of the design wave height should be based on the statistical analysis of long-term extreme wave height measurements.

2.2 Sources of Wave Data

There are three sources of wave data, which are generally used for the estimation of design wave conditions for the offshore structures:

i. Visually observed wave data reported by various ships
ii. Instrumentally recorded wave data and
iii. Hindcast wave data.

2.2.1 Visually Observed Wave Data

Visual observations of wave data are made from various ocean-going vessels. The ship observed visual data are compiled by the India Meteorological Department (IMD) and reported in the form of daily weather reports. The ship observed wave height is primarily a matter of personal judgment and estimation. Moreover, these ships are usually unlikely to ply through areas of 'pre-warned' storms, thereby missing some of the important storm wave information. Ship recorded wave data for Indian sea, if available is for short period and only for few locations along the coasts. Moreover wave data are expensive and sparse and also many times inconvenient to record.

2.2.2 Instrumentally Recorded Wave Data

Many governmental/non-governmental agencies in the world have been conducting long-term wave measurements or short-term project-oriented wave measurements for limited duration at various sites by deploying equipment like Wave Rider Buoys. The quality and duration of measured wave data varies from site to site. The instrumentally recorded data though most accurate and reliable are costly as compared to visually observed data. As for as Indian seas are concerned recorded wave data is available for short periods and some specific places along the coasts. The recent developments in the satellite remote sensing techniques have shown that the remote sensing data can be advantageously used to obtain synoptic information on wave covering large area.

2.2.3 Hindcast wave data

Wave hindcasting is the prediction of waves based upon the past meteorological and oceanographic data. Wave hindcasting is usually done to obtain wave data from the major storms over 30 to 50 years or longer. It is a non-real time application of numerical wave models in the broad field of climatology. Wave hindcasting calls for large amount of storm data and the computational effort involves is more. Just as weather conditions, the wave conditions will change from year to year, thus a proper statistical treatment requires several years of wave data.

It is rare that there exists a sufficiently long term history of accurate measurements of extreme storm generated winds and waves. At a few sites, instrumented platforms or moored buoys have acquired data over the past twenty years or so, and satellite altimeters have measured global wave heights over about a ten-year period. However, while such data make it technically possible to compute extremes directly from the measurements, the reliability of such estimates must be questioned at least on the grounds that natural climate variability on decadal time scales is not properly represented. Therefore, even in areas with measured data it is still advisable to generate the long-term database needed to estimate the extreme wave climate through hindcast approach (Cardone, 1999).

The storm tracks and synoptic chart for the past 115years (1891-2005) passing within 300km periphery off Mumbai and Pandicherry are considered for the hindcastind of wave height. These storm tracks include all storm types such as depressions, tropical storm, cyclones or super cyclones.

2.3 Data for Extreme Wave Analysis

Indian coast is characterized by the occurrence of severe storms in Arabian Sea and Bay of Bengal during and after the monsoon. These storms give rise to very high sea particularly during tropical storms. As such, in the extreme value analysis for determining the design wave conditions for large return period, it is necessary to consider the storm wave climate i.e. long term wave data. The Indian Meteorological Department (IMD) provides the records of these storms in the form of synoptic charts (pressure distribution) and storm tracks for the moving storm. The information on the frequency and intensity of the storms generating waves influencing the region of interest is obtained from these recorded tracks. From the storm track data, maximum wind speed of the system and fetch with their positional information are retrieved. The wind speed is determined from the pressure gradient and the latitude of the fetch area. The pressure gradient is determined from the isobar spacing shown on the synoptic charts. The details are as indicated in Chapter 4.

A satellite imageries of Indian Tropical Cyclone Track during 1951-2002, Typical Cyclones of 17th May 1998 (Bay of Bengal) and 7th May 1990(Arabian sea) with their storm track are shown in Fig. 2.1, Fig. 2.2 and Fig. 2.3 respectively.

Generally, there are three kinds of data set used for extreme wave analysis:

1. Observation of wave heights equally spaced in time
2. Largest wave height in each year and
3. Largest wave height in each individual storm exceeding a certain level.

Goda(1990) and Burcharthand Liu(1994) has recommended third type of data sets since they are directly concerned with the selection of design wave height. Accordingly the third type of data sets has been considered for the present study.

Storm generated waves play a significant role in the design of almost all coastal and offshore structures. Hence, to establish the wave characteristics during extreme wave conditions, details of severe storms that have passed within 300 km of the region of interest are required for long period analysis. Some of the storm tracks and synoptic charts, significant to the Mumbai and Pondicherry coasts are shown in the Appendix .

2.4 Conclusion

Long-term wave data is necessary for the computation of extreme wave conditions or design wave heights. A sufficiently long term history of accurate measurements of extreme storm generated waves are not available. Therefore, even in areas with measured data, it is advisable to generate the long-term database needed to estimate the extreme wave climate through hindcast approach.

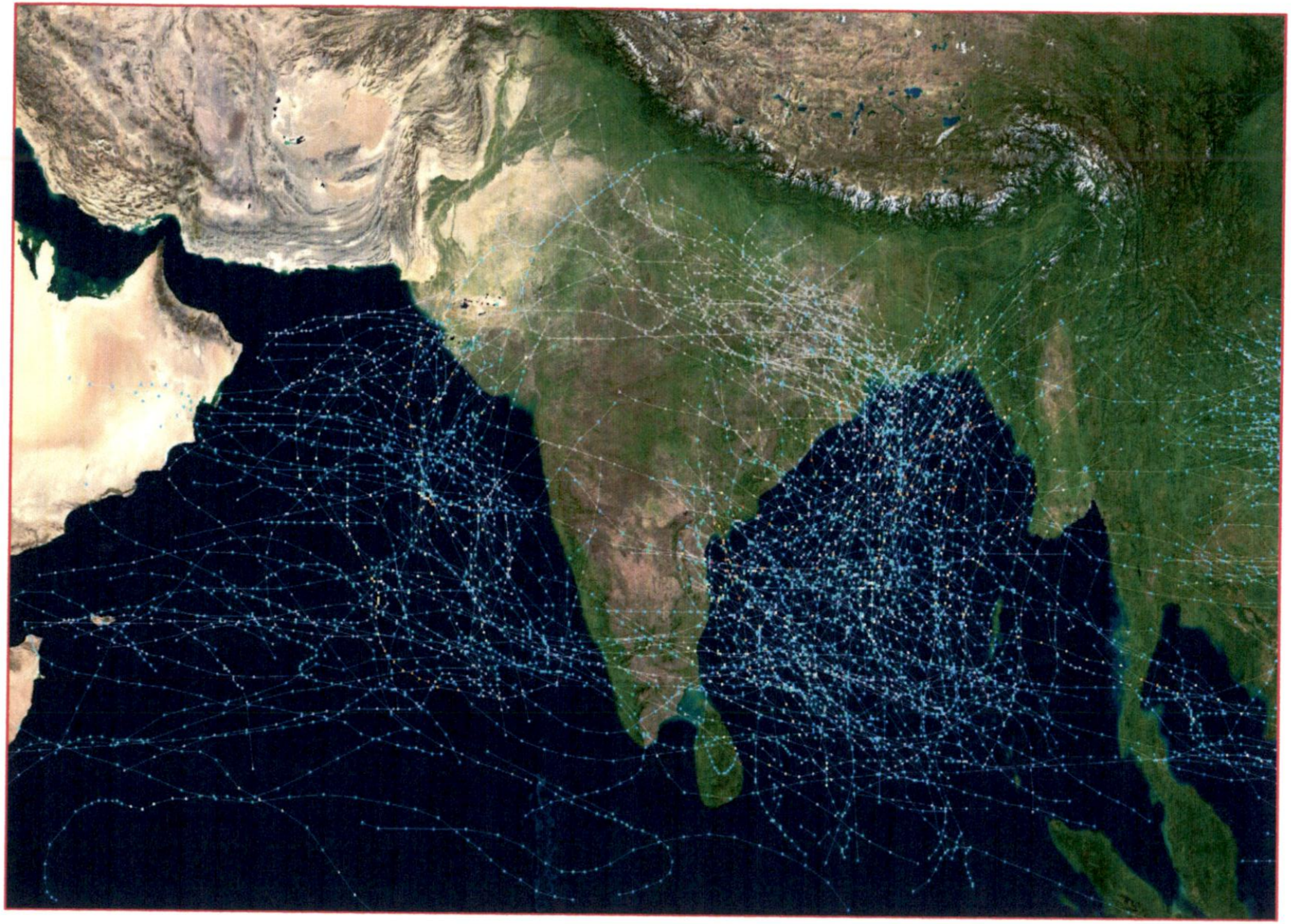


Fig. 2.1: Indian Tropical Cyclone Tracks during 1951-2002

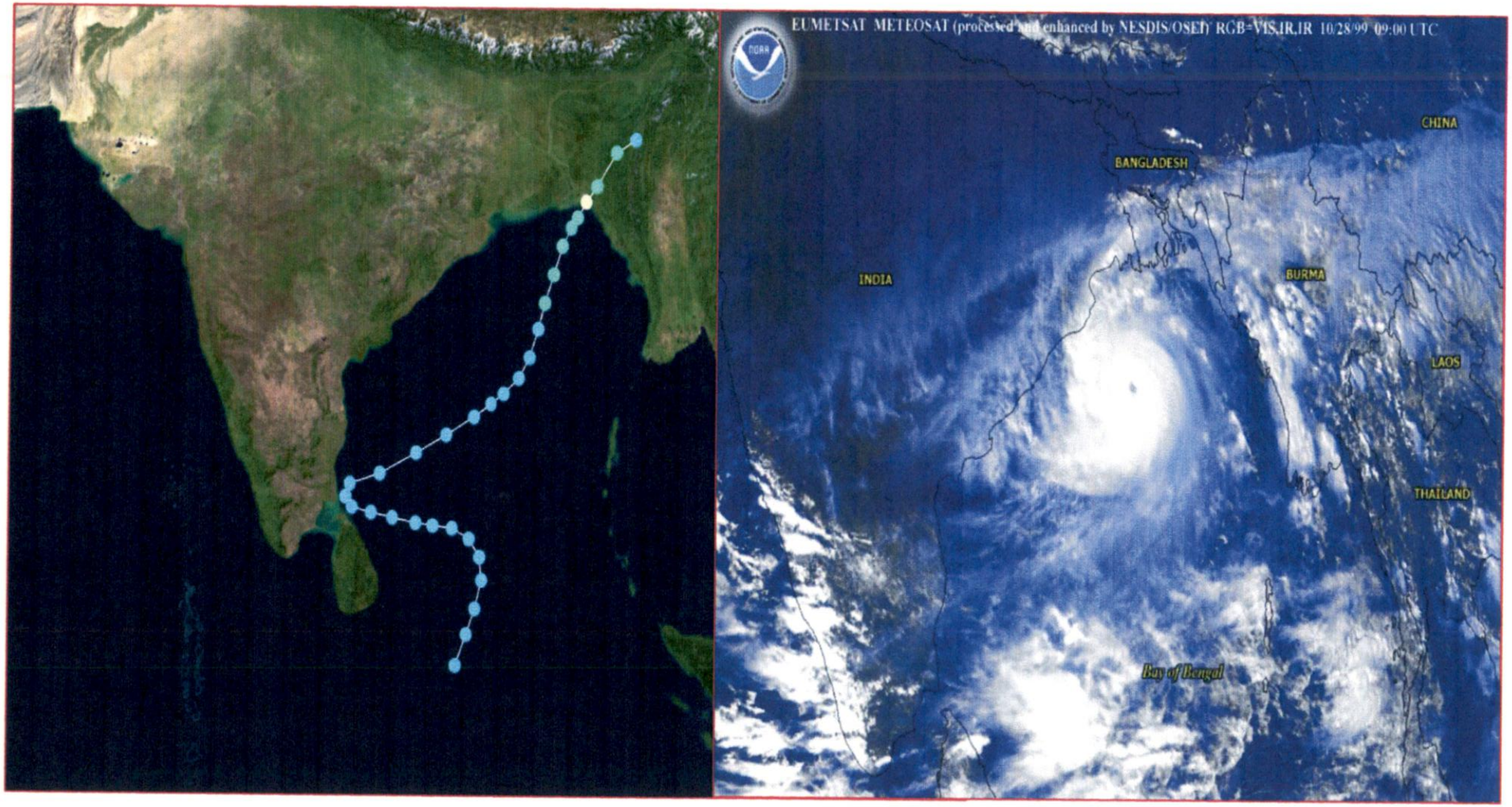


Fig. 2.2: Satellite Image of Typical Cyclone (17 May 1998) and it's Track in Bay of Bengal

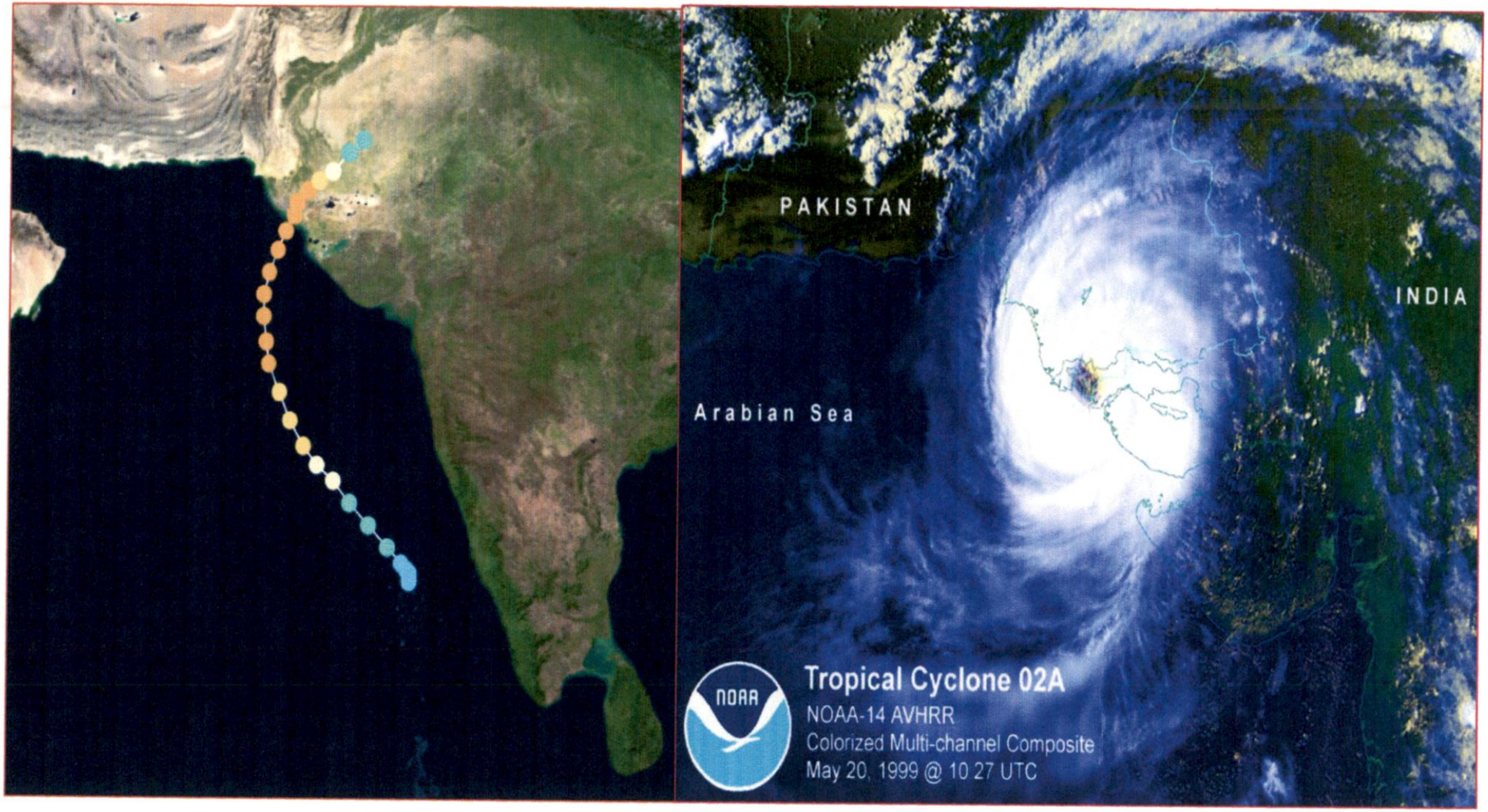


Fig. 2.3: Satellite Image of Typical Cyclone(7 May 1990) and it's Track in Arabian sea

LITERATURE REVIEW

3.1 Wave Forecasting Techniques

The importance of the ocean wave prediction was first felt in early 1940's for the planning of naval fleet operations during the Second World War. Because of the generation of waves at a location by wind is a purely non-deterministic phenomenon; it is very difficult to model a wind-wave relationship. Majority of the routine wave prediction for field usage has been therefore mainly done through simple empirical formulations. Conventionally waves are predicted by using the input of wind parameters. One of the first wave prediction methods was due to Sverdrup and Munk (1947), which was based on significant wave height approach. Though an empirical method, it is still widely used because of its simplicity and efficiency. Later the spectral concept was incorporated in wave forecasting in the early 1950's, and further the energy balance equation was introduced in 1960. Additional wind-wave formulation includes Scripp's Institute formula, Suthen's formula, Derbyshire's formula, Neumann's method, wave-forecasting diagrams of WMO (1988), SMB curves, and Hasselmann method. The latter two techniques are perhaps more widely accepted (Shore Protection Manual, 1984).

SMB (Sverdrup-Munk-Bretschneider) relationships have been worked out by carrying out dimensional analysis followed by curve fitting with respect to observed data. They express non-dimensional wave height and period explicitly as a function of non-dimensional fetch provided the wind speed remains same over a fetch for minimum time duration. Graphical solutions to SMB equations were popular when PC's were not common.

The 1973 data collection project JONSWAP - (Joint North Sea Wave Project) yielded an alternative set of wave forecasting equations called Hasselmann's equations. Being an update over the SMB equations, their use (also presented graphically) is preferred over SMB (SPM, 1984).

Another empirical relationships between wave growth and wind conditions based on constant wind velocity over a fetch length at deep water depth, presented by Wilson (1965) has been widely utilized since1971 (Goda, Y 2003) for the prediction of wave heights. He has proposed the formula by using data observed by ship-borne wave recorders under various wind and wave conditions, including sever storms (Ebuchi, N. 1999).

As wind stress is the forcing mechanism for wave growth at the sea-air interface, the friction velocity U* represent the momentum transfer across the sea surface effectively rather than the wind speed at a height of 10 m (U_{10}) and the normalization using U* is considered to be more appropriate than that by U_{10} to express the wind wave growth (Ebuchi ,1999). Accordingly, based on data from laboratory experiment and observation, Demirbilek, Bratos and Thompson (1993) have proposed the relationship, which has been widely accepted by field users (Coastal Engg. Manual, Part II, 2006).

The above wind-wave relationships belong to the First Generation forecasting models which are simplified versions of complex wave spectrum based models and mostly validated in the ideal situation of constant wind field (Mandal & Nayak, 1984, Mukherjee & Shivaramakrishnan, 1983).

The second generation models are used under varying wind fields (Joshep 1987,Holthuijsen, 1983). Here the sea surface is defined as the sum of a large number of individual wave components, each wave propagating with constant frequency according to wave theory. In order to calculate the energy spectrum of one such component (from the original coastline to the forecast point) is first calculated by the conventional methods. Then considering its interaction with wind, sea bed, other wave components and finally considering loss in breaking, the energy gained or released in the process is evaluated till it reaches the forecast point. This procedure is repeated for different frequencies and direction. Thus a two-dimensional wave spectrum is obtained for a large area in time and space. This process involves use *of* energy balance equation which is given by:

$$\frac{\partial E(f,\theta,x,t)}{\partial t}+C_g(f,\theta).\nabla E=S=S_{in}+S_{nl}+S_{dl} \tag{3.1}$$

Where $E(f,\theta,x,t)$ is the 2-D wave spectrum dependent on frequency f and propagation direction θ at a given location x and at time 't', $C_g(f,\theta)$ is the group velocity. The total source function S is represented by S_{in} = input by wind, S_{nl} = non-linear wave-wave interaction, and, S_{ds} = the dissipation.

The wave spectrum involved in the above equation has a fixed shape. The Third Generation models remove this restriction and simulate the non-linear wave-to-wave interaction realistically. They are based on a complete representation *of* all the three source terms.

WMO (1988) lists the various numerical wind-wave models used in different countries. These models differ in the way they account for the source function terms and also in the numerical solution schemes. In India, the second generation model named 'Dolphin' is used along with the third generation 'WAM' model (Swain *et at.*1997, Mandal *et al.,* 1984).

When the results *of* such numerical models are validated with actual wave measurements, rather limited accuracy is seen. (Fig. 3.1, Reproduced from World Meteorological Organization, WMO, 1988). This is because the phenomenon of generation of wave from wind is inherently uncertain and difficult to catch in a mathematical model. Hence a way out would be to collect actual wave data at a site by instruments like wave rider buoy, pressure gauge or satellite-based remote sensing and make wave forecasts by analyzing such historical wave records. However this does not seem to be a practice owing presumably to the heavy expenditure involved in installation and maintenance of the wave recorders.

The numerical wave models developed, based on energy balance equation requires various components of the source function as inputs. These numerical models solve energy balance equation throughout the grid points over the water, surface where the active wave generation is taking place. These model requires abundant bathymetric, meteorological and oceanographic data.

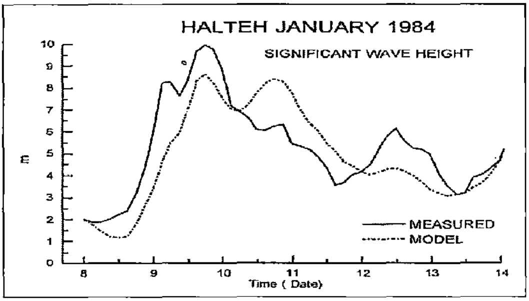


Fig.3.1: A Sample Comparison of Measured Waves with those predicted by a numerical Model

In some regions these data are not available and numerical modeling is both difficult and expensive (Browne et. al, 2007). Moreover, for first estimates in many cases, the use of these models is not economically justified (Goda, 2003) Therefore in these cases engineers tend to use parametric wave prediction models that are based on interrelationships between dimensional analysis. (U.S. Army, 2006).

Instead of parametric wave prediction models, an ANN is also one of the wave prediction model which is successful now a days. The brief literature review is as follows:

3.2 ANN Technique

An artificial neural network, or simply a neural network, is an interconnected system of computational elements called neurons. It is used for a variety of purposes like function approximation, pattern recognition, association, classification and optimization. Consequent to stagnation in computer hardware and software in early 1980s researchers started studying enormous power of human brain and devised a network of artificial neurons imitating that of a biological neuron. Even though the concept of a neuron was introduced in 1963 by McCullough and Pitts (1943), its use became popular following advocation of back- propagation learning algorithm by Rumelhart et at, (1986).

A perceptron with three layers of neurons, namely input, hidden and output, is common in engineering applications. Such a perceptron where the information flow is in the forward direction only is called a multi-layer feed forward Network. It is stated to have capability to model any nonlinear functional relationship.

In this network input variable values are fed through the input layer of neurons. A hidden layer neuron collects each input value, multiplies it by a connection weight, adds such weighted inputs together, attaches a bias value and passes on the result through a non-linear function like that of a sigmoidal one. The resulting value is fired to the output neuron (or to the subsequent hidden layer, if present), which replicate the same process and produce in the end the values of the output variables.

Before its actual application the network is required to be trained with the help of a set of input-output pattern and using an appropriate training algorithm. Details of these can be found in standard books of Kosko (1992), Wasserman (1993), Wu (1994) and Adeli and Hung (1994). Three important networks are back propagation (The ASCE Task Committee, 2000) Cascade Correlation (Fahlman and Lebiere, 1990) and Conjugate Gradient (Fletcher and Reeves, 1994).

Application of Neural Network in water resources involve forecasting rainfall runoff, water level, ground water parameter, water quality parameters as well as decision on water policy. The readily available papers in this regard are due to French (1992), Karunanthi et al.(1994), Thirumalaiah and Deo (1998,2000), SajiKumar and Thomdareswara (1999), Liong et al. (2000), Shin and Salas (2000), Tokar and Markins (2000), Ray and Klindworth (2000). Extensive reviews of NN application in water resources are given in the ASCE Task Committee (2000), Maijer and Dandy (2000).

Unlike the case of water resources discussed above application of neural networks to solve problems in ocean engineering including harbour, coastal and offshore works are very few and sparse. Deo and Kiran Kumar (2000), showed how the networks can work out wave heights over small intervals from their values available over longer intervals. Agarwal and Deo (2001,) predicted on line wave height while Deo and Naidu (1999) predicted real-time wave height. A limited study of forecasting waves from simple networks was attempted by Deo, Jha, Chaphekar and Ravikant(2001); Londhe and Deo, (2004); More and Deo, (2003); Subba Rao and Mandal, , (2005). Prediction of wave heights and period from wind speed and fetch was attempted in Deo et al. (2001).

Most of the attempts of applying NN seem to be oriented towards providing an alternative to the statistical and stochastic techniques of mapping random input-output patterns, with some relive advantages. The advantages are that the neural networks are data oriented rather than model driven, and hence more flexible and adaptable, they do not require (as a precondition) the knowledge of the underlying physical process, they are data error tolerant (including data noise) and further they do not call for data pre-processing.

3.3 Extreme Wave Analysis

There are a large number of works done by many scientists around the world on extreme value prediction of waves. Gumbel (1958) was the first who had developed a statistical method for predicting the extreme values of natural random events like wind speed. Gumbel's extreme value distribution is widely used by the wind engineering community around the world, since the method is simple and robust. The procedure to extreme wave height predictions is explained in Sarpkaya and Isaacson (1981) and in Kamphuis (2000). Extreme value analysis for waves is discussed in detail in Maithesen *et. al.* (1994), Goda *et al.* (1993) and Goda (1992). Coles (2001) has provided the statistical details of extreme value prediction based on the annual maximum data points and Peak over Threshold (POT) method. All these literatures provide the information and knowledge for carrying out a detailed extreme value analysis for the present work.

3.4 Conclusion

Prediction of waves from the knowledge of generating wind is difficult to model by using deterministic equations hence empirical as well as ANN models were adopted in this study. The extent to which the neural network technique becomes successful seem to be dependent on the problem under consideration and hence in many fields their applicability is required to be assessed.

BASIC PRINCIPLES OF OCEAN WAVES

4.1 General

Ocean waves are caused by factors like, wind, attraction of sun and moon, landslides, earthquakes and ship movements. Out of resulting oscillations, wind-generated waves are of prime importance to civil engineers owing to complicated dynamic effects produced by them. These waves are also called' gravity waves' because the force of gravity acts as a restoring agency in their vibration cycles.

The most important ocean dynamic, with maximum impact on human activity at sea, is the sea surface wave. The formation of waves are related to continuous change in temperature over the rotating earth, producing corresponding changes in the atmospheric pressure, which initiate the wind and allow it to blow with different energy at different regions following the atmospheric pressure gradient. The relatively higher energy contained by the wind is transferred to the calm water surface as pressure acting normal to the sea surface as well as shear exerted tangential to it. The disturbance induced by the wind is restored to calm state by the action of gravity in the space-time continuum. The resulting oscillations of water surface due to wind action are called wind-induced surface gravity waves. The size of the wave formed by the wind depends on its speed, the time it blows in one direction, and the distance it has blown across the water. In a storm, a complicated mix of superimposed waves and ripples, known as "sea waves" develop. The direction a sea wave moves is the same as the direction of the local area wind where the wave was generated. After the winds die, the waves continue moving away from the generating area. After leaving the generating area, the waves change, becoming more regular. Long, smooth, regular waves outside the generating area are known as "swell" waves.

Wave growth and the size of the waves depend on the amount of energy transferred to the water by the winds. This transfer is accomplished in two ways:

tangential stress and pressure transfer. Considering the forces of gravity and surface tension, ripples or wavelets should form on the surface at wind speeds of approximately 1 to 3 mph. Observations indicate that ripples appear at about one mph. This is due to the tangential stress.

Pressure transfer is caused due to the turbulence in wind flow at the water surface. Eddies are formed on the lee-side of the wavelets. Wind exerts a pressure on the windward side, while on the lee-side suction will occur. Observations show that ripples appear at speeds of <2 km/hr, due to the effects of pressure. This condition will prevail as long as the wave velocity is less than the wind speed. If the wave velocity exceeds wind speed, the wave will still gain energy from stress but it will lose energy due to resistance.

4.2 Fully Developed

All short waves begin their development in a given fetch area (Fig. 4.1). Since a surface wind field is highly variable (on an oceanic scale), the wave spectrum is composed of varying frequencies and directions. Studies have determined that for each wind speed there is a maximum amount of energy that

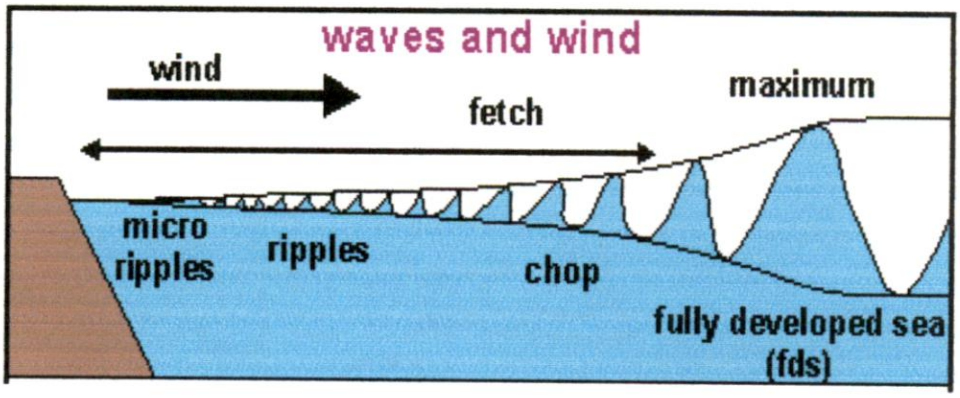


Fig.4.1: Wave Development

can be transferred to the sea surface, and additional energy dissipates as the wave breaks. If the wind is transferring more energy to the waves than is being dissipated, the waves will continue to grow. When dissipation is equal to input energy, the waves stop growing and the sea are said to be "fully developed".

The maximum height to which the waves will grow depends on wind speed, duration, and the length of the fetch. For every wind speed there exist a minimum fetch and a minimum duration to form a fully developed sea.

If the wind stops before the seas are fully developed, then the seas are said to be "duration limited." If the fetch is too short for a fully developed sea to occur, the sea is said to be "fetch limited".

When the wind is unable to impart its maximum energy to the waves, the sea does not fully develop. This happen under two circumstances: (1) when the distance over which the wind blows is limited (the fetch is not long enough); or (2) when the wind is not in contact with the sea for a sufficient length of time (the wind hasn't been blowing long enough).

4.3 Fetch-limited sea

When the fetch length is too short, the wind is not in contact with the waves over a distance sufficient to impart the maximum energy to the waves. The ranges of wave frequencies and heights are therefore limited. The wave frequencies are smaller and the wave heights are less than those of a fully developed sea. The wave generation process is cutoff before the maximum energy can be imparted to the waves and the fetch reaches a steady state. Therefore, for every wind speed, a minimum fetch distance is required for the waves to become fully developed. If this minimum fetch requirement is not met, the sea is fetch limited.

4.4 Duration-limited sea

When the wind has not been in contact with the waves for long enough duration, it had insufficient time to impart the maximum energy to the waves, and the growth of the frequency range and wave heights ceases before the fully developed state of the sea has reached. Such a situation is known as a duration time limited sea. It should be recognized that this condition is rarely met in nature; consequently, this condition should be used with great caution.

4.5 WIND FIELD COMPUTATIONS

The storm generated hindcast models depend to a large extent on the quality of the driving wind fields. Wind speed and effective fetch are the two basic requirements for the hindcasting of storm wave. These are briefly described under two heads as:

4.5.1 Wind Speed

Globally, the two major driving factors of large scale winds are the differential heating between the equator and the poles and the rotation of the planet. Outside the tropics and aloft from frictional effects of the surface, the large-scale winds tend to approach geostrophic balance. Near the Earth's surface, friction causes the wind to be slower than it would be otherwise.

The winds above the wave field can be considered as a profile Fig. 4.2. Some 1000 m or so above the surface, the wind are driven mainly by geostrophic balance between Coriolis and pressure gradient force. Below this level, the frictional effects due to the presence of the ocean, distort the wind field; thus wind speed and direction are dependent upon elevation above the mean surface, roughness of the surface, air sea temperature differences etc. Below the geostrophic, the boundary layers may be divided into two sections, a constant stress layer 10m to 100m in height and above that an Ekman layer as shown in Fig. 4.2. Emphasis is placed on the constant stress layer.

The pressure gradient force is not actually a 'force' but the acceleration of air due to pressure difference (a force per unit mass). It is usually responsible for accelerating a parcel of air from a high atmospheric pressure region to a low pressure region, resulting in wind. In meteorology, pressure gradient force refers to the horizontal movement of air according to the equation:

$$\frac{F}{m} = -\frac{1}{\rho}\frac{\partial p}{\partial z} \tag{4.1}$$

The term $\frac{F}{m}$ is equal to the acceleration $\frac{\partial v}{\partial t}$, because this is an expression of Newton's law $F = m.a$. $\frac{\partial p}{\partial z}$ is the component of the pressure gradient along the x-axis. ρ is the mass density and $(\frac{1}{\rho})$ shows that as the mass density increases, the acceleration due to the pressure gradient becomes smaller.

The pressure gradient force acts at right angles to isobars in the direction from high to low pressure. The greater the pressure difference over a given horizontal distance, the greater the force and hence the stronger the wind.

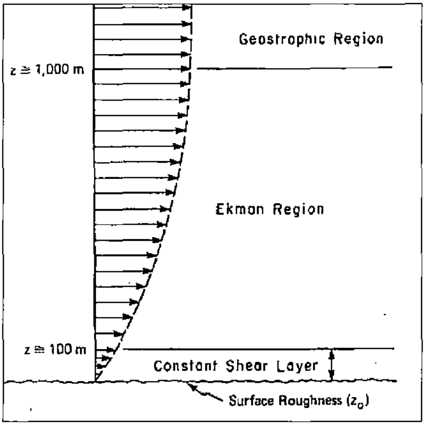


Fig 4.2: Atmospheric Boundary Layer over Waves

The Coriolis force is an apparent force due to rotation of earth. It depends on the latitude and the speed of movement of air parcel. The higher the latitude, the larger the coriolis force means zero at equator and maximum at the poles. The Coriolis force always acts at right angles to the direction of movement i.e. to the right in the Northern Hemisphere and to the left in the Southern Hemisphere.

The other forces acting on a horizontally moving parcel of air include; surface friction, Coriolis force, centrifugal force. In large-scale atmospheric flows, the Coriolis force generally balances the pressure gradient force, producing winds blowing largely along the isobars; however, near the surface, the friction term is also important, generally giving a resulting net wind direction diagonal to the isobars.

The most obvious and accurate way to determine wind speed over a fetch is to average the reported values from ships. This method has the advantage of not requiring a correction for gradients or stability. But often a few ship reports are available, and they are subject to error in observation, encoding, or transmission.

A second way to determine wind speed is to measure the geostrophic wind from the isobaric spacing and then correct it for curvature and stability. The reason for correction to geostrophic wind is that the isobars must be straight for a correct measure of the wind. When the isobars curve, other forces enter into the computations. The wind increases or decreases depending on whether the system is cyclonic or anticyclonic in nature. The stability correction is a measure of turbulence in the layer above the water. Cold air over warmer water is unstable and highly turbulent, making the surface wind more nearly equal to the geostrophic wind. Conversely, warm air over colder water produces a stable air mass and results in the surface wind being much smaller than the geostrophic wind.

Geostrophic wind is the flow in a straight line in which the horizontal components of the pressure gradient force (PGF) balances the Coriolis force (deviating force) above the friction layer as represented in Fig. 4.3. Only these two forces (no frictional force) are supposed to act on the moving air. It blows parallel to straight isobars or contours. Geostrophic winds occur above the friction layer and develop in response to gradients in atmospheric pressure over large regions of the surface of the earth.

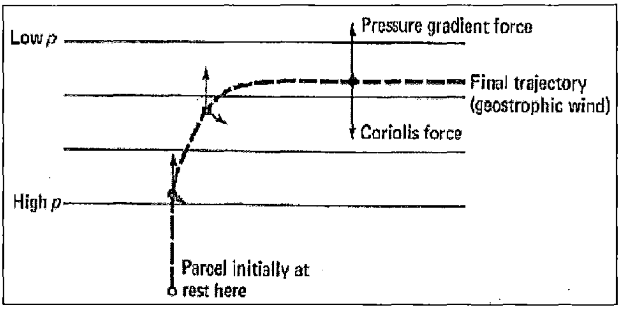


Fig.4.3: Geostrophic Balance

An air parcel initially at rest will move from high pressure to low pressure because of the pressure gradient force. However, because the earth is rotating, an apparent force called the Coriolis force, producing what is called the Coriolis Effect, deflects the winds. As an air parcel begins to move, it is deflected by the Coriolis force to the right in the northern hemisphere (to the left on the southern hemisphere). As the wind gains speed, the Coriolis Effect increases in magnitude until it balances the pressure gradient force. The result is an un-accelerated horizontal wind blowing parallel to isobars that is called the geostrophic wind.

The geostrophic wind speed: $$U_g = \frac{1}{\rho_a f}\frac{\Delta p}{\Delta n} \qquad (4.2)$$

Where ρ_a= air density =1.367 gm/cm^3

f = coriolis parameter= 2 ωsin ϕ

ω =7.292x10^{-5} rad/s ϕ = latitude in degree

Δn =Isobar spacing measured in degrees latitude

$\frac{\Delta p}{\Delta n}$ = Horizontal gradient of atmospheric pressure

All wind data were first corrected to a 10 m elevation, by applying the graph of wind velocity profile as shown in Fig. 6.3 (Shore Protection Manual, 1984).

Surface wind speed at 10 m elevation: $U_{10}= R_g \times Ug$ (4.3)

Where R_g is a multiplying factor which is a function of the geostropic wind.

In some wave prediction model as in SBM, Wave growth formulas are expressed in terms of adjusted wind-stress factor, $\boldsymbol{U_A}$. Predicted winds are usually adjusted so that the horizontal frictional stress remains nearly independent of elevation. A critical parameter affecting wave growth is the air-sea temperature gradient. Since this gradient information is often unavailable, the wind speed at a 10-m elevation under the condition of neutral stability (ΔT=0) is often used to characterize the wind-stress causing waves. So,

$$U_A = 0.71 \times U_{10}^{1.23}$$ (Shore Protection Manual, 1984) (4.4)

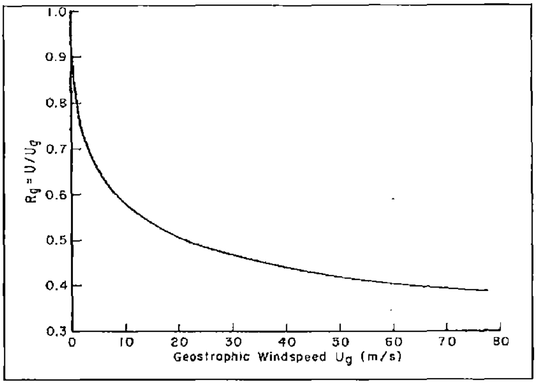


Fig. 4.4: Ratio of R_g of wind speed U at 10m elevation to geostrophic Wind speed U_g (modified from Resio and Vincent, 1977)

Since the friction velocity U^* represents the momentum transfer across the sea surface rather than the wind speed at a height of 10m, U_{10}. So, the normalization using U^* is considered to be more appropriate than that by U_{10} to express the wind-wave growth. Moreover, it is not appropriate to scale wave results with U_{10} because the 10 m height is really arbitrary and bears no relation to any length scale in the physical system. However, accurate field measurements of U^* are too few to derive a reliable formula. In order to estimate U^* from U_{10}, the drag coefficient C_D, which is defined as,

$$C_D = (U^* / U_{10})^2 \qquad (4.5)$$

is conventionally utilized, though there seems to be considerable disagreement about the value of C_D among investigators (e.g., Blanc, 1985). Several studies (e.g., Toba *et al.*, 1990; Donelan *et al.*, 1993) reported that the value of C_D depends not only on the wind speed but also on the sea state.

A number of empirical forms have been devised for this relationship (Van Dorn 1953, Reid et al. 1977, Large and Pond 1981) for use in wind wave modeling. The drag coefficient relationship adopted for an open ocean is of the following form:

$$C_D = 0.001\,(1.1 + 0.035U_{10})\,U_{10} \qquad (4.6)$$

This form, although parabolic, nearly represents a straight-line approximation of the drag coefficient versus wind speed for low values of wind speed. The historical measurements have clearly demonstrated that drag coefficient reduced to 10-m height and neutral conditions is independent of stability and fetch but increases with wind speed above 10 m/sec. Below U_{10} = 10 m/s, C_D does not vary appreciably with wind speed and should remain essentially constant (Garratt 1977 and Smith 1980). The best constant should be in the range 1.1 x 10^{-3} to 1.3 x 10^{6} (Large and Pond 1981).

For open ocean situations and for higher wind speed, the following expressions, obtained directly from field measurements, have been suggested and used extensively in offshore engineering (CEM 2006)

$$C_D = 0.001\ (1.1 + 0.035U_{10}) \tag{4.7}$$

4.5.2 Effective Fetch

A fetch has been defined as a region in which the wind of reasonable constant speed and direction blows over the water surface to generate the waves. The effect of fetch width on limiting ocean wave growth in a generating area may usually be neglected since nearly all ocean fetches have width about as large as their length.

A recommended procedure (SPM, 1984) for determining fetch length consists of constructing 9 radials from the point of interest at 3 degree intervals, centered about the direction from which the wind is blowing and extending these radials until they first intersect the shorelines. The mean length of the 9 radials is the effective fetch. This process must be repeated for each location and for each direction under consideration

Effective Fetch calculation (after CERC1984):

$$F_e = \frac{\sum(\cos\alpha_i).F_i}{\sum(\cos\alpha_i)} \tag{4.8}$$

Where

F_e = Effective Fetch in Kilometers

F_i = the fetch distance in kilometers along the direction i

α_i = angle (°) between the wind direction and the direction i

This method is based on following assumptions:

1. Wind blowing over water surface transfers energy to the water surface in the direction of wind and in all directions within 12° on either side.
2. Wind transfers the unit amount of energy to the water surface along the central radial in the direction of the wind, and along any other radials, an amount modified by the cosine of the angle between the radial and the wind direction.
3. Waves are completely absorbed at shorelines.

   Fetch distance determined in this manner are usually less than those based on maximum straight line distances over open water because of the fetch restrictions on the total amount of energy transferred.

But, in the case of an open sea areas where the fetches are largely related to size and tracks of the weather system, there is a dominant fetch and small changes in wind direction don't significantly change fetch length or the direction of the generated wave. So, the fetch distance has been determined based on maximum straight line distances over open water.

Fortunately, the wave parameters are not very sensitive to absolute error in fetch length for these large fetches. As a limit for storms of normal size, changes in wind direction make it unlikely that fetch would be greater than 500km.

4.6 Conclusion

By this chapter, the storms condition depending upon the wind field can be recognized. The strong wind (speed>62 km/hr) blow constantly over the fetch area is recognized as a storm(IMD report). Under such conditions, one can expect very active air-sea interactions including transfer of momentum, energy, heat and other substances and it is expected that waves will reach a fetch limited state of development.

Conditions of duration-limited growth are difficult to fulfill in practice and, from the point of view of the analysis of experimental data, two other idealized cases are more important. One is the case of fully developed waves; the other, more frequently occurring, situation is the fetch-limited case.

DIFFERENT APPROACHES FOR STORM WAVE HINDCASTING

5.1 General

The hindcasting of an individual historical storm consists of two basic steps. First, the surface marine wind field must be specified as accurately as possible. The calibration of ocean response models by using the above wind fields as input is the second part of the process.

Several parametric wave prediction models have been developed in past decade, such as SMB, Wilson, JONSWAP, SPM (USR army, 1984) that has been superseded by recently CEM (U.S. Army, 2006). These are the parametric models based on a synthetic storm wind field database. The model takes the concept of an equivalent fetch within a storm originally proposed by Bretshneider (1957) to apply fetch limited wave growth relationships. Later on Joint North Sea Wave Program (JONSWAP) (Hasselmann et al., 1973) justify the equivalent fetch criteria.

5.2 Different Approaches for Storm Hindcasting

Following approaches have been used for storm hindcasting in the present study. A brief description is as follows:

5.2.1 SMB Approach

Sverdrup and Munk in 1942, developed the first practical forecasting technique for forecasting the height and period of wind waves at sea from the knowledge of the wind velocity, its duration and fetch over which it blows. On the basis of additional empirical data, the technique was modified by Bretschneider (1952) to form the empirical method, now known as SMB method. This method was also verified by the JONSWAP based on research on wave spectra in growing seas by Hasselmann et.al. 1973 (CERC, 1984).

According to this method, to accomplish fetch limited condition, the wind duration must be greater than t_{min} that is: $$\frac{gt_{min}}{U_{10}} = 68.8\left(\frac{gF}{U_{10}}\right)^{\frac{2}{3}} \tag{5.1}$$

Where t_{min} is the minimum duration of the wind blowing over the fetch (F).U_{10} is the wind speed at 10 m elevation above water surface and g is the acceleration due to gravity.

The predicted wave height in deep water depth is given by:

$$\frac{gH_s}{U_A^2} = 1.6\times10^{-3}\left(\frac{gF}{U_A^2}\right)^{1/2} \tag{5.2}$$

Where H_s is the significant wave height and U_A is the adjusted wind stress factor. If the wind duration is smaller than t_{min} the condition is called duration limited. In this condition equivalent fetch must be calculated by substituting the wind duration into the equation (5.1). Then, significant wave heights are estimated by substituting the equivalent fetch into equation (5.2).

For fully developed sea, (waves are a function of wind speed only):

$$\frac{gH_s}{U_A^{\,2}} = 2.433\times10^{-1}\ ; \tag{5.3}$$

5.2.2 Wilson Approach

Another empirical relationships between wave growth and wind conditions based on constant wind velocity over a fetch length at the elevation of 10m above sea surface presented by Wilson (1965) have been using as standard formula since1971 (Goda, Y. 2003). Under the condition of sufficiently long duration of wind blowing, the significant wave height is expressed as:

$$\frac{gHs}{U_{10}^{\,2}} = 0.30\left\{1-\left[1+0.004\left(\frac{gF}{U_{10}^2}\right)^{1/2}\right]^{-2}\right\} \tag{5.4}$$

And the minimum duration for the full growth at a given fetch length is approximately calculated by (Wilson, 1965):

$$t_{min} = 1.0\,\frac{F^{0.73}}{U_{10}^{\;0.46}} \tag{5.5}$$

Alternatively, the minimum fetch length F_{min} (km) necessary for full wave growth under a given wind duration t(h) is expressed as below:

$$F_{\min} = 1.0 t^{1.37} U_{10}^{0.63} \tag{5.6}$$

5.2.3 CEM Approach (U S Army, 2006)

In this method, the definition of constant wind is used for the determination of wind duration. The minimum wind duration for accomplishing fetch-limited condition is expressed as:

$$t_{\min} = 77.23 \frac{F^{0.67}}{U_{10}^{0.34} g^{0.33}} \tag{5.7}$$

In the fetch limited condition, the equation governing wave growth :

$$\frac{gH_s}{U_*^2} = 4.13 \times 10^{-2} \left(\frac{gF}{U_*^2} \right)^{1/2} \tag{5.8}$$

In duration limited condition, equivalent fetch length is calculated as:

$$\frac{gF}{U_*^2} = 5.23 \times 10^{-3} \left(\frac{gt}{U_*} \right)^{\frac{3}{2}} \tag{5.9}$$

In this equation 't' is the wind duration blowing over the fetch. The fetch length estimated from this equation must then be substituted into equation (5.8) to obtain estimates of wave height in duration limited condition.

For fully developed sea wave conditions, H_s are given by;

$$\frac{gH_s}{U_*^2} = 2.115 \times 10^2 \tag{5.10}$$

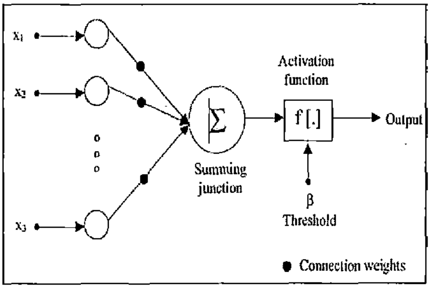
Equations governing wave growth with duration can be obtained by converting duration into an equivalent fetch given by equation (5.4).

A given calculation for a duration should be checked to ensure that it has not exceeded the maximum wave height for the given wind speed and fetch. It is essential that fetch-limited wave calculations be checked to see if they are duration limited; likewise, duration-limited cases should be checked to see if they are really fetch limited.

5.2.4 ANN approach

An artificial neural network (ANN) is an information processing method that is inspired by the biological nervous system, such as the human brain, process information. The key element of this method is the structure of the information processing system. The working of neurons is represented in Fig.5.1. It is composed of highly interconnected processing elements (neurons) working in unison to solve specific problem. ANNs, like people, learn by example. An ANN can be configured for a specific application, such as pattern recognition or data classification. Learning in a biological system involves adjustment to the synoptic connections that exist between the neurons. ANN works in a similar way with the ANN parameters, weights and biases, being adjusted as part of a learning process supervised or unsupervised. This modeling methodology does not attempt to understand explicitly the underlying physics. The physics of the problem is captured in the choice of the input data sets and the choice of the ANN structure (with larger number of hidden neurons enabling more non-linear relationships). If the input data sets do not contain the physical forcing parameters associated with the event being forecasted, the ANN will not be able to establish a relationship between inputs and outputs.

A 3-layered feed forward type of neural network (Fig. 5.2) is commonly preferred in many engineering applications because of its ability to approximate any nonlinear mathematical dependency structure. This type of network model is equivalent to a multivariate multiple nonlinear regression model. Input values are fed to input nodes which transmit them to the hidden layer nodes, each of which sums up the received values from all input nodes, adds a "bias" to this sum and then passes them on through a nonlinear transfer function, like the sigmoid function. The result is fired to the output layer nodes that operate identically to the hidden. The resulting transformed output forms the network output.



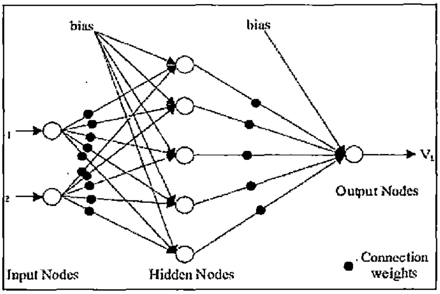


Fig.5.1: Working of a Neurons

Fig 5.2: Typical 3-layered feed Forward Network Structure ($I_2H_5O_1$)

Mathematically, the feed forward artificial neural network is expressed in the form of

$$Y_k(x) = \sum_{j-1}^{M} (W_{kj} * T_r(Z)) + b_{ko} \tag{5.11}$$

$$\text{Where } Z = \sum_{j-1}^{M} (W_{ki} * x_i + b_{jo})$$

And x is considered to be the original parameter space of dimension D, W_{ji} and W_{kj} are weighting parameters, b_{jo} and b_{ko} are bias parameters, M is the number of nodes in the hidden layers and $T_r(z)$ is the activation function. This activation function follows a non-linear conversion of the summed inputs. It has the form of a hyperbolic tangent sigmoid function $T_r(z)$ as:

$$T_r(z) = \frac{2}{(1+e^{-2z})} - 1 \tag{5.12}$$

Here z corresponds to the summed weighted input from the input layer. This is a key element of the model. The bias parameters for the hidden and output layers allow offsets to be introduced.

Before its actual application, the network is required to be trained and this is done by using a variety of training algorithms, like Back Propagation, Cascade Correlation and Conjugate Gradient.

All training algorithms are basically aimed at reducing the global error, E, between the network output and the actual observation, as defined below:

$$E = \frac{1}{2}\sum_{1}^{M}(On - Ot) \quad (5.13)$$

Where O_n is the network output at a given output node and O_t is the target output at the same node. The summation is carried out over all output nodes for a given training pattern and then over all training patterns.

In the back propagation method, error minimization is done using the steepest descent or the gradient descent approach wherein the network weights and biases are adjusted by moving a small step in the direction of negative gradient of the error function during each iteration. The iterations are repeated till a specified convergence is reached or until a given number of iterations are over. Due to the fixed step size, it converges slowly and may exhibit oscillatory behavior and hence the back propagation network with updated algorithms i.e.Quickprop, Rprop, TrainLm (Levenberg- Morquqrdt) are used.

In estimation of parameters of wave forecasting model, the available data are divided into, two parts. The first 80% data are considered to train the neural network and the remaining 20% are kept for comparison with the NN predicted data. The professional version of MATLAB 7.0.1 software is used in the present study. This software supports various updated algorithms including LM which is used in this work.

Finally, the models are tested using the performance evaluation criteria based on correlation coefficient (R).

5.3 Conclusion

The adoption of the above parametric model depends on the wind field variables. SMB and Wilson model consider U_{10} as the reference wind speed which is mainly based on practical considerations rather than the dynamic significance of 10 m elevation in the marine boundary layer. It is believed that U_* is preferable as it represents the actual wind stress applied at ocean surface, than U_{10} to serve as the scaling wind speed. So, CEM which includes U_* in its model may give the good approximation.

SMB model assumes a constant wind speed; a definable direction, fetch boundaries and minimum storm movement. In reality, storm fetch has no clear-cut boundaries, the wind speed varies throughout the fetch, and the fetch is continually moving sometimes a variable direction. If the wind field is only slightly irregular and storm movement is relatively slow, then the SMB method may gives acceptable answer. However, when the conditions are highly irregular and the variables are ill defined, the Wilson method may be a good approximation because Wilson has considered those variables in his model.

Considering advantages and disadvantages over the above parametric models an ANN can be used an alternative technique and has been applied successfully to storm prediction problems.

DATA ANALYSIS FOR WAVE HINDCASTING

6.1 General

The hindcast wave heights for storms passing within 300 km of the region of interest were determined from storm tracks and synoptic chart over the past 115years. These storm tracks include all storm types such as depressions, tropical storm, cyclones or super cyclones. From the tracks approaching the coast the predominant directions of approach of the storms can be observed. As the storm data is 300 km radius around the study area, these storms are likely to have a maximum role on the extreme wave climate of the coasts.

The storms shown on storm track are classified as:

Depressions -wind speed less than 62km/hr

Storms -wind speed between 62km/hr and 87km/hr

Sever storm - wind speed between 87km/hr and 117km/hr

Sever Cyclonic Storms- wind speed between 117km/hr and 200km/hr

Super Cyclones - wind speed above 200km/hr

The statistics of long term ocean wave prediction requires that the individual data points used in the statistical analysis be statistically independent. An hourly wave height is very much related to the wave height of the previous hours and hence the theoretical condition of statistical independence is not met. In order to produce independent data points, only storms should be considered. The hindcast wave data were analyzed to find storms, which passed by the area of interest and are significant to the above areas for design purposes. A threshold wave height of 3.0 m to separate wave heights into storms is selected for the present analysis based on peak over threshold method in which value are adopted for one standard deviation from the mean. For normal distribution this accounts 68.26% of the data set.

6.2 Wave Height Calculations

The wave prediction models (SMB, Wilson and CEM) were applied for the calculation of wave height for each storm. Most of the calculated wave heights were found to be below 3.0 m, which are not significant for the design of any marine structures. Moreover, the values below threshold do not much affect the best-fit line in the distribution criteria. So, from the available data of 115 years, 54 and 55 storms were found significant producing more than 3.0 m wave height off Mumbai and Pondicherry coast respectively and were considered for the analysis of Extreme wave heights. The hindcast wave height, which were significant for both the coasts respectively are presented in Table 6.1 and Table 6.2 respectively.

The calculations are performed in a tabular form. In this, column 4 to 7 is the date wise input variables extracted from the storm tracks and synoptic charts. Column 8 to 12 is the wind speed details computed from the equations 4.2 to 4.7 respectively and column 13 to 15 shows the fetch-limited predicted wave heights based on equations 5.2, 5.4, 5.8 respectively. Wave height predictions for fully developed sea (FDS) were also computed based on CEM (equation 5.10.) and other two approached. Minimum values out of the three wave heights have been given in the column no 16.The sample calculation for the first row of table 6.4 is given as follows;

From eq. 4.2 $U_g = \dfrac{1*10^{-3}}{1.367*2*7.292*10^{-5}}\left(\dfrac{1.7}{0.54}\right) = 46.16$ col. 8

From fig 4.4 for U_g =46.16 ; R_g=0.43

Fromeq.4.3 U_{10}=0.43*46.16=19.70m/s col. 9

From eq.4.4 U_A=0.71*(19.70)1.23=27.76 m/s col. 10

From eq.4.6 C_D = 0.001* (1.1 + 0.035*19.70)*19.70=0.00179 col. 11

From eq.4.5 U_*=19.70*$(0.00179)^{1/2}$ =0.833 m/s col. 12

From eq.5.2 $H_s=(27.76^2/9.807)*\{1.6*10^{-3}*(9.807*146/27.76^2)^{1/2}\}$=5.45m col.13

From eq.5.4 $Hs=(19.7^2/9.807)*\{1\text{-}[1+0.004(9.807*146/19.7^2)^{1/2}]^2\}$=4.19m col.14

From eq.5.8 $Hs=(0.833^2/9/807)*\{0.413*10\text{-}2*(9.807*146/0.833^2)^{1/2}\}$=4.2m col. 15

From eq.5.10 $Hs=2.115*10^2*(0.833^2/9/807)$=14.98m col. 16

Table 6.1: Wave Hindcasting using Storm Data off Mumbai

Sl. No.	Details of storm		Effective Wind Area Details				Wind Speed Details					Predicted Wave Height Details			
	DD/MM	Year	Latitude	Δp	Δn	F	U_g	U_{10}	U_A	C_D	U_*	SMB	Wilson	CEM	FDS
			°	mb	°	Km	m/sec	m/sec	m/s		m/s	m	m	m	m
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
1	19-Nov	1893	20	1.7	0.54	146	46.16	19.70	27.76	0.00179	0.833	5.45	4.19	4.20	14.98
2	20-Nov	1896	18.6	1.7	0.76	192	35.17	15.65	20.91	0.00165	0.635	4.45	3.39	3.67	8.70
3	15-Jun	1903	17.78	1.7	0.69	336	40.46	17.62	24.21	0.00172	0.730	7.24	4.74	5.58	11.50
4	25-Oct	1917	18.15	1.7	0.74	228.2	36.98	16.33	22.04	0.00167	0.668	5.44	3.79	4.21	9.62
5	10-Jun	1920	18.33	1.7	0.39	229.8	69.51	27.77	42.35	0.00207	1.264	10.37	7.64	7.99	34.46
6	29-Oct	1930	17.82	1.7	0.56	107.7	49.75	20.98	30.00	0.00183	0.899	4.68	4.05	3.89	17.42
7	17-May	1933	17.17	1.7	0.38	187	76.00	29.91	46.40	0.00215	1.386	10.24	7.75	7.90	41.42
8	18-Aug	1944	18.08	2	0.37	113.8	87.35	33.56	53.47	0.00227	1.601	9.20	7.27	7.12	55.27
9	18-Nov	1946	17.92	2	0.64	123.2	50.93	21.40	30.74	0.00185	0.920	5.54	4.37	4.26	18.27
10	17-Apr	1947	19.15	2	0.34	109.1	89.93	34.38	55.07	0.00230	1.650	9.28	7.35	7.19	58.72
11	24-Sep	1948	18.48	2	0.64	141.4	49.44	20.88	29.81	0.00183	0.893	5.75	4.46	4.43	17.20
12	21-Nov	1948	18.01	2	0.31	155.8	104.65	38.95	64.21	0.00246	1.933	12.93	9.87	10.06	80.59
13	9-Jun	1954	18.69	2	0.63	103.1	49.68	20.96	29.96	0.00183	0.898	4.94	3.98	3.80	17.37
14	9-Oct	1956	17.8	2	0.51	137.5	64.33	26.03	39.12	0.00201	1.167	7.41	5.80	5.71	29.40
15	10-Nov	1957	12.99	2	0.6	252.5	74.37	29.37	45.38	0.00213	1.355	11.64	8.49	8.98	39.60
16	10-Oct	1958	17.07	2	0.57	212	59.95	24.54	36.37	0.00196	1.086	8.57	6.34	6.60	25.44
17	26-Nov	1958	13	2	0.86	235.7	51.85	21.73	31.31	0.00186	0.937	7.80	5.63	6.00	18.94
18	20-May	1959	11.64	2	0.45	206.3	110.47	40.72	67.81	0.00253	2.046	15.72	11.67	12.26	90.29
19	15-Oct	1963	18.19	2	0.42	122.2	76.50	30.07	46.71	0.00215	1.395	8.33	6.58	6.43	41.98
20	9-Jun	1964	16.53	2	0.49	122.2	71.94	28.58	43.87	0.00210	1.310	7.83	6.20	6.04	36.99
21	30-May	1970	17.29	2	0.35	110	96.42	36.41	59.11	0.00237	1.774	10.00	7.88	7.76	67.91
22	21-Sep	1974	17.01	2	0.42	122.2	81.63	31.74	49.91	0.00221	1.492	8.90	7.02	6.88	48.02
23	4-May	1975	12	2	0.67	247.5	72.00	28.60	43.90	0.00210	1.311	11.15	8.15	8.60	37.05
24	22-Oct	1975	19.19	2	0.67	177.8	45.54	19.48	27.38	0.00178	0.822	5.94	4.42	4.57	14.58
25	2-Jun	1976	17.9	2	0.23	105.3	141.88	49.93	87.14	0.00285	2.664	14.81	11.05	11.40	153.09

Sl. No.	Details of storm		Effective Wind Area Details				Wind Speed Details					Predicted Wave Height Details			
	DD/MM	Year	Latitude	Δp	Δn	F	U_g	U_{10}	U_A	C_D	U_*	SMB	Wilson	CEM	FDS
			°	mb	°	Km	m/sec	m/sec	m/s		m/s	m	m	m	m
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
26	10-Jun	1977	16.85	4	0.51	178.3	135.69	48.15	83.35	0.00279	2.541	18.01	13.35	14.15	139.30
27	17-Nov	1977	12.36	2	0.58	274.9	80.79	31.46	49.38	0.00220	1.476	13.21	9.56	10.21	47.00
28	11-Nov	1978	20.83	4	0.46	168.1	122.64	44.35	75.32	0.00265	2.284	15.78	11.84	12.35	112.49
29	27-Nov	1978	13.96	2	0.49	122.2	84.85	32.77	51.91	0.00225	1.553	9.26	7.29	7.16	52.03
30	17-Jun	1979	15.82	2	0.63	193.2	58.40	24.01	35.41	0.00194	1.058	7.96	5.96	6.13	24.12
31	16-Nov	1979	16.39	2	0.53	107	67.07	26.95	40.82	0.00204	1.218	6.82	5.48	5.25	32.01
32	6-Jun	1980	18.47	2	0.42	68.76	75.38	29.71	46.01	0.00214	1.374	6.16	5.11	4.75	40.72
33	1-Nov	1981	17.94	2	0.41	258.9	79.42	31.02	48.53	0.00219	1.450	12.60	9.18	9.73	45.37
34	7-Nov	1982	13.61	2	0.69	412.6	61.77	25.16	37.52	0.00198	1.120	12.32	8.25	9.49	27.05
35	29-May	1985	16.53	2	0.39	206.3	90.39	34.53	55.36	0.00231	1.659	12.83	9.59	9.94	59.35
36	8-0ct	1985	19.47	2	0.61	116.7	49.33	20.84	29.74	0.00183	0.891	5.22	4.14	4.01	17.13
37	10-Jun	1988	16.49	2	0.89	229.9	39.70	17.34	23.74	0.00171	0.717	5.87	4.13	4.53	11.07
38	15-Nov	1993	18.85	2	0.39	359.6	79.60	31.08	48.64	0.00219	1.454	14.88	10.38	11.50	45.58
39	6-Jun	1994	18	1	0.4	110	40.57	17.67	24.28	0.00172	0.732	4.15	3.29	3.20	11.56
40	14-0ct	1995	16.16	2	1.05	358.1	34.32	15.33	20.39	0.00164	0.620	6.32	3.95	4.89	8.29
41	18-Jun	1996	17.9	2	0.6	154	54.39	22.62	32.90	0.00189	0.984	6.62	5.09	5.09	20.87
42	25-0ct	1996	18.4	2	0.8	220	39.72	17.35	23.75	0.00171	0.717	5.75	4.07	4.43	11.08
43	8-Jun	1998	16.67	2	0.63	209.5	55.50	23.01	33.60	0.00191	1.004	7.88	5.82	6.06	21.74
44	8-0ct	1998	13.23	2	1.04	240.6	42.14	18.24	25.26	0.00174	0.761	6.38	4.48	4.92	12.48
45	14-0ct	1998	13.7	2	1.8	484	23.53	11.10	13.71	0.00149	0.428	5.01	2.59	3.93	3.95
46	18-May	1999	16.07	2	0.3	173.2	120.78	43.80	74.18	0.00263	2.247	15.77	11.82	12.34	108.94
47	24-May	2001	16.47	2	0.46	208.7	76.91	30.21	46.96	0.00216	1.403	10.95	8.18	8.45	42.45
48	26-Sep	2001	17.12	2	0.67	243.2	50.85	21.38	30.69	0.00185	0.919	7.77	5.57	5.98	18.21
49	10-0ct	2001	17.75	2	0.75	206.3	43.87	18.87	26.33	0.00176	0.792	6.15	4.46	4.74	13.52
50	9-May	2004	15	2	0.61	322.9	63.53	25.76	38.61	0.00200	1.153	11.22	7.84	8.64	28.65
51	10-Jun	2004	16.54	2	0.72	349	48.93	20.69	29.50	0.00182	0.884	8.94	5.99	6.89	16.85
52	1-0ct	2004	16.35	2	0.67	380.7	53.18	22.19	32.15	0.00188	0.962	10.17	6.78	7.82	19.94
53	21-Jun	2005	20	2	0.47	179.1	62.40	25.38	37.91	0.00199	1.131	8.20	6.22	6.31	27.61
54	14-Sep	2005	18.18	2	0.73	300	44.04	18.93	26.44	0.00176	0.795	7.45	5.06	5.74	13.63

Table 6.2: Wave Hindcasting using Storm Data off Pondicherry

Sl. No.	Details of storm		Effective Wind Area Details				Wind Speed Details					Predicted Wave Height Details			
	DD/MM	Year	Latitude	Δp	Δn	F	U_g	U_{10}	U_A	C_D	U_*	SMB	Wilson	CEM	FDS
			°	mb	°	Km	m/sec	m/sec	m/s		m/s	m	m	m	m
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
1	26-Nov	1952	11.64	2	1.04	394	47.80	20.29	28.79	0.00181	0.863	9.28	6.05	7.15	16.07
2	28-Oct	1956	13.94	2	0.65	250.05	64.05	25.94	38.94	0.00201	1.162	9.95	7.23	7.66	29.13
3	20-Nov	1958	12.59	2	0.71	196.4	64.81	26.19	39.41	0.00202	1.176	8.92	6.70	6.88	29.84
4	10-Dec	1962	13.17	4	0.71	183.3	124.01	44.75	76.16	0.00267	2.311	16.67	12.41	13.05	115.16
5	21-Nov	1964	13.32	2	0.42	123.04	103.65	38.65	63.59	0.00245	1.914	11.38	8.85	8.85	79.00
6	22-Dec	1964	10.21	2	0.46	150.7	123.01	44.46	75.55	0.00266	2.291	14.99	11.33	11.73	113.22
7	8-Nov	1965	13.17	2	0.66	128.31	66.70	26.83	40.59	0.00204	1.212	7.43	5.86	5.72	31.65
8	1-Jan	1966	12.37	2	0.51	130.48	91.80	34.97	56.24	0.00232	1.686	10.36	8.08	8.03	61.30
9	30-Apr	1966	12.27	2	0.44	212.3	107.26	39.75	65.83	0.00249	1.984	15.48	11.48	12.05	84.88
10	**3-Nov**	**1966**	**13.64**	**4**	**0.38**	**93.2**	**223.85**	**71.97**	**136.62**	**0.00362**	**4.329**	**21.65**	**15.58**	**17.43**	**404.20**
11	18-Nov	1966	12.79	2	0.79	172.48	57.35	23.65	34.75	0.00193	1.038	7.39	5.61	5.69	23.25
12	20-Nov	1966	14.59	2	0.57	241.92	69.85	27.88	42.56	0.00208	1.270	10.69	7.83	8.24	34.81
13	7-Dec	1967	11.19	2	0.42	93.2	123.06	44.47	75.58	0.00266	2.292	11.68	9.20	9.23	113.31
14	**24-Oct**	**1968**	**13.6**	**2**	**0.21**	**110**	**203.12**	**66.62**	**124.24**	**0.00343**	**3.902**	**21.31**	**15.47**	**17.07**	**328.43**
15	17-Dec	1968	11.53	2	0.38	111.84	132.05	47.10	81.11	0.00275	2.469	13.88	10.63	10.89	131.51
16	22-Oct	1969	12.37	2	0.34	93.2	137.71	48.73	84.58	0.00281	2.581	13.22	10.19	10.39	143.70
17	7-Nov	1969	16.35	2	0.42	205.04	84.83	32.76	51.90	0.00225	1.553	11.99	8.98	9.27	52.01
18	19-Nov	1970	12.28	2	0.62	251.64	76.06	29.93	46.44	0.00215	1.387	11.89	8.68	9.18	41.49
19	4-Dec	1972	13.05	2	0.42	205.04	105.76	39.29	64.90	0.00248	1.955	15.00	11.16	11.67	82.40
20	5-Nov	1973	14.4	4	0.68	242.32	118.62	43.16	72.85	0.00261	2.205	18.32	13.36	14.32	104.88
21	25-Nov	1975	12.45	2	0.34	93.2	136.84	48.48	84.05	0.00280	2.564	13.13	10.13	10.32	141.79
22	**16-Nov**	**1976**	**14.22**	**4**	**0.49**	**92.94**	**166.66**	**56.86**	**102.25**	**0.00309**	**3.161**	**16.02**	**12.06**	**12.71**	**215.44**
23	24-Nov	1976	11.97	2	0.6	166.6	80.60	31.40	49.27	0.00220	1.473	10.26	7.86	7.93	46.77
24	3-Nov	1978	11.8	2	0.43	11.58	114.06	41.80	70.03	0.00256	2.116	3.85	3.29	3.00	96.57
25	**23-Nov**	**1978**	**9.53**	**2**	**0.3**	**154.6**	**201.94**	**66.31**	**123.53**	**0.00342**	**3.878**	**25.11**	**17.96**	**20.11**	**324.36**
26	10-May	1979	12.37	2	0.62	167.76	75.52	29.75	46.10	0.00214	1.377	9.64	7.38	7.44	40.87
27	5-Dec	1980	14.15	2	0.48	149.12	85.48	32.97	52.30	0.00225	1.565	10.30	7.96	7.97	52.83

Sl. No.	Details of storm		Effective Wind Area Details				Wind Speed Details					Predicted Wave Height Details			
	DD/MM	Year	Latitude	Δp	Δn	F	U_g	U_{10}	U_A	C_D	U_*	SMB	Wilson	CEM	FDS
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
28	17-Dec	1980	9.32	2	0.39	93.2	158.80	54.69	97.47	0.00301	3.003	15.28	11.57	12.09	194.42
29	8-Dec	1981	15.69	4	0.8	265.44	92.72	35.26	56.81	0.00233	1.703	14.93	10.86	11.57	62.58
30	11-Nov	1984	11.67	2	0.37	146.72	134.02	47.67	82.32	0.00277	2.508	16.13	12.13	12.67	135.68
31	30-Nov	1984	12.1	2	0.39	239.1	122.69	44.36	75.35	0.00265	2.285	18.83	13.72	14.73	112.60
32	13-Dec	1985	12.97	2	0.42	111.86	106.40	39.49	65.29	0.00248	1.967	11.14	8.71	8.68	83.45
33	12-Nov	1986	13	2	0.5	91.7	89.17	34.14	54.60	0.00230	1.636	8.43	6.77	6.53	57.70
34	1-Feb	1987	10.5	2	0.59	177.08	93.29	35.44	57.16	0.00234	1.714	12.27	9.30	9.51	63.38
35	2-Nov	1987	14.16	4	0.67	110.04	122.39	44.28	75.17	0.00265	2.279	12.74	9.85	9.97	112.02
36	27-Nov	1988	15	4	0.78	280.41	99.37	37.33	60.93	0.00241	1.831	16.46	11.89	12.79	72.31
37	8-Nov	1989	14.69	2	0.36	152.28	109.87	40.54	67.44	0.00252	2.034	13.43	10.24	10.47	89.26
38	18-Nov	1989	12.29	2	0.65	216.36	72.49	28.76	44.21	0.00211	1.320	10.50	7.81	8.10	37.57
39	7-May	1990	12.2	4	0.67	110	141.68	49.87	87.02	0.00285	2.660	14.78	11.25	11.64	152.62
40	18-Dec	1990	14.6	2	0.52	220	76.52	30.08	46.72	0.00215	1.396	11.19	8.31	8.63	42.00
41	26-Apr	1991	13.53	2	0.44	194.04	97.44	36.73	59.74	0.00239	1.794	13.42	10.08	10.42	69.41
42	28-Oct	1991	11.96	2	0.78	172.48	62.05	25.26	37.69	0.00198	1.125	8.00	6.10	6.16	27.30
43	14-Nov	1991	11.56	2	0.33	54.09	151.67	52.70	93.13	0.00294	2.860	11.11	8.67	8.77	176.35
44	13-Nov	1992	8.16	2	0.66	202.65	107.07	39.69	65.71	0.00249	1.980	15.10	11.24	11.76	84.55
45	8-Dec	1993	10.76	2	0.51	225.6	105.34	39.16	64.64	0.00247	1.947	15.67	11.56	12.19	81.72
46	20-Dec	1993	11.95	2	0.49	134.15	98.86	37.17	60.62	0.00240	1.821	11.33	8.78	8.80	71.54
47	23-Nov	1995	12.63	2	0.67	247.5	68.46	27.42	41.70	0.00206	1.244	10.60	7.73	8.16	33.40
48	26-Dec	2000	10.51	2	0.68	141	80.86	31.49	49.43	0.00220	1.478	9.47	7.37	7.32	47.09
49	25-Dec	2002	8.81	2	0.75	220	87.32	33.55	53.45	0.00227	1.600	12.79	9.50	9.90	55.23
50	2-Oct	2004	13.25	2	1	467.5	43.76	18.83	26.27	0.00176	0.790	9.24	5.72	7.12	13.46
51	26-Oct	2005	13.66	2	0.98	348.79	43.34	18.68	26.00	0.00175	0.782	7.91	5.20	6.09	13.20
52	21-Nov	2005	11.46	2	0.98	268.3	51.51	21.61	31.11	0.00186	0.931	8.26	5.84	6.36	18.69
53	30-Nov	2005	15	2	0.5	247.5	77.51	30.40	47.34	0.00216	1.414	12.01	8.80	9.28	43.13
54	6-Dec	2005	12.38	2	0.48	183.33	97.46	36.74	59.75	0.00239	1.795	13.05	9.85	10.13	69.45
55	28-Oct	2007	14.25	2	0.75	288.75	54.33	22.60	32.87	0.00189	0.983	9.05	6.35	6.96	20.82

6.3 Data Analysis for Storm Wave Hindcasting

From the storm data of 115 years (during 1891 to 2005), the storm conditions passing through the area in the vicinity of Mumbai and Pondicherry were identified. It was seen that there were 153 and 192 such storm conditions, which were of significant to the Mumbai and Pondicherry coast respectively. The break-up of these storm conditions is given in Table 6.3:

Table 6.3: Break-up of the Storm Condition of Mumbai and Pondicherry

Sl. No.	Storm	Mumbai	Pondicherry
1	Depressions	86	85
2	Storms	40	58
3	Sever storm	16	13
4	Sever Cyclonic Storms	11	32
5	Super Cyclones	00	04

The storm data of the past 115 years indicated that the frequency of occurrence of storms passing through the West Coast near off Mumbai is low as compared to the East Coast near off Pondicherry. This may be due to the fact that the number of storms originating in the Arabian Sea is comparatively less than storms originated in the southern part of the Bay of Bengal.

It is also observed that most of the storms which are significant for both the coast have occurred either during the month of May /June or October / November. The month wise breakup of these storms is as given in Table 6.4 and in Fig. 6.1.

Table 6.4: Month Wise Break-Up of Storms of Mumbai and Pondicherry

Month	Jan	Feb.	Mar.	April	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.
Mumbai	00	00	00	04	20	40	04	01	14	37	31	02
Pondicherry	03	03	01	05	19	2	00	00	5	43	73	38

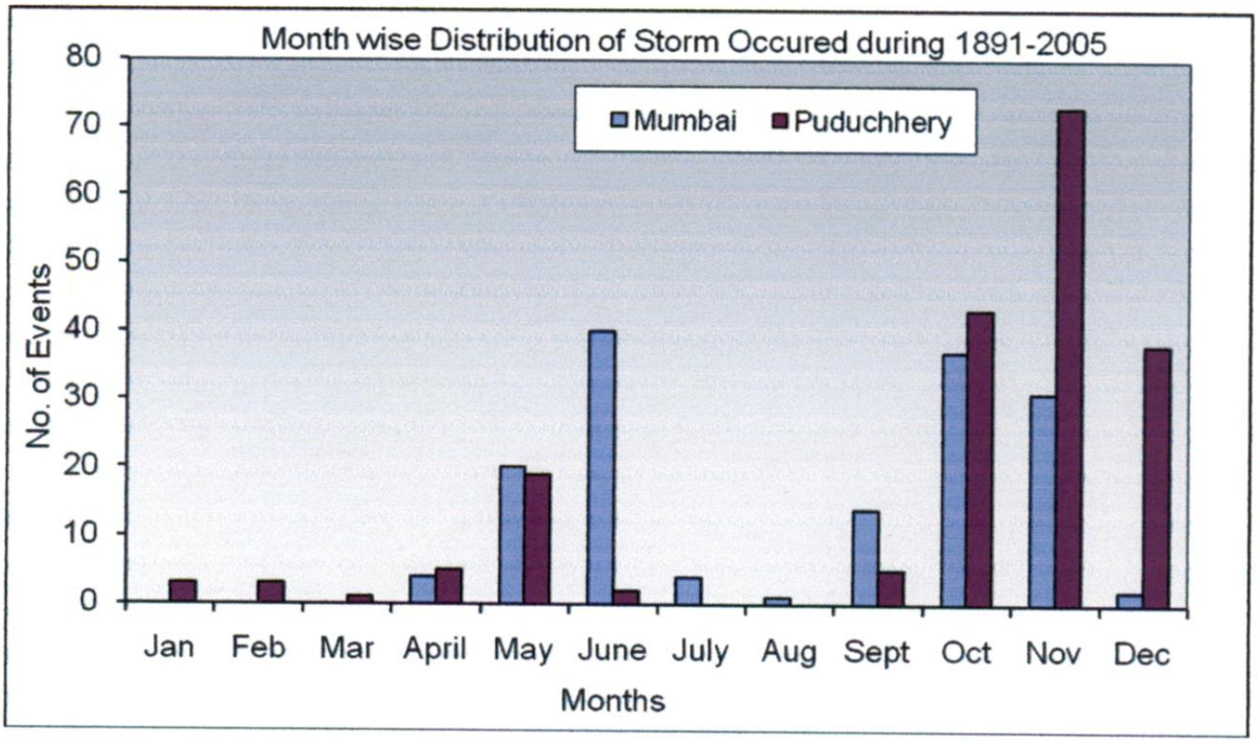


Fig. 6.1: Month Wise Distribution of Storms off Mumbai and off Pondicherry

The predicted wave height using CEM method for fully developed and fetch limited growth for both the locations are represented in Fig. 6.2 and Fig. 6.3 respectively. Figures show a very high value of predicted wave heights on both the locations for fully developed sea, which are not in the possible range. Moreover, fully developed sea for a severe storms (speed >50Km/hr) requires more than 630 km fetch length. The present data is not showing any such condition.

So, it may be concluded that over the Indian subcontinent, fully developed sea condition for severe storms is restricted due to comparatively short fetch.

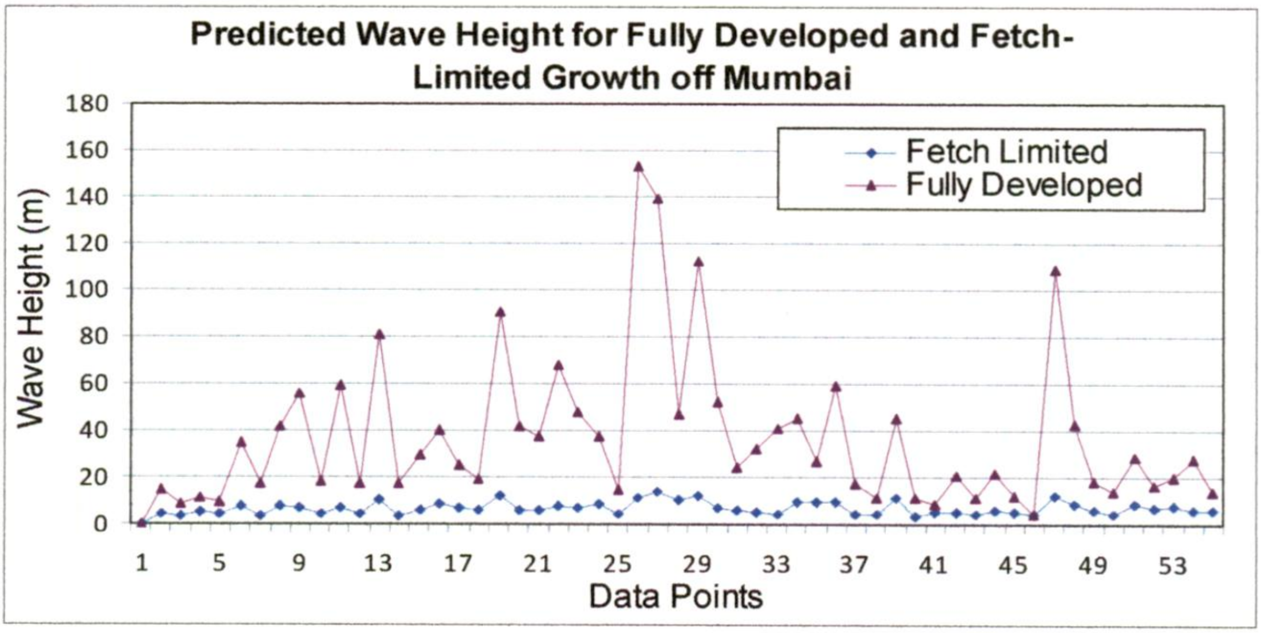


Fig.6.2: Predicted Wave Height of Fully-Developed and Fetch-Limited Growth, Off Mumbai

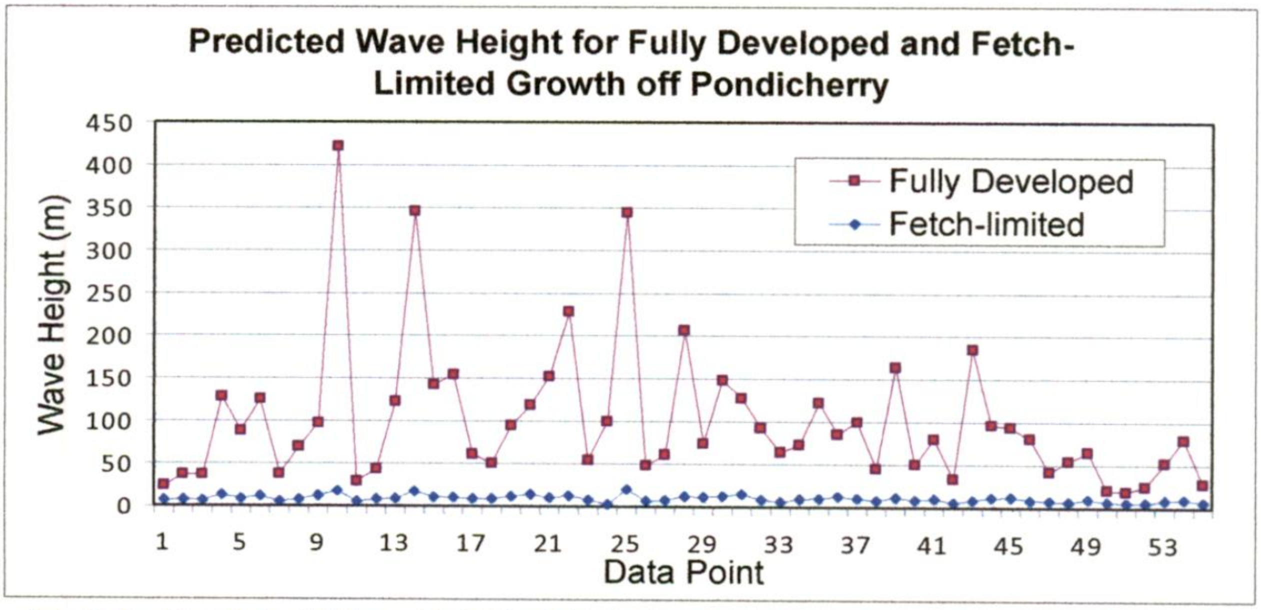


Fig.6.3: Predicted Wave Height of Fully-Developed and Fetch-Limited Growth, Off Pondicherry

Fig. 6.4 and Fig. 6.5 show the wave height predicted through SMB, Wilson and CEM, model. The analysis show, a good agreement of wave heights obtained by Wilson and CEM model, which are within the comparable range, while SMB in general show a tendency towards higher values as compared to above two methods.

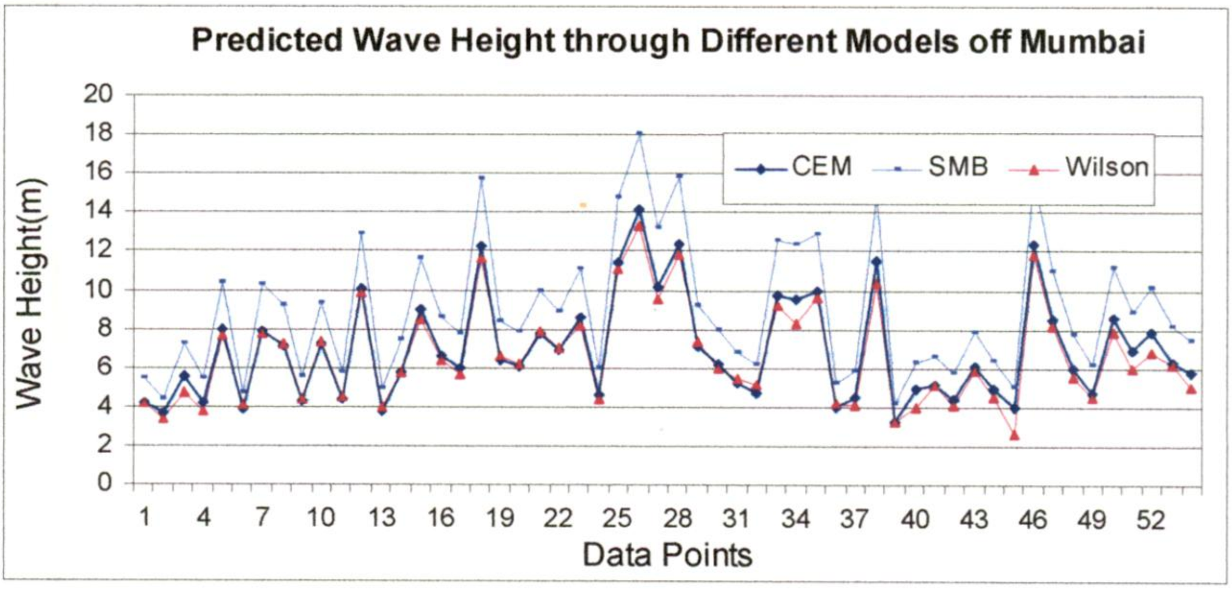


Fig.6.4: Prediction of Wave Height through different Models, Off Mumbai

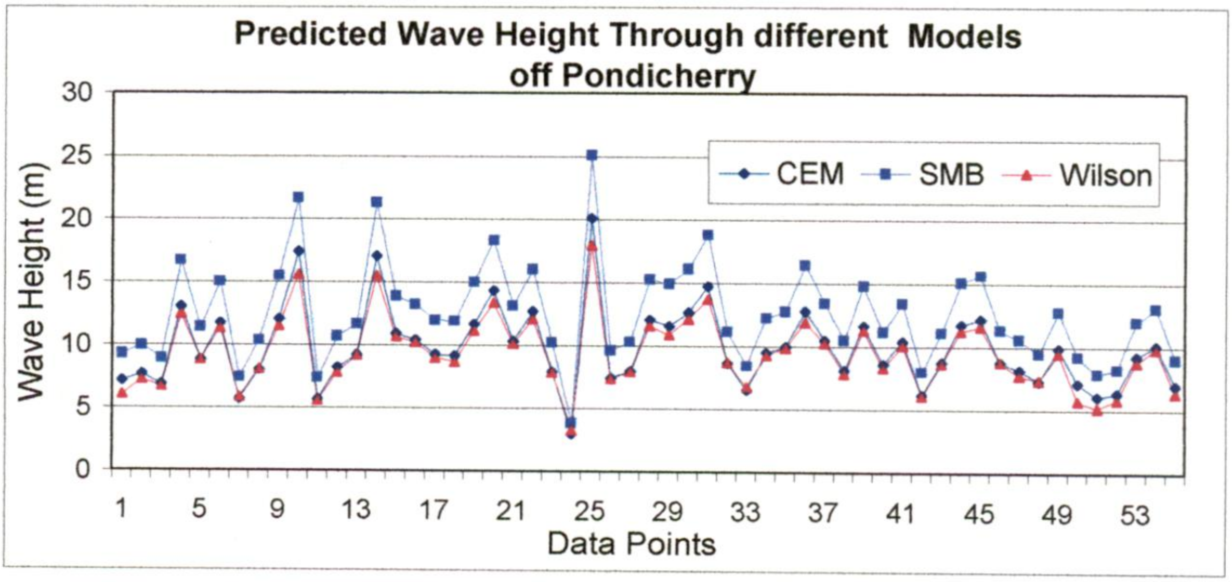


Fig.6.5: Prediction of Wave Height through Different Models, Off Pondicherry

The discrepancies among the wave height prediction through different models are caused mainly by stability conditions and the spatial variation of wind fields. Usually the wave growth data are reported with the neutral wind speed U_{10} serving as the scaling winds velocity. The adoption of U_{10} as the reference wind speed is mainly based on practical considerations rather than the dynamic significance of 10 m elevation in the marine boundary layer. It is believed that U_* is preferable as it represents the actual wind stress applied at ocean surface, than U_{10} to serve as the scaling wind speed.

Another reason may be due to assumptions in the SMB model that were made includes a constant wind speed; a definable direction, fetch boundaries and minimum storm movement. In reality, storm fetch has no clear-cut boundaries, the wind speed varies throughout the fetch, and the fetch is continually moving sometimes a variable direction.

If the wind field is only slightly irregular and storm movement is relatively slow, then the SMB method gives acceptable answer. However, when the conditions are highly irregular and the variables are ill defined, the Wilson method may be a good approximation. Since the procedures for obtaining surface wind speed adopted for the above prediction models are same, the average error in the wave heights will be nearly same.

In the present data set, 4 super cyclones have occurred in the East coast off Pondicherry i.e. during 3Nov.1966,24 Oct.1968, 16 Nov.1976 and 23Nov.1978. In these cases, models appear to predict higher wave heights because of curvature effect of the storm track. In this case, a gradient wind, which accounts the centrifugal forces in addition to the coriolis and pressure gradient force, should have been taken into accounts. But due to unavailability of sufficient data required for the analysis, these have been considered as storms.

In the absence of any observed data at the present locations, as indicated earlier CEM and Wilson model predicted comparable results, accordingly average value of the two predictions has been applied as input (observed) value for ANN model.

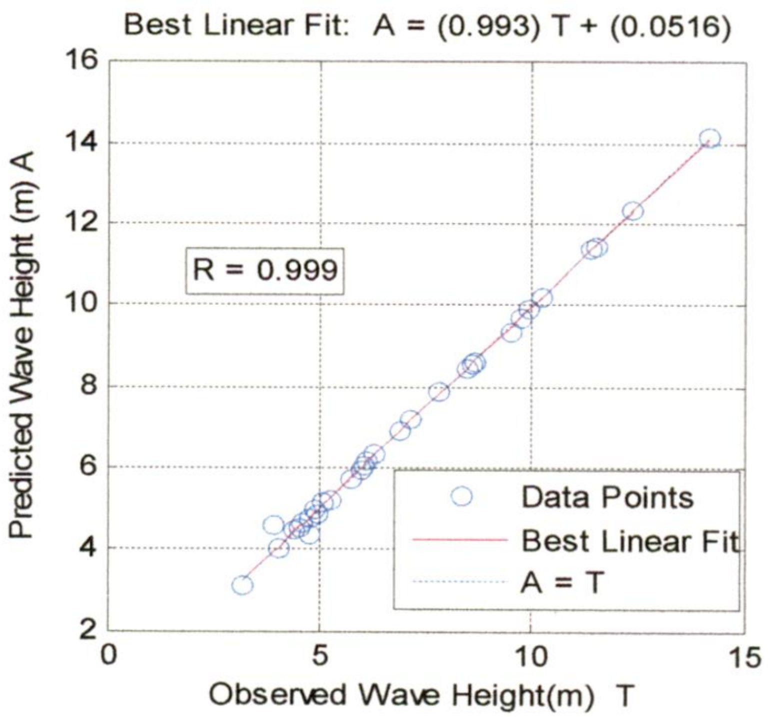
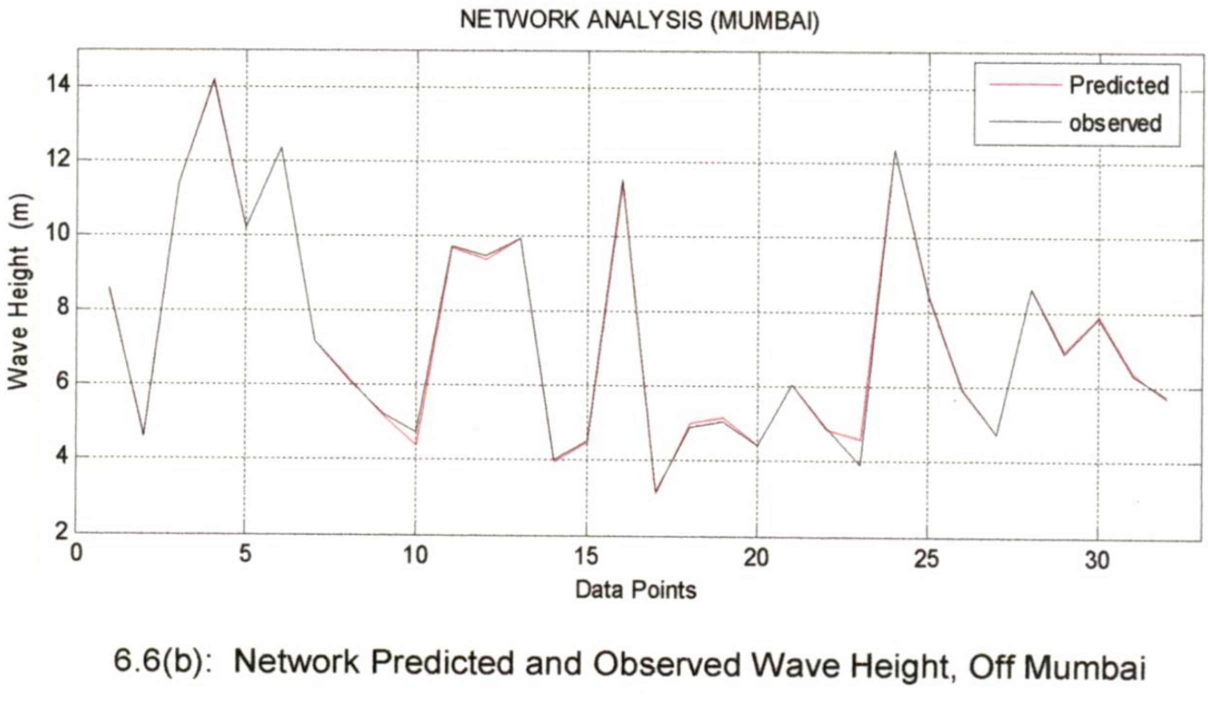


Fig.6.6 (a): Scatter diagram Off Mumbai



6.6(b): Network Predicted and Observed Wave Height, Off Mumbai

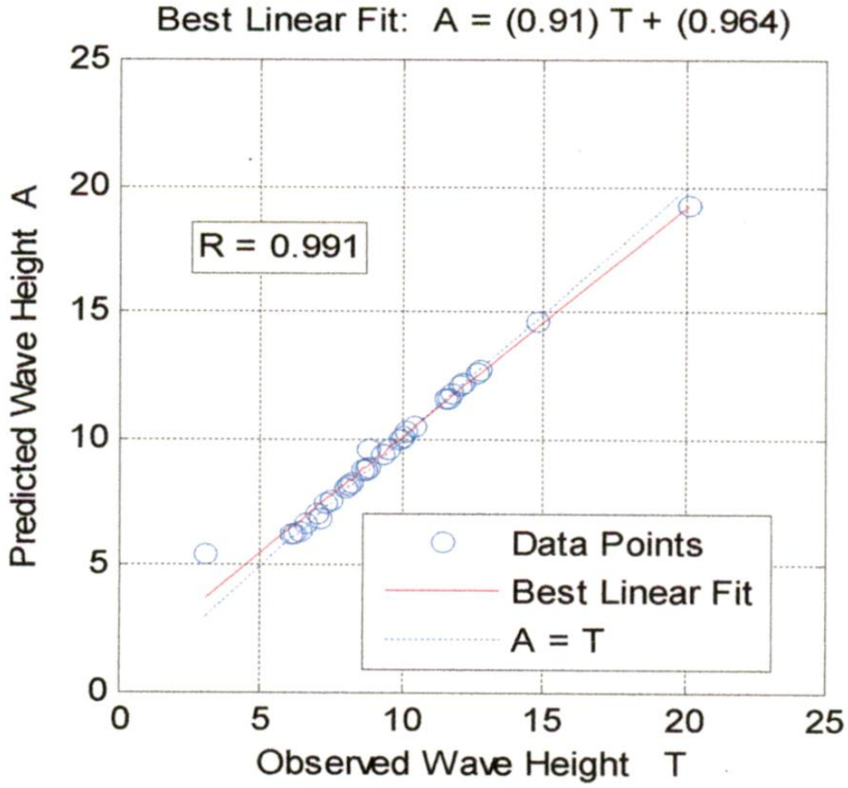


Fig.6.7 (a):Scatter diagram Off Pondicherry

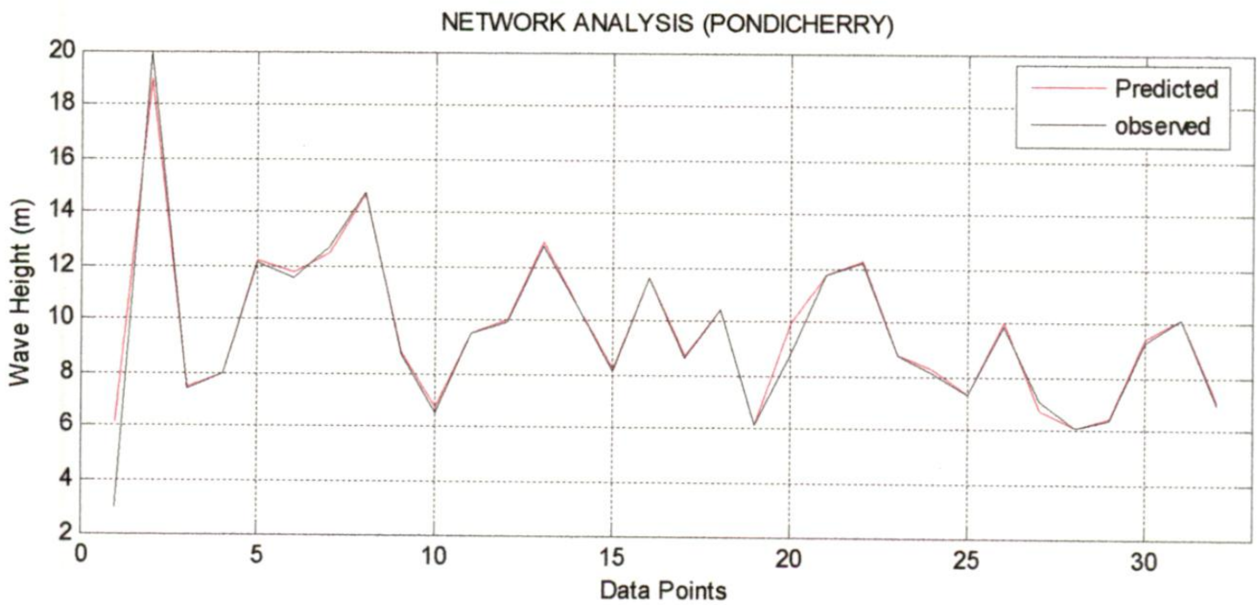


Fig.6.7 (b): Network Predicted and Observed Wave Height, Off Pondicherry

The back propagation feed forward neural network with LM updated algorithm were used to estimate the wave height (1 output) based on storm field parameters (2 input), i.e. geostrophic wind speed and fetch. The network structure of $I_2H_4O_1$ were used for this model.

Here in the case off Mumbai coast, out of 153 data, 121 data were considered to train the neural network and the remaining 32 were used for its comparison with the NN predicted data similarly in the case off Pondicherry coast, out of 192 data, 150 data were considered for training and the remaining 42 were used for its validation.

The applicability of ANN to the problem of wave prediction indicated that the appropriate trained network could provide satisfactory results. A qualitative comparison in terms of scatter plots and time history as shown in Fig. 6.6 and Fig. 6.7 indicated a very little deviation of wave height value. The high correlation coefficients obtained for both the locations confirm that the wave height estimated using Neural Network Model closely matches with those estimated using CEM and Wilson models. This shows that neural network with LM updated algorithm can be used as an effective tool in estimating storm generated wave heights.

6.4 Conclusion

The analysis show, a good agreement of wave heights obtained by Wilson and CEM model, which are within the comparable range, while SMB in general show a tendency towards higher values as compared to above two methods. The average value of the two predictions has been applied as input (observed) value for ANN model. The applicability of ANN to the problem of wave prediction indicated that the feed forward back propagation neural network with LM updated algorithm can be used as an effective tool in predicting storm generated wave heights.

EXTREME VALUE ANALYSIS

7.1 General

Prediction of extreme wave height over a life span of 50 years or 100 years of the structures is required for selection of the design waves. In order to predict long-term wave heights from limited hindcast records, extreme value analysis is carried out. The statistical analysis for determination of various return period wave heights from the data set involves (Burcharth et al, 1994) the choice of theoretical distribution for the extreme wave height distribution, fitting of wave height to the distributions, comparison of the fitting goodness among the distributions and estimation of wave height corresponding to a certain return period. The commonly employed distribution models in extreme wave analysis are Gumbel, Weibull and Log-normal distributions, (Kamphuis, 2000) applicable for the storm wave data. These distributions are on the basis of the following assumptions:

1. The statistics of long-term prediction of wave heights requires that the individual data points (storms) used in the statistical analysis be statistically independent.
2. Storms are assumed to come from the same probability distribution function meaning the mean, standard deviation and min/max value are not increasing or decreasing over the time
3. The probability of given storm will only occur once a time.
4. The period for which an extreme is computed is assumed sufficiently large so that a limiting extreme value distribution will be an adequate model for the distribution of the observed extremes.

The data must be fitted to some distribution function to enable estimation of the various return values. The return values are computed by fitting the following distribution models to the sequence of extreme values using the method of moments. i.e.

$$Y_T = A\,X_T + B \qquad (7.1)$$

Here Y is the transformed probability axis, often called reduced variate, and X is the wave height axis. The coefficients A and B are the slope and intercept of the straight line relationship and they are determined by linear regression analysis.

In this method the extreme wave data are first rearranged in descending order. The plotting probability is assigned and the reduced variate (Y_T) is calculated from the following distribution models as reproduced in Table 8.1

Table 7.1: Distribution Models

Y = A X + B

Model	Equation	Y	X	A	B
Log-Normal	$P = \phi\left(\frac{LnH - \overline{LnH}}{\sigma}\right)$	$\phi^{-1}(P) = Z$	L_n H	$\frac{1}{\sigma}$	$\frac{\overline{LnH}}{\sigma}$
Gumbel	$P = \exp\left(-\exp\left(-\frac{H-\gamma}{\beta}\right)\right)$	$-Ln\left(Ln\left(\frac{1}{P}\right)\right)$	H	$\frac{1}{\beta}$	$-\frac{\gamma}{\beta}$
Weibull	$Q = \exp\left(-\left\{\frac{H-\gamma}{\beta}\right\}^{\alpha}\right)$	$\left(Ln\frac{1}{Q}\right)^{\frac{1}{\alpha}}$	H	$\frac{1}{\beta}$	$-\frac{\gamma}{\beta}$

Where:

σ= Standard deviation P= Probability of Non-exceedance

α, β = Weibull and Gumbel parameter Q= Probability of Exceedance = 1-P

H= wave height

γ = Lower limit of H i.e. threshold value in a peak over threshold data set

Here Gumbel and Lognormal distributions have two parameters (β and γ) only whereas Weibull distribution has one additional parameter i.e. α. Linear regression provides only two constant (A,B) and if we want to continue to use linear regression analysis, the determination of third parameter (α) will require some trial and error. Repeated regression analysis will determine what value of α provides the best straight line relationship.

Often the return period (T) of the event is specified rather than the exceedance probability. If (1-P) denote the exceedance probability in a year, the return period T is defined as

$$T = \frac{1}{1-P} \tag{7.2}$$

Correspondingly, the T-year event X_T is the level, which on the average exceeded once a T-year.

Since only extreme value of wave height and their ranking are usually known, they must somehow be converted into a plotting position, representing probability of exceedence. Goda (1990) has recommended the following plotting probability formula, for the respective distribution model. The probability of exceedence, Q is calculated using the expression:

$$Q = \frac{I - C_1}{N + C_2} \tag{7.3}$$

Where i is the ranking of the data point and N is the total number of points. The simplest estimate of plotting position assumes c_1=0 and c_2=1, but Table 7.2 represents coefficient for a so called unbiased plotting position for each distribution.

Table 7.2: Constants for Unbiased Plotting Position

Distribution	Log-Normal	Gumbel	Weibull
C_1	0.250	0.440	0.2+0.27α
C_2	0.125	0.120	0.2+0.23α

Since α influences both the plotting position and the curvature of Wiebull graph, some trial and error is necessary. The value of α is varied from 0.8 to 1.3 with an increment of 0.05 and the value of α, which gives best fit for the data set is selected.

7.2 Data Analysis for Extreme Waves

The dominant storms which were found significant off Mumbai (54 Nos.) and Pondicherry coast (55Nos) respectively were considered for the analysis of Extreme wave heights. This represents maximum wave heights during storms where a storm was defined as when the wave height exceed the threshold value as 3.0m. The break-up of storms considered is given in Table 7.3.

Table 7.3: Break-up of Storms Considered for Extreme Wave Heights

Sl. No.	Storm	Mumbai	Pondicherry
1	Depressions	02	00
2	Storms	25	6
3	Sever storm	16	13
4	Sever Cyclonic Storms	11	32
5	Super Cyclones	00	04

These data were ranked in decreasing order and the distribution models as tabulated in Table 7.2 were applied on each of the dominant storms considered for extreme wave analysis. The parameters used for extreme value analysis for both the locations are tabulated in Table 7.4 and 7.5.

The probability of exceedences (Qg and Qw) were computed from equation 7.3 and shown in column (3) and (5). The reduced variates G, W and Z were tabulated in column (4) , (6) and (8) respectively as computed according to Table 7.2. In the present data set α=1.3 and α=1.2 produces a best fit line respectively for off Mumbai and off Pondicherry locations.

Table 7.4: Extreme Value Parameters for off Mumbai

Rank	Hs	Qg	G	Qw	W(α=1.3)	Ln(Hs)	Z=φ-1(P)	Rank	Hs	Qg	G	Qw	W(α=1.3)	Ln(Hs)	Z=φ-1(P)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1	14.15	0.01	4.56	0.01	3.20	2.65	2.10	28	6.13	0.48	0.44	0.51	0.74	1.81	-0.14
2	12.35	0.03	3.60	0.03	2.64	2.51	1.73	29	6.06	0.49	0.39	0.53	0.71	1.80	-0.17
3	12.34	0.04	3.10	0.05	2.35	2.51	1.73	30	6.04	0.51	0.34	0.54	0.68	1.80	-0.18
4	12.26	0.06	2.76	0.07	2.16	2.51	1.71	31	6.00	0.53	0.29	0.56	0.65	1.79	-0.20
5	11.50	0.08	2.50	0.08	2.01	2.44	1.54	32	5.98	0.55	0.24	0.58	0.62	1.79	-0.21
6	11.40	0.10	2.29	0.10	1.88	2.43	1.52	33	5.74	0.56	0.19	0.60	0.60	1.75	-0.32
7	10.21	0.11	2.12	0.12	1.78	2.32	1.22	34	5.71	0.58	0.14	0.62	0.57	1.74	-0.33
8	10.06	0.13	1.97	0.14	1.68	2.31	1.19	35	5.58	0.60	0.10	0.64	0.54	1.72	-0.39
9	9.94	0.15	1.83	0.16	1.60	2.30	1.15	36	5.25	0.61	0.05	0.66	0.52	1.66	-0.56
10	9.73	0.17	1.71	0.18	1.53	2.28	1.10	37	5.09	0.63	0.00	0.67	0.49	1.63	-0.64
11	9.49	0.18	1.60	0.19	1.46	2.25	1.03	38	4.92	0.65	-0.05	0.69	0.46	1.59	-0.73
12	8.98	0.20	1.50	0.21	1.40	2.19	0.88	39	4.89	0.67	-0.09	0.71	0.44	1.59	-0.75
13	8.64	0.22	1.41	0.23	1.34	2.16	0.78	40	4.75	0.68	-0.14	0.73	0.41	1.56	-0.83
14	8.60	0.23	1.32	0.25	1.28	2.15	0.76	41	4.74	0.70	-0.19	0.75	0.39	1.56	-0.83
15	8.45	0.25	1.24	0.27	1.23	2.13	0.72	42	4.57	0.72	-0.24	0.77	0.36	1.52	-0.93
16	7.99	0.27	1.16	0.29	1.19	2.08	0.57	43	4.53	0.74	-0.28	0.78	0.34	1.51	-0.95
17	7.90	0.29	1.09	0.31	1.14	2.07	0.54	44	4.43	0.75	-0.33	0.80	0.31	1.49	-1.01
18	7.82	0.30	1.02	0.32	1.10	2.06	0.51	45	4.43	0.77	-0.38	0.82	0.29	1.49	-1.01
19	7.76	0.32	0.95	0.34	1.05	2.05	0.49	46	4.26	0.79	-0.44	0.84	0.26	1.45	-1.12
20	7.19	0.34	0.89	0.36	1.01	1.97	0.28	47	4.21	0.80	-0.49	0.86	0.24	1.44	-1.15
21	7.16	0.36	0.82	0.38	0.98	1.97	0.27	48	4.20	0.82	-0.54	0.88	0.21	1.44	-1.16
22	7.12	0.37	0.76	0.40	0.94	1.96	0.26	49	4.01	0.84	-0.60	0.89	0.18	1.39	-1.28
23	6.89	0.39	0.71	0.42	0.90	1.93	0.17	50	3.93	0.86	-0.66	0.91	0.16	1.37	-1.34
24	6.88	0.41	0.65	0.43	0.87	1.93	0.17	51	3.89	0.87	-0.73	0.93	0.13	1.36	-1.36
25	6.60	0.42	0.59	0.45	0.84	1.89	0.05	52	3.80	0.89	-0.80	0.95	0.10	1.34	-1.42
26	6.43	0.44	0.54	0.47	0.80	1.86	-0.01	53	3.67	0.91	-0.87	0.97	0.07	1.30	-1.52
27	6.31	0.46	0.49	0.49	0.77	1.84	-0.06	54	3.20	0.93	-0.95	0.99	0.04	1.16	-1.88

Table 7.5: Extreme Value Parameters for off Pondicherry

Rank	Hs	Qg	G	Qw	W(α=1.2)	Ln(Hs)	Z=φ-1(P)	Rank	Hs	Qg	G	Qw	W(α=1.2)	Ln(Hs)	Z=φ-1(P)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1	20.11	0.01	4.63	0.01	3.57	3.00	1.84	29	9.27	0.49	0.39	0.49	0.75	2.23	-0.15
2	17.43	0.03	3.60	0.03	2.91	2.86	1.48	30	9.23	0.51	0.34	0.51	0.72	2.22	-0.16
3	17.07	0.04	3.10	0.04	2.58	2.84	1.42	31	9.18	0.53	0.29	0.52	0.69	2.22	-0.17
4	14.73	0.06	2.76	0.06	2.35	2.69	1.04	32	8.85	0.55	0.24	0.54	0.66	2.18	-0.27
5	14.32	0.08	2.50	0.08	2.18	2.66	0.97	33	8.80	0.56	0.19	0.56	0.64	2.17	-0.28
6	14.18	0.10	2.29	0.10	2.03	2.65	0.95	34	8.77	0.58	0.14	0.58	0.61	2.17	-0.29
7	13.05	0.11	2.12	0.11	1.91	2.57	0.73	35	8.68	0.60	0.10	0.59	0.58	2.16	-0.32
8	12.79	0.13	1.97	0.13	1.81	2.55	0.68	36	8.63	0.61	0.05	0.61	0.56	2.16	-0.33
9	12.71	0.15	1.83	0.15	1.72	2.54	0.66	37	8.24	0.63	0.00	0.63	0.53	2.11	-0.45
10	12.67	0.17	1.71	0.16	1.64	2.54	0.66	38	8.16	0.65	-0.05	0.64	0.50	2.10	-0.47
11	12.19	0.18	1.60	0.18	1.56	2.50	0.56	39	8.10	0.67	-0.09	0.66	0.48	2.09	-0.50
12	12.09	0.20	1.50	0.20	1.49	2.49	0.53	40	8.03	0.68	-0.14	0.68	0.45	2.08	-0.52
13	12.05	0.22	1.41	0.22	1.43	2.49	0.53	41	7.97	0.70	-0.19	0.70	0.43	2.08	-0.54
14	11.76	0.23	1.32	0.23	1.37	2.46	0.46	42	7.93	0.72	-0.24	0.71	0.40	2.07	-0.55
15	11.73	0.25	1.24	0.25	1.31	2.46	0.46	43	7.66	0.74	-0.28	0.73	0.38	2.04	-0.64
16	11.67	0.27	1.16	0.27	1.26	2.46	0.45	44	7.44	0.75	-0.33	0.75	0.36	2.01	-0.71
17	11.64	0.29	1.09	0.28	1.21	2.45	0.44	45	7.32	0.77	-0.38	0.76	0.33	1.99	-0.76
18	11.57	0.30	1.02	0.30	1.16	2.45	0.42	46	7.15	0.79	-0.44	0.78	0.31	1.97	-0.82
19	10.89	0.32	0.95	0.32	1.12	2.39	0.27	47	7.12	0.80	-0.49	0.80	0.29	1.96	-0.83
20	10.47	0.34	0.89	0.34	1.07	2.35	0.17	48	6.96	0.82	-0.54	0.82	0.26	1.94	-0.88
21	10.42	0.36	0.82	0.35	1.03	2.34	0.15	49	6.88	0.84	-0.60	0.83	0.24	1.93	-0.92
22	10.39	0.37	0.76	0.37	0.99	2.34	0.15	50	6.53	0.86	-0.66	0.85	0.22	1.88	-1.05
23	10.32	0.39	0.71	0.39	0.96	2.33	0.13	51	6.36	0.87	-0.73	0.87	0.20	1.85	-1.12
24	10.13	0.41	0.65	0.40	0.92	2.32	0.08	52	6.16	0.89	-0.80	0.89	0.17	1.82	-1.20
25	9.97	0.42	0.59	0.42	0.88	2.30	0.04	53	6.09	0.91	-0.87	0.90	0.15	1.81	-1.23
26	9.90	0.44	0.54	0.44	0.85	2.29	0.02	54	5.72	0.93	-0.95	0.92	0.13	1.74	-1.39
27	9.51	0.46	0.49	0.46	0.82	2.25	-0.08	55	5.69	0.94	-1.05	0.94	0.10	1.74	-1.40
28	9.28	0.48	0.44	0.47	0.79	2.23	-0.15	56	3.00	0.96	-1.17	0.95	0.08	1.10	-3.05

Best-fit straight lines were fitted by using least square techniques (linear regression analysis) for all distributions through the points to represent a trend. From this trend line, the statistical parameters of the probability distributions were obtained. The above distribution models were used for predicting wave heights for return periods 25, 50, 100 and 150 years. A typical Gumbel, Weibull and Log-Normal distribution plot for the reported locations off Mumbai and off Pondicherry are represented in Fig. 7.1 to Fig. 7.3 and Fig.7.4 to Fig. 7.6 respectively. It is seen from the figures that the individual points do not lie exactly on a straight line. The equation of the best- fit-line and the correlation coefficients for all distributions are also shown in the same plot.

The biased points at the upper level shown in figures (Fig. 7.1 to 7.6) indicate the wave height generation from the super cyclonic storms. These have been considered as storms in the present analysis. It is also observed from the analysis that in spite of the maximum values changed in the data set, there is no remarkable change in the extreme values. This may be due to the fact that cyclone does not occur frequently and hence these highest values not much effect in extreme wave heights.

In the present analysis to reduce the geostrophic wind speed to surface wind, a procedure used was based on empirical relations which may not be sufficiently accurate for the reported locations. Since the procedure for obtaining surface wind speed adopted for all the models is same, the average error in the wave heights will be nearly same.

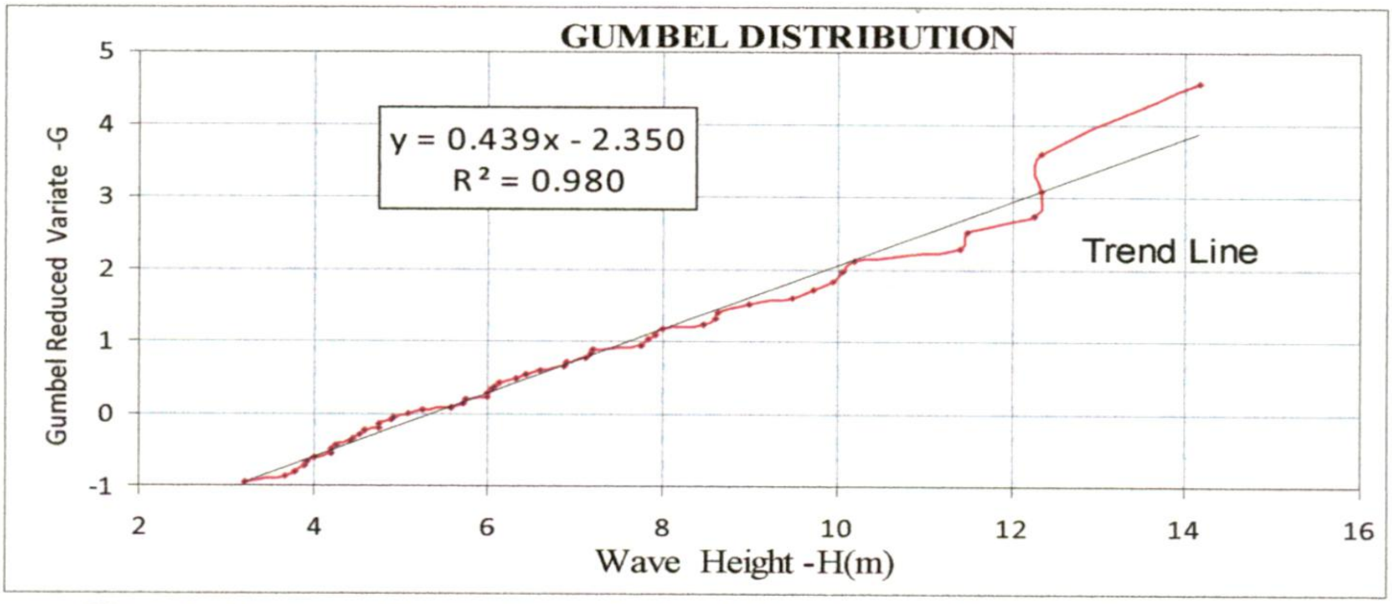


Fig.7.1: Hindcast Storm Wave Data off Mumbai on Gumbel Distribution

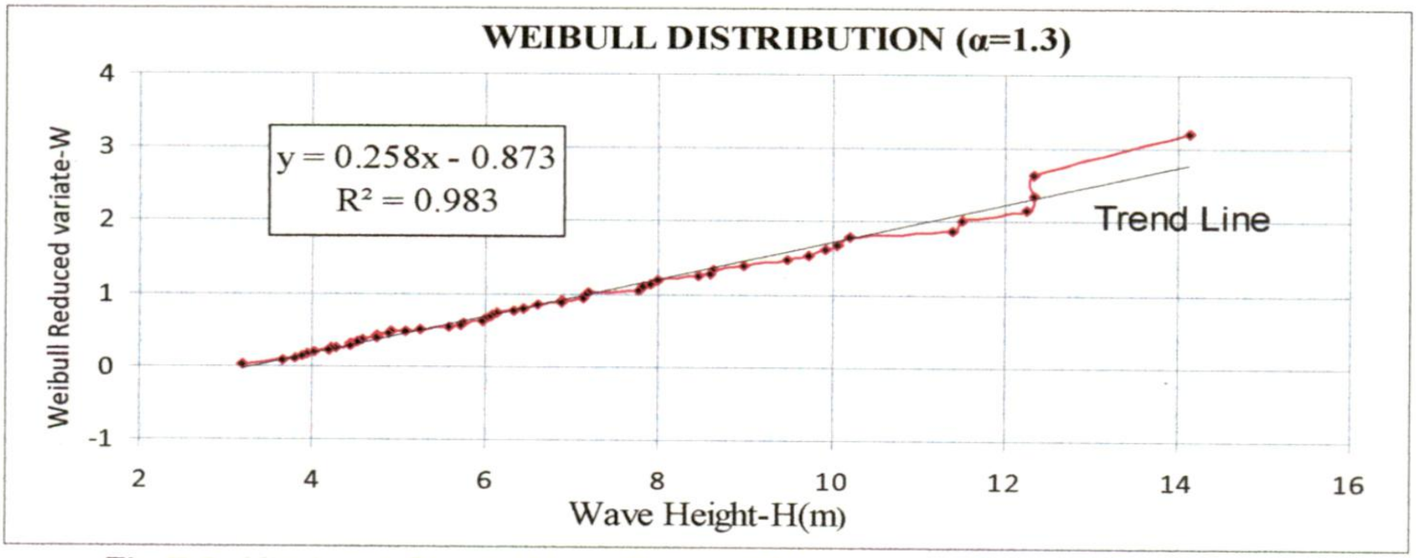


Fig.7.2: Hindcast Storm Wave Data off Mumbai on Weibull Distribution

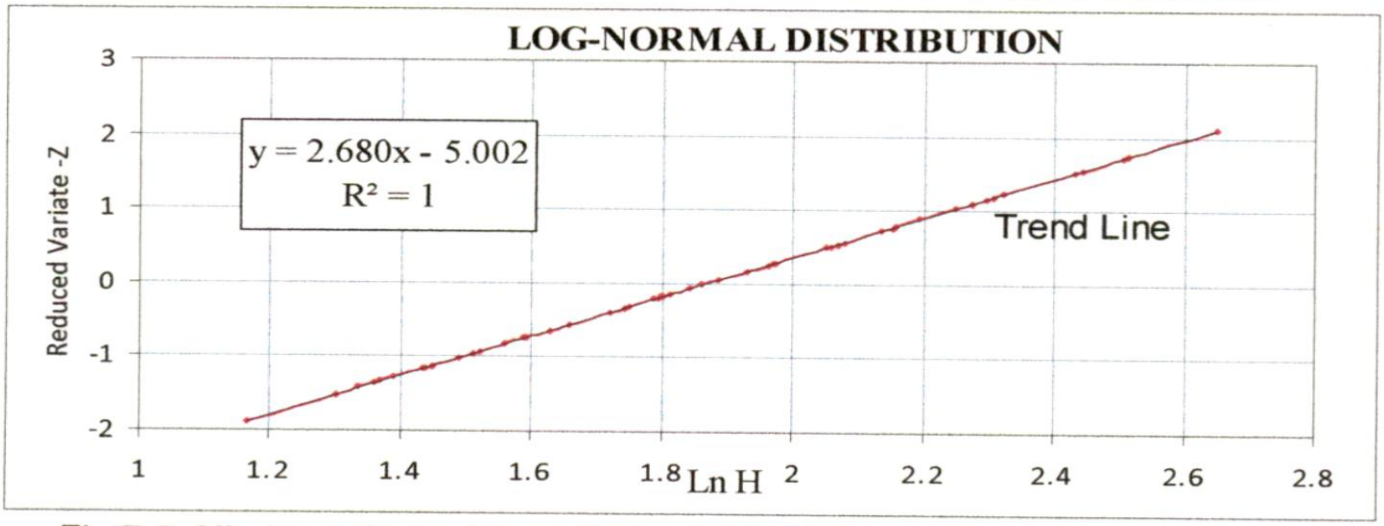


Fig.7.3: Hindcast Storm Wave Data off Mumbai on Log-normal Distribution

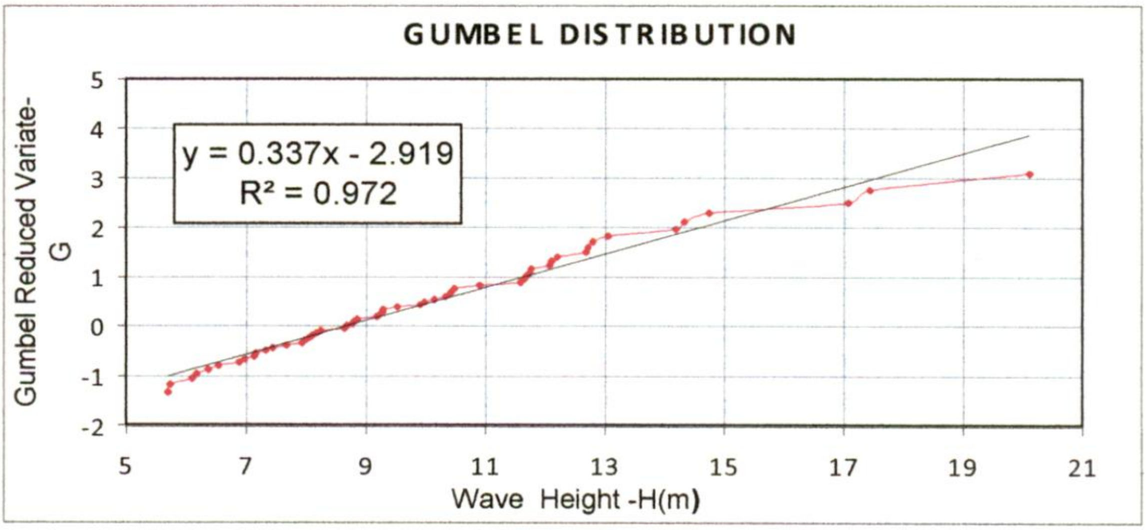


Fig.7.4: Hindcast Storm Wave Data off Pondicherry on Gumbel Distribution

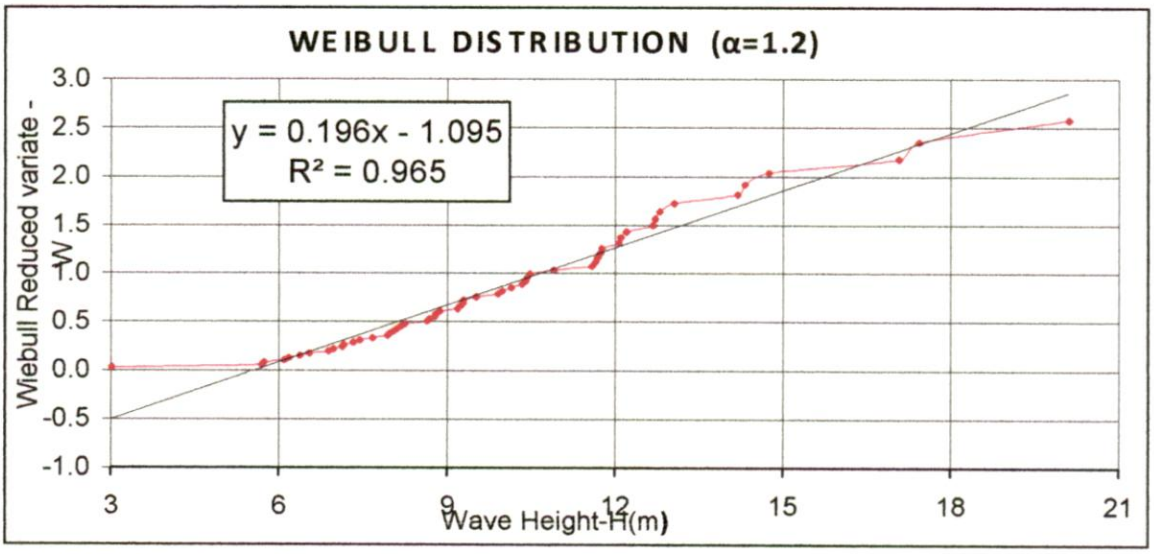


Fig.7.5: Hindcast Storm Wave Data off Pondicherry on Weibull Distribution

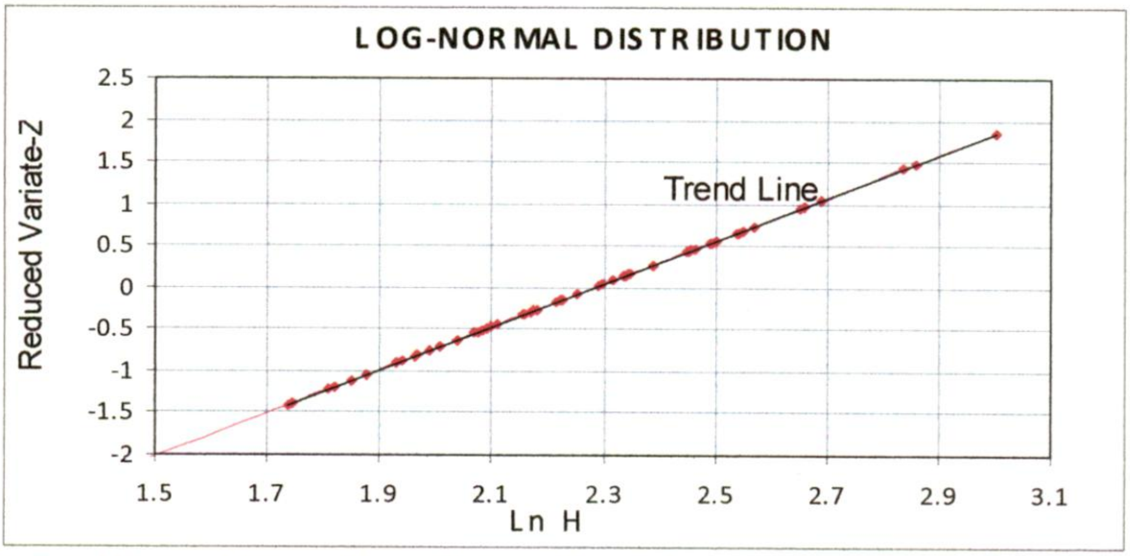


Fig.7.6: Hindcast Storm Wave Data off Pondicherry on Log-normal Distribution

It is found from this analysis that the coefficient of regression for the best line fit for both the location is closer to 1.0 and the results of the extreme wave heights corresponding to various return periods obtained from above three distribution are presented in the Table 7.6. It is seen that the wave height predicted using Gumbel, Weibull and Log-Normal distribution are in good agreement with each other.

Table 7.6: Predicted Significant Wave Height for Various Return Periods.

Sl. No.	Return period (in Years)	Significant Wave Heights (m) Off Mumbai			Significant Wave Heights (m) Off Pondicherry		
		Gumbel	Weibull	Log-Normal	Gumbel	Weibull	Log-Normal
1.	25	12.6	12.9	12.4	18.2	19.1	19.4
2.	50	14.2	14.4	13.9	20.2	21.5	21.8
3.	75	15.2	15.3	14.6	21.5	22.8	23
4.	100	15.8	15.8	15.4	22.3	23.8	24.3
5.	150	16.6	15.9	16.1	23.5	25.1	25.5

The uncertainties of the estimated return values were calculated by using asymptotic variance of the extreme value parameters. This approach produces confidence intervals. The confidence interval indicates the limits about the calculated value between which the true value can be said to lie with a specific probability based on sampling error only. In particular it does not account the variability of the parameters used in the distributions. The extreme values with respect to return periods as shown in Table 8.4 have been checked with 95% confidence bounds and found that all the values lie within the confidence band. A sample figure indicating to 95% confidence band is as presented in Fig. 7.7.

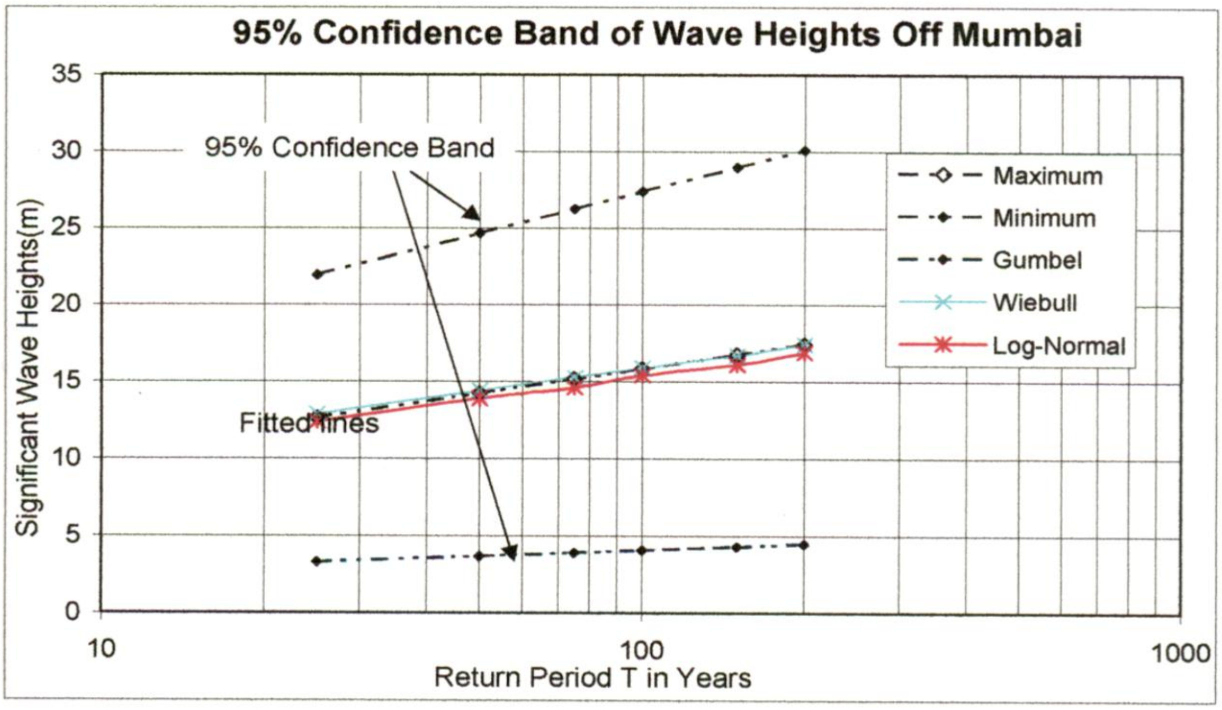


Fig. 7.7: 95% Confidence Band of Wave heights for off Mumbai

7.3 Conclusion

Gumbel, Weibull and Log-Normal distribution were used for the extreme wave height for the significant storms. These three distributions fit the extreme wave data well and since no theoretical justification is available as to which distribution is to be used (Burcharth and Liu, 1994). The average of these three values for each return period has been taken as a design wave height predicted for both the locations, and is presented in Table 7.7

Table 7.7: Predicted Extreme Wave Height (m) for Various Return Periods

Return period (in Years)	Off Mumbai	Off Pondicherry
25	12.6	18.9
50	14.2	21.2
75	15	22.4
100	15.7	23.5
150	16.2	24.7

CONCLUSIONS AND SCOPE FOR FUTURE STUDIES

Based on present studies the following conclusions are drawn

1. In this study, the importance of hindcasted wave data for the extreme wave analysis of ocean wave has been shown. The performances of the SMB, Wilson and CEM models for prediction of wave heights were investigated. Results shows that CEM and Wilson model gives more comparable and permissible results while SMB model overestimate the wave values in Indian Ocean region. The reason for this may be the fact that SBM has taken wind speed at U_{10} at 10m elevations at neutral stability conditions which is an arbitrary and bears no relation to any length scale in the physical system

2. Results of wave height using ANN have been compared with the average results of CEM and Wilson model using the same data sets. Results show a good agreement between both the model predictions. The very high correlation coefficient of about 0.99 obtained in both the cases confirms that Neural Network can be effectively used for the storm generated wave prediction.

3. Extreme wave height values computed for different return periods are shown in the above table (8.7). Distribution of extreme wave heights in the Indian Ocean shows differences in occurrences of extreme wave height in East and West coastal basins. In West coast, wave height is low whereas in East coast near off Pondicherry, the wave height variation is higher. The reason for this is the fact that the cyclonic occurrence over Bay of Bengal is much more severe than those over Arabian Sea.

4. It is also observed from the analysis that in spite of the maximum values changed in the data set, there is no remarkable change in the extreme values. This may be due to the fact that cyclone does not occur frequently and hence these highest values not much effect in extreme wave heights.

In the present analysis to reduce the geostrophic wind speed to surface wind, a procedure used was based on empirical relations which may not be sufficiently accurate for the reported locations. Though the procedure for obtaining surface wind speed adopted for all the models is same, the average error in the wave heights will be nearly same but there is a need to improve the wind field computations.

The methodology adopted in this study for storm wave hindcasting seems to be realistic for practicing of coastal engineers; however, it fails to reproduce the exact directivity of the wind waves in cyclonic situations because the gradient wind has not been taken into account. Long-term prediction of design events is often statistical and is based on using the probability of non-exceedence or exceedence; return period and the associated encounter probability to assess risks. Thus, a clear understanding of this subject is required in order to make correct decisions to optimize the design wave height and to avoid natural hazard associated with the failures of important projects; especially, in the dynamic environment of the ocean.

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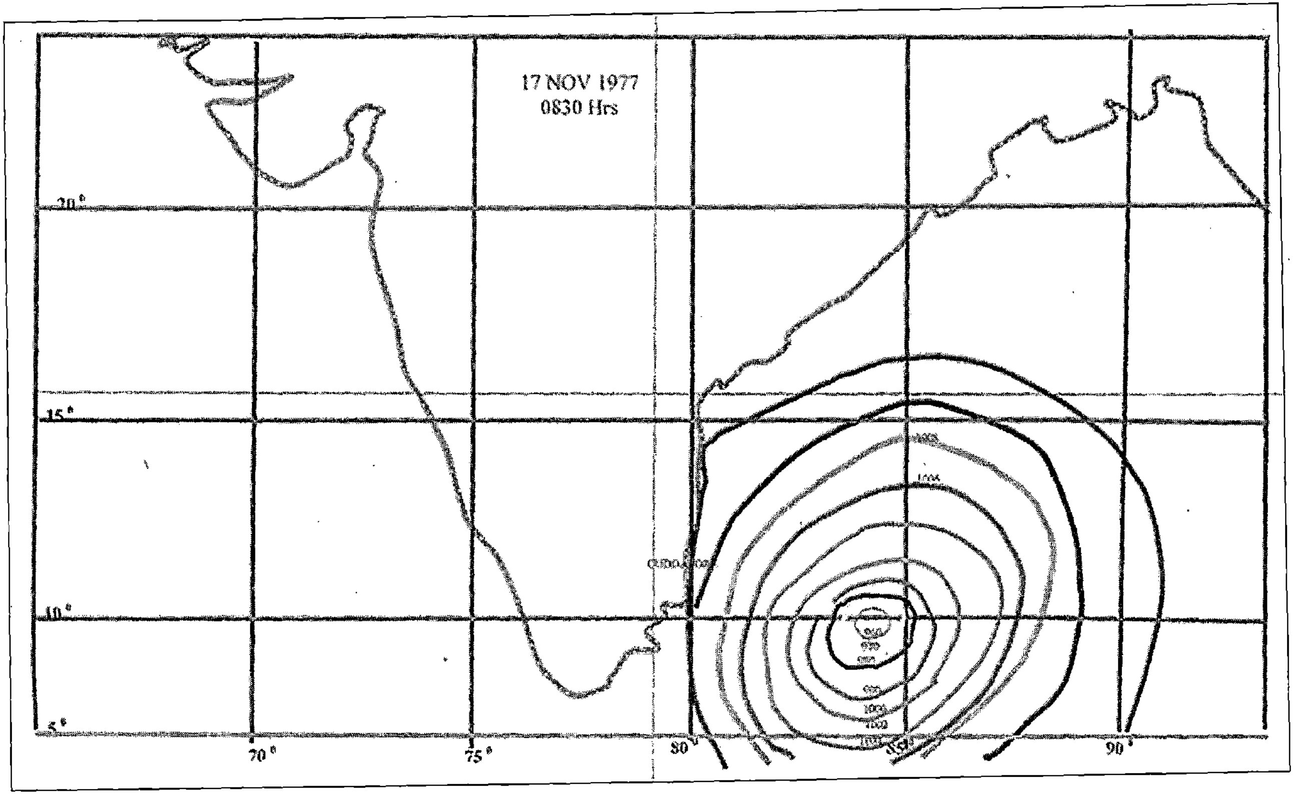

Fig. : Typical Synoptic Charts of Storm on 17th Nov. 1977 (0830Hrs.) near off Pondicherry

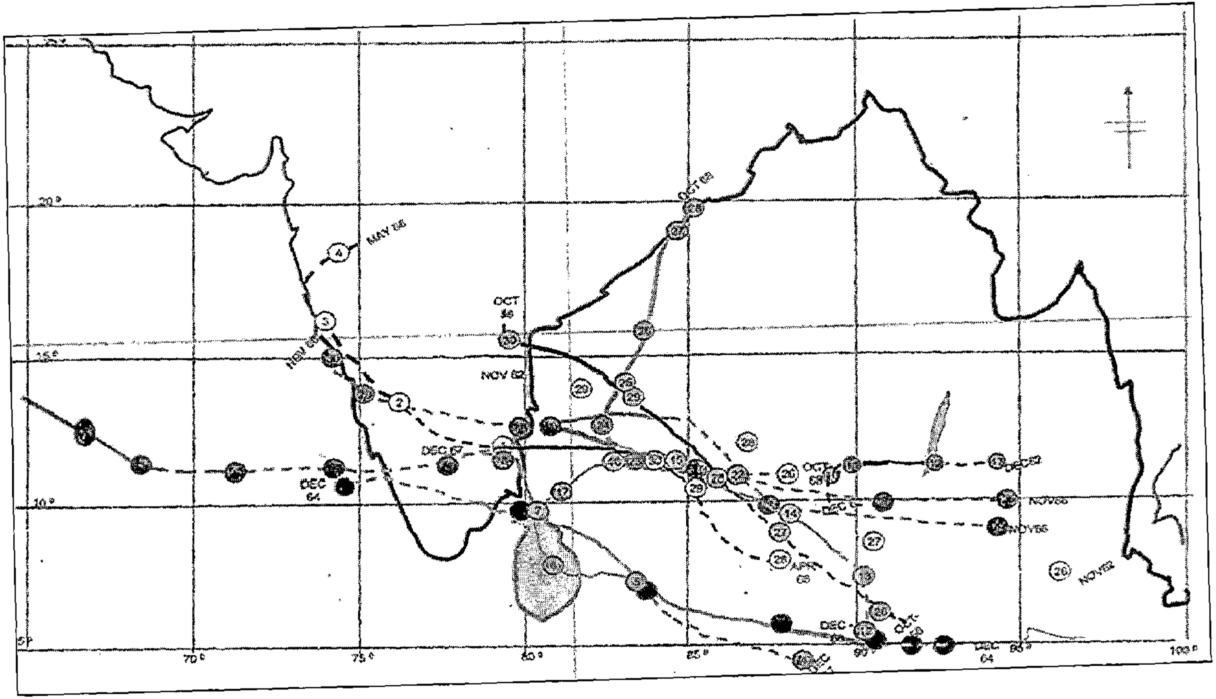

Fig. Typical Storm Tracks near Pondicherry

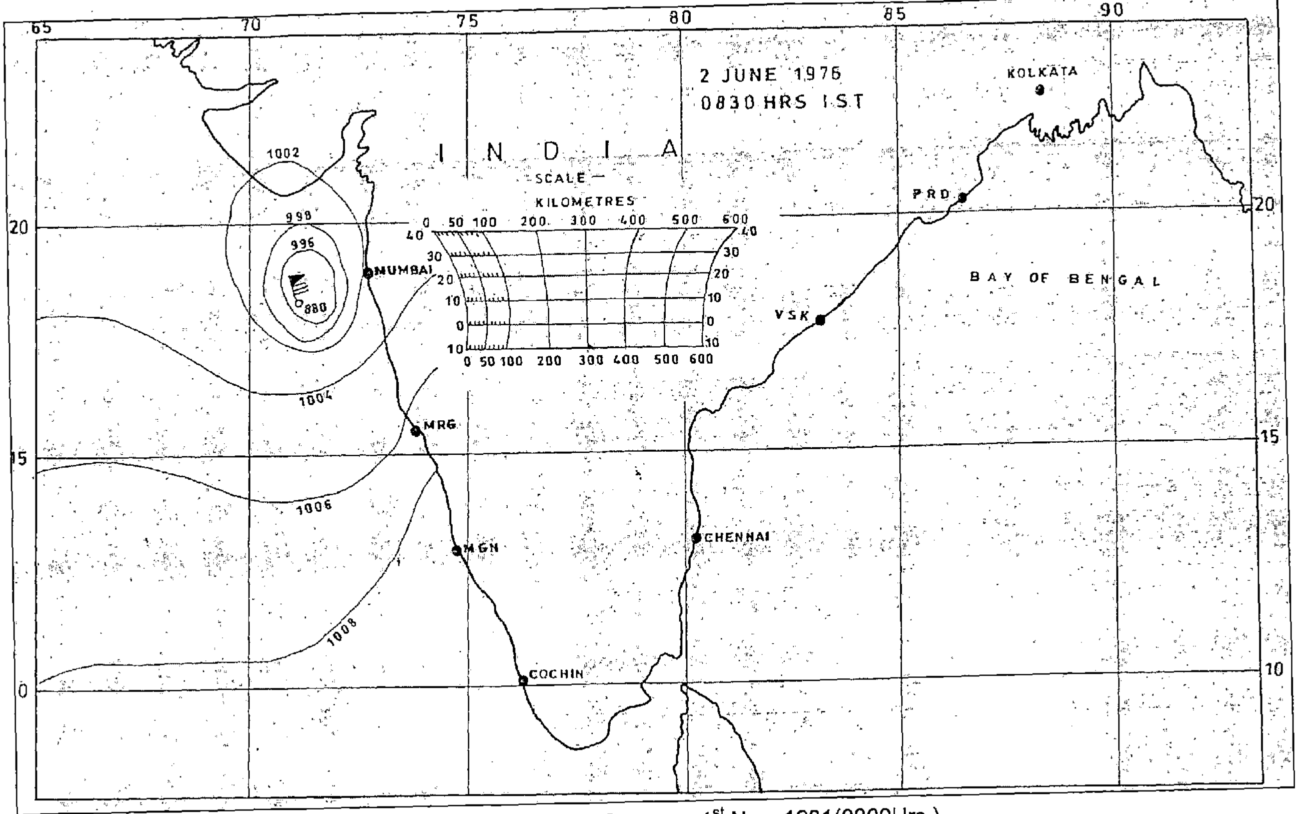

Fig. Typical Synoptic Chart of Storm on 1st Nov. 1981(0800Hrs.)

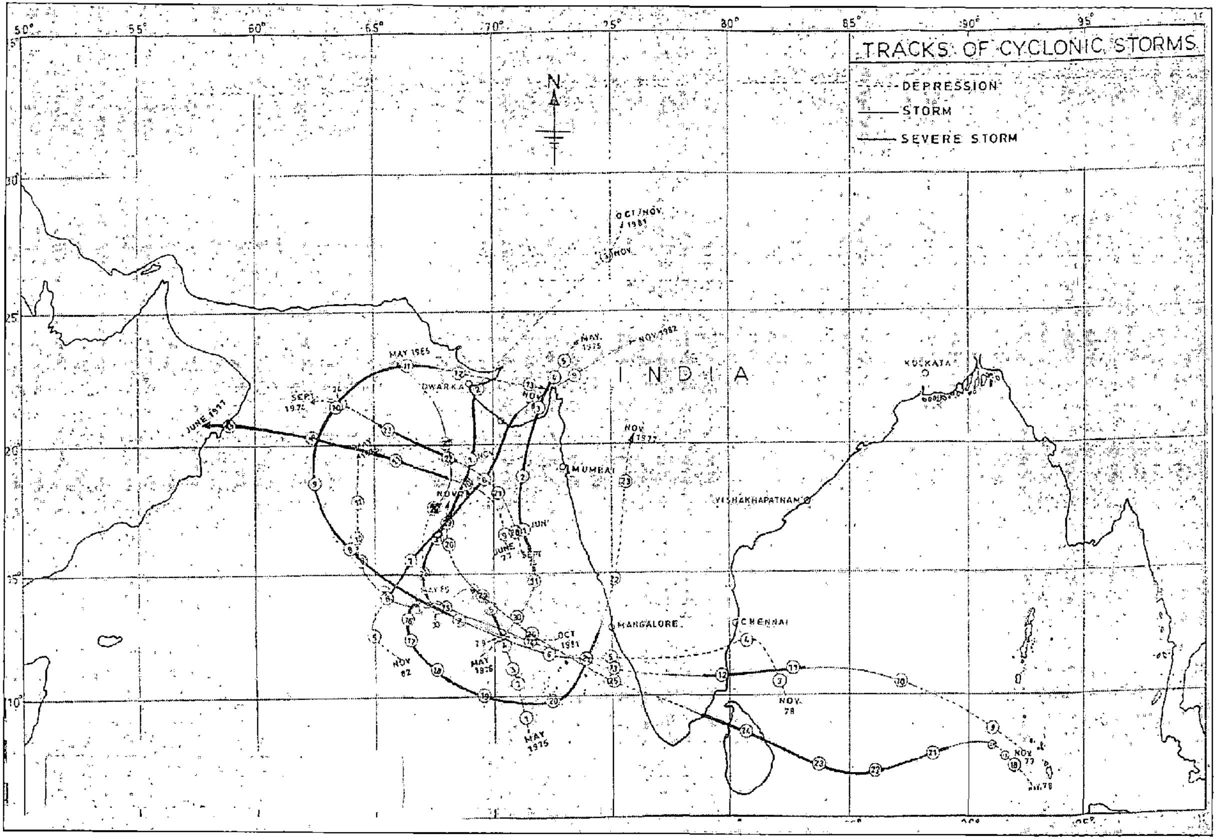

Fig. Typical Storm Track near off Mumbai During 1971-1990