APPLICATION OF ARTIFICIAL NEURAL NETWORK TO PREDICT THE WAVE CHARACTERISTICS

A THESIS SUBMITTED TO THE GRADUATE SCHOOL OF APPLIED SCIENCES OF NEAR EAST UNIVERSITY

By
YAZID SALEM

In Partial Fulfillment of the Requirements for The Degree of Master of Science in Civil Engineering

NICOSIA, 2017

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Yazid Al Hodairy: **APPLICATION OF ARTIFICIAL NEURAL NETWORK TO PREDICT THE WAVE CHARACTERISTICS TO IMPROVE THE SEA WAVES AND CURRENTS FORCES APPLIED ON THE JACKET PLATFORM LEGS**

Approval of Director of Graduate School of Applied Sciences

Prof. Dr. Nadire ÇAVUŞ
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We certify that, this thesis is satisfactory for the award of the degree of Master of Science in Civil Engineering

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I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

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Date:

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All praise is for Allah, the exalted. With high gratitude to Him who gave me the ideas and physical strength in preparing this thesis. Completion of thesis of this nature requires more than just the efforts of the author.

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ABSTRACT

In this study the wave characteristics (height and period of wave) were simulated by applying the Bretschneider spectrum and equations presented by Sverdrup-Munk-Bretschneider (SMB) by using the recorded data such as wind velocity and duration, differences between water and air temperature and the fetch length. It is essential for all offshore structures analysis to estimate the forces generated by the wave and current by developing a program for modeling wave and current forces on offshore structural members. Airy wave theory (linear theory) has been implemented in the present study, based on its attractiveness for engineering use. The Morison equation was used for converting the velocity and acceleration terms into resultant forces. For calibration and for comparison purposes, a developed program was checked against a well-known professional software package called Structural Analysis Computer System (SACS).

Furthermore, a wide range still exists to improve the presented models as well as provides alternative to deterministic models. Therefore, this study investigates the possibility of utilizing the relatively current technique of artificial neural networks (ANN) for this purpose. Besides, the comparison of ANN models with the two characteristic prediction methods based on equations of SMB and Bretschneider equations showed a better performance for ANN models rather than SMB and Bretschneider equations. Different ANN architectures were used to by using sets of data with different parameters used in training process. The results confirm that a suitably trained network might supply acceptable outcomes in open wider areas, as well as when the sampling and predicting interval is enormous in order of magnitude of a week.

Keywords: Bretschneider spectrum and equations, neural networks, offshore structures analysis, airy's linear theory, structural analysis computer system

ÖZET

Deniz suyundaki dalgaların üretimi ve gelişimi çoğunlukla deniz yüzeyinde üfleme rüzgarları tarafından kontrol edilir. Bu çalışmada, dalga özellikleri (Yüksekliği ve süresi) Bretschneider spektrumunun ve Sverdrup-Munk-Bretschneider (SMB)'in kayededilen verilerle (rüzgar hızı, rüzgar süresi ve su / hava sıcaklığı farkları) kullanarak Simüle edildi. Dalga karakteristiğini tahmin etmek için sunulan çeşitli belirleyici modellere Karşın rüzgârın özelliklerinden, mevcut modelleri iyileştirmek veya onlara alternatif sunmak için geniş bir kapsam mevcuttur. Halbuki, bu araştırma maksadi, yeni yapay sinir ağları tekniğini (YSA) kullanilabilecek yontemleri kesfediyor. Etkili parametreleri belirlemek için, Çeşitli giriş parametrelerinin kombinasyonları ile farklı modeller düşünüldü. Rüzgar hızı,süresi ve getirme uzunluğu gibi paramentreler kullanimaktadir. Dahası, YSA modellerinin SMB ve Bretschneider denklemlerine dayanan iki karakteristik tahmin yöntemi ile karşılaştırılması YSA modelleri için daha iyi bir performans gösterdi.şebeke farklı YSA yapi ile eğitilmektedir. Sonuçlar, düzgün eğitilmiş bir ağın açık geniş alanlarda, derin sularda ve öngörme aralığı bir hafta büyüklüğüne göre büyük durumda tatmin edici sonuçlar verebileceğini gösterir.Basit bir 3 katmanlı ileri besleme tipi, deterministik modellerin aksine .

Tüm açık deniz yapıların analizi için, açık deniz yapısal üyelerde dalga ve akım kuvvetlerinin modellenmesi için bir program geliştirerek dalga ve akım tarafından üretilen kuvvetleri tahmin etmek esastır.Bu çalışmada, lineer teori, mühendislik kullanımındaki cazibesine dayanarak uygulandı. Morrison denklemi hız ve ivme terimlerini sonuç kuvvetlerine dönüştürmek için kullanılmıştır. Kalibrasyon ve karşılaştırma , Yapısal Analiz Bilgisayar Sistemi adlı iyi bilinen bir profesyonel yazılım program karşın kontrol edildi

Anahtar Kelimeler: Bretschneider spektrumu ve denklemleri, Nöral ağlar, Açık deniz yapıları analizi, Airy’s lineer teori, Yapısal Analiz bilgisayar sistemi.

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LIST OF ABBREVIATIONS

ANN:	Artificial Neural Network
API-RP2A:	Recommended Practice for Planning, Designing, and Constructing Fixed Offshore Platforms
BPNN:	The backpropagation Neural Network
FPSO:	Floating Production, Storage and Offloading
JONSWAP:	Joint North Sea Wave Project
KEPCO:	Iranian Company for Exploration of Oil in Caspian Sea
MSL:	Mean Sea Level
RMSE:	Root Mean Square Error
RT:	Stability Factor
SACS:	Structural Analysis Computer System
SESAM:	Software for structural and hydrodynamic analysis of ships and offshore structures from GeniE
USFOS:	Computer program for nonlinear static and dynamic analysis of space frame structures
WMO:	World Meteorological Organization

CHAPTER 1

INTRODUCTION

1.1 Background of Study

The protection of coastal environments is very important especially with more than 9,600 offshore fields worldwide. Offshore structures, such as platforms and wind Turbines are commonly adopted for such protection (Sadeghi, 2007). In recent years, the protection of offshore structures has been extensively studied; an understanding of their interaction with wind-wave relationship is far from complete.

The major factor in coastal engineering design and analysis is a wave action on which must be taken into account. Much is known about wave mechanics when the wave height and period (or length) is known. Knowledge about waves and the forces they generate is important for the design of coastal projects since predication of wave conditions are needed in almost all coastal engineering studies (Holmes, 2001). Actual waves found in nature are mostly random; but for the sake of analytical simplicity they are many times assumed to be regular. With physical processes the wave parameters can be predicted in complex circulation patterns based on wind recoded data (Bouws et al., 1998).

In last decades, the wind-wave models by numerical equations uses have became essential for a prediction of wave characteristics. Generally, modeling is based on empirical, simplified or parametric and numerical or elaborate methods as deterministic equations. However, the numerical methods are far more accurate than the parametric and give information over a number of locations simultaneously (Tolman, 1992).

Actually the damage that could happen to offshore structures occasionally arises; there are two general modes of failure modes being evident. Firstly, the wave forces that acting on structure members of jacket platform that caused incur substantial damage or even collapse in it. Secondly, the liquefaction or the erosion or the erosion in the surrounding area of the structure, subsequently, may led to the collapse of the structure as a whole (Cha et. al., 2011).

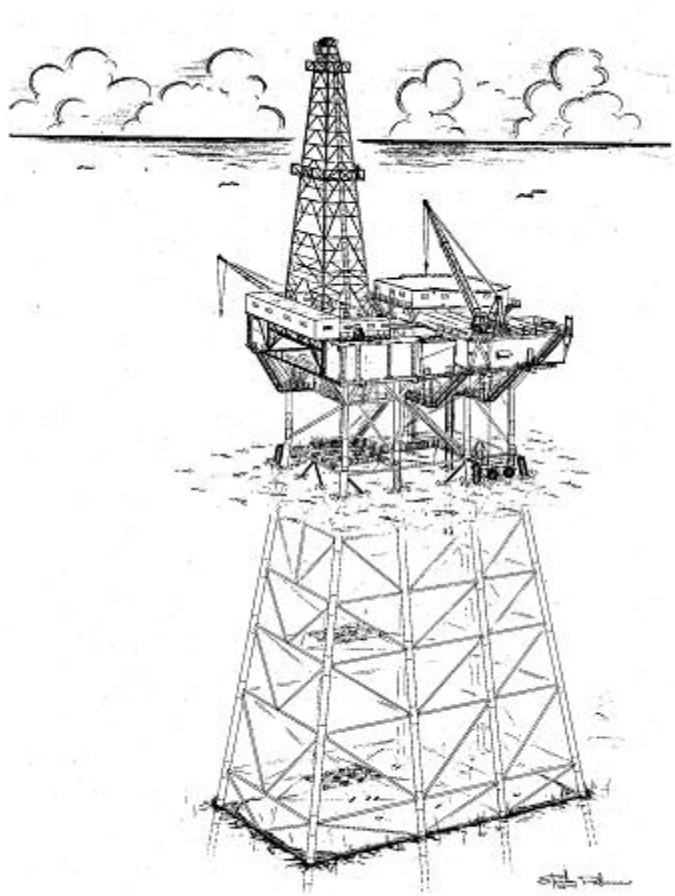


Figure 1.1: Configuration of a jacket platform (Sadeghi, 2007)

Consequently, the protection of offshore structures increased significantly due to growing attention of marine geotechnical and coastal engineering operations. The major concern for civil and coastal engineers in this field is that, attempting to deal with more accurate predictions of wave characteristics (height and period of wave) rather than unique wave height and period values of the above simplified schemes (Bouws et al., 1998).

1.2 Artificial Neural Network

Much research attention has been centered on solving one problem: "How does the human brain work?" Artificial Neural Networks have been used to try to solve this problem. (Hagan et al., 1995) report that, the preliminary research in neural networks field is back to 1943, by (McCulloch and Pitts, 1943) when they assumed a simple mathematical process

to give details about the way neurons are working biologically. This was apparently one of the first significant study on artificial neural networks (ANN) (Hagan et al., 1995).

The technique of (ANNs) is an alternative possible methodology. Many investigations and works for more than five decades found that the biological neural system was must suitable way to apply ANNs in real world. ANN is helpful in many cases where the essential process of physical for prediction are still not completely understood and compatible in dynamical systems modeling that based on period of time. However, until 1980's the ANNs it has not been applied on a large scale to the problems of the real world. Therefore, common application were not training by algorithms because of the lack of their sophisticated (Cha et al., 2006).

According to (Huang et al., 2009), ANNs are one of the latest data-processing technologies available in the engineer's toolbox. They serve as an important function in engineering applications. In particular for predicting the evolution of dynamical systems, modeling the memory and performing pattern recognition.

In contrast to conventional approaches derived from engineering mechanisms, the only requirement for obtaining accurate predictions with ANN models is a reliable dataset to achieve suitable training database with accurate predictions for a variety of engineering problems (Cha et al., 2011).

1.3 Wave Forces on Offshore Structures

Brief discussion on the theoretical aspect and simulation of the wave forces on offshore structural members has been presented. A computer program written in the FORTRAN language working under the Microsoft Power Station environment validated with a standard commercial package called Structural Analysis Computer System (SACS, version 5.7) (Noorzaei et al., 2005).

1.4 Contributions of the Research

The evaluation of wave characteristics (wave height & wave period) is important for civil and coastal engineers that involved in the design of coastal structures. In recent years, great efforts have been made for in predicting the wave characteristics by physical modeling and using traditional engineering methods including complicated deterministic equations. In this research, Artificial Neural Network (ANN) technology has been adopted to assist in the prediction of wave characteristics (Galavi et al., 2012; Sadeghi, 2007).

The objective of this study is to establish an alternative approach for the prediction of wave characteristics (wave height & wave period) which is Artificial Neural Network (ANN). The database was generated using numerical models (Deo et al., 2001; Sadeghi, 2007).

The specific goals of this study are to:

- Exam the accuracy of various structured ANNs for the prediction of wave characteristics predicted by numerical methods.
- Recommend the most effective and acceptable ANN model for the coastal engineering practice
- To couple the written program to an existing 3-D finite element program (SACS).

1.5 Thesis Structure

Chapters are organized as:

- **Chapter 2** deals with the review of published literature (thesis, journal and articles).
- **Chapter 3** a discussion of the methodology of the research area, test samples, test procedures and statistical analysis were conducted in this chapter.
- **Chapter 4** a comparison of the developed models with other existing models was also performed under this chapter.
- **Chapter 5** the conclusion and recommendation of the study are given in Chapter five.

CHAPTER 2

LITERATURE REVIEW

2.1 Background

The wave's generation in deep water is naturally caused by blow of wind over the sea level. Once the ocean surface hit by winds for an adequately limited duration and fetch, the growing of waves parameters are containing until they reach their maximum values in a particular conditions. From this point the wave period will stay constant even as they propagate into shallow water. "Theories and mechanics of waves together with classifications of wave, governing different wave theories and their equations, for instance, Airy theory, Stockes^{2nd}, Stockes^{5th}, Cnoidal, Solitary and Stream Function" (Deo, 2013; Sadeghi, 2008).

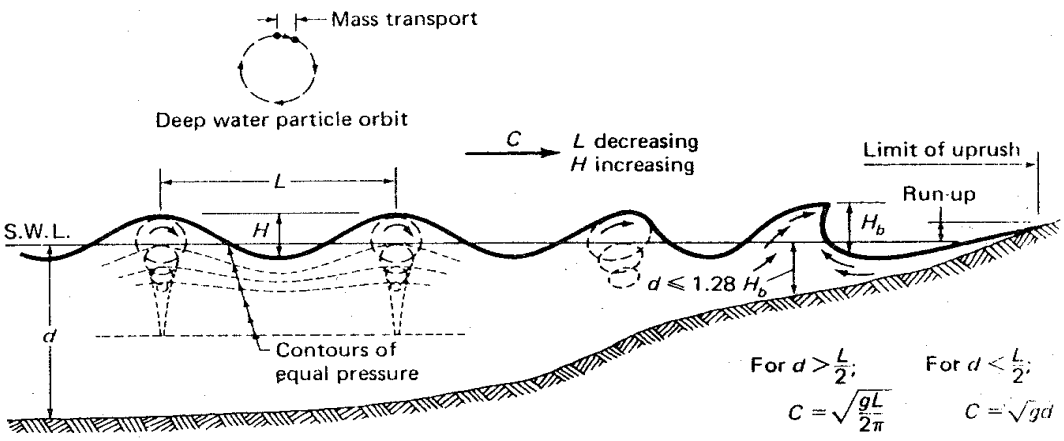


Figure 2.1: Wave progress to shoreline (Sadeghi, 2008)

Likewise, the most advanced prediction need techniques which currently are not available in any laboratories because needs to highly advanced equipment, as well as the complexity of those models. The knowledge of magnitude and behavior of ocean waves as well as the understanding of heights and periods of oscillatory short waves on the site which is a necessary for any activities in the offshore projects included design and planning, construction and operation related to harbor, coastal and structures (Shahidi, 2009; API, 2007) .

Due to the assumptions that regarding the wave prediction based on traditional engineering mechanics, therefore, the application of the existing models limited by it. As a result, Artificial Neural Networks (ANNs) have been applied to various fields, such as business, science, and the engineering sphere (El-Reedy, 2012). It is a fresh approach to apply ANNs to the problem of wave predicting in marine environments. Thus, in this section, previous research for the wave height and period production is reviewed first, and then followed by the wave forces on subsea structural member (Bouws et al., 1998).

2.2 Wave Characteristics Prediction

The relationship between wind and wave has been investigated over more than five decades in the past by establishing empirical and numerical equations that solving the equations of wave prediction (Sadeghi, 2007).

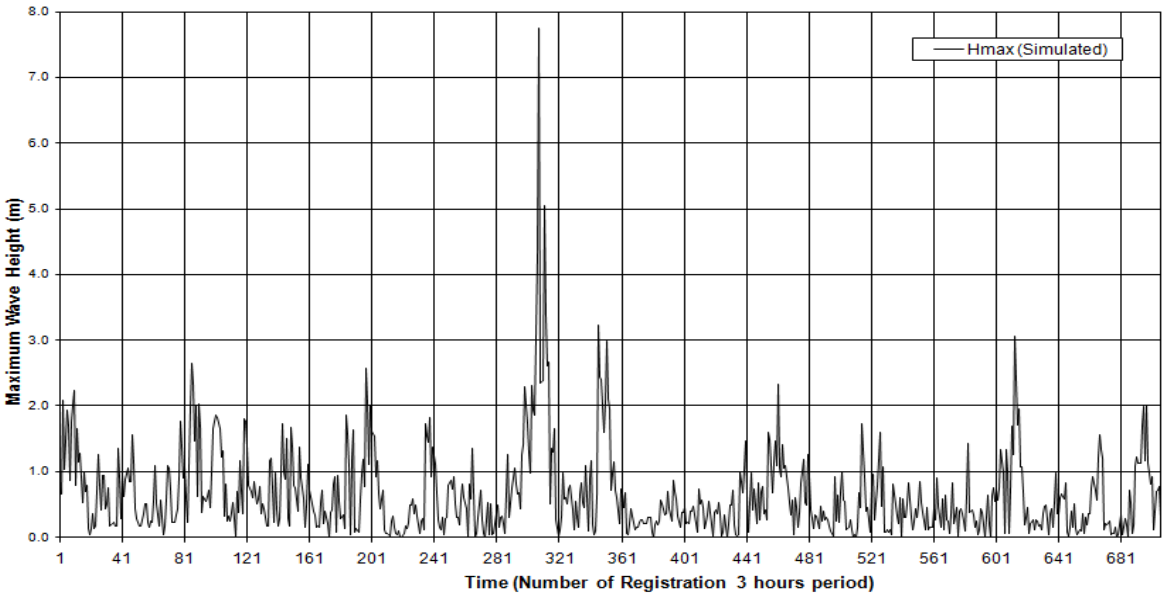


Figure 2.2: Wave height predicting reproduced from (Sadeghi, 2007)

However, the wave generation phenomenon complexity still exists despite of significant advances in techniques of computational, the solutions that found are not exactly uniformly can be applicable at all sites and times. Figure 2.2 reproduced from (Sadeghi, 2007), it shows comparison between recorded heights of wave with the predicted values that applied by using Bretschneider spectrum and equations (Manual, S. P., 1984).

2.3 Empirical Methods

The most two widely used empirical models are the Bretschneider and SMB (Sverdrup-Munk and Bretschneider) models. Several other models exist, including those of Darbyshire and Draper (1963), Kruseman (1976), Toba (1978), Mitsuyasu et al. (1980) and Donclan (1980). The Sverdrup-Munk and Bretschneider (SMB) equations are based on dimensional analysis considerations. Empirical wave models can be applied to enclosed water bodies where swell is insignificant. The main assumption of these models is that the wind field over the wave generating area at any one time can be represented by a single value of velocity (Deo, 2007).

Sverdrup and Munk (1947) devised an empirical method to predict a so-called "significant wave height to describe the locally generated sea state. Since the birth of coastal engineering at that time, wave prediction models have evolved to the extent that computer models can now predict ocean wave spectra on a global scale (Bishop and Donelan, 1989).

Dimensional analysis by Kitaigorodskii (1962) showed that all wave variables, when non-dimensionalized in terries of the acceleration due to gravity “g” and wind speed, should be functions of the dimensionless fetch $gF/U2$ (Applications in Coastal Modeling edited by (Bishop and Donelan, 1989).

2.4 Numerical Wave Modeling

Ocean wave characteristics are mainly determined through field measurements, numerical simulation, physical models and analytical solutions. Each method has its own advantages and disadvantages. Numerical models were emerging as the most powerful method for the study of wave’s characteristics and sea water surface. It is expressed in the concepts of physical phenomena of wave numerical model, which depends on how the expression of the best phenomena in numerical schemes, in this case, the parameters can be estimated more accurately wave data (Thomas and Dwarakish, 2015).

The wave models was based on numerical models developed on the energy balance equation with the different components function as an input sources (Deo, 2007).

The energy balance equation is given as:

$$\frac{ds(f, x, t, \theta)}{dT} = S = In + nl + Dis \tag{2.1}$$

where,

f : Represents the frequency

θ : Represents the propagation direction

t : Represents the time

x : Represents the geographic coordinates

S : Represents the source function

Where, they are dependent on each of the wave spectrum and the external factors of making wave such as local wind and current.

Sørensen et al. (2004) developed a model and simulated for the North Sea, parts of Norwegian Sea and the Baltic Sea. The results are validated from wave rider buoy and found that the model is better in prediction than which does not use fine mesh. But due to the fine mesh the computing time required was higher at that time.

Numerical wave models can be incorporated with sediment dynamics problems to understand the problem more in detail. A spectral wave model helps to assess the sediment dynamics. Using (WAVEWATCH III) parameters like Significant Wave Height (Hs), Peak Period (Tp), Mean Wave Direction (MWD), Wind Velocity ($U10$) and Mean Wind Direction was extracted. This helped the authors to understand the wave energy in different coastal sectors. But the model (WAVEWATCH III) is mainly suitable for deep water regions and use of that model in coastal problems affected the accuracy of the study (Sørensen et al., 2004).

At 2003, an investigation began in the English Channel, a campaign of measurement and evaluation where four of the widely numerical analysis of wave models were used. At that time, they summed up with taking into consideration that the specific agreement between

simulated and recorded wave parameters improved by currents, however the (RMSE) of the results of model were in actuality bigger than with the currents. That study was remarkable to solve some numerical models problems that were used. In particular, the artificial cause of swell on the wind sea growth was found to be a problem, It is a common feature of the development of standards derived from (Komen et al., 1984).

2.5 Artificial Neural Networks

ANN was originally introduced as simplified models of brain-function. The human brain consists of billions of interconnected neurons. These are cells which have specialized members that allow the transmission of singles to neighboring neurons (Cha et al., 2011).

The neural networks theoretical concepts can be found in many studies as well as books include, (Kosko, 1992). Network applications in civil engineering prediction such as (French et al., 1992), (Kasperkiewicz et al., 1995), (Grubert, 1995), (Thirumalaiah and Deo, 1998)and (Deo and Kumar, 2000), with many application that connected to prediction of rainfall, concrete strength and waves in onshore and offshore parts.

Additionally, it has been applied ANN models in different engineering problems, for instance, the generation of wave equations that based on hydraulic data (Dibike et al., 1999), parameters of water quality prediction (Maier and Dandy, 1997), tidal prediction (Lee et al., 2002), prediction of shallow foundation settlement (Mohamed et al., 2002), dynamic amplification of the soil analysis prediction (Hurtado et al., 2001) and the prediction of concrete strength concrete (Rajasekaran et al., 2003). In this study, we will further apply ANNs to the prediction of the wave characteristics in the deep water conditions.

2.5.1 Artificial neural networks applications in engineering

The last five decades have witnessed several applications of ANN in engineering prediction. These include heights and periods predicting (Deo et al., 2001), wave reflection (Zanuttigh and Meer, 2008), and water level prediction (Patrick et al., 2003). Some previous work related to Artificial Neural Networks application in the area of engineering

and science will be summarized under the headings: structural engineering, geotechnical engineering, water resources, and coastal engineering.

Makarynskyy et al., (2004) discussed the ANN approach to the problem of improving the prediction of the wave. In this paper, they used two different approaches. First, they used the initial simulations of the wave parameters with leading times from 1 to 24 hours. Second, they allowed for merging the measurements and initial forecasts. These results showed that an ANN model can provide accurate simulation and demonstrated the ability of neural networks to improve the initial expectations, it is estimated in terms of the correlation coefficient, root mean squared error and scatter index.

Deo et al., (2001) presented practical methodologies for designing better ANN architectures for wave prediction. It demonstrates an improved in the predictions result and the actual observations which represented in the improvement of the correlation coefficient (R^2) of 68%. They concluded that smaller differences in the characteristics of the wind at this location coupled with the single location wave and wind measurements led to improvement in predictions.

Lee et al., (2001) developed an ANN model to predict the behavior of stub-girder system in structural analysis. In this paper, they believed that it is difficult task to modeling stub-girder involving complex material behavior by traditional numerical modeling in computational. They concluded that, many of uncertainty and empirical problems within an approximate structural analysis can be solved successfully by the ANN models that require both an fast calculation with acceptable margin of error in structural engineering.

Kim et al., (2001) presented how to utilize an accumulated database to evaluate particular tunnel sites and prediction of ground surface settlements due to tunneling using an ANN model. The ANN model based on past tunnel records that used as reliable database which leading to predicted the settlements of ground surface. They suggested that the ability to predict an accurate result is completely reliant on data quality and quantity that used in training ANNs.

In water resources engineering, (French et al., 1992) used an ANN to predict rain- fall intensity. They used back-propagation network for the training, and they compared natural

rainfall history with an ANN predicted fields model. Their results indicated that the ANN is capable of learning the complex relationships describing the space-time evolution of rainfall that is inherent in a complex rainfall simulation model.

Maier and Holger (2000) applied ANNs in prediction of water quality parameters. The authors reviewed the differences between ANNs and more traditional predicting methods, such as time series and physically based models, and applied the ANN model to predicting salinity in the River Murray at Mruuay Bridge, South Australia. They concluded that ANN models appear to be a useful tool for predicting salinity in rivers, even if they had difficult in determining the appropriate model inputs. Later, they investigated the relative performance of various training algorithms using feed-forward ANNs for salinity predicting.

2.6 Hydrodynamic Forces

The hydrodynamic forces evaluation that acts on platform legs requires knowledge of vector of stress which includes gradients of the velocity and dynamic pressure. However, the fluid motion usually consider as steady, which means linearized, with no more boundaries. As a result, it is possible to relate the stress vector with the velocity of the rigid body relative to the fluid velocity in the far field by means of an integral equation of the first kind (Youngren and Acrivos, 2006).

This approach was taken for the Stokes equation. In both cases, using the matching fundamental solution, at the first order integral equations system, valid at each point of the surface of the submerged rigid body, can be gained that link the stress vector with velocity of the rigid body. The numerical methods were developed numerical by the authors to calculate the stress vector and accordingly to gain a solution with details for the vector of stress which allows authors to calculate the hydrodynamic forces, Consisting of body forces and the stresses supposed to given by a potential, on the rigid body. The wave force theories concerning offshore platforms were not existed until Morison equation was presented in 1950; the wave forces on a vertical pipe were shown to be as illustrated in Fig. 2.2:

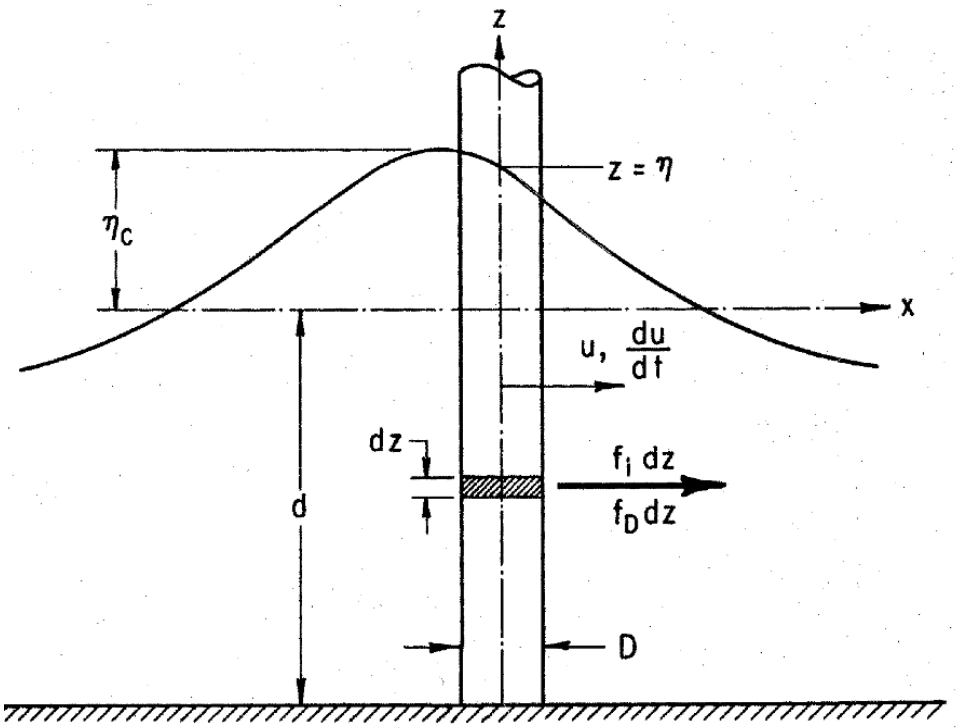


Figure 2.3: Hydrodynamic forces parameters on platform legs due to waves (Sadeghi, 2008)

The coefficients of hydrodynamic forces including drag coefficient and inertia for various types of platforms such as square, rectangular or circular sections that will be subjected to hydrodynamic forces.

The Morison formula is written below (Sadeghi, 2001):

$$f = \frac{1}{2}\rho C_D D \mid u \mid u + \rho C_I \frac{\pi D^2}{4} ax \tag{2.2}$$

$$f = F_D + F_I \tag{2.3}$$

where,

F_D : Represents the drag force

F_I : Represents the inertia force

The most important consideration in applying Morison's equation is the selection of appropriate drag and inertia coefficients. However, there is considerable uncertainty in the

C_D and C_D values appropriate for the calculation of offshore structural members, with many values in publication.

Some published studies reviewed by (Cassidy, 1999) in the literatures in his “PhD diss”. He evaluated that C_D ranged between (0.6 - 1.2) depends on cylinder configuration. For C_D ranged from (1.75 – 2.0) depends on cylinder configuration as well.

Morison Equation is based on following assumptions:

i. Flow is assumed unstable by the presence of the structure

ii. Force calculation is empirical calibrate by experimental results

iii. The right coefficients should be used rely on the shape of the structure body

iv. Validity range shall be checked before use and generally, the validity suitable range for most jacket type structures is D/L less than 0.2.

where,

D : Represents the diameter of the structural member

L : Represents the wave length

The forces and moments due to waves that applied on structure member such as legs, piles and braces are important for process design of offshore platforms. Different amount of forces and moments applied on those members in each moment caused by a particle suspended in a fluid. From the combination of drag force (FD) and inertia force (FI), the total amount of forces and moments can be calculated, with respect to a force sign (Sadeghi, 2008).

CHAPTER 3

METHODOLOGY

3.1 Introduction

The research was conducted in accordance with the following procedure; in this chapter, The SMB and Bretschneider equations are described to how predicting the wave characteristics. The effects of wind blowing velocity, wind duration, air/sea temperature difference, and fetch length are taken into account by Bretschneider equations (Manual, S. P., 1984).

To ensure the accurate prediction of a wave's characteristics using artificial neural network (ANN) model which need to establish a reliable database. Consequently, database was established by using numerical simulation of waves characteristics and downtime done by (Sadeghi, 2007). From the prediction of wave's characteristics it can develop a program for modeling wave and current forces on a vertical and inclined cylinder offshore structural member.

3.2 S.M.B Formulas

The predictions of wave characteristics based on equations within methods such as S.M.B. (Sverdrup-Munk-Bretschneider), Hasselmann , Pierson – Moskowitz and (JONSWAP) (Deo, 2007). The Sverdrup-Munk and Bretschneider (SMB) equations are based on dimensional analysis consideration for predict of wave characteristics which are the adjustment later by Bretschneider in 1958.

The equations are set bellow:

For deep-water conditions (Kabir Sadeghi, 2008):

$$\frac{gH}{U^2} = 0.283 \tanh\left[0.0125\left[\frac{gF}{U^2}\right]^{0.42}\right] \tag{3.1}$$

$$\frac{gT}{2\pi U} = 1.20 \tanh\left[0.077\left[\frac{gF}{U^2}\right]^{0.25}\right] \tag{3.2}$$

The above (H, T) values would occur only if the wind blows for a duration time given in terms of fetch (F) as follows (Sadeghi, 2008):

$$\frac{gt}{U_A} = 68.8\left[\frac{gF}{U_A^2}\right]^{\frac{2}{3}} \tag{3.3}$$

For shallow water conditions and fixed waterdepth (d) (Sadeghi, 2008):

$$\frac{gH}{U^2} = 0.283\ \tanh\left[0.530\ \left[\frac{gd}{U^2}\right]^{0.75}\right]\ \tanh\left\{\frac{0.0125\ \left[\frac{gF}{U^2}\right]^{0.42}}{\tanh\left[0.530\left[\frac{gd}{U^2}\right]^{0.75}\right]}\right\} \tag{3.5}$$

$$\frac{gT}{2\pi U} = 1.2\ \tanh\left[0.833\ \left[\frac{gd}{U^2}\right]^{0.375}\right]\ \tanh\left\{\frac{0.077\ \left[\frac{gF}{U^2}\right]^{0.25}}{\tanh\left[0.833\left[\frac{gd}{U^2}\right]^{0.375}\right]}\right\} \tag{3.6}$$

$$\frac{gt}{U} = K\exp\left\{\left[A\left[In\left[\frac{gF}{U^2}\right]\right]^2 - B\ In\left[\frac{gF}{U^2}\right] + C\right]^{\frac{1}{2}} + D\ In\ \left[\frac{gF}{U^2}\right]\right\} \tag{3.7}$$

where,

$\exp\{x\}=e^{\{x\}}$,

$In = \log_e$,

K=6.5882,

A=0.0161,

B=0.3692,

C=2.2024,

D=0.8798

3.3 Bretschneider Formulas

In Bretschneider equations, air-sea temperature difference (Ta° and Ts°) taken in consideration for prediction of wave characteristics. (Sadeghi, 2008):

$$\frac{gH_{m0}}{U_A^2} = 1.6 \times 10^{-3} \left[\frac{gF}{U_A^2}\right]^{\frac{1}{2}} \tag{3.8}$$

$$\frac{gT_m}{U_A} = 2.857 \times 10^{-1} \left[\frac{gF}{U_A^2}\right]^{\frac{1}{3}} \tag{3.9}$$

$$\frac{gt}{U_A} = 6.88 \times 10 \left[\frac{gF}{U_A^2}\right]^{\frac{2}{3}} \tag{3.10}$$

The following equations can be used , in fully developed wave case (Sadeghi, 2008):

$$\frac{gH_{m0}}{U_A} = 2.433 \times 10^{-1} \tag{3.11}$$

$$\frac{gT_m}{U_A} = 8.134 \tag{3.12}$$

$$\frac{gt}{U_A} = 7.15 \times 10^{4} \tag{3.14}$$

Bretschneider's method with waterdepth effect (Sadeghi, 2008):

$$\frac{gH}{U_A^2} = 0.283 \tanh\left[0.530 \left[\frac{gd}{U_A^2}\right]^{\frac{3}{4}}\right] \tanh\left\{\frac{0.00565 \left[\frac{gF}{U_A^2}\right]^{\frac{1}{2}}}{\tanh\left[0.530 \left[\frac{gd}{U_A^2}\right]^{\frac{3}{4}}\right]}\right\} \tag{3.15}$$

$$\frac{gT}{U_A} = 7.54 \tanh\left[0.833 \left[\frac{gd}{U_A^2}\right]^{\frac{3}{8}}\right] \tanh\left\{\frac{0.0379 \left[\frac{gF}{U_A^2}\right]^{\frac{1}{3}}}{\tanh\left[0.833 \left[\frac{gd}{U_A^2}\right]^{\frac{3}{8}}\right]}\right\} \tag{3.16}$$

$$\frac{gt}{U_A} = 5.37 \times 10^2 \left[\frac{gT}{U_A}\right]^{\frac{7}{3}} \tag{3.17}$$

where,

$$U_A = 0.71U^{1.23}\ m/s$$

$$U = RT \times U_{10}\ m/s$$

3.3.1 Stability factor

Stability factor (RT) defined by Resio and Vincent in 1977 and consider as a significant factor in wave characteristics prediction within Bretschneider equations. RT can be from Figure 3.1, Which allows to consider the difference in temperature between the air and the sea (Sadeghi, 2008).

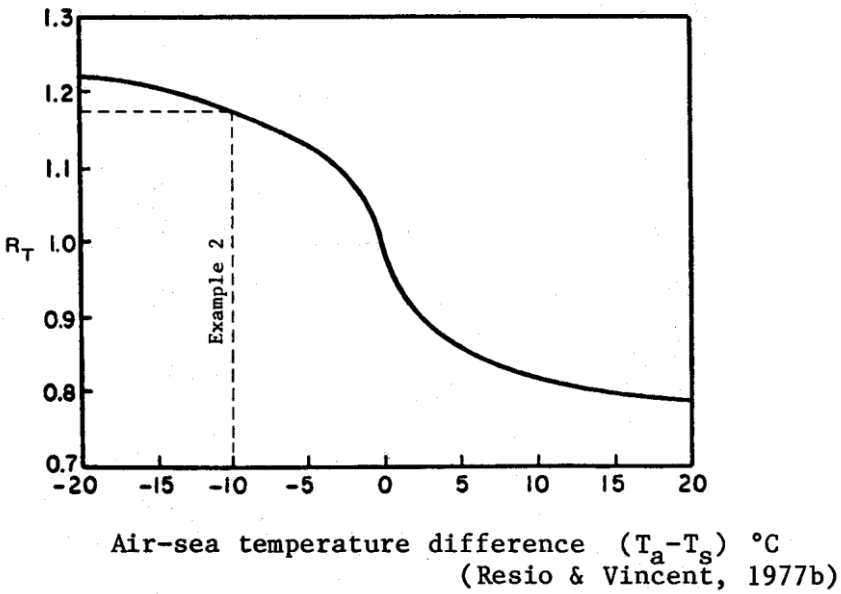


Figure 3.1: Stability factor RT graph.

3.3.2 Distribution of wave heights

These wave prediction methods are based on semi-empirical relations, which link the significant wave height Hs and significant wave period to wind speed, fetch, and waterdepth (Vandever et al., 2001).

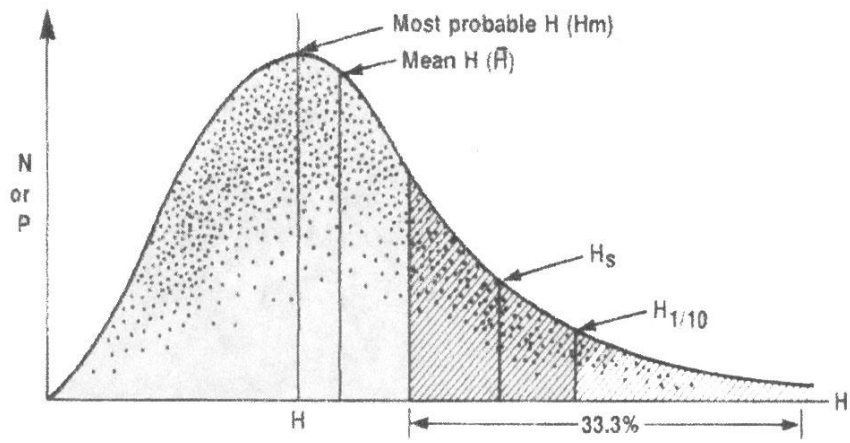


Figure 3.2: Statistical distribution of wave heights

where,

H_m (Mean wave height) = 0.64 times Hs

H_s or $H_1/3$ = Significant wave height

$H_1/10$ (Highest 10% wave height) = 1.27×Hs

$H_1/100$ (Highest 1% wave height) = 1.67×Hs

H_{max} (Max probable wave height for a large sample) = about 2.0×H_s

3.4 Basis of Empirical Equations

The majority of the mathematical calculations are based on two basic elements: wavelength L_o and wave height H_o (the subscript o indicates fully developed deepwater conditions). Fully deep-water waves subject to various changes as they approach the shoreline (Le Roux et al., 2010).

where,

$$L_o = 1.56 * T^2 \text{ (m)} \tag{3.18}$$

Firstly, after decreasing in wave height, after the water particle velocity reaches a maximum in the wave crest, the breaking height will increase, also expected decrease in the wavelength decrease that will happen and cause change in the form of a wave from a sinusoidal through trochoidal to reach cnoidal profile with the respect to the still water level shoreline with increasing of mean water level (Le Roux et al., 2010).

Table 3.1: The parameters of water/air temperature from the recorded wind characteristics in the Caspian Sea

B	C	D	E	F	G
Day	**Month**	**Year**	**Ta (Air temp.) (ºC)**	**Ts (Sea water temp.) (ºC)**	**Ta-Ts (ºC)**
21	11	88	14.1	18.1	-4.0
21	11	88	15.0	18.1	-3.1
21	11	88	14.9	18.2	-3.3
22	11	88	14.3	18.1	-3.8
22	11	88	16.2	18.4	-2.2
22	11	88	16.3	18.4	-2.1
22	11	88	14.7	18.2	-3.5
22	11	88	12.6	12.2	0.4
22	11	88	14.1	18.0	-3.9
22	11	88	15.2	17.9	-2.7
22	11	88	15.6	18.0	-2.4
22	11	88	15.8	18.1	-2.3
23	11	88	15.7	17.9	-2.2
23	11	88	15.3	18.1	-2.8
23	11	88	16.9	18.3	-1.4

All input and output data in the spreadsheet, except the operation criteria, are in SI units. In the data input area (cells B4:BA2728), measured wave height and period conditions are entered, where available. The parameters of water/air temperature in cell (cells E4:F2728) is required to differences in cell G, although the value in this cell may contains some negative values.

Table 3.2: The parameters of wind in the Caspian Sea

Y	Z	AA	AT	AU	AV
$U_{(10)}$ Total Ave. Wind speed (m/s)	**Wind gust (knot)**	**Wind gust Direction (degree)**	**Wind Duration (sec)**	**$U = R_T \times U_{(10)}$ (m/s)**	**$U_A = 0.71 \times U^{1.23}$ (m/s)**
2.06	6.70	47	16200	2.293	1.970
3.09	9.30	77	16200	3.413	3.214
6.17	14.70	59	16200	6.838	7.555
1.39	4.70	2	16200	1.545	1.21
3.45	10.00	-152	16200	3.750	3.61
0.67	2.70	-17	16200	0.725	0.48
2.73	6.70	-175	16200	3.025	2.77
2.42	8.70	-29	16200	2.379	2.06
3.09	7.30	-156	16200	3.436	3.24
3.60	9.30	-110	21600	3.969	3.87
3.76	10.00	-109	16200	4.116	4.05
5.14	14.00	-126	16200	5.617	5.93
3.09	8.00	-86	16200	3.358	3.15
1.70	5.30	71	16200	1.873	1.54
0.36	2.00	-90	16200	0.380	0.22

The sustained wind velocity which represented as (U10) is measured at a distance of 10 m above the SWL that supplied in cell Y as average in m/s units. The measured wind gust and its direction can also be entered in columns Z and AA, which automatically calculated values of wind duration in seconds in column AT. Correction to account for the non-linear relation between the measured wind speed and its stress on the seawater.

Due to the shortage in date of wind for all points in southern part of Caspian Sea, wind data recorded at the buoy site mentioned above which located 30 km from Neka Harbor at a waterdepth of 35 m and operated by KEPCO were used for all points of the south Caspian Sea considering different fetch lengths (Sadeghi, 2007). The wind input such as fetch distance and duration of wind might be not necessary in neural networks.

3.5 Equations for Deepwater Wave Conditions

The parameters that calculate as shown in Table 3.3 are included significant wave height (Hs), maximum height of wave (Hmax), significant period of wave (Ts) and peak period (Tm) were calculated by the Bretschneider equation taking into consideration the air-sea water.

Table 3.3: Output data of area of wave characteristics from the recorded wind characteristics in the Caspian Sea (Sadeghi, 2007)

AX	AY	AZ	BA
H_{m0}=H_s (Simulated) (m)	**H_{max} (Simulated) (m)**	**T_m (Simulated) (sec)**	**T_s (Simulated) (sec)**
0.127	0.235	1.965	1.867
0.234	0.433	2.510	2.384
0.681	1.259	3.848	3.656
0.07	0.13	1.54	1.46
0.27	0.50	2.66	2.53
0.02	0.04	0.97	0.92
0.19	0.36	2.33	2.21
0.13	0.25	2.01	1.91
0.24	0.44	2.52	2.39
0.37	0.68	3.18	3.02
0.31	0.58	2.82	2.68
0.50	0.93	3.41	3.24
0.23	0.42	2.48	2.36
0.09	0.17	1.74	1.65
0.01	0.01	0.65	0.62

Columns AX15, AZ Table 3.3 calculate the significant wave height and significant wave period by using equations (3.8) and (3.9), respectively. While the maximum wave height ratio normally more than significant wave height by two. The Rayleigh ratio was used in this study for the benefit of simplicity (Sadeghi, 2001).

3.5.1 Wave theories

Wave theories yield the information on the wave motion such as the water particles kinematics and wave speed, using the input of wave height, its period and depth of water at

the site. There are more than a dozen different theories available in this regard. However, only a few of them are common in use and these are described below (Deo, 2013):

- All wave theories involve some common assumptions
- The waves have regular profiles
- The flow is two-dimensional
- The wave propagation is unidirectional (or long crested)
- The fluid is ideal i.e. in-viscid, incompressible and irrational
- The sea bed is impermeable and horizontal

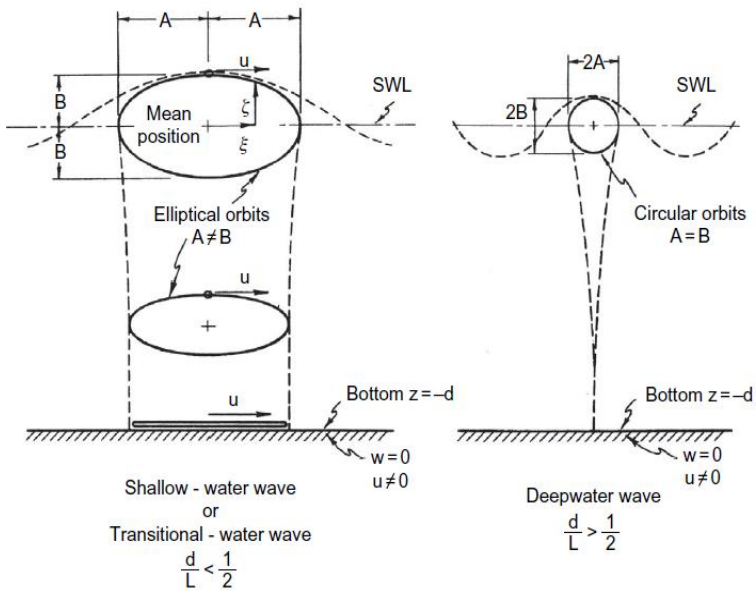


Figure 3.3: Displacement of water particle for shallow and deepwater waves

The wave theories can be categorized into two types (El-Reedy, 2012):

- Linear or Airy's (or sinusoidal amplitude) wave theory
- Non-linear (or finite amplitude) wave theories.

3.5.1.1 Formulation of Airy's linear theory

A relatively simple theory of wave motion, well-known as Airy's linear theory, was given by George Biddell Airy in 1842 (Dawson, 1983). This description assumes the form of a sinusoidal wave shape, it has a slight increase in comparison with the wave length and depth of the water. Although not capable of strict application of the waves of the usual

design used in marine structural engineering, this theory is the value to preliminary calculations for the detection of the basic characteristics of a wave caused by the movement of water (Dawson, 1983).

Airy's linear theory provides an expression for vertical and horizontal velocity particle of water at place (x, y) and time, t as (Dawson, 1983):

$$u = \frac{\omega H}{2} \frac{\cosh ky}{\sinh kd} \cos(kx - \omega t) \tag{3.19}$$

$$v = \frac{\omega H}{2} \frac{\sinh ky}{\sinh kd} \sin(kx - \omega t) \tag{3.20}$$

The wavenumber, k and wave angular frequency, ω are related through the Airy's linear theory by the dispersion equation:

$$\omega^2 = gk \tanh kd \tag{3.21}$$

Using the dispersion equation above, the wave speed may be expressed as:

$$c = (\frac{g}{k} \tanh kd)^{1/2} \tag{3.22}$$

The water particle accelerations are obtained as:

$$ax = \frac{\omega^2 H}{2} \frac{\cosh ky}{\sinh kd} \sin(kx - \omega t) \tag{3.23}$$

$$ay = \frac{\omega^2 H}{2} \frac{\sinh ky}{\sinh kd} \cos(kx - \omega t) \tag{3.24}$$

Where,

$$ax \approx du/dt,$$

$$ay \approx dv/dt$$

The underlying assumption in the derivation of linear theory has its limits of y = d, which does not account above the SWL (i.e. y > d). This predicament is resolved by the linear surface correction, (Noorzaei et al., 2005):

$$\eta = \frac{H}{2}\cos(kx - \omega t) \tag{3.25}$$

Thus, at the free water surface, the vertical position of the wave becomes:

$$y = \eta + d \tag{3.26}$$

The Morrison equation uses to transform the wave velocity and acceleration into forces, especially, for slender offshore structures such as jacket platform (Henderson, 2003). The Morison equation maybe expressed as:

$$f = \frac{1}{2}\rho C_D D \mid u \mid u + \rho C_I \frac{\pi D^2}{4} ax \tag{3.27}$$

The graph that used to selecting the validity wave theory in different waterdepths and for various environmental conditions is given above in Figure 3.14.

where,

ρ : Represents denotes water density,

C_D and C_I : denote the drag and inertia coefficients respectively

D : Represents the diameter of the member

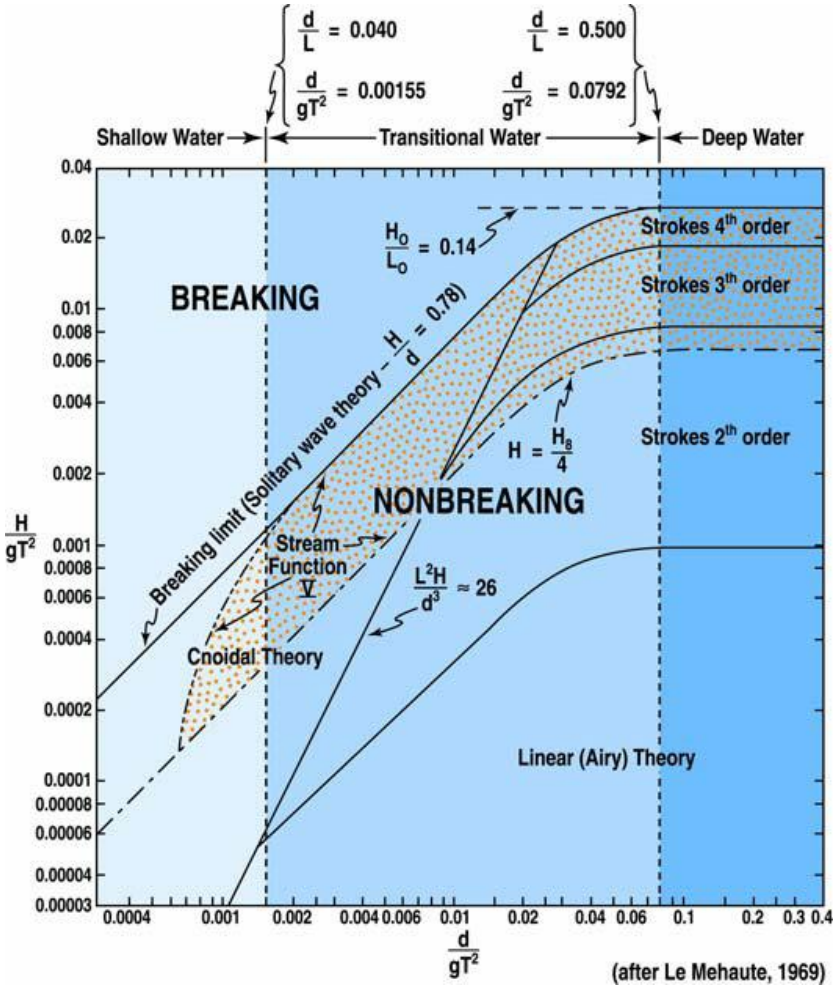


Figure 3.4: Validity of wave theories graph (Sadeghi, 2008)

The term that on the right hand of this equation, is referred to the drag term and is proportional to the square of the water velocity and the second term is referred to the inertia term and is proportional to the water acceleration (Sadeghi, 2008).

The values of horizontal velocity particle of water (u) and water particle accelerations (ax) in the Morison equation are calculated from a suitable wave theory, together with chosen values of C_D and C_I in Eqn. (3.27) yields at any instant in the wave cycle, the force distribution all along the member.

3.6 Artificial Neural Network

An artificial neural network is a computing system consisting of number highly interconnected processing elements and processing of information by responding to the dynamics of the external input case (Caudil, 1987). The following section is a brief overview of the architecture, training rules, selection, and advantage and disadvantage of ANN models.

3.6.1 Architecture of ANN

The process of information with neural networks represent by trillions of neurons (nerve cells) formed the networks, electrical pulses occur by exchanging between cells called action potentials. Computer algorithms that imitative these structures of biological are properly called artificial neural networks to characterize them from the squishy things inside of animals (Birdi et al., 2013).

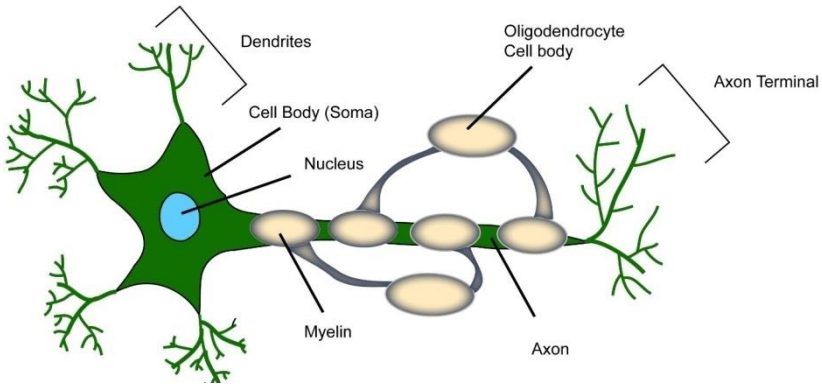
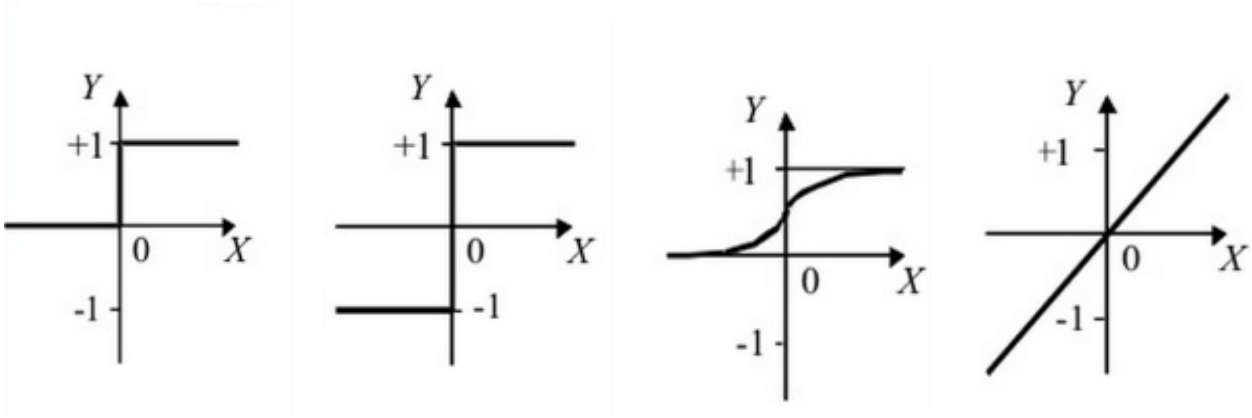


Figure 3.5: Construction of a single neuron in the brain

Figure 3.3 illustrates the relationship of a single neuron of the brain to its four parts, known by their biological names: dendrites (Input), soma (Process), axon (Turn input into output) and



Step function Sing function Sigmoid function Liner function

Figure 3.6: Different types of activation functions

Generally, there are three fundamentally different classes of networks, which are based on network architecture: single layer feedforward, multi-layer feedforward, and recurrent network (Haykin, 2004).

3.6.1.1 Single layer feedforward

A single layer feedforward network has a single layer of artificial neurons, and it processes input signals in a forward directional manner (Cha et al., 2011).

3.6.1.2 Multi-layer feedforward

The multi-layer feedforward is development of the single layer network, where used to for much more difficult and complicated problems cat not be solved by in single layer method or consume more time. It formation from the most important three part in any networkers which are an input layer of neurons, one or more hidden neurons layers and an output neurons layer (as illustrated in Figure 3.5). The hidden layer gives the network its power and allows it to extract extra features from the input (Cha et al., 2011).

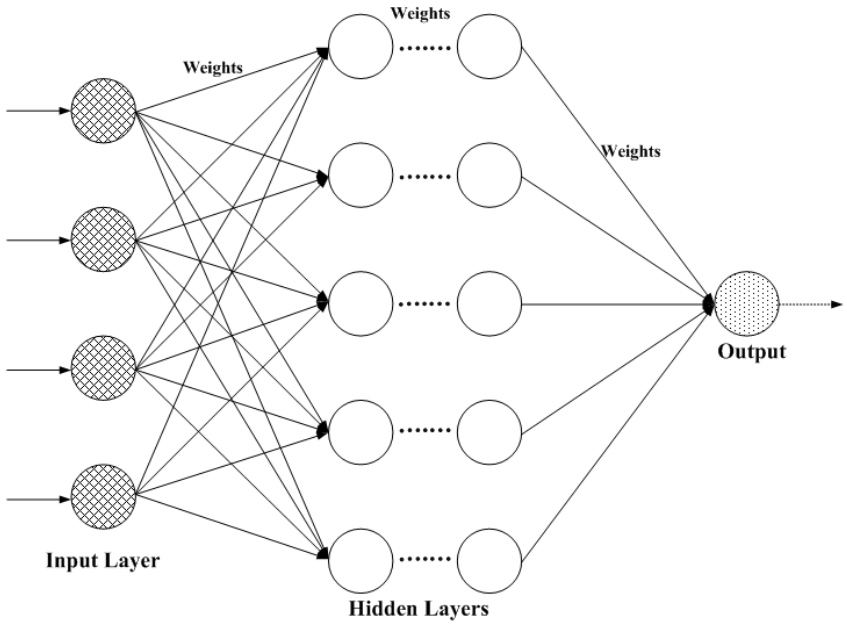


Figure 3.7: Typical multi-layer feedforward architecture

3.6.1.3 Recurrent network

A recurrent network has similarities to a feedforward neural network, but it differs by having at least one feedback loop. These feedback connections propagate the outputs of some nodes or the network back to the inputs layers or nodes to perform repeated computations (Cha et al., 2011).

3.6.2 Training of ANN

An ANN has to be formation like that the application that produces desired outputs in response to training set of inputs. This study adopted the back propagation as a network training for all models, (BPNN) are the common network architecture (Rumelhart et al., 2013). Algorithms are training in a supervised style by BPNNs. The input and output are used to train a network until the network can reach the minimum error (Haykin, 2004). This method is used for most of our ANN models. In general, the networks trained with four algorithms and all achieved satisfactory results. The highest and fastest results were obtained when trained with resilient backpropagation algorithm (*trainrp*).

Furthermore, these training algorithms can be divided into two categories, such as supervised and unsupervised training.

3.6.2.1 Supervised training

Inside the supervised training style, comparison between actual outputs and desired output of an ANN, therefore it attempts that desired solutions are known for the training data sets. This consists reduce error with the passing time by adjusting the weights input until acceptable network accuracy is reached. Most representative supervised training algorithms use the backpropagation algorithm, which has been used since (McClelland et al., 1986).

3.6.2.2 Unsupervised training

In contrast, unsupervised training does not require a correct desired data set. In fact, the fundamental in the data or the links between the patterns in the data is exposed and organized into categories. This is especially useful when solutions are unknown (Cha et al., 2011).

3.6.3 Feedforward, back-propagation network

The feedforward, backpropagation architecture was presented by the early of 1970's by several independent source (Rumelhart et al., 2013). Therefore, proliferation of articles

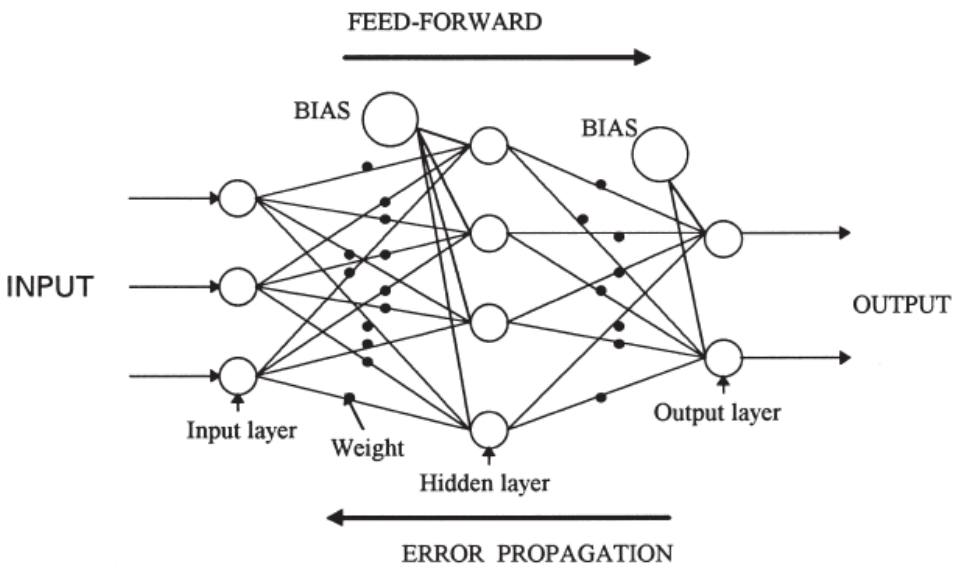


Figure 3.8: Back propagation architecture

and talks at various conferences attempts to stimulate that entire industry to achieve this independent co-development.

At the present time, this interactive developed of backpropagation architecture is become popular, valuable, and easy learning even for complex models, such as multi-layered networks. The greatest strength of ANN is in its dealing with nonlinear solutions to indefinite problems. The professional back-propagation network has an input layer, an output layer, and at least one hidden layer (Demuth and Beale, 2002).

BP algorithm is one of the most popular ANN algorithms. Rojas, (2013) claimed that BP algorithm could be packed up to four major steps. Once the weights chosen randomly, compute of necessary corrections are done by back propagation algorithm. The algorithm can be expressed in the following four steps (Cilimkovic, 2010):

- Computation of feed-forward
- Back propagation to the output layer
- Propagation to the hidden layer
- Weight updates

While the function error value may become small enough, the algorithm is stopped. It considers being the basic formula for BP algorithm. With the variations proposed by other scientists, Rojas definition seems to be fairly accurate and simple to follow. The last step, weight updates is happening throughout the algorithm (Demuth and Beale, 2002; Rojas, 2013).

3.6.4 Selection of ANN

The concept of neurons, transfer functions and connections are the essential elements that ANNs based on. The similarity between the different structures of ANN can be found in many studies. The majority of the variation stems from the various learning rules, as well as how these rules modify a network's typical topology. Generally, most applications of ANN can be divided following four categories (Cha et al., 2011):

- **Prediction:** Uses input values to predict some output. The backpropagation network model is most commonly used for engineering predictions. It is a

powerful mechanism for building nonlinear transfer functions between a number of continuous valued inputs and one or more continuously valued outputs. The network basically uses multi-layer perception architecture and gets its name from the manner in which it processes errors during training. In the current study we also build an ANN model for the prediction of wave characteristics based on this model.

- **Classification:** Uses input values to determine the classification. This model is generally used for pattern recognition.
- **Data association:** Used simulate the classification, while also recognizing data that contains errors.
- **Data filtering:** Analyses input data and makes it smooth for the output, such as taking noise out of telephone signals.

3.6.5 Advantages and disadvantages of ANN

3.6.5.1 Advantages

The handle difficulty with very many parameters is the major advantage of neural network methods. Further, they are able to successfully to give accurate values and classify objects, despite the chaotic distribution of the objects.

The ANN can incorporate the nature of the dependency without the need to be prompted, for example, where is no need to assume a model or to modify it. Besides, it goes directly from the data to the model without any of intermediary, recording, binging and without any simplification or questionable interpretation.

Additionally, there are no conditions attached to the predicted variables. As a result the outputs can be a (Yes/No), a continuous value, or one or more classes, etc. Finally the ANN is handled with ease, requires less human intervention than does a traditional analysis, and the ones does not to be need competent in nor have a mathematical background (Cha et al., 2011).

3.6.5.2 Disadvantage

The biggest disadvantage of neural networks is that they consume a lot of time, particularly in the training phase, especially supervised training. Thus, for example the training is repeated until the desired output data is satisfied. Another significant disadvantage is the difficulty of determining how the decision is made in the net. Consequently, it is hard to determine which of the input data being used are significant and valuable for the prediction, and which are worthless.

There are also limitations with training data. For instance, the capability of the ANN to identify indicators that intrusion is completely dependent on a training system. Hence, the effective outcomes are dependent upon both training data and the training methods that are critical to in each network. Therefore, qualified training data sets are essential to meet the desired results.

In this study, we also face these difficulties and limitations. However, we nevertheless decided that it was still an interesting approach to use to predicting of wave parameters by using an ANN model (Cha et al., 2011).

3.7 Modeling of Wave and Current Forces on Simple Offshore Structural Members

It is essential for all offshore structural analysts to estimate the forces generated by fluid loading given the description of the wave and current environment (Borthwick et al.,1988). Considering the many applications of these platform structures mainly Jacket platform in marine industry. The design will be under large forces caused by wave plus current forces.

The Morison equation is usually used to determine the hydrodynamic forces working on the cylinder submerged as a result of environmental actions such as wave action. “The force is expressed as the sum of a velocity dependent drag force and an acceleration-dependent inertia force” (Chandler et al., 1984).

In this case, Morison (1950) equation is typically used as a computational method which requests two different coefficients, named drag (C_D) and inertia(C_I), to calculate the inline

force. In considering wave forces, the sea comprises of a large number of periodic wave components with different wave heights, periods and directions of travel which all occur at the same time in a given study area. The randomly varying sea surface elevation due to overlap of these entire wave components coupled with their dispersive behavior leads, which can be treated by statistical methods. However, to provide engineering solutions, the use of regular wave theories is common, since regular wave theories yield good mathematical models of long crested periodic waves, which are components of an irregular sea. There is a wide range of regular wave theories ranging from the simple Airy's linear theory to the higher order formulations (Noorzaei et al., 2005).

The combination of wave and current inline is used for a non-collinear current. Moreover, the presence of the current changes the apparent wave period. The wave particle velocity (u) is computed based on the apparent wave period. Therefore, the wave loading for a unit length of a structure member is founded from the modified Morison equation:

The tidal currents and wind drift currents are the common currents considered in offshore structural analysis (Dawson, 1983). Both of them are usually considered as horizontal and varying with waterdepth.

The tidal current velocity profile at any vertical distance from the seabed may be determined as (Dawson, 1983):

$$U_T(y) = U_{oT}(\frac{y}{d})^{1/7} \tag{3.29}$$

The wind drift current velocity profile may be determined as:

$$U_w(y) = U_{oW}(\frac{y}{d}) \tag{3.30}$$

Where, d denotes the waterdepth, y is the vertical distance from the seabed, U_{oT} and U_{oW} denote the tidal and wind drift current velocity at the water surface respectively. For regular design waves and a horizontal current of arbitrary waterdepth variation, the force exerted on an offshore structure is normally calculated by simply adding the horizontal water velocity caused by the waves to that component of current velocity (Dawson, 1983).

3.8 SACS Software

SACS is an integrated finite element structural analysis package of applications that uniquely supply for the design of offshore structures, including oil and gas platforms, wind farms, and topsides of FPSOs and floating platforms (El-Reedy, 2012).

The software depends on a collection of modules that should be used in each analysis. The main program carries the nodes, members, and loads on it, and other modules do the subroutine used for every analysis you need to perform. We briefly describe an in-place analysis as simple example of SACS software which has others analysis's such as dynamic analysis, Seismic analysis, Collapse analysis and Fatigue analysis.

The first step in SACS is to develop the name of the project as in (Figure 4. (Appendix 4) and define the location of the folder for this new project. Note that organizing the folder is very essential and important, as we will run a lot of input and output files during the analysis (El-Reedy, 2012).

Figure 4.2 (Appendix 4) shows that you have three options, which modify an existing model that we performed before, create a new one, or just open the last one.

To create a new model, a menu appears, as in Figure 4.3 (Appendix 4), to ask about start from blank or use the existing library and choose the units. A wizard is available for fixed offshore platforms, so it is easy to use structure definition wizard.

Start building the structure model through the Structure Definition dialog box; define the jack/pile using the following settings in the Elevations tab, as shown in Figure 4.4 (Appendix 4). The input data that we can supply as following:

- Working Point Elevation
- Pile Connecting Elevation
- Waterdepth
- Mudline Elevation
- Pile Stub Elevation
- Leg Extension Elevation
- Generate Seastate Hydrodynamic Data

- Other elevations

After that, click on the legs tab, as in Figure 4.5 (Appendix 4), to enter the data for the jacket legs and set the following data:

- Number of legs
- Leg type
- Leg spacing at working point
- Row Labeling
- Pile/Leg Batter

For the conductor data, Click on the Conductors tab, set the following data should be set as shown in Figure 4.6 (Appendix 4).

- Number of conductor well
- Top conductor elevation
- First conductor number
- Number of conductors in X direction
- Number of conductors in Y direction
- Coordinate of LL corner
- Distance between conductors
- Disconnected elevations

Then, the connectivity tab is pressed to choose the bracing system for the jacket as shown in Figure 4.7 (Appendix 4).

To define the properties of the leg and the bracing members that can be created using size tab as shown in Figure 4.8 (Appendix 4) and put the input sets easily. But for more details on the precede toolbar, select Property > Member Group as Figure 4.9 (Appendix 4). The Member Group Manage dialog box appears. After named the group for example XPL, we highlight it in the Undefined Groups window, and then click on the Add button to define the section and material properties of XPL.

3.8.1 Input the load data in SACS software

After you define geometry, the next step is to define the loads and the environmental load as wave, current, and wind. Illustrated here is the environmental load.

To define the wave, current, wind, and dead/buoyancy load we go to Environment > Loading > Seastate. The data can be found in the design specifications.There are five tabs, then two for each Wave I and Wave II, Wind I and Wind II, Current I and Current II, Dead, and Drag. As shown in Figure 4.10a (Appendix 4), this is for load case LC1 the wave height is 10.67 m and time period is 9.67 s, the direction is zero. For Current, enter the data of the current from the seabed to the sea level. As shown in Figure 4.10b (Appendix 4).

3.8.2 Output data from SACS software

The output data is presented by the postvue icon. When you select a member, it is identified in the menu on the right by its nodes, from Member > Review Member. Select the member.

CHAPTER 4

RESULTS AND DISCUSSION

The main objectives of this chapter are:

i. To demonstrate the ANN model's capability in the prediction of the wave parameters

ii. To write a computer program that is able to simulate wave plus current forces on template offshore legs using traditional numerical methods with minimal sacrifice towards accuracy and couple the written program to an existing 3-D finite element program, with show the applicability of the coupled program by analyzing a simple offshore structure.

4.1 Study Area

The Caspian Sea was selected as study area for this study; because of the sufficient properties of wave data are not available for some parts at that time in the sea (Sadeghi, 2007).

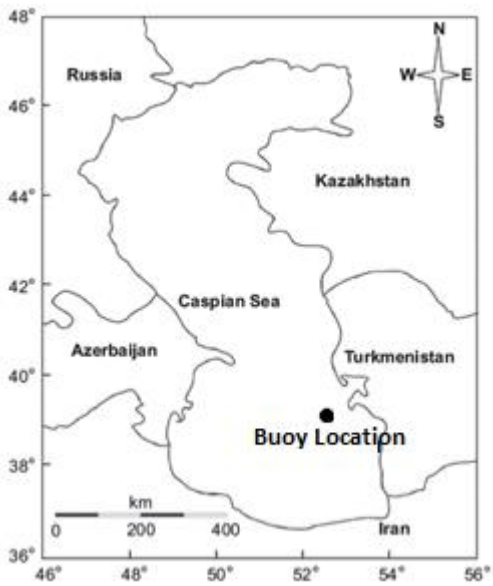


Figure 4.1: Caspian Sea and the location of khazar buoy

4.2 Data Employed

The Caspian Sea is the largest enclosed basin in the world, five countries are surrounded the Sea including; Iran, Turkmenistan, Kazakhstan, Russia and Azerbaijan. Consequently, important economic activities in the Caspian Sea, such as rich resources of oil and gas, agriculture, fisheries and the potential of transportation between Asia and Europe have made this sea vital.

Wave characteristics (height & period) were predicted in the deep waters of the Caspian Sea on the basis of recorded wind data. The Bretschneider equations were used with various modeling equations (Sadeghi, 2001; Manual, S. P., 1984).

4.3 ANN Models for Prediction of Wave Parameters

Wave's generation by wind by using physical process is not yet fully understood which make them extremely complex and uncertain. Neural network helps to model inputs in random environment to predict accurate output, besides; their application does not need to complex physical process as a precondition, which makes it applicable in various areas in yet to be proved (Shahidi and Mahjoobi, 2008)

4.4 Establishment of Database

A most important component in the successful execution of an ANN model is the dataset, which is essential for ANN model learning. As described in Chapter 3, ANN models are trained and perform through data collected in physical tests, historical records or analytical solutions. Therefore it is critical to set up a suitable dataset to ensure accurate findings. As noted in previous work (Sadeghi, 2007), the most important factors that affect wave height calculation are:

The inputs of wave characteristics

a) Average wind speed *(U10 m/s),*

b) Depth *(d),*

c) Fetch Length *(f)*,

d) Stability Factor *(RT)*,

e) Water/air temperature differences *(Ta-Ts (C°))*,

f) Wind Duration *(t sec.)*,

g) Corrected wind speed *(U m/s)*,

To establish a good quality dataset covering all possible realistic ranges of environmental data, values were varied from the above parameters. As seen in the tables of the theoretical model that (outlined in Chapter 3) to predict the wave characteristics for more than 2500 samples.

4.5 The Neural Network

ANNs, can be defined as simplified models that established by layers which are consisting of a number of neurons, among the layers being interrelated by identical weights sets. The information that given in the form of initial input goes through the input layer as neurons, from which the different transfer functions are used to obtain the outputs. The transfer functions that adopted in this study are expressed as,

a) Log-sigmoid transfer functions

$$f(x) = logsig(n) = \frac{1}{1 + e^{-n}} \tag{4.1}$$

b) Tan-sigmoid transfer function

$$f(x) = tansig(n) = \frac{2}{1 + e^{-2n}} - 1 \tag{4.2}$$

The interconnection weights in process of learning were adjusted in the input values, and this process is essential in the ANN model work. The algorithm of back-propagation was adopted for model training, because in a variety of ANN applications it is known as one of the best representative model. The hidden layer(s) is responsible for reduce the error of the network by propagated the data backward from the output to the input in sequential practice that called “incorporation”, until that the network achieves the target outputs.

Thus, the aim is to apply specific inputs in the network to obtain accurate outputs by use the error function, which is expressed as:

$$E = \frac{1}{n}\sum(Dx - Ox)^2 \tag{4.3}$$

4.5.1 Training of ANN

In the current study, resilient backpropagation (TRAINRP function) was adopted as optimizing network by using a multi-layer network ANN, with a fixed network structure. The neuron is made as a combination of a bias and weighted input through a transfer function in the neural network to produces an output. Also, the network could have more than one connected neural layer. The weights and biases are determined by the function of learning, where a set of example of input as well as target output of an accurate behavior of network. The iterative process of learning of the biases and the weights within the network are adjusted until the network performance function reduced, for instance, (Mean Squared Error (MSE)) which is a default tool within feed forward network.

4.5.2 Standard ANN model

The ANN model does not need a traditional approach; it can perform training and testing procedures using an actual dataset. Generally, an ANN only needs reliable input data for predicate valid output data. It is one of the advantages of the ANN model. The chosen the ANN models that used for the prediction of wave characteristics, are illustrated in Figures (4.2), (4.3), (4.4), (4.5) and (4.6). The most commonly used in either engineering prediction or predicting problems is backpropagation network.

The back propagation can be used to train a network by pairs of input and output until the network can create a function (Haykin, 2004). Different functions with constant architecture such as [(inputs-hidden layers-outputs) (2-20-2)] were training by using the LOGSIG and TANSIG functions in the input layer and using the LOGSIG in output layer for the end results.

The preferable network structural design can be found by choosing a various number of neurons in one or more hidden layers where the minimum of neurons can be found by used Equation 4.4 (Haykin, 2004):

$$\text{Number of Hidden layer } (HN) = \text{Number of Input layer } (IN) + 1 \tag{4.4}$$

In this case study, we used more than 1670 training samples of predict the wave characteristics from the numerical model, to get networks with ability to give an appropriate prediction, the training was conducted by using almost 80% of the database.

This model feature is less time consuming and its simplicity. The model adopts two of high performance algorithms that able to converge 10 to100 times faster than the origin gradient descent, and gradient descent algorithms with momentum. Every algorithm in this section is operated in the batch mode and is invoked using train. The different numbers of hidden units tested by training function, adaption learning function and perform various functions. Among the results, we selected five cases of the most accurate results of prediction of the wave height by using the proposed ANN model.

4.5.3 Description of the modeled cases

The preliminary statistical analysis was the basis for formulating five predictions with more than 2300 inputs data. The cases differ from each other with regard to the methods of wave prediction methods and practically based on S.M.B. and Bretschneider equations.

The parameters that used in Model (M 1.1) are:

1 Average wind speed (U10)

2 Fetch Length

Three parameters used in Model (M 1.2) are:

1 Average wind speed (U10)

2 Fetch Length

3 Depth

Four parameters used in Model (M 2.1.1) are:

1 Corrected Wind Speed

2 Depth

3 Fetch Length

4 Wind Duration

Two parameters used in Model (M 2.1.2) are:

1 Corrected Wind Speed

2 Wind Duration

Five parameters used in Model (M 2.2)

1 Average wind speed (U10)

2 Depth

3 Fetch Length

4 Wind Duration

5 Wind Speed

Figure 4.1: Training and testing periods of built networks

Training period	**Testing period**
From $21^{st}$of November1988 to $23^{rd}$of August 1989	From 24^{th}Of February 1989 to 24th of March 1989

The effect of the following parameters was investigated and analyzed:

i. Neurons number in hidden layer

ii. Training algorithms

iii. Transfer function in hidden layer

iv. Initial weight change

4.5.4 Architecture of the proposed ANN:

Model (M 1.1)

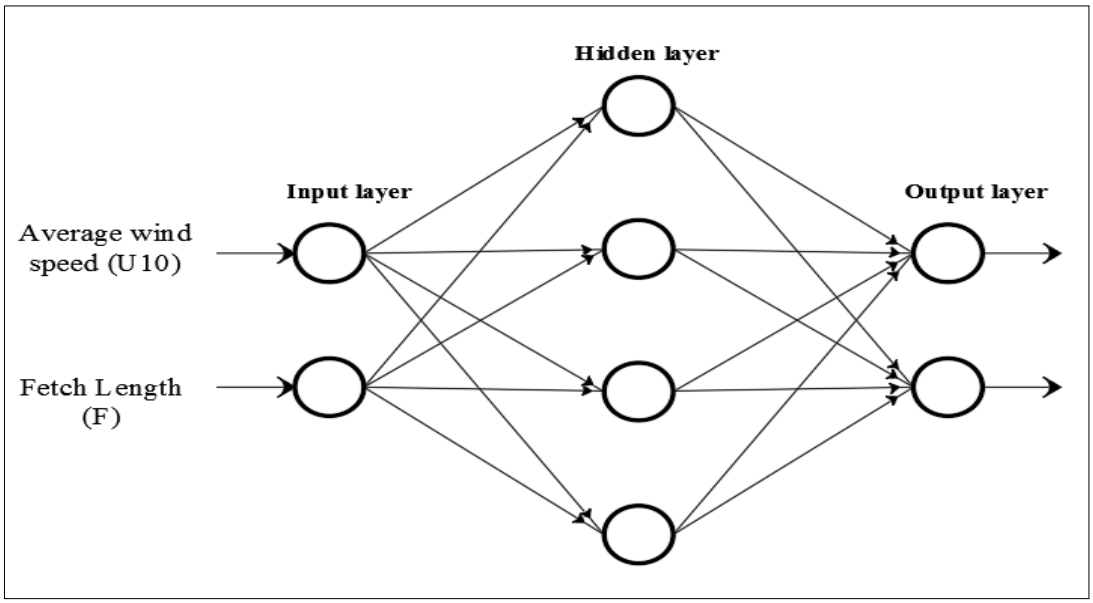


Figure 4.2: Construction of the proposed ANN model for (M 1.1)

Model (M 1.2)

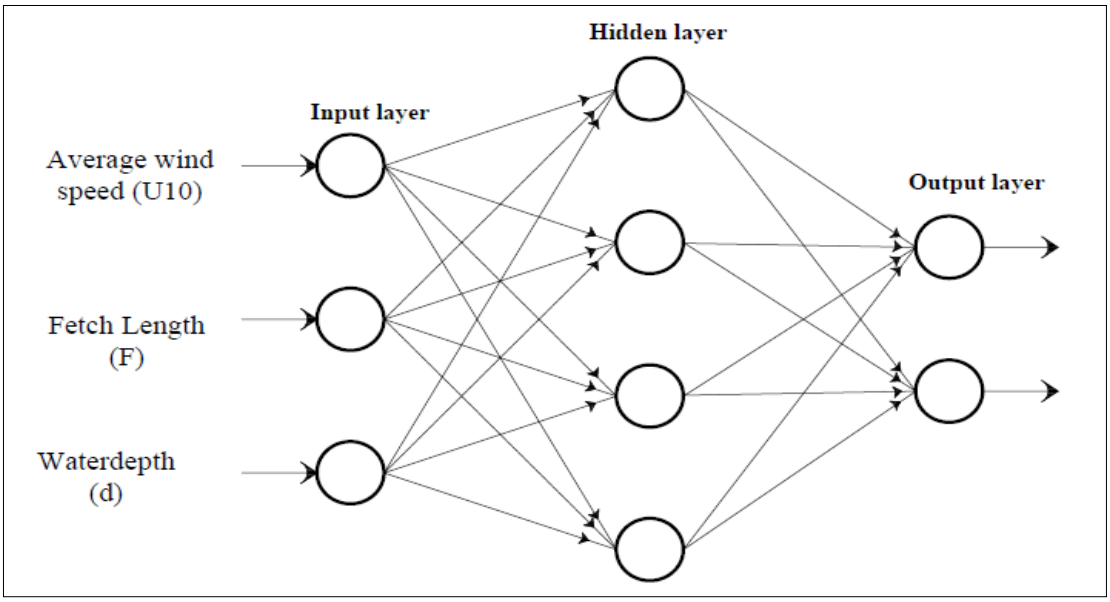


Figure 4.3: Construction of the proposed ANN model for (M 1.2)

Model (M 2.1.1)

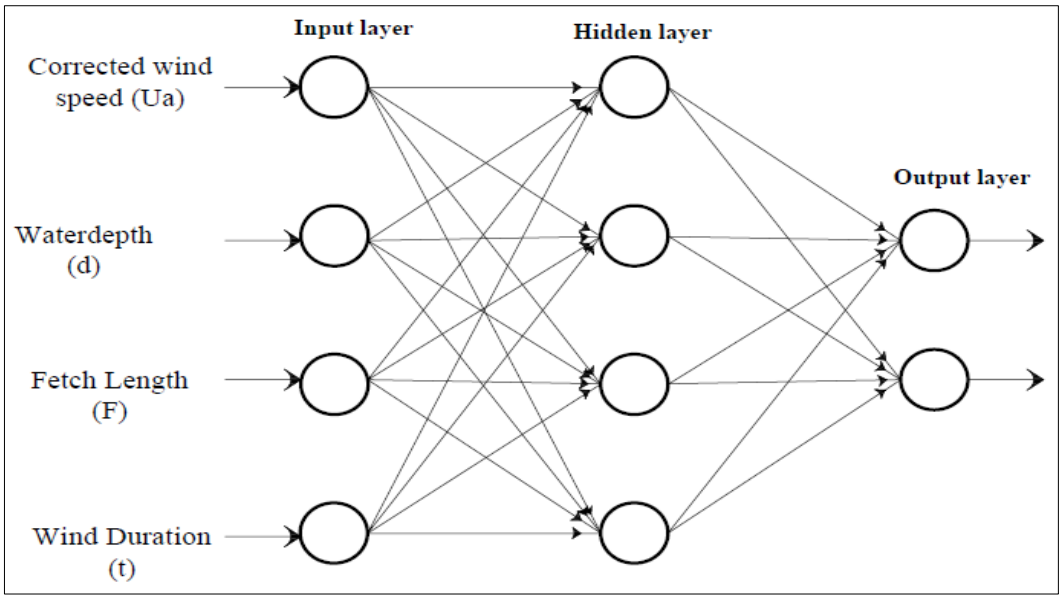


Figure 4.4: Construction of the proposed ANN model for (M 2.1.1)

Model (M 2.1.2)

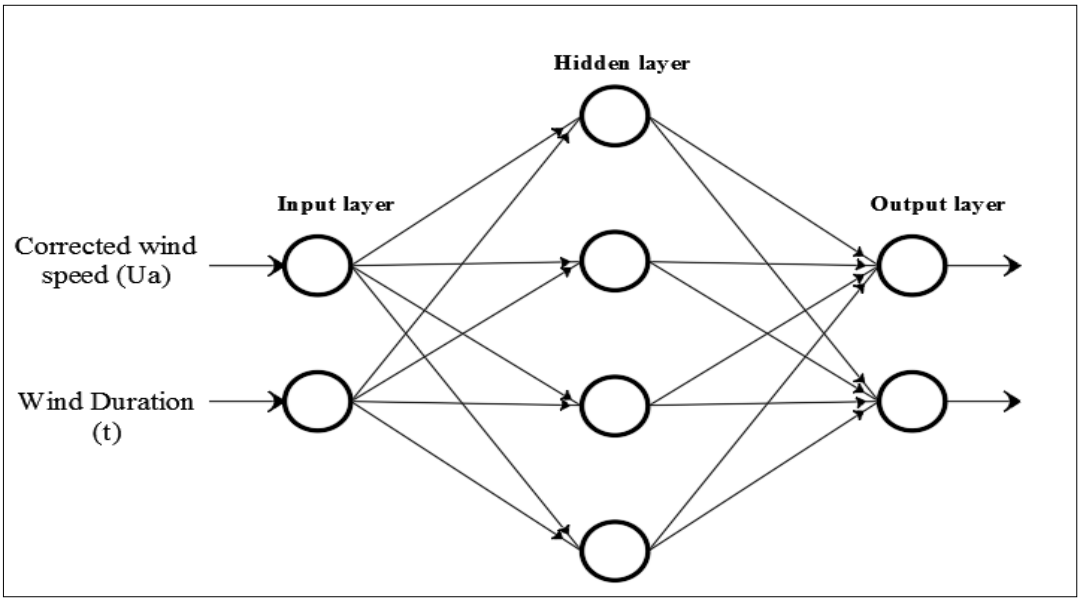


Figure 4.5: Construction of the proposed ANN model for (M 2.1.2)

Model (M 2.2)

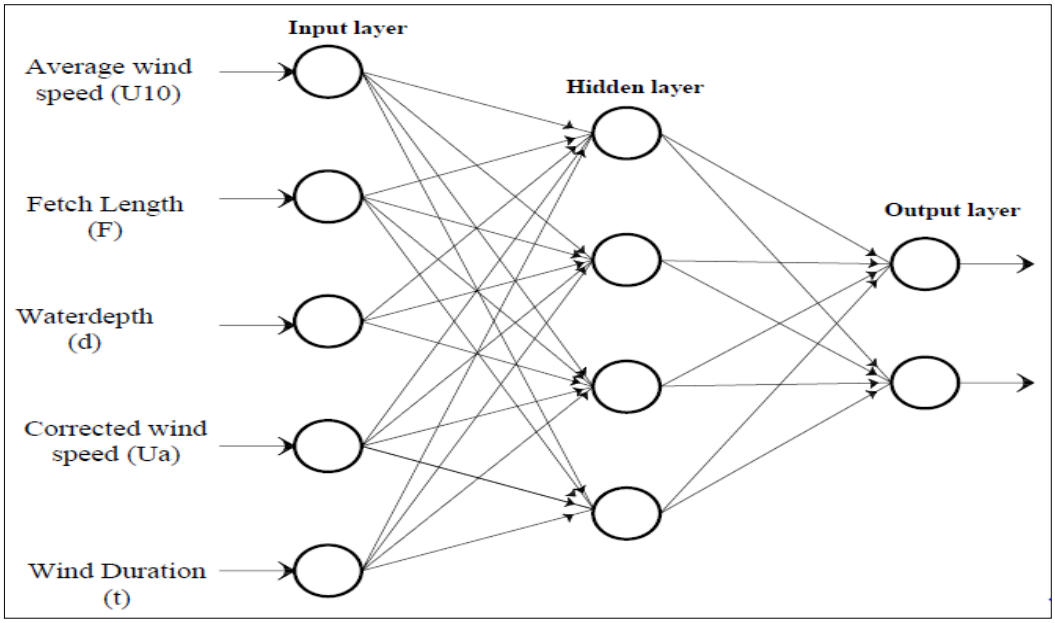


Figure 4.6: Construction of the proposed ANN model for (M 2.2)

Generally, the wave characteristics prediction determining based on the variability and different equations. Therefore, a separate ANNs models were used to simulate each wave parameter take into consideration the prediction methods (S.M.B and Bretschneider). However, Bretschneider equations are the adjustment of Sverdrup-Munk equations by Bretschneider in 1958. It was assumed that S.M.B equations have the first two models and Bretschneider equations have the last three models. As mention, the training algorithm that adopted and implemented was the resilient backpropagation (trainrp) whit maximum epochs number in each simulation was used which is equal 1000; the ANN models were established within a MATLAB environment.

4.6 Network Modeling

This study builds upon results presented by K. Sadeghi (2007) to evaluate the validity of this study as satisfied results correlation coefficient (R^2) method was used. The parameters are defined as follows:

$$R^2 = \frac{\sum(Lo - Lo')(Lt - Lt')}{\sum(Lo - Lo')^2 \sum(Lt - Lt')^2} \tag{4.7}$$

$$Lo' = \sum \frac{Lo}{n} \tag{4.8}$$

$$Lt' = \sum \frac{Lt}{n} \tag{4.9}$$

Lo Represents the wave height or wave period from observed data divided by number of the wave height; *Lt* represents the wave height from numerical model from the ANN model divided by number of the wave height.

The efficiency of models prediction was determined by utilized the correlation coefficient (R^2). A relationship between two random variables was indicated by using the correlation coefficient, which is the relative predictive power of a model. It is a descriptive measure between -1 and +1. Minus sign indicates inverse proportion between two variables whilst plus sign represents a direct proportion. High correlations between two independent variables may indicate over-fit in the model.

Table 4.1: A measure of correlation accuracy by R^2

R^2 values	**Accuracy**
< 0.25	Not good
0.25 - 0.55	Relatively good
0.56 - 0.75	Good
> 0.75	Very good

The results of the case study K. Sadeghi (2007) were acceptable as an engineering application with correlation coefficient (R^2) was over 80% as showed in Table (4.2).

Table 4.2: The case study validity

No.	**R^2**
674	83.072%

The objective was to obtain the best values of Hs and Ts by simultaneous of input some parameters. The neurons numbers within layers were selected due to prediction methods basic parameters for each. Table 1 shows that, the use of two inputs nodes (fetch Length (F) and wind speed (U_{10})). The data were separated into five cases, in each, the different number of neurons layer was training and testing separately.

Generally, the correlation coefficient (R^2) values used to evaluate the efficiency of the prediction. These results are the most successful results among the ANN model tests conducted using these different parameters a. The overall prediction for wave characteristics agree with observed data. The correlation of the ANN model and the wave characteristics height and period was approximately over 95%, and this is acceptable for an engineering application.

Figure (4.7) illustrates the predicted the height and period of wave obtained using the ANN model (M 1.1) versus the observed data, which two parameters were used (fetch length and wind speed).

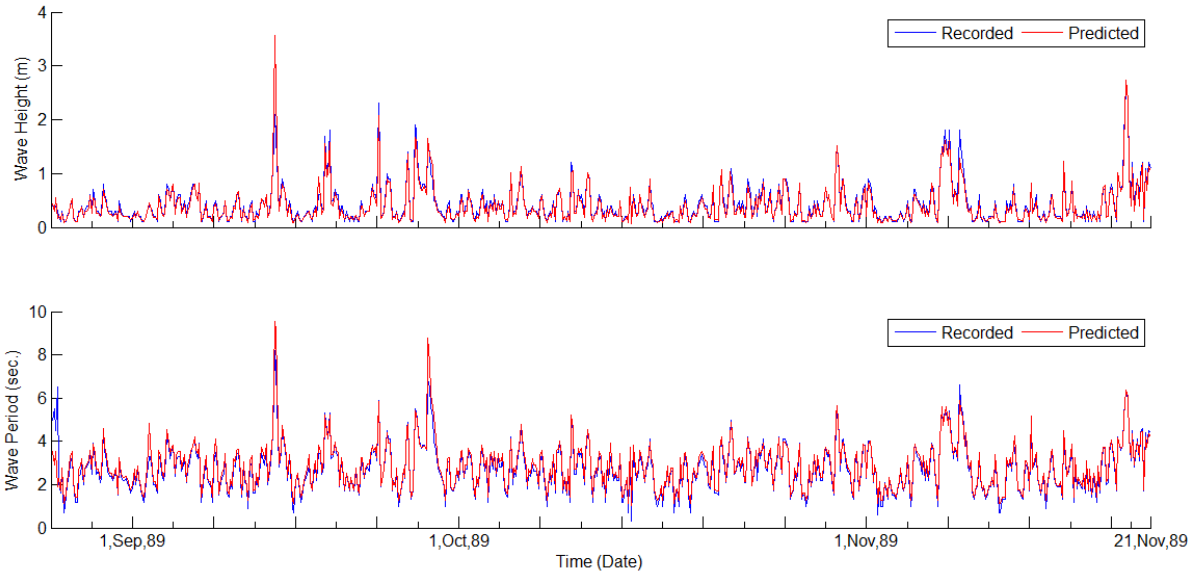


Figure 4.7: Predict wave characteristics using model (M 1.1) H and T predicting

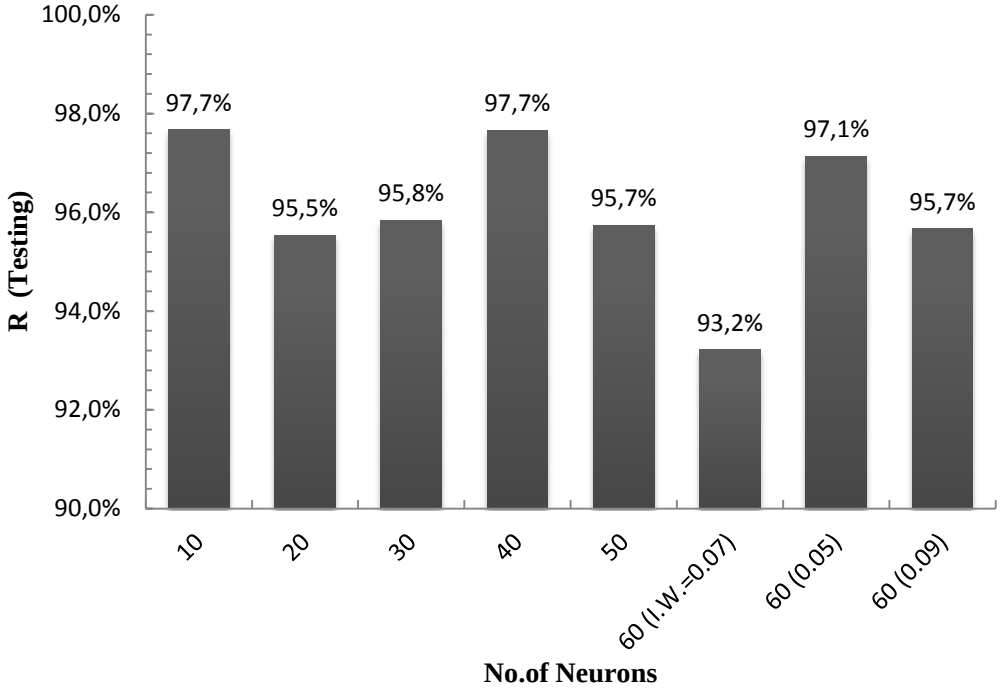


Figure 4.8: Network performance of (M 1.1(2-60-2)) network according to initial weight change

Table 4.3: Training details and result for (M 1.1) model

Model	Case	No. of neurons	Initial weight change	Training No.	Performance goal	R^2
M 1.1	1	10	0.07	3	0	97.67%
	2	20	0.07	6	0.01	95.54%
	3	30	0.07	8	0.01	95.84%
	4	40	0.07	2	0	97.66%
	5	50	0.07	4	0.01	95.73%
	6	60	0.07	11	0.001	93.22%
			0.05	2		97.13%
			0.09	4		95.66%
					Average	96.06%

The Figure (4.8) and Table (4.3) explains the saliency analysis application which based on changed rationally the number of neurons to simulate Hs and Ts. Table 4.3 analysis, for instance, shows that the use of 10 neurons layers and corresponding to three times training try improved the correlation coefficient of predict. A further complicate of the ANN architecture (2x60x2 net) produced a mixed effect: with initial weight 0.07 was less successful although with more number of neurons. Therefore, some changed was done in training parameters to improve the model performance as shown in Figure (4.8). The best result is Case 1 with 97.7% (R^2).

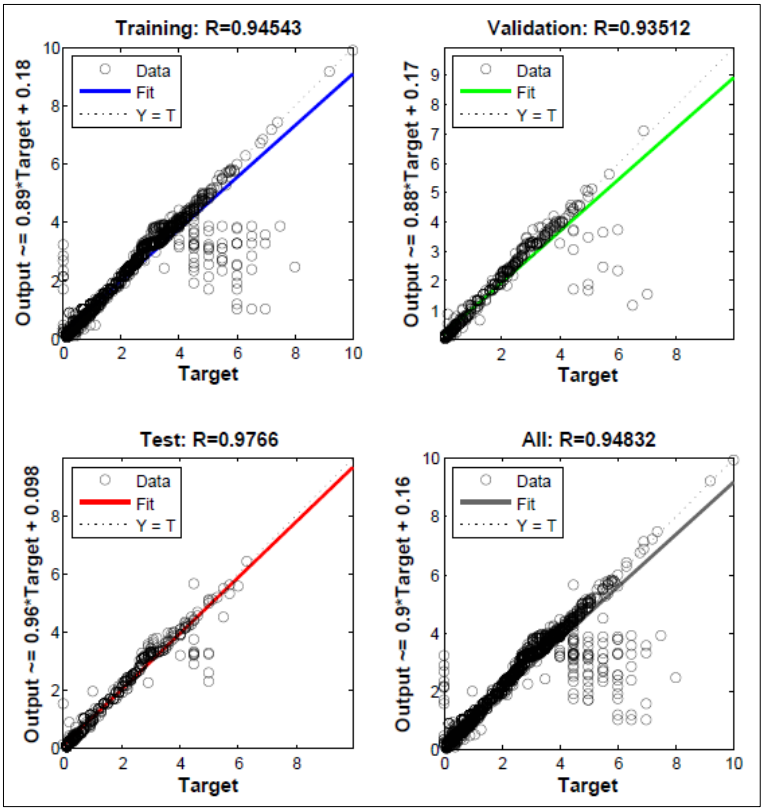


Figure 4.9: Scatter diagrams for (Case 6 (I.W. = 0.09)) predict

Figure (4.9) illustrates the case1 (the most successful testing correlation coefficient with (R^2 = 0.977) within the ANN model (M 1.1) against the observed data. As shown by the figures, the well predictions of wave characteristics, by using ANN model (M 1.1), show a good agreement with the observed data. The average of correlation coefficient of the ANN model and the observed data is more than 96%. In this way, Case 6 is the best result within this model with 97.128% (R^2). All the test results are tabulated in Table 4.3.

As shown in Figure (4.10), network of model (M 1.2) trained with three parameters (e.g. Average wind speed, Fetch length and waterdepth), the results of the average prediction shows a clearly agree between the wave characteristics predicted by using the ANN model and the wave observed data with more than 96% (Table (4.4)) . The best result shown in Figure 4.14, which is demonstrated by (Case 5 (I.W. = 0.09)) with (R^2 = 96.89%).

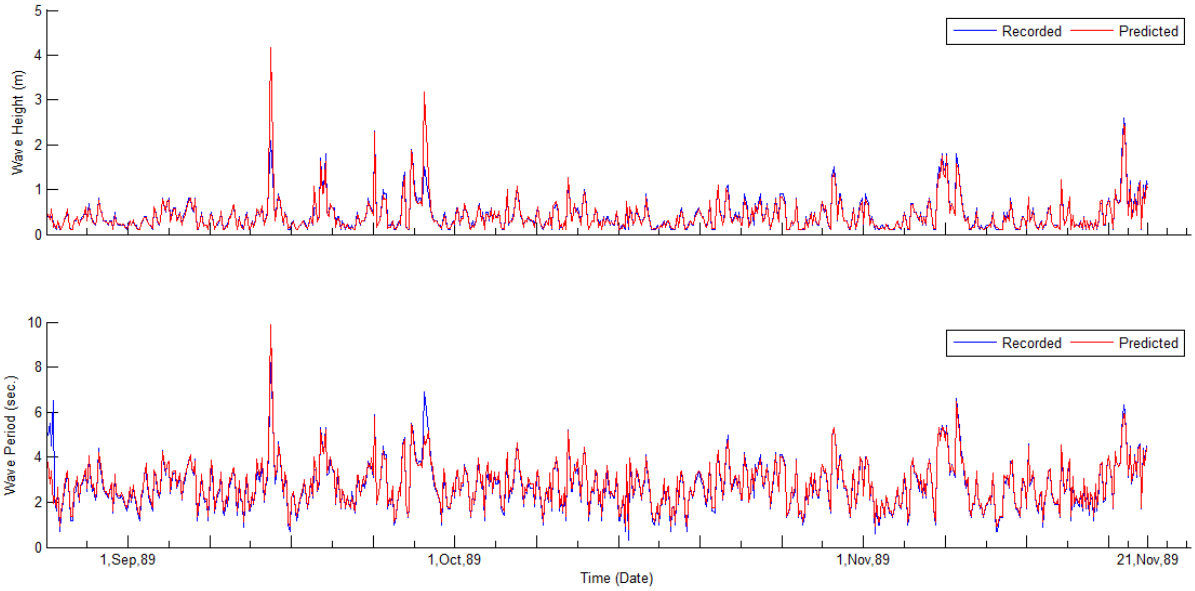


Figure 4.10: Predict wave characteristics using model (M 1.2) for Hs and Ts predicting

From both of Figure 4.11 and Table 4.4, fairly good predictions of the significant wave height and period were produced for all cases. The predictions of wave characteristics, using the ANN model (M 1.2), agree with the observed data. The results included two cases lower than 95%, but with changed in training parameters, , e.g. Initial weight show sufficient improvement in comparison with the previous results in case 6, where the result increase to 0.954 to 0.968 after initial weight changing with range (0.05 – 0.09), respectively as shown in Figure (4.10).

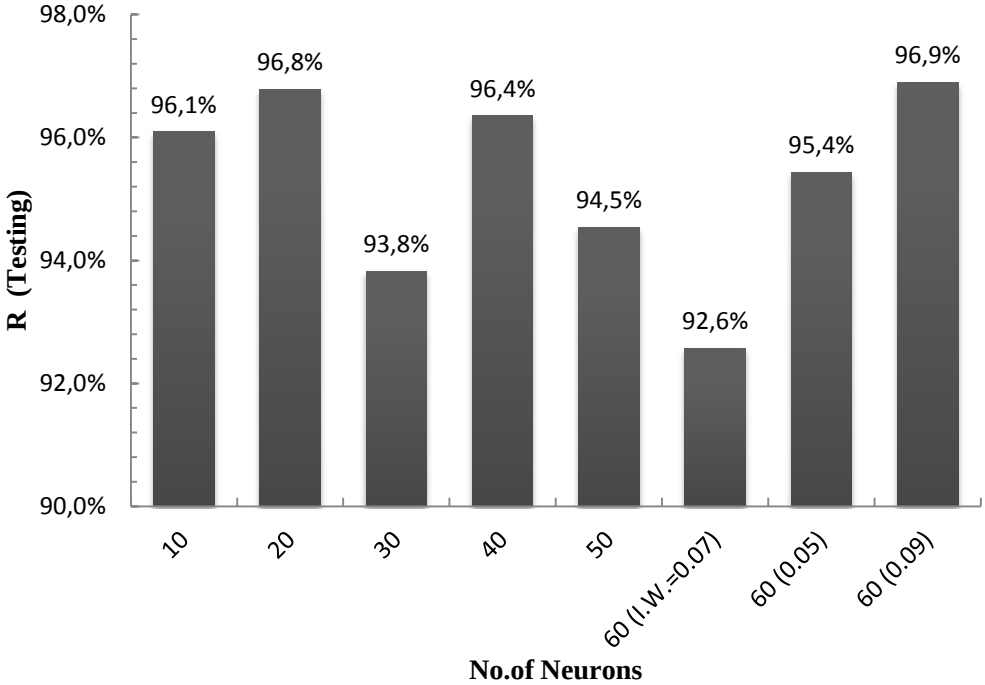


Figure 4.11: Network performance of (M 1.2) network according to initial weight change

Table 4.4: Training details and result for (M 1.2) model

Model	Case	No. of neurons	Initial weight change	Training No.	Performance goal	R^2
M 1.2	1	10	0.07	4	0.01	96.09%
	2	20	0.07	3	0.01	96.78%
	3	30	0.07	7	0.01	93.82%
	4	40	0.07	5	0.01	96.35%
	5	50	0.07	6	0.01	94.54%
	6	60	0.07	4	0.01	92.57%
			0.05	4		95.43%
			0.09	3		96.89%
					Average	95.31%

Figure 4.12 shows a good comparison between the wave characteristics and wave observed data within model (M 1.2). The best result demonstrated by (Case 6 (I.W = 0.09)) with 96.89% (R^2) tabulated in Table 4.4 with the rest of study results.

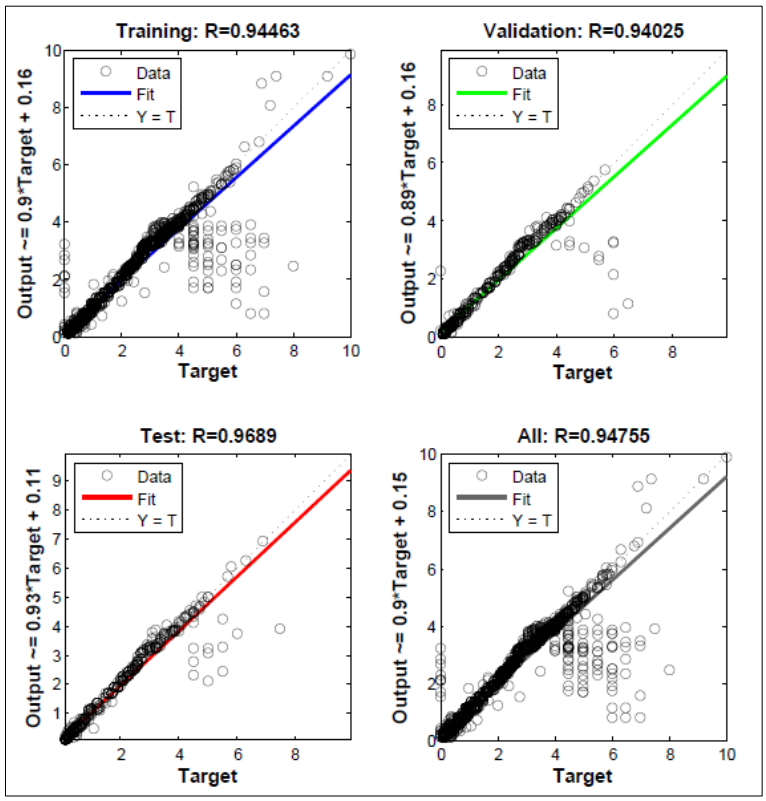


Figure 4.12: Scatter diagrams for (Case 6 (I.W. = 0.09)) predict

The results that shown in figure (4.13) of the average prediction of wave characteristics using the ANN model (M 2.1.1) agree with the wave observed data with average correlation of the ANN model and the observed data more than 96%. The best result shown in figure (4.14), which is demonstrated by (Case 5 (I.W. = 0.09)) with (R^2 = 96.89%).

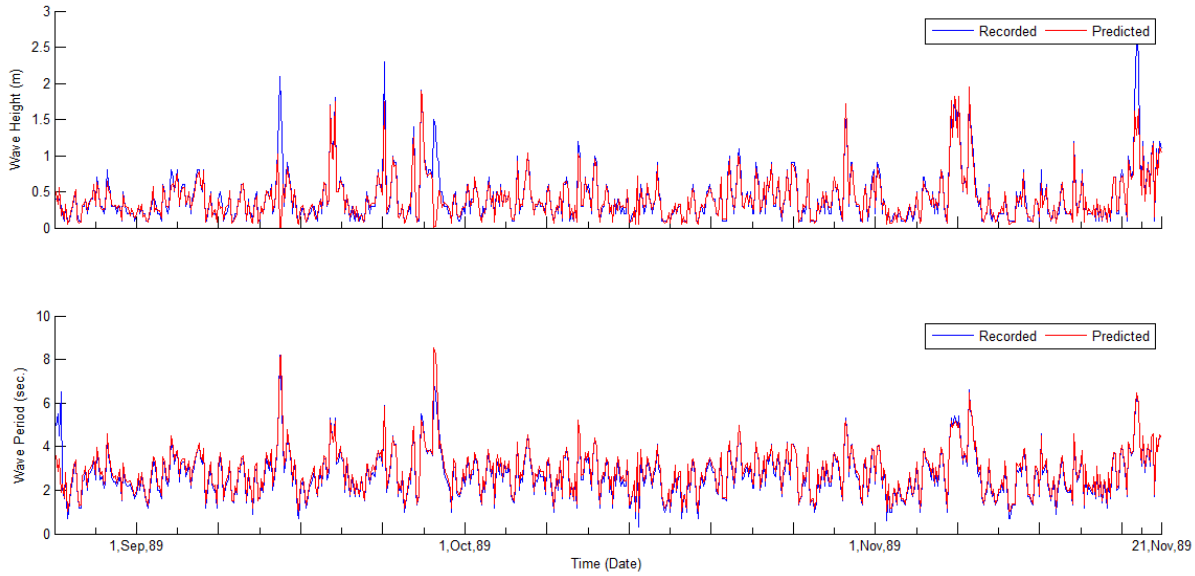


Figure 4.13: Predict wave characteristics using model (M 2.1.1) for Hs and Ts predicting

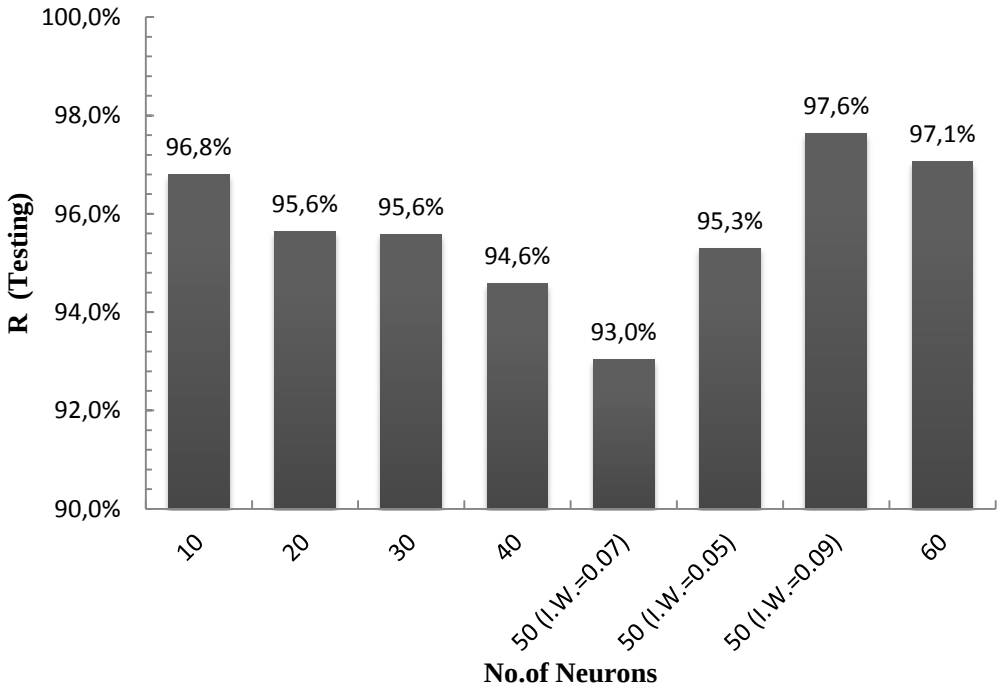


Figure 4.14: Network performance of (M 2.1.1) network according to initial weight change

Table (4.5) tabulates results of model (M 2.1.1) predicting of wave characteristics versus corresponding observations. The model exhibited a successful performance with

correlation coefficient as such the previous models. The values were more than 97% in cases 5 and 6.

Table 4.5: Training details and result for (M 2.1.1) model

Model	Case	No. of neurons	Initial weight change	Training No.	Performance goal	R^2
M 2.1.1	1	10	0.07	3	0.01	96.81%
	2	20	0.07	3	0.01	95.64%
	3	30	0.07	5	0.01	95.59%
	4	40	0.07	7	0.0001	94.58%
	5	50	0.07	3	0.0001	93.05%
			0.05	3	0.0001	95.30%
			0.09	3	0.0001	97.64%
	6	60	0.07	3	0.01	97.07%
					Average	95.71%

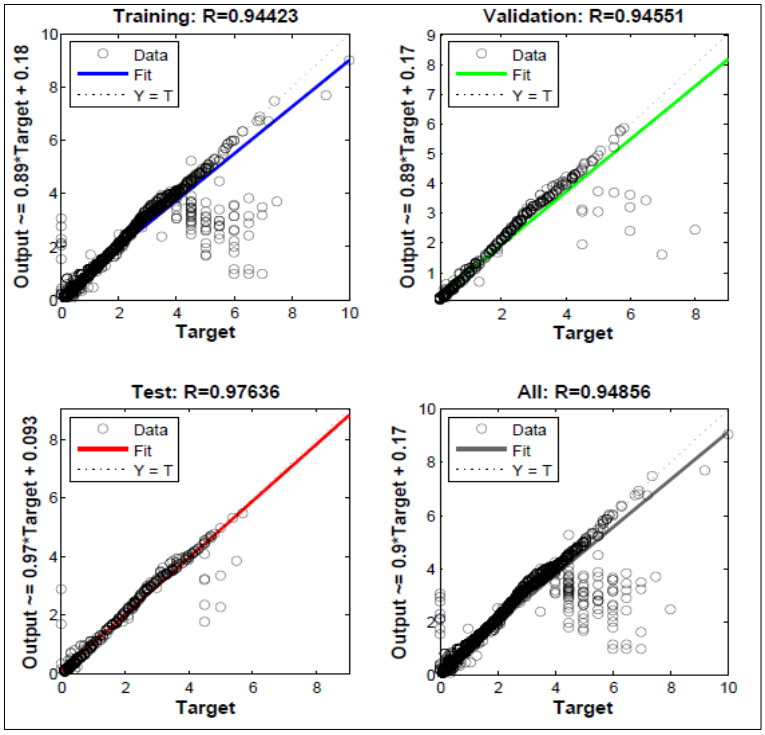


Figure 4.15: Scatter diagrams for (Case 6 (I.W. = 0.09)) predict

Figure (4.15) shows a comparison between the predictions of wave characteristics and ANN network. The values of training and testing coefficients obtained from MATLAB tool box method were 94.4% and 97.6% respectively.

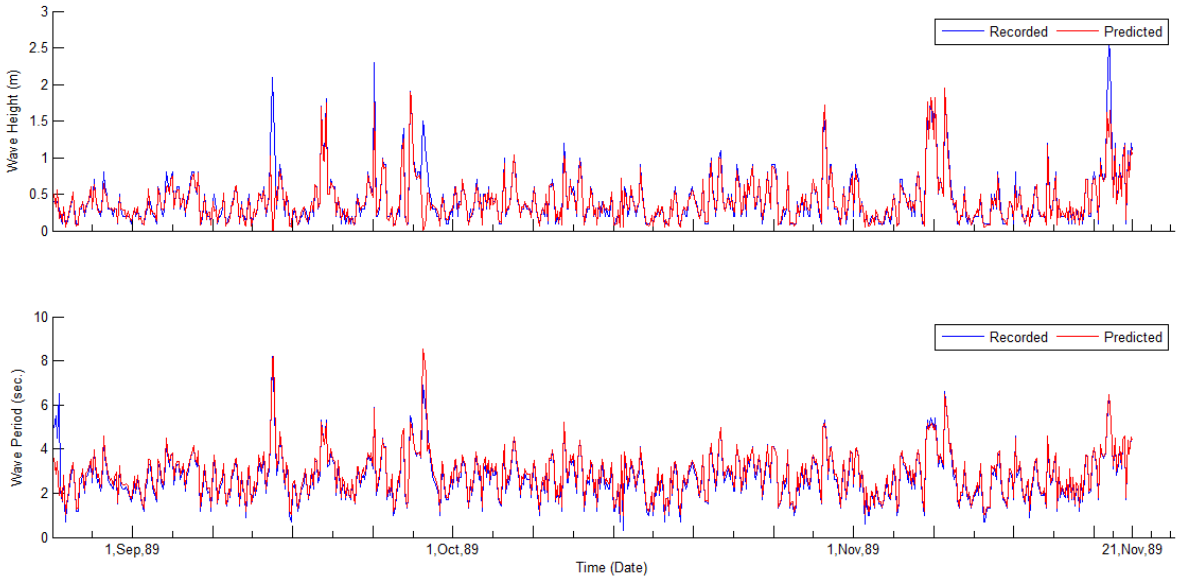


Figure 4.16: Predict wave characteristics using model (M 2.1.2) for Hs and Ts predicting

Figure (4.16) illustrates the predicted the height of wave obtained using the ANN model versus the wave observed data using model (M 2.1.2), which were trained with two parameters (wind duration and corrected wind speed).

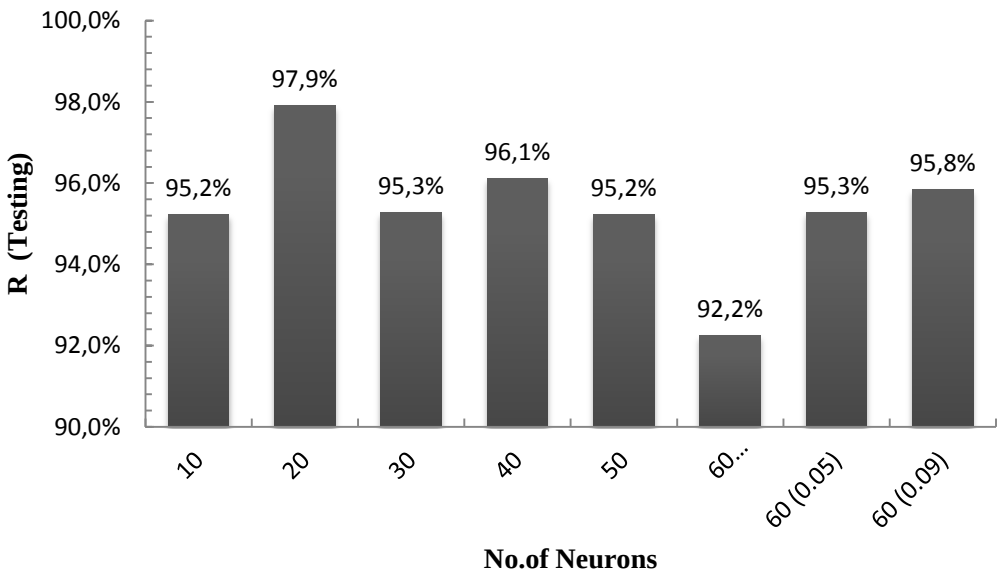


Figure 4.17: Network performance of (M 2.1.2) network according to initial weight change

In this model, the results are tabulated in Table 4.6. The correlation of the ANN model and the wave observed data is on average 95.38%, which is clearly less than the previous results. Indeed, the average prediction of wave characteristics using the ANN model agree with the wave observed and acceptable as seen in Figure (4.17)

Table 4.6: Training details and result for (M 2.1.2) model

Model	Case	No. of neurons	Initial weight change	Training No.	Performance goal	R^2
M 2.1.2	1	10	0.07	4	0.01	95.22%
	2	20	0.07	1	0.01	97.91%
	3	30	0.07	5	0.01	95.27%
	4	40	0.07	2	0.01	96.11%
	5	50	0.07	5	0.01	95.22%
	6	60	0.07	7	0.01	92.24%
			0.05	6		95.27%
			0.09	6		95.84%
					Average	95.38%

The overall best performance model was obtained with this model were relatively good with an even less number of nodes in both hidden and input layer(s) processing training with 97.91% (R^2). The rest of test results are tabulated in Table (4.6) and Figure (4.17). Figure (4.18) showsx, the results of the average prediction of wave characteristics using the ANN model agree with wave observed data. The average correlation of the ANN model and the wave observed data is more than 97%.

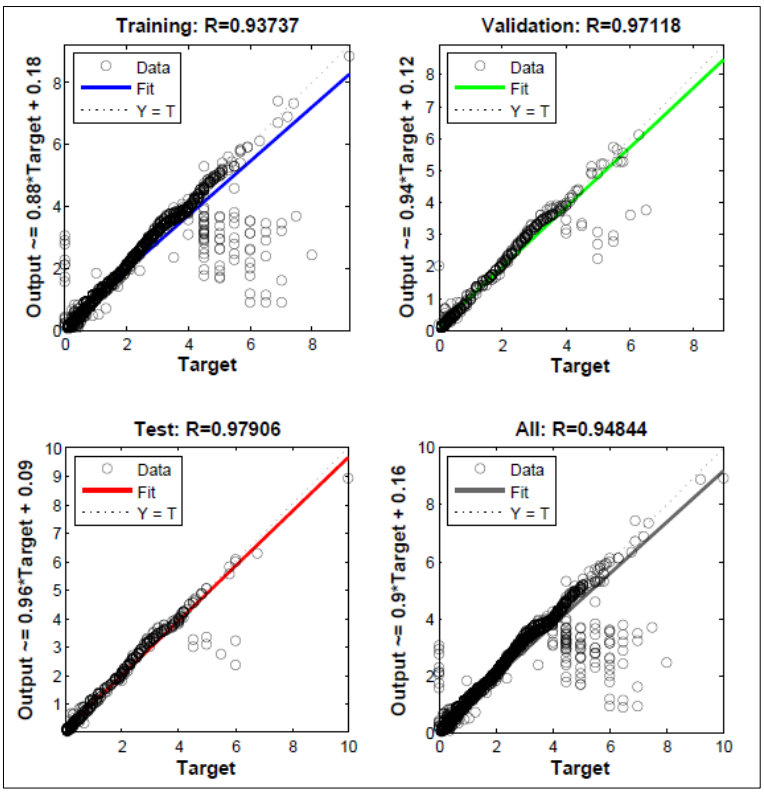


Figure 4.18: Scatter diagrams for (Case 5 (I.W. = 0.09))

The best results are demonstrated by Case 2 with 97.38% (R^2). In Table (4.6) and Figure (4.18), the rest of test results are tabulated and shown respectively.

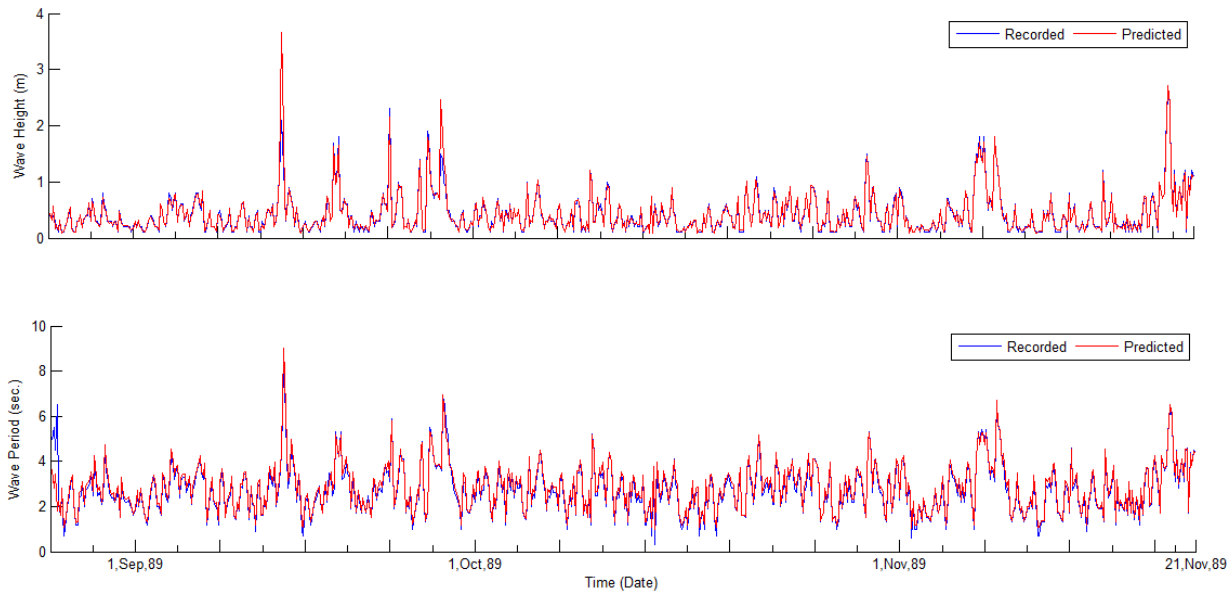


Figure 4.19: Predict wave characteristics using model (M 2.2) for Hs and Ts predicting

Figure (4.19) illustrates the predicted wave characteristics obtained using ANN model

versus the wave observed data (include five of wind parameters). The prediction was agreed between for wave characteristics and the observed data.

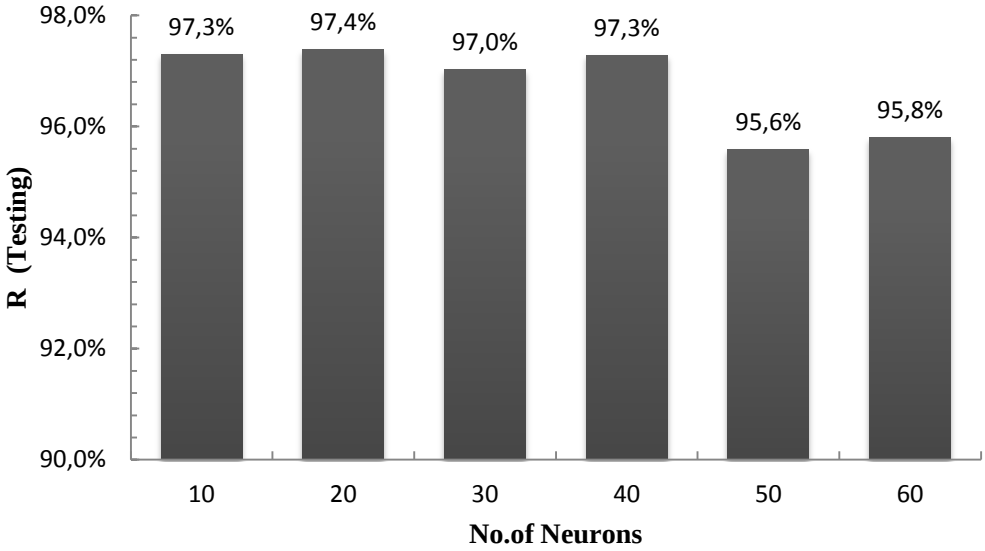


Figure 4.20: Network performance of (M 2.1.2) network according to initial weight changing

The results clearly indicate that the average of correlation coefficient is better than the previous ANN models, such as in model (M 1.1) and Case (M 2.1.1) where the R^2 is greater than 96%.

Table 4.7: Training details and result for (M 2.2) model

Model	Case	No. of neurons	Initial weight change	Training try	Performance goal	R^2
M 2.2	1	10	0.07	2	0	97.30%
	2	20	0.07	2	0	97.38%
	3	30	0.07	2	0	97.02%
	4	40	0.07	2	0	97.28%
	5	50	0.07	4	0.01	95.59%
	6	60	0.07	4	0.01	95.80%
					Average	96.73%

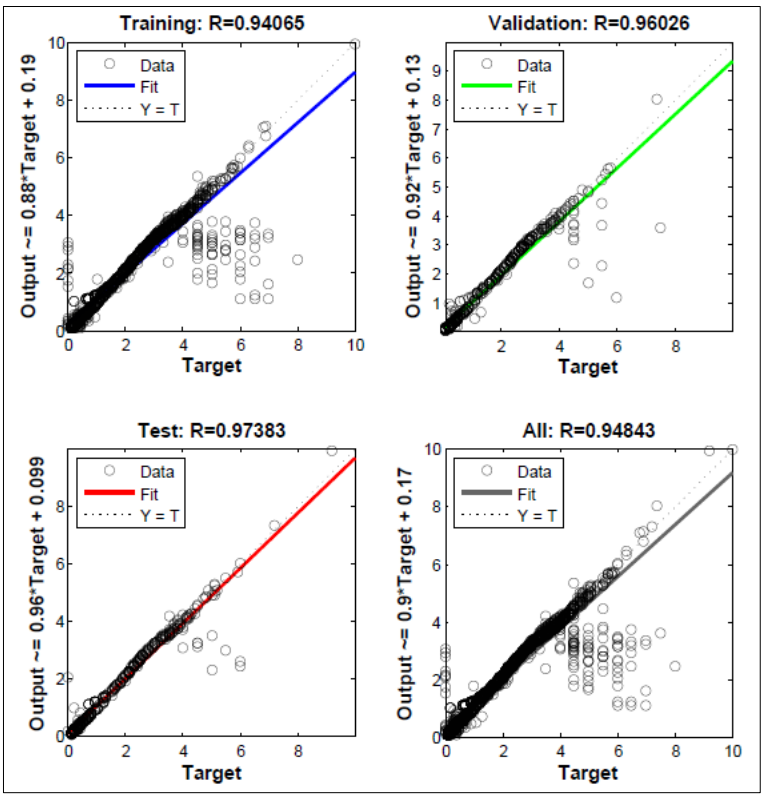


Figure 4.21: Scatter diagrams for case 2

From the results, we can identify that prediction outcome are vary with each ANN model even if we trained and tested the same cases. This difficulty commonly occurs when applying artificial neural networks to engineering. The ANNs training are based on a group of databases, composed of parameters from (Kabir Sadeghi, 2007) numerical simulation model. When we calculate wave characteristics using a numerical model, each parameter, such as wind speed, fetch, etc. are individually, important factors, and directly affect the results. However, when we apply these parameters to determine wave height using ANN model, each parameter is become one of the ANN neuron in the input layer. In other words, even if one parameter was missed as an input to the ANN model, it is still possible to obtain reasonable results.

4.7 A Comparison of Recorded wave Data with those Predicted by Bretschneider Equations and ANN Method.

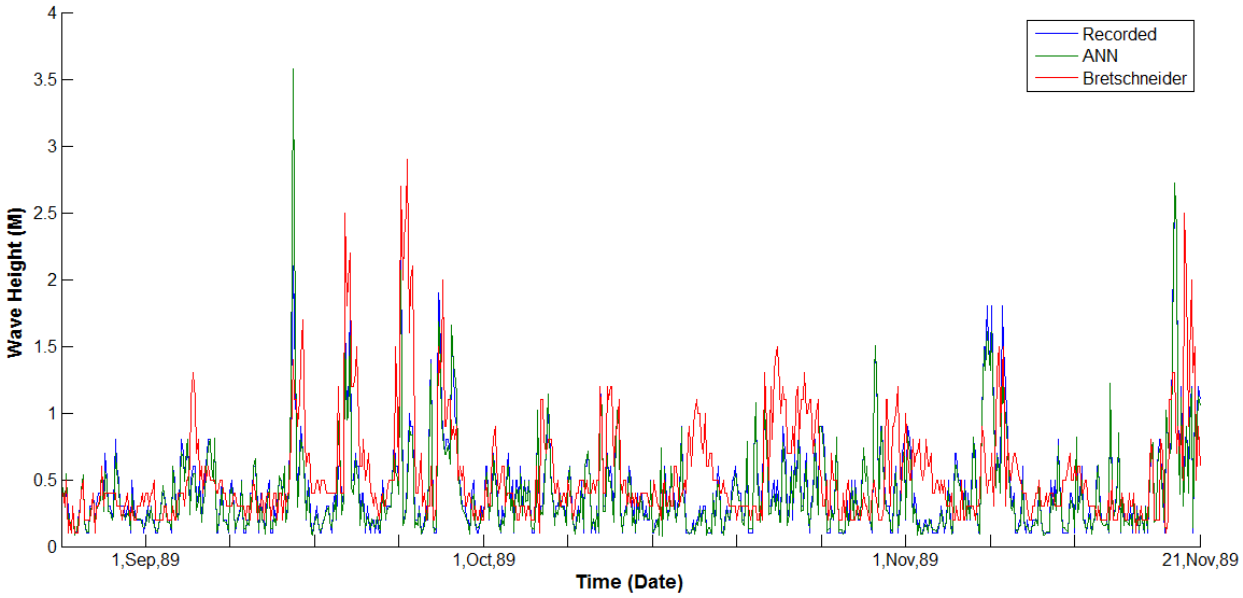


Figure 4.22: Comparison of wave height between prediction methods and recorded data (Model 1.1)

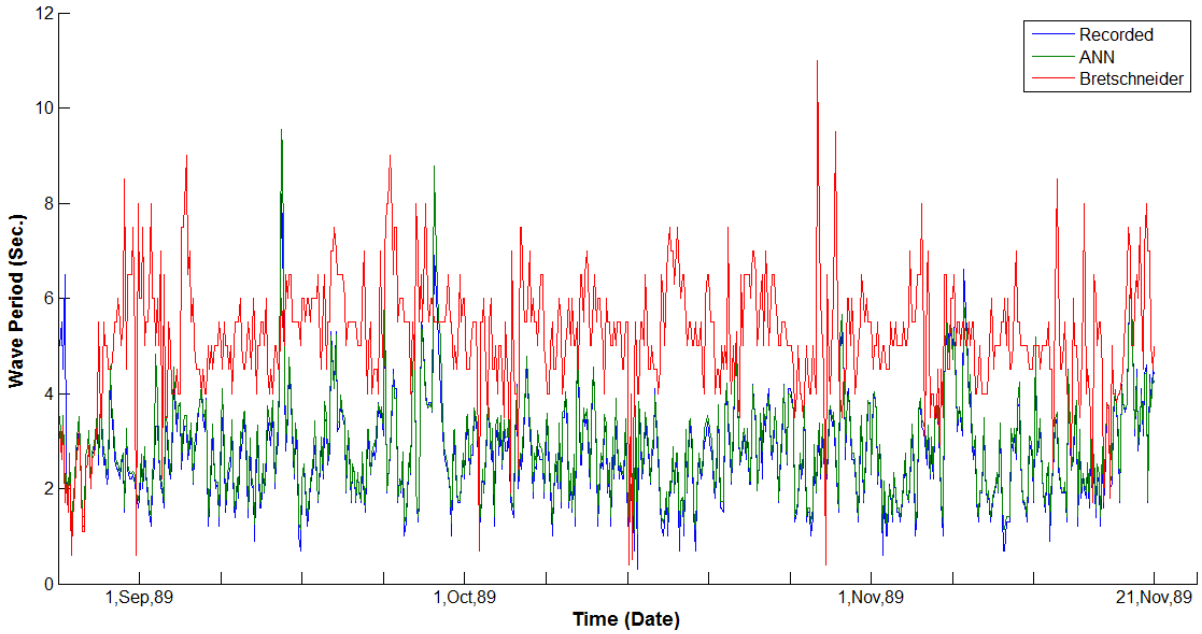


Figure 4.23: Comparison of wave period between prediction methods and recorded data (Model 1.1)

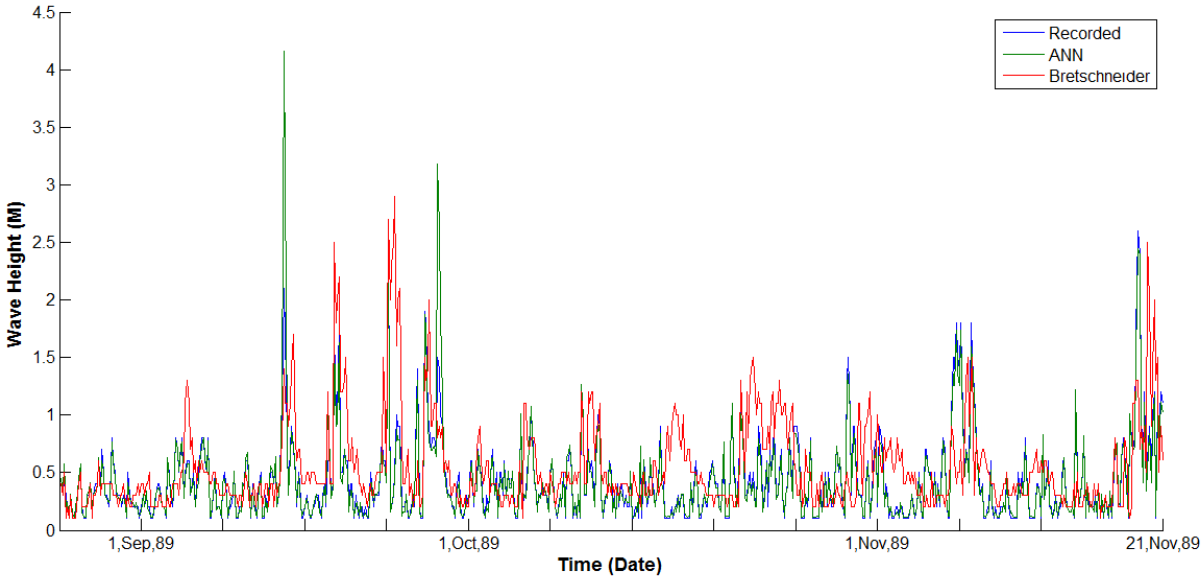


Figure 4.24: Comparison of wave height between prediction methods and recorded data (Model 1.2)

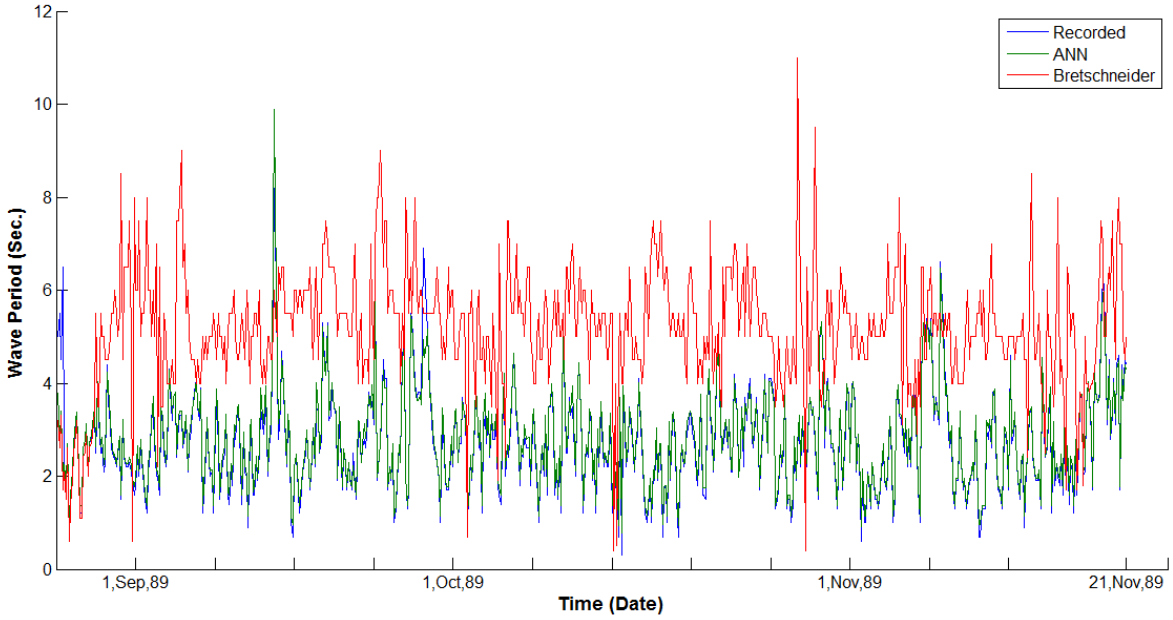


Figure 4.25: Comparison of wave period between prediction methods and recorded data (Model 1.2)

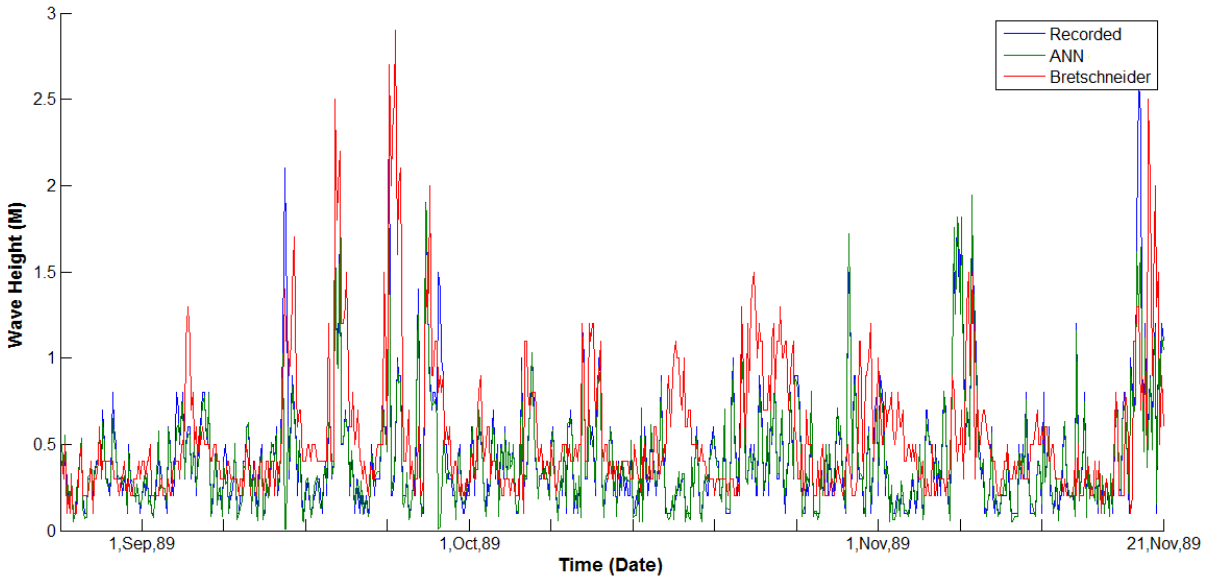


Figure 4.26: Comparison of wave height between prediction methods and recorded data (Model 2.1.1)

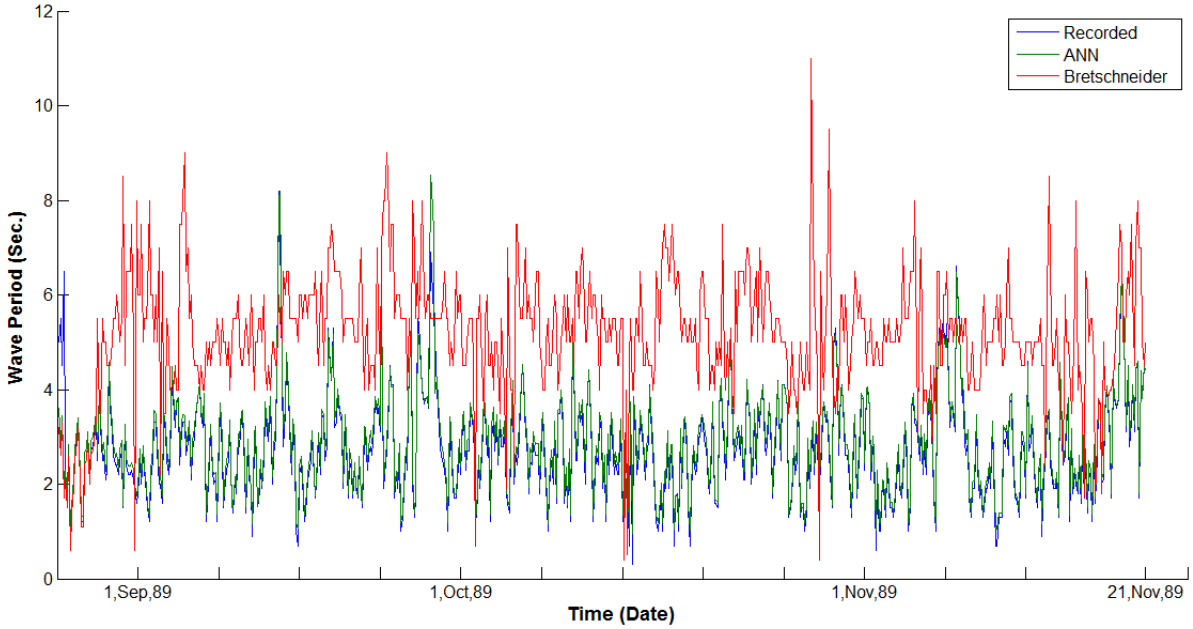


Figure 4.27: Comparison of wave period between prediction methods and recorded data (Model 2.1.1)

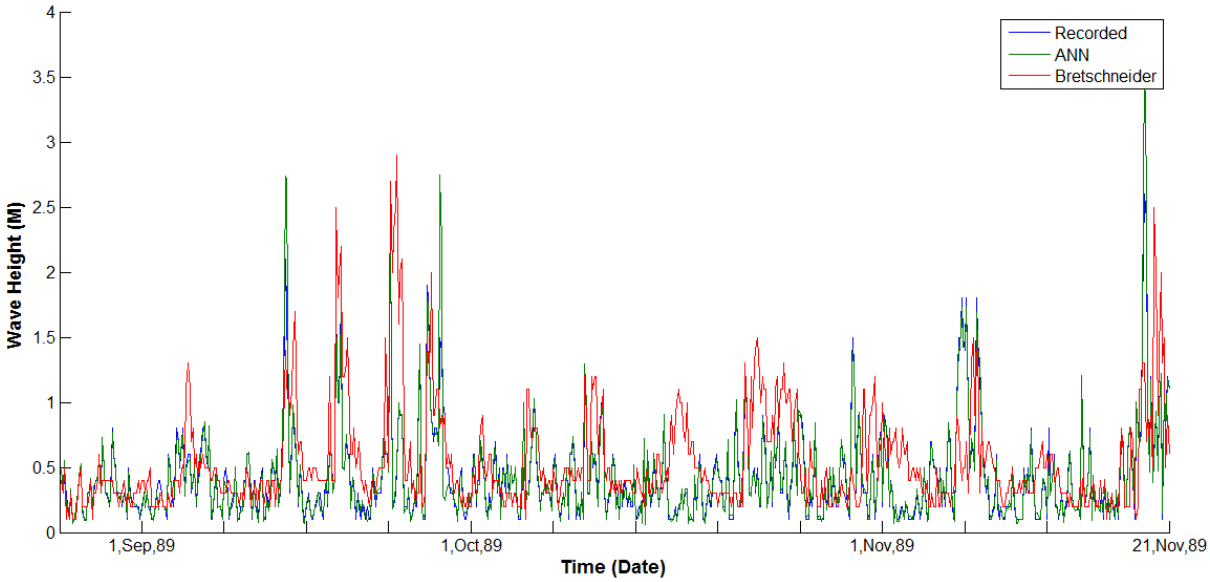


Figure 4.28: Comparison of wave height between prediction methods and recorded data (Model 2.1.2)

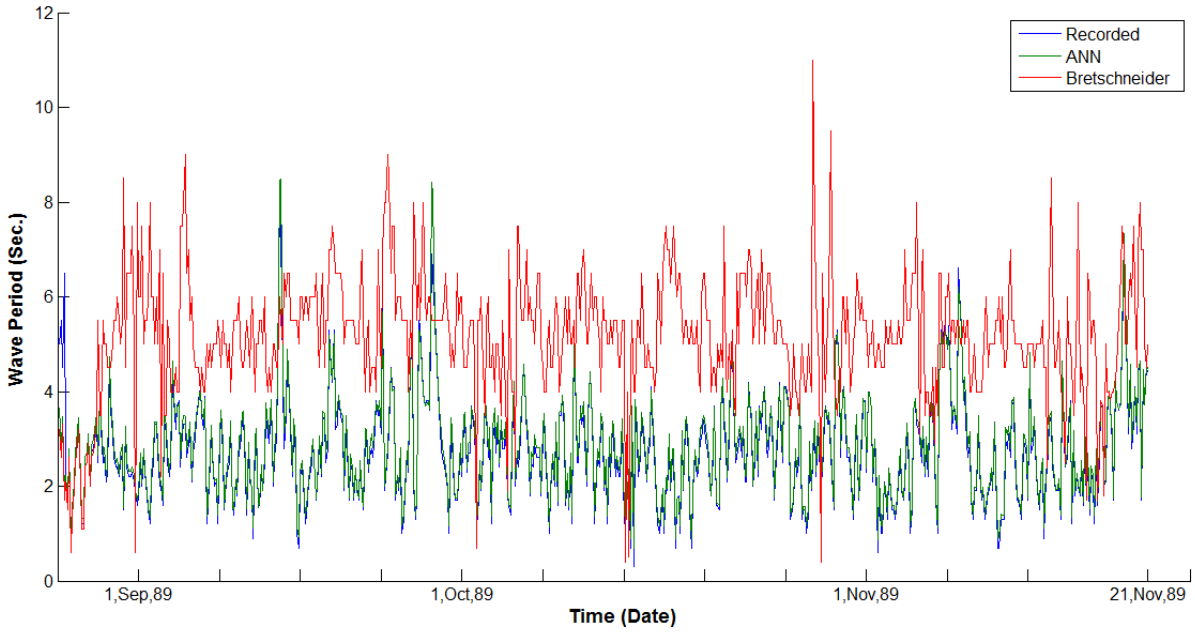


Figure 4.29: Comparison of wave period between prediction methods and recorded data (Model 2.1.2)

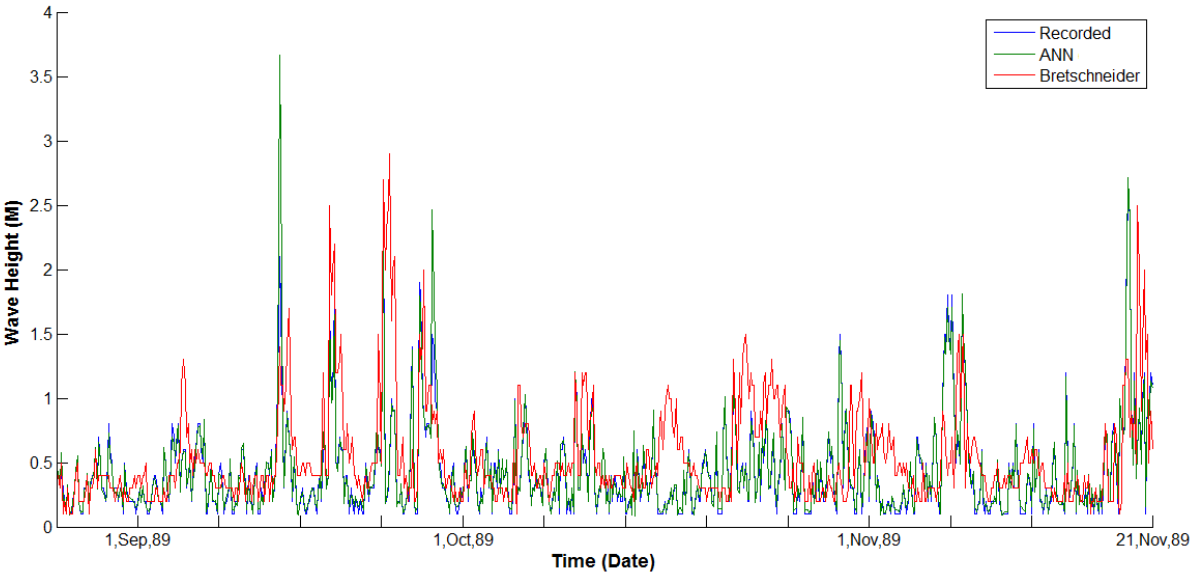


Figure 4.30: Comparison of wave height between prediction methods and recorded data (Model 2.2)

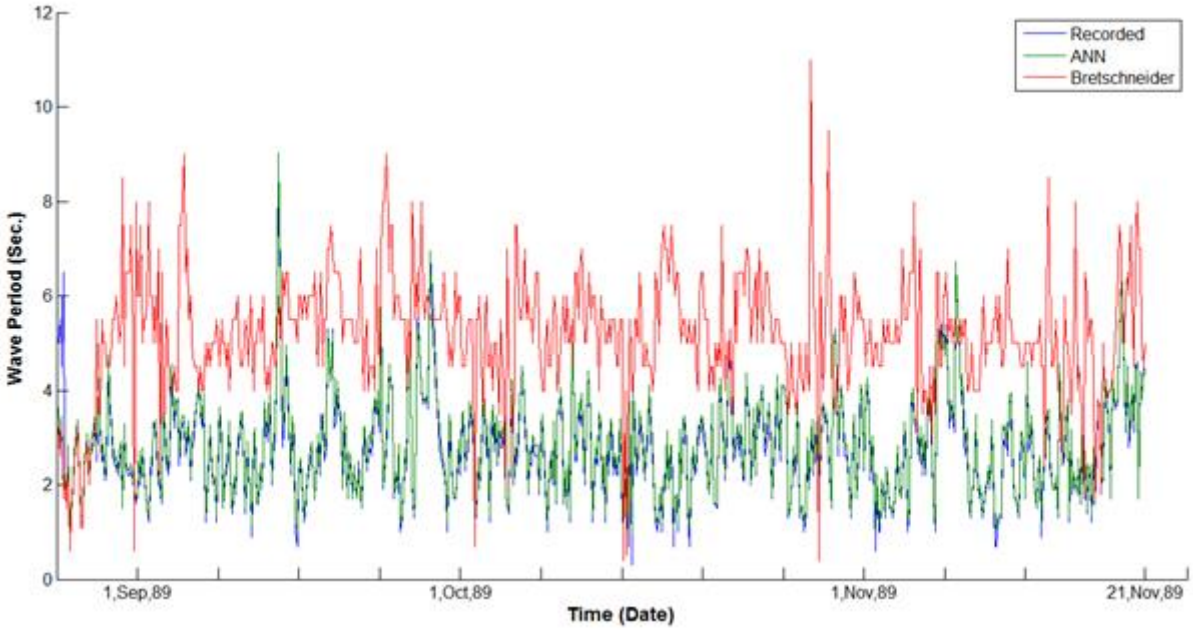


Figure 4.31: Comparison of wave height between prediction methods and recorded data (Model 2.2)

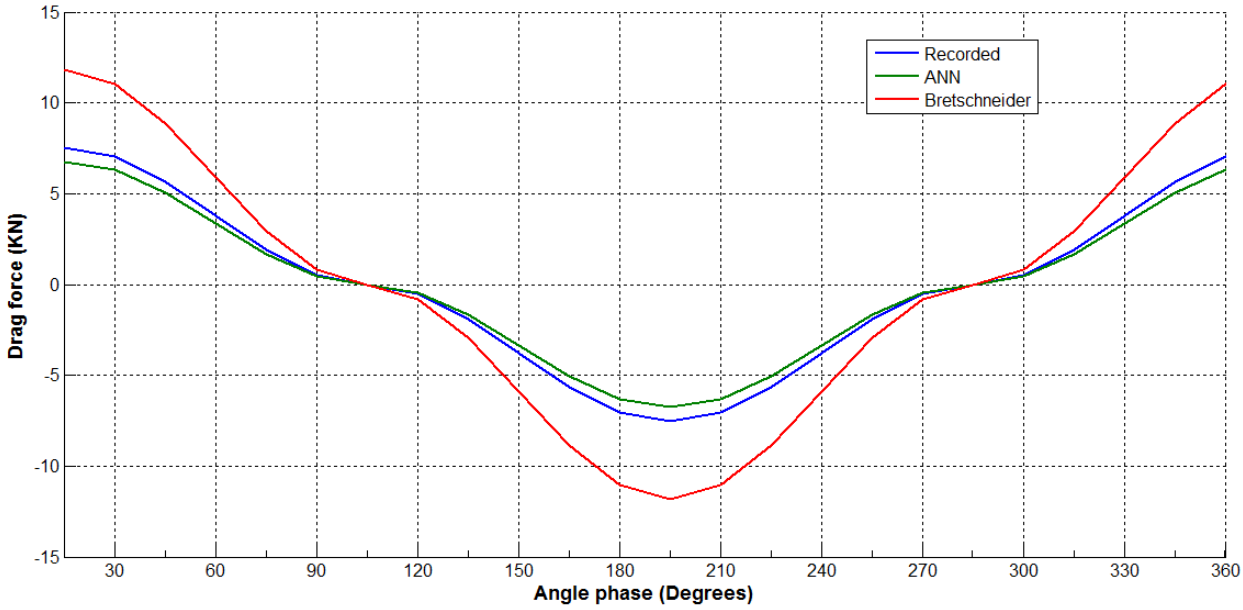


Figure 4.32: Comparison of drag force from the maximum recorded wave data with the maximum of those predicted by Bretschneider equations and ANN

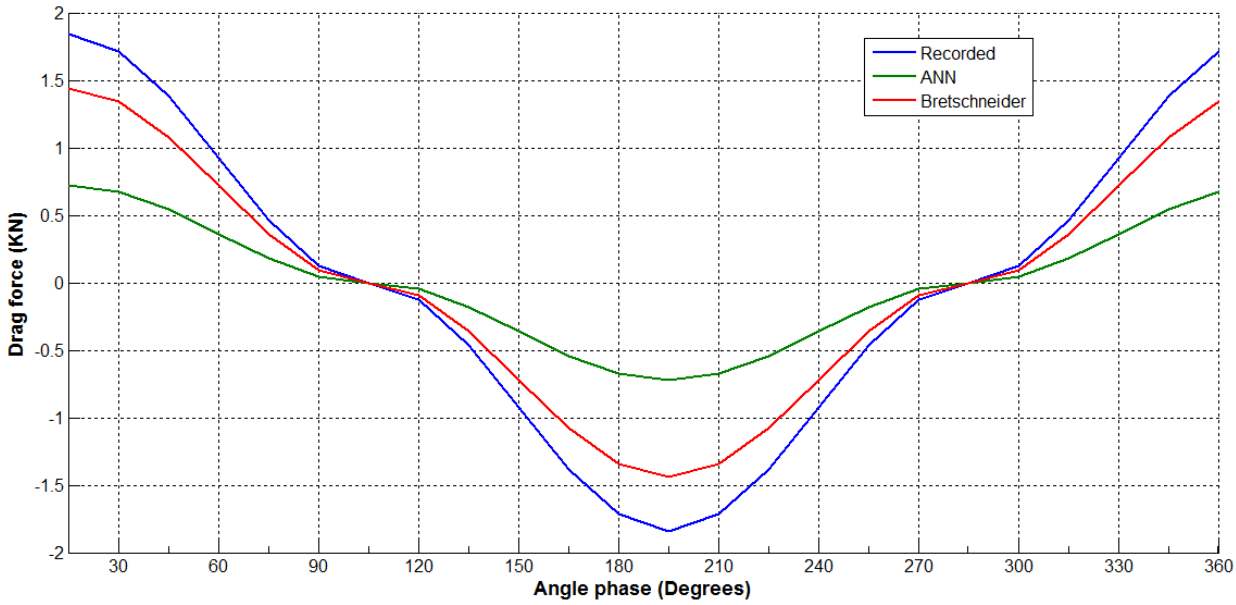


Figure 4.33: Comparison of drag force from the average recorded wave data with the average of those predicted by Bretschneider equations and ANN

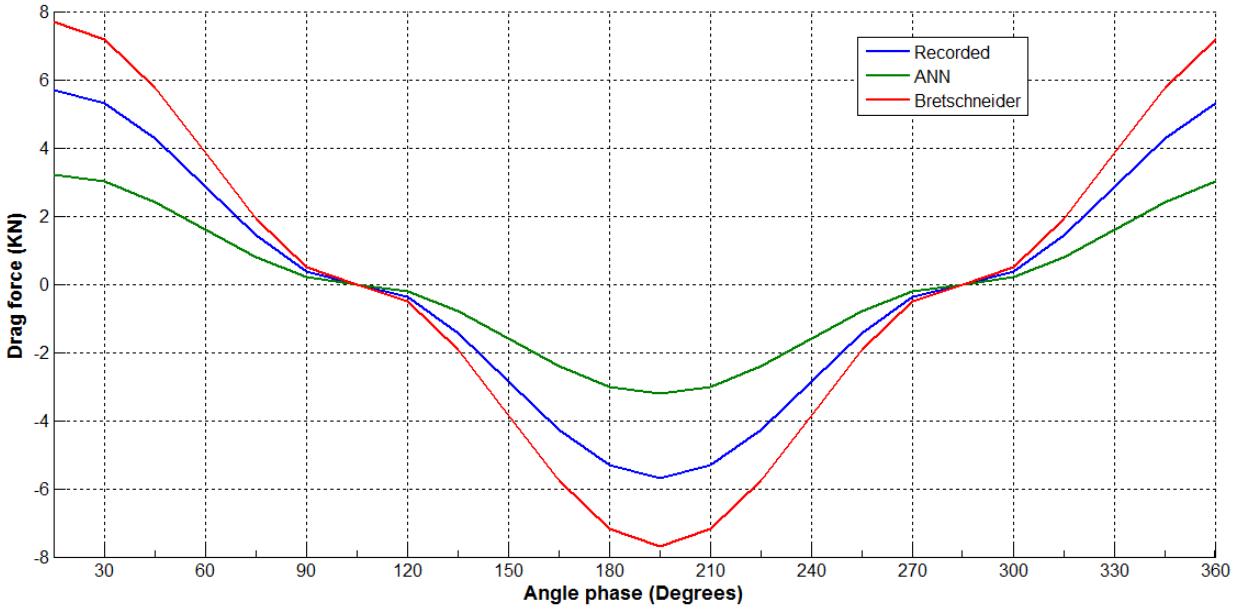


Figure 4.34: Comparison of drag force from the average of the maximum and the average recorded wave data with the average of those predicted by Bretschneider equations and ANN

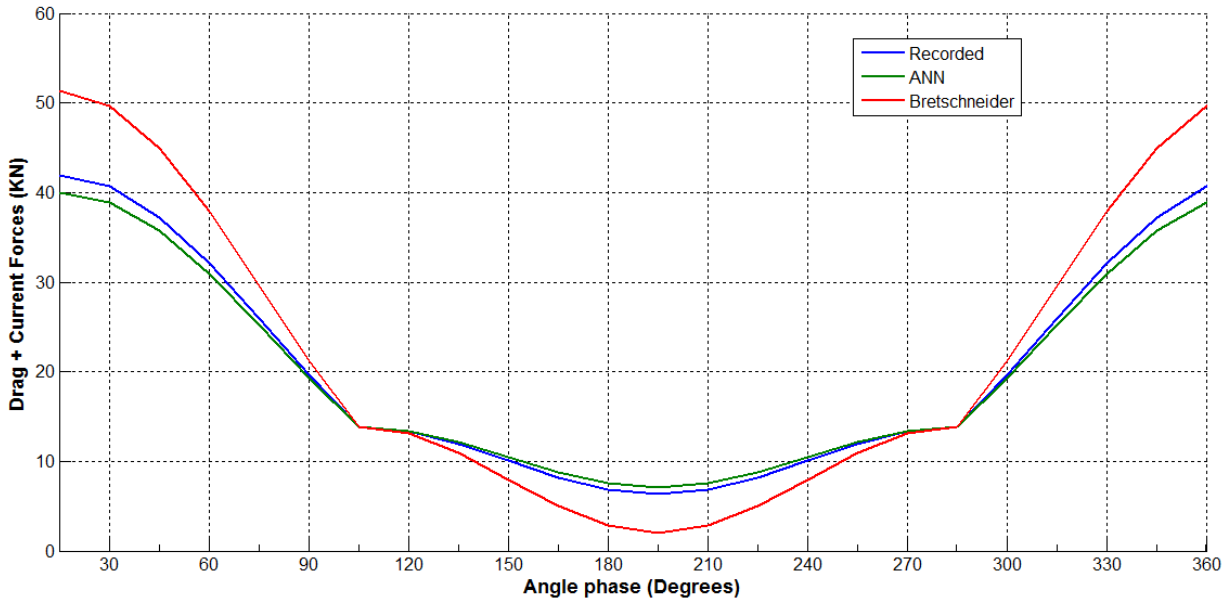


Figure 4.35: Comparison of drag & current forces from the maximum recorded wave data with the maximum of those predicted by Bretschneider equations and ANN

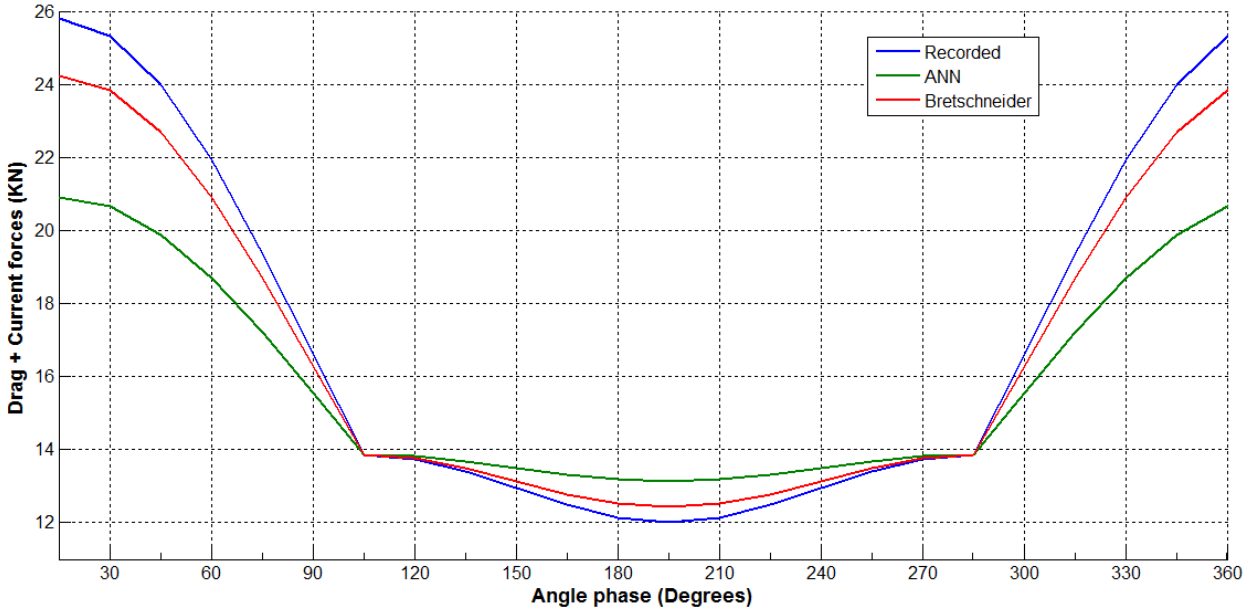


Figure 4.36: Comparison of drag & current forces from the average recorded wave data with the average of those predicted by Bretschneider equations and ANN

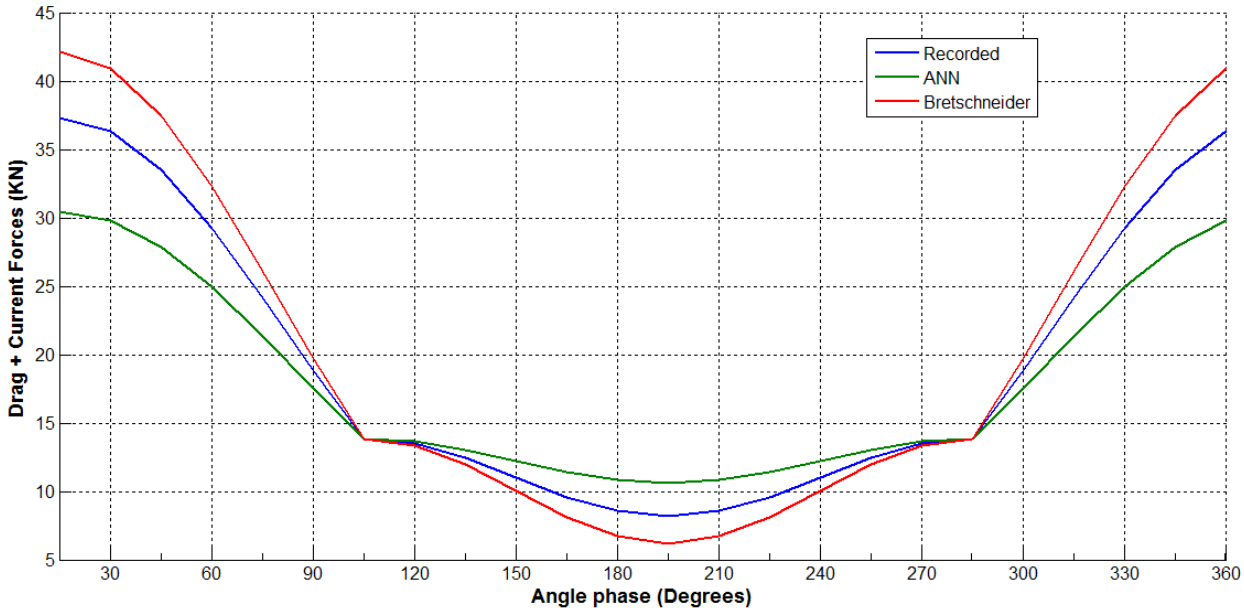


Figure 4.37: Comparison of drag & current forces from the average of the maximum and the average recorded wave data with the average of those predicted by Bretschneider equations and ANN

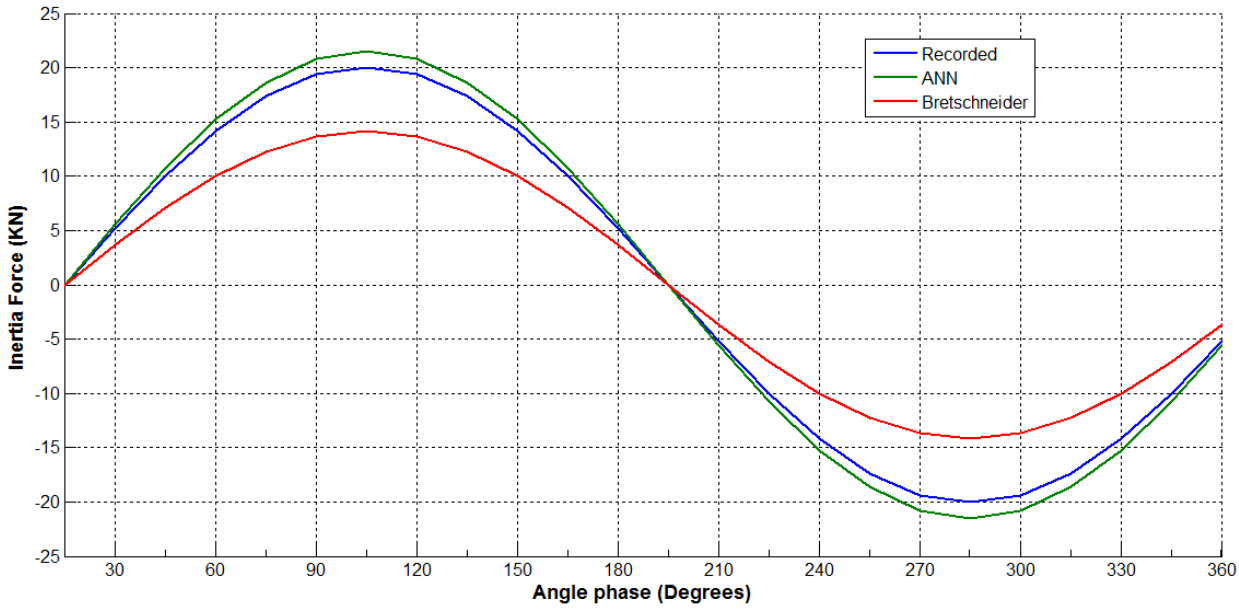


Figure 4.38: Comparison of inertia force from the maximum recorded wave data with the maximum of those predicted by Bretschneider equations and ANN

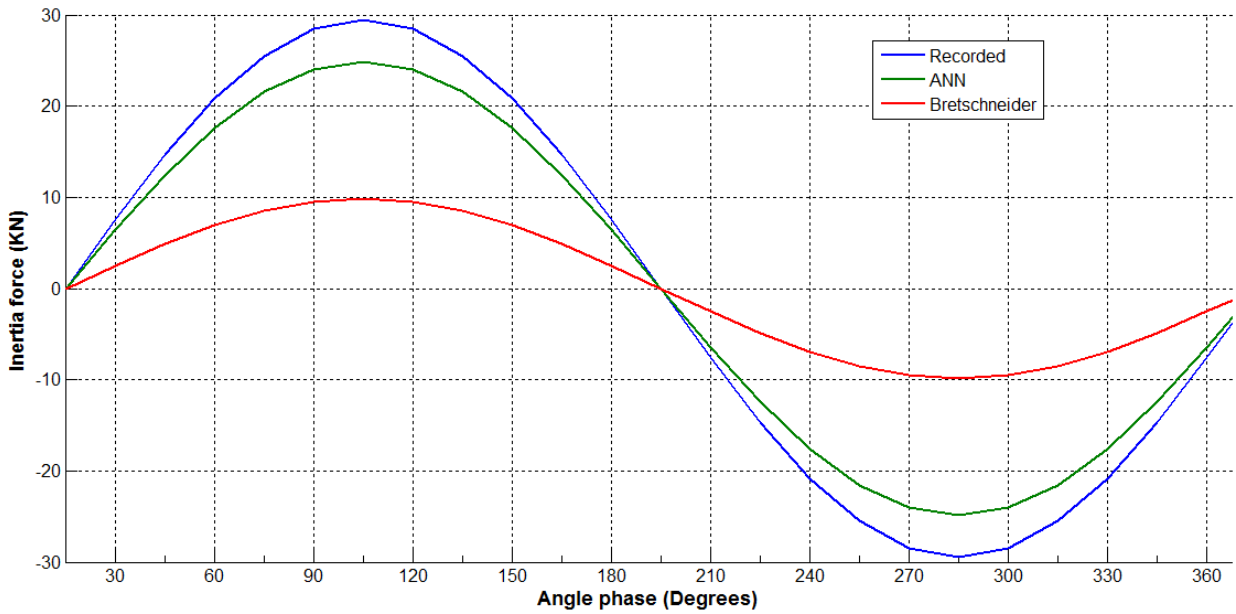


Figure 4.39: Comparison of inertia force from the average recorded wave data with the average of those predicted by Bretschneider equations and ANN

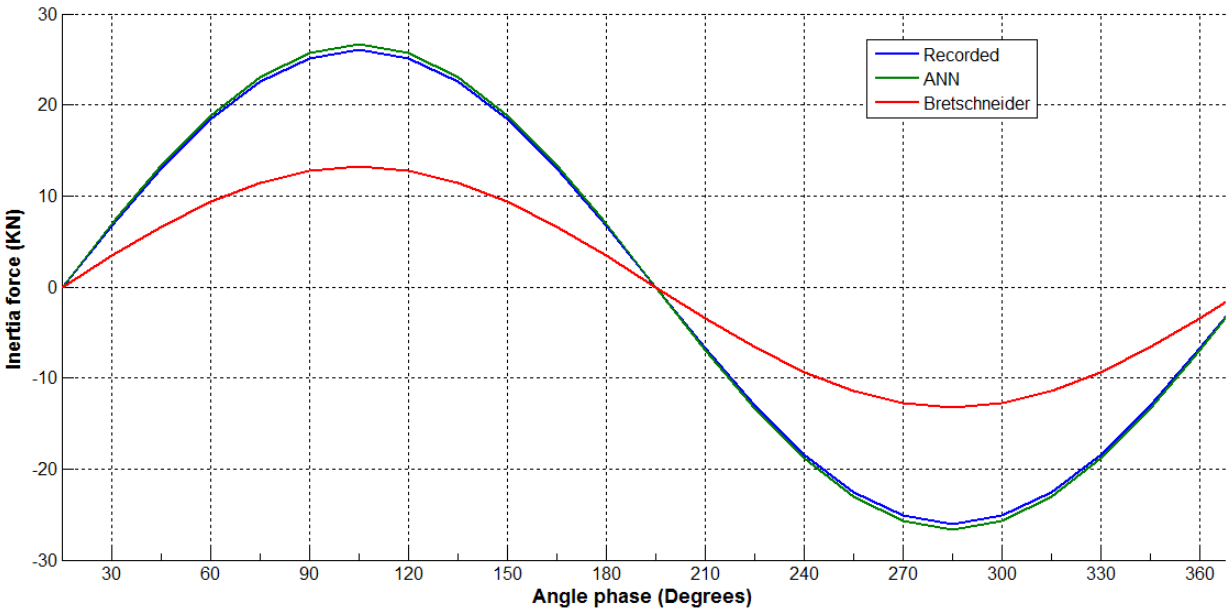


Figure 4.40: Comparison of inertia forces from the average of the maximum and average recorded wave data with the average of those predicted by Bretschneider equations and ANN

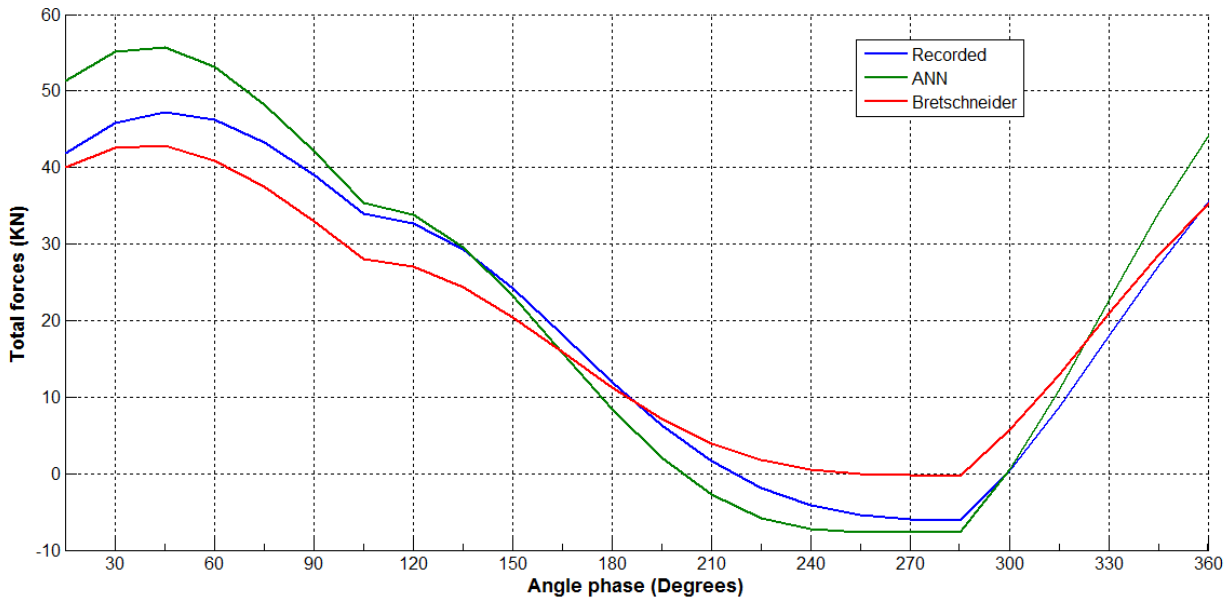


Figure 4.41: Comparison of total force from the maximum recorded wave data with the maximum of those predicted by Bretschneider equations and ANN

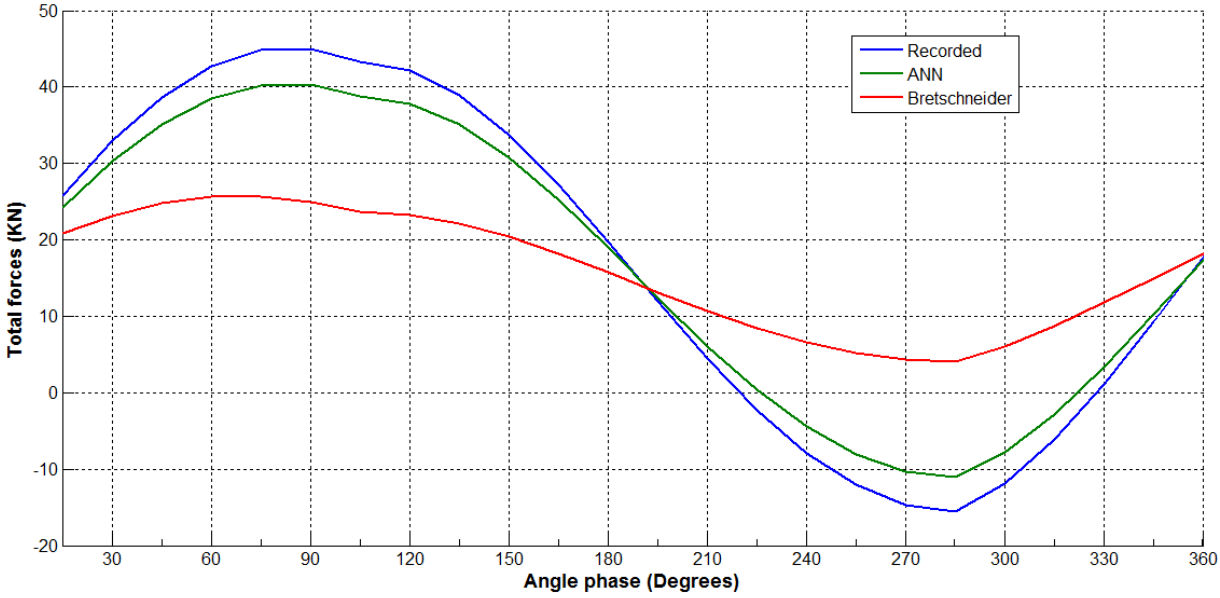


Figure 4.42: Comparison of total force from the average recorded wave data with the average of those predicted by Bretschneider equations and ANN

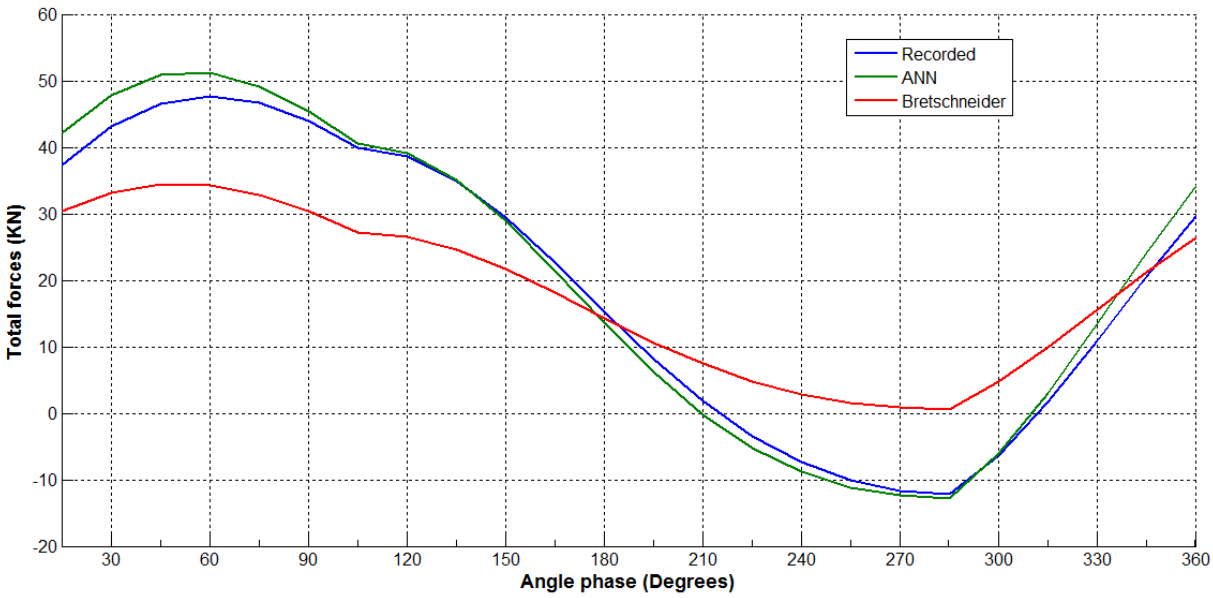


Figure 4.43: Comparison of total forces from the average of the maximum and average recorded wave data with the average of those predicted by Bretschneider equations and ANN

The results of ANN models in this study were compared with (Sadeghi, 2007) for the prediction of the wave characteristics using Bretschneider's formula for a specific area in the Caspian Sea which gave results considered satisfactory. However, there is a improvement in this study were 96.73, 95.71 and 96.06 % better for models (2.2), (2.1.1) and (1.1), respectively, in case to compared with that previous study (Sadeghi, 2007).

Furthermore, an important issue is that the wave period output from Bretschneider's formula (Sadeghi, 2007) gave overestimated unlike the wave height result in that location. This study results showed that wave characteristics obtained from almost all models leads to less error and higher correlation in comparison with the other models. This means that the ANN models are more appropriate than the other models for forecasting the wave characteristics for this location.

4.8 Hydrodynamic Loads Calculation

In this section, the primary objectives of the present study will be

i. To write a computer program that is able to simulate wave and current forces on template offshore structures using traditional numerical methods with minimal sacrifice towards accuracy.
ii. To couple the written program to an existing 3-D finite element program.

Fixed offshore consider as unique structures because of their located in the ocean or sea, they construct to carry staff accommodations and offices as well as the equipment of industry that services oil and gas drilling and production.

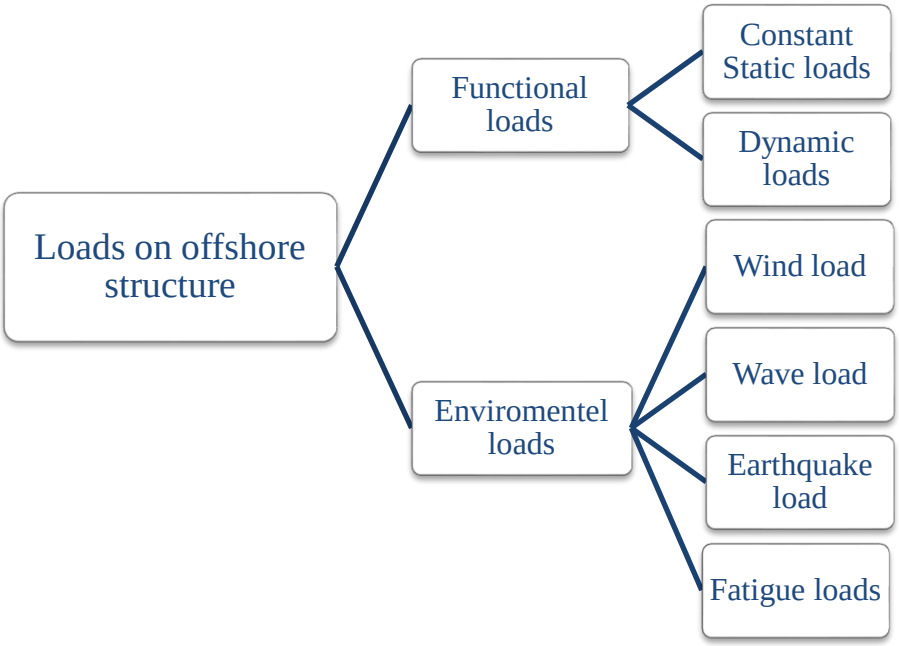


Figure 4.44: The important loads act on the Jacket platforms

The robust design of jacket offshore structure is reliant on defining the total applied load accurately. Most of loads that affect the platform laterally, such as wind and waves, are variable, so we depend on metocean environmental data for the location of the platform.

4.8.1 Wave loads

Wave loads are generated according to Morison's formula. Environmental conditions are based on the hydrodynamic coefficients of tubular members are taken in accordance with the recommendations of the API-RP 2A 21st edition.

Table 4.7: Drag and inertia coefficients for vertical cylinders (Deo et al., 2001)

	Cm	**Cd**
Linear Theory	0.95	1.0
	2.0	1.0 to 1.4

Forces on the structure will be determined by applying Morrison's equation. Choosing an appropriate method for determining these coefficients for a specified data is hard and their computing is a time-consuming affair. Basic drag and inertia coefficients (C_d and C_I) will be used to evaluate wave forces on cylindrical surfaces, which should be smaller than the values given in Table 4.9:

For offshore design, the theories that will be used are determined by the policy under which the designing engineers are working. The selection of the best method is defined by the curve in Figure 3.14, (outlined in Chapter 3), from APIRP2A

Where,

H/gT^2 : Represents dimensionless wave sleepiness.

d/gT^2 : Represents dimensionless relativewaterdepth.

d : Represents mean waterdepth.

T : Represents wave period

H : Represents wave height

g : Represents the acceleration of gravity.

For the purposes of calibration and comparison, two numerical examples have been selected, namely:

- Numerical Example I - (comparing the results of total forces of the present study to that of SACS for a vertical cylinder by using Airy's linear theory).
- Numerical Example II - (comparing the results of total forces of the present study to that of SACS for vertical cylinder by using $\mathrm{stock}^{5\mathrm{th}}$ order theory).

Table 4.8: The wave parameters and cylinder details

Wave period (Sec.)	9.3
Gravity $(^{m}/_{s})^{2}$	9.81
Depth (m)	22.8
Wave height (m)	10.67
Diameter (m)	1.22
Density $(^{kg}/_{m^3})$	1030
Kinematic viscosity(m^2/s)	1.17E-06

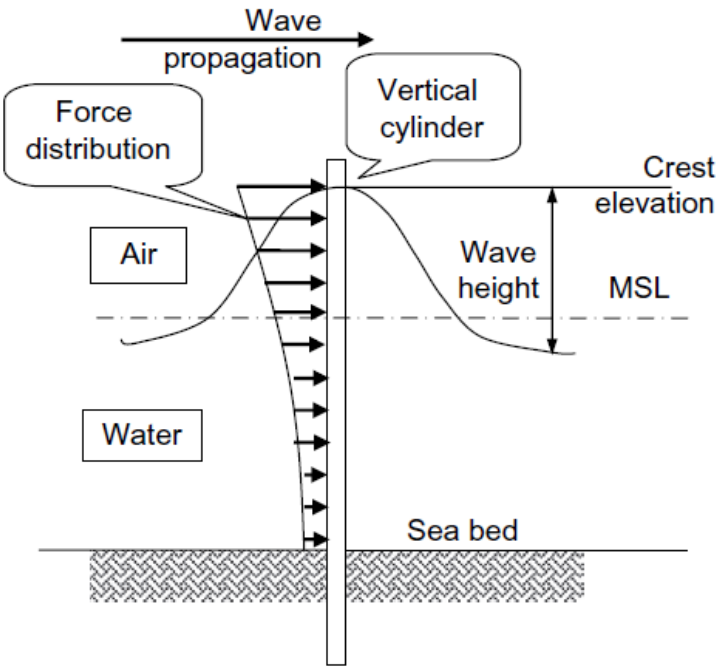


Figure 4.45: Wave force distribution on a cylinder pipe

A spreadsheet has been developed to calculate manually the wake kinematics, , and the corresponding fluid forces, through Morison equation, for a cylinder which is considered to be in the vertical position. The distributed wave force acting on that cylinder arising from the present study to calibrate and compare to the results of the SACS program as shown in

Figure 4.46. The wave parameters and cylinder details used in both of numerical examples are presented in Table 4.7.

Table 4.9: Wave force calculations

Deep water wave length: using Equation (3.18)	134.92
Relative waterdepth (d/Lo)	0.1689835
Wave length for intermediate waterdepth L using Table C-2 "	114.57
Wave Number: using Equation (3.22)	0.0548414
Maximum horizontal velocity: using Equation (3.20)	5.5013097
Wind drift current (m/s) using Equation	1.5
Drag coefficient (C_D) using Table (4.9)	1
Inertia coefficient (C_M) using Table (4.9)	2

The results obtained from of two different wave kinematic theories: Airy´s linear wave theory and stock^{5th} theory were compared with a SACS static wave analysis, presents a comparison of the base shear force, per phase angle (Appendix 5-A).

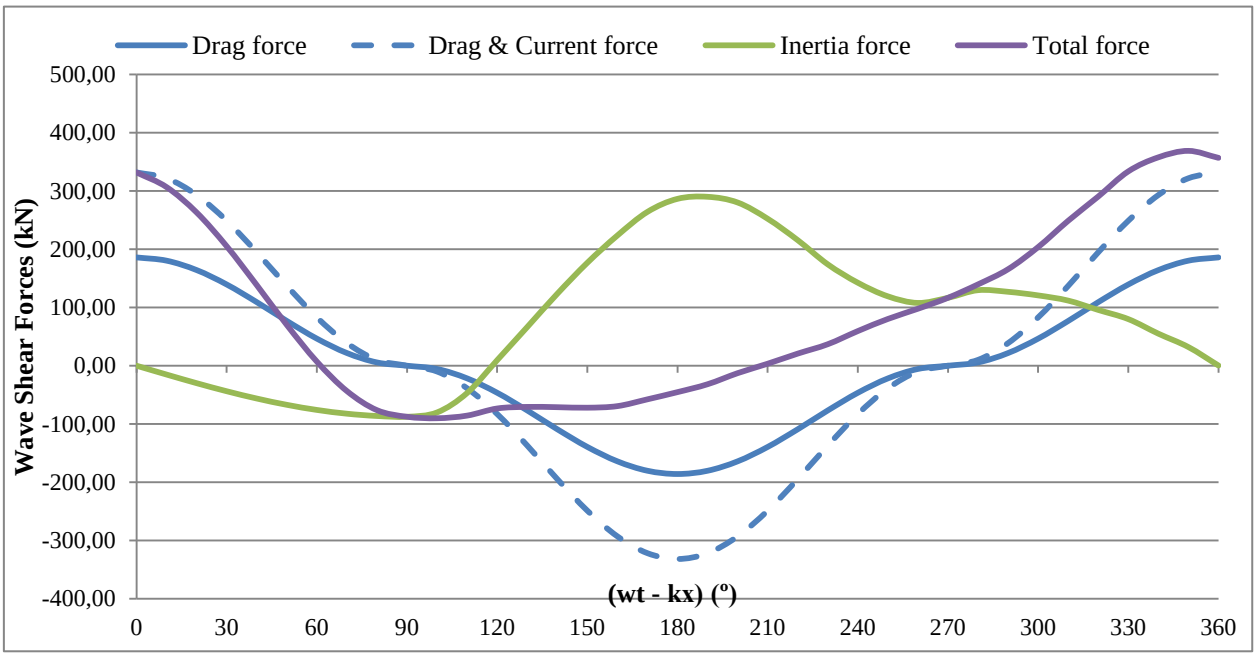


Figure 4.46: Base shear distribution per phase angle

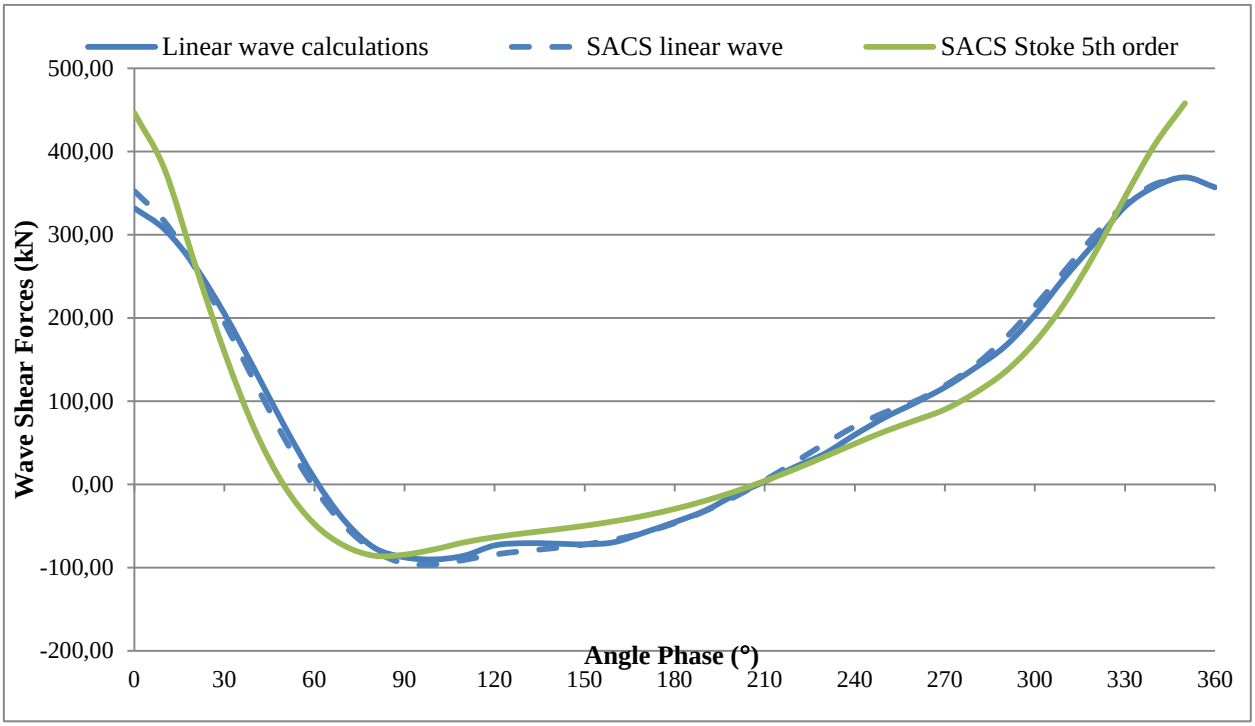


Figure 4.47: Base shear distributions, per phase angle, comparison between linear wave calculations and SACS results

A similar trend can be seen to that of the results of the 1st numerical example, with all results of the present study slightly underestimating the results of the SACS program.

Figure 4.47shows the distribution of wave forces plus currents for a vertical cylinder arising from both Airy and stock^{5th}order theory for different phase angles. The average difference between the linear wave theory results between manual and SACS calculations was of less than 2%, the results can be considered as acceptable results. The differences in the results may lie in the tolerance for wave number (k) which is used in most equations of the wave kinematics, thus affecting subsequent results. (Appendix 5-B) presents a comparison between linear wave calculations and SACS results.

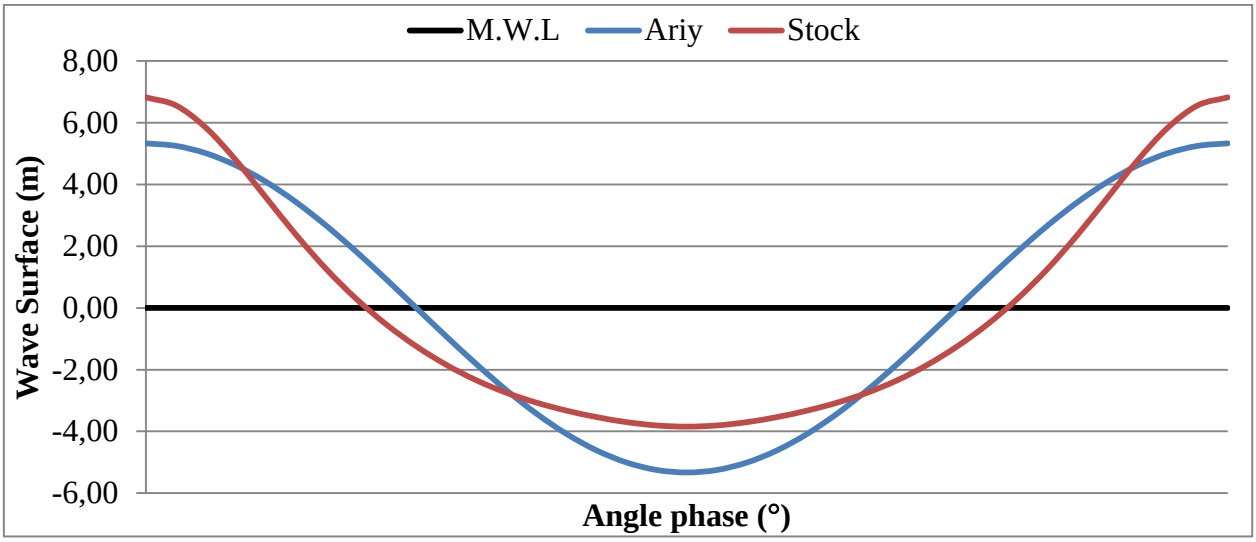


Figure 4.48: Wave surface comparisons for different theories

Obviously, wave loads predicted from stock^{5th}order theory are significantly higher compared to that of Airy's linear theory. In Figure 4.21 the maximum horizontal force arising from Airy's linear theory predicted by SACS is 352.39KN and the maximum horizontal force arising from stock^{5th}order theory predicted by SACS is 446.33KN respectively.

Apparently, the stock^{5th}order theory gave noteworthy higher load values than that we got by spreadsheet in linear theory as shown in Figure 4.47. In this Case, Airy's linear theory underestimated the forces arising from stock^{5th} order theory by 23.5%, which would be logically as expected, because of the correction made to the linear sinusoidal function of the wave surface equation with steeper crests and flatter troughs, as shown in Figure 4.48, where the stock^{5th}order theory results show considerable higher peak values for the base shear force and smaller values for the low points.

CHAPTER 5

CONCLUSION AND FUTURE WORKS

5.1 Conclusion

In this study, ANN was used for predicting the significant wave height and period values at buoy location in the south of the Caspian Sea. For this purpose, a feed forward-backpropagation network that contains different transfer functions (log and tan-sigmoid) as well as one hidden layer consisting of limited range of neurons was used.

The key of the current study was to apply ANNs to the complex process of wave characteristics prediction. One advantage of ANNs is that they do not require traditional engineering procedures or practices such as complex mathematical operations. We used ANN models for the prediction of wave height and period, then compare with numerical equations presented by typical engineering practice (e.g. K. Sadeghi, 2007 model).

A comparison of the various ANN models with prediction methods of wave height and period are established by equations of S.M.B. (Sverdrup-Munk-Bretschneider) and Bretschneider. The equations were conducted (presented in Chapter 4). The results from the current study have extended previously known Artificial Neural Network (ANN) procedures for a specific control engineering dilemma, viz. the prediction of wave characteristics. The following six points summarize the research that has been added to the exiting knowledge:

- A general ANN model for the prediction of height and wave period established and tested, provided that the results are acceptable from an engineering view-point, within the following average range of correlation coefficient (R^2): 92 % to 97%.
- There was no notable change in the results that obtained by resilient algorithm (trainrp) that we used in all prediction models if we compared it with a distinguishable three training algorithms such as: (1) traincgf, (2) trainoss and (3) trainlm. However, these algorithms provide similar accuracy in less epochs training requiring a smaller amount of computation.
- The results show that increasing in the input layer of neurons, as well as hidden

layers of neurons has no special effect that leads to increase of the predictive accuracy (e.g. the correlation coefficient for the model (M 1.1) in case 1 and case 2 (97.67% and 97.128%). However, the results show that increasing with applied the initial weight parameter to project better training.

- The prediction of wave characteristics can be improved by using a multi artificial neural network model instead of single artificial neural network model, where the numerical results that were obtained in this study given prove that (MANN) are good for prediction of wave height and period.
- SACS give larger results due to auto segmentation compared to dividing the load distribution into equal segments.

5.2 Further work

While the present study has extended current knowledge in the area of ANN for the prediction of wave characteristics, the following tasks need to be further considered in future studies.

- The over fitting can be avoided or eliminated by used of some techniques such as suitable pre-processing procedure or by undergoes of data set through optimal training.
- The development of alternatives to feed-forward neural networks techniques to prediction techniques, such as Support vector machine (SVMs), Radial basis function network (RBF) Networks. Those techniques could provide a wider array of options for engineers requiring the practical solution of engineering problems.

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APPENDICES

APPENDIX (1-A)

MATLAB code for Wave Simulation plots

```
% Create database

x=HR

y=HP

x1=PR

y1=PP

n=(1:674)

hold on

% Create figure

figure1 = figure('Color',[1 1 1]);

% Create subplot

subplot1 = subplot(2,1,1,'Parent',figure1,...

    'XTickLabel',{'','','','','','','','','','','','','','','','},...

    'XTick',[0 50 100 150 200 250 300 350 400 450 500 550 600 650 674],...

    'XMinorTick','on');

box(subplot1,'on');

hold(subplot1,'all');

% Create multiple lines using matrix input to plot

plot1 = plot(n,x,n,y,'Parent',subplot1);

set(plot1(1),'DisplayName','Observed');

set(plot1(2),'Color',[1 0 0],'DisplayName','Predicted');

% Create ylabel

ylabel('Wave Height (m)');

% Create legend
```

```
legend1 = legend(subplot1,'show');

set(legend1,'Orientation','horizontal');

% Create subplot

subplot2 = subplot(2,1,2,'Parent',figure1,...


'XTickLabel',{'','1,Sep,89','','','','1,Oct,89','','','','','1,Nov,89','','',
'','21,Nov,89'},...

    'XTick',[0 50 100 150 200 250 300 350 400 450 500 550 600 650 674],...

    'XMinorTick','on');

box(subplot2,'on');

hold(subplot2,'all');

% Create multiple lines using matrix input to plot

plot2 = plot(n,x1,n,y1,'Parent',subplot2);

set(plot2(1),'DisplayName','Observed');

set(plot2(2),'Color',[1 0 0],'DisplayName','Predicted');

% Create xlabel

xlabel('Time (Date)');

% Create ylabel

ylabel('Wave Period (sec.)');

% Create legend

legend2 = legend(subplot2,'show');

set(legend2,'Orientation','horizontal');
```

APPENDIX (1-B)

MATLAB code for a comparison between different prediction methods

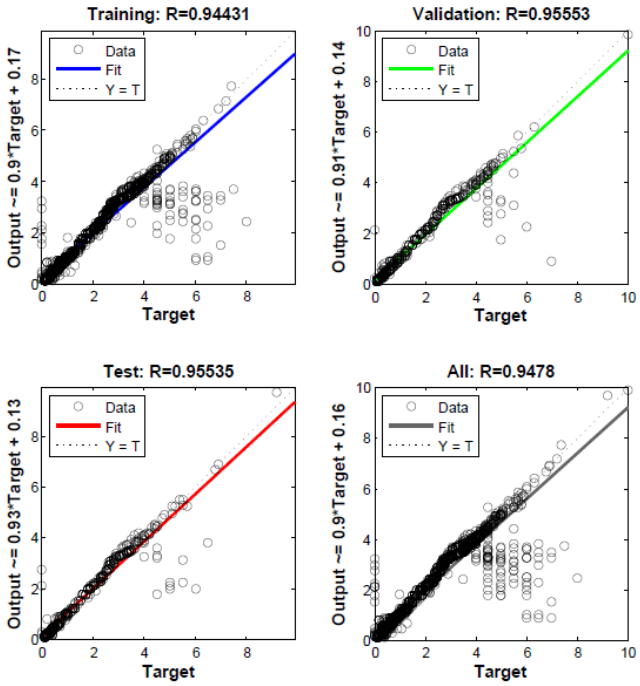
```
% Create database

x=HR

y=HP

x1=PR

y1=PP

n=(1:674)

hold on
```

```
% Create figure

figure1 = figure('Color',[1 1 1]);

% Create axes

axes1 = axes('Parent',figure1,'XTickLabel',{'','','','','','','',...

    'Position',[0.13 0.709264705882353 0.775 0.215735294117647]);

hold(axes1,'all');

% Create plot

plot(X1,Y1,'Parent',axes1,'DisplayName','Recorded');

% Create axes

axes2 = axes('Parent',figure1,'XTickLabel',{'','','','','','','',...

    'Position',[0.13 0.409632352941176 0.775 0.215735294117647]);

hold(axes2,'all');

% Create plot
```

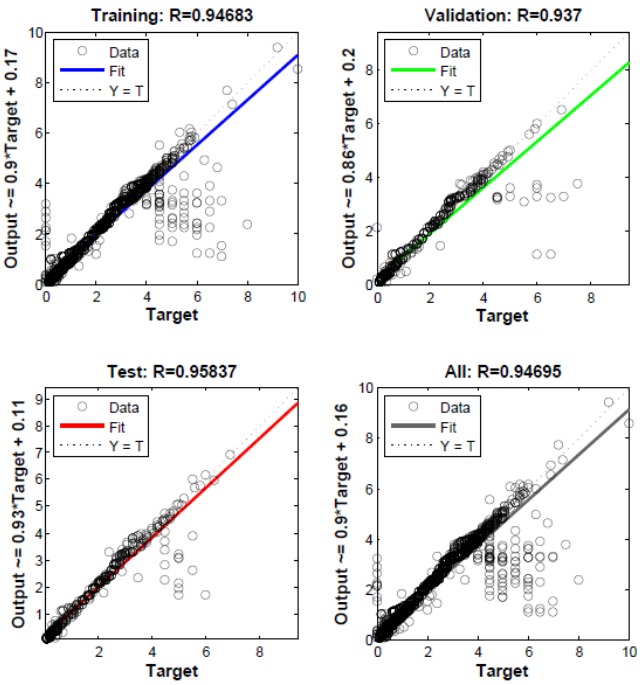
```
plot(X1,Y2,'Parent',axes2,'Color',[0 0.498039215803146 0],...

    'DisplayName','ANN (S.M.B)');

% Create ylabel

ylabel('Wave Height (m)','FontWeight','bold','FontSize',14);

% Create axes

axes3 = axes('Parent',figure1,...


'XTickLabel',{'','1,Sep,89','','','','1,Oct,89','','','','','1,Nov,89','','',
'','674'},...

    'XTick',[0 50 100 150 200 250 300 350 400 450 500 550 600 650 674],...

    'Position',[0.13 0.107481108312343 0.775 0.215735294117647],...

    'FontSize',12);

hold(axes3,'all');

% Create plot

plot(X1,Y3,'Parent',axes3,'Color',[1 0 0],'DisplayName','Bretschneider');



% Create xlabel

xlabel('Time (Date)','FontWeight','bold','FontSize',14);

% Create legend

legend1 = legend(axes3,'show');

set(legend1,...

    'Position',[0.727696078431373 0.30098189240313 0.227941176470588
0.0714199263608266]);
```

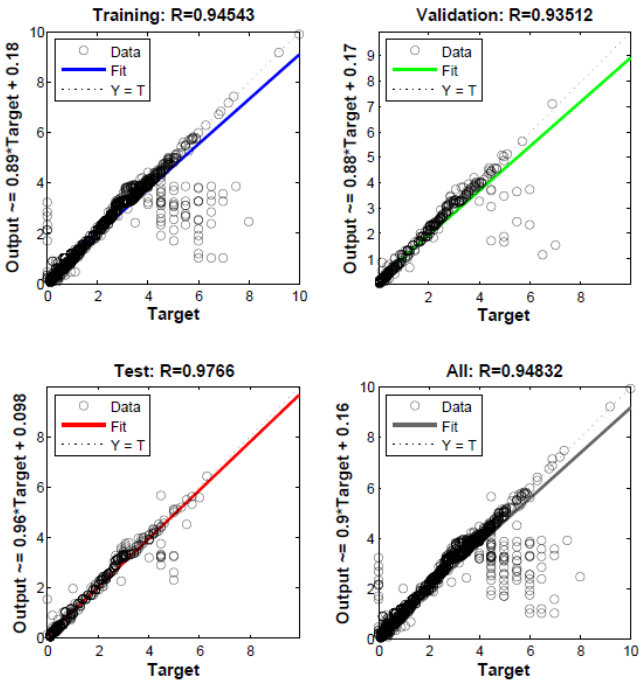
```
% Create legend

legend2 = legend(axes2,'show');

set(legend2,'FontSize',12);

% Create legend

legend3 = legend(axes1,'show');

set(legend3,'FontSize',12);
```

APPENDIX (2-A)

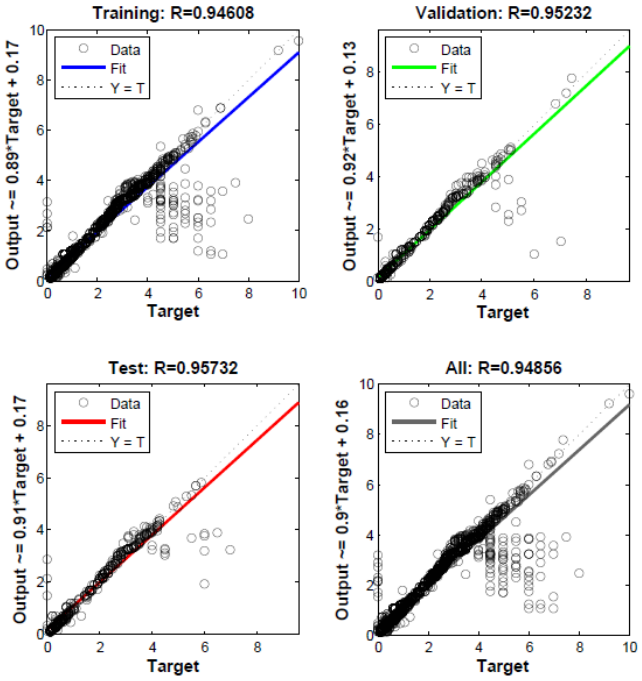


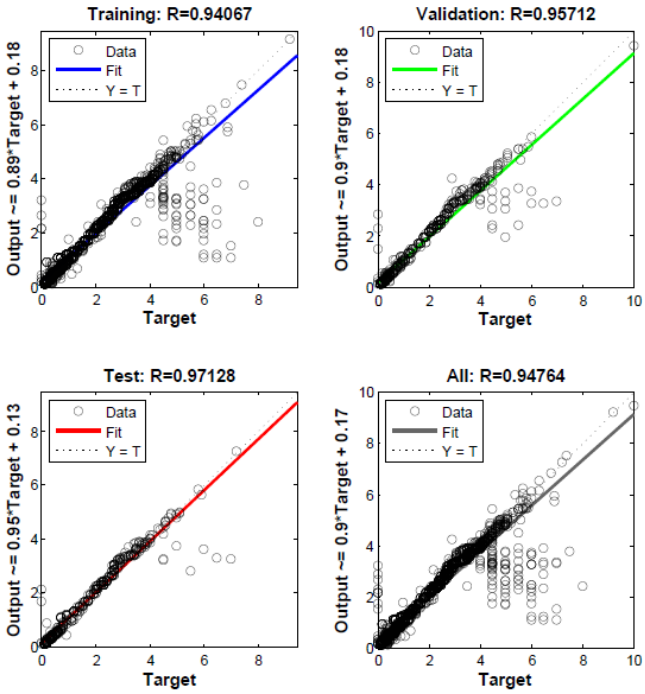
Figures 2.1, 2.2: Scatter diagrams for cases (2) and (3) in model (M 1.1)



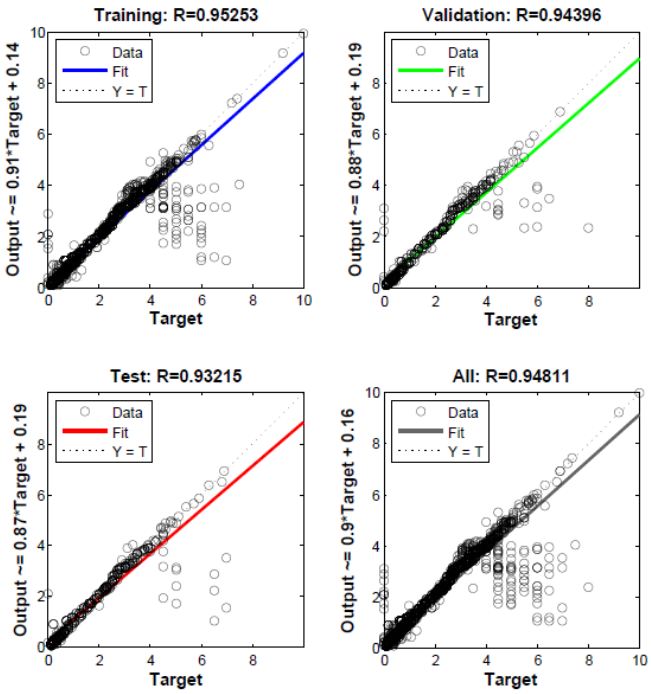


Figures 2.3, 2.4: Scatter diagrams for cases (4) and (5) in model (M 1.1)





Figures 2.5, 2.6: Scatter diagrams for cases (6a) and (6b) in model (M 1.1)



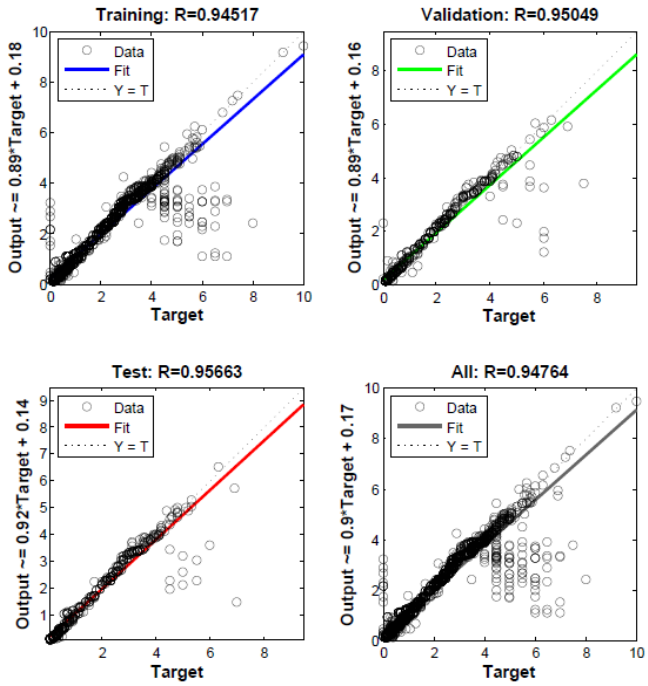
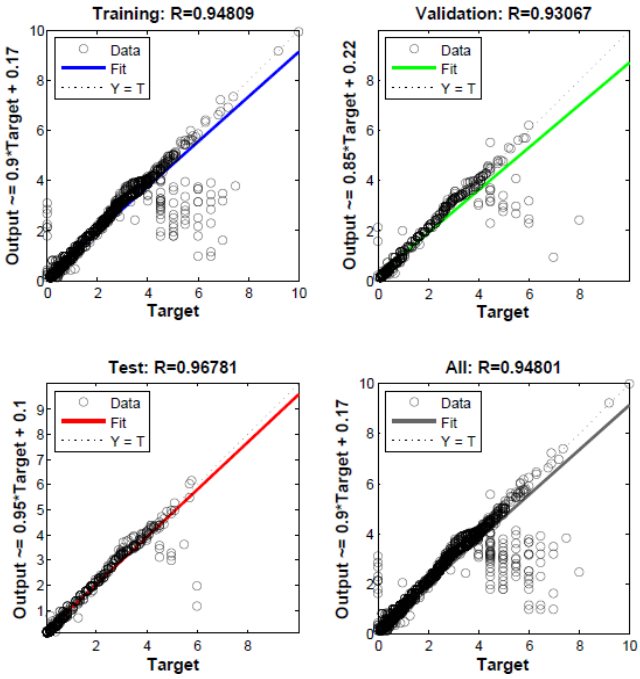
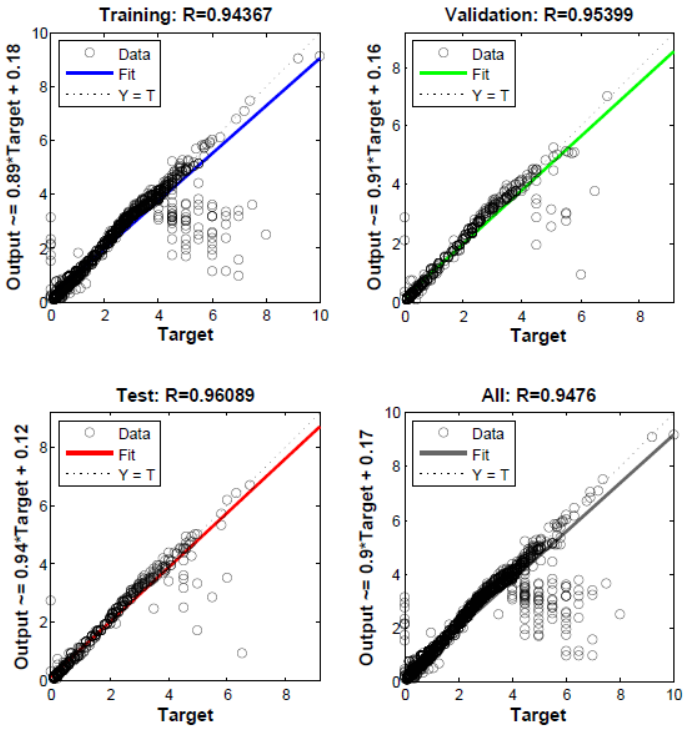


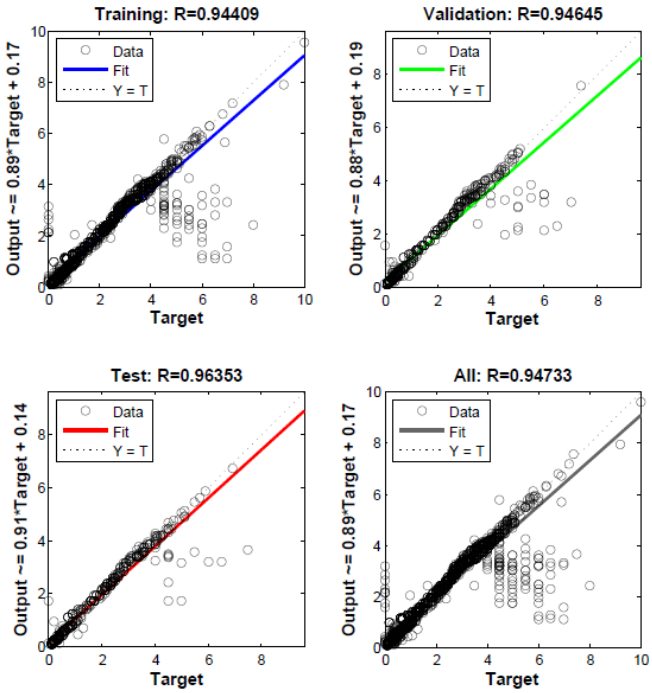
Figure 2.7: Scatter diagrams for case (6c) in model (M 1.1)

APPENDIX (2-B)

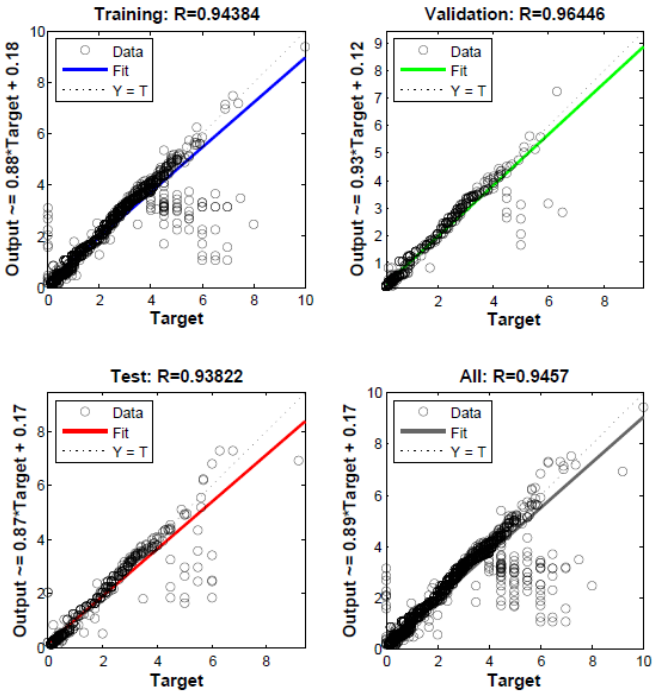


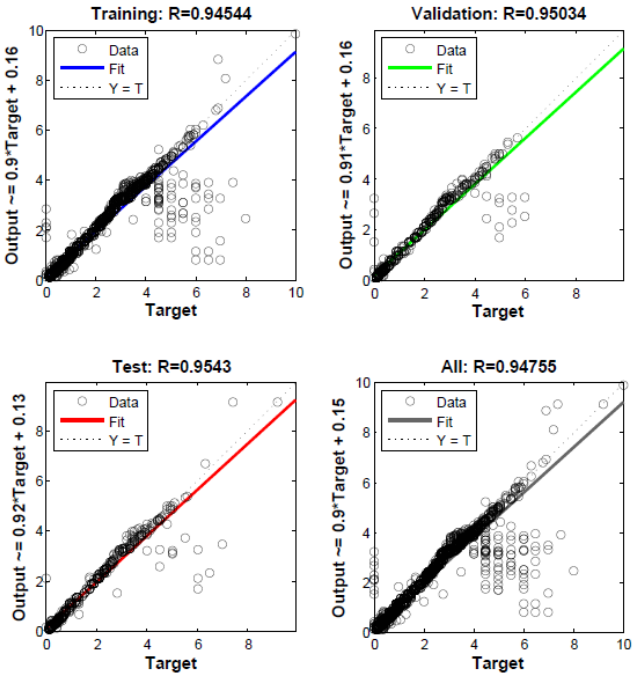
Figures 2.8, 2.9: Scatter diagrams for cases (1) and (2) in model (M 1.2)



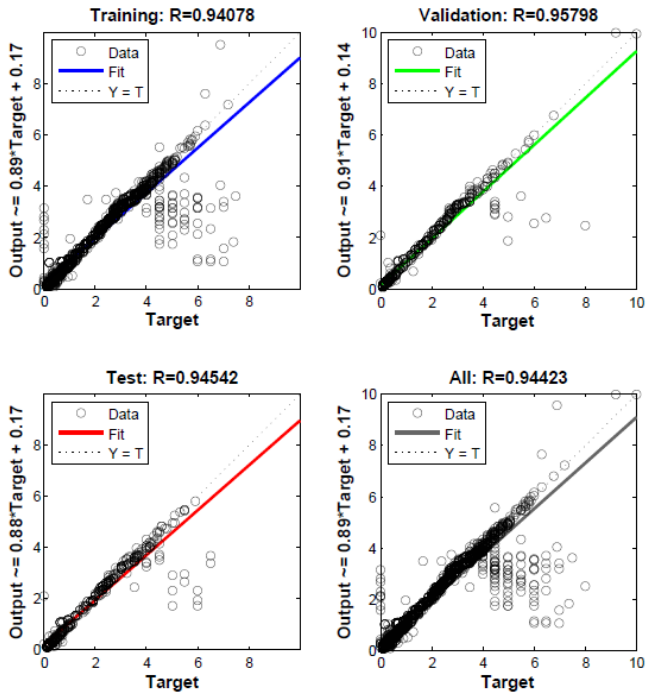


Figures 2.10, 2.11: Scatter diagrams for cases (3) and (4) in model (M 1.2)





Figures 2.12, 2.13: Scatter diagrams for cases (5) and (6a) in model (M 1.2)



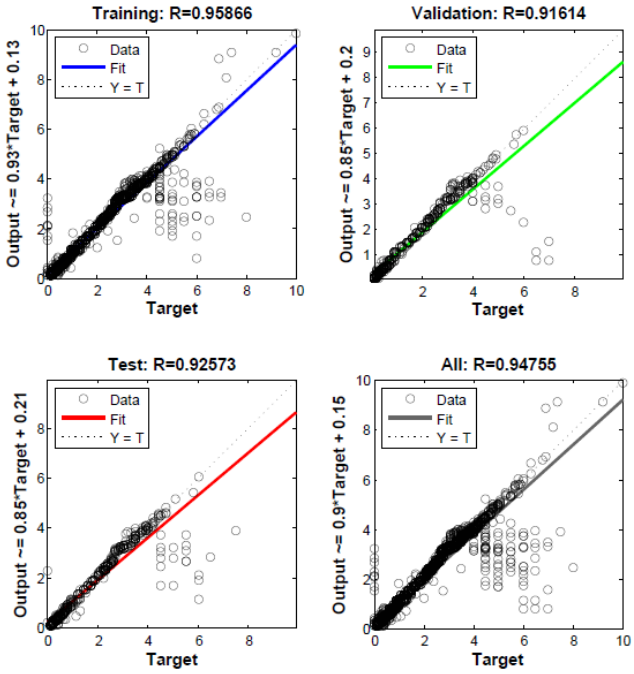
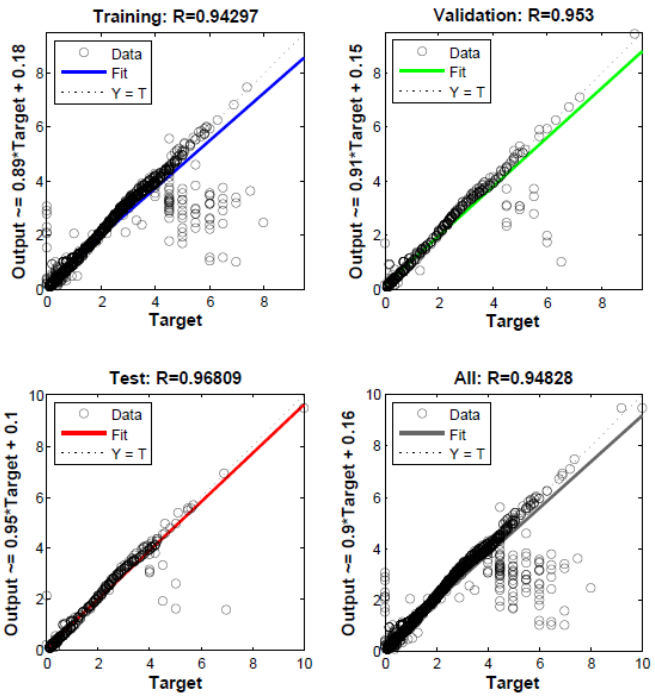
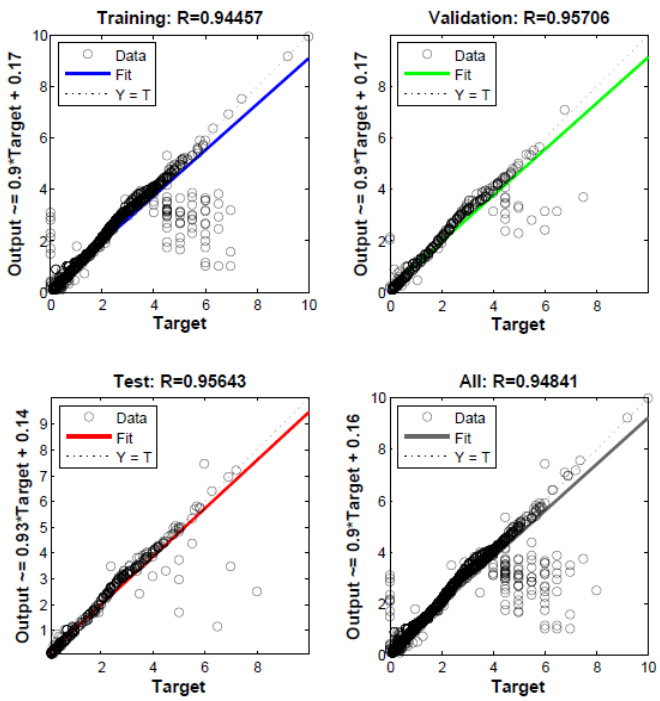


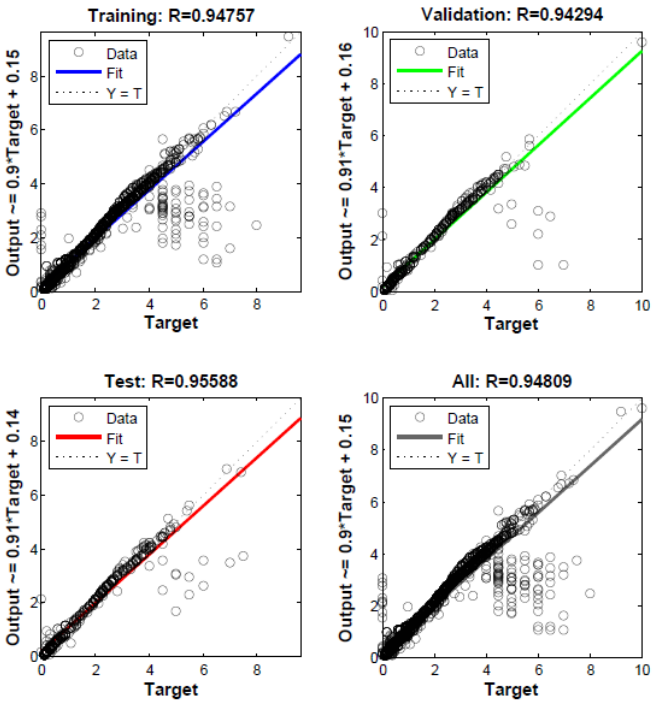
Figure 2.14: Scatter diagrams for case (6b) in model (M 1.2)

APPENDIX (2-C)

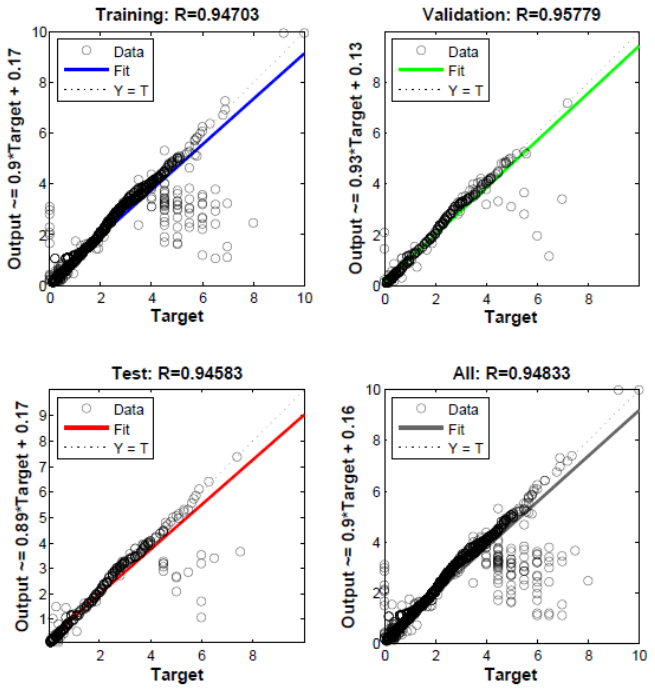


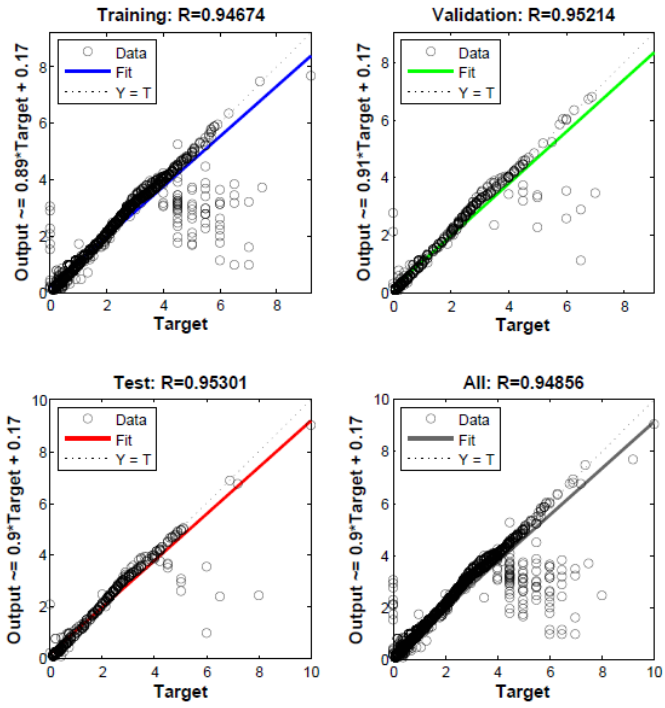
Figures 2.15, 2.16: Scatter diagrams for cases (1) and (2) in model (M 2.1.1)



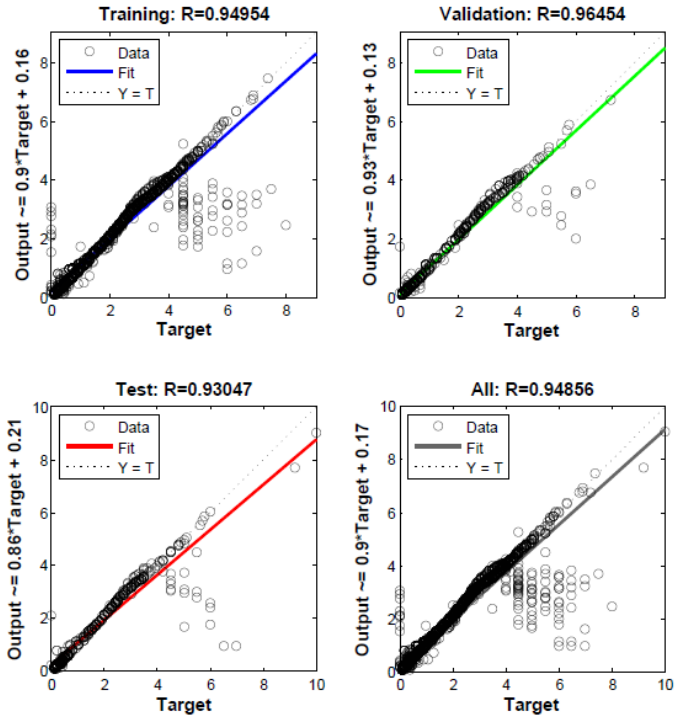


Figures 2.17, 2.18: Scatter diagrams for cases (3) and (4) in model (M 2.1.1)





Figures 2.19, 2.20: Scatter diagrams for cases (5a) and (5b) in model (M 2.1.1)



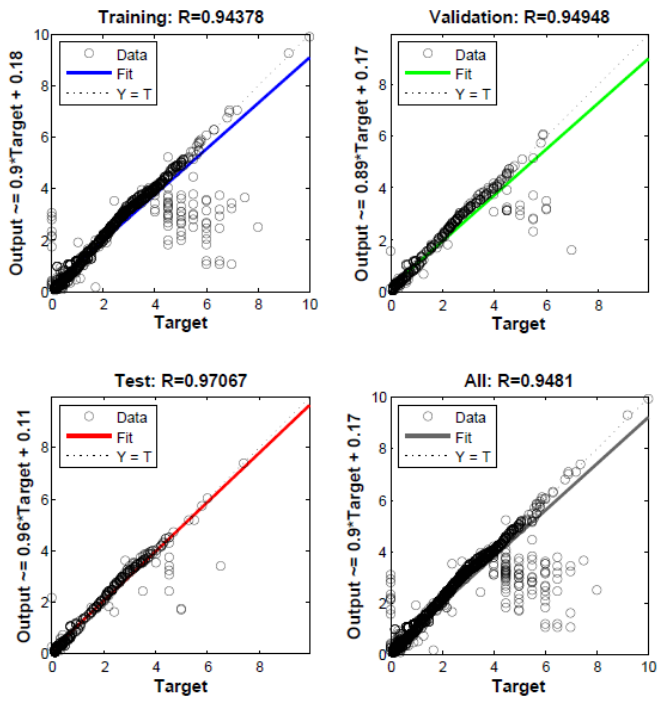
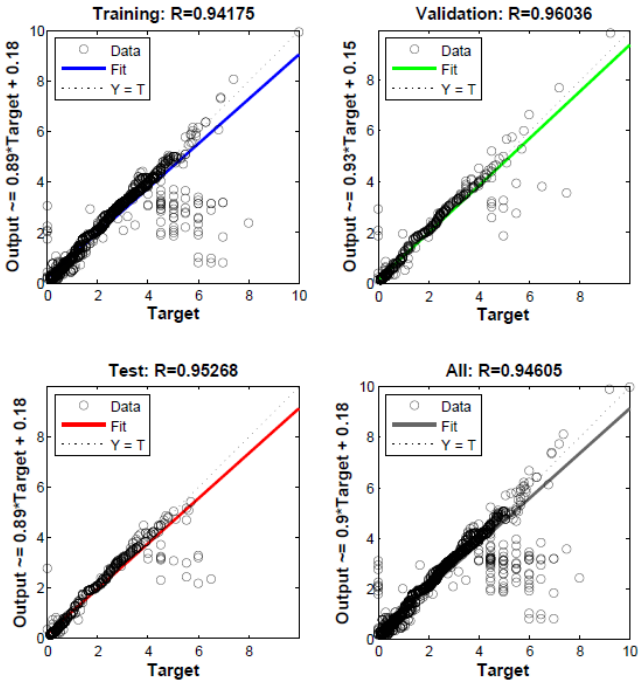
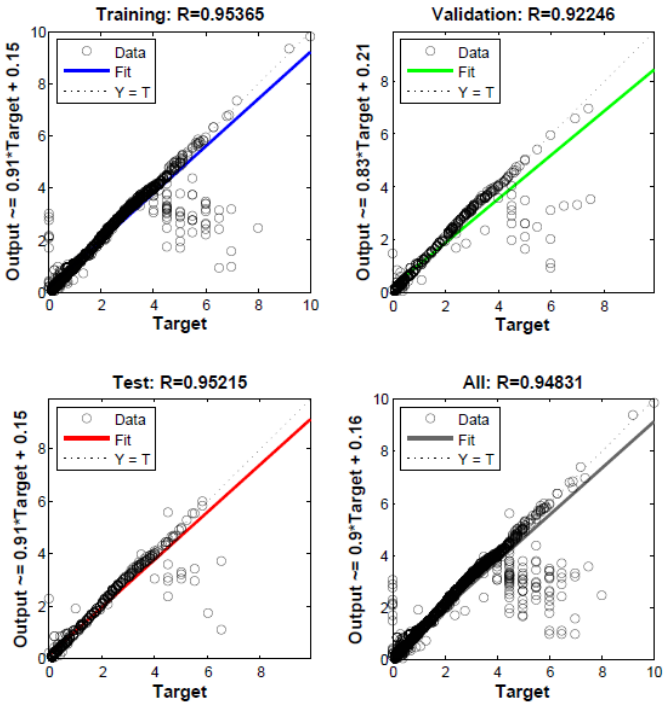


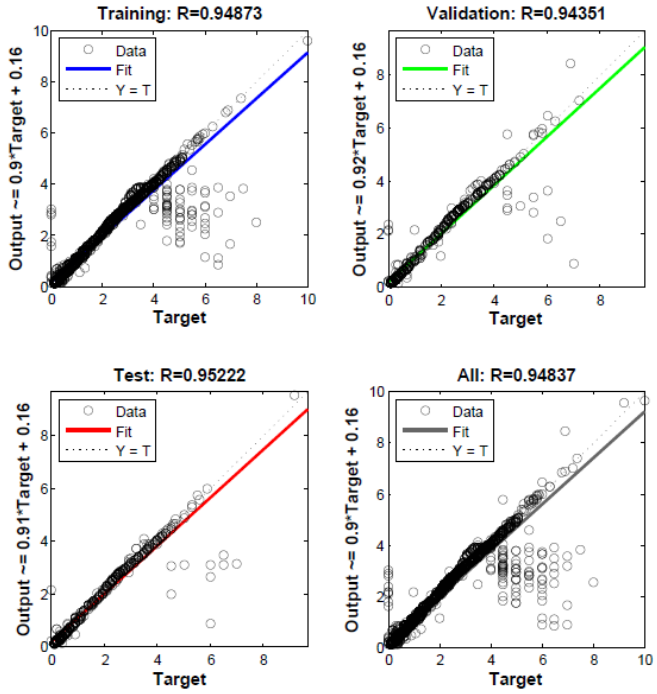
Figure 2.21: Scatter diagrams for case (6) in model (M 2.1.1)

APPENDIX (2-D)

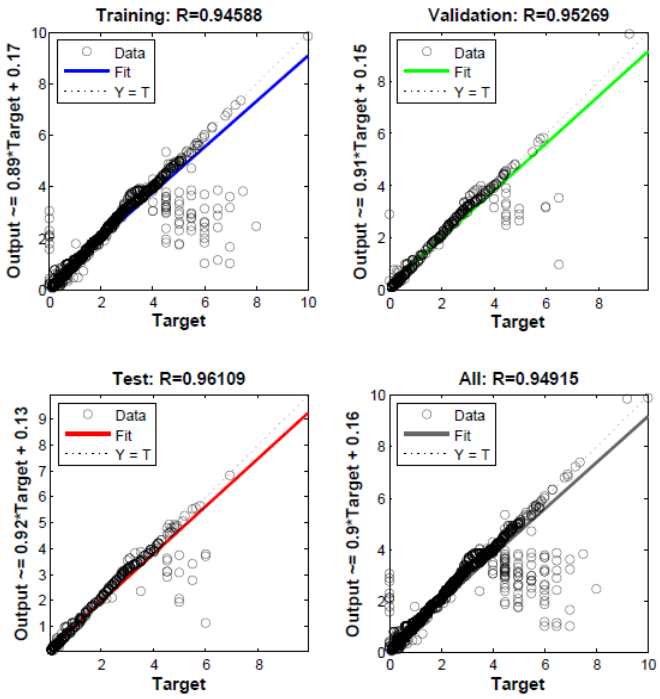


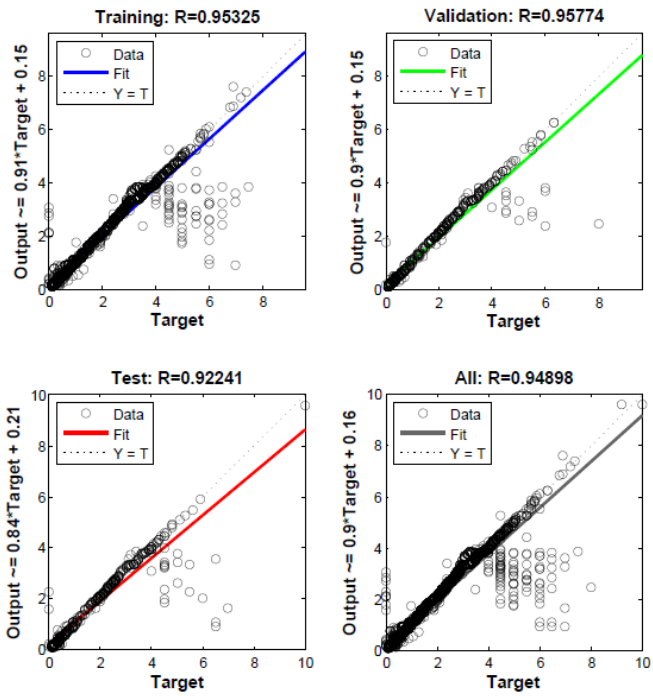
Figures 2.22, 2.23: Scatter diagrams for cases (1) and (3) in model (M 2.1.2)



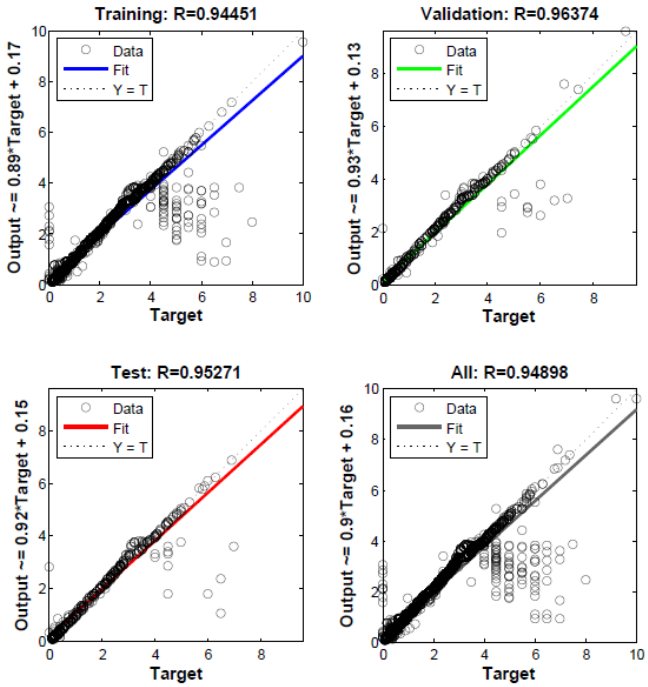


Figures 2.24, 2.25: Scatter diagrams for cases (4) and (5) in model (M 2.1.2)





Figures 2.25, 2.26: Scatter diagrams for cases (6a) and (6b) in model (M 2.1.2)



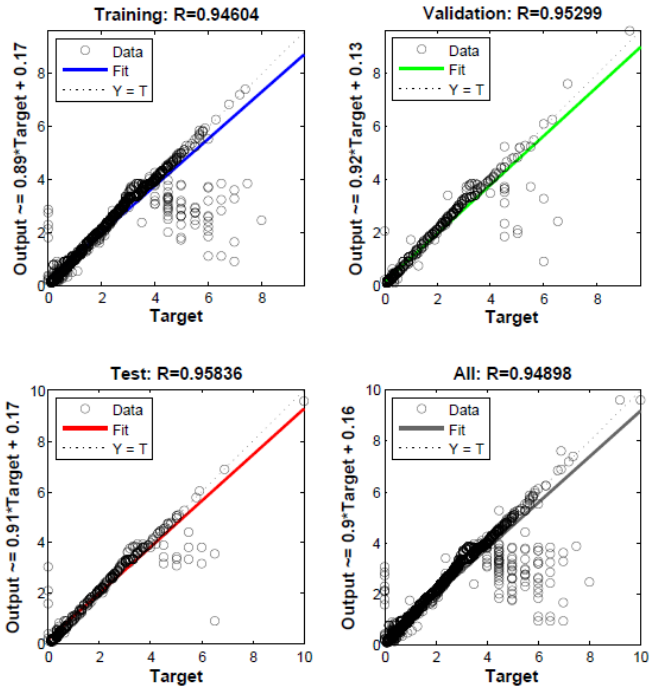
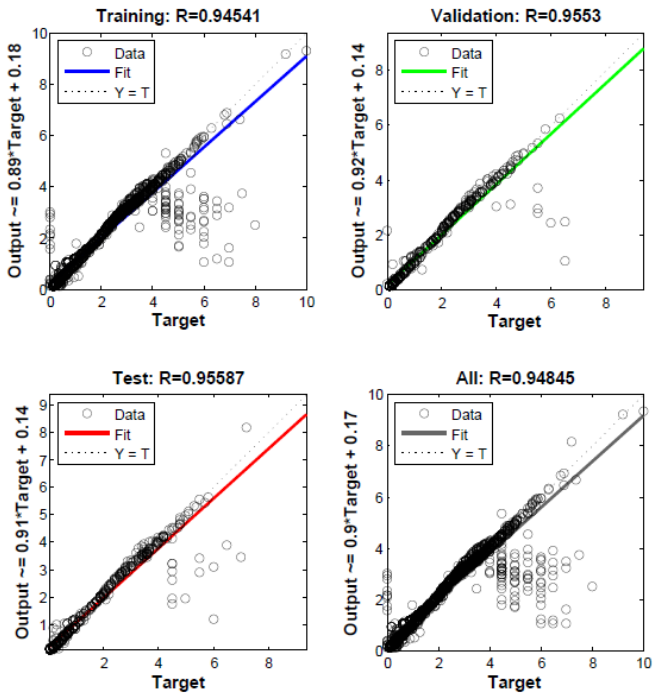
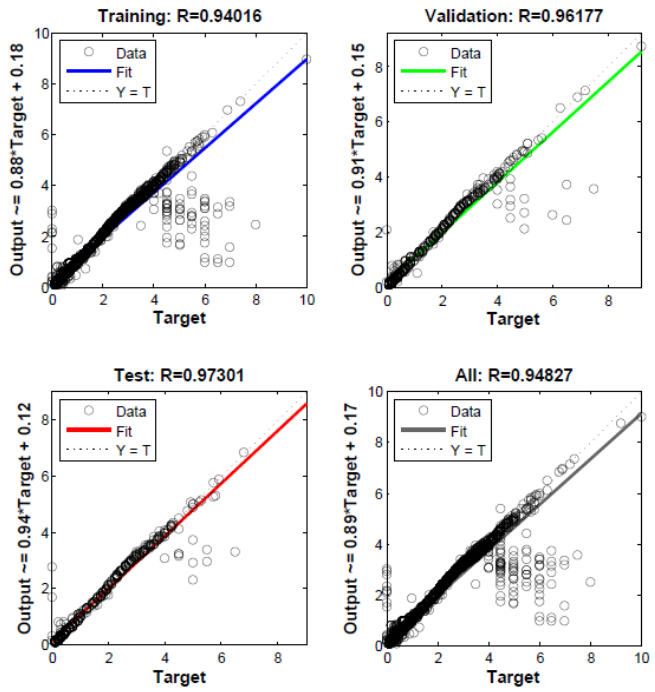


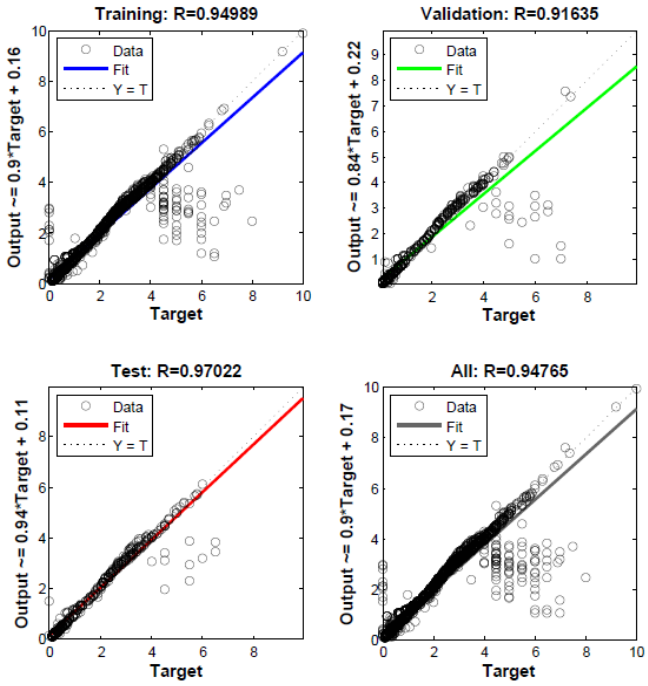
Figure 2.27: Scatter diagrams for case (7) in model (M 2.1.2)

APPENDIX (2-E)

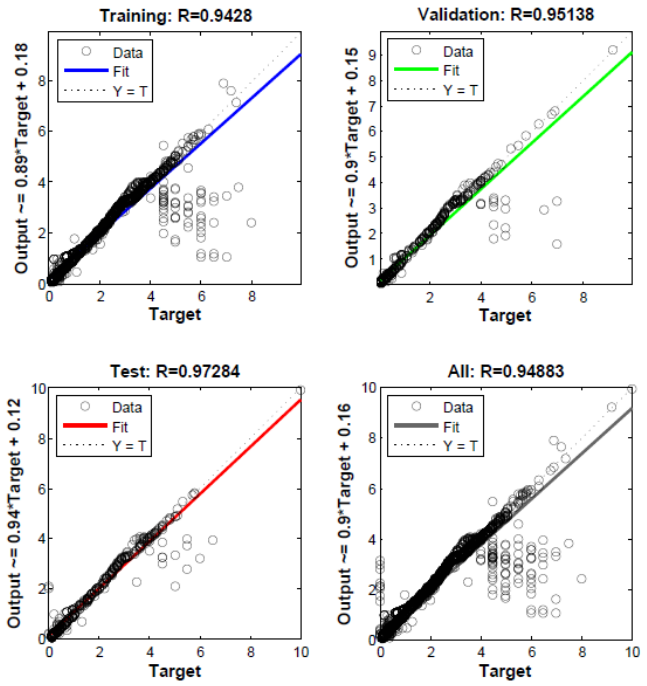


Figures 2.28, 2.29: Scatter diagrams for cases (1) and (3) in model (M 2.2)





Figures 2.30, 2.31: Scatter diagrams for cases (4) and (5) in model (M 2.2)



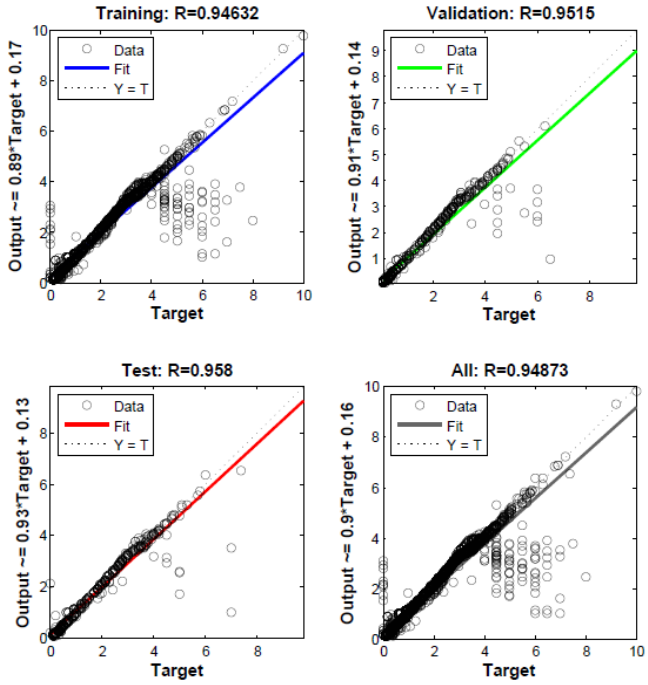


Figure 2.32: Scatter diagrams for case (6) in model (M 2.2)

APPENDIX (3)

Progress of calculation (SACS Software)

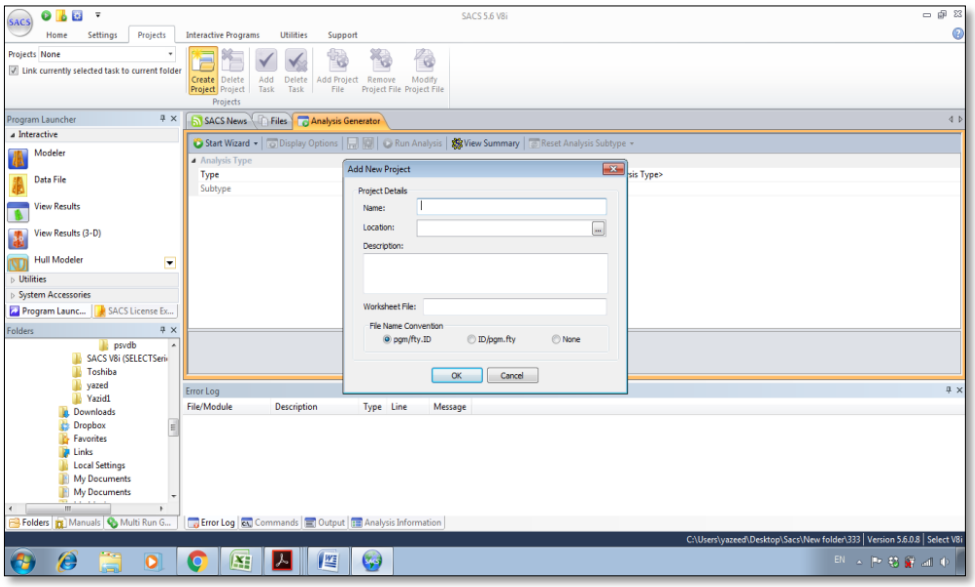


Figure 3.1: Define the location

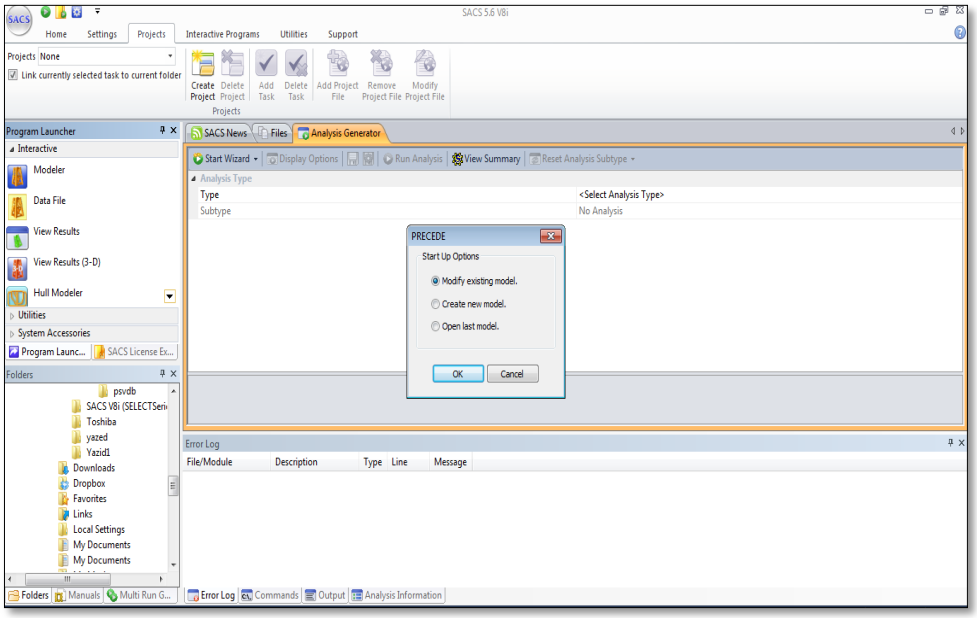


Figure 3.2: Create a new model

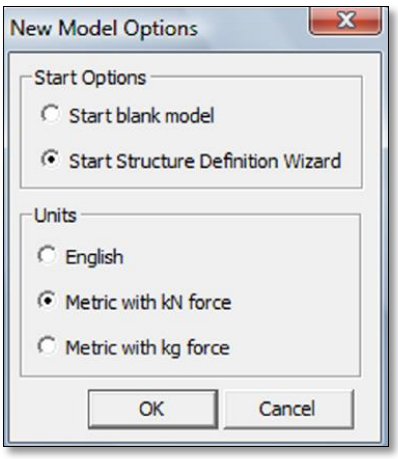


Figure 3.3: Menu of selecting a new model

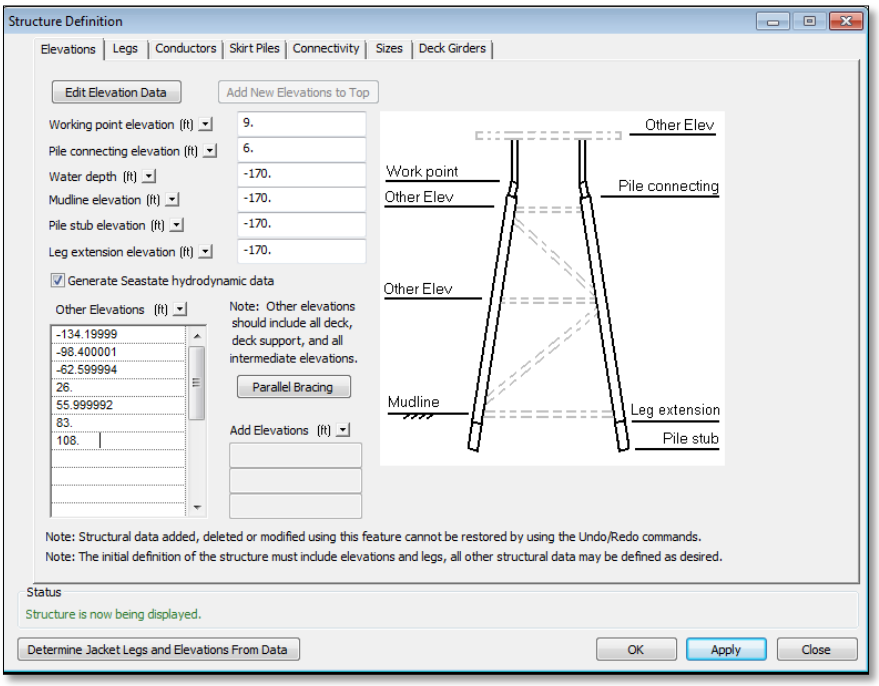


Figure 3.4: Elevations tab

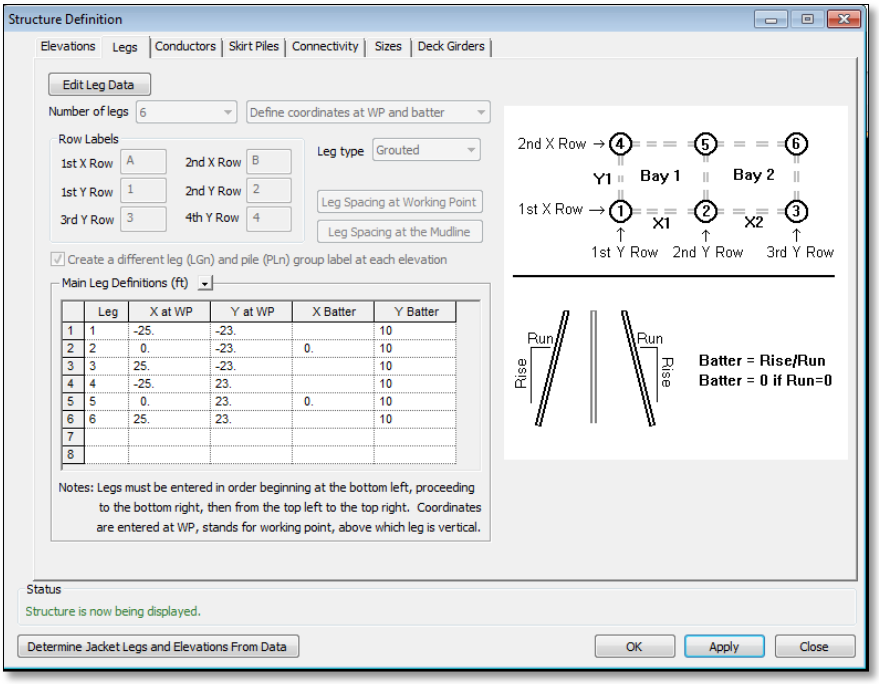


Figure 3.5: Legs tab.

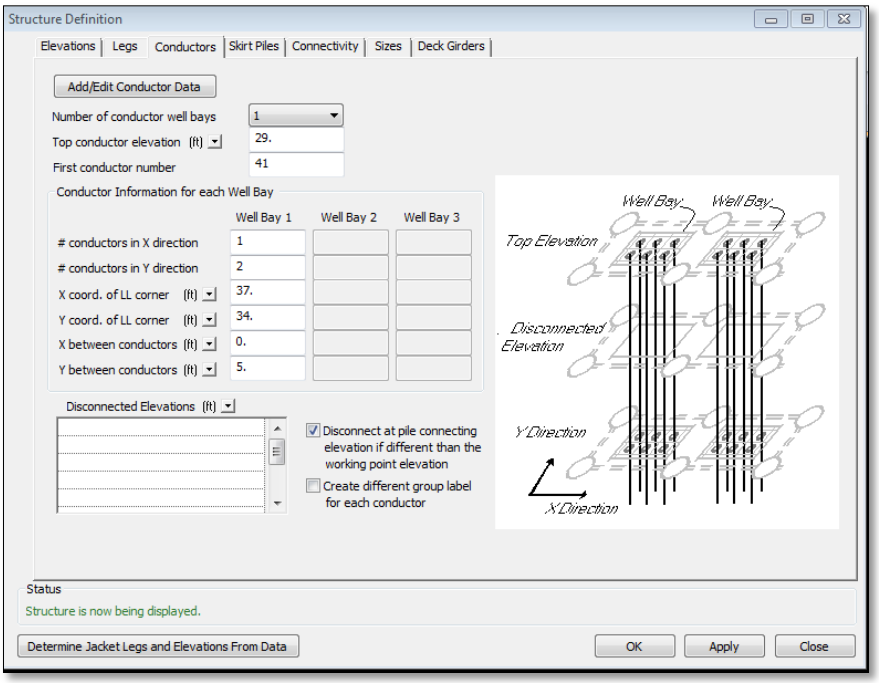


Figure 3.6: Conductor data.

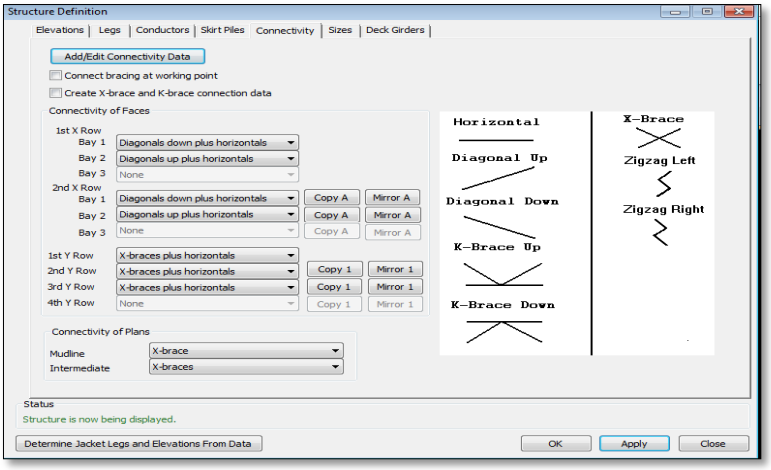


Figure 3.7: Connectivity tab

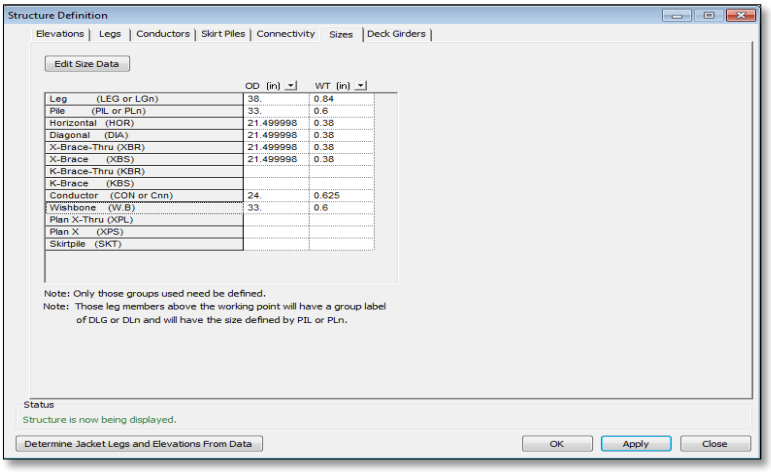


Figure 3.8: Size tab

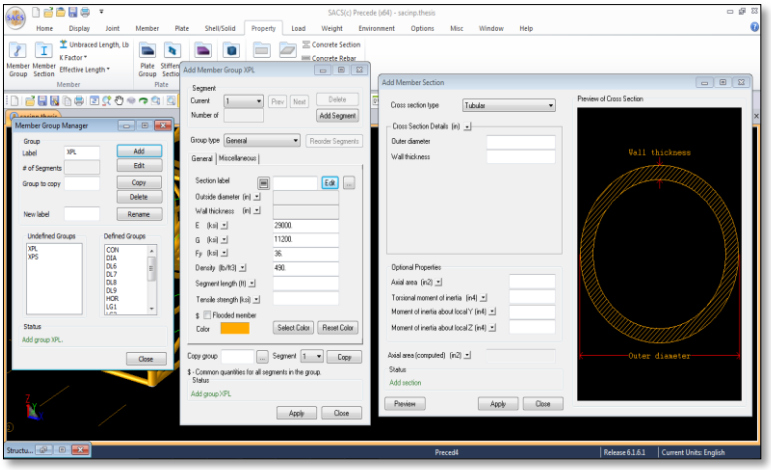


Figure 3.9: The member group manage dialog box

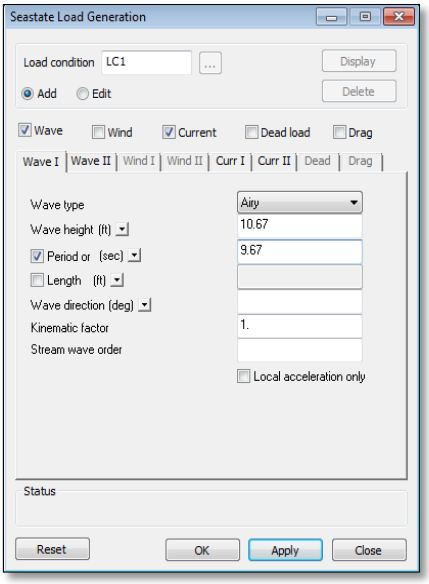


Figure 3.10 a Seastate load generation Wave tab

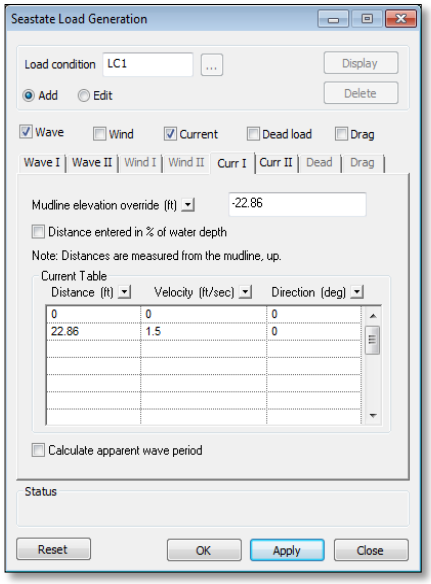


Figure 3.10 b Seastate load generation Current tab

APPENDIX (4)

Functions of d/L for even increments of d/L (from 0.1100 to 0.1690)

d/L	d/L_o	$2\pi d/L$	TANH $2\pi d/L$	SINH $2\pi d/L$	COSH $2\pi d/L$	N/N_o	K	$4\pi d/L$	SINH $4\pi d/L$	COSH $4\pi d/L$	n	C_g/C_o	W
.1100	.06586	.6912	.5987	.7175	1.249	.9197	.8010	1.382	1.861	2.118	.8703	.5211	13.77
.1110	.06690	.6974	.6027	.7554	1.253	.9175	.7980	1.395	1.893	2.141	.8684	.5234	13.58
.1120	.06795	.7037	.6067	.7633	1.258	.9153	.7949	1.407	1.920	2.165	.8665	.5257	13.41
.1130	.06901	.7100	.6107	.7712	1.263	.9131	.7919	1.420	1.948	2.189	.8645	.5279	13.23
.1140	.07006	.7163	.6146	.7791	1.268	.9111	.7888	1.433	1.975	2.214	.8626	.5301	13.06
.1150	.07113	.7226	.6185	.7871	1.273	.9091	.7858	1.445	2.003	2.239	.8607	.5323	12.90
.1160	.07220	.7289	.6224	.7951	1.278	.9072	.7827	1.458	2.032	2.264	.8587	.5344	12.74
.1170	.07327	.7351	.6262	.8032	1.283	.9054	.7797	1.470	2.060	2.290	.8568	.5365	12.59
.1180	.07434	.7414	.6300	.8112	1.288	.9035	.7766	1.483	2.089	2.316	.8549	.5386	12.43
.1190	.07542	.7477	.6338	.8193	1.293	.9017	.7735	1.495	2.118	2.343	.8529	.5406	12.29
.1200	.07650	.7540	.6375	.8275	1.298	.9000	.7704	1.508	2.148	2.369	.8510	.5425	12.14
.1210	.07759	.7603	.6412	.8357	1.303	.8983	.7673	1.521	2.178	2.397	.8491	.5444	12.00
.1220	.07868	.7666	.6449	.8439	1.309	.8967	.7642	1.533	2.208	2.424	.8471	.5463	11.87
.1230	.07978	.7728	.6486	.8521	1.314	.8951	.7612	1.546	2.239	2.452	.8452	.5482	11.73
.1240	.08085	.7791	.6520	.8604	1.319	.8935	.7581	1.558	2.270	2.480	.8432	.5500	11.61
.1250	.08198	.7854	.6558	.8687	1.325	.8920	.7549	1.571	2.301	2.509	.8413	.5517	11.48
.1260	.08308	.7917	.6594	.8770	1.330	.8905	.7518	1.583	2.333	2.538	.8393	.5534	11.35
.1270	.08419	.7980	.6629	.8854	1.336	.8890	.7487	1.596	2.365	2.568	.8374	.5551	11.23
.1280	.08530	.8043	.6664	.8938	1.341	.8876	.7456	1.609	2.398	2.598	.8354	.5568	11.11
.1290	.08642	.8105	.6699	.9022	1.347	.8863	.7424	1.621	2.430	2.628	.8335	.5584	11.00
.1300	.08753	.8168	.6733	.9107	1.353	.8850	.7393	1.634	2.464	2.659	.8316	.5599	10.89
.1310	.08866	.8231	.6768	.9192	1.358	.8837	.7362	1.646	2.497	2.690	.8296	.5614	10.78
.1320	.08978	.8294	.6801	.9278	1.364	.8824	.7331	1.659	2.531	2.722	.8277	.5629	10.67
.1330	.09091	.8357	.6835	.9364	1.370	.8812	.7299	1.671	2.566	2.754	.8257	.5644	10.56
.1340	.09204	.8420	.6868	.9450	1.376	.8801	.7268	1.684	2.600	2.786	.8238	.5658	10.46
.1350	.09317	.8482	.6902	.9537	1.382	.8789	.7237	1.696	2.636	2.819	.8218	.5672	10.36
.1360	.09431	.8545	.6934	.9624	1.388	.8778	.7205	1.709	2.671	2.852	.8199	.5685	10.26
.1370	.09546	.8608	.6967	.9711	1.394	.8767	.7174	1.722	2.707	2.886	.8179	.5698	10.17
.1380	.09659	.8671	.6999	.9799	1.400	.8757	.7142	1.734	2.744	2.920	.8160	.5711	10.07
.1390	.09773	.8734	.7031	.9887	1.406	.8747	.7111	1.747	2.781	2.955	.8141	.5724	9.983
.1400	.09888	.8797	.7063	.9976	1.412	.8737	.7080	1.759	2.818	2.990	.8121	.5736	9.894
.1410	.1000	.8859	.7094	1.006	1.419	.8727	.7048	1.772	2.856	3.026	.8102	.5748	9.806
.1420	.1012	.8922	.7125	1.015	1.425	.8718	.7017	1.784	2.894	3.062	.8083	.5759	9.721
.1430	.1023	.8985	.7156	1.024	1.432	.8709	.6985	1.797	2.933	3.099	.8064	.5770	9.638
.1440	.1035	.9048	.7186	1.033	1.438	.8700	.6954	1.810	2.972	3.136	.8044	.5781	9.556
.1450	.1046	.9111	.7216	1.042	1.445	.8692	.6923	1.822	3.012	3.173	.8025	.5791	9.476
.1460	.1058	.9174	.7247	1.052	1.451	.8684	.6891	1.835	3.052	3.211	.8006	.5801	9.398
.1470	.1070	.9236	.7276	1.061	1.458	.8676	.6860	1.847	3.092	3.250	.7987	.5811	9.321
.1480	.1081	.9299	.7306	1.070	1.464	.8668	.6829	1.860	3.133	3.289	.7968	.5821	9.246
.1490	.1093	.9362	.7335	1.079	1.471	.8661	.6797	1.872	3.175	3.329	.7949	.5830	9.173
.1500	.1105	.9425	.7364	1.088	1.478	.8654	.6766	1.885	3.217	3.369	.7930	.5839	9.101
.1510	.1116	.9488	.7392	1.098	1.485	.8647	.6734	1.898	3.260	3.410	.7911	.5848	9.031
.1520	.1128	.9551	.7421	1.107	1.492	.8640	.6703	1.910	3.303	3.451	.7892	.5856	8.962
.1530	.1140	.9613	.7449	1.116	1.499	.8634	.6672	1.923	3.346	3.493	.7873	.5864	8.894
.1540	.1151	.9676	.7477	1.126	1.506	.8628	.6641	1.935	3.391	3.535	.7854	.5872	8.828
.1550	.1163	.9739	.7504	1.135	1.513	.8622	.6610	1.948	3.435	3.578	.7835	.5880	8.763
.1560	.1175	.9802	.7531	1.145	1.520	.8616	.6579	1.960	3.481	3.621	.7816	.5887	8.700
.1570	.1187	.9865	.7558	1.154	1.527	.8611	.6547	1.973	3.526	3.665	.7797	.5893	8.638
.1580	.1199	.9928	.7585	1.164	1.535	.8605	.6516	1.985	3.573	3.710	.7779	.5900	8.577
.1590	.1210	.9990	.7612	1.174	1.542	.8600	.6485	1.998	3.620	3.755	.7760	.5907	8.517
.1600	.1222	1.005	.7638	1.183	1.549	.8596	.6454	2.011	3.667	3.801	.7741	.5913	8.459
.1610	.1234	1.012	.7664	1.193	1.557	.8591	.6423	2.023	3.715	3.847	.7723	.5919	8.401
.1620	.1246	1.018	.7690	1.203	1.564	.8586	.6392	2.036	3.764	3.894	.7704	.5925	8.345
.1630	.1258	1.024	.7716	1.213	1.572	.8582	.6361	2.048	3.813	3.942	.7686	.5930	8.290
.1640	.1270	1.030	.7741	1.223	1.580	.8579	.6331	2.061	3.863	3.990	.7667	.5935	8.236
.1650	.1281	1.037	.7766	1.233	1.587	.8575	.6300	2.073	3.913	4.039	.7649	.5940	8.183
.1660	.1293	1.043	.7791	1.243	1.595	.8571	.6269	2.086	3.964	4.088	.7631	.5945	8.131
.1670	.1305	1.049	.7815	1.253	1.603	.8567	.6239	2.099	4.016	4.138	.7613	.5950	8.079
.1680	.1317	1.056	.7840	1.263	1.611	.8564	.6208	2.111	4.068	4.189	.7595	.5954	8.029
.1690	.1329	1.062	.7864	1.273	1.619	.8561	.6177	2.124	4.121	4.241	.7576	.5958	7.980

APPENDIX (5-A)

Wave surface comparison for different theories

(wt - kx) (º)	η Airy (m)	η Stoke (m)	Ft Manual (N)	Ft SACS Linear	Ft SACS Stoke
0	5.33	6.82	331.86	352.39	446.33
10	5.25	6.56	306.63	316.12	379.25
20	5.01	5.83	263.06	261.62	266.68
30	4.62	4.78	205.06	194.86	158.96
40	4.08	3.57	138.39	123.47	66.65
50	3.43	2.37	69.96	55.10	-2.10
60	2.67	1.26	7.04	-4.02	-47.72
70	1.82	0.30	-43.56	-49.67	-73.83
80	0.93	-0.54	-76.33	-79.89	-85.84
90	0.00	-1.24	-87.67	-94.91	-84.47
100	-0.93	-1.85	-90.20	-95.97	-78.05
110	-1.82	-2.35	-85.63	-90.74	-69.64
120	-2.67	-2.75	-73.40	-84.26	-63.51
130	-3.43	-3.07	-70.70	-80.10	-58.74
140	-4.08	-3.33	-71.20	-76.55	-54.39
150	-4.62	-3.54	-72.10	-72.27	-49.74
160	-5.01	-3.70	-69.40	-66.26	-44.25
170	-5.25	-3.81	-57.70	-57.85	-37.59
180	-5.33	-3.85	-45.34	-46.59	-29.51
190	-5.25	-3.81	-31.80	-32.30	-19.90
200	-5.01	-3.70	-12.80	-15.03	-8.68
210	-4.62	-3.54	3.42	4.86	4.08
220	-4.08	-3.33	20.80	26.58	18.20
230	-3.43	-3.07	36.90	48.82	33.30
240	-2.67	-2.75	59.50	69.63	48.76

250	-1.82	-2.35	80.30	86.42	63.61
260	-0.93	-1.85	97.80	99.76	76.62
270	0.00	-1.24	116.60	118.70	89.98
280	0.93	-0.54	139.70	142.91	109.73
290	1.82	0.30	165.70	175.05	134.95
300	2.67	1.26	203.70	214.00	170.70
310	3.43	2.37	248.90	257.01	218.18
320	4.08	3.57	290.50	299.70	277.70
330	4.62	4.78	333.70	336.44	345.18
340	5.01	5.83	357.80	360.78	408.43
350	5.25	6.56	368.90	367.20	457.95
360	5.33	6.82	356.90		

APPENDIX (5-B)

Forces distribution per phase angle

(wt - kx) (°)	η (x,t) (m)	Fi (KN)	Fd+c (KN)	Fd (KN)	Ft (KN)	Ft Airy SACS (KN)	Ft Stokes SACS (KN)
0	5.330	0.000	331.861	185.950	331.861	352.390	446.330
5	5.310	-7.641	329.340	184.538	321.700	334.170	412.250
10	5.249	-15.224	321.854	180.343	306.631	316.120	379.250
15	5.148	-22.690	309.631	173.494	286.940	288.480	325.290
20	5.009	-29.984	293.041	164.198	263.056	261.620	266.680
25	4.831	-37.050	272.589	152.738	235.538	227.440	209.450
30	4.616	-43.834	248.896	139.463	205.062	194.860	158.960
35	4.366	-50.285	222.682	124.775	172.397	157.930	109.310
40	4.083	-56.352	194.744	109.120	138.392	123.470	66.650
45	3.769	-61.991	165.931	92.975	103.939	87.700	29.360
50	3.426	-67.158	137.117	76.830	69.959	55.100	-2.100
55	3.057	-71.814	109.179	61.176	37.365	23.750	-27.090
60	2.665	-75.923	82.965	46.488	7.042	-4.020	-47.720
65	2.253	-79.455	59.272	33.212	-20.182	-28.660	-62.340
70	1.823	-82.382	38.820	21.752	-43.561	-49.670	-73.830
75	1.380	-84.682	22.230	12.456	-62.451	-66.450	-81.790
80	0.926	-86.337	10.007	5.607	-76.330	-79.890	-85.840
85	0.465	-87.335	2.521	1.413	-84.814	-88.830	-86.030
90	0.000	-87.669	0.000	0.000	-87.669	-94.910	-84.470
95	-0.465	-86.679	-2.521	-1.413	-89.200	-96.030	-81.200
100	-0.926	-80.193	-10.007	-5.607	-90.200	-95.970	-78.050
105	-1.380	-66.960	-22.230	-12.456	-89.190	-94.160	-73.450
110	-1.823	-46.810	-38.820	-21.752	-85.630	-90.740	-69.640
115	-2.253	-18.218	-59.272	-33.212	-77.490	-86.760	-66.210
120	-2.665	9.565	-82.965	-46.488	-73.400	-84.260	-63.510
125	-3.057	37.179	-109.179	-61.176	-72.000	-81.650	-60.890
130	-3.426	66.417	-137.117	-76.830	-70.700	-80.100	-58.740
135	-3.769	95.031	-165.931	-92.975	-70.900	-77.960	-56.410
140	-4.083	123.544	-194.744	-109.120	-71.200	-76.550	-54.390
145	-4.366	150.882	-222.682	-124.775	-71.800	-74.170	-51.970
150	-4.616	176.796	-248.896	-139.463	-72.100	-72.270	-49.740
155	-4.831	200.489	-272.589	-152.738	-72.100	-69.110	-46.940
160	-5.009	223.641	-293.041	-164.198	-69.400	-66.260	-44.250
165	-5.148	246.331	-309.631	-173.494	-63.300	-61.970	-40.900
170	-5.249	264.154	-321.854	-180.343	-57.700	-57.850	-37.590
175	-5.310	278.210	-329.340	-184.538	-51.130	-52.190	-33.550
180	-5.330	286.521	-331.861	-185.950	-45.340	-46.590	-29.510

185	-5.310	290.440	-329.340	-184.538	-38.900	-39.460	-24.710
190	-5.249	290.054	-321.854	-180.343	-31.800	-32.300	-19.900
195	-5.148	288.131	-309.631	-173.494	-21.500	-23.700	-14.290
200	-5.009	280.241	-293.041	-164.198	-12.800	-15.030	-8.680
205	-4.831	269.249	-272.589	-152.738	-3.340	-5.120	-2.290
210	-4.616	252.316	-248.896	-139.463	3.420	4.860	4.080
215	-4.366	234.382	-222.682	-124.775	11.700	15.720	11.190
220	-4.083	215.544	-194.744	-109.120	20.800	26.580	18.200
225	-3.769	193.831	-165.931	-92.975	27.900	37.780	25.840
230	-3.426	174.017	-137.117	-76.830	36.900	48.820	33.300
235	-3.057	155.079	-109.179	-61.176	45.900	59.460	41.170
240	-2.665	142.465	-82.965	-46.488	59.500	69.630	48.760
245	-2.253	130.072	-59.272	-33.212	70.800	78.490	56.400
250	-1.823	119.120	-38.820	-21.752	80.300	86.420	63.610
255	-1.380	112.320	-22.230	-12.456	90.090	92.950	70.300
260	-0.926	107.807	-10.007	-5.607	97.800	99.760	76.620
270	0.000	116.600	0.000	0.000	116.600	118.700	89.980
280	0.926	129.693	10.007	5.607	139.700	142.910	109.730
290	1.823	126.880	38.820	21.752	165.700	175.050	134.950
300	2.665	120.735	82.965	46.488	203.700	214.000	170.700
310	3.426	111.783	137.117	76.830	248.900	257.010	218.180
320	4.083	95.756	194.744	109.120	290.500	299.700	277.700
330	4.616	80.000	248.896	139.463	333.700	336.440	345.180
340	5.009	55.000	293.041	164.198	357.800	360.780	408.430
350	5.249	32.000	321.854	180.343	368.900	367.200	457.950
360	5.330	0.320	331.861	185.950	356.900		