

NEURAL NETWORKS FOR ESTIMATION OF OCEAN WAVE PARAMETERS

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Abstract

Ocean wave parameters play a significant role in the design of all coastal and offshore structures. In the present study, neural networks are used to estimate various ocean wave parameters from theoretical Pierson-Moskowitz spectra as well as measured ocean wave spectra off Mormugao, west coast of India. The correlations of neural network and Scott spectra are also compared. Once the network is trained, the ocean wave parameters can be estimated for unknown measured spectra, whereas significant wave height and spectral peak period are required to generate the Scott spectra. This study shows that the missing field wave data can be generated using trained network.

1.0 INTRODUCTION

Wave spectra that have been employed to describe ocean waves along Indian coast are Pierson-Moskowitz (1964) and Scott (1965) spectra as reported by Dattatri et al., (1977), and Narasimhan and Deo (1979). Ocean waves are mostly generated by winds. They are very complex in nature and tend to change very much in rough weather. The studies of wave parameters play a significant role in the design of all coastal and offshore structures. Despite their obvious importance, the complex process active in their generation is only beginning to be understood. Progress in understanding the phenomenon has been hindered due to lack of wave data. Neural networks provide a good alternative to predict the behavior of ocean waves in different weather conditions.

Neural networks have the ability to recognize the hidden pattern in the data and accordingly estimated the values. Provision of model-free solutions, data error tolerance, built in dynamism and lack of any exogenous input requirement makes the neural network attractive. A neural network (NN) is an information processing system modeled on the structure of the dynamic process. Its merit is the ability to deal with information whose interrelation is ambiguous or whose functional relation is not clear. Deo and Naidu (1999), Prabakaran (2001) and Makarynsky (2004) have carried out some applications of the NNs for wave forecasting using neural network.

This paper describes the NNs that are used to estimate ocean wave parameters from PM

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spectra as well as field data and also how the neural network is more effective than Scott spectra, which is widely represented for Indian coastal condition (Dattatri et al., 1977; and Narasimhan and Deo, 1979). Here the backpropagation neural network with Rprop updated algorithms (Reidmiller and Braun, 1993) is used. The present study can generate missing wave data. Suppose some wave data are missed for particular location at particular time period, then ocean wave parameters or spectral energy can be generated using trained neural network.

2.0 NEURAL NETWORK

One of most widely used types of network is the backpropagation neural network, which is the extension of the feed-forward neural network. This type of network model is equivalent to a multivariate multiple non-linear regressions model and is used in this study. It consists of a layer of nodes that accept various inputs. These inputs, depending on the complexity of the network architecture, are fed to further layers of nodes and ultimately to a layer of outputs, which produce a response. The aim of the technique is to train the network such that the response to a given set of inputs corresponds as closely as possible to a desired output. Multi-layer feed-forward networks have the property that they can approximate to arbitrary accuracy any continuous function, defined on a domain provided that the number of internal hidden nodes is sufficient.

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

$$y_k(x) = \sum_{j=1}^M w_{kj} * T_r(z) + b_{ko} \quad (1)$$

$$z = \sum_{i=1}^D w_{ji} * x_i + b_{jo} \quad (2)$$

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

$$T_r(z) = 2/(1+e^{-2z}) - 1 \quad (3)$$

here z corresponds to the summed weighted input from the input layer. This is a key element of the model. The bias parameters for the hidden and output layers allow offsets to be introduced. Using Rprop algorithm, the weights to both the hidden and output layers are adjusted to minimize the error between the NN's simulated output and the actual output.

3.0 WAVE ANALYSIS

The wave parameters used in the present analysis are significant wave height (Hs), zero crossing period (Tz), spectral peakedness parameter (Qp), spectral width parameter (Sp), maximum spectral energy (Emax), and time period corresponding to maximum spectral energy (Tp).

3.1 Theoretical wave analysis

In order to establish the neural network between theoretical wave spectrum and ocean wave parameters, a fully developed sea Pierson-Moskowitz spectrum (Pierson and Moskowitz, 1964) was used. The statistical parameters were evaluated using the spectral moments (Kumar et al., 2003) as follows:

$$\text{Significant wave height, } H_s = 4 \sqrt{m_0}$$

$$\text{Zero crossing wave period, } T_z = \sqrt{(m_0/m_2)}$$

$$\text{Spectral width parameter, } Sp = \sqrt{[1-(m_2^2/(m_0*m_4))]}$$

$$\text{Peakedness parameter, } Q_p = (2/m_0^2) \int_0^{\infty} S^2(f) df$$

where, $m_n = \int_0^{\infty} S^n(f) df$ and f the frequency from 0.01Hz to 0.6Hz with $df=0.005\text{Hz}$.

The wave period corresponding to maximum spectral energy (Tp) and maximum spectral energy (Emax) is found from spectral energy values $S(\omega)$. Using the above formulae spectral data sets and corresponding wave parameters were obtained for wind velocities ranging from 5-25 m/s. Sixteen of those data sets were used for training and remaining five data sets were used as test patterns. In first step using spectral energies six ocean wave parameters have been obtained using the network 120-6-6 (Fig.1). The correlation coefficients (CC) for PM wave parameters are very close to one for most of the cases as shown in Table 1. The graphical representation is also shown in Figs.2 to 7. This shows that the neural network once trained can estimate theoretical wave parameters more accurately.

Table 1. Correlation coefficients (CC) for PM wave parameters.

Wave parameters	CC	
	Train	Test
Significant wave height (Hs)	0.9999	0.9978
Zero crossing period (Tz)	0.9998	0.9985
Maximum spectral energy(Emax)	0.9999	0.9997
Wave period corres. to Emax(Tp)	0.9996	0.9981
Spectral peakedness (Qp)	0.9608	0.9204
Spectral width (Sp)	0.9987	0.9909

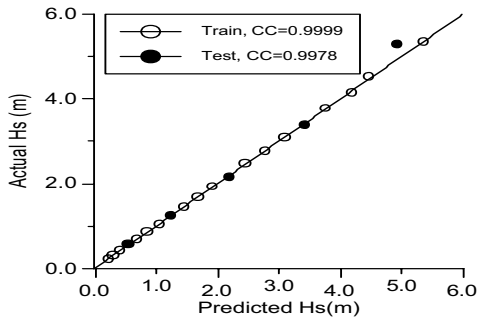
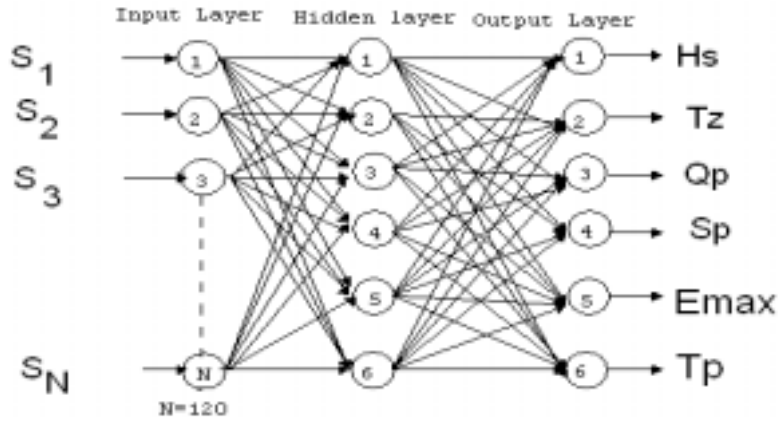


Fig. 2. Actual Hs v/s Predicted Hs (PM).

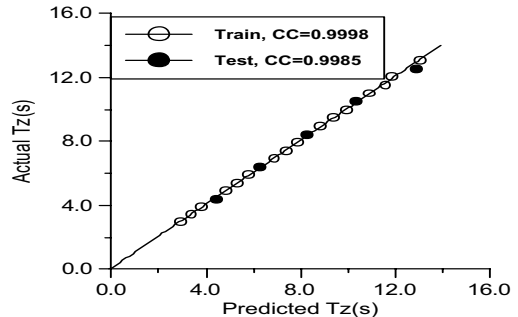


Fig. 3. Actual Tz v/s Predicted Tz (PM).

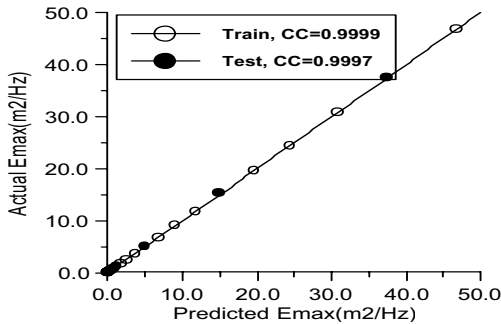


Fig. 4. Actual Emax v/s Predicted Emax (PM).

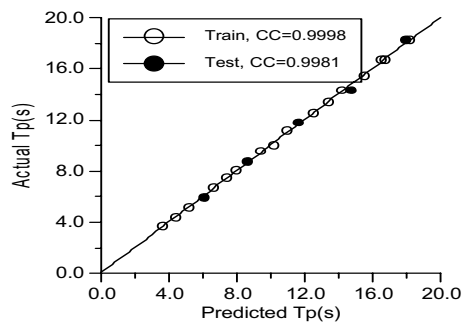


Fig. 5. Actual Tp v/s Predicted Tp (PM).

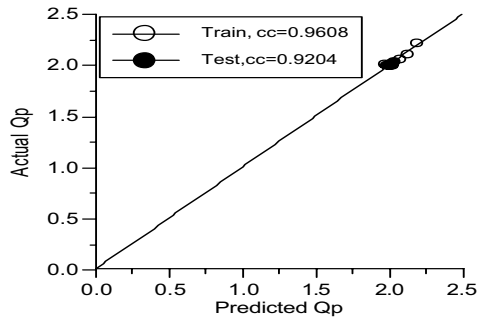


Fig. 6. Actual Qp v/s Predicted Qp (PM).

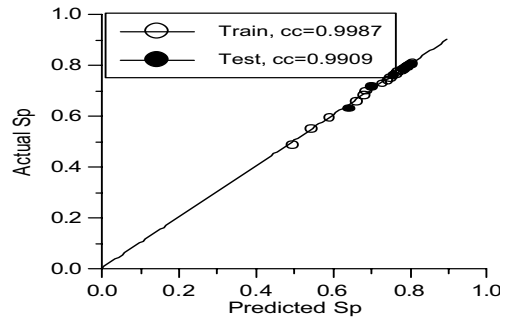


Fig. 7. Actual Sp v/s Predicted Sp (PM).

3.2 Field wave analysis

The wave data collected off Mormugao, west coast of India at a water depth of 23 m during July 1996 is used for the present study. Three hourly ocean wave spectral parameters over the period are used for training the network.

From the measured spectral energy, six wave parameters i.e. H_s , T_z , Q_p , S_p , E_{max} and T_p are calculated. 72 data sets considered are divided into two parts, i.e., 60 data sets for training the network and remaining 12 data sets for testing. In first step from spectral energy the six-ocean wave parameters are calculated. The network structure 64-15-6 is trained and tested (Fig. 8). The correlation coefficients are calculated as shown in Table 2. The high correlation coefficients, 0.89 to 0.99 for training field data shows that the training has been done correctly for all input patterns. The distribution of measured waves is not purely Gaussian, but having multiple peaks with noise/spikes and because of this the correlation coefficient for test data is between 0.86 to 0.95.

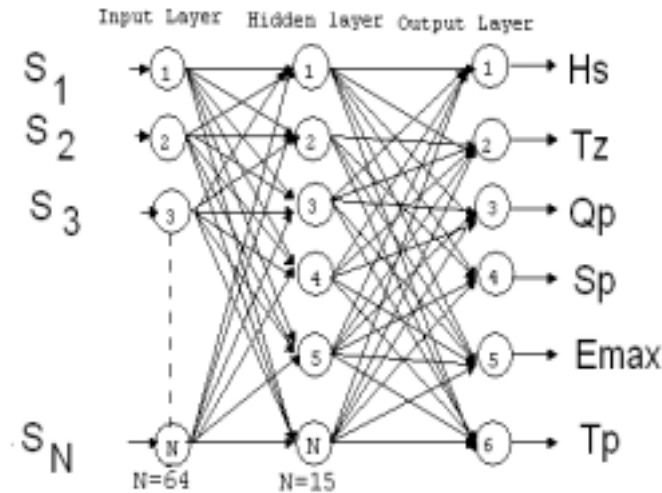


Fig. 8. ANN structure (Field data) N-64-15-6.

Table 2. Correlation Coefficients (CC) for wave parameters (field data)

Wave parameters	CC	
	Train	Test
Significant wave height (H_s)	0.9549	0.9495
Zero crossing period (T_z)	0.9662	0.9449
Maximum spectral energy (E_{max})	0.9895	0.9874
Wave period corres. to E_{max} (T_p)	0.8904	0.8694
Spectral peakedness Q_p	0.9585	0.9008
Spectral width (S_p)	0.9137	0.8908

3.3 Comparison between Scott and NN spectrum

Scott spectrum (Scott, 1965) was recommended for the west coast of India by Dattatri et al. (1977), Narasimhan and Deo (1979), Baba et al. (1989) and Kumar et al. (2003) by analyzing the data collected off Mangalore, Mumbai High, Cochin and Karwar respectively. The probable reason might be the fact the original validation of Scott spectrum was carried out using considerable swell dominated data. Similar situation usually prevails at many sites along the Indian coast. The Scott spectra were estimated for the same Mormugao wave data and it was shown that average CC's of wave parameters are 0.8 (Kumar et al., 2003). The measured, neural network and Scott spectra are shown in Fig.10. The CC's of NN6 (from 6 wave parameters to spectrum), NN4 (from 4 wave parameters to spectrum) and Scott spectra (from H_s and T_p to spectrum) are comparable as shown in Table 3. However, the maximum energies are better estimated by neural network as compared to Scott. Once the network is trained the ocean wave parameters can be estimated for unknown measured spectra, whereas H_s and T_p are required to generate the Scott spectra and thereafter other wave parameters can be estimated.

Table 3. CCs for NN and Scott Spectra.

Field wave data	CC for NN6	CC for NN4	CC for Scott
G9607080351	0.9441	0.9541	0.9018
G9607080651	0.9515	0.9207	0.9680
G9607081019	0.9711	0.9206	0.9745
G9607081249	0.9410	0.9133	0.9204
G9607081548	0.9464	0.9604	0.9798
G9607081852	0.9367	0.9486	0.9711
G9607082151	0.9035	0.9513	0.8938
G9607090050	0.8503	0.8518	0.9095
G9607091849	0.9244	0.8477	0.9401
G9607092149	0.9577	0.9295	0.9516
G9607100052	0.9397	0.9231	0.9638
G9607100351	0.9769	0.9467	0.9536

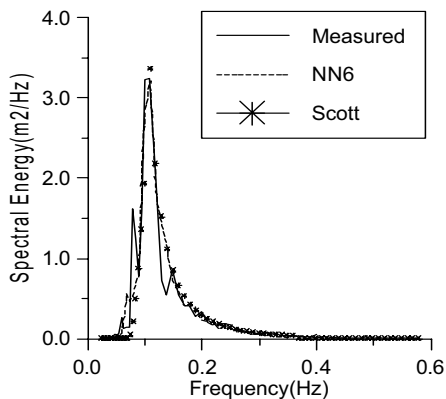


Fig.10.1. Measured/NN6/Scott Spectra (G9607080351).

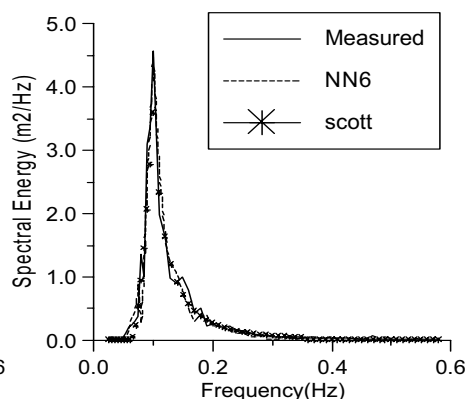


Fig.10.2. Measured/NN6/Scott Spectra (G9607081019).

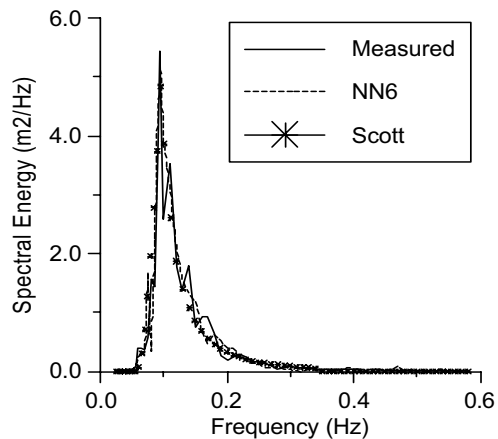


Fig.10.3. Measured/NN6/Scott Spectra (G9607092149) .

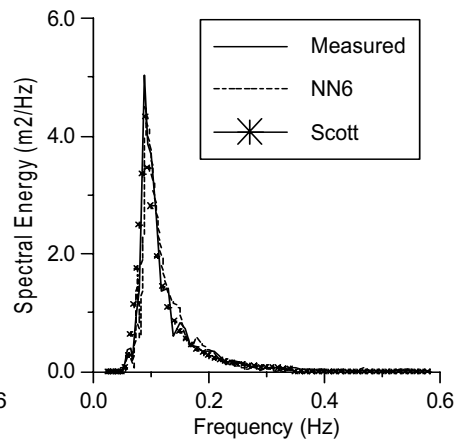


Fig.10.4. Measured/NN6/Scott Spectra (G9607100351).

4.0 CONCLUSIONS

Following conclusions are drawn based on the present investigation:

Since users mostly apply theoretical (PM) spectra in the absence of measured ocean waves, here first the PM spectral data sets are generated and used for network training and testing. Very high correlation coefficients for H_s , T_z , E_{max} and T_p in training and testing for PM spectra owing to Gaussian distribution justify the use of neural networks.

The distribution of measured waves is not purely Gaussian, but having multiple peaks with noise/spikes. Hence the CCs for train and test field wave data are relatively less as compared to CCs for PM spectra.

The CCs of NN and Scott spectra are comparable, but the maximum energies are better estimated by NN as compared to Scott.

This study shows that the ocean wave parameters can be directly obtained from the measured spectra using trained neural network.

This study shows that the missing field wave data can be generated using trained network.

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