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Ocean wave parameters estimation using backpropagation neural networks

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Abstract

In the present study, various ocean wave parameters are estimated from theoretical Pierson–Moskowitz spectra as well as measured ocean wave spectra using backpropagation neural networks (BNN). Ocean wave parameters estimation by BNN shows that the correlations are very close to one. This substantiates the use of neural networks (NN). For Indian coast, Scott spectra are used as it reasonably represents the measured spectra. The correlations of NN 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 first generate the Scott spectra and then estimate other ocean wave parameters.

Keywords: Wave models; Backpropagation neural network; Ocean wave spectra; Correlation coefficients

1. Introduction

The ocean wave model hindcasts ocean wave parameters based upon the past meteorological and oceanographic data. Wave forecasting by wave models is useful in the planning and maintenance of marine activities. Just as weather conditions, the wave conditions will change from year to year, thus a proper statistical analysis requires several

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years of wave data and quite often from many locations simultaneously. Estimation of ocean wave parameters is useful for the design of harbors, coastal structures, offshore structures, defense purposes, planning, operations, coastal erosion, sediment transport and wave energy estimation. Waves are mostly generated by winds. They are very complex in nature and tend to change very much in rough weather. Despite their obvious importance, the complex processes are active in their generation is not a simple task. Progress in understanding the phenomenon has been hindered due to lack of wave data. Neural networks (NN) provide a good alternative to predict the behavior of ocean waves in different weather conditions. For any engineering work, short term (say, three hourly) sea wave parameters, namely significant wave height, zero crossing period, spectral peakedness parameter, spectral width parameter, maximum spectral energy, spectral peak period, spectral narrowness parameter, etc. are required. For better representation of the sea state, these wave parameters are to be accurately estimated from wave spectra.

Wave spectra that have been employed to describe ocean waves in Indian coast are Pierson–Moskowitz [1] and Scott [2] spectra as reported by Dattatri et al. [3], Narasimhan and Deo [4] and Kumar et al. [5]. NN have the ability to recognize the hidden pattern in the data and accordingly estimates the values. Provision of model-free solutions, data error tolerance, built in dynamism and lack of any exogenous input requirement makes the NN attractive. A 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 [6] and Deo et al. [7] have carried out applications of the NN for wave forecasting and Subba Rao et al. [8] have worked on wave propagation using backpropagation neural network (BNN). Subba Rao and Mandal [9] have hindcasted storm waves using NN. Deo et al. [10] have investigated dependency of the spreading parameter on the characteristic wave parameters using NN. Non-linear wave–wave interaction source term of the energy balance equation is simplified using artificial NN [11] and thereby improved the ocean wave predictions. Londhe and Deo [12] have carried out wave tranquility using NN. Altunkaynak and Ozger [13] have used perceptron Kalman filtering technique for estimation of significant wave height from wind speed.

This paper describes the BNN that is used to estimate ocean wave parameters, namely significant wave height (H_s), zero crossing period (T_z), spectral peakedness parameter (Q_p), spectral width parameter (S_p), maximum spectral energy ($E_{\max}$) and time period corresponding to maximum spectral energy (T_p) from Pierson–Moskowitz spectra as well as field data and also how the NN is more effective than Scott spectra, which is widely represented for Indian coastal condition [3,4]. Here the BNN with updated algorithms Rprop [14] is used.

2. Backpropagation neural network

NN are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the network function is determined largely by the connections between elements. A NN can be trained to perform a particular function by adjusting the values of the connecting weights between the elements. BNN are adjusted or trained to establish a required path/trend, so that a particular input leads to a specific target output. Such a situation is shown in Fig. 1. Here, the network is adjusted, based on a comparison of the output, and the target, until the network output matches the target.

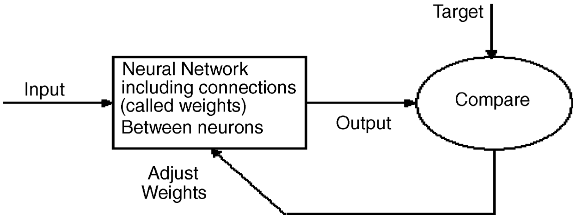

Fig. 1. Basic principle of artificial neural networks.

Typically, many such input/output pairs are used to train a network. Batch training of a network proceeds by making weight and bias changes based on an entire set of input vectors. Incremental training changes the weights and biases of a network as needed after presentation of each individual input vector.

One of most widely used types of network is the BNN, which is the extension of the feed-forward NN. 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 hidden layer's 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 of any continuous function, defined on a domain provided that the number of internal hidden nodes is sufficient.

Mathematically, the feed-forward artificial NN is expressed in the form

$$y_k(x) = \sum_{j=1}^{M} w_{Kj} \times T_r(z) + b_{k\mathrm{o}}, \tag{1}$$

$$z = \sum_{i=1}^{D} w_{ji} \times x_i + b_{ji}, \tag{2}$$

where x is considered to be the original parameter space of dimension D, w_{kj} and w_{ji} are weighting parameters, $b_{k\mathrm{o}}$ and b_{ji} 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

$$T_r(z) = \frac{2}{1 - \mathrm{e}^{-2z}} - 1, \tag{3}$$

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. The overall objective of a training algorithm is to reduce the global error, E is defined below:

$$E = \frac{1}{p} \sum_{p=1}^{P} E_p, \tag{4}$$

where P is the total number of training patterns, E_p is the error at pth training pattern is given by

$$E_p = \frac{1}{2}\sum_{k=0}^{N}(O_k - t_k)^2, \tag{5}$$

where N is the total number of output nodes, O_k is the output at the kth output node and t_k is the target output at the kth output nodes.

2.1. Backpropagation learning

Backpropagation is the most widely used algorithm for supervised learning with multi-layer feed-forward networks. The idea of the backpropagation learning algorithm is the repeated application of the chain rule to compute the influence of each weight in the network with respect to an arbitrary error function E:

$$\frac{\partial E}{\partial w_{ij}} = \left[\frac{\partial E}{\partial s_i}\right] \times \left[\frac{\partial s_i}{\partial net_i}\right] \times \left[\frac{\partial net_i}{\partial w_{ij}}\right]. \tag{6}$$

Here, w_{ij} is the weight from neuron j to neuron i, s_i is output, and net_i is the weighted sum of the inputs of neuron i. Once the partial derivative for each weight is known, the aim of minimizing the error function is achieved.

Various adaptive techniques [15] are available to efficiently minimize the error function. Here resilient propagation (Rprop) adaptive technique is applied. It performs a direct adaptation of the weight step based on local gradient information. Reidmiller and Braun [14] introduce for each weight its individual update value Δ_{ij}, which solely determines the size of the weight update. During the learning process the adaptive updating weight evolves based on its local sight on the error function E, which is given below:

$$w_{ij}^{(t+1)} = w_{ij}^{(t)} + \Delta w_{ij}^{(t)}, \tag{7}$$

where Δw_{ij}, is given as,

$$\Delta w_{ij}^{(t)} = \begin{cases} -\Delta_{ij}^{(t)} & \text{if } \dfrac{\partial E^{(t)}}{\partial w_{ij}} > 0, \\ +\Delta_{ij}^{(t)} & \text{if } \dfrac{\partial E^{(t)}}{\partial w_{ij}} < 0, \\ 0 & \text{else.} \end{cases} \tag{8}$$

3. Wave analysis

The ocean wave parameters used in the present analysis are significant wave height (H_s), zero crossing period (T_z), spectral peakedness parameter (Q_p), spectral width parameter (S_p), maximum spectral energy ($E_{\max}$) and time period corresponding to maximum spectral energy (T_p). There could be some ambiguities on accurate estimation of measured ocean wave parameters using NN which do not have a clear-cut straight-forward optimal system. Therefore, using NN wave parameters are estimated from a theoretical Pierson–Moskowitz wave spectrum to first confirm the usefulness of NN. The trained network having fixed weights and biases, estimates ocean wave parameters, which should be very close to the estimated theoretical wave parameters. Thereafter, NN are applied for estimating the measured ocean wave parameters.

3.1. Theoretical wave analysis

In order to establish the NN between theoretical wave spectrum and ocean wave parameters, a fully developed sea Pierson–Moskowitz spectrum is used

$$S(\omega) = \frac{A}{\omega^5} \times \exp\left(\frac{-B}{\omega^4}\right), \tag{9}$$

where $A = 0.0082\,\mathrm{g}^2$, $B = 0.74(\mathrm{g/v})^4$, v is the wind speed in m/s at a height of 19.5 m above mean water level, g the gravitational acceleration in m/s^2, $\omega = 2\pi f$, f is the frequency in Hz

The statistical parameters were evaluated using the spectral moments [5] as follows:

$$\text{Significant wave height, } H_s = 4\sqrt{m_0}, \tag{10}$$

$$\text{Zero crossing wave period, } T_z = \sqrt{(m_0/m_2)}, \tag{11}$$

$$\text{Peakedness parameter, } Q_p = (2/m_0^2)\sum f \times S^2(f) \times df, \tag{12}$$

$$\text{Spectral width parameter, } S_p = \sqrt{(1 - (m_2^2/(m_0 \times m_4)))}, \tag{13}$$

where $m_n = \sum f^n \times S(f) \times df$ and f the frequency from 0.01 to 0.6 Hz with $df = 0.005$ Hz. The wave period corresponding to maximum spectral energy (T_p) and maximum spectral energy ($E_{\max}$) are found from spectral energy values $S(\omega)$.

Using the above formulae spectral data sets and corresponding wave parameters are generated for wind velocities (V) ranging from 5 to 25 m/s as shown in Table 1. Sixteen of those data sets are used for training and remaining five data sets are used as test patterns. In first step using wind velocity six-ocean wave parameters have been obtained. The network structure N-1-4-6 is obtained (Fig. 2). In order to properly understand the working of NN and after estimating weights and biases (Tables 2 and 3) using BNN, the procedure for calculation of wave parameters is explained below.

Here once the network is trained, the weights and biases are fixed. For the present case of a trained network (N-1-4-6) for 16 sets of inputs–outputs, fixed values of weights and biases are estimated as shown in Fig. 2. n_i (summation function of neuron i) and F_i (hyperbolic tangent sigmoid transfer function of neuron i) are obtained. These values (F_i) are neurons, belong to hidden layer. The transfer function was chosen as described in Eq. (3) and also shown as F_i function. In output neurons, summation functions are only selected as output values which are H_s (m), T_z (s), Q_p, S_p, $E_{\max}$ (m^2/Hz) and T_p (s). For this purpose *purelin* was chosen [4] as transfer function. To estimate the above six-ocean wave parameters, the following formulations are used:

$$\text{Transfer functions, } F_i = \{2/(1 + \exp(-2 \times n_i)) - 1\}, \quad i = 1 \text{ to } 4. \tag{14}$$

For trained network, estimated weights and biases (shown in Fig. 2) are used as given below:

$$n_1 = V \times (0.0807) - 12.5160,$$

Table 1
Wave parameters for PM spectra

Sr. no.	Wind speed (m/s)	H_s (m)	T_z (s)	Q_p	S_p	E_{max} (m^2/Hz)	T_p (s)
1	5	0.20	2.93	2.214	0.49	0.02	3.64
2	6	0.30	3.39	2.103	0.55	0.04	4.35
3	7	0.42	3.87	2.056	0.59	0.08	5.13
4	8	0.55	4.36	2.033	0.63	0.16	5.88
5	9	0.69	4.86	2.021	0.66	0.28	6.67
6	10	0.85	5.34	2.013	0.68	0.48	7.41
7	11	1.04	5.86	2.009	0.70	0.77	8.00
8	12	1.23	6.37	2.006	0.71	1.19	8.69
9	13	1.45	6.87	2.005	0.73	1.78	9.52
10	14	1.68	7.38	2.004	0.74	2.56	10.00
11	15	1.93	7.89	2.003	0.75	3.63	11.11
12	16	2.19	8.40	2.002	0.76	5.02	11.76
13	17	2.47	8.92	2.002	0.76	6.80	12.50
14	18	2.77	9.43	2.001	0.77	9.04	13.33
15	19	3.09	9.94	2.001	0.78	11.76	14.28
16	20	3.42	10.46	2.008	0.78	15.26	14.29
17	21	3.78	10.97	2.007	0.79	19.57	15.38
18	22	4.14	11.49	2.006	0.79	24.35	16.66
19	23	4.53	12.01	2.005	0.80	30.83	16.67
20	24	4.93	12.52	2.004	0.80	37.62	18.18
21	25	5.35	13.04	2.003	0.81	46.79	18.18

$$F_1 = 2/(1 + \exp(-2 \times n_1)) - 1,$$

$$n_2 = V \times (0.3327) - 7.6137,$$

$$F_2 = 2/(1 + \exp(-2 \times n_2)) - 1,$$

$$n_3 = V \times (0.2401) - 4.2457,$$

$$F_3 = 2/(1 + \exp(-2 \times n_3)) - 1,$$

$$n_4 = V \times (0.1195) - 0.5811,$$

$$F_4 = 2/(1 + \exp(-2 \times n_4)) - 1,$$

where V is the wind speed, n_1–n_4 and F_1–F_4 represent summation function and transfer function of each neuron at hidden layer, respectively.

The six-ocean wave parameters, i.e., H_s, T_z, Q_p, S_p, E_{max} and T_p are computed as

$$H_s = F_1 \times (1.3749) + F_2 \times (0.9601) + F_3 \times (1.1238) + F_4 \times (1.4855) + 0.7951, \quad (15)$$

$$T_z = F_1 \times (3.2842) + F_2 \times (1.0535) + F_3 \times (1.9428) + F_4 \times (4.7756) + 2.5119, \quad (16)$$

$$Q_p = F_1 \times (0.4839) + F_2 \times (-0.0197) + F_3 \times (0.0348) + F_4 \times (-0.1766) + 1.6593, \quad (17)$$

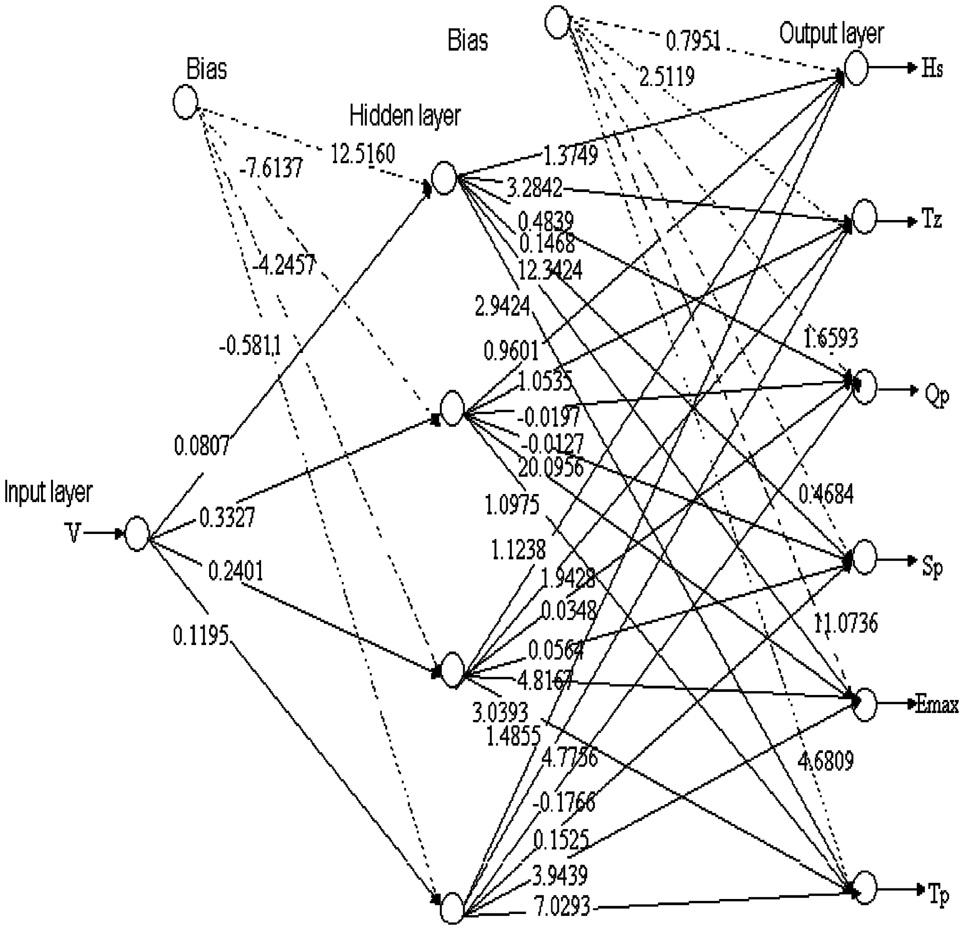

Fig. 2. ANN structure (PM) NN-1-4-6.

Table 2
Weights (W_{ih}) and bias (B_{hl}) between input and hidden layers

W_{ih} for input wind speed	Bias values of hidden layer nodes (B_{hl})
0.0807	12.5160
0.3327	−7.6137
0.2401	−4.2457
0.1195	−0.5811

$$S_p = F_1 \times (0.1468) + F_2 \times (-0.0127) + F_3 \times (0.0564) + F_4 \times (0.1525) + 0.4684, \tag{18}$$

$$E_{\max} = F_1 \times (12.3424) + F_2 \times (20.0956) + F_3 \times (4.8167) + F_4 \times (3.9439) + 11.0736, \tag{19}$$

Table 3
Weighs (W_{ho}) and bias (B_{ol}) between hidden and output layers

W_{ho} for hidden node 1	W_{ho} for hidden node 2	W_{ho} for hidden node 3	W_{ho} for hidden node 4	Bias values of nodes (B_{ol})
1.3749	0.9601	1.1238	1.4855	0.7951
3.2842	1.0535	1.9428	4.7756	2.5119
0.4839	−0.0197	0.0348	−0.1766	1.6593
0.1468	−0.0127	0.0564	0.1525	0.4684
12.3424	20.0956	4.8167	3.9439	11.0736
2.9424	1.0975	3.0393	7.0293	4.6809

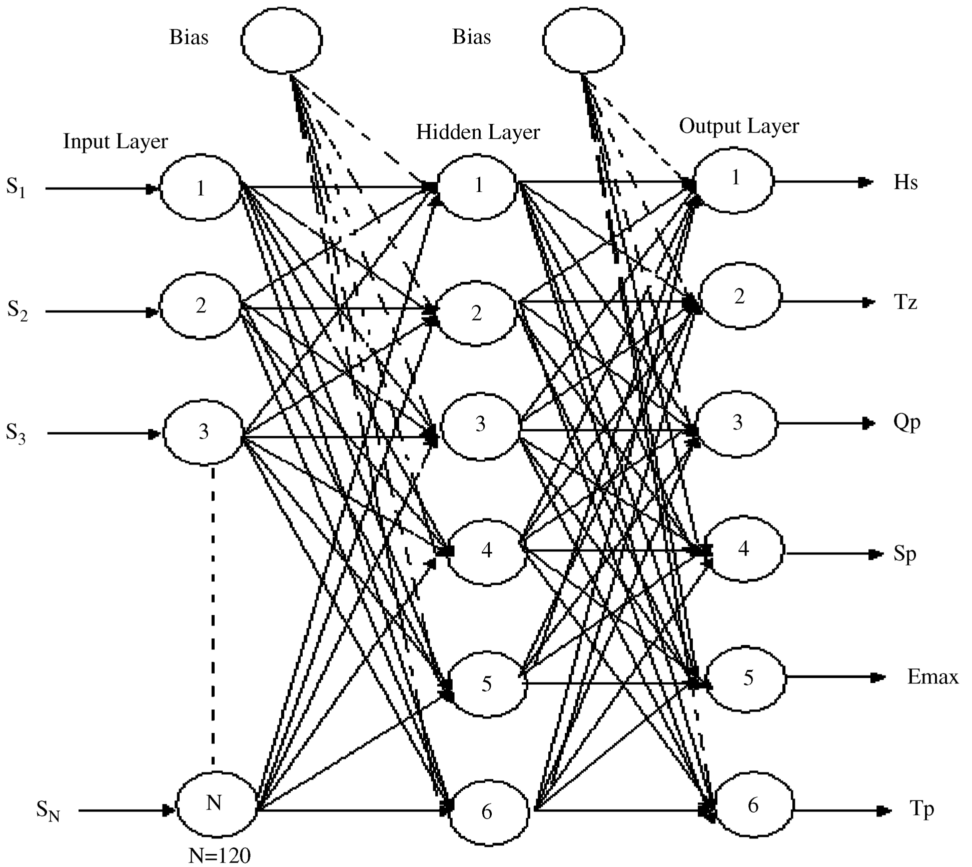

Fig. 3. ANN structure (PM) NN-120-6-6.

$$T_p = F_1 \times (2.9424) + F_2 \times (1.0975) + F_3 \times (3.0393) + F_4 \times (7.0293) + 4.6809. \quad (20)$$

In second step using spectral energies, six-ocean wave parameters have been obtained. The network structure N-120-6-6 is obtained (Fig. 3). Estimated ocean wave parameters by NN are compared with actual values as shown in Figs. 4–9. The correlations for ocean

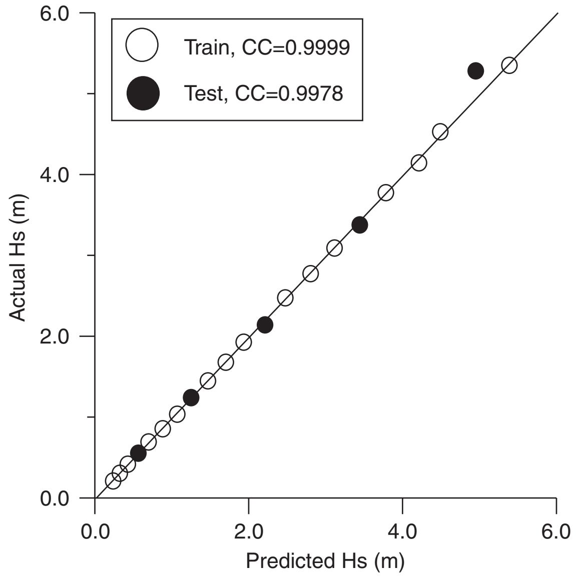

Fig. 4. Actual H_s vs. predicted H_s.

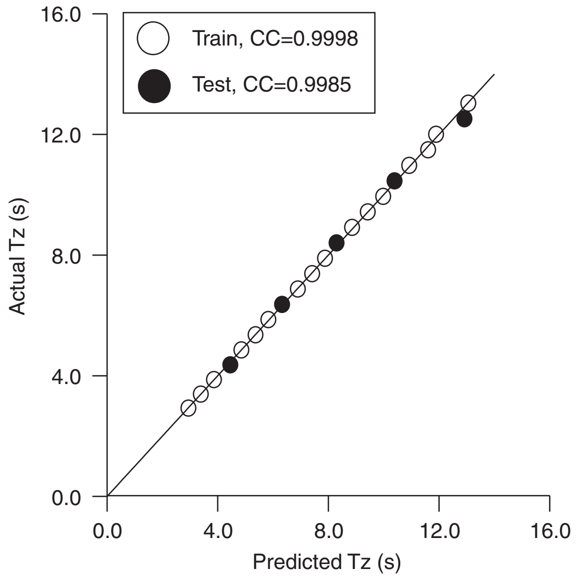

Fig. 5. Actual T_z vs. predicted T_z (PM).

wave parameters, namely, H_s, T_z, E_{max}, T_p and S_p are close to one, except for Q_p. Since the actual values of Q_p are about 2 and there is marginal variation as compared to other 5 parameters, predicted values of Q_p are not close to one. This substantiates the use of NN. A 45° line is drawn in above graphs which represents the correlation coefficient (CC) of

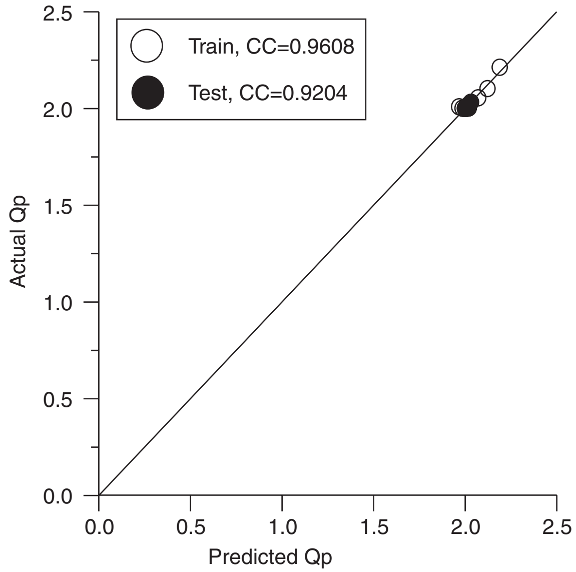

Fig. 6. Actual Q_p vs. predicted Q_p (PM).

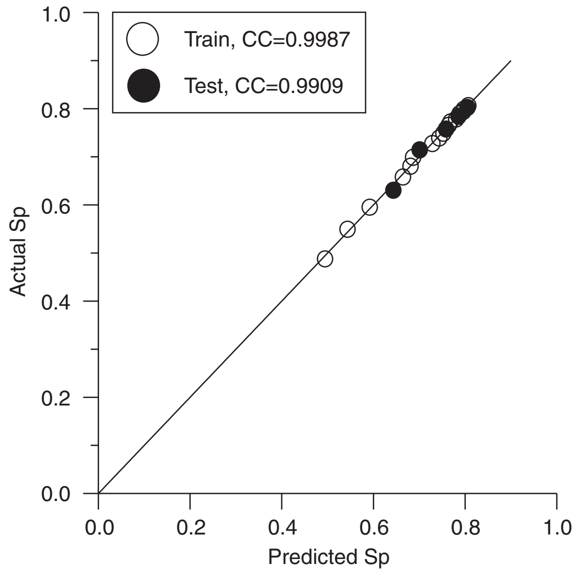

Fig. 7. Actual S_p vs. predicted S_p (PM).

one. The deviation of points from this line will reduce the CC between the two variables, i.e., target and actual output. Since the theoretical ocean wave parameters are estimated from the PM spectra using various wind speeds, both above procedures yield correlations close to one as shown in Table 4. This leads to an established NN procedure to the estimation of wave parameters from ocean wave spectra.

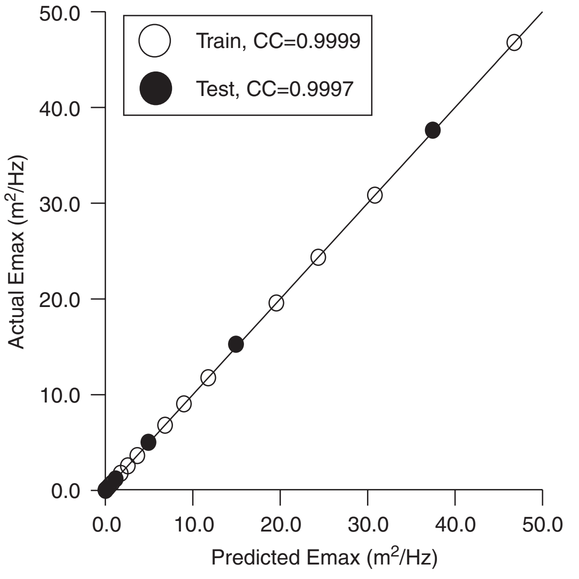

Fig. 8. Actual E_{max} vs. predicted E_{max} (PM).

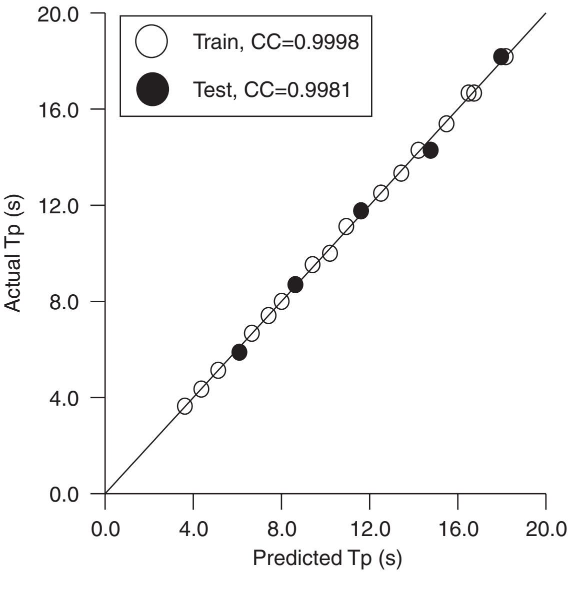

Fig. 9. Actual T_p vs. predicted T_p (PM).

3.2. Field wave analysis

The wave data collected off Marmugao, west coast of India (Lat 15° 27.9′ N, Lon 73° 41.0′ E) 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.

Table 4
Correlation coefficients (CCs) for wave parameters from wind speed and spectral energy

Wave parameters	CC from wind speed	CC from spectral energy
Significant wave height (H_s)	0.999	0.998
Zero crossing period (T_z)	0.999	0.999
Maximum spectral energy (E_{max})	0.999	0.999
Wave period corres. to E_{max} (T_p)	0.995	0.998
Spectral peakedness (Q_p)	0.961	0.920
Spectral width (S_p)	0.972	0.991

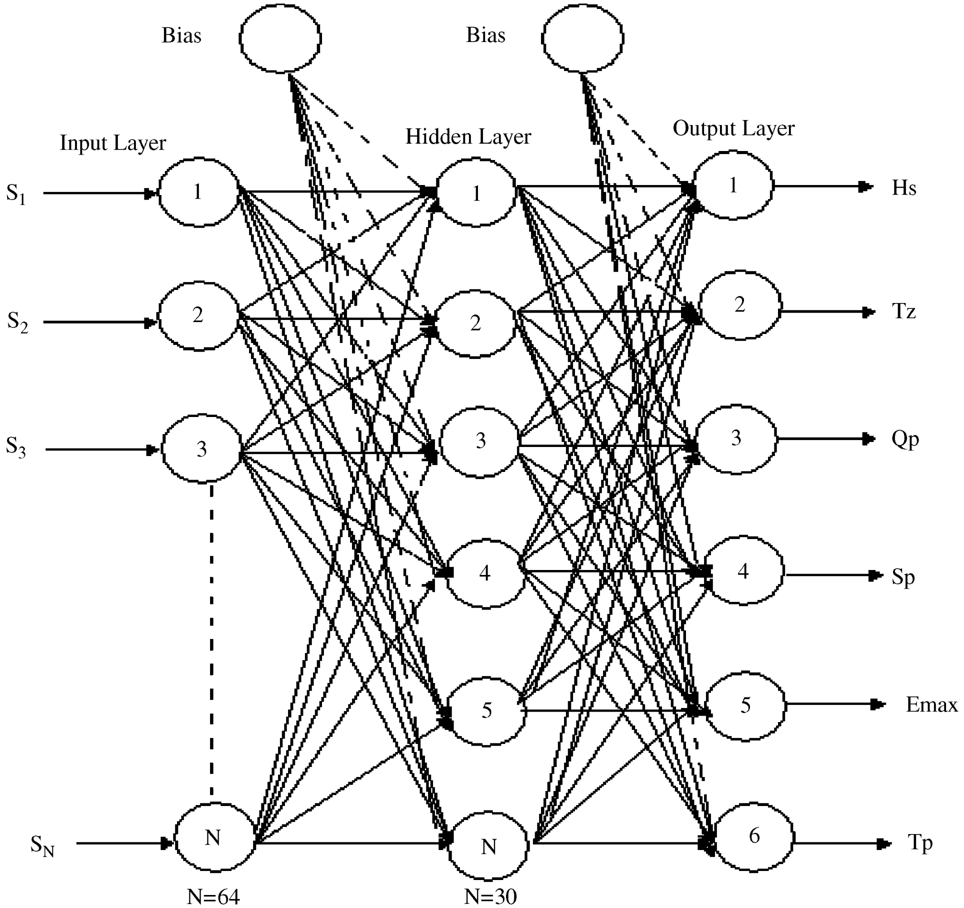

Fig. 10. ANN structure (field data) NN-64-30-6.

The ocean wave parameters, i.e., H_s, T_z, Q_p, S_p, E_{max} and T_p are calculated from the measured spectral energy by using Eqs. (10)–(13). From 72 wave data sets considered, 60 data sets are used 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 NN structure 64-30-6 (Fig. 10) is trained and tested. Figs. 11–16 are the graphs for six-wave parameters

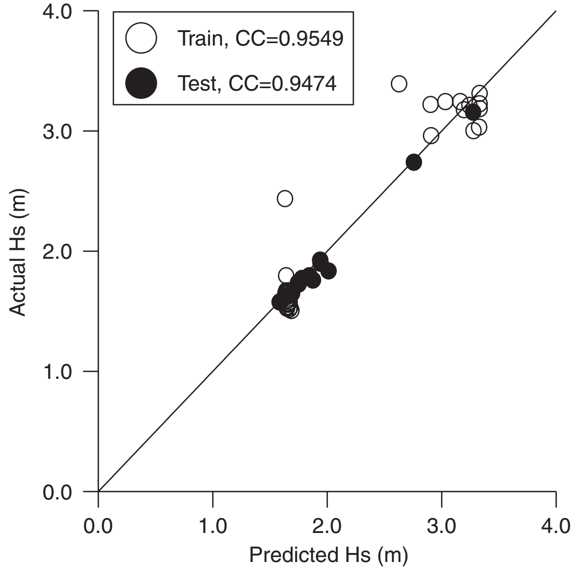

Fig. 11. Actual H_s vs. predicted H_s (field data).

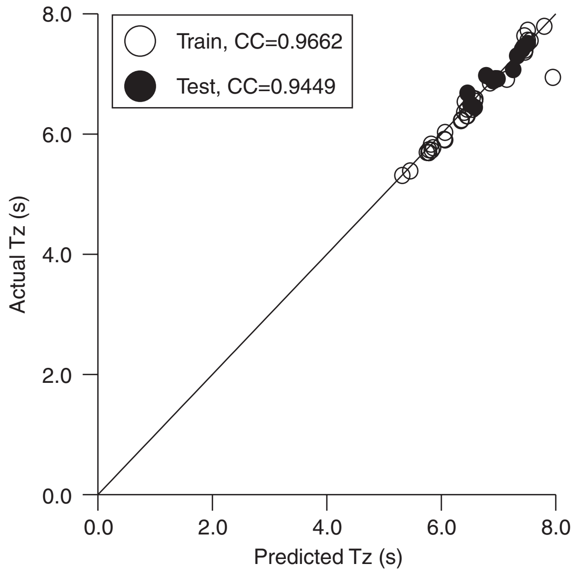

Fig. 12. Actual T_z vs. predicted T_z (field data).

which are estimated from field spectra using Eqs. (10)–(13) and NN. The CCs (trained network) of wave parameters, i.e., H_s, T_z, $E_{\max}$ T_p, S_p and Q_p are above 0.9. The estimation (test) of H_s, T_z and $E_{\max}$ are very good (CCs are above 0.94). The correlation of T_p ($CC = 0.8825$) is less as compared to other parameters owing to relatively poor training ($CC = 0.9001$) of this parameter as can be observed in Fig. 16. Similarly correlation of S_p

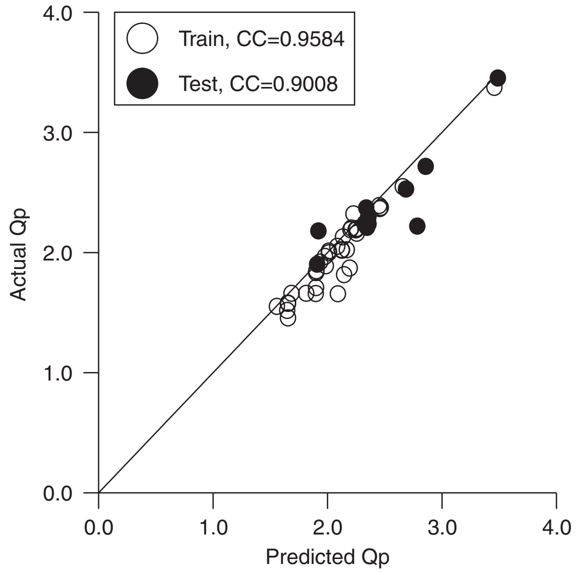

Fig. 13. Actual Q_p vs. predicted Q_p (field data).

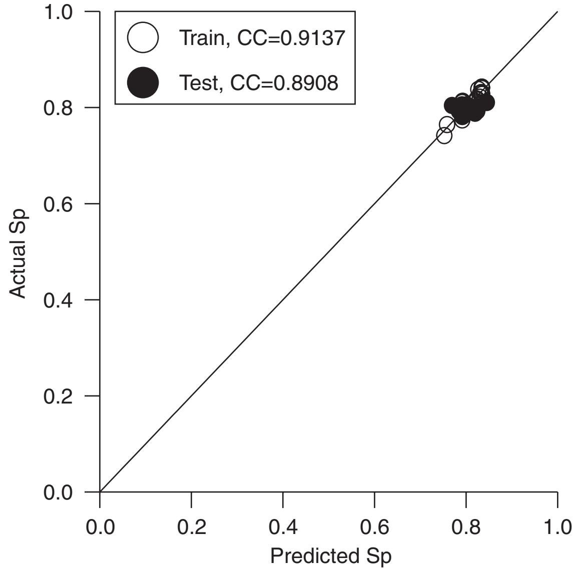

Fig. 14. Actual S_p vs. predicted S_p (field data).

is less than 0.9. This is owing to marginal variation of this parameter as compared to other parameters. A 45° line drawn in above graphs which represents the CC of one. Similarly the network structure 64-15-4 for 4 parameters (H_s, T_z, $E_{\max}$ and T_p) is also used for above data sets. The CCs are calculated as shown in Table 5. Comparing NN estimated all

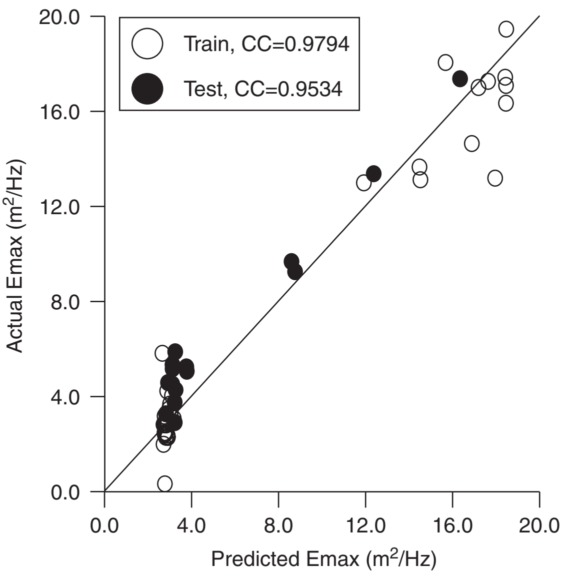

Fig. 15. Actual E_{max} vs. predicted E_{max} (field data).

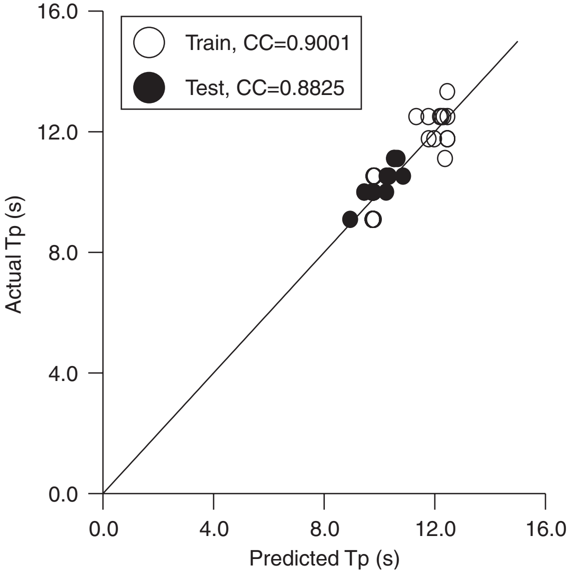

Fig. 16. Actual T_p vs. predicted T_p (field data).

six-wave parameters of PM spectra and field data, the two wave parameters namely spectral width and peakedness parameters have less influence on estimation of spectral energies. The high CCs, 0.89–0.99 for training field data shows that the training has been done correctly for all input patterns. The distribution of measured waves is not purely

Table 5
Correlation coefficients (CCs) for wave parameters (field data) obtained from actual field spectrum and NN method

Wave parameters	CC for 6 parameters		CC for 4 parameters	
	Train	Test	Train	Test
Significant wave height (H_s)	0.955	0.947	0.926	0.914
Zero crossing period (T_z)	0.966	0.945	0.938	0.929
Maximum spectral energy ($E_{\max}$)	0.979	0.953	0.974	0.956
Wave period corres. to $E_{\max}$ (T_p)	0.900	0.883	0.885	0.840
Spectral peakedness (Q_p)	0.958	0.901	—	—
Spectral width (S_p)	0.914	0.891	—	—

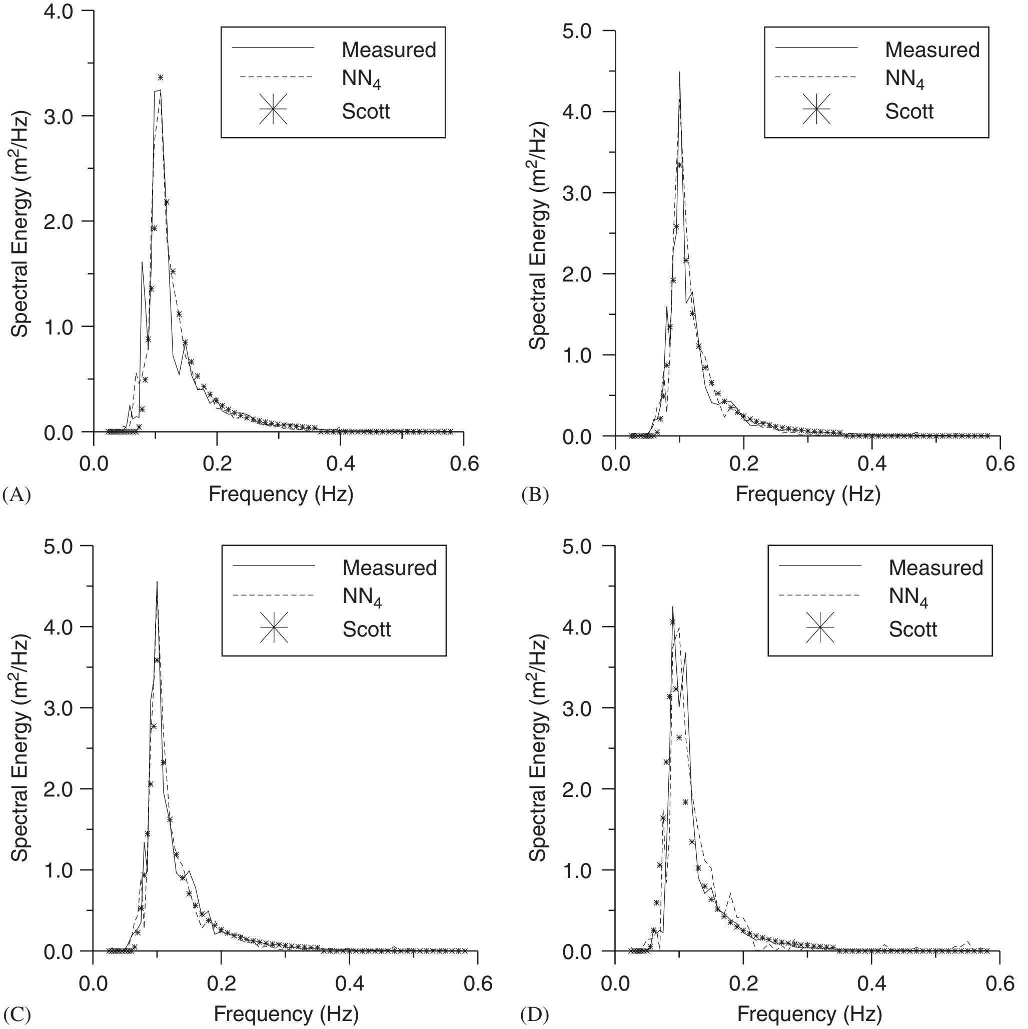

Fig. 17. Variation of measured/NN_4/Scott spectra.

Gaussian, but having multiple peaks with noise/spikes and because of this the CC for test data is between 0.87 and 0.95. In the absence of spectral width and spectral peakedness, CCs for H_s, T_z, $E_{\max}$ and T_p are relatively less as compared to six-wave parameters estimation.

3.3. Comparison between Scott and NN spectra

Scott spectrum [2] was recommended for the west coast of India by Dattatri et al. [3], Narasimhan and Deo [4], Baba and Dattatri [16] and Kumar et al. [5] by analyzing the data collected off Mangalore, Mumbai High, Cochin and Karwar, respectively. The reason is that 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 spectrum is given by

$$\begin{aligned} S(\omega) &= 0.214 \times H_s \times \exp\left(-\frac{(\omega-\omega_p^2)}{0.065(\omega-\omega_p+0.26)}\right)^{1/2} \\ &= 0 - 0.26 < (\omega-\omega_p) < 1.65, \end{aligned} \tag{21}$$

where $S(\omega)$ is the spectral density at angular wave frequency 'ω', H_s is the significant wave height and ω_p is the peak angular wave frequency.

The Scott spectra are estimated for the same Marmugoa measured wave data (using H_s and T_p) and it is shown that average CC of wave parameters are 0.8 [5]. Here 4 wave parameters, namely H_s, T_z, $E_{\max}$ and T_p are used as input to estimate the NN_4 spectra. The measured, neural network (NN_4) and Scott spectra are compared as shown in Fig. 17. The CCs of NN_4 and Scott spectra are comparable as shown in Table 6. However, the estimated NN spectra are better represented in peak frequency region as compared to that of Scott spectra. Once the network is trained the ocean wave parameters can be estimated for measured unknown spectra, whereas H_s and T_p are required to first generate the Scott spectra and then estimate other ocean wave parameters.

Table 6
CCs for NN and Scott spectra

Field wave data	CC for NN_4	CC for Scott
G9607080351	0.941	0.902
G9607080651	0.921	0.968
G9607081019	0.921	0.974
G9607081249	0.913	0.920
G9607081548	0.946	0.980
G9607081852	0.936	0.971
G9607082151	0.901	0.894
G9607090050	0.852	0.909
G9607091849	0.848	0.940
G9607092149	0.929	0.952
G9607100052	0.923	0.964
G9607100351	0.947	0.954

4. Conclusions

Based on the present investigation the following conclusions are drawn:

The Pierson–Moskowitz spectral data sets are generated and used for network training and testing. Very high CCs for H_s, T_z, E_{max} and T_p in training and testing for Pierson–Moskowitz spectra owing to Gaussian distribution justify the use of NN. The distribution of measured waves is not purely Gaussian, but having multiple peaks with noise/spikes. Hence the CCs for training and testing field wave data are relatively less as compared to CC for theoretical spectra. The CCs of NN and Scott spectra are comparable, but the spectra in peak frequency region 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 NN.

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