‘Temporal significant wave height estimation from wind speed by perceptron Kalman filtering’

by A Altunkaynak and M Ozger, Ocean Engineering, 2004, 31, 1245-1255

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The significant wave heights and periods are conventionally forecasted from the wind information on the basis of the wind–wave relationship. However, the error may become large due to many uncertainties in the wind generation prediction and wind–wave relationship. This is also confirmed by the authors, where the correlation (r) between measured wind speeds and significant wave heights is found to be 0.595 (r^2 = 0.3541). The authors have rightly mentioned the restrictive uses of regression method, especially for predicting wind generated waves.

The authors have established the two layered Perceptron based on Kalman Filtering (PKF) technique to estimate the significant wave height (Hs) amounts for future time intervals from the wind speed speed (V) measurements only as stated in the *title* and *abstract* of the paper. However, the authors described the forecasting of Hs and V simultaneously based on previous step values as mentioned in their paper. In other words, one-step ahead Hs and V values are used to predict present step Hs and V. Since, the PKF model predicts Hs based on previous wind speed, there could be some inconsistencies in prediction of Hs when there is a next sudden very high or very low wind speed.

Interestingly the PKF model is a two layered network (input and output) without hidden layer. Also it is a fact that numerical or physical models have restrictions by certain assumptions and conditions, whereas artificial neural network (ANN) has no such restrictions. The PKF or any ANN model tries to find the relationship between the inputs and outputs of a particular dynamic system without understanding any physical processes or priori-restrictions.

The authors have chosen a problem where one should have a continuous program of measurement of winds as well as waves in offshore location. Measuring accurate waves over a longer period especially in cyclone prone area is not a simple task, whereas wind speed can be measured easily by installing a weather station near or on the offshore/coastal structures. Since the authors have mentioned that the Hs is estimated from wind speed, they may also establish the neural network between Hs and V based on initial measured winds and waves, so that the trained neural network needs only wind speed for which Hs is to be predicted. This procedure not only avoids the long-term wave measurement program but also simplifies the prediction system. Also on-line prediction of Hs based on wind speed has many direct applications as stated by the authors. Generating wind-driven ocean waves by the PKF model after 1h, 3h or 7h may not actually represent the actual ones for that particular wind speeds. Since wind generated waves are predominant in offshore areas, wind-driven ocean waves should be reliable.

The parameters of the trained network used by the authors, i.e. weights (a11, a12, a21, *a*22) and biases/system errors (w1, w2) are kept on changing/updating for each time step prediction. This means that for each next step prediction, one has to update weights and biases. This shows that it is a short-time phenomenon and the trained network is not fixed.

Similar work with next step (3h, 12h and 24h) prediction of Hs was carried out by Deo and Naidu (1999), Rao et. al. (2001), and Mandal and Prabaharan (2003). Deo and Naidu (1999) have compared the predicted Hs by autoregressive model and neural network in the form of correlation coefficient (*r),* which is defined as

$$r = \frac{\Sigma xy}{\sqrt{(\Sigma x^2 \, \Sigma y^2)}} \qquad (1)$$

Where,

$x = X - X'$

X = Measured significant wave height

X' = mean of X

$y = Y - Y'$

Y = predicted significant wave height

Y' = mean of Y.

The autoregressive (AR) model exhibited slightly lower values of the correlation coefficients than the neural network which shows that the ANN methods are more adaptive and online applicable. Rao et al (2001) using backpropagation neural network, Mandal and Prabaharan (2006) using nonlinear recurrent neural network, have further shown the improvement of neural network prediction of Hs. Comparison of the correlation coefficients is shown in Table-1.

Table-1 Correlation coefficients of Hs forecasting with lead time

Forecasting lead time	Deo and Naidu (1999)		Rao *et al* (2001)	Mandal and Prabaharan (2006)
	AR	ANN		
3 hour	0.78	0.81	0.93	0.95
6 hour	--	--	0.88	0.90
12 hour	0.72	0.78	0.80	0.87
24 hour	0.70	0.71	0.73	0.73

Similarly authors may discuss by providing a table comparing correlation coefficients (as defined in Equation-1) for 1h, 3h and 7h ahead predicted Hs by the PKF and regression method (RM) for the data used. This would clearly explain the advantages of PKF over RM technique.

The location with latitude and longitude and water depth for the measured data would provide meaningful description.

The authors mentioned in '*Introduction'* that the results of the PKF model obtained in this paper was with the 10% relative error, which should have been discussed in '*Application'* chapter.

Lastly the authors have defined an error relationship, i.e., average relative error percentage (AREP), but it is neither estimated nor discussed in their paper. The variation of wind speed with significant wave height for observed, RM and PKF shows that for the wind speed of less than 8m/s, RM prediction.is better than that of PKF, and PKF prediction is better for the wind speed of more than 8m/s.

A step further to the study carried out by the authors is shown by Tsai et al (2002). They have carried out forecasting of significant wave heights and periods at a desired location directly from the observed wave records using a supervised artificial neural network with error back-propagation procedures. They have evaluated the interconnection weights among multi-stations based on the previous short-term data, from which a time series of waves at a station can be generated for forecasting. Similar to the above work also leads to further application of neural network in the study of wave transformation.

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