



## MULTIRESOLUTION WAVELET-ANN MODEL FOR SIGNIFICANT WAVE HEIGHT FORECASTING

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### ABSTRACT

*Hybrid wavelet artificial neural network (WLNN) has been applied in the present study to forecast significant wave heights (Hs). Here Discrete Wavelet Transformation is used to preprocess the time series data (Hs) prior to Artificial Neural Network (ANN) modeling. The transformed output data are used as inputs to ANN models. Various decomposition levels have been tried for a db3 wavelet to obtain optimal results. It is found that the performance of hybrid WLNN is better than that of ANN when lead time increased considering various performance indices.*

### INTRODUCTION

Forecasting of significant wave height and other wave parameters are important for planning and maintenance of any marine activities (Mandal et al, 2005). Although there are many advantages of Artificial Neural network (ANN) in modeling of ocean parameters for non-stationary time series data, the performance of ANN models are not satisfactory in precision as they are following only few aspects of the characteristics of the time series (Wensheng, 2003). The effects of data preprocessing on the ANN model performance was investigated by Cannas et al (2006) using continuous and discrete wavelet transforms. The results showed that network preprocessed with trained data performed better than networks trained with undecomposed and noisy raw signals. Nourani et al.(2009) effectively used Multivariate ANN Wavelet approach in rainfall runoff modeling for short and long term prediction and results were encouraging.

To enhance the precision, a wavelet analysis has been coupled with ANN. Wavelet technique provides a mathematical process for decomposing a signal to multiple levels of details and analysis along with extracting local information of the time series.

### WAVELET TRANSFORM

The wavelet transform breaks the signal into its *wavelets (small wave)* which are scaled and shifted versions of the so called *mother wavelet*. The wavelet transform allows exceptional localization both in the time domain via translations of the wavelet, and in the frequency (scale) domain via dilations.

Discrete Wavelet Transformation (DWT) is used in the signal processing to decompose the discrete time signals. In the discrete case, filters of different cutoff frequencies are used to analyze the signal at different scales. The signal 'X(t)' is passed through a series of high pass filters (g[n]) to analyze the high frequencies, and it is passed through a series of low pass filters (h[n]) to analyze the low frequencies as shown in the Figure 1. The output from the high pass and low pass filters are the approximation coefficients (appcoef) and detail coefficients (detcoef).

### WAVELET NEURAL NETWORK (WLNN)

In recent years, the wavelet transform has been successfully applied in ocean engineering field (Lee and Kwon, 2003; Haung, 2004; Lin and Liu, 2004, Yuxiang et al, 2010; Ozger, 2010). This technique is particularly suitable for non-stationary process and can yield localized time frequency information that is not available in traditional transformation (Liu, 2000). Ozger (2010) developed a model for forecasting significant wave height using wavelet

fuzzy approach, in their study reveals that the combination of wavelet and fuzzy model gives better performance over lead time >24hours.

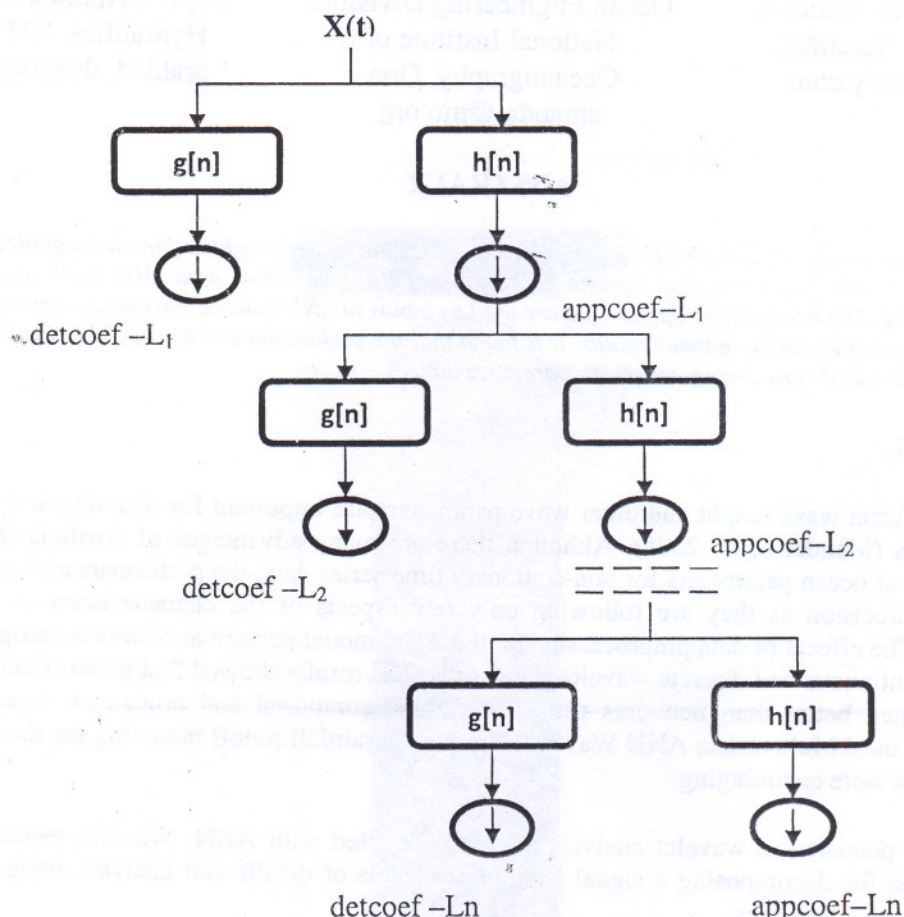


Fig.1 Discrete Wavelet Decomposition Tree

In the WLNN, the wavelet transformation does the data preprocessing and the output from the wavelet transformation are the approximations (low frequency contents) and details (high frequency contents) and these outputs are fed into ANN models. The ANN models analyze these inputs as a signal and extract the information from both approximation coefficients and detail coefficients and trained accordingly as depicted in Figure 2. In the present study, Discrete Wavelet Transformation is used to decompose the signal. The data is first converted as time domain signal and then it is decomposed to required levels to obtain the DWT coefficients. Considering irregularities in the wave height time series, an irregular wavelet called Daubechies of order 3 (db3) was adopted as mother wavelet and decomposition at various levels has been tried in the study. The db3 wavelet is considered to be suitable for removing localized spiky noise whose peak widths are the same as the sampling interval (Daubechies, 1988; Huang, 2004).

For ANN model, the network structure consists of TRAINGDX as training function, PURELIN as transfer function and two hidden layers. The feed forward backpropagation network structures are adopted using MATLAB, 2009.

## STUDY AREA

The present study uses the wave data of three hourly significant wave heights ( $H_s$ ) over the period collected off Marmugao Port, west coast of India at a water depth of 23m in the year 1996. Higher fluctuations are observed during the months of August to October month. Hence these data are used to assess the performance of the proposed models. Here, time series 489 data points are used for model building and 246 data points are used for

model testing. The highest significant wave height observed was 3.25m and lowest was 0.75m during the study period with fluctuations as shown in Figure 3.

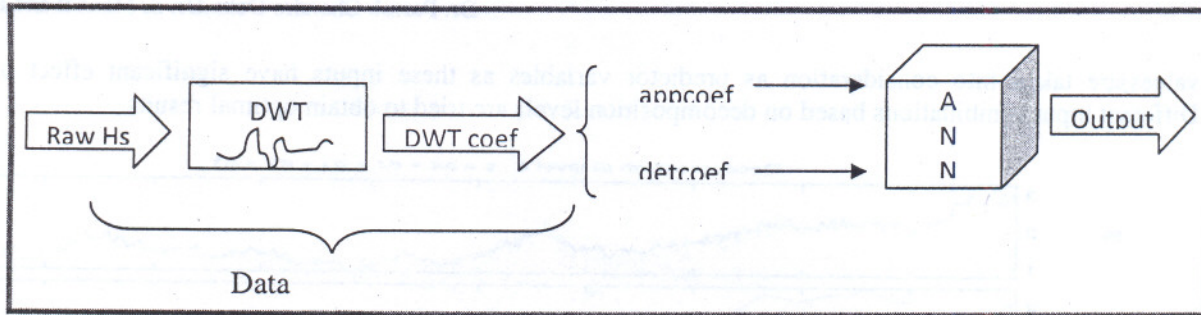


Fig.2 Schematic Diagram of the Proposed WLNN Model

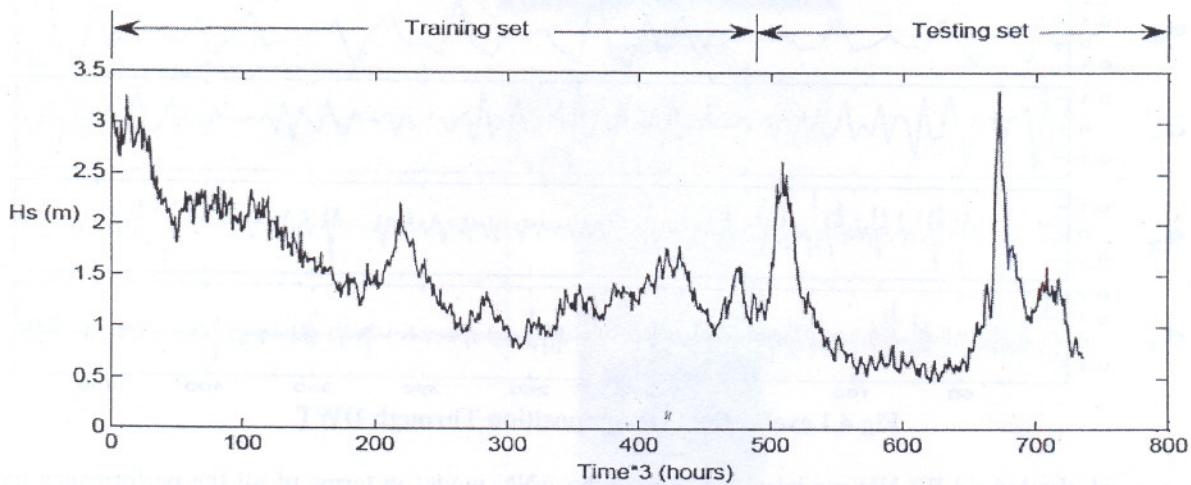


Fig.3 Time Domain Signal Of Monsoon Data

**PERFORMANCE INDICES**

To check efficiency of the model, following performance indices based on goodness of fit are used.

1. Coefficient of Efficiency,  $CE = 1 - \frac{\sum(x-y)^2}{\sum x^2}$  where  $x = X - X_{mean}$

2. Mean Absolute Error (MAE),  $MAE = \frac{\sum|x-y|}{N}$

3. Root Mean Square Error (RMSE),  $RMSE = \sqrt{\frac{\sum_{i=1}^N (X - Y)^2}{N}}$

Where, X=observed values, Y=predicted values and N = total number of values

**RESULTS AND DISCUSSION**

The output of the DWT in the form of approximations and details for level 4 is shown in figure 4. The results of the proposed WLNN model are compared with ANN models using same network structure for different lead times of 3hr and 6hr, which are presented in Table 1. Wave height values up to previous 6h (two previous time step

values) are taken into consideration as predictor variables as these inputs have significant effect on output. Different input combinations based on decomposition levels are tried to obtain optimal results.

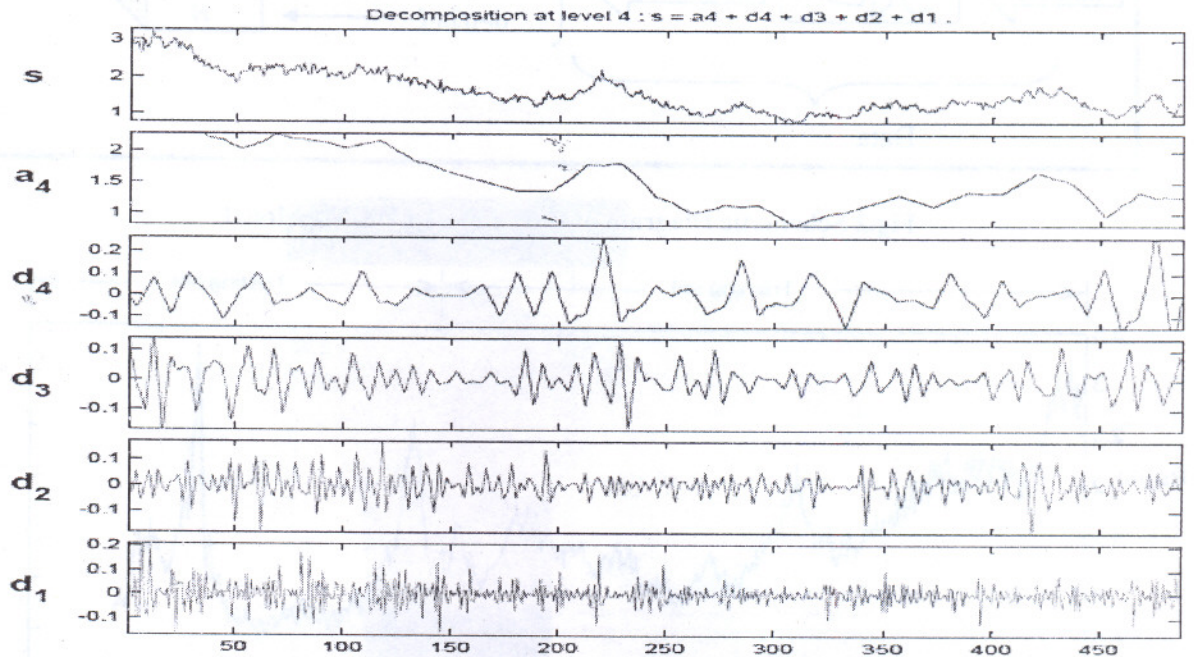


Fig.4 Level-4 Data Decomposition Through DWT

In general, the hybrid WLNN model outperformed the ANN model in terms of all the performance indices. The significant influential effect of various decomposition levels are observed from the testing results presented in Table 1. Both in 3hr and 6 hr lead time prediction, the performance of WLNN are almost similar or with insignificant difference for all the decomposition levels. On the other hand, ANN model performance suffers in higher lead time forecasting compare to WLNN models. It can be concluded that WLNN model is almost consistent for higher lead times forecasting which captured attention for more extended lead time.

Table 1 (Testing Results)

Model/Performance	3hr prediction			6 hr prediction			Rank
	MAE	RMSE	CE	MAE	RMSE	CE	
ANN	0.204	0.239	0.809	0.241	0.289	0.724	4
WNN-Level-3	0.200	0.237	0.813	0.217	0.256	0.783	3
WNN-Level-4	<b>0.192</b>	<b>0.229</b>	<b>0.825</b>	<b>0.214</b>	<b>0.250</b>	<b>0.792</b>	<b>1</b>
WNN-Level-5	0.194	0.230	0.823	0.216	0.257	0.785	2

Results obtained for the different performance indices shows that the decomposition level-4 is performing better compared to the lower level decomposition and it is almost similar with level-5. Beyond level-5, there is no significant improvement of the results. The decomposition level-4 appears as an optimum level for the better performance of the network. The scatter plots between observed and predicted significant wave heights are shown in figure 5 and figure 6 for both the models for different lead times. It is observed that the forecast by WLNN model is almost satisfactory than ANN model.

Also the WLNN model results are compared with the observed values to visualize the trend and deviation during various time duration and magnitudes as shown in figure 7. It is observed that the WLNN model results almost in good agreement with observed values in transition and peak values in general. On the other hand, the

WLNN model could not capture the observed trend fully but over estimated during lower values. The reasons may be due to the absence of other influential meteorological input parameters such as wind and wind related components. Also selection of type of wavelet might affect the performance in a significant way which will be taken care in future scope of study.

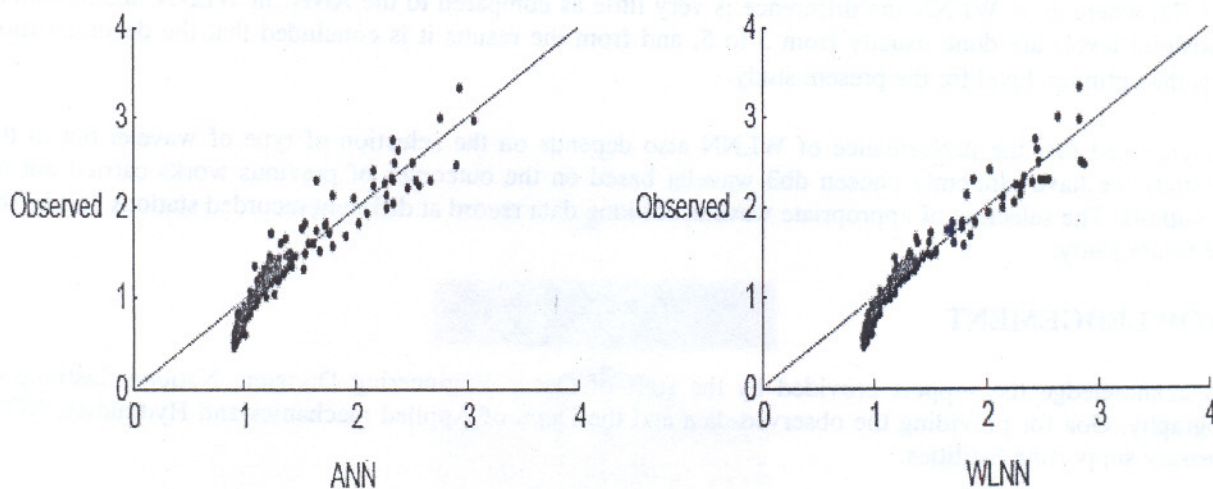


Fig.5 Scatter Plot for 3hr Hs

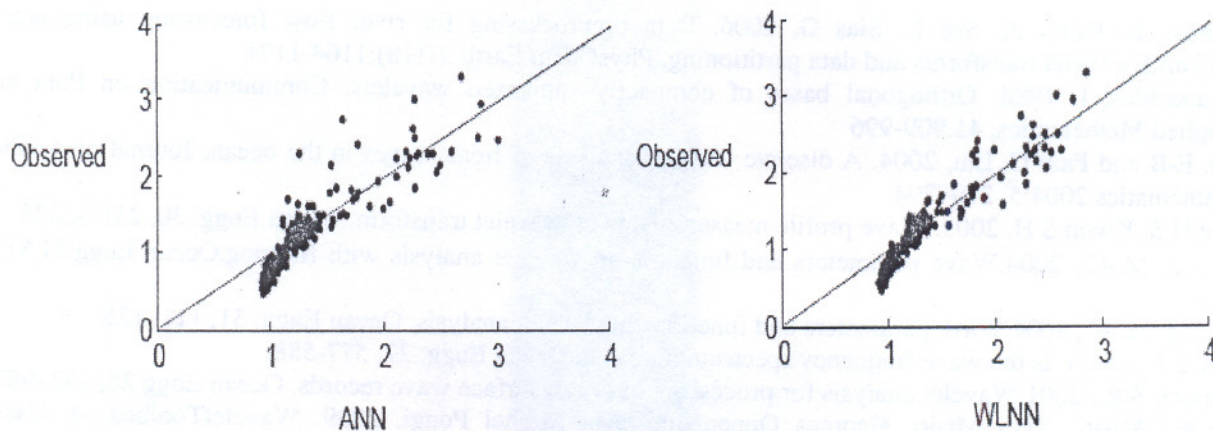


Fig.6 Scatter Plot For 6 Hr Hs

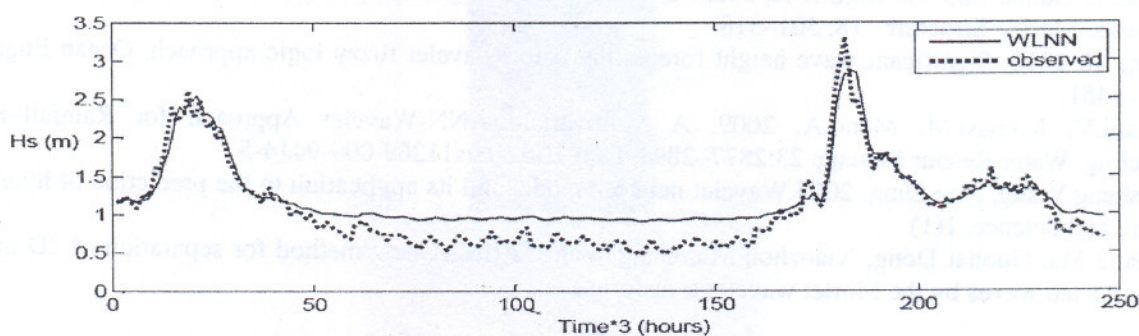


Fig. 7 Model Performance (3 Hr Prediction) During Testing Period

**CONCLUSIONS**

In this study, a hybrid model of wavelet and ANN has been applied to forecast significant wave height for 3hr and 6hr lead time. The proposed hybrid wavelet ANN model performs better in terms of various performance criteria than ANN. It is observed that when the lead time increases (3hr to 6hr), the CE value for ANN is decreased from

0.80 to 0.72, where as in WLNN the difference is very little as compared to the ANN. In WLNN, the minimum decomposition levels are done usually from 3 to 5, and from the results it is concluded that the decomposition level-4 is the optimum level for the present study.

It is expected that the performance of WLNN also depends on the selection of type of wavelet but in the present study we have randomly chosen db3 wavelet based on the outcomes of previous works carried out by various authors. The selection of appropriate wavelet for long data record at different recorded stations will be the focus of future study.

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