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Forecasting of Time Series Significant Wave Height Using Wavelet Decomposed Neural Network

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Abstract

In this current study, a hybrid model of wavelet and Artificial Neural Network (WLNN) has been developed to forecast time series significant wave height for lead times up to 48 h. The data used in the hybrid model are significant wave heights (Hs) belongs to two stations, one near to New Mangalore port, Indian ocean and another near to west of Eureka, Canada in North Pacific ocean. The three hourly significant wave height data for a period of one year was first decomposed through discrete wavelet transformation in order to obtain frequencies of different bands in the form of wavelet coefficients. Later these coefficients are used as inputs into Levenberg Marquardt artificial neural network models to forecast time series significant wave heights at multistep lead time. Two different methods WLNN-1 &WLNN-2 employed for the first station data to forecast significant wave heights at higher lead times. From the result it is found that the second method (WLNN-2) in wavelet-ANN model performed better than first method (WLNN-1).Model results obtained for two stations showed good predictions at lower lead times but slight deviation observed at higher lead times. As compared to first station results, the second station results are slightly poor because of more statistical variations in the data set.

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Keywords: Time series; multistep; hybrid model; artificial neural network; discrete wavelet; frequency bands

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1. Introduction

Time series modelling is an important research and application area. Many real world tasks are time dependent in nature to name a few, Rainfall runoff, ocean waves, river flow, sediment transport, weather forecasting etc. Since the last few decades, wavelet transform has emerged as a useful technique for analysing variations, periodicities, and trends in time series. Recently Hybridisation of wavelet transformation with other models has been reported in different fields to improve the forecasting accuracy; Wang et al. (2003) used Wavelet-ANN combination in hydrology to predict hydrological time series. Chen et al. (2007) used the same combination to forecast tides around Taiwan and South China Sea, and concluded that the proposed model can prominently improve the prediction quality. Zhou et al. (2008) developed a wavelet predictor-corrector model for prediction of monthly discharge time series. Recently many authors viz. Krishna (2014), Khandekar and Deka (2013), Deka and Prahlada (2012), Rajee et al.(2011), Prahlada and Deka (2011), Ozger (2010), Nourani et al. (2009), Kisi (2009) used hybrid wavelet models such as wavelet-ANN and Wavelet-fuzzy to forecast timeseries data in different fields. Study of all these recent works showed better performance of hybrid wavelet models over a single prediction models.

2. Wavelet Analysis

Wavelet transform is a mathematical tool used in signal analysis. Wavelet transforms decomposes a signal in to number of sub signals of different frequency bands. The earlier signal processing techniques such as Fourier transform (FT) and Short Time Fourier transform (STFT) have major drawbacks in terms of time information and also in high resolution. In wavelet analysis, the use of a fully scalable modulated window solves aforementioned problems. As in wavelet analysis the window or mother wavelet is shifted at every position of the signal, hence it is possible to calculate the spectrum at each position of signal. Basically there are two types of wavelet transformations viz. Continuous wavelet transformation and Discrete wavelet transformation.

2.1. Continuous Wavelet Transformation (CWT)

The continuous wavelet transform (CWT) is defined in terms of dilations and translations of a mother wavelet function, and it can be expressed as (Zhou, 2008; Kisi, 2009)

$$W_{\psi} f(a,b) = |a|^{-\frac{1}{2}} \int_{Re} f(t) \bar{\psi}\left(\frac{t-b}{a}\right) dt$$

As seen in the above equation, the transformed signal is a function of two variables ‘a’ and ‘b’ the scale and translation parameter respectively, $\bar{\psi}$ denote the complex conjugate of ‘t’ (Mallat,1989), f(t) is the input signal and Ψ (t) is the transforming function, and it is called the mother wavelet.

2.2. Discrete Wavelet Transformation (DWT)

As CWT produces N^2 coefficients from a data set of length N; hence unnecessary information is locked up within the coefficients, which may or may not be desirable property (Rajaee T. et al., 2011). Whereas by using DWT it is possible to overcome from the above difficulty as DWT calculates wavelet coefficients on discrete dyadic scales and positions in time.

$$\Psi_{m,n}(t) = \frac{1}{\sqrt{a_0^m}} \Psi\left(\frac{t - b_0 a_0^m}{a_0^m}\right)$$

Where m and n are integers that control the wavelet dilation and translation, respectively; b_o is the location parameter and must be greater than zero; a_o is a specified fixed dilation step greater 1. The appropriate choices for a_o and b_o depend on the wavelet function. The dyadic wavelet can be written in more compact notation as

$$\Psi_{m,n}(t) = 2^{-m/2}\, \Psi(2^{-m}\, t - n)$$

For a discrete time series x_t, where x_t occurs at discrete time, the dyadic wavelet transform becomes

$$W_{m,n}(t) = 2^{-m/2} \sum_{i=0}^{N-1} \Psi\left(2^{-m} t - n\right)\chi_t$$

Where $W_{m,n}$ = wavelet coefficient for the discrete wavelet of scale $a = 2^m$ and location $b = 2^m n$. Above equation considers a finite time series, x_t, t= 0, 1, 2,…, N - 1, and N is an integer power of 2: $N = 2^M$; n is time translation parameter. This gives the range of m and n as, respectively, $0 < n < 2^{M-m} - 1$ and $1 < m < M$.

3. Study area and Data

The significant wave height (Hs) data collected at two stations have been used in this current study. At first 3 hourly Hs data belong to first station (Id: SW4) collected during the year 2004-2005 was obtained from New Mangalore Port Trust (NMPT). The data obtained from station SW4 is a wave rider buoy data, the buoy is located near west coast of India having Latitude $12^0 56'31''$ and longitude $74^0 43'58''$ as shown in Fig.1.

Fig.1. Location of the study area of station-1 (Id: SW4)

The data collected at second station (Id: 46006) during 2004-2005 was downloaded from NOAA's National Data Buoy Center (http://www.ndbc.noaa.gov/ climate.phtml). The buoy station "46006" is located in deep sea of Pacific Ocean (Latitude. $40^0 45'16''$ and longitude$137^0 27'51''$) near west of eureka, Canada as shown in Fig.2.

Fig.2. Location of the study area of station-2 (Id: 46006)

The frequency of the data collected at this station is an hourly significant wave height data. The statistical properties of the data collected at two stations are given in Table 1.

Table1. Statistical properties of significant wave height

Station ID	Min (m)	Max (m)	Mean (m)	Skewness	Kurtosis	Std. deviation (m)
SW4	0.25	3.09	1.025	0.78	0.4867	0.6289
46006	0.92	11.05	2.821	1.186	1.93	1.413

4. Model development

4.1 ANN model

Artificial neural network (ANN) is a data-driven method with flexible mathematical structure having an interconnected assembly of simple processing elements or nodes, which emulates the function of neurons in the human brain. It possesses the capability of representing the arbitrary complex non-linear relationship between the input and output of any system. Mathematically, an ANN can be treated as universal approximators having an ability to learn from examples without the need of explicit physics.

The network used in the present study is multilayer perceptron (MLP) feed forward back propagation network and Levenberg Marquardt algorithm as a training algorithm. After selecting network type and training algorithm, the network was initially trained by keeping Mean square Error as a performance evaluator to optimize the parameters such as number of epochs, number of neurons, learning rate, and momentum coefficient. While in the initial analysis observation was also made to identify suitable activation functions for both hidden and output layers. Later it was found that the network performance with tangent sigmoid activation function was the best amongst others.

Once After obtaining optimized network parameters, each MLP was then trained with 1-20 hidden neurons and the same network structure followed for different lead predictions and also for combined wavelet-ANN model (WLNN).

4.2 Wavelet neural network model :method-1(WLNN-1)

After dividing the data in to training set and testing set, these data sets then fed to discrete wavelet transformation as inputs to obtain DWT coefficients. To perform wavelet analysis, here db4 and haar wavelets have been selected as mother wavelets and various decomposition levels have been tried. The function of discrete wavelet transformation is to discretize the non-stationary Hs data in to stationary sub signals to separate the periodic properties, non linearity and dependence relationship. These sub signals usually in the form of approximation coefficients (A1, A2.., An) and detail coefficients (D1, D2.., Dn).

After obtaining DWT coefficients, next task was to train the neural network using these coefficients as input and target. Once network is trained in this pattern, during simulation or testing stage the network gives output as coefficients only but not Hs. In order obtain the Hs, the output coefficients from ANN were reconstructed using inverse wavelet function. Figure.3 depicts the procedure for WLNN-1 and WLNN-2 methods. From the analysis experience it was found that the method one was laborious and time consuming.

The analysis for ANN part was performed by using “nntool” MATLAB 2009 and for obtaining DWT coefficients a Matlab code was developed.

4.3 Wavelet neural network model: method-2(WLNN-2)

In WLNN-2 as represented in the Figure.3 inputs given to ANN as coefficients but maintained direct Hs values in target data instead of coefficients like in the previous case. The output from this method was a direct Hs values and not required to do any reconstruction afterwards

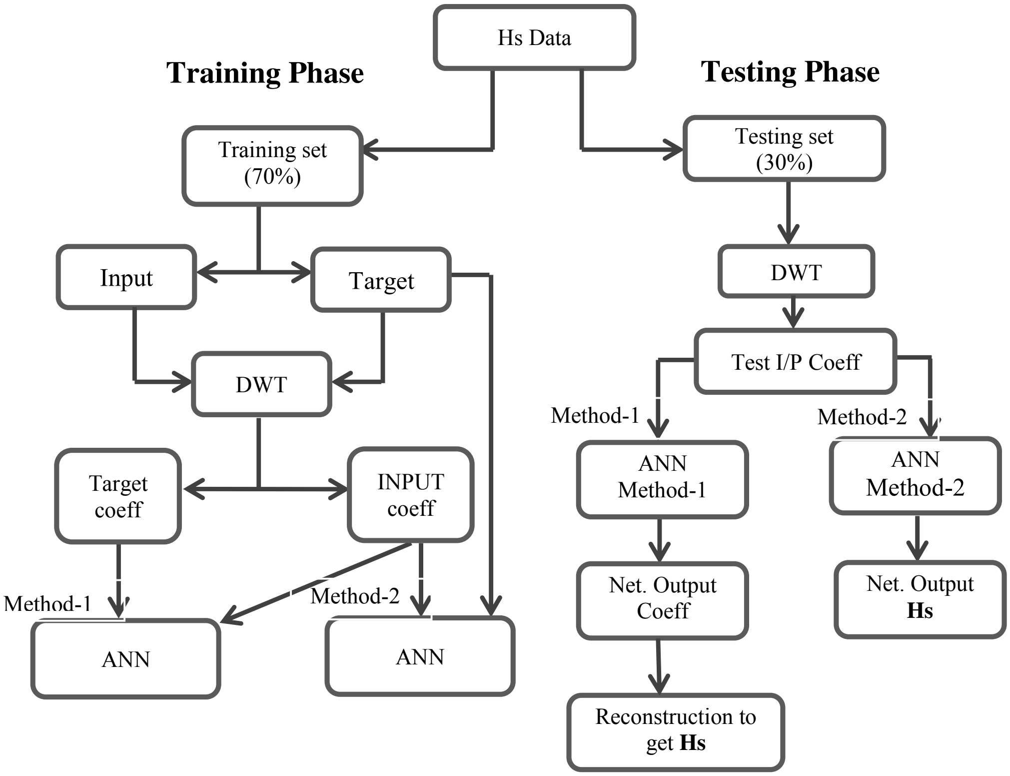

Fig. 3. Flow chart showing working procedure of WLNN model

4.4 Model performance indicators

To evaluate the model performances various performance indices can be used. The conventional performance evaluation such as correlation coefficient is seems to be unsuitable for model evaluation (Legates and McCabe, 1999). But in this study performance indicators such as Mean Relative Error (MRE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Coefficient of determination (R^2) used to asses model results.

5. Results and Discussion

5.1 Results of First station data (SW4)

In the present work only significant wave height (Hs) of previous time steps were used as predictors. Here, wave height values up to previous 12 hours were taken in to consideration as predictor variables to predict Hs(t+n). The scenarios formed by various predictor configurations are: (1) Hs(t), (2) Hs(t), Hs(t-1), (3) Hs(t), Hs(t-1), Hs(t-2), and (4) Hs(t), Hs(t-1), Hs(t-2), Hs(t-3). Where, Hs(t) is the current wave height, Hs(t-1), Hs(t-2), Hs(t-3) are previous time steps significant wave height, Hs(t + n) is the future significant wave height and ‘n’ denotes the lead time in hours. These input scenarios were used for both single ANN model and also for WLNN models.

In WLNN model the wave data divided as training set (70%) and testing set (30%) were first used in discrete wavelet analysis to obtain DWT coefficients at different decomposition levels (up to 6). The sub signals obtained after the discrete wavelet transformation is shown in Figure.4. These sub signals later used to ANN as inputs and targets in WLNN-1 model. Forecasting was carried up to 48 hour lead times with different input scenarios as mentioned above. The best result obtained is from input scenario-3 i.e. three time step previous wave heights.

Analysis also carried out for WLLN-2 model up to 48hr lead time by supplying only input coefficients to ANN model. For both WLNN-1 & WLLN-2models the optimum decomposition level for different lead time predictions worked out to be in the range of level 4 to level 6. For lead times 3hr to12 hrs the optimum decomposition level is found to be 4 and 5 and for higher lead time say 24hr and 48hr optimum level found to be 6.

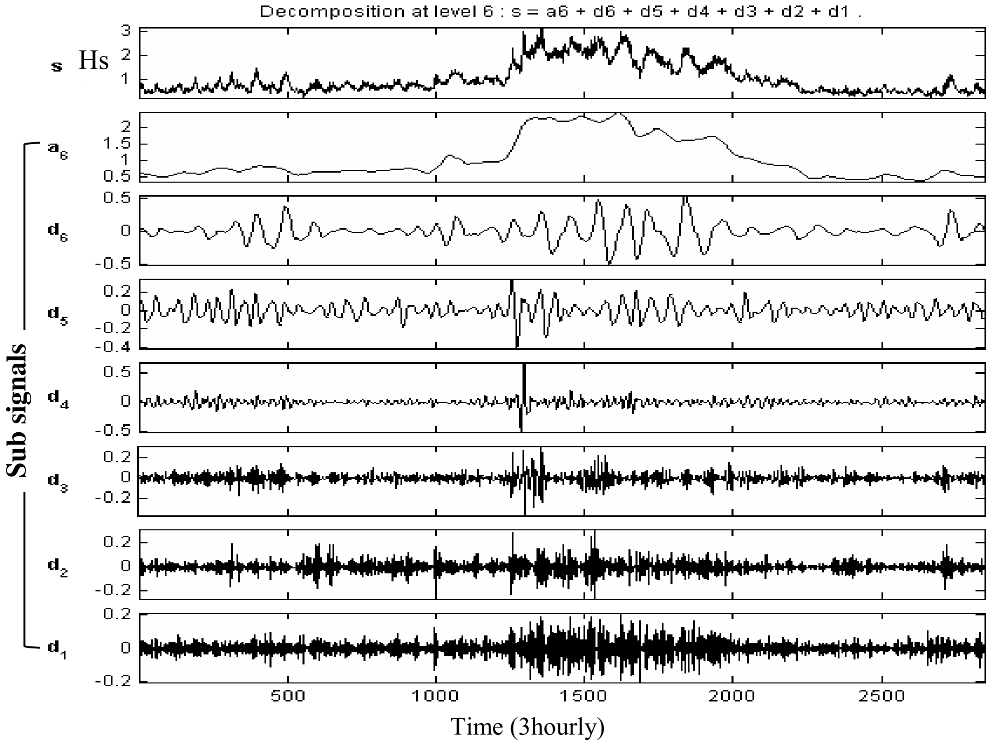

Fig.4. Sub signals after data decomposition through DWT using db4 wavelet at level-6

The optimum decomposition level in DWT is a level at which the model produce higher R^2 value and lesser error (Deka and Prahlada, 2012).

The adaption of two different methods in WLNN model in the present study is to identify the best method based on model performance and to fire the other in further studies. Results presented in Table 2 shows satisfactory performance of WLNN-2 model over WLNN-1 model. Hence method-2 is said to be good and suggestible method for WLNN models as it takes less time and produces better results.

Table2. Test results of ANN and WLNN models for station-1 (SW4)

Lead time	ANN			WLNN-1			WLNN-2		
(hrs)	MRE %	RMSE (m)	R2	MRE %	RMSE (m)	R2	MRE %	RMSE(m)	R2
3	8.253	0.058	0.888	6.905	0.046	0.930	6.368	0.045	0.932
6	13.599	0.084	0.806	8.906	0.060	0.881	8.902	0.058	0.886
12	16.509	0.104	0.680	11.076	0.071	0.829	10.448	0.071	0.831
24	20.219	0.120	0.615	14.542	0.094	0.704	13.813	0.093	0.711
48	32.111	0.177	0.329	20.156	0.119	0.519	16.542	0.113	0.564

5.2 Results of Second station data (46006)

Hourly significant wave height data belong to station-2 (46006) divided in to75:25 ratios as training data and testing data respectively. Same input scenarios as motioned early were used in the ANN and WLNN models and the best result was obtained from input scenario-4. Here in WLNN model, method-2 is adapted to train the network as method-1(WLNN-1) in previous case (First station) was unable produce satisfactory results over WLNN-2. The discretization of data is done using haar wavelet up to9 levels.

Results obtained from WLNN-2 model are presented in Table 3. As we can see from the results that the optimum decomposition level for lead time up to 12 hrs is in between 4 to 6, and as lead time increase to 24 and 48 hrs optimum levels also surged up to 9.

Table3. Test results of WLNN model for station -2 (46006)

Decomposition Levels									
	L-2	L-3	L-4	L-5	L-6	L-7	L-8	L-9	Optimum Level
			3rd hour						
MRE (%)	7.918	7.697	7.782	7.773					L-4
R2	0.918	0.925	0.929	0.926					
RMSE(m)	0.397	0.380	0.371	0.376					
			6th hour						
MRE (%)	12.593	11.925	11.597	11.555	11.699				L-5
R2	0.797	0.823	0.837	0.842	0.828				
RMSE(m)	0.624	0.581	0.559	0.549	0.575				
			12th hour						
MRE (%)	19.270	18.861	17.422	16.998	17.499	17.773			L-6
R2	0.539	0.561	0.621	0.636	0.644	0.614			
RMSE(m)	0.941	0.915	0.852	0.834	0.830	0.849			
			24th hour						
MRE (%)	28.337	27.692	26.349	24.613	23.363	24.480	24.302	24.149	L-9
R2	0.156	0.165	0.205	0.298	0.346	0.371	0.419	0.421	
RMSE(m)	1.290	1.289	1.251	1.159	1.112	1.090	1.048	1.044	
			48th hour						
MRE (%)	32.355	33.063	32.462	31.076	28.603	23.036	25.206	24.716	L-9
R2	0.015	0.013	0.019	0.052	0.198	0.374	0.398	0.403	
RMSE(m)	1.463	1.459	1.439	1.394	1.247	1.097	1.087	1.076	

Table.4. Station wise model test results

Lead time	Station-1						Station-2					
	ANN			WLNN-2			ANN			WLNN-2		
	MRE %	RMSE (m)	R2	MRE %	RMSE (m)	R2	MRE %	RMSE (m)	R2	MRE %	RMSE (m)	R2
3	8.253	0.058	0.888	6.368	0.045	0.932	8.698	0.423	0.907	7.782	0.371	0.929
6	13.599	0.084	0.806	8.902	0.058	0.886	13.013	0.631	0.794	11.555	0.549	0.842
12	16.509	0.104	0.680	10.448	0.071	0.831	19.014	0.934	0.550	17.499	0.830	0.644
24	20.219	0.120	0.615	13.813	0.093	0.711	27.836	1.296	0.167	24.149	1.044	0.421

48	32.111	0.177	0.329	16.542	0.113	0.564	33.182	1.471	0.013	24.716	1.076	0.403

From the results presented in Table 4 it is clear that WLNN models performing better than single ANN model both at lower lead times as well as at higher lead time predictions. As compared to station -1 results, station -2 results are slightly poor and this was expected due to its more statistical variations in the wave data as we can see in table.1. More statistical variation in data also demanded more decomposition levels (up to 9) in DWT for making more linear inputs to ANN.

6. Conclusions

Main purpose of this study is to carryout wavelet-ANN model for different station data to analyse the model performance for different data structure. Also to identify a best methodology in wavelet-ANN model which gives a good result amongst other. Two different methods WLNN-1 &WLNN-2 employed for the first station data to forecast significant wave heights at higher lead times. From the result it is clear that the second method (WLNN-2) in wavelet-ANN model performed better than first method (WLNN-1). Hence method-2 is said to be a good and suggestible method for WLNN models as it takes less time and produces better results.

Model results obtained for two stations showed good predictions at lower lead times but slight deviations are observed at higher lead times. As compared to first station results the second station results are slightly poor because of more statistical variations in the data. Also, this statistical variation in data demanded more decomposition levels (up to 9) in DWT to make it more linear inputs to ANN. Hence it is clear that more statistical variations in data lead to more number of decomposition levels and thus it increases the analysis time.

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