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Discrete wavelet neural network approach in significant wave height forecasting for multistep lead time

Paresh Chandra Deka *, R. Prahlada

Department of Applied Mechanics & Hydraulics, National Institute of Technology Karnataka, Surathkal, Karnataka 575025, India

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ABSTRACT

Recently Artificial Neural network (ANN) was extensively used as non-linear inter-extrapolator for ocean wave forecasting as well as other application in ocean engineering. In this current study, the Wavelet transform was hybridised with ANN naming Wavelet Neural Network (WLNN) for significant wave height forecasting near Mangalore, west coast of India, upto 48 h lead time. The main time series of significant wave height data were decomposed to multiresolution time series using discrete wavelet transformations. Then, the multiresolution time series data were used as input of the ANN to forecast the significant wave height at different multistep lead time. It was shown how the proposed model, WLNN, that makes use of multiresolution time series as input, allows for more accurate and consistent predictions with respect to classical ANN models. The proposed wavelet model (WLNN) results revealed that it was better forecasted and consistent than single ANN model because of using multiresolution time series data as inputs.

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1. Introduction

Real time forecast of ocean waves generated by wind over a time step of a few hours or days at a specific location is required for planning and maintenance of any marine activities. The time series of significant wave height (Hs) can be modelled as a random process. But Hs is not random, it has some correlation that can be exploited to extrapolate the future from its past values. In order to analyse such processes, recently soft computing approach such as artificial neural networks, fuzzy logic and genetic algorithms has been gaining popularity since last decade due to its versatility in handling non linearity and somewhat extent to handle non stationarity. Classical time series models such as ARMA (Auto regressive moving average), ARIMA (Auto regressive integrated moving average) are basically linear models assuming that data are stationary, and have a limited ability to capture non-stationarities and non-linearity in data series. On the other hand, soft computing normally utilises tolerance to uncertainties, imprecision, and partial truth associated with input information in order to come up with robust solution handling non-linearities and non-stationarities effectively.

Forecasting of ocean wave parameters using Artificial Neural Networks (ANN) was carried out by different authors since last decade. Deo and Naidu (1999), Rao et al. (2001) used ANN to forecast significant wave height for lead time up to 24 h. Agarwal and Deo (2002) compared ANN with ARMA and ARIMA using a 3hourly significant wave height series and found that ANN was more accurate than latter for 3 and 6 h lead time. Makarynskyy et al. (2005) used ANN to forecast significant wave height and zero-up-crossing wave period for a leadtime up to 24 h.

ANN is suitable for handling large amounts of dynamic, noisy and non-linear data, specially for partially understood underlying physical processes. This makes them effective to time series modelling problems of data-driven nature (Nourani et al., 2009). In spite of suitable flexibility of ANN, it may not be able to cope with non-stationary data if pre-processing of the input and output data is not performed (Cannas et al., 2006). As non stationary signals are frequently encountered in a variety of engineering fields such as ocean and earthquake, hybridisation of ANN with other techniques may provide effective modelling.

In the last decade, wavelet transform has become a useful technique for analysing variations, periodicities, and trends in time series (Lu, 2002; Xingang et al., 2003; Coulibaly and Burn, 2004; Partal and Kucuk, 2006).

Wavelet analysis is multiresolution analysis in time and frequency domain and is the important derivative of the Fourier transform. Here, the original signal is represented by different resolution intervals using discrete wavelet transform (DWT). In other words, the complex significant wave height time series may be decomposed into several simple time series using a DWT. Thus, some features of the subseries can be seen more clearly than the

* Corresponding author. Tel.: +91 0824 2474000x3315; fax: +91 0824 2474033.
E-mail addresses: paresh_deka@sify.com (P.C. Deka), prahlad_dwba@yahoo.com (R. Prahlada).

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original signal series. These decomposed time series may be given as inputs to ANN which can handle non-linearity efficiently; higher forecasting accuracy may be obtained. Forecasts are more accurate than that obtained by original signals due to the fact that the features of the subseries are obvious. This is why the hybridisation of wavelet transformation and neural network can performs better than single ANN model.

In practice, analysing non-stationary and non linear time series is difficult because this series is affected by complex factors. Using only one resolution component to model the significant wave height time series does not easily clarify the internal mechanism of the phenomenon (Chou and Wang, 2004). Therefore, the hybrid wavelet transform and neural network that uses several resolution components could be applied to model significant wave height time series. The proposed Hybrid model which uses multiscale signals as input data may present more probable forecasting rather than a single pattern input.

A hybrid wavelet predictor-corrector model was developed by Zhou et al. (2008) for prediction of monthly discharge time series and showed that the model has higher prediction accuracy than ARIMA and seasonal ARIMA. Recently hybridisation of wavelet and fuzzy has been applied by Ozger (2010) to forecast significant wave height and average wave period for a lead time up to 48 h and the results obtained was satisfactory and better than auto-regressive, ANN, and Fuzzy logic model.

In this study, it is aimed to illustrate a new approach to significant wave height forecasting based on combination of discrete wavelet transform and artificial neural network techniques. This approach can improve the low level model accuracies in long range (> 24 h) significant wave height forecasting. For this purpose, wavelet neural network (WLNN) algorithm has been introduced and employed to develop a significant wave height forecasting model which has an ability to make forecasts up to 48 h using 3hourly wave height observed data. The results of WLNN model are compared with the results obtained from single ANN model. Also, the proposed WLNN model performance are evaluated to assess the model efficiency in the higher lead times alongwith different decomposition levels.

2. Wavelet theory

A Wavelet transformation is a signal processing tool like Fourier transformation with the ability of analysing both stationary as well as non stationary data, and to produce both time and frequency information with a higher (more than one) resolution, which is not available from the traditional transformation (Fourier and Short Term Fourier Transform).

The wavelet transform breaks the signal into its wavelets (small wave) which are scaled and shifted versions of the original wavelet (mother wavelet).

The wavelet transformation is of two kinds:

- Continuous wavelet transformation (CWT) and
- Discrete wavelet transformation (DWT).

2.1. Continuous wavelet transformation (CWT)

The continuous wavelet transform (CWT) is defined in terms of dilations and translations of a mother wavelet function $\Psi(t)$

$$\mathrm{CWT}_x^{\psi} = \psi_x^{\psi}(\tau,s) = \frac{1}{\sqrt{s}}\int_{-\infty}^{\infty} x(t)\psi^*\left(\frac{t-\tau}{s}\right)dt \tag{1}$$

Where s is the scale parameter, τ is the translation parameter and the * denotes the complex conjugate, $\Psi(t)$ is the transforming function, and it is called the mother wavelet, and $x(t)$ is the input signal.

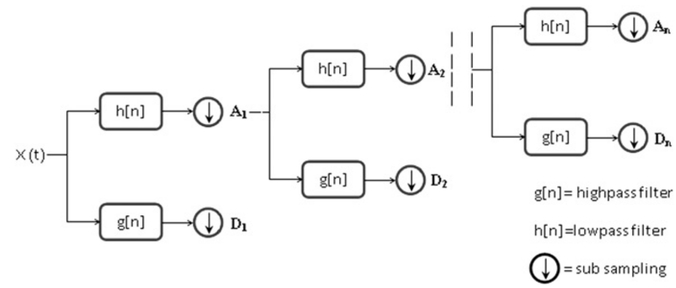

Fig. 1. Multiresolution decomposition tree.

As from above equation the analysis of a signal starts with keeping a mother wavelet $\Psi(t)$ at the beginning of the signal $x(t)$ and it is shifted forward over entire length of the signal. After covering the full length of signal, a set of wavelet coefficients are generated at each step which are the measure of correlation between wavelet and the signal.

2.2. Discrete wavelet transformation (DWT)

Like continuous wavelet transformation the discrete wavelet transformation calculates the wavelet coefficients at discrete intervals of time and scale. In the DWT, filters of different cut-off frequencies are used to analyse the signal at different scales. The signal $x(t)$ is passed through a series of high pass filters and low pass filters and down sampled (i.e. throwing away every second data point) to analyse the high frequencies and low frequencies, respectively, as shown in the Fig. 1. The output from the high pass and low pass filters are the approximation coefficients (A_1, $A_2\ldots$ A_n) and detail coefficients (D_1, $D_2\ldots D_n$), respectively. The process of decomposing a signal in to its sub bands or sub signals as represented in the Fig. 1 is also termed as multiresolution signal decomposition.

The Discretized continuous wavelet transform produces N^2 coefficients from a data set of length N; hence additional, or redundant information is locked up within the coefficients (Katul et al., 1994), which may or may not be a desired property. The continuous wavelet transform and its discretization are redundant; that is the signal, which for real applications will be specified as discrete data set, is over specified by the transform coefficients.

The choice of wavelet transformation is in fact an important part of wavelet analysis and depends very much upon both the properties of the signal under investigation and what the investigator is looking for. The continuous and discrete transform each have their own favourable properties. Due to its redundancy, or over specification of the signal, the continuous wavelet transform is computationally expansive and does not lend itself well to statistical analysis, whereas the zero redundancy of the discrete transformation lends itself to the statistical analysis of the signal (Addison et al., 2001).

Logarithmic uniform spacing (Mallat, 1998) can be used for the s scale discretization with correspondingly coarser resolution of the locations, which allows a complete orthogonal wavelet basis to be constructed. It allows for N transform coefficients to completely describe a signal of length N, i.e. with zero redundancy. These discrete wavelets are not specified continuously, but rather at discrete locations on the time axis. The resulting discrete wavelet transform (DWT) can only be translated and dilated in discrete jumps.

For the signal $x(t)$, the discrete wavelets have the form:

$$\psi_{m,n}\left(\frac{t-\tau}{s}\right) = \frac{1}{\sqrt{s_0^m}}\psi\left(\frac{t-n\tau_o s_o^m}{s_o^m}\right) \tag{2}$$

where m and n are integers that control the wavelet dilation and translation, respectively, so is a fixed dilation step greater than 1; s is the scale and τ is the location parameter and must be greater than zero. From the Eq. (2), it can be seen that the translation steps $n\tau_o s_o^m$ depend upon the dilation, s_o^m. Hence, discrete wavelet transform using Mallat algorithm was selected for decomposition and reconstruction of time series.

3. Methodology

Here, considering the dominance of persistence in the wave height time series future significant wave heights to be forecasted from the past/previous wave heights. Significant wave height upto previous four time steps (3hourly data $\times$ 4 = 12 h) were taken as predictor variables. The input scenarios formed by various predictor configurations are;

[1] $Hs(t)$
[2] $Hs(t)$, $Hs(t-1)$
[3] Hs(t), $Hs(t-1)$, $Hs(t-2)$
[4] $Hs(t)$, $Hs(t-1)$, $Hs(t-2)$, $Hs(t-3)$.

Where $Hs(t)$ is the current significant wave height.

Also $Hs(t-1)$, $Hs(t-2)$, $Hs(t-3)$ are onetime step, two time step and three time step past wave height, respectively. The predictand is $Hs(t+n)$ where n is the lead time. These input and output scenarios are same for both ANN and WLNN model. For both the models, testing data were selected from the same portion of entire data which is the last 25% of the year.

Here, wavelet and ANN techniques are used together as a combined method. While wavelet transform is employed to decompose significant wave height time series into their spectral bands, ANN is used as a predictive tool that relates predictand (output) and predictors (inputs).

The real world observed time series are discrete, such as streamflow, waveheight, etc. So discrete wavelet transform were selected for decomposition and reconstruction of significant waveheight time series. The original non-stationary time series were decomposed into a certain number of stationary time series through discrete wavelet transform such as, periodic properties, non-linearity and dependence relationship of the original time series were separated, so each wavelet transform series has obvious regularities. Then the ANN model was used to simulate the wavelet transform series in the form of approximations and details coefficients and gives reconstructed predicted significant wave heights in the output. Therefore, the prediction accuracy was expected to improve.

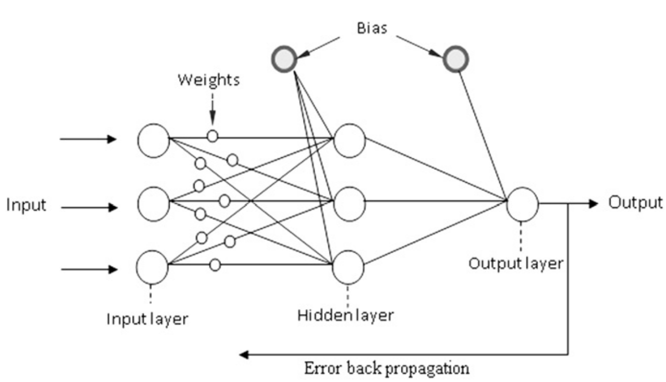

Fig. 2. Basic ANN model structure.

4. Artificial neural network

ANN is a 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.

In this study, a single layer feed forward network with a back propagation learning algorithm was been selected for the ANN model as shown in Fig. 2. Here, TRAIN LM (Levenberg–Marquardt) learning function, Tangent Sigmoid as transfer function was chosen and the analysis was carried out for different input scenarios of previous time steps significant wave height data. The optimal structure of the ANN was selected based on mean square error during training. The ANN model implementation was carried out using MATLAB routines.

Here, the ANN was trained using Levenberg–Marquardt (LM) technique because it is more powerful and faster than the conventional gradient descent technique (Hagen and Menhaj, 1994; Kisi, 2007). The application of LM to neural network training is described in Hagen and Menhaj (1994).

5. Wavelet neural network (WLNN)

Combination of wavelet transformation with other models was reported since few years in different fields. 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. Nourani et al. (2009) applied wavelet-ANN to rain fall runoff modelling to forecast both long term and short term runoff discharges for one day ahead. Deka et al. (2010) used hybrid Wavelet-ANN model to forecast significant wave height of station near marmugao port, Arabian Sea, and the results obtained for two time steps ahead prediction was found satisfactory.

In the proposed (WLNN) model, the Discrete Wavelet Transformation discretized the input data (Hs) in to number of sub signals in the form of approximations and details and henceforth, these sub signals were used as input to ANN. The schematic diagram of proposed WLNN model is shown in Fig. 3.

The objectives of WLNN model is to forecast t-hours ahead significant wave height from previous wave heights. Here, future wave heights were taken as predictand and past wave heights as predictor. After decomposing the time series into several

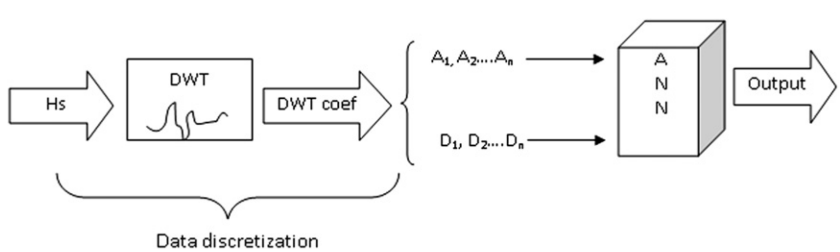

Fig. 3. Schematic diagram of the proposed WLNN model.

resolution levels, each level subseries predictand data were estimated from its corresponding separated predictor level.

Here, ANN part was constructed with appropriate sub-series belongs to different scales as generated by DWT. These new series consists of details and approximations were used as input to ANN. The sensitivity analysis for subseries variables with corresponding output variables was not performed for determining effective input variables as it was focussed only on decomposed subseries inputs.

In the proposed WLNN model, only input signals were decomposed into wavelet coefficients so that ANN was exposed to large number of weights attached with higher input nodes during training. Hence, the higher adaptability was achieved for input–output mapping. The output signals were kept as original series without decomposition where reconstruction was not required.

6. Performance indices

The conventional performance evaluation such as correlation coefficient is seems to be unsuitable for model evaluation (Legates and McCabe, 1999). Correlation coefficient has been used in several data analysis. But as discussed by Kim and Park (Ocean Eng., 2005), it is not the best error statistics and may be misleading compared to other error statistics such as Root Mean Squared Error (RMSE). Also, Keren and Kisi (J. Hydrology, 2006) also had a good discussion showing that a correlation coefficient value of close to one does not necessarily means a good prediction. The correlation coefficient shows the degree to which two variables are linearly related. Here, coefficient of efficiency is used to test the performance of model better than average or not. However, mean relative error, mean absolute error and Root mean square error can be used for better evaluation of model performance. In this study, following performance indices based on goodness of fit are used.

1. Coefficient of efficiency,

$$CE = 1 - \frac{\sum (X-Y)^2}{\sum x^2}$$

2. Mean absolute error,

$$MAE = \frac{\sum |X-Y|}{N}$$

3. Root mean square error,

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (X-Y)^2}{N}}$$

4. Mean relative error, (%)

$$MRE = \frac{1}{N} \sum_{i=1}^{N} \frac{|X-Y|}{X} \times 100$$

where, X=observed values, Y=predicted values, N=total number of values, and $x = X - X_{mean}$.

7. Study area

The data used in the current study are processed significant wave height (Hs) of the station SW4 (Latitude 12°56′31″ and longitude 74°43′58″) located near west coast of India as shown in Fig. 4, which was collected from New Mangalore Port Trust (NMPT) for the year 2004–2005.

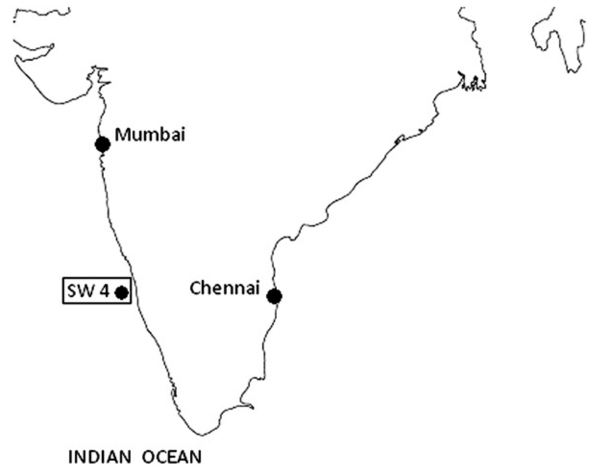

Fig. 4. Location of the study area.

Table 1
Statistical properties of the data.

Min	Max	Mean	Skewness	Kurtosis	Std. deviation
0.25	3.09	1.025	0.78	0.4867	0.6289

From the statistical properties of the wave data presented in Table 1, it revealed that the data used in this study is not having much significant variation. The value of standard deviation and kurtosis is also small means the most of the data are closely spaced. Out of one year total data points of 2920 with three hourly (3 hr) time resolution, initial 75% of the data was used for training and remaining 25% of the data was used for testing the model as shown in the Fig. 5.

8. Analysis and results

The data sets from one station located in Indian Ocean (west coast) were used for model applications. The proposed WLNN model results were compared with classical ANN model results. Models were tested for various lead-times of 3, 6, 12, 24 and 48 h. Different input combinations as mentioned earlier were tried for significant wave height variables.

At the first stage, a multilayer perceptron (MLP) feed forward ANN model without data pre-processing was used to forecast significant waveheight. Each MLP was trained with 1–10 hidden neurons in the hidden layer with Levenberg–Marquardt back propagation as the training algorithm with sigmoidal activation function to optimise the parameters which were sufficient to produce results for all lead-times.

In this study, a number of ANN models has been developed and the best model (optimised structure) out of various input combinations were selected. The best ANN model testing results obtained for input three (3rd scenarios) with seven (7) neurons in the hidden layer based on various performances indices were presented in Table 2.

It can be seen from the Table 2 that C.E (Coefficient of efficiency) values changes with respect to lead-time forecast. For significant wave height, the C. E values were found ranges from 0.888 for 3 h lead-time to −0.071for 48 h lead-time. For short time forecasting, it seems to be quite satisfactory. But for longtime forecasting, it is beyond acceptable accuracy.

The model efficiency is decreasing drastically as lead-time progresses beyond 6 h lead-time. The Root mean squared error

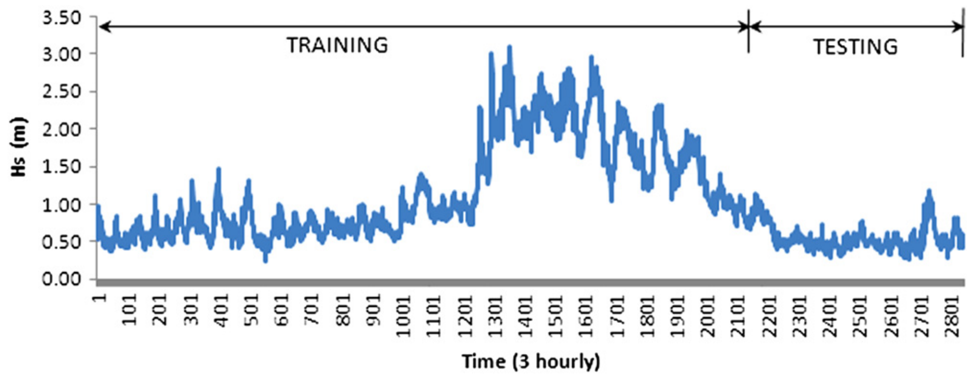

Fig. 5. Time series data of significant wave height (*Hs*).

Table2
Test results of ANN for different lead times.

Lead time (h)	MAE	MRE %	RMSE	CE
3	0.043	8.253	0.058	0.888
6	0.067	13.599	0.084	0.766
12	0.082	16.509	0.104	0.639
24	0.099	20.219	0.120	0.511
48	0.152	32.111	0.177	−0.071

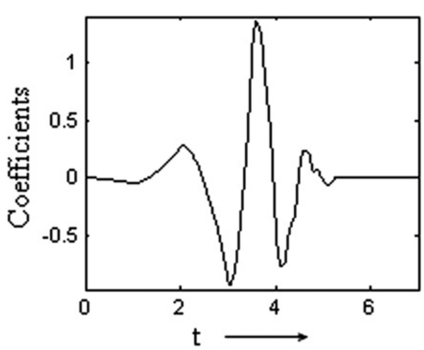

Fig. 6. 'db4' wavelet function.

(RMSE) also increases from 0.058 m to 0.177 m for 3 h and 48 h lead-time, respectively, which followed similar trend to C.E. Both Mean absolute error (MAE) and Mean relative error (MRE) are also showing high error as lead-time progresses. This may be due to significant fluctuations of the data around mean value such as skewness and standard deviation are high (Table 1), where short term regression between data is minimised.

In the second stage, for hybrid wavelet neural network (WLNN) model, decomposed subseries significant wave height data were given to ANN model to improve the model accuracy. For wavelet analysis, Discrete Wavelet Transformation (DWT) was used and Daubechies wavelet order-4 (db4) (Daubechies, 1992) was selected as a mother wavelet considering the shape similarity with time series signal. The selected mother wavelet 'db4' is a simplest wavelet having only four wavelet filter coefficients with exact reconstruction possibilities. Also the db4 wavelet is a compactly supported and asymmetric in shape as shown in Fig. 6.

Here, discrete wavelet transform (DWT) was used for processing of significant wave height time series data in the form of approximations and details at different levels so that gross and small features of a signal (significant wave height data) can be separated. These coefficients of details and approximations were used as input to ANN component of the hybrid model to obtain predicted output.

Table 3
Test Results of wavelet-ANN (WLNN) model.

	Decomposition Levels						**Optimum level**
	L-2	**L-3**	**L-4**	**L-5**	**L-6**	**L-7**	
				3rd hour			
MAE	0.035	0.034	0.033	0.040	–	–	
MRE%	6.994	6.474	6.368	8.388	–	–	L-4
RMSE	0.046	0.045	0.045	0.051	–	–	
CE	0.930	0.931	0.932	0.914	–	–	
				6th hour			
MAE	0.052	0.046	0.049	0.045	0.044	–	
MRE%	10.478	8.900	9.883	8.902	8.454	–	L-5
RMSE	0.065	0.060	0.062	0.058	0.059	–	
CE	0.859	0.881	0.869	0.886	0.885	–	
				12th hour			
MAE	0.073	0.060	0.055	0.057	–	–	
MRE%	14.574	11.991	10.448	11.180	–	–	L-4
RMSE	0.093	0.075	0.071	0.072	–	–	
CE	0.707	0.810	0.831	0.824	–	–	
				24th hour			
MAE	0.101	0.090	0.087	0.077	0.072	0.075	
MRE%	20.958	18.415	17.733	15.848	13.813	14.407	L-6
RMSE	0.122	0.111	0.106	0.096	0.093	0.100	
CE	0.500	0.582	0.617	0.686	0.711	0.662	
				48th hour			
MAE	0.136	0.141	0.132	0.098	0.087	0.089	
MRE	28.173	29.510	27.475	19.393	16.542	17.366	L-6
RMSE	0.164	0.169	0.161	0.122	0.113	0.116	
CE	0.086	0.027	0.115	0.495	0.564	0.545	

Similar to ANN models, here also a number of WLNN models were developed using different input combinations (mentioned earlier) with different ANN architecture. The best results in terms of performance indices were obtained for third input scenarios (three inputs) for various decomposition levels and results are presented in Table 3.

In this work, the effects of various decomposition levels on model efficiency have also investigated to optimise the result. The output result from the discrete wavelet transformation in the form of 'approximations' and 'details' sub signals at different levels are presented in Fig. 7. The mechanism inside the network was somewhat transparent in WLNN. When coefficients are used as inputs, as the number of input layers increases accordingly number of weights also increases. The analysis has been done for different decomposition levels from level 2 to 7 to obtain optimal results. In each case, as the decomposition level increases, the number of input layers also increases and the network was trained and tested accordingly.

The results from the above model (WLNN) for different decomposition levels clearly revealed the better performance of the proposed model (WLNN) both in low as well as higher lead time compared to ANN (Table 2), considering various

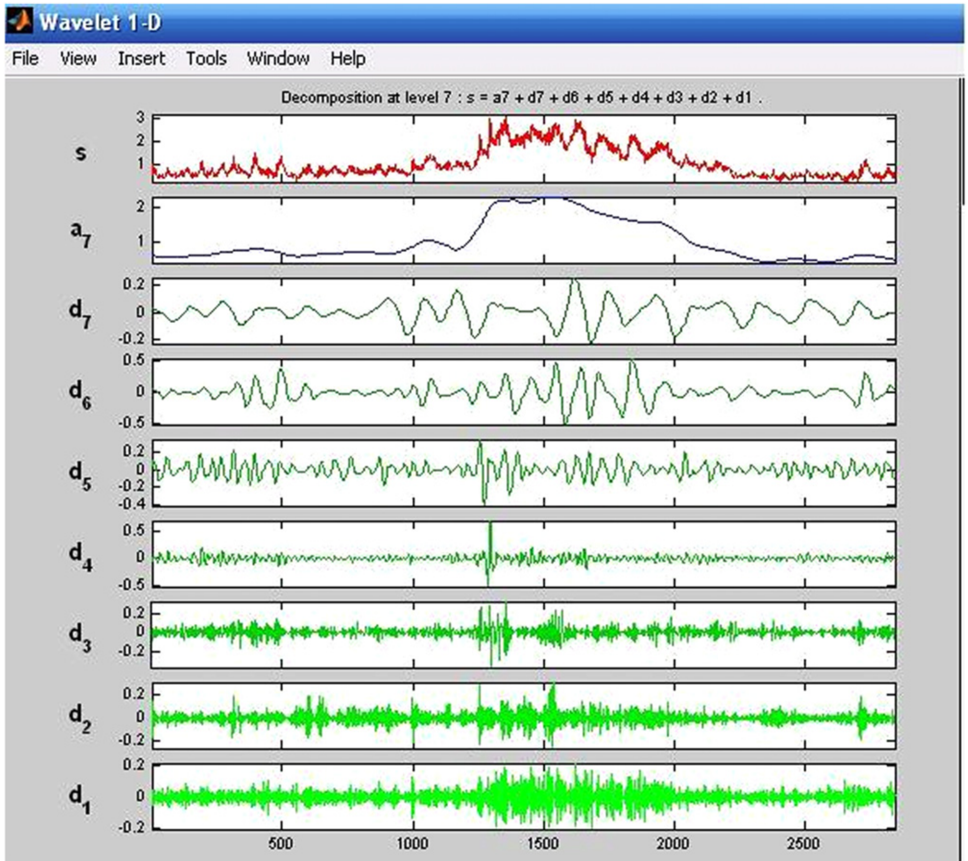

Fig. 7. Sub signals after data decomposition through DWT at level-7.

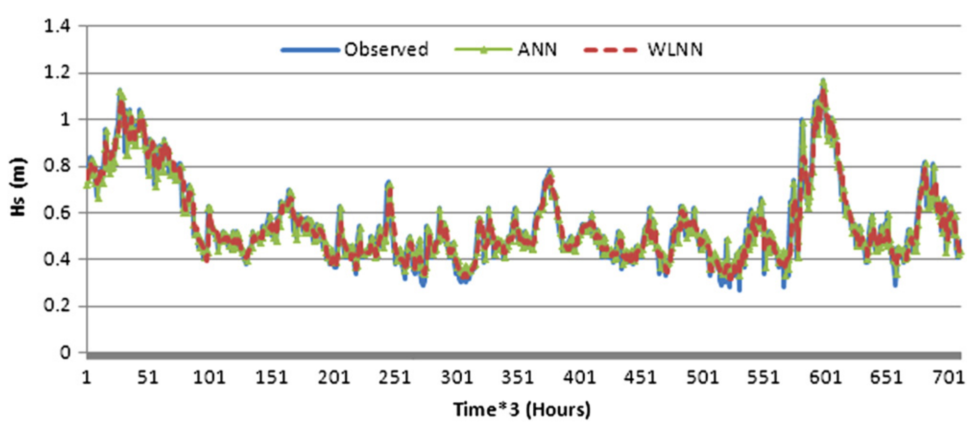

Fig. 8. Observed and predicted time series for 3rd hour prediction.

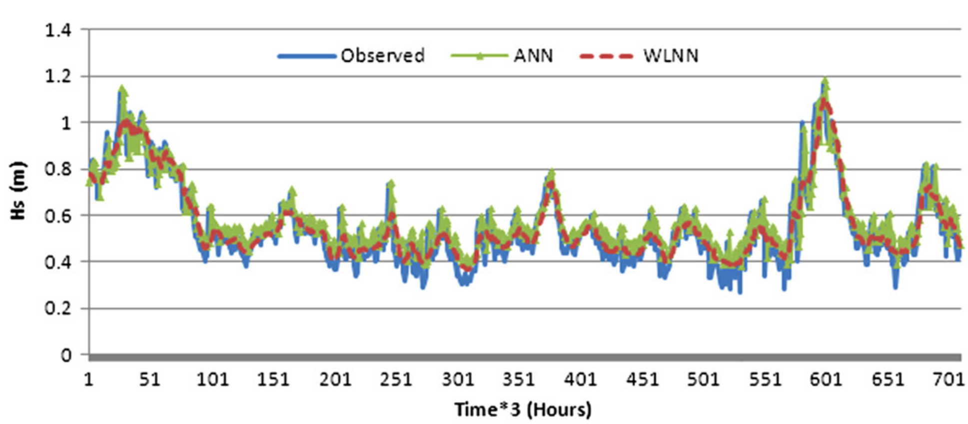

Fig. 9. Observed and predicted time series for 6th hour prediction.

performance indices. The basic WLNN model of decomposition level 2 (L-2) was performing better than best ANN model considering coefficient of efficiency and least error criteria. Also, other WLNN improved models based on different decomposition levels (L-3, L-4, L-5, L-6, and L-7) performed better than ANN model.

For shorter lead times, performances of WLNN models were almost same and observed no significant variations. But in the higher lead time forecast, significant variations were observed among the performance of WLNN models. For low lead time with low decomposition levels, the model is performing in a better way than in higher lead times. All the performance indices are

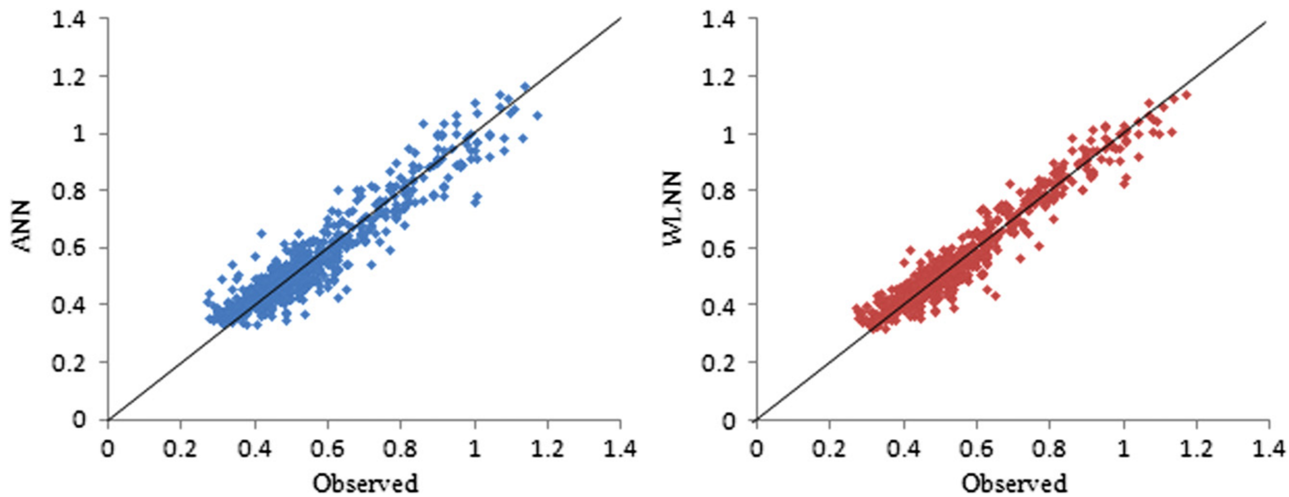

Fig. 10. Scatter plot of observed vs ANN and WLNN predicted for 3rd hour.

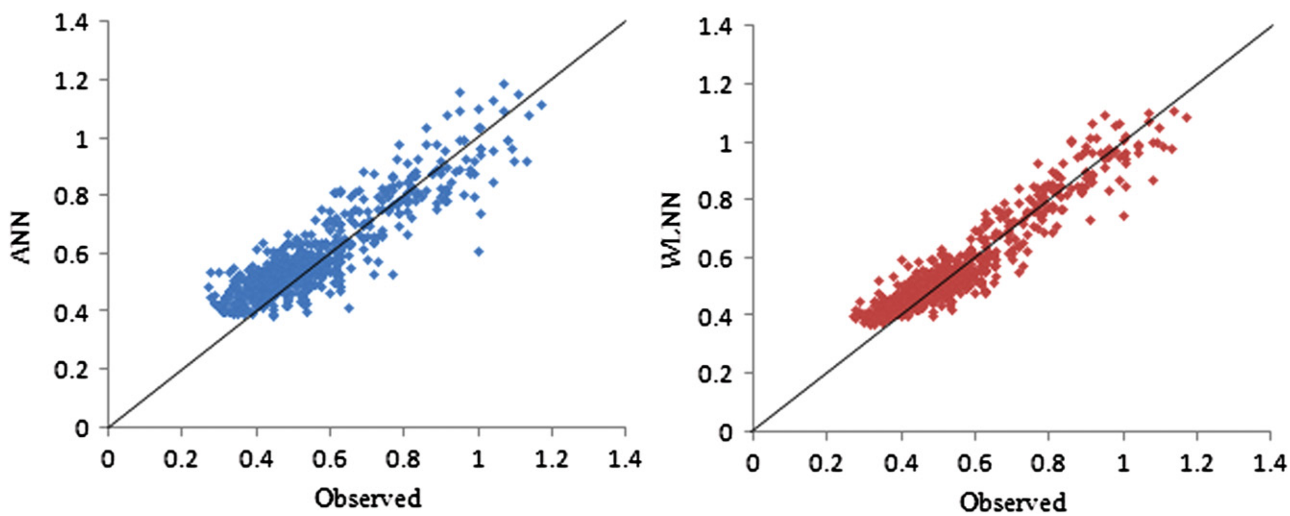

Fig. 11. Scatter plot of observed vs ANN and WLNN predicted for 6th hour.

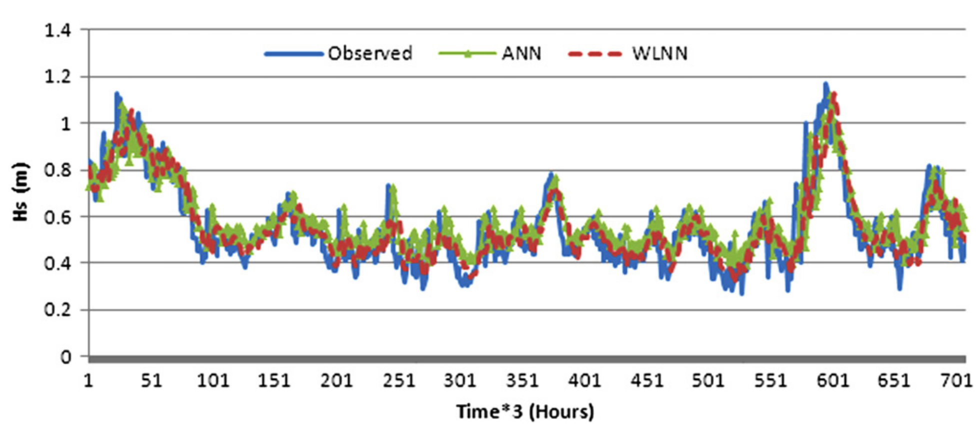

Fig. 12. Observed and predicted time series for 12th hour prediction.

showing similar trend to rank a model based on low variation of maximum and minimum data value.

Again from the time series plot in Fig. 8 for three hours prediction, it was observed that the ANN and WLNN model results were closely following the observed data. But in lower values, ANN was deviating far from WLNN and observed points in sixth hour prediction (Fig. 9). The scatter plot ANN vs observed and WLNN vs observed also reveals the same conclusion mentioned already as shown in Fig. 10 and Fig. 11. It was clearly observed that the correlation was stronger between WLNN and observed points compared to ANN and observed points.

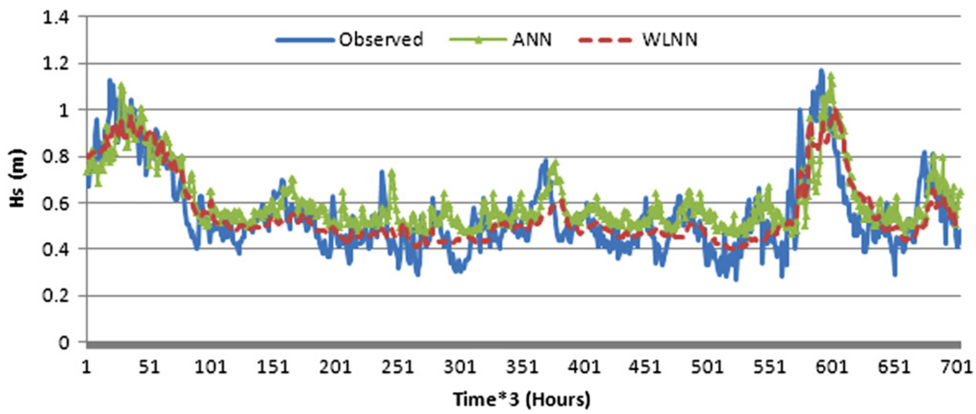

Fig. 13. Observed and predicted time series for 24th hour prediction.

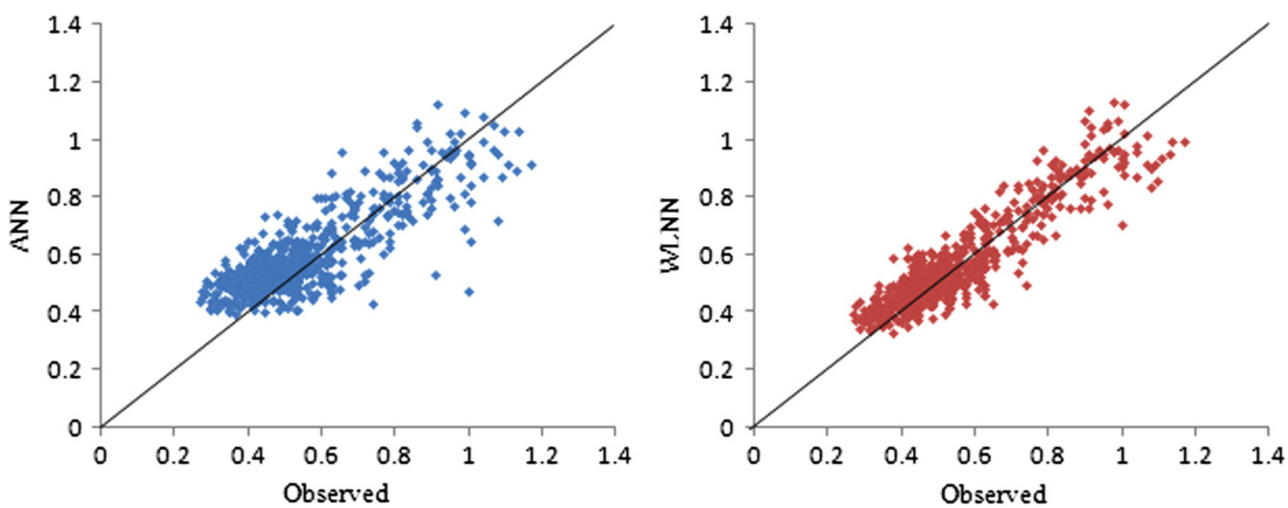

Fig. 14. Scatter plot of observed vs ANN and WLNN predicted for 12th hour.

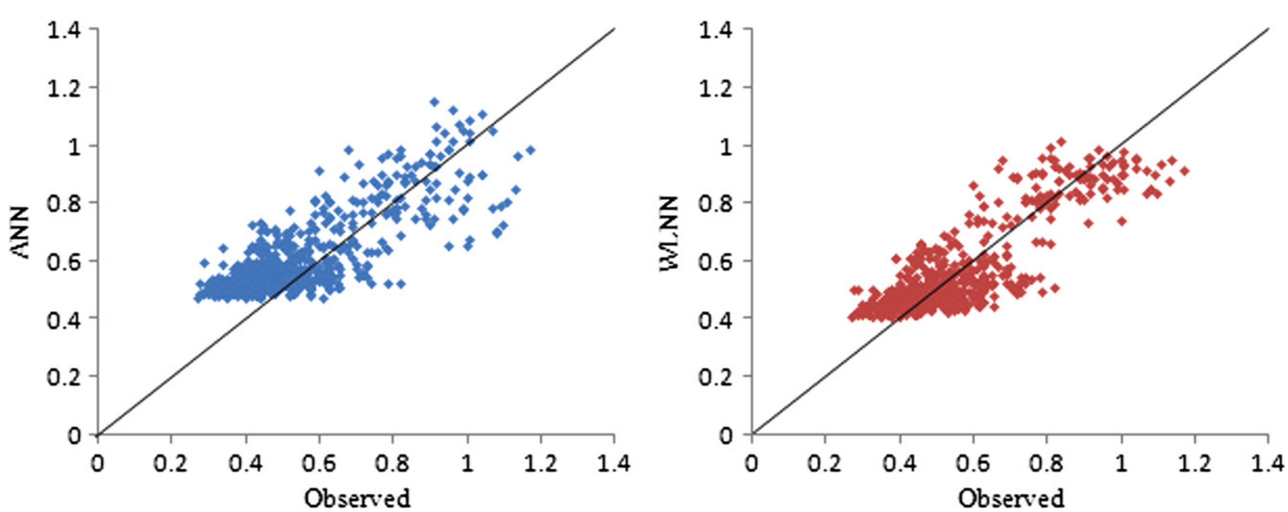

Fig. 15. Scatter plot of observed vs ANN and WLNN predicted for 24th hour.

As lead time increases, the performances of ANN decreases drastically but, WLNN performance decreases gradually as shown in Figs. 12 and 13 in the time series plot and also in the scatter plots shown in Figs. 14 and 15. For lead time 48 h, the performance of both the models was highlighted in Figs. 16 and 17. It was observed from the Figs. 16 and 17 that the proposed WLNN model was almost following the trend of observed plot as compared to ANN. Also, the variation of RMSE for different lead time forecasting was presented for ANN and WLNN in Fig. 18. A gradual decline change was observed for WLNN where as sudden decline change was appeared for ANN after 24 h prediction.

In the WLNN, the results obtained for different lead times had undergone different decomposition levels starting from 2 to 7. In each lead time analysis, there was an increasing trend in the performance from low decomposition levels towards higher decomposition levels. At the stage where the optimum value (higher C.E or lower Errors) is reached, the performance started to decline, and the analysis for the further decomposition levels was stopped. The result corresponding to an optimum value was considered to be the optimum decomposition level as illustrated in Fig. 19 and it was considered as the best model among the WLNN models.

Based on the results, it was noticed that the number of decomposition levels had some impact on the results. Since the random parts of original time series were mainly in the first resolution level, obviously the prediction errors were also mainly in the first resolution level. Thus, the errors were not increased proportionately with the resolution number. Usually, multilevel/multiresolution decomposition was performed to explore the finer details of the signal. Higher level approximation showed smoother version of the signal, while the lower level decomposition was less smooth and had similar smoothness to the original signal (Fig. 7). Multilevel decomposition in the details indicates different natures of the signal.

Again for higher lead time forecast, higher model efficiency was obtained at higher or optimum decomposition levels. These may be due to the effect of correlation of more smoothened signals with flattened variability between the inputs and output. The generalisation capability of ANN seems to be very high with

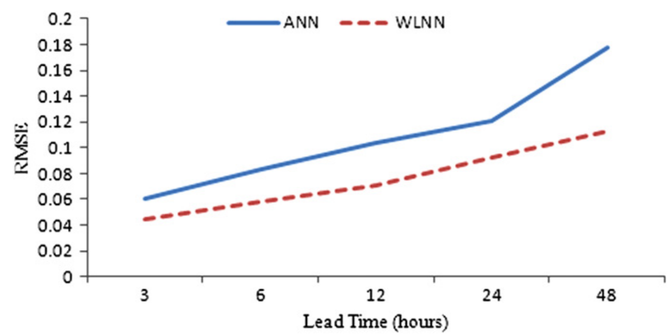

Fig. 18. Variation of RMSE over a lead time.

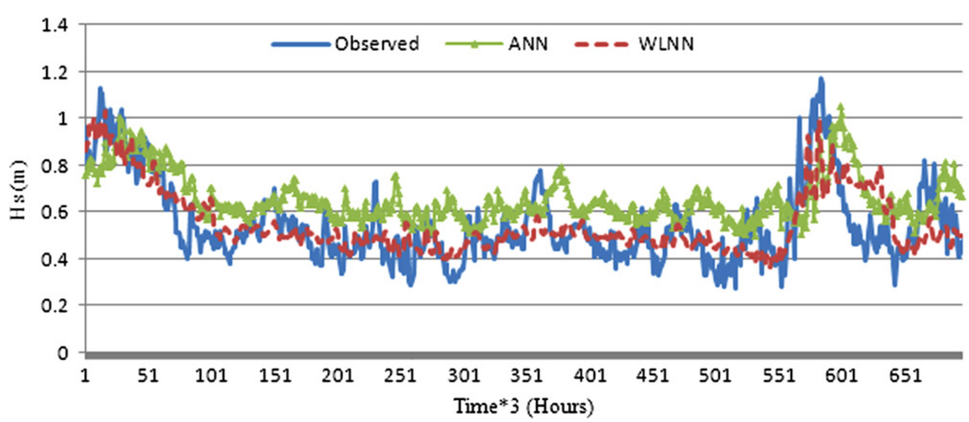

Fig. 16. Observed and predicted time series for 48th hour prediction.

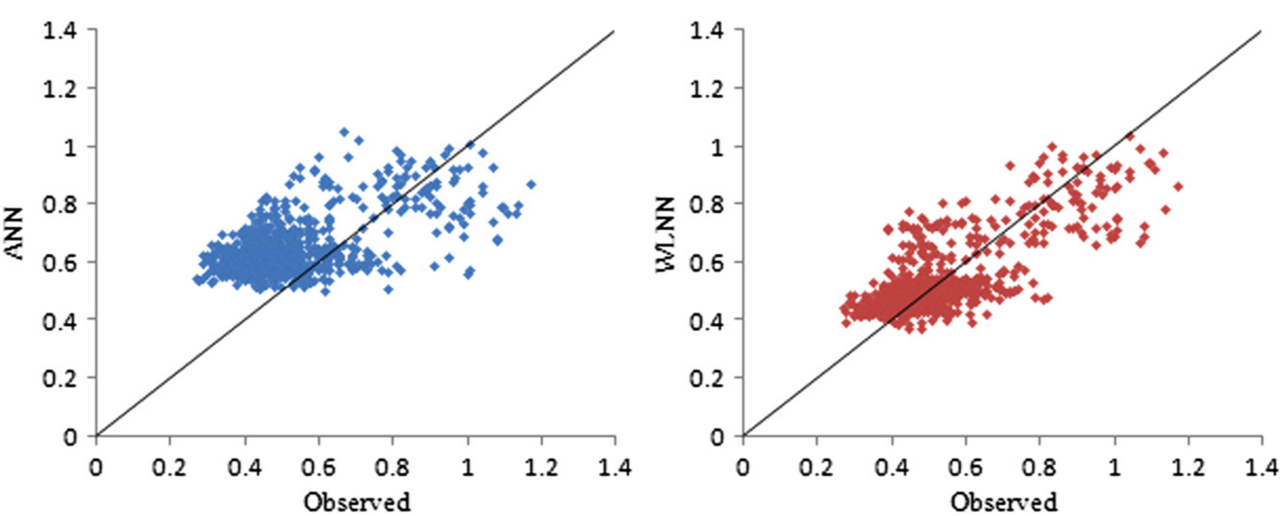

Fig. 17. Scatter plot of observed vs ANN and WLNN predicted for 48th hour.

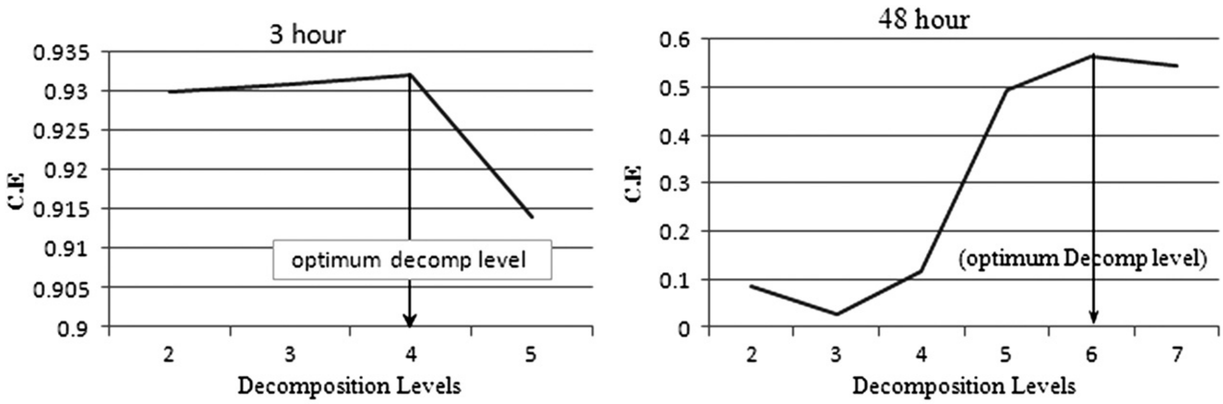

Fig. 19. Depiction of optimum decomposition level for 3rd and 48th hour.

more wavelet transformed sub signals as inputs with optimal hidden neurons upto certain lead-time or optimal lead-time.

However, in wavelet transformation, higher decomposition levels provide details and coefficients similar to persistence upto certain level which can be assumed as optimum level. Although increasing of decomposition level can progress the model ability, an optimum level was selected by trial and error in the study.

The main reason for WLNN performance improvement is that WLNN model can extract the characteristics of wave height variation processes through decomposing the non-stationary time series of significant wave height into several stationary time series. In significant height time series, approximation coefficients denotes the deterministic components, such as tendency/trend, period and approximate period, etc. whereas details coefficients denotes the stochastic components and the noise. These stationary time series can exhibit the fine structures of the wave height time series, reduce the interference between the deterministic components and the stochastic components, and increase the stability of the data variation. Therefore, the prediction accuracy is improved.

9. Conclusions

In this study, a hybrid model of wavelet and ANN (WLNN) has been developed to forecast significant wave height for higher lead times up to 48 h at west coast of India. The accuracy of WLNN model has been investigated for forecasting significant wave height in the present study. The WLNN models were developed by combining two techniques such as ANN and DWT. The WLNN model results were also compared with single ANN model in the study. The WLNN and ANN model performance were tested by applying to different input scenarios of past significant wave height data near west coast station of India. The accuracy of WLNN models was found to be much better than ANN model in modelling significant wave height.

For the present study, the decomposition levels 4 and 5 were the optimum levels for lower lead times (3 h–12 h). For the higher lead times (24 h–48 h), the decomposition level 6 was appeared to be the optimal level as per analysis. From the results, it is confirmed that for lower lead times, lesser decomposition levels are enough to achieve optimal performance. In higher lead time, the uncertainty demands more decomposition levels.

In this study, only one buoy station data of 3hourly time resolution for one year was used and further studies using more data from various stations may require reinforcing the conclusions. Also, Mallat algorithm with db4 type wavelet was used for DWT for the time series data. Other type of wavelet with different algorithm could be used for construction of WLNN models.

The proposed wavelet model (WLNN) results shows that it is better forecasted and consistent than single ANN model due to the use of multiresolution time series sub signals as inputs.

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