Integrating LSTM and EEMD methods to improve significant wave height prediction

1st Ashkan Reisi-Dehkordi
Computer Science and Engineering
University of Nevada
Reno, NV, USA
ashkanreisi@nevada.unr.edu

2nd Alireza Tavakkoli
Computer Science and Engineering
University of Nevada
Reno, NV, USA
tavakkol@unr.edu

3rd Frederick C. Harris, Jr.
Computer Science and Engineering
University of Nevada
Reno, NV, USA
fred.harris@cse.unr.edu

***Abstract*—One of the most significant reliable and renewable energy sources is wave energy which has the most energy density among the renewable energy sources. Significant Wave Height (SWH) plays a major role in wave energy and hence this study aims to predict wave height using time series of wave characteristics as input to various machine learning approaches and analyze these approaches under several scenarios. Two different machine learning algorithms will be implemented to forecast SWH. In the first approach, the SWH will be forecasted directly using a Long Short Term Memory (LSTM) network and in the second approach an LSTM and an Ensemble Empirical Mode Decomposition (EEMD) method are proposed for SWH prediction. For this purpose, the elements of wave height will be initially decomposed and used for training an LSTM network to calculate the time series of SWH. Also, the calibration and verification of the modeled wave characteristics will be done using real data acquired from buoys. The results imply that the EEMD approach provides more accurate results and calculating the wave height through the decomposition and prediction of its main wave components can deliver more accurate outcomes considering various error indices. Also, it can be inferred from the results that the accuracy of the predictions will decrease as the forecasting time horizon increases.**

***Index Terms*—Deep learning optimization, Ensemble empirical mode decomposition, Long short term memory network, Neural network in coastal engineering, Ocean wave decomposition, Ocean wave height forecasting, Regression algorithms, Time series analysis, Wave characteristics prediction, Wave energy prediction**

I. Introduction

Fossil fuel combustion has been shown to have negative effects on our living environment and is one of the main drivers of global climate change. As such, the world is trying to move on from pollutional energy sources to clean and renewable ones [1]. Renewable energy resources including wind, solar, and ocean energy (i.e. thermal, tidal, waves, and currents) are among the common types of renewable energy sources that are employed by industries throughout the world.

Ocean waves provide energy densities which are significantly greater than wind and solar resources [2]. This energy density and its renewable property has triggered a surge of efforts in the world to try to harness ocean wave energy. Because of this, wave energy prediction plays a crucial role in planning placement of wave energy converter. The most crucial element of wave energy is Significant Wave Height (SWH) and its prediction plays a significant role to plan for a proper energy converter.

Waves are generally generated because of winds and the fluctuations in wave periods and heights are derived from the continuous shifts and changes in various wind's features [3]. Also, wave conditions are varied over monthly, seasonal, and annual timescales [4]. Through analyzing ocean wave characteristics obtained from buoy or satellite measurements in various locations, and employing deep-water numerical models, the average wave energy can be determined in those locations [5] [6].

The rest of this paper is structured as follows: Section II covers the related work, Section III presents the employed methodology, Section IV presents the results, provides discussion about them and compares the results of the two developed frameworks, and finally Section V draws conclusions and presents ideas for future work.

II. Related Work

Researchers have investigated solutions to accurately predict the oceanographic parameters altering wave power and height. The implemented approaches have included a wide range of methods namely statistical methods, numerical methods, empirical models, and hybrid approaches [7]. Of these, the empirical methods are easy and quick to use but cannot provide proper accuracy with results unless being utilized over large horizons [3]. Numerical models can become handy to achieve increased accuracy and wider applicability [3]. For instance, numerical forecasting studies have been made to the Persian Gulf [8] and China Sea datasets [9]. Finite element methods have also been vastly used for the prediction purposes. However, these models suffer from some inherent uncertainties in real-world cases. [10]. Besides, in most cases the accuracy of numerical models is highly dependent on mesh sizes which also directly affects the computational time [11]. Soft computing methods analyze data structure to find potential relations to predict outcomes. To be more specific, knowing the inputs and desired outputs, supervised learning neural networks can be developed using back propagation algorithm and these methods are one of the most significant tools which use approximation to determine patterns and relations within the provided data [12] [13]. Using a back propagation neural network, [14] predicted the ocean wave height. Their method could provide the anticipated outcomes quickly while reaching a certain accuracy.

In another study, it was concluded that the machine learning-based method could present better results when compared to physics-based models. However, the accuracy decreased as the prediction period increased [15]. Also, [16] and [17] investigated SWH prediction based on an artificial neural network. In their studies, classical time series models and neural network models were applied to observed SWHs along the Indian coast. The outcomes implied that the neural network could predict short-term outcomes with more accuracy whereas the results of the neural network model for long-term predictions were similar to classical models.

Considering soft computing's limited forecasting capability, it couldn't gain the trust to be widely applied in operational forecasting marine systems [18]. Hence, in recent years, machine learning, especially deep learning has been applied in marine and meteorological forecasting [19]. One of the mostly applied regression prediction neural network algorithms is a Recurrent Neural Network (RNN) [19]. RNNs are a type of Artificial Neural Network that use internal memories to model temporal dynamic behavior. They can be a good fit to properly learn from non-linear time series and hence, they have been implemented in analyzing many time series problems [20]. Accordingly, they can be a good framework for forecasting systems.

The problem with RNNs is that they suffer from the issue of vanishing gradient and as a result, errors cannot be back propagated to a previous neuron in a faraway layer [16]. A solution to this problem is the LSTM network. In these networks, long and short-term memory components take the place of the hidden neurons containing activation functions. Consequently, the network can store values of data in any length of time and the problem with vanishing gradients in RNNs is solved. An example of the LSTMs' efficiency was demonstrated by [21] to conduct predictions using a hybrid Simulating Waves Nearshore (SWAN) LSTM framework. This developed framework enhanced the accuracy of predictions by nearly 65% when compared to SWAN model simulations. Another study used various datasets to compare the wave model from the European Centre for Medium-range Weather Forecasts (ECMWF) with LSTM and multi-layer perceptron models [22].

The measured marine wave data used as input for neural networks, are consisted from several components having different properties including various frequencies and periods which all form non-stationary time series. Accordingly, in this study an LSTM framework is developed and is used to predict the SWH time series for various time forecasting windows. In the next step, the developed framework is integrated with a decomposition method and is employed for the same prediction as previous step. Afterwards, the performance of the two developed frameworks are compared.

III. Methodology and Implementation

Figure 1 shows the flow chart of the wave height prediction models used in this study. As it is depicted, the buoy data is first processed to find the missing records in the time series dataset, and linear interpolation is employed to prepare the training set. In this study, two LSTM model structures are

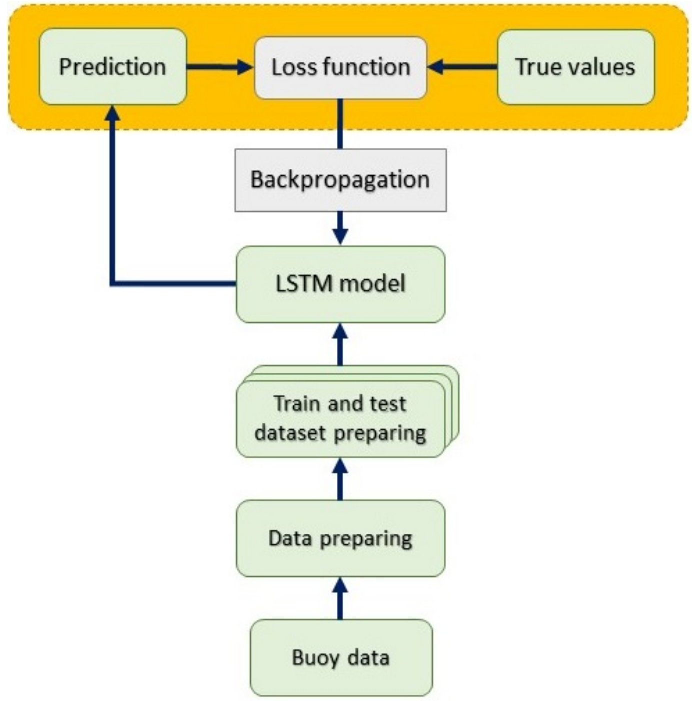

Fig. 1. Flow chart of the LSTM and EEMD-LSTM wave height models

developed to predict the wave heights for various lead times. The first LSTM model uses a sequence of wave heights as its input. As it is shown in the Figure 2, for the second model, an EEMD is used as a time-frequency data analysis method which divides wave height time series into a number of components, called intrinsic mode functions (IMFs). These IMFs correspond to various frequencies and a residue. To be more specific, EEMD has the ability to adaptively analyse a signal regardless of any prior assumption about the composition of it. To do that, it outlines IMFs consecutively through interpolating between peak values.

In this study, the underlying abilities of EEMD are utilized since the nonlinear nature of the waves can be more efficiently processed by neural networks through decomposing the waves. The decomposed components will be independently learned by the LSTM. The reversibility ability in wavelet decomposition is a beneficial asset for analysing the results here and hence the LSTM outcomes can be merged to create the final prediction results as it is depicted in the Figure 2.

A three-layer LSTM framework is developed where each of the decomposed waves in the EEMD model as well as the waves in the Non-EEMD one are trained for 100 epochs with a batch size of 64. The dataset includes more than 25,000 wave records that were measured using buoy with one hour

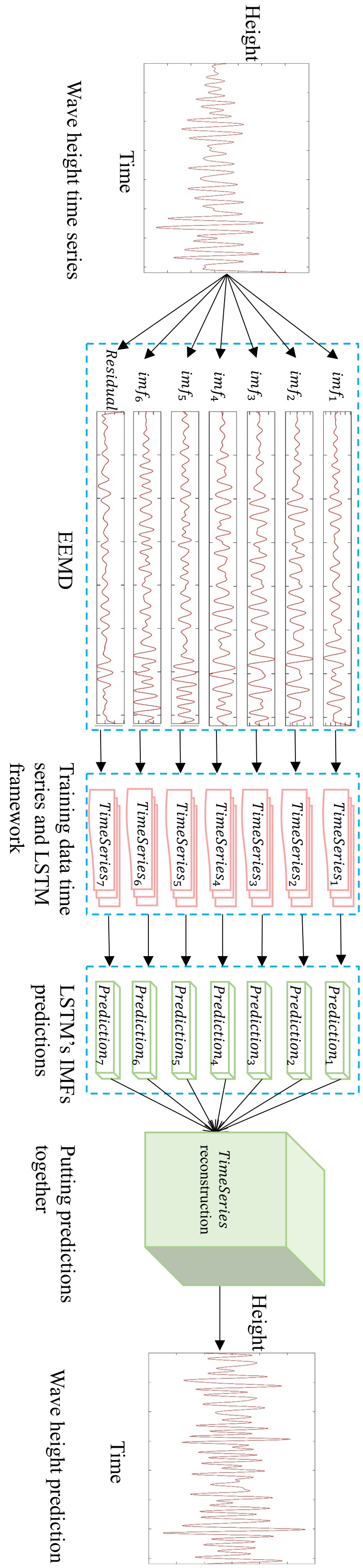

Fig. 2. EEMD-LSTM wave height framework

intervals between the records. This data was then normalized between 0 and 1 for this study. Also, 85% of these data is used for training and verification of the frameworks and the rest is dedicated for testing purposes.

IV. Comparisons and Results

In order to quantitatively evaluate the results and measure the performance of the models, their error indices are calculated and compared. These indices are derived for the two developed LSTM model structures separately and for various prediction scenarios. The employed error indices are bias, root mean square error (RMSE), scatter index (SI), mean absolute error (MAE), mean absolute percentage error (MAPE), and correlation coefficient (CC):

$$Bias = \bar{y} - \bar{x}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (x_i - y_i)^2}{n}}$$

$$SI = \frac{RMSE}{\bar{x}}$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} \mid x_i - y_i \mid$$

$$MAPE = \frac{100}{n} \sum_{i=1}^{n} \frac{\mid x_i - y_i \mid}{x_i}$$

$$CC = \frac{\sum_{i=1}^{n} ((x_i - \bar{x}) \times (y_i - \bar{y}))}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2 \times \sum_{i=1}^{n} (y_i - \bar{y})^2}}$$

where n is the total number of data and x_i and y_i represent the observed and predicted values, respectively. The term $\bar{x}$ is the mean value for buoy measured data and $\bar{y}$ is the one for predicted data. Also, it should be noted that the calibration of the model was carried out using Mean Square Error (MSE) index.

Table I shows the comparison of error indices associated with the two models for testing data. It can be inferred that the two models predictions are in good match with ground truth wave data. Also, the EEMD-LSTM framework could succeed to reach a decrease of 0.12 in RMSE error value comparing to the one for LSTM framework since the two frameworks were devised to minimize the RMSE index. The RSME value of the two models is mentioned in the Table I. Additionally, it can be noted in Fig. 3 - Fig. 6 that the EEMD-LSTM framework has successfully reconstructed the decomposed wave components into one final wave height time series after processing the components by LSTM network.

As depicted in Fig. 3, both LSTM models achieved good performances, demonstrating the capability of LSTM network components to learn and simulate the underlying relationships exist between various wave height input elements. Additionally, the EEMD based method could impressively establish relationships between the various decomposed waves and performed much better than the Non-EEMD LSTM algorithm.

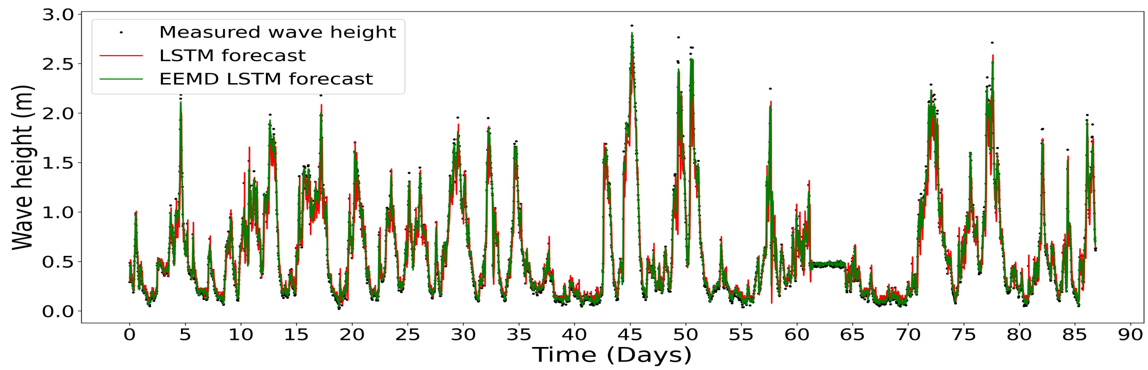

Fig. 3. EEMD LSTM Model - 1hour forecasting window

This accuracy improvement of EEMD over the Non-EEMD LSTM framework can be seen easier in the error indices presented in Table I.

TABLE I
ERROR INDICES OF PREDICTION RESULTS FOR THE TWO ALGORITHMS - PREDICTION WINDOW OF 1 HOURS

Method	RMSE	MAE	MAPE	CC	SI	Bias
EEMD-LSTM	0.07	0.04	12.85	0.97	0.12	-0.005
LSTM	0.20	0.12	32.51	0.86	0.32	0.02

To analyse the frameworks' capability in various scenarios and the efficiency of the EEMD implementation for longer forecasting windows the frameworks were again trained and tested for 6, 8 and 12 hours prediction windows shown in Figs. 4, 5, and 6. The networks' performance can also be seen from the error indices of Tables II, III, and IV.

TABLE II
ERROR INDICES OF PREDICTION RESULTS FOR THE TWO ALGORITHMS - PREDICTION WINDOW OF 6 HOURS

Method	RMSE	MAE	MAPE	CC	SI	Bias
EEMD-LSTM	0.14	0.11	29.66	0.91	0.25	-0.004
LSTM	0.37	0.24	73.26	0.72	0.58	0.35

TABLE III
ERROR INDICES OF PREDICTION RESULTS FOR THE TWO ALGORITHMS - PREDICTION WINDOW OF 8 HOURS

Method	RMSE	MAE	MAPE	CC	SI	Bias
EEMD-LSTM	0.19	0.13	38.28	0.87	0.31	-0.008
LSTM	0.41	0.29	86.3	0.39	0.63	0.67

From Tables I-IV it can be inferred that the EEMD-LSTM framework has always outperformed the Non EEMD-LSTM framework. In other words, the implementation of the EEMD algorithm helps the framework to significantly enhance the results. For instance, in the case of the 6 hour prediction window, although the implemented LSTM framework has provided good results, the implementation of EEMD decomposition

TABLE IV
ERROR INDICES OF PREDICTION RESULTS FOR THE TWO ALGORITHMS - PREDICTION WINDOW OF 12 HOURS

Method	RMSE	MAE	MAPE	CC	SI	Bias
EEMD-LSTM	0.25	0.18	56.24	0.77	0.40	-0.018
LSTM	0.46	0.33	104.7	0.25	0.74	0.05

method has helped the framework to increase its accuracy by 62%. A similar case can be inferred for the other prediction windows according to the provided tables and error indices. Also, various error indices of different prediction windows indicate the decrease of the two framework accuracy as the prediction horizon increases. This is shown in Figs. 3 - 6.

These figures also present the comparison of measured wave heights recorded by buoys along with the models' prediction. The LSTM network outputs follow the approximate waveform of the targets, however they fail to correctly predict several local peaks. In contrast, the proposed EEMD-LSTM framework showed its ability to take care of local peaks thanks to decomposing frequency domain of the training data in an explicit way. This decomposing feature makes the framework capable enough to gain a better insight to the characteristics of the data. This feature is more apparent when the window prediction time goes up as seen in Figs. 5 and 6.

V. CONCLUSIONS AND FUTURE WORK

In this study, two LSTM frameworks were developed for predicting Significant Wave Height (SWH) where one of them is utilized with the EEMD method. It was shown that the LSTM framework can demonstrate good performance. It can explore relationships between various records of data and establish waveform trends effectively. Additionally, by integrating the EEMD as a decomposition method with an LSTM neural network, the model can significantly outperform the Non-EEMD LSTM prediction model by nearly 60%.

It can be inferred that the EEMD-LSTM model's superiority lies within the embedded decomposition asset that feeds the network with more and segregated data elements for training. Accordingly, the results highlight the underlying benefits of

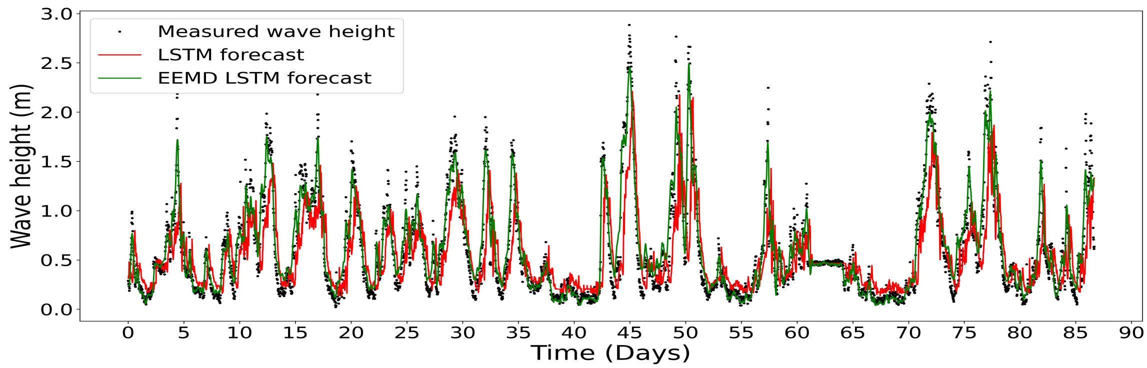

Fig. 4. EEMD and LSTM Models - 6hour forecasting window

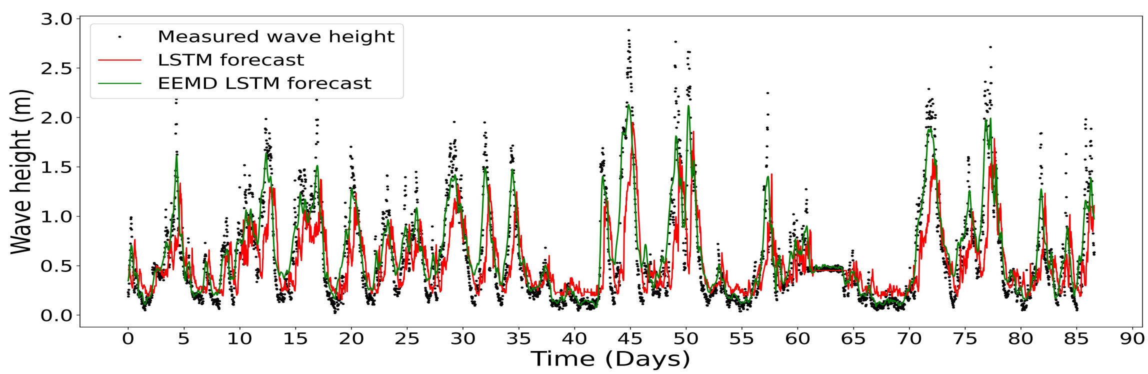

Fig. 5. EEMD and LSTM Models - 8hour forecasting window

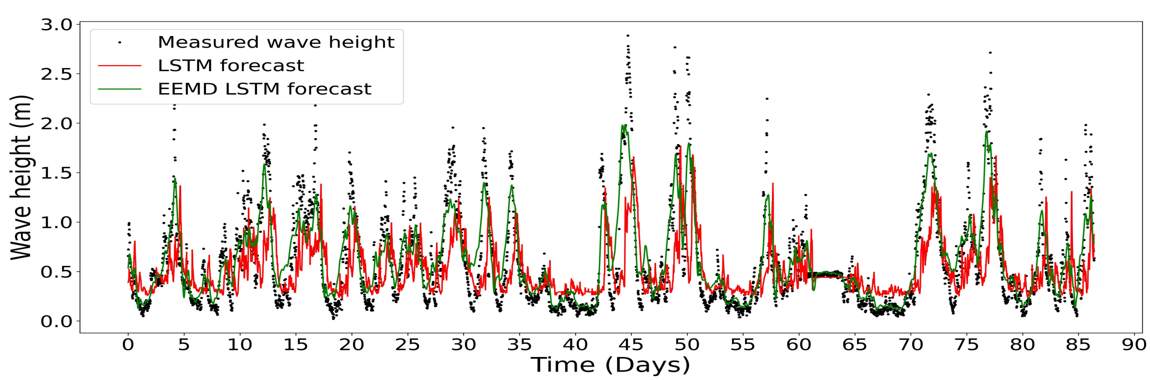

Fig. 6. EEMD and LSTM Models - 12hour forecasting window

wavelet decomposition and reconstruction by EEMD. Besides, it is revealed that LSTM and EEMD methods can be mixed and matched together for SWH prediction purposes. While this is currently a good asset, future work can involve the integration of numerical simulation methods to make the EEMD-LSTM framework more robust against longer prediction horizons and different wave characteristics.

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