

Article

Wave Power Density Prediction with Wind Conditions Using Deep Learning Methods

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Abstract

The uncertainty and enormous potential of wave energy have drawn attention and research efforts on predicting offshore wave behavior to aid wave energy harvesting. The movement of offshore waves generates huge amounts of available renewable energy and creates a unique offshore energy source. Because offshore waves are mainly generated by wind, this paper focused on using wind speed as the main factor to predict offshore wave power density to assist wave energy harvesting. The dynamic behaviors of wave energy were displayed in this paper in a format of wave power density distribution, which was extracted and visualized in MATLAB. The model was reconstruction based on a long short-term memory (LSTM) neural network for one week and 3 h wave power density forecasting, integrated with wind conditions as input in two scenarios. One scenario explored the location effect for wave density forecasting. Another scenario compared the influence of different time series input of the structure. RMSE was used as a criteria estimator of the accuracy. The data period ranges from 1979 to 2019 in the Gulf of Mexico exacted from WaveWatch III. The lowest RMSE among different locations is 0.104, while the different time step scenario has an RMSE of 0.715. Because wind speed data is much easier to get from either hindcast dataset or actual measurement, the proposed method with the resulting accuracy will make the forecasting of wave power density much easier. The method has the ability to be implemented in other wave thriving locations, which fills the gap of forecasting on wave height and period based on buoy data given a lack of measurements, as well as reflecting the correlations between wind speed and wave density, thus providing support for a quantitative correlation model based on a deep-learning-based model [1].

Keywords: wave power density; wind energy; visualization; WAVEWATCH III; forecasting; deep learning



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1. Introduction

The theoretical annual wave energy potential along the coasts of the U.S. is about 2.64 trillion kW, which is equivalent to about 64% of the total utility-scale electricity generation in the U.S. in 2021. Wave energy has broad commercial prospects and strategic value and has been considered one of the potential ways to tackle the global energy crisis and substitute fossil fuels. Wave energy has also been considered one of the best compensations to integrate with wind and solar energy to achieve consistent and reliable hybrid renewable energy systems [2–6]. However, all of these promising facts depend on the accurate estimation, commercial harvesting, and high utilization rate of wave energy. The spatial and temporal uncertainty in ocean wave energy has caused very slow development in

wave energy harvesting compared to wind and solar energy [7–11]. The EIA's report on U.S. electricity shows that renewable energy sources generated 22% of U.S. utility-scale electricity in the first six months of 2022, expecting to increase the entire percentage from solar and wind energy to 24% in 2023 [12]. The intrinsic properties of wave energy and the obstruction of wave energy converter development have resulted in lags in progression. Many researchers are focusing on breaking the erratic and complicated situation of no large-scale commercial use of wave energy [13–15].

Wave energy forecasting, which requires a thorough understanding of wave energy behavior, is critical to wave energy converter design and wave energy harvesting. Due to the modest output of wave energy during its harvesting process, large-scale commercial utilization of wave energy has not been reached [12], while small-scale wave energy projects have been developed in Portugal, the U.K., China, Norway, and the U.S. over decades. The European Union aims to install a capacity of 100 GW ocean energy including wave, tidal, and thermal conversion by 2050 [12]. To reach large-scale commercial utilization, comprehensive analysis and forecasting for wave energy behavior are imminent, which will help overcome many existing challenges, including low utilization efficiency, uncertainty variations, low robustness for energy devices, etc. [12]. So, behavior exploration, harvesting forecasting, movement analysis and tracking, stability management, and device design optimization form a fundamental and necessary path to move forward.

Increasing the accuracy of forecasting for wave energy behaviors has been a major research focus, which may accelerate and assist wave energy harvesting. Deep learning methods have been utilized in different fields of renewable energy, including convolution neural network (CNN), recurrent neural network, long short-term memory (LSTM), deep brief network, deep neural network (DNN), gated recurrent network (GRU), and deep hybrid models [16–21]. Wave energy density is decided by the wave height and wave period, which are normally measured through buoy or satellite remote sensing. Because wind is the main driven resource of waves and obtaining wind conditions is more convenient compared to wave conditions, the correlation between wave energy and wind conditions has contributed to the development of quantitative models [13–15]. Exploration of the correlation between offshore wind and wave energy is one of the possibilities for forecasting wave energy behavior through wind conditions. In addition, the results of correlation analyses may assist to reduce the variation of power output of hybrid renewable energy farms by canceling out the fluctuation in time series on both wave and wind parameters [22–25]. Quantifying the correlations between wave energy and wind conditions will assist wave behavior analysis thoroughly and validate wave energy prediction in different ways. According to recent publications, wave height, wave period, wind speed, wind directions, and power generation are the most common forecasting variables [26–31]. In addition, the concept of the wave power density hotspot has been introduced and analyzed to different extents [10]. Among all of the methods, long short-term memory (LSTM) models have the intrinsic advantage of memories of previous steps and feedback from the training mechanism. A combination of CNN and LSTM has been used for wind forecasting [15,16]. Because wave and wind conditions may be sensitive on time series, it would improve short- and long-term prediction [32,33].

In this paper, the authors performed forecasting of wave power density using hindcast wind speed and wave power density in the same location and time period. The study area is the Gulf of Mexico (18–30° N, 80–98° W), which has thriving activities and a considerable number of oil and gas platforms along its offshore coast. Wave power density was calculated and visualized through meteorological data from WAVEWATCH III in 3 h intervals, while the realistic coordinates, wave power density, and wind speed were obtained for each grid area under the resolution of $1/6 \times 1/6$ degrees in longitude and

latitude. The wind speeds were calculated through horizontal and vertical components, which were extracted 10 m above sea level. The LSTM method was implemented to train the forecasting model. GRU layers were introduced to accelerate training progress. Two scenarios were conducted based on the trained models. Calculated wind power density and wind speeds were adjusted to keep the same time series, which were trained as two features of input to predict the next 3 h wave power density. One of the scenarios was chosen to find out the location's effect on target location forecasting. The other scenario was selected to investigate longer durations of time for forecasting the target point. RMSE was used to evaluate the forecasting model's performance. The forecasting model was tested at six randomly selected locations, including areas with offshore platforms, coastal areas, and offshore areas. The testing results of the six locations were compared and analyzed under different seasons and time steps.

2. Materials and Methods

The meteorological data (1979–2019) was extracted from WAVEWATCH III [34], operated by the National Oceanic and Atmospheric Administration (NOAA), located in the Gulf of Mexico area (18–30° N, 80–98° W). The study area was divided into grids based on the resolution of $1/6 \times 1/6$ degrees (0.167 degrees), which is critical for matching wind speed and wave power density coordination, as they both were calculated through the directly obtained meteorological data.

2.1. Data Pre-Processing

Data pre-processing is critical for handling raw data with missing data, incorrect values, different spatial and temporal resolutions, and different units, used as the training data for the model. The nearest 40 years with a spatial resolution of one sixth on both longitude and latitude were downloaded from NOAA FTP. The inputs of the LSTM structure in this paper were extracted and calculated from significant wave heights, significant wave periods, and wind speeds in both horizontal and vertical directions. Missing data in the years 1986, 1989, 1990, 2004, and 2008 was deleted, while the remaining data was aligned as the time series of wind power density and wind speeds as 2 features to predict wave density. The prediction of wave energy is affected by many parameters, including surface temperature, salinity, weather, seasons, locations, and wind conditions. The method in this paper considered the wind speed as the main parameter to explore how wind speed influences wave energy prediction through wave density displaying. In addition, the authors also expect that the surrounding locations of the target area have correlations that affect each other, which was considered as a feature in the forecasting models. This paper utilized 8 grid areas surrounding the target area, making it a 9-grid area to generate 18 features as the input group, and each grid area was embedded with wind speed and wave density properties. Six representative points were randomly chosen to test the prediction accuracy.

Wave power density was calculated as Equation (1) only when the water depth is greater than $\frac{1}{2}$ of the wavelength.

$$P = \frac{\rho g^2}{64\pi} H_s^2 T_e \approx \left(0.5 \frac{kW}{m^3 \cdot s} \right) H_s^2 T_e \quad (1)$$

where P is the wave energy flux per unit of wave crest length; H_s is significant wave height (m); T_e is the wave energy period (s); ρ is water density; and g is acceleration by gravity.

To keep wind speed and wave power density (features) unit compliance, standardization was implemented to convert wind speed and wave density on the same scale. Each calculated or observed value was subtracted from the mean and then divided by the standard deviation. The training data of wind speed and wave density is a 3-dimensional

matrix with coordination (latitude and longitude) and time steps. The data was extracted and visualized using MATLAB (version R2021a and 2022a) daily, monthly, and annually.

Many criteria are available to evaluate the efficiency and performance of models, including the mean absolute error (MAE), mean absolute percentage error (MAPE), root mean square error (RMSE), coefficient of determination (R^2), mean absolute percentage error (MAPE), and scatter index. RMSE squares the errors before averaging, which forces the LSTM model to be conservative and avoids large and potentially destructive miscalculations, as wave power fluctuates significantly. Unlike R^2 or MAPE, RMSE aligns the unit as wave power density. In addition, RMSE provides a stable measurement to smooth the period across the entire 40-year dataset without mathematical explosions that plague the percentage. In this study, RMSE was selected to show the standard deviation of the prediction output and observation inputs, which was adequate and utilized as an indicator of two scenarios' accuracy in Equation (2).

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (X_i - \hat{X}_i)^2} \quad (2)$$

where X_i and $\hat{X}_i$ are the measured and output forecasting wind speed at time i and N is the number of test data.

2.2. Deep Learning Model

LSTM is derived from the recurrent neural network (RNN), which is sensitive in sequential recognition, identification, and prediction. RNN has the issue of vanishing or exploding gradients, which results in memory loss or short memory; when the learning rate shrinks too much to continue the learning process, it will stop. LSTM is the version that converges the RNN structure and has better performance with long-term memories. In addition, the architecture solves the over-fitting issue of RNN. We combined LSTM with CNN, GRU, the differential evolution algorithm (DE), and Kalman filters to improve the weights, balance the hidden layers, and avoid offset accuracy [35–38]. Bidirectional LSTM was adopted in many applications when the training sequences, forward and backward, were obtained and known. Due to the two-direction processing within two hidden layers, output on the same layer worked better for long-term contexts for each direction; however, its prediction performance relied on previous data. The application of RNN in multiple fields can be developed in LSTM to improve accuracy.

3. Results

The distribution of wave energy density hotspot in the Gulf of Mexico was visualized in a grid of 7957 (1/6 by 1/6 degree) areas between a latitude and longitude of 18–30° N and 80–98° W. The entire Gulf of Mexico was divided into a 73 by 109 matrix by latitude and longitude. To train the model with different locations as inputs, each target grid was considered as one element in the matrix. Thus, each element has eight neighbors surrounding itself, except for the initial and end rows/columns. The center coordinates of the nine locations may not be included within the irregular shape. So, it was reasonable to adopt the surrounding points with different wave density values to predict the level of the center point. To have each element in the matrix aligned in training, the training set started from the second row and column to ensure each element has eight neighbors as input data, so the final grid matrix was changed to 71 by 107, corresponding to coordination in latitude and longitude. Collecting the observed point and eight points as one cell, the cell matrix was compound of 7597 cell elements. The wind speed cell matrix and the wave power density cell matrix were handled as two feature cells for each neighbor. A total of 18 features

for each neighbor were utilized as the input for the LSTM architecture. Standardization was used to scale the inputs before training. LSTM and GRU layers were combined for sequence feature training through “Adam” optimization for training and regression with prediction, as shown in Tables 1 and 2 and Figure 1. The LSTM structure was input with significant wave height, wave period, and horizontal and vertical direction wind speed. Multiple inputs of different locations only have one output, which is the predicted wave density over 3 h. The training datasets for different location scenarios were chosen from one month of data from January 1979, with 248 time steps in 3 h increments. Observation data from February 1979 was used as the testing dataset.

Table 1. Parameters used in training processes.

Parameter	Value
Initial Learning Rate	0.0050
Learning Rate Schedule	Piecewise (drop 0.2/125 periods)
Gradient Threshold	1 (l2norm)
L2 Regularization	1.0000×10^{-4}
Mini Batch Size	150
Max Epochs	10
Sequence Length	Longest

Table 2. Layers used in the model architecture.

Layer	Configuration
Input Layer	Size: 18 (spatial–temporal cell matrix)
BiLSTM Layer	128 hidden units (tanh/sigmoid)
Fully Connected	Input: 256/output: 18
Output Layer	Regression (MSE)

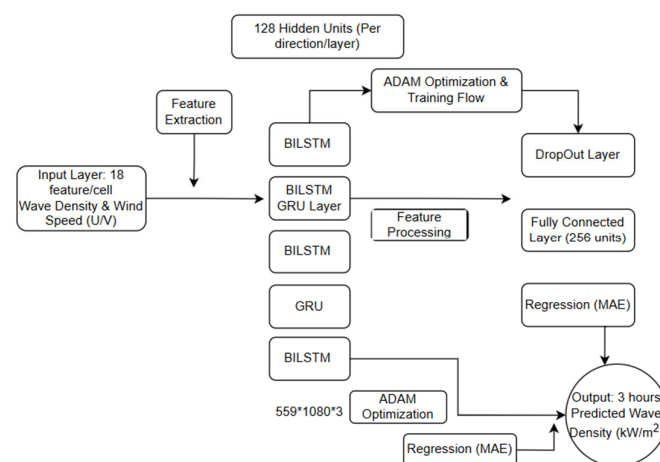


Figure 1. Overview of the model architecture.

The predicted wave power density over the short term of 3 h was compared with the observation values in Table 3. Six grid elements (Figure 2) were randomly chosen for accuracy testing by RMSE, and the results are visualized over the entire Gulf of Mexico in Figures 3–5. The locations were chosen as different representatives of the entire Gulf of Mexico area, including near-shore, offshore, the middle area, and a concentrated thriving

area. For corresponding coordination, RMSE values predicted in either winter or summer in 1979 and 2018 were listed in Table 3, as well.

Table 3. Six (6) randomly chosen pixels forecasting accuracy.

#	Matrix Row	Matrix Column	Latitude	Longitude	RMSE			Location
					1979-08	2018-02	2018-08	
1	30	20	24.999	−94.667	0.45513	0.19841	0.16142	Near-shore
2	30	71	24.999	−86.167	0.10393	0.17172	0.12662	Offshore
3	63	67	19.499	−86.833	0.45350	0.3237	0.39500	Yucatan Strait coast
4	3	68	29.999	−86.667	0.15867	0.20456	0.15758	Near-shore oil platform
5	69	81	18.499	−84.500	0.46485	0.38399	0.44763	Yucatan Strait
6	35	6	24.166	−97.000	0.35035	0.27070	0.40632	Western near-shore

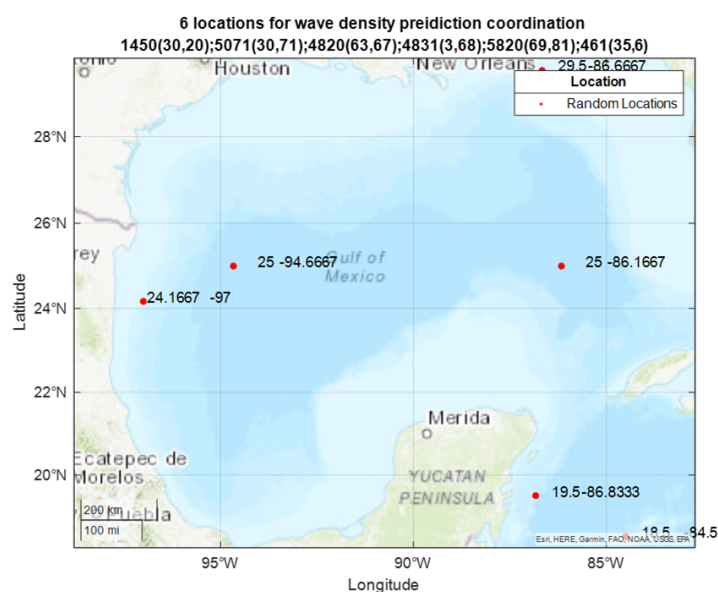


Figure 2. Six randomly selected locations in the Gulf of Mexico for testing.

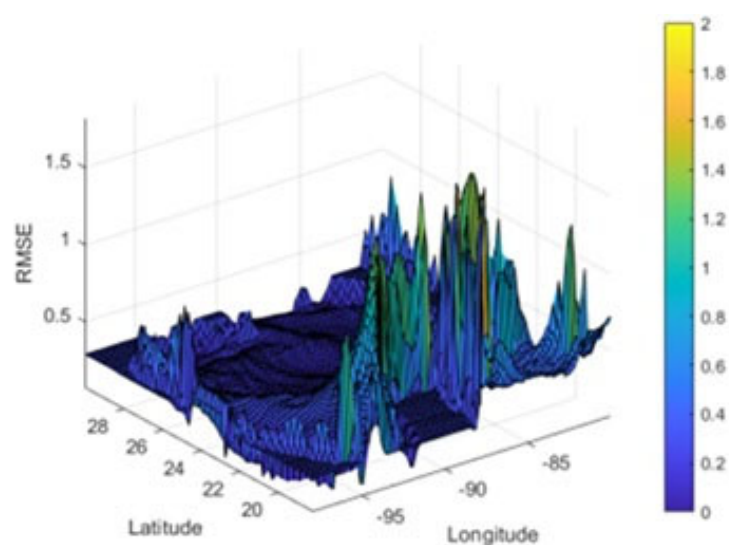


Figure 3. RMSE visualization of Gulf of Mexico in 1979-08.

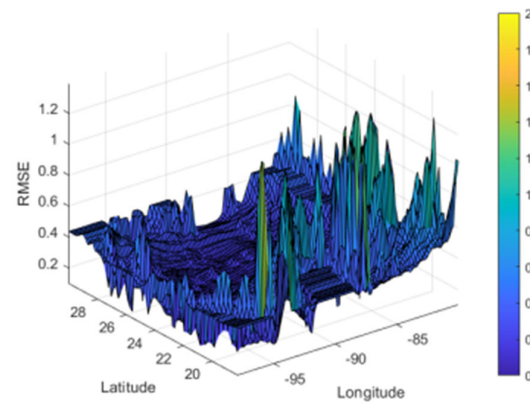


Figure 4. RMSE visualization of Gulf of Mexico in 2018-02.

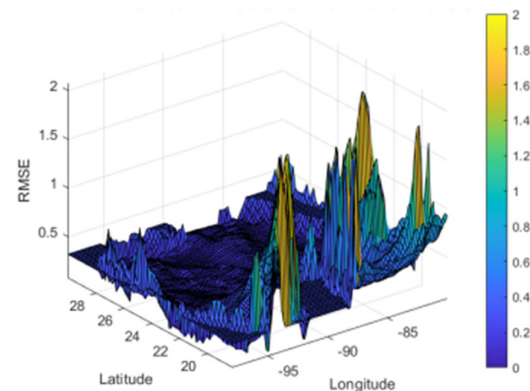


Figure 5. RMSE visualization of Gulf of Mexico in 2018-08.

Figures 6–11 show that the mean RMSE value and frequency of predicted wave density fluctuated in one month time series at the six selected testing locations during different time frames. From the results comparison, areas with higher RMSE values were centralized along with the western center and the Yucatan Strait, where the wave energy has a higher concentration level. The RMSE values fluctuated more than that of the near-shore area. The near-shore area (strength level within 20–65 kw/m) has a lower offset with the observation value, where accuracy is higher than that of the offshore area.

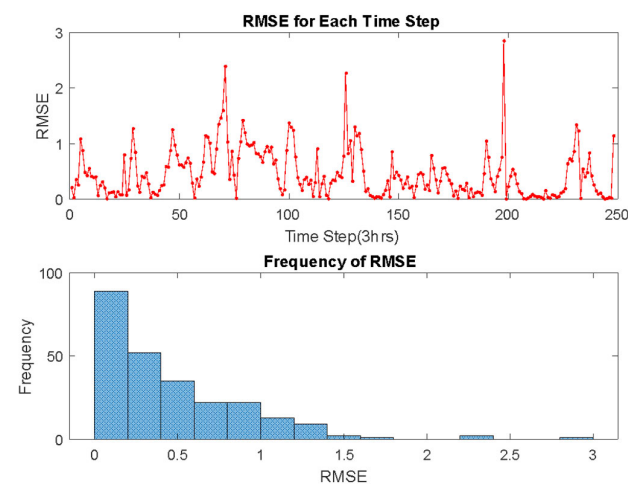


Figure 6. RMSE values of one month prediction at locations #1 on 1979-08.

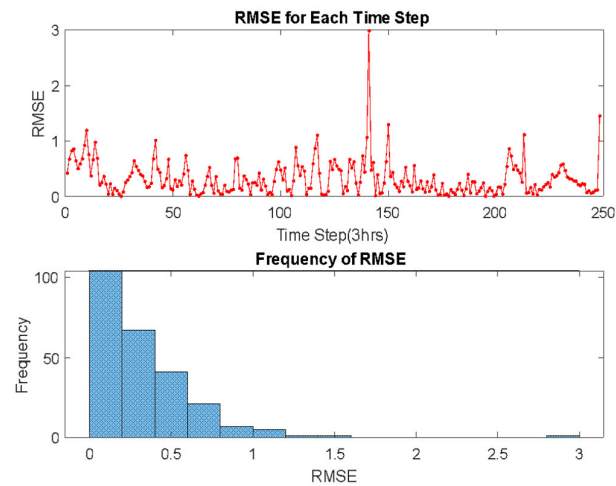


Figure 7. RMSE values of one month prediction at locations #2 on 2018-02.

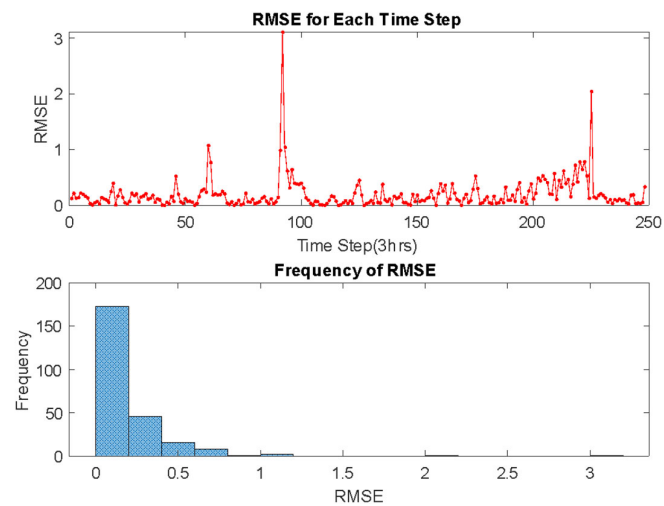


Figure 8. RMSE values of one month prediction at locations #3 on 2018-08.

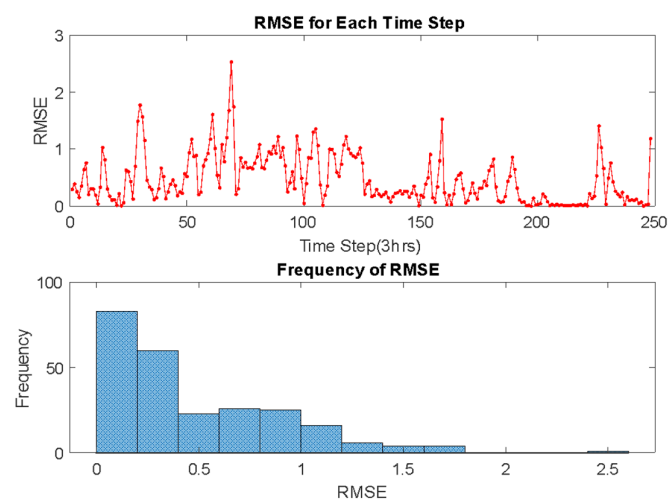


Figure 9. RMSE values of one month prediction at locations #4 on 1979-08.

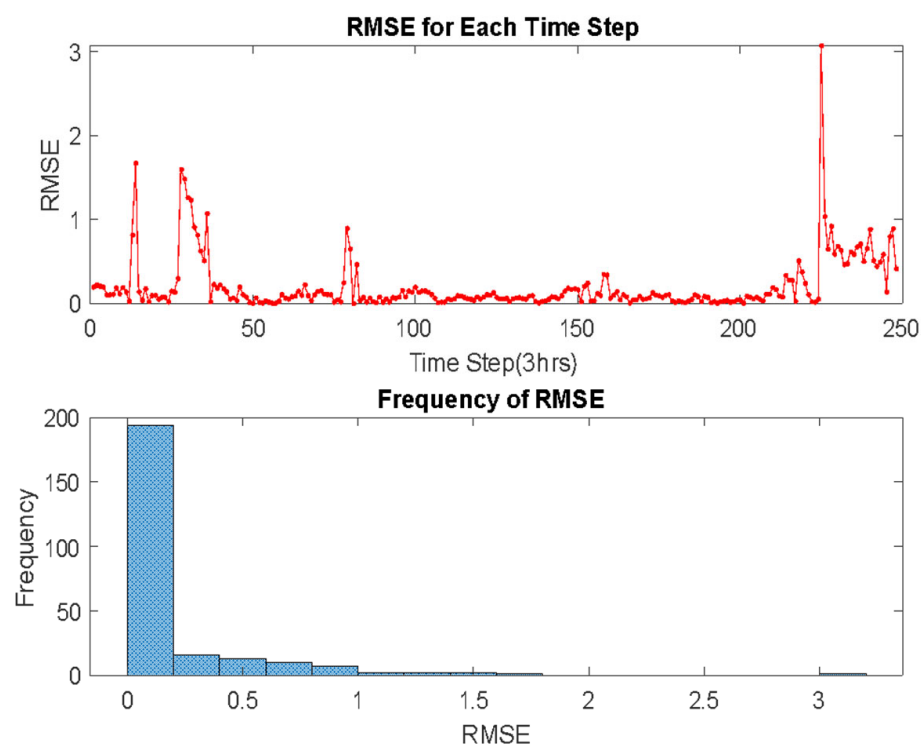


Figure 10. RMSE values of one month prediction at locations #5 on 2018-02.

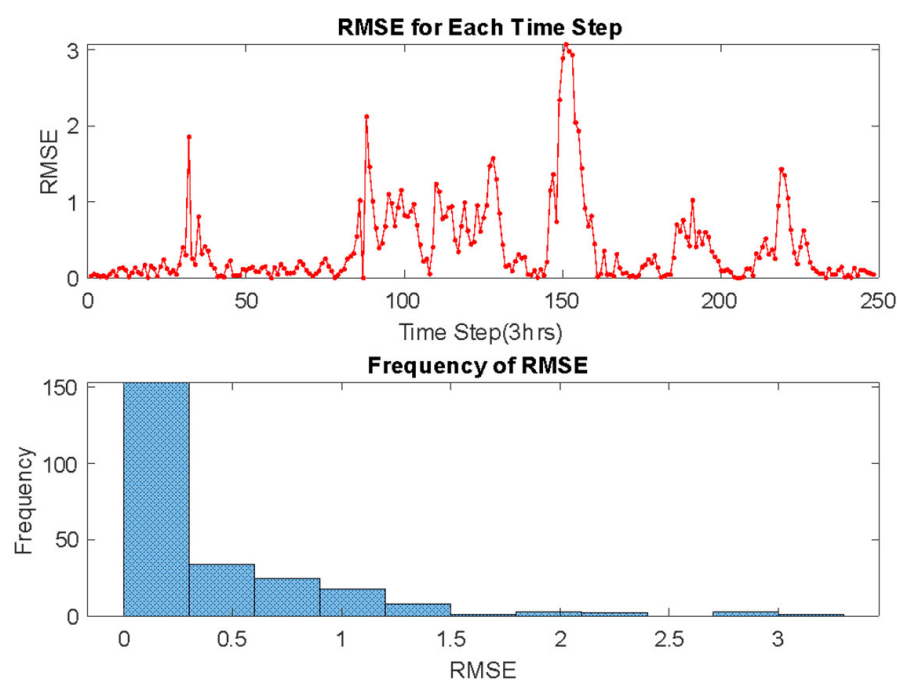


Figure 11. RMSE values of one month prediction at locations #6 on 2018-08.

Figures 12–17 show the comparison of the prediction results and observation values of the six testing locations in selected time frames; in addition, two features (wave density and wind speed) of each location are shown at the bottom of each figure, where the red lines are wind speed and the yellow lines are wave density.

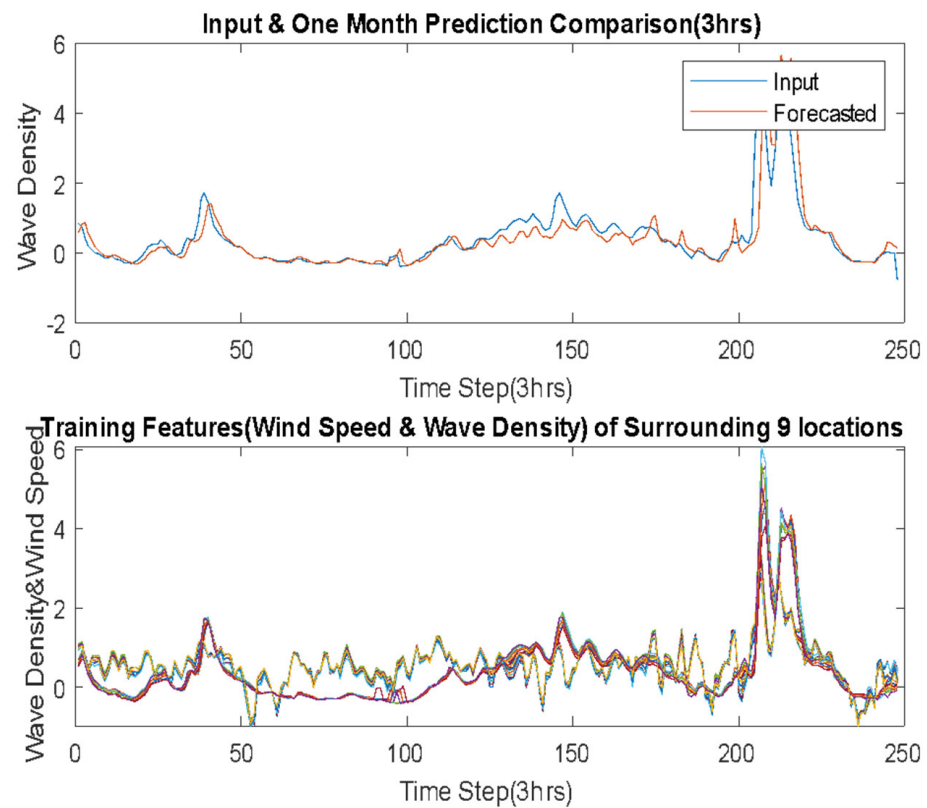


Figure 12. Comparison of predicted values versus actual values at locations #1 on 1979-08.

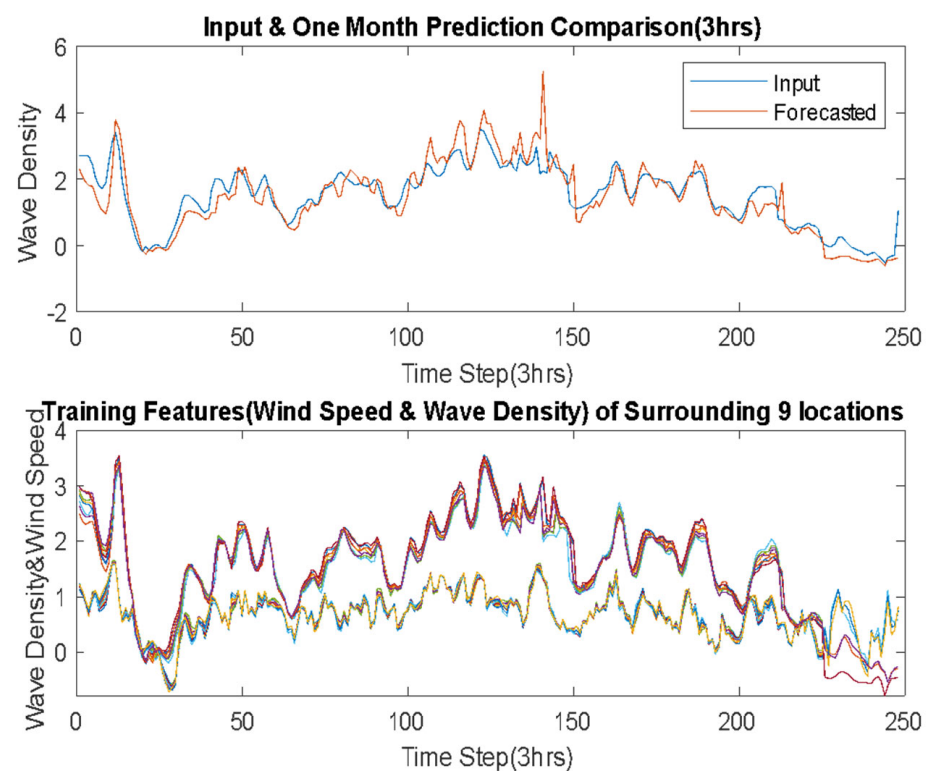


Figure 13. Comparison of predicted values versus actual values at locations #2 on 2018-02.

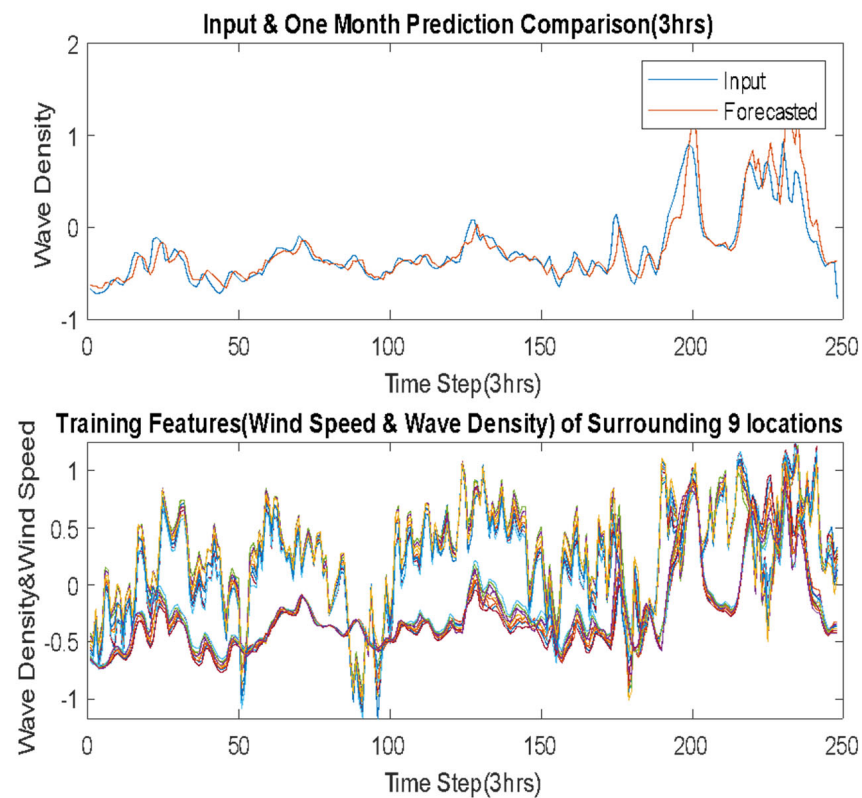


Figure 14. Comparison of predicted values versus actual values at locations #3 on 2018-08.

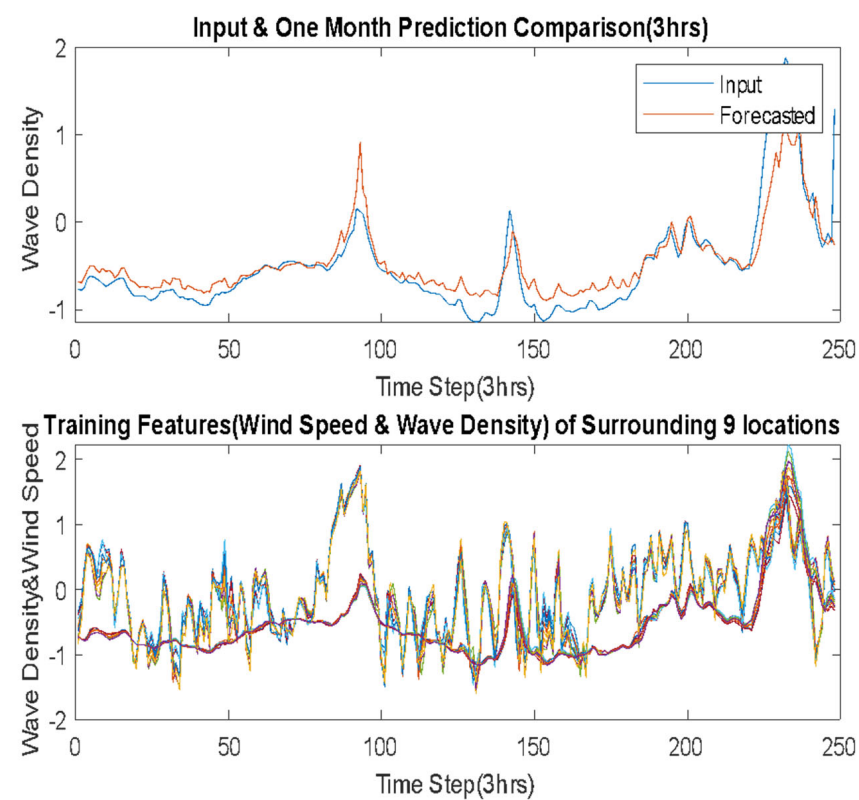


Figure 15. Comparison of predicted values versus actual values at locations #4 on 1979-08.

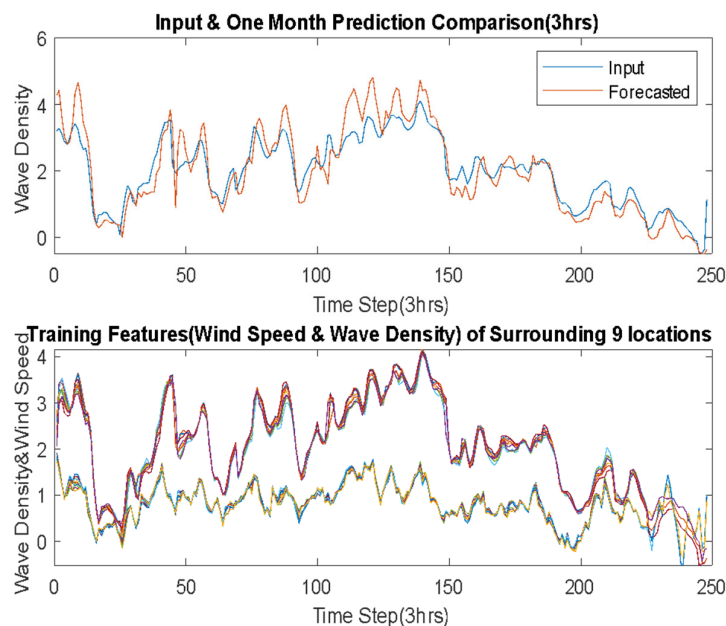


Figure 16. Comparison of predicted values versus actual values at locations #5 on 2018-02.

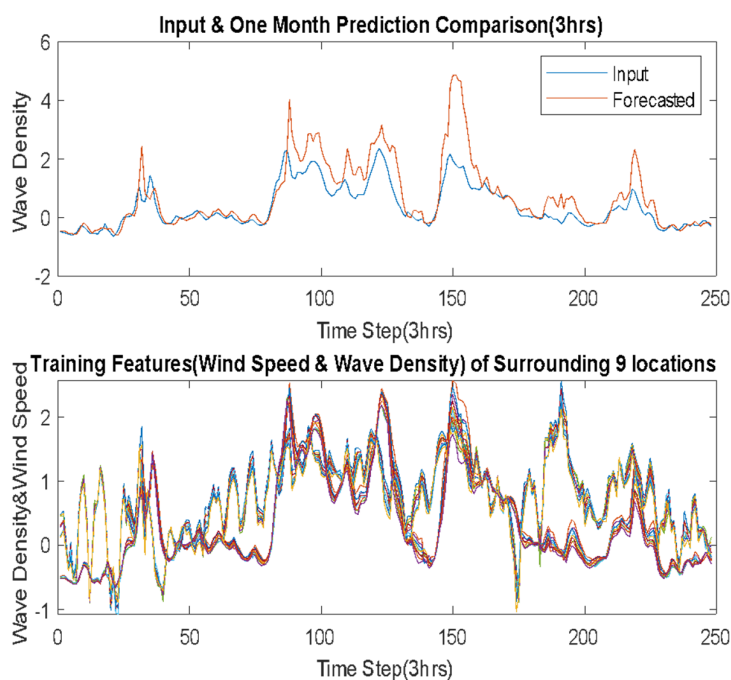


Figure 17. Comparison of predicted values versus actual values at locations #6 on 2018-08.

The surrounding locations affect the center locations' future trends and development from the results of the model. It is reasonable to consider that any impact occurs if different time series are implemented as input to predict the wave density in the same location. The training dataset has one year of data from year 2009, and output of training was utilized as data offset of one week to train the model instead of 3 h. Test datasets from the year 2010 calculated wave density and wind speed. According to Figure 18, the realistic coordinate matched the simulated matrix during training. Pixels of the image matched the ones all over the color bar. Each pixel in Figure 18 matched the geographic coordinate in latitude and longitude to locate the RMSE value.

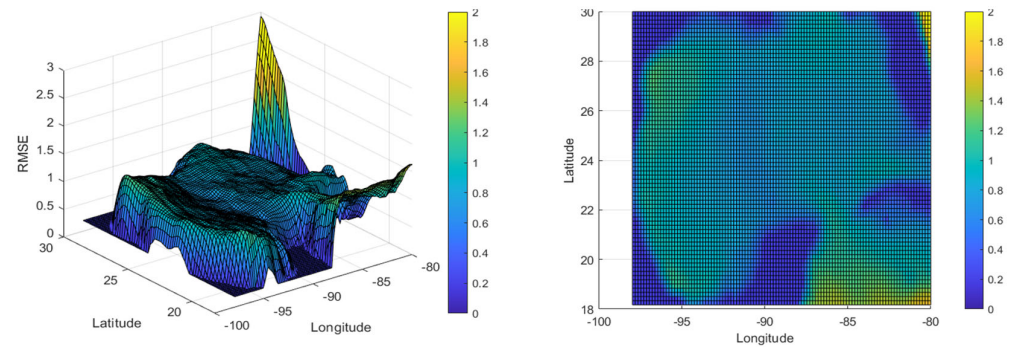


Figure 18. Testing result of one week prediction output in year 2010 for the Gulf of Mexico (Lat (18°, 30° N), Lon (−98°, −80° W)).

Figure 18 shows the geographic coordinates of all of the RMSE over the study's time series. The coastal line of the Gulf of Mexico was added to constrain all of the hotspot points within the scope of the Gulf of Mexico.

The high RMSE was concentrated along the Yucatan Strait and the bay of Campeche with a high level of 50–65 kW/m wave density, while the offshore platform area has relatively stable results compared with the observation status. The mean accuracy is 0.715 of the one-week prediction results, which is slightly higher than 3 h prediction on the one month training data. It was reactive, as the large training set did not increase the accuracy, and the longer prediction term has the same trend of distribution of wave energy density hotspots, which is within the acceptable range for prediction accuracy compared with current publications.

4. Conclusions

In this paper, a deep-learning-based LSTM model was integrated with GRU layers to predict the wave energy behavior, i.e., wave energy density, using wind speed and wave density data from the surrounding areas of the targeted area. The training data was calculated based the hindcast data obtained from WaveWatch III.

First, the results show very good predication accuracy with only two selected input values. Considering the dynamic behavior of offshore waves, using only wind speed and previous wave energy density to accurately predict the current and future wave energy density has a significant impact on enhancing wave energy harvesting.

Second, the LSTM model shows excellent performance in predicting time series data in this study. Due to the limitation of the data source, this study had to limit the prediction in any given area with a size of 1/6 in longitude and latitude within 18–30° N and 80–98° W. Considering surrounding areas as individual locations and inputs helped achieve the resulting accuracy. The GRU layer also helped to accelerate the model training processes.

Third, it is also noticed that better forecasting accuracy was obtained in oil and gas platform assembling areas, and it drifted higher in the area with more hurricane activity and higher wave density strength areas. The observation is in line with the general trend of offshore waves' dynamic behavior.

At last, one week time series prediction shows higher fluctuation with observation values, and even increasing the training datasets did not reduce the RMSE offset. In the future, if data with finer resolution in both spatial and temporal dimension becomes available, the model could be re-trained using the finer-resolution data to perform predictions that are more applicable for wave energy harvesting.

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C.G.; writing—original draft preparation, C.G.; writing—review and editing, H.L.; visualization, C.G.; supervision, H.L.; project administration, H.L.; funding acquisition, H.L. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The WaveWatch III dataset used in this research can be found from this website: <https://polar.ncep.noaa.gov/waves/wavewatch/>, accessed on 15 January 2022.

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Conflicts of Interest: The authors declare no conflicts of interest.

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