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Uncertain Accessibility Estimation Method for Offshore Wind Farm Based on Multi-step Probabilistic Wave Forecasting

Hao ZHANG [1], Jie YAN [1*], Shuang HAN [1], Li LI [1], Yongqian LIU [1], David Infield [2]

[1] State Key Laboratory of Alternate Electrical Power System with Renewable Energy Sources, North China Electric Power University, Beijing, China
[2] University of Strathclyde, UK
[*] yanjie@ncepu.edu.cn

Abstract: Accessibility estimation is significant to the offshore wind farm operation and maintenance (O&M) due to the extremely limited weather window and its sensitive effects on O&M tasks. Wave forecasting can be one solution to help maintenance decision-making. However, the uncertain and dynamic properties of wave forecasts are seldom considered in the accessibility estimation process. This paper presents an uncertain accessibility estimation method based on a multi-step probabilistic wave height forecasting (MPWHF) model and Monte Carlo simulation. Firstly, an MPWHF model is proposed using the wavelet decomposition and the sequence to sequence(Seq2Seq) network with quantile outputs. Secondly, the O&M missions are randomly given a start time and simulated in the O&M flow chart by the Monte Carlo method. Finally, several access indexes, including accessibility probability, delay time, and delay probability, are evaluated based on the simulation results. Verification of the proposed MPWHF model and uncertain accessibility estimation is based on 7-year observation data of a buoy station. The results show that the MPWHF model outperforms other counterparts and the probability of offshore accessibility is nonlinearly dependent on the weather limits and the O&M required time.

1. Introduction

Offshore wind energy has achieved remarkable progress in recent years[1-3]. However, maintenance is still an intractable technical problem for offshore wind farms due to the harsh weather condition [4]. Bad accessibility will significantly delay the maintenances and increase the downtime and energy losses of the offshore wind turbines [5]. Expenditure on capable service vessels improves the offshore wind farm accessibility. For instance, the availability is 90% with 65% of accessibility, while the availability increases up to 95% with advanced service vessels in Horns Rev offshore wind farm [6]. Nonetheless, better transportation systems (vessels and helicopters) will significantly increase the O&M cost. According to [7], the costs of transportation systems can amount to 73% of O&M costs. Since the O&M costs account for 15%-30% of the total cost of the offshore wind energy project [8-9], the costs associated with accessibility will directly influence the investment rewards of an offshore wind farm. Therefore, the variation of accessibility could bring highly complex and uncertain effects to the life cycle cost of offshore wind farm projects [10-12]. It is critical to estimate the wind farm accessibility for the balance of good availability and high O&M costs [13].

Many efforts have been made for the offshore wind farm accessibility estimation using measurements, reanalysis, or forecasts of the oceanic weather data. Based on the climate reanalysis database, a comprehensive analysis of offshore wind farm accessibility at the North Sea is carried out using the mathematically defined concepts of approachability, weather window, accessibility, and waiting time [14]. With the wave data measured from two wave buoys on the west coast of Ireland, the levels of access and waiting time between accessible weather windows are quantified at various O&M access limits [15]. By considering the reliability of wind turbine key components, use time for repair, and access constraints, the probabilities of offshore access and the expected repair delays are calculated by Monte Carlo and Event Trees [16]. Tomas Gintautas predicts the weather windows suitable for offshore wind farm operation by estimating the expected probabilities of operation failure when the specified offshore service vessels exceeded their allowable magnitudes [13]. Francois [8] presents a maintenance optimisation model and estimates the maintenance delay caused by weather and work shift restriction based on Monte Carlo and measured wind and wave data. Petros proposes an opportunity-based hourly maintenance schedule strategy that uses wind speed and wave height as weather limits and distinguishes offshore accessibility by short-term and long-term [17]. Ciaran develops a data-driven vessel motion model to predict the vessel heave heights. The proposed vessel motion model is used to provide uncertain access forecasts[18].

However, there are still two challenges for the accurate accessibility estimation.

(1) Inaccurate weather forecasts bring significant uncertainties to accessibility estimation. However, the uncertainty of accessibility comes from weather forecasts is rarely explored. A standard alpha-factor method and ensemble weather forecasts were employed to count for the forecast uncertainty [13], [19], but the model performance is sensitive to the intuitively selected alpha value.

(2) Due to the Offshore weather conditions are always changing rapidly, the real-time updated weather forecasts are more valuable for offshore O&M arrangements. However, the dynamic properties of real-time wave forecasts are not considered in the previous accessibility estimation studies.

In order to fill the research gap, this paper presents an uncertain accessibility estimation method for offshore wind farms based on a real-time multi-step probabilistic wave height forecasting (MPWHF) and O&M simulation. Our contributions can be concluded as the following three points. And Table 1 lists the difference between the previous literature's contribution and our contribution.

TABLE 1. THE PREVIOUS LITERATURE'S CONTRIBUTIONS AND OUR CONTRIBUTION

Publication	Data Type	Accessibility Evaluation
[8]	Wind and wave measurements	Alternative transportation means are modeled (different CTV and helicopter).
[13]	Multi ensemble weather forecasts	The Alpha-factor method is used to address the uncertainties related to weather forecasting.
[14]	Long-term and high-resolution climate reanalysis database	The spatial and temporal variability of accessibility parameters in the North Sea is analyzed.
[15]	Wave measurements	Levels of access at various operations are modeled.
[16]	Wind and wave measurements	Enabling very fast probability calculations of offshore access probabilities and expected delays
[17]	Wave and wind speed forecasts	The offshore accessibility considers the short-term and long-term weather forecasts.
[18]	Weather forecast data	A probabilistic vessel heave prediction model is proposed.
Our method	Multi-step probabilistic wave forecasts	Multi-step Probabilistic wave prediction and dynamic simulation are used to evaluate the uncertain accessibility with various indexes.

(i) A real-time MPWHF model is proposed to obtain the uncertain and dynamic properties of wave height forecasts based on wavelet decomposition (WD) and sequence to sequence(seq2seq) network. The proposed model can predict the quantile wave height sequence for the next 12 hours.

(ii) The probabilistic, dynamic, and nonlinear characteristics are considered in the O&M simulation based on the MPWHF results and a Monte Carlo model. In contrast to accessibility estimation using a deterministic pre-planned schedule, the O&M activity schedules are dynamically adjusted based on real-time multi-step probabilistic wave height forecasts. Thus, dynamic and probabilistic characteristics of the weather forecasts will be utilised. Moreover, the nonlinear relation between accessibility and O&M settings is modeled in the Monte Carlo process.

iii) Different accessibility indexes and their uncertainty are evaluated in the simulation model. Accessibility probability, delay time, delay probability, and their confidence intervals are presented. These indexes comprehensively depict the variation of accessibility under different access vessel capabilities limits and O&M repair time.

The rest of the paper is organised as follows. Section II presents the MPWHF model. Section III provides the O&M flow chart and Monte Carlo simulation details. Section IV shows the performance of the proposed MPWHF model and the results of the uncertain accessibility at the selected buoy site. Finally, the conclusions of this work are given.

2. Multi-step probabilistic wave height forecasting model

The offshore accessibility and O&M activities are strictly restricted by weather conditions and the performance of the O&M vessels. The relevant weather parameters for offshore accessibility include significant wave height(SWH), wind speed, visibility, etc. According to the previous studies, wave height is paramount in the accessibility evaluation and O&M decision-making of offshore wind farms [20].

In this section, an overview of wave height prediction is given, then the proposed multi-step probabilistic wave height forecasting (MPWHF) model is described. Several multi-step forecasting counterparts are also introduced here to validate the performance of the proposed MPWHF model.

2.1 An Overview on wave height prediction

In general, wave height forecasting is divided into two categories, the numerical and data-driven method [21,22]. The numerical method produces the wave forecasts by solving the spectral energy-balance equation without dependence on the historical measurement data. However, the numerical method needs a heavy computational burden and long computational time. Therefore, it is not easy to support real-time forecasts. Since fast and accurate prediction performance without reliance on specific physical information of the prediction sites, data-driven methods have received more attention. For instance, Auto Regressive and Moving Average (ARMA) [23], Artificial Neural Network (ANN) [24-27], Support Vector Regression (SVR) [28,29], Adaptive Neuro-Fuzzy Inference System (ANFIS) [30], had been used in the literature. Although previous studies have demonstrated that wave height forecasting uncertainties are vital for judging whether a specific weather window justifies the mobilisation of O&M vessels, most of the wave prediction methods mentioned above only produce deterministic wave forecasts. There are few probabilistic wave height prediction studies [31-33]. In [31], a designed time series method for wave height density forecasts is established. The decision of whether to mobilise an O&M vessel is made in terms of minimising the expected cost. A parametric probabilistic forecasting approach based on log-Normal distribution is introduced in [32], but it is used in the wave energy flux prediction. A significant wave height and peak wave period probabilistic forecasting model based on statistical post-processing of NWP and a data-driven vessel motion model is proposed to produce the vessel-specific accessibility forecasts[33]. Still, the accessibility had not strictly been assessed in this study.

For the offshore O&M simulation involving the future weather window, multi-step wave forecasting is indispensable. However, traditional data-driven methods have inherent defects that cannot generate multi-step temporal structured forecasts. For instance, ARMA, SVR, ANFIS are single output models that cannot learn the temporal dependency between the outputs at different lead times. While traditional ANN could output multi-dimensional vectors, the outputs vectors do not have the required temporal structure [34,35]. In recent years, deep learning (DL) has demonstrated excellent performance in the modeling and forecasting of time series, e.g., LSTM (Long Short Term Memory) [36], CNN-GRU [37], Temporal Convolution Network (TCN) [38], sequence to sequence [39], and attention models [40]. Sequence to sequence learning (seq2seq) is a kind of encoder-decoder learning architecture that takes a structured sequence as inputs and another structured sequence as outputs. The seq2seq model could easily implement the multi-step wave height forecasting, and the probabilistic information can also be conveniently expressed as quantile or probability density by using different loss functions.

2.2 Wavelet Decomposition

Wavelet Decomposition (WD) is an essential pre-processing tool for non-stationary time series analysis. WD is able to decompose a non-stationary significant wave height series into several frequency bands, and it has been a basic technique in SWH forecasting. In the WD process, the original SWH series pass through a low-pass filter and a high-pass filter to produce approximation coefficients and detail coefficients. The approximation coefficients (from the low-pass filter) are low-frequency and long-scale, the detail coefficients (from the high-pass filter) are high-frequency and short-scale. Then approximation coefficients are subsampled by 2 and further used to produce the approximation coefficients and detail coefficients of the next level.

For a given significant wave height series x, if $a_0 = x$, the approximation coefficient a_{j+1} and the detail coefficient d_{j+1} are produced by the following equation：

$$\begin{cases} a_{j+1} = H(a_j)\downarrow 2 \\ d_{j+1} = G(a_j)\downarrow 2 \end{cases} \quad j = 1, 2, 3, \dots J \tag{1}$$

where $H(*)$ is the low-pass filter and $G(*)$ is the high-pass filter. $\downarrow 2$ represents the subsample operation by 2. When x is decomposed J times, a new series structure $[a_J, d_j, \dots d_1]$ is produced.

However, the length of a_{j+1} and d_{j+1} are half of the a_j. Interpolation reconstruction, shown in Eq (2), is applied to ensure that A and D have the same length before the model training.

$$\begin{cases} A_j = (H^*)^j a_j \\ D_j = (H^*)^{j-1} G^*(d_j) \end{cases} \quad j = 1, 2, 3, \dots J \tag{2}$$

where H^* is the dual operator of H, G^* is the dual operator of G. $[a_J, d_j, \dots d_1]$ is converted to $[A_J, D_j, \dots D_1]$, and $x = A_J + D_j + \dots + D_1$.

2.3 Sequence to Sequence Model (seq2seq)

The seq2seq network is constructed by a sequence encoder and a sequence decoder. The sequence encoder takes a sequence as input and produces an encoder vector. The sequence decoder then takes the encoder vector to produce the target sequence. In general, recurrent neural networks (RNN), such as the Long-short memory network (LSTM) or the gated recurrent unit (GRU), are often used as the sequence encoder and decoder [36, 39].

2.3.1 Long-Short Term Memory Network (LSTM)

LSTM is a variant of RNN. In contrast to the conventional RNN, LSTM uses a unique gate mechanism to avoid the vanishing gradients problem in the process of backpropagation through time. LSTM is used as the sequence encoder and decoder due to its powerful sequence modelling capability. Formally, a standard LSTM could be formulated as follows. At the time step t, x_t is the input vector, c_t is the memory state vector, and h_t is the hidden state vector. Under the control of the input gate i_t, forget gate f_t and output gate o_t, the information from inputs x_t and last hidden state h_{t-1} are conditionally selected and updated for the next time step. LSTM can be expressed as follows.

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \tag{3}$$

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f) \tag{4}$$

$$\tilde{C}_t = \tan h\,(W_C \cdot x_t + U_C h_{t-1} + b_C) \tag{5}$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{6}$$

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + V_o C_t + b_o) \tag{7}$$

$$h_t = o_t \tan h\,(C_t) \tag{8}$$

where, W_f, W_i, W_i, W_c, W_c, U_i, U_o, V_o are the weights belonging to the corresponding gate, b_f, b_i, b_o, b_C are the bias vector belonging to the corresponding gate. σ is the sigmoid activation function. $tanh$ is the tanh activation function.

Figure 1 shows the structure of the LSTM. As shown in Figure 1, three gates (input gate, forget gate, output gate) are used to control the input information and output information of the LSTM cell. At each time step, the LSTM cell takes the x_t, c_{t-1} and h_{t-1} as the inputs. The useful sequence information will be retained, and the unimportant information will be forgotten. Finally, c_t and h_t for the next step will be outputted by the LSTM cell.

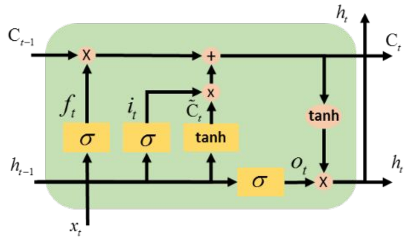

Fig.1 The network structure of an LSTM cell

2.3.2 LSTM Based Seq2Seq Network

With different encoder and decoder strategies, there are different kinds of Seq2Seq structures. The simplest seq2seq model is used to predict the approximation coefficient and the detail coefficient of SWH. Figure 2 shows the used seq2seq model. The LSTM encoder takes a sequence as input and produces the encoder vector C. Then the C is repeatedly inputted into the LSTM decoder at each time step. The outputs of the LSTM decoder are transformed by a linear dense layer to get the final probabilistic results in a parameter share manner.

The final output form of the seq2seq model is quantile. Therefore, the output x_t^Q is a vector that has Q dimensions. The final loss function of the Seq2Seq model is:

$$L(y, f) = \sum_{t=1}^{N} \sum_{i=1}^{Q} q_i max\,(y - f_t^{q_i}, 0) + (1 - q_i) max\,(f_t^{q_i} - y, 0) \tag{9}$$

where, q_i is the i_{th} quantile, $f_t^{q_i}$ is the predicted value correspond to quantile value q_i, N is the maximum prediction length. The function $max\,(a, b)$ is used to choose the maximum number from a and b.

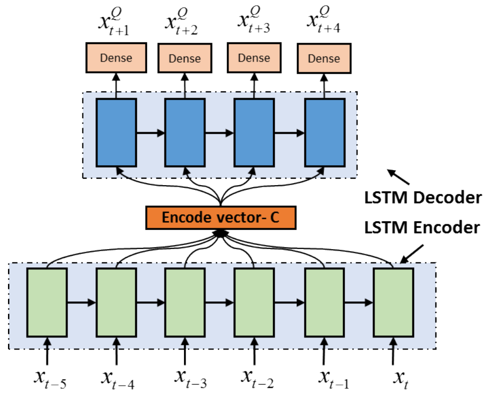

Fig. 2 The structure of the sequence to sequence network

2.4 Multi-step Probabilistic Wave Height Forecasting Model

The proposed MPWHF model combines WD and probabilistic seq2seq techniques (WD-seq2seq). The original significant wave height series $x(t-\tau{:}t)$ are first decomposed and reconstructed into Jdetail coefficients sequence $D_1(t-\tau{:}t)$, …, $D_j(t-\tau{:}t)$and one approximation coefficients sequence $A_J(t-\tau{:}t)$. Then the seq2seq model is applied to each coefficient sequence. The outputs of all seq2seq models are a set of quantile prediction sequence with Q dimensions,

$D_1^Q(t+1:t+p)$to $D_j^Q(t+1:t+p)$ and $A_J^Q(t+1:t+p)$. The summation of all quantile prediction sequences is the final multi-step probabilistic wave height forecast sequence. The overall schematic diagram of the proposed MPWHF model is illustrated in Figure 3. With the proposed MPWHF model, the probabilistic SWH for the next p hours can be generated at each time step.

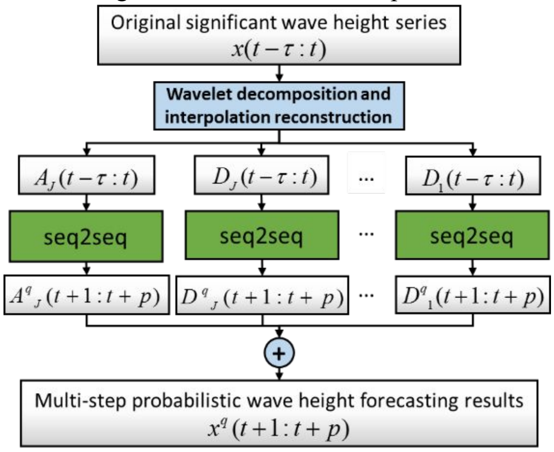

Fig.3 Multi-step probabilistic significant wave height forecasting model

2.5 Comparison Models

Multi-step probabilistic SWH forecasting is still challenging because the error accumulation problem will become more severe as the prediction horizon grows. In the previous literature [34], [35], five kinds of multi-step ahead time series forecasting strategies are developed. These strategies include Recursive, Direct, DirRec(Direct and Recursive), MIMO(Multi-input and Multi-output), DIRMO(Direct and MIMO). Direct strategy and MIMO strategy are used to build the comparison models.

(1) Direct strategy: Two single-output nonlinear regression methods, Gradient boosting regression (GBR) and support vector regression (SVR), are used to build the regression model at each time horizon. When getting the deterministic prediction results, kernel density estimation (KDE) is used to quantify the probabilistic density of forecasting errors. Quantile forecasts are acquired based on deterministic forecasts and forecasting error distribution.

(2) MIMO strategy: Lazy Learning (LL) method [34] and Feedforward Neural Network are used to establish Multi-input and Multi-output forecasting model. The lazy learning method can only provide deterministic results. Therefore, the same technical route mentioned in (1) is used to produce the quantiles forecasts. The feedforward neural networks (FNN) can be optimised by the quantile loss. Therefore, the probabilistic results are obtained directly by FNN.

3. The uncertain accessibility estimation model

Based on the real-time SWH forecasts, the uncertain accessibility is dynamically estimated by the simplified O&M flow chart and Monte Carlo simulation.

3.1 Uncertain Accessibility Estimation O&M Flow Chart

The uncertain accessibility estimation flow chart could transform the weather forecasts to the various accessibility indexes. Based on the O&M procedure analysis, an offshore O&M flow chart that considers three different access delay types is proposed.

3.1.1 O&M Procedure Analysis

As shown in Figure 4, the offshore wind farm O&M procedures are divided into five parts. In the first part, an O&M task is determined when a fault occurs. The following four parts are logistical preparation, weather delay, transportation, and maintenance. In those procedures, logistical preparation time (LPT), weather delay time (WDT), transportation time (TT), and maintenance required duration time (MRDT) directly determine the accessibility of offshore wind farms.

Firstly, the WDT is the most important factor causing the uncertainty of offshore accessibility. No weather window and unusable short weather window will lead to WDT. Moreover, with the increase of MRDT, more prolonged weather windows will be required, which will make WDT increase rapidly.

Secondly, the TT is easily estimated when transportation vessels and wind farm sites are known. LPT and TT determine whether a weather window is long enough. We can assume that if a weather window is larger than LPT +2*TT+ τ, this weather window is usable for executing O&M tasks. τ is a worthwhile maintenance time. The worthwhile maintenance time restricts the length of the weather window to ensure that some necessary maintenance work can be done in the weather window.

Thirdly, the offshore wind farm O&M tasks include many different inspection and maintenance activities or their combinations. The different MRDT represents various O&M tasks.

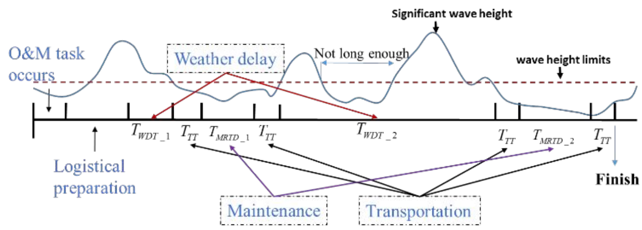

Fig. 4 The offshore wind farm O&M procedures

3.1.2 The offshore O&M Flow Chart

According to the above analysis, the uncertain accessibility estimation flow chart is designed. The flow chart shown in Figure 5 is similar to the approach in [12], but there is a big difference that the real-time MPWHF model is used to identify the weather window is suitable or not at every simulation step.

In the O&M flow chart, we divide the weather delay time into three parts.

- ✧ Delay type 1: the weather condition exceeds the weather limits.
- ✧ Delay type 2: the weather window size is too short to cover the specific transportation and maintenance procedures.
- ✧ Delay type 3: the situation that bad weather arrives, and the maintenance should be interrupted, so the maintenance technicians must return to the dock.

For uncertain accessibility estimation, the access probability, the total delay time, and the delay probability are most concerned. The access probability here is defined as the likelihood of delay type 1 and delay type 2 being equal to zero, which means the O&M vessel can reach the wind farm site. The total delay time is the summation of delay type 1, delay time 2, and delay type 3. The delay probability is defined to describe whether an O&M task will be delayed.

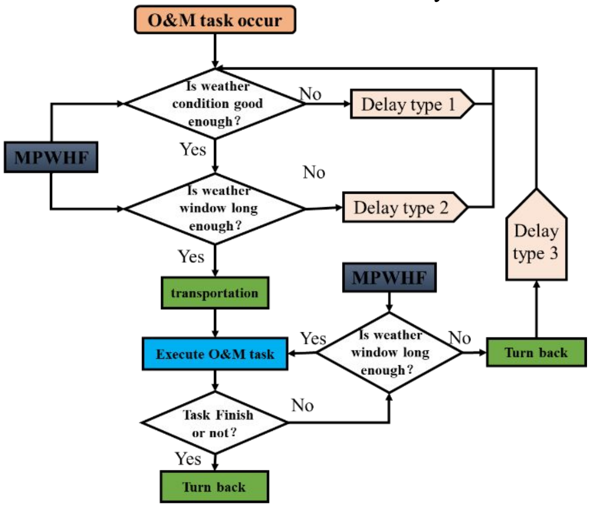

Fig. 5 the uncertain accessibility estimation flow chart

3.1.3 Assumptions Used in the O&M Flow Chart

In order to make the flow chart more reasonable, the following assumptions are used:

(1) SWH is enough for evaluating the offshore wind farm accessibility [20].

(2) Although the weather limits are different for offshore transportation and safe working, the maximum limits of these two activities are considered.

(3) For a specific O&M task, the total delay time is uncertain, but the MRDT is assumed to be certain.

(4) The required maintenance resources are sufficient. Maintenance resources typically include vessels, repair tools, maintenance technicians.

(5) Maintenance technicians are on service 12 hours a day, seven days a week. The work shift arrangement can be developed well in advance [8].

3.2 Monte Carlo Simulation

Monte Carlo (MC) method solves the problems that are uneasy to directly obtain results by relying on repeated random sampling. For accessibility estimation, the MC method randomly generates the start time of an O&M task, which equals selecting an initial simulation point in the significant wave height series. Then the different O&M tasks are simulated by the flow chart. The three types of delay times are recorded in every simulation process, allowing the accessibility index to be obtained from repeated simulation.

4. Case Study

4.1 MPWHF Forecasting

By using opening data sets, the proposed MPWHF method is compared with several benchmarks. In this subsection, the wave height prediction results are presented.

4.1.1 Data and Evaluation Criteria

The SWH data comes from the NOAA (National Oceanic and Atmospheric Administration) open data sets. The selected buoy site is station 44064, located at the First Landing bay, Virginia, US. The data is available from 2011/7/1 to 2018/12/31. Time resolution is one hour. The maximum significant wave height is 3.5m, the mean significant wave height is 0.58m. the corresponding maximum wind speed is 19.1m/s, mean wind speed is 5.48m/s. The selected buoy station is 9 kilometers from the shore. Therefore, a wind farm 9 kilometers from the coast is assumed. The dataset is divided into a training set (80%) and a testing set (20%). Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are used to evaluate the deterministic forecasting performance. Reliability (Re) and Interval Sharpness (IS) are introduced to assess the probabilistic results.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(S_{p,i} - S_{m,i})^2}{N}} \tag{10}$$

$$MAE = \frac{\sum_{i=1}^{N}|S_{p,i} - S_{t,i}|}{N} \tag{11}$$

where $S_{p,i}$ is the predicted SWH values, $S_{m,i}$ is the measured SWH values. N is the sample number.

Reliability shows the probability of the measured significant wave height locates in the constructed Prediction Interval. Larger reliability indicates that more measured significant wave height values fall within the prediction interval. Reliability is shown as:

$$RE = \frac{1}{n}\sum_{i=1}^{n} I \tag{12}$$

$$I = \begin{cases} 1, & S_{m,i} \in [L_i, U_i] \\ 0, & S_{m,i} \notin [L_i, U_i] \end{cases} \tag{13}$$

where L_i and U_i are the lower bound and the upper bound of the prediction interval.

IS evaluates the probabilistic results by considering the reliability and the interval width. The IS closer to zero means that the narrower prediction interval contains more measured significant wave values. Therefore, the larger the IS of the prediction model, the better. The IS is expressed as:

$$IS = \frac{1}{N}\begin{cases} -2\alpha\delta_i^{\alpha} - 4[L_i - S_{m,i}], & if\ S_{m,i} < L_i \\ -2\alpha\delta_i^{\alpha}, & if\ S_{m,i} \in I_i^{\alpha} \\ -2\alpha\delta_i^{\alpha} - 4[S_{m,i} - U_i], & if\ S_{m,i} > U_i \end{cases} \tag{14}$$

$$\delta_i = U_i - L_i \tag{15}$$

where δ_i is the width of the prediction interval.

4.1.2 Experiment Settings

The hyper-parameters of the proposed MPWHF model are shown in Table.2. The hyper-parameters of other counterparts are shown in Table.3. The proposed model is implemented by the deep learning library (Keras) [41]. The training of the proposed MPWHF model is done on a computing server with a GeForce GTX-1080-Ti GPU.

TABLE.2 THE HYPER-PARAMETERS OF THE WD-SEQ2SEQ MODEL

hyper-parameters	
Decomposition level	[3, 4, 5, 6, 7]
Input series length	[24, 48, 72, 96, 120, 144]
Output quantiles	[0.05, 0.5, 0.95]
encoder hidden unit	256
decoder hidden unit	256
Activation function	ReLU
Optimiser	Adam
Learning rate	0.001

TABLE.3 THE HYPER-PARAMETERS OF COMPARISON MODELS

WD-LL	None
WD-MO-GBR	Estimators number=100, Learning rate=0.1
WD-MO-SVM	kernel='RBF', C=20, Gamma=1
WD-FNN	Hidden Layer number=2, Hidden node number= 256, Activation function=ReLU Optimizer=Adam Learning rate=0.01 Output quantiles= [0.05, 0.5, 0.95]

WD-FNN	Hidden Layer number=2, Hidden node number= 256, Activation function=ReLU Optimizer=Adam Learning rate=0.01 Output quantiles= [0.05, 0.5, 0.95]

4.1.3 Forecasting Results

The optimal decomposition level of the WD-seq2seq is verified. Figure 6 shows the RMSE and IS of WD-seq2seq under different decomposition levels. WD-seq2seq with 5, 6 and 7 decomposition levels get the lower RMSE than 3, 4 decomposition levels. Under the 90% confidence level, the IS of 5, 6 and 7 decomposition levels are closer to zero than 3 and 4 decomposition levels. After careful consideration, 6 decomposition levels are deemed optimal.

The input sequence length is another crucial factor influencing forecasting performance. As shown in Figure 7, using 96 historical points as model inputs obtains more accurate and sharp forecasting results. 96 historical points correspond to the previous 4 days' historical significant wave height series.

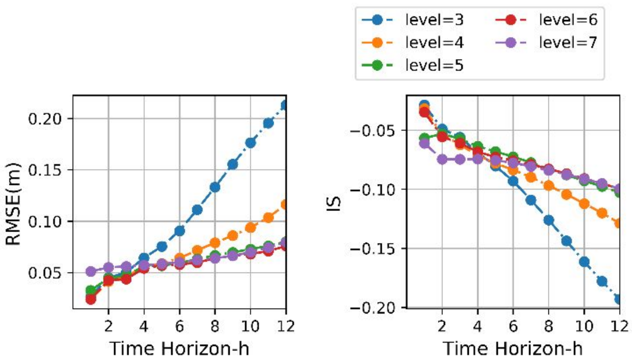

Fig. 6 Wavelet decomposition selection

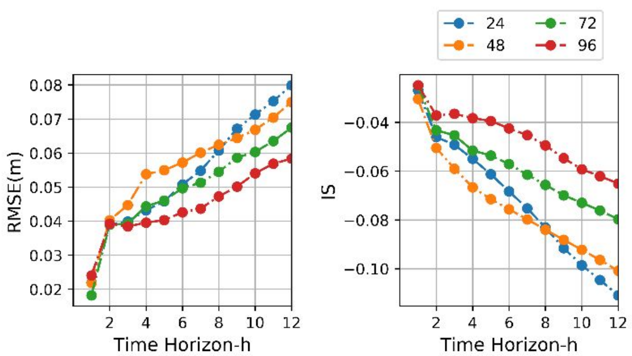

Fig. 7 Input length selection

The RMSE, MAE, Re and IS of the proposed model are compared with the widely used alternative multi-step forecasting methods in Figure 8. The RMSE and MAE of the WD-seq2seq are lower than the other four counterparts. With 90% nominal confidence level, the reliability and interval sharpness of WD-seq2seq are higher than other multi-step prediction models. It is clear to see that none of the other models perform better than the proposed model at any prediction horizon. As the proposed MPWHF model produces a quantile sequence as output, the quantile prediction results for the next 4, 8 and 12 hours are presented in Figure 9. As can be seen, the interval range between 0.05 and 0.95 quantile sequence is still narrow even when the lead time is 12 hours.

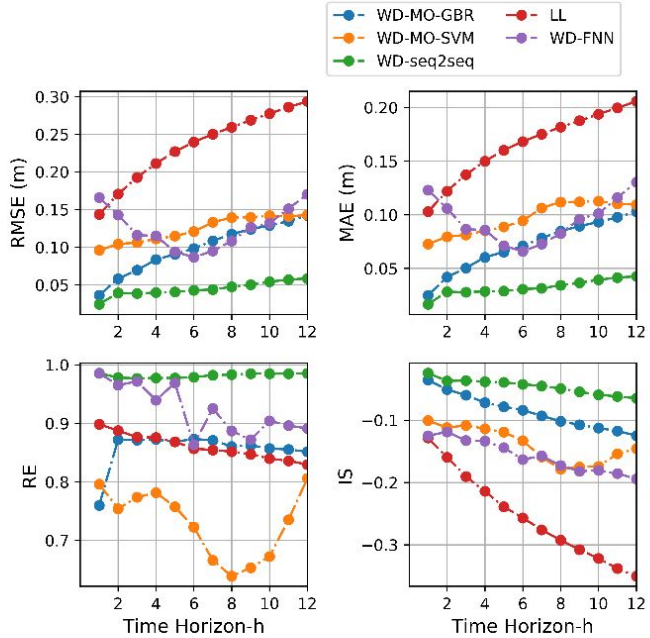

Fig. 8 the RMSE, MAE, RE and IS of the proposed model and other counterparts

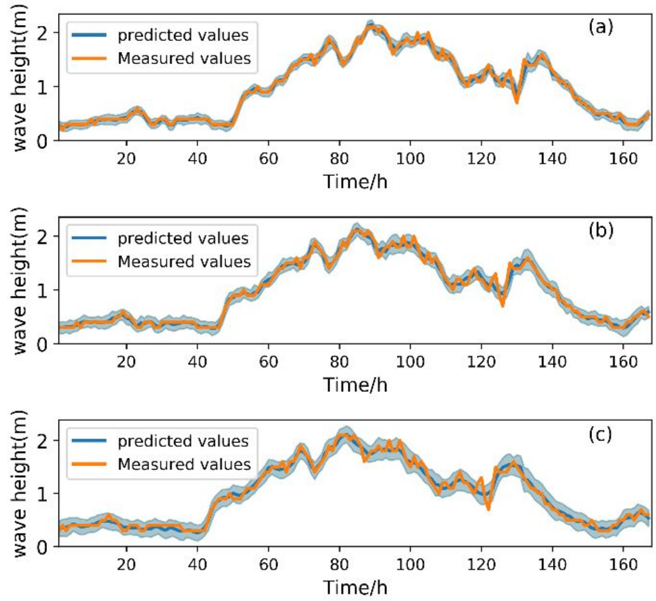

Fig. 9 Probabilistic forecasting results of next 4, 8, 12 hours with 90% nominal confidence. (a) Prediction horizon is 4, (b) Prediction horizon is 8, (c) Prediction horizon is 12

4.2 Uncertain Accessibility Estimation

With the real-time significant wave height forecasts obtained by the MPWHF model, several accessibility indexes and their uncertainty are evaluated by the proposed offshore O&M flow chart.

4.2.1 Parameters in Monte Carlo Simulation

Different vessels and MRDTs are simulated on the given uncertain accessibility estimation flow chart. Different O&M vessels have various weather limits and speeds. According to [14, 15], when the weather limits are 1, 1.5, 2 and 2.5 meters, the vessel speeds are 20, 20, 25 and 15 knots. MRDTs from 1 to 144 hours are modeled. The related simulation parameters are listed in Table.4.

TABLE.4 THE SIMULATION PARAMETERS IN THE UNCERTAIN ACCESSIBILITY ESTIMATION FLOW CHART

Simulation parameters	
Significant wave height limits	[1:0.25:2.75] (m)
O&M task required time	[1:1:144] hours
Vessel speed	[20, 20, 25, 15] (knot)
Distance	9km
Monte Carlo simulation times	10000

4.2.2 Uncertain Accessibility Estimation Results

For the given site, access probability is evaluated under different weather limits. As shown in Figure 10, the uncertain range of access probability narrows with the increase of the access limits. When the access limit is 1m, the mean access probability is between 0.56 to o.65. When the access limit is higher than 2.25m, the mean access probability is between 0.99-1. These results indicate that the weather condition at the selected site is mild, and transportation on this site is rarely prevented when the hired O&M vessels can operate and access in waves up to 2.25m. In addition, Vessels that have higher access limits will bring less uncertainty to O&M activities.

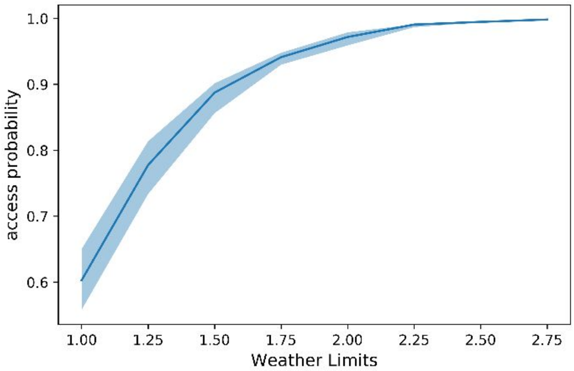

Fig. 10 Access probability of the selected buoy

By considering different MRDTs and weather limits, the total delay time and delay probability are shown in Figure 11. The total delay time and the uncertain range of delay time increase with the increment of MRDT. Moreover, the delay probability and the uncertain range of delay probability also increase with the increment of MRDT. These results are in accordance with the intuitive experiences that when more maintenance time is needed, the possibility of encountering the harsh weather condition is higher, and the uncertain degree of delay probability is also higher. It also can be seen that there is a nonlinear relationship between accessibility, weather limits and MRDT.

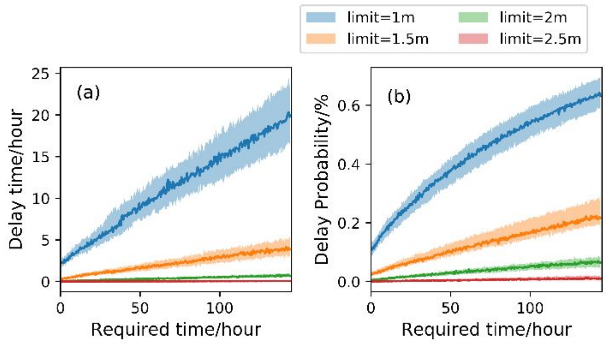

Fig. 11 Total delay time and delay probability of the selected buoy.
(a) Total delay time, (b) Delay probability

The ratios of the three types of delay time are presented in Figure 12. Delay type 1 accounts for the highest proportion of the total delay time, but the ratio decreases with the increase of MRDT. The ratio of Delay type 2 does not change too much, which means the influence of the short unusable weather window is relatively constant. The proportion of delay type 3 is tiny when the MRDT is small, but as the MRDT increases, the proportion of delay type 3 first rises and then stabilises. In addition, the proportions of delay time with 2m and 2.5m access limits are different from the other two kinds. The possible reason is that when the accessibility is high, the total delay times drastically decrease and the number of delays is too little to obtain stable statistical results. In order to get more stable results, it is necessary to increase the length of the measured sequence and the simulation times.

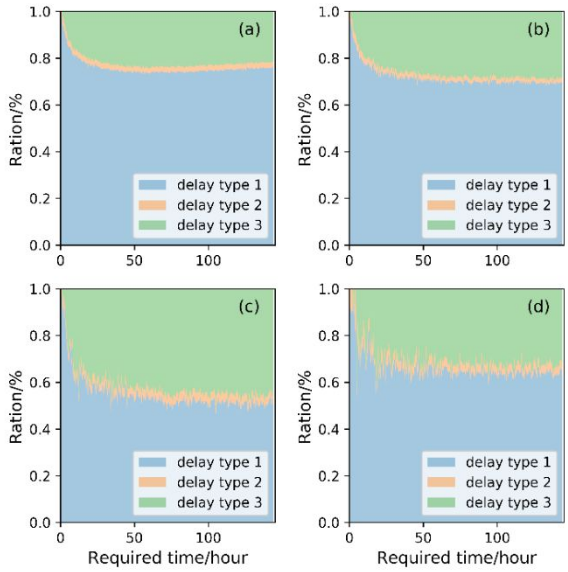

Fig. 12 The ratios of three types of delay time by using different weather limits. (a) weather limit=1m, (2) weather limit=1.5m, (3) weather limit=2m, weather limit=2.5m

5. Conclusion

The uncertain accessibility of offshore wind farms is estimated using an MPWHF model and the Monte Carlo simulation. The proposed MPWHF model is constructed by the wavelet decomposition and seq2seq network. With the real-time probabilistic significant wave height prediction, the access indexes, including access probability, delay time and delay probability, are evaluated by Monte Carlo simulation.

Based on the case study, the following main conclusions are obtained:

(1) the proposed MPWHF model uses the sequence encoder to extract the historical series information and the sequence decoder to generate structured probabilistic significant wave height forecasts. The optimal input length is 96, and the optimal decomposition level is 6. Compared with the other four classical multi-step forecasting algorithms, the proposed WD-seq2seq model has a more accurate and stable prediction performance.

(2) With higher vessel access limits, the access probability nonlinearly increases, and the uncertainty degree decreases. With the increment of the O&M task duration time, the delay time and delay probability increase nonlinearly, and their uncertain degree also increases at the same time. The proportion of different delay types changes with different vessel access limits.

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8. CRediT contribution for each author

Hao ZHANG: Conceptualization (lead), investigation, methodology (lead); writing – original draft (lead); formal analysis (lead); validation; visualization; writing – review and editing (lead).
Jie YAN: Writing – Conceptualization (lead), Writing – original draft (lead); Writing – review and editing (supporting).
Shuang HAN: writing – review and editing (supporting).
Li LI: writing – review and editing (supporting).
Yongqian LIU: Conceptualization (supporting); Writing – review and editing (equal).
David Infield: Conceptualization (supporting); Writing – original draft (supporting).