Assessing marine operations with a Markov-switching autoregressive metocean model

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Abstract
This article presents a metocean modelling methodology using a Markov-switching autoregressive model to produce stochastic wind speed and wave height time series, for inclusion in marine risk planning software tools. By generating a large number of stochastic weather series that resemble the variability in key metocean parameters, probabilistic outcomes can be obtained to predict the occurrence of weather windows, delays and subsequent operational durations for specific tasks or offshore construction phases. To cope with the variation in the offshore weather conditions at each project, it is vital that a stochastic weather model is adaptable to seasonal and inter-monthly fluctuations at each site, generating realistic time series to support weather risk assessments. A model selection process is presented for both weather parameters across three locations, and a personnel transfer task is used to contextualise a realistic weather window analysis. Summarising plots demonstrate the validity of the presented methodology and that a small extension improves the adaptability of the approach for sites with strong correlations between wind speed and wave height. It is concluded that the overall methodology can produce suitable wind speed and wave time series for the assessment of marine operations, yet it is recommended that the methodology is applied to other sites and operations, to determine the method’s adaptability to a wide range of offshore locations.

Keywords
Stochastic processes, Markov-switching autoregressive model, marine operations, weather risk, offshore wind

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Introduction
Metocean models are commonly used to produce data sets for planning, modelling and review of marine operations for a variety of offshore industries. These models are often employed when there is insufficient recorded data for a specific offshore location. Increasing efforts have been made in the offshore wind industry to better predict the uncertainties in the progression of weather sensitive operations. To exemplify, offshore wind installation costs can account for up to one-third of the overall project cost and a better understanding of the potential delays during marine operations will support developers to reduce the levelised cost of energy (LCOE). Future projects are planned for increasingly remote locations accompanied with challenging weather conditions such as high winds and wave heights that can cause significant disruption to a planned operational schedule, thus increasing the overall risk profile for installation or operation and maintenance (O&M) campaigns. It is therefore important that marine operations can be scrutinised in advance to ensure the correct planning, resourcing and equipment decisions can be made.1–3

Operating within metocean conditions brings significant challenges in understanding the variability of the weather characteristics with the combined impact on operational downtimes or health and safety risks. As metocean conditions are site specific, this requires a bespoke assessment for each project and therefore

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adaptable assessment tools are necessary to simulate the characteristics of each site.

The generation of stochastic metocean time series has been widely researched for a variety of offshore applications. By generating a significant number of stochastic weather series that resemble the variability in key metocean parameters, probabilistic outcomes can be obtained to predict the weather windows, delays and subsequent installation durations for specific tasks or multiple marine operations. In recent years, dedicated probabilistic simulation tools have been developed, to predict the progression of marine operations and the suitability of resourcing strategies against synthetically produced metocean data. Embedding a stochastic metocean model within these simulation tools allows the users to first input observed weather data for a finite number of years and generate many synthetic realisations of the weather to assess the progression of marine operations. Using a stochastic weather model is beneficial as it draws more certainty on predicted outcomes, yet still encloses the random variability that exists within the observed weather data.4–6

To cope with the variation in the offshore weather conditions at each project, it is vital that a stochastic weather model is adaptable to account for seasonal or monthly variations to produce realistic weather time series. The Markov-switching autoregressive (MS-AR) model included in the METIS MATLAB toolbox, developed by Monbet and Ailliot,2 has been investigated in this study and configured to produce monthly realisations of observed time series. More specifically, we investigate the application of an MS-AR model to produce stochastic wind speed and wave height time series, based on observed data sets. The aim of this article is the implementation and assessment of MS-AR techniques for metocean modelling when assessing offshore wind installations. The MS-AR generated time series is cross examined against a typical offshore operation, to validate the adopted methodology and MS-AR model configurations. By demonstrating that the model is capable of producing characteristics such as the average length of operational weather windows and monthly workability, this supports the case to implement MS-AR metocean models in offshore simulation tools.

To contextualise the application of the MS-AR model, we present a case study on a personnel transfer task from a crew transfer vessel (CTV) to a pre-installed wind turbine transition piece, which is constrained by specified working limits. This task has been selected as it has particularly conservative restrictions and is relevant to a wide range of offshore sectors. The outcomes of completing this task across simulations from three separate sites are first contrasted against the corresponding observed data set, and then the results from three sites are compared to discuss the general outcomes and the overall suitability of the presented methodology. A discussion on the impact of the results for metocean applications and offshore wind risk assessments is presented, and we provide recommendations to build on this study.

Literature review

There has been extensive research on the development and application of environmental models to produce offshore weather series. In Monbet et al.,5 Monbet and Ailliot, the authors of the METIS toolbox, present a review of stochastic models to generate wind and sea state characteristics. Their study begins with Gaussian processes such as the ‘Box and Jenkins’ approach and the ‘Translated Gaussian Process’ (TGP). The Box and Jenkins method is widely regarded as the most classical method where the data are first made stationary by blocking it into monthly or seasonal sets and then applying a Box–Cox transformation. This produces a time series with a Gaussian like marginal distribution, and finally an autoregressive integrated moving average (ARIMA) model is fitted to generate the synthetic time series. An ARIMA model uses the process of differencing many times, to reduce the forecast to an autoregressive moving average process (ARMA). An ARMA model relies on a set number of previous values in a given time series and memory function described denoted by the ‘MA’ or moving average, to produce forecasts. TGP can be described in three steps. For a univariate process, it starts by transforming the observed data into a Gaussian variable, then generating a second-order random time series with the same spectral properties. This second-order time series can then be re-transformed back into a full univariate time series, and it is noted that auto and partial correlation functions may reveal significant differences between the original and synthetically produced data.

It is remarked that while these methods are less sensitive to noisy data, they are reliant on large data sets to generate estimates and have difficulty reproducing an accurate distribution of stormy and calm conditions within the generated time series. Non-parametric methods are investigated including block resampling and resampling Markov chains. Block resampling is described as a method to implement bootstrapping techniques, where each ‘block’ is representative of a time step in the observed data set and random sampling of the blocks are used to reconstruct a sequence of values. This process demonstrates sensitivity to the size of block, as short blocks can struggle to replicate the existence of storms and larger blocks commonly reproduce the observed time series, negating any benefit from employing such models.

Resampling Markov chains such as ‘nearest-neighbour’ are also presented, which begin with a few starting values and searches the data for the nearest lying neighbours to particular points. One of these neighbours is then randomly selected and allocated to the given time step in the series. The authors also discuss the inclusion of selection weighting of closer points by
introducing higher probabilities to these values and further sophistications such as the Local Grid Bootstrap method have demonstrated good reproduction of the weather characteristics such as the distribution of storm durations and marginal distributions. Parametric approaches such as artificial neural networks (ANN), MS-AR and generalised autoregressive conditional heteroskedasticity (GARCH) models are promoted for their ability in describing particular weather regimes. ANN models are described for application in short-term forecasts and correcting meteorological models but it is stated that these models are inherently difficult to interpret. Alternatively, MS-AR models and GARCH models are identified as easily interpretable and are capable of restoring the weather regimes similar to those in observed data sets. These models can be reviewed and broken down to understand the embedded computations whereas ANN examples are less accessible for interpretation. However, it is remarked that choosing the correct model types can take some time, by applying steps such as maximum likelihood and least squares. Assessments can be made using the statistical properties from each computation by applying Akaike information criterion (AIC) and Bayesian information criterion (BIC), which provide quantifiable values to identify the best model for the meteorological data.

Ailliot and Monbet\textsuperscript{9} investigate the specific application of homogeneous and non-homogeneous MS-AR models to produce wind time series. These models are composed of a blend of autoregressive (AR) models to describe the evolution of the wind speeds over different intervals, and the switching between each AR model is handled by a hidden Markov chain. Their experience highlights that MS-AR models with Gaussian innovations are preferable to those with Gamma innovations due to computational benefits and numerical issues associated with the Gamma case. The study demonstrates the operability of a homogeneous MS-AR model, which is expanded to account for diurnal and seasonal fluctuations by applying a non-homogeneous MS-AR model. The impact of inter-annual variations that can be observed in historical data, associated with climate change, are also considered where they advise the potential inclusion of trend models to improve long term predictions.

Taylor and Jeon\textsuperscript{10} investigate various probabilistic forecasting methods for wave height estimates, including kernel density estimation, time-varying parameter regression and various ARMA-GARCH model combinations. Their study considers the suitability of these techniques to support service vehicle mobilisation decisions for offshore wind turbine maintenance campaigns. Kernel density estimation is described as a non-parametric approach and uses kernel smoothing on the empirical distribution of historical data, which can be applied across varying window lengths. A Gaussian kernel function with predefined bandwidth is included in the calculation to control the degree of smoothing applied, and the authors use the continuous ranked probability score to optimise the selection of the bandwidth over a 12-month estimation sample. Time-varying parameter regression models applied to independent estimates of wave height, wave period and wind speed are presented and noted for their relative success in previous short-term forecasting studies. The authors propose three separate models to produce wave height, wave period and wind speed forecast. Each model includes a Gaussian white noise error term and estimated parameters using ordinary least squares. Their models are considered for various lags, with a 4-h lag intended for short-term forecasts and 24-h lag for cyclical predictions.

Univariate ARMA-GARCH models are described for their ability in modelling of autoregression in the mean and the variance of a time series. The authors note that such models are capable of capturing diurnal and annual cyclical patterns and introduce trigonometric terms to account for diurnal behaviour. Maximum likelihood estimates are used to estimate the model parameters, and the Schwarz Bayesian information criterion (SBC) is applied to select the order of the four lag polynomials relating to the AR, MA, GARCH and ARCH components of the model. It is identified that the unconditional distribution of the wave heights in the observed data were not Gaussian and therefore a Box–Cox transformation is applied to reduce skewness and suit the Gaussian distribution. Bivariate ARMA-GARCH models are investigated to account for the dependency between wave heights and the strength of the wind. A vector error correction (VEC) bivariate ARMA-GARCH model is used by the authors, which includes a conditional covariance matrix of the error term, which restricts the prediction of the bivariate outcomes based on positivity of the covariance matrix. For both univariate and bivariate models, the Gaussian, student $t$ and skewed $t$ distributions of the error term are investigated. Assessments of the models are completed using continuous ranked probability, maximum absolute error for point forecast accuracy and a brier score to statistically assess the probability of 1.5-m wave height limit being satisfied. Overall, it is concluded that the most accurate method was the bivariate ARMA-GARCH model for combined wave height and wind speed data.

Mao et al.\textsuperscript{11} present a new method to find parameters in the Weibull distribution to produce reliable wind speed statistics and evaluate the benefits of new green shipping concepts using auxiliary wind propulsion. A spatio-temporal transformed Gaussian model was fitted to a 10-year reanalysis of wind time series, which can be applied at fixed positions or along vessel transit routes. The method is validated against wind speeds measured directly by vessels operating in the North Atlantic and Mediterranean Sea. It was found that the method performed better for westbound compared to eastbound voyages, where significant difference was observed against the measured distribution.
from the vessels. It is concluded that the eastbound inaccuracies can be attributed to captain’s actions and that further assessments should consider the impact of transit route strategies.

De Masi et al.\textsuperscript{12} investigate the application of a first order multivariate Markov chain model to produce 20 years of synthetic time series for significant wave height ($H_s$), peak wave period ($T_p$) and wave direction. It is demonstrated that the statistical properties such as mean values, correlations and probability distributions are reproduced in the simulated time series. The authors apply threshold ($H_s$) values to compare persistence and waiting times between operable weather windows, and it is shown that similar distributions are produced by the model. This method provides a useful means to compare the results and concludes that the outcomes from Markov chain model are suitable to conduct operability analysis. The authors also suggest that the model could be extended to consider other meteorological parameters and highlight that varied temporal scales could also be applied to support the analysis of different marine operations.

Hagen et al.\textsuperscript{4} present a multivariate Markov chain model to produce time series for wind speed ($U$), wave height ($H_s$), wave period ($T$), wind direction ($\Phi$) and wave direction ($\Theta$). Two methods of handling seasonal variations in observed data set are presented, where the transition probabilities for the Markov chain and subsequent weather states are identified. In the first method, the transitions probabilities are produced separately for each month, where the transition to the next state is applied at monthly boarders. The second approach applies a transformation, taking the empirical mean and standard deviation, implementing seasonal transitions without monthly restrictions. To assess the application of these models for offshore O&M tasks, these are reviewed in terms of persistence and waiting times for a specified weather window of $H_s \leq 2$ m, $U \leq 10$ m/s and $T \leq 5.5$ s at 3-h time steps. This assessment demonstrates that both model types can reproduce the persistence statistics in the observed data with very slight variations. It is concluded that both Markov chain models are suitable to assess the weather availability for marine operations but are dependent on suitably long observed data sets of 20 years or more to prevent replications in the simulated outcomes.

Tzortzis et al.\textsuperscript{13} explain that the optimisation of a ships energy system is complicated by time dependencies such as weather conditions and time-varying loads. Their study employs differential algebraic equations and three simultaneous optimisation levels to assess the impact of these dynamic conditions by applying an example weather profile. It is stated that propulsion power is a function of vessel speed and weather conditions, which vary spatially as vessels progress along a route and the optimisation of transit speeds at different intervals can be considered to minimise operating costs. It is recognised that the predominant impacts on vessel speed are wind speed and direction and wave height and direction. The method is adaptable to different weather states, while it is acknowledged that the stochastic nature of the weather conditions is not captured by their simplified deterministic approach.

Leontaris et al.\textsuperscript{14} indicate that large observed data sets of approximately 20 years are required in order to produce useful meteorological estimates from a copula model. The scarcity of long observed environmental time series is a key driver for their study, where they use copulas to reproduce multiple years of wind speed ($U$) and significant wave height ($H_s$). Copulas are defined as functions that joining multivariate distributions, which can be broken into univariate marginal distributions with a copula to describe the dependence between random variables. The authors review the dependence of $U$ and $H_s$ by considering three copula families, Gaussian, Clayton and Gumbel. They identify that the Gumbel copula describes the dependence between both parameters for all months with the exception of November and December where the Gaussian copula was selected. To compare the 1000 years of simulated $U$ and $H_s$ time series against 10 years of observations, the mean monthly workability and persistence of weather windows were reviewed for 6-h time steps. Primarily, one operation of $H_s \leq 1.5$ m and $U \leq 12$ m/s is defined to assess the persistence and mean workability characteristics. It is shown that the mean workability and persistence cumulative distribution function (CDF) is very similar to the observed data and verifies that this method can reproduce realistic time series and highlights the importance of the correlation between for $U$ and $H_s$. To assess the progression of sub-tasks below 6 h within an infield cable installation scenario, linear interpolation of the generated time series to hourly time steps is discussed. This improves the resolution of the simulated data, and it is shown that scaling up the time series in this way leads to similar results as was observed with 6-h intervals. Finally, the impact of dependently and independently produced environmental parameters is discussed and it is suggested that if the dependence between variables is ignored in similar models, this will reproduce inaccurate time series.

**Methodology**

This article applies the homogeneous MS-AR model with Gaussian innovations, embedded within the METIS MATLAB tool box, for application in offshore planning and simulation tools. This section describes the observed meteorological data sets, the MS-AR model tested, the model selection process and a summary of the steps to produce the final time series. It is important to note that the theoretical and computer-based MS-AR models have been adopted for this study. In this article, we present a generic methodology that can be used to generate annual time series of $U$ and $H_s$ and the steps used to assess the results.
The main steps of the overall method are shown in Figure 1. A brief summary of these steps are as follows. We begin with observed data that are resampled to three hourly intervals and compiled into monthly sets to obtain stationary, non-seasonal collections. The METIS MS-AR model is first used to assess various model type configurations using the expectation maximisation (EM) algorithm, which are individually evaluated using BIC to identify the most suitable model for each month. The simulation produces 1000 years of synthetic time series of $U$ and $H_s$, which we then compare against the observed data using cumulative distributions and Q-Q plots. Assuming satisfactory plots are obtained, the separate $U$ and $H_s$ simulations are paired simply by taking the mean of each monthly realisation, which is used to rank these in ascending order and therefore define the corresponding months of $U$ and $H_s$. It is appreciated that this approach may not account for the close correlation between wind speed of wave height, yet we have implemented this practical technique to investigate its impact when assessing marine operations. The simulated data are then interpolated from 3 h to hourly intervals. A final weather window assessment is then used to assess the validity of the overall methodology to assess and predict the progression of marine operations. In the following sections, we present the key stages of this process.

**Data**

Three different environmental data sets have been sourced to review the consistency of the MS-AR model simulations at various sites with different energies. Wind speed (m/s) and significant wave height (m) are the two meteorological parameters under investigation. The wind speed is taken at a reference height of 10 m, and significant wave height represents the average of the highest third of individual waves over a specified period of time at each site.15

A summary of each data set is included in Table 1, all of which have a 3-h resolution. These data sets were selected as they are originated from locations close to existing and proposed offshore wind farms. It should be noted that all three data sets were originally recorded at hourly intervals and were subsequently resampled to 3-h observations by extracting the relevant time steps for each day, beginning at 00:00 then every 3 h through to 21:00. Fundamentally, this step reduces the order of the AR model and hence the complexity of the MS-AR model overall. We have chosen the 3-h time step as a compromise between 6- and 1-h intervals. Our experience testing the model has found that the 3-h time step provides a suitable balance between accuracy and simulation time. However, our experience modelling marine operations in various softwares has highlighted that time steps of at least 1 h should be used as an input weather data series, as this provides reasonable resolution for intermediate interpolation, facilitating the simulation of tasks with a time step of less than 1 h. Therefore, it was decided that 3-h results from the MS-AR model would be linearly interpolated to 1-h intervals and compared against the original data sets, originally recorded at an hourly resolution. The validity of this approach is of interest to the authors and follows.

![Figure 1. MS-AR modelling and verification methodology.](image-url)
on from the recommendations of Leontaris et al., who indicate that simulations should be completed at the same scale as the observed data set and then interpolated to the required resolution.

**MS-AR model**

This section describes the homogeneous MS-AR model used to generate wind speed ($U$) and wave height time series ($H$). The model is included with the METIS toolbox and was obtained directly from the authors. The description of the model is based on the information included in the METIS toolbox documentation and a description of the most standardised MS-AR model, included in Section 2 of Ailliot and Monbet. The following description summarises the functionality of the MS-AR model and should provide sufficient detail to support the reader’s understanding of the computational steps.

Wind and wave data and recorded time series commonly demonstrate non-stationary, which is characterised by daily factors, seasonal fluctuations and inter-annual variations. The issue of seasonality in a wind time series can be treated by dividing the data into months and fitting a separate model to each month, which assumes that the same month across each year is an individual representation of a common stochastic process. Segmentation of monthly wind data sets from the original 3-h meteorological file was necessary to inform the MS-AR algorithm. Within the METIS toolbox, three different MS-AR models are provided: Gaussian MS-AR model, Gamma or Lognormal MS-AR model and a Non-homogeneous gamma MS-AR model, which was developed to handle bivariate processes for wind speed and direction. The Gaussian MS-AR model was selected for review in this study as Monbet and Ailliot state that the formulas for the estimation step can be explicitly described, supporting overall interpretation in this study. As the majority of the available metocean data sets did not include comprehensive wind speed and directional observations, the bivariate case was not applicable. To fundamentally describe the MS-AR model, it is important to consider the different evolutions in the wind speed that can occur over a month. As such, the MS-AR model applies a dedicated AR model to accurately resemble the evolution of the wind speed within each hidden state or ‘weather type’, defined as $S_t \in \{1, \ldots, M\}$.

The embedded Markov chain controls the transition between the AR models based on the most likely distribution of the weather types across the times steps in each month.

An MS-AR model involves a discrete time process with two components $\{S_t, Y_t\}$. In this context, $\{Y_t\}$ represents the wind speed or wave height in $(0, +\infty)$ and $\{S_t\}$ is a non-observable or ‘hidden’ process where $S_t \in \{1, \ldots, M\}$ represents the weather type at time $t$. $\{S_t\}$ is a Markov chain within the finite space $S = \{1, \ldots, M\}$, with $M > 0$ the number of weather types. Ailliot and Monbet state that the MS-AR process is characterised by two conditional independence assumptions as follows:

- The conditional distribution of $S_t$ given the values of $\{S_r\}_{r < t}$ and $\{Y_r\}_{r < t}$ only depends on the value of $S_{t-1}$. In other terms, we assume that the weather type $S_t$ is a first-order Markov chain which evolution is independent of the past wind conditions;
- The conditional distribution of $Y_t$ given the values of $\{Y_r\}_{r < t}$ and $\{S_r\}_{r < t}$ only depends on the values of $S_t$ and $Y_{t-1}, \ldots, Y_{t-p}$. For our particular application, it means that the wind speed process $\{Y_t\}$ is an AR process of order $p \geq 0$ which coefficients evolve in time with the weather-type sequence.

The standardised AR($p$) model with Gaussian innovations, where ($p$) represents the order of the AR model, or in other terms the number of immediately preceding values used to produce a forecast, is described by Ailliot and Monbet as follows

$$Y_t = \alpha_0^{(s)} + \alpha_1^{(s)} Y_{t-1} + \cdots + \alpha_p^{(s)} Y_{t-p} + \sigma^{(s)} \epsilon_t$$

where $\epsilon_t$ denotes a white noise or error term, which in this case is a sequence of independent and identically distributed Gaussian variable with zero mean and unit variance, independent of the Markov chain $S_t$. This can be described differently where the conditional distribution $P(Y_t|Y_{t-1}, \ldots, Y_{t-p} = y_{t-p}, S_t = s_t)$ is assumed to be a Gaussian distribution with conditional mean and variance.

**Table 1.** Observed time series.

| UK North East | Redcar | English Channel |
|---------------|--------|-----------------|
| $\mu U$(m/s) (10 m) | 6.63 | 7.13 | 7.48 |
| $\mu H$(m) | 1.15 | 0.72 | 0.85 |
| First observation date | 01/01/1981 | 01/07/1988 | 01/01/1994 |
| Years of data | 34 | 19 | 21 |
| Sampling frequency (h) | 3 | 3 | 3 |
| Number of measurements | 99,345 | 55,513 | 61,361 |
\[ E(Y_t | Y_{t-1} = y_{t-1}, \ldots, Y_{t-p} = y_{t-p}, S_t = s_t) = a_0^{(s_t)} + a_1^{(s_t)} y_{t-1} + \ldots + a_p^{(s_t)} y_{t-p} \]
\[ \text{var}(Y_t | Y_{t-1} = y_{t-1}, \ldots, Y_{t-p} = y_{t-p}, S_t = s_t) = \left(\sigma^{(s_t)}\right)^2 \]

METIS uses the EM to fit the MS-AR model for the prescribed values \( p \) and \( M \). This algorithm is based on the work of Baum et al.\(^{16}\) and extended by Dempster et al.\(^{17}\) The EM is applied in three steps. First, randomly chosen values are used to identify an interesting maximum. The EM is applied across each of the initial values in the time series, and a maximum likelihood reveals the most suitable parameters of \( \mu \) and \( \sigma \). Ailliot et al. embed a ‘forward–backward’ computation from the Baum–Welch Algorithm, which is used to identify the unknown parameters within a hidden process. The EM is continuously applied, retaining the parameters from each recursion, until the algorithm converges at \( 10^{-7} \) or reaches the maximum number of 600 iterations. This was altered from the default 100 iterations in an attempt to ensure convergence is reached or at least the recursions come very close to convergence. The final estimate is then identified using a quasi-Newton algorithm, which identifies the most likely sequence of hidden states or weather types. The EM function provides the estimated parameters of the MS-AR model and the log likelihood of the model. The EM function computes smoothing probabilities, which relate to the conditional distribution of the hidden state across the number of observations \((y_1, \ldots, y_N)\) for the month in question

\[ P[S_t = s | Y_1 = y_1, \ldots, Y_N = y_N] \]

where \( s_t \in \{1, \ldots, M\} \).

A Viterbi algorithm is used in the METIS toolbox to provide a visual representation of the path of the hidden states, and the plot indicates which AR weather regime is most likely, given the observation time as shown in Figure 2. This plot was produced for model with six lags and three hidden states for the December at the UK North East location. In this plot, the allocation of the first weather type or regime is denoted by the solid line, regime two by the dashed line and regime three with the dotted line. An accompanying table listing the parameters of the AR model operating in each hidden state is also included in Figure 2. In regime two, the wind speed demonstrates greatest variability, whereas in regime one, the wind speed appears to change much slower, as confirmed by the values for \( \mu \) and \( \sigma \) in the table. Regime three appears to serve as an intermediate state and makes up the predominant allocation of states in this example. This indicates that the model is capable of defining weather types and that the allocation of a separate AR model to each of these states should result in well-informed predictions upon simulation of the weather series. The same plot and parameters were produced for significant wave height in Figure 3, which exemplifies the allocation of a different model type consisting of three lags and six hidden states.

Wave heights are directly affected by wind speed, the length of time the wind blows and fetch, which is
the distance on the water surface the wind blows. This means that during periods of low wind speed, the waves will be small, irrespective of wind duration or fetch. If wind speeds are high for a short period even with a large fetch, the waves will remain low. For high wind speeds over a short fetch, the wave heights are still low. It is only when these three conditions combine that large waves will form. It seems that these forces may be apparent in Figures 2 and 3, where higher wave heights are noticeable in Figure 2 at time steps shortly after higher and prolonged wind speeds in Figure 3.

The MS-AR model can then produce the defined number of monthly sets through simulation. The simulation function simulates the AR process with Markovian switching, which are dictated by the hidden Markov chain. This computation uses the path of the hidden Markov variable, identified as part of the Viterbi algorithm and the parameters of the AR models. The matrix of the initial observations is used to define the output dimension of the simulated instances.

### Model selection

In order to identify the best model for $U$ and $H_s$ for every month at each location, the model parameters $p$ and $M$ can be adjusted to suit the weather conditions within an observed time series. Monbet and Ailliot have found that the BIC is suitable for selecting the best combination of AR model order $p$ and the number of hidden states $M$. The BIC is defined as follows

$$BIC = -2 \log L + k \log N$$

$L$ indicates the likelihood of the data, $k$ is the number of parameters and $N$ is the number of observations required, all of which can be obtained after the EM algorithm has converged for each model type for all months of data. It should be noted that in order to complete the BIC assessment, the various combinations of AR order and hidden states must be predefined, meaning an iterative approach at testing a range of model types is necessary before arriving at the most suitable model for each month.

To understand the number of previous values or lags that are statistically significant for the AR part of the MS-AR model, the monthly data of all three locations in Table 1 were assessed in terms of the autocorrelation function (ACF) and partial autocorrelation function (PACF). The PACF can be used to define the partial correlation of a time series against its own lagged values. The purpose of this approach was to try and identify a ceiling for the AR model order and therefore constrain the maximum number of model types to be considered in the BIC assessment process. The ACF included in Figure 4 shows a fast geometrical decline, which is representative of stationary processes and that

### Table 2. Percentage difference, average and absolute average error for wind speed $U$ and wave height $H_s$—observed and simulated.

| UK North East | Redcar | English Channel |
|---------------|--------|-----------------|
| **$U$ (m/s)** | **$H_s$ (m)** | **$U$ (m/s)** | **$H_s$ (m)** | **$U$ (m/s)** | **$H_s$ (m)** |
| **% difference** | **% difference** | **% difference** | **% difference** | **% difference** | **% difference** |
| $\mu$ | 0.50 | 0.90 | 0.76 | -0.05 | -0.21 | 0.67 |
| January | 0.20 | 0.23 | 0.20 | -3.25 | -0.44 | 2.93 |
| February | 0.76 | 0.73 | 1.21 | 1.34 | -0.27 | 1.49 |
| March | -0.58 | 1.26 | 0.53 | 0.06 | -0.23 | -0.24 |
| April | -0.71 | 0.63 | -0.48 | 2.60 | -0.64 | 0.34 |
| May | -0.38 | 0.34 | 0.33 | 0.47 | -0.63 | -1.96 |
| June | 0.25 | 1.14 | 1.05 | 0.86 | 0.54 | 1.65 |
| July | 0.74 | 1.72 | 1.43 | -0.84 | -1.06 | -2.27 |
| August | 0.90 | 0.59 | 0.64 | 0.69 | -0.29 | -1.40 |
| September | -0.02 | 1.51 | 1.64 | -1.01 | -0.01 | -0.74 |
| October | 0.99 | 0.38 | 0.92 | -0.84 | -0.12 | 2.33 |
| November | 1.86 | 2.03 | 0.16 | -0.23 | 0.60 | 2.28 |
| December | 1.43 | 1.07 | 1.53 | -0.62 | -0.19 | 1.84 |
| $|\mu|$ | 0.74 | 0.97 | 0.84 | 1.07 | 0.42 | 1.62 |

![Figure 4. Sample autocorrelation (ACF) and partial autocorrelation (PACF) correlograms – $U$ (m/s) – UK North East – March.](image-url)
an AR model is suitable to describe the data. Moreover, the PACF shows that up to as many as six lags are statistically significant for the AR model prediction. It should be noted that the example shown in Figure 4 is taken from the UK North East data set and that the month of March was one of few months to demonstrate the dependence of up to six lags, which for three hourly samples corresponds up to 18 h in the past. The same process was followed for significant wave height, and it was identified that up to three lags were statistically significant.

Once a ceiling value for the AR model order is identified, the process of checking the MS-AR model types can be completed. This involves running the EM algorithm in the METIS toolbox to obtain the parameters $L$, $N$ and $k$ from model combinations $p\{1 \ldots 6\}$, $M\{1, \ldots, 6\}$. In all, 36 model types were assessed for both $U$ and $H_s$ across each month at all three sites. The BIC score was produced for each model combination across all months, and the model with the lowest BIC score was selected to produce the synthetic weather series.

It is time expensive to run the EM algorithm for all of the model types each time a new observed weather series is to be assessed. Therefore, a review of the model types selected across the three sites was completed and the results are shown in Figures 5 and 6. It is shown that for the wind speed $U$, the selection of the AR model order $p$ mainly switches between five and six lags, while the number of hidden states $M$ jumps between two and five states. The AR model selection for the wave height $H_s$ fluctuates between two to four lags and the number of hidden states between five and six. Generally, it is shown that the wind speed tends to a larger number of AR lags and a lower number of hidden states while the opposite is observed in the wave height. However, the model types shown in Figures 5 and 6 show a consistent range across the three sites and therefore reduce the number of model types that should be considered for each month to eight and six models for $U$ and $H_s$, respectively. By accounting for three different sites, each with different average characteristics, we can take confidence that constraining the model search to these windows should be adaptable to a variety of different offshore locations.

**Simulation and time series composition**

Once the most suitable model for each month and meteorological parameter is identified, the simulation process can be summarised as follows:

- The EM algorithm is run once again for each month based on the value for $p$ and $M$ identified from the BIC scoring process. The EM algorithm first relies on randomly selected initial state probabilities, transition matrix and parameters for each AR model, one for each hidden state $S_i \in \{1, \ldots, M\}$. The EM algorithm is then run to determine an estimate for the parameters of the MS-AR models identifying the likelihood of the model and most probable sequence of hidden states.
- For each simulation (normally 1000), the estimated parameters from the EM algorithm are then used to
simulate one instance of the Markov chain, which allocates the hidden states to each time step and thus the allocation of each AR model across the time series.

- This distribution of hidden states is then carried into the AR simulation. The AR simulation takes a random year of observations for the given month, which provides a reference for the first set of previous values corresponding with the model order $p$. Then for each step, the evolution of the weather series is handled by taking the conditional probabilities for the AR($p$) lags within the hidden state allocation, which are then multiplied against the $p$ lag values calculated in the previous time step. This produces a new value for the next time step which is altered accordingly with the associated parameters $\mu$ and $\sigma$ for the AR model that operates in the hidden state.

- This process continues following the path of the hidden states until a new time series is produced. The process is repeated for each month for as many simulations specified by the user, resulting in variable time series realisations, stemming from a combination of independent state allocations, random selection of observed data and the AR computation.

After the simulations are completed, multiple realisations of each month for $U$ and $H_s$ produced. Following the steps in Figure 1, the monthly realisations of $U$ and $H_s$ are produced independently. Therefore, a method to pair each $U$ and $H_s$ time series was necessary to ensure realistic data sets were produced. To account for the correlation between wind and wave excitation, a pragmatic approach was implemented by calculating the mean of each time series of $U$ and $H_s$ and then ranking these in ascending order. This ordering was then used to pair the $U$ and $H_s$ time series, before linear interpolation was applied to scale the realisations to hourly time steps. Finally, monthly sets are combined into annual data series, retaining the same ranking as before. We have found that this method can produce realistic time series for offshore applications as we will show in the next section. It should be noted that the MS-AR model is capable of producing negative values. These observations are very rare, so a screening process to replace any negative values with zeros is also included to ensure realistic predictions can be drawn from the generated time series.

Results

Simulation results

In this section, we begin with the visual and numerical outputs from the presented methodology. Table 2 compares the mean metocean values across all three sites. The mean values for the observed and simulated data have not been included, and instead the percentage difference is listed to convey the variation between the observed and modelled data.

It is shown that the MS-AR model tuned to each site and month is capable of following the seasonal changes in the observed series, with the majority of errors below 2%. Generally, the models were found to have larger average values for $U$ and $H_s$, with the exception of wave height at Redcar and the wind speed for the English Channel location. The largest average difference for wind speed and wave height was recorded for Redcar at 0.76% and for UK North East at 0.90%, respectively. The largest singular differences are recorded for $H_s$ at UK North East, which has an absolute average percentage variation of 1.62% across all months and it can also be noted that the average percentage difference for wave height is greater than wind speed across the three sites. For the majority of the sites, the largest variations are observed for the winter months, particularly for $H_s$ at Redcar and the English Channel. Despite these observations, the differences between the model and observed series are generally small and indicate that the produced data sets can be progressed for further analyses.

Comparisons for the UK North East site are used in the following to summarise the typical outcomes of the analysis. In Figures 7 and 8, the CDFs are shown for the wind speed and wave height, respectively. Each figure represents the distribution of $U$ and $H_s$ across 34 years of observed data and 1000 years of simulated data. The solid line represents the observed data, the dashed line for the simulated data with 90% confidence interval indicated by the dotted line. The confidence intervals represent the range of simulated data series for the 5th and 90th percentiles from the 1000 years of data.

It is evident in Figures 7 and 8 that the CDF of the simulated data follows the observed years of annual data. Looking at the lower wind speeds and wave
heights in both figures shows that there is a tendency for the model to over predict the occurrence of $U$ and $H_s$ below 3 m/s and 0.4 m, respectively. The Kolmogorov–Smirnov distance was used to identify the maximum absolute difference between the observed and simulated CDFs. This test produces the maximum vertical distance between the two CDFs, which were recorded as 0.018 and 0.014 for $U$ and $H_s$, respectively. This is indicative that both simulations are statistically representative of the observed data.

An additional visual inspection uses a quantile–quantile plot (QQ plot) of the annual observed and simulated time series. This tests if the simulated outcomes are related to the same distribution as the observed data. The QQ plots for $U$ and $H_s$ variables are shown in Figures 9 and 10. Both plots show a predominantly linear outcome, which indicates that the simulated data are from the same distribution as the observed. In Figure 9, a right skew tail is shown, which indicates that some extreme wind speeds may have been produced in the simulation compared to the observed data set. However, the concentration of the points is quite low, especially for the most extreme points. Figure 10 shows a much slighter skew than was observed with the wind speed. A review of the two other sites has demonstrated similar behaviour at the tails as shown in both figures, and it should be noted that Figure 9 demonstrates the largest skew observed across the three sites and two weather parameters.

**Weather window assessment**

This section presents the results for a weather window assessment across all three sites investigated. By considering a typically constrained offshore task against the simulated data series, the suitability of the employed methodology and generated time series can be reviewed.

For this assessment, specified weather limits and duration for a personnel transfer operation were applied against the three data sets, which are summarised in Table 3. This type of task is regularly completed during offshore wind installation, particularly when personnel are transferred to transition pieces for turbine installation. Similar tasks are also completed regularly in other marine sectors and therefore presents a relevant case study. A weather window can be defined simply as weather conditions that are less than or equal to the environmental limits of a task for a period of time. In some instances, a fixed periods less than or equal the environmental limits are specified for the weather window criteria. These predefined window lengths are often applied in offshore planning to account for uncertainties in weather forecasting, ensuring that suitable contingencies are included that allow safe completion of the marine operations.
To demonstrate the application of the MS-AR model, we present a case study on a personnel transfer task from a CTV to a pre-installed turbine transition piece, which is constrained by specified working limits, described in Table 3. We begin with an assessment for weather window persistence and average window length, which considers only the wave height and wind speed parameters. This is applied to assess the characteristics of the simulated and observed data without considering a constraint for a minimum weather window duration.

In Figure 11–13, we show the weather window persistence and average window length for each location. The weather window persistence is presented as normalised frequencies of 10-h bins and for all three sites, the same clustering towards the lower bin values between 10 and 40 h is observed. The comparison of the observed and simulated data shows reasonable consistency with the largest differences shown for the English Channel. It is apparent that the simulations have a tendency to over predict the frequency of weather windows between 20- and 100-h bins, particularly for UK North East and the English Channel, while Redcar shows the closest comparison overall.

Table 3. Weather window requirements.

| Parameter | Limit          |
|-----------|----------------|
| Wind speed $U$ | $\leq 13.6$ m/s |
| Wave height $H_s$ | $\leq 1.5$ m   |
| Duration$^a$      | $\geq 30$ h   |

$^a$Applied in workability assessment only.

Figure 11. UK North East – weather window persistence histogram and average window length $\leq 13.6$ m/s and $\leq 1.5$ m: (a) weather window persistence – 10-h bins – UK North East and (b) average weather window duration – UK North East.

Figure 12. Redcar – weather window persistence histogram and average window length $\leq 13.6$ m/s and $\leq 1.5$ m: (a) weather window persistence – 10-h bins – Redcar and (b) average weather window duration – Redcar.
The general outcome of persistence histograms shows little difference between the observed and simulated data, which indicates that the modelled time series captures the characteristics at each site.

The average weather window length for each month and location are shown in Figures 11(b), 12(b) and 13(b). The largest difference is again seen for the English Channel, which demonstrates that the modelled data generally produce smaller weather windows for each month by approximately 10–20 h. A similar outcome is shown for UK North East, but with smaller average differences. Redcar again shows the closest outcome for the average window length with no predominant over or under prediction identified. The outcomes for UK North East and the English Channel suggest that some difference could be expected when simulating the progression of marine operations against the modelled data, which we will review in the following section.

**Average monthly workability.** In this section, we consider an assessment of all limitations included in Table 3. This is completed to extend the weather window assessment for a predefined duration of more than or equal to 30 h. This duration constraint is introduced to assess the modelled time series with a realistic condition that may be applied to an operation from marine warranty surveyors or planning personnel. This assessment considers the average percentage workability of the personnel transfer operation, which considers the average amount of time available to complete the operation for each month and location, above or equal to the 30-h threshold. In Figures 14–16, we show scatter plots for the workability across the three sites.

In Figures 14–16, error bars are included for a 90% confidence interval from the observed and simulated data sets. The site with the closest percentage workability was Redcar with the largest variations observed for
January, July and March. Overall the modelled data were found to have 1.5% more workability on average when compared to the observed data set. The next closest prediction was identified at UK North East at approximately 3% less workability on average with the modelled data showing larger variations in the winter months, with the largest recorded at 9.8% less workability for February. The English Channel site reveals considerable deviations, and the workability of the simulated outcomes was found to exhibit 7.2% less workability on average. Particularly, large deviations are observed for the winter months, most notably December, January and February at approximately 25%, 21% and 16%, respectively.

Overall, Figures 14–16 show that the simulated data have a tendency to under predict the workability in the winter months and over predict in the summer months. The under predictions in the winter months are much greater than the over predictions in each case, and the absolute percentage difference for UK North East, Redcar and the English Channel was found to be 3.5%, 1.9% and 8.9%, respectively. The 90% error bars show that the mean outcomes for the simulated data are within the range of the observed data sets across all months for UK North East and Redcar. In Figure 16, it is shown that the mean outcome lies outside the 90% confidence interval for January, February, October, November and December.

To produce a further perspective on these results, the average number of weather windows in each month was analysed for the three sites as shown in Table 4. Both Redcar and UK North East show very similar outcomes between the observed and simulated data indicating realistic working durations would be predicted using the simulated data. However, the English Channel showed the largest absolute percentage difference. On average, the modelled data exhibit more windows for the first 6–7 months. It should be noted that this does not necessarily mean more workability in the simulated data and is more likely due to the fragmentation of weather windows, which are believed to be less prominent in the observed data. Nevertheless, this outcome shows that despite the larger deviations in the winter months, there would likely be a similar amount of time to complete the required marine operations in each month. However, if the English Channel time series were comprised within a dedicated planning and simulation tool, it is likely the modelled data set would exhibit an increase in waiting times or more frequent interruptions, than the observed data set.

The plots in the previous section showed significant deviations for the winter months, particularly for the English Channel location. It was originally suspected that the complex relationship between the wind and waves within an enclosed passage might have introduced a sensitivity to the

Table 4. Average number of weather windows $U \leq 13.6\ m/s$, $H_s \leq 1.5\ m$ for $\geq 30\ h$.

| Month    | UK North East $\mu$ of observed weather windows | UK North East $\mu$ of simulated weather windows | Redcar $\mu$ of observed weather windows | Redcar $\mu$ of simulated weather windows | English Channel $\mu$ of observed weather windows | English Channel $\mu$ of simulated weather windows |
|----------|-----------------------------------------------|-----------------------------------------------|----------------------------------------|---------------------------------------|-----------------------------------------------|-----------------------------------------------|
| January  | 4                                             | 5                                             | 5                                      | 5                                     | 4                                             | 5                                             |
| February | 4                                             | 4                                             | 4                                      | 5                                     | 4                                             | 4                                             |
| March    | 5                                             | 5                                             | 5                                      | 5                                     | 5                                             | 5                                             |
| April    | 4                                             | 4                                             | 4                                      | 4                                     | 4                                             | 4                                             |
| May      | 4                                             | 4                                             | 3                                      | 3                                     | 4                                             | 4                                             |
| June     | 3                                             | 3                                             | 3                                      | 3                                     | 4                                             | 4                                             |
| July     | 2                                             | 1                                             | 2                                      | 2                                     | 4                                             | 6                                             |
| August   | 3                                             | 3                                             | 3                                      | 3                                     | 4                                             | 4                                             |
| September| 4                                             | 4                                             | 4                                      | 4                                     | 4                                             | 5                                             |
| October  | 5                                             | 5                                             | 5                                      | 5                                     | 5                                             | 5                                             |
| November | 5                                             | 5                                             | 5                                      | 5                                     | 5                                             | 5                                             |
| December | 4                                             | 5                                             | 5                                      | 5                                     | 5                                             | 5                                             |

Correlated pairing method. The plots in the previous section showed significant deviations for the winter months, particularly for the English Channel location. It was originally suspected that the complex relationship between the wind and waves within an enclosed passage might have introduced a sensitivity to the
methodology. However, a further review found that in many cases the wave time series contrasted against the wind pattern, which when used in a logistical simulation package, may lead to significantly conservative estimates for the progression of marine operations.

\[ \rho(A, B) = \frac{1}{N-1} \sum_{i=1}^{N} \left( \frac{A_i - \mu_A}{\sigma_A} \right) \left( \frac{B_i - \mu_B}{\sigma_B} \right) \]  
where:
- \( A \) is the monthly realisations of wind speed,
- \( B \) is the monthly realisations of significant wave height and
- \( N \) is the number of observations in each monthly realisation.

To assess the severity of this mismatch between the simulated wind speed and wave height time series, the correlation between both parameters was investigated using the Pearson \( r \) correlation coefficient. The expression to define the Pearson \( r \) correlation coefficient or ‘Pearson \( r' \) is listed in equation (6). The Pearson \( r \) between the wind speed at 10 m and \( H_s \) for the English Channel location was found to be 0.9. A review of the wind and wave correlations was completed for simulated English Channel data for the paired by means method, which resulted in a Pearson \( r \) of around 0.06.

It was not expected that the simulated data would be a perfect meteorological replication of the relationship between the wind and the waves; however, such a low coefficient did question the overall robustness of the weather model when compared to the correlation coefficient of the observed data for the English Channel. To improve this relationship, a second approach, which uses Pearson \( r \) coefficients to pair the wind and wave time series, was investigated. In this process, each monthly wind speed and wave height realisation were compared using the Pearson \( r \) correlation coefficient. For each wind speed realisation, the wave height with the largest Pearson \( r \) was selected for pairing. This resulted in the selection of a number of duplicate wave height series, which removed some unique realisations from the final composition. However, this approach was found to significantly improve the outputs for all months at the English Channel site, as shown in Figure 17. Once paired, the time series were again expanded to hourly time steps using linear interpolation.

It should be noted that the final Pearson \( r \) for the simulated time series was around 0.5, which was 0.4 lower than the observed series for the English Channel. The final composition had approximately 4% less workability on average overall across the 12 months. When compared to the mean pairing approach, this is an increase of 4% workability on average. Notably large increases in workability were calculated for January, February and December compared to the first pairing method, increasing by approximately 15%, 12% and 17%, respectively. A reduction in workability is observed for April and August by 1% and 3%, respectively. A comparison of the average workability plots in Figures 16 and 17 shows that the data in correlated pairing approach fall well within the 90% confidence error bars of the observed outcomes, indicating a considerable increase in similarity between the two data sets. This result demonstrated a significant improvement using the correlation pairing approach for a site with a strong correlation between wind speed and wave height, which provides more flexibility to the modelling methodology overall.

**Discussion**

In this article, a methodology to produce annual time series of wind speed (\( U \)) and wave height (\( H_s \)), and an approach to assess these outcomes against a typical offshore operation, has been presented. The outcomes of the various analyses and the impact of the results for the planning of marine operations are discussed in this section.

The authors were particularly interested in a dynamic metocean model that could be adapted to any location and select the best model types for each month. The MS-AR model developed by Monbet and Ailliot\(^7\) can be applied to monthly data using a dedicated model in each instance, to produce monthly outcomes with similar characteristics to observed time series. The MS-AR model addresses the inadequacy of using a single AR model to describe the evolution of weather parameters, and in each month, it applies numerous AR models that operate within defined weather regimes. To reduce the number of model types and subsequent number of simulations, it is proposed that a future assessment could segment the data into seasonal sets and reviewed using the same methods in this article. This could determine if similar results are obtained within a reduced overall simulation time.

Ailliot and Monbet\(^7\) have found that the BIC is a suitable method to select the best model order and number of hidden states to fit the data, despite
acknowledging that this approach is not theoretically justified for MS-AR models. As such, an investigation using this assessment approach was presented and it was found that an envelope of model types was consistent across the three offshore sites for $U$ and $H_s$. The numerical outputs, CDF comparisons in Figures 7 and 8 and the Q–Q plots in Figures 9 and 10 demonstrate that the identified models produce good outcomes for $U$ and $H_s$ and therefore confirms the validity of this model selection process. However, it is likely that there would be some variation in the model selections each time the BIC scoring process is re-run, due to the probabilistic nature of the EM algorithm. Therefore, it is important that a model selection envelope is incorporated if this modelling methodology is included as part of an offshore planning simulation tool, allowing for this variation and adaptability to any offshore location. It should be noted that if a seasonal modelling approach is investigated, this may require an alteration to this model envelope and therefore a broad assessment of model types should be completed prior to running full simulations.

The simulated outcomes for $U$ and $H_s$ were found to show similar characteristics to the observed data as exemplified by the various plots we present section ‘Simulation results’. In Figures 7 and 8, the CDF of the simulated data follows the observed years of annual data. Looking at the lower wind speeds and wave heights in both figures shows that the model has a tendency to over predict the occurrence of $U$ and $H_s$ below 3 m/s and 0.4 m, respectively. This observation is consistent with similar observations completed by Ailliot and Monbet, who note that this behaviour will have limited impact for applications that are insensitive to lower magnitudes, such as the intended application in this article. Furthermore, climate change trends could be incorporated to adjust the resulting simulated $U$ and $H_s$ time series, drawing on publicly available projections such as Copernicus Climate Change Service. It is proposed that these trends could be used to modify the monthly simulated time series before to pairing the individual $U$ and $H_s$ realisations. However, it should be noted that current climate models anticipate limited change in wind and wave climates for the regions investigated in this article.

In Figure 9, a right skew tail is shown, which indicates that some extreme wind speeds may have been produced in the simulation compared to the observed data set. However, the concentration of the points is quite low, especially for the most extreme points. Figure 10 shows a much slighter skew than was observed with the wind speed. This behaviour at the tails is expected to have little impact for marine planning applications as these extreme values are likely to span well beyond the operational constraints for these tasks.

To assess the validity of the overall methodology, the final annual compositions of $U$ and $H_s$ were initially compared using weather window persistence histograms and average monthly weather window durations for a crew transfer task. The plots included in Figures 11–13 were produced to summarise characteristics relevant for the assessment of marine operations, providing a perspective on how simulated logistical scenarios may progress when using the synthetic time series. It was shown that for UK North East and Redcar both the weather window persistence and average weather window lengths have good agreement while the results for the English Channel location had the greatest difference overall. The 10-h bins were used in the histograms to maximise the perspective of the weather window availability across the three sites, which demonstrates some sensitivity when comparing the data for the English Channel. Figure 12(a) suggests that the synthetic data for this site may produce different outcomes when used to plan marine operations and a comparison of smaller bin sizes could be applied to highlight the extent of the inconsistencies in the generated time series.

The workability plots presented in Figures 14–16 provide a further insight to on the characteristics of the simulated data by introducing a 30-h minimum threshold for the weather window limitations. The scatter plots have shown that the mean percentage workability of the simulated data falls within the 90% confidence interval for all months at each site with the exception of 4 months for the English Channel. The average number of weather windows was also reviewed for the same thresholds across the three sites, which revealed the fragmentation of the windows was fairly consistent with the observed data for UK North East and Redcar. The English Channel generally shows a larger number of weather windows in the simulated data, which indicates that more frequent delays or interruptions may be predicted using the generated time series. This gives a further indication that the simulated outcomes for the English Channel may lead to incorrect predictions if used for offshore planning and simulation applications. The observed data for the English Channel are shown to have the largest average wind speed for all three sites in Table 1, which may indicate the MS-AR model types considered have difficulty recreating data with larger excitations. However, when the values listed in Table 2 were reviewed, it was found that the largest absolute average percentage difference was recorded for the wave height simulations at the English Channel. Despite this outcome, the 1.62% difference is relatively small, which indicates that the cause of the differences exhibited in the weather window and workability plots may stem from elsewhere in the overall methodology.

The independently simulated $U$ and $H_s$ monthly realisations were ranked by average value and paired accordingly, to produce the final time series composition. While this approach has demonstrated its ability to produce realistic characteristics for two locations, it is possible that this pairing method is not suitable for sites with certain characteristics. The English Channel is located between two land masses, and this narrowing
effect or limited fetch may have an influence on the complexity of the relationship between the wind and the waves at this site. Therefore, the alternative correlated pairing technique was applied to accommodate for sites with these characteristics and it was shown in Figure 17 that the workability was significantly improved for the English Channel using this method. It is apparent that this approach is incapable of reconstructing wind wave correlations with a Pearson $r$ greater than approximately 0.5, highlighting a limitation for the overall methodology presented in this article. Furthermore, the authors are keen to investigate different pairing techniques, adopting other methods such as the Kendal or Spearman rank correlation. The authors are keen to assess a full set of logistical tasks based on the primary installation phases of an offshore windfarm, to extend and validate the application of the simulated weather scenarios for marine weather risk assessments.

Conclusion

This article has presented a metocean modelling methodology using an MS-AR model with Gaussian innovations to produce stochastic wind speed and wave height time series for inclusion in marine risk planning tools. The METIS MATLAB toolbox developed by Monbet and Ailliot provided the main simulation framework which was reconfigured to produce annual sets of wind and wave height data. The versatility of the MS-AR model for differing metocean regimes has been discussed, and we have implemented a BIC scoring process to select the most suitable model type for each weather parameter.

The MS-AR model was originally intended to produce wind speed outputs, yet it is demonstrated that realistic wave height simulations can be produced. Two approaches to pair the individual wind speed and wave height simulations have shown their validity to finalise the composition of simulated realisations. Some extreme and negative values were also identified in the simulated data sets. These instances were fairly infrequent and the negative values were subsequently replaced with zeros, while the extreme values are presumed to have a negligible impact as these values are far beyond the weather constraints considered for metocean planning.

Summarising statistics have been produced to compare the simulated and observed data against the weather limits of a personnel transfer operation. It is shown that the data for two out of three sites provide realistic predictions for the progression of this operation, indicating the suitability of the proposed modelling approach for metocean risk planning activities. An average percentage workability assessment is completed across the three sites, which demonstrates that the simulated data have consistently realistic characteristics for two locations using an initial pairing approach using mean values from each monthly realisation. The second correlated pairing technique showed an improvement in the workability percentages for the English Channel site, yet the simulated data were generally pessimistic overall. Both pairing methods are limited, and it is recommended that the overall methodology is used for sites with Pearson $r$ correlations of $\leq 0.5$ between the wind speed and wave height.

The constrained 90% confidence error bars for the simulated outcomes demonstrate that the modelling process can provide a means to pinpoint overall predictions, and would be suitable to calculate metrics such as exceedance probabilities that are commonly used to summarise marine risk profiles. It is concluded that the methodology presented will produce suitable wind speed and wave time series for the assessment of marine operations. It is recommended that the methodology is applied to other sites with strong correlations between wind speed and wave height, to determine the method’s adaptability to a wide range of offshore locations.

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