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A multivariate Markov Weather Model for O&M Simulation of Offshore Wind Parks

Brede Hagen[a,*], Ingve Simonsen[a], Matthias Hofmann[b], Michael Muskulus[c]

[a]Department of Physics, Norwegian University of Science and Technology, NO-7491 Trondheim, Norway
[b]SINTEF Energy Research, Sem Sælands vei 11, NO-7034 Trondheim, Norway
[c]Department of Civil and Transport Engineering, Norwegian University of Science and Technology, NO-7491 Trondheim, Norway

Abstract

A multivariate Markov chain model is presented for generating sea state time series based on observed time series. The sea state is represented by the wave height, wind speed, wave period, wind direction and wave direction. Two ways of capturing the seasonal variation in the sea state parameters resulted in two distinct models. Their quality was assessed by comparing their statistical properties to what was obtained from observed time series. In one of the models (Model 1) transition probabilities were estimated separately for each month, while in the other (Model 2) a monthly transformation of the data were performed. Two different sea state data sets were considered in the validation, and it was found that both models compared favorably to the empirical data. It was concluded that Model 1 worked best for the longest data set considered, but was challenged by the shorter time series, where Model 2 worked best. Model 2 uses the observed data more efficiently, but relies on stationarity after removing the monthly variability. This seems to be a reasonable approximation for the data considered. The effect of changing the wave height resolution in the modeled time series was also investigated.

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Keywords: Markov Chain models (MCMs); sea state modeling; operation and maintenance (O&M); Offshore wind;

1. Introduction

One important limiting factor for operation and maintenance (O&M) of offshore wind farms are the weather conditions, typically characterized by significant wave height and wind speed. Hence, optimal O&M strategies need to take weather conditions into account. The objective of this study was to create a stochastic weather model for the sea state conditions based on observed time series, which can be used in an O&M simulation tool. The mean feature of the model is the ability to generate synthetic multivariate sea state time series different from the observed ones, but with the same statistical properties. Statistical properties of interest are the persistence of operational weather windows and the waiting times between these weather windows, in addition to the first and second order moments, correlations and the probability distribution of the sea state parameters.

*Corresponding author. Tel.: +47-95945598.
E-mail address: bredeand@stud.ntnu.no.

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A broad survey of different stochastic models available for simulating the sea state can be found in [1]. One such model class is the fairly simple Markov Chain Models (MCMs), which nevertheless have been found to produce realistic persistence statistics for weather windows [2],[3]. However, the drawback of a MCM is its discrete nature, and a high resolution of the modeled sea state parameter implies a large set of transition probabilities that need to be estimated. The MCMs assume the Markov property, which may be a too strong assumption, but which seems to work well in practice.

A MCM has recently been created and used in an operating tool for an Offshore wind farm [4]. This model generated time series for significant wave height and it was concluded to be suitable. However, other sea state parameters such as wave period, and wind- and wave direction may also be important in an optimal (O&M) simulation tool. For this purpose a more flexible model is needed.

The main purpose of this paper is to report on two generalized MCMs that are flexible in the sense that they are able to generate sea state time series independent of the number of different weather parameters considered. In addition a new method for handling the seasonal variation of the sea state parameters has been implemented.

This paper is organized in the following way. In Sec. 2 the two models that we are concerned about are presented, and so is the evaluation procedure. The results obtained from these models are shown in Sec. 3, and the discussion is given in Sec. 4. The conclusions that can be drawn from this study are presented in Sec. 5.

2. Methodology

2.1. Data

The following sea state parameters have been analyzed:

- H_s: Significant wave height, defined as the average of the highest one third of the waves.
- U: Wind speed. The speed of air particles 10 meters above mean sea level averaged over a fixed time period, typically 20 minutes.
- T: Mean wave period of the wave spectrum.
- Φ: Wind direction.
- Θ_m: Mean direction of the waves.

Multivariate time series including all five parameters listed above were obtained for two different locations in the North Sea (Table 1). The first data set was obtained from the ERA-Interim database of the European Centre for Medium-Range Weather Forecasts, hereafter denoted "ERA-data". The second one is a data set from Doggerbank and made available in the FAROFF-project, hereafter denoted "FAROFF-data".

Table 1. Observed time series

	ERA-data	FAROFF-data
First observation	1990-01-01	1957-09-01
Years of sampling	20	50
Sampling frequency (hours)	6	3
Number of measurements	19220	155837
Location	$60^o N$,$0^o E$	58°N,2°E

2.2. Markov chain model

A Markov chain is a discrete stochastic process which satisfies the Markov property [5]. The Markov property implies that the process is without memory, i.e., applying a MCM for weather modeling assumes that the future weather (next state of the weather) only depends on the current state of the weather, and is independent of the weather in the past (all previous weather states). In other words, it is assumed that the current state of the weather contains all the relevant information about the weather situation and its possible future development. The development of the weather can then be described by stochastic transitions. For computational efficiency and simple use, we work in a discrete setting here.

The process variable X_t takes on discrete integer values representing the state at time t. The number of states is finite and will be denoted by N. This means that the possible values for X_t, i.e. the state space is given by $\Omega = \{1, 2, 3, ..., N\}$. Under the Markov property all conditional transition probabilities from state i to state j for arbitrary $1 \leq i, j \leq N$ are independent on time and can be written in terms of matrix elements:

$$P(X_{t+1} = j | X_t = i) = p_{ij}. \tag{1}$$

This defines the square $N \times N$ transition matrix

$$\mathbf{P} = \begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1N} \\ p_{21} & p_{22} & \cdots & p_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ p_{N1} & p_{N2} & \cdots & p_{NN} \end{pmatrix}$$

Each row in the transition matrix is a conditional probability distribution and therefore the row sums of $\mathbf{P}$ are one. This matrix, combined with a probability distribution of the initial condition $P(X_1 = x_1)$, defines the Markov chain model. Given a sequence $\{X_t\}$ of data realized by such a process, the maximum likelihood estimator for the transition probabilities is [2]:

$$\hat{p}_{ij} = \frac{N_{ij}}{N_i}, \tag{2}$$

where N_{ij} is the number of observed transitions from state i to state j, and N_i is the total number of occurrences of the state i in the sequence. In order to fit an observed time series of data to the Markov Chain model and estimate the transition probabilities a set of multivariate weather states is needed. The weather state denoted by $\{X_t\}$ is represented by an integer and contains information about the values for all sea state parameters with an uncertainty corresponding to the desired resolutions. Discretization of each sea state parameter was performed by dividing their range into equal sized bins. The number of bins was determined by the desired resolution for the sea state parameters. The range of values within a bin corresponds to a single state, and the weather state represents a combination of such states for all five sea state parameters. Values for the modeled sea state parameters were chosen as the midpoint values for the bins the weather state represents. The Markov Chain model requires a stationary time series and two ways of dealing with seasonality resulted in two distinct models.

2.3. Model 1: Monthly Models

This model assumes piecewise stationarity, by only considering data from one month when estimating the transition probabilities. This way of handling the seasonal variation has been used in previous studies [3], [4].

2.3.1. Simulation details for Model 1

The first weather state in the simulated time series was chosen randomly from a normalized histogram for all values in $\{X_t\}$ for the starting month. The rest of the values were generated in a simulation loop and chosen by the relevant transition probabilities. Thereby, the weather develops from one state to the next, within the limits of the observed transitions only, and with preference for the most likely of these transitions (including both development according to the synoptic situation, but also random influences). In practice the transition matrices do not need to be constructed explicitly. Instead, all relevant transitions from the current model state were determined online by searching through the available data, and one of these was chosen randomly. This method is equivalent to estimating one row in the transition matrix for the current month, and saves a lot of memory on the computer. Consider one of the following cases:

- The $modeled$ time series enters a new month.
- The chosen transition to determine the current model state occurred at the border between two months in the $observed$ weather state time series.

Both cases imply that there may not exist any relevant transitions in the data. In that case a new search for observed transitions without any month restrictions was performed to determine the next modeled weather state. By repeating this procedure through a time window of 20 years a time series of modeled weather states was generated.

2.4. Model 2: Data transformation

This method of dealing with the seasonal variation in the sea state has to the authors knowledge never been applied with a Markov Chain model before.

Before constructing the weather states the observed time series for significant wave height, wind speed, and wave period were normalized by the following transformation:

$$y^*_{t,p} = \frac{y_{t,p} - \overline{y_p}}{S_p}, p = 1, 2, \ldots, 12 \tag{3}$$

for $y_{t,p} = H_s, U, T$ where $\overline{y_p}$ and S_p are the empirical mean and standard deviation for the observed values in the month p. The assumption for this model is that the seasonal variation in the mean and standard deviation for H_s, U and T are the dominant components of the time series non-stationarity. The resulting transformed time series was therefore assumed to be stationary, i.e., the statistical parameters under consideration were assumed to be independent of the season of the year. This implies that one can consider all relevant transitions to determine the modeled weather states without any month restrictions. After the simulation the modeled time series was inverse transformed. The transformation given by (3) was used in [6] for an univariate significant wave height time series, but not in the context of a MCM.

2.5. Model evaluation

In order to quantify the models' ability to simulate realistic weather scenarios, statistical parameters for observed and modeled time series were calculated and compared. For significant wave height, wind speed and wave period the empirical mean, standard deviation and cumulative distribution function (CDF) of these variables was calculated. In addition, histograms for Θ_m and Φ with the same bins as the modeled data were calculated. The correlations between the sea state parameters were calculated as a 5×5 correlation matrix where each matrix element corresponds to Pearson's sample correlation coefficient between each combination of two sea state parameters. In order to remove the circular characteristics of the directional parameters, Φ and Θ_m were transformed according to $\Phi' = |180 - \Phi|$ in the calculations.

Persistence and waiting time for weather windows are of special interest, since O&M on offshore wind farms needs suitable weather which in this work is characterized by waves with a large period, and small amplitudes combined with calm wind. More precisely, in order to count as suitable weather at a given time t, the following must be fulfilled: $H_{s_t} \leq 2$m, $U_t \leq 10$m/s and $T_t \geq C_T$, where $C_T = 5.5$s when using ERA-data and $C_T = 4.5$s when using FAROFF-data. Two different values for C_T were chosen because of the different distributions of the mean wave period for the two data sets. Persistence statistics for weather windows were calculated by identifying the time duration of all weather windows and creating a histogram with a bin size of 6 hours. The persistence histogram was normalized such that one bin in the histogram represents

$$\frac{\text{Total time duration of the weather windows in the bin}}{\text{Total time duration of the time series}}. \tag{4}$$

The waiting time is defined as the time duration from a given point in time until a suitable weather window of at least 12 hours starts. All waiting times were saved as a histogram with resolution of 24 hours. All statistical parameters were calculated for the whole time series, and on a monthly scale.

The statistical properties for the observed and modeled time series were compared visually and by calculating test statistics. Empirical means and standard deviations for observed and modeled time series were compared by calculating the relative difference. Observed and modeled correlation matrices were compared by averaging the absolute value of the difference between the observed and modeled correlations. Empirical cumulative probability functions (CDF) were compared by calculating the Kolmogorov-Smirnov(K-S) distance [7]. This distance corresponds to the maximum vertical difference between the two CDF's. Histograms were compared by calculating their overlap or intersection. For normalized histograms H_1 and H_2 that contain n equal sized bins the histogram intersection H is defined by:

$$H(H_1, H_2) = \sum_{i=1}^{n} \min(H_1(i), H_2(i)) = 1 - \frac{1}{2}\sum_{i=1}^{n} |H_1(i) - H_2(i)| \quad (5)$$

In order to quantify the uncertainty 100 synthetic time series were generated. For each simulation the test statistics were calculated. The models' ability to reproduce a certain statistical property was measured as as the empirical standard deviation of the 100 corresponding test statistics with respect to the empirical mean of the same test statistics.

To summarize the models ability to reproduce the statistical parameters, an equal weighted average of all averaged test statistics (all statistical parameters based on whole time series and on a monthly scale) was performed. In this calculation all average histogram intersections $\overline{H}$ were replaced by $1 - \overline{H}$ and all negative relative differences were replaced by their absolute values. The resulting number, an average of 182 individual numbers, is an indicator of the total performance of the models.

3. Results

In this section results are presented. The first part consists of an investigation of how the results depend upon the wave height resolution, the model, and the data set chosen. In the second part one simulation for both models is analyzed in more detail. In both cases some parameters were held constant in addition to the critical values which define the weather window: The resolutions for wind speed, wave period, wind direction and wave direction were chosen to be $\Delta U = 1$m/s, $\Delta T = 1$s and $\Delta\Phi = \Delta\Theta_m = 45^o$. These resolutions determine the number of weather states for the model, which typically was in the order of 5000-25000, depending on the model, data set and the wave height resolution. The simulation time window was also held constant at 20 years.

3.1. General results

Figure 6 shows how the *average error* is distributed as a function of the wave height resolution ΔH_s for the two models and data sets. There is a decreasing trend in the average error with respect to decreasing the resolution ΔH_s. For constant ΔH_s the average error is smallest using Model 1 for the FAROFF-data set.

Table 2. Comparison between observed and modeled statistical parameters given as $average \pm uncertainty$. Based on 100 simulations for FAROFF-data. The values for correlation are absolute differences between the correlations in the observed and the synthetic data.

Model	Wave height resolution	Mean Wave height	Mean Wind speed	Correlation	Persistence	Waiting time
1	0.1	$2.8\% \pm 1.3\%$	$0.1\% \pm 0.9\%$	0.016 ± 0.004	$93.8\% \pm 0.4\%$	$97.4\% \pm 0.6\%$
1	0.9	$0.1\% \pm 1.1\%$	$0.2\% \pm 0.8\%$	0.020 ± 0.003	$93.3\% \pm 1.0\%$	$93.2\% \pm 0.9\%$
2	0.1	$0.0\% \pm 1.2\%$	$-0.1\% \pm 0.8\%$	0.030 ± 0.006	$93.4\% \pm 0.9\%$	$96.2\% \pm 0.8\%$
2	0.9	$0.1\% \pm 1.2\%$	$0.0\% \pm 0.9\%$	0.034 ± 0.007	$93.5\% \pm 1.0\%$	$95.5\% \pm 0.9\%$

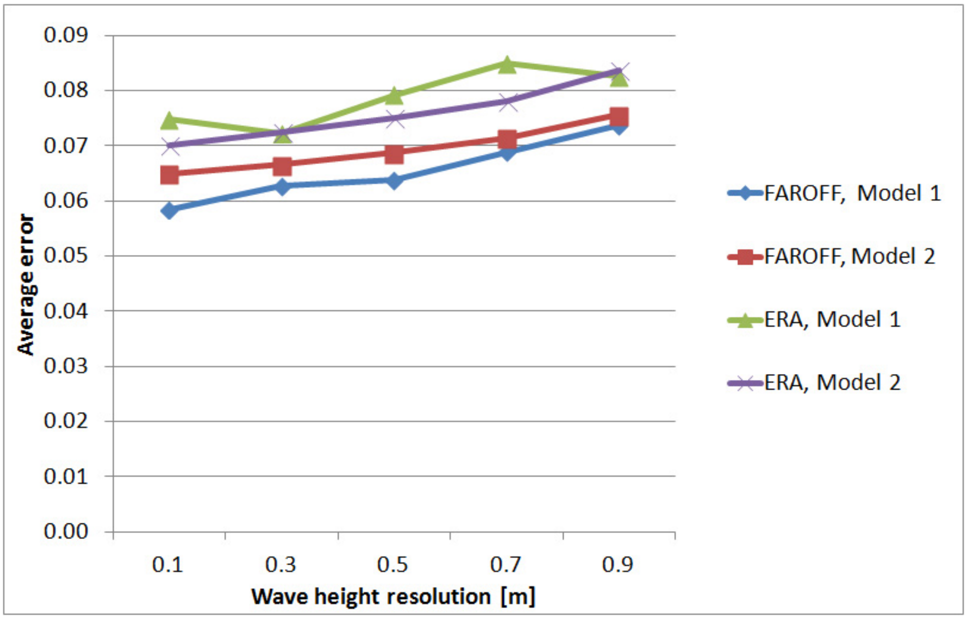

Fig. 1. The *average error* as a function of wave height resolution for both models and data sets.

Table 3. Comparison between observed and modeled statistical parameters given as $average \pm uncertainty$. Based on 100 simulations for ERA-data. The values for correlation are absolute differences between the correlations in the observed and the synthetic data.

Model	Wave height resolution	Mean Wave height	Mean Wind speed	Correlation	Persistence	Waiting time
1	0.1	$-0.5\% \pm 1.2\%$	$-0.5\% \pm 0.9\%$	0.016 ± 0.006	$87.5\% \pm 1.4\%$	$96.5\% \pm 0.9\%$
1	0.9	$0.1\% \pm 1.1\%$	$0.1\% \pm 0.8\%$	0.018 ± 0.006	$87.7\% \pm 1.3\%$	$96.9\% \pm 0.7\%$
2	0.1	$-0.1\% \pm 1.0\%$	$-0.1\% \pm 0.8\%$	0.029 ± 0.010	$87.8\% \pm 1.2\%$	$97.6\% \pm 0.6\%$
2	0.9	$-0.1\% \pm 1.0\%$	$-0.1\% \pm 0.7\%$	0.028 ± 0.009	$87.6\% \pm 1.1\%$	$97.8\% \pm 0.6\%$

Regarding individual statistical parameters, Tables 2 and 3 present results for some key parameters. These statistical parameters are in general well reproduced by the models. However, some results are worth commenting. The mean value for significant wave height is overestimated with 2.8% when using Model 1 for the FAROFF-data set, using a wave height resolution of 0.1m. This overestimation is caused by the fact that the resolution of the modeled wave heights is equal to the observed ones, which results in a systematic overestimation of 0.05m, since the modeled wave heights are given by the midpoint values. Regarding the correlation, a more accurate result is obtained using Model 1 compared to Model 2. Histograms for persistence and waiting time are in general well reproduced by both models, with histogram intersection around $90 - 95\%$. A slightly more accurate result for the persistence statistics is obtained using FAROFF-data compared to ERA-data. Results for the monthly statistics are not shown, but they are incorporated in the *average error* shown in Figure 6.

3.2. Detailed results

In this section simulation results using both models for FAROFF-data with $\Delta H_s = 0.1$m are presented in detail.

The modeled and observed mean values for wind speed are shown in Table 4. A variation in the mean value with respect to the months is observed which confirms that the seasonal variation in the sea state parameters must be taken into account. Both models capture the seasonal variation in the mean value for wind speed reasonably well, with relative errors less than 5%.

Empirical CDF's for wave height and wave period are shown in Figure 2-3. In both cases the modeled CDF's tend to follow the observed one, but relatively large deviations are observed for the wave period CDF using

Table 4. Observed and modeled mean values for wind speed

	Model 1	Model 2	Observed	Relative difference Model 1	Realative difference Model 2
All	8.52	8.40	8.43	1.0%	-0.4%
January	10.50	10.0	10.52	-0.2%	-4.9%
February	9.38	9.66	9.65	-2.9%	0.1%
March	9.06	9.00	9.11	-0.5%	-1.3%
April	7.56	7.82	7.67	-1.4%	2.0%
May	7.13	7.21	6.97	2.3%	3.5%
June	6.60	6.27	6.49	1.8%	-3.3%
July	6.72	6.54	6.47	3.9%	1.1%
August	6.88	6.76	6.89	-0.1%	-1.9%
September	8.33	8.11	8.03	3.8%	1.1%
October	9.33	8.89	9.15	2.0%	-2.8%
November	10.41	10.09	10.07	3.3%	0.1%
December	10.32	10.51	10.15	1.6%	3.5%

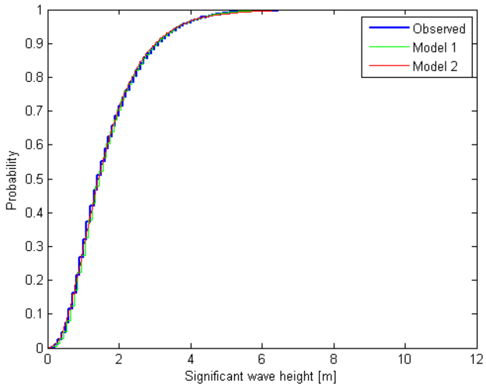

Fig. 2. Empirical CDF of the significant wave height H_s. Blue: Observed FAROFF-data, green: Modeled with Model 1, red: Modeled with Model 2.

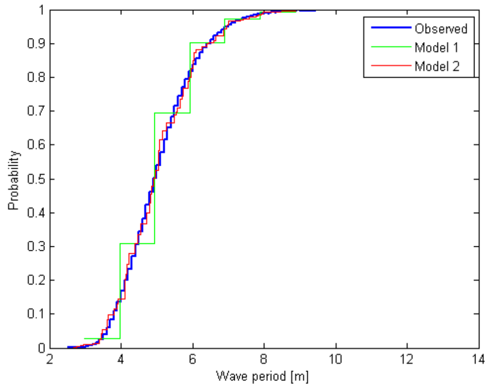

Fig. 3. Empirical CDF of the mean wave period T. Blue: Observed FAROFF-data set, green: Modeled with Model 1, red: Modeled with Model 2.

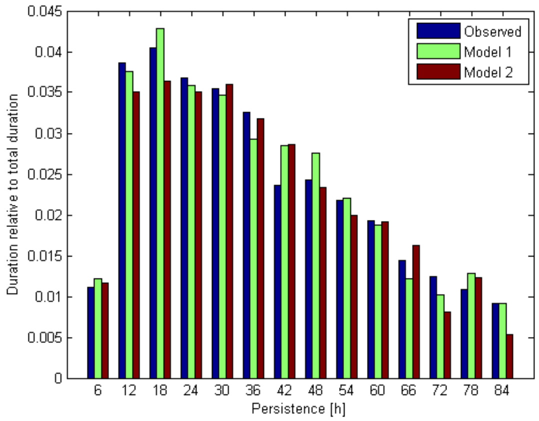

Fig. 4. Histogram of the persistence of weather windows. Blue: Observed FAROFF-data, green: Modeled with Model 1, red: Modeled with Model 2. Persistence values greater than 84 hours are excluded.

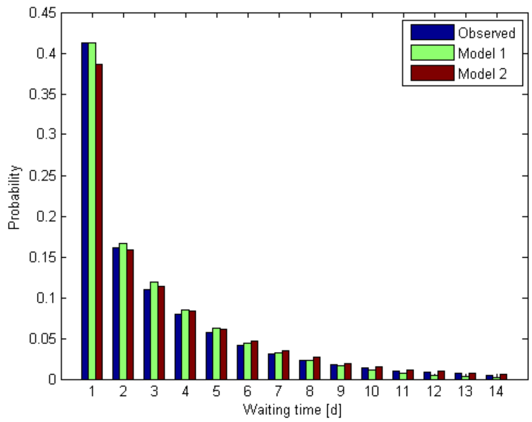

Fig. 5. Histogram of the waiting times for weather windows of at least 12 hours. Blue: Observed FAROFF-data, green: Modeled with Model 1, red: Modeled with Model 2.

Model 1, caused by the discrete states. The greater set of unique modeled wave period values caused by the inverse transformation is the explanation why Model 2 does not result in such large jumps in the modeled wave

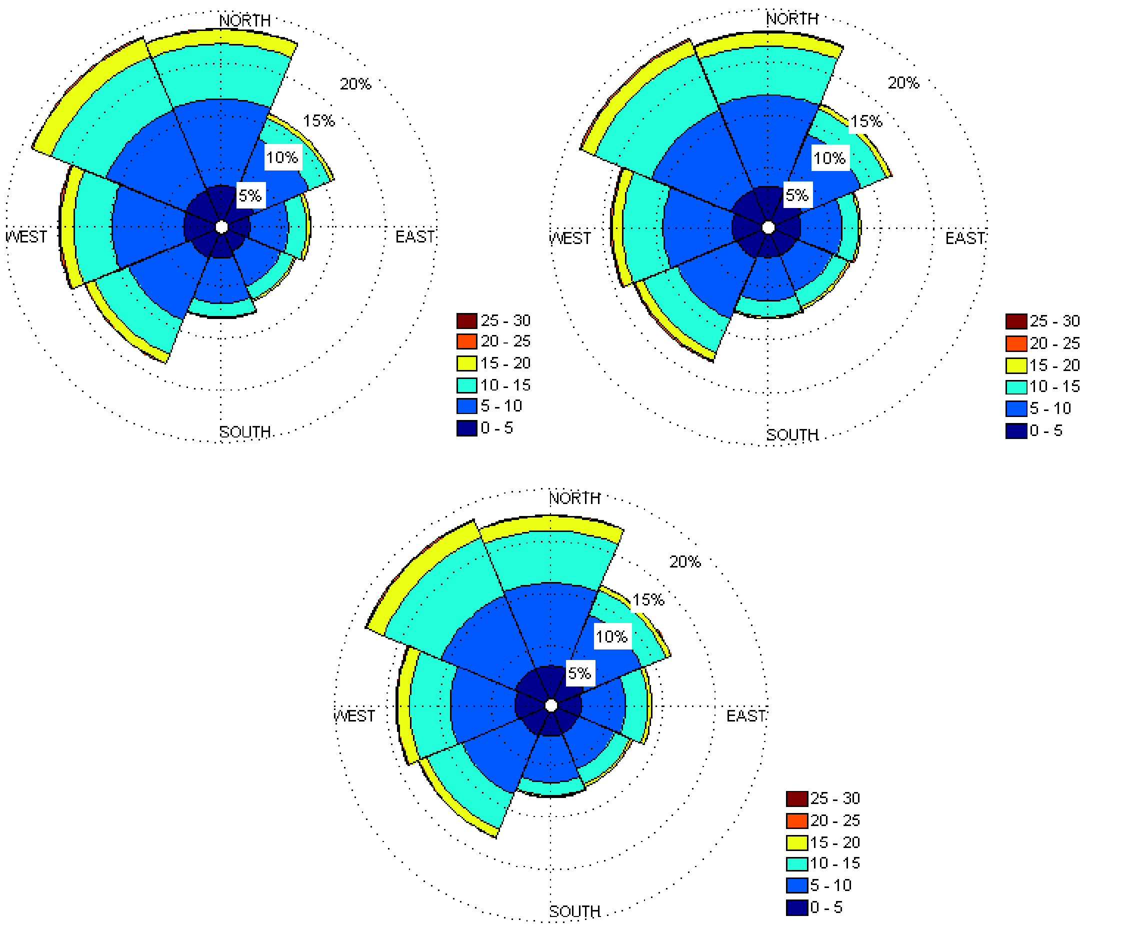

Fig. 6. Wind roses. Upper left: Modeled with Model 1, upper right: Modeled with Model 2, lower: Observed FAROFF-data.

period CDF.

Important results for O&M simulation are the weather window statistics, which are shown in Fig. 4-5. Fig 4 shows that the Markov Chain models successfully reproduce the persistence statistics also in the multivariate case. There are some small differences between the observed and modeled distribution, but no systematic deviations. Waiting time histograms were also well reproduced. As shown in Fig. 5, both modeled waiting time histograms closely follow the observed one.

Both models also captures the combination of wind speed and wind direction. Observed and modeled wind roses are shown in Fig. 3.2, and there are no obvious deviations visible.

4. Discussion

The intention of this work has been to create a stochastic multivariate weather model, for the application in an O&M simulation tool. The work resulted in two models which both have shown the ability to reproduce important statistical properties for this purpose.

Regarding Model 2, which includes a new way of dealing with the seasonal variation in the sea state parameters, a study of the stationarity of the transformed time series has not been performed, but the fact that the statistical properties were reproduced well using Model 2 is an indication that the seasonal variation was removed by the transformation. However, as indicated in the results, the correlations were captured best with Model 1, which may indicate that some residual seasonal variation appears in the correlation between the sea state parameters. In addition, the seasonal variation in the directional parameters has not been quantified and therefore not been taken into account in Model 2. Including the seasonal variation in the correlations, or the directional parameters in the transformation may therefore improve Model 2, and such studies are left for further work.

The wave height resolution determines the accuracy of the modeled wave heights. For both models the *average error* decreases with lower wave height resolution, but a low value for this parameter has some important implications which should be discussed. The most intuitive implication of a high wave height resolution is the number of weather states. As shown in Figure A.7 the number of states depends strongly on the significant wave height resolution. A high number of weather states implies that more transition probabilities have to be estimated and they may be not estimated accurately then. Especially Model 1, which only considers transitions from one month when estimating the probabilities, may be limited for a large number of weather states. This could be an explanation why the *average error* for Model 1 is biggest for ERA-data, which is the smallest data set.

An important property of the modeled time series, which so far has not been discussed, is that it has to be different from the observed one. A modeled time series equal to the observed one is worthless. The fact that the test statistics differ for each simulation is an indication that the model generates synthetic time series. However, comparing the number of states with the number of measurements for ERA-data there is no doubt that many of the estimated transition probabilities equal zero. The modeled weather states were determined according to the transition probabilities, and if there is only one transition from the given state in the observed time series, only one transition probability will be nonzero, and the modeled weather state will be determined without any uncertainty. This fact may cause the model to replicate the observed weather over a certain period of time.

Figure A.8-A.11 shows the distribution of the number of possible transitions using the smallest data set for different combinations of model and wave height resolution. Since the transition matrices were not created explicitly, these distributions were calculated by counting the number of nonzero transition probabilities for each modeled weather state in the simulation loop. Figure A.8 and A.9 also show how often all transition probabilities equal zero for Model 1. As discussed in Sec. 2.3.1, the transition probabilities were in this case estimated by all observed transitions without any month restrictions.

The most extreme case, which corresponds to Figure A.8, was Model 1 for ERA-data, with a wave height resolution of 0.1 m. In this case around 65% of the modeled weather states were determined from a distribution with only one nonzero transition probability. At the same time around 10% of the time there were no possible transitions, which means that the seasonal variation was dropped 1 out of 10 times.

The main point here is to illustrate that a low value for the wave height resolution may not be the best option even though this resolution gave the lowest average error. It is also illustrated that Model 1 is most limited with respect to a low value for the wave height resolution. The implications of a large number of weather states should probably be further investigated. A good idea could be to investigate the duration of periods where the modeled weather state is determined by only one nonzero transition probability. In these periods the model replicates the observed weather.

5. Conclusion

In this project two flexible multivariate Markov Chain models with the purpose of generating synthetic sea state time series based on observed ones have been implemented in MATLAB. The method of handling the seasonal variation in the sea state parameters distinguishes the two models. A general way of constructing multivariate states was implemented, which to the authors knowledge has never been applied for sea state time series before.

The models were assessed by comparing statistical properties, and two data sets were considered in the validation. Both models reproduce the statistical parameters well, especially the results for persistence and waiting time for weather windows were promising. Both models were therefore concluded to be suitable for O&M simulations of offshore wind parks. Due to a high number of weather states both models need long datasets to ensure that the simulated time series is different from the observed one, but it has been demonstrated that Model 2 is less restrictive.

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Appendix A. Some extra plots for the discussion part

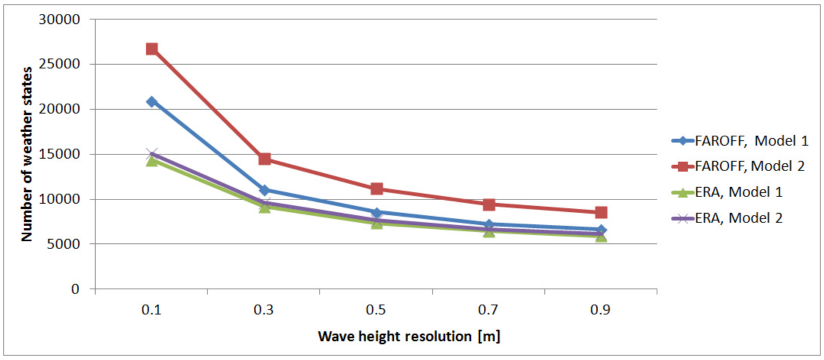

Fig. A.7. The number of weather states as a function of wave height resolution for both models and data sets.

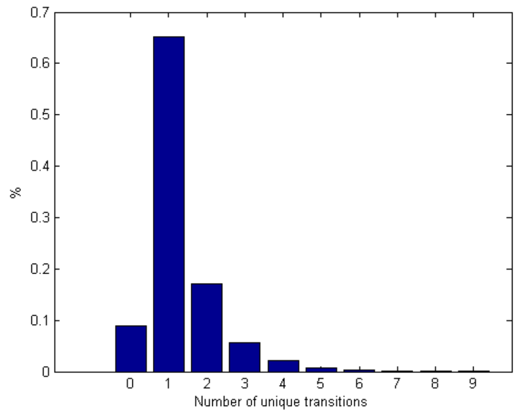

Fig. A.8. The distribution of the number of possible transitions using ERA-data, Model 1, wave height resolution = 0.1m.

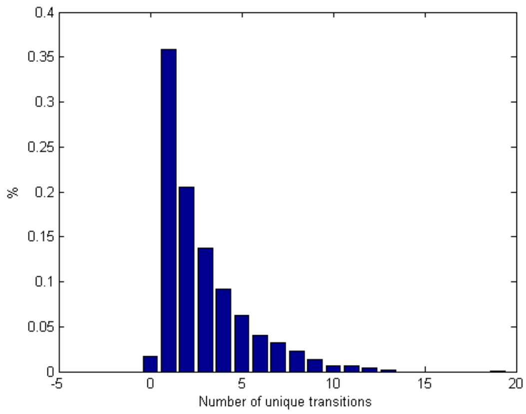

Fig. A.9. The distribution of the number of possible transitions using ERA-data, Model 1, wave height resolution = 0.9m.

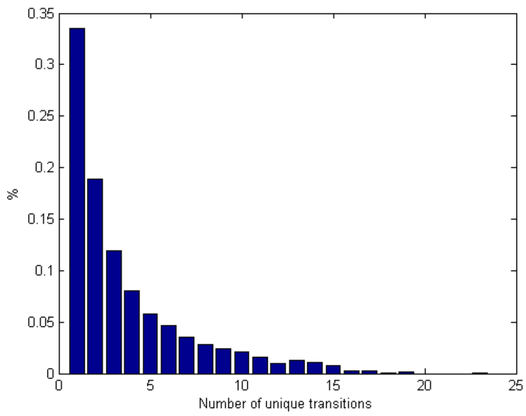

Fig. A.10. The distribution of the number of possible transitions using ERA-data, Model 2 and wave height resolution = 0.1m.

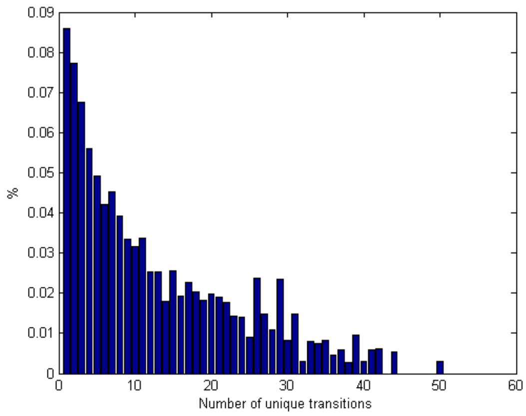

Fig. A.11. The distribution of the number of possible transitions using ERA-data, Model 2 and wave height resolution = 0.9m.