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Probabilistic forecasting of wave height for offshore wind turbine maintenance

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ABSTRACT

Wind power continues to be the fastest growing source of renewable energy. This paper is concerned with the timing of offshore turbine maintenance for a turbine that is no longer functioning. Service vehicle access is limited by the weather, with wave height being the important factor in deciding whether access can be achieved safely. If the vehicle is mobilized, but the wave height then exceeds the safe limit, the journey is wasted. Conversely, if the vehicle is not mobilized, and the wave height then does not exceed the limit, the opportunity to repair the turbine has been wasted. Previous work has based the decision as to whether to mobilize a service vessel on point forecasts for wave height. In this paper, we incorporate probabilistic forecasting to enable rational decision making by the maintenance engineers, and to improve situational awareness regarding risk. We show that, in terms of minimizing expected cost, the decision as to whether to send the service vessel depends on the value of the probability of wave height falling below the safe limit. We produce forecasts of this probability using time series methods specifically designed for generating wave height density forecasts, including ARMA-GARCH models. We evaluate the methods in terms of statistical probability forecast accuracy, as well as monetary impact, and we examine the sensitivity of the results to different values of the costs.

1. Introduction

Wind power constitutes a significant part of the rapidly growing global renewable sector. In contrast to onshore wind farms, offshore locations provide stronger and steadier sources of energy, and are criticized less for blemishing the landscape. In Europe, several countries have ambitious plans for new offshore installations, most notably Denmark, Germany and the UK. In China, there are impressive targets for offshore development, with a plan to increase total installed offshore capacity from less than 1GW to 30GW by 2020. In the United States, although recent years have seen considerable growth in wind power generation, it has been entirely onshore. Staid and Guikema (2015) explain that, while many of these onshore locations have great wind resource, they tend to be far from the many densely populated urban areas on the coast. This implies a need for investment in new transmission lines, which presents an obstacle to the development of wind power, and motivates offshore wind power generation. The first commercial offshore farm in the United States began generating power near Rhode Island in December 2016, and many more installations are under construction, including a 1GW wind farm off Martha's Vineyard. In terms of construction, offshore locations are challenging and costly (Irawan, Song, Jones, & Akbari, 2017; Ursavas, 2017). This is also the case for offshore operations and maintenance, which has been described as a fast developing sector in its own right (GL Garrad Hassan, 2013). Although turbine design and manufacturing has improved, the harsh marine environment and increasing turbine size mean that reliability will continue to be a challenge for offshore wind farm operators (Caroll, McDonald, & McMillan, 2016).

Irawan, Ouelhadj, Jones, Stålhane, and Sperstad (2017) describe how offshore maintenance can be predetermined, condition-based, or corrective. Predetermined maintenance can include work performed at predetermined intervals. Condition-based maintenance is work carried out in response to the condition of equipment revealed by ongoing monitoring. Corrective maintenance is in response to an equipment failure that has already occurred. Our interest in this paper is in the timing of maintenance for an offshore turbine that is either unable to operate, or has been shut down due to some level of fault. Service vehicle access to the turbine is limited by the weather, with wave height being the important

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factor in deciding whether access can be achieved safely. Dinwoodie, Catterson, and McMillan (2013) present wave height limits for various forms of vehicle, including helicopters and various sea vessels. They explain that the wave height limits apply for the duration that the service vehicle is at sea. We refer to this period as the *mobilization window*. In this paper, we follow Catterson et al. (2016) by focusing on the simplest form of crew transport vessel, which is used to transfer crew and tools for common maintenance work. They consider the limit of 1.5 meters, and compare wave height point forecasts from different time series methods in terms of their ability to predict whether this limit will be exceeded during the mobilization window. The decision as to whether to send the vessel is dictated by these predictions. An appealing feature of the work of Catterson et al. (2016) is that they evaluate the resulting decisions in terms of monetary cost. A wasted trip by the service vehicle will have an associated cost, and an opportunity cost will be incurred if an opportunity to send the vessel and repair the turbine is missed.

In this paper, we extend the work of Catterson et al. (2016) to incorporate probabilistic forecasting, and to investigate whether a probabilistic approach to decision making should be preferred to the deterministic approach that they employ. Conveying forecast uncertainty through probability estimates is important to improve situational awareness, as well as to enable rational decision making. This is discussed by LeClerc and Joslyn (2015), Winkler (2015) and Ursavas (2017) in the context of decisions based on weather forecasts. We first show that, in terms of minimizing expected cost, the decision as to whether or not to send the service vessel depends on the probability of wave height being below 1.5 meters for the duration of the mobilization window. We then produce forecasts of the probability using time series methods for generating forecasts of the probability density function, which are termed *density forecasts*. We evaluate wave height density and probability forecast accuracy using statistical measures, as well as the monetary cost resulting from the decision based on the probability forecast. We also use monetary cost to compare decision making based on probabilistic and point forecasts.

The time series methods that we use to produce density forecasts include kernel density estimation (KDE), time-varying parameter (TVP) regression models, autoregressive moving average generalized autoregressive conditional heteroscedasticity (ARMA-GARCH) models, and density forecast combining. Catterson et al. (2016) did not consider these methods in their analysis, as their focus was point forecasting. Although other time series methods have been proposed for wave height forecasting, such as artificial neural networks (see Reikard, Robertson, & Bidlot, 2015), we chose methods that are suited to density forecasting. A discrete choice model could perhaps be used to model directly the probability of wave height being below 1.5 meters. Taylor (2017) uses a model of this type to predict wind power exceedance probabilities. However, the use of such models for our application is not straightforward, with a separate model needed for each lead time within the mobilization window of interest. Furthermore, the use of a discrete choice model is often motivated by the lack of an obvious distributional assumption, as in Taylor's (2017) study of wind power, but we show that this is not a concern for our wave height data, if standard transformations are applied. Several of the methods that we consider involve the modeling of wave height in terms of wind speed. For these methods, wind speed forecasts are essentially generated autoregressively within the model. This has practical advantages in terms of convenience and cost, as the forecasts can be generated subject simply to the condition that historical wind speed observations are available. However, wind speed forecasts could be generated from other approaches, such as a numerical weather prediction system.

In the next section, we describe how the decision as to whether or not to mobilize the service vessel should depend on the probability that the wave height will be below 1.5 meters for the duration of the mobilization window. We then describe our dataset. The section that follows presents methods for wave height density forecasting. The next section describes an empirical study in which we compare forecasts in terms of statistical measures, as well as monetary cost. The final section provides a summary and concluding comments.

2. The need for probability forecasts

Catterson et al. (2016) use wave height point forecasts from a variety of time series methods to predict whether or not a limit of 1.5 meters will be exceeded during the mobilization window. If, and only if, the point forecasts for all periods in the window are below the limit of 1.5 meters, mobilizing the service vessel is considered to be the optimal decision. Catterson et al. (2016) explain that, in terms of monetary outcome, it is the forecasts that lead to decisions with poor outcomes that have negative consequences, while forecasts that lead to decisions with satisfactory outcomes carry no penalty. If the vessel is mobilized, and the wave height then exceeds the limit during the mobilization window, the trip will have been wasted, with an associated cost C_{trip}. If the vessel is not mobilized, and the wave height turns out not to exceed the limit during the mobilization window, an opportunity to send the vessel and repair the turbine would have been missed, and this can be viewed as carrying an opportunity cost C_{opp} equal to the revenue that has been lost due to power not being generated. Catterson et al. (2016) use these costs to evaluate the decisions resulting from the point forecasts from different methods. By contrast, we base our decision making on these costs and probability forecasts.

Let p be the probability that a wave height of 1.5 meters is not exceeded during the mobilization window. The expected cost of opting to mobilize the vessel is:

$$E_{Mobilize} = p \times 0 + (1 - p) \times C_{trip}$$

The expected cost of the alternative of opting not to mobilize the vessel is:

$$E_{NoMobilize} = p \times C_{opp} + (1 - p) \times 0$$

Using the criterion of minimizing expected cost, it is optimal to mobilize the vessel when $E_{Mobilize} < E_{NoMobilize}$, which is the case when probability p is greater than a critical value $p_{critical}$ given by:

$$p_{critical} = C_{trip} / \left(C_{opp} + C_{trip} \right) \quad (1)$$

This provides a threshold for the probability that a wave height of 1.5 meters is not exceeded during the mobilization window. Expression (1) shows that, if the cost of the trip C_{trip} is low relative to the opportunity cost C_{opp}, it will be optimal to mobilize even for quite low values of p, but that, if the cost of the trip is relatively high, p would have to be high for mobilizing to be optimal. Our proposal is to base the decision, as to whether to mobilize, on whether or not the forecast for p is more than $p_{critical}$.

The cost of the trip is calculated as (Catterson et al., 2016):

$$C_{trip} = MobilizationWindowHours \times (FuelPricePerHour + VesselHirePricePerHour) \quad (2)$$

Note that wind farm operators do not own vessels, and so have to hire them instead (Catterson et al., 2016). The opportunity cost is the revenue that would have been generated from selling electricity if the turbine had been repaired. Catterson et al. (2016) calculate this for the duration of the mobilization window, because