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Received: 5 April 2022 | Revised: 10 November 2022 | Accepted: 16 January 2023

DOI: 10.1002/we.2806

RESEARCH ARTICLE

WILEY

A Bayesian hierarchical assessment of night shift working for offshore wind farms

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Funding information
Engineering and Physical Sciences Research Council, Grant/Award Number: EP/L016680/1

Abstract

This article presents a Bayesian data-modelling approach to assessing operational efficiency at offshore wind farms. Input data are provided by an operational database provided by a large offshore wind farm which employs an advanced data management system. We explore the combination of datasets making up the database, using them to train a Bayesian hierarchical model which predicts weekly lost production from corrective maintenance and time-based availability. The approach is used to investigate the effect of technician work shift patterns, specifically addressing a strategy involving night shifts for corrective maintenance which was employed at the site throughout the winter. It was found that, for this particular site, there is an approximate annual increase in time-based technical availability of 0.64%. We explore the effect of modelling assumptions on cost savings; specifically, we explore variations in failure rate, price of electricity, number of technicians working night shift, extra staff wages, months of the year employing 24/7 working and extra vessel provision. Results vary quite significantly among the scenarios investigated, exemplifying the need to consider the question on a farm-by-farm basis.

KEYWORDS
Bayesian modelling, decision making, failure modelling, night shifts, offshore wind, OM

1 | INTRODUCTION

Offshore wind has become an attractive option for decarbonizing electricity production. As such, it is expected to contribute an increasingly significant proportion to the world's energy mix in the coming decade. Collectively, European countries aim to increase offshore wind capacity by 89 GW.[1] Asian countries (most prominently China, Taiwan and Vietnam) aim for up to 100 GW by 2030.[2] The US plans to increase their capacity from a single 12 MW demonstration project to 28.1 GW.[1] With over 200 GW of new offshore wind capacity to be installed over the next decade, research into cost reduction opportunities for offshore wind continues to be relevant and advantageous to the industry.

This gearshift in the scale of deployment in the industry is made possible by recent progress in lowering the cost of offshore wind farms (OWFs). Countries in Europe have seen especially auspicious trends, with both German[3] and Dutch[4] projects placing bids for zero-subsidy funding in recent years. In the UK, it has resulted in Contract for Difference (CfD) Allocation Round 3 strike prices announced in September 2019 which where around 30% lower than the previous 2017 auction, ranging between £39 and £41/MWh (in 2012 prices).[1] This reduction has exceeded expectations for the industry—a fact which is highlighted by considering the target levelized cost of energy (LCoE) of £100/MWh set jointly by the UK government and industry in 2012.[5]

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A significant proportion of this cost can be attributed to the operations and maintenance (O&M) phase of the project, with estimates generally in the region of 25%.[6] Reducing risk during this most lengthy phase of the project can lead to significant savings, a fact which has made O&M a prominent area of research in the offshore wind community. Leveraging this research to reduce operating costs is one way in which to ensure financial viability for OWFs put under pressure by competitive CfD auctions to place progressively low bids. As a result of this financial lever, operators must continuously optimize their O&M strategy to address the unique challenges associated with maintaining offshore wind turbines. This consists of reducing turbine unavailability in the most cost-effective manner under the constraints of weather restrictions on safe access and expensive vessel charters.

This effort has been helped along by the development of O&M simulation tools of varying complexity, relating to both long-term strategy[7,8] and day-to-day decision making.[9–13] On top of this, the advent of increasingly sophisticated tools for on-site data collection, management and analysis is becoming steadily more influential. The majority of these, however, are in the area of conditional monitoring—so much so that it now predominates in the wider O&M research space.[14,15] Studies focusing directly on real-world operational data are comparatively scarce. There is a good reason for this—such data are generally hard to come by and can be unreliable. Reder et al[16] provide an insight of how this effects failure data analysis. In particular, they highlight the following: the general lack of availability and poor quality of such data, the nonuniformity of its treatment and the difficulty of augmenting reliability analyses with other data-streams. International Energy Agency (IEA) Wind task 33 also explored this theme, summarizing that 'there is broad industry recognition of the relevance of reliability data collection and analyses for optimizing both profit margins and LCoE. However, the lack of standards associated with reliability data is adversely impacting industry progress in addressing reliability issues'.[17] These are issues which may equally be said of the operations dataset as a whole.

This study aims to fill a small but important part of the research gap. It is based on the analysis of a high-quality operations database provided by an OWF with an advanced data management system. Specifically, the study is concerned with technician work patterns, and how these effect wind farm performance and maintenance efficiency. The potential effect of well-planned shift patterns is significant, as responding to turbine failures in a timely manner will have a significant impact on availability. Increasing the amount of time technicians have to carry out repairs (otherwise known as accessibility) will decrease average downtime and opportunity cost. From the point of view of the owner/operator, this means more profits. From the point of view of the Original Equipment Manufacturer (OEM), it means a higher chance of meeting their contracted availability. More specifically, we present a cost benefit analysis of the decision to repurpose Crew Transfer Vessels (CTVs) for corrective actions at night. This exemplifies well the trade-off constantly undertaken at OWFs to increase profit while maintaining high standards of safety. It presents an opportunity to reduce turbine downtime and improve operational efficiency; however, it comes with the potential for increased risk for technicians.

In order to gain insight from the data set, we propose the use of a Bayesian hierarchical model (BHM). BHMs map well to the problem for three reasons. First, a Bayesian hierarchical structure allows us to stratify the analysis of wind turbines into different operational categories. In Section 3.3.1, we use this feature to categorize the data by month and by various types of night shift. In alternative frequentist approaches, this might mean building separate models for each month, for which there would be insufficient samples. However, due to the influence of informative priors on the model, we are still able to make inferences. This ability to include external domain knowledge, as described by Constantinou et al,[18] is the second reason. Indeed, we also include additional 'outside' knowledge of the problem via retroactive algorithms which act on the data and inform the model on the influence of night shifts. Third, several recent studies have shown that the effect of statistical uncertainty of reliability/maintainability variables on wind turbine availability[2,19,20] is significant. The BHM has an inherent capability to handle uncertainties robustly.

The rest of the paper is structured as follows. Section 2 presents a literature review of previous studies addressing night shifts (Section 2.1), a brief justification of Bayesian modelling for analysing OWF operational data (Section 2.2) and a review of BHMs applied to offshore wind (Section 2.3). Section 3 describes the stages of the methodology employed, with Section 3.1 describing data pre-processing, Section 3.2 covering the construction of retrospective algorithms which explore the effects of night shifts, Section 3.3 covers Bayesian hierarchical modelling and Section 3.4 cost-modelling assumptions. Section 4 presents the results in the form of posterior predictive distributions and a comparison of means between night shift and non night shift posterior densities. This includes a section on posterior predictive checking (Section 4.1), on estimated monetary savings afforded by night shifts and their sensitivity to modelling assumptions (Section 4.2), on improvements in time-based availability afforded by night shifts (Section 4.3), a brief review of operational risk for offshore night working (Section 4.4) and a general discussion of results (4.5). Section 5 contains concluding remarks.

2 | LITERATURE REVIEW

2.1 | Night shifts

There are two primary benefits of adopting a night shift for corrective maintenance. The first is to avoid lost production due to downtime from turbine faults. This benefit is presumably most prevalent in months characterized by high wind speeds, where access conditions are difficult and the opportunity cost associated with unplanned downtime is high. There may also, however, be an indirect cost associated with spreading resources and avoiding redundancy, as noted by Dalgic et al.[21]—a benefit which depends largely on the planning and foresight of the operator.

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There are a few studies which address 24/7 working in the literature. Night shifts have been analysed using the StrathOW-OM cost-modelling tool,[21] Besnard et al.'s maintenance support organization model[22] and via a business case by Poulsen et al.[23] All studies presented considerable advantages to employing 24/7 working. Dalgic et al[21] simulated different configurations of CTV utilization, presenting their results in a £/MWh format. They concluded that '10 out of the most costly 17 configurations do not have CTV for Night Shift' and that 'the number of CTVs during Day Shift and Night Shift is distributed evenly (or close to even) in best configurations such as 4-4 and 5-4, because the resources are utilized in an optimum manner with minimum redundancy'. Besnard et al[22] concluded that 'the availability increases by almost 1% for each logistic solution by using 24/7 work shifts instead of 12/7 work shifts' and report a financial benefit amounting to 5%–15% of O&M costs. Poulsen et al[23] concluded that by implementing 24/7 working savings of approximately 1,800,000€ per year can be realized via a series of expert interviews and dedicated focus groups.

In this study, we address the same question but provide novelty by employing a data-modelling approach in the form of a BHM. This means that, in contrast to previous studies examining night shifts for OWFs, the methodology we employ provides real-world evidence of night shift effectiveness. We investigate 24/7 working as it was utilized at the site: by repurposing CTVs for corrective maintenance activities for a night shift. This strategy was used throughout the months of November, December, January and February in an attempt to improve accessibility in times where the industry regards turbine failures both most frequent and most costly.

2.2 | A Bayesian perspective on decision making

Making improvements on operational decision making tools for the future requires a more thorough treatment of both aleatory and epistemic uncertainties. Previously, Zitrou et al[24–26] set out explicitly to tackle both of these categories within the field of offshore wind. In the first of the studies cited,[24] epistemic uncertainty is handled via expert knowledge, but statistical uncertainty is also accounted for in the model. The second[25] focuses specifically on epistemic uncertainty via an expected value of perfect information approach. The third[24] again highlights how both epistemic and aleatory uncertainty are modelled via a general marked point process model. While these models are probabilistic (in that they use Monte Carlo simulations to derive probability distributions of variables), they are not Bayesian, as they do not depend on Bayes rule. Likewise, cost-modelling tools which simulate the O&M phase via Monte Carlo simulations are probabilistic but do not necessarily make use of the advantages of Bayesian modelling. This study is driven by a similar objective—that decision making can be improved via a more thorough understanding of uncertainty. However, we differ in our means by the use of Bayes rule. This allows for real-world evidence to update prior beliefs on a decision taken by an operational wind farm.

Zitrou et al.'s tools are designed for use in the pre-operational stage of a wind farm. We propose that there is value to be had in an alternative approach—in retrospective analysis of operational data. In outlook, this is more closely aligned with the work of Dinwoodie et al.[27] Decisions at OWF are dynamic. Changes in strategy require synthesis of historical data and some form of hypothesized solution. Bayesian modelling provides a means to do this with small datasets, allowing a framework of new data integration and integration of different sources of knowledge. By design, it is flexible and allows for uncertainty quantification. The Bayesian hierarchical approach is somewhat different from the dynamic Bayesian network they propose. The primary motivation behind this difference is the ability of hierarchical approach to share statistical strength among operational contexts.

We demonstrate the use of Bayesian modelling in this study by applying a BHM to an operational dataset produced by an advanced data management system. As a result of this system, parts of the database are of relatively high quality—this is a key factor in deriving value from a retrospective analysis. There are detailed transfer of control logs conveying precise information about task times. Maintenance task types are clearly delineated, meaning that reliability can be estimated at least at a turbine level. We augment the analysis of this 'Operations' dataset by also incorporating SCADA and weather data. The hierarchical modelling approach allows us to track the aleatory uncertainty of variables under different operational assumptions and ultimately address an issue which was of interest to the operator. However, we propose that the approach could be useful for undertaking more thorough reliability analyses (or questions of strategy) based on data from multiple sites.

2.3 | Bayesian hierarchical modelling in offshore wind

BHMs have seen some previous use in wind energy research. Predominantly, they have been used for weather modelling and wind speed forecasting. Dobigeon and Tourneret used a BHM to account for correlations between wind speed and direction.[28] Miranda and Dunn[29] developed BHM to model the autocorrelation structure of consecutive wind speed data.

BHMs have seen a limited application to modelling operational data from OWFs. Wilke and Galasso used the technique to assess WT capacity factors in a recent study.[30] This is arguably the most closely aligned application of the methodology to the case study presented here. However, to the authors' best knowledge, there are no studies which apply hierarchical models to questions of strategy or maintainability of WTs.

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Abaei et al[31] use a hierarchical Bayesian framework to assess the reliability of a modular tide generator. They argue that the method's capability to handle uncertainties robustly has the potential to 'minimize perceived risks and reduce the associated cost for operation and maintenance'. Despite similar data issues that plague offshore wind research and recent interest surrounding uncertainty in cost modelling (as highlighted by Seyr and Mulkulus,[15] Scheu et al[20] and Dao et al.[2]), no similar studies have been applied in the wind industry.

We argue that this presents a research gap. Questions of operational strategy at OWFs can be informed by data analysis, which can play a central role in substantiating the analyses of O&M modellers with real-world evidence. It is important to understand, and put into context, not only what operators can expect to happen in general but also the uncertainty associated with that expectation. The Bayesian hierarchical approach we propose presents a case study were the uncertainty is integrated into the decision making process. Given a small sample size, this is no trivial task. However, the selected methodology allows for statistical strength to be shared among categories while also accounting for variation due to seasonality, night shift organization and failure rate. This means that improved estimates are possible compared with the outputs of cost-modelling tools, of both mean values and uncertainty. Since operational decision making is concerned not only with predictions but how certain decision makers are with them, this is vital.

3 | METHODOLOGY

We assess the different work-shift strategies by drawing inferences based on the historical dataset for the site. The methodology employed to do so consists broadly of four steps:

1. Data manipulation—consisting of data cleaning, integration, selection and transformation.
2. Synthetic data creation. Using the data resulting from step 1, we explored hypothetical scenarios by adjusting the historical dataset via a series of if-then pieces of logic.
3. Bayesian inference. Constructing a Bayesian model to assess differences in wind farm performance, as evidenced by the synthetic datasets created in step 2.
4. Cost modelling and sensitivity analysis. Defines key cost assumptions which are applied to model outputs and varies these to explore their relationship to the results obtained.

The following subsections elaborate on these steps. Note that the novelty of the methodology is found in applying Bayesian hierarchical modelling to data coming from a currently operational OWF.

3.1 | Data manipulation

3.1.1 | Data Source

The current analysis is based on a historical database provided by a large, currently operational OWF. It consists of Supervisory Control & Data Acquisition (SCADA), weather and operational data describing the performance, meteorological conditions and maintenance actions performed for a large group of modern, geared wind turbines with a multi-MW power rating. The farm utilizes a typical condition-based maintenance strategy and is located around an hour-long trip from its operational base by CTV.

3.1.2 | Data preprocessing

The first step in constructing Bayesian inferences from the historical data is to collate relevant information from the database into a set of more compact data tables. By data table, we refer to a two-dimensional labelled data structure, where columns often contain different types of data. This was particularly important for the section of the database which can be characterized as containing 'operational' data, which contained 249 different data tables summarizing daily operations at the farm. Naturally, not all of these contain complete or useful information, so data reduction and cleaning is vital. This first step was achieved mainly via the Standard Query Language (SQL) for databases. A summary of those data tables which proved to be most important to the following analysis is detailed in Table 1. These data tables were condensed by data type (i.e. into the categories *Operational*, *SCADA*, *Weather* and *Turbine Properties*), and the resultant data tables became the core of the analysis going forward. A number of intermediary steps led to the creation of these condensed tables, of which the most noteworthy are as follows:

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TABLE 1 Metadata table containing the parts of the operational database used here.

Data type	Data table	Description	No. of entries
Operations	Operations Planned Movements	Contains information on planned technician movements for every shift. Crucially contains manual acknowledge and card swipe times recording technician transfers to/from turbines.	319,554
	Vessel Stops	Similar information as operations planned movements, but with less reliable timestamps and the extra information: stop type (pick-up or drop-off), stop order and a task ID.	103,263
	Operations Shift Tasks	Mainly a connection point for other important tables. Includes a shift ID, task ID, vessel ID and information about whether the task was completed or aborted.	40,667
	Tasks	Contains some information about every task performed or scheduled. Provides a description for each task, however descriptions for corrective works are mostly a single alarm code. Also contains some unreliable timestamps relating to task commencing/ending dates.	59,656
	Task Types	A set of 79 work order types which categorize entries in Tasks. Many are for individual actions of grouped works and can be reduced down to broader categories (e.g. INSPECTION - Lift —> Inspection).	79
SCADA	SCADA by time period (e.g. July 2019)	Typical WT SCADA data recording: anemometer wind speed, active power, yaw direction, wind direction, generator speed, pitch angle, rotor speed and operational state at 10 min intervals for every turbine.	31,806,965
Weather	Wave Buoy Readings	Hourly significant wave height recordings from two wave buoys at the site. Wave height typically taken as an average of the two.	45,572
	Met Mast Readings	Hourly wind speed averages measured at 20 and 80 m heights; hourly wind direction averages at measured 76 m height; hourly tide level readings.	143,122
Turbine properties	Turbines	Records each turbine's latitude and longitude, and provides a water depth recording at their position.	Confidential
	Turbine Groups	Records each turbine's accessibility restraints as one of: tidally restricted or severely tidally restricted.	4
Combined datastreams	Downtime Catalogue	Contains a list of downtime events for each turbine. Labelled with: downtime start/end time, first drop-off time, last pick-up time, maintenance category, total downtime, repair time, number of visits, number of transfers, access restrictions, distance to base, location, failure type, man hours.	12,215
	Turbine Regressors	Records each turbine's active power regression coefficients to it's nearest neighbours and the farm average power output.	Confidential
	Night Shift Lookup Table	A record of the maintenance actions carried out on each night shift. Each night contains info. on which turbines were visited and how many technicians visited them. Also contains indices indicating whether the work could have been completed were there only nine or six technicians on night shift.	482
	Weekly Performance Records	A breakdown of each turbine's lost production due to corrective maintenance in every week.	29,750

1. The 79 maintenance task types listed in *Task Types* were further categorized into nine categories: Annual Services, Blades, Corrective, Corrective - Balance of Plant (BOP), Cables, Defects & Tasks, Inspection, Retrofit and Other.
2. Planned movements were separated according to whether they had been acknowledged by technicians, and the resulting list of time-stamps was used as the basis of the condensed 'Operations' data table. Further information regarding each stop's purpose, the technicians and vessel involved, the location and shift was added.

Next, the table *Downtime Catalogue*, also summarized in Table 1, was created by cross-referencing *Operations* and *SCADA*, so that every period of turbine downtime is associated with a corresponding set of maintenance tasks. *Turbine Properties* was merged, and various queries were made to estimate pertinent metrics for each downtime event. At this stage, *SCADA* was also used to create the table *Turbine Regressors*, which records regression coefficients for each turbine's active power to that of its nearest neighbours, as we have described in a previous study.[32] *Night Shift Lookup Table* was created from *Downtime Catalogue* and *Operations* to use as reference for estimating the impact of varying technician team size on night shift effectiveness.

The final step of data manipulation consisted of combining *Downtime Catalogue* and *Turbine Regressors* and splitting the data into either monthly or weekly time periods to create *Monthly Performance Records* and *Weekly Performance Records*, respectively. While it is typical for operators to track monthly Key Performance Indicators (KPIs) for OWFs, *Weekly Performance Records* was created so that there would be more samples to inform the following Bayesian analysis. *Weekly Performance records* is therefore used as the input to the Bayesian model.

3.2 | Synthetic data creation

The impact of night shifts on lost production due to repairs was analysed using two pieces of logic.

The first addressed the period of November through February (inclusive), where night shifts were in operation at the site. This involved estimating the reduction of downtime achieved by the work which was undertaken at night, which involved reusing CTVs for a shift starting at 10 p.-m. This time of year is characterized by a higher wind energy content, so the opportunity cost from any given failure is expected to be greater. Also, the industry tends to regard the winter months as a time of high failure rates. Research in academia has corroborated this notion.[33,34] Algorithm 1 provides the psuedocode used for estimating a hypothetical lost production for each event, which was used to update *Weekly Performance Records*. Effectively, we displace the work undertaken at night to the next available shift, then assume a knock-on effect of subsequent works. There is a clause in the algorithm which estimates the effect of having different numbers of technicians in the night team, which we evaluate at 12, 9 and 6. For technician teams of six or nine, *Night Shift Lookup Table* was used to estimate which maintenance actions could still go ahead with less technicians available and would therefore lead to reduced lost production.

The second piece of logic addressed the period between March and October (inclusive), where night shifts were not in operation. This switches the question from *how much 'lost production' was avoided by employing night shifts?* to *how much 'lost production' could be avoided by employing night shifts over the entire year?* We look at all corrective events which had overnight downtime. We assume that one vessel would be repurposed to address corrective works at night and that there is suitable resources in terms of technicians to do so. The algorithm employed (Algorithm 2) incorporates the *Weather* data table, seeks out weather windows during the night where the significant wave height does not exceed 1.3 m and 're-orders' the timeline of repair works such that turbine downtime is reduced. 1.3 m was used as it is the threshold used by the site during the day shift. There is a shortcoming with this approach: namely, that it is unable to capture all of the operational factors which are inherent in deciding which turbines to visit during a given shift. This will differ given availability of spare parts, severity of fault and/or availability of appropriately qualified technicians. Since it is assumed that one vessel is in use during any given night shift, faults are selected simply by their proximity to the O&M service base. Again, we evaluate the strategy with a team of 12 technicians, 9 technicians and with a team of 6.

Algorithm 1 Pseudocode for estimating avoided lost production during winter

```
for each row in Downtime Catalogue do
    Cut Operations down to between start & end of downtime event
    Cut Operations again to jobs that occurred during night shift
    Re-sample resulting Dataframe by night shift
    Group by turbine and shift
    if no. techs available = 12 then
        Calculate number of night-tasks completed & total hours completed
    else no. techs available < 12
        Use Night Shift Lookup Table to estimate how many tasks would have been completed
        Calculate number of night-tasks completed & total hours completed
    end if
end for
if no. night shifts > 0 then
    Cut Weather down to above end of downtime event
    Label subsequent day-shift hours as work hours or non-work hours
    Count out the requisite number of extra day work hours required to complete the task in question
    Store hypothetical task end time
else return 0
    Employ turbine regressors to calculate lost production and hypothetical lost production
end if
```

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Algorithm 2 Pseudocode for estimating the potential for avoided lost production for the months March through October

```
for each row in Downtime Catalogue do
    Cut Operations down to between start & end of downtime event
    Create daily lookup table with shift starting time and amount of time spent undertaking works for each downtime event
    Cross-reference look up table with Weather to determine hourly wave-height readings throughout duration of downtime
    Update lookup table to include fictitious night shifts
    Determine whether fictitious night shifts are weather-appropriate for undertaking maintenance works
    Lookup entries of fictitious night shift already recorded to assess whether there are enough technicians to perform work
end for
for each row in Lookup Table do
    if there exists available night shifts then
        if there are day shifts where weather conditions are fine but no work has been carried out then
            Assume insufficient resources and return 0 change in lost production
        else
            Reshuffle lookup table so that most immediate shifts are utilized in maintenance work
            Employ turbine regressors to calculate lost production and hypothetical lost production
        end if
    end if
end for
```

3.3 | Bayesian hierarchical modelling

Hierarchical modelling is a generalization of the typical Bayesian network (BN). It differs from BNs in that they directly characterize the relationships manifest in structured data types. This is represented by Figure 1, where a simple BN consisting of variables A, B and C takes on three different structural forms in an attempt to capture dependence between the subcategories BI and BII. The relationship between 'subnodes' BI and BII is referred to as a 'part-of' relationship by Gyftodimos and Flach.[35] The left-most diagram characterizes this particular part-of relationship via a 'nested node'. The middle diagram represents a 'tree structure' where the variables of the model are descendants of a top-level composite node *t*. The right-most diagram shows how the structure can be flattened back into a regular BN.

This step from the nonhierarchical BN to the hierarchical model introduces some key differences which allow us to approach many multi-parameter problems in a more natural and intuitive way. In particular, the concept of 'partial pooling' becomes useful in many applications. This relates to phenomena which may be assumed to have a 'global' effect, the influence of which varies under different conditions or between different subgroups. To take an example from the wind industry, all wind turbines share a similar set of failure mechanisms; however, the frequency or consequence of those failures is assumed to vary with wind speed/turbulence, maintenance strategy, WT type and access conditions. In the absence of hierarchical modelling, there are two options to account for these variations:

1. Estimate a global average from the broad pool of all wind turbines.
2. Consider failure rates and downtimes separately for (e.g.) each category of WT type.

Taken more generally, approach (1) is an example of a pooled model and approach (2) an unpooled model. Both will lead to inaccuracies in prediction. The first is insufficient for large datasets because it discards information relating to the inherent relationships in the data, and the second is in danger of overfitting, meaning that it fits existing data very well but lacks any predictive power. A BHM finds a compromise such that information can be shared between groups while also maintaining the benefit of the global averages. The three approaches are summarized in Figure 2, which represents some modelling of parameters θ_i based on observations y_i. In Bayesian modelling, option 2 (C) is achieved not by specifying probabilistic distributions for θ_i in themselves but via so-called hyperprior distributions for the parameters μ,σ. In this way, the conditional probability distributions of separate groups (θ_i)'s are viewed as a sample from a common population distribution and share information via their common hyperpriors. This results in shrinkage of group means away from their individual sample towards the mean of the collective, an effect which is particularly useful for groups with small sample sizes. In specifying our priors, we therefore have influence over the mean and variance of posterior estimates for the hyperpriors μ,σ, influence over the mean and variance of parameters θ_i and influence over the shrinkage effect of those θ_i parameters from the global mean.

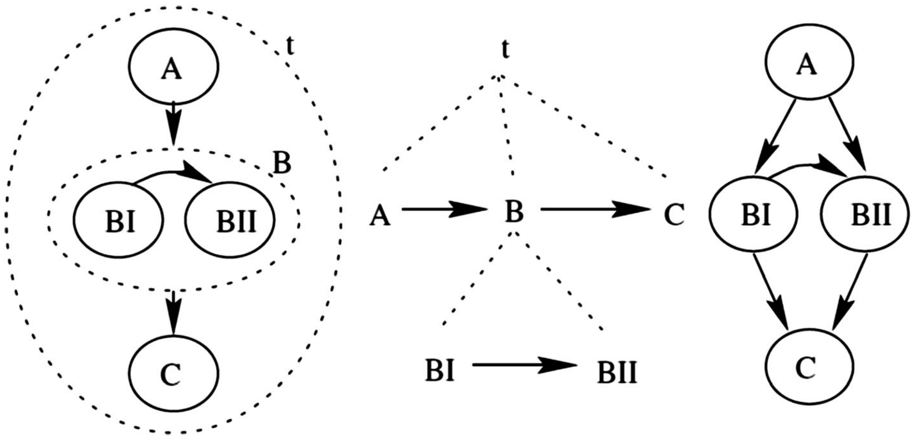

FIGURE 1 Various visualizations of related variables within a Bayesian network (BN). Taken from Gyftodimos and Flach[35].

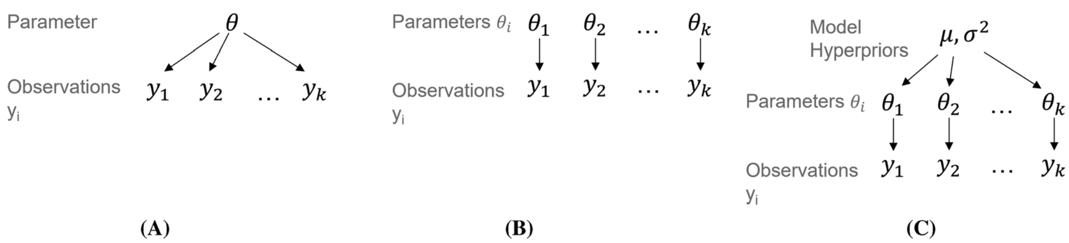

FIGURE 2 An example of (A) pooled, (B) unpooled and (C) partial pooled models for some parameters θ_i, observations y_i and hyperpriors μ and σ^2.

3.3.1 | Model specification

We build two models to explore two Key Performance Indicators (KPIs), namely:

1. Opportunity cost, presented in units of £/MW installed capacity. Calculated by estimating lost production due to corrective maintenance per week via the model, applying a constant price of energy (see Section 3.4) to each posterior density point and dividing by the capacity of the farm.
2. Time-based technical availability. Defined as the ratio of downtime due solely to corrective maintenance time, measured as a percentage.

We model both variables (denoted y_{LP} and y_{av}) via truncated normal distributions, such that

$$y^{LP} \sim Normal(\theta^{LP}_{NS,seas}, \sigma^{LP}_y); y^{LP} \in [0, \infty], \tag{1}$$

$$y^{av} \sim Normal(\theta^{av}_{NS,seas}, \sigma_y); y^{av} \in [0,1], \tag{2}$$

Beyond this point, both models have the same formulation with different priors. We therefore drop the superscript index and define generic variables for both. With that in mind, variables $\theta_{NS,seas}$ and σ_y are defined as follows:

$$\theta_{seas,NS} = \alpha_{seas} + \beta_{seas} x_{NS}, \tag{3}$$

and

$$\sigma_y = Exponential(\lambda). \tag{4}$$

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The variable α_{seas} represents the expected lost production or availability per month, β_{seas} represents the variation of lost production or availability values due to the presence of night shifts and x_{NS} represents a binary data label specifying whether night shifts are on or not. We model α_{seas} and β_{seas} via a multivariate normal distribution, such that the covariance between them can be modelled as follows:

$$\begin{bmatrix} \alpha_{seas} \\ \beta_{seas} \end{bmatrix} = MV\ Normal\left(\begin{bmatrix} \alpha \\ \beta \end{bmatrix}, \Sigma\right), \tag{5}$$

where α represents the mean value of lost production over each week, β represents the mean difference in each week due to night shifts and

$$\Sigma = \begin{pmatrix} \sigma_\alpha & 0 \\ 0 & \sigma_\beta \end{pmatrix} C \begin{pmatrix} \sigma_\alpha & 0 \\ 0 & \sigma_\beta \end{pmatrix}, \tag{6}$$

where C is a correlation matrix between seasonal-and-night-shift dependent parameters. This formulation, known as a Cholesky decomposition,[36] allows us to induce a prior on the covariance matrix given a prior is defined for C. We define the prior using the Lewandowski–Kurowicka–Joe (LKJ) distribution,[37] which is dependent on a regularization parameter ζ. $\zeta = 1$ implies a noninformative uniform distribution on correlation matrices, and the magnitude of correlations between components decreases as ζ increases. We select $\zeta = 2$ so as to have some regularization on C.

As part of the sensitivity analysis, we also categorize the data via failure rate. We explore the influence of failure rate by altering the hierarchical model to include it as another feature. In order to do so, we discretize the turbines into 'high', 'medium' and 'low' failure rates. This is based on the sample quantiles, such that there are an approximately equal number of turbines in each bin. We altered the priors shown in Figure 3 to accommodate the change in the model. This followed the same process as before but with fewer turbines in the simulation. Where failure rates are introduced, we extend the hierarchical structure to accommodate two levels. In this case, the only thing that changes is the number of indices for the α and β parameters:

$$\theta_{seas,fr,NS} = \alpha_{seas,fr} + \beta_{seas,fr} x_{NS}, \tag{7}$$

where the index fr denotes failure rate quantiles.

3.3.2 | Hyperprior elicitation

In hierarchical models, prior information is introduced via so-called hyperpriors which regularize global averages and variances. In this case, the hyperpriors are the μ and σ parameters. Broadly speaking, there are a two categories of prior we can consider:

1. Noninformative or weakly informative priors. Noninformative or weakly informative priors are used when there are no or little existing data or firm expert judgement available which relates to the problem in question. In this case, it might seem convenient to assign equal probabilities to all possibilities (a uniform prior) or to use (e.g.) a very diffuse normal distribution. In our case, there are two arguments against this. The first is a generic argument against the use noninformative priors,[38] which are discouraged. The second relates to this dataset in particular. Given that we condense data into weekly segments, there are <200 weeks overall to inform the model and <20 for each month of the year. To let the data dominate the posterior may therefore lead to poor inferences, in the same way that frequentist approaches with small sample sizes may do.
2. Informative priors are at the other end of the scale—they convey precise information about a variable. This is achieved either by expert elicitation or by some empirical Bayesian method. The latter category encompasses methods by which to estimate priors from the dataset itself, before undertaking a formal Bayesian analysis. This is something of a compromise between frequentist and Bayesian approaches which negates some of the benefits of our proposed methodology, so we deem it unsuitable for this study. Of the former category, a metadata analysis of other studies may be hindered by common confidentiality practices of the industry, and surveyed expert opinions are outwith the scope of the project. We judge that the most robust treatment of our prior knowledge can be provided by a O&M cost-modelling tool, of which there are many examples in the literature.[15]

We therefore rely on the use of the StrathOW-OM tool,[7] an O&M cost model designed for strategic planning purposes. Prior estimates for α and $\beta, \sigma_\alpha, \sigma_\beta$ and λ are obtained via a two-stage Bayesian updating approach as described by Yu et al,[39] where the output of the StrathOW-OM is considered as historical data. First, we specified weakly informative *pre-priors*, in the form of normal distributions for α and β, σ_α and σ_β with large variances in comparison with the means and exponential distribution for σ_y with a weakly informative rate parameter; the StrathOW-OM was run with the input assumptions described in Table 2. The outputs were adjusted so that we could retrieve the lost production and availability per

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TABLE 2 Input assumptions for the StrathOW-OM tool used for prior elicitation.

Variable	Description and source
Failure rates, repair times	We make an assumption of zero prior knowledge of failure rates at the current site before the implementation of the Bayesian model. Failure rates and repair times therefore come from Carroll et al.[40]
Vessels	We assume there are six CTVs operating at the site via a long-term charter, which is closest to the average of 6.33 vessel used per day, each having a 12-person capacity.
Weather	Weather readings from the on-site met and wave measurement equipment are fed into the tool, which in turn simulates weather conditions with similar characteristics.
Power curve	The power curve was estimated using the SCADA readings from the site, by binning data by wind speed and averaging power output within each bin.
Governing weather criteria	CTV: wave height - 1.3 m, SOV: wave height - 1.3 m, heavy-lift vessel: wind speed - 10 m/s.

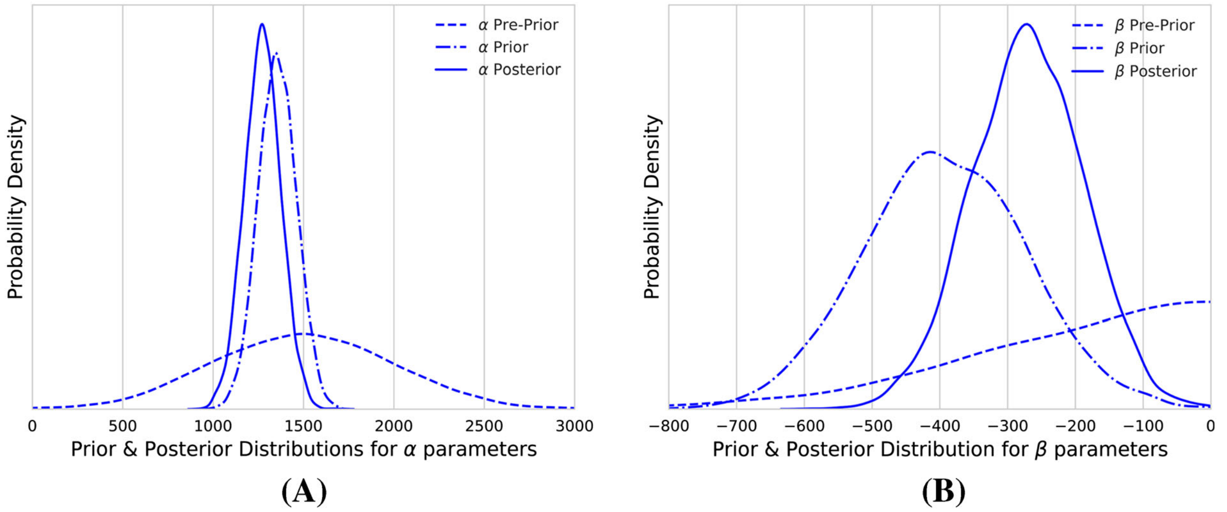

FIGURE 3 Kernel density estimate plots showing pre-prior, prior and posterior distributions for the hyperparameters (A) α and (B) β, representing the weekly lost production average value and the average savings value afforded by night shifts [Colour figure can be viewed at wileyonlinelibrary.com]

week. More informative priors could then be estimated by retrieving posterior inferences for model parameters from the BHM, using the StrathOW-OM model output as the likelihood. The refinement of the parameters α and β for the lost production model, from the weakly informative 'pre-priors' to the priors and eventually to the posterior estimates, is shown in Figure 3A,B.

3.3.3 | Posterior calculation

Posterior calculation is the name given to the step of conditioning on observed data. This step is the key principle of Bayesian inference and is neatly encapsulated within Bayes' theorem. For the model specified as above, this looks like:

$$p(\theta_{seas,NS}|y) = \frac{p(\theta_{seas,NS})p(y|\theta_{seas,NS})}{p(y)}, \tag{8}$$

where the conditional probability distribution of the unobserved quantities of interest, $p(\theta_{seas,NS}|y_{seas,NS})$, is estimated. This is commonly referred to as the *posterior* distribution. $p(y_{seas,NS})$ is the nonzero probability of observation y, which is given by a sum over all possible values of θ:

$$p(y) = \int_{\theta_{seas,NS}} p(\theta_{seas,NS})p(y|\theta_{seas,NS})d\theta_{seas,NS}, \tag{9}$$

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While the numerator is easily solved for, solving for the denominator is much more difficult, often proving intractable for many problems. For this reason, the posterior is often calculated by some approximate statistical inference methods, as outlined below.

3.3.4 | Sampling method

Since researchers cannot typically rely on exact posterior inference via an analytical solution of Bayes's rule, they turn to numerical integration techniques, of which there are two categories: deterministic and stochastic. Within the family of stochastic techniques, a general class of algorithms named Markov Chain Monte Carlo (MCMC) has been particularly important in making Bayesian inference practical for generic hierarchical models.[41] MCMC allows the Bayesian researcher to draw a series of correlated samples that will converge in distribution to the specified target distribution of the model.[42]

Among this family of algorithms, Hamiltonian Monte Carlo (HMC) is often considered the most effective.[43] HMC works by treating probabilistic systems as if they are physical systems, shifting the problem from that of sampling from a target distribution to the simulation of Hamiltonian dynamics.[44] This allows for much more efficient sampling, as it avoids for the computationally inefficient random walk behaviour characteristic of algorithms such as Metropolis[45] or Gibbs[46] sampling to be done away with. A particular advantage of using PYMC3 software is the application of the No-U-Turn Sampler (NUTS), a variation on the typical HMC algorithm[43] which eliminates the need to hand-tune HMC via a parameter which defines the number of steps in the simulation. This provides a certain accessibility to practitioners, as tuning of the model usually requires some prior experience or expertise, and can be time-consuming.

The NUTS sampler is therefore readily applicable to the model. However, there are a few parameters which need to be specified before samples can be drawn from the posterior. We use 1000 tuning steps, which effectively act as an initial training period for the sampler to converge to the target distribution by optimizing the step size parameter of the HMC. The number 1000 was selected by experimentation—for computational efficiency, it is best to minimize this while maintaining a robust model. Once this initial tuning has taken place, these samples are discarded as there is no guarantee that they have asymptotically come from the target distribution. We go on to sample 4000 draws from the target posterior distribution using four chains (pymc3 uses 1 CPU core per chain—four chains reflect a 4-core computer). Again 4000 draws are something of a compromise between computational efficiency and having enough posterior samples to draw from to reflect the target distribution. The number of chains specifies the number of Markov chains to run and is useful for checking that the model has converged to a stationary target distribution.

Figure 4 explores the convergence of the NUTS algorithm given the above parameters. As described by Betancourt,[47] when the marginal energy and energy transition distributions of any given Hamiltonian Markov transition are well matched, the Markov chains are likely to be performing robustly and will present small autocorrelations.

3.4 | Cost-modelling assumptions

There are additional expenses and savings to be considered in the case of night shifts, for which assumptions must be made. These relate to cost modelling, and are detailed below:

1. The number of vessels needed & the cost of their charters. We assume that the effect of night shifts is to 'displace' a vessel from the day shift to the night, effectively allowing the opportunity to avoid a vessel charter by reusing a day-time vessel. Further, we assume a daily vessel charter rate of £1750, as is assumed by Dinwoodie et al.[7]
2. The value of electricity. This will vary from farm to farm depending on the support mechanism employed in each case. For simplicity, we consider a constant value of 120 £/MWh as the base case and consider varying values of constant prices between 40 and 150 £/MWh within the sensitivity analyses.
3. Technician and support staff wages. There are three scenarios to select from: one that supports 6 technicians per night shift, one that supports 9 and one that supports 12, as well as onshore support staff and vessel skippers. For each scenario, we assume that there are two onshore staff and two vessel operators. We assume that all staff receive £20 an hour (based on the average technician salaray[48]) and assume a baseline case that staff receive time and a half for their work. This amounts to a weekly added cost of £13,400 in the case of 12 technicians, £10,920 in the case of 6 technicians and £8400 in the case of 6 technicians. It is assumed that there are night workers on call for the entirety of the period that night shifts are in operation.
4. Months per year working 24/7. In the sensitivity analysis below, we only include profitable months in yearly calculations. For example, if night shifts are not found to be profitable in the Summer months, they are excluded.

Where cost parameters are considered in the model, they are added to the posterior predictive distributions as a deterministic value.

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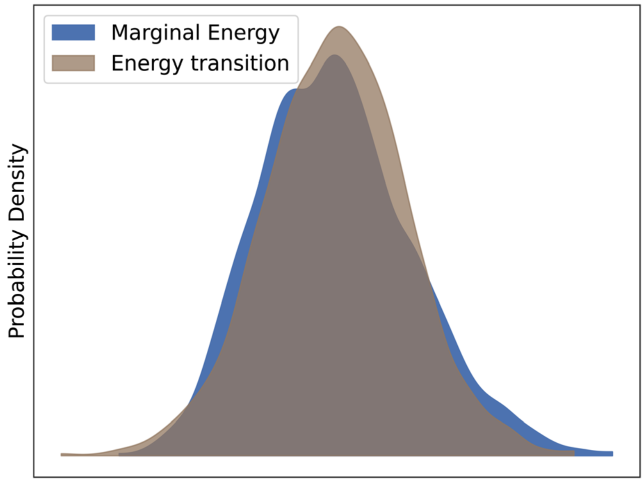

FIGURE 4 Energy plot showing the marginal energy and energy transition distributions of the Markov chains simulating model variables. Similar density functions imply a well-sampled parameter space [Colour figure can be viewed at wileyonlinelibrary.com]

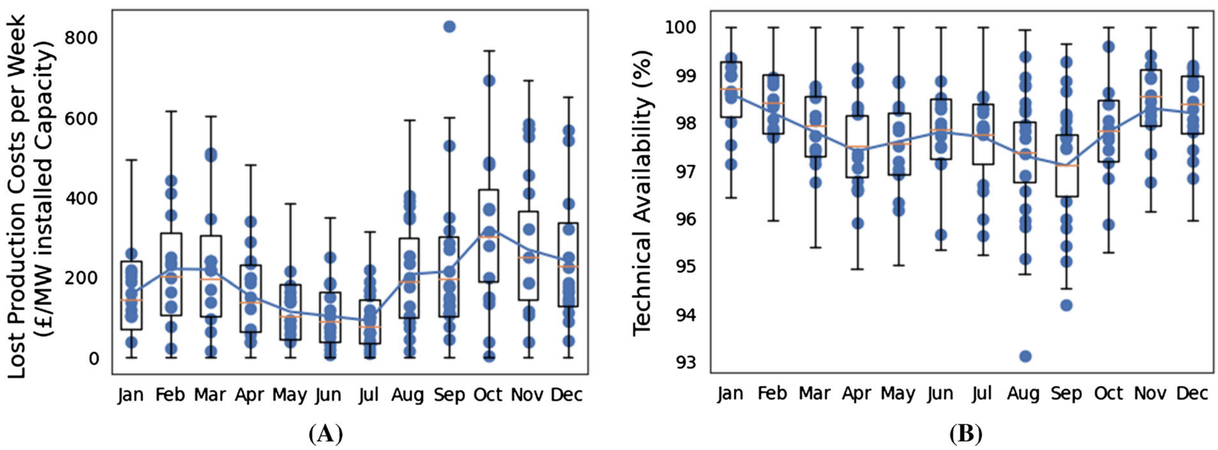

FIGURE 5 Posterior density functions describing (A) lost production per week and (B) technical availability. Mean likelihood values calculated from the data are shown by the blue line and individual data points by the blue dots [Colour figure can be viewed at wileyonlinelibrary.com]

4 | RESULTS AND DISCUSSION

4.1 | Posterior predictive checking

Posterior predictive checking is the Bayesian's way of evaluating the fit of the model and interpreting the consequences of the posterior distribution. Important questions to ask as a researcher are the following[41]:

1. *Do inferences from the model make sense in light of the substantive knowledge?*
2. *How sensitive are results to modelling assumptions?*
3. *What aspects of reality are* (inevitably) *not captured by the model?*

These questions are important for statistical analyses in general, especially so for anything under the broad heading of machine learning and specifically for Bayesian analysis for the reason that not everything can be encapsulated in a set of probability distributions.

Figure 5A,B provides an immediate sanity check that the model is behaving as it should. Here, the posterior predicted values for (A) lost production and (B) availability in each month are plotted according to the operational strategy actually employed at the site (without any inclusion of 'expert knowledge'). They confirm that data generated form the posterior parameters of the model reflects observed values. We observe more lost production in the winter months, where wind energy content is higher, access conditions least favourable and it is thought that wind turbine

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failures are more likely to occur.[33] We also observe that winter months (where night shifts are in operation) are characterized by the highest time-based availability. Elsewhere, the number of repairs carried out per month roughly reflects the trend observed by the SPARTA initiative[49]—the operator takes advantage of the favourable access conditions to carry out most minor repairs in the months with higher accessibility. Interestingly, a significant uptick in costly failures is observed in August, where wind conditions are still comparably light, and continues throughout the Autumn months. This might be a peculiarity of this site; however, it may also provide some evidence of a 'hangover' effect from the more intense summer months where the majority of scheduled maintenance and retrofitting work takes place.

Figure 6A,B explores the effect of Bayesian updating on the probability density functions (PDFs) of weekly lost production in the months of July and October, respectively. The posterior predictive distribution in both cases is significantly different to the prior beliefs which were used to derive estimates of priors for variables. This illustrates the usefulness of the Bayesian hierarchical approach in re-assessing strategy based on (statistically speaking) limited data-points. Given an operator considering extending night shifts from winter to other times of the year, a state-of-the-art operational cost model would estimate quite significant savings of opportunity cost in July. Likewise, they would have a misleading perception of October, where opportunity cost has been higher than expected. On the other hand, the data alone would be an insufficient means upon which to base future operational strategy, as the small number of samples in each month also provide an incomplete picture. The Bayesian hierarchical approach is a compromise between the two, such that samples in different months can be partially pooled to share statistical strength.

4.2 | Night shift cost savings

Results of the baseline scenario are shown in Figure 7 and column 1 of Table 3. Figure 7 shows the mean weekly lost production value throughout the year for three of the different scenarios considered: where there are no night shifts in operation and where there are night shifts in operation with either 6 or 12 technicians. The PDFs with and without night shifts show similar shapes. The 'Night Shift' scenario PDF shifts the most likely values for each month to lower values of lost production. Profits from employing night shifts are predicted to be greater in the winter than summer months. However, profits are also substantial during the months of August, September and October, where the wind energy content tends to be lower than winter. The benefit of night shifts on corrective works therefore does not solely vary with wind speed but also resource organization throughout the year and potentially on the noncorrective works being undertaken at the site. Applying the baseline scenario assumptions, as defined by the costs laid out in Section 3.4, lead us to infer a financial yearly saving of £1,625 per MW installed capacity.

Additional simulations were undertaken so that the impact of cost-modelling assumptions on the viability of the night shift regime could be assessed. The first of these was the price of electricity, which at a constant rate can be assumed to have a linear effect on the estimated costs during any given month. This is explored in columns 4–6 of Table 3. Months characterized by higher lost production values are more sensitive to the price of electricity variable. The months of June and July, for instance, are mainly influenced by savings which can be achieved via vessel leasing costs. The months of September and October vary much more. As do the winter months of January and February which are characterized by high energy content. The yearly costs, as described in the final row of Table 3, vary significantly. At lower costs of energy, the additional risk of undertaking work at night may not be worthwhile. However, there are still significant savings to be had at lower costs of energy with fewer technicians on night shift.

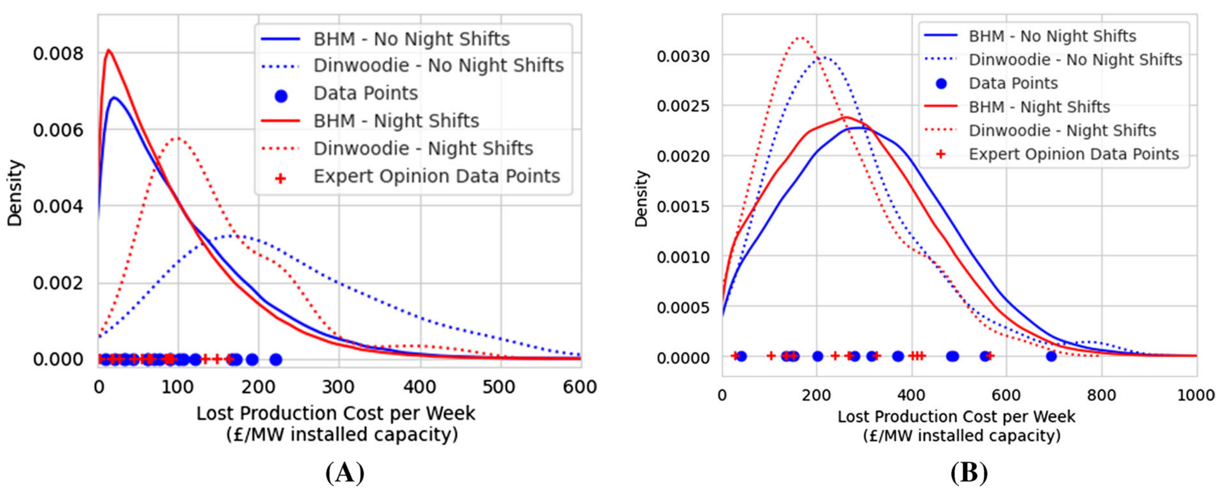

FIGURE 6 Conditional probability density describing lost production for the months of (A) July and (B) October. Probability density functions derived via the Dinwoodie model are shown via dotted lines, those derived via the hierarchical model by solid lines. Night shift scenarios are shown in red, non night shifts in blue [Colour figure can be viewed at wileyonlinelibrary.com]

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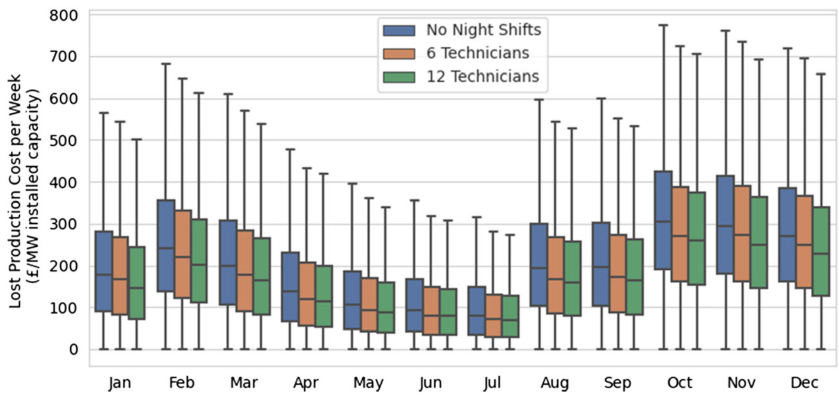

FIGURE 7 Seasonal variation of predicted lost production values in the scenarios where night shift are in operation with 12 technicians (green), in operation with 6 technicians (orange) and out of operation (blue) [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 3 Table exploring sensitivity of the baseline scenario to modelling assumptions.

	Weekly mean Δ night shift - no night shift (£/MW installed capacity)								
		Failure rate		Electricity price			Support staff wages		Extra vessel savings
	Baseline	Low	High	£40/MWh	£80/MWh	£150/MWh	(x2)	(x1)	No savings
January	27	12	42	11	17	33	15	47	8
February	33	20	57	13	21	41	16	54	14
March	29	24	37	14	19	37	16	50	10
April	22	17	30	14	18	28	12	42	6
May	19	14	21	12	15	20	10	36	4
June	18	14	18	13	15	20	9	35	3
July	17	11	14	12	14	19	7	33	1
August	28	14	32	16	22	37	15	49	9
September	30	21	32	15	21	34	15	51	11
October	39	20	69	17	27	49	20	60	20
November	37	16	84	14	24	49	18	57	17
December	37	17	50	13	23	45	17	57	17
Yearly total	1625	930	2162	745	1202	2000	806	2520	677

Results are similarly sensitive to support staff and vessel leasing costs. In the scenario where no vessel savings were achieved, there is a significant reduction in the yearly savings. At lower prices of energy, employing a night shift where we could assume no savings in vessel leasing costs could become completely unfeasible for low income months such as June and July. We draw similar conclusions in the more costly case where staff are paid double time for night shifts (the column [x2]). The effects of higher staff wages are mitigated, however, by optimizing for the most profitable number of technicians per night shift. Where technicians are paid the same as they would be on day shifts (x1), savings are most significant. Providing no incentive for night shift work, however, is bad practice for businesses considering the disruption to life it causes staff.

The final sensitivity parameter was failure rate, which was explored by extending the model to include another level in the hierarchy. The 'Low' and 'High' categories are explored in columns 3 and 4 of Table 3. There is some variability on how this effects results month-to-month. In the high wind speed months of January and February, the disparity is significant between high and low failure rate turbines. Likewise in the months October, November and December. For the yearly simulated data, the difference in the means was substantial. Savings in the summer months are more consistent. Turbines in the 'low' failure rate category see just over half the savings as the high. Figure 8A,B explores how failure rate categories effect uncertainty. Introducing night shifts has a more significant effect on higher failures. This is down not only to a reduction in the mean expected value but also to a reduction in the likelihood of high values of opportunity cost. These plots show how including additional

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parameters such as failure rate can lead to a more thorough uncertainty quantification. The uncertainty for the 'High' failure category is significantly greater than that observed in Figure 7.

4.3 | Availability savings

Results of the baseline scenario for availability are shown in Figure 9 and columns 1 and 5 of Table 4. Figure 7 shows the weekly availability posterior density throughout the year for three of the different scenarios considered: where there are no night shifts in operation and where there are night shifts in operation with either 6 or 12 technicians. Again, the 'Night Shift' scenario PDF shifts the most likely values for each month to higher availabilities. In contrast to the lost production model, the benefit of night shifts on availability is more consistent throughout the year. Repairs during the favourable access conditions of the summer are preferable to repairs in the winter.

The first half of Table 4 explores mean availability savings further. Differences in availability due to the number of technicians on night shifts are explored. On top of this, we calculate the percentage of weeks where the availability exceeds 98%. This reflects the structure of contracts for turbines which are still under warranty, where Original Equipment Manufacturers (OEM) must meet a contracted availability. Employing just one team of six technicians itself has an appreciable effect on availability, ranging between 0.36 per week in January to 0.57 in August and a yearly mean difference of 0.48. The scenario likewise has a significant effect on yearly percentages of an arranged lower availability estimate, which are met 93% more of the time than the non night shift scenario. More technicians on night shift translates to better availabilities. Employing 12 technicians means that the farm could expect to surpass a yearly time-based technical availability of 98% 99 times out of a hundred.

The second half of Table 4 explores the output of the extended availability model, which includes failure rate quantiles. Turbines with higher failure rates benefit more from night shifts. However, the disparity in availability savings between the high failure rate scenario and the baseline is not very significant, implying that night shifts can offer consistent savings on availability for OEMs or operators. In this case, OEMs would get

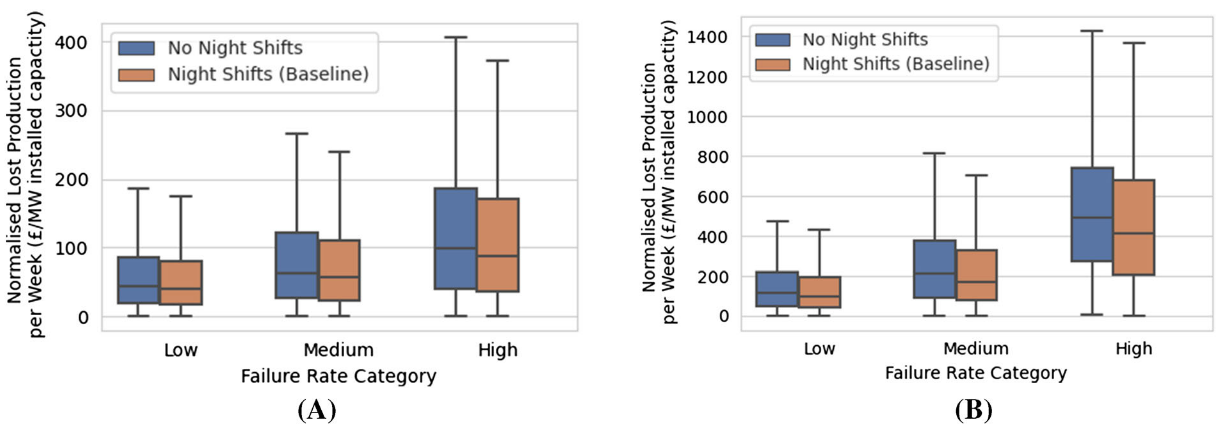

FIGURE 8 Box-plots exploring the effect of night shift baseline scenario in (A) July and (B) October for different failure rate categories [Colour figure can be viewed at wileyonlinelibrary.com]

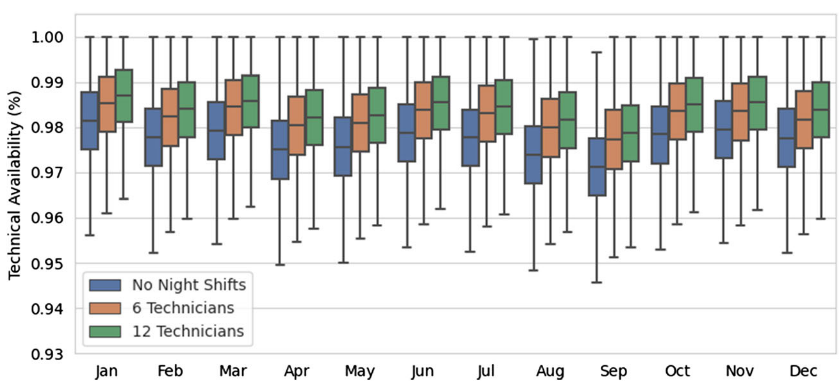

FIGURE 9 Seasonal variation of predicted availability in the scenarios where night shift are in operation with 12 technicians (green), in operation with 6 technicians (orange) and out of operation (blue) [Colour figure can be viewed at wileyonlinelibrary.com]

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TABLE 4 Table exploring night shift scenarios on availability modelling outputs.

	Mean availability difference (%)			Difference in percentage of occurrences > 98% (%)		
(All failure rate quantiles)	12 techs	9 techs	6 techs	12 techs	9 techs	6 techs
January	0.53	0.36	0.36	23	16	16
February	0.59	0.43	0.43	26	19	19
March	0.61	0.56	0.48	27	25	21
April	0.70	0.64	0.53	30	27	22
May	0.68	0.63	0.51	29	27	22
June	0.64	0.59	0.48	28	26	21
July	0.67	0.61	0.52	30	27	23
August	0.74	0.69	0.57	31	29	23
September	0.74	0.71	0.61	27	26	15
October	0.64	0.57	0.49	28	26	21
November	0.56	0.40	0.39	25	18	21
December	0.60	0.40	0.40	27	17	17
Yearly average	0.64	0.55	0.48	99	97	93
(Failure rate = high)						
January	0.44	0.28	0.27	14	10	10
February	0.76	0.61	0.58	22	18	15
March	0.54	0.47	0.42	19	16	15
April	0.70	0.65	0.56	23	20	18
May	0.74	0.67	0.56	22	20	26
June	0.53	0.48	0.34	17	16	11
July	0.58	0.53	0.44	18	16	13
August	0.88	0.82	0.72	24	23	19
September	0.95	0.86	0.77	23	22	19
October	0.49	0.44	0.42	16	15	14
November	0.70	0.53	0.47	11	16	15
December	0.74	0.59	0.53	22	17	15
Yearly average	0.68	0.56	0.50	93	89	83

more benefit from targeting certain months. For this farm, they would be August and September, which show significant savings in average availability (0.88% and 0.95%), respectively.

Unlike the cost savings presented above, availability is not normalized by the size of the farm. The results of the analysis may therefore vary according to number of turbines or existing technician work pattern structure. However, given the differences in the percentage of occurrences above the 98% availability threshold, there is evidence that night shifts can provide a significant benefit. This can be achieved with only one vessel in operation during night, with a small maintenance team.

4.4 | Operational risk

Offshore wind turbine maintenance is a balancing act. On the one hand, operators try to lower their cost of energy by reducing direct O&M costs and maintaining a high power output. On the other, they must take care to ensure the safety and well-being of their staff. The question of introducing night shifts exemplifies this risk-profit trade-off well, as the potential financial boost comes with it potential safety implications to consider for technicians.

Consideration of these safety implications for night shifts on OWFs is hindered by a lack of scrutiny by health and safety (H&S) experts, as it is currently a very under researched area. However, there are a few factors characterizing the current state of the offshore wind industry which may stimulate interest in H&S for 24/7 working. namely:

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1. Where safety regulations have typically restricted operational practices to be conducted in the daylight (as suggested by Dalgic et al.[21]), there is evidence of at least one large operational OWF moving beyond this regulatory regime.
2. Where early wind farm installations are situated in the most convenient locations closest to shore, the industry will need to explore further offshore sites if it is to meet the ambitious targets it has set. This means that operators may have to look for new ways to improve accessibility.
3. The potential advent and use of so-called flotels, mothership concepts, Service Operation Vessels (SOVs) and walk-to-work schemes for O&M activities for far-OWFs can facilitate 24/7 working with shorter distances to travel, potentially making it more appealing to operators.
4. It can be argued that the competitive nature of CfD-like auctions which are proliferating many European countries have driven the cost reduction in offshore wind. This culture might be assumed to continue into the near future and OWFs will continue to adopt money-saving measures to get a leg-up on the competition. This argument becomes especially pertinent when OWFs transition to postsubsidy financing models.

Publications in academia, or indeed industrial technical reports, about the H&S implications of night shifts for offshore wind are sparse. Garrido et al[50] come the closest by examining the effect of shift schedules on sleep patterns of OWF workers in Germany via an online questionnaire. Surprisingly, they found no effect of night shift working on sleep disorders. To the authors' best knowledge, this is the only publication to explore the subject for offshore wind; however, there are publications focusing on 24/7 working in the oil & gas industry and offshore working in general which may provide a more comprehensive frame of reference.

A notable review study[51] of offshore workers in the petroleum industry found that more sleep problems were consistently reported by night workers compared with day workers, with workers generally adapting to night shifts within one to two weeks' work. Concerning accidents occurring during night shift, it reported inconsistent findings. Two studies recorded higher H&S incidents rates during night than day,[52,53] while another[54] reported no such disparity. Interestingly, effects of reaction times (a good indicator of job performance) due to night shifts were consistently negligible across four studies.[55–58] Reaction times only suffered during the first day transitioning to night shift in a study by Waage et al.,[56] and the first day transitioning back to day shift by Bjorvatn et al.[55] A publication from the Health & Safety Executive in the UK[59] encourages a 14D/14N shift pattern for offshore oil platforms "unless there are very strong reasons why it cannot be implemented in particular circumstances", in order to allow for readjustment of circadian rhythm for workers. While in this case some of the stresses of the night shift pattern will be mitigated by the fact that technicians will be sleeping on land, these studies might prove informative for the offshore wind industry.

4.5 | Further discussion

The new findings of this paper consist of a real-world case study of night shift working. The proposed methodology, Bayesian hierarchical modelling, is novel in the sense that it has not previously been applied to failure, work order and SCADA data to aid decision making at an OWF. As a result of the methodology, uncertainty quantification for various night shift scenarios have been presented, allowing for differences in the probability distributions of various operational contexts to be explored. This is what makes the proposed methodology so well suited to the analysis of operational data. Given we measure the input data on a weekly basis, there are too few samples in each month to build statistically robust inferences. A combination of informative priors and sharing of statistical strength across categories directly addresses the issue. We provide further novelty over previous studies in the field via three means. There is something to be said of each of these in terms of benefits afforded and limitations created.

First, we assess a night shift strategy is employed by a currently operational OWF. It therefore supports a data-driven model, which provides real world evidence, over a simulation model. To the authors best knowledge, this is the first time such real world evidence has been presented in the literature. A disadvantage of the current methodology is that the case study is restricted to the data describing this one wind farm - we cannot generalize results. As a result, it is difficult to compare results with previous studies, although this would be desirable. We can make a rudimentary attempt by comparing the baseline results arrived at here to those of arrived at by Besnard et al.[22] Subtracting scenario 8 from 5 & dividing difference by the installed capacity used, we arrive at a figure of £1680/MW installed capacity to compare to our £1625/MW installed capacity. At first glance, these figures agree very well, however it is difficult to judge how coincidental this similarity is. Their conclusion that each "the availability increases by almost 1% for each logistic solution by using 24/7 work shifts instead of 12/7 work shifts" is not supported by this analysis, where the baseline scenario presents 0.64% difference. Due to confidentiality reasons, we cannot compare results to the generic figure given by Poulsen et al.[23] of 1.8M€ per year. If we take hypothetical wind farms of 200 MW, 500 MW and 1 GW, we estimate respective savings of 325,200€, 812,500 €, 1,625,000€.

Second, we undertake a sensitivity analysis to explore the impact of modelling assumptions on results. While the baseline scenario shows reasonable savings for the strategy explored, these are quickly negated by increasing support staff wages and in the case where savings in vessel charters cannot be assumed. These will grow more substantial with reduced prices of electricity or in the case of turbines with low failure rates. Each wind farm will have a unique set of circumstances to contend with, so these considerations are significant. In terms of sensitivity to these factors, Table 3 is a step on from the examination in previous studies. However, there is a lot of room for modelling assumptions to be more

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thoroughly explored, especially in modelling staff wages and vessel leasing costs. Such figures are notoriously difficult to come by in the public domain. Uncertainty in their values might still be elicited by expert judgement—a method used almost routinely in Bayesian modelling in other fields like the social sciences. Another step forward would be to more accurately capture price of energy fluctuations by some form of price modelling. This would more accurately represent the nature of CfDs or indeed postsubsidy financing. A more comprehensive Bayesian network model could also provide an estimate for LCoE. This would require the estimation of a number of additional cost parameters which were not available during the current analysis. The focus of the study was to extract value from the data that is available, and showcase the benefit of the proposed methodology in doing so. In opting to explore opportunity cost, we were able to utilize the lost production as measured from the data. Likewise, measurements of technical availability can be used to update prior estimates directly. Via these means, we could explore the KPIs which are most pertinent to the Operator and OEM. An exploration of LCoE in the Bayesian framework, on the other hand, would require a more detailed dataset.

Third, we provide evidence of the benefit of Bayesian hierarchical modelling in retroactive analysis of OWF operational data. A review of Bayesian methods in the wind industry[60] has previously suggested that this could be an advantageous avenue to explore in the wider field of Bayesian analysis, which has shown promise in addressing uncertainties in OWF maintainability. Given that there are *some* requisite data available to inform the model, the methodology provides a simple and computationally undemanding approach to draw inferences (and value) form operational data. For this specific question of night shifts, the approach was useful. However, more sophisticated model parameterizations will be needed to explore models with time-dependent covariates. As is typically the case in wind energy research, more data from other wind farms would make inferences more robust. For instance, in the results the highest probability for significant lost production from corrective maintenance was in October. It would be interesting to see if this is consistent across multiple sites or simply a peculiarity of this one. Certainly, the industrial assumption in the UK is that turbine failures are more numerous and more costly in the winter. More research into the effect of annual services on corrective maintenance requirements could shed some light on the apparent contradiction evidenced by our results.

The brief review of HSE publications pertaining to offshore night working provided inconclusive results. More research into the HSE implications would give operators a more informed decision as to the trade-off expected. There are four studies agreeing on similar reaction times for day and night shifts. This is a positive finding in favour of night shifts. However, the uncertainty surrounding accident rates and adverse health effects for staff may prove too much of a risk, especially at low prices of energy or in the case of high turbine reliability, where profits are not as substantial.

5 | CONCLUSIONS

This work presents an assessment of night shifts for OWFs. We consider a particular strategy where one crew transfer vessel was repurposed to carry out corrective maintenance work during a night shift. In contrast to previous studies exploring the theme, we relied on a Bayesian data-driven model. Data were provided by a large operational offshore wind farm. A hierarchical model was used to model the two operational metrics: opportunity cost and technical time-based availability. The hierarchical nature of the model allowed us to explore the variation of these values throughout the year, and to introduce estimates of lost production and availability from hypothetical alterations in strategy. The Bayesian nature of the model allowed us to make inferences from a relatively small sample size via the use of informative priors derived from the StrathOM-OW tool. The more generic advantage that Bayesian models provide inherent uncertainty handling was also evident in the results. There is something to be said of this feature in itself, as statistical uncertainty in maintainability has been identified in recent studies as both significant and under-investigated for offshore wind turbines. These hypothetical scenarios were in the form of retroactive algorithms applied to the data to assess the benefit of night shifts undertaken at the site. Samples from the posterior of this model provided financial implications of the lost production. We made assumptions as to the cost of extra staff wages and avoided vessel costs to retrieve estimates for a baseline case when night shifts were in operation and out of operation. Comparing the mean values of yearly simulated data, it was found that £1625 per MW installed capacity could be saved. There are a number of factors which influence this figure, which we explored via a sensitivity analysis. Altering the price of energy reduced the difference in means to £745/MW capacity at £40/MWh. It increased the difference in means to £2000 at £150/MWh. Support staff wages and assumed savings in vessel charters also had a significant impact. The assumptions made for these variables were rudimentary and could be explored further. Extending the hierarchical model to include failure rates also proved informative. Those turbines in the lowest failure rate category saw roughly half the savings from those in the high failure rate category, at £745/MW and £2162/MW installed capacity, respectively. Availability savings were more consistent. Maintenance service providers would see a significant improvement in the number of times they would exceed a time-based technical availability of 98%.

ACKNOWLEDGEMENTS

This work was supported through the UK's Engineering and Physical Sciences Research Council via the Wind & Marine Energy Systems Centre for Doctoral Training, grant number EP/L016680/1.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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PEER REVIEW

The peer review history for this article is available at https://publons.com/publon/10.1002/we.2806.

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How to cite this article: Anderson F, McMillan D, Dawid R, Garcia Cava D. A Bayesian hierarchical assessment of night shift working for offshore wind farms. *Wind Energy*. 2023;1-20. doi:10.1002/we.2806

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