Maintenance & failure data analysis of an offshore wind farm

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Abstract. Offshore Wind (OW) continues to grow globally at a rapid pace, with growth estimates of 630GW by 2050. To facilitate this rapid growth, costs must continue to be reduced. Reducing operations and maintenance (O&M) costs, which are estimated at 30% of the lifetime costs of wind farms, offers opportunity. This could be achieved by moving current maintenance strategies to a prescriptive strategy. Prescriptive strategies use the turbine monitoring data to determine component remaining useful lifetimes or predict failure windows and then provide an optimised maintenance plan. The first stage of a framework, that can be applied to operational assets, for improving maintenance schedules with failure predictions is presented. Analysis of the SCADA system and the maintenance logs, at an operational offshore wind farm (OWF), with the purpose of identifying turbine failure rates, availabilities and losses and costs from maintenance and failures has been performed. The analysis has revealed two types of maintenance actions, one is cost of maintenance driven and the other cost of downtime driven. It is proposed that, given different characteristics, they should be approached differently in the context of failure predictions. It is also revealed that electrical components are critical to the failure rate and energy losses due to maintenance at the OWF. Electrical components represent approximately 28% of all failures and nearly 40% of revenue loss due downtimes from failure for the period analysed. The power converters drive most electrical failures and are of key commercial interest to the farm. As a result, the power converters should be the target for future prognostic model development. The analysis also shows that with perfect prediction and maintenance scheduling, this OWF could generate an extra 0.26% revenue and a generic 1GW OWF could generate an extra 0.6% extra energy and approximately £1.4m in revenue. This analysis did not reveal the benefit of taking fewer maintenance actions, which should be assessed in future work. Producing a combined prognostic maintenance scheduling method will generate extra wind farm revenues, reduce the number of maintenance actions taken and facilitate the work of maintenance teams.

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1. Introduction

Offshore wind developments continue to grow globally at a rapid pace, with growth estimates of 630GW between 2022 and 2050 [1]. To facilitate this rapid growth costs must continue to be brought down. Reducing operations and maintenance (O&M) costs, estimated at 30% of the lifetime costs of a wind farm [2], offers opportunities. With offshore wind farms (OWFs) increasing in size, moving further offshore and the first floating offshore wind farms getting deployed it is increasingly important to develop and deploy optimised O&M strategies to continue to drive down costs.

This paper presents the first stage of a data driven framework to be used by wind farm operators, illustrated graphically in Figure 1, for reducing O&M costs at an operational wind farm. This first stage is analysis of the maintenance and failure data, considering downtimes, lost energies, lost revenues, and costs to identify the main opportunities for maintenance optimisation. Stage 2 aims to reduce O&M costs and lost revenues by developing failure prediction models for the components identified in stage 1. Stage 3 makes use of the developed models as well as the knowledge of the other maintenance actions and constraints to improve the wind farm maintenance scheduling whilst stage 4 assesses the quality of these improvements against the baseline of current maintenance.

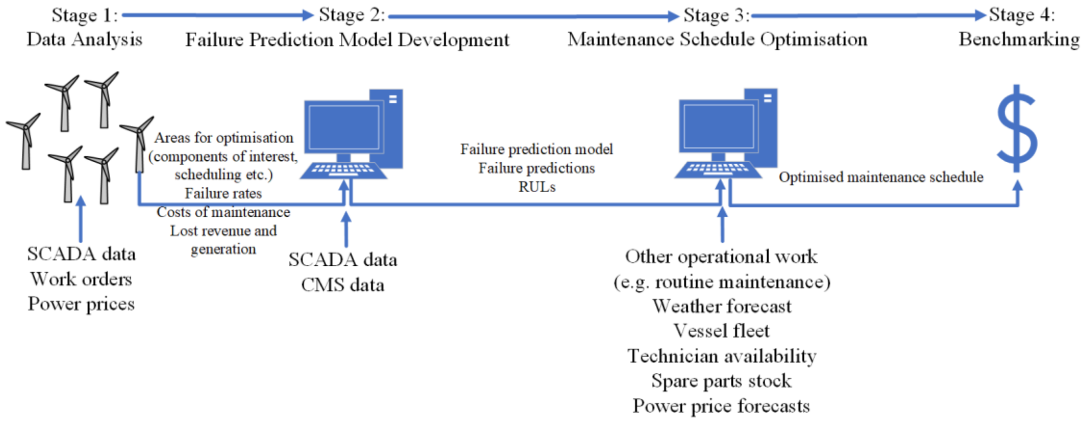

Figure 1. Data driven framework for optimisation of an operational wind farm.

1.1. OWF Maintenance Strategies

Most offshore wind O&M strategies are corrective-periodic [3]; however, there is increasing effort to implement condition based maintenance (CBM) techniques [4] as existing strategies are not deemed optimal [5]. CBM consist in taking maintenance decisions based on evidence of actual health states. Such evidence can be obtained from monitoring apparatus, inspections, or data analytics. CBM can be extended to prognostic maintenance with predictions of remaining useful life (RUL) of specific components [6] and impending failures. With accurate knowledge of RUL, maintenance can be scheduled to both reduce wasted component life and minimise revenue losses due to downtime from failures [7]. Development of failure prognosis and maintenance models requires monitoring and failure data for training, test and validation. Data helps to develop the predictive ability of models and producing accurate maintenance model constraints. An analysis of the maintenance and monitoring data can direct which turbine systems to produce prognostic models for; estimate the potential benefits of optimised scheduling and provide some of the maintenance constraint inputs for maintenance models.

1.2. OWF reliability analysis

There are few publicly available datasets for wind farm reliability studies, the most commonly used sources are summarised in [8]. Several reviews into these databases [8–13] have established general patterns and trends. Pfaffel et al. [8] provide a comparison of the performance and reliability between the data sources, including offshore wind turbines. Time-based and energy-based availabilities are compared. OWF time-based availability is given as ~92% and energy-based availability as ~88%. A reliability analysis is also performed, highlighting significant differences in the results between different data sources. Overall, the rotor system, driven by the failures of the pitch system accounts for the highest share of failures (10-25%), followed by the transmission (2.5-35%) and control system (5-32.5%). When downtime is considered, the two largest assemblies are the rotor and drive train system whilst the transmission and control systems are responsible for much less downtime. This indicates that failures in the drive train whilst fewer in number than the transmission and control systems are more severe and cause longer downtime. This was repeated by Faulstich et al. [11]. Their results are illustrated in Figure 2. They demonstrate that the pattern of failure rates over time varies by subassembly, for example the failure rates for the control system decreases with time whilst the failure rate for the electrical system is increasing with time. Overall, failure rates are approximately constant over a large period of turbine life, shown in Figure 3.

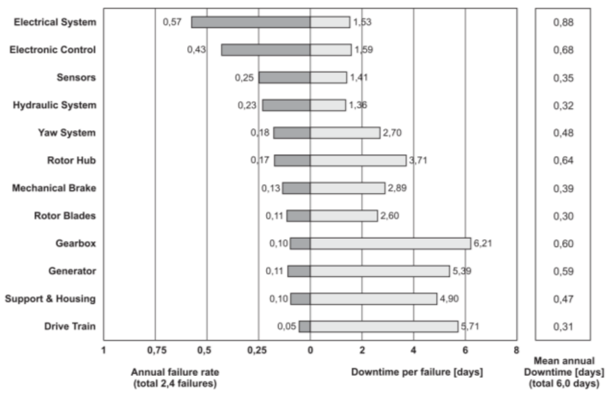

Figure 2. Reliability characteristics for different subassemblies in the WMEP programme [11].

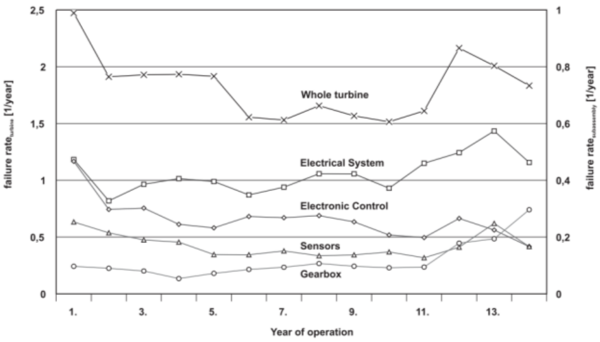

Figure 3. Development of failure rate with year of operation [11].

For offshore wind turbines the data and analysis from Strathclyde university provide the main results. It is shown that the frequent failure modes are: pitch and hydraulic systems (13% of total failures); 'Other Components' (12.2% of total failures); generator (12.1% of total failures); gearbox (7.6% of total failures) and blades (6.2% of total failures) [12]. The common failure modes are confirmed by Cevasco et al. [13] which provides a comprehensive review of failure data for both onshore and offshore wind turbines, whilst they also confirm the variability in failure rates between data sources. The authors highlight the disparity between failure rate and downtime share for the drive train components, indicating that, whilst they fail infrequently, failures lead to large downtimes and repair costs. They also show that for offshore wind farms and changing turbine architectures higher failure rates and corrective maintenance costs can be expected for the transmission systems (particularly the power electronics), noting that effort should be made for these systems to improve their design and implement monitoring systems on them. Finally, it is shown that there are higher failure rates for offshore wind turbines.

In the context of the OWF operator identifying areas for O&M cost improvements, the current literature has two key limitations. Firstly, the reviews all present data from a collection of turbines from different wind farms. This is useful for developers to identify the most reliable turbines or for OEMs to determine where reliability improvements should be made. For an OWF operator; however, these analyses are not granular enough to identify site specific issues and therefore tailor targets for maintenance improvements to the site. Secondly, whilst the revenue losses from downtime are calculated in work done by Strathclyde in [14], the results are estimates based on an O&M model. To the author's knowledge no analyses have calculated and presented precise revenue losses based on the OWF's revenue mechanism and power prices. This paper builds on the previous literature by performing the analysis from the viewpoint of the OWF operator. The originality is given by two aspects addressing the limitations described. Firstly, the importance of considering individual OWF performance is demonstrated by a comparison of reliability data for a single windfarm to the results found in literature.

Secondly, the lost revenues, split by turbine subsystem, are calculated and presented using the specific revenue mechanism and power prices for this OWF.

1.3. Data

We have access to data from an operational OWF which is composed of 27, 2.3MW turbines. The data sources are the maintenance logs from the Computerized Maintenance Management System (CMMS), the measured values from the SCADA system, wave heights from a wave buoy on site, and day ahead power prices. 8 years of data from years 2 to 9 of operation is available. Detailed cost data is only available from year 6 onwards, therefore cost analysis only includes data from years 6-9. This provides a case study on an operational wind farm with a significant history of data. To determine which components are most critical for improving maintenance costs, analysis was performed on the SCADA system data and the CMMS. The analysis revealed the most commonly replaced components together with the costs induced by their replacement, the lost energy generation and lost revenues. This helped to focus on where the highest cost savings could be made from developing prognostic models. Following this, analysis was performed to calculate the potential cost savings if the maintenance schedules were optimised.

1.4. Aims & objectives.

The aim of this study is to demonstrate the first stage of a data-driven maintenance cost reduction framework by assessing which components are most critical for optimising maintenance costs and where the greatest opportunities for implementing CBM lie. The objectives are as follows:

- Estimate the energy losses, costs, revenue losses and downtimes due to maintenance for components and turbine subsystems.
- Identify the components that will benefit most from prognostic methods.
- Estimate the potential benefits of prognostics and optimised maintenance scheduling.

2. Method

To perform the analysis the following steps are taken.

1. Preprocess and clean the data.
2. Calculate turbine power curves.
3. Lost energy generation, revenue losses, costs and downtime per maintenance action calculated.
4. Failure rates calculated.

2.1. Pre-processing

All the data sources must be preprocessed to allow them to be combined to calculate the aggregate statistics. The SCADA data is provided for the tags shown in Table 1 where the data are either sampled at 10-minute intervals or asynchronously (once per day or as the value changes). First, missing timestamps are found in the interval 2015-2023 and missing values are filled with NA. In this study “Status” and “Operation State” are tags that describe if the turbine is in operation and are the only asynchronous tags. Asynchronous timestamps are resampled to 10-minute averages, the value which occurs for the longest-time in a 10-minute timestamp is taken as the value for that timestamp and values for in between measurements are taken as the value measured at the previous timestamp. Finally missing wind speed values are imputed from the turbines whose wind speeds are most correlated to each other.

The maintenance logs are cleaned by, where necessary, correcting the descriptions of the maintenance actions for typos and incomplete entries and correcting dates. Entries are then sorted into, failure, replacement, repair, or inspection and then by subsystem. Maintenance actions which have consumed a component are categorised as replacements whereas repairs only use ancillary parts. For example, a gearbox replacement requires a full new gearbox whereas a repair might only need lubricant. The following subsystems are considered: blade, coolant, electrical, gearbox, general (for any entries that could not fit into the others), generator, main bearing , pitch, tower yaw. Specific components are also identified. Component costs are contained within the maintenance logs, and technician hourly rates

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and vessel hire costs are taken from the maintenance contract details. The wave buoy data is provided at 30-minute intervals. This is resampled to 10-minute intervals by interpolating linearly between timestamps. The energy price data did not require preprocessing.

Table 1. SCADA tags used in this study.

Tag	Sample Rate
DateTime	10-minute
ActivePower	10-minute
Amb_WindSpeed	10-minute
DateTime Status	Asynchronous
Status	Asynchronous
DateTime Operation State	Asynchronous
Operation State	Asynchronous
Turbine	N/A

2.2. Downtimes, lost energy, revenues, and costs.

To calculate the energy losses due to the turbine being offline for failure and/or maintenance individual power curves are first calculated for each turbine. This is done following the method outlined in [15]. Then the start and end dates of each maintenance action are taken from the maintenance logs and the SCADA data are filtered to contain data for the relevant turbine between these start and end dates with a 1-week buffer to account for any delays in repairing the turbine after a failure. Where necessary, a new start date is identified, which is the point at which a failure first occurs. This is determined by identifying anomalous periods of turbine performance. These are a consecutive period where the wind speed is between the cut-in and cut-out speeds, and the turbine output power is either 0, negative or NA. Between the start and end dates, the energy produced by the turbine and the theoretical energy based on the calculated power curve are found. For the anomalous periods the theoretical energy is calculated using the derived power curves and summed to find the lost energy due to downtime. The length of the anomalous periods is summed to calculate the downtimes.

The cost of maintenance in $£_{2022}$ is calculated using equation (*1*).

$$C_{total}=C_{spare\ parts}+C_{technician\ time}+C_{vessel}+C_{fuel} \tag{1}$$

The wind farm generates revenue through selling electricity to the market as well as benefiting from the UK renewables obligation certificate (ROC) scheme, details of which are found at [16]. Revenue for the wind farm is therefore calculated using equation (*2*).

$$R_{tot}=\left(E\times P_{day\ ahead}\right)+(E\times ROC_{multiplier}\times(P_{ROC}+P_{ROC\ recycle})) \tag{2}$$

Where R_{tot} is the total revenue in $£_{2022}$, E is the energy generated in MWh, $P_{day\ ahead}$ is the day ahead energy price in £/MWh, $ROC_{multiplier}$ is the number of ROC certificates granted in ROCs/MWh, P_{ROC} is the ROC market price in £/ROC and $P_{ROC\ recycle}$ is the ROC recycle fund price in £/ROC. The revenue generated by the wind farm is calculated at each time stamp. Lost revenue due to downtime is found by summing the theoretical revenues for all anomalous periods. The lost revenue can also be considered a cost and in this study is combined with the maintenance costs in the term “maintenance opportunity cost”. It should be noted that (*2*) only reflects one possible revenue strategy for wind farms. Others are available but are not relevant for this wind farm.

2.3. Failure rates.

A widely used metric in reliability analyses is the failure rate which is defined as the number of failures within a given period, typically given as failures/year. The failure rate is calculated by summing the number of failures identified in the work order database and dividing by the length of the period. It is calculated as an aggregate failure rate, split by subsystem and by component. It is also split by wind turbine and aggregated for the whole wind farm. Both a rolling failure rate and individual yearly failure rate are calculated. The rolling failure rate is a rolling sum of failures divided by a cumulative sum of period length.

3. Results
In this section the results from the above analysis are described and discussed.

3.1. Downtimes, lost energy, revenues, and costs
The normalised total downtimes, energy losses, revenue losses, and costs incurred, per turbine and for the wind farm are shown in Figure 4. All entries are normalised against the total producing time, energy production and revenue generation, respectively, for each turbine. All maintenance is included. There is large variance between turbines for each of these values. Downtimes, lost energy, and revenues are of similar magnitude with turbine downtime as a percentage of total park producing time slightly larger than energy and revenue losses. As a percentage of total revenue generated by the windfarm the maintenance costs are approximately 4x larger than the losses due to turbine downtime. For some wind turbines this ratio is significantly larger, for example WT13 where maintenance costs are 58 times larger than the revenue losses due to downtime. These large maintenance costs are driven by the costs of gearbox replacements which are by far the most expensive maintenance actions performed at the wind farm.

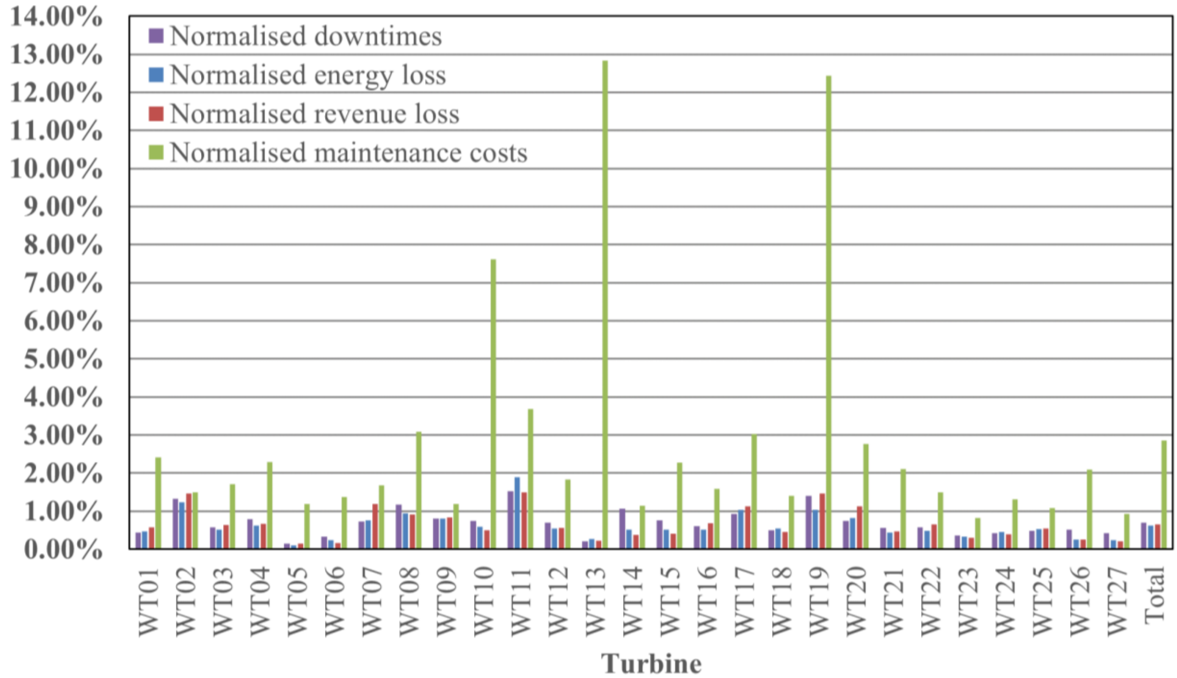

Figure 4. Normalised downtimes, energy losses, revenue losses and maintenance costs for the OWF.

Table 2 gives the above data split by subsystem. The gearboxes and electrical systems account for the largest costs. The gearboxes account for the largest maintenance cost; however, they have relatively low downtime, revenue, and energy losses. By contrast the electrical systems incur approximately half of the maintenance costs of the gearboxes but have a revenue loss due to downtime of 4.5x greater. This is illustrated in Figure 5, which plots, per subsystem the maintenance costs and revenue losses due to downtime, normalised by the maintenance opportunity cost. In this chart the gearboxes and electrical systems account for 32% and 27% of the maintenance opportunity cost, however; the revenue lost from downtime for the electrical systems accounts for 10% of this cost whilst for gearboxes it is only 2%. This difference is explained by the fact that there were no gearbox failures in operation. Their slow to develop failure mechanisms and high levels of monitoring allow their replacement to be planned well in advance of failure. Conversely the electrical systems, driven by failures in the power converters, are not well monitored and have had many failures in operation leading to large downtime costs. This reveals two different types of maintenance actions. One which is primarily cost of replacement driven (COR), e.g., the gearboxes, and one which is cost of downtime driven (COD), e.g., the electrical systems.

For all systems, except for the blades, yaw and coolant systems, most maintenance costs are incurred by replacement over repairs. This indicates replacements are more costly and therefore supports the possibility of maintenance cost reductions by being able to predict failures.

Table 2. Normalised downtimes, energy losses, revenue losses, and maintenance costs for the OWF split by subsystem.

Subsystem	Normalised downtimes	Normalised energy loss	Normalised revenue loss	Normalised maintenance costs
Gearbox	0.06%	0.05%	0.06%	1.15%
Electrical	0.25%	0.23%	0.26%	0.64%
General	0.09%	0.08%	0.08%	0.31%
Blade	0.07%	0.05%	0.04%	0.23%
Coolant	0.07%	0.06%	0.08%	0.17%
Pitch	0.04%	0.03%	0.03%	0.13%
Yaw	0.08%	0.08%	0.07%	0.11%
Tower	0.03%	0.03%	0.03%	0.08%
Generator	0.02%	0.01%	0.01%	0.03%
Main Bearing	0.00%	0.00%	0.00%	0.00%
Total	0.70%	0.62%	0.66%	2.85%

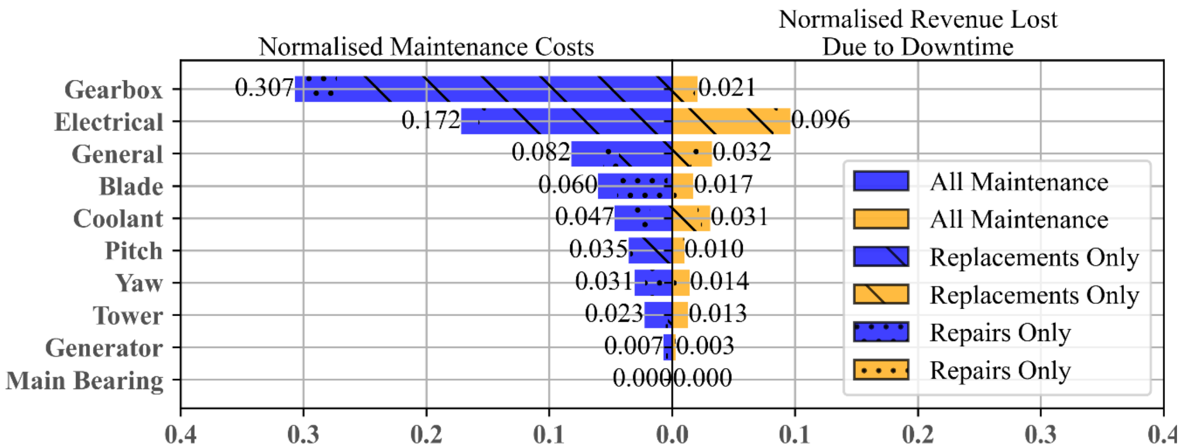

Figure 5: Back-to-back bar plot comparing normalised maintenance costs and revenue losses due to downtime for the turbine subsystems.

These results have been confirmed by the maintenance team at the OWF and an internal study by the operator. The results also agree with previous analyses mentioned in section 1.1. with regards to the converters having the largest failure rates [9] and gearbox failures accounting for the largest proportion of maintenance costs [12]. Power converters were also identified as a critical component for reliability across all turbine generations [13]. This analysis shows large downtimes for the electrical components and low downtimes for the gearboxes which is the opposite relation compared to [9] and [12]. This highlights the importance, when looking to improve maintenance costs, of considering not just a fleet level analysis but also an individual OWF. At this wind farm we do not have large downtimes and revenue losses caused by gearbox failures in operation as the maintenance team already sufficiently perform replacements before failure. The OWF instead suffers from large revenue losses caused by the power converters. If the results from literature were to be used by an operator looking to reduce their costs, they could incorrectly assume that they must develop methods for reducing gearbox downtime failure, where in fact there is little scope for improvement here.

3.2. Failure rates

The rolling failure rate split by subsystem for each year of the wind farm is illustrated in Figure 6. The failure rate remains approximately constant across the full time, with a jump in "General" failures between years 5 and 6 and an increasing electrical failure rate. This is the year that the maintenance contract was transferred from the turbine manufacturer to the operator of the OWF. This transfer could explain this increase with different reporting systems taking place. The constant failure rate could indicate that the wind farm has not approached the wear-out phase of the bathtub curve and therefore the proportions of maintenance costs presented in this study could be subject to change as the OWF continues to age.

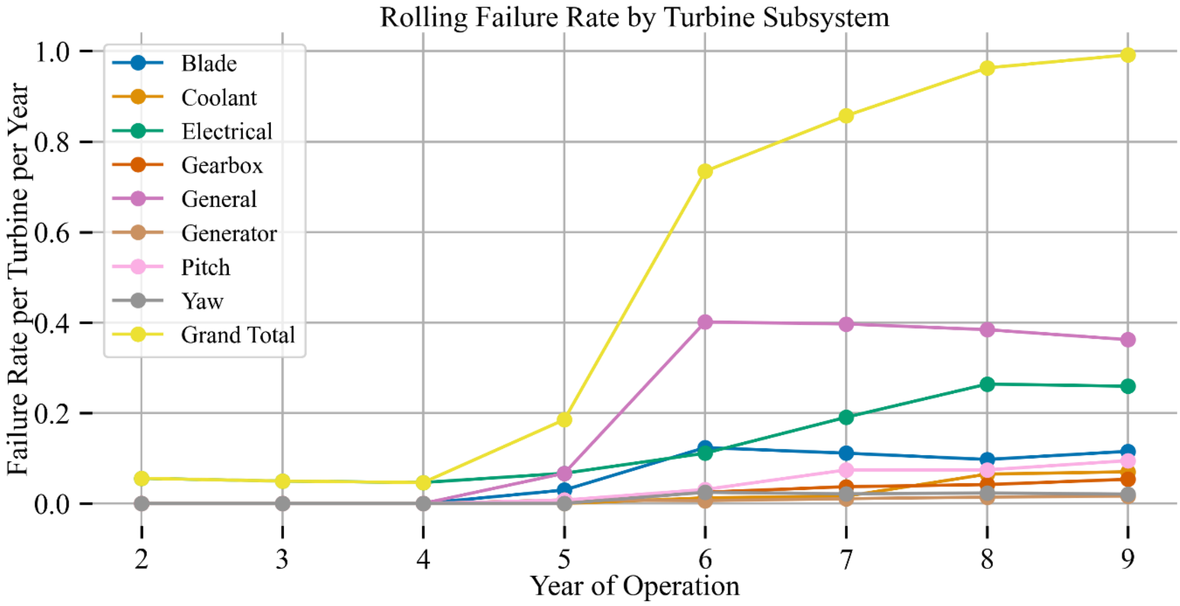

Figure 6: Rolling failure rate, split by subsystem for each year of operation of the wind farm.

4. Benefits of predictive maintenance and improved maintenance scheduling

Using the calculated energy losses and revenue losses due to downtime we can make an estimate of the potential benefits of improving maintenance scheduling and combining this with predictive failure models. The effect of a predictive model is simulated by eliminating the downtime due to failure before maintenance can occur, whilst the effect of improved scheduling looks to move maintenance to periods of lower revenue loss. The theoretical predictive model could take many forms. Fox et al. [6] provides an excellent and detailed review of the different types of predictive models that can be used. For the analysis we assume perfect prediction ability for all maintenance actions and we can reschedule every maintenance action by 1-year, 6-months, 3-months, and 1-month. The results are shown in Table 3. It is assumed that the time required to perform each maintenance action is the same as it originally took. For our wind farm it is estimated that an extra 0.6% of total energy production and 0.26% of revenue could be generated per year. For a 1GW wind farm at the AR6 strike price of £73/MWh this is approximately an extra £1.4m revenue yearly. These are relatively small numbers, especially considering the idealised scenario presented. This is an indication that a much larger impact in reducing maintenance costs could be seen by improving turbine designs and eliminating the root cause of failures.

The analysis only considers reductions in the revenue losses from downtime, it does not consider other maintenance costs such as the cost of a preventative versus corrective replacement. Additionally, the potential benefits of extending component lifetimes and doing less maintenance is not explored. Furthermore, the wind farm analysed is close to shore, therefore downtimes due to failure are limited as response time is relatively fast. As wind farms move further offshore and maintenance is harder plan, the potential benefits could increase.

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Table 3. Estimated benefits from incorporating predictive maintenance and optimised maintenance scheduling.

	Rescheduling Horizon			
	One Year	**Six Months**	**Three Months**	**One Month**
% increase in revenue generation	0.26%	0.26%	0.25%	0.24%
% increase in energy generation	0.59%	0.59%	0.57%	0.54%
1GW OWF extra revenue per year (£k)	1372.34	1362.80	1310.97	1248.39

5. Conclusions

The first stage of a framework that an OWF operator can apply to an asset to reduce O&M costs has been developed. An analysis of the maintenance logs and monitoring data at a single OWF has revealed the gearboxes and electrical systems, 32% and 27% of the maintenance opportunity cost respectively, as the two systems that with the largest contributions to the O&M costs. The gearbox costs are cost of replacement (COR) driven whilst the electrical systems are cost of downtime (COD) driven. For an operator, the reduction of these costs requires two different approaches. For COR driven maintenance, we need to eliminate unnecessary maintenance actions. For COD driven maintenance, we need to eliminate downtime due to failure before maintenance can occur. In turn this leads to two different approaches for developing failure prediction models. For COR we need prognostic models that give an accurate RUL to stop early replacement of components. For COD we more simply need a failure prediction model that identifies faulty components in advance of their replacement.

Developing predictive models requires both monitoring data and the presence of enough failures in the dataset. For the windfarm in this study the failures in the electrical system provide the best opportunity for minimising maintenance costs, as there have been many failures in operation and they are monitored in the SCADA. By contrast, other systems have not incurred sufficiently large costs; do not have sufficient monitoring; or enough failures in the dataset to benefit from the development of predictive methods. For example, there have only been three gearbox replacements, and each has happened in advance of absolute failure, therefore there is no ground truth for the lifetime of each gearbox. The electrical failures at this wind farm are driven by failures of the power converters. These should be the focus for future predictive models.

The approach outlined above can be used by wind farm operators to clearly identify the components that incur the largest maintenance opportunity costs, classify them into COR or COD driven maintenance and decide on the strategy to tackle these cost reductions. By eliminating downtimes due to failures and rescheduling maintenance, the analysed OWF could generate an extra 0.26% revenue each year.

The analysis suffered from a few limitations. Firstly, the data is for the first 9 years of the OWF life. An analysis with data for the full lifecycle of an OWF should be repeated to understand how the identified trends change as the OWF enters the “wear out” period. Secondly the benefits of failure predictions and improved scheduling are only assessed in the context of reducing revenue losses for an OWF close to shore. An analysis which considers the benefits of taking fewer maintenance actions, cost differences between corrective and predictive maintenance and varying OWF sizes and locations should be considered. Building on this, a full cost benefit analysis considering the costs of collecting, storing and processing data; and developing and deploying predictive models should be performed.

Future work will involve the development of stages 2, 3 and 4 of the proposed framework with a focus on predictive models for power converter failures.

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