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Evaluation of Predictive Models for Reducing Wind Turbine Power Converter Failure Downtime for a Wind Farm Operator Using SCADA Data

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Abstract. To facilitate the continued growth of offshore wind farm developments, operations and maintenance (O&M) costs, which are estimated at 30% of the lifetime costs of wind farms must be reduced. This could be achieved by moving current maintenance strategies to a predictive strategy. Predictive strategies use the turbine monitoring data to determine component remaining useful lifetimes, predict failure windows or detect drops in performance and then provide an optimised maintenance plan. To enable these strategies in practice, failure prediction models must be developed, that are useable by the wind farm operator for key components. This work identifies that power converters are responsible for significant downtime at some wind farms and prediction of their failures could offer significant improvements in turbine availability. Through an analysis of their failure mechanisms, the signals required to detect failures in the power converters are identified and the insufficiencies in the SCADA data available to operators are highlighted. Several machine learning and deep learning models are trained on the SCADA to predict the power converter failures, and a novel scoring function is applied to evaluate their performance when applied to the operational decision-making context. Results suggest that implementing an artificial neural network failure prediction model offers approximately 40% reduction in power converter maintenance costs compared to business as usual. Further improvements to these models will require the acquisition of high frequency monitoring data specific to the power electronics in the power converters. Applying predictive maintenance strategies will generate extra wind farm revenues, reduce the number of maintenance actions taken and facilitate the work of maintenance teams.

1 Introduction

Offshore wind developments continue to grow globally at a rapid pace, with growth estimates of 630GW between 2022 and 2050 (Kuhn et al., 2022). Reducing operations and maintenance (O&M) costs, estimated at 30% of the lifetime costs of a

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wind farm (BVG Associates, 2019; Stehly and Duffy, 2021), offers opportunities to reduce costs and facilitate continued growth. With offshore wind farms (OWFs) increasing in size; moving further offshore; and the first floating offshore wind farms being deployed recently (GWEC, 2023), it is increasingly important to develop and deploy O&M strategies that can reduce costs.

A method of reducing O&M costs is to move from existing maintenance strategies towards condition based maintenance (CBM) techniques (Tian et al., 2011) as existing strategies are not deemed optimal (Leite et al., 2018). CBM consists in taking maintenance decisions based on evidence of actual health states, to find the optimal point between corrective and preventative maintenance (Artigao et al., 2018). Such evidence can be obtained from monitoring apparatus, inspections, or data analytics. Implementing CBM strategies requires the development of models that can assess the health, or predict failures, of key turbine components. Therefore, developing methods of predicting failures for key components at wind farms is essential for implementing a CBM strategy. Furthermore, it is important to understand and evaluate the performance of failure prediction models in an operational setting to assess how they can be applied in practice. This paper presents a systematic method for developing failure predictions for use in operation and applies this method to the case study of wind turbine (WT) power converter failures at an operational wind farm. The method can be split into the following steps, which are detailed in the remainder of the paper:

1. Root cause failure analysis. To identify the symptoms of failures and data required to detect them. This helps with feature selection for failure prediction models.
2. Collection of the relevant data for training of failure prediction models.
3. Training of failure prediction models.
4. Evaluation of failure prediction models in an operational context.

1.1 Aims & objectives

The aim of this paper is to implement the method described above on a case study of power converters at an operational wind farm. It further aims to develop failure prediction models based on the data available to most wind farm operators (without need for additional sensors to be installed) to reduce revenue losses from converter failures in operation. This involves an analysis of failure modes to identify leading indicators of per converter failure; a gap analysis of the data available to operators and that which is needed to detect failures; and finally, the development and evaluation of failure prediction models in an operational setting. The objectives are:

- Review the symptoms of power converter failures and what data is needed to monitor and predict these.
- Identify gaps between required monitoring data and data available to operators.
- Develop and understand the performance of a failure prediction model using the data available at an operational wind farm.
- Develop a novel scoring function that assesses failure prediction models based on their operational use.
- Produce practical recommendations for minimising the effects of power converter failures on O&M costs and losses at a wind farm.

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1.2 Contribution and paper structure

This paper provides three main contributions. Firstly, it presents the improvements in data collection required at operational wind farms to realise power converter failure prediction models that are useable by the wind farm operator. Thus far models have been developed on test benches or simulations and do not use the SCADA data that is available to operators when monitoring power converters and therefore cannot be implemented in practice. Secondly, a set of failure prediction model architectures, trained on historic SCADA data are presented. Finally, a novel method of assessing the performance of these models focussed on their use in an operational context is presented. The rest of the paper is structured following the four steps described above: in Sect. 2 the existing literature on power converter failure modes, monitoring systems and fault diagnosis is reviewed. From this analysis, the data needed for developing failure prediction models is identified. In Sect. 3 the methodology for developing failure prediction models using the data available to OWF operators for the power converters is presented. The differences in the data available to operators and that which is required is highlighted. The results of the developed failure prediction models and a discussion of their performance and the limitations of the training data are presented in Sect. 4. The paper closes with recommendations to operators and OEMs to allow development of power converter failure prediction models and minimise revenue losses from their failures; a summary of the main conclusions, and outlook for future work in Sect. 5.

2 Literature review

2.1 Wind turbine power converters

A comprehensive description of power converter designs is provided by (Fischer et al., 2012). Power converters are an essential component of nearly all wind turbines. They are positioned between the generator and the transformer (e.g. Fig. 1). Their purpose is to convert the irregular wave form generated by the variable speed turbine to a sinusoidal, compliant with the fixed frequencies required by the grid. There are four common generator topologies:

1. Doubly-fed induction generators (DFIG);
2. Squirrel-cage induction generators with full-scale converters (SCIG);
3. Permanent-magnet synchronous generators with full rated converters (PMSG);
4. Electrically excited synchronous generators with fully rated converters (EESG).

The power converters are either located in the nacelle or the tower base. All topologies typically have the same converter technology of insulated gate bipolar transistor (IGBT) converters in a back-to-back AC-DC-AC configuration, with a generator-side rectifier and grid-side inverter connected by a DC-link, illustrated in Fig. 2. Details of IGBTs can be found in (Wintrich et al., 2015). The converters consist of stacks which are made up of half-bridge or single-switch IGBTs, typically connected in parallel; a set of sensors; and driver boards which link the generator control to the IGBT modules. The stacks are mounted on a heat-sink and are either water-cooled or air-cooled. Each half-bridge is further composed of many IGBTs. The IGBTs normally have a reverse blocking ability of 1200V or 1700V with a DC-voltage level between 750 and 1200V.

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Nominal AC-line voltages are typically between 490 and 690V. The purpose of the DC-link is to provide fault ride through capability, which allows the turbine to remain connected to the grid in the case of grid faults by dissipating excess power (Moheb et al., 2022). Stacks are typically combined into phase modules, or units, of which there are three per side. In a DFIG topology the generator-side rectifier has a rated power larger than that of the grid-side inverter, as it needs to fulfil additional generator control requirements. In full-scale converters the ratings on both sides are identical. A typical converter module is seen in Fig. 3.

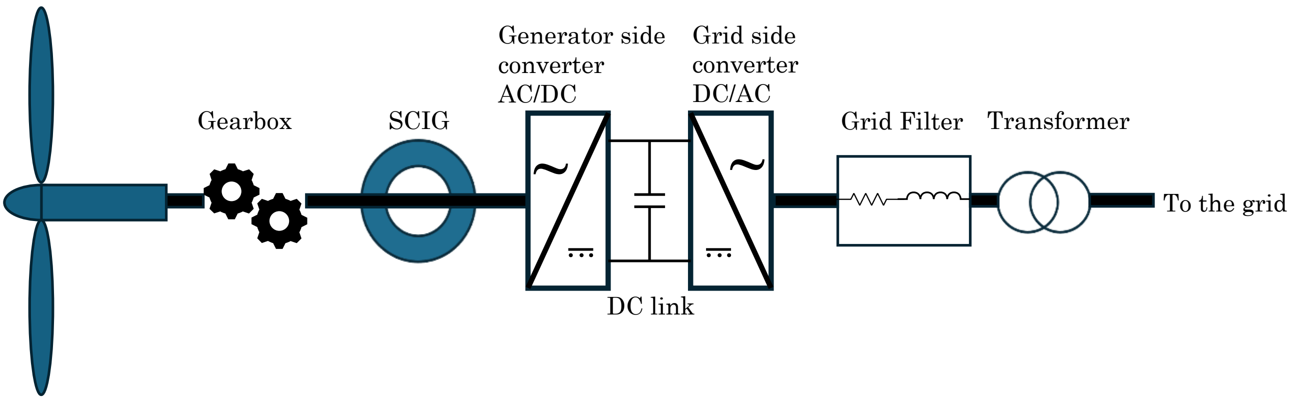

Figure 1: Example diagram for an SCIG wind turbine layout with the converters shown. Adapted from (Attouri et al., 2023).

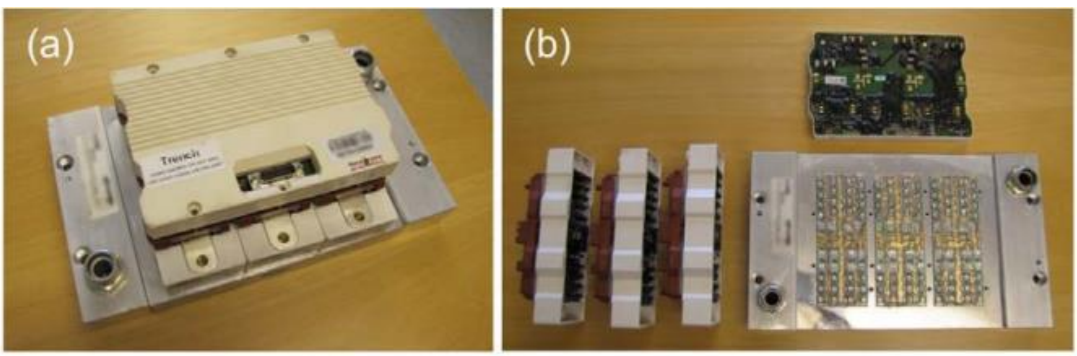

Figure 2: Converter modules used in WTs, (a) exterior view, (b) disassembled. Taken from (Fischer et al., 2012).

The modules are packed to connect multiple semiconductor chips and the circuit, connect the modules to cooling systems and to protect the chips (Wintrich et al., 2015). There are two packaging types, shown in Fig. 4, press-pack and power module technology. The power module technology is the most used technology. Within this technology, as shown in Fig. 5, modules either come with or without a baseplate. Modules without a baseplate are typically only used in lower power applications. The IGBT chips are then also covered with an insulating layer to protect the components from shock and vibrations. By contrast the driver boards are not well protected and are accessible for air which can carry contaminants.

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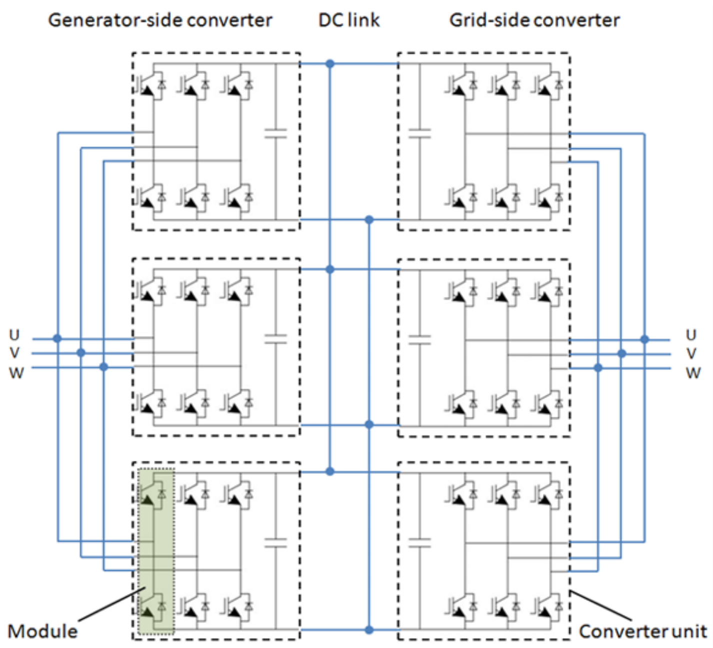

Figure 3: Example circuit diagram of a WT power converter made up of six units each containing three converter modules. Taken from (Fischer et al., 2012).

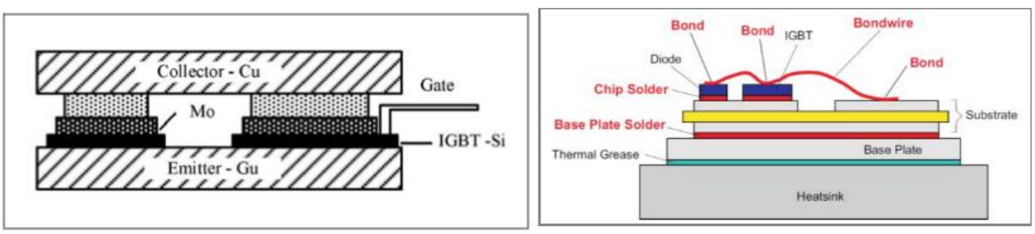

Figure 4: Different packaging technologies. Press-pack left, power module right. Taken from (Fischer et al., 2012).

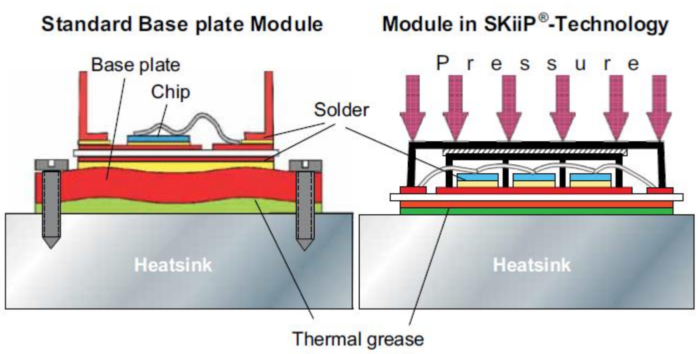

Figure 5: Power modules with (left) and without (right) baseplates. Taken from (Wintrich et al., 2015).

2.2 Wind turbine power converter reliability

An analysis of the failure data for an OWF, presented in (Moros et al., 2024a) and which will be used as a case study in this paper, revealed that the electrical systems of the WTs account for 27% of the total maintenance costs at the wind farm, illustrated graphically in Fig. 6. The electrical systems also make up the largest proportion of costs associated to lost revenues due to downtimes (10% of all maintenance costs). A further internal reliability study across a fleet of OWFs has shown that downtime and failures of converters has accounted for 15% of total maintenance costs in one year, these costs were up to 62% for certain turbine models.

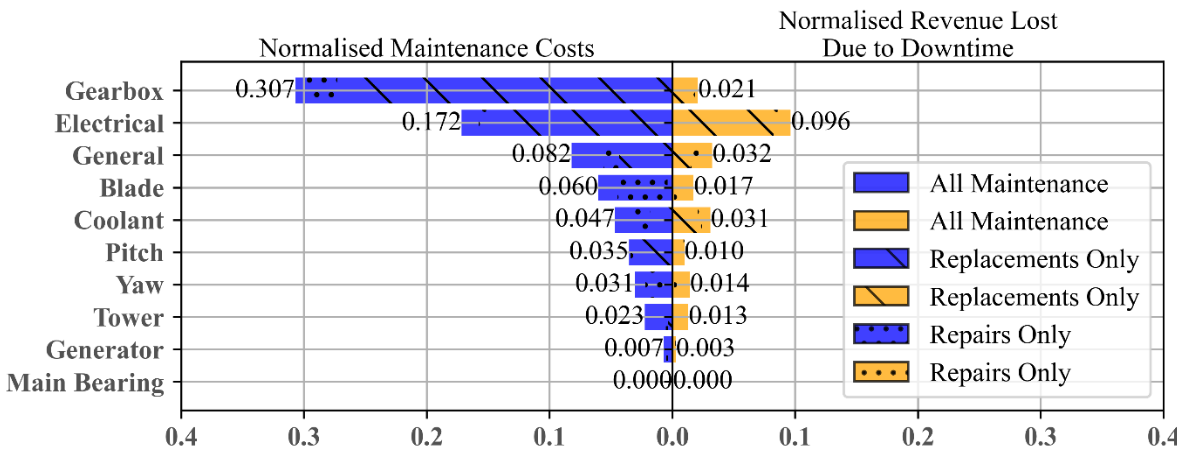

Figure 6: Back-to-back bar plot comparing normalised maintenance costs and revenue losses due to downtime for the turbine subsystems (Moros et al., 2024a).

The importance of downtime due to electrical system faults is confirmed across the industry (Bakdi et al., 2019; Faulstich et al., 2011; Liang et al., 2022; Reder et al., 2016; Stenberg and Holttinen, 2010), with downtimes and fault rates by wind turbine component shown in Fig. 7. As seen in Fig. 8, 65% of the electrical failures, at the OWF in (Moros et al., 2024a), are attributed to the power converter, composed of the phase module and other converter or inverter failures. This trend is confirmed by Xiao et al. (2021) which states that the "phase module" accounts for the largest share of power converter failures. The phase module includes power semiconductor modules with gate-driver boards, the DC-link capacitors, and busbars. These results highlight that it is essential to reduce the impact of power converter modules on wind turbine maintenance costs, firstly through improved design which would reduce failures in operation. Secondly through improved monitoring and failure predictions to allow replacement of faulty converters before their failure, reducing the downtime and revenue losses caused by failures in operation. Furthermore, it is shown that converter failure rates have not improved with newer generations of turbines, (Fischer et al., 2019b), and therefore have not been designed out of newer fleets, highlighting the continued importance of power converter failures to wind turbine performance.

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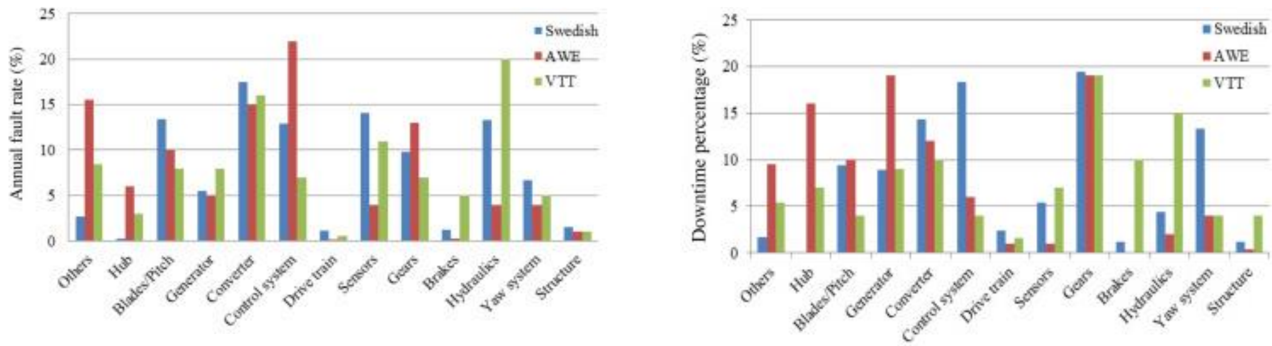

(a) **(b)**

Figure 7: Annual fault rate (a) and downtime percentage (b) of wind power system main components. Taken from (Liang et al., 2022).

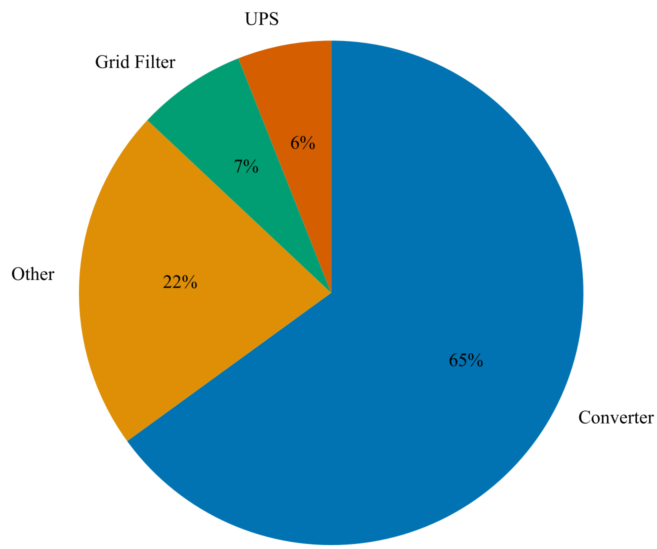

Figure 8: Proportion of electrical failures at an OWF by component.

2.3 Power converter failure modes

A comprehensive review on power converter failure mechanisms and statistics, covering a range of converter manufacturers, has been done by (Fischer et al., 2012, 2015, 2019a, b, 2021; Pelka and Fischer, 2022). Fischer et al. (2019b) demonstrate that within the converter the components responsible for the largest number of failures are the phase modules (26% of failures) followed by the cooling systems and the control boards. Within the phase module, the power modules and driver-boards account for the largest share of failures, happening at similar frequencies. They are the dominant failure locations over the DC link capacitors or busbars.

Failure mechanisms can be split as open-circuit (OC) or short-circuit (SC) faults (Song and Wang, 2013). SC faults are typically characterised by overcurrents and explosive failures with severe damage. Their faults can develop rapidly, therefore, most SC fault detection systems are based around hardware circuits, such as circuit breakers or fast fuses, to offer

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rapid protection by shutting down the converter. Their root cause can be difficult to identify due to the damage caused to the components. By contrast OC faults develop slowly and generally cause less damage but do degrade the performance of the overall converter. They are typically characterised by generator torque oscillations and a reduction in grid power factor. Whilst initial damage is low, they can cause secondary damage to other components and can develop into more severe and damaging faults. They do not cause significant changes in currents and voltages and therefore can remain undetected for a long time.

Failure mechanisms can be further split, as per Yang and Chai (2016), as package-based, chip-based or DC-based. Package-based failure mechanisms describe the failures that are attributable to components outside of the chips themselves. Chip-based failure mechanisms are attributable to the chips themselves or the driver boards, although they may be interlinked with package-based modes for a failure event. DC-based failure mechanisms refer to failures on the DC-link. The monitoring of power electronic devices is still in its early stages with many significant advancements needed to practically implement accurate online monitoring methods (Yang et al., 2010). Moreover, many of the methods have limited applicability due to required sensitivity of measurements or modifications required to be made for converter devices (Choi et al., 2017). It is incredibly challenging to develop monitoring systems due to the small physical size of the power electronic devices and the fast acting and sometimes minimal changes in the degradation signals.

2.3.1 Open circuit faults

Package-based

Package-based OC faults are typically due to thermal degradation and ageing due to fluctuations in temperature cycles and can be one of the following:

- Bond-wire lift-off
- Solder fatigue
- Degradation of thermal paste
- Fretting corrosion

Traditionally these are taken as the dominant failure modes for power converters, in particular bond-wire lift-off and solder fatigue, across all industries. Both statistical analysis and through forensic inspections of both failed and operational converter modules concluded that this is not a critical failure mode for wind turbines (Fischer et al., 2012) and (Fischer et al., 2019a).

Bond-wire lift off, solder fatigue and fretting corrosion arise due to the different coefficients of thermal expansion (CTE) between the materials in the power modules. As the temperature in the module increases the materials expand by differing amounts. Lifetime estimation models based on the accumulated damage from thermal cycles are well developed and can be used to estimate the remaining life of a module (Infineon, 2021). Bond-wire lift off is typically detected through monitoring of changes in the ON-state voltage (VCE,sat) or resistance (RON) (Choi et al., 2017; Sun et al., 2017; Yang et al., 2010) or through an installed sensor which measures voltage drop across the bond wires (Lehmann et al., 2003). Deviation in these

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values can be used to detect bond-wire lift off. Solder degradation is typically detected by monitoring the thermal resistance Rth of the module (Yang et al., 2010), where an increase indicates crack formation in the solder. This is calculated through sensors which monitor junction temperatures Tj, case temperatures Tc, heat sink temperature Ts and device current. Power losses can also be used to with thermal models and cycle counting methods that estimate the total damage. Xiang et al. (2012) developed a method that looks at changes in the harmonics in the output voltage of the device to detect solder-fatigue for devices under steady state operation. As a thermal based degradation mechanism thermal paste degradation detected using the same methods as for solder fatigue failures (Avenas et al., 2015). Fretting corrosion, which can also arise due to vibrations in the converter, is monitored using the ON-state voltage (VCE,sat) or resistance (RON) (Liu et al., 2023) where an increase in these values indicates its occurrence. Arcing can also be detecting by abnormal acoustic emissions (AE) (Liu et al., 2023). Bond-wire liftoff and solder fatigue have been refuted as a dominant failure mechanism in wind turbine applications for the following reasons (Fischer et al., 2019a):

1. Generator side converters in DFIGs, which are subject to stronger thermal cycling do not have larger failure rates than the grid side converters.
2. There is not an increasing failure rate with age but rather infant mortality.
3. Investigations into destroyed and working chips have shown no signs of degradation.

At the OWF presented by Moros et al. (2024), the failure rates of the converters have been approximately constant over the lifetime of the wind farm so far. Additionally, a plot of the lifetimes of the failed converters, shown in Fig. 9, reveals that the 80% of the converters have a lifetime of less than 5 years, with 37% of failed converters having a lifetime of less than 250 days. These findings, along with discussion of the observed failure mechanisms at the wind farm (which are typically overcurrent failures) support the hypothesis that age or fatigue related failures of the converters are not amongst the relevant failure modes. Evidence of degradation in the thermal paste has been found in wind turbines (Fischer et al., 2012, 2015). However, measurements by manufacturers have instead showed improvements in the thermal conduction with ageing (Fischer et al., 2019a). Thermal paste degradation is likely a relevant but not dominant failure mode for wind turbines. Fretting corrosion is not considered an important failure mode for wind turbine power converters. An analysis of failure rates against converter location showed that there was no disadvantage of the converter being positioned in the nacelle, where it would be subject to larger vibrations, compared to the tower base (Fischer et al., 2019b).

Chip -based

Chip-based OC faults are typically due faults in the driver boards which can be from:

- Manufacturing defects
- Electromagnetic interference
- Insufficient gate voltages

As described earlier, the driver boards account for a significant portion of power converter failures. Manufacturing defects can often only be detected based on detailed inspections. High electromagnetic interferences can be monitored through measurement of gate switch time. In IGBTs switch times are in the range of 10-500ns making direct measurement impractical (Yang et al., 2010). To overcome this limitation an under-sampling and reconstruction technique based on the

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collector voltage VCE is proposed by Zhong et al. (2017). Where the gate voltage provided is too low for full switching of the IGBT there is a switching operation with a large loss as the on resistance is increased. The large power loss can lead to rapid thermal destruction of the IGBT. This type of failure mode could be monitored through measurement of the gate voltage signals or the power losses across the converter (Yang et al., 2010). These are all considered as important failure modes for wind turbine power converters and their occurrence is exacerbated by the presence of moisture in the converter (Fischer et al., 2019a).

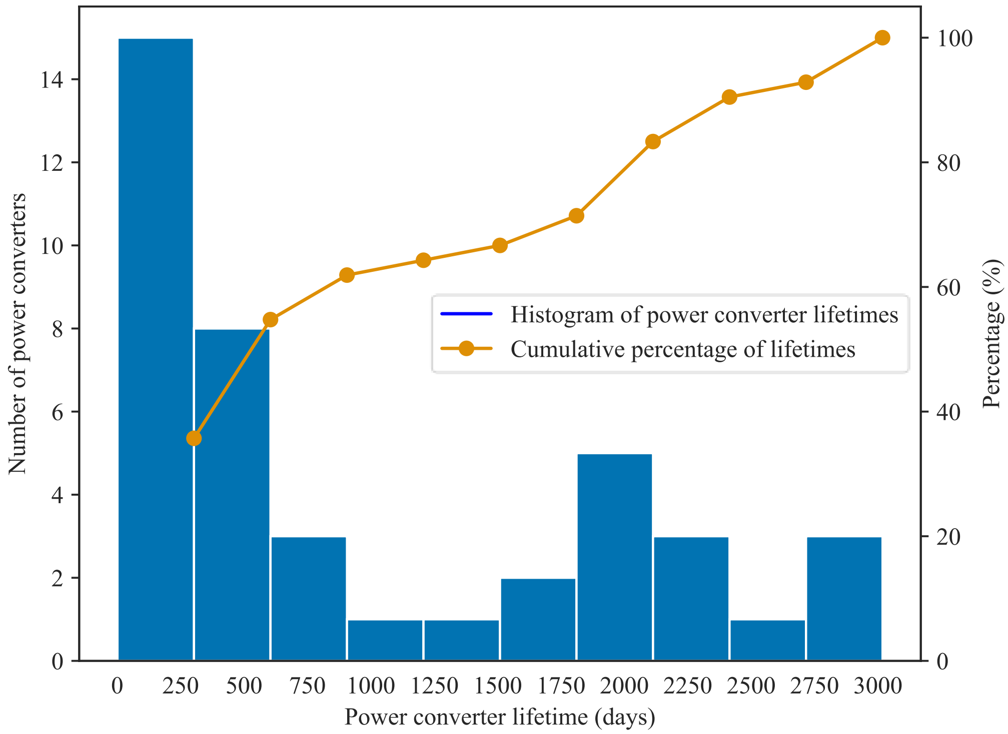

Figure 9: Histogram of lifetimes of failed case-study OWF power converters.

DC-based

DC-based OC faults can arise when there is a detachment of the film-roll inside the snubber capacitor. This increases the capacitors inductance, reducing its ability to limit high-frequency over-voltages leading to failures of the semiconductor devices. This is considered an important failure mode at wind turbines. Degradation of the capacitors is typically monitored by measuring the capacitance (C) or the equivalent series resistance (ESR) of the capacitors (Soliman et al., 2016).

2.3.2. Short-circuit faults

Package-based

Package-based SC faults can be due to the formation of tin whiskers, shown in Fig. 10, which can cause highly destructive short-circuits. Their growth mechanism is not well understood and they can have incubation periods ranging

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from days to 20 years (McDowell, 1992). There is not an established monitoring method for detecting them except for manual inspection using hand-held X-ray fluorescence devices (Barr, 2007). Given that damage can occur in ms, detecting their presence in monitoring signals is unlikely. The forensic investigation by Fischer et al. (2015) did not detect the presence of any tin whiskers.

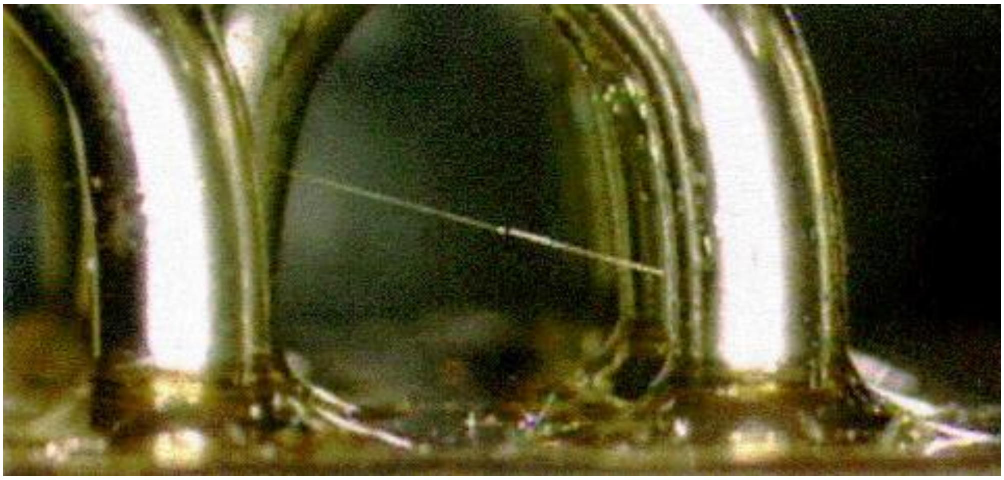

Figure 10: Tin Whisker growing between terminals of an electromagnetic relay. Taken from (Basic Information Regarding Tin Whiskers, 2024).

Chip-based

Chip-based failure mechanisms are dominated by SC faults, which are typically one of the following:

- Electrical overstress (EOS)
- Latch-up and triggering of parasitic inductances
- Electrostatic discharge (ESD)
- Contamination
- Electrochemical migration and corrosion
- Single event breakdown due to cosmic rays
- Lightning Strikes

EOS covers failure mechanisms that cannot be explained due to the explosive damage caused, as seen in Fig. 11, which account for one-fifth to one-third of failures at wind turbine power converters (Fischer et al., 2019a). There are no sufficient monitoring systems in place for these types of failures because their exact cause is unknown, and they can happen rapidly. They can sometimes be mitigated with fast fuses or circuit breakers (Liang et al., 2022). A general method for detecting short-circuit faults is based on the voltage waveform during IGBT turn-on which displays a different pattern between faulty and faultless (Rodríguez et al., 2007). This requires a high frequency measurement of the gate voltage signal.

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Figure 11: Destroyed IGBT module. Taken from (Fischer et al., 2019a).

The result of parasitic inductances, caused by a too rapid rate of change of voltage during turn OFF for an IGBT, is a difference in the currents between phases that parallel connected IGBTs are subjected to. This results in either current overloads or accelerated lifetime consumption of the more heavily loaded devices. Latch-up is avoided through intelligent circuit design (Yang et al., 2010). Current asymmetries can be monitored by measurements of the input and output currents on each phase and comparing them (Sattarov et al., 2023). Current asymmetries are considered to play a role in converter failures at wind turbines (Fischer et al., 2019a). ESD can cause arc-flash events or lead to gate failures. Arc-flash events can be monitored with AE. Gate failures can be monitored by measuring the rate of decay of gate charge (Grant and Gower, 1989). ESD is thought to be an unlikely cause of failures at wind turbines because in practice static should be discharged bypassing the converters (Fischer et al., 2015).

The power converters can become contaminated by coal or environmental dust, salt, insects, and moisture. Contamination can lead to short circuit failures by reducing the clearances between parts or creating conducting paths. Additionally, moisture can cause failures through a degradation of the insulation materials, for example in the DC-link leading to short-circuit failures. Contamination can only practically be monitored through visual inspections. Moisture levels can possibly be estimated through humidity measurements in the converter cabinets as there is a strong indication that humidity has an influence on failure rates (Pelka and Fischer, 2022). It is considered a significant cause of failure at wind turbines (Fischer et al., 2019a), particularly in the case of moisture contamination.

Electrochemical migration can cause short circuits to form or reduce the blocking ability of the semiconductors. The effect is susceptible to humidity (Zhong et al., 2017). Typically the degradation of blocking devices and presence of short circuits is monitored through measuring of the leakage currents (Zorn and Kaminski, 2015). As with moisture contamination, humidity could be used as a way of estimating the presence of an electrolytic later. As a humidity driven failure mode, it is an important cause of failures at wind turbines (Fischer et al., 2019a).

Cosmic radiation particles can interact with the silicon atoms in the power converter and lead to a destruction of the device in single event breakdown (SEB) (Zhong et al., 2017). The frequency of these events varies at approximately 11-year cycles. Given the spontaneous nature of SEB, it is not possible to detect it in advance of failure. This is not considered an important failure mechanism for wind turbines, as an investigation of failure rates with radiation flux has revealed no correlation, and based on a theoretical failure-rate due to cosmic radiation, only a negligible number of failures could be explained (Fischer et al., 2019a).

Lightning can lead to converter destruction by striking the turbine and finding a discharge path through the converter. This would be characterised as an overvoltage event. These are not events that can be predicted, although they can be mitigated by ensuring that the lightning protection systems are sufficiently well maintained. Fischer et al. (2015) found a significant correlation between lightning strikes and converter failures indicating an importance in power converter failure modes.

DC-based

DC-side short-circuit faults can arise for the following reasons (Fischer et al., 2019a):

- Insulation degradation
- Snubber or DC-link capacitor failure

Insulation degradation is exacerbated by the presence of moisture. The importance of this failure mechanism in wind turbines is dependent on the manufacturer. Short circuit faults are harder to directly monitor. However, C and ESR can be used to infer some of the key properties such as abnormal currents, temperatures and voltages (Soliman et al., 2016).

2.4. Power converter fault diagnosis

Fault diagnosis (FD) of power converters identifies the causes of failure and aims for rapid detection after the fault has developed. These can be seen as the first stage in anticipating and minimising the effects of converter failures. .Liang et al. (2022) and Catalan et al. (2023) have performed a comprehensive review on FD methods for power converters.

FD methods can be broadly split as per Yang et al. (2010) into model based and signal based. Model based methods create a model of the power converter system based on physical knowledge of the system and then residuals between the measured values and the estimated values are analysed to identify a fault. Signal based methods can be further split into threshold-based methods and data-driven or system identification methods. Threshold-based methods study the measured signals in the build-up to failure and set thresholds on them to differentiate between faulty behaviour and normal behaviour. Data-driven methods make use of a history of operation data to identify a system state and then either fault pattern recognition is trained, or residuals are calculated between an estimated signal and a measured signal which are analysed to identify the presence of a fault. Note that there is overlap between the methodologies. A common point between them is that they require the monitoring of signals produced by different components of the power converters. The data-driven approaches can also attempt to approximate these signals without direct measurement by training models on more easily measurable data, such as the converter input currents and output voltages, as an input to predict the fault signals (Mohagheghi et al., 2009). A limitation of most methods is that they have been developed using simulations or lab tests rather than under actual operating conditions and using the data available to operators. To the best of the author’s knowledge the method developed by Xiao et al. (2021) is the only one that makes use of the SCADA data available to operators.

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2.4.1. Signal based fault diagnosis methods

Many methods to detect converter faults use the signals described in Sect. 2.1. but methods have also been developed based on input or output currents and voltages. Current-based methods are applicable across a range of faults whilst voltage-based methods are applicable to switch faults. Current-based methods typically don't require the implementation of extra sensors, whilst voltage-based methods do. Liang et al. (2022) provide a detailed review of these in the context of wind power. A summary of the key methods will be presented here.

Threshold-based Methods

Threshold-based methods can use either a fixed threshold or an adaptive threshold, which can respond to the varying operating conditions of the converter, to detect deviation from normal (healthy) operation of the converter. They can be considered a form of normal behaviour model (NBM), which is an approach that predicts the normal behaviour of a turbine and detect faults by analysing difference between a predicted signal and a measured signal (Tautz-Weinert and Watson, 2017). NBMs are often seen in data-driven models.

Current-based approaches have attracted most attention because they have been developed to avoid installation of additional sensors. These methods all have a foundation in Park's current vector approach (Mendes, 2023). An advantage of the additional hardware often required for voltage-based methods is that they can allow designing of fault tolerant systems, e.g. in (Shahbazi et al., 2018), whereby a fault on an IGBT can be bypassed through the installation of additional IGBTs which are used in the case of faults. In general voltage-based methods provide a quicker identification of a fault.

Data-driven Methods

Data-driven methods look to identify faulty performance of a system by analysing changes in the system response with component degradation. There are a variety of methods employed which can generally be split into statistical, probabilistic, machine learning (ML), deep learning (DL) and expert systems. Typically, they require a signal processing and feature extraction phase followed by a pattern training and recognition phase. Their success is reliant on the volume of data provided and a correlation existing between the measured data and the fault being detected.

The methods analysed are dominated by ML methods and DL methods. These include support vector machines (SVM) (Duan et al., 2020; Liang et al., 2020; Wang et al., 2016); long-short-term-memory (LSTM) models (Han et al., 2022; Xue et al., 2020) and convolutional neural networks (CNN) (Xiao et al., 2021; Xue et al., 2019). Probabilistic methods developed include hidden Markov models (HMM) (Kouadri et al., 2020) and Bayesian networks (BN) (Cai et al., 2017). Finally fuzzy logic has been applied in an adaptive neuro-fuzzy inference system (ANFIS) (Liu et al., 2015).

An advantage of data-driven methods over model-based and signal-based methods is that they are relatively easier to create and implement without detailed knowledge of the system. Additionally, none of the methods assessed require the installation of extra hardware, instead most use the high frequency (kHz scale) current and voltage measurements available to the controller. Their main drawback lies in a heavier computational load in training than other methods, this is most of the time acceptable as the training only needs to be done in the models' design phase and can be done using cloud services for a reasonable price. Once the model is deployed, the computational load is minimal.

2.4.2. Model Based Fault Detection Methods

Model based methods can work either by state estimation or parameter estimation. State estimation creates a model of a system to estimate a set of outputs given a set of inputs and calculate the residuals between the measured and estimated signals. A healthy system has minimal residuals. Parameter estimation instead estimates the parameters related to a fault and then analyses the parameters to obtain a fault state. Development of models and comparison to a measured signal is analogous to an NBMs. In general, the model-based methods have a slower response time than the threshold-based methods.

2.5. Summary

The traditionally assumed dominant failure modes for power converters of thermally induced fatigue are not the most applicable for wind turbine applications. Instead faults at the driver boards, contamination, electrochemical migration, and parasitic inductances drive most failures at wind turbines. Many failures remain unexplained and fit into the EOS category. The main signals that can be used for monitoring are, VCE, switch times, gate voltages, input and output currents and leakage currents. It should be noted that due to the random nature or rapid development of some of the failure modes, it is not possible to monitor for their development. Humidity is a significant influencing factor on the development of many of these failure modes. Table 1 lists the failure modes; their relevance in wind turbine converter failures; what signals can be used to monitor them; and the main influencing factors.

Table 2 provides a summary of some of the FD methods, covering their approach; the faults that they can be used for; the signals used; their fault detection time and validation methods. Approximately 75%, of methods have been developed for OC faults (Liang et al., 2022), with particular focus on the fatigue driven thermal cycling failures. This attention is explained by two factors. Firstly, they are the considered the dominant failure mechanisms for power converters, outside of the wind industry. Secondly, they are slower to develop than SC faults and they offer clearer degradation signals in the monitored data. As discussed, these are not the dominant failure modes for wind turbines which instead are more frequently driver board or chip-based failures which tend to develop much more quickly or don't have obvious degradation signals. More effort must be given towards detection and prediction of these faults. Only Xiao et al. (2021), have validated their method against operational wind turbine data. This method has the benefit of using the 10-min averaged SCADA data available to the operator and was able to detect some faulty converters 3 days in advance of the full failure. The other methods rely on high frequency signals that either require extra hardware or use the signals that are fed into the controller of the converter. The controller signals are not available to the wind farm operator, therefore more attention must be paid to developing methods that make use of the SCADA, or efforts should be made to gain access to the controller signals. Additionally, it is the only method reviewed that has been tested on an operational wind farm's data. More efforts should be made to validate

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proposed methods on an actual wind farm where the operating conditions can differ significantly from simulations and experiments.

Whilst FD offers the potential to reduce the damage of faults, it does not offer a solution to reducing the downtime caused by converter faults. Once a fault is detected the turbine must still be shut down until the faulty component can be replaced. Given the rapid development of faults from detection time to complete failure implementing FD methods will have a negligible impact on the revenue losses due to downtime from converter faults. Failure prediction models that can predict or detect a faulty converter, days in advance of its full failure, are needed. This will allow time for mobilisation and replacement of a converter, thus avoiding failures in operation.

Table 1: Summary of power converter failure modes, their importance in wind turbines, commonly used monitoring signals and influential factors.

Failure Mode	Importance for wind turbine converters	Monitoring Signals	Influencing Factors
Bond-wire lift-off	Low	$V_{CE,Sat.}$ R_{ON}	Temperature cycles
Solder fatigue	Low	R_{th}, T_j, Tc, T_s	Temperature cycles
Degradation of thermal paste	Medium	R_{th}, T_j, Tc, T_s	Temperature cycles
Fretting corrosion	Low	$V_{CE,Sat.}$ R_{ON}, AE	Vibrations
Tin whiskers	Low	X-ray Inspections	Unknown
Driver board faults	High	Inspections, V_{CE}, switch times, gate-voltages	Manufacturing defects, interference, humidity
EOS	High	Potentially gate voltages	Unknown
ESD	Low	AE, decay of gate charge	Faulty discharge paths
Parasitic inductances	High	Input and output currents to the converter and IGBTs	Improper converter design
Contamination	High	Inspections	Humidity, converter cabinet design
Electrochemical migration	High	Leakage currents	Humidity
SEB	Low	N/A	Geographical location
Lightning strike	High	N/A	Faulty lightning protection systems
DC faults	Medium	C, ESR	Humidity

Table 2: Summary of FD methods for power converters.

Source	Method	Faults Detected	Signal Used	Sampling Frequency	Fault detection time	Validation method
(Xu et al., 2022)	Instantaneous current amplitude	General IGBT OC faults	Converter Input and Output 3-phase currents	kHz scale	~3ms	Simulation & Experimental
(Qiu et al., 2016)	Current vector pattern	General IGBT OC faults	Converter Input and Output 3-phase currents	kHz scale	-	Simulation & Experimental

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Source	**Method**	**Faults Detected**	**Signal Used**	**Sampling Frequency**	**Fault detection time**	**Validation method**
(Shahbazi et al., 2018)	Residuals between estimated and measured voltages	IGBT OC switch faults	Pole Voltage, DC-link voltage	kHz scale	30μs	Simulation & Experimental
(Ismail et al., 2019)	Short time Fourier Transform to detect DC-link oscillations.	General IGBT OC faults	DC-link voltage	kHz scale	9ms	Simulation
(Kouadri et al., 2020)	HMM	General IGBT OC and SC faults	Converter input and output currents, generator speed, DC-link voltage, output power	kHz scale	-	Simulation
(Duan et al., 2020)	SVM	General IGBT OC faults	Converter Input and Output 3-phase currents	kHz scale	~1ms	Simulation
(Cai et al., 2017)	BN	General IGBT OC faults	Converter output line-to-line voltages	kHz scale	-	Simulation & Experimental
(Liu et al., 2015)	ANFIS	General IGBT SC faults	Converter three phase output voltages	kHz scale	-	Simulation
(Han et al., 2022)	LSTM	General IGBT OC and SC faults	IGBT arm currents	kHz scale	-	Experimental
(Xiao et al., 2021)	CNN	General converter faults	Wind speed, rotor angle, active power, reactive power, rotor speed, grid side converter voltage, generator torque set point	10-min averages	-	Operational
(Deng et al., 2015)	Kalman filter with thresholds	General IGBT OC faults	IGBT arm voltages and currents	kHz scale	~100ms	Simulation & Experimental
(Zhang et al., 2020)	Measured voltages compared to reference voltages	General IGBT OC faults	IGBT voltages	kHz scale	200μs	Experimental
(Jlassi et al., 2015)	Luenberger observer with thresholds	General IGBT OC faults	Converter 3-phase input and output currents	kHz scale	3ms	Simulation & Experimental

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3. Methodology

3.1. The offshore wind farm for case-study

The operational wind farm used for case-study in this paper is composed of 27, 2.3MW turbines. The WTs have a squirrel cage induction generator (SCIG) topology with the converters located in the tower. Data have been accessed for 8 years of operation, corresponding to years 2-9 of the wind farm's life, for the Computerised Maintenance Management System (CMMS) and for four years of operation, corresponding to years 6-9 of the wind farm's life, for the SCADA system, which monitors key turbine components. Along with a condition monitoring system (CMS) installed on the WT gearboxes and metocean data these make up the suite of data available to the operators of the wind farm. This allowed consideration of the development of failure prediction methods in a live operational setting to highlight the constraints in data availability and requirements for operators to use them.

3.2. Data

Given the failure mechanisms and fault detection methods identified in Sect. 2.3., the ideal monitoring signals for detecting faults at WT power converters are high frequency measurements of gate voltages, switch times, VCE, leakage currents, input and output currents and capacitance. Table 3 gives a list of the data fields and sampling rates available tags available to the operator at the case-study wind farm that are most applicable to power converter failure predictions. There is a clear gap between the signals required and those available, particularly in sampling frequency, gate voltages, switch times, VCE, leakage currents and capacitance. Therefore, it is likely to be difficult to predict converter failures using the SCADA data available to operators. Furthermore, the faults such as EOS, lightning strikes, and contamination, are either undetectable or happen randomly, further making it harder to predict all power converter failures.

Table 3: List of SCADA tags available and their sampling rate.

Tag	Sample Rate
Active Power	10-min averages
Wind Speed	10-min averages
Generator RPM	10-min averages
Ambient Temperature	10-min averages
Three phase converter input currents	10-min averages
Three phase converter output voltages	10-min averages
Converter coolant pressure	10-min averages
Converter coolant temperature	10-min averages
Tower Humidity	10-min averages

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Nevertheless, failure prediction models were trained to attempt to classify power converters as healthy or unhealthy, and therefore requiring replacement, based on their monitoring data. Data-driven methods were chosen because they can easily be applied to the historical data without requiring new sensors and based on the data available to the operator and the review of established methods in Sect. 2.2. are the most sensible. The purpose of the trained models is not to identify a root cause of failure but to anticipate a failure in advance of it occurring, whether the model detects this based on secondary symptoms or root causes is not important; however, it will be more likely to predict these failures based on the correct data identified in the root cause failure analysis.

4 years of data from the case-study wind farm were used. The data sources were the maintenance logs from the CMMS and measurement time series from the SCADA system. From the CMMS data 16 corrective converter replacements have taken place. Each intervention can correspond to one or multiple individual phase modules, for example sometimes one phase module on the grid side is replaced and sometimes three on grid and generator side are replaced. It is unknown; however, which phase modules have been replaced in each instance. Therefore, each intervention is considered as a single maintenance action and will be referred to as a corrective replacement (CR) from hereon. Each CR has a corresponding timestamp which allows precise identification of the failure point. SCADA data is then taken for 6 months before each replacement and 12 months after each replacement in order to capture all seasonality variation in healthy data. The 18 months considered corresponds to ~70k timestamps for each CR. Whilst the dataset doesn't correspond to a full turbine lifecycle, the converter failure rate has been shown to be relatively constant, and ageing-related failures of converters at OWFs have been discarded as a significant failure mode, therefore there should be little sample bias of the models towards early lifetime failures. Furthermore, the models can be retrained as the wind farm ages further and more data becomes available to the operator.

3.3. Failure prediction model architectures

The problem is set up as a binary classification problem, where the target variable is the time to failure interval and the input variables are the SCADA tags and any derived features. The time to failure interval is split as greater than 8 weeks to failure and less than 8 weeks to failure. This failure interval was chosen based on tests where it was shown that an ANN can best distinguish between a faulty and healthy converter at the 8 weeks until failure point. The following 8 model architectures were used:

1. Logistic Regression (LR) – 6 input features
2. Decision Tree (DT) – 6 input features
3. Random Forest (RF) – 6 input features
4. XGBoost (XGB) – 6 input features
5. ANN (ANN6) – 6 input features
6. ANN (ANN12) – 12 input features
7. InceptionTime network (IT6) – 6 input features
8. InceptionTime network (IT12) – 12 input features

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16 models were trained for each architecture, with one CR kept separate as the test data in each instance. The data for the remaining CRs were used as the training data. For example, if CR 1 was held back as test data, the model was trained on CRs 2-16, illustrated in Fig. 12. This allowed investigation of the effects of different training splits on the performance of the models. A set of healthy converters on which there were no recorded failures or maintenance was also used as a test set to identify if the models predict false positives.

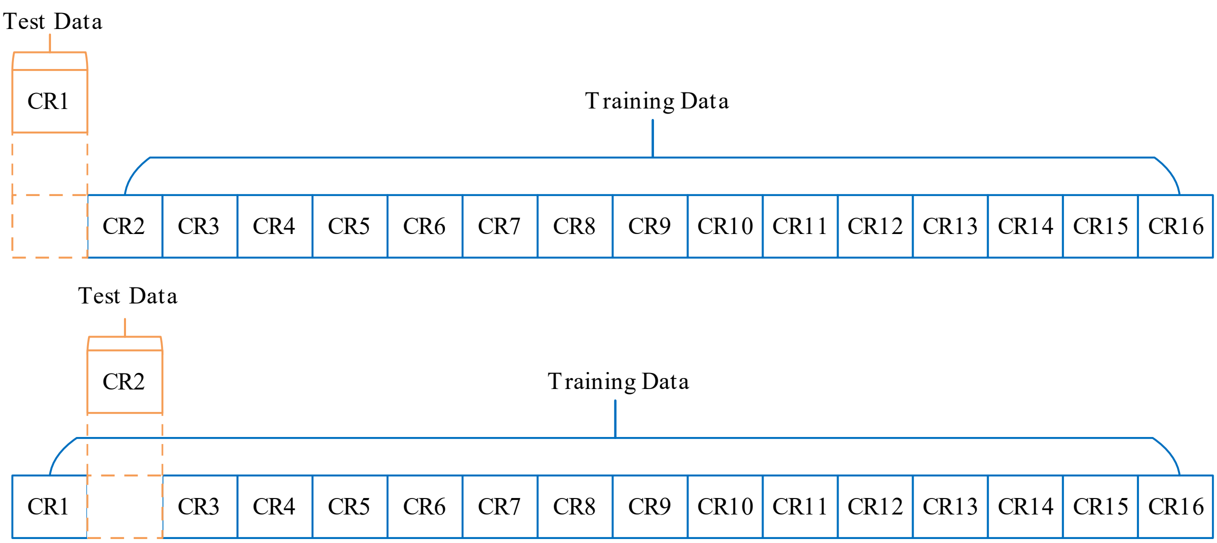

Figure 12: Examples of training and test data split by CR.

The ANN models were first introduced in (Moros et al., 2024b) with a description of their hyperparameters. The LR, DT, RF and XGB models had their hyperparameters tuned in an exhaustive grid search procedure. Along with the ANN models they do not make use of the temporal structure of the data. They consider each 10-minute sampled point in isolation and do not utilise information that came before it. The IT6 and IT12 models were used to leverage the time series nature of the data and are based on the InceptionTime architecture introduced by Fawaz et al. (2020) which is the state of the art in time-series classification. The InceptionTime architecture is based on an ensemble of 5 Inception networks, illustrated in Fig. 13. Each Inception network is composed of two connected residual blocks made up of 3 Inception modules each. The Inception modules, illustrated in Fig. 14, take a multivariate time-series, reduce its dimensionality in a bottleneck layer, apply multiple convolutions and form an output multivariate time-series which feeds to the next module. It was expected that utilising a model that could exploit the temporal structure of the data would lead to better predictions.

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3.4. Preprocessing

Before being used to train predictive models, the SCADA data were pre-processed using the following steps:

1. The installation date of each converter is identified, and the cumulative energy converted from installation to each timestamp is calculated. This captures an energy-based ageing of the converter.
2. The data for each corrective replacement were checked to see if it overlaps with a separate pre-emptive replacement. Timestamps for 8 weeks prior to a pre-emptive replacement were removed.
3. The data were under and oversampled to a ratio of 5:1 between the greater than 8 weeks to failure and less than 8 weeks to failure classes to address the class imbalance problem.
4. Current and voltage difference features are engineered by subtracting one phase from the others. E.g. current L1 – L2 and current L1-L3.
5. Data are assigned a time to failure interval of longer than 8 weeks to failure or within 8 weeks.
6. Features are scaled using either min-max scaling or for the active power, against the rated power. Missing values are replaced with the mean of the timestamps before and after.
7. The target variable is ordinal encoded.
8. Highly correlated features are removed.

The selected pre-processed features for the models that use 6-input features and those that use 12-input features are shown in Table 4 below. The difference is that the 6-input feature models do not make use of the current and voltage measurements.

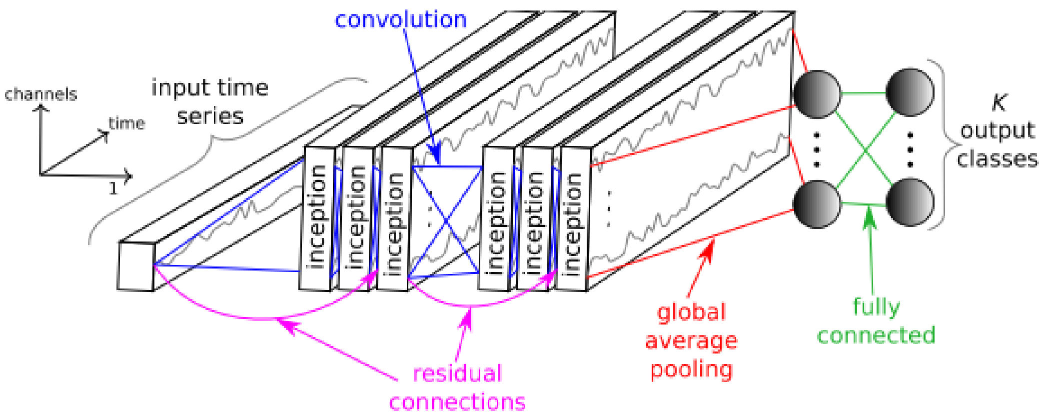

Figure 13: Inception network. Taken from (Fawaz et al., 2020).

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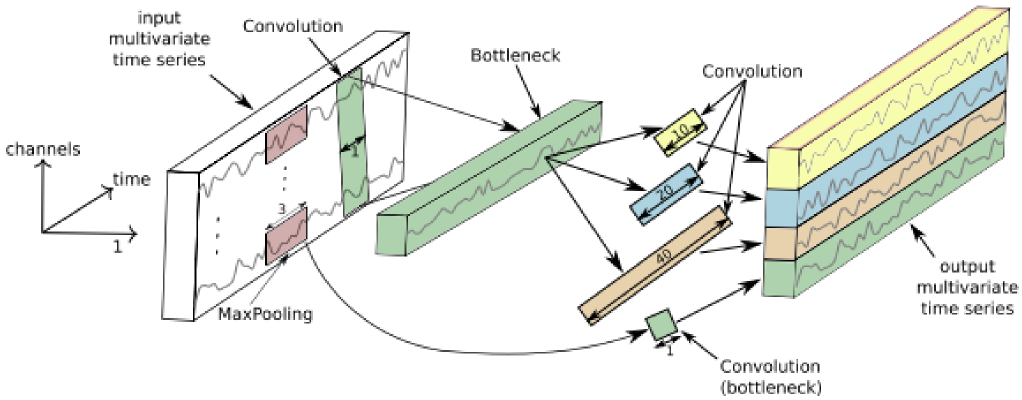

Figure 14: Inception module. Taken from (Fawaz et al., 2020).

Table 4: pre-processed features and the models they were used for.

Feature	6-feature models	12- feature models
Active power	✓	✓
Wind speed	✓	✓
Converter coolant temperature	✓	✓
Inverter coolant pressure	✓	✓
Tower humidity	✓	✓
Cumulative energy converted	✓	✓
Current phase L1-L2 difference	×	✓
Current phase L1-L3 difference	×	✓
Current phase L2-L3 difference	×	✓
Voltage phase L1-L2 difference	×	✓
Voltage phase L1-L3 difference	×	✓
Voltage phase L2-L3 difference	×	✓

For the IT6 and IT12 models there was an extra pre-processing step to convert the input data for the models into a 3D tensor, where each sample corresponds to the previous week of measurements. The data were stepped forward by one day for each sample, meaning that the output of the models was a daily prediction of failure (or not) within 8 weeks based on the previous week's worth of data.

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3.5. Performance Metrics

Typical performance metrics for imbalanced problems are precision and recall. In the case of wind turbine prognostics, high recall models will miss fewer component failures but may lead to a higher number of unnecessary maintenance interventions. Whereas a high precision model will lead to fewer unnecessary maintenance interventions but will miss more component failures, potentially leading to more catastrophic failures. Based on an analysis of the wind farm cost data a failure in operation costs approximately 4 times as much as a preventative replacement, including revenue losses from downtime, therefore more false positives can be afforded than false negatives.

These metrics; however, do not capture the true cost of deployment of models when used in operation. How will the operator make decisions based on the output of the models and what impact does this have on costs? When deployed, the operator of the windfarm will need to make a replacement decision based on the output of the model. Based on the criteria for making decisions, the performance of the models will change from just the recall and precision metrics. Therefore, a new metric for scoring the models based on the estimated costs of deployment is introduced. Firstly, one prediction every 10 minute is not useful for an operator to decide on replacement. Therefore, the modal daily predictions are calculated. Then a threshold for decision making is determined, this can be done through discussion with the operating teams or through an optimisation process. For example, after three consecutive unhealthy predictions a decision is made to replace the component. Then based on the data and decision threshold a failure rate of x failures per turbine per year; a false positive replacement rate of y per turbine per year; and a successful detection rate of z are calculated. Then for a time frame of n years equation (1) can be used to calculate the expected cost of deployment:

$$C=c_p(ny+nzx)+c_c nx(1-z) \quad (1)$$

where c_p and c_c are the cost of a preventative replacement and the cost of a corrective replacement, respectively. This allows calculation of a single metric that can be used for assessing the actual cost of deploying a model. The decision-making threshold for determining if a replacement should be made is decided based on the time requirements for planning maintenance. For example, replacement of small components that are always kept in stock and do not require specialist technicians or vessels can be scheduled on a time scale of days in advance of the failure. On the other hand, major component replacement (MCR) activities, such as gearbox replacements require a timescale of months for planning. In this way, the operational planning constraints, such as vessel availability and waiting for a suitable weather window can be considered. In addition, Eq. (1) considers the cost of false positive replacements which also require time and resource. A business as usual (BAU) baseline should be calculated which considers the current status of anticipating failures of that component. By comparing the models evaluated in their operational context with the current performance of the offshore wind farm potential reductions in costs related to the component of interest can be calculated. For each model 10-different decision-making thresholds were used to evaluate the expected cost of deployment. 3-day, 5-day, 7-day, 10-day, 21-day and 28-day consecutive faulty prediction thresholds and weekly, 2-weekly, 3-weekly and 4-weekly modal predictions. These thresholds were determined based on consultation with the case-study windfarm based on the minimum time that would be

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needed by the maintenance teams to prepare for the replacement of the power converters. In this case, the required planning time is relatively short as the spare parts are always kept in stock and replacement of a power converter does not require any specialist technicians or vessels, so therefore the logistical constraints are always available on site. Three days was given as the minimum time, because the technicians at the wind farm do not work on the weekends, therefore if a failure were to happen on a Monday, the earliest it could be replaced in advance is the preceding Friday.

4. Results and discussion

4.1. Results

Table 5 shows the average precision and recall for each model architecture. The full breakdown of precision and recall by corrective replacement for the models can be found in the appendix. The performance of the models is highly variable depending on which CR is held back as the test data. The LR model has no predictive ability whilst the two best performing models are the ANN6 and XGB models. The two time-series based models perform poorly with low recall meaning that several failures were missed.

Table 5: Precision and recall average across 16 CRs for each model architecture.

Model	Average Recall (%)	Average Precision (%)
LR	0	0
DT	26	49
RF	51	24
XGB	56	29
ANN6	57	39
ANN12	24	34
IT6	14	100
IT12	15	100

Figure 15 illustrates an example of the variability in performance depending on which CR is held back. It shows for ANN6, a model that performs well and a model that performs poorly. For the model where the test data were from CR2 the model correctly makes healthy predictions until just before the 8-week to failure mark after which it consistently predicts an unhealthy converter. For the model where the test data were from CR5; however, the model makes a majority of healthy predictions even when there are fewer than 8 weeks to failure, with a scattering of unhealthy predictions before this point. It cannot be used for failure predictions.

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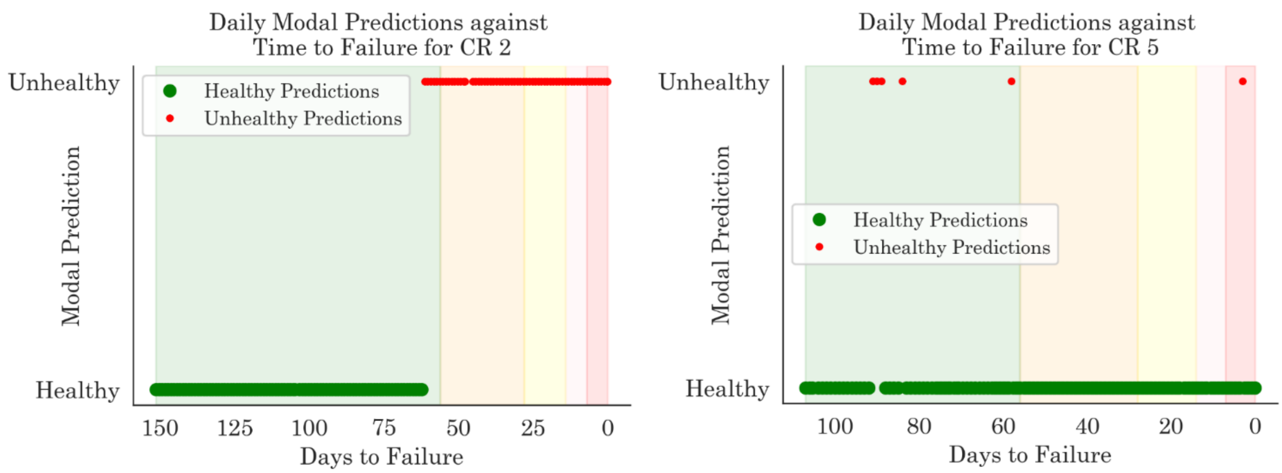

Figure 15: Modal daily predictions for a good model (left) and a bad model (right)

It is important to consider the results of the models in the context of their operational performance. For each model, and each replacement decision threshold described in Sect. 3.4., the number of successful failures that would have been detected in time for a replacement, the number of missed failures and the number of false positives have been calculated, based on the performance of the models on the test datasets. Each successful replacement and false positive replacement were assigned a cost of 1, whilst missed failures were assigned a cost of 4. This leads to a "business as usual" (BAU) case, where no false replacements were made but all failures were missed, having a cost of 64. The expected cost of deployment was also calculated using equation (1) with an n of 15 years; a failure rate of 0.17 per turbine per year; and a c_p of 1 and a c_c of 4. The BAU baseline is therefore a score of 10. A comparison of the total costs of deployment for the replacement decision thresholds is given in Table 6.

Table 6: Comparison of replacement decision thresholds by average, minimum and maximum costs.

Decision Threshold	Average Total Cost	Minimum Total Cost	Maximum Total Cost
3-day consecutive	69.6	37.0	102.0
5-day consecutive	56.4	40.0	65.0
7-day consecutive	56.3	43.0	64.0
10-day consecutive	55.3	46.0	64.0
21-day consecutive	60.3	46.0	66.0
28-day consecutive	62.1	46.0	68.0
Weekly modal	66.0	40.0	90.0
Two weekly modal	59.3	40.0	72.0
Three weekly modal	59.5	43.0	72.0
Four weekly modal	58.5	46.0	66.0

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Whilst the 3-day consecutive threshold has the lowest minimum cost it also has the largest maximum cost. The large maximum cost is driven by many false positives replacement decisions made by the DT, RF and XGB models. Taking the approach that a decision threshold is as a good as its best model, the four best thresholds to use would be the 3-day consecutive threshold; 5-day consecutive threshold; the weekly modal threshold and the two weekly modal threshold. There are improvements in the BAU baseline for all cases. Table 7 provides a breakdown for the 3-day consecutive, 5-day consecutive and weekly modal replacement decision thresholds of the expected costs of deployment, which are illustrated graphically in Fig. 16. When considering the expected cost of deployment, only the ANN6 and ANN12 models lead to improvements on the BAU baseline. This is not the case if only the total cost, scored only on the test datasets, is used. In this case more models show improvement over the BAU baseline, in particular for the 5-day consecutive threshold all models show an improvement in this score. This shows the importance of considering the expected cost of deployment of the models over a long term rather than just for the test dataset. The test dataset is naturally limited by the amount of data available and therefore doesn't capture the long-term behaviour of the model. The best model to choose would be the ANN12 model with a 3-day consecutive replacement decision threshold which would lead to an expected reduction in costs of approximately 42% over the BAU baseline. Even though this model does not have the highest successful detection rate, 0.56 compared to 0.88 for the XGB model with a weekly modal replacement decision threshold, it has a significantly lower false positive rate bringing the long-term costs of deployment down. Despite the relatively low detection rate of 0.56, improvements are seen over the BAU case because there are currently no monitoring or prediction systems in place at the wind farm, therefore even though some failures will remain undetected, these same failures would remain undetected under the current monitoring and processes at the wind farm.

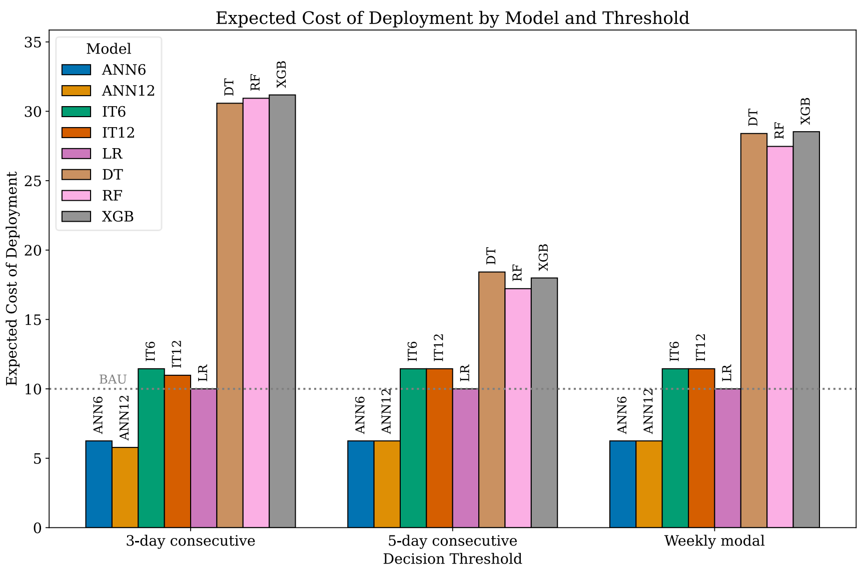

Figure 16: Comparison of expected cost of deployment for each model and decision threshold and compared to the BAU case.

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Table 7: Comparison of models and replacement decision thresholds with expected costs of deployment.

Decision Threshold	Model	Successful Failures Prevented	Missed Failures	False Positives	Total Cost	Detection Rate	False Positive Rate	Expected Cost of Deployment (n=15)
3-day consecutive	ANN6	8.00	8.00	0.00	40.00	0.50	0.00	6.25
3-day consecutive	ANN12	9.00	7.00	0.00	37.00	0.56	0.00	5.78
3-day consecutive	IT6	3.00	13.00	4.00	59.00	0.19	0.19	11.45
3-day consecutive	IT12	4.00	12.00	4.00	56.00	0.25	0.19	10.98
3-day consecutive	LR	0.00	16.00	0.00	64.00	0.00	0.00	10.00
3-day consecutive	DT	13.00	3.00	73.00	98.00	0.81	1.78	30.58
3-day consecutive	RF	12.00	4.00	73.00	101.00	0.75	1.77	30.94
3-day consecutive	XGB	13.00	3.00	77.00	102.00	0.81	1.82	31.18
5-day consecutive	ANN6	8.00	8.00	0.00	40.00	0.50	0.00	6.25
5-day consecutive	ANN12	8.00	8.00	0.00	40.00	0.50	0.00	6.25
5-day consecutive	IT6	3.00	13.00	4.00	59.00	0.19	0.19	11.45
5-day consecutive	IT12	3.00	13.00	4.00	59.00	0.19	0.19	11.45
5-day consecutive	LR	0.00	16.00	0.00	64.00	0.00	0.00	10.00
5-day consecutive	DT	12.00	4.00	35.00	63.00	0.75	0.94	18.42
5-day consecutive	RF	12.00	4.00	33.00	61.00	0.75	0.86	17.22
5-day consecutive	XGB	12.00	4.00	37.00	65.00	0.75	0.91	17.99
Weekly modal	ANN6	8.00	8.00	0.00	40.00	0.50	0.00	6.25
Weekly modal	ANN12	8.00	8.00	0.00	40.00	0.50	0.00	6.25
Weekly modal	IT6	3.00	13.00	4.00	59.00	0.19	0.19	11.45
Weekly modal	IT12	3.00	13.00	4.00	59.00	0.19	0.19	11.45
Weekly modal	LR	0.00	16.00	0.00	64.00	0.00	0.00	10.00
Weekly modal	DT	13.00	3.00	64.00	89.00	0.81	1.63	28.40
Weekly modal	RF	12.00	4.00	59.00	87.00	0.75	1.54	27.47
Weekly modal	XGB	14.00	2.00	68.00	90.00	0.88	1.67	28.53

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4.2. Discussion

4.2.1. Variable performance with CR

Depending on which CR was used for the test dataset, the precision and recall metrics vary significantly. The variation in model performance could be explained by either the data used, or the model used. As shown in Sect. 2.3., converters have different failure mechanisms. Where the models perform well, it is possible that the pattern in the data of their failure mechanism is represented by another replacement in the training dataset. It is also possible that the failure mechanism is detectable in the 10-minute average time series. Where the models don't perform well; however, could be attributed to the inverse. Either their failure mechanisms are unique and not captured by patterns in the data for other failures in the training dataset, or the failure mechanisms are not detectable in the 10-minute averaged SCADA data. Considering that many failure mechanisms are either short circuits that develop in µs or are only detectable with high frequency measurements with internal converter signals it is likely that most failures are not predictable using the SCADA data. The data either do not have the correct measurements or the sampling rate is too low. Furthermore, within the SCADA data many of the data features are not directly measuring the converter, for example a general tower humidity measurement is provided rather than the converter cabinet humidity, whilst they will be linked some error will be introduced by this. There are no details of the failure mechanisms for each converter; therefore, it cannot be confirmed if the presence of shared failure mechanisms in the training data with the test data leads to better model performance. All these factors, highlight the challenge of trying to develop failure prediction models as the wind farm operator and stress the importance of developing models based on real world data rather than idealised lab tests.

To tackle the variety of failure mechanisms more data should be utilised, either by collecting data from more failures or using synthetic data. Collection more data of converter failures at the case-study OWF would be a slow process with ~ only 6 per year. Alternatively, converter failure data from other wind farms which use a similar turbine architecture could be used. The other wind farms will have different operating conditions and therefore perhaps different failure patterns, but this offers a much faster way to increase the size of the dataset. Generating synthetic data (Khan et al., 2021) could offer a way to generate a large volume of new training data and address the class imbalance problem. There are many methods to generate synthetic data and Generative Adversarial Networks (GANs) have been shown to be effective (Figueira and Vaz, 2022) in improving ML model performance. The main drawback of only utilising synthetic data is that it will only generate data similar to that which it is trained on, therefore it could not capture additional failure modes that have not been seen at the case-study OWF. A combination of the two approaches could be of value.

4.2.2. Poor time series model performance

Contrary to expectation the IT6 and IT12 models do not offer an improvement in predictive performance over the ANN6 and ANN12 models and have very low detection rates. Either there are no obvious temporal patterns of degradation in the

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input data, or the models are not suitable for the data available. The InceptionTime architectures are large with approximately 500k parameters to fit, there may not have been enough input data to fit these models correctly.

4.3. Summary

Data-driven methods can offer a promising method of developing failure prediction models for WT power converters. Their success; however, is limited when trained on the SCADA data available to operators. It is likely that the failure modes described in the previous sections, are either unpredictable in enough time to alleviate their impacts on turbine downtime or their fault signatures do not appear in the SCADA data. The best prediction success rate of 56% is low and whilst it is an improvement over the BAU case, the computational effort and time required to further improve these models is perhaps not worth it. Before significant effort is made in developing improved converter failure prediction models, increased efforts need to be made to understand the fault symptoms of the various failure modes and high frequency data collected in their buildup. There is a gap between the 10-minute averaged SCADA data available to operators and the data in which faulty converter signals are detectable. This must be bridged to allow deployment of converter failure predictions at operating wind farms and beyond just simulation and laboratory tests. It has also been shown that when designing failure prediction models their performance needs to be evaluated in the context of maintenance decision making. When considered in the context of a model's impact on long term maintenance costs it is shown that a "good" model may lead to increases in long term costs.

5. Conclusions and recommendations for operators

A method that an OWF operator can apply to an asset to reduce O&M costs has been demonstrated on the case study of power converter failures. The approach outlined above can be used by wind farm operators to follow a step-by-step process for developing failure prediction models. By first understanding the failure mechanisms of each component and their fault signals, operators can understand what data is required to detect the faults and identify gaps in the data currently available to them. If it is apparent that the data available are insufficient, a data collection strategy can be designed avoiding wasted effort on developing failure prediction models that will perform poorly due to insufficient data. There is a clear gap between the data that are available to the operators and that which is required to detect power converter failures at wind farms. Turbine OEMs or wind farm operators should install sensors and collect data that captures the symptoms of the dominant power converter failure modes. This involves high frequency measurements of IGBT V_{CE}, switch times, gate voltages, input and output currents and leakage currents. This gap has been demonstrated through the performance of trained failure predictions models where even the best model was only able to achieve a 56% faulty detection rate. Finally, it has been shown that predictive models need to be analysed in the context of their use in operation. A new scoring function which combines preventative and corrective costs, false positive rates and fault detection rates has been demonstrated. It is shown that considering the long-term performance of models through this scoring function can change the conclusions on whether a model is successful or not.

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The analysis suffered from a few limitations. Firstly, the failure mechanism and precise location of failure for the converters is unknown. These details could allow grouping of failures into their own test and training datasets, allowing for more precise failure prediction models to be developed. Secondly data for converter failures were only available for four years. A larger dataset is especially beneficial for data-driven models and would perhaps allow exposure to a greater range of failure mechanisms. Finally, the operational scoring function does not consider the knock-on effects of planning maintenance for these predicted failures on all other wind farm maintenance. There are limited resources for planning maintenance and there is therefore an opportunity cost associated with deciding to perform one maintenance action over another. Future work should consider the opportunity costs and optimal assignment of jobs based on predictive model success by developing decision making models that can be used by the maintenance teams. Despite this, the operational scoring function remains a step towards considering the performance of predictive models in a live environment.

Appendix A – Precision and recall by CR

Table A1: Precision and Recall on test CR data for LR & DT & RF.

Test CR	LR		DT		RF	
	Precision	Recall	Precision	Recall	Precision	Recall
CR 1	-	0.00%	0.00%	0.00%	0.00%	0.00%
CR 2	-	0.00%	50.00%	3.85%	100.00%	3.85%
CR 3	-	0.00%	73.47%	64.29%	77.08%	66.07%
CR 4	-	0.00%	5.26%	1.72%	5.26%	1.72%
CR 5	-	0.00%	25.00%	14.04%	6.67%	3.51%
CR 6	-	0.00%	100.00%	56.52%	100.00%	57.39%
CR 7	-	0.00%	94.12%	41.03%	100.00%	43.59%
CR 8	-	0.00%	100.00%	44.35%	98.15%	42.74%
CR 9	-	0.00%	63.64%	12.28%	50.00%	5.26%
CR 10	-	0.00%	63.16%	63.16%	71.15%	64.91%
CR 11	-	0.00%	60.66%	64.91%	60.32%	66.67%
CR 12	-	0.00%	43.48%	17.54%	37.50%	10.53%
CR 13	-	0.00%	8.33%	3.51%	9.52%	3.51%
CR 14	-	0.00%	0.00%	0.00%	0.00%	0.00%
CR 15	-	0.00%	3.23%	2.78%	0.00%	0.00%
CR 16	-	0.00%	100.00%	22.81%	100.00%	19.30%

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Table A2: Precision and Recall on test CR data for XGB & ANN6 & ANN12.

Test CR	XGB		ANN6		ANN12	
	Precision	Recall	Precision	Recall	Precision	Recall
CR 1	0.00%	0.00%	-	0.00%	3.33%	0.25%
CR 2	100.00%	3.85%	5.31%	2.99%	0.18%	0.06%
CR 3	81.82%	80.36%	88.94%	100.00%	50.46%	25.63%
CR 4	0.00%	0.00%	85.15%	100.00%	7.95%	22.30%
CR 5	17.24%	8.77%	45.09%	33.76%	33.07%	15.18%
CR 6	98.68%	65.22%	29.81%	2.04%	61.60%	23.59%
CR 7	100.00%	52.99%	68.08%	66.31%	63.95%	35.55%
CR 8	100.00%	50.81%	16.05%	5.25%	26.17%	42.44%
CR 9	100.00%	12.28%	99.57%	30.02%	28.56%	5.61%
CR 10	75.51%	64.91%	71.31%	98.13%	79.81%	75.40%
CR 11	56.41%	77.19%	99.69%	64.60%	62.32%	44.85%
CR 12	48.00%	21.05%	0.00%	0.00%	44.22%	15.34%
CR 13	7.69%	3.51%	52.87%	100.00%	5.83%	2.25%
CR 14	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
CR 15	3.45%	2.78%	93.62%	7.84%	28.87%	68.78%
CR 16	100.00%	14.04%	99.79%	17.59%	44.06%	8.30%

Table A3: Precision and Recall on test CR data for IT6 & IT12.

Test CR	IT6		IT12	
	Precision	Recall	Precision	Recall
CR 1	-	0.00%	-	0.00%
CR 2	100.00%	9.09%	-	0.00%
CR 3	-	0.00%	-	0.00%
CR 4	-	0.00%	-	0.00%
CR 5	100.00%	42.41%	100.00%	51.27%
CR 6	100.00%	68.79%	100.00%	61.78%
CR 7	100.00%	57.23%	100.00%	63.52%
CR 8	100.00%	49.56%	100.00%	58.41%
CR 9	-	0.00%	-	0.00%
CR 10	-	0.00%	-	0.00%

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CR 11	-	0.00%	-	0.00%
CR 12	-	0.00%	-	0.00%
CR 13	-	0.00%	-	0.00%
CR 14	100.00%	1.15%	-	0.00%
CR 15	-	0.00%	100.00%	3.23%
CR 16	-	0.00%	-	0.00%

Data availability

The data used in this paper cannot be shared due to confidentiality reasons.

Author contributions

Demitri Moros Conceptualisation, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Visualisation, Validation, Writing – original draft, Writing – review and editing

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Competing interests

The authors declare that they have no conflict of interest.

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