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# On the Development of Offshore Wind Turbine Technology: An Assessment of Reliability Rates and Fault Detection Methods in a Changing Market

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**Abstract:** Offshore wind turbine drive train technology is evolving as developers increase size, aim to maximise availability and adapt to changing electricity grid requirements. This work first of all explores offshore technology market trends observed in Europe, providing a comprehensive overview of installed and planned capacity, showing a clear shift from smaller high-speed geared machines to larger direct-drive machines. To examine the implications of this shift in technology on reliability, stop rates for direct-drive and gear-driven turbines are compared between 39 farms across Europe and South America. This showed several key similarities between configurations, with the electrical system contributing to largest amount of turbine downtime in either case. When considering overall downtime across all components, the direct-drive machine had the highest value, which could be mainly attributed to comparatively higher downtime associated with the electrical, generator and control systems. For this study, downtime related to the gearbox and generator of the gear-driven turbine was calculated at approximately half of that of the direct-drive generator downtime. Finally, from a perspective of both reliability and fault diagnostics at component level, it is important to understand the key similarities and differences that would allow lessons learned on older technology to be adapted and transferred to newer models. This work presents a framework for assessing diagnostic models published in the literature, more specifically whether a particular failure mode and required input data will transfer well between geared and direct-drive machines. Results from 35 models found in the literature shows that the most transferable diagnostic models relate to the hydraulic, pitch and yaw systems, while the least transferable models relate to the gearbox. Faults associated with the generator, shafts and bearings are failure mode specific, but generally require some level of modification to adapt features to available data.

**Keywords:** wind energy; offshore; reliability; fault detection; geared; direct drive; transfer learning



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## 1. Introduction

Wind turbine generator and drive train technology has developed rapidly over the last decade as utility-scale wind turbines have increased in size and contribute to a greater share of the electricity market [1–3]. This fundamental shift in the energy mix requires wind turbines to cope with greater flexibility in generation, with wind farms now operating more like traditional power plants to reach increased demand that meets current electricity grid conditions. As the generator and wider drive train configuration has adapted to meet changing grid requirements, wind turbine developers and operators have also been challenged to lower the overall LCOE by reducing the OPEX. The response to this challenge has been to find opportunities to maximise availability, increase system reliability, decrease the cost of repairs, reduce downtime and minimise lost production over the lifetime of a site due to unplanned maintenance activities [4]. In recent years, system reliability issues have also been addressed by simplifying and reducing the number of potential points of failure, with some OEMs taking the strategic decision to remove the gearbox and focus on direct-drive technology.

### 1.1. Problem Statement

In the offshore environment, where turbines are now increasing to 14 MW rated power, not only is access at a premium, but lost production is also very expensive to operators, with research recently suggesting that O&M could contribute up to 30–40% of the total LCOE [5]. This scenario provides developers with extra motivation to increase overall wind turbine reliability. This has lead some OEMs to focus on eradicating components that have conventionally caused expensive repairs and high amounts of downtime relative to other elements of the drive train. Examples of this behaviour would be in removing the gearbox for a direct-drive machine, or removing the high-speed stage of the gearbox for a medium-speed machine. For wind energy to continue to be financially viable, the wind industry must continue to adapt and improve technology; however, it must also ensure knowledge gained from older systems is understood and transferred where possible to ensure any lessons learned are appropriately recorded and applied.

When a new technology or wind turbine model is deployed, there is little or no operational data and maintenance records to understand reliability at a system-wide level. The transition to larger turbines with direct-drive train technology therefore poses an interesting hurdle to asset owners and operators that are looking to scale and optimise maintenance activities; in the context of wind turbine reliability and condition monitoring, how much insight can be drawn from data gathered on older technology and applied to modern direct-drive machines?

### 1.2. Motivation, Paper Structure and Novelty

Literature surrounding wind farm O&M commonly falls into several distinct categories; reliability analysis, performance optimisation, fault diagnostics, failure prognostics and maintenance optimisation. To date, reliability analysis has been used to determine critical components in order to focus efforts on fault detection, failure prediction and maintenance optimisation to minimise both OPEX and lost production, a process which has been identified as a key driver to achieve higher wind farm availability. Papers published to date have proposed a range of fault diagnostic methods primarily focusing on using SCADA data to detect anomalies across the wind turbine gearbox [6–8], blades [9], generator [10,11], pitch [12] and yaw [13] systems and main bearing [14]. Earlier approaches such as [15] used a linear auto-regressive model model to detect generator bearing failure by modelling bearing temperature and [16], which developed higher-order polynomial models of drive train temperatures. More recently, nonlinear auto-regressive neural networks with exogenous inputs (NARX) models have been used in [17,18] to detect gearbox issues. Several review papers [19–22] have also been published over the last several years providing a comprehensive overview. That being said, no study to date has attempted to review and evaluate previous work with an emphasis on highlighting the potential of transfer learning between direct-drive and geared machines.

Section 2 of this paper aims to provide a comprehensive overview of geared and direct-drive train taxonomy, with an emphasis on highlighting the key differences and similarities at assembly and component level that can be used to gather and transfer information. In addition, this section will take a look at real-world SCADA data to evaluate what information is typically gathered across different monitoring systems for each drive train configuration. This initial assessment is a vital step to determine which failure modes are likely to be common across both configurations and what associated monitoring data are readily available.

Using standardised research methods observed in the literature, Section 3 will present new results from a reliability study of 617 wind turbines across Europe and South America with a combined total of 217 operational years. Wind turbine stoppage rates and downtime related to a range of components are assessed, with the study encompassing both direct-drive and gear-driven systems all under 3.2 MW rated power. Initial results are then compared to results from other reliability studies found in the literature.

Section 4 builds on previous sections and presents a framework to assess existing literature in the area of fault diagnostics and prognostics. The aim of this review is to provide an overview of existing techniques and case studies that are most applicable to direct-drive machines, making use of existing datasets made up of mainly gear-driven wind turbines. Not only does this allow for some immediate insight into the direct-drive machines, this study also opens up opportunities in areas such as transfer learning and reinforcement learning to adapt models as more data and information are made available for modern, larger, direct-drive machines. Finally, drive train components and failure rates common to both configurations are brought together to assess which components are most critical for future research into direct-drive diagnostics and prognostics. In the context of existing literature in this area, the contribution of this work is to:

- Provide an overview of the current technology trends observed in the European offshore wind sector.
- Present results from a new reliability study of over 617 wind turbines, directly comparing down times associated with direct-drive and geared machines.
- Introduce a framework for evaluating how transferable previous diagnostic models published in the literature using older technology are when considering newer large-scale direct-drive generators.
- Deliver insight into key components that must be considered a priority for large-scale direct-drive generators with regards to diagnostic and prognostic modelling considering both reliability and previous research.

## 2. Drive Train Configuration Trends

When describing a wind turbine drive train configuration, it is typically expressed as a series of assemblies and components required to convert the kinetic energy in the rotor to electrical energy needed for a stable grid connection. In modern utility-scale wind turbines, there are four major categories as described in [4,23]. Note configuration type A and B from [4] have been excluded due to a focus on current utility-scale technology applicable to the offshore environment that meets modern grid requirements [24,25].

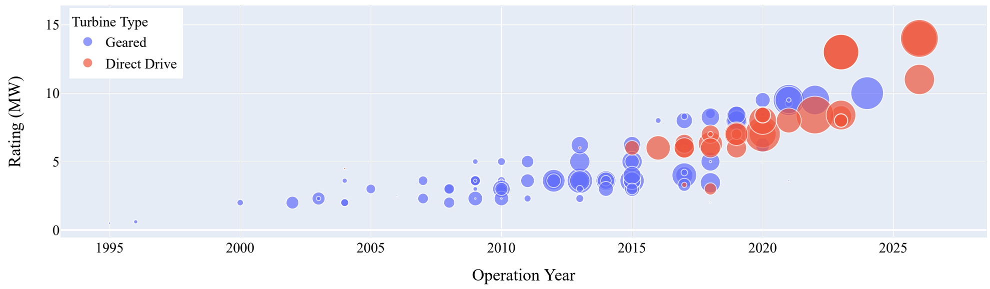
Full details of each configuration type along with schematic diagrams can be found in [4,23]; however, a brief overview of the important configurations used in this work will be provided. Configuration one is the doubly-fed induction generator (DFIG). A partial power converter is used to control the electrical current in the generator's rotor. Configuration two has a full-power converter which enables the decoupling of the generator and grid frequency. This means that the frequency on the generator side can be fully controlled allowing for enhanced grid services and the use of a gearbox can be avoided. A synchronous electrical generator (which can be either an electrically excited synchronous generator (EESG) or a permanent magnet synchronous generator (PMSG)) is directly coupled to the main shaft of the rotor. Configuration three is a gearbox-equipped wind turbine with a full-power converter and medium/high-speed synchronous generator, which can be EESG or PMSG. In this arrangement, it is possible to choose between a relatively small gearbox (with moderate gear ratios) at the expense of using a large medium-speed synchronous generator. On the other hand, it is possible to assemble a gearbox with a higher gear ratio in order to reduce the size of the generator (high-speed configuration with synchronous generator). Configuration four is a gearbox-equipped wind turbine with a full-power converter; however, it has a high-speed asynchronous generator. As the full-power converter enables the speed to be controlled by modifying the operating frequency, a squirrel cage induction generator (SCIG) is generally employed in this configuration. In the context of offshore wind energy more broadly, configuration three corresponds to a geared multistage high-speed wind turbine, configuration two is a direct-drive machine, while type three and four are hybrid models. In relation to the work completed in this paper, configuration two makes up the direct-drive wind turbine category, while configurations one, three and four are grouped together into the gear-driven wind turbine category.

According to the JRC Wind Energy Database, in terms of market share, geared turbines have dominated the global onshore market, with the vast proportion of these turbines onshore made up of a DFIG arrangement below 3 MW rated power output. This is particularly true across Europe, Asia and North America. Further analysis presented in [1] shows the evolution of configuration types with geographical location, with configuration four more prevalent in North America and configurations two and three having more market share in Europe and Asia. If we look offshore across Europe, DFIG models dominated the early market predominately close to shore. This has vastly changed over the last 5–7 years, with direct-drive and hybrid models now making up a significant proportion. PMSGs have seen an explosion in the Asian market in particular, while EESGs are typically more common in European waters. Conversely, PMSGs have been gaining more traction in Europe as turbines increase beyond 5–6 MW [2,23,26–29]. The technological shift towards direct-drive PMSGs over other types of generators is predominately due to the perceived increase in reliability that can be achieved with fewer components and importantly, no gearbox. Whether the reliability of the system as a whole does in fact increase is still up for debate, with further evidence required in order to conclusively state either way. This topic will be discussed in greater detail throughout the reliability analysis section of this paper.

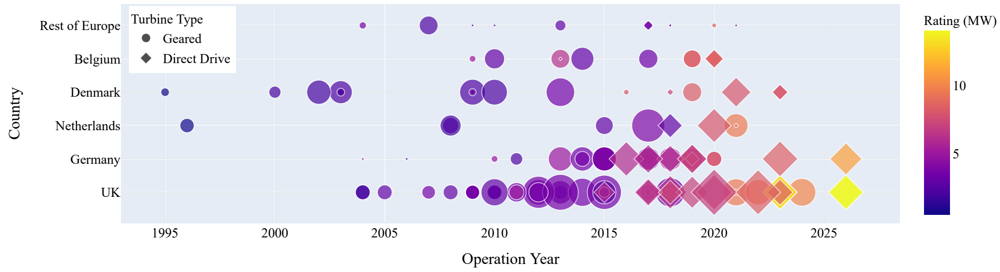
Looking offshore, this shift is even more apparent, with direct-drive machines starting to dominate the UK market over the last 5 years. In fact, from the 1725 wind turbines currently installed or under development in UK waters since 2016, 70.1% (or 1221) have direct-drive PMSG technology. This accounts for an installed capacity of just over 11.1 GW since 2016, 73.4% of total capacity either installed or under development.

Figure 1 shows the technology shift in the UK and wider European market from the first offshore wind farm to all current wind farms either operational or currently in development (due to be commissioned by 2026). These plots were developed by the authors using open source information found in [30]. In Figure 1a, each circle represents a wind farm, with the size of each circle scaled with the number of turbines that make up the site. Direct-drive configurations are shown in red, while gear-driven wind turbines are represented in blue. The y-axis displays individual wind turbine rated power of each site which, as shown on the plot, has increased significantly over the last 20 years along with the average site size. Figure 1b shows these same technology trends but split into each European country for comparison. Observed trends are similar, with turbine rating and total site capacity getting larger, with a large number of direct-drive machines entering the market over the last 5 years. Looking more closely at wind turbine manufacturers, Figure 2 shows a breakdown of OEM market share across Europe. SGRE currently has the largest share, with over 58% of installed capacity, followed by Vestas (28%) and GE Renewable Energy (11%).

Each wind turbine drive train configuration can be broken down into a common series of major components, each assigned a unique set of failure categories, which will be discussed extensively throughout the next section. Looking specifically at SCADA data related to the generator and gearbox, Figure 3 shows the average number of data channels recorded for both direct-drive and geared machines. Three examples of each configuration type were used, each ranging from 1 to 3 MW rated power. This information has been included to showcase the key differences when it comes to which sensors are available to create features for fault detection. This approach will later be used to assess model transferability. Based on these examples, direct-drive models have on average fewer channels and sensors than their geared counterparts. With regards to the generator specifically, temperature readings are typically available for the bearings, stator and rotor across both configurations, along with generator shaft speed and electrical current, voltage and power measurements.




(**a**)




(**b**)

**Figure 1.** Overview of offshore wind turbines drive train technology trends in Europe. (**a**) Comparison of geared and direct-drive offshore wind turbine installed capacity in Europe; (**b**) installed capacity of different drives by country.

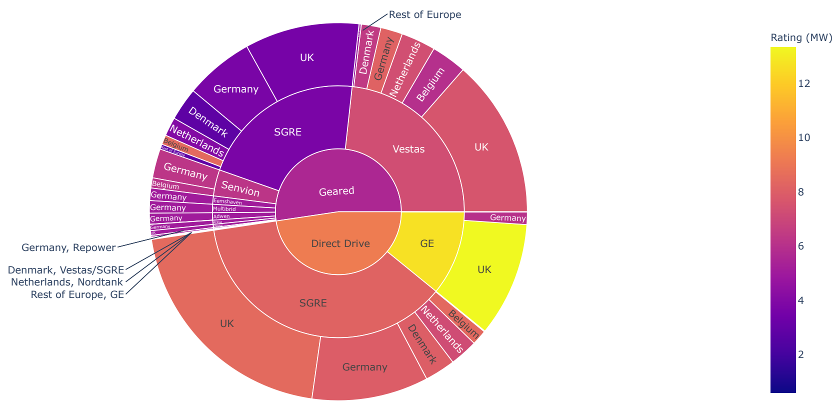



**Figure 2.** European offshore wind installed (or planned) capacity by drive train type and OEM.

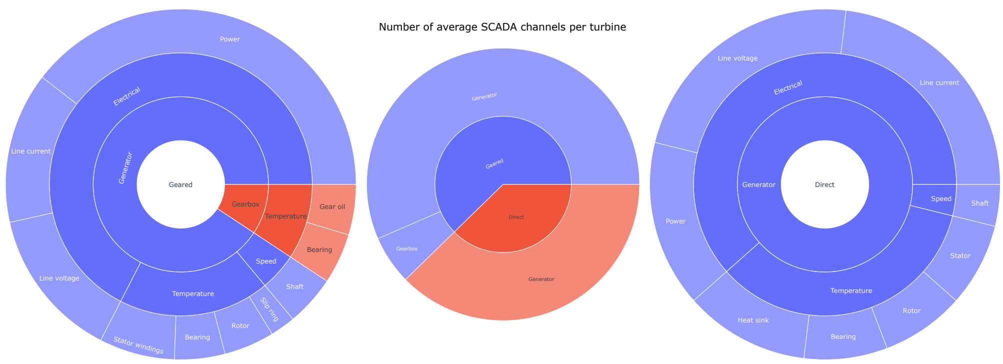



**Figure 3.** Number of SCADA channels assigned to each drive train category and component (showing only generator and gearbox).

## 3. Wind Turbine Stop Rate Analysis

Wind turbine reliability rates cover a range of metrics regarding wind turbine reliability. These can be wind turbine failure rates, stop rates, downtimes, or possibly lost production. For the purposes of this paper, the reliability rates examined are the stop rates and downtimes for wind farms in Europe and South America.

Wind turbine stoppages can occur for a range of reasons, from manual stops relayed from the owners or operators of the turbine to faults in the turbine components. Different metrics have been used in the past to assess the reliability of wind turbines, and their components. These metrics provide different levels of information, such as turbine availability percentage, stop rates, or failure rates. Wind turbine failures differ from wind turbine stops, and therefore cannot be directly compared. However, the general trends may still be examined and discussed, as stop rates will also include any failures, or faults, that caused the turbine to stop.

Previous studies have investigated the reliability of wind turbines, typically focusing on failure rates of wind turbine components. These are usually presented as number of failures per turbine per year, and are presented alongside the number of hours of downtime per turbine per year.

Several studies have collated reliability results from papers that have investigated wind turbine datasets. These studies typically present failures by component group, and these are usually similar with some slight variations in category definitions. The results presented in this section will be compared against the various past studies. Several of these studies also present the downtime per turbine per year in hours for the datasets. The studies cover wind turbines from across Europe, Asia, and the USA. The majority of these studies are focused on onshore turbines, and typically gear-driven turbines with some direct drives. In particular, a study from S. Ozturk et al. [31] has compared sub-1 MW geared and direct-drive wind turbines from the WMEP dataset in Germany. The papers collated in these reviews are described in Table 1.

The data provided for this study consisted of 39 farms, located in either South America or Europe. The majority of turbines assessed were located in South America, approximately 470, and the others, approximately 150, located in Europe. The European turbines are from either around the Mediterranean sea, or the British and Irish Isles.

Three of the farms investigated consisted of direct-drive turbines, approximately 50 turbines in total, with all of these located in Europe. The turbines rated between 1.5 and 3.5 MW, and aged between 2 and 13 years. The majority of turbines were operating for less than 7 years, with a small minority in operation longer. The data provided cover the life of the turbines investigated from when they were first operational until the beginning of 2020. A factor that is of interest in the wind energy community is how wind turbine reliability rates, such as stoppages, scale with turbine size. This link is unfortunately beyond the scope of this paper, as the dataset is limited to turbines of similar rating. Future work, utilising a dataset with more varied turbine rating, could examine the change in reliability rates between small and large rated turbines.

**Table 1.** Failure rate studies featured in the reviews previously discussed.

| Author | Title | Dataset | Turbine Number | Years Collected | Country | Top 3 Failures | Top 3 Downtimes |
|---|---|---|---|---|---|---|---|
| M. Reder [32] | Wind Turbine Failures—Tackling current Problems in Failure Data Analysis | AWESOME | 4300 | - | Europe | <1 MW: (Gearbox, Blades, other blade brake) | <1 MW: (Gearbox, Generator, Blades) |
| | | | | | | >1 MW: (Gearbox, Controller, Pitch) | >1 MW: (Gearbox, Generator, Blades) |
| | | | | | | DD: (Controller, Met Station, Yaw) | DD: (Generator, Blades, Controller) |
| G. Wilson [33] | Assessing wind farm reliability using weather dependent failure rates | Blacklaw and Whitelee | Over 250 | - | Scotland | Control, Drivetrain, Yaw | - |
| V. Hines [34] | Continuous Reliability Enhancement for Wind (CREW) Database: Wind Plant Reliability Benchmark | CREW | 800–900 | 2013 | USA | Rotor, Generator, Controls | Yaw, Brakes, Controls |
| Y. Lin [35] | Fault analysis of wind turbines in China | CWEA | 111 | 2010 | China | Pitch, Frequency Converter, Generator | - |
| | | | 560 | 2011 | | Frequency Converter, Generator, Pitch | |
| | | | 640 | 2012 | | Frequency Converter, Generator, Pitch | |
| C. Crabtree [5] | Wind Energy: UK experiences and offshore operational challenges | Egmond aan Zee | 36 | 3 years | Netherlands | Control, Yaw, Scheduled, Pitch | Gearbox, Generator, Blades |
| I. Dinwoodie [36] | Analysis of offshore wind turbine operation & maintenance using a novel time domain meteo-ocean modeling approach | Egmond aan Zee | 36 | 3 years | Netherlands | Control, Yaw, Scheduled, Pitch | Gearbox, Generator, Control |
| J. Ribrant [37] | Survey of failures in wind power systems with focus on Swedish wind power plants during 1997–2005 | Elforsk | 786 | 2000–2004 | Sweden | Electric, Sensors, Blades/Pitch | Gearbox, Control, Electric |
| J. Ribrant [38] | Reliability performance and maintenance—A survey of failures in wind power systems | Elforsk | 786 | 2000–2004 | Sweden | Electric, Sensors, Blades/Pitch | Gearbox, Control, Electric |
| | | VTT | 92 | 2000–2004 | Finland | Hydraulics, Blades/Pitch, Gearbox | Gearbox, Blades/Pitch, Hydraulics |
| | | WMEP | 650 | 2003–2004 | Germany | Electric, Control, Sensors/Hydraulics | Generator, Gearbox, Drivetrain |
| Z. Ma [39] | A Study of Fault Statistical Analysis and Maintenance Policy of Wind Turbine System | Huadian | 1313 | 2015 | China | Transformer, Generator, Pitch | Transducer, Generator, Control |

**Table 1.** *Cont.*

| Author | Title | Dataset | Turbine Number | Years Collected | Country | Top 3 Failures | Top 3 Downtimes |
|---|---|---|---|---|---|---|---|
| C. Su [40] | Failures analysis of wind turbines: Case study of a Chinese wind farm | Jiangsu 1 | 61 | 2009–2017 | China | Control, Pitch, Electrics | Control, Pitch/Blade, Electrics |
| | | Jiangsu 2 | 47 | 2011–2017 | | Pitch, Control, Electrics | Pitch/Blades, Control, Electrics |
| G. Van Bussel [41] | Reliability, Availability and Maintenance aspects of large-scale offshore wind farms, a concepts study | LWK | 643 | 1995–1999 | Germany | Control, Inverter, Gearbox | - |
| G. Herbert [42] | Performance, reliability and failure analysis of wind farm in a developing Country | Muppandal | 15 | 2000–2004 | India | Blades, Gearbox, Hydraulics | - |
| M. Wilkinson [43] | Measuring wind turbine reliability: results of the Reliawind project | Reliawind | Around 350 | - | Europe | Electrics, Rotor, Control | Electrics, Rotor, Control |
| R. Bi [44] | A survey of failures in wind turbine generator systems with focus on a wind farm in China | SUZHOU | 134 | 2011 | China | Pitch, Control, Sensors | Cables, Pitch, Control |
| F. Spinato [45] | Reliability of wind turbine subassemblies | Windstats Denmark (WSDK) | 2345–851 | - | Denmark | Converter, Yaw, Generator | - |
| | | Windstats Germany (WSD), Schleswig Holstein (LWK) | 1295–4285, 158–643 | - | Germany | Electrical, Converter, Rotor | - |
| P. Tavner [46] | Reliability analysis for wind turbines | Windstats Germany (WSD) | up to 4500 | 1994–2004 | Germany | Grid/Electrical, Yaw, Pitch Control | - |
| | | Windstats Denmark (WSDK) | up to 2500 | | Denmark | Yaw, Hydraulic, Generator | - |
| S. Ozturk [31] | Failure Modes, Effects and Criticality Analysis for Wind Turbines Considering Climatic Regions and Comparing Geared and Direct Drive Wind Turbines | WMEP—DD 500 kW | 1500 | 1989–2006 | Germany | Control, Electric, Generator/Hub | Rotor Blades, Parts/Housing, Drive Train |
| | | WMEP—GD 200 kW | | | | Control, Electric, Hydraulic | Gearbox, Electric, Rotor Blades/ Control/Parts/Housing |
| | | WMEP—GD 300 kW | | | | Electric, Control, Hydraulic | Gearbox, Generator, Rotor Blades |
| | | WMEP—GD 500 kW | | | | Electric, Control, Yaw | Generator, Control, Electric |
| S. Faulstich [47] | Wind turbine downtime and its importance for offshore deployment | WMEP | 1500 | 1989–2006 | Germany | Electrical system, Electrical Control, Sensors | Gearbox, Drivetrain, Generator |
| B. Hahn [48] | Reliability of Wind Turbines: Experiences of 15 years with 1500 WTs | WMEP | 1500 | 1991–2006 | Germany | Electrical, Plant Control, Sensors | Generator, Gearbox, Drivetrain |

The categories used here were defined based on a combination of two reliability studies [5,49], which was done to allow for ease of comparison with previous work. The first set of categories were taken from Figure 8 in [49], with the addition of Grid from [5], and finally Nacelle, Shafts and Bearings categories were added.

Stop rate was calculated by taking the number of stops in each category and dividing through by the number of turbines and years of operation in each farm, this gave a number of stops per turbine per year.

$$S = \frac{N_s}{N_T * T} \tag{1}$$

where $S$ is the stop rate, $N_s$ is the number of stoppages recorded for that category, $N_T$ is the number of turbines in that farm, and $T$ is the years in operation for that farm. Downtime was calculated, for each farm, by dividing the total days of downtime per category by the number of turbines in the farm and the number of years in operation.

$$DT = \frac{T_D}{N_T * T} \tag{2}$$

where $DT$ is the downtime, $T_D$ is the total days of downtime for recorded, $N_T$ is the number of turbines in the farm, and $T$ is the years in operation for that farm. These two values allow for fair comparison across all farms and turbines, as it negates the effect of farm size or age.

Figure 4 shows the average stop rates and downtimes for the direct-drive and gear-driven farms respectively. As can be seen, the generator has roughly double the stop rate in direct-drive turbines, and there is also a much greater average downtime for direct-drive generators. The top three stoppage and downtime categories for each turbine type are shown in Table 2. There are some similarities between both turbine types; however, from Figure 4, it can be seen that direct-drive turbines seem to have higher overall downtimes. Even for components that are assumed to be similar between turbine configurations, there are quite large differences in stop rate and downtimes. For example, the sensors and pitch systems both have differences in stop rate and downtime, whilst being components that should not differ too much between configuration. It is possible that the pitch system could be hydraulic or electric, and this could bring about some of the change. There may also be a difference in turbine operation that could account for these differences.

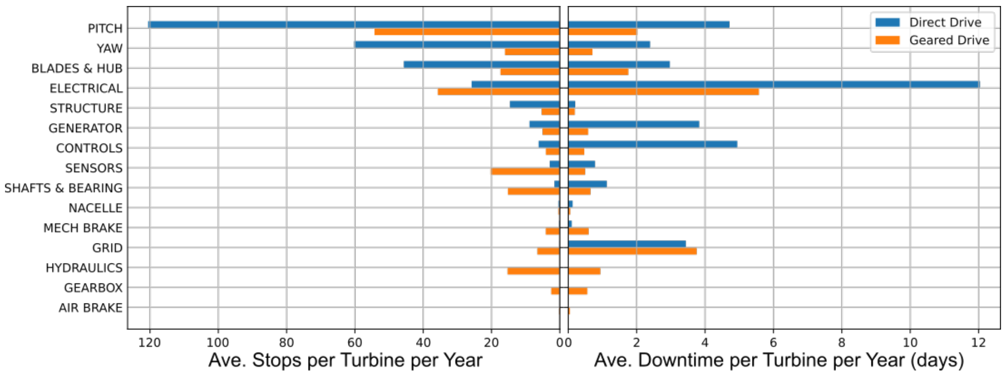



**Figure 4.** Comparison of the Geared and Direct Drive turbines within the dataset based on average stop rates and downtimes for each configuration.

Before any comparisons are made between the results presented here and in other studies, it is important to note that stoppages are not the same as failures, therefore a direct comparison cannot be made. Stoppages can include failures; however, they also include stoppages due to alarms. These alarms can be for any reason, such as temporary overheating of a component. It is possible that these stops are indicators of failure; however, developing a model to represent this link is beyond the scope of this paper.

**Table 2.** Top three stoppage and downtime categories per turbine type.

| Turbine Type | Top 3 Stoppage Categories | Top 3 Downtime Categories |
|---|---|---|
| Direct-Drive Turbines | Pitch, Yaw, Blades and Hub | Electrical, Controls, Pitch |
| Gear-Driven Turbines | Pitch, Electrical, Sensors | Electrical, Grid, Pitch |

*Comparison with Previous Studies*

Table 1 presents the details of previous failure rate and downtime studies examined. The table outlines the different databases used by each paper, the number of turbines contained, the time period examined, and the country of origin for each database. The last two columns of the database present the top three turbine components by failure rate, and downtime per failure respectively. From this table, two studies examined the reliability data for direct-drive turbines in Europe. The first, from M. Reder et al. [50], found that the top three, in descending order, components by failure rate were the Controller, Met Station, and Yaw systems, and by downtime were the Generator, Blades, and Controller. The second study, from S. Ozturk et al. [31] found that the top three components by failure rate were Controls, Electric Systems, then the Generator and Hub were tied for third. The top three by downtime were the Rotor Blades, Parts/Housing, and then the Drivetrain. When this is compared against Figure 4, it can be seen that there are some differences. The top three categories are shown in Table 2; however, these are for stoppages rather than failures. So it may not be appropriate to make a direct comparison.

The frequency of which each component is featured within the top 3 failures or downtimes is plotted in Figure 5. This bar chart plots the number of times each component was featured in the top three of either metric in Table 1. This chart can then be used to find out the overall top three components for both failure rates and downtimes. For failure rates, the top three components were the Controller, Pitch, and Generator, with the Controller, Gearbox, and Generator coming in at top three for downtime.

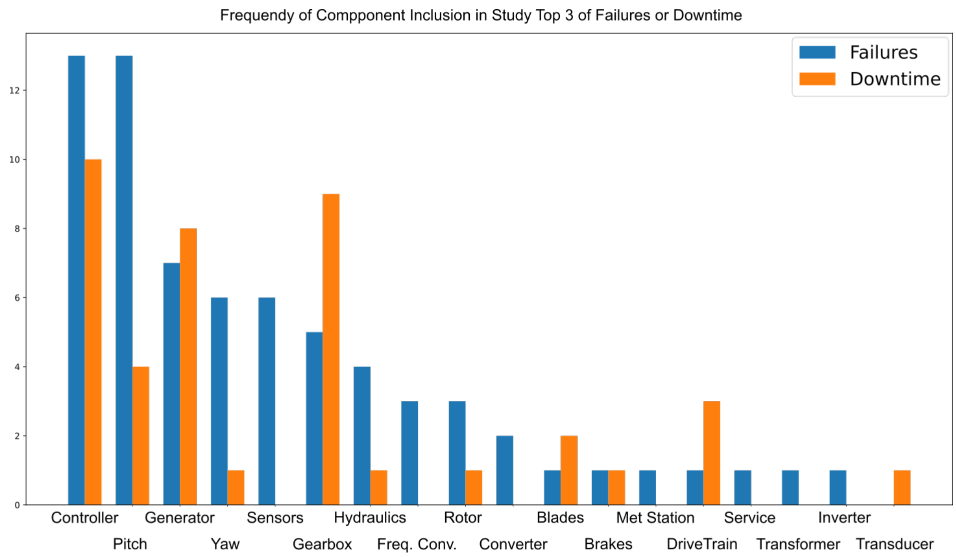



**Figure 5.** Frequency of each component being within studies top three failures or downtimes from Table 1.

One review from Crabtree et al. [5] presented the stop rate for the Egmond aan Zee offshore wind farm situated in the Netherlands. This farm consisted of 36 turbines with 3 years of operational data. These were geared 3 MW turbines, and unlike other studies presented stop figures instead of fault data. The control system, yaw system, and service stop categories were the top three, with the Gearbox, Generator, and Blades stops being the top three categories for downtime. This review is of particular interest as it presents stop rates, which can be directly compared against the results presented here.

Compared with Figure 4, the geared turbines from this study have relatively low stops due to the yaw and control systems, and low service stops on average with quite extreme outliers. For the downtime, the Generator, Gearbox, and Blades were relatively low.

Stop rates are explicitly different from failure rates in several ways—for example stop rates are caused by an wind turbine stoppage, whereas failure rates are due to an unscheduled, or unplanned, failure of the turbine due to some fault or malfunction. Therefore, several categories are found in stop data that would not be found for failure data, such as scheduled service as these are known in advance, or grid failures which are outwith the operator control. Stoppages are also typically more frequent and should have lower downtimes on average per stoppage as they are usually less severe than turbine failures. Within the stop data there will be failure examples, as these are examples of wind turbine stoppages; however, they will be less frequent.

## 4. Framework for Assessing the Transferability of Diagnostic Techniques between Drive Trains

### *4.1. Framework*

In the previous section, reliability rates (wind turbine stop rates and downtimes) for both direct and geared wind turbines were presented, where several key differences were highlighted. Building on these results, a framework for assessing the transferability of failure modes and associated sensors will now be presented. The aim for this framework is to help determine how well a particular fault could be diagnosed in modern direct-drive wind turbines using data and diagnostic models demonstrated on geared wind turbines. This framework does not make any attempt to predict future reliability rates of larger direct-drive machines. Stop rates and downtimes presented in Section 3 will be used in conjunction with the framework to assess which components need to be the focus of future diagnostic research. An example of how this framework can be used is presented later in this section, which examines previous fault detection papers by assessing their failure mode and input data to examine how transferable the fault case from each paper was. By doing this, we can see which components in particular are suitable to assessment in the future with direct-drive machines, and whether the data inputs used previously would be suitable or would require some level of processing. The transferability of each paper was assessed over two dimensions to examine overall transferability. The first dimension examined how transferable the sensors, or data channels, used by each paper to predict, or diagnose, the fault. The second dimension assessed how well the specific failure mode transferred between geared and direct-drive turbines based on fundamental understanding of the physics of failure.

Two small-scale decision trees were drawn up to assess each paper examined for their transferability, one for each dimension. The first tree, Figure 6, is used to assess the transferability of the sensors, or channels, used in each paper. So this assesses the paper's selection of features for modelling a particular failure mode—and how well these features, and required sensors, transfer from a geared to a direct-drive machine. The first question, in the top diamond, asks if the direct-drive would have all the sensors required for the features used by the paper. The second question, in the middle two diamonds, asks if the majority of the sensors used in the paper would be in the same location within the turbine. The third question, the bottom four diamonds, asks if these sensors are of the same specification as those on an arbitrary direct-drive machine. This question is essentially used to assess if the general expected data range you would get from this sensor would be the same as one on a geared machine. An example could be bearing temperature, you could consider if a similar thermistor could be used to cover the expected range and resolution of recorded temperatures. This helps to assess scale of component as well, for example a generator bearing in a direct-drive machine will be much larger than one in a similarly rated geared machine. For all of these questions, it was assumed that the direct-drive and geared machines were of the same arbitrary turbine model; however, the only difference being that the the direct-drive machine had no gearbox and the generator was of an appropriate size for the same power rating as the geared machine.

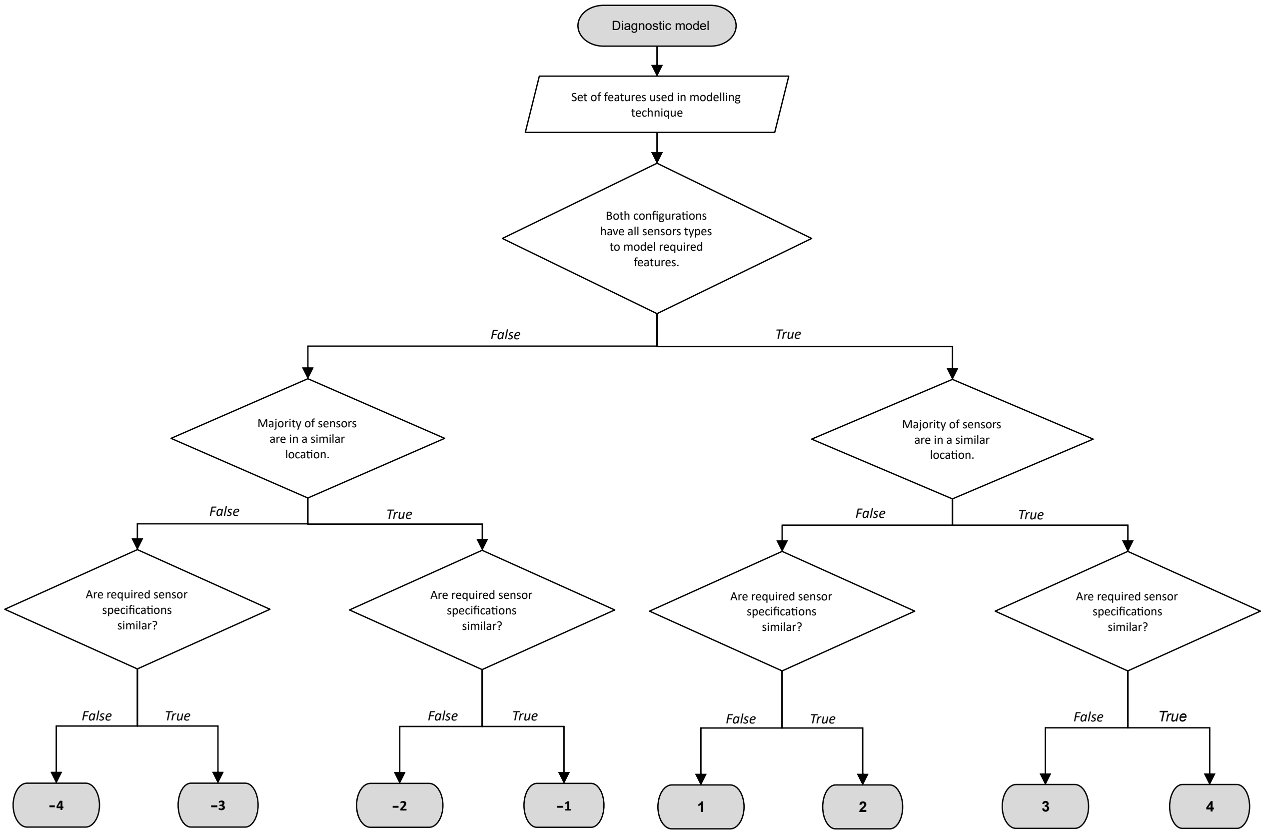



**Figure 6.** Decision tree for sensor/channel group transferability.

The second decision tree, Figure 7, assesses how transferable the physics of failure mode of each paper is. This tree examines the particular component that failed, and any failure mode information provided by each paper. First the papers are split by if the fault, or damage, can be found anywhere across either turbine configuration. Next it is split by whether it can be found on a specific component—if it can then it asks if the fault progresses in the same physical manner, and if not then it asks if the model corresponds to a specific failure mode. If it cannot be found on a specific component, then the questions determine if it is on an assembly within the turbine, and then if it follows the same physical manner, and lastly if it is specific to the failure mode examined. Again these questions were answered under the assumption that the turbines would be of similar models, with the exception of the gearbox and generator.

To test these decision trees, a database of past fault detection papers were collected and their fault and input data were collated. Table 3 shows all the past papers examined, and their scores based on the decision trees referenced earlier. The majority of these faults occurred on the drivetrain, with some in the blades. SCADA data were the focus of this study; however, some papers were assessed that used images as their input data. The input data that each paper utilised were assessed with the first decision tree, and the fault itself was assessed using the second decision tree. The data ranged both in terms of years assessed, but also in the turbine rating. All the turbines within the dataset of papers examined were geared turbines.

**Table 3.** Database of papers examined for their transferability.

| Author | Year | Turbine Rating | Fault Examined | Data | Sensor Score | Component Score |
|---|---|---|---|---|---|---|
| Dhiman [6] | 2021 | Sub 1 MW | Gearbox | SCADA | −4 | −5 |
| L. Yang [7] | 2021 | Unknown | Gearbox | SCADA | −4 | −5 |
| X. Yang [51] | 2021 | Unknown | Blade Damage | Images | 4 | 5 |
| Turnbull [10] | 2020 | 0.5–1 MW | High Speed Shaft | SCADA | −2 | −2 |
| | | 2–4 MW | Generator Bearing | | 3 | 2 |
| W. Chen [52] | 2021 | 1.5 MW | Blade Ice Accretion | SCADA | 4 | 5 |
| S. Moreno [53] | 2020 | 2 MW | Load and Wind Sensor Failure | SCADA | 4 | 4 |
| X. J. Zeng [54] | 2018 | 1.5 MW | Gearbox Oil Temperature Over Limit Fault | SCADA | −3 | −3 |
| M. Beretta [11] | 2020 | 2 MW | Bearing HSS Replacement | SCADA | 3 | 1 |
| | | | Generator Brushes | | | |
| | | | Generator Non-Drive End Bearing | | | |
| J. Chen [55] | 2020 | 1.6 MW | Overheating Generator Bearing | SCADA | −2 | 2 |
| Rezamand [9] | 2020 | ∼2.5 MW | Blade Fault | SCADA | 4 | 4 |
| X. Liu [56] | 2020 | Unknown | Gearbox and Generator | SCADA | −2 | −5 |
| McKinnon [57] | 2020 | Unknown | High Speed Shaft Faults | SCADA | 3 | 2 |
| Y. Wang [58] | 2019 | Unknown | Blade Damage | Images | 4 | 5 |
| J. Carroll [59] | 2019 | 2–4 MW | Gearbox Bearing | SCADA and Vibration | −4 | −2 |
| | | | Gear Tooth Fault | | −2 | −5 |
| McKinnon [57] | 2020 | 2–4 MW | Intermediate Gear Fault | SCADA | −4 | −5 |
| H. Yun [60] | 2019 | Unknown | Ice Detection | SCADA | 4 | 5 |
| C. Yang [61] | 2019 | Unknown | Pitch Limit Switch and Angle Encoder | SCADA | 3 | 5 |
| L. Wei [12] | 2018 | 2 MW | Pitch System | SCADA | 4 | 5 |
| R. Pandit [13] | 2018 | 2.3 MW | Yaw Error | SCADA | 4 | 5 |
| H. Zhao [62] | 2018 | 1.5 MW | Gearbox | SCADA | −4 | −5 |
| | | | Generator Rear Bearing | | 3 | 2 |
| | | | Inverter Failure | | 3 | 5 |
| Y. Zhao [63] | 2017 | 1.5 MW | Generator Fault | SCADA | 3 | 3 |
| Y. Zhao [64] | 2016 | Unknown | Generator Fault | SCADA | 3 | 3 |
| M. Beretta [14] | 2021 | 2 MW | Main Bearing | SCADA | −2 | 5 |
| McKinnon [65] | 2021 | 1.8 MW | Pitch System Bearing | SCADA | 4 | 5 |
| M. Cardoni [66] | 2021 | Unknown | Oil leaks between HSS and Generator | Images | 4 | 5 |
| P. Mucchielli [67] | 2021 | Unknown | A Range | SCADA | 4 | 1 |
| X. Liu [68] | 2021 | Unknown | Gearbox Planetary Bearing | SCADA | −2 | −2 |
| | | | Gearbox HSS Bearing | | −2 | 1 |
| | | | Gearbox | | −4 | −5 |
| A. Heydari [69] | 2021 | 2 MW | Gearbox Bearing Fault | SCADA | −2 | −2 |
| L. Xiang [70] | 2022 | 750 kW | Gearbox Gear Failure | SCADA | −2 | −5 |

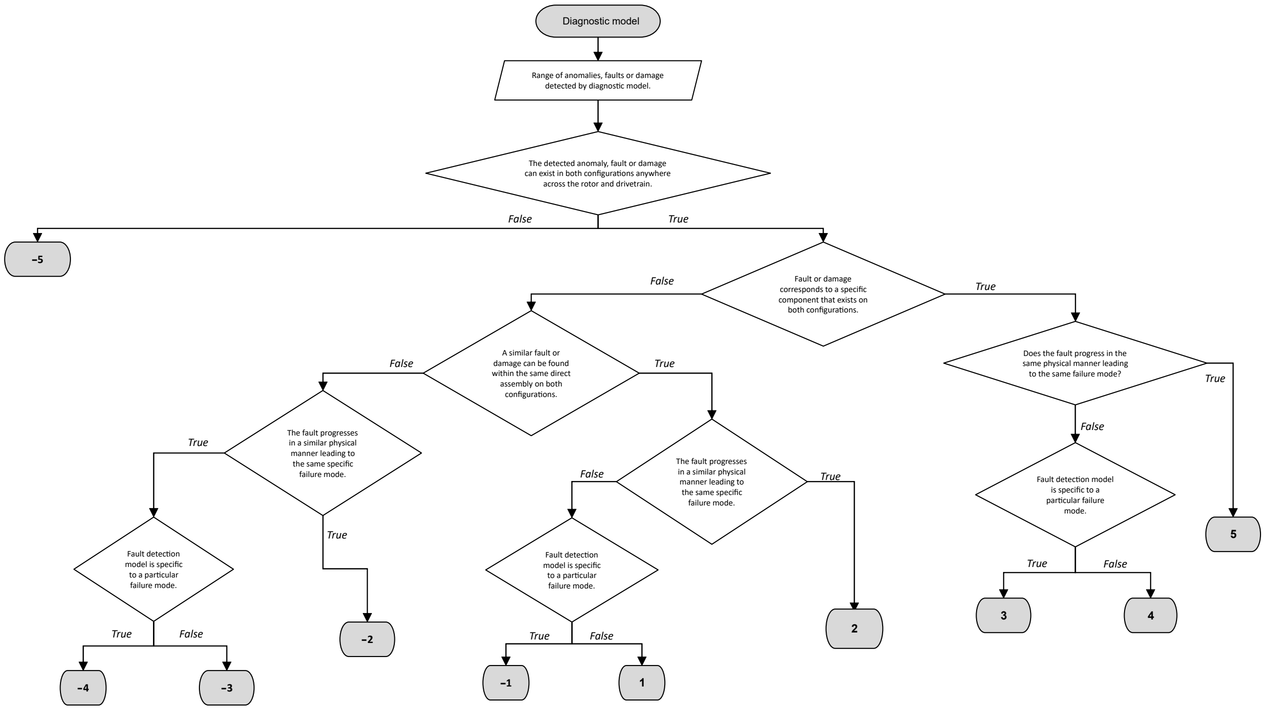



**Figure 7.** Decision tree for component failure mode transferability.

This technique could potentially be expanded to papers that utilised high-frequency conditon monitoring systems (CMS) data, which is commonly used in the literature. SCADA data, which is 10 min aggregate data, is what is examined here. High-frequency CMS data may be of interest in transfer learning for two reasons, the first being the lack of direct-drive data for the larger machines, but also because CMS data are much more difficult to acquire. SCADA systems are commonly installed on wind turbines; however, CMS sensors are less so (particularly on older machines). Typically, CMS data are specifically used to target an area of interest; however, it is becoming cheaper to install relative to power output and therefore more common.

### *4.2. Framework Application Results*

Results are presented based on the framework explained in the above section for the literature stated in Table 3. Figure 8 shows the component tranferability scores on the x-axis and the sensor tranferability scores on the y-axis. Each single point represents a diagnostic model presented in the literature (see Table 3) with the fault grouped into the corresponding component or wider assembly. The mean value per component for each axis was calculated and plotted as a larger cross on Figure 8. Note that this does not correspond to any particular model, but simply represents the average transferability of that component or assembly. All 35 models from Table 3 are shown, although some points have identical coordinates and cannot be easily distinguished. The most transferable diagnostic models relate to the hydraulic, pitch and yaw systems, which makes sense due to them being mostly universal to different wind turbine drive train configurations. For this same reason, sensor faults and electrical issues also scored highly. The least transferable models were, as expected given the drive train topology, associated with the gearbox. The components with the most variability in scoring were the the generator, shafts and bearings. For these, the overall transferability was largely dependent on both the sensors required to create model features and specific failure mode being diagnosed.

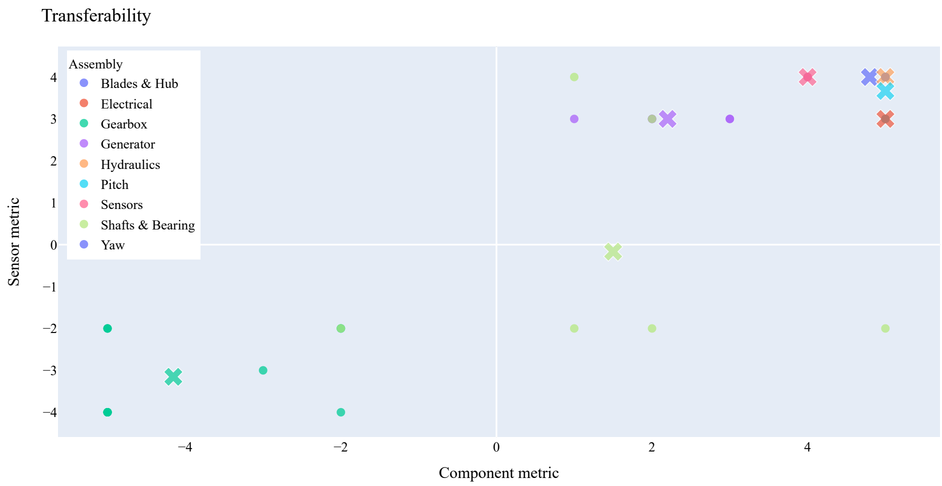



**Figure 8.** Results showing transferability of diagnostic model.

### 4.3. Discussion

The framework presented is built upon several questions determined by the authors to distinguish diagnostic models by two key metrics. The first decision tree (Figure 6) is designed to split models and features by which channels and sensors are similar across both turbine configurations. This decision is of course influenced by the selection of features used in each paper, which can lead to some variation in what channels were deemed relevant. The papers chosen for this study have been peer reviewed; therefore, it is assumed that the channels were selected either through some expert domain knowledge, or through a data-driven technique to select variables relevant to the component examined. For this reason it can also be assumed that these features would prove to be related to the component and how transferable these features are will help decide how transferable each particular failure mode is.

The second decision tree (Figure 7) is designed to compare faults across different components, as well as the manner in which a particular fault is likely to develop through time. Although the decision tree itself is designed to be as general as possible, the specific failure modes related to the diagnostic models presented here do not represent all possible failure modes, or even components, within the wind turbine. In Figure 7, faults to be diagnosed are first split at a component level, as this is the fundamental aspect of how transferable a fault is. From here, faults are split by the manner they are likely to progress and present themselves, which is more specific to the fault and failure mode itself. This requires some expert knowledge of wind turbines and mechanical or electrical systems depending on the individual fault.

Some papers presented in Table 3 were less specific about the fault than others. For example, Dhiman [6] presents a gearbox fault, whereas Zeng [54] presents a gearbox oil temperature over limit fault. The more specific a fault, the easier it can be scored using the decision trees; however, it is more sensitive. Conversely, as a more general fault is harder to score without further information about the failure mode from the authors, more general faults will typically score lower than a specific fault. Similarly, those papers which utilise a wider range of SCADA channels, compared to ones that use channels picked for their relevance to the fault, will typically score lower. By using a wider range of data, it is less likely that all of the features used will still be transferable to a direct-drive machine. For example, while a paper may examine a generator fault which is fairly transferable, the authors may incorporate many features from the gearbox. Obviously, most SCADA channels in the gearbox will not be transferable to those in a direct-drive turbine.

The transferability of each diagnostic model is shown in Figure 8. Each quadrant relates to a different level of transferability. The bottom left quadrant is the least transferable section, with both the required sensors and physics of failure relating to a particular component fault being unsuitable. The top left quadrant is where the sensors required to create the model features are available, and hence more transferable, but the fault is not relevant. An example of this could be a gearbox failure sensed through other means such as power curve analysis. The bottom right quandrant represents models which scored a high score on the component metric, but a low score on sensor metric. An example of this could be in detecting a high-speed bearing fault using features primarily created from sensors associated with the gearbox. Although the sensors are not available across both configurations, high-speed bearing faults could still be relevant to a lower-speed shafts on the direct-drive machine. The top right quandrant consists of the most transferable fault cases, with both the sensors and components being relevant and transferable.

The most transferable components in this upper right quandrant appear to be the components more ubiquitous across turbine configurations, such as pitch and yaw systems. The channels relevant to these faults are usually quite ubiquitous as well. The generator is also a fairly transferable component; however, due to its size compared to that of a direct-drive turbine, some processing may be required to the channels to engineer more appropriate features. As expected, the least transferable component is the gearbox; however, as can be seen, some failure modes and sensors are slightly more transferable to a direct drive. For example, a gearbox bearing may exhibit similar behaviour to other bearings within a direct-drive turbine. One interesting component group is general shafts and bearings of the turbine. These are typically transferable faults; however, the choice of sensors may need examined. Many of these failures focus on the high-speed shaft, which is not present in a direct-drive turbine, but could be transferred with some feature engineering.

## 5. Conclusions

This paper presents a comprehensive look at the future trends in European offshore wind energy. First, it was shown that offshore wind in Europe is currently moving more towards direct-drive turbines, with each individual installed turbine having a higher rated power. Overall capacity of new sites is also increasing on average. To examine the implications of this change, the stop rates for direct-drive and gear-driven turbines were compared between 39 farms across Europe and South America. It was found that there was some differences, and in particular the top components by stop rate and downtime were different from previous papers that had examined failure rates of wind turbines. In the future, it would be of value to develop a way of mapping stop rates to failure rates, thereby allowing a more direct comparison to be made.

Finally, this paper presented a framework for analysing how well published fault detection models transfer between geared and direct-drive turbines. For this, two decision trees were created to enable a quantitative score to be placed on both the required input channels and failure mode respectively. Overall transferability could then be assessed by considering both metrics together. It was found that components, or assemblies, that were ubiquitous across turbine configurations, such as the pitch system, were more transferable. Whereas, as expected, the gearbox was the least transferable component. The generator, shafts and bearings were somewhat transferable; however, in general, these would require some level of feature engineering to improve the potential performance. While this paper has examined over 25 papers in testing of the proposed framework, not all turbine components or fault conditions were presented. Further study may be needed to apply this framework to these components. Additionally, this paper has focused mostly on SCADA data from wind turbines; however, this technique could be applied to papers that have utilised high-frequency CMS data.

Based on market trends, it is important for researchers to focus their efforts on developing fault detection techniques for the most critical components related to large direct-drive technology. Since no such reliability study exists in the literature on large direct-drive wind turbines, for the time being, previously observed reliability rates must be used and adapted where appropriate. Based on these studies, the most common critical components stated with extended downtime are related to the controller, pitch system, generator and gearbox. Based on the transferability scores presented in this paper, the components that would require further work are those related to the direct-drive generator. Additional work is required in this area in order to utilise, adapt and improve existing fault detection methods.

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## Abbreviations

The following abbreviations are used in this manuscript:

| | |
|---|---|
| CMS | Conditon monitoring systems |
| DFIG | Doubly-fed induction generator |
| EESG | Electrically excited synchronous generator |
| LCOE | Levelised cost of energy |
| OPEX | Operational expenditure |
| O&M | Operations and maintenance |
| OEM | Original equipment manufacturer |
| PMSG | Permanent magnet synchronous generator |
| SCADA | Supervisory control and data acquisition |
| SCIG | Squirrel cage induction generator |

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