Fault diagnostics of wind turbine electric pitch systems using sensor fusion approach

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Abstract. Failures in wind turbine pitch systems can cause significant outages in offshore wind turbines due to the finite weather windows for maintenance. In a complex system such as the pitch system, a fault in the gearbox can contaminate the motor current signals and result in a misdiagnosis. This paper investigates a sensor fusion technique to reliably diagnose faults in pitch motors and multistage planetary gearboxes in pitch drives. A support vector machine classifier is used for fault diagnosis based on features extracted from motor currents and gearbox vibration signals. The approach is validated with three commonly occurring pitch drive faults, namely, the stator turns fault in the pitch motor, input shaft bearing and planet gear fault in the planetary gearbox. The developed diagnostic method is validated with artificially seeded faults in a laboratory setup of a scaled pitch drive.

1. Introduction
Offshore wind is among the renewable energy sources that are growing at a rapid pace. The European Union aims to shift 20% of its energy reliability to renewable energy sources by 2020 and the European Wind Energy Association estimates about 16.5% of this to be fulfilled by wind energy [1]. Higher wind energy production translates to larger offshore wind farms (OWFs) located farther offshore. While the OWFs have gained significant momentum around the world, their reliability and availability are lower than their onshore counterparts [2] owing to their location, weather conditions and expensive logistics involved in maintenance. A comprehensive maintenance strategy is imperative to operate these large OWFs reliably and profitably [3]. Such a maintenance strategy should be sensitive to the health of each WT and proactively plan optimal maintenance actions by considering the constraints posed by logistics, inventory and resources. Condition monitoring (CM) and condition-based maintenance (CBM) play an important role in realising this goal. However, the commercial CM solutions at present cater only to a select few of the WT components, such as the main bearing, generator and gearbox. The pitch systems have reported high failure rates [4], but they were rarely considered for CBM. The pitch system in a WT operates intermittently, depending on the wind conditions to reduce structural loads and improve the turbine efficiency. These are either hydraulically or electrically actuated. It is estimated that the market is equally split between the two types of actuation [5]. In the case of onshore WTs, these pitch systems can be easily replaced reactively upon failure and hence contribute to low downtime, therefore CBM may not be necessary. However, such reactive maintenance tasks can be expensive in OWFs and time consuming, given the limited weather-windows for maintenance action. Therefore, this article examines the pitch systems for CM and reliable fault diagnosis.
There has been considerable focus in literature on the control problem of the pitching mechanism \[6\] and fault tolerant control \[7\], but the CM of pitch systems received considerably less attention. Nielsen et al. in \[8\] discussed the possibility of using the motor torque and current data for condition monitoring of the pitch system, based on supervisory control and data acquisition (SCADA). Cho et al. in \[9\] described a Kalman filter based method for diagnosing pitch sensor and actuator faults, but incipient fault detection was not clearly stated. Artificial intelligence based methods were described in \[10, 11\] for fault prognosis based on SCADA data. This approach could detect the pitch system fault, but fault diagnosis to a subcomponent level remains unanswered. Although SCADA based techniques are beneficial for a preliminary fault diagnosis, the component level fault resolution becomes important as it contributes to maintenance and inventory planning. For instance, distinction between a pitch motor fault and pitch bearing fault may result in a better choice of maintenance task and maintenance plan. Component level reliability and failures in onshore WTs have received attention in recent research \[12, 13\]. However, a detailed breakdown of frequent failures to the component level in offshore WTs has been rare in literature. Lin et al. \[14\] provides insights into the common failure modes of electric pitch systems experienced in China, in which faults in the stator winding due to over-heating and poor ventilation are found the most common among pitch motors. Furthermore, it was shown in \[15\] that in induction motors supplied by frequency converters, stator winding failures are the most common, surpassing the bearing failures, because of higher harmonics supplied by the frequency converters. The pitch gearboxes on the other hand, were reported to have bearing and gear failures due to lubrication starvation and high static loads. The objective of this article is to develop a diagnostic technique for the pitch system, encompassing both the pitch motor and the gearbox. The technique should also be scalable for implementation across the OWF. Earlier, the authors have investigated the use of classical signal processing techniques such as the motor current signature analysis (MCSA) for pitch motor diagnostics \[16\], considering the pitch motor faults in isolation and under the assumption that the gearbox is healthy. However, a fault in the pitch gearbox can contaminate the current spectrum resulting in a misdiagnosis as a pitch motor fault. To avoid such false alarms and provide accurate diagnosis of the pitch system faults, this paper proposes a sensor fusion approach that takes into consideration the three-phase current measurements from the pitch motor as well as vibration signals from the pitch gearbox and utilises a support vector machine (SVM) for accurate fault classification. The method is demonstrated in the scaled pitch drive with three pitch system faults, namely, the bearing fault (BRG) and planet gear fault (PLT) in the pitch gearbox and stator turns fault (STF) in the pitch motor. The objective of SVM classification is to separate two or more fault classes by drawing an optimum hyper-plane in the multidimensional feature space of given labelled training data. Then, for a new data set, this trained optimum hyper-plane can be used to identify the fault class of new data samples. Since the classification problem is solved as an optimisation problem, the separating hyper-plane is an optimal solution. The motivation for utilising an SVM classifier comes from its ability to map features in a non-linear feature space, and its efficiency. Other classifiers, such as k-nearest neighbour (KNN) and decision tree (DT), are also viable options, and the performance of the SVM will be compared to these two.

The main contribution of this paper therefore, is a fault classification algorithm that is capable of diagnosing pitch motor and pitch gearbox faults accurately. The method is suitable for implementation in large OWFs. The approach is advantageous as it relies only on current and vibration measurements and these sensors can be easily installed in a pitch system. Besides, the pitch systems can be monitored intermittently by transmitting the features generated at the WT level to a classifier located centrally to the OWF. Such an architecture is beneficial for two reasons, 1) the data transmitted from each WT can be economised, and 2) the computationally expensive classification algorithms need not be replicated at each WT.

The remainder of the paper is organised as follows: Section 2 briefly describes the WT electrical pitch system and the scaled pitch drive that is used to demonstrate the sensor fusion approach. The pitch system faults, namely the planetary gearbox BRG and PLT as well as the pitch motor STF are discussed in Section 3. The SVM classifier is briefly introduced in Section
4. The features extracted from the current and vibration signals for fault classification are described in Section 5 and the results of the SVM classification are discussed in Section 6. Finally, the paper is concluded in Section 7.

2. The electrical pitch system
The active pitch-controlled WT consists of at least one pitch actuation system for each blade, located in the hub. An electrically operated pitch system consists of a multi-stage planetary gearbox with an electric motor as prime-mover. Typically, the pitch systems are manufactured by third parties and hence the choice of components are not necessarily unique. The pitch motor is either an induction motor or a permanent magnet synchronous motor that is driven by a variable frequency drive (VFD). The WT power controller provides the reference pitch angle depending on the generated power. The actual pitch angle is measured at the blade root through a position sensor. The pitch control system then drives the pitch system to achieve the reference command. The pitch gearbox drives the blade bearing through a pinion. The WT blade is rigidly mounted to the outer-ring of the blade bearing and due to this arrangement, the blade root loads are transferred to it. The pitch system therefore experiences the periodic gravitational loads and aperiodic wind disturbances and gyroscopic loads that result in wide variations in the operating profiles of the system. Hence, it is necessary to study the accuracy of the fault classification scheme under various load and speed conditions. To this end, a laboratory setup was developed.

2.1. Laboratory setup
A laboratory setup of a scaled pitch drive was built to validate pitch system diagnostics in a laboratory environment. The system consists of a 1.1 kW three-phase 4-pole induction motor as the pitch motor. The pitch motor is coupled to a 2-stage planetary gearbox with gear ratio of 1 : 48.1. The motor is controlled using a VFD with field-oriented control (FOC). The scaled pitch drive is coupled to a bevel-planetary-helical (BPH) gearbox with gear ratio 1 : 27.1, which is used to apply variable load torque. The BPH gearbox has a 2.2 kW three-phase 8-pole induction motor as prime-mover, referred to as load motor. The load motor is also controlled using a commercial VFD with FOC. The pitch motor is equipped with three Hall-effect sensors for motor diagnostics and the pitch gearbox has single-axis accelerometers installed to measure vibrations in the vertical (Y) and lateral (X) planes. The laboratory setup, shown in Fig. 1 is built in such a way that several failure modes of pitch systems can be artificially seeded and evaluated for diagnostics. In this article, the focus is on three failure modes, the planetary gearbox BRG, PLT and the STF in the pitch motor, which will be discussed in the following section. These faults are artificially seeded in identical gearbox and motor and the healthy units were replaced by the faulty units for testing. In this way, the tests were performed on three different components of the same specifications.

3. Pitch system failure modes
As the WT pitch systems are typically manufactured by third parties and there exists several WT manufacturers and operators, consolidation of component-level failure rates is difficult as the failure information is not shared across [17]. However, a study on the most common failure modes of the WT main gearbox indicates that nearly 76% of the faults are due to bearings and the planet gear failures contribute to 3% of the total faults [18]. The planet gears undergo the most complex operation in a planetary gearbox, but they are rarely treated in the literature [19]. Therefore, the BRG and the PLT are chosen for diagnostics in this research. Apart from these, the STF is considered because it contributes to nearly 40% of all the motor faults in induction motors operating under closed-loop with VFDs. This section details the selected failure modes.

3.1. Bearing faults
Bearings are made of four major components: An inner-race which is often fastened to the shaft, an outer-race that is stationary in a housing, rollers (or balls) that transfer loads between
the two races, and a cage that keeps an even distance between rollers. Normally, there can develop faults on the surface of rollers/balls, the inner-race, and the outer-race. Incipient BRGs at either location are characterised by an increase of impulsive bearing vibration at the characteristic frequency (CF) for that fault. Each CF can be calculated based on the geometry of the bearing and the shaft speed [20]. The CF for the outer-race, the inner-race, and the rollers are, respectively, given by [20]:

\[
f_o = \frac{n f_r}{2} \left( 1 - \frac{d}{D} \cos \phi \right), \quad f_i = \frac{n f_r}{2} \left( 1 + \frac{d}{D} \cos \phi \right), \quad f_r = \frac{D f_r}{2d} \left( 1 - \left( \frac{d}{D} \cos \phi \right)^2 \right)
\]

where \( f_o \) is the ball pass frequency outer-race (BPFO), \( f_i \) is the ball pass frequency inner-race (BPFI), \( f_r \) is the ball spin frequency (BSF), \( n \) is the number of rollers, \( f_r \) is the shaft frequency, \( d \) is the roller diameter, \( D \) is the bearing pitch diameter, and \( \phi \) is the contact angle. It should be noted that, due to slip and non-zero contact angle, the actual CF in practice may deviate up to 2% [20]. The bearing fault vibration can be modelled as an amplitude modulation of the resonance frequency vibration. To acquire the modulation frequency, the signal is first demodulated by means of the absolute-valued analytic signal acquired by using the Hilbert transform [21]:

\[
v_{env} = \sqrt{v^2 + \mathcal{H}\{v\}^2}.
\]
where $H$ is the Hilbert transform, and $v$ is the vibration signal. Applying the Discrete Fourier Transform (DFT) returns the envelope spectrum, and allows for the determination of modulation frequencies in the vibration signal:

$$V_{env} = \mathcal{F}\{v_{env}\}, \quad (3)$$

where $\mathcal{F}$ is the DFT. The state of a bearing can be determined by monitoring the envelope spectrum amplitudes at integer multiples (harmonics) of the bearing CFs. A BRG fault with a 2mm through-hole in the outer race is artificially seeded in the planetary gearbox of the scaled pitch drive, described in Section 1, as shown in Fig. 2. Vibration measurements were captured during healthy and faulty bearing conditions. The two envelope spectra calculated using (3) are presented in Fig. 4. Here, the healthy spectrum is plot in blue, the faulty in red, and the black stapled lines indicate harmonics of the BPFO. The $X$-axis is denoted orders, where one order is defined as the shaft speed. As seen in the figure, the vibration energy at the characteristic frequency is increased during a faulty state. Interested readers are referred to [20] for a more in-depth explanation for BRG fault detection using vibration signals.

![Figure 4: Vibration envelope spectrum of the healthy gearbox (blue) and the faulty gear-box bearing (red). The black stapled lines show the first four harmonics of BPFO.](image)

### 3.2. Planet gear fault

A planetary gearbox is a compact gearbox that can deliver large gearing factors and high torque, while being smaller in volume compared to fixed-axis gearboxes. The biggest disadvantage is the increased complexity of the gearbox. The planet gears undergo the most complex motion, meshing simultaneously with the sun gear and the ring gear while revolving around the sun gear. Therefore, they do not have a constant transmission path to the outer ring gear. The CF of the planet gear $f_p$ is given by:

$$f_p = \frac{4z_s z_r}{z_r - z_s} f_{in} \quad (4)$$

where $z_s$ and $z_r$ are the no. of teeth on the sun gear and ring gear, respectively, while $f_{in}$ is the input shaft rotational frequency (Hz) [22]. Further, vibration at integer multiples of the gear mesh frequency $f_{m1}$ is normally always visible in a vibration signal. Once a tooth on a certain gear is worn, the vibration at the CF increase in energy. The CFs are given by the location of the fault and the frequency of the shaft [23]. The planet fault can be observed in the frequency spectrum from energy increase at sidebands spaced $f_{cl}$ away from the meshing frequency harmonics [23], where $f_{cl}$ is the rotating frequency of the planet carrier given by

$$f_{cl} = \frac{z_s}{z_s + z_r} f_{in} \quad (5)$$

The PLT is artificially seeded in the scaled pitch drive by partially damaging a tooth on one planet gear in the first stage of the planetary gearbox, as shown in Fig. 3. The vibration data from the planetary gearbox was measured in both healthy and faulty conditions and analysed. Fig. 5 shows two vibration spectra; one calculated during healthy condition (blue), and one...
during a planet fault (red). The two subfigures (a) and (b) show a spectrum window near the first and third gearbox mesh harmonics. The black stapled lines are the center meshing harmonic and \( f_{s1} \) sidebands. The first harmonic shows little changes between healthy and faulty conditions. However, the third harmonic shows a high energy increase at the meshing frequency and the left side-band.

![Vibration frequency spectrum of the healthy gearbox (blue) compared to the faulty case with a damaged planet gear (red).](image)

Figure 5: Vibration frequency spectrum of the healthy gearbox (blue) compared to the faulty case with a damaged planet gear (red). (a) is centered at the first harmonic. (b) is centered at the third harmonic. The black stapled lines in each subfigure are the meshing frequency center harmonic and two sidebands spaced apart by the carrier frequency.

### 3.3. Stator turns fault

The STF occurs due to loss of stator winding insulation and they account for nearly 30 to 40% of all the motor failures [15]. The insulation is made to withstand electrical stresses within design limits. However, the pitch systems operate in corrosive environments without proper ventilation, with loads above design limits and undergo frequent start-stop operations. All of these factors contribute to accelerated wear in the winding insulation. The loss of insulation causes in shorted turns on one of the phases resulting in an asymmetry in the three phase stator windings. A healthy induction motor is designed to operate in symmetry, with equal resistances and inductances in each phase winding and in each rotor bar, and a uniform airgap. A fault in the motor results in asymmetry, which recurs in every rotation of the rotor. This periodic repetition of the fault manifests as a particular frequency in the current spectrum that is detected through motor current signature analysis. In the case of faults in induction motors operating in closed-loop with VFDs, the extend Park’s vector analysis has been reported as a reliable diagnostic metric for induction motor faults. The direct and quadrature axis currents (\( i_d, i_q \)), as well as the extend Park’s vector \( i_P \), are described by:

\[
\begin{align*}
  i_d &= \sqrt{\frac{2}{3}} i_A - \sqrt{\frac{1}{2}} i_B - \sqrt{\frac{1}{6}} i_C, \quad i_q &= \sqrt{\frac{1}{2}} i_B - \sqrt{\frac{1}{2}} i_C, \quad \sqrt{\frac{1}{2}} = (i_d + j i_q)
\end{align*}
\]

(6)

where \( i_{A,B,C} \) are the three-phase motor currents [24]. The STF occurs due to the shortage of a phase winding, resulting in an imbalance of the three-phase currents. This imbalance manifests as a fault frequency of

\[
\begin{align*}
  f_{STF} &= 2 f_s
\end{align*}
\]

(7)

in the spectrum of \( i_P \), where \( f_s \) is the supply frequency [24]. The STF was artificially seeded in the lab setup described in Section 2.1, by shorting 10% of the windings of the same phase, as shown in Fig. 6. The motor was run at 1400 rpm and loaded to 60% of the rated load. The corresponding spectrum of \( i_P \) is shown in Fig. 7. The supply frequency for the motor was 47.4 Hz and the corresponding \( 2 f_s \) at about 94.8 Hz can be seen in the spectrum. The experiments were repeated at several speed and load conditions, but those results are not shown here for brevity. The magnitude of \( 2 f_s \) in the spectrum of \( i_P \) was observed to have little effect due to changes in load besides, the even harmonics (\( 4 \times, 6 \times, .. \)) can be also seen in the spectrum. The \( 2 f_s \) in the spectrum of \( i_P \) was found to be considered as a consistent marker for STF. However, it remains to be seen if the these fault frequencies appear in the spectrum of \( i_P \) in the case of planetary gearbox faults.
3.4. Effect of gearbox faults on \( i_P \)
The diagnostics of pitch motors based on \( i_P \) was demonstrated successfully in the case of STF. However, a fault in the gearbox can also induce disturbances in the uniform operation of the connected motor, causing changes in the current spectrum. Therefore, it is necessary to examine if the gearbox faults can be misdiagnosed as motor faults. To this end, the FFT spectrum of \( i_P \) is studied in both of the seeded planetary gearbox faults.

Effect of bearing fault  The three-phase motor currents were collected along with the vibration signals during the tests with seeded BRG faults in the pitch gearbox. The FFT spectrum of \( i_P \) is inspected for characteristic frequencies of the bearing fault [25] given by

\[
f_{BRG,i_P} = f_o, \ 2f_o, \ |2f_o - f_s| \tag{8}
\]

A test case wherein the motor was run at 1400 rpm and loaded to 60% of the rated load is considered here. The corresponding spectrum of \( i_P \), shown in Fig. 8, has no indications of the bearing fault frequencies. However, the even harmonics \( 2f_s \) and \( 4f_s \) are present in the spectrum, which are a characteristic of the STF. Although the amplitudes of these even harmonics are much smaller than the STF, there is a possibility of misdiagnosis of a gearbox fault as an early stage stator fault, if the current sensing is analysed in isolation.

Effect of planet gear fault  Similar to the bearing fault condition, the motor current spectra were also analysed during the PLT tests. Zhang et al. [26] demonstrated that the planetary gearbox ring gear faults result in sidebands of the ring gear characteristic frequencies in the current spectrum. However, to the authors’ knowledge, the effect of PLT on the motor currents was not investigated so far. A test case where the pitch motor was run at 1400 rpm and loaded to 60% of the rated load is described here as an example. The spectrum of \( i_P \) shown in Fig. 9, also presents the even harmonics \( 2f_s, 4f_s \) and \( 6f_s \). Besides, the frequency \( f_p \) described in (4) and the sidebands at the second harmonic of gearmesh frequency \( 2f_{m1} + f_{c1} \) as described in (5) are also visible in the spectrum of \( i_P \).

These results clearly indicate that in the case of complex connected systems such as the pitch system, a diagnostic decision based solely on one type of measurement can lead to misdiagnosis if the effects of connected components are not considered and thresholds are improperly implemented. Hence, a sensor fusion approach is adopted that considers both the current and vibration measurements for accurate fault diagnosis. The SVM classifier is chosen to achieve this objective.

4. Support Vector machine based classification algorithm
The SVM classifier distinguishes classes by drawing an optimum hyper-plane in a multi-dimensional hyperspace spanned by the feature set. This is achieved by solving an optimisation problem [27]. A pictorial representation in two-dimensional feature space is shown in Fig. 10.
The mathematical formulation of linear SVM classification for binary (two classes) case is discussed in this section. However, the same concept can be extended for multi-class linear as well as nonlinear classification problems. Consider the training data set with inputs \( x_i \in \mathbb{R}^m \) and binary outputs \( y_i \in \{ \pm 1 \} \) and

\[
(x_i, y_i) \in \mathbb{R}^m \times \{ \pm 1 \}, \quad i = 1, \ldots, N
\]  

(9)

Through training, the SVM classifier derives a decision function given by

\[
f_{w,b}(x) = \text{sgn}(wx + b)
\]

(10)

where \( w \) is the coefficient vector and \( b \) is the bias of the hyper-plane. Where \( \text{sgn} \) is the binary signature function. Ideally, the following condition should be satisfied by the hyper-plane of the classifier

\[
y_i[wx_i + b] \geq 1, \quad i = 1, 2, \ldots, N
\]

(11)

Among the hyper-planes satisfying (11), the optimal hyper-plane is the one with the maximum distance to the closest point. Based on structural risk minimisation inductive method, the training of an SVM is to minimise the guaranteed risk bound as follows:

\[
\arg \min_{w,e,b} J(w,e,b) = \frac{1}{2} w^T w + \frac{1}{2} C \sum_{i=1}^{N} e_i^2
\]

subject to \( y_i[wx_i + b] \geq 1, \quad i = 1, 2, \ldots, N \)

(12)

where \( e_i \) is a slack variable \( e_i \geq 0 \), which accumulates the error in case an optimal solution is not possible.

The SVM algorithm considers only the boundary data to define the optimal hyper-plane. The SVM can work with both linear and nonlinear classification problems [27]. However, for the
classification of the induction motor faults, a quadratic SVM is employed.
Since the SVM classifies the faults based on features, in the following section, statistical features for \( i_p \) and condition indicators for vibration signals are developed. Since the tests are performed using artificially seeded faults, the SVM classifier may be trained using a portion of the data. Once trained, the new data may be classified as shown in Fig. 11.

5. Feature selection

5.1. Current features

The extend Park’s vector \( i_p \) was observed to show some of the fault frequencies in planetary gearbox faults as the STF, but at lower magnitude. Therefore, a set of statistical features on time and frequency domain, shown in Table 1 were drawn for the SVM fault classification. Earlier, the authors have utilised these time and frequency features, to detect and classify faults in pitch motors [28]. The described features are calculated on \( i_p \) collected during tests with healthy, STF, BRG and PLT faults.

5.2. Vibration features

The vibration features are chosen to focus on fault detection in bearings and planetary gearbox gears.

**Bearings** As described in Section 3.1, bearing faults are often identified by analysing the envelope spectrum for an increase in energy at the characteristic frequencies. The vibration signal \( v \) is first acquired using an accelerometer. Let \( V_{en}(i) \) be the amplitude of the \( i \)’th envelope spectrum bin, and \( f_{en}(i) \) be the frequency of the \( i \)’th envelope spectrum bin. The first vibration features for bearing faults is the sum of amplitudes at integer multiples of the BPFO \( f_o \):

\[
F_{17} = \sum_{i=1}^{I} V_{en}(x) : x = x_m \{i, f_{en}, V_{en}, f_o, \Delta i_b\},
\]

where \( I \) is the number of harmonics in the spectrum, and \( x_m \) is the DFT bin that maximises \( V_{en} \) within a search interval \( \Delta i_b = 0.02 \). The bin that maximises the value is found using:

\[
x_m{\{i, f, Y, f_x, \Delta i\}} = \arg \max_x \{Y(x) \& f(x) \in f_{int}{\{i, f, Y, f_x, \Delta i\}}\}
\]
where \( f \) and \( Y \) is the input DFT frequency and amplitude, \( f_x \) is the CF, \( \Delta i \) is the input search width, and \( f_{int} \) is the maximum value search interval. This search interval is calculated using:

\[
f_{int}\{i, f, Y, f_x, \Delta i\} = \begin{cases} 
((i-\Delta i)f_x, (i+\Delta i)f_x] & \text{if } i = 1 \\
([i-i \Delta i], (i+i \Delta i))^{(i)}(i) : x = x_m\{i-1, f, Y, f_x\} & \text{else} 
\end{cases}
\]

where 15 is the search interval. If \( i = 1 \), the search interval is given by the CF \( f_x \) and the search width \( \Delta i \). If \( i \neq 1 \), the search interval is given by the updated CF found at the previous harmonic iteration. Similarly, the vibration features for the inner-race and roller fault are, respectively, calculated using:

\[
F_{10} = \sum_{i=1}^{I} V_{env}(x) : x = x_m\{i, f_{env}, V_{env}, f, \Delta i_b\}, \\
F_{19} = \sum_{i=1}^{I} V_{env}(x) : x = x_m\{i, f_{env}, V_{env}, 2f_r, \Delta i_b\}.
\]

In (17), \( 2f_r \) is used as the characteristic frequency as the roller would hit the inner and outer race during a single revolution around its own axis.

**Gearbox** In addition to three vibration features that are specialised for bearings, four other features that follow the trend of a planetary gearbox are also implemented. In [29], two features are proposed for monitoring the health of planetary gearboxes. The first feature is the sum of amplitudes at harmonics of the planetary gearbox carrier rotating frequency \( f_{c1} \). It is calculated using [29]:

\[
F_{20} = \sum_{i=1}^{I} V_{pow}(x) : x = x_m\{i, f_{pow}, V_{pow}, f_{c1}, \Delta i_p\}
\]

where \( V_{pow} = F\{v\} \) is the frequency spectrum of the vibration signal, \( f_{pow} \) is the frequency of the vibration spectrum, and \( \Delta i_p = 0.02 \) is half the width of the maximum value search area. In addition to calculating the sum of carrier frequency amplitude in the vibration signal, the envelope signal is also used in case of high-frequency resonance cycles:

\[
F_{21} = \sum_{i=1}^{I} V_{pow}(x) : x = x_m\{i, f_{env}, V_{env}, f_{c1}, \Delta i_p\}
\]

The second feature in [29] is the difference spectrum between a vibration spectrum at a known healthy state, and a vibration spectrum captured at an unknown state. The difference spectrum is summed and normalised using [29]:

\[
F_{22} = \frac{\sum_{j=1}^{J} |V_{pow}(j) - V_{pow, h}(j)|}{V_{pow}(j)}
\]

where \( V_{pow, h} = F\{v_h\} \) where \( v_h \) is a vibration signal captured during a known healthy state of the system. This feature is also modified for the envelope spectrum:

\[
F_{23} = \frac{\sum_{j=1}^{J} |V_{env}(j) - V_{env, h}(j)|}{V_{env}(j)}
\]

where \( V_{env}(j) = F\{\sqrt{v_h^2 + H\{v_h\}^2}\} \) is the envelope of the vibration signal captured at a known healthy condition. The feature set with the aforementioned 23 features were calculated on a combination of current and vibration signals and supplied to the SVM for training and classification.
6. Results

The SVM classifier described in Section 4 is trained to classify the faults listed in Section 3. The fault classes used in this research are Healthy, BRG, PLT and STF. The features that are used to classify the faults are described in Section 5. Each feature sample is calculated based on current and vibration data captured for the duration of 100 motor shaft revolutions. The SVM is tested in two different cases. Case 1, the SVM was trained using feature datasets calculated upon various speed conditions and under low load. The SVM was then tested using new feature datasets captured at the same variety of speed conditions, but at higher loads. In total, 540 samples are used for training the SVM, and 680 samples are used for testing. The trained SVM achieves a 100% accuracy for the training data. This is common and expected as the SVM trains excellent boundaries for the data that is presented during training. Using the trained SVM for classifying the testing dataset, the results are different. The accuracy has dropped to 78.09%, which means that more than a fifth of the samples are incorrectly classified. The confusion matrix for this test is shown in Fig. 12 (a). A confusion matrix makes it easy to visualise how well the SVM classifier labels new data. The sum of numbers on each row is equal to 1.0, i.e. 100% of the feature samples with that true label. To get 100% accuracy, the confusion matrix should be all diagonal with unity values. From this confusion matrix, it is apparent that a high number of bearing fault samples (92%) were misclassified as samples belonging to a PLT. In addition, 33% of samples belonging to a healthy condition were classified as stator faults.

The high number of misclassifications in Case 1 are explained by the lack of training data at higher loads. The training and testing data features are therefore revised in Case 2 to achieve a higher accuracy. In this case, about 2% of the data recorded under high load conditions was also served during training. In Case 2, the trained SVM classifier using the training data achieved a 100% accuracy for training data. Using the trained classifier for the testing data yields an accuracy of 97.53%, which is higher than in Case 1. The confusion matrix for Case 2 is shown in Fig. 12 (b). From this confusion matrix it can be seen that the classifier properly labels the Healthy, BRG and PLT classes. However, a few STF samples are classified as Healthy. This result shows that it is vital to train the SVM classifier using features captured during a variety of speed conditions and load conditions to achieve a high accuracy.

The performance of the SVM is compared to two other classifiers to verify its viability, namely the K-nearest neighbour (KNN) and the decision tree (DT) classifiers. A brief introduction to the KNN and DT are given in [30] and [31], respectively. To compare the performance, test...
Case 2 is utilised. The resulting confusion matrices from using a trained classifier on the test dataset are shown in Figure 13. The accuracy of the KNN and DT classifier are shown in subfigures (a) and (b), respectively. With a total of 96.6% and 99.85% accuracy for the two classifiers, respectively, it is determined that they are also suitable for classifying the faults using the supplied features. Although the DT appears to yield a better accuracy, it is known to suffer from increase in complexity with number of classes and data. Furthermore, SVM is efficient in determining the optimal hyper-plane in the feature space to distinguish among various classes as it only evaluates the data near the overlapping regions and not the entire set [27]. In the future, the authors intend to evaluate hybrid methods wherein the features are extracted using DT and an SVM classifier to distinguish classes [32].

7. Conclusion

In complex connected systems, a fault in one of the subsystem can result in misdiagnosis as a fault in another. This paper presented a sensor fusion approach to circumvent such a scenario in pitch system diagnosis by taking a combination of vibration and current measurements to generate a diagnostic decision. The support vector machine was able to successfully detect and classify faults with high accuracy. As a demonstration of the concept, only three faults of the pitch system are considered. However, since the faults were seeded in identical motor and gearbox but not the same equipment, the method was tested on components of similar specification. The approach can be extended to other failure modes of pitch systems and to many pitch systems across a wind farm, if the assumption that all WTs in a wind farm are of the same specification holds, and if not, then the features extracted from vibrations need to be modified according to the specification. However, it must be stated that while the results presented here demonstrate the feasibility of a sensor fusion approach, the results may not be generalised until more tests are done on large sets of data collected across several pitch systems.

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