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Application of Anomaly Technique in Wind Turbine Bearing Fault Detection

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***Abstract*—Bearing faults are the most common cause of wind turbine failures. Availability and maintenance cost of wind turbines are becoming critically important, with their fast growing in electric networks. Early fault detection can reduce outage time and costs. This paper proposes Anomaly Detection (AD) machine learning algorithms for fault diagnosis of wind turbine bearings. The application of this method on a real data set was conducted and is presented in this paper. For validation and comparison purposes, a set of baseline results are produced using the popular one-class SVM methods to examine the ability of the proposed technique in detecting incipient faults.**

***Keywords*—wind turbine, bearing, fault diagnosis, machine learning, SVM, anomaly detection.**

I. Introduction

Information technologies have made numerous progresses [1-3; 24-26]. Several research have been conducted on various areas of information technology [27-31] including data mining [32-33].

Wind turbines, as part of renewable energy generation technology, are increasingly deployed throughout electricity networks around the world. Low speed rotating components, such as gearbox and bearing, play an important role in determining wind turbines' efficiency. According to the Department of Trade and Industry (DTI) in the UK, Condition Based Maintenance (CBM) in wind turbine rotating elements has contributed to a saving of up to £1.3 billion per year [1]. Hence, Condition Monitoring (CM) of bearings has become a popular approach to increase performance and reduce costs [2-4].

As wind turbines are prone to failure due to high stress on the gearbox and the bearing, application of appropriate fault diagnosis techniques, especially for bearings in wind turbine maintenance has been the topic of many studies in recent literature [2, 5]. Figure 1 displays the different components of a rolling element bearing, including the inner race, outer race, rolling element (ball) and cage, which despite their simplicity have a complex internal operation [6, 7]. In recent literature, several studies have been conducted on bearing fault analysis using vibration and Acoustic Emission (AE) techniques [8].

Tandon *et al.*[9] presented a comprehensive review of the vibration and AE techniques including vibration measurements in both time-and frequency-domains, the shock pulse methodology, sound measurements and AE for bearings CM. Kim *et al.*[10] presented techniques for vibration and wear debris analysis by studying railway freight cars that include vibration, spike energy, spectrographic oil analysis, shock pulse and chip detection. Watson *et al.*[11] used wavelet techniques for Doubly Fed Induction Generator (DFIG) bearing faults detection based on power output data. R. Sehgal *et al.*[12] presented different factors, that brought about faults and fatigues in bearings. These factors included excessive preloading during installation, overloading and stray electric currents.

The majority of existing methods for bearing fault detection are focused on detecting the type of fault that has already occurred and for which data samples are available [36]. This is while collecting all possible types of faulty data is almost impossible. The existing methods are thus prone to erroneous behavior when presented with previously unseen data.

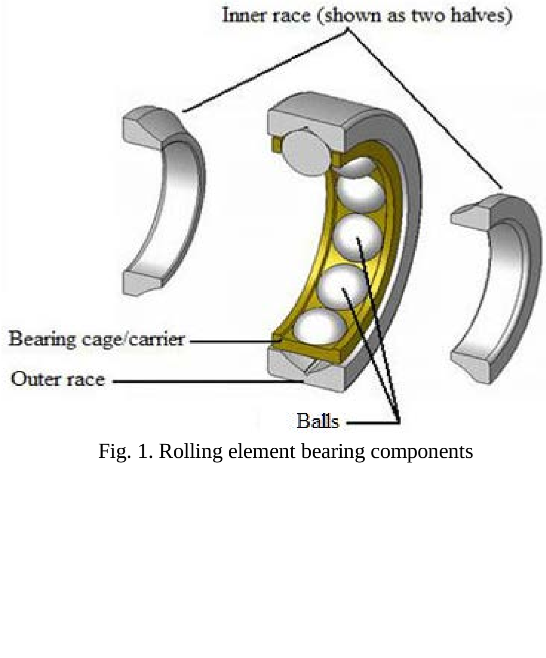

Fig. 1. Rolling element bearing components

On the contrary, data-mining methods, and machine learning techniques in particular, are able to predict defects and the existence of abnormal data without such conditions [35]. One of the more popular machine learning techniques, which has been widely applied across multiple disciplines and has improved over the past decade, is Artificial Neural Network (ANN) [13]. This technique, however, has some drawbacks such as structure identification difficulty, identification ability difference, local convergence which owes to learning process, and poor generalization ability as it originally designed to apply Experience Risk Minimization (ERM) [14, 15]. Another popular classification technique is the use of Support Vector Machine (SVM), which has recently become a very popular learning method[16]. The use of SVM classifiers simplifies a classification task by reducing the problem to a binary classification. The drawback of using SVM however, lies in issues with computational density and massiveness that bring about limitations and difficulties.

In this paper a fault diagnosis method based on supervised learning technique named anomaly detection (AD) is proposed. The training data set used for this method mostly includes normal data, which is easier to collect in practice. The AD algorithm is then able to capture any new types of intrusions or inconsistencies from normal data[17]. The point that needs to be taken into account is that if the training data does not contain normal variations of the data, the algorithm may not recognize future abnormalities and will assume they are normal. The training and application of this method provides the CM system with the ability to diagnose bearing fault in its early stages with a higher accuracy. The high sensitivity of this method means that it can provide a higher precision in fault detection, when compared to the previous state-of-the-art bearing fault detection algorithms.

The contents in the rest of this paper are organized as explained in the followings. Section II gives the details on SVM method (most commonly applied machine learning approaches), and explains Anomaly Detection technique used in this paper. Real data from the dataset of rolling element bearings is used in Section III to evaluate the proposed approach results as compared with SVM the baseline method. The comparison is carried out to illustrate the robustness and efficiency of the proposed technique. Conclusions are provided in Section IV.

II. Machine Learning Approaches

A. One-Class Support Vector Machine

Among various learning approaches, SVM is extensively used for different classification purposes and has been established as a popular machine learning method. SVMs are employed in numerous diagnosis applications like bearing faults, induction motor, rotating machines, etc. [18]. Traditionally, many classification techniques try to categorize two or multi-class situations. The aim of applying machine learning techniques is to identify test data between a number of classes, using training data. In the case where only one class of data is available, new data needs to be tested to determine whether or not it contains faulty data. To overcome this problem, researchers have proposed the use of the One-Class Support Vector Machine [34].

Training data samples need to be injected to the one-class SVM model to train the classifier. After that, the model has the ability to classify new data and distinguish whether it inconsistent with the trained model or not. Typically in fault diagnostics the combination of one-class SVMs with other techniques, like kernel functions, are used [19]. In this paper, AD and SVM are applied on a real bearing data set for comparing the techniques and to examine the application of learning techniques in fault diagnosis.

B. Anomaly Detection (AD)

AD is a machine learning approach based on classification techniques, which provides the user with the ability to classify data, where generally only a single class of data is available or a second class of data is under-represented. This method typically consists of two phases, the first is the training phase and the second is the testing phase. In the former phase, the algorithm is trained using a labeled dataset, which consists of mostly normal data. In the latter, the learned algorithm is applied to new and unseen data or a cross validation dataset. To put it more formally, the classifier learns a functional mapping
$f : \mathbb{R}^N \rightarrow \{C_0 , C_1\}$of the training dataset to an unknown probability distribution $p(\mathbf{x},y)$, where the normal samples are $(x, y) \in C_0$ and the abnormal samples are $(x, y) \in C_1$. This can be represented in the following manner:

$$(x_1, y_1), \dots , (x_n , y_n) \in \mathbb{R}^N \times Y, \qquad Y = \{C_0, C_1\}$$

The AD algorithm is trained based on the presumption that *anomalous* data are not generated by the source of *normal* data and that the training set contains a huge percentage of normal data, the algorithm then detects any other data which is not normal and displays intrusive behavior[20]. The main procedure of algorithm is based on the use of Gaussian distributions and it contains three phases: *1.Gaussian distribution, 2.Estimating parameters,* and *3.Selecting threshold,* ε. In phase 1 and 2, all data are modeled and the Gaussian parameters are defined. In phase 3, the algorithm selects a threshold to recognize anomaly cases by using the F_1 score. This can be expressed using the following equations:

$$F_1 = \frac{2.prec.rec}{prec+rec} \tag{1}$$

while, the *prec* and *rec* are obtained from:

$$prec = \frac{tp}{tp+fp} \tag{2}$$

and,

$$rec = \frac{tp}{tp+fn} \tag{3}$$

where *tp* is the number of true positives, and refers to the ground truth dataset labels that reflect anomaly and are also correctly classified by our algorithm. The complementary measure *fp*, is the number of false positives. This is when anomaly does not exist in the ground truth labels, but the data is incorrectly classified as containing anomaly. Finally, *fn* is the number of false negatives and reflects the cases of the data that are labeled as anomalies in the ground truth labels but are incorrectly classified as not being anomalous by our algorithm. The algorithm will try several values of ε to find the best value based on the F_1 score, using only the training data. Once the best ε is selected, the algorithm then applies this threshold to the evaluation data in order to find the data that fall beyond the threshold boundaries and classifies them as anomalies of the data.

III. Experimental Results

The vibration data employed in this paper was collected from the dataset of rolling element bearings from the NSF I/UCR Centre for Intelligent Maintenance Systems (IMS – imscenter.net) with support from Rexnord Corp. in Milwaukee, WI [21]. As Figure 2 illustrates, four bearings were installed on a shaft. An AC motor is coupled to the shaft via rub belts to keep the rotation speed at a constant 2000 RPM and a radial load of 6000 lbs is added to the shaft and the bearings by a spring mechanism. All bearings are force lubricated. Vibration data was collected every 10 min for 164h with a sampling rate of 20 kHz. An outer race defect occurred at the end of this experiment on bearing 1.

The data of the horizontal accelerometer of bearing 1 have been applied, in which the bearing consists of 16 rollers in each row, with a pitch diameter of 2.815 in., a roller diameter of 0.331 in., and a tapered contact angle of 15.17. The majority of past studies on bearing fault diagnostics have been conducted using simulated or seeded damage. The experiments employing these types of faults are not appropriate for detecting natural early defects. As the main objective of this paper is to present a method with the ability to detect bearing faults at early stages, this dataset is completely appropriate for our purpose.

A. *Model description:*

In order to test this technique and compare it to the previous applied method for the same bearing, as used in [22], We carried out extensive evaluations. In this experiment 100 normal operating conditions were captured and used as the training dataset (16hr), and then time-domain parameters (kurtosis and NGS [23]) were extracted for each sub-band of the raw data. These parameters are independent of the energy of the signal and have a proper distribution for machine learning data analysis. The sub-bands are selected with 50 ms length and 25 ms shift. The shift is employed to provide overlapping of the sub-bands of the dataset.

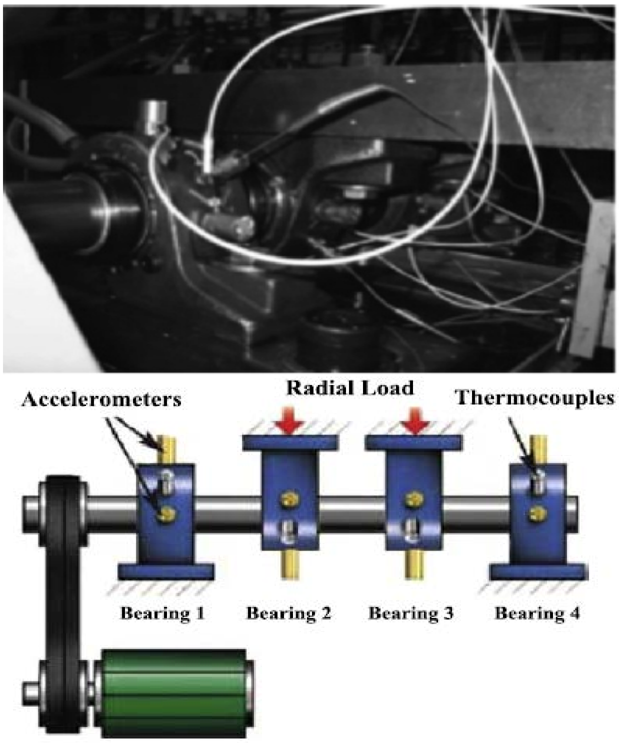

Fig. 2.Bearing test rig and sensor placement [21]

The obtained data, gathered using feature extraction, is then applied as an input to the algorithm. These features are processed by the three AD steps of *Gaussian distribution, estimating parameters for a Gaussian*, and *selecting the threshold.* In step 1 a Gaussian model is applied to the distribution of the data. The Gaussian distribution is obtained by equation (4) where μ is the mean, σ^2 is variance, and *p* is the probability density function:

$$p(x;\ \mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{(x-\mu)^2}{2\sigma^2}} \qquad (4)$$

In the next step, Gaussian parameters are calculated by utilizing the training dataset. The algorithm then examines several values of ε to find the best value based on the F_1 score. Once the best ε is selected, the algorithm finds the data that fall beyond the threshold boundaries, which are then marked as anomalies in the dataset. The F_1 score represents the accuracy of the algorithm, in which a score of 1 means 100% accuracy. It can be seen that the algorithm can identify all anomalies in the dataset.

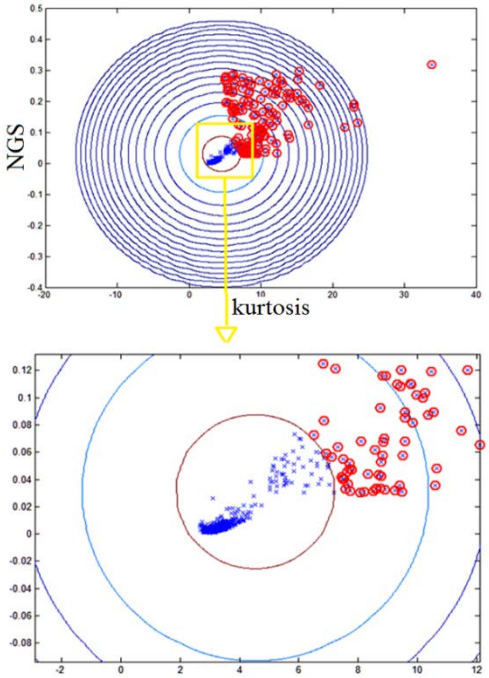

Fig.3. Anomaly Detection result visualizing schematic

Figure 3 depicts a schematic of the anomaly visualizing for fault diagnostic when the defect is occurred, and as can be seen in the zoom out section the anomaly detector has the ability to recognize bad data from the incipient stage, and all anomalies are detected, shown in a red circle in the visualizing schematic. Figure 4 depicts the SVM clustering schematic for the same data set through a similar algorithm which can determine the best Kernel parameters for the data set.

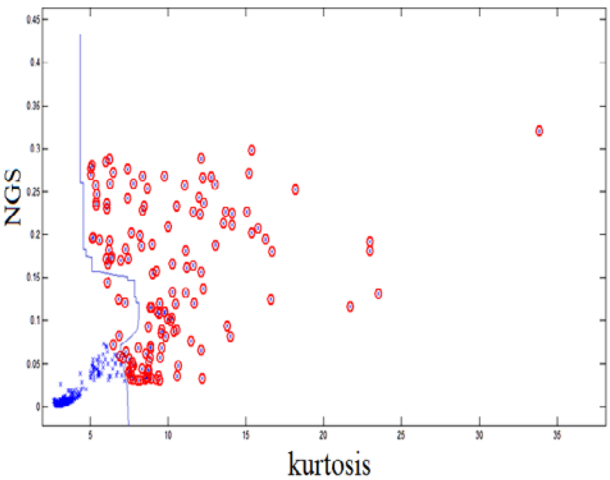

Fig.4. SVM result visualizing schematic

Incipient fault detection is one of the most important aspects of this method. Figure 5 and Figure 6 display the exact time that each technique has detected the first anomaly point. Figure 5 has been adopted from the results of past research of Kaewkongka *et al.* that has been conducted on the same dataset [22]. In this figure the Y axis is the output of SVM system and the red dots show the points where the methods detect a change in behavior for the first time, for the one-class SVM. This is 75h before the crack makes the machine stop working. Using AD method, in figure 6, the first anomaly was detected in 100h before the major defect occurs, causing the bearing breakdown.

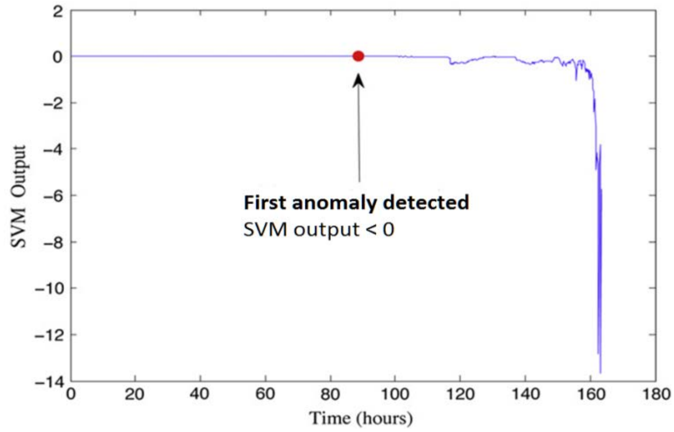

Fig 5. SVM output [22]

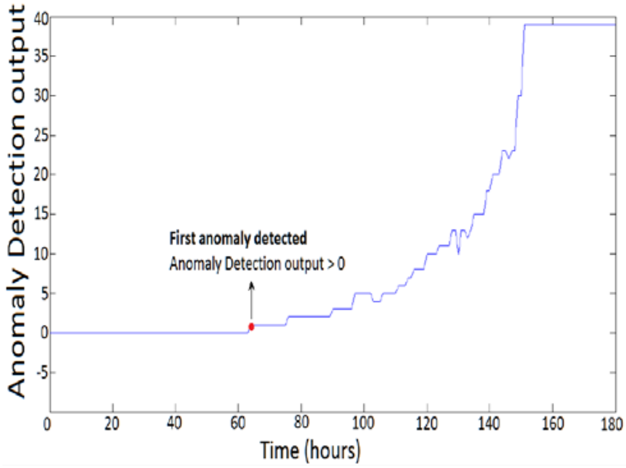

Fig.6. Anomaly Detection output

IV. Conclusions

Bearing condition monitoring and incipient fault detections are very important for wind turbine generating units to cut maintenance costs and increase availability. There are a variety of condition monitoring and fault diagnosis techniques that are used to detect incipient faults and failures in wind turbine bearings. However, the majority of these techniques need huge samples of faulty data for the development/training phase of the algorithm. In practice, these kinds of datasets are not easily available. In order to overcome this problem, this paper proposed anomaly detection as part of a machine learning approach for fault diagnosing, applied to bearings in wind turbines. The results obtained from this method were compared with that of a SVM based state-of-the-art approach. The results indicated that the proposed AD learning technique provides a higher accuracy, as well as the ability to detect incipient faults earlier.

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