A knowledge-based diagnosis algorithm for broken rotor bar fault classification using FFT, principal component analysis and support vector machines

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Abstract: Despite their ruggedness and reliability, induction motors experience faults due to stresses and manufacturing errors. Early detection of these faults is important in preventing further damages and minimising down-time. In this study, a machine learning algorithm is proposed for detection and classification of broken rotor bar (BRB) faults according to their severity. Removal of high frequency components then amplification was performed on the measured single-phase current. Features were then extracted using FFT and principal component analysis (PCA). Support vector machines (SVM) was used for classification. Two classification schemes were analysed; one classifying in one step and another in two steps. Experiments were performed to evaluate the algorithms by analysing their recognition rates. Six different SVM kernels were studied. Recognition rates as high as 97.9% were achieved. False negative rate as low as 0% was also realised. Furthermore, it was found out that using more principle components does not yield significant improvements.

Keywords: squirrel cage induction motor; IM; SVM; support vector machines; PCA; principal component analysis; BRB; broken rotor bar; fault diagnosis; machine learning.

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1 Introduction

Induction motors (IM) are the most widely used electric machines industrially and domestically. Ruggedness, compactness and reliability of these machines are the main reasons that this popularity can be attributed to (Taher and Malekpour, 2011; Ojaghi et al., 2014). Despite the much desired robustness, faults may still occur due to one or several reasons. These faults occur because of manufacturing errors or as a result of thermal, dynamic, environmental or mechanical stresses among other reasons (Zhongming and Bin, 2000; Abbaszadeh et al., 2001). The need of having condition-based maintenance stems from the need to prevent unnecessary downtime as well as reducing maintenance costs (Taher and Malekpour, 2011; Ojaghi et al., 2014). Furthermore, detection of faults, especially during the stage of their inception is an important task because faults that happen in one part of the machine may lead to faults that are more severe in another part of the machine; a phenomenon known as 'cascade sequence' (Abbaszadeh et al., 2001).

The more commonly occurring IM faults can be broadly categorised into stator faults, bearing faults, eccentricity-related faults and rotor faults (Nandi et al., 2005).

Stator faults, also referred to as armature faults, occur as a result of insulation defects that occur in the stator winding brought about by either moisture, high temperature, system surge or faulty earth practices. The stator faults lead to asymmetry in the stator impedance by causing short circuits in the turns, windings and the stator body. Consequently, unbalanced phase currents are drawn by the motor. Stator faults account for 30–40% of the IM faults (Zhongming and Bin, 2000; Haji and Toliyat, 2001).

Accounting for about 50% of the reported IM faults, bearing faults occur as a result of mechanical stresses exerted on the bearing rings, raceways, balls or rolling elements. Bearing faults may occur due to fatigue despite the motor working under normal operating conditions with balanced loads and good alignment. Other causes of bearing faults are: contamination and corrosion, improper lubrication and improper installation of the bearings (Nandi et al., 2005).

Unequal air gap exists between the rotor and the stator. This condition is known as machine eccentricity (Heller and Hamata, 1977; Cameron et al., 1986; Vas, 1993); and when it becomes large it leads to unbalanced radial forces which may cause the rotor and stator to be damaged (Nandi et al., 2005).

Broken rotor bar (BRB) arise from thermal stresses, magnetic stresses, residual stresses that arise from manufacturing faults, dynamic stresses, environmental stresses and mechanical stresses (Nandi et al., 2005). These faults can be classified into three categories (Arabacı and Bilgin, 2010): high-resistance broken or cracked rotor bars or end-rings resulting into high resistance; poor connection (high resistance) between the rotor bars and the end-rings and short-circuit rotor laminas. Despite BRB and end-ring faults making up only about 5–10% of IM faults, they can cause faults to happen in other parts of the motor (Ahamed et al., 2014); therefore their early detection is necessary so as to avoid more serious problems.

Fault detection algorithms can be categorised into three main categories (Edomwandekhoe, 2018): signature extraction based, model-based and knowledge-based techniques.

Signature-based techniques involve monitoring the current, voltage and vibration signals among other operational process parameters (Duan and Živanović, 2014; Edomwandekhoe, 2018). Detection of BRBs has been performed through vibration analysis (Su and Chong, 2007), instantaneous power monitoring (De Angelo et al., 2010), and magnetic field analysis (Mirafzal and Demerdash, 2005; Faiz et al., 2007).

The most popular techniques in this category are vibration monitoring and motor current signature analysis (MCSA) (Benbouzid, 2000). However, due to their cost, vibration sensors are only reasonable to use in expensive and load-critical motors (Ghate and Dudul, 2010).

In MCSA, the stator current is used as the monitoring signal. The advantage of using the stator current over other signals is that it is relatively easy to measure (Haji and Toliyat, 2001) and has the capability of remote monitoring (Edomwandekhoe, 2018). Moreover, current sensors are included for control purposes in many motor drive systems (Liu and Bazzi, 2017).

One popular MCSA-based technique is the fast Fourier transform (FFT) method (Benbouzid, 2000). This method has some drawbacks like spectral leakage, need for high resolution, varying load conditions and ambiguous frequencies (Matić et al., 2012). Methods like Park's vector approach, wavelet transform, Hilbert transform (Saddam et al., 2018) and ZOOM-FFT (Tan et al., 2013) have been applied to overcome these limitations.

For signature-based methods, priori knowledge of the IM system is usually necessary. For instance, information on the motor slip is required in order to detect the broken bar faults from the side-band frequencies; and this information is not always available (Wang et al., 2012). Parameter estimation is one method that can be used to get the motor slip, but this leads to high computational complexity (Ilonen et al., 2005).

Model-based methods on the other hand use mathematical models that represent the motor faults. An example of this method is proposed in Ikeda and Hiyama (2007) for the detection of unbalanced voltage problems. Another example of this approach is described in the work of Arkan et al. (2005) for the simulation of stator inter-turn faults. Despite being able to give warnings of faults at the early stage, the model-based approaches rely majorly on explicit motor models and these models are not always available (Ali et al., 2019).

Lastly, knowledge-based algorithms apply artificial intelligence and machine learning for fault diagnosis through directly emulating the relationship between the inputs and outputs without giving much attention to the intermediate results of the system (Liu and Bazzi, 2017). Relatively new compared to the other two categories, this group of algorithms has recently gained so much popularity among researchers. In the literature, it is reported that machine learning algorithms such as Naïve Bayes (NB), k-nearest neighbour (KNN), support vector machines (SVM), artificial neural network (ANN), repeated incremental pruning to produce error reduction (RIP), and C4.5 Decision Tree (C4.5) have been successfully applied for fault detection.

Hajiaghajani et al. (2004) proposed using Bayes Theorem for the detection of eccentricity-related faults in DC motors. They used the motor current as the input for the system.

Wang et al. (2012) proposed using Naïve Bayes, KNN and SVM classifiers to detect stator, rotor and bearing faults in IM. In this research, they compare the effectiveness of using features extracted from the motor current and those extracted from the envelope of motor current as the input for the classifiers. The results of their experiments show improvement in the accuracy and effectiveness of classification in using the envelope of current for feature extraction.

Ondel et al. (2006) used the KNN classifier to detect BRB faults under varying mechanical loads. In the work, they use the voltage and current signal as the input for the system.

Wavelet-decomposition and principal component analysis (PCA) have been applied for the detection of eccentricity faults in synchronous motors as presented by Ebrahimi et al. (2013). The algorithm presented analyses the stator current in the frequency domain. In their experiments, the authors used a frequency inverter for speed control and torque variation. For classification, they used KNN and a fuzzy support vector machines (FSVM) was used to give the degree of eccentricity.

Konar and Chattopadhyay (2011) presented a system which combines SVM and continuous wavelet transform (CWT) to detect bearing faults. They used vibration signals as inputs for the system proposed. Their study tested the system under no load, half the rated load and nominal load conditions. The research concludes that the CWT-SVM approach is a better alternative compared to using Discrete Wavelet Transform with ANN.

SVMs have also been used to detect 'balls', inner race and outer race bearing faults (Li et al., 2013). In this study, ant colony optimisation was used to select suitable SVM parameters yielding a faster and more accurate fault classification system.

Another important machine learning method used for fault diagnosis that appears in the literature is the decision trees method. Random forests and C4.5 decision tree methods have been used to identify bearing faults in IMs according to the research presented by Peng and Chiang (2011). In the work, mechanical vibration signals in the time and frequency domain were used as the input of the systems. PCA and linear discriminant analysis (LDA) were used for feature extraction and dimensionality reduction.

The researchers in Aydin et al. (2014) propose a boundary analysis algorithm in conjunction with fuzzy classifier in their study in which they used a graphical representation of the current signal for the detection of rotor faults in IMs. The graphical image of the current was generated through the use of Hilbert transform. The classifiers with which the comparisons were made were the Gaussian mixture models, negative selection algorithm based on genetic algorithm, ANN, artificial Immune classifier with learning particle swarm and C4.5 classifiers.

Application of ANNs for fault diagnosis appears in several other publications in the literature. Bossio et al. (2013) presented neural network schemes which employ self-organising maps for fault diagnosis in IMs. They successfully identify load unbalance and shaft misalignment faults using one of the schema and classify BRB and oscillating load faults using the other.

The study carried out by Ertunc et al. (2013) used ANN and neuro-fuzzy (ANFIS) models to give a diagnosis of the bearings in an IM. Analysis in the work was performed on the vibration and stator current in the time and frequency domains.

Hybrid machine learning models that use neural network fuzzy min-max (FMM) and random forest classifiers have been used to monitor the condition of IMs (Seera et al., 2014). In the study the experiments were performed under 25%, 50%, 75% and nominal torque. The inputs of the system were obtained through the MCSA method from the stator current.

Konohen self-organising maps classifier has been used to detect rotor, stator and bearing faults (Ilonen et al., 2005). The system captured the acoustic data from the IMs using several microphones and extracted the features using wavelet transform.

The authors in Tahar and Djalel (2017) used artificial neural fuzzy interference system (ANFIS) so as to improve the reliability and efficiency of the diagnosis. They analyse the magnitude of energy level of the stator current's wavelet decomposition.

In Ouhibi et al. (2018) probabilistic NN, multi-layer perceptron NN, and generalised regression NN have been proposed for the task of fault detection in asynchronous machines; where the inputs are the RMS of the 3-phase voltages and currents.

Of the mentioned classification algorithms, SVMs stand out due to their high classification performance, less training time and the ability to give good results in cases of a small number of training data (Bacha et al., 2012). The research performed by Palácios et al. (2015) which evaluates these intelligent methods shows that ANNs with multilayer perceptron (ANN/MLP) has given accuracies of more than 99.7% for the detection of BRB faults. Experiments performed for bearing faults indicate that SVMs are accurate and robust and have the best performance judging by their accuracy and processing time.

The performance of pattern recognition algorithms depends majorly on the features extracted. In the literature several feature extraction techniques have been used to obtain the fault indicators found in the mechanical and electrical signals of the IMs. The motor current is often available in the industry thanks to advancement in communication technology that has enabled drives and microprocessor-based protection to be included in IMs (Pezzani et al., 2018). The research performed in Gangsar and Tiwari (2017) indicates that vibration signals do not add more information important for electrical faults detection than the current signals. In the work, statistical features like kurtosis, skewness obtained from the IM current signals were used as the input for the intelligent classifiers.

Despite there being many publications in the literature which show success in detection of BRB, industrial application remains a problem due to some challenges. One of these challenges is that some operating conditions like load oscillations and voltage supply oscillations produce symptoms that are similar to those produced by broken bars (Pezzani et al., 2018). Such problems result in false alarms; thus, the analysis of false negatives and false positives remains an active area of study. In this study, we present two fault diagnosis schemes which use current measurements as the monitoring signal. Feature extraction is achieved through the PCA transform on the motor current in the frequency domain. Classification is performed by SVM. One of the proposed schemes directly detects if there is a fault and gives the severity of the fault in one go. The other scheme gives the diagnosis in two steps using two classifiers; the first classifier detects the fault and the second one gives its severity. The classifiers are evaluated through experimental study.

2 Background

2.1 Principal component analysis (PCA)

The PCA algorithm is a popular technique that researchers have employed for feature extraction in pattern recognition applications. The main idea of PCA is projecting high-dimensional data to lower dimensional data while retaining the information by preserving features that have higher variance (Ozgonenel and Yalcin, 2010). Many times, features are related to each other, and PCA expresses these features as a linear combination of new features transforming correlated features into uncorrelated features known as principal components. Commonly used in face recognition and image compression applications, PCA has also been applied in fault detection (Peng and Chiang, 2011).

The steps of PCA involve creating a training matrix from the training data, then finding the covariance of the matrix. Then the eigenvectors and eigenvalues of this covariance matrix are computed and arranged in descending order. The number of principal components to be extracted is then selected and the projection matrix built. This is used to project the input samples into the PCA feature space (Barnouti et al., 2016).

2.2 Support vector machines (SVM)

SVM is a supervised machine learning algorithm that works well as a classifier when there is small number of samples (Kankar et al., 2012). They were initially developed as a solution for binary classification. Two linearly separable classes can be separated by several linear classifiers referred to as hyper-planes; however one of the hyper-planes is able to perform maximum separation. This hyper-plane is known as the maximum separating hyper-plane and has the maximum margin. The margin is the distance between a hyperplane and the nearest data point of each class (Vapnik et al., 1994). The aim of SVM is to create an optimal hyperplane. The data points that lie either on or within the margin are caller support vectors. In the case of the data not being linearly separable, an appropriate kernel function is used to map the data into a higher dimensional feature space where it becomes linearly separable; then constructing the hyperplane to separate the data classes (Gangsar and Tiwari, 2017). The types of kernel functions are linear, polynomial and Gaussian radial basis function (RBF) (Ali et al., 2018). The SVM can be enhanced through selection of the suitable kernel function (Ameur et al., 2017). For multi-class problems, they are divided into several binary problems and solved using methods like one-vs.-one (OVO) and one-vs.-all (OVA) (Gangsar and Tiwari, 2017).

3 Materials and methods

Apart from small differences in the structure of IMs and Submersible induction motors (SIMs), the working principle of the two is the same. SIMs has smaller diameters resulting from the well diameter constraints and longer rotors to compensate for that. The rotor bars and end-rings are made from aluminium casting in conventional IMs and copper bar and plate in SIMs. The bars and plate are connected through welding.

The welded regions are prone to faults that result from mistakes that may have occurred in the manufacturing process or later due to the stresses exerted on the motor. This could result in poor conductivity in the rotor bars and end-rings; thus causing current not to flow. These faults are what are termed as 'BRB' faults.

Detection of BRB faults can be achieved through monitoring the supply current of the motor. The fault diagnosis techniques in this study are divided into three main sections: data acquisition, feature extraction and decision (classification).

In this research, experimental data was used to develop a machine learning system to detect and classify BRB faults in IMs according to their severity.

3.1 Data acquisition, signal processing and feature extraction

The signals were obtained using Hall-effect current sensors. The current signals acquired were processed and analysed in the frequency domain. The transformation was performed using FFT. A total of 24 samples was collected for each of the five studied classes; giving a total of 120 samples.

PCA transformation was then performed on the current signals in frequency domain for feature extraction and dimensionality reduction. To find the optimal number of principal components to use, the first 2, 5, 10, 20, 30, 40, 50, 60, 70, 80, 90 and 100 principal components were extracted to create the feature vectors and stored in a database. These were used separately as the inputs for the classifiers in the experiments carried to train and test the different classifiers studied. Figure 1 shows the flowchart of the proposed algorithm (On the diagram, 'Ind. Motor' stands for Induction Motor).

3.2 Decision (classification)

For classification, SVM with different kernel functions were used in several experiments carried out. The SVM kernel functions studied were: linear, quadratic, cubic, fine Gaussian, medium Gaussian and coarse Gaussian. Two classification schemes were designed and analysed and their performance compared.

3.2.1 Classification scheme 1

The first scheme directly classified the input sample into one of the five studied classes: healthy, 1 BRB, 2 BRB, 3 BRB or half BRB. The database used to train and test this method contained 24 samples from each class. A 5-fold cross validation method was used to evaluate the performance of each classifier studied. Figure 2 shows the flow chart of the technique used in scheme 1. Figure 3 gives the flowchart of the experiments performed for the evaluation of this technique.

Figure 1 Flowchart of the proposed algorithm (see online version for colours)

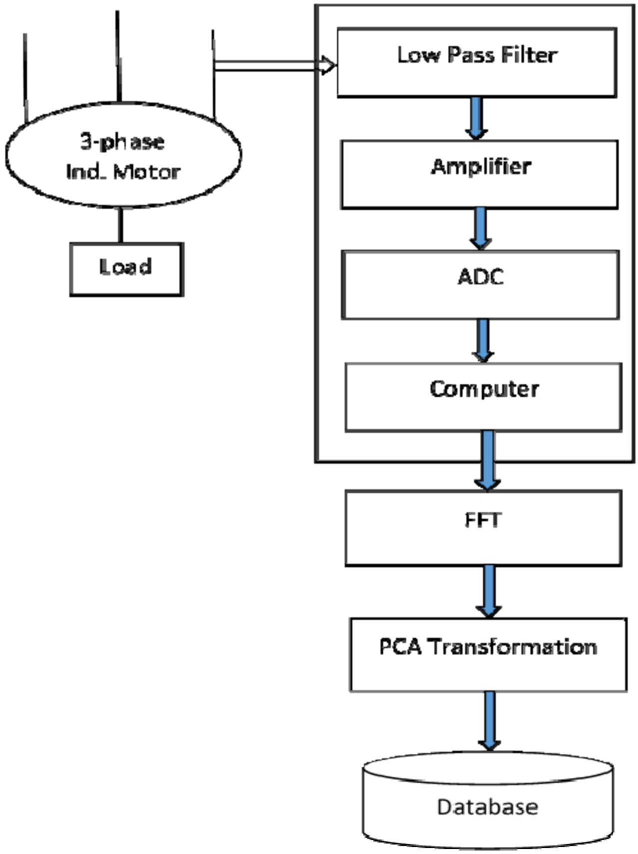
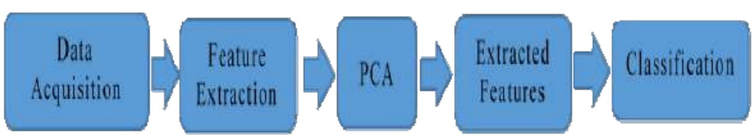


Figure 2 Flowchart for the proposed 'scheme 1' (see online version for colours)



3.2.2 Classification scheme 2

In the second scheme, classification was performed in two steps; step 1 determined if the motor was healthy or faulty and step 2 determined the severity (for a faulty motor) of the fault as shown in the Figure 4.

Step 1: Is the motor healthy or faulty?

In the first step of scheme 2, after the current was measured, the signal processed and the features were extracted, the classifier was used to classify it into either being healthy or faulty.

To test the performance of the classifiers used in the first step, the data was divided into four datasets each containing all the 24 samples of the 'healthy' class and six samples from each of the four studied faults so as to have an equal number of samples for the two classes. The samples of the 'faulty' class contained in each dataset was different (in terms of load conditions), so as to provide a more accurate behaviour of the system under different conditions.

5-fold cross validation method was used to test each classifier and the accuracy of fault detection recorded. To evaluate this step in the proposed algorithm, the overall accuracy was calculated by averaging the individual accuracies of using the four datasets.

Figure 3 Flowchart for the experiment to evaluate 'scheme 1' (see online version for colours)

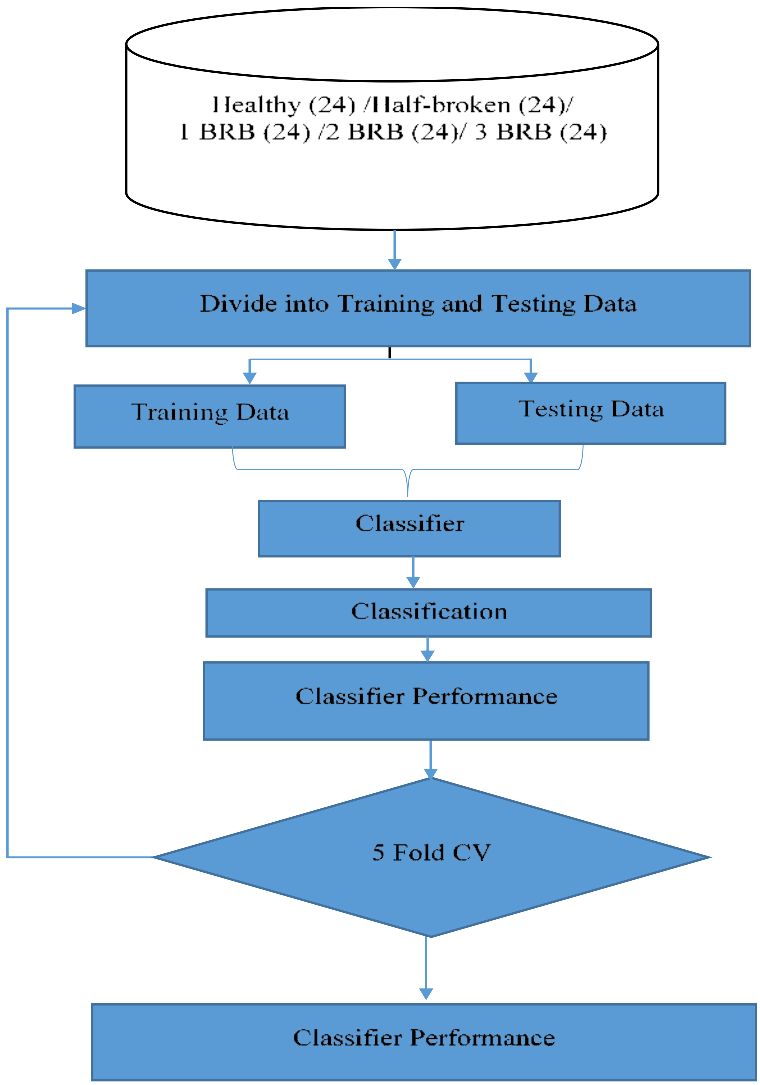
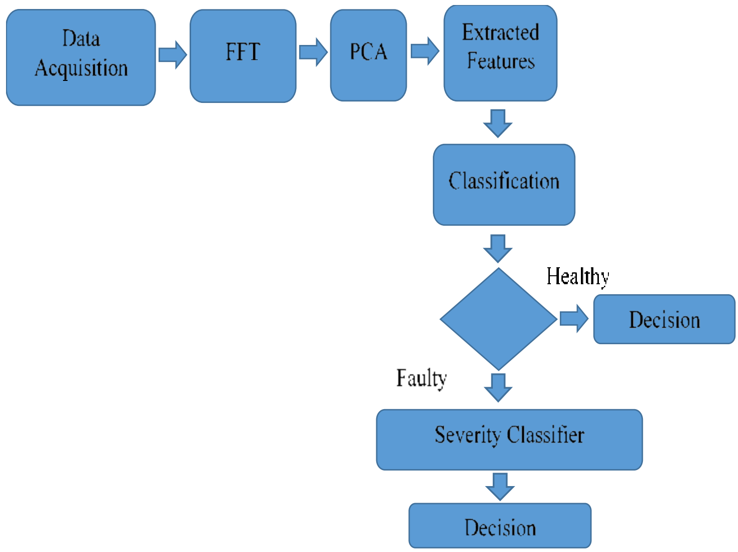


Figure 4 Flowchart of the proposed 'scheme 2' (see online version for colours)



Step 2: If the motor is faulty, what is the severity?

For the second step, only samples from the faulty motors were considered as the aim of this step was to classify the fault by its severity (after it has been detected in step 1).

To test the performance of the classifiers in performing this step, 24 samples from each of the faulty conditions were used to create the database. 5-fold cross validation method was used to evaluate the performance of the classifiers studied. To evaluate this step in the proposed algorithm, the overall accuracy was calculated by averaging the individual accuracies of using the four datasets.

4 Experimental setup

The experiments in this study were performed in a SIM factory using a motor-generator system. Motor loading was performed using a generator and levelling of the load was carried out through resistors conducting to the generator. Figure 5 shows the picture taken of the experimental setup.

The squirrel-cage motors used to perform these experiments had the following specifications:

- power: 25 HP
- number of bars: 22
- rotor diameter: 71 mm
- bar diameter: 6.1 mm
- stator diameter: 72 mm
- rotor length: 520 mm.

Figure 5 Picture taken of the experimental setup (see online version for colours)

The broken rotor faults were simulated in the factory during the production stage; and with the aim of ensuring that accurate measurements were recorded, the faults were fabricated separately. That is, five different motors were used for the five studied classes. Creating the broken bar faults involved drilling through the middle section of the motor bars thus reducing the conductivity of the bar or making it zero, therefore high resistance. The half BRB fault was simulated by drilling until half-way through the bar giving the effect of reduced conductivity; thus also high resistance. This half-bar fault represents the incipient stages of the studied faults.

The simulated faults were as listed below:

- one broken bar
- two broken bars
- three broken bars
- a half broken bar.

5 Experimental study and results

5.1 Data acquisition, signal processing and feature extraction

Sampling of the single-phase current was performed using a hall-effect sensor. A low-pass filter was then used on the analogue signal to remove the undesirable high frequency components. Then, the signal underwent amplification and in turn maximising the use of the analogue-to-digital (ADC) converter's input range; which sampled the filtered current signal at a predetermined sampling rate of 7.5 kHz. Figures 6 and 7 show the current signals sampled from a healthy motor and a motor with 3 BRBs under the same load conditions respectively.

Figure 6 Current of a healthy motor (see online version for colours)

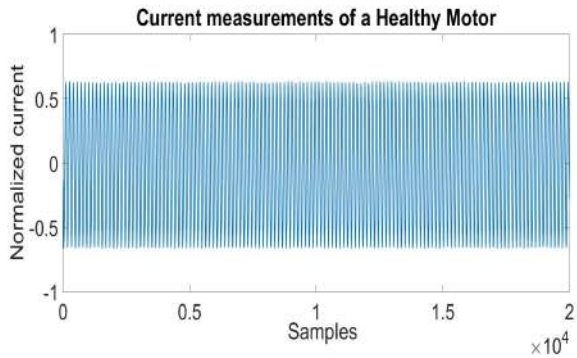


Figure 7 Current of a motor with three BRBs (see online version for colours)

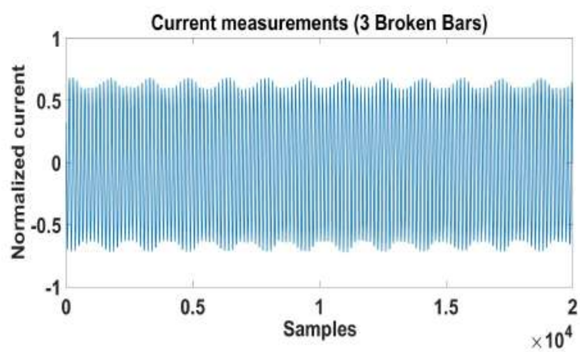
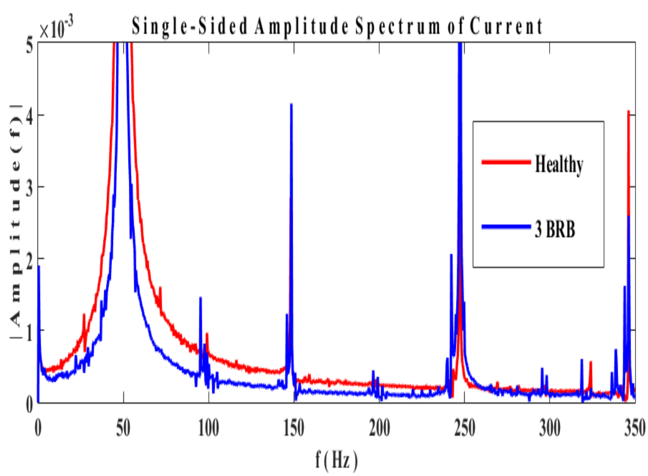


Figure 8 Amplitude of power spectra (healthy vs. three broken bars) (see online version for colours)



FFT was then performed on the current signals and analysis performed in the frequency domain. Figure 8 shows a comparison between the amplitude of power spectra of the current of a healthy motor and that of motors with the studied BRB faults under the same load conditions.

Feature extraction (PCA) results

There was a total of 120 samples (24 samples per studied condition) used in this study, and each sample of the data was a 10,001 by one matrix at this point. PCA was used for feature extraction and dimensionality reduction and was performed as in the steps described below:

1 The samples were concatenated into a training matrix A with size (120 by 10001).

2 The covariance of matrix A was computed giving a covariance matrix C (10001 by 10001).

3 The eigenvectors and eigenvalues were then obtained from the covariance matrix C.

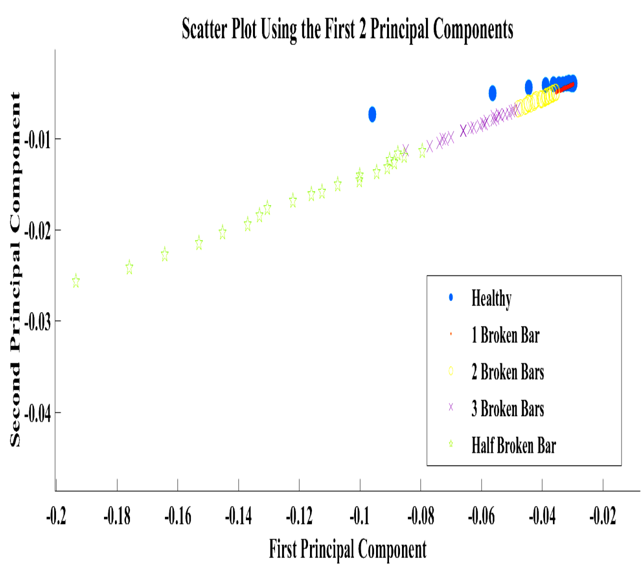
4 The eigenvectors were sorted according to their corresponding eigenvalues in descending order, thus the first ones having larger variance.

5 To get the first 'x' principal components, the PCA transformation matrix was created using the eigenvectors with the largest 'x' eigenvalues. The size of the transformation matrix was 10001 by 'x'.

6 The PCA transformation matrix was used to project the original samples into the PCA feature space resulting into feature vectors of dimensions of 'x' by 1 representing their respective sample.

7 Step 5 and 6 were repeated for 'x' equal to 2, 5, 10, 20, 30, 40, 50, 60, 70, 80, 90 and 100.

Figure 9 Scatterplot of the data in PCA feature space using the first two principal components (see online version for colours)



Databases were created to contain the samples of each condition in the PCA feature space. Since one of the targets of the study is to evaluate the effect of the number of principal components used on the performance of the system, 12 separate databases were created and each one contained 120 samples (24 per class). The first 2, 5, 10, 20, 30, 40, 50, 60, 70, 80, 90 and 100 principal components were considered as the inputs for the classifiers. Figure 9 gives the scatterplot of the data in PCA feature space using the first two principal components.

5.2 Classification results

After the database was created, experiments were performed to evaluate the two classification schemes studied in this work.

5.2.1 Scheme 1

In the first scheme, an input sample was classified directly into the condition as either healthy or faulty (together with the severity). This scheme used the database with the 120 samples (24 samples per class) as the input signals. A five-fold cross validation method was used to evaluate the performance of the SVM classifiers with different kernel functions.

Table 2 provides the recognition rate of the best performing classifier from studied kernel function in scheme 1 and the number of input features with which the results were achieved.

From the results of the experiments, it was seen that the detection accuracy as well as the severity classification accuracy of the coarse Gaussian SVM classifier was poor.

Using the other kernel functions produced higher and more reasonable results. The best overall recognition rate was realised by the 'cubic SVM/2 principal components' (95%), followed by 'linear SVM/2 principal components' and 'quadratic SVM/2 principal components' at second (92.5%).

Although the medium Gaussian SVM classifier produced reasonable accuracy with two principal components, the accuracy drops drastically with the increase in the number of features used.

Despite some of the classifiers achieving high accuracy in classifying the fault into their appropriate severity category, the false positive rate (i.e., healthy motors being categorised as faulty) and the false negative rate (i.e., faulty motors categorised as healthy) are still high in some of them. The four best performing systems built from scheme 1 had the false positive and false negative rates as shown in Table 1.

Table 1 Overall accuracies, false positive and false negative rates of the best performing methods for scheme 1

Kernel/No. of features	*Average accuracy* (%)	*False positive rate* (%)	*False negative rate* (%)
Cubic/2	95	8.3	0
Linear/2	92.5	8.3	2.08
Quadratic/2	92.5	4.2	3.125
Medium Gaussian/2	92.5	4.2	4.167

Table 2 Recognition rate of the best performing methods in scheme 1

Kernel	*No. of PC*	*Recognition rate* (%)					
		Healthy	*Half BRB*	*1 BRB*	*2 BRB*	*3 BRB*	*Over-all*
Linear	2	91.7	91.7	91.7	95.8	91.7	92.5
Quadratic	2	95.8	91.7	83.3	100	91.7	92.5
Cubic	2	91.7	95.8	95.8	100	91.7	95
Fine Gaussian	5	87.5	100	87.5	95.8	91.5	92.5
Medium Gaussian	2	95.8	91.7	83.3	95.8	95.8	92.5
Coarse Gaussian	10	16.7	41.7	100	83.3	79.2	64.18

5.2.2 Scheme 2

In the second scheme proposed, the diagnosis of the motor was given in two steps. Firstly, the motor was diagnosed as either healthy or faulty and if faulty, the severity of the fault was given in the second part. These two steps were evaluated separately.

To test the performance of the first step, the data was divided into four datasets. Each dataset had 24 samples of the 'healthy' class and 24 samples of the faulty class (six samples from each severity level).

Tables 3 and 4 show the best accuracy achieved by each kernel function studied and the number of the principal components used as input for scheme 2/step 1 and scheme 2/step 2 respectively.

The Gaussian kernels produced unacceptable step 1 (fault detection) results while the Quadratic SVM produced better results; but still unacceptable for industrial applications due the high false negative rate.

Linear (with two principal components) and cubic (with 5 and 10 principal components) SVM methods produced the best results. Of the two, linear SVM had lower false positive and false negative rates (4.2% each).

For step 2 (categorising according to severity), all the SVM classifiers produced reasonable accuracy except for the coarse Gaussian SVM.

Table 3 Best performing algorithm from each studied kernel and the number of features used (for scheme 2/step 1)

Kernel	*No. of principle components*	*Recognition rate* (%)		
		Healthy	*Faulty*	*Overall*
Linear	2	95.80	95.80	95.80
Quadratic	2	91.68	89.60	90.64
Cubic	10	94.78	92.70	93.74
Fine Gaussian	2	86.45	79.18	82.81
Medium Gaussian	2	95.80	56.25	76.03
Coarse Gaussian	20	97.90	26.03	61.96

Table 4 Best performing algorithm from each studied kernel and the number of features used (for scheme 2/step 2)

Kernel	*No. of PC*	*Recognition rate* (%)				
		Half BRB	*1 BRB*	*2 BRB*	*3 BRB*	*Overall*
Linear	40	95.8	95.8	100	95.8	96.85
Quadratic	5	87.5	95.8	100	95.8	94.78
Cubic	5	100	95.8	100	95.8	97.90
Fine Gaussian	5	100	95.8	95.8	95.8	96.85
Medium Gaussian	100	95.8	100	95.8	95.8	96.85
Coarse Gaussian	40	50	95.8	100	83.3	82.28

6 Discussion and conclusion

In this study a series of experiments were performed to simulate BRB faults in IMs; and the aim was to use the experimental data to develop a machine learning system that would detect the problem as well as provide its severity. The motor current was used as the monitoring signal and feature extraction was performed using PCA transformation on the current signals in frequency domain (obtained through FFT).

Two classification schemes (namely scheme 1 and scheme 2) for the detection of BRB and classification according to severity were developed from experimental work. Scheme 1 gives diagnosis in one step and scheme 2 in two steps.

For the algorithm to be suitable in an industrial setting it should be able to distinguish accurately between healthy and faulty motors. Therefore it is important to analyse the false positive and false negative rates to avoid false alarms as well as to avoid faults going undetected.

When comparing the methods created from the two schemes, the cubic SVM method with two principal components as inputs created from scheme 1 proved to produce the best fault detection results with zero False Negative rate recorded from the experiments; that is, no faulty motor was undetected. False Positive rate was recorded at 8.3%, thus an increased rate of false alarms. In comparison, the best performing system developed by scheme 2 for fault detection (Linear SVM with two principal components as input), had 4.2% false positive and 4.2% false negative rates. Although this shows an improvement in preventing false alarms, there is an increased risk of faults going undetected.

For the purpose of fault classification, the methods created using scheme 2 produced better severity classification results in general. The best overall performance for this purpose was recorded at 97.9% when using cubic SVM with five principal components as inputs. The rest of the SVM classifiers that use different kernel functions (except for Coarse Gaussian SVM) also produced reasonable classification rates.

Furthermore no significant improvement was seen from using more principal components as input. In fact lesser number of features proved more effective in detection and classification and more efficient as the diagnosis is given faster.

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