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STATOR FAULT DIAGNOSIS OF BLDC MOTOR AT VARYING SPEED OPERATION USING LEAST SQUARE SUPPORT VECTOR MACHINE

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Abstract

In BLDC motor applications, stator failure is a common occurrence. Therefore, this study presents a method to diagnose stator failure in BLDC motor when it is operated at a different speed. Furthermore, this study examined the motor in normal condition and the motor with a stator fault. The vibration and current signals are measured from BLDC motor operating at 400 rpm, 450 rpm and 480 rpm. The signals are recorded at a sampling rate of 10 kHz, and the time and frequency domain features are extracted from the sample signals. The distance evaluation technique is used to select the features with the highest effectiveness factor, and a combination of features in the time and frequency domains is used as a predictor in the Least Square Support Vector (LSSVM) model. The results show that the LSSVM model performs very well in diagnosing BLDC stator failure at different speeds using both vibration and current signals. The classification accuracy is 96.5% and 98.83% for vibration and current data, respectively. With its high prediction accuracy, the proposed method has the potential to be developed as a maintenance tool in the industry.

Keywords: BLDC motor, stator fault, distance evaluation technique, LSSVM

1. INTRODUCTION

BLDC motors are widely applied as a primary source of power for electric vehicles due to their numerous advantages such as its durability, great dynamic response, high efficiency, good speed and torque characteristics, noiseless operation, high-speed range, and large torque to weight ratio (1). The motor along with the battery is the heart of the electric vehicle, and it is crucial to monitor and diagnose the working condition of these components to prevent failure and ensure the safety of the vehicle.

Frequent failures in BLDC motors include stator faults, such as current leakage of winding, open circuit of winding, and change of resistance, as well as rotor faults, such as eccentricity, rotor unbalance, permanent magnet damage, and bearing fault, along with inverter faults (2). These failures are caused mainly by high working temperature, overload, improper armature current, corrosion, metal fatigue, improper installation, and unbalance (3). The existence of failures will change the working condition of the motor, and monitoring the condition is carried out using certain sensors that can be used to identify the faults. Therefore, maintenance management can determine what actions are necessary to address the issue.

The method of identifying faults in mechanical systems can be divided into three approaches. These are the model-based method, the signal-based method, and the intelligent method based on the measurement data (4). The model-based method involves building a composite model of a specific fault based on physical laws. This is done by comparing the predicted output of the model with the output that is actually detected. By comparing the two outputs, maintenance personnel can determine whether a fault has occurred in the motor.

In order to classify the inter-turn fault in BLDC motors, several modeling techniques have been explored, including Electrical Equivalent Circuit (EEC), Improved Winding Function Theory (IWFT), Magnetic Equivalent Circuit (MEC), and Numerical Method (NM) (5). Additionally, a model has been presented in (6). that evaluates a set of residuals calculated based on the systematic redundancy relationship. Although the model-based method can effectively identify motor faults by penetrating the internal laws and physical nature of the motor, it requires an accurate motor model to achieve optimal results.

Signal-based methods used signals obtained from the mechanical system to identify the existence of the faults. Subsequently, features are extracted and analyzed using prior experience or knowledge to determine the occurrence of a fault, and a signals

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commonly used in fault diagnosis are current and vibration signals. For example, a park vector analysis spectrum from a motor current signal is used to diagnose electrical and mechanical faults in an induction motor (7). In addition, rotor faults in BLDC motors under nonstationary conditions are analyzed based on stator current using Winger-Ville distribution, Windowed Fourier Ridges, and Wavelet Transform, as described in (8,9). The current signal analysis is also used to detect inter-turn faults in BLDC motor (10), while vibration signals are used for diagnosing rolling element bearing faults (11). and bearing faults in an induction motor (12) and detecting rotor motor faults (13). A combination of vibration and current signals is also applied to diagnose short circuit faults in BLDC stator (14). The main advantage of signal-based methods is that they do not require accurate modeling of the mechanical system, as they only use the output signal, ignoring the impact of the input. However, the signal processing stage that converts the signal into information stating the existence of a failure requires complex analysis and a high level of expertise.

AI model-based failure diagnosis of mechanical systems offers easy modeling through a straightforward computational method that does not require an in-depth understanding of system behavior. In fault diagnosis, the most commonly used approaches include artificial neural networks (ANN) (15–18), random forest (19,20), support vector machine (SVM) (21–26), and deep learning (27–29). Among these methods, ANN and SVM have received the most attention from researchers, given their high accuracy in fault diagnosis. SVM is more straightforward, faster, and requires fewer data samples than ANN (30). However, in some applications, SVM outperforms ANN, such as in rolling bearing fault diagnosis (31,32), and centrifugal pump (33). LSSVM is a variation of the standard SVM algorithm. It modifies the traditional SVM by reformulating the optimization problem, replacing the inequality constraints with equality constraints. This results in a linear system of equations that can be solved more easily than the quadratic programming problem in traditional SVMs. The LSSVM technique has been applied in machine diagnostics, as demonstrated in (26,34,35),. which showed that it is simpler and requires less computational time. Therefore, this study aims to apply the LSSVM method to diagnose BLDC stator faults under varying operating conditions.

2. METHODOLOGY

The aim of this study is to diagnose stator faults in BLDC motors using vibration and current data based on the LSSVM learning machine. The laboratory testing involved simulating healthy and faulty BLDC motors on a motor test rig to obtain motor damage data. Figure 1 illustrates the test apparatus, which includes a BLDC motor, motor controller, DC power supply, an accelerometer, a current sensor, a tacho sensor, and data acquisition system. Table 1 shows BLDC motor specifications.

Table 1. The BLDC motor spesification

Rated voltage	48 VDC
Rated power	750 – 1,000 W
Rotor speed	2,800 rpm
Output speed	400, 450, 485 rpm
Gear ratio	1:6
Rated torque	15.36 N.m

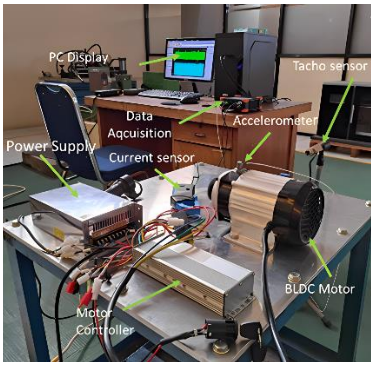

Fig. 1. BLDC motor tes-rig

Fig. 2 below depicts the flowchart for diagnosing a BLDC motor faults.

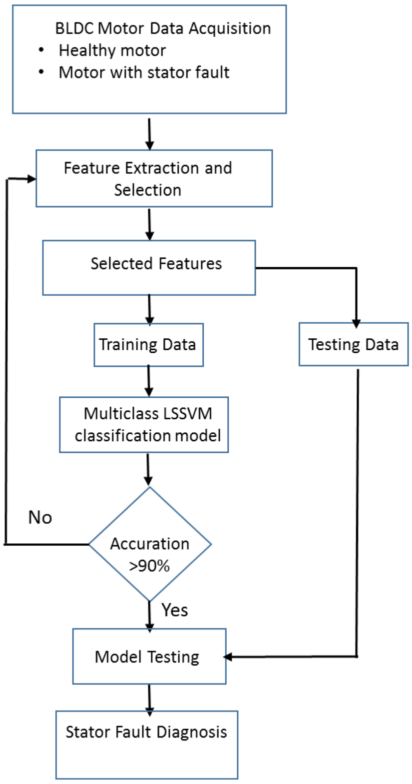

Fig. 2. Flowchart of the BLDC motor fault diagnosis

The BLDC motor used in the test rig comes from a tricycle conversion set. It was equipped with a planetary gear set and a motor control, achieving output speeds of 400 RPM, 450 RPM, and 485 RPM.

The stator fault was simulated by connecting two adjacent phases of the stator winding, as proposed by (36). To capture the vibrational signals, an accelerometer was attached radially to the motor casing at the output shaft, and the signals were recorded at a sampling rate of 10,000 Hz. At the same time, the motor controller's current from the DC power source was detected by the current sensor. Data were recorded using a Dewesoft 4-channel data acquisition system, and the time and frequency domains of the features were extracted. Features were selected using the distance evaluation method suggested by (37), and the two characteristic curves with the highest efficiency were used as predictors.

2.1. The Least Square Support Vector Machine

In this study, the signals obtained from BLDC motor are being classified using the LS-SVM method to analyze the motor faults. LS-SVM is a variation of support vector machines (SVM), and its theory is being presented in this section, as described by Suykens and Vandewalle (38). The classification problem is being reformulated to create a least-squares version of the SVM classifier, which is as follows:

$$\underset{w,b,e}{minimize}\,\frac{1}{2}\boldsymbol{w}^T\boldsymbol{w}+\gamma\frac{1}{2}\sum_{i=1}^{N}e_i^2 \qquad (1)$$

Subject to the equality constraints,

$$y_i[w^T\phi(x_i)+b]=1-e_i, i=1,\ldots,N \qquad (2)$$

The solution of the LS-SVM is found by defining the Lagrangian first as:

$$L(w,b,e,\alpha)=\frac{1}{2}w^Tw+\gamma\frac{1}{2}\sum_{i=1}^{N}e_i^2-\sum_{i=1}^{N}\alpha_i\{y_i[w^T\varphi(x_i)+b]-1+e_i\} \qquad (3)$$

where α_i are Lagrange multiplier.

The prerequisites for optimality are:

$$\frac{\partial L}{\partial w}=0\Rightarrow w=\sum_{i=1}^{N}\alpha_i y_i\phi(x_i)$$

$$\frac{\partial L}{\partial b}=0\Rightarrow\sum_{i=1}^{N}\alpha_i y_i=0$$

$$\frac{\partial L}{\partial e_i}=0\Rightarrow\alpha_i=\gamma e_i, i=1,\ldots,N$$

$$\frac{\partial L}{\alpha_i}=0\Rightarrow y_k[w^T\phi(x_i)+b]-1+e_i=0, i=1,\ldots,N \qquad (4)$$

The following set of linear equations can be solved quickly using the circumstances mentioned above:

$$\begin{bmatrix} I & 0 & 0 & -Z^T \\ 0 & 0 & 0 & -Y^T \\ 0 & 0 & \gamma I & -I \\ Z & Y & I & 0 \end{bmatrix}\begin{bmatrix} w \\ b \\ e \\ \alpha \end{bmatrix}=\begin{bmatrix} 0 \\ 0 \\ 0 \\ \vec{1} \end{bmatrix} \qquad (5)$$

where $Z = [\varphi(x_1)^T y_1; \ldots ;\varphi(x_N)^T y_N]$, $Y = [y_1; \ldots;y_N]$, $\vec{1} = [1; \ldots;1]$, $e = [e_1; \ldots;e_N]$, $\alpha = [\alpha_1; \ldots ; \alpha_N]$.

The solution is also given by:

$$\begin{bmatrix} 0 & -Y^T \\ Y & ZZ^T+\gamma^{-1}I \end{bmatrix}\begin{bmatrix} b \\ \alpha \end{bmatrix}=\begin{bmatrix} 0 \\ \vec{1} \end{bmatrix} \qquad (6)$$

Mercer's condition is applicable to the matrix $\Omega = Z Z^T$, where:

$$\Omega_{ij}=y_i y_j\phi(x_i)^T\phi(x_j)=y_i y_j K(x_i,x_j) \qquad (7)$$

$\psi(x_k . x_l)$ is the kernel function that typically has the following choices: linear, polynomial, or radial basis function kernel. As a result, instead of the quadratic programming used in the original SVM formulation, the classifier is determined by solving the linear set of equations (6) and (7).

The Radial Basis Function (RBF) kernel offers several advantages. Some of them are its ability to handle non-linearity, its flexibility and power to capture very intricate patterns and decision boundaries, the fact that the process of modal tuning is straightforward, effective for high-dimensional data, and its robust performance. Therefore, the RBF kernel will be used as the kernel function.

2.2. Feature Extraction

Various types of features are identified based on their ability to reveal the system's state, which can be in the time, frequency, or time-frequency domains. Examples of features in the time domain include mean, root mean squares (RMS), variance, skewness, kurtosis, among others. In contrast, features in the frequency domain consist of content at the feature frequency, the amplitude of the FFT spectrum, and others. Additionally, features in the time-frequency domain include statistical properties of the short-time Fourier transform (STFT), the Wigner-Viller distribution, the wavelet transform, among others. For this study, 13 characteristics from the vibration signal are considered, including three features in the frequency domain and ten in the time domain. These features include the mean, the RMS value, the shape factor, the skewness, the kurtosis, the crest factor, the entropy estimation value, the entropy estimation error, the upper and lower bounds of the histogram, the RMS frequency, the frequency center value, and the root variance frequency value. With the aid of the distance evaluation (DET) method, the features were selected.

2.3. Distance Evaluation Technique

The features for classification input are selected using DET. Three considerations led to the use of these feature selection techniques:

- simplified model for easier interprestation,
- reduced training time,
- improved generalization by eliminating overfitting.

By selecting a portion of the original features that still has enough information for classification, the feature selection procedure directly reduces the quantity of the original features. A lot of unnecessary features are typically included in large feature sets. Such characteristics are not only useless for classification but can occasionally affect a classifier's performance since they are built using a limited number of training samples. In this situation, eliminating the useless features can increase classification accuracy. The four steps in this method are as follows:

Step 1: The average distance of the same condition data (d_{ij}) is calculated, then the average distance of all conditions is obtained (d_{ai}). The following is a definition of the equation:

$$d_{i,j} = \frac{1}{N \rightleftarrows x \rightleftarrows (N-1) \rightleftarrows} \sum_{m,n=1}^{N} \left| p_{i,j}(m) - p_{i,j}(n) \right|;$$
$$(m, n = 1,2,\ldots,N, m \neq n) \qquad (8)$$

where N is the total number of the same condition, $p_{i,\,j}$ is its eigenvalue, $d_{i,\,j}$ is its average distance, and i and j are the total number of the conditions and parameters, respectively. .

$$d_{ai} = \frac{1}{M} \sum_{j=1}^{M} d_{i,j} \qquad (9)$$

where M denotes the number of different conditions.

Step 2: The average distance between various condition data is calculated (d_{ai}).

$$d'_{ai} = \frac{1}{Mx(M-1)} \sum_{m,n=1}^{M} \left| p_{ai,m} - p_{ai,n} \right|; (m, n = 1,2,\ldots,M; m \neq n) \qquad (10)$$

where d'_{ai} is the average distance of different conditions data, $p_{ai,j}$ is the average value of the same condition data.

$$p_{ai,j} = \frac{1}{N} \sum_{n=1}^{N} p_{i,j}(n); (n = 1,2,\ldots,N) \qquad (11)$$

Step 3: The ratio d_{ai} / d'_{ai} is calculated

Step 4: The feature parameters are chosen between high values and low values. The better d_{ai} is the smaller, whereas the superior d'_{ai} is the bigger. So, bigger represents the feature well.

$$\alpha_i = d'_{ai}/d_{ai} \qquad (12)$$

Where α_i is the feature's effectiveness factor.

3. RESULTS AND DISCUSSIONS

The BLDC motor is operated in 2 conditions at three different speeds. Therefore, there are six classes of data as shown in Table 2.

Table 2. The BLDC motor Classes

Classes	Conditions
Class 1	Normal motor at 400 rpm
Class 2	Normal motor at 450 rpm
Class 3	Normal motor at 485 rpm
Class 4	Faulty motor at 400 rpm
Class 5	Faulty motor at 450 rpm
Class 6	Faulty motor at 485 rpm

The problem of diagnosis becomes a multiclass classification task. The data collected from the motor measurement consists of the vibration and current data, these data are then processed to develop the LSSVM diagnosis model. The results are presented in the next sections.

3.1. Diagnosis using Vibration Data

The vibration signal's samples are showed in Figs. 3 to 8.

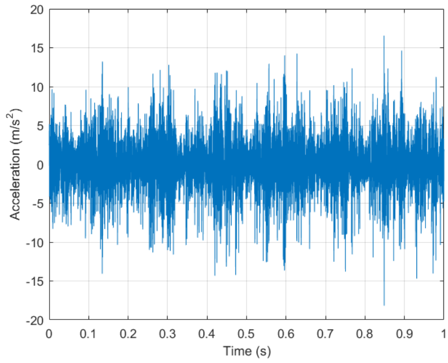

Fig. 3. Vibration signal of normal motor at 400 rpm

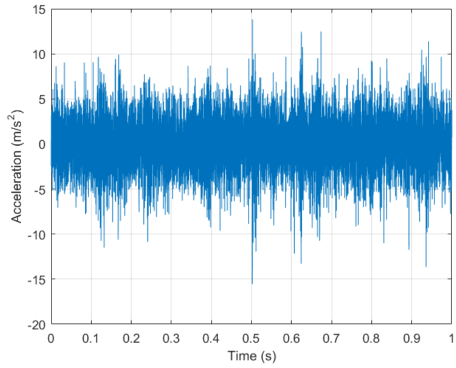

Fig. 4. Vibration signal of normal motor at 450 rpm

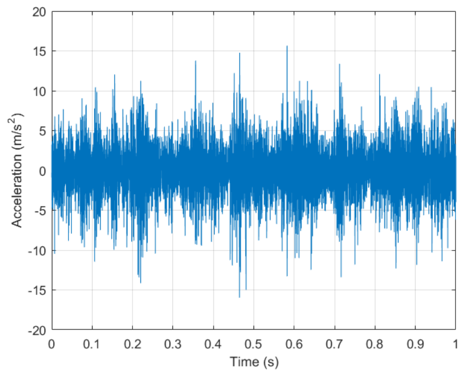

Fig. 5. Vibration signal of normal motor at 485 rpm

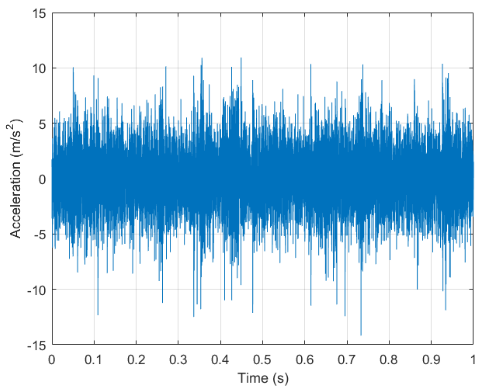

Fig. 6. Vibration signal of faulty motor at 400 rpm

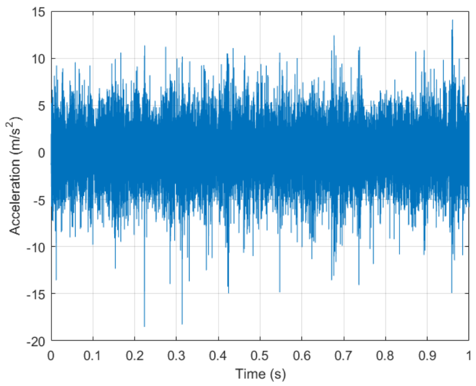

Fig. 7. Vibration signal of faulty motor at 450 rpm

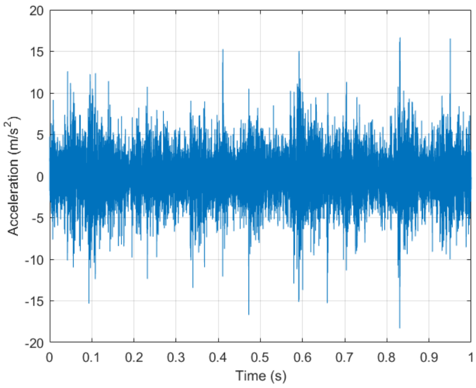

Fig. 8. Vibration signal of faulty motor at 485 rpm

In order to develop the classification model, 50% of the data was utilized for training while the remaining 50% was used for testing. A total of 200 samples were collected for each motor state, and features were calculated in both the time and frequency domains from the sample data. The following features were sorted in the following order:

1. Mean;
2. RMS value;
3. Shape factor;
4. Skewness;
5. Kurtosis;
6. Crest factor;
7. Entropy estimation value;
8. Entropy estimation error;
9. Histogram upper bound;
10. Histogram lower bound;
11. RMS frequency;
12. Frequency center value;
13. Root variance frequency value.

Features no 1 to 10 are time domain features, while features no 11 to 13 are frequency domain features. Combination of features in time and frequency domain will be chosen as the classification predictor. The feature selection is based on their effectiveness factor.

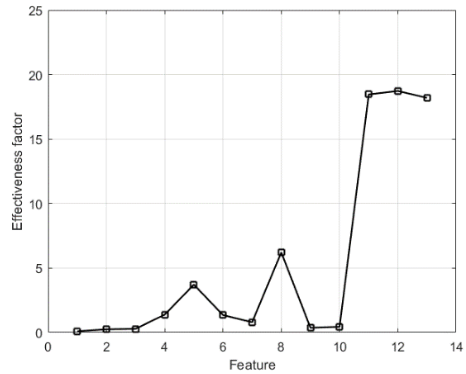

Fig. 9. Effectiveness factor of the features of the vibration signal

Fig. 9 shows the feature's effectiveness factor. Entropy estimation error has the highest effectiveness factor in the time domain feature, whereas frequency centre value is the highest among frequency domain features. As a result, these two features were chosen as predictors to build the LSSVM model for multi-class classification with a one-vs.-one strategy and RBF kernel. The RBF kernes was selected to handle non-linearly separable data. By mapping the input space to a higher-dimensional space, the LSSVM model can find a linear separating hyperplane in the transformed space. Fig. 10 shows the result.

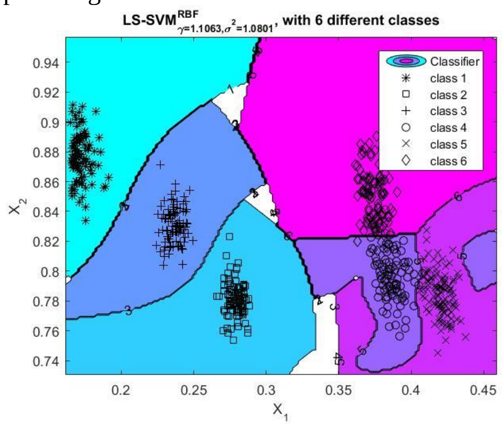

Fig. 10. The LSSVM model for multiclass classification of BLDC motor with stator fault using vibration data

Fig. 10 shows the accuracy of the model in identifying different motor states, with distinct areas representing various speeds and conditions of the motor. The regularisation parameter **g** and the kernel parameter σ^2 are found by using a combination of coupled simulated annealing (CSA) and the standard simplex method. After fifteen iterations, the values **g** = 1.1063 and σ^2 = 1.0801 are obtained. 5-fold cross-validation is used to validate the LSSVM model. The model is then evaluated using test data, resulting in 96.5% accuracy in predicting motor conditions. Subsequently, out of the 600 recordings, 21 were misclassified and are listed below as the misclassified data.

1. 9 data in class 3 are misclassified;

2. 2 data in class 4 are misclassified;
3. 1 data in class 5 is misclassified;
4. 9 data in class 6 are misclassified.

3.2. Diagnosis using Current Data

The samples of the current signals of healthy motors at 400 rpm, 450 rpm, and 485 rpm are depicted in Figs. 11 to 13, while Figs. 14 to 16 show the current signals of faulty motors at 400 rpm, 450 rpm, and 485 rpm.

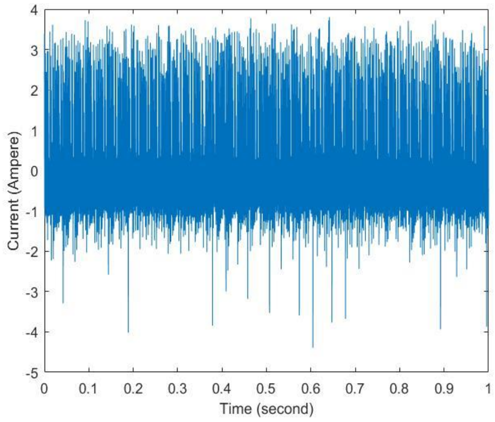

Fig 11. Current signal of normal motor at 400 rpm

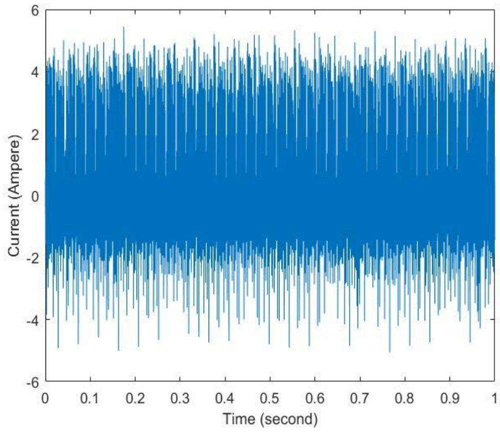

Fig 12. Current signal of normal motor at 450 rpm

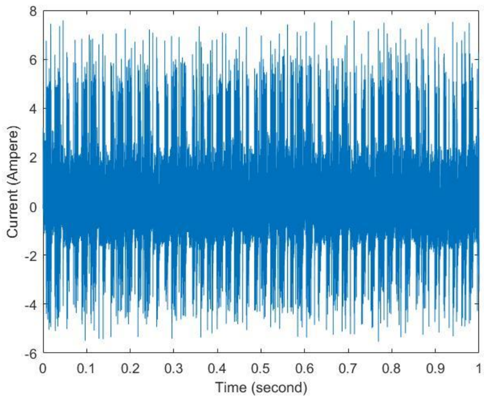

Fig 13. Current signal of normal motor at 485 rpm

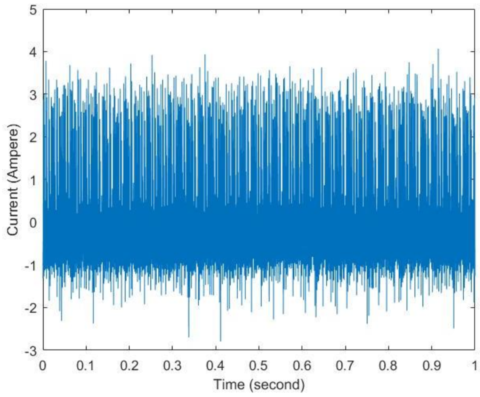

Fig 14. Current signal of faulty motor at 400 rpm

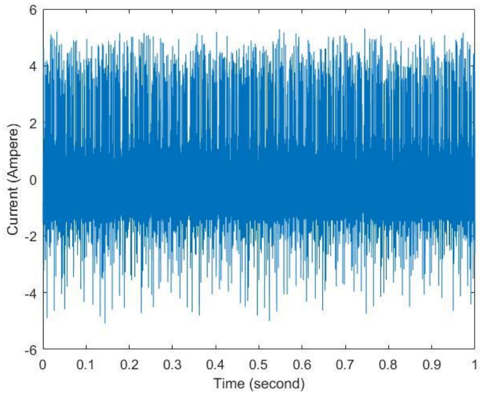

Fig 15. Current signal of faulty motor at 450 rpm

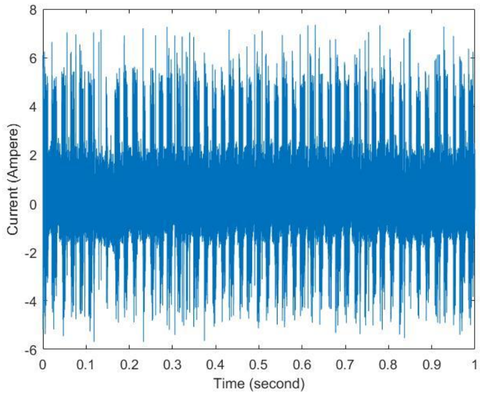

Fig 16. Current signal of faulty motor at 485 rpm

The process for extracting and choosing features is the same as the process for diagnosing vibration signals. Fig. 17 depicts the output of the feature selection process.

The effectiveness of features in the time and frequency domains is evaluated. It is found that RMS has the highest effectiveness factor in the time domain feature, whereas frequency centre value is the highest among frequency domain features. As a result, these two features were chosen as predictors to build the LSSVM model using current signals. The LSSVM model is constructed using these two features as a predictor, and the resulting model is shown in Fig. 18.

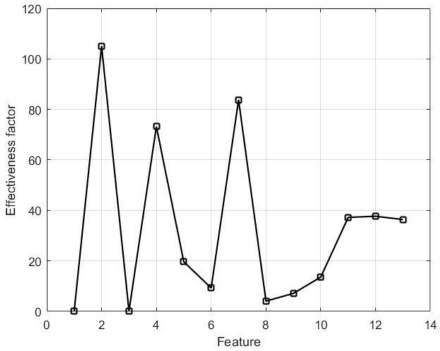

Fig 17. Effectiveness factor of the features of the current signal

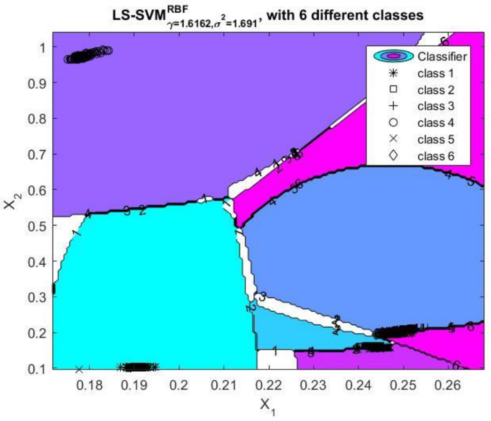

Fig 18. The LSSVM model for multiclass classification of BLDC motor with stator fault using current data

Fig. 18 shows the result of the LSSVM model classification for various speeds and conditions of the motor using current signals. The regularisation parameters **g** = 1.6162 and σ2 = 1.691 are obtained after fifteen iterations. The motor condition is classified into six different classes in different areas. Samples from classes 1 and 4, i.e., motors with normal and stator faults operating at 400 rpm, are clearly observed. Meanwhile, samples from the motor operating at 450 and 485 rpm are closely located but in different areas. Furthermore, the model's performance is being evaluated using the testing data, and the accuracy of the prediction is 98.83%. Only 7 data points out of 600 are misclassified. They are as follows:

1. 4 data in clas3 are misclassified;
2. 1 data in class 5 is misclassified;
3. 2 data in class 6 are misclassified.

The results demonstrate the effectiveness of the LSSVM approach in diagnosing the BLDC winding stator defect using both vibration and current data. The proposed model accurately detects the presence of faults at various operation speeds, with an accuracy that exceeds the required methodology threshold of 90%. The diagnosis accuracy using the current signal is slightly higher than the vibration signal. However, the diagnosis using a vibration signal allows for better separation and visualisation of each class of motor condition.

4. CONCLUSSION

In this study, the LSSVM method has been shown to be effective in detecting stator faults in BLDC motors operating at various speeds using vibration and current signals. By combining features from the time and frequency domains with the highest effectiveness factor, the proposed method achieved excellent performance in motor state diagnosis with high classification accuracy of 98.83% and 96.5%, respectively. Due to its excellent prediction accuracy, the proposed method has potential as an industry maintenance tool. A future study will investigate the LSSVM method's performance in diagnosing multiple BLDC motor faults and the size of the testing data.

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Author contributions: *research concept and design, D.D.S; Collection and/or assembly of data, U.U.; Data analysis and interpretation, U.U., A.R.P.; Writing the article, D.D.D., U.U., A.R.P.; Critical revision of the article, D.D.S.; Final approval of the article, D.D.S.*

Declaration of competing interest: *The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.*

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