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Research Paper

Simultaneous Bearing Faults Detection in Three Phase Induction Motor Based on Feature Fusion Method and Random Forest Algorithm

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Abstract— *Fault detection and classification (FDC) is a vital area in the health monitoring of three-phase induction machines. According to the failure survey of three three-phase induction machines, bearing-related faults cause a percentage of motor failures in the range of almost 41-50% which is very significant. These faults may occur one or multiple at a time in the bearing. With a well-designed fault detection method, failure of the motor can be reduced and productivity can also be increased. This paper proposes the simultaneous bearing fault detection and classification in three three-phase induction machine using the combination of feature fusion method and intelligent random forest (RF) algorithm. The paper contributes in two folds. In the first part of the paper, the performance of traditional methods such as vibration and current analysis is tested in which statistical parameters obtained from current and vibration signals are passed separately to the intelligent random forest classifier. In the second part of the paper, statistical parameters obtained from current and vibration signals are fused together and used as inputs to the RF classifier. The accuracy and various other performance measures are calculated and based on experimental results; a remarkably high detection/classification performance is achieved.*

Keywords—Bearing fault, fault detection and classification, induction motor, random forest.

NOMENCLATURE

Abbreviations

ANN	Artificial neural network
BB	Ball broken
CNN	Convolutional neural network
CV	Cross validation
DWT	Discrete wavelet transform
EPRI	Electrical power research institute
FDC	Fault detection and classification
FFT	Fast fourier transform
FP	False positive
GA	Genetic algorithm
IEEE	Institute of electrical and electronics engineers
IM	Induction motor
IR	Inner race
MAE	Mean absolute error
MCSA	Motor current signature analysis
MEMS	Micro-electro-mechanical-systems
ML	Machine learning
MLP	Multi-layer perceptron
NI	National instruments
NN	Neural network
OR	Outer race
PVA	Park's vector approach
PVM	Park's vector modulus
RAE	Relative absolute error
RF	Random forest
RMSE	Root mean squared error
RNFC	Removing non-bearing fault component
RRSE	Root relative squared error
SD	Standard deviation
TP	True positive
TPIM	Three-phase induction machine
WPT	Wavelet packet transform
WT	Wavelet transform
XWT	Cross-wavelet transform

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1. INTRODUCTION

Three-phase induction motors (TPIM) are playing a vital role in production and process industries. These motors are frequently used in important areas like aerospace and armed forces applications. They are also playing a vital role in sensitive applications such as nuclear plants, where the reliability of motor functioning is very important [1]. While in operation, TPIMs are forced to thermal, electrical, and mechanical stresses. If these stresses become slightly higher than a normal case, it may create faults in the motors. The significant faults in TPIM are distinguished as stator, rotor, bearing, eccentricity and load faults [2]. If these faults are not sensed at the proper stage, they result in premature failure of the motor and lead to costly downtime of the plant. Substantial research has been carried out in the last few decades in this direction. The focused area is based on analyzing vibration, current and other signals such as temperature, and torque. Many tools nowadays are available in the market for detecting faults. Still, several industries are facing unexpected breakdowns and it leads to a reduction of motor life. Out of the total faults, the bearing-related faults cause a percentage of motor failures in the range of almost 40-45% as shown in Fig.1. Consequently, it is essential to detect such incipient faults to avoid loss of revenue and to enhance the life of the machines. Very recently, the authors in [3] presented a review of fault detection methods related to stator, rotor and bearing faults and also highlighted new areas for fault detection in the near future.

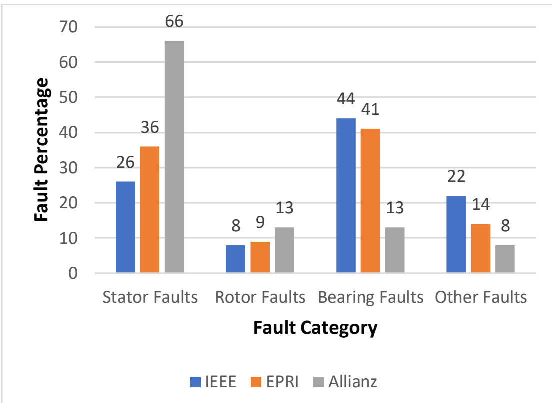

Fig. 1. Percentage of fault distribution.

Bearing faults originate from distributed types in the form of race way roughness and waviness, and are then converted into local faults like cracks, pits, and spalls. According to the location of faults, these can be sub-alienated into inner-race (IR), outer-race (OR), and ball-broken (BB) faults. Many researchers have proposed vibration analysis techniques for detecting these faults [4]. The authors studied the various standard data sets such as Case Western Reserve University (CWRU), Paderborn University, FEMTO, MFPT and IMS dataset for bearing fault detection and among all the datasets CWRU dataset is observed to be the most widely used dataset for the classification and detection of fault diagnostics of machinery bearings. Deep learning (DL) has advantages and has been used in many applications including bearing fault detection. The author summarizes the recent works that use the CWRU-bearing dataset in machinery fault detection and diagnosis employing deep learning algorithms. The authors in [5] have reviewed the published works and presented the working algorithm, result, and other necessary details. In [6], the combination of auto-regression and Modulation signal bi-spectrum methods to eliminate the non-Gaussian noise for the simulated signal is proposed. The method is further validated on real-time vibration signals. With the proposed method, authors detected outer race and inner race bearing faults and claimed superior performance compared to traditional ones [6]. The imbalanced data is the characteristic of real-world applications. In [7], authors investigated the inner race, outer race, and contaminant-bearing faults under data imbalance conditions. Over sampling using a Deep convolutional generative adversarial network with gradient penalty (DCWGAN-GP) is suggested to enhance performance and improve the classification accuracy under data imbalance [7]. The various bearing conditions like healthy, inner ring fault, ball fault, and outer ring fault, respectively are detected and classified successfully using an improved artificial bee colony algorithm and optimized XGBoost classifier in which one-dimensional ternary pattern (1-DTP) is used for feature extraction. In [8], the Authors compared results with the traditional classification strategy and showed performance improvement. J. Zarei *et al.* [9] designed removing non-bearing fault component (RNFC) filters for detecting bearing faults using a neural network. It is shown that satisfactory results are achieved when the filtered component of the vibration signal is used for fault classification instead of the use of the original vibration signal.

The curvilinear component analysis (CCA) is used to find the most significant features and a hierarchical neural network is used for classifying the faults under various operating conditions [10]. Further in [11], the bearing faults are detected using the non-Gaussian model in which a combination of kurtogram and alpha–stable model is proposed. The most advanced signal processing time-frequency tool such as S-transform has been used to detect the various bearing faults in [12]. Furthermore, in [13], it is claimed that MEMS accelerometers can be used to identify various bearing faults in induction machines. However, during this experimentation, it has been noticed that along with electrical and mechanical noise, signals are also found to be affected by the intrinsic vibration modes of the system. R. R. Schoen *et al*. [14] addressed the detection of bearing faults using stator current monitoring by correlating the relationship between vibration and current frequencies. The obtained signatures fall at locations that are different from the supply and slot harmonics of the motor with a relatively small magnitude. With spectral resolution techniques, current monitoring will be an effective way for bearing fault detection. Consequently, stator current-based bearing fault detection has received more and more attention in research. J. Zarei and J. Poshtan [15] implemented an FFT analysis of the Park vector modulus (PVM) signal of currents for bearing fault detection. The obtained results are compared with the MCSA and it is concluded that the proposed method is reliable for detecting bearing faults in the induction motor.

A. Picot *et al.* [16] addressed bearing fault detection with a statistical parameter of particular frequency bins in high-speed permanent magnet synchronous machines. The method is also compared with the vibration method and obtained satisfactory results. L. Frosini *et al.* [17] calculated the statistical parameters of the stray flux signals. These signals are acquired using a special flux probe and placed at multiple locations around the motor for detecting localized bearing faults in the induction motor.V. N. Ghate and S. V. Dadul [18] have developed the radial basis function multi-layer perceptron cascade connection NN-based fault-detection scheme for the small and medium sizes of three-phase induction motors. Simple statistical features of stator current are extracted and are optimized using principal component analysis. The algorithm is tested with uniform and Gaussian noises for detecting stator fault, rotor eccentricity fault and combined fault. The generalized feed-forward network and support vector machine-based classifier is developed for detecting various faults in the induction machine. S. Singh *et al.* [19] presented the detection of outer race faults using current monitoring. The technique is based on the application of continuous wavelet transform to the current signal and compared the results with the FFT technique. A common review of stator current analysis for bearing fault detection with different signal processing techniques is presented in [20]. The bearing faults are mainly classified into single-point defect and generalized roughness. Accordingly, the review is subdivided into two classes: single-point defect and generalized roughness.

The localized bearing faults such as inner race and outer race faults are detected using stator current and vibration envelope analysis based on squared envelope spectrum analysis in an induction motor. Statistical features like Kurtogram and spectral Kurtogram are estimated and energy in these two features is used to estimate the sensitivity of the bearing fault. The advantage of current based methods is that stator currents are easily available for measurement. However, the main limitation of these methods is that the stator current spectrum contains harmonics components that are generated due to voltage supply distortion, air gap space, slotting or unbalanced load along with characteristic harmonics generated due to bearing faults. Further in [21], the superiority of the method based on the analysis of squared envelope spectrum current over existing stator current or vibration monitoring techniques is proposed. A soft computing approach has been matured enough and has been employed to enhance the accuracy of bearing fault detection. Many methods are proposed using support vector machines SVM) [22–24] and artificial neural networks (ANN) for bearing fault detection [25–28]. ANN and SVM with genetic algorithm (GA) are also suggested for bearing fault detection [29]. A random forest algorithm is proposed for classifying the gearbox-related faults in [30]. The advantage of soft computing methods is that they do not require information of machine parameters for analysis. The bearing faults are detected using the passive thermo-graphy-based technique in which Convolutional Neural Networks (CNN) with Transfer Learning (TL) are used to the faults under varying working conditions. In [31], is it proved that the suggested method enables and speeds up the training process of CNN towards accurate adaptation for fault diagnosis approach in the escalated time frame [31].Later the work presented in [32] is recommended to detect outer race fault with three different severities using motor dynamic strain signals acquired from sensors based on Fiber Bragg grating. The number of experiments is carried out under no-load conditions with 47 different power supply frequencies and the robustness of the method is claimed. Thermal imaging-based fault detection is used to detect the various faults in bearings under different loading conditions [33].

In electrical machines, the noise and vibrations occur due to various faults. One of the major faults is the bearing fault which creates the unbalanced magnetic pull in electrical machines. In [34], the authors estimated the magnitude of unbalanced magnetic force (UMF) in permanent magnet brushless DC (PMBLDC) machines with diametrically asymmetric winding and investigated UMF variations in the presence of phase advance angle.Selecting an appropriate control strategy for driving an electric motor during fault conditions is one of the most important issues mainly for safety-critical applications. Authors in [35] have suggested two methods i.e. indirect and direct vector control methods to operate the star-connected three-phase induction motor in the faulty condition. It is shown that by using a suitable transformation matrix and some changes in the control parameters, it is possible to control the faulted drive system. The achieved results showed the good performance of the introduced control systems in different operating conditions. In addition, the results demonstrated the performance of the proposed VC strategies and that of the previous works are almost the same. However, the proposed VC methods in this paper need fewer modifications in the structure of the standard VC strategy than in the previous works. For induction motors, the effect of phase shift in the motor causes overheating, which is caused by the overlap voltage. It results in hysteresis losses, copper losses, and winding losses. The authors in [36] investigated the technique for phase shift fault detection in an induction motor based on an IoT system which can resolve the issues of overheating and also can increase the life of the machine. Among the various losses in the induction motor, it is more difficult to determine the value of stray load losses. A systematic review is given by the authors to determine the stray losses in induction motors [37].

The key interest of this paper is to propose a random forest algorithm to detect and classify bearing faults in TPIM. In this work, electrical and mechanical signals of the motor are sensed together. These signals are pre-processed and simple statistical parameters are estimated for current and vibration signals. The paper contributes in two folds. In the first part of the paper, statistical parameters obtained from currents and vibrations are separately supplied to the random forest intelligent classifier, and performance is observed. It is observed that the performance of the random forest classifier with individual signals is not satisfactory. To improve the performance and accuracy of the classification problem, statistical parameters of vibration and current signals are fused together and the performance is checked. It is observed that the results obtained from the proposed method are more prominent and accurate than the conventional method. In an intelligent system, along with accuracy, other parameters are equally important to judge the performance. Accordingly, mean absolute error (MAE), root mean squared error (RMSE), relative absolute error (RAE), root relative squared error (RRSE), true positive rate (TP), false positive rate (FP), precision, recall, and F-measure along-with accuracy are evaluated. The proposed algorithm is tested using WEKA software. For the manifestation of the proposed techniques, experimental results are presented to make the classifier algorithm more robust and practical. The remaining part of the paper is organized as follows. Section 2 covers data sensing, acquisition, and feature extraction. Results and discussions are elaborated in Section 3. Future Challenges or Limitations and Scope are elaborated in Section 4. The paper is concluded in Section 5.

Table 1. Specifications of three-phase induction motor.

Parameter	Value	Parameter	Value
Power (P)	2.2 kW	Connection star/delta)	Star
Speed (N)	1440 rpm	Number of pole pairs (p)	2
Voltage (V)	400 V	Number of stator slots	32
Current (I)	4.5 Amp	Number of rotor bars	28
Frequency (f)	50 Hz		

2. Data Acquisition and Feature Extraction

An experimental work is carried out on a 3-phase, 3-Hp, 4-pole, 415V, 50 Hz custom-designed squirrel cage induction machine. The detailed parameters of the induction motor are listed in Table 1. The block diagram of the proposed scheme is shown in Fig. 2 and the actual photograph of the experimental setup is given in Fig.3. Three current transformers are connected in supply lines to measure line currents and two vibration sensors are located to sense radial and axial vibrations of the motor. Three current signals are acquired by NI DAQ-6212 and two vibration signals are acquired using the SKF Microlog FFT analyzer. The current signal is sampled at a frequency of 16.896 KHz and the vibration signal is sampled at 25 KHz.

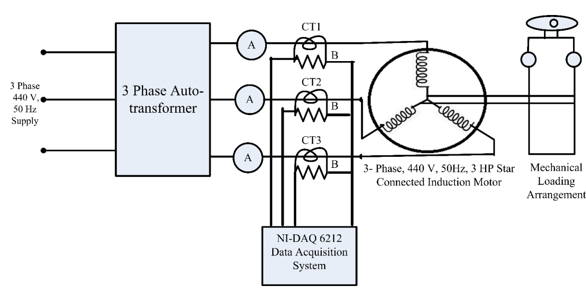

Fig. 2. Schematic diagram of the proposed scheme.

The main aim of the research is to detect various bearing faults in the squirrel cage induction motor. Bearing faults are influenced by three effects: 1) repetition of impulses which depends on rotation frequency 2) generation of vibrations from the impulse, which can be established experimentally and 3) increase in the total level of noise. In order to simulate the bearing faults, four identical healthy bearings (SKF 6205) are considered. Three different bearing faults are considered for analysis. The inner race and outer race faults are created by drilling the hole using an Electrical discharge machine (EDM). The hole is 2mm in width and 7mm in depth and drilled towards the shaft end side of a four-pole motor. Out of nine balls, one ball is removed from the bearing cage to simulate the ball's broken fault. The actual picture of healthy and faulty bearings is given in Fig. 4.

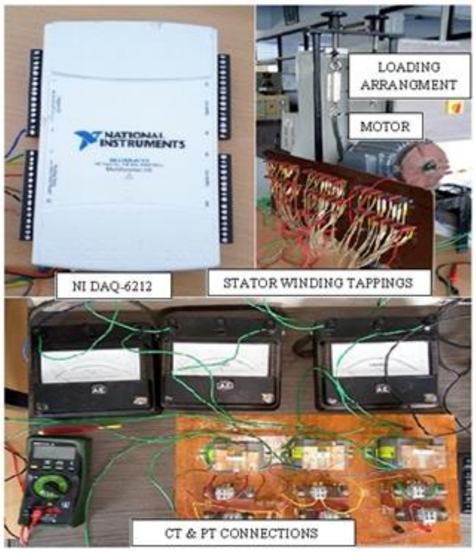

Fig. 3. Original picture of the experimental setup.

Fig. 4. Healthy bearing (H), Outer race fault(OR), Inner race fault(IR), Ball broken fault bearing(BB).

The motor is run at various loading conditions using mechanical loading arrangements with healthy and faulty configurations. As mentioned earlier, four cases have been considered as healthy (H), inner race fault (IR), outer race fault (OR), and ball broken fault (BB). The motor is run under different circumstances and accordingly, a total of 200 observations are considered for analysis. The data size for each class is 50 x 10000 samples. The data is recorded using Lab view software and stored in all the files in "xlxs" format. The stored data have been used for classification problems.

In established methods, a vibration signal or stator current is directly used for fault detection. The visual inspection of current and vibration signals shows that bearing faults would have a negligible effect on these signals. Hence, it becomes essential to extract some unique features from these signals. Hence, it is necessary to extract some meaningful features for fault detection. Accordingly, in the study, a total number of 14 statistical features are evaluated as formulated in Table 2 for each condition. Every feature is having its own characteristics to distinguish the signal under healthy and faulty conditions. The evaluated parameters include the maximum, minimum, mean, median, sum, and standard deviation. The mean and median are calculated on an individual

Table 2. Vehicle class parameters.

Minimum value	$X_{\min} = \min(x_i)$	(1)
Maximum value	$X_{\max} = \max(x_i)$	(2)
Mean	$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i$ $\mathrm{N} = \text{thetotal number of samples}$	(3)
Median	$median = \left(\frac{(N+1)}{2}\right)^{th} value$	(4)
Standard deviation	$S = \sqrt{\frac{\sum_{i=1}^{N}(x_i-\mu)^2}{N-1}}$	(5)
Variance	$S^2 = \frac{\sum_{i=1}^{N}(x_i-\mu)^2}{N-1}$	(6)
Sum	$Sum = \sum_{i=1}^{N} x_i$	(7)
Skewness	$Skewness = \frac{1}{N}\frac{\sum_{i=1}^{N}(x_i-\mu)^3}{\sigma^3}$	(8)
Kurtosis	$Kurtosis = \frac{1}{N}\frac{\sum_{i=1}^{N}(x_i-\mu)^4}{\sigma^4}$	(9)
Energy	$Energy = \sum_{i=1}^{N} x_i^2$	(10)
R.M.S. value	$x_{rms} = \frac{\sqrt{\sum_{i=1}^{N} x_i^2}}{N}$	(11)
Absolute value of the sum	$Abs(Sum) = \left\lvert\sum_{i=1}^{N} x_i\right\rvert$	(12)
Shape Factor	$S.F. = \frac{x_{rms}}{Abs(Sum)}$	(13)
Peak Factor	$C.F. = \frac{x_{\max}}{x_{rms}}$	(14)

dimension basis. The mean or variance is used to express the probability density function of a time-varying signal. The skewness factor is a measure of the symmetry of a distribution. If the distribution is close to symmetrical around its mean, the value of the skewness factor is close to zero. Positive and negative values of skewness indicate that the distribution function has a longer tail to the right and left of the mean respectively. Kurtosis is also another parameter that indicates the proportion of samples that deviate from the mean by a small value compared with those that deviate by a large value. It is not sensitive to Gaussian noise. Basically, it measures the flatness of a distribution. For normally distributed data, the value of kurtosis is zero, whereas negative for flatter top and positive for sharper peak than the normal distribution. Other parameters such as shape factor, energy, and crest factors are also proposed to enhance the accuracy.

3. Result and Discussion

Experimentation is carried out on the motor with healthy and faulty cases at different loading conditions. Three-phase stator winding currents and two vibration signals are acquired using the NI DAC 6212 and FFT analyzer, respectively. These signals may contain many unwanted components due to the load and supply unbalanced condition. It is necessary to remove these components that do not provide useful failure information. Normally, these components are present in the high frequency spectrum which can be easily removed by designing a suitable low-pass filter. Accordingly, a low pass filter is designed and all the signals are passed through this filter before analysis. Further, fourteen statistical features as mentioned in Table 2 are calculated for each phase current and vibration signal. These features are given as input to the intelligent random forest (RF) algorithm. The designed parameters used for the RF classifier are the same as the default values determined by the WEKA software. The detailed flowchart for the proposed algorithm is shown in Fig. 5. The percentage split of training and test data is tuned to 66%. The order of selection is done randomly. The performance of the algorithms is tested on the data set of 200 observations. The result and discussion are divided into the three sub sections as follows.

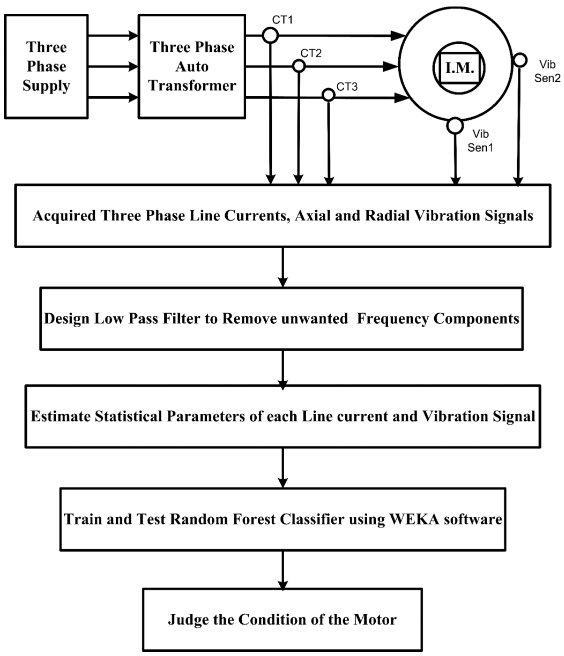

Fig. 5. Flowchart of the proposed scheme.

3.1. Bearing faults detection and classification based on the current monitoring method

In this part of the study, three current signals of each phase are acquired using the NI DAQ-6212 data acquisition system. The stator winding current through the R-phase for healthy and faulty conditions is represented in Fig. 6. These signals contain many unwanted components due to the load and supply unbalanced condition. It is necessary to remove these components which do not provide meaningful information related to fault detection. Further, these components are present in the high frequency spectrum which can be easily removed by designing a suitable low-pass filter. Accordingly, a low pass filter is designed and all the signals are passed through this filter before further analysis. Fourteen statistical features as mentioned in Table 2 are evaluated for each phase of filtered current. Accordingly, forty-two statistical parameters obtained from three-phase currents are fed to the random forest (RF) intelligent classifier. RF classifier is based on the grouping of trees for regression and classification. It is a combination of tree predictors such that each tree depends on the values of a random vector sampled independently and with the same distribution for all trees in the forest. The distinctive training set is completed by using bagging. The procedure bagging means extracting a fixed quantity from the training set randomly to improve classification, and regression models according to stability and classification accuracy. This process decreases variance and avoids over-fitting. The absolute results are made by adding the scores of component predictors on every class and then choosing the successor class in terms of the number of scores to it. The error for forests converges to an optimized value as the number of trees in the forest becomes large. The error of classifiers also depends on the strength of the individual trees and the correlation between them.

For testing and training the proposed algorithm, Weka software (Ver. 3.8.0) is used as a tool. The use of this Weka software is very common in both academic and industrial studies. The parameters used for the algorithm are the same as the default values suggested by the software. The algorithm is tested on data sets of 200 numbers of observations to check the performance of the classifier. The ratio of training to testing ratio is equal to 0.66 and the cross-validation fold is equal to 10 considered for analysis. It is observed from Table 3 that an accuracy of 75% is obtained for testing data and only 50% for cross-validated data. Root mean squared error (RMSE) which is one of the important performance measures of the classifier algorithm is also calculated and observed to be 0.3241 and 0.376 for testing and cross-validated data respectively. The accuracy and RMSE obtained by this method is not satisfactory.

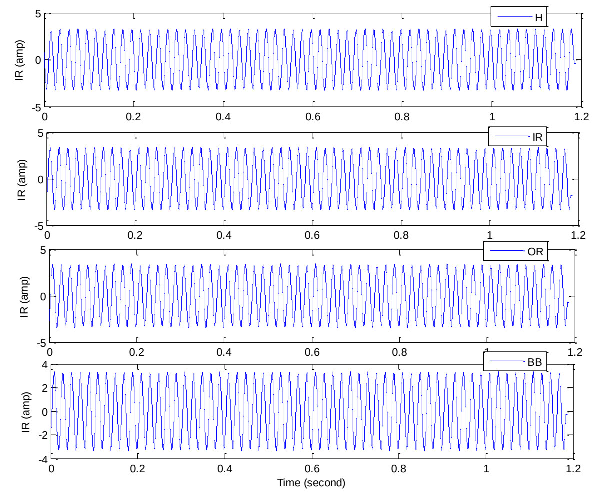

Fig. 6. Current signal at constant load condition: (H) Healthy, (IR) Inter race, (OR) Outer race, (BB) Ball broken conditions.

3.2. Bearing faults detection and classification based on vibration monitoring method

In this part of the study, two accelerometers are used for sensing radial and axial vibrations. These signals are acquired using an FFT analyzer. The nature of these signals for healthy and faulty conditions is represented in Figs. 7-8. Fourteen statistical features as mentioned in Table 2 are evaluated for each vibration signal. Twenty-eight statistical parameters obtained from two vibration signals are fed to the random forest (RF) intelligent classifier and performance is observed. The algorithm is tested on data sets of 200 numbers of observations to check the performance of the classifier. The ratio of training to testing ratio is kept the same at 0.66 and the cross-validation fold is 10.It is seen that the maximum accuracy obtained is 96% and 95.6% for testing cross-validated data respectively as presented in Table 3. The magnitude of RMSE is also reduced to 0.0585 and 0.1214 for testing and CV data, respectively as given in Table 3.

It is observed from both the traditional current and vibration techniques that the accuracy and RMSE are not acceptable to detect and classify the various simultaneous faults in three three-phase induction motors. Hence, there is motivation to improve the classification accuracy and other performance measures of three phase induction motor.

3.3. Bearing faults detection and classification based on feature fusion method

In the proposed work, the feature fusion method is implemented in which statistical parameters obtained from three-phase currents

Table 3. Performance of vibration and current monitoring on testing and C.V. data.

Classifier Performance	Testing on statistical parameters of vibration signals		Testing on statistical parameters of current signals	
	Test data	C.V. data	Test data	C.V. data
Accuracy	95.32	96	75	50
RMSE	0.0585	0.1214	0.3241	0.376

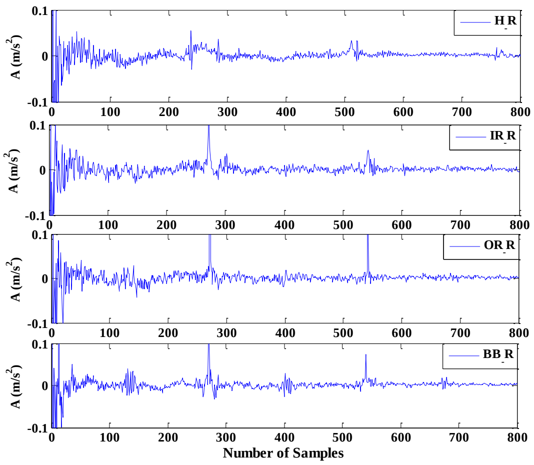

Fig. 7. Radial vibration signals at constant load condition: (H) Healthy, (IR) Inter race, (OR) Outer race, (BB) Ball broken conditions.

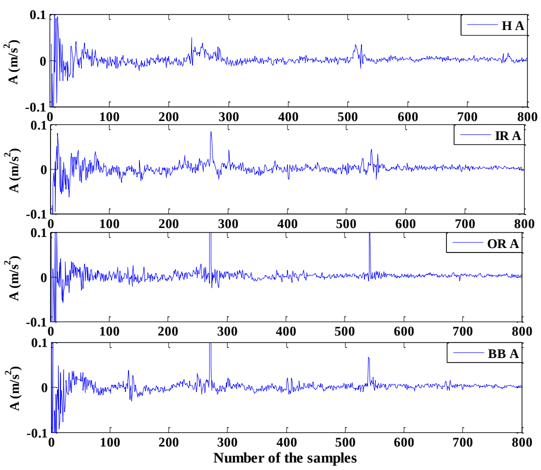

Fig. 8. Axial vibration signals at constant load condition: (H) Healthy, (IR) Inter race, (OR) Outer race, (BB) Ball broken conditions.

and two vibration signals are fused together. Seventy statistical parameters are fed to the random forest (RF) intelligent classifier and performance is observed. The algorithm is tested on the same data set of two hundred numbers of observations. The ratio of training to testing and cross-validation fold is also kept the same at 0.66 and 10, respectively. It is observed from Table 4 that the accuracy of the algorithm is almost enhanced to 100% and RMSE is significantly reduced to 0.0248 and 0.0288 for testing and cross-validated data. To study the detailed performance of the proposed method, true positive rate (TP), false positive rate (FP), precision, recall, and f-measure are also calculated. The magnitudes of these measures are also listed in Table 5. The values of all these measures are also very close to the target value. The confusion matrix gives the information about the number of correct and false observations in Table 6. All two hundred observations are successfully classified and the false prediction rate is reduced to zero. These results are satisfactory not only because of the increase in the number of features but also due to the fusion of features.

Table 4. Comparison of performance measures for the proposed method.

Parameter	RF Classifier	
	C.V. data	Test data
% Overall Accuracy	100	100
MAE	0.0081	0.0143
RMSE	0.0248	0.0288
%RAE	2.1667	3.7736
%RRSE	5.7388	6.585

Table 5. Comparison of performance parameters for the proposed method.

Parameter	RF Classifier			
	H	IR	OR	BB
True Positive Rate	1	1	1	1
False Positive Rate	0	0	0	0
Precision	1	1	1	1
Recall	1	1	1	1
F-Measure	1	1	1	1

4. Future Challenges or Limitations and Scope

4.1. Future challenges

Some of the challenges and possibilities for simultaneous bearing fault detection are listed below:

- Complexity of Fault Pattern: Simultaneous bearing faults can manifest in various patterns and combinations (e.g., inner race and outer race faults). Intelligent techniques may struggle to accurately detect and differentiate these complex fault patterns, especially if they have overlapping or intertwined features.
- Noise and Interference: Electrical noise and interference from other components or external sources can affect the accuracy of the intelligent technique in detecting bearing faults. Filtering out this noise while retaining relevant fault signatures is a significant challenge.
- Non-Stationary Operation: The operating conditions of the motor can change over time, leading to non-stationary behavior in the data. Adapting intelligent techniques to handle varying operating conditions and fault severity levels is a difficult task.
- Feature Extraction and Selection: Identifying the most relevant features for bearing fault detection from the raw sensor data is a crucial step. Intelligent techniques heavily rely on accurate feature extraction and selection, and choosing the right features is challenging for complex fault scenarios. Extracting relevant and informative features from motor signals is crucial for fault detection and classification. Developing efficient

Table 6. Confusion matrix for the proposed method.

Classified Output	RF Classifier			
	H	IR	OR	BB
H	50	0	0	0
IR	0	50	0	0
OR	0	0	50	0
BB	0	0	0	50

feature extraction techniques that capture the distinctive characteristics of different faults is a challenge.
- Noise and Interference: Motor signals are often contaminated with noise and interference, which can affect the accuracy of fault detection algorithms. Finding robust methods to mitigate the impact of noise and interference is a research challenge.
- Fault Severity Assessment: Determining the severity of a detected fault is important for timely maintenance and decision-making. Developing accurate fault severity assessment methods that provide reliable information about the extent of the fault is a challenge.
- Cost and Implementation Challenges: Implementing advanced intelligent techniques can be costly, particularly for small-scale or budget-constrained applications. The cost of sensors, data acquisition systems, and computing infrastructure may limit the feasibility of using these techniques.
- Imbalance Data Handling: The issue of imbalanced datasets, which is a common difficulty in fault detection and classification problems. Explore techniques such as oversampling, under-sampling, and synthetic data generation to handle class imbalance effectively.

4.2. Future scope

A lot of research is carried out on the simultaneous bearing fault detection of three-phase induction motors using the most advanced intelligent techniques. However, the following areas might evolve in the future based on industrial automation, machine learning, and intelligent techniques. Some of the challenges and possibilities are listed below:

- Integration of Advanced Machine Learning Algorithms: Future studies may focus on the integration of advanced machine algorithms such as deep learning, reinforcement learning, and ensemble learning for more accurate and robust simultaneous detection of multiple bearing faults in three three-phase induction motors.
- Hybrid and Ensemble Approaches: Hybrid approaches combining multiple intelligent techniques might be investigated to leverage the strengths of each individual technique for improved accuracy and efficiency.
- Utilization of Big Data and Industrial IoT: In the next era, studies may consider the utilization of big data analytics and the Industrial Internet of Things (IoT) for real-time data collection, processing, and analysis.

Addressing these research challenges can lead to the development of more accurate, reliable, and efficient fault detection and classification methods for three-phase induction motors, improving their overall reliability and performance.

5. Conclusion

In this paper, an intelligent and innovative approach for multiple bearing fault detection and classification is suggested for a three-phase induction machine. In this work, the most common types of bearing faults such as ball broken fault, inner race fault, and outer race fault are detected and classified. During the experimentation, three-phase currents and vibration signals of the motor are acquired using a data acquisition system. These signals are pre-processed using a low pass filter and simple statistical parameters are estimated. In the first part of the paper, statistical parameters obtained from currents and vibrations are separately supplied to the intelligent RF classifier and performance is observed. In the case of the statistical-based current monitoring method, a maximum of 75% accuracy is obtained whereas 96% accuracy is obtained for vibration monitoring. In the proposed method, all statistical parameters are fused together and the performance is checked. The accuracy of the algorithm is almost enhanced to 100% and the root mean squared error (RMSE) is reduced to 0.0248 and 0.0288 for testing and cross-validated data. Other performance measures like Mean Absolute error (MAE), root mean squared error (RMSE), relative absolute error (RAE), root relative squared error (RRSE), true positive rate (TP), false positive rate (FP), precision, recall, and F-measure are also evaluated to study the performance and giving satisfactory results.

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