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Bearing/Incipient/Open Phase Fault Detection and Diagnosis of Multi-Phase Induction Motor Drives Equipped By GBDTI2HO Technique

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Abstract

In this paper, a hybrid system is performed with fault detection and diagnosis on multi-phase induction motor (IM). The proposed method is hybrid of integrated Harris Hawk optimization (IHHO) and gradient boosting decision trees (GBDT) thus called the GBDTI2HO method. Here, additional operators are included in this paper to improve HHO's search behaviour namely crossover and mutation. Distorted waveforms are generated by different frequency patterns to indicate the time domain frequency as an assessment of failure. For this signal representation, the discrete wavelet transformation (DWT) is suggested. It extracts the characteristics and forwards them to IHHO technique to form the possible data sets. After the generation of the data set, GBDT classifies the ways of failure reached as winding of stator in multi-phase IM. The implementation of the proposed system is compared with existing systems, such as ANN, S-Transform and GBDT. The proposed method is executed on MATLAB/Simulink work platform to demonstrate the successfulness of proposed system, statistical measures are determined, as precision, sensitivity and specificity, mean median and standard deviation. For demonstrating the successfulness of proposed system, statistical measures are determined as precision, sensitivity, specificity, mean median as well as standard deviation. In 50 trails the proposed method, 0.98 for accuracy, 0.96 for specificity, 1.60 for recall as well as 0.97 for precision. In 100 trail the proposed method, 0.96 for accuracy, 0.93 for specificity, 0.87 for recall as well as 0.99 for precision.

Keywords: Multi-phase induction motor, Fault, Distorted waveforms, Frequency components, Stator winding, Statistical measures

1. INTRODUCTION

Three-phase engines should suggest the economy measures and technology that have been shown to control the speed in market drive use. However, the current initiatives have taken advantages of different phase machines with high point, and also get key methods that can be completed to three phase standards [1]. Fault tolerance is therefore implemented in various phases of redundancy in single-character machines, with industry initially focused on maximal reliability system as aerospace, traction or wind energy, with different stages of twisting machines on three stages. The electrical machine fault diagnosis is used to observe as rising failures, and correction leads to shorter idle hours and faster unplanned preservation to minimize harmful side effects. More kinds of failure (for instance broken rotor bars or failure among turns, to name a few) should be assumed and more detection time may be permitted. Although multiphase units have some methods for fault detection in bibliography they are mainly based on discrete wavelet transform or hilbert-huang transform, but no one meet the goal [2, 3].

2. RELATED WORKS

Various research methods in the literature that rely on multi-phase induction machine fault diagnosis used as several methods and features. Some of them are reviewed here.

Contreras-Hernandez et al. [4] has suggested an innovative engine fault detection system due to evaluation of signal as quaternion. Singh and Shaik [5] have employed the allocation, detection and location of defective bearings as IM on three-phase use from support vector machine and Stock-well transformer. Shao et al. [6] has suggested a deep studying due to various signals, because the failure diagnosis technique harnesses powerful studying capacity of convolution neural network (CNN). Failure diagnostic technique due to machine learning was suggested to Ali et al. [7] in induction motor as experimental data. Several unique and multi-electrical/ mechanical failures were performed on induction dual motor similar to the laboratory test. Hajary et al. [8] have presented a new fault diagnosis strategy in open phase is operated as three-phase of induction motor driven among entire speed range at various methods of burden.

Analysis of the current investigation shows a significant contribution to the observation of IM failures. More quantities of electrical units are installed as commercial plant. Therefore, the detection of health in individual engines is critical methods. Observing various failure modes as network neural, generalized likelihood ratio test (GLRT), fast Fourier transformation (FFT) so on. The artificial neural network (ANN) has the potential to use the impact of motor monitoring and observation as an economic, reliable and non-invasive system. Therefore, it cannot be executed as reasoning for heuristic failure observation systems. Consequently the major drawback of AI system is that the black box data structure methods and their maximal computation cost are done in real world applications. In addition, there is a problem with the first training stage, but require a maximal set of stator current databases for several state systems. This method is crucial as operation of optimal and misleads or outcomes obtain as restricted system set. Therefore, the impact of FFT assessment as another frequency domain method is required, as the rolling system frequency is known as pre-estimated. Another weakness is the increased trouble of spectrum classification since the signal-to-noise ratio is minimal and the spectrum as vibration has maximal frequency components depending on complexity of system. Although previous methods are used to predict failures among shifts, the complexity of algorithm is increased interms of largest number of samples required. To overwhelm such systems, it is necessary to observe the optimal use of the promoted method.

Objectives and Contribution

[a] In the proposed study, a hybrid system is performed interms of fault detection and diagnosis on multi-phase IM. The proposed method is hybridization of integrated Harris Hawk optimization (IHHO) and gradient boosting decision trees (GBDT) thus called the GBDTI2HO method. First, the analysis of faults like bearing, incipient and open phase fault is explained in multiphase drives. The feature extraction, dataset generation and fault classification is described. By then the performance efficiency of the proposed detection and classification of multiphase induction motor faults is performed on matrix laboratory/Simulink working platform and implementation is evaluated with existing systems.

[b] In traditional Harris Hawk Optimization (HHO), the slowest rate of prey search and premature convergence are the limitations. Therefore, additional operators are included in this paper to improve the HHOs search behavior namely crossover and mutation.

(c) There are three main functions in the proposed study to solve the optimization issue. The initial function of the proposed system is performed using discrete wavelet transform (DWT). In the proposed work, DWT is utilized to extract features and the extracted features are formed as a dataset to detect and classify failure due to frequencies using the GBDTI2HO technique.

(d) The second function of the proposed system is performed using Integrated Harris Hawk Optimization (IHHO). Here, the extracted features from DWT are fed to the IHHO technique to collect the possible datasets. The collected dataset is generated to classify the faults in the multiphase IM.

(e) The third function of the proposed system is performed through Gradient Boosting Decision Trees (GBDT). Here, GBDT is used to allocate the fault of the multiphase IM. Hence, ordinary and unordinary data are assessed at the beginning to demonstrate its unity. GBDT input as stator winding current.

Remaining manuscript is organized as below: Session 2 delineates literature survey and its background. Section 3 explains analysis of faults on multi-phase induction motor (IM) drives. Section 4 delineates multiphase IM is evaluated utilize as proposed hybrid method. Section 5 describes the outcomes get with proposed and existing techniques. Session 6 concludes the manuscript.

3. ORIGINALITY

In this section, the fault evaluation in multi-phase induction motor (IM) is explained for this section. In the field of electric drive design, the problems shows above are the most challenging factors [9].

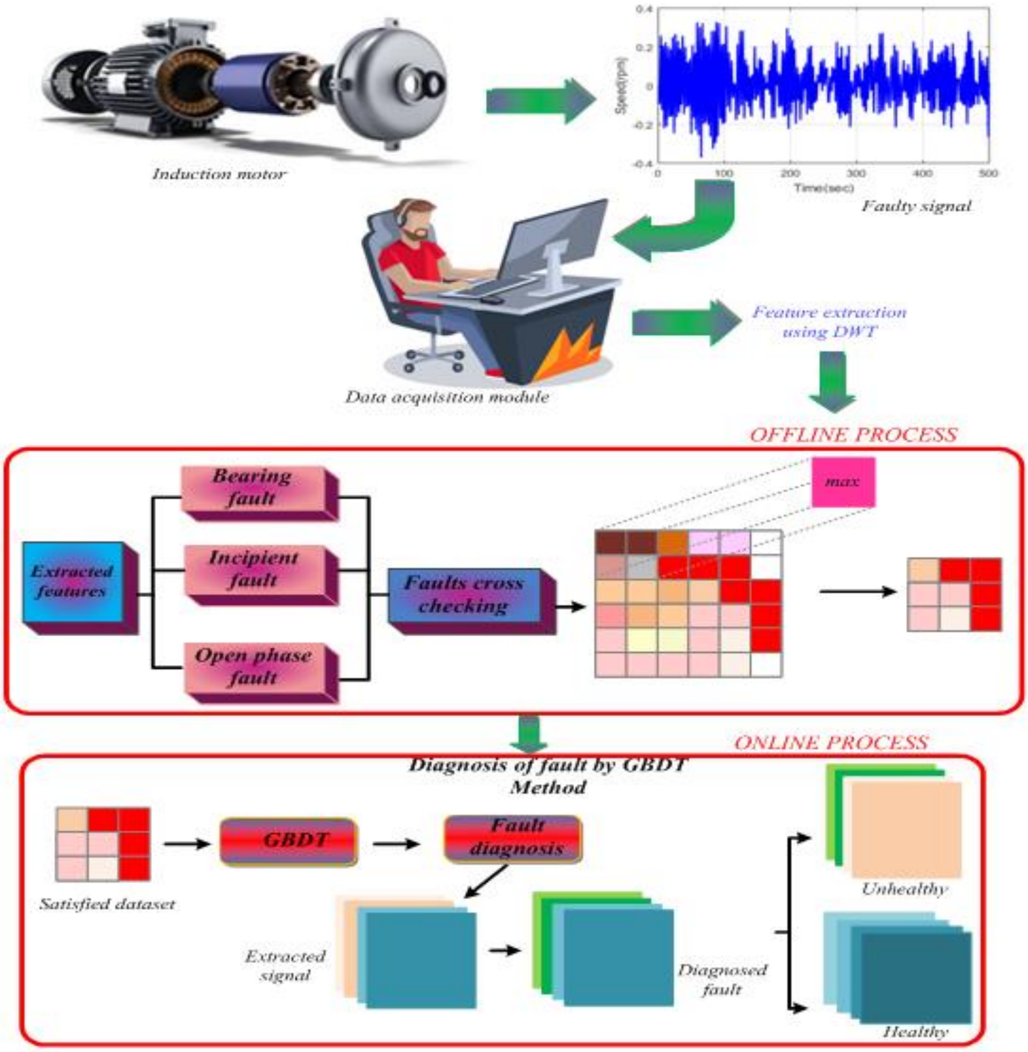


Figure 1: Proposed schematic for fault detection and classification on multi-phase IM drives

For continuous operation, various phase drives does not require additional apparatus as superior operation of failure control. This requires only an appropriate superior scheme of failure control. Therefore, multi-phase drives are optimal for security reasons i.e. traction and aerospace applications [10]. Fig 1 delineates the proposed observation scheme and assigns faults to IM in multi-phase drives. The main allocation of general failures in electric drives is formulated in the reference [11-16].

4. SYSTEM DESIGN

In this method, the multiphase evaluation of IM proposed hybrid methods. The proposed model is detained in next session.

4.1. Feature Extraction Using Discrete Wavelet Transform (DWT)

Discrete wavelet transform (DWT), in extract, refers to adjustment of linear works data as vector length becomes equal to the numerical vector of diverse length, since the power is two integers [17]. In this document, DWT is utilized to extract the characteristics and extracted characteristics are formed as a set of data to detect and classify failure due to frequencies using the GBDTI2HO technique. Hence, original transient current and multi-phase IM failure signals are broken down into a matrix of two coefficients namely approximate matrix and the detail coefficients. Here, the matrix of approximation coefficients such as cA, the matrix of detail coefficients such as cH, cV and cD (horizontal, vertical and diagonal, respectively). The maximum component of the frequency signal is referred to as minimum-scale decomposition that represents the coefficients. The minimum component of frequency signals is referred to as large-scale decomposition called approximate coefficients. Thus, signals must be normalized to decrease the difficulty based on current magnitudes. In course of operation is stable state of multi-phase IM, current winding stator is normalized to evaluated value of peak. The most normalization factor is characterized by its competence to evaluate the multiphase IM failures of different evaluated values.

4.2. Dataset Generation Using Integrated Harris Hawk Optimization (IHHO)

In this section, the extracted features from DWT are fed to the IHHO technique to collect the possible datasets. The collected dataset is generated to classify the faults in the multiphase IM. In this article, a new population due to optimization paradigm, inspired by nature, known as Harris Hawks Optimization (HHO) [18, 19]. HHO search behaviour is enhanced by crossover and mutation operator.
Steps of IHHO

Step 1: Initialization: In this step, the initialization process and random generation is carried out. Here the input parameters such as stator winding current signals of multiphase IM.

Step 2: Evaluation: To utilize IHHO, four ways of data are collect as ordinary and plan cases, like cA, cH, cV and cD. These outputs are used to analyze the fault type. If fault obtains in winding of multiphase IM stator, the failure character is also presented in wavelet coefficients of signals as current. When any condition of failure present in multiphase IM, it resends the coefficients of current wavelet for the fault allocation type.

Step 3: Exploration Phase: To enhance as similar opportunity q as every hanger method, they perch due to the positions of family members other (to be close sufficient they attack) and rabbit.

Step 4: Exploitation Phase: In this phase, Harris's hawks carry out the surprise attack (seven murders as indicated) to find expected prey detect as previous phase.

Step 5: Crossover and Mutation: The solution can be improved by rearranging the Harris Hawks location using modes for consequent updating process using the crossover and mutation operator [20].

$$X = \frac{N_{GX}}{L_c} \tag{15}$$

$$M = \frac{M_p}{L_c}$$

(16)

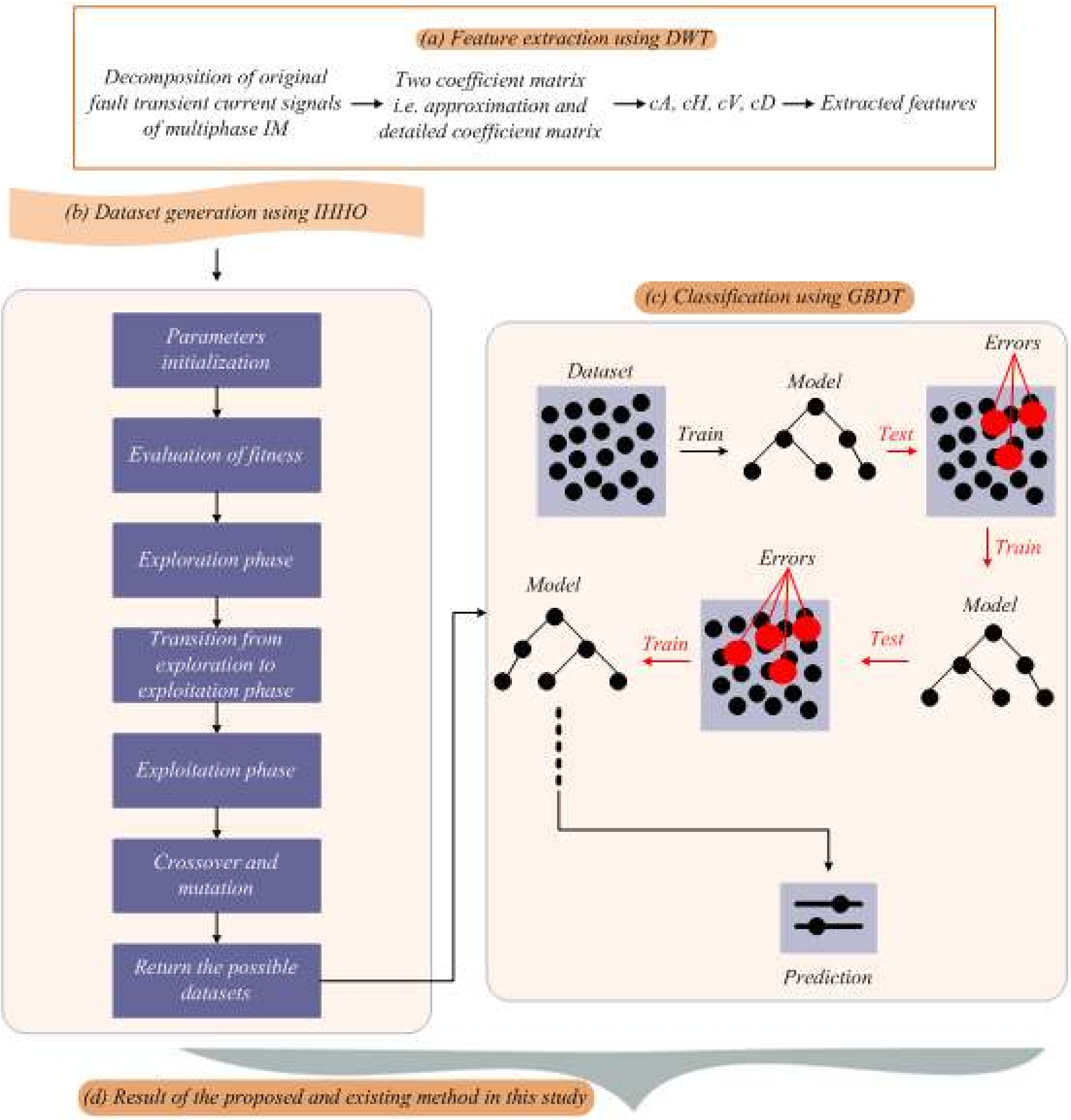
where N_{GX} indicates the number of individuals crossover, M_p denotes point of mutation as well as L_c denotes prey length.

Step 6: Termination: Here, the best solution of the stator current signals are determined, in light of the fitness values and the network is prepared to give the possible dataset as indicated by multiphase IM fault. The algorithm of outer IHHO, which is programmed as the equations below, contains the data set to the minimum and maximum frequency as current stator.

$$DS_{IHHO} = \begin{bmatrix} cA^1 \\ cA^2 \\ \vdots \\ cA^n \end{bmatrix}^{c,v} \begin{bmatrix} cH^1 \\ cH^2 \\ \vdots \\ cH^n \end{bmatrix}^{c,v} \begin{bmatrix} cV^1 \\ cV^2 \\ \vdots \\ cV^n \end{bmatrix}^{c,v} \begin{bmatrix} cD^1 \\ cD^2 \\ \vdots \\ cD^n \end{bmatrix}^{c,v}$$

(17)

where $cA_n^{c,v}$, $cH_n^{c,v}$, $cV_n^{c,v}$ and $cD_n^{c,v}$ denotes as minimum & maximum signal of current frequency. Datasets are provided for GBDT input. Figure 2 elucidates the flowchart of the proposed hybrid technique.



Fault diagnosis Method	Detection Time	Robustness	Cost	Sensitive to parameters	Implementation Effort	Computation Amount
ANN	>1cycle	Medium	Low	Low	Low	Medium
S-transform	<1/4cycle	Low	Low	High	Low	Low
GBDT	≈1/4 cycle	High	High	Low	High	High
Proposed	<1/2	High	Low	Low	Low	Low

Figure 2: Flowchart and obtained outcomes of proposed hybrid technique

4.3. Fault Classification of Multiphase IM Using Gradient Boosting Decision Trees (GBDT)

In this section, GBDT is used to allocate the fault of multiphase IM. Hence, ordinary and unordinary data are assessed at the beginning to demonstrate its unity. GBDT refers to internal winding current stator. Gradient augmentation utilize machine learning method as a reversal and allocation impact, which maintains a model of forecast form as a set of weak forecast techniques, decision tree as typical [21]. In this method, goal function is assessed due to computation of precision for every allocation. To compute the accuracy is,

$$Accuracy\,(\%) = \frac{TP + TN}{TP + FN + FP + TN} \times 100$$

(20)

Here TP and TN represents the number of forecast correction for actual class as true and false. FN and FP represents number of forecast incorrect for actual class as true and false. Finally, the minimized value of the error is computed to obtain the inputs. Due to the behavior ability, GBDT is trained as optimal and obtain optimal results and classification related precision is calculated. The outcome of simulation of proposed hybrid method with the existing method analyzed at MATLAB/Simulink platform. They are comes under the following section.

5. EXPERIMENT AND ANALYSIS

This session, depicts the outcomes and conversation of fault detection and classification in multiphase IM. It contains three kinds of fault (1) bearing (2) incipient (3) open phase. Initially, Induction motor (IM) behaviors are analyzed under normal and faulty conditions. Then performance of current stator is normalized with peak value rate. Then, the performance of failure functions of signal in current is extracted as a Discrete Wave Transformation. Extracted characteristics are handled in an advanced manner to provide the failure types. The performances of the DWT system is assessed and compared to ANN, GDBT, S-Transform methods, and statistical measures like precision, sensitivity, specificity values also evaluated.

5.1. Bearing Fault

Figure 3 describes the DWT performance of multiphase IM speed under normal operation. Figure 4 shows the performance of multiphase IM speed under ball fault. Figure 5 shows the performance of multiphase IM speed on cantered fault. Figure 6 shows the performance of multiphase IM speed under inner race failure.

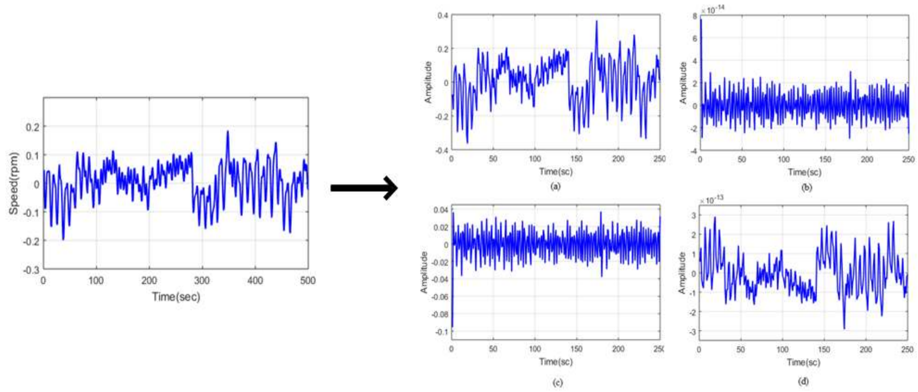


Figure 3: DWT Performance of Multiphase IM speed under normal operation (a) cA (b) cD (c) cH (d) cV

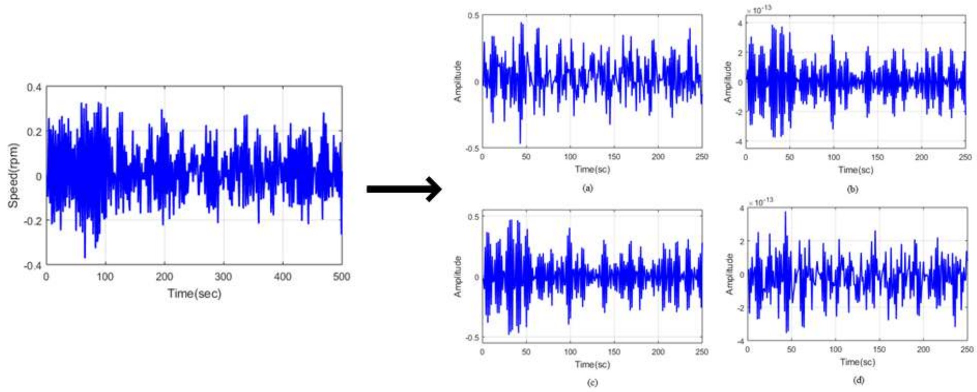


Figure 4: DWT Performance of Multiphase IM speed under ball fault (a) cA (b) cD (c) cH (d) cV

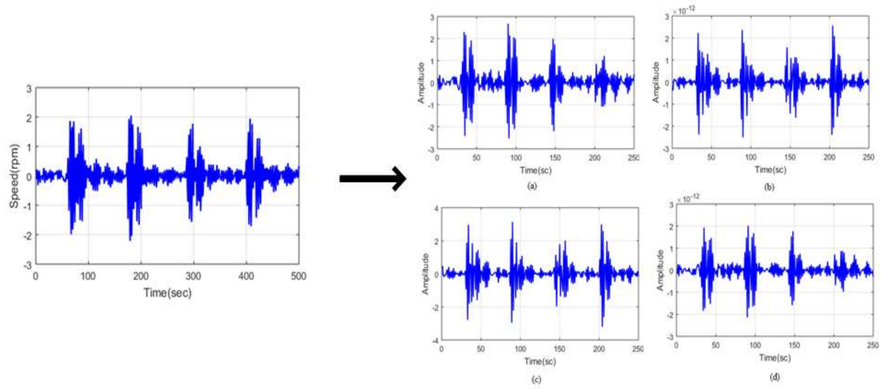


Figure 5: DWT performance of Multiphase IM speed under centred fault (a) cA (b) cD (c) cH (d) cV

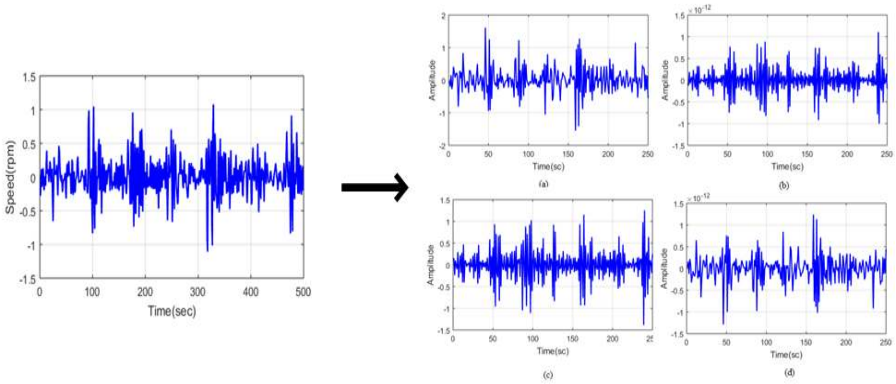


Figure 6: DWT performance of Multiphase IM speed under Inner race fault (a) cA (b) cD (c) cH (d) cV

5.4. Performance Analysis

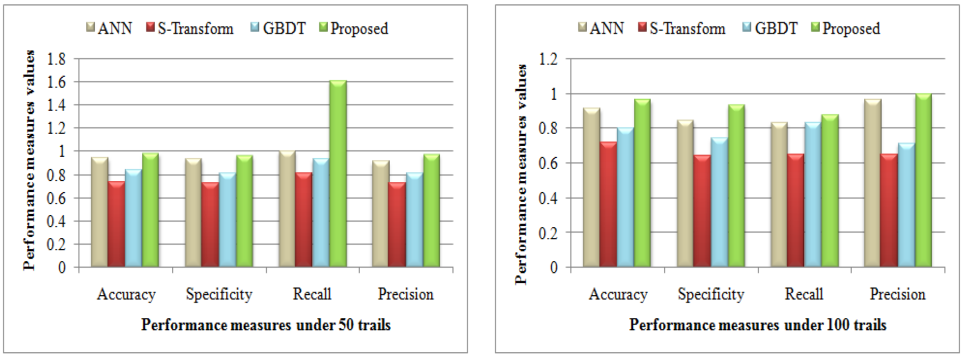
This session shows the performance of proposed GBDTI2HO method. Subject to classes true positive (TP), true negative (TN), false positive (FP) and false negative (FN), the yields of the assignment are suggested.

5.5. Modeling Metrics Evaluation

The modeling metrics are calculated for error computation on this section, as (1) Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and Mean Bias Error (MBE). Table 1 displays accuracy, sensitivity and specificity of GBDTI2HO technique.

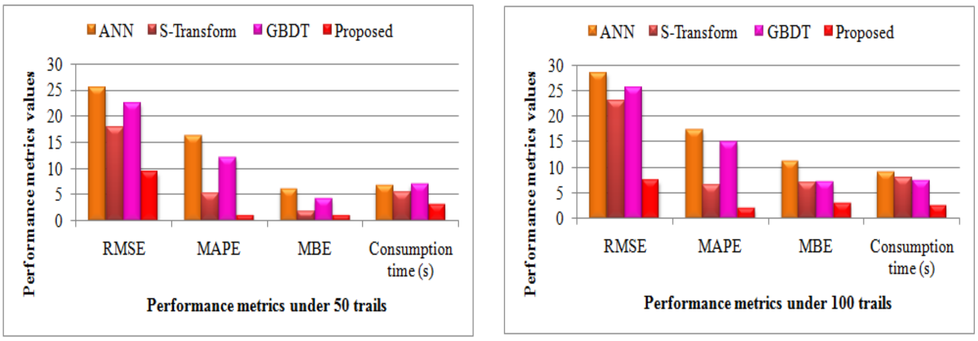
Table 1: Accuracy, Sensitivity, and Specificity of GBDTI2HO technique

Types of fault		**TP**	**TN**	**FP**	**FN**	**Accuracy**	**Sensitivity**	**Specificity**
Bearing fault	Ball	2	14	1	1	0.95	0.63	0.90
	Centered	2	15	1	1	0.94	0.68	0.89
	Inner race	2	12	0	1	0.95	0.64	0.89
	Opposite	3	11	0	2	0.95	0.65	0.89
	Orthogonal	2	12	0	2	0.95	0.62	0.90
Incipient fault	A	1	12	1	1	0.95	0.68	0.90
	B	2	13	0	2	0.95	0.63	0.90
	C	2	14	1	2	0.95	0.63	0.91
	AB	3	14	0	1	0.95	0.63	0.91
	BC	4	14	1	1	0.95	0.62	0.90
	AC	4	11	1	1	0.95	0.66	0.90
	ABC	3	11	1	2	0.95	0.66	0.89
Open phase fault	A	4	12	1	2	0.95	0.61	0.89
	B	3	14	0	1	0.95	0.67	0.90
	C	1	11	1	2	0.94	0.63	.91
Normal	Normal Signal	4	12	1	2	0.95	0.61	0.89



(a) (b)

Figure 7: Analysis comparison of GBDTI2HO with existing technique in line signal (a) 50 (b) 100 number of trails



(a) (b)

Figure 8: Modeling metrics of proposed to existing technique due to turn insulation failure of (a) 50 and (b) 100 trails number

Fig 7 shows the precision, specification, recall and precise of proposed and existing technique for 50 and 100 trails is presented. Figure 8 shows the MAPE, RMSE, MBE as well as time for consumption in proposed and existing technique.

Fig 9 displays the statistic evaluation of proposed and existing system. Table 2 shows the comparison of fault detection between proposed and existing method. Figure 10 (a) displays fitness of proposed method. Here the fitness is 1 in iteration 25. In Figure 10 (b) fitness comparison of proposed as well as existing method is presented. Compared to existing system fitness of GBDTI2HO system is optimal. In general, it clearly displays which proposed hybrid technique reach best outcome contrast to existing methods.

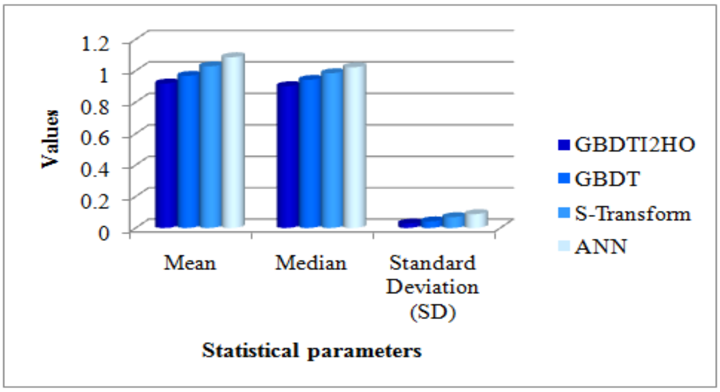


Figure 9: Statistic parameters of GBDTI2HO and existing systems

Table 2: Comparison of fault detection between proposed and existing methods

Fault diagnosis system	Detection Time	Robustness	Cost	Sensitive to parameters	Implementation Effort	Computation Amount
ANN	>1cycle	Medium	Low	Low	Low	Medium
S-transform	<1/4cycle	Low	Low	High	Low	Low
GBDT	≈1/4 cycle	High	High	Low	High	High
Proposed	<1/2	High	Low	Low	Low	Low

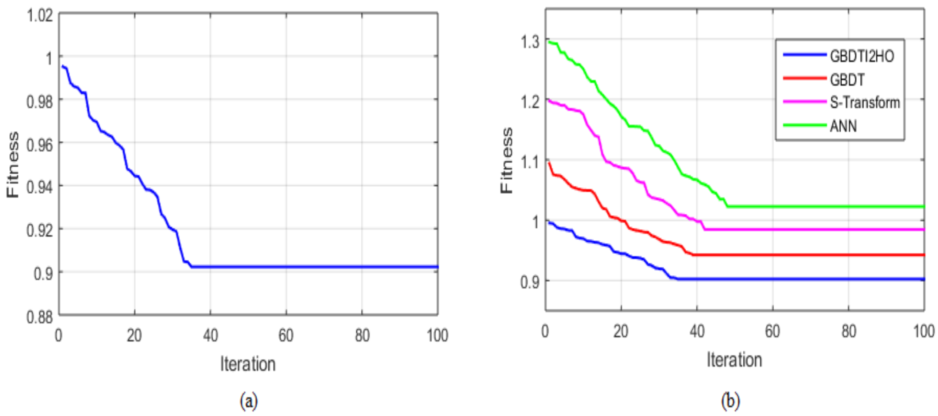


Figure 10: Fitness analysis (a) GBDTI2HO system (b) Comparison of GBDTI2HO and existing technique

6. CONCLUSION

In this paper, GBDTI2HO system, fault detection and classification are examined in the multiphase IM. The fault signals are evaluated like DWT is provided for removing the characters from the interior signals as minimal and maximal frequency components. The IHHO employed for generating probable datasets. GBDT used for allocating the signals as failure or not. The proposed system for recognizing the path of failure is evaluated to MATLAB/Simulink platform. The success of GBDTI2HO system is associated. The efficiency of the GBDTI2HO method is verified using statistic measures like accuracy, sensitivity and specificity, in addition to S-Transform, ANN, and GBDT system. It is best by the existing system for determining the GBDTI2HO system interms of performance variant and statistical measure.

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