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**Research Article**

# An Induction Motor Fault Diagnosis Using Space Phasor Method and Artificial Neural Network

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**ABSTRACT**

This paper showcases a unique technique for the fault identification in induction motor using the Space Phasor Method (SPM), Artificial Neural Networks (ANN) and Ant Colony Optimization (ACO). The method aims to classify four distinct motor conditions: healthy, interturn fault, bearing fault, and rotor-bar crack. 3-phase space phasor is derived from the motor stator currents using SPM. Further Fourteen statistical features are extracted from the space phasor current. To enhance the feature selection process, ACO is applied, resulting in a significant reduction in the number of input parameters for the ANN. This optimization leads to an improvement in classification accuracy, achieving a 100% accuracy rate. The proposed methodology demonstrates high effectiveness in fault diagnosis of induction motor, offering a robust, efficient, and cost-effective solution for real-time motor monitoring. The results suggest that the integration of SPM, ACO, and ANN holds significant potential for improving fault diagnosis in induction motor.

**Keywords**:

## 1. INTRODUCTION

Most important components in today's industrial landscape is induction motor. Widely used across various sectors for diverse applications, it is often referred to as the "workhorse of the industry." Given its critical role, it is essential to enhance the reliability of induction motors under any conditions. Timely and accurate determination of fault, no fault and identification of faults are crucial to prevent unexpected breakdowns, costly overhauls, and shutdowns. Numerous methods exist for fault detection and diagnosis, including temperature measurement, infrared thermography, acoustic noise analysis, vibration analysis, Hall Effect sensors, artificial intelligence (AI)-based approaches, partial discharge testing, finite element methods, and motor current signal analysis(Bahgat, Elhay, & Elkholy, 2024). Each method has its advantages and disadvantages and can be sorted into invasive and non-invasive techniques.

Invasive methods involve modifications to the motor, such as installing sensors, which can incur additional costs and complexities. Non-invasive methods, on the other hand, avoid these issues by utilizing external data collection techniques. Selecting the appropriate method requires careful consideration of factors such as cost, accuracy, speed, complexity, scalability, and environmental sensitivity. There are many methods developed for the fault detection and classification; the paper presents three different techniques for identifying rotor bar crack faults in induction motors. The authors compare Motor Current Signature Analysis (MCSA), Modified Motor Current Signature Analysis (MSCSA), and Principal Component Analysis (PCA) to determine their effectiveness in identifying faults.(Pires, Martins, Pires, & Rodrigues, 2016) Many review paper give the methods used for the fault recognition and differentiation some of them are Vibration Analysis, Thermal Imaging, Acoustic Emission Analysis, Model-Based Methods, Artificial Intelligence and Machine Learning. The paper also states that there is need to improve the Artificial and machine Learning method for motor fault classification. Also it gives information that by combining the methods one can make better decision for fault classification.(Jigyasu, Sharma, Mathew, & Chatterji, 2018) One of the paper focuses on the recognition, prediction and classification of eccentricity faults in induction motor. The author focuses on challenges in detecting and predicting eccentricity faults and proposes an intelligent identification system that combines Neural Network (NN) and Hidden Markov Model (HMM) into a unified framework to

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overcome challenges.(Bouchareb, Lebaroud, Cardoso, & Lee, 2019) The Parth Sarathi Panigrahy etal gives a comprehensive exploration of data-driven intelligent systems for condition monitoring of electrical equipment. The authors emphasize the importance of feature selection techniques to reduce irrelevant and redundant input features, which can otherwise lead to computational inefficiency and poor classification accuracy. (Panigrahy, Santra, & Chattopadhyay, 2017)

The paper presents a robust and efficient methodology for fault diagnosis in induction motors by combining three techniques: the Space Phasor Method (SPM) for fault signature extraction, Ant Colony Optimization (ACO) for selection of important features, and Artificial Neural Networks (ANN) for classification. The Space Phasor Method is used to obtain phasor currents from the motor's current signals, which reflect the motor's electrical state under various operating conditions. Fourteen statistical parameters are then extracted from these signals. These features are optimized using the ACO technique, which improves the feature selection process by identifying the most relevant characteristics, thereby reducing the dimension of the input dataset. The optimized features are subsequently fed into an ANN for accurate fault classification.

## 2. METHODOLOGY

### 2.1 Space Phasor Method

The Space Phasor Method (SPM) is a powerful technique used in electrical motor fault diagnosis, particularly for induction motors. It involves representing motor currents in a two-dimensional plane using phasor diagrams. The Space Phasor Model for the 3-phase to neutral current values of a 3-phase induction motor can be derived using equation (1)

$$S(t) = \frac{2}{3}[I_a(t) + \alpha I_b(t) + \alpha^2 I_c(t)] \qquad (1)$$

Where $\alpha = e^{j2\pi/3}$ and $\alpha^2 = e^{j4\pi/3}$

A contour plot of S(t) is a graphical representation that shows the variation in the two- dimensional space of real and imaginary components of signal. Under ideal conditions in healthy induction motor the phasor generated from the three-phase stator currents forms a perfect circle. Under fault conditions, the current waveform becomes distorted, leading to a non-sinusoidal pattern in the phasor and the contour plot show elliptical or irregular shapes, deviating from the perfect circular pattern.(Bagheri & Bollen, 2018; Ignatova, Granjon, & Bacha, 2009; Kankale, Paraskar, & Jadhao, 2021).

### 2.2 Ant Colony Optimization (ACO)

Inspired by the foraging behaviour of ants an algorithm was developed by Marco Dorigo in the early 1990s, called as Ant Colony Optimization (ACO). Ants communicate using pheromone trails, which help them identify the shortest path to food sources. This behavior is translated into an optimization algorithm where artificial ants build potential solutions and update pheromone trails to guide subsequent ants towards better solutions.

#### *2.2.1 Application in Dimension Reduction*

In induction motor fault classification, for efficient and accurate diagnosis managing high-dimensional data is essential. ACO is used for dimension reduction, identifying a subset of the most informative features while discarding redundant or irrelevant data. This enhances the fault classification model's efficiency and performance by improving computational speed and accuracy.

ACO Works for Dimension Reduction in following steps:-

**1) Initialization:** A population of artificial ants is initialized, each representing a potential solution (a subset of features).

**2) Solution Construction:** Ants construct solutions by selecting features based on a probabilistic model influenced by pheromone levels and heuristic information.

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**3) Pheromone Update:** After constructing solutions, ants evaluate their quality based on a fitness function (e.g., classification accuracy). Pheromones are updated to reinforce good solutions and evaporate to reduce the influence of poor solutions.

**4) Iteration:** The process is repeated for several iterations, with ants progressively finding better feature subsets. (Misra & Chakraborty, 2024; Wang, Zhang, Wang, & Chen, 2023), (Hashemi & Dowlatshahi, 2024).

### 2.3 Artificial Neural Network

Neural networks, inspired by biological systems, are computational models made up of processing units, connections, and associated weights. The processing units act as neurons, connections represent the learning and recall mechanisms, while the weights are the coefficients assigned to these connections. The arrangement of an Artificial Neural Network (ANN) is shown in Figure 1. ANNs possess several essential features such as adaptability through learning, generalization capability, large-scale parallel processing, resilience, associative memory, and the ability to handle spatiotemporal data(Shanmuganathan, 2016). Artificial intelligence, and specifically neural networks, have applications across various fields like pattern recognition, speech recognition, biomedical diagnosis, and induction motor fault detection(Sadeeq & Abdulazeez, 2020). The neural network shown here consists of three layers: an output layer, a hidden layer, and an input layer. A feed forward network topology has been adopted for simplicity. For training the input patterns, a feed forward approach is used, and errors are calculated with adjustments to weights performed using back propagation. The input given progresses sequentially from the input layer through the hidden layer to the output layer.

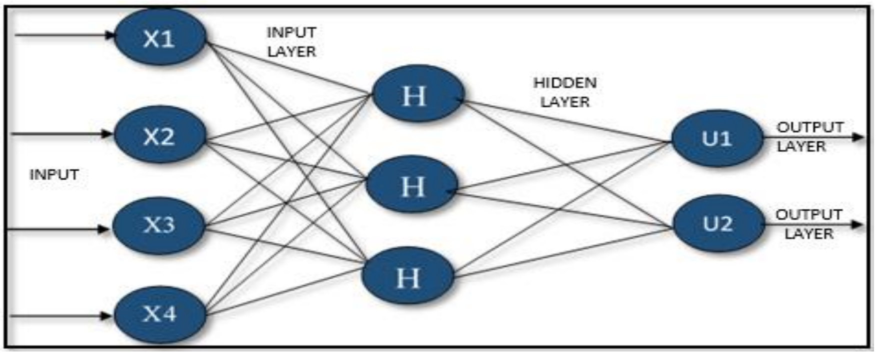


Figure 1. Architecture of Artificial Neural Network

## 3. EXPERIMENTAL SETUP

For the purpose of experimentation and data generation the test bench is comprised of the computer, mains fed 2 H.P., 415 volts, 3-phase, 4 poles, 50 Hz squirrel cage induction motor. Motor under experimentation has 24 coils, 36 slots at all. Each phase consists of 8 coils carrying 300 turns. A tapping configuration is applied to each phase, with the tapping starting at 10 turns from the neutral point. With each group containing approximately 70 to 80 turns, tapping are drawn from these coils. The motor is coupled with a DC generator and an electrical load of 3 kW is used for loading purpose. The Figure 2 shows the setup of an experiment. To capture the current and voltage signals, an ADLINK DAQ system is used, operating at a sampling frequency of 1 kHz, and data is collected under various load and supply conditions for the following cases.

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Figure 2. Experimental Setup

### 3.1. Healthy Condition

A 3-phase balanced supply is given to 2 H.P motor, where load on the motor is varied from no load to full load. Stator current signals and phase voltages are captured for various loading conditions.

### 3.2. Bearing Defects (Inner and Outer Race)

Two bearing numbers 6204 and 6205 is used in motor under test as shown in Figure 3. During regular operation of motor, bearings have developed natural defects same bearings are used in experimental studies. Various combination of bearings having inner race defects and outer race defects are fitted in motor. The stator currents and voltages for each bearing combination are captured and compared to the condition of a healthy bearing. To evaluate the performance of bearings and its effect on the performance of the motor, various experiments were conducted with different combinations of rear side and load side bearings.

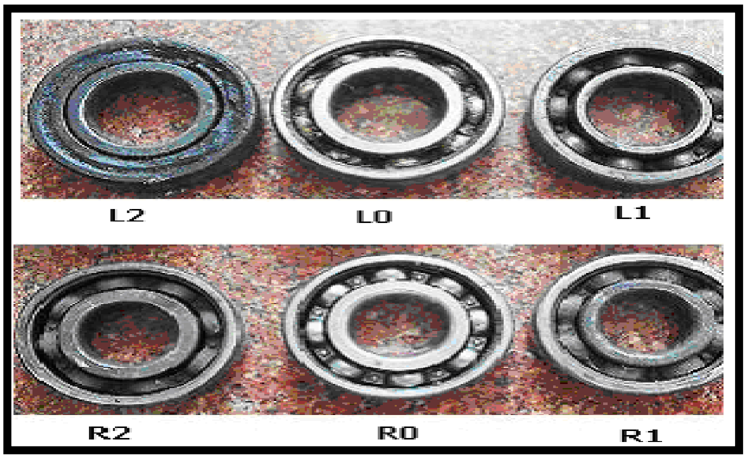


Figure 3. Bearings under Test

### 3.3. Stator Interturn Short Circuit

To introduce short circuits in the motor, stator windings of induction motor were modified to have several accessible tapings. Each tapping is made after 10 turns, for this experimentation phase A is tapped. Various experiments were performed with 10 turns short-circuited in phase A of the motor, and phase voltage and stator current signals were recorded under different loading conditions.

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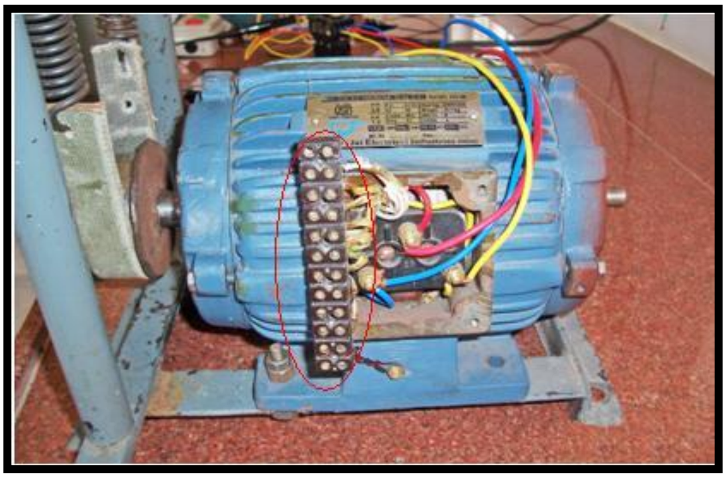

Figure 4: Tapping arrangement on Induction Motor

### 3.4 Broken Rotor Bar

The tested induction motor is equipped with 32 rotor bars. For the rotor broken bar test, two rotor bars were deliberately damaged near both ends of the end rings, as depicted in Figure 5. Stator current signals were then measured under various loading conditions.

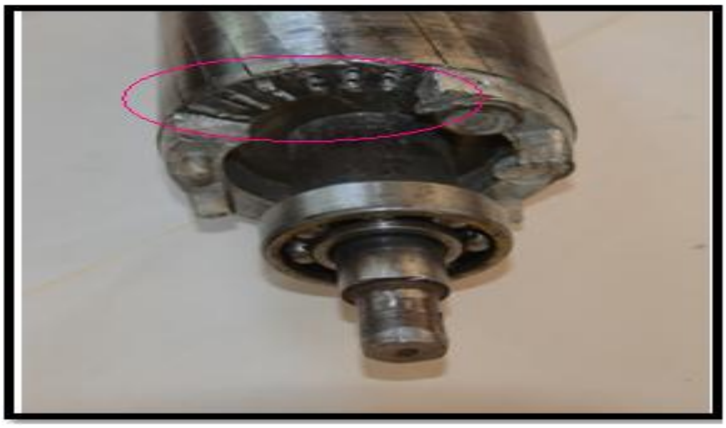

Figure 5: Induction motor with broken rotor bars

Figure 6(a) to 6(d) presents the stator current signals captured from the motor at full load under normal and different fault conditions.

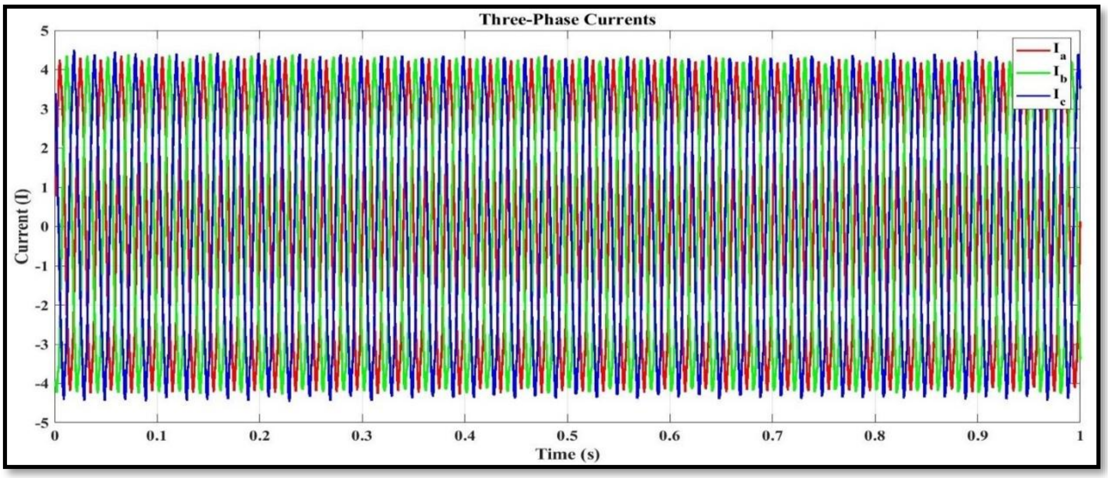


Figure 6(a). Stator current signals of healthy condition.

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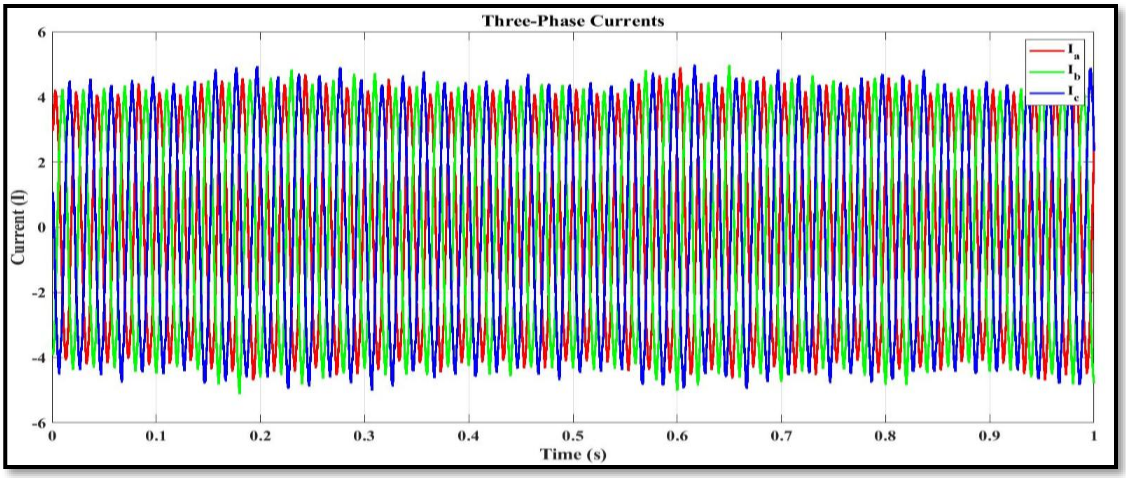


Figure 6(b). Stator current signals for bearing fault.

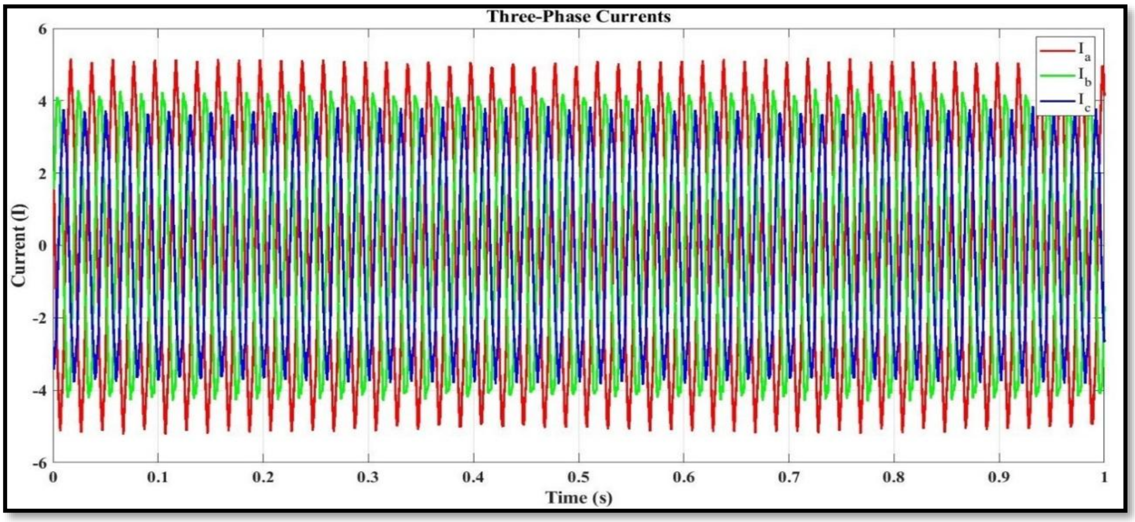


Figure 6(c). Stator current signals for inter-turn fault.

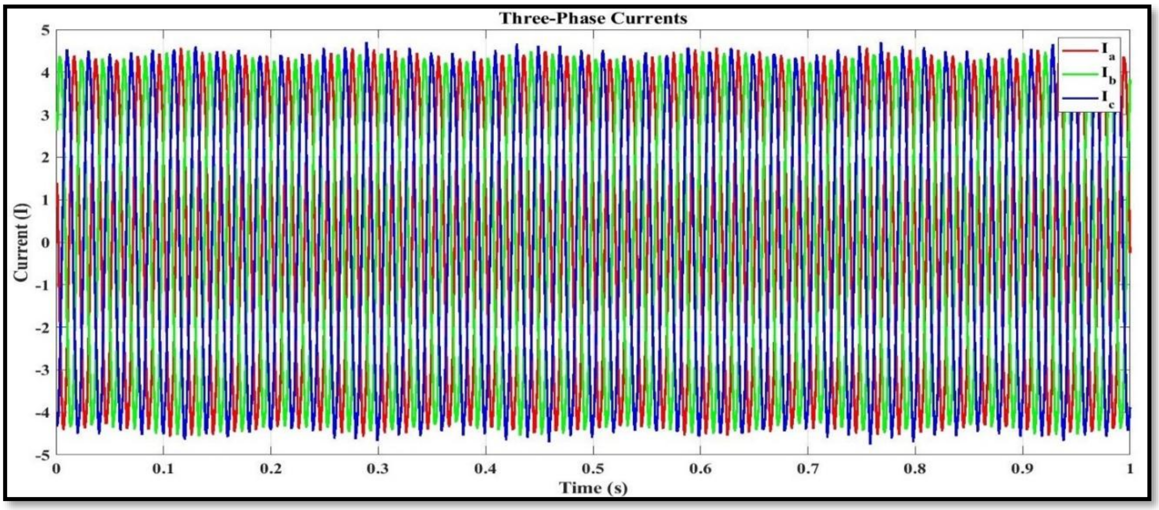


Figure 6(d). Stator current signals for broken rotor-bar fault.

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## 4. SPACE PHASOR METHOD BASED APPROACH

Under ideal supply conditions S(t) contour trajectory is perfectly a circle. But as the supply conditions are not perfectly sinusoidal during the experimentation, S(t) is not exactly circle, the pattern deviates from its ideal pattern. Figure 7(a) to 7(d) shown the contours for healthy condition, bearing fault, interturn fault and broken rotor bar conditions of 3-phase induction motor respectively.

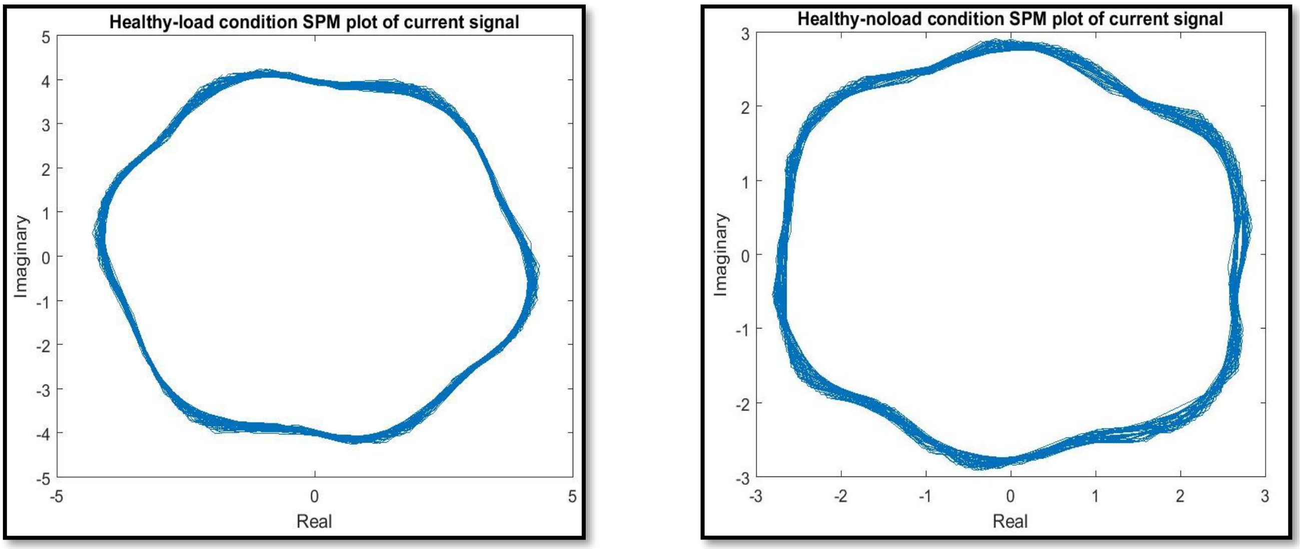


Figure 7a. SPM contour for healthy condition

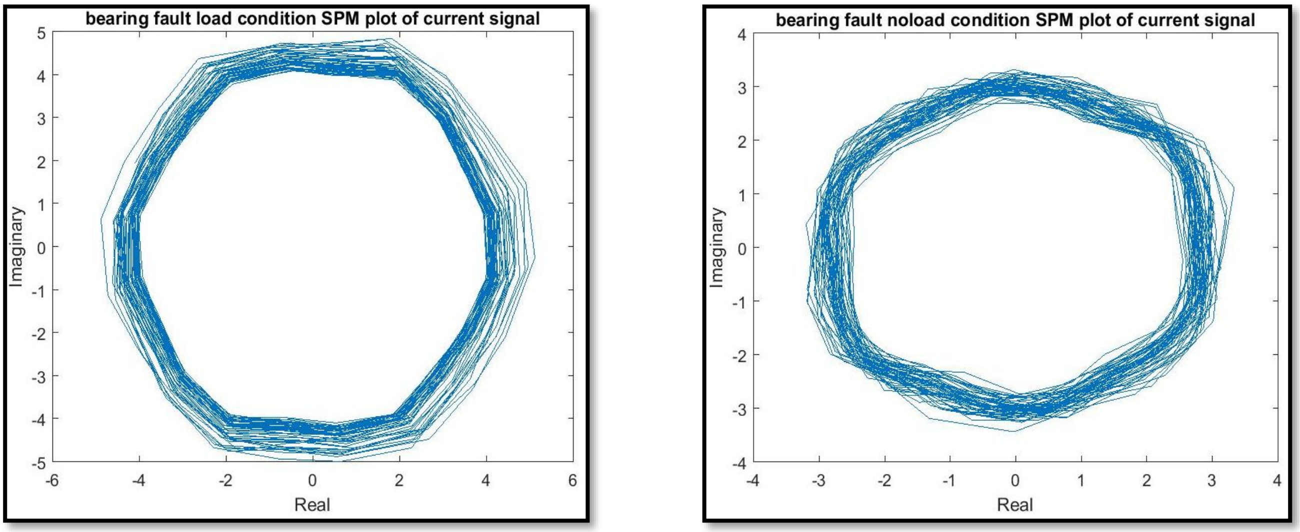


Figure 7b. SPM contour for bearing fault condition.

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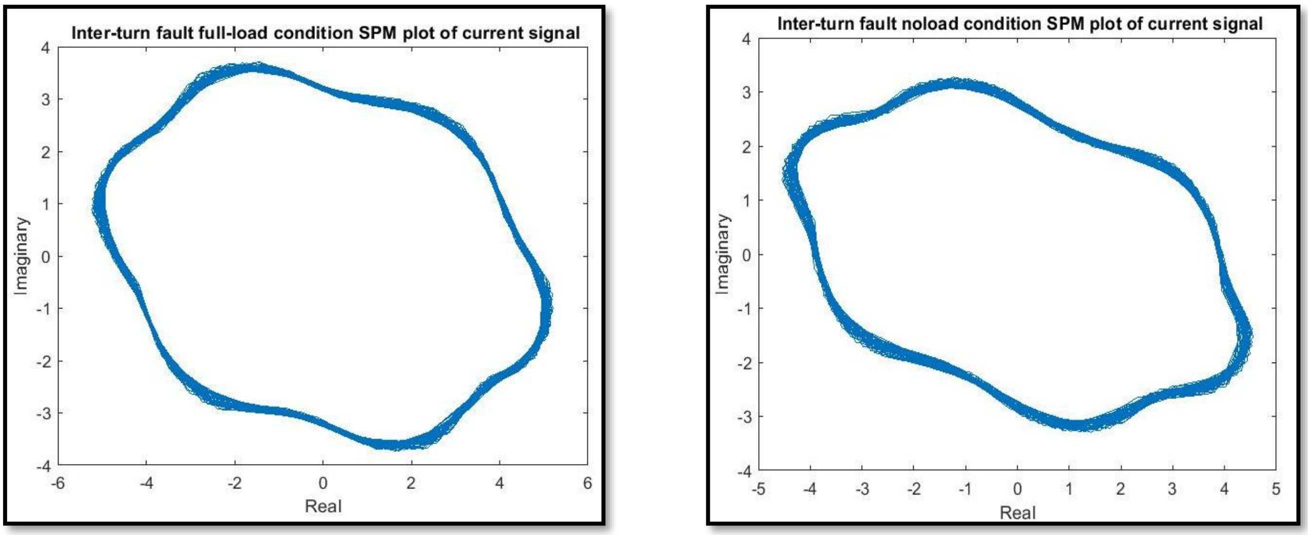


Figure 7c. SPM contour for Inter-turn fault condition.

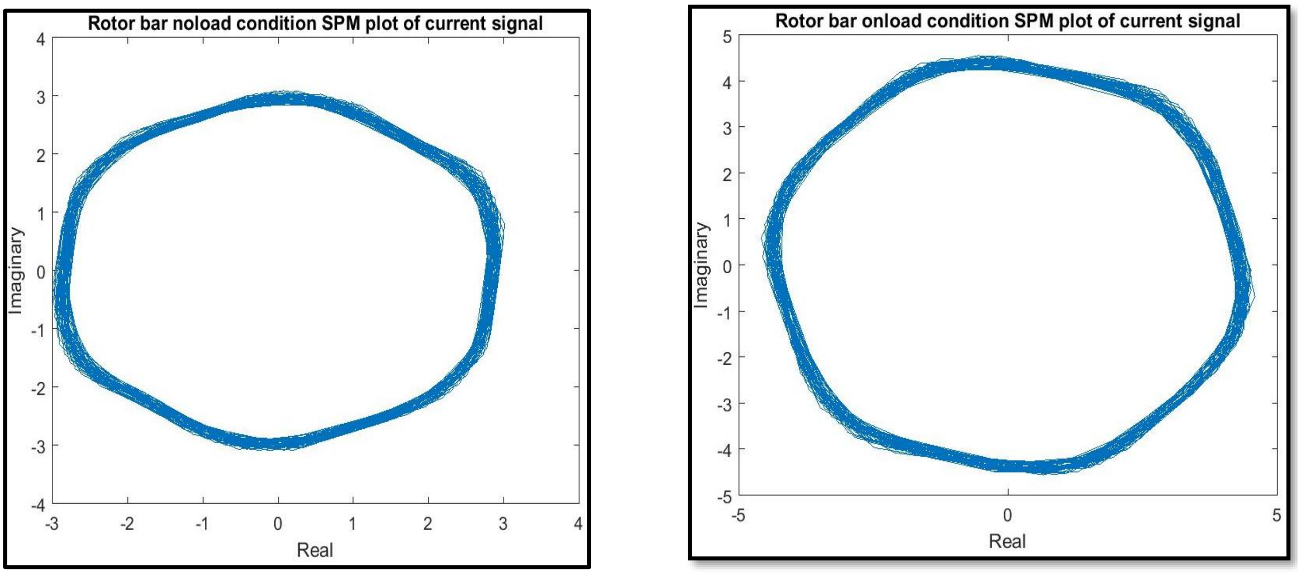


Figure 7d. SPM contour for Rotor-bar fault condition.

An insight, analysis of Figure 7a to Figure 7d leads to an obvious classification of induction motor fault according to a specific deformation in SPM contour pattern. However, the deformation in patterns is somewhat ambiguous in the sense that patterns for some particular fault conditions (healthy and rotor bar fault at light loads) are not distinct and thus is difficult to successfully interpret the information from it. The patterns are then described in terms of features. Features based on statistical approach are extracted from the space phasor S(t); overall fourteen statistical parameters are determined and fed as input to ANN. These statistical parameters include maximum, minimum, median, mean, sum, rms value, energy, absolute sum, crest factor, kurtosis, shape factor, variance, standard deviation and skewness of current signals S(t). (ANJALI P. WADEKAR & ANJALI U. JAWADEKAR, n.d.)

## 5. RESULTS AND DISCUSSION

For induction motor fault classification, the ANN can be used as classifier due to its excellent pattern recognition capabilities. A supervised learning algorithm for training called back propagation is used with a three-layer Feed Forward Artificial Neural Network (FFANN). FFANN consists of one output layer, one hidden layer and one input layer. The input layer consists of 14 processing elements which correspond to 14 statistical parameters computed from space phasor signal S(t), 01 hidden layer optimized with a momentum of 0.7 and learning rate of 0.8, output layer consists of four processing elements representing healthy condition, interturn fault, rotor bar crack and bearing fault. The model uses 70% of data for training and 30% for testing, with classification based on minimizing squared error. This configuration achieves 100% accuracy in classifying induction motor conditions such as bearing fault, interturn fault, broken rotor bar and healthy condition. Figure 8 shows the training model of ANN.

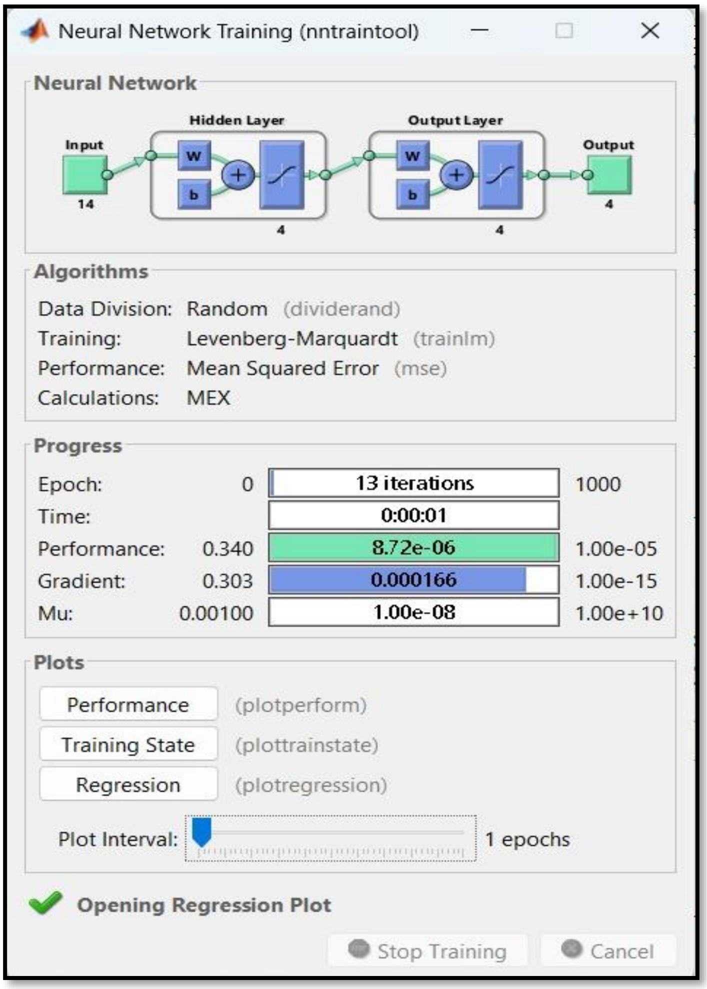


Figure 8. ANN training Model obtained for classification of induction motor faults

Figure 9 shows the confusion matrix obtained after classification.

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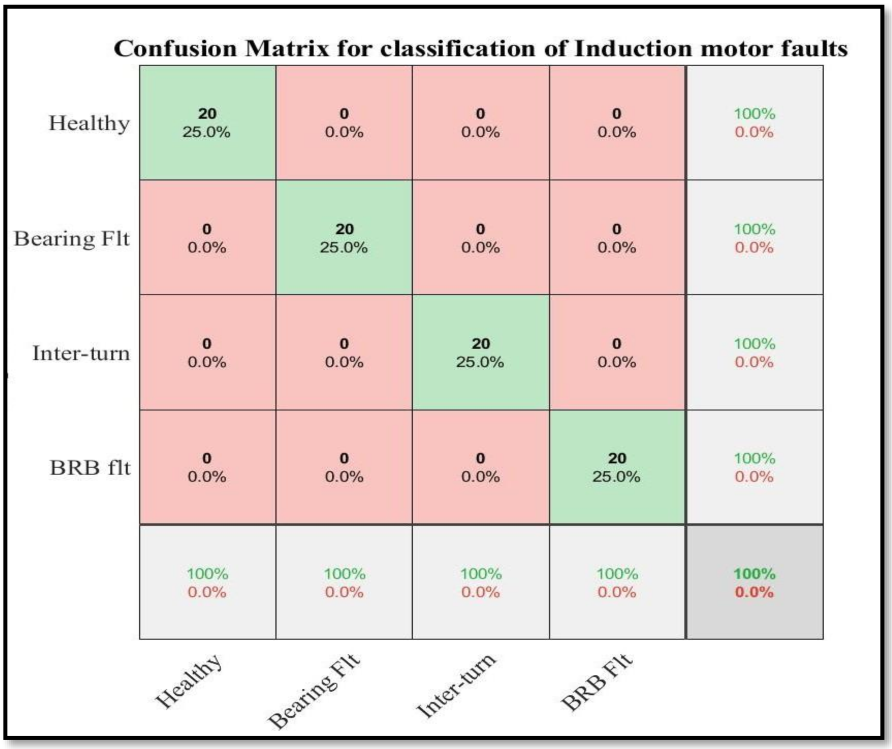


Figure 9: - Confusion matrix obtained for classification of induction motor faults

Figure 10 shows variations of percentage accuracy of classification with respect to the number of processing elements.

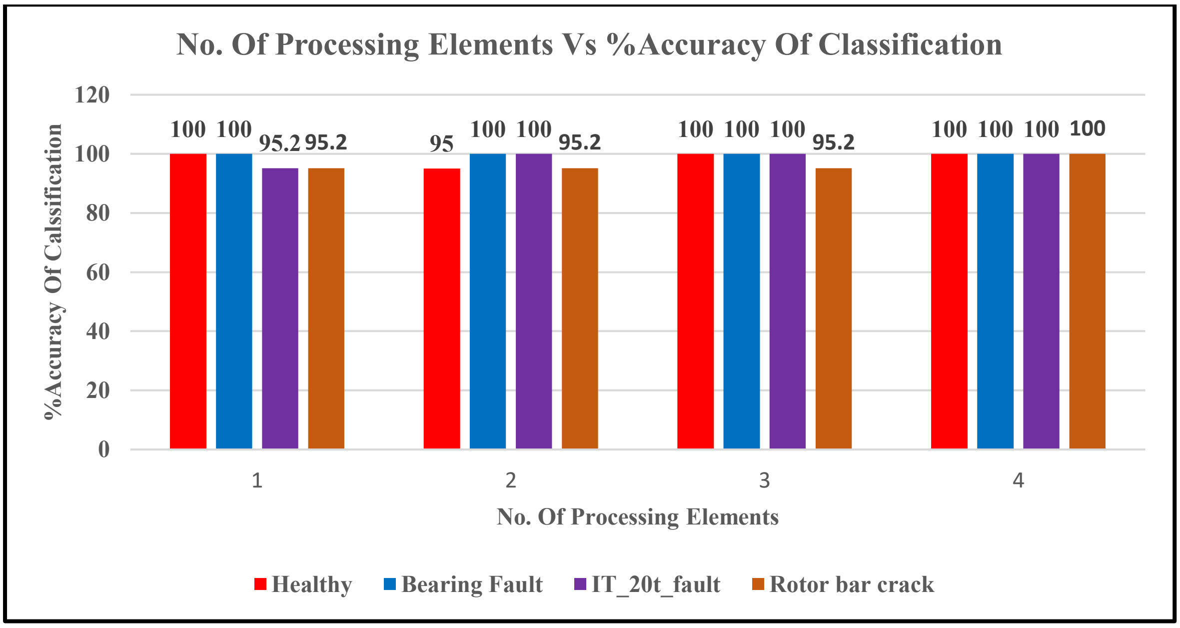


Figure 10. Percentage classification Accuracy with respect to the number of processing elements

With fourteen statistical parameters as input to ANN 100% classification accuracy is obtained, further an attempt is made to reduce the dimension of input matrix using Ant Colony Optimization technique.

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### *5.1 Statistical Parameters and Feature Selection with ACO*

In the process of fault diagnosis for induction motors, 14 statistical parameters are initially extracted from the space phasor S(t). These parameters include statistical measures maximum, minimum, median, mean, sum, rms value, energy, absolute sum, crest factor, kurtosis, shape factor, variance, standard deviation and skewness which capture essential characteristics of the motor's electrical signals under various operating conditions (healthy and faulty).(ANJALI P. WADEKAR & ANJALI U. JAWADEKAR, n.d.)

However, not all of these features contribute equally to the classification accuracy. Redundant or less relevant features may increase computational complexity without significant improvement in results. To achieve classification with optimized inputs Ant Colony Optimization (ACO) is employed as a feature selection algorithm. ACO parameters selected are given in Table1 for optimization.

**Table 1: Ant Colony Optimization Parameter Value for Dimension Reduction**

| Parameter | Value |
|---|---|
| Total Number of Ants | 15 |
| Total Number of Features | 14 |
| Number of Iterations | 100 |
| Importance Of Pheromone(α) | 1 |
| Importance of heuristic information(β) | 2 |
| Evaporation rate of pheromone (ρ) | 0.5 |
| Constant related to pheromone deposit (Q) | 1 |

After iterating ACO gives out the best feature weights. These features weights are calculated based on pheromone deposit and ant-weights. The features having value more than 0.7 are considered to be dominant. The dominant features selected as input to ANN are maximum, standard deviation, variance, RMS, absolute sum, and shape factor these features are selected and their best feature weight is shown in Figure 11.

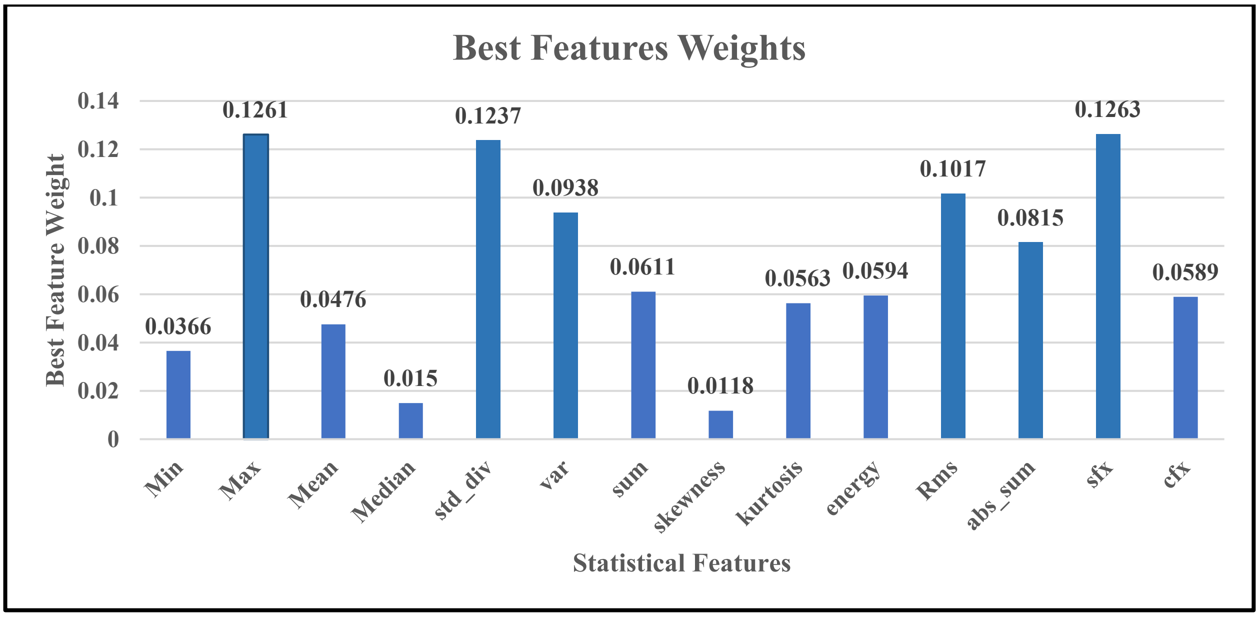


Figure 11. Best features for classification of induction motor faults based on Ant Colony Optimization

With one hidden layer and 6 features as input, ANN gives 100 % accuracy for classifying induction motor faults. The Figure 12 represents the ANN training model for induction motor fault classification with ACO optimization.

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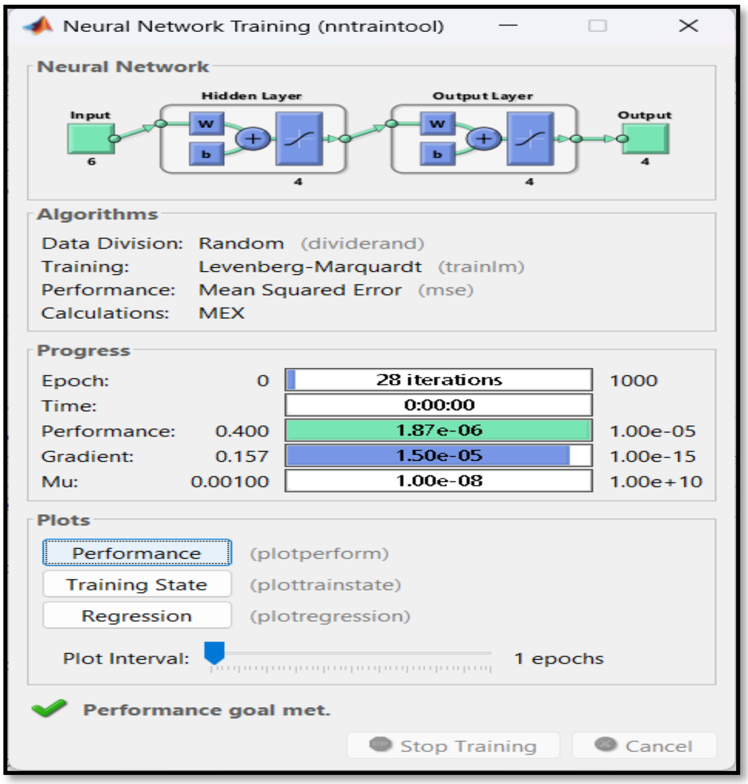


Figure 12. ANN Training Model for classification of induction motor fault.

Figure 13 shows the confusion matrix obtained.

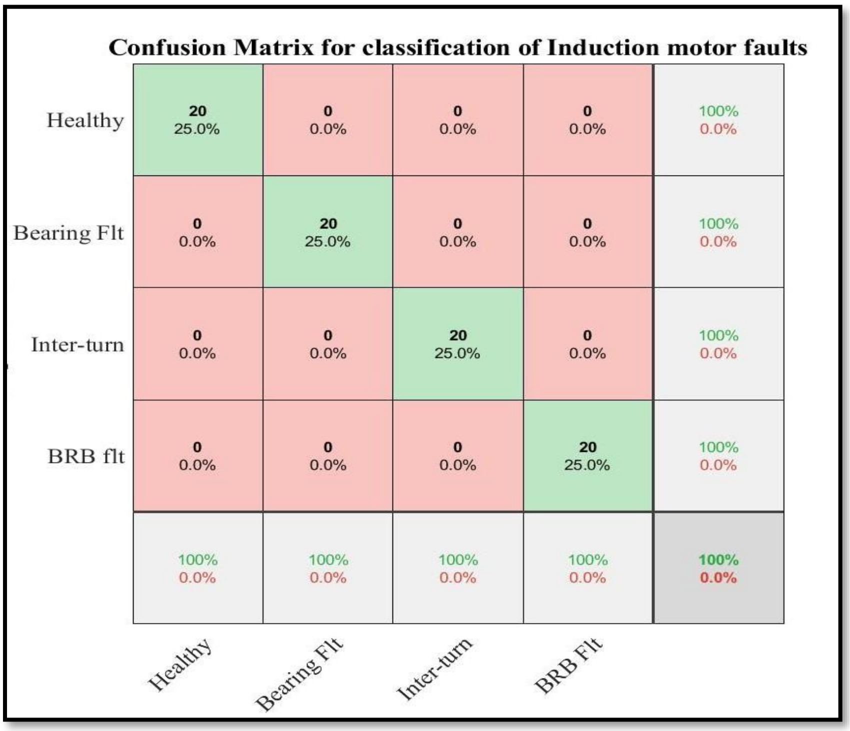


Figure 13. Confusion matrix for classification of induction motor fault

The Figure 14 shows the variations of percentage accuracy of classification versus the number of processing elements required for induction motor fault classification.

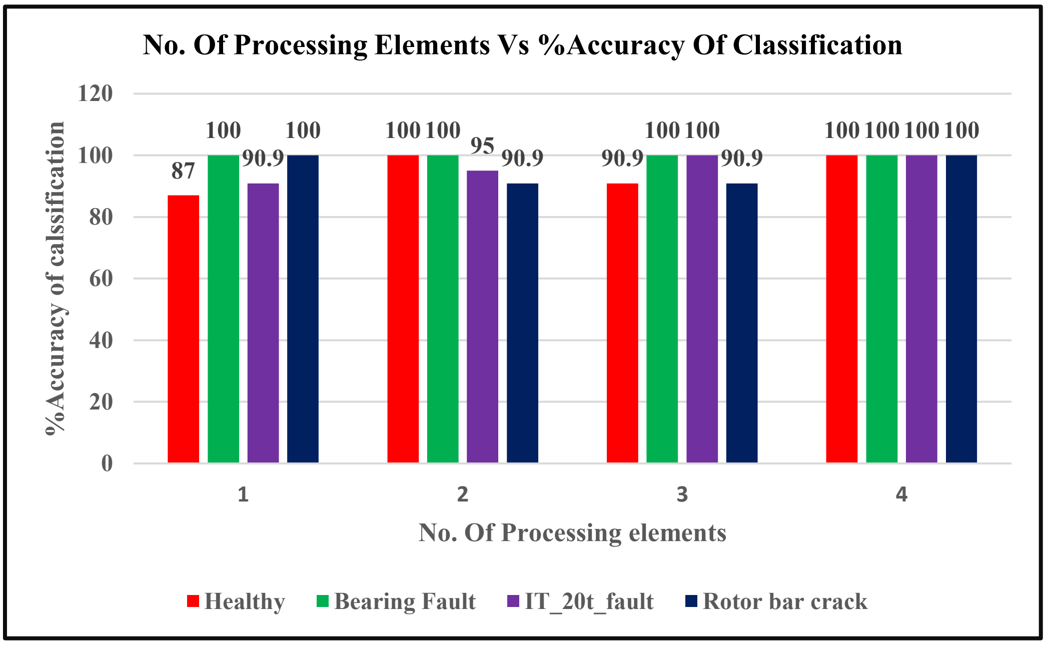


Figure 14: - Percentage Classification accuracy with respect to the number of processing elements.

The Table No. 2 shows the comparative details of ANN required for induction motor classification with and without Ant colony optimization. The Table 2 shows that the induction motor fault classification can be achieved and substantial decrement in the system requirement is achieved using Ant Colony Optimization.

**Table 2. Comparison Of Input To ANN For Induction Motor Fault Classification.**

| ANN training model system parameter to achieve 100% classification of Induction motor fault | | |
|---|---|---|
| **ANN Input parameters** | **Before Ant Colony Optimization** | **After Ant Colony Optimization** |
| **Neurons Input** | 14 | 6 |
| **Neurons Output** | 4 | 4 |
| **Hidden Layer** | 1 | 1 |
| **Hidden Neurons** | 4 | 4 |

## 6. CONCLUSION

In this paper the induction motor fault classification using new approach has been presented. The Space Phasor Method (SPM) is used for induction motor faults classification. The contour obtained from SPM are showing distinct difference for four various conditions but the contour obtained for no-load condition rotor bar crack and the healthy condition of induction motor during no-load are found to be similar with small variation. So, the statistical parameters are calculated of Space phasor signal S(t). ANN is used for classification of various faults. ANN gives 100% classification with and without optimization for induction motor fault classification. To optimize the input parameters required by ANN, Ant Colony Optimization is used which reduces the dimension of the input required for classification. The proposed method gives 100% classification for induction motor fault classification. The future scope of work would be to discriminate the interturn faults severity, estimate the number of broken rotor bar and online implementation of fault diagnosis of method.

## 7. ACKNOWLEDGMENT

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