Prognostics and health management of induction motor by supervised learning classifiers

R Jigyasu¹, V Shrivastava¹, S Singh¹

¹Department of Electrical and Electronics Engineering, National Institute of Technology, Delhi-110040, India

Corresponding author’s email- rajvardhan@nitdelhi.ac.in

Abstract. Current occasions are tied in with being modern and bringing down the expense of working the framework. Albeit the underlying interest in the framework can't be changed, which is fixed, the methodology is to bring down the expense of activity of the machine with the goal that the support cost is limited since the chance of disappointment will be lower. The machine might be in a distant area where physically checking the status or performing upkeep won't be effective. Accordingly, to improve execution and increment plant profitability, predictive support can be planned in such a way that numerous machines can be overhauled simultaneously. What's more, this will expand the general uptime of the plant all in all. For most machines, condition monitoring is a custom-fitted way to deal with predictive support. Also, late patterns show that AI is the quickest and most proficient approach to accomplish the ideal answer for this issue. In this work, predictive maintenance is done for two major occurring faults broker rotor bar and bearing faults. Time-domain analysis has been used to develop hundred feature vectors, which are utilized for training, testing, and validation. The best suitable classifier model to predict faults is developed after comparison of Artificial Neural Network, Ensemble, and Decision Tree smart classifiers based on model accuracy. Out of these, the maximum accuracy is obtained by Artificial Neural Network.

1. Introduction
With industrialization on one side, demand for human resources got reduced, but on the other side era of development had started. People started learning about the new technologies and their journey of skilled labor from just a worker started. With this advancement use of machines, especially 3 phase machines [1], increased because of their reliability, ruggedness, robustness, and less maintenance, etc. advantages. But as said by Heraclitus, "nothing is permanent in this world except change," machines also degrades, and little maintenance is required from time to time. Only repairing machines as possible during the initial days after loss, but with the advancement in technology, predictive maintenance [2] came into existence. With these preventive techniques, the loss of time, money, and lives got reduced to nearly no value.

There are different methods in this preventive maintenance, such as current signature analysis (MCSA), vibration analysis, acoustic analysis, thermal analysis, etc. [3]. These techniques are also known as monitoring techniques. In [4] MCSA technique,[5] vibration,[6] acoustic, [7] thermal analysis, and many more in [8-10] were used for the recognition of various kind of faults such as broken rotor bar (BRB), eccentricity, stator, bearing, etc. faults. According to [11], the percentages of occurrence of different faults are given in Figure 1.
There are several signal processing techniques available for preventive maintenance. Root mean square (RMS) Calculation, where RMS vibration velocity indicates vibration severity and RMS of stator current indicate motor loading. Time-Domain (TD) Analysis uses TD features such as RMS, Variance, Kurtosis, Peak value, Skewness, Median, etc. Frequency Analysis- FFT, which includes frequency domain (FD), features like average frequency (AF), median frequency (MF), Lower Band Power (LBP), Upper Band Power (UBP), etc. Time-Frequency Analysis, which is a combination of TD and FD analysis but better than them because of scaling and windowing techniques in it, and Stator Current Park's vector in which Stator faults diagnosed very effectively and works best in steady-state. This technique is a vector sum of 3 phase stator currents. For fault classification and detection, there are several classification methods such as an ANN, Support vector machine (SVM), Nearest Neighbour, Decision tree, etc. The above methods are used to identify different kinds of faults, such as bearing, rotor, eccentricity, soft foot, etc. For example, in [12], automatic recognition and classification of rotor cage defects in squirrel cage Induction motors (IM) took place, and 98.33% accuracy was achieved. In [13], 1-BRB, 2-BRB, and 3-BRB faults and 10% stator winding faults due to short circuits are diagnosed successfully using the SVM technique. In [14] Diagnosis of bearing failures has been done Using Weighted K-Nearest Neighbor, and an accuracy of 100% was achieved using Mahalanobis distance metric. In [15], the decision tree algorithm and vibration-based fault diagnosis model of a monoblock centrifugal pump with 100% accuracy were achieved.

This paper is divided into 6 sections starting from the beginning dedicated to condition monitoring and its applications. After that used techniques; Artificial Neural Network (ANN), Ensemble and Decision Tree, experimental unit, and results obtained in this paper are discussed, ended with a conclusion.

2. Technique Used
This paper focuses on the finding of the best classifier for induction motor current signals. And in this process, several techniques are combined to carry out the overall results. These techniques are validation scheme, ANN classifier, Ensemble classifier, and Decision Tree classifier which are explained below.

2.1. Artificial Neural Network
It is genuinely said that the working of ANN takes its foundations from the neural organization present in the human brain. ANN works on something referred to as Hidden State. The NN takes input information, train themselves to perceive patterns found in the information, and afterward predict the output for a new set of data. The ANN comprises of multilayer structure, where the signature goes through from between layers. These layers are made up of nodes called neurons. ANNs is capable to be trained and demonstrate non-straight and composite connections; it can sum up the model and anticipate on inconspicuous information. Numerous investigations have indicated that ANNs can more readily show heteroskedasticity. It is accepted that neural models having just two layers and sigmoid activation function can estimate any design boundary to subjective exactness [16].

The ANN has a vast range of applications such as in [17] ANN is used for translation of Sanskrit language to English and results are compared with Support Vector Machine and Naïve Bayes classifiers. In [18] ANN is used for predicting an alcohol user, this model achieved an accuracy of
98.7% which is quite good. In [19] model for the detection of the Brain, the tumor is developed with an accuracy of 99% using an advanced version of neural network i.e. Convolution Neural Network.

2.2. Decision Tree
A Decision tree is a classifier communicated as a recursive segment of the example space [20]. In a Decision tree, each inside node parts the case space into at least two sub-spaces as per a specific discrete capacity of the input attributes values. This method of classification deals with the impurity present in the sample of the data, here impurity means deviation from the desired value. And based on the level of impurity, each data sample from the dataset is divided into subcategories of a lesser number of impurities. Indecision trees classifier the method is slightly complex as each data sample has to be compared multiple times with the node available in a tree. The node of a tree is a base for the division of the data sample. For 2 class problem of the decision tree following equations are used:

\[
\text{InformationGain(IG)} = \sum_{i=1}^{v} \left( \frac{J}{J+K} \cdot \log \left( \frac{J}{J+K} \right) + \frac{K}{J+K} \cdot \log \left( \frac{K}{J+K} \right) \right)
\]

(1)

\[
\text{Entropy(E(A))} = \sum_{i=1}^{v} \frac{1}{J+K} \cdot I(J,K_i)
\]

(2)

\[
\text{Gain} = \text{IG} - \text{E(A)}
\]

(3)

In the above conditions, J and K are the quantities of potential results in entire objective examples; v is the number of tests in a single section. This gain chooses the root node in the grouping tree.

2.3. Ensemble
This technique works on the voting principle. There are two types of Ensemble Classifiers first homogeneous type and other heterogeneous types [21]. In homogenous type, the output is decided using the same type of classifier but the algorithm followed will be different. And heterogeneous type the output is decided using different classifiers such as decision tree, nearest neighbor, random forest, etc. The training and testing are done using the bagging and boosting techniques. Basic architecture is shown in Figure 2.

![Figure 2. The basic architecture of the Ensemble Classifier](image)

3. Experimental Setup
The test machine is a 3 phase squirrel cage induction motor rated at 1 hp (Table 1 shows the motor specifications). The instrumentation system is mounted close to the drive end bearing shown in figure 3. The various conditions shown in figure 4 introduced in the induction motor are described as follows: 1) healthy; 2) with outer race fault in bearing; 3) with inner race fault in bearing (Table 2 shows the bearing details); 4) 1 Broken Rotor Bars; 5) 3 Broken rotor bars. The current transducer LA 55P is used to alter the current signal into a scope of the MYDAQ data acquisition device. The fault is delivered on the bearing by cutting a 2mm distance across the two sides of the bearing. Broken rotor bar fault has been made by exhausting openings of 6mm distance over the rotor to eliminate the rotor bar.
Figure 3. Experimental Setup

Table 1. Motor Specifications

| Sl. No. | Parameters   | Description                                             |
|--------|--------------|---------------------------------------------------------|
| 1      | Company Name | Bharat Bijlee                                           |
| 2      | Type         | IE2 High Efficiency-2H (3 ph. SCIM)                     |
| 3      | Serial Number| U1S54767|2H08453                                                 |
| 4      | Duty Type    | S1 (Continuous)                                        |
| 5      | Efficiency   | 79.6 %                                                 |
| 6      | Bearing Number| Drive End: 6004 2Z Non-drive End: 6004 2Z               |
| 7      | Motor Power  | 0.75 kW/1HP                                              |
| 8      | Frequency    | 50 Hz ±5%                                               |
| 9      | Supply Voltage| 415 V±10%                                              |
| 10     | Power Factor | 0.77                                                    |
| 11     | Speed        | 1410 RPM                                                |
| 12     | Insulation Class | F                                   |
| 13     | Temperature  | 50 °C (temperature rise: B)                            |
| 14     | Protection Type | IP55                               |

Table 2. Bearing Specifications

| Sl. No. | Parameters     | Description                                      |
|--------|----------------|--------------------------------------------------|
| 1      | Bearing Number | 6004 2Z                                          |
| 2      | Type           | Shielded Deep Groove Ball Bearing                |
| 3      | Contact Angle  | 0°                                                |
| 4      | Inner Race Diameter | 20 mm                         |
| 5      | Outer Race Diameter | 42 mm                        |
| 6      | Width          | 12 mm                                            |
| 7      | Material       | Steel                                            |
| 8      | Cage material  | Steel                                            |
| 9      | Race type      | Plain                                            |
4. Signal Processing and Feature Extraction
Features are the qualities of a signal. This paper has utilized time-domain specifications for feature extraction. The technique of this experiment has appeared in Figure 5. Features are the qualities of a specific signal. The Time-domain features are mean, variance, kurtosis, skewness, and so on are utilized.

Before feature extraction signal division happens. In this progression, the got signal was confined into twenty overlapping pieces. All of them contain 8000 samples. After feature extraction normalization is done before utilizing them for training. The normalization was in the degree of [0, 1] except for skewness, which was to the extent of -1 to 1.

5. Result and Discussion
The smooth running of motor saves from loss of lives and economic disturbances. To classify the faults Artificial Intelligence-based classifiers were used. The output results are shown below in terms of accuracy attained by the classifier with different validation schemes. Three classifiers are compared concerning accuracies attained under different schemes. The classifiers are trained and tested using experimentally acquired data. There are 4 types of faults classified in this database based on the different time-domain features.

5.1. Results obtained using ANN
The basic architecture of ANN is based on the human brain. It is a supervised learning method follower classifier. The power signal was acquired from the healthy and faulty motor and training and testing were performed. Table 3 and Table 4 show the obtained results for different activation functions.

From Table 3, it can be seen that the training functions trainlm trainscg, traincgp, and traincfg based classifiers performed best for no validation case. The Traindm based classifier achieved the worst percentage accuracy i.e. 22%.

Table 3. Percentage accuracy for different transfer functions without validation.

| S.No. | Transfer Function | % Accuracy |
|-------|------------------|------------|
| 1     | trainscg         | 98.7       |
| 2     | trainbfg         | 95.6       |
| 3     | traincgb         | 97.8       |
| 4     | traincfg         | 98.4       |
| 5     | traincgp         | 98.5       |
The Overfitting problem of classifiers is solved using the validation schemes. From Table 4., the trainlm based classifier performed with a percentage accuracy of 99.1875% with a different number of hidden neurons.

Table 4. Percentage accuracy for a different transfer function with validation.

| S.No. | Transfer Function | % Accuracy |
|-------|-------------------|------------|
| 1     | trainscg          | 89         |
| 2     | trainbfg          | 66.7       |
| 3     | traincgb          | 89.6       |
| 4     | traincgf          | 79.7       |
| 5     | traincgp          | 91.7       |
| 6     | trainlda          | 89.2       |
| 7     | trainlgx          | 94.22      |
| 8     | trainlm           | 99.18      |
| 9     | trainoss          | 82.4       |
| 10    | trainrp           | 90.2       |

Figure 6. Average accuracies for different training functions.

From Figure 6, the mean percentage accuracies attain by different training functions based classifiers, the trainlm based classifier performed best in both cases. The training and testing of NN were done for a different number of neurons in the hidden layer and Validations. For the validation case, 10% data was used for validation, 70% for training, and 20% for testing. For no validation case, 75% data for training and 25% for testing from total samples. The classification was done using ‘patternnet’ NN having a different number (2, 4, 6, 8, 10, 12, 14, 16) of hidden layer neurons.
5.2. Results obtained using ensemble classifier
This category of classifiers is a special case, where the classification approach of two classifiers is combined and categorized as an ensemble classifier. Table 5, furthermore, Table 6, shows distinctive accuracies acquired from the Ensemble Classifier on different validation schemes. From the outcomes, it tends to be seen that the precision acquired without validation achieved maximum accuracy of 74.66% with the Subspace Discriminant algorithm while validation achieved 98.9% with the Bagged type algorithm.

### Table 5. Percentage accuracies using ensemble classifier without validation.

| S.No | Type                   | % Accuracy |
|------|------------------------|------------|
| 1    | Boosted                | 43.66      |
| 2    | Bagged                 | 69.66      |
| 3    | Subspace Discriminant  | 74.66      |
| 4    | Subspace KNN           | 61.33      |
| 5    | RUS Boosted Trees      | 44.66      |

### Table 6. Percentage accuracies using ensemble classifier with validation.

| S.No | Type                   | % Accuracy |
|------|------------------------|------------|
| 1    | Boosted                | 73.33      |
| 2    | Bagged                 | 98.9       |
| 3    | Subspace Discriminant  | 79         |
| 4    | Subspace KNN           | 98.8       |
| 5    | RUS Boosted Trees      | 64.33      |

5.3. Results obtained using Decision Tree
It is the way toward picking a game-plan from among choices to accomplish the ideal objective. A Decision tree is a graphical portrayal of potential answers for a choice dependent on specific conditions. It's known as a Decision tree since it begins with a solitary box (or root), which at that point diverges into a few arrangements, actually like a tree. A Decision tree has just blasted nodes (parting ways) however no sink nodes (combining ways). The results of with and without validation schemes have appeared in Table 7., and Table 8. Table 7 shows the percentage accuracy achieved by various Decision trees without validation. The most accomplished percentage accuracy was 62.33% with a complex algorithm. It can be seen that the accuracy obtained with validation is better than no validation, which is 83.66% with complex and medium both.

### Table 7. Percentage accuracies using decision tree classifier without validation.

| S.No | Type | % Accuracy |
|------|------|------------|
| 1    | Complex | 62.33      |
| 2    | Medium | 62.33      |
| 3    | Simple | 51.66      |

### Table 8. Percentage accuracies using decision tree classifier with validation.

| S.No | Type | % Accuracy |
|------|------|------------|
| 1    | Complex | 83.66      |
| 2    | Medium | 83.66      |
| 3    | Simple | 61.66      |

6. Conclusion
A methodology of fused techniques has been presented in this work, to aid in predictive maintenance of induction motor by developing an instrument that performs continuous condition monitoring using the current signature of the machine. There are several factors on which the classifier's accuracy
depends for example data size, features, data quality means low data redundancy, etc. This paper finds out the way of detection as well as diagnosis of two faults BRB and bearing. Out of the three compared techniques, the ANN performed best with an accuracy of 99.18%. For the Ensemble classifier maximum attained accuracy was 98.9% and for the decision tree its 83.66%. In the case of ANN, for trainlm, the accuracy was nearly invariable for a different number of processing elements. However, the average accuracy was improved for different training functions with increasing network size with processing elements. For future scope, more techniques can be compared along with optimization in feature selection.

7. References

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