An Elegant Machine Learning Model to Detect Static Eccentric Fault in Induction Motors

Abstract**—** In this work authors have proposed an elegant machine learning model to detect static eccentricity fault in three phase induction motors. The proposed method utilizes the k-nearest neighbour algorithm to classify static eccentricity from healthy operating condition. The biggest advantage of the scheme is that it uses line voltage signals in time domain to perform fault diagnosis. Moreover, only two features, kurtosis and root of sum of squares, are needed to perform the classification. Furthermore, the proposed method is capable of classifying static eccentricity fault independent of load level, fault severity and machine parameters such as stator slot, rotor bar combinations. Experimental data acquired from a 3-phase, 45-bar squirrel cage induction motor has been used to train and test the machine learning model.

I. INTRODUCTION

Eccentricity, one of the major faults in motors, is a condition in which the air gap distribution around the rotor is not uniform [1], [2]. Eccentricity faults can be further classified as static eccentricity (SE), dynamic eccentricity (DE) and mixed eccentricity (ME). Static eccentricity is typically caused due to manufacturing tolerances and structural deformity in the stator. In case of static eccentricity, the point of minimum air gap remains fixed in space. Eccentricity fault leads to unbalanced magnetic pull, which in turn affects the life and performance of the motor. Therefore, it is important to detect eccentricity fault.

Several approaches have been reported in literature to detect static eccentricity fault. In one approach, sensors have been used inside the machine [3]. However, they are expensive and invasive in nature. To overcome these drawbacks, researchers have focused on model-based eccentricity fault detection schemes [1], [2]. In model-based approaches, induction motor is modelled under normal and faulty conditions. The models are used to predict signals such as current signatures, which are then compared to ascertain the existence of faults. Model-based schemes are non-invasive in nature. However, they are not robust. They are negatively impacted by non-ideal conditions such as supply harmonics, manufacturing tolerances, load variations etc. [4]. In recent times, researchers have focused on data-based schemes for static eccentricity fault detection [5], [6]. In these methods, data obtained from motor are used to train the machine learning models. The models so trained are utilized to detect a faulty condition. Most of the reported work have extracted features from motor line currents and voltages by transforming them to frequency domain [7]. Some of the approaches have used a combination of features synthesized from motor line currents in time-domain and frequency domain [8]. In the reported work, motor line voltage data is used to train a machine learning model that will detect static eccentricity fault in three phase squirrel cage induction motors. Features have been extracted solely from time-domain analysis of motor's line voltages.

II. Proposed Approach

In this research, the developed algorithm is confined to the time-domain as it is computationally less rigorous. Moreover, motor line voltage data alone was chosen to carry out fault detection because the voltage signal had a consistent magnitude regardless of load condition or fault severity. This enhanced robustness of features extracted and thus, a more reliable prediction could be made. Additionally, it was found that just two features, root of sum of squares (RSS) and kurtosis, were sufficient to detect static eccentricity fault. Kurtosis is a description of the shape of a distribution peak. This will give an indication if a peak is sharp or is more plateaued. Kurtosis is given by the following mathematical formula:

$$X_{kur} = \frac{\frac{1}{n}\sum_{j=1}^{n}(X(j)-\mu)^4}{(X_{std})^4} \tag{1}$$

where μ is the mean of a random variable X, X_{std} is the standard deviation of a random variable X. The root of sum of squares (RSS) measures the level of variance of a random variable X. The root sum of squares is given by the equation:

$$X_{RSS} = \sqrt{\sum_{j=1}^{n}|X(j)|^2} \tag{2}$$

The selected time domain voltage features group data according to either a healthy or a faulty condition. The k-NN algorithm is best suited to classify data based off similar data points or feature vectors. This means that given a certain amount of training vectors, k-NN algorithm identifies the 'k' number of nearest neighbours to a new vector and then groups it with that corresponding class. Evidently, the time-domain features selected should distinguish classes in distinct groupings of vectors or data points. The k-NN method can be tailored to further improve results by selecting an appropriate 'k' number of neighbours, distance metric and distance weighting. The method has been used for fault detection in induction motors [9].

III. Training And Testing

To implement the proposed approach, a total of 12 datasets from a 3-phase, 208 V, 3 hp squirrel cage induction motor were collected at a sampling rate of 3600 Hz. Each dataset contained 15 seconds long data. Among the twelve datasets, two were used for training data while ten were used for testing. These data sets come from the same motor operating under various operating conditions. Details about the datasets will be furnished in the full paper.

Two training data sets; one corresponding to a healthy motor and the other a 20% SE motor were used to train the algorithm used in this study. During data processing and feature extraction, each feature set is constructed from the two voltage features, kurtosis and root of sum of squares, along with a third feature known as a response variable. The response variable labels given data to the algorithm for training purposes. During the training phase this 'response variable' notifies the algorithm which data corresponds to which class. In this study, a numeric value is assigned to each set of features to classify it as either healthy or faulty. This allows the algorithm to construct two classes of data: one for healthy motors and one for motors suffering from static eccentric conditions. The algorithm is constructed using the k-NN method. It considers the 5 nearest data points during classification and uses a Euclidean distance metric with equal weight. MATLAB's Classification Learner application identifies this algorithm to be 100% accurate upon creation.

The input data for the algorithm is strictly voltage data which is received in a 15 second data set sampled at 3600Hz. The data is then parsed into 15 separate sets which corresponds to 1 second of data each. Since the machine being tested is a 3-phase induction motor this means there are 15 data sets of 1 second for each of the 3-line voltages. Therefore, the input for a single test contains 45 data buffers. Consequently, the prediction algorithm is designed to make a prediction on each of the 45 data buffers previously mentioned. This is done to improve the accuracy of prediction by examining a single data set in sections and making a prediction on each one. The prediction mean is derived from this output sequence of 1's and 2's.

Table I below gives the prediction results obtained for each of the 10 test data sets. A prediction mean of 1.5 to 2.0 is considered as faulty while a prediction mean of 1 to 1.49 is classified as healthy. Based on the results it is evident that the proposed scheme is able to classify all the data sets accurately.

TABLE I - RESULTS OF THE PREDICTION ALGORITHM

Test	Data Type (Ground Truth)	Algorithm Prediction	Prediction Mean
Healthy	Healthy (1)	Used for training	X
SE-Fault	Fault (2)	Used for training	X
Test 1	Fault (2)	Fault (2)	2.0000
Test 2	Fault (2)	Fault (2)	1.7111
Test 3	Healthy	Healthy (1)	1.3333
Test 4	Fault (2)	Fault (2)	1.9778
Test 5	Healthy (1)	Healthy (1)	1.3333
Test 6	Healthy (1)	Healthy (1)	1.3333
Test 7	Healthy (1)	Healthy (1)	1.4222
Test 8	Fault (2)	Fault (2)	1.6667
Test 9	Fault (2)	Fault (2)	1.6667
Test 10	Fault (2)	Fault (2)	1.6667

Moreover, the prediction results were captured pictorially by using scatter plot of kurtosis vs. root of sum of squares. Fig. 1 shows the result obtained from the algorithm on a training dataset and one of the test datasets (Test 1). More results will be shared in the full paper.

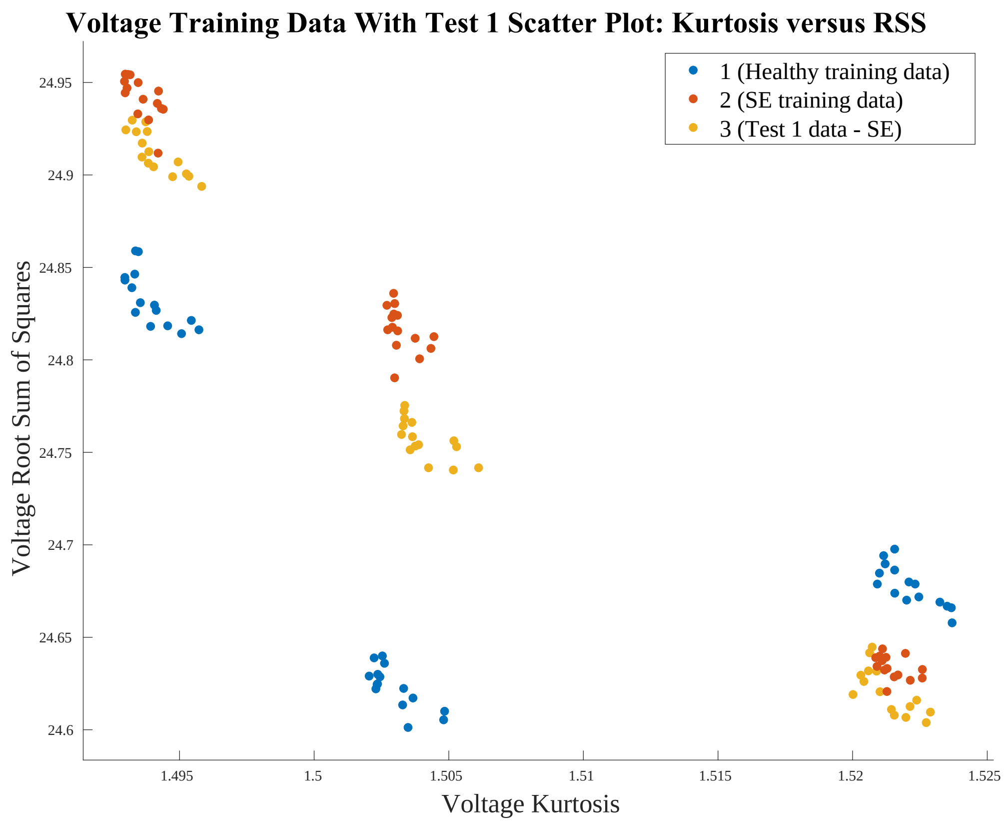

Figure 1: Scatter plot of kurtosis vs. root of sum of squares of Test 1 dataset along with a training dataset. The three clusters of each color correspond to different line voltages.

IV. CONCLUSIONS AND FUTURE WORKS

The proposed work has been successful in detecting static eccentricity fault condition from healthy operating condition in three phase squirrel cage induction motors. The scheme utilizes only two features of line voltage data, namely kurtosis and root of sum of squares, to achieve successful detection. The usage of line voltage data and time-domain features make the scheme simple to implement. In addition, the approach is capable of detecting the fault irrespective of load variations, fault severity and machine parameters. Thus, the scheme is quite robust. In future, the approach will be utilized to determine if fault severity could be classified.

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