Classifier Comparison for Failure Detection of Induction Motors Using Current Signal

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***Abstract*—**Induction motor is widely used in the industry area and the bearing is one of the key mechanical components. The bearing minimizes the friction between the rotating part and stationary part of the rotating machine. It is important to monitor the bearing condition to give a warning before serious failures occur. The fault detection through electrical monitoring has been studied for the last several decades. Although they detect warning signs before serious problems occur, it does not always work when the sampling time is short. This research proposes a learning model for induction motor to diagnose bearing failures which learns features from electrical signatures. This experimental study uses data obtained from 415V, 55KW induction motor and clearance modified plain bearings.

Keywords—classifier, fault diagonosis, plain bearing

I. Introduction

Since Industry 4.0 and Information and Communication Technology (ICT) have been popular issue over the past recent years, smart factory and smart city became attractive area of research. For factories and cities to be fully automated, various types of sensors are needed to gather different types of data from various sources and motors should be controlled properly. If sensors are damaged or data from sensors are corrupt, sensors need to be repaired or replaced before serious accident happens. In case of factory, one malfunctioning motor can ruin entire process, thus detecting the sign of motor failure is significant. Motor failure occurs due to various reasons, such as mechanical defect, misalignment, shaft imbalance, shaft looseness, bearing wear. In this paper, well known machine learning classifiers are used to detect symptoms of motor failure caused by clearance of plain bearing.

II. Motor Fault and Detection Method

A. Plain Bearings

Bearing is a mechanical component that reduces friction between rotary and shaft support of rotating machine. There are 2 common types of bearing commonly used on rotating machine: rolling-element bearing and plain bearing (or plain bearing).

Rolling-element bearing minimize friction with rolling elements placed between outer-race and inner-race of bearing. Unlike rolling-element bearing, plain bearing does not have rolling elements. It only uses lubricant contained in bearing to reduce friction. As shaft rotates lubricant inside bearing forms lubricant film between the shaft and surface of bearing. The lubricant also absorbs heats from rotary motion and its pressure protect damages from shock load. Due to these characteristics of plain bearing, it is commonly applied on heavy load motors with high capacity and high voltage. [1]

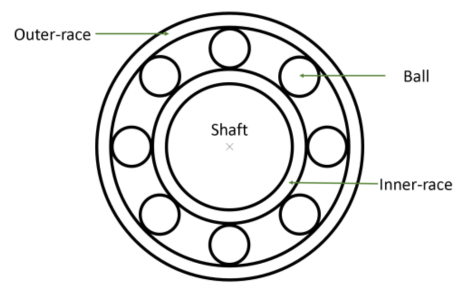

Fig 1. The basic scheme of rolling-element bearing

Plain bearing breaks down, because of instabilities, rub, wear, cavitation, etc. When rotor rotates in high speed, lubricant film can be formed thick enough to support weight of rotor. While the speed of rotation is insufficient, lubricant film cannot be formed properly. Therefore, fretting is inevitable when operation of motor starts and stops. Besides this reason, inappropriate lubricant in bearing or contaminant contained in lubricant cause wear off. As wear progresses, clearance between shaft and bearing widens. Excessive width of clearance causes severe vibration which leads to inefficiency and serious instability. [2]

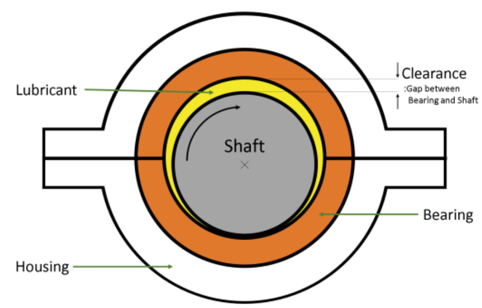

Fig 2. The basic scheme of plain bearing

B. Motor Current Signature Analysis (MCSA)

To diagnosis the defects of induction motor, temperature, vibration and current signal of motor are monitored and analyzed. [3] Temperature and vibration monitoring methods help to evaluate status of the motor, but sensors easily break down and cost is too high. [4] Recently, a research has been done to diagnose using air-gap flux variations. However, this method cannot be applied to diagnosis the state of operating induction motor because a sensor to measure flux needs to be inserted on stator slot. [5]

Also, signal injection method that diagnoses failures by measuring the changes from random signals has been studied, but it bears few problems such as occurring harmonic wave in stator current. [3] On the other hand, motor current signature analysis(MCSA) can be applied on running induction motor to acquire current signals from the motor and analyze the status of induction motor. [6]

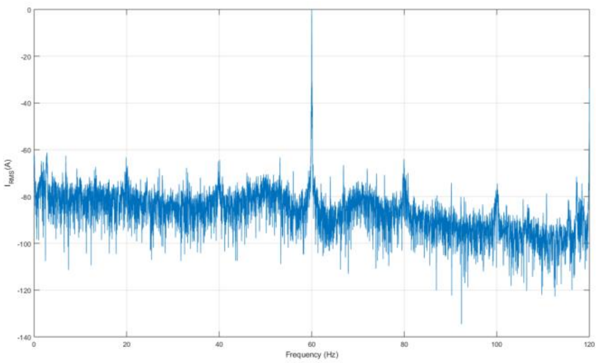

Fig 3. Current Spectrum of Normal Bearing

Generally, MCSA is an analyzing method by applying Fast Fourier Transform (FFT) to current signal supplied into induction motor. Fig.3 shows the resulting spectrum after FFT is applied to current signal.

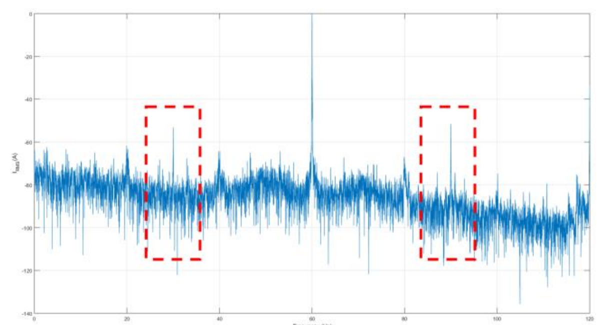

Fig 4. Current Spectrum with Fault Component

In case of signal from broken motor, component of failure will be observed at the point of f_s - $f_m \times (1\text{-}1/2)$ or f_s - $f_m \times$ (1-1/3) symmetrically based fundamental frequency(f_s). As shown in Fig4, fault components are found at the point of 30Hz and 90Hz which is f_s - $f_m \times (1\text{-}1/2)$ of 60Hz. Existing MCSA method has its limitations. However, existing MCSA methods have limitations. It is difficult to distinguish fault components because the frequency of the fault component and fundamental frequency are close to each other. When the fundamental frequency f_s is low, frequency of fault component f_s - $f_m \times 1/2$ and f_s - $f_m \times 1/3$ is only 3~5Hz apart from the fundamental frequency. If the data is received within less than 0.3 seconds, the resolution is lowered, and data is lost. To solve this problem, interpolation can be used to restore the lost intermediate values, but clear results are not being expected. In common cases in industry, average value of data collected within 1 seconds and repeated several times is used in diagnosis. If the MSCA technique is applied to the data measured in less than 1 second, the above-mentioned resolution problem occurs, and it is difficult to identify the fault component as shown in Fig 5.

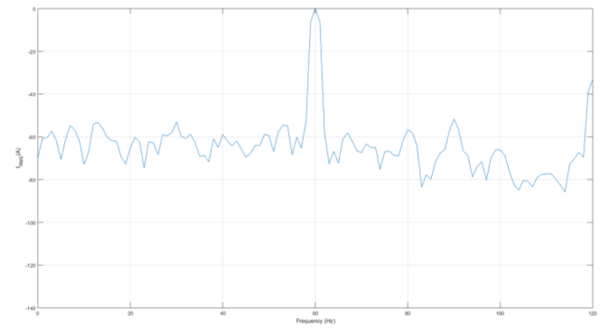

Fig 5. Current Spectrum with Fault Component Measured Under 1sec

III. CLASSIFIERS

Before using machine learning algorithms for predictions and classifying systems, researchers greatly relied on human intuitions. However, the development of learning-based algorithms has resulted in better performance than human intuition in certain areas such as classification. This section provides a brief overview of the algorithms used in this study.

A. Logistic Regression (LR)

Logistic Regression(LR) is one of the commonly used classification models for prediction and forecasting. Just like any other regression models, it estimates relationships between dependent variables and independent variables.

B. Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis(LDA) is a feature vector dimension reduction method to find a linear combination of features. LDA reduces feature vector dimension by maximizing ratio of between-class scatter to within-class scatter.

C. K-NN (k-Nearest Neighbors)

k-nearest Neighbors(k-NN) is a non-parametric statistics method for regression or classification that uses distributions. To set distribution on the average, both classification and regression weights the contributions of neighbors so that the closer the neighbors are, the more they contribute to the average than the farther neighbors

Selecting the best k is dependent on data. Generally, effect of noise reduces as value of k gets larger, as well as boundaries of classes gets less distinct.

D. Classification and Regression Trees (CART)

Decision tree is a predictive model that concludes relationship between observed value and target value of an item. There are two main types of decision tree: classification tree and regression tree. Classification tree is a type of decision tree models with categorical target variable uses a discrete set of values. The decision tree model with continuous target variables is called regression tree.

Classification And Regression Trees (CART) is a type of non-parametric decision tree which produces either classification or regression trees, depending on the dependent variable. By recursive partitioning of the data, CART sequentially splits data into smaller pieces to create subsets of the data using information contained within a set of predictors.

E. Naïve Bayesian (NB)

Naïve Bayesian classification is a probabilistic classifier based on Bayes' theorem, when features are assumed to be independent. It is a family of algorithms based on a common principle assumes that the presence of a particular feature in a class is independent of the value of any other feature.

F. Support Vector Machine (SVM)

Support Vector Machine (SVM) creates a non-probabilistic binary linear classifier model to assign new examples to category based on each example of given set of training examples marked as its category which it belongs to. The classification model, created to find optimized bandwidth, is represented as a boundary in the space where data is pointed, and the SVM algorithm is the algorithm that looks for the boundary with the largest width.

Although training Example includes nonlinear optimization, the problem is relatively straightforward because the target function and solution of optimization are convex.

G. Adaboost

Boosting is an ensemble algorithm to increase accuracy of given learning algorithm. The basic idea of boosting is creating strong learning algorithm by combining multiple weak learning algorithm.

Every round AdaBoost progresses, misclassified data are weighted with observed variables obtained by applying previous classification rules. On contrast, properly classified data are given a low weight. In this way, weak learners can correct the misclassification of the previous classifiers. These characteristics leads Adaboost adaptive and robust to overfitting then other learning algorithms.

H. Gradient Boosting Machine

Learning is a process to find parameters that minimize loss function. One way to find the best parameter is the Gradient Descent. The gradient is obtained by differentiating the loss function by parameters. Moving the parameters in the direction of smaller values reaches the point where the loss function is minimized.

In Gradient Boosting, the loss function is differentiated by a model function learned to date rather than a parameter. Gradient Boosting transfers this differential value to the target of next weak learner. Set the residual of the current model as target and fit a new model. Existing models absorb new model to reduce Bias. Then get the residual again and add it by fitting the model. Repeating this process produces the final model.

I. Random forest

The biggest problem of the decision tree is that it tends to be overfitted to training data. Random forest uses multiple decision tree with different structure to solve overfitting issue. The main concept of random forest is based on assumption that each decision tree predicts comparatively well, but it tends to be overfitted to few data. Consider there is enough number of decision trees with each tree works properly and overfits in different directions. By averaging results from each tree, random forest corrects the overfittings.

J. Extremely Randomized Trees(Extra trees)

Random Forest uses only part of the data samples. However, during node isolation, instead of comparing all independent variables and selecting the best independent variable, the independent variable dimension is randomly reduced and then the independent variable is selected. This reduces the variation in model performance because the correlation between the individual models is reduced. Extreme application of this method is the Extremized Trees model, in which case independent variables are selected randomly on each node.

IV. Experiment and Results

This experimental study uses data obtained from 415V, 55KW 2pole induction motor and clearance modified plain bearings in certain ratio. The plain bearings were modified into 6 different sizes, of which 4 sizes were classified as normal and 2 were classified as abnormal by MCSA. The signals gained from each bearing were labeled normal if the ratio is lower than standard, otherwise those were labeled fault. Total 2160 datasets (360 datasets per each clearance) were used for test. Each data set was collected at a sampling rate of 1000 Hz over 1 second. Classification accuracy and standard deviation for each classifier are listed in Table1.

As shown in Table 1, total 10 classification algorithms are used for experiment. The parameter k for k-NN was set to 3. For SVM, kernel type poly is used, and penalty parameter c was set to 0.5. SVM showed best classification performance at 98.733%. The classification rate of LDA and NB were 89.581% and 87.775%, respectively, which were the two worst classifiers used in the experiment.

TABLE I. CLASSIFICATION RATE WITH DIFFERENT METHODS

Model	Classification Rate (%)	Standard Deviation
LR	95.124	0.024
LDA	89.581	0.015
KNN	97.062	0.009
CART	96.059	0.015
NB	87.775	0.017
SVM	98.733	0.013
AB	96.593	0.014
GBM	97.128	0.012
RF	97.262	0.015
ET	97.460	0.008

V. CONCLUSION

This paper evaluated the applicability of the classification algorithm to detect the increased plain bearing clearance instead of MCSA. Different from MCSA, classifiers were able to detect failure from an example measured for 1 second and in most cases showed over 96% of classification rate.

The results of this work demonstrated that the induction motor can be analyzed through simple classification algorithms. By training the examples of various faults using more complex methods of learning or neural networks, more general and accurate fault diagnosis also seems plausible.

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