Fault Detection for Railway Traction Motor Bearing through Leakage Current

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Much research on detecting machinery faults in the early stage is being conducted for the purpose of preventing failure and reducing maintenance effort simultaneously. In this paper, a bearing fault detection method for a railway traction motor through leakage currents is proposed. The proposed detection method combines octave band analysis and machine learning. Experiments simulating abnormalities due to defective bearings were conducted and the effectiveness of the proposed method was verified. These experiments showed that the proposed method can successfully detect failures in railway traction systems in relation to specific conditions and that leakage current could potentially be used to detect bearing faults.

Keywords: fault detection, bearing fault, leakage current, octave band analysis, machine learning, one-class classification, nearest neighbor

1. Introduction

Failures in railway traction systems occasionally lead to disastrous accidents and therefore periodic maintenance is performed to keep railway vehicles safe. In order to enhance the safety of railway traction systems, much research is being carried out into condition monitoring for vehicle equipment. With respect to general motor failures, almost half originate from bearings [1] and therefore early stage bearing fault detection is important.

As the number of sensors has increased, a lot of condition monitoring methods relying on physical properties such as vibration, acoustic emission, temperature and winding current have been proposed so far [2]-[6]. They often use signal processing techniques and some of them combine those techniques and machine learning. Among them, vibration are widely used in condition monitoring system because of its reliability as a bearing fault defect indicator. When applying vibration monitoring to a railway traction system, a vibration sensor has to be attached to the railway traction motor directly, which exposes it to severe conditions. Moreover, a long signal line that extends from an underfloor traction motor is needed. Therefore, it is preferable to refer to physical properties other than vibrations for monitoring the condition of railway traction systems. This paper focuses on leakage currents, which can be acquired directly from the inverter that provides power to the motor. No sensor has to be attached to the motor.

Leakage current is the current that occurs in an unwanted current path under normal conditions [7]. One of the causes for unwanted current is common mode voltage. Inverters generate a common mode voltage, which causes the common mode current (CMC) flowing from the motor windings to take an unintended path to the ground. Current, which flows through the shaft and the bearings, causes a discharge between the bearing parts and causes deterioration in the contact surface of the bearing. The damage from discharge to the bearing is known as electrical corrosion. There are two approaches to prevent electrical corrosion: bearing insulation and bearing conduction [8]. In Japan, electric corrosion of railway traction motor bearings used to be a serious problem, but insulated bearings were developed to prevent it [9]. Nowadays electrical corrosion is not a major issue for railway traction motors in Japan because of insulated bearings. However, insulated bearings may work as capacitors due to the insulation layer of the outer race. Due to the capacitance and the number of voltage pulses from the inverter, a small leakage current may flow through the bearing. This means that there is a possibility that a bearing fault could be detected from leakage current variance due to the bearing fault. In addition, research is being conducted into bearing fault detection using common mode currents [10]. In this research, two bearing diagnosis methodologies were proposed. The first method counts the number of discharge pulses that exceed a prefixed threshold value. According to the research, the amplitude of CMC discharges decreases with faulty bearings so this means the number of large pulses decreases as the bearing deteriorates. Second method is to analyze the CMC in frequency domains. The frequency of the highest peak shifts to the low frequency side with bearing degradation so they can be detected by monitoring the CMC peak shifts. In this research, experiments were conducted and demonstrated that a fault in a bearing affected the CMC somehow.

In parallel, a method for monitoring the condition of equipment on diesel railway cars is also being developed. The method combines octave band analysis of vibrations and machine learning algorithms. Octave band analysis is a frequency analysis method, which is often used for acoustic emissions and noise evaluations. In addition, a classification technique using machine learning was adopted. In one-class classification, the detection of abnormalities is conducted only by using normal condition data. The effectiveness of the method was verified through bench tests and experiments using actual cars [11]-[15]. The method has a general applicability so it was applied to detect bearing faults through leakage current.
The following section introduces a bearing fault detection method combining octave band analysis and machine learning [16]. Experiments were conducted by simulating an inner race fault with a defective bearing. Section II describes the diagnostic method. Section III describes the experimental procedure and results of the measurement and diagnosis. Section IV discusses the results and the conclusion is given in Section V.

2. Diagnosis method

For the bearing fault detection from a leakage current, a method combining octave band analysis and one-class classification was used. The method was originally developed as a vibration monitoring system for railway diesel cars.

Faults in railway traction equipment often produce abnormal noise and are thus detected by train crews or passengers unfamiliar with train installations. This implies that special knowledge about traction gears is not required to detect a problem if one is aware of how a train normally sounds. In order to diagnose railway traction equipment problems in the same way humans can, octave band analysis, which is similar to human hearing, is used to detect vibrations.

In order to conduct a diagnosis amid the complex vibrating environment of a railway traction system, classification technique in machine learning was used. For classification, a classifier is trained with a sufficient amount of data for each predefined group, so that it can classify the data correctly. When using machine learning, sufficient data for respective classes are needed for correct diagnosis. However, data relating to failures in railway traction systems is hard to obtain. Thus in this study, a fault detection system was developed using a one-class classification method [17], which only uses normal data.

![Schematic diagram of the fault detection method](image)

For the detection of abnormalities in diesel railway cars, the one-class classification method was designed, which is based on the nearest neighbor principle. The method works as follows:

Signals are measured and 1/12 octave band analysis is applied to those signals every second. Next, the dimensions of the analyzed data are reduced by principle component analysis (PCA). The number of principle components is set to 6. Then, preprocessed data is plotted in a multi-dimensional space. If two pieces of data have similar frequency components, the two must be plotted closely in this space. Therefore, normal data items are plotted closely together as shown in Fig. 1 when normal condition signals are similar and stable.

In the case of fault detection, the diagnosis program learns what a normal condition is from the training data (normal data). After the training, test data is plotted in the multi-dimensional space and the distance between the test data (point X) and the nearest training data (point A) is calculated. The test data is diagnosed as abnormal when the distance is longer than the reference distance. The reference distance is determined so that 99% of the data are diagnosed as normal when the training data are diagnosed as the test data. The degree of abnormality is defined below.

\[
f(x) = \frac{|x - NN(x)| - 1}{d}
\]

where \(x\) and \(NN\) are the coordinates of the test data and the nearest point among the training data respectively, and \(d\) is the reference distance. The degree of abnormality becomes positive when the data is diagnosed as abnormal.

The above value is affected by false-positive data in the training data. Therefore, the average of the distances between the test point and a certain number of nearest points should be used as the value representing the degree of abnormality. The detail of the refined degree of abnormality is described in [15]-[16]. The program was created using a scikit-learn machine learning library [18].

This method needs neither abnormal data nor parameter adjustments with respect to the equipment. The abnormality simulation experiments were conducted with the engine test bench and it was shown that the diagnosis program detected the fault [13]. This diagnostic method has general applicability, and therefore the same method was applied for fault detection through leakage current in railway traction motor bearings.

3. Experiment simulating abnormality

3.1 Conditions of the experiment

The experiment simulating an abnormality was conducted to verify the proposed diagnosis method. Currents leakages in the motor were measured on normal and abnormal bearings under various conditions. Both bearings
were insulated. The test equipment is shown in Fig. 2. Two induction motors that had been mounted in a train were used. One motor was used as a test motor and sensors were attached to it. The other one was used as a load, which generated torque against the traction motor.

Their output shafts were connected to each other through a torque gauge and the torque was measured during the experiment. The test motor was cooled with a forced convection cooling system with the air volume adjusted to 20 m³/min. Thermocouples were installed in the motor to check the temperature and prevent overheating. The leakage current was measured using a current sensor (Pearson 301X) as shown in Fig. 3.

The experimental conditions are shown in Table 1. First, an experiment with a normal bearing was conducted. Before starting the experiments, the load-side and anti-load-side bearings of the test motor were removed. Then the cleaned anti-load-side bearing was replaced with a brand new bearing (shown in Fig. 4) was installed to the load-side. After the installation, the traction motor was driven for 3 hours to stabilize the grease in the bearing.

To simulate a bearing abnormality, a bearing with an artificial fault was made. Simulating a local defect, the surface of the inner race was machined to make it partially flat as shown in Fig. 5. Then the bearing was cleaned and new grease was packed into it. After completion of the experiment with the normal bearing, the load-side bearing was replaced with the defective bearing and the experiment was conducted after a running in.

For normal and abnormal bearings, the experiments were conducted at six different speeds with full-load and no-load. With the full-load, the load motor generated torque against the test motor. The torque of the load motor depended on the rotational speed of the test motor as shown in Fig. 6. Without a load, the load motor did not generate torque and the test motor generated small torque.
to maintain the rotational speed. In each case, the motor was accelerated from a standstill, continued rotating at the specified rotational speed for 180 seconds at least and then stopped. First, the “1st Normal run” experiment was conducted using a brand new bearing. Then, a “2nd Normal run” was performed using the same bearing for the same experiment. After this, an “abnormal run” was performed with the defective bearing.

The leakage current was measured using the developed condition monitoring system. The sampling frequency for monitoring was 12.5 kHz and octave band analysis was applied to the measured signals every second. The specifications of the condition monitoring are shown in Table 2. The recorded and processed data were saved automatically in an external USB device when the specified input value exceeded the preset threshold values.

### 3.2 Measurement results

The condition monitor saves the root mean square (RMS) values and octave band analysis data from the measured values. This section presents the octave band analysis data from each experiment.

The octave band analysis results of the leakage current are shown in Fig. 7. Each colored domain in the graph represents the range in fluctuation of magnitude during the 180 seconds for each running condition. The blue and orange lines represent no-load and the green and red lines represent the full-load condition. The blue and orange bands are results of the normal bearing and the green and red bands are that of the abnormal bearing. The X and Y axes show the frequency of the leakage current and the root-mean-square value of the leakage current, respectively.

Under a full-load, some peaks were found. The highest peak came from the inverter current frequencies, which corresponds to the product of rotational speed and the pole pairs of the induction motor. The effect of the bearing fault on leakage current was small, and two band graphs overlapped at almost all the frequencies.

With no-load and during the PWM mode (900 and 1800 rpm), the two band graphs overlap and the effect of the bearing fault was small. However, when the inverter shifted to the rectangular wave mode, the magnitudes of frequency components (especially more than 1000 Hz) changed obviously. The bearing fault increased the high frequency components of the leakage current by more than 10 dB.

From the octave band analysis results, the effect of the bearing fault on the leakage current frequencies were shown especially for the no-load condition and during the rectangular wave mode.

### 3.3 Diagnosis results

This section evaluates the performance of the diagnosis based on leakage currents, using measured data. Training and normal test data were created from “1st Normal” and “2nd Normal” experimental data. Data corresponding to the same load and speed conditions were mixed and then separated randomly into training data and normal test data. The diagnostic program studied “normal conditions” based on training data and diagnoses were conducted using normal and abnormal test data.

From the octave band analysis results, it was shown that impact of a fault differed with frequency. As shown in Fig. 7, the effect of a fault on a low frequency component (less than 100 Hz) is lower than on a high frequency component. In this paper, only the high-frequency band (more than 1000 Hz) are used for the diagnosis.

The diagnosis results obtained using the high-frequency band (1000-5000 Hz) are shown in Fig. 8. Abnormalities in the normal test data had negative values under all conditions and correct diagnoses were obtained for the normal bearing. In the case of abnormality detection with a full load, the diagnosis program only detected a fault at 3600 rpm and the calculated abnormalities were small. In the case of no-load, the diagnosis program did not detect any fault when the inverter was operated in PWM mode. However, when the inverter shifted to the rectangular wave mode (more than 3600 rpm), all the abnormalities became positive values and the diagnosis program successfully detected the fault in the bearing. Abnormalities increased in accordance with the speed and it was confirmed that the bearing fault was detected clearly when there was no load during the rectangular wave mode.

### 4. Discussion

A comparison of measurements and results of the diagnoses with previous work [10], led to the following findings:

**Different fault types could affect the leakage current differently and the impact of each defect on the leakage current was unclear.**

According to previous work, the capacitance of the bearing decreases as the bearings and their lubricant deteriorate. As shown in Fig. 5, the fault type in this study was a single point defect and the high frequency components of the leakage current increased when there was no load during the rectangular wave mode. This suggests the likelihood that capacitance increased due to the bearing fault. Although strict comparisons are not possible because the experimental conditions were not identical, different bearing fault types could have a different impact on the leakage current.

**The operating conditions of the motor such as load and inverter operation mode, could also affect the leakage current.**

The degree of abnormality calculated from the high frequency components of the leakage current grew when the motor was operated with no load during the rectangular wave mode. Moreover, the high frequency components did not change with a full load or in PWM mode. The operating conditions of the motor could influence the leakage current. In previous work [10], variations were found in the leakage
current but the operating conditions of the motor were not described in detail.

5. Conclusion

In this paper, a fault detection method based on leakage current was proposed and experiments simulating abnormalities were carried out using a bearing with an artificial fault, to verify the effectiveness of the proposed method.

Using the newly developed condition monitoring system, the RMS values and results of octave band analyses conducted on leakage currents, were recorded during the experiment. From the average values, it was deduced that the bearing fault decreased the impedance of the bearing and increased the leakage current values. The octave band analysis results revealed that the bearing fault affected the high frequency components of the leakage current especially when there was no load in the rectangular wave mode.

Abnormalities were then diagnosed through octave band analysis, followed by one-class classification. Using the diagnosis program, the degree of abnormality in normal and abnormal test data was calculated. Using the high frequency bands of the leakage current, the diagnosis program was capable of detecting the bearing fault correctly when there was no load, during the rectangular wave.
mode. These results verified that leakage current could potentially serve as an index for abnormalities in the form of bearing faults, under specific conditions. Leakage current may however be influenced by other components, which were not included in the present experiments. This means that the mechanisms underlying leakage current variance have to be clarified.

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