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Lubrication Leakage Alarm of Wind Power Gearbox Based on K-nearest Neighbor and Back Propagation Neural Network

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Abstract: This study proposes a lubrication leakage alarm approach which can detect the lubrication leakage of a gearbox by only using generator current without any additional measurement apparatus. First, in the study, the 11 current signals on each lubrication level from full to empty, at 10% intervals, were tailor-made. Second, their features are extracted, from which the criteria of detection system are selected. Finally, the k-nearest neighbor and back propagation neural network are employed to detect the lubrication leakage. The results indicate that this approach can trigger the alarm system precisely when the remaining lubrication levels are less than 30%, in which the accuracies are all reach 97.5%.

Key words: Lubrication leakage alarm, generator currents, feature extraction, K-nearest neighbor

INTRODUCTION

A wind turbine is expensive and it often malfunctions due to a single fault component, especially a gearbox which plays a key role in a wind generator system (Izidi *et al*., 2011; Barzdaitis *et al*., 2010, 2011). Inadequate lubrication or lubrication leakage may lead to gear attrition which may cause vibration, noise or damages with high temperature effect. Therefore, users or operators should avoid the problems by monitoring the lubrication level of gearbox anytime. Today, many literatures about gearbox faults focus on the solutions for the gear attrition in (Yang *et al*., 2007; Rajagopalan *et al*., 2006; Mohanty *et al*., 2006), but not for the observation problems of lubrication leakage. Li *et al*. (2010) and Yang *et al*. (2008, 2010) accelerometers are employed to detect if a gearbox malfunctions by examining its operation vibration signals. However, the results will be affected by numerous reasons (1) Aging facilities, (2) Lots of accelerometers are needed to investigate the status of a gearbox, (3) Environmental disturbances and (4) High price of accelerometer apparatus. Therefore, this study proposes utilizing a Lubrication Leakage Alarm (LLA) approach without any accelerometer to analyze the current signals of a generator. It efficiently reduces the cost of detection and maintenance and can be applied to monitoring the status of a wind turbine

The LLA approach for a gearbox can be divided into two parts (1) Measurement and handling of the current signals and (2) LLA system. First, the features of the measured current signals are extracted to be the detection criteria of the system. Second, the detection models of 11 different lubrication levels are manufactured. Then the system can alarm the gearboxes whose lubrication level is below the threshold.

Artificial neural networks (Bagheri *et al*., 2010; Wu *et al*., 2009; Huang *et al*., 2007) with great recognition are often used to detect the status of a gearbox. There are many algorithms of neural networks, for example, Back Propagation algorithm (BP) which is used most widely in (Babu *et al*., 2008) but has drawbacks such as over-training and locally optimum in the training process; fuzzy algorithm in (Aguero *et al*., 2007; Stan *et al*., 2009; Sahraei *et al*., 2010) which works as the fuzzy data is complete enough; Probabilistic Neural Networks (PNN) in (Yang *et al*., 2006; Stasiskis *et al*., 2010) whose classification standard is the maximum of multiple probability density functions. This study adopts K-Nearest Neighbours (KNN) to detect the lubrication levels, because it is simple and fast without training in advance. Compared with BP and other algorithms, KNN is more suitable for online detection. Thus, the handling methods of signals and the LLA approach can achieve the same detection accuracy as the vibration analysis without extra accelerometer apparatus.

The experiment procedures contain (1) Driving wind generator with a dynamometer test bed instead of wind energy to obtain output current signals of the generator

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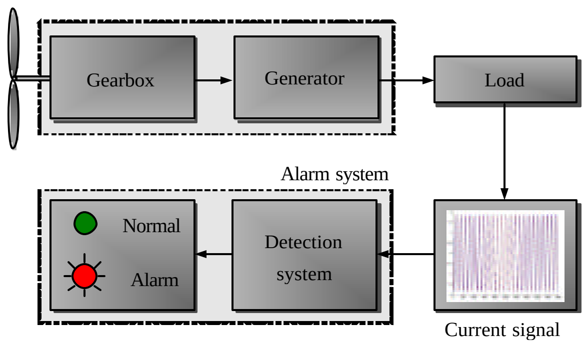

Fig. 1: Lubrication leakage alarm (LLA) flowchart

on different lubrication levels, (2) Extracting features of the current signals and training the detection systems by the feature vector, (3) Utilizing the trained system to detect the lubrication level of a gearbox and (4) Showing alarm signals to those gearboxes whose lubrication level is below the threshold. The process is shown in Fig. 1.

CURRENT MEASUREMENT AND ANALYSIS

Structure of the measurement: The measurement steps are (1) Measuring the current signals and (2) Constructing the alarm system. This study uses a dynamometer test bed composed of a 11 kW driving motor, a 10:1 deceleration gearbox to drive a 300 W-360 rpm wind generator. The output current of the generator is delivered to the electronic loads and recorded by the National Instruments (NI) PIX-1033 signal recorder. In the experiment, there are 1,100 current signals obtained at 10% intervals from full to empty. The 100 samples are extracted from the signals depending on every lubrication level. We used 90 samples for training and the remaining 10 samples for testing.

Feature extraction and selection: Seven characteristics are extracted from the acquired signals, including maximum (MAX), minimum (MIN), average, Standard Deviation (SD), Mean Squared Error (MSE), variance and median. To advance the efficiency of the detection system, the dimension of input characteristic vectors must be decreased. This study randomly selects three characteristics into a group and sifts the most accurate characteristic by the system which will be the detection criterion of KNN and BPNN, as shown in Fig. 2 and 3.

DETECTION SYSTEM

This study proposes a detection system which provides the threshold lubrication alarm level. And the

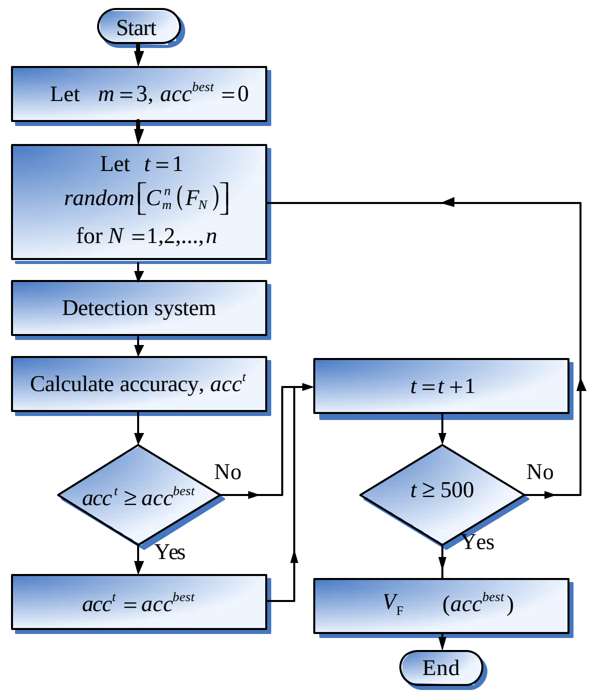

Fig. 2: Feature extraction and selection flowchart

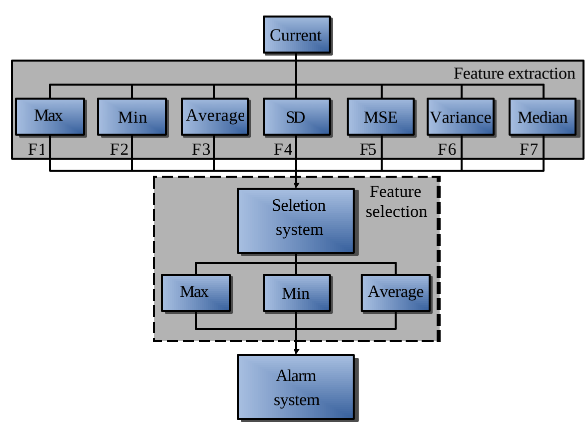

Fig. 3: Feature extraction and selection structure

threshold depends on the recognition accuracies obtained by the KNN and BP. The detection model, including the measured currents of each lubrication level, is built up, as shown in Fig. 4, in which the from the (n+1)th to (n+m)th levels can be successfully recognized as a fault alarm.

k-nearest neighbour (KNN): KNN, a type of supervised learning, is the simplest one among all machine learning algorithms. In KNN classification, similarities between labelled feature vectors and unlabelled feature vectors are compared and k nearest labelled feature vector in a feature

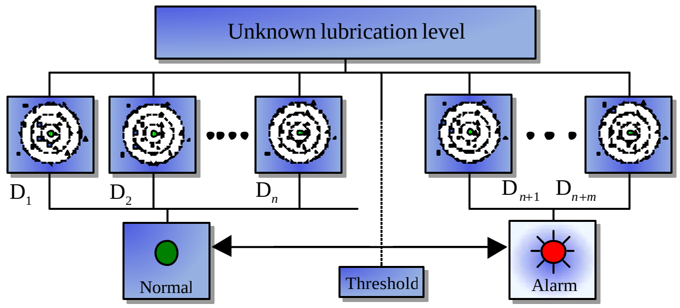

Fig. 4: Detection system structure

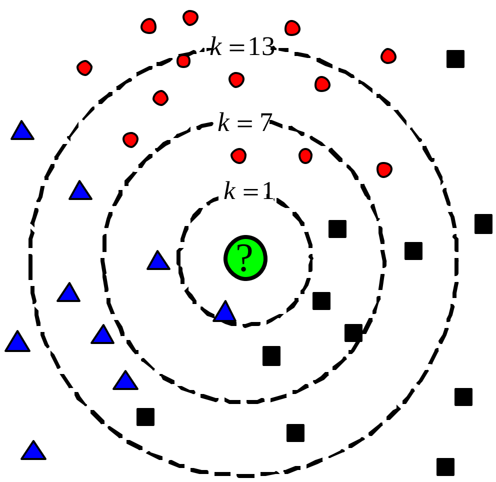

Fig. 5: Example of KNN classification

space is considered to decide the type of unlabelled feature vector based on the majority, as shown in Fig. 5, in which, for example, the test sample (green circle) should be classified to the black squares, the red circles or the blue triangles. If k = 1, it is assigned to the blue triangles. If k = 7, it is assigned to the black squares. If k = 13, it is assigned to the red circles. Euclidean distance is used as the distance metric as shown in Eq. 1:

$$dist^i = \sqrt{\sum_{m=1} (p_m - x_m)^2} \tag{1}$$

where, dist is Euclidean Distance; i is the i-th classification; m is the m-th type of feature vector; p_m is m-th type of feature in unknown vector; x_m is m-th type of feature in know vector.

Back propagation (BP): BP algorithm is a multi-layer feed-forward neural network, including input layers, hidden layers and output layers, as shown in Fig. 6. It is a type of supervised learning for dealing with the nonlinear relationship between input and output in (Babu *et al*., 2008). Input training vectors and its corresponding expected values are trained, as shown in Eq. 2-4. Steepest descent method is used to modify the weights and the biases, as shown in Eq. 5-6. After k times training, error function is minimized in Eq. 7:

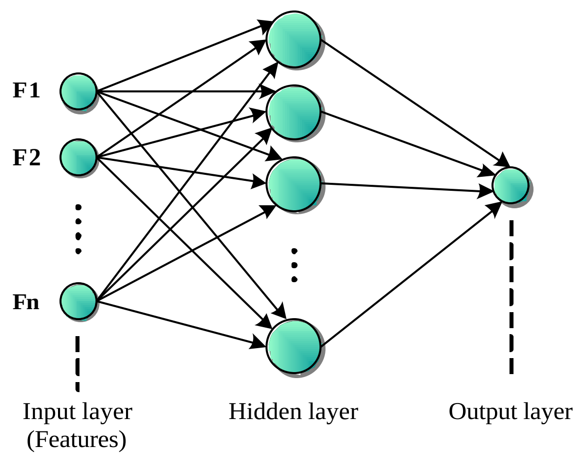

Fig. 6: Neural network structure

$$a^{m+1} = f^m(a^m w+b) \tag{2}$$

$$a^0 = p \tag{3}$$

$$e(k) = t-a(k) \tag{4}$$

$$w^m(k+1) = w^m-aea^{m-1} \tag{5}$$

$$b^m(k+1) = b^m(k)-a^e \tag{6}$$

$$F(k)Se^2(k) \tag{7}$$

where, p is the feature of input; t is target value; a(k) is the output after k times training; $f^m(.)$ is transfer function; w_m is weight of m-th layer; b_m is bias of m-th layer.

RESULTS AND DISCUSSIONS

We chose 11 lubrication levels which are from empty to full at 10% intervals and the current signals on each level of the gearbox was measured. Assume that the full level is healthy and the other levels should be recognized as abnormal statuses for triggering the alarm system. The generator currents of each lubrication level were compared to that of the full level. For example, the D0 means the comparison of the full level and remaining 0% level, empty level. The feature spaces of the D0-D9 are shown in Fig. 7-16 which means that the lubrication gets fewer, the features disperse much extremely. Thus, the D0-D9 recognition accuracies were obtained by 10-times cross-validation, as shown in Table 1. The results show that when the remaining lubrication level is below 30%, the detection accuracy of KNN is 97%; however, BP

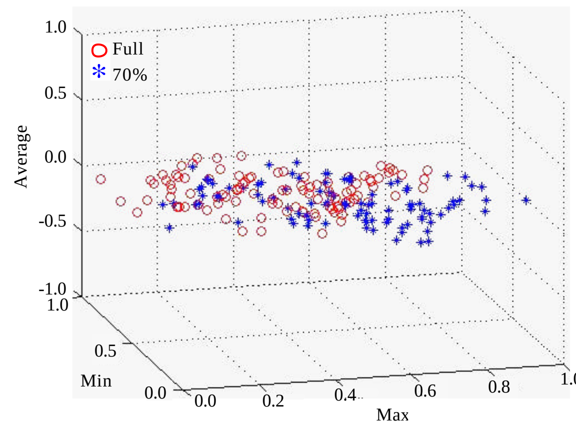

Fig. 9: The feature spaces D7

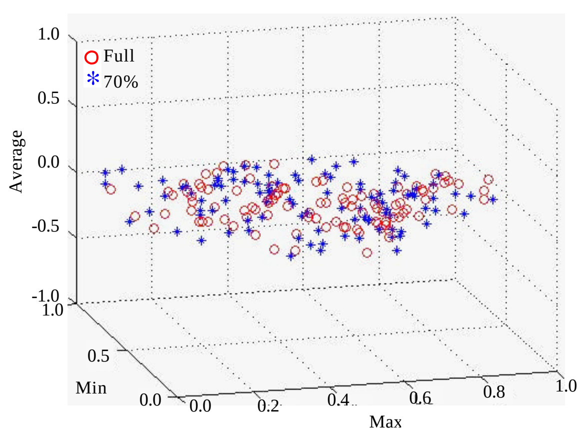

Fig. 7: The feature spaces D9

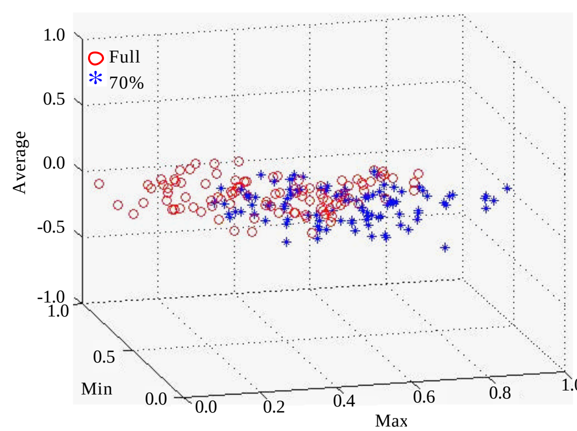

Fig. 10: The feature spaces D6

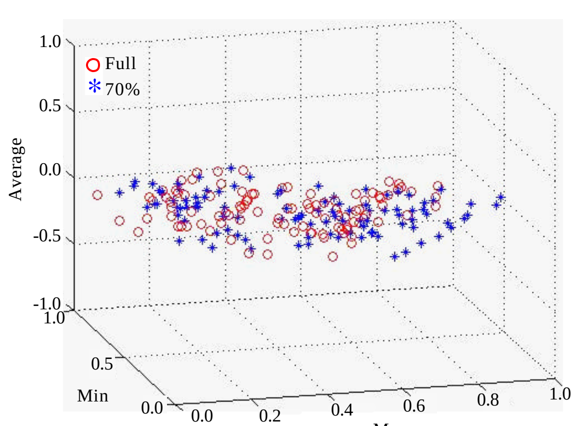

Fig. 8: The feature spaces D8

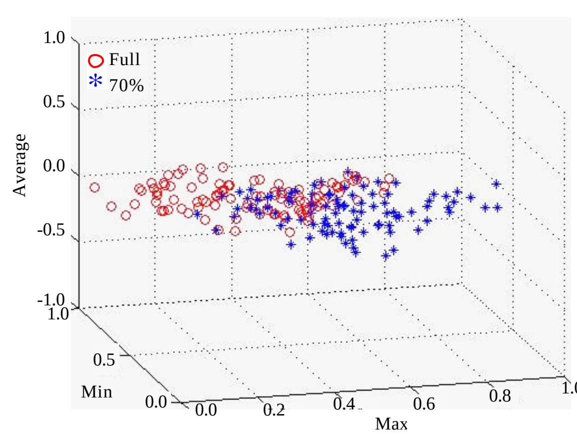

Fig. 11: The feature spaces D5

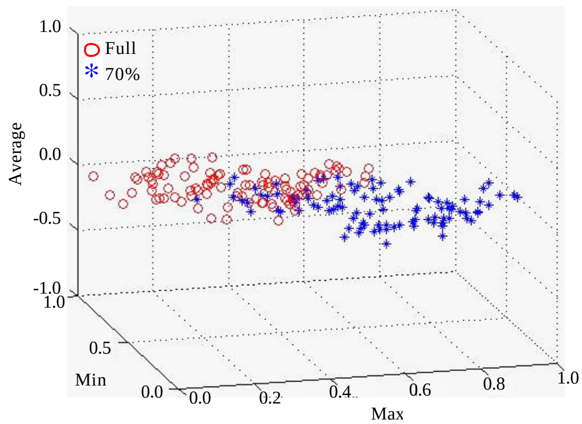

Fig. 12: The feature spaces D4

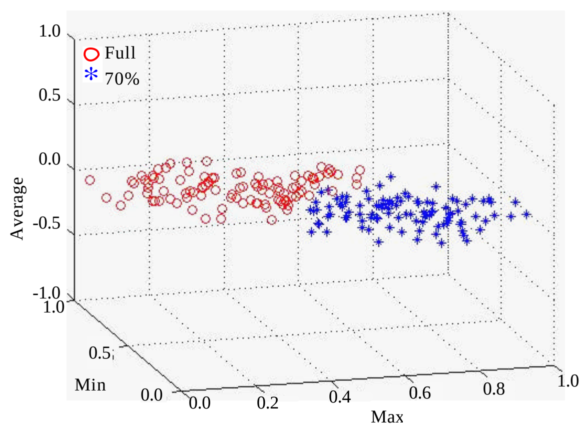

Fig. 13: The feature spaces D3

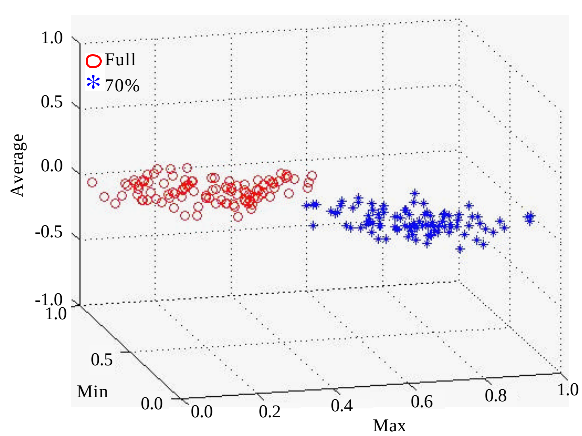

Fig. 14: The feature spaces D2

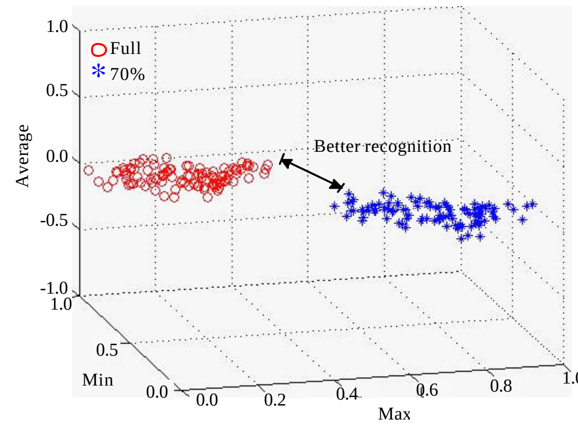

Fig. 15: The feature spaces D1

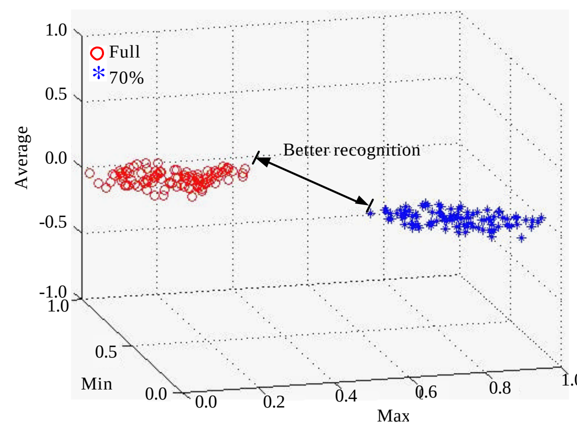

Fig. 16: The feature spaces D0

Table 1 Recognition accuracy of the detection system

Method	KNN (%)	BP (%)
D9	56.0	50.0
D8	55.0	50.0
D7	60.5	50.5
D6	71.0	56.0
D5	71.5	62.5
D4	79.0	68.5
D3	97.0	89.5
D2	98.5	97.5
D1	99.0	98.5
D0	99.0	99.5

reaches the accuracy 97.5% only when the lubrication is below 20%. Consequently, 30% lubrication level is chosen to be the threshold of LLA because of the reliable recognition alarm and the alarm system will be triggered when the lubrication level is less than 30% in the study.

CONCLUSION

This study proposes a LLA approach utilizing output current signals of a generator instead of traditional vibration signals. The features of the signals are extracted, from which the selection system selects appropriate features. KNN and BP are used as the detection methods. The results indicate that the threshold can be decided by the two detection methods. From the results, levels less than 20% lubrication based on the BP method can be efficiently recognized which the accuracies are all over 97.0%. Moreover, using KNN method to recognize the lubrication levels, the system is available to the levels less than 30% and the recognition accuracies can all reach 97.5%. Thus, the KNN-based LLA is superior than BP- based LLA in accuracy and detection levels.

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