Classification of damage for planetary gear of wind turbine simulator

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ABSTRACT
A planetary gear of a wind turbine is a critical component in the view of condition monitoring and fault detection because the fault of the gear needs much cost and time to fix or replace it. In this paper, classification of damage for a planetary gear is proposed and validated by the experiment of wind turbine simulator in order to evaluate the possibility of the application to fault detection of a real wind turbine. Vibration data for various faults of a gear are acquired in wind turbine simulator. Then, effective metrics induced by the gathered vibration data are determined by using vibration data with constant rotational speed. Finally, classification of damage is performed by using neural network with normalized features and bin concept when rotational speed of wind turbine simulator is varied.

Keywords: Gear, Damage detection, Damage classification, Bin, Artificial neural network

1. INTRODUCTION

Operation and maintenance(O&M) costs are critical factors to determine efficiency and cost-effectiveness of a wind turbine system. Especially, if a wind turbine is installed on offshore and its size increases dramatically, reduction of O&M cost is a primary objective in order to make wind energy more competitive. Since the O&M cost is directly dependent on reliability and availability of a wind turbine, condition monitoring and fault detection, which enable proactive maintenance planning and decrease downtime, are essential and imperative technologies for a wind turbine.

It is widely known that fault or damage of the reduction gearbox requires much cost and time to fix or replace. Correspondingly, damage detection of gearbox has been attractive to many researchers during several decades. In result, there are many techniques and methods to detect and identify the damage of gearbox for a rotating machine with constant rotational speed[1-5]. A few of the researches explained frequency components to evaluate their amplitude by using analytical models[6, 7]. Most of the research was to use experimental methods, which found the characteristics of measured signal. Especially, there have been few researches for a rotating machine with non-stationary operation such as a wind turbine.

In this paper, damage classification method in addition to damage detection is proposed. By employing the concept of bin, which tolerates a little variation of rotational speed, It is shown that a simple classification method using artificial neural network(ANN) is feasible to apply to a gearbox of a wind turbine even if rotational speed of the wind turbine varies. Vibration data acquired by wind turbine simulator with four types of damaged gear are used to show that the proposed method is able to classify the type of damage successfully.

2. Damage metrics for a gearbox

There are numerous techniques which were developed for damage detection of gear[1-3]. Vibration-based techniques among them are known as the most effective and efficient techniques to

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detect the damage or fault of the gear. The simplest way to use vibration signal is to define a metric, which is usually called as a monitoring index, and then observe the metric. If the metric is below a pre-defined threshold, the gear is regarded as being heathy. On the other hand, if the metric exceeds the threshold, it can be considered that damage or fault on the gear occurs.

Many researchers have contributed to develop and propose various statistical metrics by using acquired vibration signal. Representative metrics are listed on Table 1[2].

Table 1 – Various metrics for damage detection of gear

Metric name	Abbreviation	Definition*	
Root mean square	*RMS*	Root mean square below 1 kHz	Each sensor
High frequency band pass	*HFBP*	Root mean square from 1 kHz to 12 kHz	Each sensor
Sideband energy ratio	*SER*	$\sum_i A_i^{sideband} \Big/ A^{GMF}$	Each gear mesh frequency
Crest factor	*CF*	A^{P-P} / RMS	Each sensor
Peak ratio	*FM0*	$A^{P-P} \Big/ \sum_i A_i^{GMF}$	Each sensor
Energy ratio	*ER*	$\left(RMS \Big/ \sum_i A_i^{GMF} \right) - 1$	
Normalized GMF	*N-GMF*	$\left(\sum_i A_i^{sideband} + A^{GMF} \right) \Big/ RMS$	Each gear mesh frequency
RMS ratio	*RMS_ratio*	$RMS / (RMS + HFBP)$	1500

* $A_i^{sideband}$: Amplitude of ith sideband

A^{GMF} : Amplitude of gear mesh frequency(GMF)

A^{P-P} : Peak-to-peak amplitude

3. Strategy of damage classification for a gearbox of a wind turbine

3.1 Concept of bin

Because a wind turbine is forced by natural wind, the rotational speed of the wind turbine, which is determined by wind speed, continues to vary. As damage detection methods of a rotating machine were generally developed for constant speed, an additional procedure to the damage detection method is needed in order to apply it to the wind turbine. In this paper, the concept of bin is chosen as a tool to consider the characteristic of varying rotational speed. The bin was proposed by International standard IEC 61400-25-6 to implement the efficient triggering for storing data of condition monitoring system(CMS). Then, it can be applied to damage detection and classification successfully.

Bin is a statistical term to represent a range of a variable. If a variable stays within a range, which is called as a bin, for a certain period, we can consider that the variable belongs to the bin. Similarly, if operational condition of a wind turbine stays within a range defined by operator for a certain period, status of the wind turbine can be considered as being quasi-stationary although real operational conditions of the wind turbine continue to vary in accordance to the speed of wind. If the concept of bin is applied to the damage detection of a wind turbine, the damage detection is not always carried out for all the operational conditions. Instead, the damage detection is executed when an operational condition, which is exemplified by rotational speed of the wind turbine, stays in the bins.

Damage detection using the bin has two advantages: 1) damage detection method with constant rotational speed can be applied to wind turbine with varying rotational speed. It is not necessary to utilize complicated signal processing methods in order to manipulate non-stationary signal. 2) Damage detection for various rotational speeds can be realized. As an operator determines the number of the bins, the number of rotational speeds, on which damage detection is performed, is decided.

3.2 Artificial neural network

Artificial neural network(ANN) has been used popularly for pattern recognition and damage detection for several decades. Basically, ANN is a classifier to gather information and then make a decision for status of a target system. Therefore, ANN is able to distinguish a type of damage by damage metrics as well as detect the existence of damage. After vibration data are acquired for various types of damage for a gearbox when the gearbox operates in constant speed, ANN is trained by a supervised learning algorithm. Then, measured data are inserted into trained ANN and the type of damage is identified from the output of the trained ANN. Even if such procedure is a general method for damage detection, one additional treatment is required with the concept of bin employed when the ANN is trained. Since the rotational speed of a wind turbine is varied slightly in spite of staying on a bin, the variation of train data due to the variation of rotational speed should be considered. The train data are made by adding the Gaussian noise to the original train data in order to tolerate the variation of measured data like Eq. (1)

$$\mathbf{v}_{training} = \mathbf{v}_{original}\left(1+\alpha n\right) \tag{1}$$

Here $\mathbf{v}$ is a vector as an input of ANN and n is the Gaussian random noise with zero mean and unit variance. α is the magnitude of the noise. α means amount of variation of vibration within one bin. The determination of α is dependent on the width of the bin and characteristics of the gearbox.

3.3 Metric selection

Among various damage metrics, good ones should be chosen for effective classification of damage because the selection of the metrics is critical to determine the ability of the classification. There are two conditions for effective classification of damage when we want to classify the type of damages by using the concept of bin. One is that a good metric should have little variance for a type of damage. For different rotational speeds, the good metric should have almost same values with respect to the same damage. The other is that the good metric should have large variance for one of rotational speed. For the same rotational speed, the good metric should have definitely different values with respect to the different types of damage. Mathematically, two conditions are represented by Eq. (2) and (3)

$$\text{Minimize } \sum_i \text{var}[damage]_i \tag{2}$$

$$\text{Maximize } \sum_j \text{var}[speed]_j \tag{3}$$

Here, $\text{var}[damage]_i$ is variance of metrics of a damage case in i^{th} rotational speed and $\text{var}[speed]_j$ is variance of metrics of a rotational speed in j^{th} rotational speed.

To combine both conditions of Eq. (2) and (3), rank analysis is performed in terms of each condition. Then, good metrics for the classification are chosen to minimize the summation of ranks.

4. Experiment

4.1 Wind turbine simulator

Wind turbine simulator shown in Figure 1 is constructed to acquire vibration responses for damaged bearing and gearbox easily because actual bearing and gearbox installed in wind turbine are too difficult to manipulate. The wind turbine simulator consists of flywheel, which represents blades, main bearing, planetary gear and motor which operates instead of a generator. Moreover, a driving servo motor is equipped to make the simulator run instead of natural wind, and a planetary gearbox is installed to introduce damaged gear for each type of gearbox.

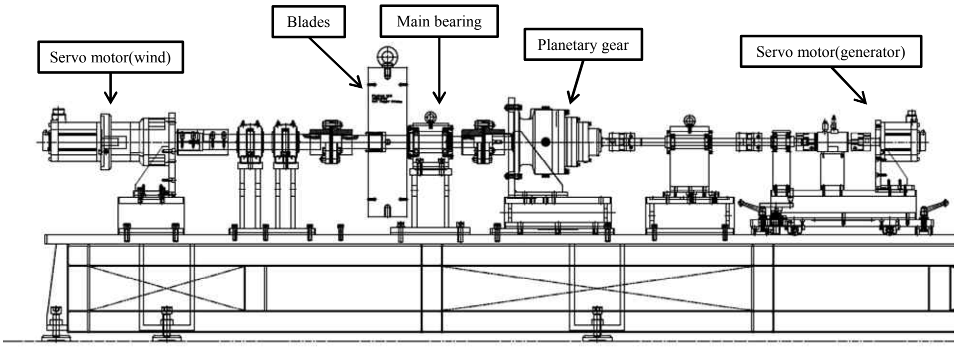
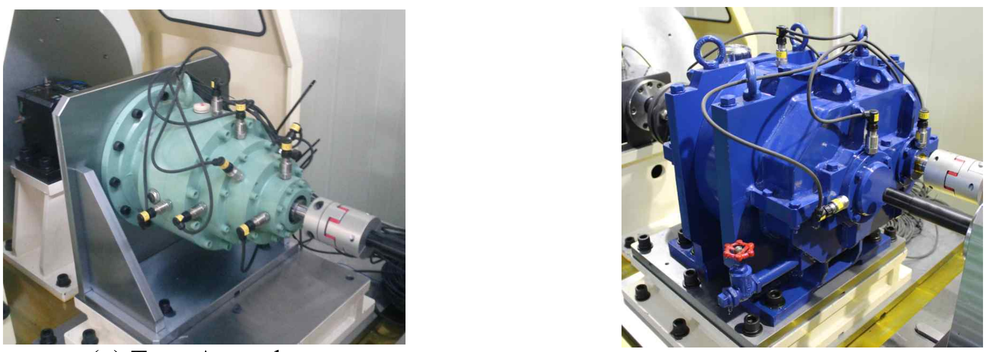


Figure 1 Wind turbine simulator

In this paper, two types of planetary gearboxes are considered to classify the damage. Type A gearbox consists of pure planetary gears with three stages. Type B gearbox has two planetary stages and one parallel stage. The specifications and pictures are shown on Table 2 and Figure 2. Then, horizontal and vertical accelerometers are installed on each of stages to measure vibration.

Table 2 – Specifications of gearboxes

		Type A	Type B
The number of stages		3	
First stage	Type	Planetary	Planetary
	Gear ratio	3.87	4.24
	Meshing order (ref. input shaft)	89	55
Second stage	Type	Planetary	Planetary
	Gear ratio	3.87	6.34
	Meshing order (ref. input shaft)	89	90.9
Third gear	Type	Planetary	Parallel
	Gear ratio	6	3.32
	Meshing order (ref. input shaft)	95	73



(a) Type A gearbox (b) Type B gearbox

Figure 2 Two types of Gearboxes

4.2 Damage cases

It is reported that general faults of a reduction gear are tooth breakage, pitting, crack and wear. In this experiment, tooth breakage, pitting and crack are applied to a planet gear, and wear is employed on the sun gear for the second stage of each gear. Each of damage is made by cutting normal(healthy) gear to simulate real damage, which is shown in Figure 3. Experiment is performed by replacing each of damaged gear.

Figure 3 Damaged gears

4.3 Acquisition of vibration data

As it is described in the previous section, damage classification is carried out by using the bin. In wind turbine simulator, four bins are chosen. The width of bin is 1 rpm in terms of speed of input shaft. To acquire train data, constant speed tests are performed for 8, 11, 14 and 16 rpm which are corresponding to four bins. On the other hand, an artificial profile for rotational speed of a wind turbine, which is shown in Figure 4, is constructed in order to make validation data for the damage classification. The profile includes a little variation of rotational speed for an each bin in order to mimic the real operational condition of a wind turbine. Tests for constant rotational speed and profiled speed are repetitively executed for each of damage cases.

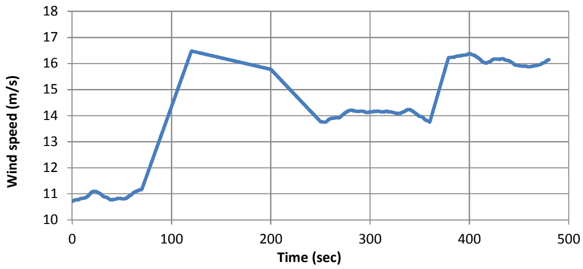


Figure 4 Wind profile for validation

4.4 Metric selection and feature vector

Various metrics which are listed in Table 1 are calculated from acquired train vibration data. Then, variances for damage cases and rotational speeds are computed so as to choose the best metric for classification in accordance to Eq. (2) and (3), respectively. Figure 5 shows the summations of variances for various metrics with respect to each of damage and rotational speed. After the rank analysis described in Section 3.3, nine metrics are selected for classification. Then, a feature vector finally is constructed with nine metric and one rotational speed like Eq (4).

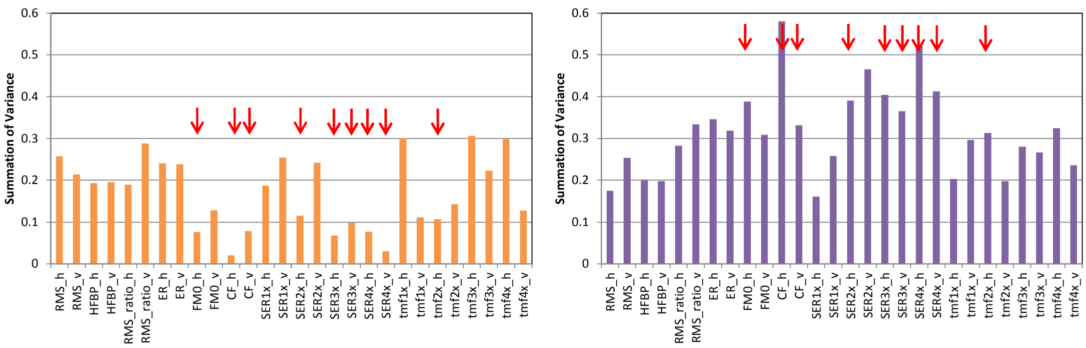


Figure 5 summations of variances

$$\mathbf{v} = \{\text{metric}_1 \quad \text{metric}_1 \quad \cdots \quad \text{metric}_9 \quad \text{rotational speed}\}^T \tag{4}$$

4.5 Train and validation for artificial neural network

An artificial neural network(ANN) is made with two layers in order to classify the type of damage for gear. Figure 6 shows a schematic diagram of the ANN. The ANN is trained by training data which are acquired in cases of constant speed tests by using back-propagation algorithm. Here the train data is made by Eq (1) to consider the variation of rotational speed and apply the concept of bin to damage classification.

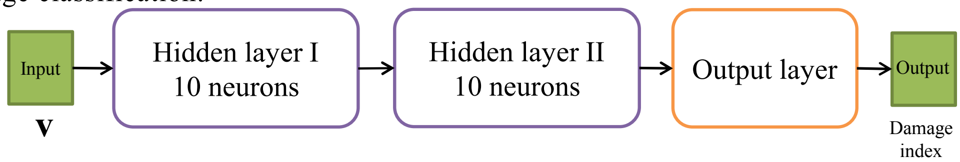
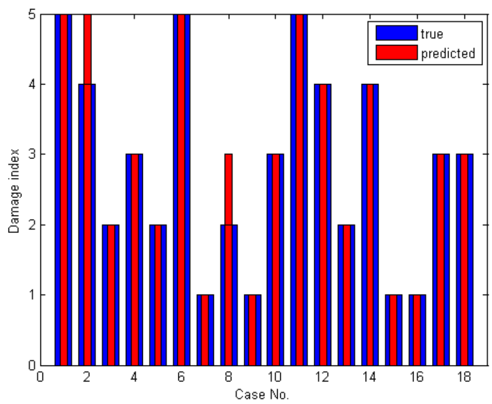
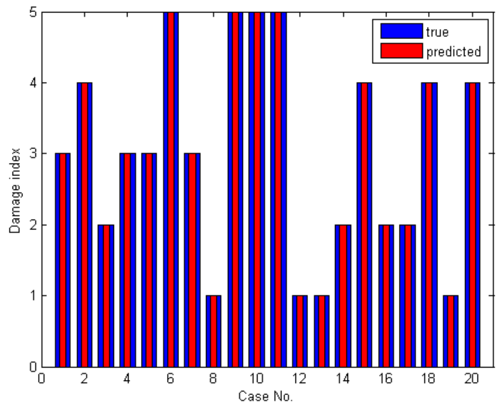


Figure 6 Artificial neural network for damage classification

Validation data, which is acquired by profiled rotational speed tests, is used as input data of the trained ANN to carry out blind tests for validation of classification ability. Figure 7 shows classification results for both type A and B gearbox. Damage indexes from 1 to 5 represent normal, tooth breakage, pitting, crack and wear, respectively. In Type A gearbox, there are 18 validation cases and the results of the classification agree with true damage status for 16 cases of 18 cases. For Type B gearbox, the ANN exactly classifies the type of damage for 20 cases.



(a) Type A gearbox



(b) Type B gearbox

Figure 7 Results of damage classification

5. Conclusion

In this paper, Damage classification method using the concept of bin and artificial neural network is proposed. Although rotational speed of a wind turbine varies continuously and amplitude of vibration also alters, we can consider quasi-stationary status if the rotational speed stays within a bin for a period. Then, Use of artificial neural network(ANN) for damage classification, which is a popular method for the machine with constant rotational speed, is possible. To validate the proposed method, the vibration data for four damage cases in the case of constant speed are generated by a wind turbine simulator. Then, the ANN is trained by the vibration data including additional noise. Finally, it is shown that the trained ANN can classify the type of damage from the vibration data for profiled rotational speed, which is similar condition to a real wind turbine. The proposed method with advanced learning algorithm is expected to be applied to condition monitoring and damage detection in order to enhance the reliability of a wind turbine in the future.

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