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PCA based Feature Extraction for Classification of Stator-Winding Faults in Induction Motors

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ABSTRACT

Nowadays, induction motors are widely used for many industrial processes. The shorted-turn fault of the stator-winding is the initial point of stator winding faults. This paper proposes using the Principal Component Analysis (PCA) to reduce the dimension of the feature set which is obtained from the Motor Current Signature Analysis (MCSA). The six original features consist of the signal power of the three-phase filtered current signal at 20 Hz to 80 Hz and 120 Hz to 180 Hz of the phases A, B and C. After using the PCA, the dimension of the feature set decreases to two new features. These two new features are then used to classify the shorted-turn phases of the stator-winding by applying the Artificial Neural Network (ANN) classifier. The experimental results demonstrate that the new feature set can decrease the complexity of the system. Additionally, the accuracy rate using the new feature set is higher than using the original feature set. Therefore, the new feature set can properly improve the efficiency of the classification.

Keywords: Induction motor, interturn short circuit fault, shorted-turn fault, stator-winding fault, Principal Component Analysis (PCA), Artificial Neural Network (ANN)

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INTRODUCTION

Induction motors are critical components of industries. Approximately 37% of the induction motor faults are those of stator-winding faults and the shorted-turn fault or the interturn short circuit fault of the stator-winding. (Bonaldi et al., 2012). Consequently, a shorted-turn fault detection system is necessary. The shorted-turn fault can be observed in harmonic components of the current signal. A popular detection method for stator faults is the MCSA which is employed to analyse the motor faults by identifying the current spectra at harmonic components of faults (Jung et al., 2006; Thomson, 2001). The current spectra are calculated by using Fast Fourier Transform (FFT). The advantage of the MCSA is it does not encroach on the motor operations. Commonly, the MCSA method provides many features from the current spectra for the fault detection. These features can be reduced by a feature extraction to decrease the dimension of features and the complexity of the system. The feature extraction transforms the original feature set into a smaller number of features without eliminating the information of features. The combination of feature reduction and an Artificial Intelligence (AI) method for induction motor fault diagnosis can improve the performance of the system (Casimir et al., 2006; Widode et al., 2007; Lei et al., 2008; Do & Chong, 2011; Sawitri et al., 2012; Gholamshahi et al., 2014; Hammo, 2014; Yang et al., 2006).

This paper presents the feature extraction method to reduce the size of the feature set using the PCA. The reduced set of the new feature is used to classify the shorted-turn phases by applying the ANN classifier. The system is verified by experiments, and the experimental results reveal that using the new feature set can improve both the complexity and the accuracy of the system.

STATOR-WINDING FAULTS

The shorted-turn fault in the stator-winding can be detected by using an air gap flux waveform. This waveform is changed by the distortion of the net MMF which is caused from the short circuit current flowed into the shorted circuit stator-winding. The harmonic frequency components of the air-gap flux waveform in a stator-winding current are calculated by (1),

$$f_{st} = f_1\left(\frac{n}{p}(1-s) \pm k\right) \tag{1}$$

where f_{st} is the harmonic frequency components, f_1 is the supply frequency, p is the pole-pairs, s is the slip, k is 1, 3, 5,… and n is 1, 2, 3,…, respectively.

The harmonic frequency components depend on a load size which is related to the slip. Normally, the harmonic frequency components dominantly appear when calculation uses parameter $k = 1$, $n = 3$, and $k = 1$, $n = 5$ (Thomson, 2001). In this paper, a three-phase, four-pole ($p = 2$) induction motor is tested at no-load condition. Therefore, the frequency components that are used to detect the shorted-turn fault are 25, 50, 75, 100, 125, 150 and 175 Hz, respectively. The line current power spectra of phase A for the normal motor is shown in Figure 1(a). Whereas, Figure 1(b) shows the harmonic frequency components of the line current power spectra of phase A in a shorted-turn motor. Since spectra components occur at 125 Hz and 175 Hz, the shorted-turn fault can be identified.

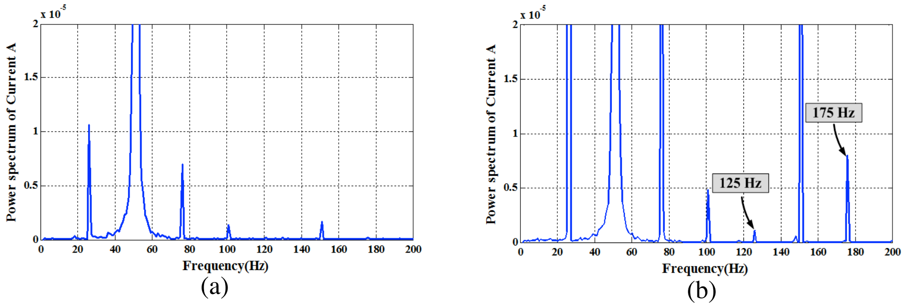

Figure 1. The current power spectra of the phase A (a) the normal motor;
(b) the shorted-turn fault in the phase A

FEATURE GENERATION

The three-phase current signals are measured and used to generate the original features. The original features are calculated by the following methods:

Signal power

The shorted-turn fault of the stator-winding can be detected by the air gap flux spectrum analysis. The ranges of the harmonic frequency components for the shorted-turn fault detection are 25, 50, 75, 100, 150, 125 and 175 Hz. Accordingly, each phase of the current signal is filtered by the band-pass filter at 20 Hz to 80 Hz and 120 Hz to 180 Hz. The filtered current signals are used to calculate the signal powers as expressed by (2),

$$P = \frac{1}{N}\sum_{n=1}^{N} x_n^2 \tag{2}$$

where P is the signal power, x is the band-pass filtered signal and N is the number of samples.

Normalization of Data

Since the signal power values at 20 Hz to 80 Hz and at 120 Hz to 180 Hz are very different, then these values should first be normalised. The signal power of each phase is normalised by the min-max normalisation technique. The normalised value can be calculated by (3)

$$x^* = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{3}$$

where x^* is the normalised value and x is the signal power value.

PRINCIPAL COMPONENT ANALYSIS

The feature extraction is one of the methods used for reducing the feature dimension. The PCA (Jolliffe, 1986) is one of the examples of the feature extraction. The dimension of features is reduced by the PCA without eliminating the signal information. The PCA is a technique that transforms an original feature set into a smaller feature set. The smaller feature set is transformed by using a function that related to the eigenvectors and eigenvalues. The procedures of the PCA have 4 steps. In the first step, the original feature set is used to calculate a covariance matrix as expressed by (4).

$$C_{ij} = \frac{1}{n-1}\sum_{m=1}^{n}\left(x_{im} - \bar{x}_i\right)\left(x_{jm} - \bar{x}_j\right) \tag{4}$$

Where C_{ij} is the covariance matrix between the feature i and the feature j, x_{im} is the sample m of the feature i, $\bar{x}_i$ is the average value of the feature i, x_{jm} is the sample m of the feature j, $\bar{x}_j$ is the average value of the feature j and n is the number of samples.

In the second step, the eigenvectors and eigenvalues of the covariance matrix are calculated using (5) and (6), respectively.

$$\mathbf{A} \cdot \mathbf{v} = \lambda \cdot \mathbf{v} \tag{5}$$

$$\left|\mathbf{A} - \lambda\mathbf{I}\right| = 0 \tag{6}$$

Where **A** is the covariance matrix, v is the eigenvector, λ is the eigenvalue and **I** is the identity matrix.

In the third step, the principal components are the eigenvectors which are selected from the eigenvalue ranking. Finally, the fourth step, the smaller feature set is calculated by (7). The smaller feature set is the new feature set which is used to classify the shorted-turn fault of the stator-winding.

$$\mathbf{Y} = \left(\mathbf{v}^T \times \mathbf{X}^T\right)^T \tag{7}$$

Where **Y** is the new feature set matrix, **X** is the original feature set matrix and **v** is the eigenvector.

ARTIFICIAL NEURAL NETWORK CLASSIFICATION

The ANN is a type of classifier. It is a model that is inspired from the study of biological neural networks. A perceptron is one type of the ANNs that it has many models depended on the number of the hidden layer and the hidden cell. In this paper, a single layer perceptron is used. The perceptron has a learning algorithm for classification and make adjustments to the weights of input and the biases of hidden layer. The updated weights and the updated biases are calculated by (8) and (9), respectively and the output is calculated by (10). The output is calculated by a transfer function which estimates the output by using the total product between the weight vector and the input vector. An error between the output and the target can be calculated by (11). Finally, the last weights and the last biases are used to classify the shorted-turn fault of the stator-winding.

$$\mathbf{W}_{k+1} = \mathbf{W}_k + e_k \cdot \mathbf{p}^T \tag{8}$$

$$b_{k+1} = b_k + e_k \tag{9}$$

$$a_k = f(\mathbf{W}_k \times \mathbf{p} + b_k) \tag{10}$$

$$e_k = t - a_k \tag{11}$$

Where $\mathbf{w}_{k+1}$ is the new weight matrix, $\mathbf{w}_k$ is the old weight matrix, e_k is the error, p is the input vector, b_{k+1} is the new bias, b_k is the old bias, a_k is the output, f is the transfer function and t is the target.

EXPERIMENTAL SETUP

The three-phase, four-pole, star-connected induction motor is used for the experiment as shown in Figure 2. The motor parameters and ratings are also illustrated in Table 1. The three-phase current signals are measured by three current sensors. National Instrument (NI) data acquisition device at 6,000 Hz sampling rate are used. These measured current signals are filtered at 20 Hz to 80 Hz and 120 Hz to 180 Hz. Then, the filtered signals are used to calculate the power signal, and the results are normalised by (2) and (3), respectively. Therefore, the normalised value is the original feature set which is reduced the dimension of features by the PCA. The block diagram of the experiment is presented in Figure 3. As mentioned before, this paper uses the ANN classifier. Classes of the fault classification include [0 0], [0 1], [1 0] and [1 1]. These classes mean a normal motor and shorted-turn faults in the phase A, B and C, respectively. The total data set contains of six features and 160 samples. The 80 samples are used as the training set, and the 80 samples are used as the test set.

Table 1
Parameters and ratings of test machines

V	Hz	r/min	kW	cosØ	A
230Δ/400Y	50Hz	1430	2.2	0.79	8.66/4.98
415Y	50Hz	1435	2.2	0.765	4.94

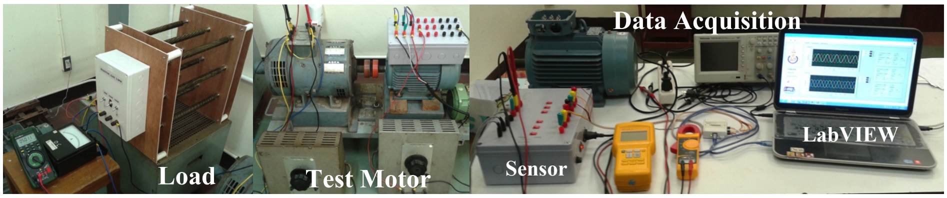

Figure 2. The experimental setup

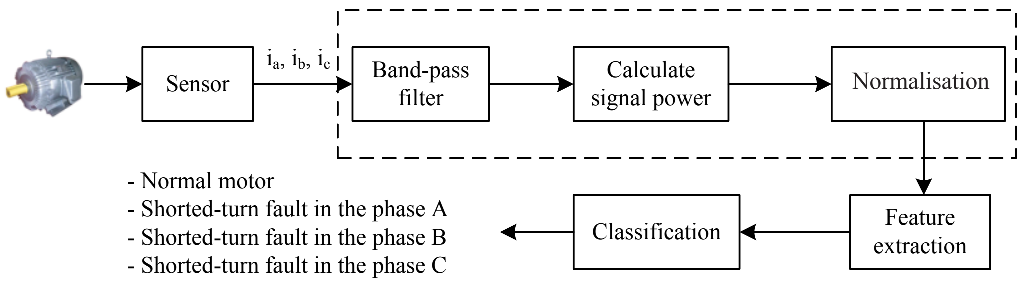

Figure 3. The block diagram of the experiment

EXPERIMENTAL RESULTS

The original data set has six features: the signal power of the 20 Hz to 80 Hz filtered signal and the 120 Hz to 180 Hz filtered signal in the phase A, B and C. The signal power values are normalised between zero to one. The original data set is reduced the size by the PCA. The PCA can extract up to two features. The two new features can be plotted the scattered graph as presented in Figure 4. From the graph, classes of the fault classification are clearly separated. The new feature set is used to create the learning system. The learning results are also shown in Table 2. From the learning results, it found that the new feature set uses less number of training epoch than the original feature set for all ratio of the train/test data. Similarly, the new feature set has less numbers of error samples than the original feature set. Finally, the efficiency of the classification is illustrated in Table 3. According to such results, the new feature set has the number of training and the classification error less than the original feature set. The new feature set provides an accuracy rate that is higher than the original feature set. As reason of the result, the new feature set is the reduced feature set, but it does not eliminate the information of features. Therefore, the new feature set can decrease the complexity of the system and increase the accuracy rate of the classification system.

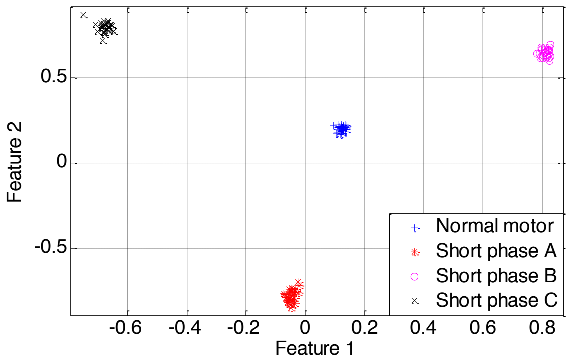

Figure 4. The scattered graph of the new features

Table 2
The number of training

Train/Test (%)	With the PCA		Without the PCA	
	Epochs	Error	Epochs	Error
30/70	5	0/112	134	4/112
50/50	4	0/80	46	3/80
70/30	3	0/48	40	1/48

Table 3
The number of training

	Classification (Perceptron ANN)	
	With the PCA	Without the PCA
Training sets	80	80
Test sets	80	80
Epochs	4	46
Classification error (%)	0	3.75
Accuracy rate (%)	100	96.25

CONCLUSION

This paper is on using the PCA to reduce the dimension of features. The new feature set is used to classify the shorted-turn fault of the stator-winding. Based on our experimental results, the six original features remained in only two new features. This new feature set can decrease the complexity of the classification system. The accuracy rate using the new feature set is 100% and could improve the fault classification system.

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