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진동 신호 분석을 통한 전동 모터 상태 검출

Condition Monitoring of Induction Motor with Vibration Signal Analysis

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Abstract - Condition monitoring is desirable for increasing machinery availability, reducing consequential damage, and improving operational efficiency. In this paper, a model-based method using neural network modeling of induction motor in vibration spectra is proposed for machine fault detection and diagnosis. The short-time Fourier transform (STFT) is used to process the quasi-steady vibration signals to continuous spectra so that the neural network model can be trained with vibration spectra. And the faults are detected from changes in the expectation of vibration spectra modeling error. The effectiveness of the proposed method is demonstrated through experimental results.

Key Words :Condition Monitoring,Induction Motor,Vibration Signal,Neural Network

1. Introduction

Induction machines are the majority of the industry prime movers and are the most popular for their reliability and simplicity of construction. Although induction machines are reliable, they are subjected to some mode of failures. In general, fault detection of induction motors has concentrated on sensing failures in one of the three major components, the stator, the rotor, and the bearings [1].Thus, for safety and economic considerations, there is a need to monitor the behavior of motors working in critical production processes.Even though electrical sensing with an emphasis on analyzing the motor stator current have been utilized widely, vibration based condition monitoring has attracted the attention of many researchers working in the area of induction machines and has gained industrial acceptance, as vibration analysis techniques are quite effective in assessing a machine's health [2].

Based on the dynamic behavior of the machine, the fault detection is made by comparison of indirect measurements of external forces.The difficulty in fault detection is the problem of sorting through the enormous number of frequency lines present in vibration spectra to extract useful information associated with the health of induction motors.

The recent success of neural network for modeling highly complex system offers the potential for minimizing the above problems and realizing model-based fault detection [3]. In this research, a model-based method using neural network modeling is developed in combination with short-time Fourier transform (STFT) to extract fault spectra features used in the detection of machine faults. Quasi-steady vibration signals are generated first and a neural network model is trained with the continuous vibration spectra to generate residuals to compute fault indicator. The effectiveness of the proposed condition monitoring system is demonstrated with experimental results on real induction motor.

2.ProposedConditionMonitoringSystem

The overwhelming majority of currently used motor fault detection systems are based on the processing and analysis of raw motor measurements, such as vibration signalsused in the proposed method. In general, the measured motor vibration signals are highly non-stationary. The quasi-steady signal can be accounted for by using segmentation. Then, the STFT is used for the processing of quasi-steady signals by windowing the signal with a shifted window function [9].A neural network model is trained with the vibration spectra to generate residuals. The residuals are then processed to

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extract fault information by computing appropriate indicators. The proposed fault detection system combines elements from model-based and signal-based approaches. The overall system is schematized as shown in Fig. 1, where all time dependence is in the discrete-time domain.

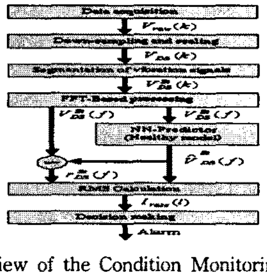

Fig. 1. Overview of the Condition Monitoring System

3.SignalProcessingandModeldevelopment

3.1Quasi-SteadySegmentation

To obtain high-performance motor model that are not influenced by fast time-varying machine characteristics, the motor signatures must be extracted from quasi-steady vibration signals without start up condition. A statistical method is used for processing the vibration signal in the time-domain, if the RMS value at successive windows does not vary, then the signal is considered stationary. The equations are shown as follows,

$$V_{rms}(i)=\sqrt{\frac{1}{N_w}\sum_{j=1}^{N_w}V_{ds}^2(j)} \tag{1}$$

$$|V_{rms}(i+1)-V_{rms}(i)|<\beta \quad i=1,2,\ldots,n \tag{2}$$

where $V_{rms}(i)$ is the RMS value of vibration signal in each window, N_w is the window size, β is a user-defined threshold, and n is the total number of windows in the signal. The comparison is carried throughout the entire signal. If this algorithm does not result in the selection of the quasi-steady segments, then the threshold can be increased to allow for relaxation of the signal stationary.

3.2NeuralNetworkModelDevelopment

In this work, we use a feedforward back-propagation network that undergoes supervised learning to model the output of the motor system in vibration spectra.The relation between inputs and outputs in multi-layer neural network can be expressed using general nonlinear input-output models, as follows,

$$\hat{y}(k;W)=f(u(k);W) \tag{3}$$

where W is weight matrix which is to be determined by the learning algorithm, f represents the nonlinear transformation of the input approximated by a network, and in here hyperbolic tangent function is used.

Using the structure of Eq. 3, the neural network model is trained using Levenberg-Marquardt (LM) algorithm. The LM algorithm is designed to approach second-order training speed without having to compute the Hessian matrix. The processing element is updated by,

$$x_{k+1}=x_k-[J^TJ+\mu I]^{-1}J^T\varepsilon \tag{4}$$

The detailed computation of the gradients involved in LM learning algorithm can be found in many neural network references, such as [11].

The windowed healthy condition vibration signal is used for neural network training and validation. The STFT vibration spectrum is expressed as $V_{DS}^{NF}(f|i)$ and is used as inputs of neural network model. The model structure of neural network is decided after various experiments while the pruning method is used also. The general structure of this network is shown in Fig. 2. Based on the discussion about neural network model above, the motor vibration spectra model $\hat{V}_{DS}(f|i)$ can be obtained as,

$$V_{DS}^{NF}(f|i)=STFT\{V_{DS}^{NF}(k)\} \tag{5}$$

$$\hat{V}_{DS}(f|i)=NN\{V_{DS}^{NF}(f|i)\} \tag{6}$$

the size of window is set user-defined, but should be the same as the window used for monitoring measurements.

Initially the motor predictor is developed for small machine, with training data representing the high-load level. After developing this baseline model, additional models valid at lower load levels are developed by incrementally tuning the baseline high-load level model. The training data set consists of 2800 samples for estimation, and 1400 samples for validation. The validation data set is used to determine the best stopping point to prevent over training.

3.3ResidualGeneration

In this research, the residuals are generated in vibration spectra. Consider one data window having the time interval $[t_1,t_2]$, the residual $r_{DS}(f|i)$ of the ith window is expressed as,

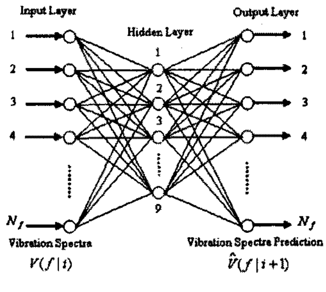

Fig. 2. General Structure of Neural Network

$$r_{DS}(f|i)=V_{DS}^T(f|i)-\hat{V}_{DS}(f|i) \tag{7}$$

where superscript T means the measurements in spectra is also after denoising processing.

3.4DescriptionofFaultIndicator

In a monitoring time interval, let the size of a moving window be $p=t_2-t_1$, which is the same as the size of the window for residual generation. And consider that the moving window moves by p at a time. The following moving window RMS values are computed for the model prediction and residual,

$$r_{rms}(i)=\sqrt{\frac{1}{N_f}\sum_{f=1}^{N_f} r_{DS}^2(f\,|\,i)}\qquad i=1,2,\dots,m \tag{8}$$

$$\hat{V}_{rms}(i)=\sqrt{\frac{1}{N_f}\sum_{f=1}^{N_f} \hat{V}_{DS}^2(f\,|\,i)}\qquad i=1,2,\dots,m \tag{9}$$

where $m=t_N-t_1$ is the total number of moving windows, N_f is the number of data in the spectrum.

The relative change in the harmonic component of the residuals can be quantified by the ratio $r_{rms}(i)/\hat{V}_{rms}(i)$. In this study, the normalized harmonic content of the residuals is used as an indicator for detecting faults as follows,

$$I_{rate}(i)=r_{rms}(i)/\hat{V}_{rms}(i) \tag{10}$$

4.ExperimentAnalysis

4.1ExperimentSettings

The experiment system is setup to collect the data needed for testing the neural network condition monitoring system. An off-site industrial scale testbed is utilized for data acquisition from larger motors.

The staged incipient faults include several mechanical faults. The results of a few of these anomalies and staged faults are presented here. A 3 - ϕ, eight pole, 597 kW Allis Chalmers motor is run directly from the power supply mains. The motor is connected to the dynamometers used to load them.

4.2ExperimentAnalysis

The vibration spectra of the output of the machine and the neural network model is compared in Fig. 3.

Two air-gap eccentricity tests are performed using the 597 kW motor. The first case consists of moving the rotating center at the end of the inboard shaft 25% upward, whereas the second case moving the rotating center at the end of the out board shaft 20% downward and 10% to the right. Detection of air-gap eccentricity faults using the proposed indicator and threshold is shown in Fig. 4. The normal condition runs for 400s, and then the first case is switched on for 200s and the second case for 200s also.

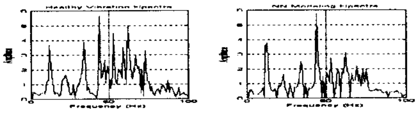

Fig. 3. Modelling of Vibration Spectra

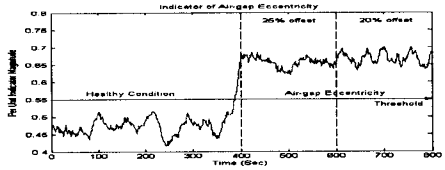

Fig. 4. Indicator of Air-gap Eccentricity

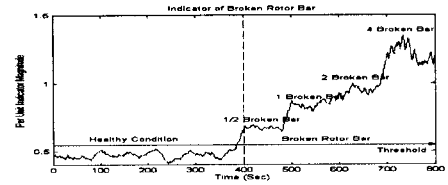

Fig. 5. Indicator of Broken Rotor Bar

Another mechanical fault is broken rotor bars. Experiments are performed to obtain motor measurements with four cases of broken bars using the 597 kW motor. The fault indicator are given in Fig. 5. The proposed indicator clearly shows the changes from the baseline to broken bar faults, and the magnitude change increases with the severity of the faults.

5.Conclusion

In this paper, the development and testing of a model-based condition monitoringand diagnosis system for induction machine is presented.The proposed system uses a vibration spectra model developed using multi-layer peception neural network. Experiments conducted on the real motor verify the conclusions from theoretical derivation. The experimental and computational results show the effectiveness of the system proposed in this paper.

Reference

[1] P. J. Tavner and J. Penman, *Condition Monitoring of Electrical Machines*, Letchworth, England, Research Studies Press, 1987.

[2] C. M. Riley, B. K. Lin, T.G. Habetler, and R. R. Schoen, "A method for sensorless on-line vibration monitoring of induction machines," *IEEE Trans. Ind. Applicat.*, vol. 34, pp. 1240-1245, Dec. 1998.

[3] A. F. Atiya and A. G. Palos, "New results on recurrent network training: Unifying the algorithms and accelerating convergence," *IEEE Trans. Neural Networks*, vol. 13, pp. 765-786, May 2000.

[4] N. Mohanti, *Signal Processing Signal Filtering Detection*, Van Nostrand Reinhold, New York, 1987.