Deep Neural Network Based Fault Detection for Three-Phase Induction Motor

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ABSTRACT

The three-phase induction motor is known as one of the most widely-used machine in the manufacturing industry. Electrical and mechanical fault of this machine is able to cause breaking down the plant facilities that leads significant productivity losses. In this paper, we will propose the fault detection method of induction motor by using deep neural network with measurement data of the electrical current signals to provide supervised classification of 2 types of motor fault, rotor broken and stator conductor fault. We also studied the size of data-set in faulty state to train the model for fault detection.

1. INTRODUCTION

The three-phase induction motors are one of the most widely used power drive in the manufacturing industry. Despite of reliability and robustness of these machines, faults such as unbalanced stator and rotor parameters, and broken rotor bars occur and cause sever distruption of manufacturing process and disastrous accidents (Bonnet and Soukup, 1992).

As a result, effective fault detection and diagnosis techniques are needed in order to reduce the maintenance and downtime costs of motors. From the literature review, useful techniques for online detection and diagnosis of induction motor faults emerge rapidly, which are able to avoid unexpected failures of induction motors. Examples include online condition monitoring techniques to analyze motor current signature (Benbouzid et al.,2003), vibration (Wang et al., 2010), and acoustic emissions (Al-Dossary et al., 2009).

Although there are lots of research about how faults are defined and which methodology for detection is effective, this is the first attempt to study how to apply deep neural network for fault detection of induction motors to identify two types of faults and how many fault data need to train model and organization of training data. Therefore, our proposed method attempt to find optimal training data set for successful learning.

2. RELATED WORKS AND POSITIONING

2.1. Faults in Three-Phase Induction Motors

The induction motors over their operation, are susceptible to various load and environmental conditions, causing the natural wear of parts.

Konar and Chattopadhyay (2011) and Ertunc et al. (2013) state that the bearing, rotor, and stator are responsible for about 78-88% of breakdowns in electric motors. Among the main faults in TIMs, about 37% are caused due to problems in the stator winding, which can be promoted by short circuits in the coils. In this paper, we will focus on detection of stator fault and rotor fault.

2.2. Artificial Neural Networks

Artificial Neural networks are a computational approach, which is based on a large collection of neural units, loosely modeling the way a biological brain solves problems with large clusters of biological neurons connected by axons.

2.3. Multilayer Perceptron

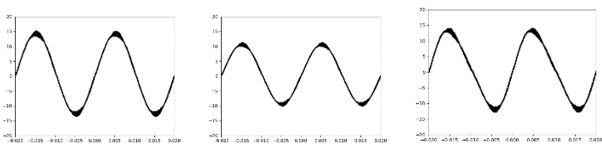
A multilayer perceptron (MLP) is a feedforward artificial neural network model that maps sets of input data onto a set of appropriate outputs. An MLP consists of multiple layers of nodes in a directed graph, with each layer fully connected to the next one. Except for the input nodes, each node is a neuron (or processing element) with a nonlinear activation function. MLP utilizes a supervised learning technique called backpropagation for training the network. MLP is a modification of the standard linear perceptron and can distinguish data that are not linearly separable.

3. IMPLEMENTATION

This section explains fault detection method from data generation to deep neural network model. Section 2.1 describes three types (normal, stator fault and rotor fault) of data generation from sample motor data. Section 2.2 presents data preprocessing for deep neural network. Section 2.3 shows building deep neural network model based on supervised learning.

3.1. Data Generation

The current signals in normal condition were gathered based on measurement from 750W induction motor operated at 50Hz grid frequency and 10kHz switching frequency. The current signals in faulty condition were generated based on modeling of stator and rotor faults (Chen and Rastko, 2010). When the stator is broken, current signal stand for lower amplitude with same frequency. To generate stator fault data, the amplitude of current signal is modified by multiplying 0.8 ~ 0.9 random variable. The broken rotor shows the presence of side band frequency components in the current spectrum. To generate rotor fault data, the amplitude of frequency spectrum at 50Hz is multiplied by random values 0.8 ~ 0.9 and the amplitude of frequency spectrum at 100Hz is added with the value of the amplitude at 50 Hz multiplied by 0.1 ~ 0.2 random values.



(a) (b) (c)

Figure 1. Time-amplitude graph: (a) normal state, (b) stator fault state and (c) rotor fault

3.2. Data Preprocessing

Before building deep neural network, the multidimensional feature vector should be set as input. To extract feature from current signal, we use FFT signal processing techniques. Due to differences of scale between each signals, y-axis values of FFT are normalized to 0 ~ 1. But, classification between normal state and stator fault state is not possible when features from FFT processing are used only as input. To resolve this limitation, another feature which is area of FFT's graph is added in feature vector. Also, this feature is normalized to 0 ~ 1.

3.3. Deep Neural Network Based on Supervised-Learning

The preprocessed three-phase current signal is used in detecting faults using DNN (Deep Neural Network) method in this paper. However, time and resource complexity is limited to train model by all of preprocessed data. Furthermore, each current signal has thousands of values and model should execute lots of big size of matrix multiplication. Due to these limitation, specific features are selected to reduce time complexity. A block diagram of this model with selecting inputs and outputs is shown in Figure 2. Several kinds of neural network structure can be considered when building model. The parameters for affecting structure of neural network such as layers, number of nodes, activation function, cost function, optimizer function and so on called in hyperparameter. In this paper, the model has two hidden layers with fixed 10 nodes. The other hyperparameters are shown in Table 1.

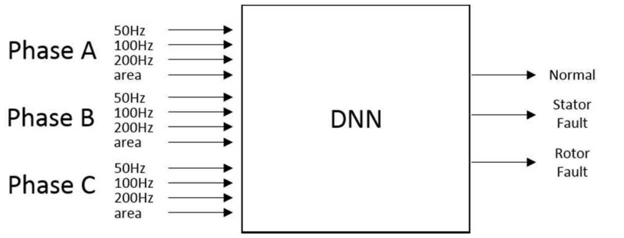


Figure 2. Inputs and outputs of the DNN.

Table 1. Hyperparameters of the DNN

Number of hidden layer	2
Number of hidden node	10
Number of input node	12
Number of output node	3
Activation function	RELU (Rectified Linear Units)
Cost function	Softmax cross entropy
Optimizer	Adam optimizer

4. EXPERIMENTAL RESULTS

The generated signals were acquired from random generation function by the method described in Section 3.1. Then, three kinds of current data was preprocessed to input data of deep neural network. After preprocessing data, neural network learn based on preprocessed data sets which are different fault data rate.

In this experiment, our testing motor is assumed to three-phase induction motor which has three states: normal, stator fault and rotor fault. The motor states are assumed to be affected by only three input current signals.

To study how many faulty data is required for classifying the fault conditions, an experiment is conducted by changing the percentage of fault on input data with same architecture of the DNN. The architecture of DNN are shown in Table1. The size of input data is fixed to 6,000 cases which are 18,000 current signals from three different phases. Specification of current signals is that time interval is 4 μs and total operation time is 40ms (data point size is 10,000). The cutoff of success training is set to 95% accuracy of prediction by training data. Each input data set with specific fault percentage is used 50 times for learning.

Figure 3. shows success number of training depending on various fault data percentage among training data set. Up to 50%, all of percentage data set has no successful learning. At the point of 60% (fault state : 60%, normal state : 40%), the number of successful learning is only 9 success among 50 learnings. When input data is consisted of fair distribution (each fault state : 33%, normal state : 34%), the result of success learning is 43 times among 50 tries.

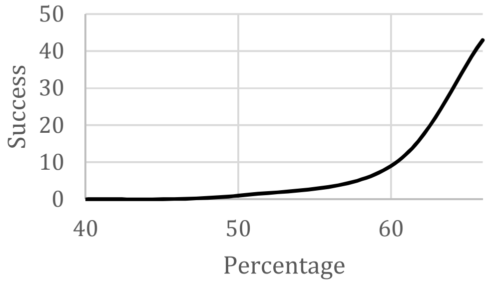


Figure 3. Success number of training.

5. CONCLUSION

All of research about fault detection for induction motor try to find optimal model which detect fault states. However, to our best knowledge, there is no approach how to organize training data and how many data are needed to train neural network. The deep neural network is designed to detect two types of fault in 3-phase induction motors: stator and rator fault. We studied to find optimal percentage of fault data for learning neural network, first. According to experiments, fair distribution (stator fault state: 33%, rotor fault state: 33%, normal state : 34%) is the best rate of training data set. Then, we tested the accuracy of fault detection by the proposed deep neural network. It shows over 97% accuracy.

For the future work, we will use generative model to generate the faulty condition data to apply fault detection by using deep neural networks in real factory environment. It is needed because the faulty data in real factory environment is very small portion of the dataset, but we found that training dataset in faulty condition is needed as much as dataset in normal condition.

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REFERENCES

Bonnett, Austin H., and George C. Soukup (1992) Cause and analysis of stator and rotor failures in three-phase squirrel-cage induction motors, IEEE Transactions on Industry Applications 28.4: 921-937.

Benbouzid, Mohamed El Hachemi, and Gerald B. Kliman. (2003) What stator current processing-based technique to use for induction motor rotor faults diagnosis?, IEEE Transactions on Energy Conversion 18.2: 238-244.

Wang, Wilson, and Ofelia Antonia Jianu. (2010) A smart sensing unit for vibration measurement and monitoring, IEEE/ASME transactions on mechatronics 15.1: 70-78.

Al-Dossary, Saad, RI Raja Hamzah, and David Mba (2009) Observations of changes in acoustic emission waveform for varying seeded defect sizes in a rolling element bearing, Applied acoustics 70.1 (2009): 58-81.

Chen, Shuo, and Rastko Živanović. (2010) Modelling and simulation of stator and rotor fault conditions in induction machines for testing fault diagnostic techniques, European Transactions on Electrical Power 20.5 611-629.

Zarei, J., Tajeddini, M. A., & Karimi, H. R. (2014). Vibration analysis for bearing fault detection and classification using an intelligent filter. Mechatronics, 24(2), 151-157.

Konar, P., & Chattopadhyay, P. (2011). Bearing fault detection of induction motor using wavelet and Support Vector Machines (SVMs). Applied Soft Computing, 11(6), 4203-4211.

Ertunc, H. M., Ocak, H., & Aliustaoglu, C. (2013). ANN-and ANFIS-based multi-staged decision algorithm for the detection and diagnosis of bearing faults. Neural Computing and Applications, 22(1), 435-446.