Available online at www.sciencedirect.com
ScienceDirect
Energy Procedia 88 (2016) 915 – 920
Energy Procedia

CUE2015-Applied Energy Symposium and Summit 2015: Low carbon cities and urban energy systems

Phase-phase short fault analysis of permanent magnet synchronous motor in electric vehicles

Zhifu Wang [a,*], Jingzhe Yang [b], Chuang Cao [a], Zhongli Gu [a]

[a]*Collaborative Innovation Center of Electric Vehicles in Beijing, Beijing, 100081, China*
[a]*School of Mechanical and Vehicle Engineering, Beijing Institute of Technology, Beijing, 100081, China*
[b]*Shanghai Volkswagen Automotive Company Limited, Shanghai, 201805, China*

Abstract

This paper proposes a methodology of phase to phase short-circuits fault diagnosis in permanent magnet synchronous motors (PMSM). The integrated network basis of such a method is composed with a BP network and two Elman networks. The three sub-networks respectively output their own result. A special simulation was applied to find relevant fault. The experimental data acquired by data acquisition system validate the potential of the method to provide helpful and reliable diagnosis results.

Keywords: Fault diagnosis; PMSM; Neural network; electric vehicle

1. Introduction

With the development of electric vehicles, the positive characteristics of PMSM diver systems make them widely used in this area [1-3]. The fault diagnosis about the PMSM problems is importance because the PMSM has huge influence on the safety and economical efficiency with the vehicles [4-6].

In order to achieve PMSM fault detection and diagnosis (FDD), there were many activities have been done by worldwide researchers. Fast flourier transform (FFT) was usually applied to deal with stator current, due to its efficiency on analyzing stationary signal [7]. Wavelet transform (WT) uses a variable-sized-regions window which was constant in FFT and so on [8].

* Corresponding author. Tel.: +86-10-68915202; fax: +86-10-68940589.
E-mail address: wangzhifu@bit.edu.cn.

doi:10.1016/j.egypro.2016.06.112

2. Methodology of fault diagnosis

It is well known that when PMSM has phase to phase short-circuits fault, the stator voltage and the current fluctuate obviously. In this paper, fundamental components of voltage, current and negative sequence current are adopted to indicate the relevant fault. The fundamental components of voltage and current can be acquired by data acquisition system. The negative sequence current I^-, the fundamental components of voltage V and the current I were decomposed by wavelet to form fault signature for the sub-networks.

PMSM faults diagnostic by means of neural network is one of the most applied methods. The flow chart of diagnosis methodology is shown in Fig.1. The sub-networks can represent the relationship between input signature and output motor states after being trained by sample signature. Hence, the sub-networks respectively give their output results including healthy state and the electric fault state by inputting test signature.

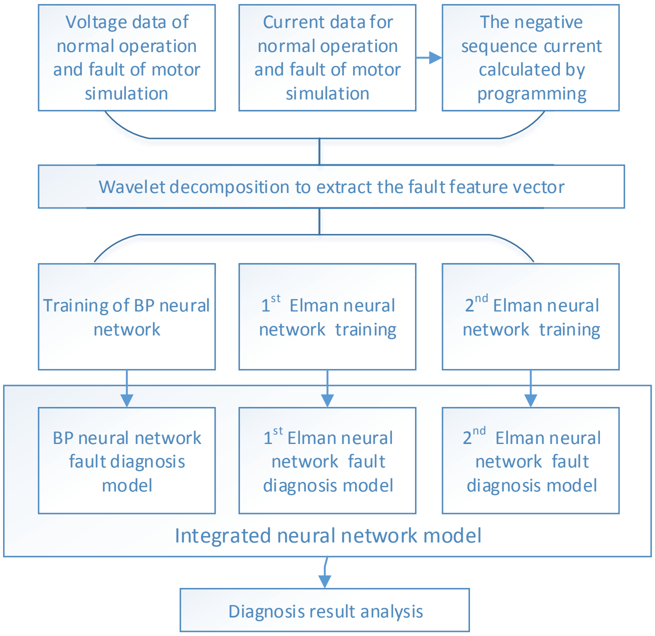

Fig. 1. Flow chart of diagnosis methodology

In this work, BP sub-network was respectively trained by stator voltage fault signature V_g, 1st Elman and 2nd Elman sub-networks were each trained by current fault signature I_g and negative sequence current fault signature I_g^-. Finally, the integrated neural network result is obtained by fusing the three sub-networks results.

3. Wavelet decomposition and integrated neural network

In this section the phase to phase short-circuits fault diagnosis methodology which consists of a signal processing and an integrated neural network was presented. The first part was the wavelet decomposition used to extract the signature. The other was the NN diagnosis system.

3.1. Signature extraction based on wavelet decomposition

The wavelet decomposition depends on the wavelet basis function was a useful time-frequency analysis tool which was a traditional methodology to decompose signal. In frequency spectrum analysis, wavelet function $\psi(t)$ was equal to a band-pass filter while its scaling function $\varphi(t)$ was equal to a low-pass filter. A signal can be decomposed into high frequency part and low frequency part by wavelet. The part of low frequency signal still can be further decomposed into relatively high frequency part and low frequency part. Those high frequency signal parts represent the detailed information of the frequency band.

In this paper, a detection signal of the fundamental components of stator voltage, current and negative sequence current is separately taking every 1001 points as a sample. These signals are wavelet decomposed into 5 layers by db6 wavelet basis function which was usually applied in fault diagnosis. The high frequency coefficients of each layer are reconstructed to be 5 sets of array. The first coefficient of every set of array is selected to be a fault signature. Every fault signature has five coefficients, so that the operation speed of integrated neural network was rapidly. And the voltage, the current and the negative sequence current sample of fault characteristic about PMSM were illustrated in Tab. 1, Tab. 2 and Tab. 3.

Table 1. Voltage sample of fault characteristic about PMSM

No	voltage fault characteristic	Motor state
1	-0.0334 -0.0182 0.0449 0.1046 -0.3734	Normal
2	-0.0418 2.1973 1.8823 5.5882 -0.3649	P-P short

Table 2. Current sample of fault characteristic about PMSM

No	current fault characteristic	Motor state
1	0.0006 -0.0363 -0.0587 -0.2351 -0.6686	Normal
2	-0.0004 -0.0159 0.2527 1.6783 -6.5803	P-P short

Table 3. Negative sequence current sample of fault characteristic about PMSM

No	negative sequence current fault characteristic	Motor state
1	0.0000 0.0000 0.0000 0.0000 0.0000	Normal
2	-0.0005 -0.0107 -0.1496 -0.8314 -0.6408	P-P short

3.2. Neural network of diagnostic system

The integrated NN was composed with three parallel sub-networks. The main structure of sub-network both BP and two Elman consists of input-layer, hidden-layer and output layer. But the Elman NN has an additional connection-layer paralleled to hidden-layer. The connection-layer was similar to a single step delay operator. BP NN was a commonly used network which applies gradient descent algorithm to modulate weight value in back propagation process. The structures of the BP NN and the Elman NN were shown in Fig.2, Fig.3.

In this paper, the three sub-networks have 5 input-layer nodes, according to the number of fault signature. The BP sub-network has 3 output-layer nodes, because the sub-networks have the same number of outputting PMSM states (normal/P-P short/phase-ground short). In the same way, 1st Elman sub-network and 2nd Elman sub-network have 3 output-layer nodes. Making suitable recognition was wondered, thus BP sub-network hidden-layer node number is determined 31 and two Elman sub-networks hidden-layer node number were determined 25.

S-type tangent function was used as hidden-layer transfer function of the three sub-networks and S-type logarithmic function was used as output-layer transfer function. BP sub-network was trained by Levenberg-Marquardt algorithm and the Elman sub-networks were trained by Gradient Descent with Momentum & Adaptive LR algorithm.

In order to determine the value of confidence weight matrix, the PMSM diagnosis results of the three sub-networks which have been well trained are compared. One set of the results comparison is shown in Tab.4.

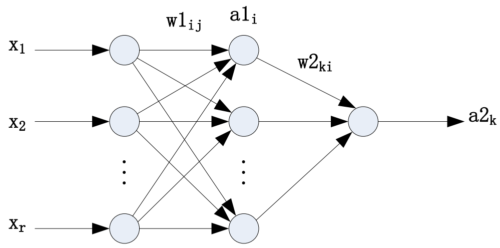

Fig. 2. The structure of the BP NN

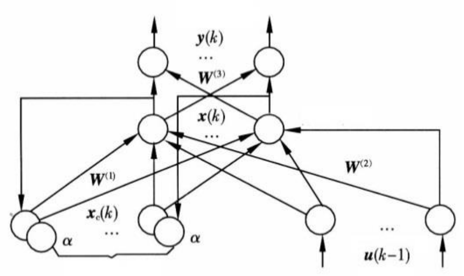

Fig. 3. The structure of the Elman NN

Table 4. PMSM diagnosis results comparison of three sub-networks

NN type	Actual output	Theoretical output	Motor state
BP	0.9926, 0.0002, 0.0015	1 0 0	Normal
1^{st} Elman	0.7867,0.0009, 0.1545	1 0 0	Normal
2^{nd} Elman	0.7981, 0.0002, 0.0087	1 0 0	Normal
BP	0.0071, 0.8856, 0.0501	0 1 0	P-P short
1^{st} Elman	0.0614, 0.9991, 0.0423	0 1 0	P-P short
2^{nd} Elman	0.0109, 0.9814, 0.0047	0 1 0	P-P short

Through the comparison of many set of diagnosis results, it was obvious that the BP NN has a better diagnosis result of the PMSM normal state, but it has worse diagnosis results of PMSM phase to phase short. Two Elman sub-networks diagnose the PMSM phase to phase short fault much more exactly than the BP sub-network. Hence, the sub-networks results can be fused by a confidence weight matrix to make a better integrated neural network result and become more reliable.

According to above analysis, the integrated neural network result contains two PMSM states: normal state, phase to phase short fault. However, the integrated neural network result will contain more PMSM states such as phase to ground fault, demagnetization fault and so on. The 3×3 confidence weight matrix W for the three sub-networks is determined as:

$$W = \begin{bmatrix} 0.4 & 0.1 & 0.1 \\ 0.3 & 0.45 & 0.45 \\ 0.3 & 0.45 & 0.45 \end{bmatrix}$$

This paper only sets the second and third outputs confidence weight of BP sub-network as 0.1, because of its occasional misdiagnosis of PMSM phase to phase short fault. Two Elman sub-networks have a better diagnosis output of PMSM phase to phase short fault. So the second and third outputs confidence weights of two Elman sub-networks are set as 0.45.

4. Experiment results

The proposed fault diagnosis methodology of PMSM was experimentally validated by using a data acquisition system and a 400W, 12V, Y-connected 8-pole PMSM drive system. In this experimental establish, the PMSM was specifically designed to generate phase to phase short fault state.

The three fault diagnosis sub-networks were trained by 18 sets of experimental fault signature data, because every output motor state of each sub-network has 3 sets of sample data. Finally, the sub-networks output results of each NN were put together to form the results matrix Y which was a 3×3 matrix. So the integrated neural network diagnosis output results were obtained by multiplying confidence weight matrix W with sub-networks results matrix Y. Consequently Tab.5 shows the two sets of obtained results after inputting test fault signature data of two motor states into the well-trained sub-networks, the main elements of matrix W^TY were regard as integrated the NN diagnosis fault coefficients.

Table 5. Diagnosis results of integrated neural network

Number	Actual output	Theoretical output	Motor state
1	0.9761, 0.0231, 0.0375	1 0 0	Normal
2	0.0052, 0.9381, 0.0224	0 1 0	P-P short

5. Conclusions

In this paper, the diagnosis method of phase to phase short-circuits in PMSM based on the wavelet decomposition and the integrated neural network was proposed, experiments were carried out on a special laboratory PMSM which can simulate relevant insulation fault and result from each sub-network are compared. It has been shown the diagnosis model based wavelet decomposition and integrated neural network showing suitableness for detecting the motor electric faults.

Acknowledgements

The research work was supported by National Natural Science Foundation (51105032) and Laboratory research project of Beijing Institute of Technology (2014BITSYA05).

References

[1] Sharma Deepali, Gaur Prerna, Mittal AP, Singh Bhim. Photovoltaic powered electric vehicle using PMSM drive scheme. *International Journal of Vehicle Autonomous Systems* 2013; 11:229-44.

[2] Li Yaohua, Liu Jingyu, Yu Qiang, Ma Jian. The Interior PMSM DTC Drive used for Electrical Vehicle. *Applied Mechanics and Materials* 2011; 97-98: 1081-4.

[3] Wang Zhifu, Ye Huiping, Wang Yupu, Shi Jianjun. Dynamic control of motor torque during the shifting process in PMSM-AMT system. In: IEEE Transportation Electrification Conference and Expo, ITEC Asia-Pacific 2014 - Conference Proceedings, October 30, 2014

[4] Zhang Chengning, Wang Fang, Wang Zhifu, Yang Jingzhe. Analysis of stator winding inter-turn short circuit fault of PMSM for electric vehicle based on finite element simulation. In: IEEE Transportation Electrification Conference and Expo, ITEC Asia-Pacific 2014, p.

[5] Wang Zhifu, Yang Jingzhe, Ye Huiping, Zhou Wei. A review of permanent magnet synchronous motor fault diagnosis. In: IEEE Transportation Electrification Conference and Expo, ITEC Asia-Pacific 2014 - Conference Proceedings, October 30, 2014.

[6] Zheng Shusong, Li Hongmei. Fault Detection of PMSM Drive System in Electrical Vehicle. *Micromotors* 2013; 46:58-62.

[7] J. Rosero, J. Ortega, J. Urresty, J. Cárdenas, L. Romeral. Stator Short Circuits Detection in PMSM by means of Higher Order Spectral Analysis (HOSA). In: Proceedings of APEC 2009. IEEE Press, 2009, p. 964-969.

[8] J. Rosero, J. L. Romeral, J. Cusido, J. A. Ortega, A. Garcia. Fault detection of eccentricity and bearing damage in a PMSM by means of wavelet transforms decomposition of the stator current. In: Proceedings of APEC 2008. IEEE Press, 2008, p. 111-116.

Biography

Zhifu Wang received the M.E. degree and the Ph.D. degree from the Beijing Institute of Technology, Beijing, China, in 2003 and 2013, both in vehicle engineering. He is currently an Associate Professor with the National Engineering Laboratory for Electric Vehicles, Beijing Institute of Technology.