Improvement of Extraction Method for Inter-turn Fault Detection in IPMSM under Transient Conditions

Gyu Tae Choi[1], Je Won Lee[1], Minho Choi[2] and Sang Woo Kim[1,2]
[1]Department of Electrical Engineering, POSTECH, Pohang, Korea
[2]Department of Creative IT Excellence Engineering and Future IT Innovation Laboratory, POSTECH, Pohang, Korea

Keywords: Extracting Non-stationary Sinusoids, Inter-turn Faults, Interior Permanent Magnet Synchronous Motor (IPMSM), Motor Current Signature Analysis (MCSA).

Abstract: Most fault detection techniques are focused on induction motors and are based on steady-state conditions. In this paper, an extraction method for inter-turn fault detection in interior permanent magnet synchronous motors (IPMSM) is proposed. The study is focused on an IPMSM under non-stationary conditions. The technique is formulated by modifying existing fixed frequency sinusoid tracking algorithms, which is based on an adaptive algorithm for extracting non-stationary sinusoids. The faults are determined using the motor current signature analysis technique. Simulations performed in this study validate that the proposed algorithm improves the extraction performance.

1 INTRODUCTION

As the depletion of natural resources has increased over the years, the electric vehicle industry faces the challenge of solving the problem of this depletion. In particular, the motor is a component that directly affects the safety of the vehicle driver. It is important to detect faults in a motor using nondestructive inspection. Until now, most research has been focused on induction motors (Seera et al, 2012). However, the permanent magnet synchronous motor (PMSM) and interior permanent magnet synchronous motor (IPMSM) are used in electric vehicles because of their high efficiency and high power, among other qualities. Furthermore, IPMSM is more durable than PMSM.

In (Gandhi et al, 2011), a review of existing techniques available for on-line stator inter-turn fault detection and diagnosis in electrical machines was presented. Recent techniques that have been used to detect faults are based on signal analysis, models, or knowledge-based systems. The first method used to detect faults is signal analysis. Signal analysis techniques include the fast Fourier transform (FFT), short-time Fourier transform(STFT), wavelet transform(WT), and adaptive algorithms. It is difficult to accurately perform an FFT on the stator current because of problems such as frequency resolution, magnitude accuracy at steady state, and more generally, data processing. The STFT and WT were proposed to overcome these drawbacks (Cusido et al, 2008). However, it is difficult to detect faults because of the high computational complexity. The second method used to detect faults is the model-based fault detection method (Vaseghi et al, 2008). In the case of IPMSMs, this method has difficulty to establishing a model because of asymmetric inductance (an inductance of d axis, L_d, is not the same as an inductance of q axis, L_q). The third method to detect faults is based on knowledge-based systems such as neurofuzzy logic or neural networks (Ayhan et al, 2006). These strategies should be considered when a specific industrial-condition-monitoring device needs to be implemented to reduce the misinterpretation of the signatures that are obscured by factors such as measurement noises and differing load conditions (Ayhan et al, 2006). In a previous paper (Barendse and Pillay, 2006), without a low pass filter, a cascaded structure was proposed for a single fixed frequency sinusoid tracking algorithm.

2 FAULTS AND DETECTION METHOD

2.1 Inter-turn Faults

Inter-turn faults are caused by the breakdown of turn-to-turn insulation as a result of the voltage, current,

Choi G., Lee J., Choi M. and Kim S..
Improvement of Extraction Method for Inter-turn Fault Detection in IPMSM under Transient Conditions.
DOI: 10.5220/0004029704270430
In *Proceedings of the 9th International Conference on Informatics in Control, Automation and Robotics* (ICINCO-2012), pages 427-430
ISBN: 978-989-8565-22-8

or thermal stress acting on the stator winding. This type of fault is responsible for one quarter of all faults. This fault can rapidly propagate to other stator turns because it creates a large circulating current in the shorted path. Since the magnitude of the second-order harmonics in the q-axis current is proportional to the number of shorted turns and operating speed, the fault becomes considerably large as the number of shorted turns and the magnitude of speed increases (Kim, 2011). Consequently, other faults such as eccentricity faults, open circuit faults, and demagnetization faults are generated by the inter-turn faults. It is necessary to detect inter-turn faults immediately because of these dangers. The early detection of stator winding failures is important in order to avoid greater risk to the drive.

2.2 Motor Current Signature Analysis (MCSA)

Motor current signature analysis (MCSA) analyzes the amplitudes of the harmonics of the stator current. When the amplitude is over a threshold value, which is denoted by the standard amplitude of a normal current, an inter-turn fault is detected. MCSA has proven to be an efficient technique for fault detection and is the most popular technique (Gandhi et al, 2011). In order to detect inter-turn faults, it is important to determine their frequencies. As shown in (Sottile, 2001), the faulty harmonics are located at

$$f_{fault} = 3 \times f_{fund}$$

where f_{fault} is the frequency component associated with inter-coil shorts within the stator winding, and f_{fund} is the stator fundamental frequency. This means that the frequency component associated with an inter-turn fault depends on the fundamental frequency. As the speed of a vehicle increases or decreases, the vehicle is in a transient state. In a transient state, the fundamental frequency should vary with the vehicle speed. Thus, the frequency of the faults should change proportionally. Hence, an extraction algorithm under transient conditions through MCSA is required.

2.3 Description of Overall System

The block diagram of the overall detection system is shown in Fig. 1. In an electric vehicle, the battery is used to power the motor, which is an IPMSM. The battery has a voltage of approximately 15V. Because the output of the battery is DC, an inverter should be used to convert DC to AC. The output of the inverter consequently becomes AC, which powers the

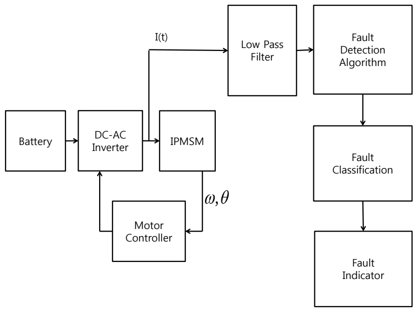

Figure 1: Block diagram of motor drive and fault detection strategy.

IPMSM. To control the speed of the IPMSM, the motor controller receives the angle and angular velocity of the IPMSM and the angle of the rotor from the resolver. The input current of the IPMSM is the target signal that is extracted to detect faults. The input current is passed through a low pass filter and then used in the fault detection algorithm. The algorithm extracts the input signal and classifies each harmonic. It is impossible to classify the harmonics from the entire signal that is received from the current sensor. Using fault equations (Barendse and Pillay, 2006), the frequencies of the faults are determined. Subsequently, the fault indicator indicates the faulty signal to the vehicle control unit. The significant harmonic components are identified by the fault detection algorithm.

3 PROPOSED ALGORITHM

3.1 Theoretical Background

In this section, the adaptive algorithm is introduced along with a description of how the algorithm is adapted in a conventional algorithm to extract the input current signal. The adaptive algorithm shows remarkable qualities in tracking and extracting the non-stationary sinusoid, while minimizing the square error. Let i(t) denote a stator current signal

$$i(t) = i_c(t) + i_n(t)$$

where $i_c(t)$ is the pure current signal, and $i_n(t)$ is the noise component. $i_c(t)$ can be represented in detail as follows;

$$i_c(t) = I_c sin(\int \omega(\tau) d\tau + \delta)$$

where I_c is the amplitude of the current, ω is the varying angular velocity dependent on time, and δ is the angle shift. Let i_{out} denote the output current estimated by the adaptive algorithm.

$$i_{out} = i_{fund} + i_1 + i_2 + .. \quad (1)$$

where i_{fund} is the component of the current at the fundamental frequency, and i_1, i_2, ... are the harmonic components.

$$i_{fund}(t) = A(t)sin(\int \omega(\tau)d\tau + \delta) \tag{2}$$

Let ϕ(t)=$\int \omega(\tau)d\tau + \delta$. The conventional algorithm is updated in detail as follows;

$$\frac{dA(t)}{dt} = \mu_1 e(t) sin(\phi(t)) \tag{3}$$

$$\frac{d\omega(t)}{dt} = \mu_2 e(t) cos(\phi(t)) \tag{4}$$

$$\frac{d\phi(t)}{dt} = \mu_2 \mu_3 e(t) cos(\phi(t)) + \omega(t) \tag{5}$$

$$e(t) = i(t) - i_{fund} \tag{6}$$

$$e_1(t) = i(t) - i_{fund}(t) - i_1(t) \tag{7}$$

The parameters μ_1, μ_2, and μ_3 are positive constants that regulates the algorithm. The values of the parameters control the convergence rate as well as the stability of the algorithm. The least squares error between input signal i(t) and the estimated sinusoidal signal $i_{fund}(t)$ is minimized by the use of the gradient descent method (Ziarani and Konrad, 2004).

3.2 Proposed Algorithm

Fig. 2 shows the conventional algorithm (Barendse and Pillay, 2006). However, it is difficult to detect harmonics accurately because (6) is used as the first step to detect i_{fund}. This means that the harmonics are also used to detect i_{fund}. The conventional algorithm does not guarantee the detection of the frequency components associated with the fault. To solve this problem, the proposed algorithm uses (8) to extract fundamental components in detail as follows;

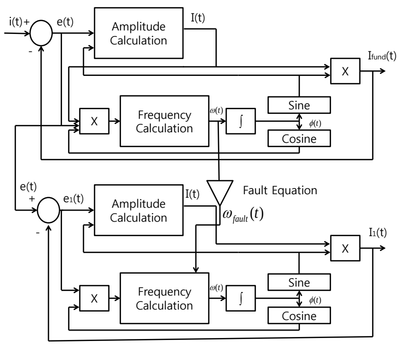

Figure 2: Block diagram of conventional algorithm.

$$e(t) = i(t) - i_{fund}(t) - i_1(t) \tag{8}$$

Further, the error in the harmonics is also used to update the algorithm using (8). As the rpm of the electric vehicle is limited from 0 rpm to 8000 rpm, the fundamental frequency of the IPMSM is also limited about 0 Hz to 500 Hz generally. It means that harmonic components of the high frequency don't need to extract to detect the inter-turn fault. Therefore, a low pass filter is established to improve extracting performance. Fig. 3 shows the proposed algorithm. The amplitude and frequency are calculated by (3) and (4), respectively. Then, each component is updated using (8).

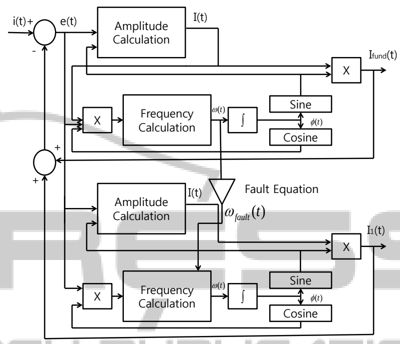

Figure 3: Block diagram of proposed algorithm.

4 SIMULATION RESULTS

To test the performance of the algorithm, a sinusoidal input current is created in a MATLAB simulation. The i_n(t) is added with white Gaussian noise. The frequency of the single-phase stator current is calculated from the rotor speed (rpm), which is varied from 400 rpm to 600 rpm over 0.75 s under no load conditions (Barendse and Pillay, 2006). If we assume that the IPMSM has four pole pairs, the frequency is calculated using the following equation :

$$frequency = \frac{rpm \times pole\ pairs}{60} \tag{9}$$

Fig. 5 shows that the input current is a sinusoidal waveform with a non-stationary frequency and also shows that the output current of the proposed algorithm and the conventional algorithm. The cutoff frequency of the low pass filter is set at 300 Hz and the sampling frequency is set at 10 kHz using the MATLAB toolbox. The values of the parameters μ_1, μ_2, and μ_3 are set at 500, 50000, 0.02, respectively. The values of the step sizes is also applied to conventional algorithm compared with proposed algorithm. These results show that the output current resembles the extracted input current. Fig. 6 shows the error, which is the difference between the input current and the output current. The results show that the proposed algorithm outperforms the conventional algorithm at extraction.

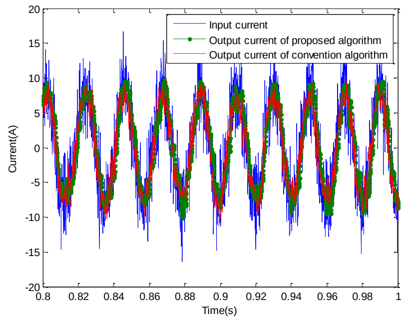

Figure 4: Test input signal and output signal.

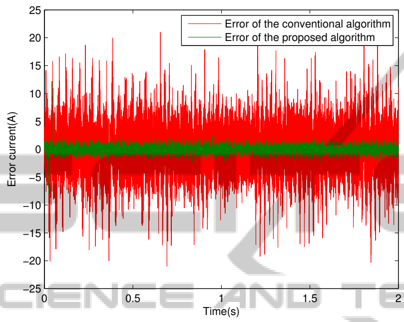

Figure 5: Difference signal from input and output.

5 CONCLUSIONS

This paper focuses on a fault detection algorithm. By using the proposed update error and the low pass filter, the extraction performance is improved. The proposed technique is tested using the MATLAB simulation. The test results show that the proposed technique is able to reduce the difference between the reference current signal and the extracted current signal. Because the high accuracy is required to detect interturn fault under non-stationary operating conditions the proposed fault detection algorithm is more suitable for identifying faults.

ACKNOWLEDGEMENTS

”This research was supported by the MKE(The Ministry of Knowledge Economy), Korea, under the ITRC(Information Technology Research Center) support program (NIPA-2012-H0301-12-2002) supervised by the NIPA(National IT Industry Promotion Agency)”

”This research was supported by the MKE(The Ministry of Knowledge Economy), Korea, under the IT Consilience Creative Program support program supervised by the NIPA(National IT Industry Promotion Agency)” (C1515-1121-0003)

REFERENCES

M. Seera, C. P. Lim, D. Ishak, H. Singh (2012). Fault Detection and Diagnosis of Induction Motors Using Motor Current Signature Analysis and a Hybrid FMMCART Model. In *IEEE Transactions on Neural Networks and Learning Systems*.

A. Gandhi, T. Corrigan, L. Parsa (2011). Recent Advances in Modeling and Online Detection of Stator Interturn Faults in Electrical Motors. In *IEEE Transactions on Industrial Electronics*.

J. Cusido,L. Romeral,J. Ortega, J. Rosero and A. G. Espinosa (2008). Fault Detection in Induction Machines Using Power Spectral Density in Wavelet Decomposition. In *IEEE Transactions on Industrial Electronics*.

B. Vaseghi, B. N. Mobarekeh, N. Takorabet, F. M. Tabar (2008). Experimentally Validated Dynamic Fault Model for PMSM with Stator Winding Inter-Turn Fault. In *Industry Applications Society Annual Meeting*.

B. Ayhan, M. Y. Chow, M. H. Song (2006). Multiple discriminant analysis and neural-network-based monolith and partition fault-detection schemes for broken rotor bar in induction motors. In *IEEE Trans. Ind. Electron.*

P. S. Barendse and P. Pillay (2006). A new algorithm for the detection of faults in permanent magnet machines. In *IEEE Industrial Electronics, IECON*.

J. H. Kim (2011). Simple Online Fault Detecting Scheme for Short-Circuited Turn in a PMSM Through Current Harmonic Monitoring. In *IEEE Transactions on Industrial Electronics*.

J. Sottile, F. C. Trutt and A. W. Leedy (2001). ‘Condition monitoring of brushless three-phase synchronous generators with stator winding or rotor circuit deterioration. In *Applications Conference, 2001. 36th IAS Annual Meeting*.

A. K. Ziarani, A. Konrad(2004). A methodof extraction of non-stationary sinusoids. In *ignal Processing*.