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NOVEL METHODS FOR PERMANENT MAGNET DEMAGNETIZATION DETECTION IN PERMANENT MAGNET SYNCHRONOUS MACHINES

By

Min Zhu

A Dissertation Submitted to the Faculty of Graduate Studies through the Department of Electrical & Computer Engineering in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy at the University of Windsor

Windsor, Ontario, Canada

2018

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Novel Methods for Permanent Magnet Demagnetization Detection in Permanent Magnet Synchronous Machines

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> > Oct 12, 2018

DECLARATION OF CO-AUTHORSHIP / PREVIOUS PUBLICATIONS

I hereby declare that this dissertation incorporates material that is result of joint research, as follows: This dissertation includes the outcome of publications coauthored with Dr. Wensong Hu, Dr. Guodong Feng and Dr. Narayan Kar from University of Windsor. In all cases, only primary contributions of the author towards these publications are included in this dissertation. The contribution of co-authors was primarily the guidance and assistance in experimentation, data analysis, and manuscript review and improvement.

I am aware of the University of Windsor Senate Policy on Authorship and I certify that I have properly acknowledged the contribution of other researchers on my dissertation and have obtained written permission from each of the co-author(s) to include the above material(s) in my dissertation. I certify that, with the above qualification, this dissertation, and the research to which it refers, is the product of my own work.

This dissertation includes selected sections and extended work of research conducted in four original papers that have been published in peer reviewed IEEE Transactions and international conferences, as follows:

| Dissertation | Publication title | Publication |
|--------------|--|-------------|
| Chapters | /full citation | status |
| | M. Zhu, W. Hu, and N. C. Kar, "Acoustic Noise | |
| | Based Uniform Permanent Magnet Demagnetization | |
| Chapter 2 | Detection in Surface Mounted PMSM for High- | Published |
| | Performance PMSM Drive," IEEE Transactions on | |
| | Transportation Electrification, Vol. 4, Issue 1, pp. | |
| | 303-313, 2018. | |
| | M. Zhu, W. Hu, and N. C. Kar, "Torque Ripple | |
| | Based Interior Permanent Magnet Synchronous | |
| Chapter 3 | Machine Rotor Demagnetization Fault Detection and | Published |

| | Current Regulation," IEEE Transactions on Industry | |
|-----------|--|-----------|
| | Applications, Vol. 53, Issue 3, pp. 2795-2804, 2017. | |
| | M. Zhu, W. Hu, G. Feng and N. C. Kar, "Vold- | |
| | Kalman Filtering Order Tracking Based Rotor Flux | |
| Chapter 4 | Linkage Monitoring in PMSM ," in Proc. IEEE | Under |
| | XXIIIrd International Conference on Electrical | Revision |
| | Machines (ICEM'2018), Alexandroupoli-Greece, | |
| | September 2018. | |
| | M. Zhu, W. Hu, G. Feng and N. C. Kar, "Multi- | |
| | Sensor Fusion-Based Permanent Magnet | |
| Chapter 5 | Demagnetization Detection in Permanent Magnet | Published |
| | Synchronous Machines," IEEE Transactions on | |
| | Magnetics, Vol. 54, Issue 11, 2018. | |

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I declare that this is a true copy of my thesis, including any final revisions, as approved by my thesis committee and the Graduate Studies office, and that this thesis has not been submitted for a higher degree to any other University or Institution.

ABSTRACT

Monitoring and detecting PM flux linkage is important to maintain a stable permanent magnet synchronous motor (PMSM) operation. The key problems that need to be solved at this stage are to: 1) establish a demagnetization magnetic flux model that takes into account the influence of various nonlinear and complex factors to reveal the demagnetization mechanism; 2) explore the relationship between different factors and demagnetizing magnetic field, to detect the demagnetization in the early stage; and 3) propose post-demagnetization measures. This thesis investigates permanent magnet (PM) demagnetization detection for PMSM machines to achieve high-performance and reliable machine drive for practical industrial and consumer applications. In this thesis, theoretical analysis, numerical calculation as well as experimental investigations are carried out to systematically study the demagnetization detection mechanism and post-demagnetization measures for permanent magnet synchronous motors.

At first a flux based acoustic noise model is proposed to analyze online PM demagnetization detection by using a back propagation neural network (BPNN) with acoustic noise data. In this method, the PM demagnetization is detected by means of comparing the measured acoustic signal of PMSM with an acoustic signal library of seven acoustical indicators.

Then torque ripple is chosen for online PM demagnetization diagnosis by using continuous wavelet transforms (CWT) and Grey System Theory (GST). This model is able to reveal the relationship between torque variation and PM electromagnetic interferences. After demagnetization being detected, a current regulation strategy is proposed to minimize the torque ripples induced by PM demagnetization.

Next, in order to compare the demagnetization detection accuracy, different data mining techniques, Vold-Kalman filtering order tracking (VKF-OT) and dynamic Bayesian network (DBN) based detection approach is applied to real-time PM flux

monitoring through torque ripple again. VKF-OT is introduced to track the order of torque ripple of PMSM running in transient state.

Lastly, the combination of acoustic noise and torque is investigated for demagnetization detection by using multi-sensor information fusion to improve the system redundancy and accuracy. Bayesian network based multi-sensor information fusion is then proposed to detect the demagnetization ratio from the extracted features.

During the analysis of demagnetization detection methods, the proposed PM detection approaches both form torque ripple and acoustic noise are extensively evaluated on a laboratory PM machine drive system under different speeds, load conditions, and temperatures.

DEDICATION

This dissertation is dedicated to my parents,

Ms. Daocui Wen and Mr. Zhenqiu Zhu,

my husband

Wensong Hu,

and my children

, John James, and David

For your unconditional love and support.

ACKNOWLEDGEMENTS

First of all, my sincere thanks goes to my advisor, Dr. Narayan Kar, for providing me enthusiastic guidance, full support and many resources for my study and research in the past four years in the Ph.D. program. He inspired me with confidence, and encouraged me to be a leader in research. Dr. Kar is gracious to us as a friend and family; he takes care of us in more than our research.

My sincere thanks also goes to Dr. Esam Abdel-Raheem, Dr. Balakumar Balasingam, and Dr. Guoqing Zhang for agreeing to serve on my committee, attending my seminars and defense, and providing valuable suggestions so that I can improve the quality of this dissertation.

I am thankful to my lab colleagues and friends who have been of great support in my study, professional activities and life. My research group leader, Dr. Wensong Hu, has provided great technical guidance towards my research work and experimental investigations. Dr. Guodong Feng has given me valuable guidance on theoretical writing. Other fellow lab members, such as Dr. Chunyan Lai, in the Centre for Hybrid Research and Green Energy (CHARGE), have given me friendly support and help whenever needed.

I am grateful to my parents and children, whose love and support have given me the strength to overcome all the difficulties during my study. My heartfelt thanks to my life partner Wensong for his unreserved love, care and the commitment he made to make our future better.

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NOMENCLATURE

A list of principal symbols is given here; there are more symbols used in this thesis, which have been defined locally. For simplicity, magnet flux is used to denote magnet flux linkage with respect to a specific machine in this thesis.

| Ψdr , Ψqr | :d- and q-axis rotor flux respectively |
|-----------------------------------|---|
| $\Psi ds, \Psi qs$ | :d- and q-axis stator flux respectively |
| $i_{ds,}\;i_{qs}$ | :d- and q-axis stator current respectively |
| $i_{dr,}i_{qr}$ | :d- and q-axis rotor current respectively |
| Vdr, Vqr | :d- and q-axis rotor voltage respectively |
| Vds, Vqs | :d- and q-axis stator voltage respectively |
| L_m | :Mutual inductance |
| $L_s, L_{r,}$ | :Stator and rotor inductance respectively |
| L _{ss} , L _{rr} | :Stator and rotor leakage inductance respectively |
| R_s, R_r | :Stator and rotor resistance |
| $\omega_{s,} \omega_{r}$ | :Synchronous speed and rotor speed respectively |
| T_m | :Mechanical load torque |
| T_e | :Electromagnetic torque |
| <i>i</i> _T | :Torque producing current |
| i_f | :Field producing current |
| Н | :Combined inertia of rotor and load |
| Pr | : Radial force |
| α | : Stator space angle |
| μ_0 | : Vacuum permeability |
| В | : Air gap flux density |
| μα | : Relative permeance |
| ω | : Electrical rotor speed |
| Р | : Number of pole pairs |
| λ | : De-noising threshold value |
| h | : Scale function |

| g | : Wavelet function |
|------------------------------|---|
| E_{TQ} | : Excitation at threshold in quiet |
| E_0 | : Excitation to the reference sound intensity |
| Ε | : Exciting value |
| Ν | : Loudness |
| Z | : Critical-band rate |
| f_{mod} | : Modulation frequency |
| $\Delta L(z)$ | : Masking depth |
| $T_c, T_\lambda, T_\lambda,$ | : Torque components |
| θ_e | : Rotor position |
| Φ_{dq} | : Armature current flux |
| $\Psi(t)$ | : Square-integrable function |
| E(a) | : Scale-wavelet energy spectrum |

CHAPTER 1 INTRODUCTION

1.1 Overview and Motivations

Energy shortage is an important issue of concern to the world today, and it is related to the improvement of the global environment and human survival. Energy efficiency is the goal of all countries in the world. Energy-saving technology is recognized as a green technology, and its research and development of related products will become the theme of industrial development in the century. At present, countries are actively carrying out research and application of energy-saving technologies. Electricity is the most important secondary energy source in the world today, and electric motors are currently the most widely used [1].

The first motor in human history was a permanent magnet motor created by Jacob in 1843. He built a magnetic field from a permanent magnet material. However, because the permanent magnet was made of natural magnetite ore and had poor performance, the motor performance was poor with the large volume. Soon it was replaced by an electric excitation motor. The asynchronous motor has the advantages of simple structure, reliable operation, long service life and convenient maintenance and repair, but it also has disadvantages such as poor mechanical properties, low efficiency, small starting torque, poor speed regulation performance, low power factor when operating at light load, and increased losses.

Due to the needs of motor development, people have conducted in-depth research on permanent magnet materials, and successively discovered permanent magnet materials such as carbon steel, Hegang and cobalt steel. In the 1920s and 1930s, nickel-cobalt permanent magnet materials appeared. In the 1950s, ferrite was discovered, and its permanent magnet performance was greatly improved, which made the permanent magnet motor develop rapidly. However, the low magnetic energy product of silver town cobalt and ferrite permanent magnet materials limited its application in motors. Since the late 1960s, rare earth cobalt and Neodymium Iron Boron (NdFeB) permanent magnet materials have been successively introduced. They have excellent performance such as high remanent density, high coercivity, high magnetic energy product and linear demagnetization, and low cost, which make permanent magnet motors have been rapidly developed in the manufacture.

Therefore, the research background of this thesis is the application of the Permanent Magnet Synchronous Machine. In general, a synchronous machines produces electromagnetic torque by the interaction between the rotor flux and stator mmf (magnet motive force), which are from rotor windings and stator coils respectively. In PMSM, the rotor windings are replaced by the PM. According to the ways of arranging the magnets on the rotor, the PMSM can be classified as surface-mounted PMSM and Interior PMSM shown in Fig. 1-1 [2]. The Fig. 1-2 [3] shows the magnets mounted on the surface of the outer periphery of the rotor laminations. This arrangement provides the highest air gap flux density as it directly faces the air gap without the interruption of any other medium such as part of rotor laminations. The Fig. 1-3 [3] shows the placement of magnets in the middle of the rotor laminations in radial orientations. Such a machine construction is generally referred to as interior PMSM. The interior PM rotor construction is mechanically robust and therefore suited for high-speed applications. Both types have been widely used in the EV applications.



Figure 1-1. The structure of permanent magnet synchronous machines [2]. (a) Surface mounted synchronous machine (SPM). (b) Interior synchronous machine (IPM).



Figure 1-2. The stator and rotor of a designed surface mounted permanent magnet synchronous machine [3].



Figure 1-3. The rotor and stator of a designed interior permanent magnet synchronous machine [3].

The reason that PMSMs are prevalent in the EVs is they have the unique advantages. Compared with induction motors, permanent magnet synchronous motors have the advantages of small size, light weight and high power density. Due to the permanent magnets on the rotor, no external excitation is required, which significantly increases the power factor. In the steady state operation, there is not rotor fundamental copper loss, so the efficiency is higher than that of the induction motor of the same specification. Moreover, rare earth permanent magnet motors have higher efficiency and power factor in the rated power range. In general, the use of energy-saving efficiencies in some longrunning (electric vehicles) or in most operating conditions for light-load operation can achieve significant energy savings compared to induction motors. The graph Fig. 1-4 compare the efficiency between PMSM and IM [12]. The table shows the specifications of a SPM in our lab. The efficiency is up to 97%.



Figure 1-4. Performance comparison of induction-motor and permanent-magnet-motor in a EV [12].

Due to its inherent characteristics, permanent magnetic materials do not require additional energy to establish a magnetic field in their surrounding space after pre-magnetization. When the permanent magnet material is applied to the motor, the higher power factor can be obtained due to the needlessness of reactive current, which reduces the stator current and the stator resistance loss, thus the high efficiency can be maintained within the rated load range. Permanent magnet motors also have advantages such as larger starting torque and wide speed range. With the application of high-performance permanent magnet materials, the volume and quality of permanent magnet motors are greatly getting reduced, and the power density is greatly being improved.

The drawbacks of the PMSM are that they have a higher initial cost, they need digital controlled inverter and cooling systems, and demagnetization due to the material. Among those demerits, the biggest disadvantage of permanent magnet motor at present, lies in the fluctuation of permanent magnetic field and the problem of permanent magnet loss. One reason is due to the material self-characters. Permanent magnet materials which have been widely used in modern industry and science and technology include cast permanent magnet

materials, ferrite, and rare earth permanent magnet material. Casting Alnico (AlNiCo) permanent magnet material has high Curie temperature T_C and good stability under high temperature, but it contains more other metals such as cobalt and nickel. The main features of ferromagnetic permanent magnet materials are abundant materials resources and favorable prices, but the remanent flux density is not high ($B_r = 0.2 \sim 0.44$ T). NdFeB permanent magnet material has high maximum flux energy product (BH)_{max}, remanent flux density remanence B_r , and coercivity H_c . NdFeB is the most widely used permanent magnet material. Although its performance is satisfactory, it also has its disadvantages, that is, the temperature characteristics are poor, which is reflected in the low Curie temperature and high temperature coefficient. The magnetic loss under high temperatures is large, and the lower half of the demagnetization curve is non-linear (curved). Because of the poor temperature stability of NdFeB permanent magnet material, its irreversible loss and temperature.

Moreover, the other reason is motor operation conditions. The air gap magnetic field of the permanent magnet motor is generated by the permanent magnet. During the operation, the motor generates heat, vibration, demagnetizing magnetic field, etc., which may cause the permanent magnet to demagnetize, and consequently reduces the working point of the permanent magnet as well as the motor performance. If the demagnetization is severe, the permanent magnet works below the knee point, irreversible demagnetization will occur and result in a decrease in the performance of the permanent magnet. The motor no-load back EMF and output torque will drop. In severe cases, the motor will not be damaged. When PMSMs are widely used in EVs and other occasions, some special working conditions may occur such as motor overload, out of step, frequent forward and reverse (charging batteries), causing a surge in current in the case of motor starting, braking or failure, and the working point moves toward the knee point of the demagnetization curve. The above conditions may cause motor vibration and permanent magnet overheating, which makes the demagnetization field more serious. With all those factors working together, there might be irreversible demagnetization of a properly designed PMSM.

Therefore, it is very necessary to study the demagnetization of permanent magnets under various working conditions.

1.2 Permanent Magnet Synchronous Machine Demagnetization

1.2.1 Definition of PM Demagnetization

Demagnetization phenomenon is usually caused by physical damage, high-temperature stress, inverse magnetic fields, and aging. For example, when a car is running in a severe condition such as steep ramp start, on rough road, in extremely hot area, or stunt show, demagnetization might happen.

However, there is not standard definition of demagnetization so far, but usually it is described as the loss of magnetization in magnet materials. During the magnetization of ferromagnetic materials, the relationship between magnetic field strength and magnetic flux density is not linear. If the ferromagnetic material is repeatedly magnetized, a curve of magnetic flux density as a function of magnetic field strength can be obtained, which is called hysteresis loop in Fig. 1-5 [13] left that shows the relationship between field strength H and magnetic density B of a PM. When an external magnetic field is applied to a PM material, the material has become magnetized. Once magnetized, the magnet will stay magnetized indefinitely. To demagnetize it requires heat or a magnetic field in the opposite direction. The second quadrant portion of the hysteresis loop of the permanent magnet material, as shown in Fig. 1-5 right, referred to as the demagnetization curve.

There are two types of demagnetization. One is called reversible demagnetization, it occurs along a line, and recover after the temperature falls. The upper half of the demagnetization curve is approximately a straight line. When it continues to increase, it will bend. The point at which the demagnetization curve begins to bend is called the knee point. Usually the permanent magnet in the permanent magnet motor works above the knee point. When the demagnetization occurs due to external conditions, the working point will decrease along the demagnetization curve. If the inflection point is not exceeded, the working point of the permanent magnet can rise to the original working point along the original demagnetization curve. If the demagnetization is more serious, the working point is below the knee. when the external demagnetization factor disappears, the working point will rise along the other curve and cannot reach the original working point. This phenomenon is called irreversible demagnetization, that is, loss of magnetism. When the flux density is lower to the knee point, it sharply dives down to zero. Then it recovers magnetism along a line parallel to the original B–H characteristic. In that process, it reaches a new remanent flux density, *Brr*, which lower than the original remanent flux density. The difference between the two points is the irreversible magnetism loss.



Figure 1-5. The hysteresis loop of magnetic characteristics and demagnetization types [13].

1.2.2 Factors Affecting PM Demagnetization

The performance of permanent magnet materials is affected by external environment temperature and applied magnetic field. There are mainly the following origins of demagnetization:

(1) Demagnetization of permanent magnet material is due to temperature change. This is mainly related to the temperature coefficient of the permanent magnet material. The lower the temperature coefficient value, the higher the temperature stability of the permanent magnet material. The temperature coefficient of NdFeB permanent magnet material is relative larger, and the effect of temperature change on its performance should be considered when NdFeB is used in electric motors. However, the temperature coefficient of rare earth cobalt permanent magnet material is low, thus the motor performance is less affected by temperature changes. The motor temperature stability is satisfied, and temperature effects can be ignored [14].

(2) Irreversible demagnetization of permanent magnet materials caused by demagnetizing magnetic field. Since the demagnetization curve of permanent magnet material NdFeB is

straight at low temperature, irreversible demagnetization will not happen at low temperature even if there is an external demagnetizing field. However, its temperature stability is poor. When the motor is working in high temperature environment, the demagnetization curve will bend. Thus, irreversible demagnetization may occur if the applied demagnetizing field exceeds a certain value [15].

(3) Demagnetization due to vibration: The permanent magnet magnetic moment direction of the internal magnetic domain may change after being subjected to severe vibration. The change causes the magnetic properties of the magnetic steel to deteriorate, which in turn causes the magnetic steel to demagnetize or even irreversibly demagnetize [16]. In the actual application, if the motor is used improperly, such as the motor is being done the stall test, the permanent magnet is easy to demagnetize.

(4) The influence of chemical factors leads to the weakening of magnetic properties. There are some chemical compositions in permanent magnet materials, such as NdFeB contains a large amount of strontium and iron. The changes in the chemical structure of the surface or internal will cause the occurrence of demagnetization when the motor is used in the sever surrounding environment such as acid, alkali, oxygen and other chemical elements [17]. In practice, various technological measures are generally taken to prevent the occurrence of oxidation or decaying candles during the manufacture, thus examples of demagnetization caused by this situation rarely occur.

(5) Demagnetization due to time. The magnetic properties of permanent magnet materials will weaken with time even after being put in an ideal environment after magnetization. The magnetism loss is linear with the logarithm of time [18]. Theoretically, permanent magnets also have a lifetime index, but it is less affected by time. In practical applications, irreversible demagnetization due to the long usage rarely occurs, so the impact of this aspect is negligible.

The demagnetization that occurs during the operation of a permanent magnet motor is theoretically caused by the combination of the above factors. However, considering the actual situation, the influence of vibration factors, chemical factors, and time factors is small and can be ignored. Therefore, generally only the effects of the first two factors, namely the temperature and the applied demagnetizing field, are considered. Temperature affected demagnetization is caused by a high temperature of the permanent magnet due to the turbulence. Physics studies show microscopic particles are all in thermal motion, which changes the direction of the magnetic moment of each atom continuously and irregularly. When the temperature is low, the electron exchange of two adjacent atoms of the permanent magnet material is much more affected than the thermal motion. When the temperature rises to a certain extent, the spatial orientation of the magnetic moment under the action of thermal motion will change, resulting in irreversible demagnetization. In a running EV, the motor temperature may reach above 130°C, and at this time the demagnetization of the permanent magnet characteristic is no longer a straight line. When the demagnetizing field strength exceeds a certain value, the working point will be lower than the knee point of the demagnetization curve and irreversible demagnetization occurs [19]. When the demagnetizing field strength reaches a certain value, the magnetic domain in the permanent magnet will have a domain wall position. The magnetic domain in the permanent magnet will undergo domain wall displacement and the magnetic moment will rotate to the direction of the demagnetization field, forming an irreversible rotation. Even the demagnetizing field disappears, the magnetic domain magnetic moment in the permanent magnet cannot return to the original magnetic moment direction, that is, irreversible demagnetization occurs. Once demagnetization occurs, in the stator winding, stator current should be much larger than the rated value to generate the same torque, and the heat generation of the motor is increased [20].

1.2.3 PMSM Demagnetization Effects

Usually when demagnetization occurs, it will cause several issues in a PMSM. For example, demagnetization will reduce the output torque because of its impact on interaction between the permanent magnet field and the stator magnetic field. Meanwhile, it will degrade the robustness, cause vibration, noise, and even lead to the motor failure.

The following Fig. 1-6 [21] are simulated results under demagnetization from a literature paper. It can be seen that both the phase current and back EMF became imbalanced during demagnetization. Meanwhile, it will increase the harmonics component. Thus the it is important to monitor the PM flux variation during motor operation and then detect the demagnetization in its early stage to maintain the healthy motor operating.



Figure 1-6. Temporal evolution of the phase currents in case of demagnetization [21].

1.3 Literature Review

Since demagnetization affects the motor performance, researchers have worked on this field by different methods. Through background study, the existing research methods for demagnetization detection can be classified into two major categories: prevention analysis and monitoring techniques.

1.3.1 Permanent Magnet Demagnetization Prevention Analysis

In order to prevent the permanent magnet motor from demagnetizing, measures to reduce the risk of loss of magnetism have to be taken in four aspects: permanent magnet material selection, permanent magnet motor design, permanent magnet motor assembly process, and permanent magnet motor use. For the permanent magnet motor designers, the permanent magnet demagnetization is prevented from the design and use of the permanent magnet motor.

The static prevention scheme optimizes the magnetic circuit from the perspective of motor design and reduces the risk of demagnetization. The static prevention technology is divided into magnetic network analysis method, finite element analysis method, magnetic field reconstruction method and multi-domain comprehensive simulation analysis method.

(1) Magnetic network analysis

The magnetic network analysis method of permanent magnet motor is based on the theory of magnetic flux management. It takes the PM part with the same material, uniform magnetic flux distribution and regular shape as an equivalent magnetic conducting unit. Each magnetic conducting unit is connected through nodes. Similar to electric network equations, the magnetic position, magnetic flux of each node in the magnetic network equation, and the relevant parameters can be obtained by using magnetic network equations. Compared with the finite element analysis, the number of nodes and the calculation time of the magnetic network equation are greatly reduced [22-24].

Since magnetic network analysis is a typical lumped parameter method, it simplifies the motor model with the idea of synthesizing magnetic field. There exit empirical formulas, corrections and coefficients, which will inevitably cause some error between the calculation result and the actual result. Especially when the method is applied to a permanent magnet motor model with complex structure, the magnetic network analysis method has to require more nodes to improve its accuracy. However, due to the analytical relationship between the magnetic permeability unit and the dimensional constant, and less calculation time, this method can provide a way for rapid optimization design.

(2) Magnetic field finite element analysis (FEA)

The magnetic field finite element analysis method is a widely used numerical calculation magnetic field method with high calculation accuracy. FEA is used to analyze the demagnetization phenomenon of the permanent magnet, and then the anti-demagnetization optimization design can be carried out.

A FEA method is proposed in [25] to set the maximum operating temperature of permanent magnet motors and the maximum armature current to simulate whether the permanent magnet is demagnetized. If there is full demagnetization, PM thickness will be increased; if only partial demagnetization occurs, the PMSM rotor structure should be optimized to prevent demagnetization. This design idea provides a way for the anti-demagnetization optimization design of permanent magnet motor.

In [26], the three different permanent magnet arrangement schemes of the built-in permanent magnet motor single layer model, V shape model, double-layer model permanent magnets are compared from the anti-demagnetization point. When the maximum torque is generated, the single layer model permanent magnet is most prone to demagnetization. In the case of short-circuit current failure, the "V shape model permanent magnet is most prone to demagnetization, while the double-layer permanent magnet arrangement is the most difficult to prevent demagnetization. Demagnetization provides a solution for the permanent magnet structure arrangement of permanent magnet motor from the anti-demagnetization angle.

A conclusion is drawn in [27] that the eddy current loss on the surface of the permanent magnet is reduced through the 3D finite element simulation of the axial segmentation of permanent magnets. Those series of studies with FEA on the effects of insulation, block number, frequency and harmonics on the eddy current loss between axial magnetic steel blocks, have provided a reference direction for the permanent magnet axial block method.

1.3.2 PM Demagnetization Monitoring and Detection Techniques

The study of permanent magnet demagnetization of magneto is not only carried out in the design process to prevent the demagnetization of permanent magnets, but also the state of dynamic PM monitoring during motor operation to detect whether permanent magnets are demagnetized. The dynamic monitoring technology including monitoring the PMSM parameters, obtaining the state information of the permanent magnet, and dynamical controls according to its state information to prevent More severe demagnetization occurs. The existing methods for demagnetization detection can be classified into five categories on the basis of the detection approaches. They are direct detection, current/voltage/torque based detection.

(1) Direct Detection

It is the traditional method of permanent magnet quality testing and uses special direct measurement equipment, gauss meter, to measure the magnetic field axis and distribution. [28] introduces an investigation to measure permanent magnet filed axis and the distribution. An details of the direct detection is guided and explained in [29] explains direct detection in details and guides the procedures using Gauss meter.

Although this method can be used to diagnose both non-uniform and uniform demagnetization of permanent magnets, the drawback is that the tested motor needs to be stopped and disassembled. In general, these techniques are good for quality control in PMSM manufactory process.

(2) Current Based Detection Approaches

Current based detection approach is popular due to the easy availability of the current signal, and simple mathematical. Researchers are trying to use current frequency distribution, harmonic component and injected current to detect the PM magnet filed fault.

Stator phase currents frequency distribution is used to describe the fault distribution by FFT averages in time domain [30], but it is not applicable to variable speed and load because frequency components appearing in symmetrical stator windings gives improper fault analysis result.

Harmonic components amplitude [31] [32] in the parallel phase winding branches [33] caused by demagnetization was used as a criterion to identify demagnetization ratios. However, it is only related to machines with parallel branches, not easy to access the currents in the branches of every machine.

Author in [34] injected d-axis current in standstill to detect the PMSM stator winding shortcircuit fault and permanent magnet demagnetization fault, but it needs additional inverters, sensitivity depends upon the design parameters of the motor.

(3) Voltage Based Detection Approaches

This method is useful when harmonics related to demagnetization do not appear in the stator current spectrum due to the winding configuration.

The author in [35] explored the instantaneous back EMF of slot conductors to predict demagnetization fault frequencies by means of FEM simulation. It is invasive and needs additional injected equipment. In [36], zero-sequence voltage component (ZSVC) was taken as a feature value in a symmetric stator winding PMSM to determine demagnetization and compared with FEM results. Like [37], this method resistor network connected to the drive system and not feasible in a EV.

(4) Torque Based Detection Approaches

Torque based approach focus on analyzing the toque radius, torque constant to obtain the demagnetization information.

Cogging torque is analyzed in [38] by a 2-D finite element method, by means of which the cogging torque signal is computed under healthy and faulty conditions. It is off-line and sensitive to the load level. The estimated torque constant was applied in [39] to monitor magnet quality to detect the demagnetization. Again, it is sensitive to the parameters of the motor, only for sever fault detection. A shaft trajectory of the PMSM in [40] was used as a criterion to identify demagnetization ratios, and the result is accurate. The entire system is complicated, and it is difficult to calibrate.

(5) Magnetic Flux Based Approaches

Magnetic flux based approach provides the demagnetization information by studying daxis flux, flux pattern, and vibrations. This kind of approaches concentrate on the direct and major impact of the demagnetization fault.

PM flux pattern was studied in [41], [42] for the magnetization and circumferential axis of the PM with high accuracy and reliability. During the experiments, the PMSM motor must be dismantled. In [43], magnetization coefficients of each piece of PMs was employed using an analytical model considering the stator slotting effect and the end winding inductances. The result of this method has lower precision. Vibration and noise were considered as criterion signals in [44] to diagnose eccentricity and partial demagnetization in PMSM with spectrum analysis. But the proposed method is not able to separate the demagnetization faults from the other motor faults.

1.3.3 Machine Learning based PM Demagnetization Detecting Techniques

An extended Kalman Filter (EKF) is applied in [45] to identify the permanent magnet flux with position sensorless control and to observe the rotor flux linkage in [46] by choosing new state variables based on demagnetization. Fast Fourier transform (FFT) was applied to average the stator current in the time domain in [47]. A complex exponential sinusoidal criterion is proposed in the frequency domain in [48] without considering speed or load variation. Acoustic noise can be considered as a non-invasive index in order to reproduce the magnet demagnetization in a practical PMSM. Vibration and noises of PMSM are

accurately predicted in [49] by using multiphysics finite-element modeling (FEM). Field reconstruction method (FRM) and mechanical impulse response are applied in [50] to calculate EM vibration and in [51] to predict the static eccentricity and partial demagnetization. EM and mechanical characterizations of noise and vibration in PMSM are studied in [52] while factoring in resonance influence. Both [53] and [54] use the Black-Box technique to detect and analyze irregular sources of noise in the PMSM, however it is unable to reveal noise changes and flux variation. In general, these methods have provided viewpoints to noise-based detection from different aspects, but most of them require detailed motor parameters and are computationally inefficient.

A direct detection method was applied in [55] and was explained in [56] to measure the field axis and distribution using Gauss meter. Though it is a good method for quality control in PMSM manufactory process, it is necessary that the motor is stopped and all the loads are disconnected in order to apply the direct method. Model-based methods, such as finite element model (FEM), have been widely applied to identify PM demagnetization and the impact on the internal electromagnetic field [57], [58], rotor field [59], [60], back electromotive force (EMF) [61] and output characteristics [62], [63]. FEM can directly obtain the PM field as well as analyzes the internal field, but it is difficult to be embedded in motor control system due to massive computation and its nature being a physical model. It is suitable for motor designing to provide the optimized design parameters as an off-line method. The third research method group is based on data-driven detection which analyzes the measured data and further provides the demagnetization information through data mining. The d-axis flux linkage was compared with current and inductance to diagnose rotor demagnetization fault [64]. The steady-state waveform of positive peak plus negative peak of phase current under pulsating field was applied in [65] to monitor magnet quality. Harmonic components amplitude [66], [67] in the parallel phase winding branches [68] caused by demagnetization was used as a criterion to identify demagnetization ratios. Fast Fourier transform (FFT) was applied in [69] to average the stator current in the time domain and be a complex exponential sinusoidal criterion in the frequency domain [70] without considering speed or load variation. Zero-sequence voltage component (ZSVC) was taken as a feature value in a symmetric stator winding PMSM to determine demagnetization in [71] and compared with FEM results. However, asymmetric PMSM structure and inverter

can lead to the ZSVC in motor stator as well. Consequently, the distinction of ZSVC caused by demagnetization from that caused by other factors would be further studied in future. Vibration and noise were considered as criterion signals in [72] to diagnose eccentricity and partial demagnetization in PMSM with spectrum analysis. Again there was the same problem in [73] as the further study was necessary in order to distinguish demagnetization from other faults. Estimated torque constant [74] or measured torque constant [75] were used to distinguish eccentricity fault from uniform demagnetization fault for different windings using inverter dc link distributed over every 60 electrical degrees. However, this method is not desirable since the load is disconnected from the machine.

In general, these methods have provided appropriate viewpoints to demagnetization detection on different aspects. Some are not feasible to diagnose a motor running in an electric vehicle. Moreover, some conventional methods, like FFT or time-frequency analysis, are not available in all cases due to the non-stable data resource.

1.4 Research Objectives

From literature review, the above approaches have been used to detect demagnetization, and most of them provided appropriate viewpoints to demagnetization detection on different aspects. However, there are some drawbacks. Some of them are model based, and need complicated analytical system or large amount of computation. Some conventional detection algorithm succeeds in detecting the fault but fail to distinguish fault ratio. Some investigation is off-line method, and could not diagnose a motor running in an electric vehicle or connect loads from the machine. Others are invasive way to access the signals, and damage the motor structure. Almost all of the existing detection methods could not implement relative corrective action after demagnetization.

Thus, the objective of this thesis are:

- On-line non-invasive PM demagnetization detection methods based on the analysis of PMSM variables through output torque ripple and/or acoustic noise.
- Post demagnetization control strategy to protect the PMSMs.

This thesis is going to propose improved ways to detect the magnetization. These ways are online, and data driven based approaches, which focus on analyzing the measurement data,

through data mining. without the requirement of accurate analytical model. The mining objects would be the torque ripple, acoustic noise and the time harmonics. This thesis will use machine learning algorithm such as GST, BP NN, and DBN to estimate the fault occurrence and find the fault level as well. After the demagnetization occurs, this thesis will also propose a control strategy to prevent the motor getting further damaged.

1.5 Research Contributions

This thesis proposes novel and advanced demagnetization techniques with the merits such as independence on machine parameters, real-time detection, and enhanced computation efficiency. Moreover, the signal processing algorithms and machine learning algorithms help to improve the prediction accuracy. Compared with the existing detection methods, the proposed approaches have major contributions are listed as follows.

(1) The first merit of those proposed approaches are that they are non-invasive methods. Those methods will not change or damage the motor physical structure and thus are feasible for on-line monitoring in a running EV.

(2) The psychoacoustic and objective indicators, which can process nonlinear signals, are introduced to reflect the comprehensive noise quality, thus the performance of the proposed approach can be improved more comprehensively than the other approaches.

(3) The computations for acoustic noise based demagnetization detection approach are less complex than standard methods, thus an online implementation is feasible due to its efficiency. The computation complexity of the torque ripple based detection method is less than the conventional method and can be implemented on-line due to its computation efficiency.

(4) The proposed signal processing method can reduce the influence of noise and improve the signal-to-noise ratio.

(5) The proposed approach does not need the nominal value of machine parameters, so the performance of the proposed approach is not influenced by the machine parameters variation.

(6) The proposed method implements the machine learning algorithms which are good at processing the nonlinear signals, and thus the performance of the proposed approach can be improved in comparison with the existing approaches.

1.6 Dissertation Layout

Chapter 2 presents the idea of detecting uniform PM demagnetization by using acoustic noises in order to develop a reliable PMSM controller. A flux based acoustic noise model is proposed to demonstrate that demagnetization will induce acoustic noise containing abnormal frequency. This chapter also analyzes online PM demagnetization detection by using a back propagation neural network (BPNN) with acoustic noise data. Firstly, seven objective and psychoacoustic indicators are proposed to evaluate the acoustic noise of healthy and demagnetized PMSMs under different speed and load conditions. Next, a novel BPNN based PM demagnetization detection method is proposed. In this method, the PM demagnetization is detected by means of comparing the measured acoustic signal of PMSM with an acoustic signal library of seven acoustical indicators.

Chapter 3 proposes the use of torque ripple for online PM demagnetization fault diagnosis using continuous wavelet transforms (CWT) and Grey System Theory (GST). Firstly, a torque ripple based rotor flux linkage detection model considering electromagnetic noises is proposed, which employs the CWT filtering, wavelet ridge spectrum, and torque ripple energy extraction. This model is able to reveal the torque variation and eliminate the effect of electromagnetic interferences. Secondly, GST is employed to facilitate the detection of demagnetization ratios and torque ripple energy pulsations caused by demagnetization. Thirdly, a current regulation strategy is proposed to minimize the torque ripples induced by PM demagnetization, which contributes to making the approach feasible to interior PMSM (IPMSM). Furthermore, the proposed real-time irreversible demagnetization detection approach can identify the demagnetization fault under different operating conditions.

Chapter 4 discusses Vold-Kalman filtering order tracking (VKF-OT) and dynamic Bayesian network (DBN) based investigation for the application of torque ripple in realtime PM flux monitoring. A torque ripple model of PMSM considering electromagnetic noise is proposed, and the torque variation is studied. In this chapter, the torque is analyzed
and processed by wavelet transform to eliminate the effects of the electromagnetic disturbances. VKF-OT is introduced to track the order of torque ripple of PMSM running in unsteady state. Therefore, torque ripple characteristics can be used as a feature to reflect changes in PM flux linkage. Moreover, this method is feasible for PMSM by applying DBN to the training data to estimate the flux linkage during motor operation.

Chapter 5 proposes the use of multi-sensor information, namely, acoustic noise and torque, for demagnetization detection through the information fusion technique. The acoustic noise and torque information are processed and analyzed using wavelet transforms for filtering and extracting features. Bayesian network based multi-sensor information fusion is then proposed to detect the demagnetization ratio from the extracted features. The proposed approach is experimentally verified on a laboratory PMSM and compared with single-sensor detection methods.

Chapter 6 summarizes the work in this thesis investigation. The limitations of the proposed methods are also discussed and possible solutions are outlined.

CHAPTER 2

PERMANMENT MAGNET DEMAGNETIZATION DETECTION BASED ON ACOUSTIC NOISE ANALYSIS

2.1 Introduction

The electromagnetic (EM) torque, excluding the reluctance torque, is proportional to the quadrature-axis current, which is in accordance with the electrical model of a surface mounted permanent magnet synchronous machine (SPMSM) in dq-axis reference frame. However, PMs in the rotor may demagnetize, which can cause speed and temperature variances during testing. This causes the output torque to be non-linear with respect to the current, which then creates abnormal acoustic noise from the resulting torque ripple. PM demagnetization, is caused by a combination of thermal, electrical, mechanical, and environment issues [1]. This alters the torque constant and reduces the PMSM motor output torque, which is produced from the interaction between the stator winding field and the permanent magnet field. Moreover, demagnetization being irreversible causes electric drive system failures in EVs. It is essential to monitor the PM flux and detect demagnetization at an early stage in order to transmit an accurate dynamic torque constant to the control system. Furthermore, an advanced control strategy should be developed to protect the PMSMs.

In practice, PM demagnetization creates fluctuation in output torques as well as noise and vibration losses that degrades the system's robustness and controllability. However, investigation of the acoustic noise is a challenge because of various interferences from harmonics produced by voltage source inverter (VSI). Moreover, the measured acoustic noise should be processed in a way that scrubs the extra noise and provides a current compensation reference value that is useful to vector control.

This chapter presents a non-invasive approach to detect the uniform permanent magnet demagnetization for SPMSM based on the acoustic noise analysis from a BPNN model. It firstly presents a PMSM flux based acoustic noise model with consideration of the switching frequency of VSI and the relevant harmonics. The provided model aims to demonstrate that the acoustic noise containing abnormal frequency measurements is induced by the demagnetization. Next, the seven indicators of noise performance used to evaluate the acoustic noise from a surface mounted PMSM under acceleration conditions are sound fluctuation, sound loudness, sound roughness, articulation index, HHT instantaneous frequency, FFT spectrum and power spectrum density. Lastly, a novel BPNN based PM demagnetization detection method is proposed, in which PM flux is identified and detected by comparing a healthy motor noise library with measurements from seven acoustical indicators.

The proposed real-time PM demagnetization detection approach is experimentally verified on a laboratory surface mounted PMSM rated at 12.5 kW; the results demonstrate that the method can identify demagnetization under different operating conditions.

2.2 Acoustic Noise Model Based on Flux Variation

A PMSM flux based acoustic noise model is proposed in this section to show that the demagnetization will induce the acoustic noise containing abnormal frequency. Acoustic noises produced by an electric machine can be viewed as a phenomenon that the electromagnetic forces interact with the stator frame [49]. According to Duhamel integral [76], the response of the PMSM machine consists of two parts: the response of the damped free vibration at the modal frequency and the response of forced vibration at the same frequency of the exciting force. When the electric motor operates at high speed with large torque, the addition of acoustic noise is typically from an EM source. When a healthy PMSM is fed with ideal sinusoidal current, the radial force is the major exciting force as in (2.1) [77]:

$$P_r(\alpha, t) = B^2(\alpha, t)/2\mu_0 \tag{2.1}$$

where P_r is the radial force, α is the stator space angle. μ_0 is the vacuum permeability, and *B* is the air gap flux density.

From (1), the free space permeability is a constant, so the exciting force depends on the square order of flux density. From this, it can be surmised that the acoustic noise from the motor is primarily affected by the air gap flux variation when the motor's mechanical modal frequency is constant; this frequency is determined by the motor's physical structure.

The air-gap flux density can be obtained as (2.2) by superposition of permanent magnet field and armature interaction field assuming that saturation is neglected.

$$B(\alpha,t) = B_r(\alpha,t) + B_s(\alpha,t)$$
(2.2)

where B, B_r and B_s are air-gap flux density, permanent magnet flux density, and stator flux density.

The permanent magnet field and armature interaction field can be expressed as follows [13]:

$$\begin{cases} B_r(\alpha,t) = \mu_{\alpha} \sum_{k=1}^{\infty} A_{r(2k-1)} \cos\left[(2k-1)p\alpha - (2k-1)\omega t + \phi_{(2k-1)}\right] \\ B_s(\alpha,t) = \mu_{\alpha} \sum_{j=1}^{\infty} A_{sj} \cos\left(jp\alpha - \omega t\right) \end{cases}$$
(2.3)

where μ_{α} is the relative permeance, $A_{r(2k-1)}$ is the amplitude of the $(2k-1)^{\text{th}}$ permanent magnet field, ω is the electrical rotor speed, P is the number of pole pairs, $\Phi_{(2k-1)}$ is the advance angle, k is the integer and A_{sj} is the amplitude of the j^{th} armature interaction field.

According to (2.2) and (2.3), (2.1) can be rewritten as follows:

$$P_{r}(\alpha,t) = \left[B_{r}(\alpha,t) + B_{s}(\alpha,t)\right]^{2}/2\mu_{0} = \frac{\mu_{\alpha}^{2}}{4\mu_{0}}\sum_{j=1}^{\infty} A_{sj}^{2}\cos(2jp\alpha - 2\omega t) \\ + \frac{\mu_{\alpha}^{2}}{4\mu_{0}}\sum_{j=1, j\neq l}^{\infty}\sum_{l=1, l\neq j}^{\infty} A_{sj}A_{sl}\left\{\cos\left[(j+l)p\alpha - 2\omega t\right] + \cos\left[(j-l)p\alpha\right]\right\} \\ + \frac{\mu_{\alpha}^{2}}{2\mu_{0}}\sum_{j}^{\infty}\sum_{k=1}^{\infty} A_{r(2k-1)}A_{sj}\cos\left[(j+2k-1)p\alpha - 2k\omega t + \phi_{(2k-1)}\right] \\ + \frac{\mu_{\alpha}^{2}}{2\mu_{0}}\sum_{j}^{\infty}\sum_{k=1}^{\infty} A_{r(2k-1)}A_{sj}\cos\left[(-j+2k-1)p\alpha - (2k-2)\omega t + \phi_{(2k-1)}\right] \\ + \frac{\mu_{\alpha}^{2}}{4\mu_{0}}\left\{\sum_{j=1}^{\infty} A_{r(2k-1)}^{2}\left[\cos\left(2(2k-1)p\alpha - 2(2k-1)\omega t\right) + 2\phi_{(2k-1)} + 1\right]\right\} \\ + \frac{\mu_{\alpha}^{2}}{4\mu_{0}}\sum_{\substack{k=1, m=1, \\ k\neq m m\neq k}}^{\infty} A_{r(2k-1)}A_{r(2m-1)}\left\{\cos\left[2(k+m-1)p\alpha - 2(2k-1)\omega t\right] + 2\phi_{(2k-1)} + 1\right\} \\ + \cos\left[2(k+m-1)\omega t + \phi_{2(k-1)} - \phi_{2(m-1)}\right] \\ + \cos\left[2(k+m)p\alpha - 2(k-m)\omega t + 2\phi_{(2k-1)} - 2\phi_{(2m-1)}\right]\right\}$$
(2.4)

where *k*, *j*, *l* and *n* are integers.

In practice, sinusoidal voltage is not transferred directly into PMSMs for EVs, instead, PMSMs are driven by the VSI with standard PWM switching frequency f_s . However, the harmonic currents of the standard PWM tend to cluster in multiples of f_s , which cause additional radial forces and result in acoustic noise. The rotor flux density considering VSI and the relevant harmonics can be rewritten as (5):

$$\begin{cases} B(\alpha,t) = B_r(\alpha,t) + B_s(\alpha,t) + B_{s,h_i}(\alpha,t) \\ B_{s,h_i}(\alpha,t) = \mu_{\alpha} \sum_{h_i} \sum_{j=1}^{\infty} A_{s,h_i} \cos[jp\alpha - h_i(\omega + \omega_s)t] \end{cases}$$
(2.5)

where h_i is the harmonic current number, $B_{s,hi}$ is the flux density caused by harmonics, and ω_s is switching speed. Substituting (2.3) and (2.5) into (2.1), the relationship between acoustic noise frequencies fed with VSI and motor speed can be obtained as (2.6):

$$N = \left\{ (2k-1)(\frac{\omega_s}{\omega} \pm 1 \pm h_i) \frac{np}{60}, 2k(\frac{\omega_s}{\omega} \pm 1 \pm h_i) \frac{np}{60}, |h_m - h_l| \frac{np}{60} \right\}$$
(2.6)

where h_m and h_j belong to the range {(2k-1) ω_s/ω , $2k\omega_s/\omega$ }.

While examining (5) and (6), a certain frequency $(2k\pm 1\pm h_i)\omega_s/\pi$ can be spotted in the noise spectrum, which is caused by VSI harmonic components, the VSI frequency, and saturation effects. Acoustic noise is evidently increased by the demagnetization fault disturbances in the air-gap flux density distribution. The increase of the noise amplifies the sideband at frequency $(2k\pm 1\pm h_i)\omega_s/\pi$.

Figure 2-1, which was obtained through experiments, shows the acoustic noise waveforms from a surface mounted PMSM with design parameters given in Table I. under different demagnetization conditions. As observed in Fig. 2-1, demagnetization amplifies the noise amplitude, which is easily obtained from (6) by replacing k and hi respectively. When the acoustic noise contains abnormal frequency or measurement, there will be PM demagnetization if there are no other mechanical or electrical faults and the system setup is the same. Therefore, it is feasible to analyze acoustic noise for diagnosing PM demagnetization and determining the demagnetization ratios.

| Rated power | 12.5 kW | 12.5 kW Continuous torque | | |
|---------------|-----------|---------------------------|----------|--|
| Rated voltage | 297 V | Pole pairs number | 4 | |
| Rated current | 35 A | Magnet flux (21°C) | 0.136 Wb | |
| Rated speed | 3,000 rpm | Magnet flux (120°C) | 0.112 Wb | |

 TABLE 2-1 PARAMETERS OF THE SPMSM MOTOR UNDER TEST



Figure 2-1. Noise variation in a SPMSM with 30 Nm at 1,000 RPM. (a) Healthy motor. (b) 10% demagnetization. (c) 30% demagnetization.

2.3 Seven Acoustic Indicators for PM Demagnetization Prognosis

To implement the proposed demagnetization detection model, acoustic noise is measured from the PMSM by a microphone, which is shown in the experimental setup in section V. Seven indicators shown in Fig. 2-2 are employed to evaluate the measured acoustic noise in terms of magnet demagnetization. The seven indicators are as follows and are described in detail in this section:

- 1) HHT instantaneous frequency, Hilbert–Huang transform.
- 2) FFT, Fast Fourier transform spectrum.
- 3) PSD, Power Spectrum Density.
- 4) Sound Fluctuation, slower amplitude modulation.
- 5) Sound Loudness, an attribute of auditory sensation scale.
- 6) Sound Roughness, sound partials or tone components.
- 7) Articulation Index, the average proportion of signals.



Figure 2-2. Flowchart of the seven indicators for proposed model training.

2.3.1 Pre-process Acoustic Noise Measurement from PMSM

Acoustic noises reflect the status information from the operating motor, which can then be used to detect demagnetization. However, from acoustic noise waveform shown in Fig. 2-3 (blue dash), it can be observed that the measured noise waveforms are non-stationary and have sharp distortions. The waveforms also contain noises from operators, environments, inverter and coolant system. In order to obtain the correct EM acoustic noise information, the background noises should be filtered out at the first stage. In this paper, Wavelet packet

transforms (WPT) are used on the acoustic noise measurements to filter them. WPT has advantages over conventional filter for representing functions, which comprise of nonstationary signals. The noise waveforms (blue dashed line) shown in Fig. 2-3, which are discontinuities and contain sharp peaks, meet the principles well, therefore, it is possible to filter the initial acoustic noise measurements by using WPT.



Figure 2-3. Measured acoustic noise from a healthy PMSM at 50 rpm.

The WPT sound filtering steps include wavelet packet decomposition, wavelet threshold filtering, and wavelet packet reconstruction. The brief introduction of those steps is shown as follows.

Step 1: Wavelet packets decomposition

The initial sound signal has to be decomposed into two parts: the approximation part that is the low frequency signal and the detail part that is the high-frequency signal. According to Mallat's algorithm, the decomposition process includes two filter groups, which is shown in Fig. 2-4, to complete the wavelet packet decomposition. In the decomposition figure, 'Lo_D' is a low-pass filter and 'Hi_D' is a high-pass filter. \uparrow 2 means inserted zeroes at odd-indexed elements while \downarrow 2 shows down sampling.

Thus, sound signal can be decomposed based on the following (2.7) according to the Mallat algorithm.

$$\begin{cases} a_{j,n} = \sum_{k} \overline{h} (2n-k) a_{j-1,k} \\ d_{j,k} = \sum_{k} \overline{g} (2n-k) a_{j-1,k} \end{cases}$$
(2.7)

where *h* and *g* represent scale function and wavelet function, respectively. $a_{j,n}$ is the smooth coefficient of j^{th} layer and $d_{j,n}$ is the detail coefficient of j^{th} layer.



Figure 2-4. Schematic flow of wavelet packet decomposition and reconstruction.

Step 2: Acoustic signal wavelet threshold filtering

The wavelet coefficients calculated by a wavelet packet represent the variation in the time series at a particular resolution. The high-frequency part of initial sound signals, which is decomposed by N scaling wavelet packets, will be threshold quantized with either hard thresholding or soft thresholding. Because soft threshold can avoid discontinuity points after the wavelet packets coefficients being quantized, we used soft thresholding in the experiments according to equation (2.8).

$$\widetilde{\omega}_{j,k} = \begin{cases} sign(\omega_{j,k}) | \omega_{j,k} - \lambda |, | \omega_{j,k} | \ge \lambda \\ 0, | \omega_{j,k} | < \lambda \end{cases}$$
(2.8)

where λ is de-noising threshold value and $\omega_{j,k}$ indicates high-frequency coefficients.

Step 3: Acoustic sound wavelet pocket reconstruction

The decomposition coefficients are reconstructed at this step based on their related frequencies. The reconstruction formula is shown in (2.9)

$$a_{j-1,n} = \sum_{k} h(n-2k) a_{j,k} + \sum_{k} g(n-2k) d_{j,k}$$
(2.9)

where h and g represent scale function and wavelet function respectively. $a_{j-1,n}$ is the smooth

coefficient of j-1th layer and $d_{j-1,n}$ is the detail coefficient of j-1th layer.

The selection of the wavelet type directly affects the wavelet packet filtering effect in the process of filtering. Following several simulations and using different orders of Daubechies (DB) wavelets, it was found that using the db-4 wavelet as the fundamental function provides the best root mean square (RMS) error; the function has a scaling level of 3, which indicates an 8-dimensional eigenvector. Table II illustrates a comparison of different filtering wavelets. The solid red curves in Fig. 2-3 show the filtered acoustic noise waveform. It can be seen that the background noises are filtered to a certain degree by using WPT and the filtered acoustic noise (red solid curves) become relatively smooth and continuous, thus they become easier to process in further steps.

| Wavelet | RMS | Wavelet | RMS | Wavelet | RMS |
|---------|--------|---------|--------|---------|--------|
| DB -1 | 9.349 | DB -5 | 10.494 | DB -9 | 9.458 |
| DB -2 | 13.467 | DB -6 | 8.656 | DB -10 | 7.639 |
| DB -3 | 6.672 | DB -7 | 13.265 | DB -11 | 5.347 |
| DB -4 | 3.169 | DB -8 | 6.923 | DB -12 | 12.255 |

TABLE 2-2 PERFORMANCE OF DIFFERENT TYPES OF WAVELETS

2.3.2 The Loudness of Acoustic Noise under Demagnetization

The loudness of noise is typically defined as an attribute of auditory sensation that can be ordered on a scale ranging from quiet to loud [78]. Specific loudness N' can be expressed as follows [79]:

$$N' = 0.08 \left(\frac{E_{TQ}}{E_0}\right)^{0.23} \left[\left(0.5 + 0.5\frac{E}{E_{TQ}}\right)^{0.23} - 1 \right]$$
(2.10)

where E_{TQ} is the excitation at threshold in quiet, E_0 is the excitation that corresponds to the reference sound intensity $I_0=10^{-12}$ W/m², and E is the exciting value corresponding to the calculated sound.

The total loudness N is then the integral of specific loudness over critical-band rate and the mathematical expression for this is:

$$N = \int_0^{24} N' dz$$
 (2.11)

where *z* is the critical-band rate and *N* is the total loudness.

Based on (10) and (11), experiments are performed to obtain the acoustic noise loudness from the tested PMSM under different working conditions. Fig.2-5 (a), which was obtained from experiments, shows that under the same degree of demagnetization, the loudness of noise increases simultaneously with the motor rotation speed. Fig. 2-5(b) shows that the loudness falls rapidly in the beginning, from 40 to 5 Nm, and then increases steadily when the motor speed is constant at 4,000 RPM (higher than the rated speed to accelerate the demagnetization) under 33% demagnetization, while factoring in the motor speed increase. The minimum noise loudness is 30.26 Sone when the torque is controlled at 5 Nm.

This drop can be explained by two reasons. One reason lies in the fact that loudness varies with the sound frequency non-linearly. For sound segments with same sound energy but in different frequencies, their loudness is different according to ISO 226:2003. When the motor started at the beginning with no load, the stator current was large and the current harmonics contributed to the vibration, which was one of the sources of the collected acoustic sound. Because of the relatively high frequency proportion, the loudness was higher than the loudness from the motor loaded with 5 Nm. In the latter case, the stator current frequency decreased compared with the start current and so did the loudness. After that, with the load increased, the amplitude of the vibration intensified and accordingly, the loudness became larger. The second reason is from the background noise. The experiments were conducted in a lab with several external noise sources such as VSI, dyno motor, and DC power cabinet. Some background noise still remained, despite using signal processing to filter it. When the motor ran at the beginning, the noises from motor were combined with background noises. However, when loaded with 5 Nm, the sound frequency went down compared with the background noises. Since the background noise frequency is much higher than the sound frequency from motor at that moment, the high frequency background noise would mask the low frequency motor sound, and thus the loudness became lower than the beginning without load. Later, with the increase in both frequency and amplitude, the loudness of the motor acoustic sound climbed up steadily.



Figure 2-5. Noise loudness of PMSM. (a) Demagnetization with speed. (b) 33% demagnetization with load at 4,000 rpm.

2.3.3 The Roughness of Acoustic Noise under Demagnetization

Roughness is a complex effect that quantifies the subjective perception of rapid (15 Hz to 300 Hz) amplitude modulation of a sound. Using the boundary condition that a 1 kHz tone at 60 dB and 100%, 70 Hz amplitude-modulated, produces the roughness of 1 Asper, the roughness R of any sound can be calculated using the equation [79]:

$$R = 0.3 \frac{f_{\text{mod}}}{1000} \int_0^{24} \Delta L_E(z) dz$$
 (2.12)

where f_{mod} is the modulation frequency, $\Delta L_E(z)$ is the function of the critical-band rate, which is proportional to size of the data for excitation level or specific loudness in (11).

According to (12), the acoustic noise roughness from the tested PMSM under different working conditions is shown in Fig. 2-6, which was obtained from experiments. Under the same degree of demagnetization, with no load, it can be seen that the noise roughness rises steadily as the motor rotation speed increases. When the motor is connected with load

torque at 40 Nm, the roughness increases rapidly as the motor speed climbs. The acoustic roughness surges along with demagnetization under the same operating conditions. When the motor speed is constant at 4,000 RPM under 33% demagnetization, Fig. 2-6(b) shows that with the motor speed growth, the trend of roughness increases steadily.



Figure 2-6. Noise roughness of PMSM. (a) Demagnetization with speed. (b) 33% demagnetization with load at 4,000 rpm.

2.3.4 The Fluctuation Strength of Noise under Demagnetization

The fluctuation strength is defined as a complex effect which quantifies the subjective perception of slower, up to 20 Hz, amplitude modulation of a sound. The fluctuation strength can be obtained from following equation [79]:

$$F = \frac{0.08 \int_0^{24} \Delta L(z) dz}{(f_{\rm mod}/4) + (4/f_{\rm mod})}$$
(2.13)

where $\Delta L(z)$ is the masking depth of the masking pattern.

According to (2.13), the acoustic noise fluctuation strength from the tested PMSM under

different demagnetization faults are obtained from experiments and shown in Fig. 2-7. Fig. 2-7(a) shows that under the same degree of demagnetization the fluctuation strength increases slower when the motor is disconnected from the load. When the PMSM is loaded, the fluctuation strength simultaneously increases with the motor's RPM and reaches the maximum value of 0.88555 Vacil under 33% demagnetization. Fig. 2-7(b) is the load torque graph when the motor is at 33% demagnetization. The fluctuation strength is stable at the beginning and then surges sharply when the load exceeds 20 Nm.



Figure 2-7. Fluctuation strength of PMSM. (a) Demagnetization with speed at 0 Nm and 40 Nm. (b) 33% demagnetization with load at 4,000 rpm.

2.3.5 The Articulation Index of Noise under Demagnetization

The Articulation Index (AI) is defined as the weighted fraction representing the effective proportion of the intelligibility of sound. AI is calculated from the 1/3 octave band levels between 200 and 6,300 Hz center frequencies. The AI mathematical equation is as follows [79]:

$$AI = \frac{M_1}{M_{all}} \times 100\%$$
(2.14)

where M_1 is the number of sound units that can be perceived, M_{all} is the total sound units.

Figure 2-8, which was obtained through experiments from (11), shows the result of AI from the tested PMSM under demagnetization. From Fig. 2-8(a), it can be observed that the AI decreases as the motor's rotational speed increases when the PMSM has the same demagnetization fault with no load. When the PMSM is loaded with 40 Nm under 33% demagnetization, the AI decreases rapidly and reaches the minimum value of 18.12% at 3,000 RPM. Fig. 2-8(b) shows that with 33% demagnetization, as the motor's RPM increases, the AI has a slow decrease and then drops significantly when the motor's load reaches 20 Nm.



Figure 2-8. Articulation index of PMSM. (a) Demagnetization with speed. (b) 33% demagnetization with load at 4,000 rpm.

2.3.6 The FFT Index of Noise under Demagnetization

FFT is a standard signal processing method to analyze the noise distribution along a frequency band. The results from using FFT on experimental data is shown in Fig. 2-9. It can be discerned that under 17% demagnetization, with no load, the frequency distribution extends to the higher frequency band. According to (2.6) in section II, the acoustic noise fundamental frequency of tested no-load motor running at 1,000 RPM should fall into the range {133, 266, 399, 532, 665, 933, 1,200...Hz} when substituting 1,000, 4,1-5 into n, p and k. The blue curve in Fig. 2-9(a) peaks at those frequencies and validates the acoustic noise model in section II.

When the PMSM is loaded with different torques under 33% demagnetization running at 3,000 RPM, the noise fundamental frequency should fall into the range {399, 798, 1,179, 1,596, 1,995...Hz} according to (2.6). However, the blue curve in Fig. 2-9(b) shows a discrepancy. Even with the harmonics and VSI influence from (2.10), the frequency band should be {200, 400, 800, 1,200, 1,600, 2,000, 2,400 Hz}. Fig. 2-9(b) shows that the frequency distribution is still distorted, especially when the connected load torque is larger. The phenomenon occurs because of the demagnetization, where the permanent magnet field strength in the PMSM weakens due to external influences such as a large current and high temperature.

Compared with the FFT results, under the same permanent magnet demagnetization fault, the amplitude of the loaded motor is much greater than the motor with no load. This discrepancy indicates that demagnetization degrading, which leads to the reduction of PM flux, contributes to the increase in acoustic noise.

Practically, there might exist resonances in the collected acoustic noise data, because the electromagnetic noise of the motor comes from the electromagnetic vibration, which is excited by the radial electromagnetic force. When the frequency of electromagnetic force and its order approaches to the inherent structure frequency of the stator, the motor will resonate and cause the electromagnetic vibration to emit noise. During the experiment, the resonance's impact on the acoustic noise was not significant. There are two reasons that can explain the phenomenon. The first reason is from the manufacturer specifications; the structure frequency of the tested motor is 1,800 Hz, 4,800 Hz and 5,400 Hz. The rated

speed of the tested motor is 3,000 RPM, which means the fundamental control frequency is far below the first order of the structure frequency and would not cause resonances. The second explanation is that, even combined with the high frequency harmonics from inverter gate switching, the portion of those resonances vibration is relatively small compared to amplitudes at other frequencies from the FFT results. Therefore, the resonances would not influence the acoustic noise feature extraction nor the demagnetization determination.



Figure 2-9. FFT analysis of PMSM acoustic noise. (a) 17% demagnetization with speed. (b) 33% demagnetization with load at 3,000 rpm.

2.3.7 Hilbert-Huang Analysis of Noise under Demagnetization

The Hilbert–Huang transform (HHT) is based on the instantaneous frequencies resulting from the intrinsic-mode functions (IMFs) of the signal being analyzed [80]. The local energy and the instantaneous frequency can be derived from the IMFs using the Hilbert

transform. From this, the full energy-frequency-time distribution of data can be obtained and thus it can be the ideal tool for non-linear and non-stationary data analysis [81].

From experiments, the result of HHT instantaneous frequency of IMF3 on the tested PMSM is shown in Fig. 2-10. It can be seen clearly that under 17% demagnetization, with the increase of torque load, or flux reduction, the amplitude of the instantaneous frequency increases sharply; almost 10 times the value of a healthy motor acoustic noise. The discrepancy shows again that increasing the load torque or degree of demagnetization contributes to the acoustic noise increase.



Figure 2-10. The instantaneous frequency of IMF3. (a) 17% demagnetization no load at 1,000 RPM. (b) 33% demagnetization with 40 Nm at 1,500 RPM.

2.3.8 The Noise PSD Spectrum of Demagnetized PMSM

The power spectral density (PSD) spectrum shows the strength of the variations (energy) as a function of frequency. It describes the signal power distribution over the frequency and allows the DSP to be obtained from the function of auto-correlation without signal processing.

The PSD distribution result from experiments with the demagnetized PMSM is shown in Fig. 2-11. It can be seen that the PSD spectrum increases significantly when more demagnetization is applied, or if PM flux is decreased.



Figure 2-11. PSD spectra of PMSM acoustic noise with demagnetization faults.

2.4 BPNN Based PM Demagnetization Detection

In this section, a BPNN based PM demagnetization detection method is proposed in order to detect permanent magnet demagnetization faults. The PM flux demagnetization is identified by comparing the measured acoustic signal of PMSM with an acoustic signal library of seven acoustical indicators. Since the seven acoustic indexes are based on nonlinear mapping, BPNN is deployed due to its strengths in analyzing non-linear mapping [82].

The proposed BPNN based PM demagnetization detection method consists of two stages: S1) Training: using the seven indicators measured from the PMSM acoustic noise to train the BPNN shown in Fig. 2-2; S2) Detection: after the training, the acoustic noise is sampled from the test machine and the seven indicators are extracted from the acoustic noise, then the developed BPNN shown in Fig. 2-12 is applied to these indicators of the test machine to detect the PM demagnetization of the test machine.



Figure 2-12. Flowchart of the proposed PM demagnetization detection.

A classic three layers BPNN model has been built including one input layer, one hidden layer and one output layer, as shown in Fig. 2-13. The input data attributes are FFT spectrum vector, HHT instantaneous frequency vector, power spectrum density vector, sound loudness, sound roughness, sound fluctuation strength, and articulation index and so the number of input layer neurons N_i is 7. The output is the rotor demagnetization percentage compared with initial PM flux linkage and there is one neuron in the output layer, denoted as neuron N_0 . The number of hidden layer neurons is determined by $N_h \cong$ $(Ni + N_0)0.5+ a$, where a = 0~10. The estimation error and time calculation are both dependent on N_h . A smaller N_h leads to a larger accuracy error, while a large N_h results in increased study time, thus after trial-and-error the Nh is chosen as 12. The activation functions of hidden layer and output layer are hyperbolic tangent function and a linear function as (2.15):

$$\begin{cases} f_{hidden}(x) = \frac{2}{1 + e^{-2x}} - 1\\ f_{output}(x) = x \end{cases}$$
(2.15)

where *x* is input variable.



Figure 2-13. BPNN model of demagnetization detection based on acoustic noise.

The proposed BPNN uses Levenberg-Marquardt back propagation and the gradient descent technique with momentum weight/bias as the learning rule and learning function respectively [83]. The mean squared error of the proposed NN drops from 0.83 to target 0.004 after 36 training epochs. Fig. 2-14 shows that the demagnetization BPNN model has a fast convergence and satisfied stability.

To evaluate the accuracy of proposed demagnetization detection model, the mean error rate (MER) E is applied as:

$$E = \frac{1}{N_n} \sum_{i=1}^{N_n} \left[\left| \frac{F_m(i) - F_e(i)}{F_m(i)} \right| \times 100\% \right]$$
(2.16)

where N_n is the number of values, $F_m(i)$ is the measured degree of demagnetization of the i^{th} acoustic noise measurement, and $F_e(i)$ is the estimated PM demagnetization value of i^{th} acoustic noise sample obtained from proposed BPNN model.



Figure 2-14. Mean squared error of demagnetization detection model training.

2.5 BPNN Based PM Demagnetization Detection

To validate the performance of the proposed method, a surface mounted PMSM is employed for testing. The design parameters of the SPMSM are given in Table I. The control strategy of the tested motor, dq-0 vector control applied in the tests, contains both current and speed feedback, and its schematic diagram is depicted in Fig. 2-15. The experimental setup shown in Fig. 2-16 illustrates a test motor and a dyno machine which can be controlled individually [84]. The tested PMSM is VSI fed and controlled by a laboratory-designed DSP based drive system. The output torque of the tested PMSM can be measured from a torque transducer. A microphone was applied to collect the sound from the PMSM motor. The selected microphone was not sensitive to sound when it was placed in air. However, it worked well when glued to the surface of the machine. Due to these characteristics, it can be assumed that the collected sounds are basically from the machine itself but combined with small amount of noises from other sources. The microphone was placed in the middle of the front surface of the motor. It was experimentally proven to be more sensitive at this place compared to a placement near the rear as the cooling fan would interfere with the motor's electromagnetic noise measurement.



Figure 2-15. Vector control schematic for PMSM with current compensation.



(c)

Figure 2-16. Experimental setups for PMSM demagnetization detection. (a) A/D circuits. (b) Universal motor drive circuit board. (c) Dyno and test motors.

The tested motor was intentionally given a demagnetization by increasing the motor internal temperature greatly. During experiments, the tested motor was loaded with a large torque provided by the dyno motor with torque control for a sufficient time resulting in sharp increase in the test motor winding temperature. There are two temperature sensors embedded in the windings of the motor under test. The lab-designed motor drive is able to

obtain the temperature signals with the pre-installed cables, thus the motor's interior temperature can be read and used to calculate the PM flux. Therefore, the proposed diagnosis method in this paper can test the irreversible uniform demagnetization phenomenon.

The PM demagnetization can be created in the experiments by increasing the motor internal temperature on purpose. There are two major steps to conduct the experiments.

The first step is to determine the tested motor PM flux variation table. At the beginning, the PMSM motor ran at the desired speed, then the Dyno motor was controlled to give a certain load to the PMSM. Both motors were operated for a long time (close to 2 hours). During this period, the current, voltage, torque, and temperature could be measured in real time from the motor drive serial port. When the temperature rose to a high degree, the PMSM motor stopped and the dyno motor drove the PMSM motor through the connecting shaft to change to the previous speed quickly. By using the motor drive, the back EMF value at that moment could be recorded. Since the back EMF is proportional to the flux linkage, which is also proportional to the PM flux in a same motor, the flux could be calculated and the flux deduction compared with the initial flux could be obtained. After repeating the above procedures at different speeds and loads, a series of flux values at different temperatures can be obtained, from which a look-up table could be built and coded into the motor drive's DSP. Therefore, the PM flux value can be calculated according to the interior temperature value. It should be noted that, though this step is time consuming, it needs to be conducted only once in order to obtain the table.

The second step is to validate the proposed algorithm with the tested motor. As described in step 1, the tested motor ran at the expected speed and then the dyno was controlled to the desired torque as a load to the tested motor. The two motors had been kept running for a long time until the motor drive LED signaled that the temperature reached the expected value, which indicates the PM flux reduced to a certain degree. Then, the acoustic noise at that moment was measured and processed. During experiments, step 2 was conducted in two groups. In group 1, the tested PMSM was operating at the rated speed of 3,000 RPM and the load was controlled to rise from 0 Nm to 40 Nm step by step. In the second group, the dyno was controlled to give a constant 40 Nm load, but the tested motor was controlled

to operate at different speeds from 0 to 4,000 RPM in steps.

Based on the above two test steps, the PM demagnetization condition can be created by referring to the motor internal temperature during the experiments, and the acoustic noise at that moment can be measured and analyzed in the further procedures. It was noted that when the torque was over 35 Nm, the winding temperature went up at the rate of about 1°C/s. After changing temperatures, the residential flux changes from 100% to 67%, as shown in Table 2-3.

| PM conditions | PM flux linkage (Wb) | Percentage (%) | |
|-------------------|----------------------|----------------|--|
| Healthy | 0.136 | 100 | |
| Demagnetization 1 | 0.113 | 83.73 | |
| Demagnetization 2 | 0.090 | 67.01 | |

TABLE 2-3 RESIDUAL FLUX LINKAGE OF TESTED PMSM

During experiments, 320 usable acoustic noise samples were measured, 290 for model training and the remaining 30 samples were put into the model as the demagnetization percentage for demagnetization estimation. Fig. 2-17 shows a comparison of the tested value and the estimated demagnetization. With the given flux linkage, the demagnetization detection can be compared with the conventional method, which used online parameter estimation with the recursive LS method [85]. Table 2-4 shows that the detection results of the flux linkage obtained from the proposed demagnetization diagnosis method were more precise.

The maximum demagnetization estimation error occurred at 30 Nm, when the motor was running at 4,000 RPM. The explanation for this is that with high speed and large torque, the sharp and sudden increase in current results in permanent magnet weakening. However, the acoustic noise produced from the internal electromagnetic forces and the stator frame interaction has a short delay since the mechanical speed is slower than the electronic speed. According to (16), the MER of BPNN model of demagnetization is 3.72%, which validates the high performance of the proposed model.



Figure 2-17. The comparison between measured and estimated demagnetization.

The purpose of vector control strategy for a PMSM is to control the stable motor performance in EVs. However, the PM demagnetization will deteriorate the motor performance and cause further damage to the motor. It is reasonable to consider the current regulation control to protect the motor as well as to prevent demagnetization being worsened after the demagnetization occurrence. Hereafter, a stator current restriction plan, shown in Fig. 2-12, should be employed in the lab-designed motor drive by decreasing the stator current to prevent further demagnetization [86]. Meanwhile, the central control panel in the EV should show the warning message to the driver and reminder them to drive as soon as possible to a service facility.

TABLE 2-4 UNIFORM DEMAGNETIZATION

| | Proposed | RLS | Measured |
|-----------------------|----------|-------|----------|
| Flux linkage (Wb) | 0.092 | 0.085 | 0.090 |
| Demagnetization Ratio | 32.06 | 37.50 | 32.99 |
| Estimation error (%) | 2.85 | 13.6 | |

FAULT DETECTION OF THE SPMSM AT OPERATION WITH 4,000 RPM, 40 NM

2.6 Conclusions

This chapter presented a novel, non-invasive approach to detect the permanent magnet demagnetization by analyzing the acoustic noise while motor is operating. It has been observed from lab experiments that the noises emitted from the motor become abnormal and loud when the demagnetization occurs. The correlation between demagnetization and noises indicates that the selected seven acoustic indicators vary with PM demagnetizations under different operating conditions. However, the hidden relationship between demagnetization and each dynamic acoustic indicator is not linear and is difficult to be described in a simple equation. With the application of model based estimation approach, these complicated relationships can be processed by comparing these indicators with the ones in healthy motor noise library. Compared to one single input system, the multi-input BPNN approach improves accuracy and reliability of the estimation. Therefore, the relationship between demagnetization levels and variances in the indicators can be obtained clearly. Using the motor winding temperature measurement and flux calculation from the lab-designed motor drive, the experimental validations can be conducted with the desired operation conditions. The validation results have demonstrated that the proposed approach is able to detect the irreversible uniform demagnetization fault under different operating conditions on-line due to its independence of motor parameters and computational efficiency.

CHAPTER 3

TORQUE RIPPLE BASED INTERIOR PERMANENT MAGNET SYNCHRONOUS MACHINE ROTOR DEMAGNETIZATION FAULT DETECTION AND CURRENT REGULATION

3.1 Introductions

PMSMs have been widely used in EVs due to their attractive features like compact structure, high power density, precise control, high efficiency and high torque-current ratio. However, PM demagnetization, caused by the combination of electrical, thermal, mechanical stresses, and environmental issues, not only reduces the PMSM motor output torque which is developed by the interaction between the permanent magnet field and the stator winding field, but also results in motor failure. When an electric vehicle is operating under power state condition (large current discharge) or in severe road conditions (causing high vibration), the temperature inside the motor increases rapidly which may result in magnet demagnetization. Moreover, deep demagnetization combined with high temperature results in irrecoverable demagnetization fault which causes the collapse of electric drive systems in EVs.

Permeant magnet demagnetization can be classified as reversible demagnetization and irreversible demagnetization based on their recoverability. The reversible demagnetization can be recovered after the motor stops so long as they are not taken above a certain operating point. The irreversible demagnetization occurs if the magnet is taken above the operating point and the magnetic flux cannot be recovered when they cool down. Irreversible demagnetization causes large acoustic noise and vibrations in the motor resulting in degradation of the overall machine performance. Therefore, it is necessary to monitor and detect the irreversible demagnetization during its initial stage of occurrence and then perform the consequent control strategy to protect the PMSMs.

In fact, demagnetization causes fluctuations in output torque due to flux linkage ripples. Then torque ripples result in noise and vibration as well as degradation of system robustness or controllability. Thus torque ripple can be looked as one index to reflect the demagnetization in PMSM. However, the research between torque ripple and demagnetization cannot be referred from publications yet. Furthermore, measuring the torque ripple is a challenge due to various noises from the PWM driving voltages produced by VSI. The measured torque signals should be processed in a proper way to provide a current regulation reference to vector control.

This chapter proposes an online PM demagnetization fault detection method based on the analysis of PMSM output torque ripple. Firstly, a torque ripple based rotor flux linkage detection model considering electromagnetic noises is proposed using continuous wavelet transforms (CWT) approach. It can extract the torque ripple ridge value from the de-noised torque ripple measurements caused by the inherent vibrations of the PMSMs. This method can reveal the torque ripple variation and eliminate the effect of VSI error. Secondly, Grey System Theory (GST) is employed to facilitate the detection of demagnetization ratios and torque ripple energy pulsations caused by demagnetization. It can yield a feedback value to the current loop in the drive system. Thirdly, a current regulation strategy is proposed to minimize the torque ripples induced by PM demagnetization, which contributes to making the proposed approach feasible in interior PMSMs. The proposed approach is experimentally verified on a down-scaled laboratory interior PMSM rated at 4.25 kW designed for EV. The result shows that the proposed real-time demagnetization diagnosis approach can identify the demagnetization fault under different operating conditions. Moreover, the proposed current regulation is validated to be able to minimize the torque ripple under demagnetization.

3.2 PMSM Torque Ripple Model Based on PM Flux

The electromagnetic torque developed across the stator and rotor surface based on structure [87] is given as follows:

$$T_{e} = T_{c} + \sum_{\lambda=1}^{\infty} T_{\lambda} \sin(\lambda \omega_{s} t - \alpha) + \sum_{\lambda=1}^{\infty} \sum_{\xi=1}^{\infty} T_{\lambda,\xi} \sin\left[\left(\lambda \pm \frac{\xi}{P}\right)\omega_{s} t - \beta\right]$$
(3.1)

where λ and ξ are integer numbers, α and β are space variables. The T_c , T_{λ} and $T_{\lambda,\xi}$ are torque components.

As can be seen from (2), there exist a certain frequency $(\lambda \pm \xi/P)f_s$ in the torque spectrum caused by voltage source inverter (VSI) harmonic components, the VSI frequency, and

saturation effects. The demagnetization fault disturbances in the air-gap flux density distribution magnify torque ripples noticeably. The increase of the torque ripple amplifies the sideband at frequency $(\lambda \pm \xi/P) f_s$.

Figure 3-1 shows the power spectral density (PSD) of the torque for the laboratory interior PMSM under different demagnetization conditions. As observed in Fig.3-1, demagnetization fault amplifies the certain side-band frequencies at 30, 75, 100, 120, 150, 175, 200, 225, 230, 300, 325 and 400 Hz, which are easily obtained from frequency $(\lambda \pm \xi/P)f_s$ in (2) by replacing 1 to 8 instead of λ and ξ respectively. Therefore, it is reasonable to analyze torque ripple for diagnosing permanent magnet demagnetization faults and determining the demagnetization ratios.

Based on the above PMSM torque ripple model, the torque ripple discrepancy is employed in this paper for irreversible demagnetization fault detection. The model is validated by irreversible partial demagnetization fault experiments.

3.3 Proposed PMSM Demagnetization Prognosis

During motor operation, the rotor magnet demagnetization distorts the magnetic density as non-sinusoidal due to the loss of magnetism. The subsequent unbalanced magnetic pull and magnetic force harmonics make PMSM emit abnormal torque ripple during operation. In order to use torque ripple as the demagnetization index, a demagnetization detection model is proposed to monitor the rotor demagnetization severity and then perform the current regulation for the motor.



Figure 3-1. Normalized torque spectra of interior PMSM with demagnetization.



Figure 3-2. Flowchart of the proposed demagnetization fault diagnosis.

The proposed demagnetization detection model consists of torque ripple measurement monitoring, signal processing, flux calculation, demagnetization detection and current regulation modules. All these modules are integrated into the machine vector control algorithm by using embedded C. The detailed implementation diagram is shown in Fig. 3-2. Among those modules, CWT module which extracts the torque ripple feature from total torque measurements is most difficult and contributes to the overall diagnosis accuracy and reliability.

3.3.1 Proposed Torque Ripple Measurement Processing

Output torque and its ripples reflect the motor running status information which can be used to detect magnet demagnetization. However, from the acquired torque ripple waveform shown in Fig. 3-3(a), it can be seen clearly that the measured torque ripple waveforms are non-stationary and full of sharp distortions. Moreover, they usually combine with other noises from operators, position measurement, current measurement, inverter and flux linkage harmonics. In order to obtain the correct torque ripple information, those electromagnetic noises should be filtered at the first stage. However, conventional

time-frequency domain algorithm does not work well to achieve the result with those signals due to the constant time-frequency resolution. Wavelet transforms have advantages over FFT for representing functions that have discontinuities and sharp peaks, and for accurately deconstructing and reconstructing finite, non-periodic and/or non-stationary signals. The torque waveforms from Fig. 3-3(a) meet the wavelet transforms principles well; therefore, it is possible to filter the initial torque measurements by using CWT.

The Hilbert transform $f_H(t)$ of torque ripple measurement f(t) with limited energy is given as:

$$f_H(t) = \frac{1}{\pi} \int_{-\infty}^{+\infty} \frac{f(\tau)}{t-\tau} d\tau$$
(3.2)

The analytical form $\tilde{f}(t)$ of torque measurement f(t) can be expressed as:

$$\widetilde{f}(t) = f(t) + jf_H(t) = a(t)e^{j\varphi(t)}$$
(3.3)

$$\begin{cases} a(t) = \left[f(t)^2 + f_H(t)^2\right]^{\frac{1}{2}} \\ \varphi(t) = \arctan\frac{f_H(t)}{f(t)} \end{cases}$$
(3.4)

When the Fourier transform $\hat{\psi}(\omega)$ of square-integrable function $\Psi(t)$ meets the permitting condition (3.5), $\Psi(t)$ is called mother wavelet.

$$C_{\psi} = \int_{R} \frac{\left|\hat{\psi}(\omega)\right|^{2}}{\left|\omega\right|} d\omega < \infty$$
(3.5)

Function family $\{\Psi_{a,b}(t)\}$ can be obtained from (6) by expanding and translating the mother wavelet, $\Psi(t)$ with scale *a* and translation parameter *b*.

$$\psi_{a,b}(t) = |a|^2 \psi\left(\frac{t-b}{a}\right) \qquad a,b \in R, a \neq 0$$
(3.6)

The analysis wavelet $\tilde{\psi}(t)$, of the real wavelet, $\Psi(t)$ is defined as

$$\widetilde{\psi}(t) = (1+iH)\psi(t) = A_{\psi}(t)\exp\left[i\varphi_{\psi}(t)\right]$$
(3.7)

where *H* is Hilbert operator.



Figure 3-3. Measured torque ripple from a healthy IPMSM motor at 50 rpm. (a) Initial torque containing a large amount of high-frequency electromagnetic noises. (b) Torque measurement de-noised by wavelet transforms.

The continuous wavelet transforms continuous torque measurement, f(t) and can be expressed as (8):

$$W_{f}(a,b) = \frac{1}{2\sqrt{a}} \int_{R} \widetilde{f}(t) \overline{\widetilde{\psi}}\left(\frac{t-b}{a}\right) dt$$

$$= \frac{1}{2\sqrt{a}} \int_{R} A_{a,b}(t) \exp\left[i\Phi_{a,b}(t)\right] dt$$
(3.8)

$$\begin{cases} A_{a,b}(t) = a(t)A_{\psi}\left(\frac{t-b}{a}\right) \\ \Phi_{a,b}(t) = \varphi(t) - \varphi_{\psi}\left(\frac{t-b}{a}\right) \end{cases}$$
(3.9)

where $\overline{\widetilde{\psi}}\left(\frac{t-b}{a}\right)$ is the conjugate of $\widetilde{\psi}\left(\frac{t-b}{a}\right)$.

In this way, wavelet transforms have energy conservation feature as (3.10) due to its equidistant characteristics.

$$\iint_{R} |f(t)|^{2} dt = \frac{1}{C_{\psi}} \iint_{R} |W_{f}(a,b)|^{2} \frac{\mathrm{d}a \,\mathrm{d}b}{a^{2}}$$
(3.10)

Based on results from several simulations and implementing different orders of Daubechies (DB) wavelets, the db-4 is applied as the fundamental wavelet $\Psi(t)$ in CWT to provide the best root mean square (RMS) error as the fundamental function with scaling level 3. Here 4 means the vanishing moments with the general filter length is 8, which represents 8-dimensional eigenvector. Table I shows the comparison of different filtering wavelets. Hereafter, the torque ripple measurement is decomposed into 3 levels by performing CWT. Fig. 3-3(b) shows the de-noised torque ripple waveform. It can be seen obviously that the high-frequency electromagnetic noises are eliminated successfully.

| Wavelet | RMS | Wavelet | RMS | Wavelet | RMS |
|---------|--------|---------|--------|---------|-------|
| DB -1 | 8.706 | DB -5 | 9.802 | DB -9 | 5.239 |
| DB -2 | 7.639 | DB -6 | 13.265 | DB -10 | 8.656 |
| DB -3 | 10.449 | DB -7 | 6.847 | DB -11 | 9.458 |
| DB -4 | 2.239 | DB -8 | 9.169 | DB -12 | 6.923 |

TABLE 3-1 PERFORMANCE OF DIFFERENT TYPES PF WAVELETS AT PM DEMAGNETIZATION DIAGNOSIS

To quantitate the torque ripple, feature values should be extracted from the torque measurements. Among the feature values, signal energy is one of the indexes to describe the torque measurement characteristics. However, the majority of extracted torque energy values reflect the DC component of the torque measurements within a certain period. In

this paper, the research is done on the effects of torque ripple fluctuations (variable) on demagnetization apart from the average torque value (constant). Therefore, energy from the torque ripple is needed apart from the energy from total torque measurements. In order to get the desired energy feature from the dynamic part of torque measurement, wavelet ridge energy, which are the centralized energy points of the normalized scalogram, is used in this process.

The wavelet ridges represent the instantaneous frequencies within the limits of the transform's resolution in the time-frequency plane. The point locations indicate the signal features. From (8), the wavelet ridge is defined as the points with 0 phase reciprocal. In CWT model plane, the ridge points are the local maximum positions while the values other than the ridge points just contain the information related to the wavelet fundamental functions.

To link the ridge points as lines and extract the ridge lines from initial signals, phase information of signal complex wavelet is needed. According to (9), the stagnation point, t_s should meet $\Phi'_{a,b}(t_s) = 0$. That means stagnation point, t_s is the function of (a,b) as (3.11).

$$\varphi'(t_s) = \frac{1}{a} \varphi'_{\psi} \left(\frac{t_s - b}{a} \right)$$
(3.11)

Then wavelet ridge line can be defined as the points in phase plane that meet $t_s(a,b)=0$. Thus, (3.12) can be obtained from stagnation point, t_s definition.

$$a = a_r(b) = \frac{\varphi'_{\psi}(0)}{\varphi''(b)}$$
(3.12)

Ridgelines can be determined as the curves that meet $\{(a,b)|a=a_r(b)\}$ in the phase plane. In order to obtain the fast algorithm to calculate the ridge lines, wavelet curves are introduced. Wavelet curves are defined as the points in phase plane with passing point $(a_r(b_0), b_0)$ and meeting $t_s(a, b_0)=b_0$. According to the definition of stagnation point, t_s , given the point (a,b) in the phase plane, (3.13) can be acquired.

$$\varphi'_{\psi}\left(\frac{b_0 - b}{a}\right) = \frac{a}{a_r(b_0)}\varphi'_{\psi}(0)$$
(3.13)

From (3.13), it can be clearly seen that wavelet curve is determined by the phase function

 $\varphi_{\Psi}(t)$ of analysis wavelet and independent of signals to be analyzed.

Let $\psi(a,b) = \arg[W_f(a,b)]$, the variation of phase angle $\Psi(a,b)$ to translation *b* along certain wavelet curve is given as:

$$\frac{\partial \psi(a,b)}{\partial b}\Big|_{t_{s}(a,b)} = \frac{\varphi'_{\psi}(0)}{a}$$
(3.14)

Only in intersection points with ridgelines, (3.14) can be true. Consequently, along with a certain fixed wavelet curve, the partial derivative of wavelet transforms phase angle to translation b, equals to the central frequency of telescopic wavelet in the intersection points with wavelet ridge. Then the wavelet ridge can be extracted based on that principle.

From (10), $|W_f(a,b)|^2/(C_{\Psi}a^2)$ can be taken as the energy density function on plane (*a*,*b*). Then (3.11) can be rewritten as:

$$\begin{cases} \int_{R} |f(t)|^{2} dt = \frac{1}{C_{\psi}} \int_{R} a^{-2} E(a) da \\ E(a) = \int_{R} |W_{f}(a,b)|^{2} db \end{cases}$$
(3.15)

where E(a) is scale-wavelet energy spectrum which indicates the signal energy variation following with scale changes.

Based on the scale-wavelet energy spectrum definition, ridge-wavelet energy spectrum scale is proposed in this paper. In ridge-wavelet energy spectrum, scale *a* is no longer a constant and varies continuously along with ridge line. Thus the signal energy down with a certain ridge line $a_r(b)$ is defined by (3.16).

$$\widetilde{E}[a_r(b)] = \int_{R} \left| W_f[a_r(b), b] \right|^2 db$$
(3.16)

where $\tilde{E}[a_r(b)]$ indicates the ridge-wavelet energy spectrum which represents the signal energy value with the certain ridge line.

Following the above steps, the results of torque ripple ridge-wavelet energy can be obtained and shown in Fig. 3-4. The ripple energy, extracted from torque ripple shown in Fig. 3-3, exactly represents the torque variation.


Figure 3-4. Torque ripple ridge-wavelet energy extracted from torque ripple for a healthy interior PMSM at speed 50 rpm.

3.3.2 Grey System Theory for Demagnetization Fault Diagnosis and Current

Regulation

Grey System Theory (GST) is applied to demagnetization fault detection due to its flexible requirements to data and data distribution. GST can provide satisfactory results with few historic data which distributes at random. GST can be one of the best solutions for demagnetization estimation due to its quick dynamic response and short sampling period. The detailed mathematical description of GST is as follows [88].

Let $X^{(0)}$ be a raw series with *n* observation values, $X^{(0)} = \{X^{(0)}(1), \dots, X^{(0)}(n)\}$, where $x^{(0)}(1) > 0, k=1, 2, \dots, n$. The first order accumulated generating operation (AGO) sequence and can be expressed as:

$$X^{(1)} = AGO[X^{(0)}] \tag{3.17}$$

Then the immediate mean operation sequence is given as:

$$Z^{(1)} = MEAN \left[X^{(1)} \right] \tag{3.18}$$

The grey differential model, GM(1,l) can be obtained as:

$$x^{(0)}(k) + a z^{(1)}(k) = b$$
(3.19)

The shadow for (3.18) is expressed as:

$$dx^{(1)}/dt + ax^{(1)} = b (3.20)$$

where *a* and *b* are the coefficients.

In Grey System theory terms, *a* is viewed as the developing coefficient, *b* is the grey input, and $X^{(0)}(k)$ is a grey derivative which maximizes the information density for a given series to be modeled. By applying the least square method (LSM), let

$$\hat{\mathbf{a}} = \left(\mathbf{B}^T \, \mathbf{B}\right)^{-1} \, \mathbf{B}^T \, \mathbf{Y} \tag{3.21}$$

$$\mathbf{B} = \begin{bmatrix} -\frac{1}{2} \left(x^{(1)} \left(1 \right) + x^{(1)} \left(2 \right) \right) & 1 \\ -\frac{1}{2} \left(x^{(1)} \left(2 \right) + x^{(1)} \left(3 \right) \right) & 1 \\ \vdots & \vdots \\ -\frac{1}{2} \left(x^{(1)} \left(n - 1 \right) + x^{(1)} \left(n \right) \right) & 1 \end{bmatrix} \mathbf{Y} = \begin{bmatrix} x^{(0)} \left(2 \right) \\ \cdots \\ x^{(0)} \left(n \right) \end{bmatrix}$$
(3.22)

where *B* is called as a data matrix.

From (3.19), the response equation for GM(1,l) is as follows

$$\hat{x}^{(1)}(k+1) = \left[x^{(1)}(0) - \frac{b}{a}\right]e^{-ak} + \frac{b}{a}$$
(3.23)

where, $k = 1, 2, \dots, n, x^{(1)}(0) = x^{(0)}(1)$.

Reducing the sequence according to $\hat{x}^{(1)}(k+1)$, the prediction sequence can be obtained as:

$$\begin{cases} \hat{x}^{(0)}(1) = x^{(1)}(0) \\ \hat{x}^{(0)}(k) = \hat{x}^{(1)}(k) - \hat{x}^{(1)}(k-1) = \left[x^{(0)}(1) - \frac{b}{a} \right] (1-e^{a}) e^{-a(k-1)} \end{cases}$$
(3.24)

The process to detect the demagnetization fault with GST modeling can be implemented with the following four steps shown in Fig. 3-5.

1) Build the relations among initial demagnetization sequences and obtain generation sequences.

2) Establish differential equation matrix.

- 3) Solve the parameter differential equations with LSM.
- 4) Detect demagnetization from step 3 according to the grey response to differential equations fitted values.



Figure 3-5. Flowchart of the demagnetization detection process using GST with four previous measurements.

3.4 Experimental Verification for Torque Ripple Based PM Demagnetization Detection

3.4.1 Hardware Platform and Control System

To validate the performance of the proposed method, an IPMSM is employed for testing, and its design parameters are given in Table II. Vector control is employed for testing and its schematic diagram is depicted in Fig. 3-6. The drive system shown in Fig. 3-7 consists of a test motor and a dyno machine which can be controlled individually [89]. The IPMSM is controlled by a laboratory-designed, inverter-fed, digital signal processor based drive system. The designed control logic has been implemented using high-performance 32-bit microcontroller DSP28335 capable of real-time control. The proposed drive system is a field-oriented vector control which contains both current and speed feedback. The torque transducer can measure the output torque of the IPMSM motor. The thermal detector can detect the temperature of the motor.

3.4.2 Experimental Validation on IPMSM with Partial Demagnetization Fault The defect of a permanent magnet can be classified as uniform demagnetization or partial demagnetization based on the distribution uniformity. The proposed method is validated on an interior PMSM designed for EV applications. During experiments, the tested motor was given a demagnetization fault by changing the PM blocks with fake ones which have no magnet flux but have same size and weight. There are two different sets of PM blocks in the lab and hence two demagnetization ratios could be realized by replacing them to the real PMs. Due to a shortage of fake PM blocks with no magnetic flux, uniform demagnetization could not be realized. Therefore, for the tested IPMSM motor, irreversible partial demagnetization fault experiments were conducted to validate the proposed diagnosis method in this paper. However, it should be noted that the proposed approach is detecting the PM demagnetization. After replacing the real PMs with one and two fake blocks, the residential flux linkages are 83% and 67% respectively as shown in Table 3-3.



Figure 3-6. Vector control schematic for a three-phase permanent magnet synchronous machine with current restriction.

In the experiment, the proposed approach is validated at a constant speed of 200 rpm with varying output torque. The connected load machine (dynamometer) is controlled to produce load torques of 10 Nm and 15 Nm respectively for the test IPMSM. When the drive system came to its steady state, the torque was measured. In fact, the torque ripple is influenced by the machine drive especially at the motor starting stage. However, when the motor reaches the steady state, the torque ripple caused by the machine controller is much

smaller when compared to the torque ripple caused by the harmonics in the magnet flux. Especially, when the motor is operating at a constant speed with the fixed control algorithm, the torque ripple caused by the machine drive can be negligible in comparison to the torque ripple caused by the harmonics in the magnet flux. In this way, the obtained torque ripple fluctuation can be viewed as the results due to magnet flux decrease (demagnetization) and thus the inference of torque ripple caused by machine drive can be effectively removed after signal processing.



Figure 3-7. Experimental setups for IPMSM partial demagnetization diagnosis. (a) Inverter and control circuits. (b) Lab-designed IPMSM motor controller. (c) Dyno and test motors.

| Rated power | 4.25 kW | Rated Torque | 20 Nm |
|---------------|---------|----------------------|---------|
| Rated voltage | 275 V | Number of pole pairs | 4 |
| Rated current | 15 A | Magnet flux (22°C) | 0.67 Wb |
| Rated speed | 575 rpm | Magnet flux (120°C) | 0.62 Wb |

TABLE 3-2 PARAMETERS OF THE PMSM MOTORS UNDER TEST

| PM conditions | PM flux at 22°C (Wb) | Percentage (%) |
|-------------------|----------------------|----------------|
| Healthy | 0.670 | 100 |
| Demagnetization 1 | 0.561 | 83.73 |
| Demagnetization 2 | 0.449 | 67.01 |

TABLE 3-3 FLUX LINKAGE OF IPMSM FAKE PMS REPLACEMENT

The proposed approach is performed following the flowchart in Fig. 3-2. Fig. 3-8 shows the torque measurement of the IPMSM with partial demagnetization fault. Fig. 3-8(a) shows that the ratio of electromagnet noise decreases by 40% when the proposed wavelet filter is employed to the healthy IPMSM. Fig. 3-8(b) shows the torque ripple when the motor is under 17% partial demagnetization fault. When 33% partial demagnetization fault occurs, the torque ripple is shown in Fig. 3-8(c). It is obvious that as the demagnetization ratio increases, the torque ripple deteriorates further. To focus further on the signal processing methods comparison, conventional signal processing methods are applied to show the filtered results.

When Butterworth filter is employed, Fig. 3-9. shows that the noise reduction of 8% is obtained. FFT analysis of the torque result is shown in Fig. 3-10. The execution of the FFT algorithm on a partially demagnetized faulty IPMSM gives rise to faulty harmonics from (3). The fundamental frequency was 100 Hz in Fig. 3-10(a). It can be seen that the faulty harmonics become large around 200 Hz and 600 Hz in Fig. 3-10(b) when demagnetization 1 occurs. When demagnetization 2 occurs, the faulty harmonics increases but are still around 200 Hz and 600 Hz as shown in Fig. 3-10(c). However, the spectra of partial demagnetization fault 1 in Fig. 3-10(b) and fault 2 in Fig. 3-10(c) appear to be similar, so the ratio of the demagnetization fault could not be diagnosed. In this way, wavelet transforms de-noise the torque measurement better than the conventional methods in the experiments.



Figure 3-8. Torque ripple measurement with wavelet transforms from IPMSM under test at 200 rpm with 10 Nm output torque. (a) Healthy operation. (b) 17% partially demagnetization fault. (c) 33% partially demagnetization fault.



Figure 3-9. Torque measurement for the Butterworth filter before and after from a healthy IPMSM at 200 rpm with 10 Nm.

Following the proposed signal processing method in Fig. 3-2 and section III, torque ripple wave ridge was defined and extracted as illustrated in Fig. 3-11. Ripple energy which reflects the torque ripple pulsation ratio was calculated and depicted in Fig. 3-12. It can be seen clearly from Fig. 3-12, that the healthy and faulty ripple energy lines have discrepancies in the 1st, 2nd, 4th and 6th vector. The different faulty torque ripple energies have different values in those iteration numbers as well. In order to detect the demagnetization faults based on Figs. 3-10(b) and (c), there are at least 1,000 elements which need to be compared if FFT is applied in fault detection. In contrast to comparing the amplitude at each frequency band from Fig. 3-12, the ridge-wavelet energy vector array which contains only 8 elements can be employed for demagnetization fault diagnosis. In this way, the proposed method computation complexity is less than the conventional FFT.

On the other hand, FFT spectrum reflects the total torque measurements which contain the average torque value and torque ripple while Fig. 3-12 just shows the differences in torque change. Therefore, the proposed method can reflect the torque ripple change clearly and simplify the calculation process. Thus it can be implemented on-line due to its computation efficiency. Fig. 3-13 verifies the energy difference from the aspect of total torque measurements using PSD analysis.



Figure 3-10. FFT analysis of torque at 200 rpm 10 Nm torque. (a) Healthy. (b) 17% partial demagnetization fault. (c) 33% partial demagnetization fault.



Figure 3-11. Torque ridge extracted from IPMSM at 200 rpm and 10 Nm.

Applying the ripple measured energy values and the given demagnetization ratios to GST flowchart in Fig. 3-5, the relation between PM flux linkage and torque ripple energy can be estimated as in Fig. 3-14. Then the partial demagnetization ratios can be calculated based on those flux linkages. With the given flux linkage result, the demagnetization detection results can be compared with the conventional method which used online parameter estimation with the recursive LS (RLS) method [90]. Tables IV and V show the more precise detection results of the flux linkage obtained from the proposed demagnetization diagnosis method.

TABLE 3-4 Partial Demagnetization Fault Detection of the IPMSM at Operation with 200 $$\rm RPM,\,10\,Nm$$

| | Proposed | RLS | Measured |
|-----------------------|----------|-------|----------|
| Flux linkage (Wb) | 0.564 | 0.672 | 0.561 |
| Demagnetization Ratio | 15.82 | 0 | 16.27 |
| Estimation error (%) | 5.37 | 19.79 | |



Figure 3-12. Torque ripple energy extracted from IPMSM at 200 rpm and 10 Nm with/without partial demagnetization.



Figure 3-13. Normalized torque spectra with partial demagnetization.

TABLE 3- 5 Partial Demagnetization Fault Detection of the IPMSM at Operation with 200 $$\rm RPM,\,15~Nm$$

| | Proposed | RLS | Measured |
|-----------------------|----------|-------|----------|
| Flux linkage (Wb) | 0.451 | 0.565 | 0.449 |
| Demagnetization Ratio | 32.69 | 16.67 | 32.99 |
| Estimation error (%) | 4.48 | 25.8 | |



Figure 3-14. Partial demagnetization fault detection of IPMSM with GST.

3.5 Current Regulation under Demagnetization

The vector control strategy for a PMSM is to control the stable motor performance during motor operation. However, the PM demagnetization produces abnormal acoustic noises and vibrations due to the decreased magnetic flux density. Those abnormal behaviors will deteriorate demagnetizations and cause further damages to PMSM. Thus, in order to protect the motor, it is important to take into account the current regulation control to prevent the demagnetization being worsened [91]. Hereafter, a stator current restriction is employed to maintain the desired stable performance by decreasing the stator current based

on ridge wavelet energy from torque ripple under demagnetization.

Three modules are integrated into the vector control algorithm as shown in Fig. 3-7. Torque ripple is measured by a torque transducer and processed in the signal processing module and the demagnetization is detected in the second module. In the third module, current restriction value is estimated based on ripple energy using Grey System theory. All those modules are programmed with embedded C language in a 32-bit DSP TMS320F28335 microchip and integrated into the speed control loop.

In particular, the CWT module in the external speed loop plays an important role in signal processing because in CWT module, the torque signals are preprocessed to de-noise the high-frequency electromagnet noises and wavelet ridge is extracted from those signals. According to continuous wavelet transforms equation (8), db-4 is applied as the fundamental wavelet $\Psi(t)$ in CWT calculation. Here 4 is the vanishing moments with the general filter length is 8, and the order is 7. During experiments, the torque is measured from the torque transducer with the torque frequency of 100 Hz. And the sampling frequency *fs* is set to 2,000 Hz according to the Nyquist law. So the bandwidth of the CWT module can be calculated as 1,000 Hz.

The estimated current restriction value (negative) is obtained by comparing the current reference i_{sqref} and actual i_{sq} in the comparator to obtain the discrepancy and pass it to the following PI module. The regulated current which depends on the torque ripple energy is realized in the vector control DSP microchip codes and performed by a lab-designed vector control drive shown in Fig. 3-7(b).

Through experiments, the optimum current decrement was obtained up to 10% of the reference current. The back EMF of the stator search coil produced by the vector controlled PMSM under rated condition before and after implementation of the online current regulation is shown in Figs. 3-15(a) and (b) respectively. The blue signal in Fig. 3-15 is the initial back EMF of the stator search coil before filtering, and the pink signal is the filtered back EMF. During experiments, a second order filter was applied in the measurement circuits, so the unfiltered signal looks like PWM waveforms while the filtered signal shows the standard sinusoid wave.



Figure 3-15. The back EMF voltage as measured using the search coil to represent the flux linkage. (a) Initial waveform. (b) After using the current regulation control.

The ripple on the waveform is created due to PM irreversible demagnetization. The voltage difference measure varies between 48 and 100 mV. The value of flux linkage as calculated and estimated by the controller with and without current restriction differs by a value of 0.1. It can be clearly seen that the fundamental voltage as shown in pink has more distortions before the control has been implemented. The ripple detection avoids PM demagnetization developing to a severe degree by using current regulation control strategy.

As can be seen from Fig. 3-15, there are spikes in the filtered waveforms. The reason is that the PWM format output control signal from the control board which contains high-frequency noise and harmonics cannot be filtered thoroughly and thus causes the spikes in signal waves. Moreover, the signal is measured from the search coil which cannot be installed perfectly inside the motor. The small installation error will cause the interference in the measured signal as well.

3.6 Conclusion

A novel torque ripple-based approach is developed and validated for online PM motor irreversible demagnetization fault detection and current regulation. In literature, the measured torque from torque transducer usually consists of high-frequency electromagnetic noise harmonics from inverter, measurement, and current. Thus, in this paper, to obtain the exact torque, torque measurement was firstly processed by signal processing with CWT to reduce the noises. Then the torque ripple energy can be extracted from the de-noised torque by applying ridge-wavelet energy spectrum analysis which is able to extract the dynamic energy indicating the torque ripple variation ratio. Moreover, GST algorithm was employed to estimate the irreversible demagnetization ratios by referring the extracted torque ripple energy. The experimental results have demonstrated that the proposed approach is able to detect the irreversible partial demagnetization fault and have good performance in minimizing the torque ripple by integrating current regulation module in the vector control under demagnetization. The future study will focus on the robustness and feasibility related concerns of the proposed approach for real EV applications.

CHAPTER 4

VOLD-KALMAN FILTERING ORDER TRACKING BASED ROTOR FLUX LINKAGE MONITORING IN PMSM

4.1 Introduction

In most PMSM controller design, rotor PM flux linkage is considered constant. However, the actual PM flux linkage changes and results in output torque fluctuations. One of the reasons is that the flux linkage decreases with the increase of temperature during motor operation. When the temperature exceeds the critical point, the flux linkage is not able to restore to the initial value and leads to permanent demagnetization [92], which may cause failures and degrade the progressive performance [93]. Therefore, monitoring the PM flux linkage variation is significant for stable motor operation and demagnetization fault detection in early stage.

This chapter presents a novel on-line method to detect the motor PM flux linkage variation under nonstationary conditions based on the tracking of the characteristic orders of torque ripple by using VKF-OT and DBN. At first, a torque ripple model considering electromagnetic noises is analyzed to demonstrate that the torque varies along with motor operation conditions. Then, in the proposed monitoring approach, torque waveforms are preprocessed to eliminate the effect of the electromagnetic interferences. Next, the VKF-OT is applied to resample the envelope of the de-noised torque ripple signals under nonstationary conditions with an equal phase increment. Moreover, the feature indicator is defined and analyzed to quantify the flux linkage variation severity. In the last step, with DBN algorithm, PM flux linkage variation trend can be estimated as a reference value for motor control according to the previous database. The contributions of this paper lie in the following aspects. Firstly, the proposed approach is independent of motor parameters and the performance of the proposed approach is not influenced by the machine parameters variation. Secondly, by applying the signal processing pre-process, the proposed method can lessen the influence of electromagnet noises and improve the signal-to-noise ratio. Thirdly, computation efficiency of the proposed method is improved compared with conventional method due to the VKF-OT algorithm. Finally, the proposed method implements the DBN algorithms which are good at processing the nonlinear signals, and

thus the performance of the proposed approach can be improved in comparison with the existing approaches. The proposed flux linkage monitoring approach are experimentally verified on an SPMSM under unsteady operation conditions. The experimental result shows that the proposed approach is able to monitor the flux linkage change under a wide speed range.

4.2 PMSM Torque Ripple Model

The electromagnetic torque is given as follows [7]:

$$T_{e} = T_{c} + \sum_{\lambda=1}^{\infty} T_{\lambda} \sin(\lambda \omega_{s} t - \alpha) + \sum_{\lambda=1}^{\infty} \sum_{\xi=1}^{\infty} T_{\lambda,\xi} \sin\left[\left(\lambda \pm \frac{\xi}{P}\right)\omega_{s} t - \beta\right]$$

$$(4.1)$$

where λ and ξ are integer numbers, α and β are space variables, *P* is the number of pole pairs, and T_c , T_{λ} and $T_{\lambda,\xi}$ are torque components. As can be seen from (4.1), there exist a certain frequency ($\lambda \pm \xi/P$) f_s in the torque spectrum caused by voltage source inverter (VSI) harmonic components, the VSI frequency, and saturation effects. Thus, the measured torque should be processed to eliminate these high-frequency electromagnet noises before applying order tracking method.

Usually the mean value of torque is one of the indexes to describe the torque measurement characteristics. However, mean value of torque values reflect the DC component of the torque measurements within in a short period. This paper focuses on the variable difference effects of torque change under demagnetization. Thus electromagnetic torque ripple is chosen as the variable to detect the demagnetization.

The ripple component of the torque is expressed as (4.2) using the *d*-*q* transformation [94].

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$$T_r = T_c + P\left\{\frac{1}{2}\left[i_{dq}^*\right]^T \frac{d\left[\phi_{dq}\right]}{d\theta_e} + \left[i_{dq}^*\right]^T \frac{d\left[\psi_{dq}\right]}{d\theta_e}\right\}$$
(4.2)

where *P* is the number of the ploe pairs, i_{dq} is the armature current vector, θ_e indicates rotor position, ψ_{dq} represents the PM flux, and Φ_{dq} is armature current flux. From (2), it can be observed clearly that the PM flux variation disturbances in the air-gap flux density distribution magnify torque ripples noticeably. In this way, it is feasible to monitor the PM flux linkage variation by analyzing the torque ripple signals when PMSM operates under the nonstationary conditions.

4.3 Order Tracking for PM Flux Linkage Monitoring

The order tracking method can identify the orders when the motor operates at various speed or with different levels of load. Compared with the other OT methods, the second generation VKF-OT provides an accurate identification of orders over a wide speed range of the studied motor with no smearing related problems, because it works directly in timedomain [91]. VKF-OT is also one of the most suitable and promising techniques for tracking the characteristic AC components, where only the speed of the PMSM and the order numbers are needed. Therefore, VKF-OT is selected and employed in this paper to track the ripple components from torque.

Assuming a dynamic torque ripple signal, y(n), measured from the operation of a PMSM contains both a specific order component x(n) as well as electromagnetic noise component, the data equation [96] of torque signal is defined as (4.3):

$$\begin{cases} y(n) = x(n)e^{j\Theta(n)} + \eta(n) \\ \Theta(n) = \sum_{i=1}^{n} \omega(i)\Delta t \end{cases}$$
(4.3)

where y(n) is the measured torque ripple, x(n) is a complex envelope of the filtered signal, $e^{j\Theta(n)}$ is a complex carrier wave, $\omega(i)$ is the discrete angular frequency, $\eta(n)$ is the measurement artifacts, and Δt is the sampling interval. The structural equation whose composition depends on the poles m (m=2 in this study) of the Vold-Kalman filter is described as:

$$x(n) - 2x(n+1) + x(n+2) = \mathcal{E}(n)$$
(4.4)

where $\varepsilon(n)$ is the unknown non-homogeneity term.

All torque signals can be arranged into vectors of size Nx1 for vectors \mathbf{y} , \mathbf{x} , $\mathbf{\eta}$ and $\mathbf{\varepsilon}$. The matrix form of data equation (4.3) and structure equation (4.4) with two-pole can be written as:

$$\begin{cases} \mathbf{A}\mathbf{x} = \mathbf{\epsilon} \\ \mathbf{y} = \mathbf{C}\mathbf{x} + \mathbf{\eta} \end{cases}$$
(4.5)

where

$$\mathbf{x} = [\mathbf{x}(1), \mathbf{x}(2)...\mathbf{x}(N)]^{\mathrm{T}},$$

$$\mathbf{\varepsilon} = [\varepsilon (1), \varepsilon (2)...\varepsilon (N-2)]^{\mathrm{T}},$$

$$\mathbf{y} = [\mathbf{y}(1), \mathbf{y}(2)...\mathbf{y}(N)]^{\mathrm{T}},$$

$$\mathbf{\eta} = [\eta (1), \eta (2)...\eta (N)]^{\mathrm{T}},$$

$$\mathbf{C} = \operatorname{diag} [e^{j\Theta(1)}, e^{j\Theta(2)}...e^{j\Theta(N)}],$$

$$\mathbf{A} = \begin{bmatrix} 1 & -2 & 1 & 0 & \cdots & 0 & 0 & 0 \\ 0 & 1 & -2 & 1 & \cdots & 0 & 0 & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & 0 & 0 & \cdots & 1 & -2 & 1 \end{bmatrix}$$

The objective function is expressed as (4.6):

$$J = r^2 \varepsilon^T \varepsilon + \eta^T \eta \tag{4.6}$$

where *r* is weighting coefficient.

The global solution of the tracked order of torque ripple envelopes \mathbf{x} can be obtained by minimizing (6) as (4.7):

$$\begin{cases} \frac{\partial J}{\partial x^{H}} = \mathbf{B}\mathbf{x} - \mathbf{C}^{H}\mathbf{y} \\ \mathbf{B} = r^{2}\mathbf{A}^{T}\mathbf{A} + \mathbf{E} \end{cases}$$
(4.7)

where **E** is the identity matrix.

Based on the least square method and derivation operation, the torque ripple envelopes \mathbf{x} is defined as (8):

$$\mathbf{x} = (r^2 \mathbf{A}^T \mathbf{A} + \mathbf{E})^{-1} \mathbf{C}^H y$$
(4.8)

By applying the VKF-OT in flux linkage variation monitoring, the proposed model consists of torque ripple measurement monitoring, signal processing, VKF order tracking, and feature extraction modules. The detailed implementation diagram is shown in Fig. 4-1. The

monitored torque signal under nonstationary condition is firstly preprocessed by the wavelet transforms to eliminate the high frequency noise. Then the torque orders are extracted from the de-noised torque with VKF-OT. Thirdly, by applying the wavelet transform again, the order energy is computed as the feature indicator. Moreover, DBN is employed to estimate the flux linkage variation indicator when motor is operating. The indicator value then is compare with the value from a normal PMSM in lab-designed motor controller, which determines the next control operation. When the indicator value is below the threshold, which means the PMSM is functioning normally, the proposed monitoring system keeps going. When the indicator value is over the threshold, the motor drive will perform the control measure such as current adjustment, which will be studied in the future.

Among those modules in Fig. 4-1, order tracking module which extracts the torque ripple envelopes from torque measurements is challenging due to its impact to the overall accuracy and reliability. All these modules are integrated into the machine vector control algorithm by using C.



Figure 4-1. Flowchart of the proposed VKF-OT based flux linkage monitoring.

4.4 Experimental Validation for Flux Linkage Monitoring

4.4.1 Flux Linkage Variation Monitoring Platform Setup

Experimental tests have been carried out to validate the performance of the proposed method using a surface mounted PMSM, whose design parameters are detailed in Table 4-1. The experimental setup, shown in Fig. 4-2, consists of a test motor and a dyno machine which can be controlled individually. The test motor is controlled by a laboratory-designed, inverter-fed, digital signal processor based drive system. The drive system is a field-oriented vector control which contains both current and speed feedback. The torque data is collected by a torque transducer and stored in the storage system.

| Rated power | 12.5 kW | Rated Torque | 75 Nm |
|---------------|-------------|----------------------|----------|
| Rated voltage | 297 V | Number of pole pairs | 4 |
| Rated current | 35 A | Magnet flux (21°C) | 0.136 Wb |
| Rated speed | 3,000 r/min | Magnet flux (120°C) | 0.112 Wb |

TABLE 4-1 PARAMETERS OF THE LABORATORY PMSM MOTORS UNDER TEST

During experiments, the tested motor was demagnetized intentionally by changing the motor internal temperature. The tested motor was given large torque for a long time, and a lab-designed smart drive was used to read the motor interior temperature through the temperature sensors embedded in the motor. By computing the back EMF, the PM flux can be calculated under different temperature condition. Then in the later experiments, the demagnetization ratio could be controlled according to the temperature. In this way, the demagnetization phenomenon can be confirmed to test the proposed diagnosis method in this paper. After providing the motor with different range of torques, the PM flux decreased due to the high temperature. By letting the temperature increasing, the residential flux changes from 100% to 73% continuously.

4.4.2 Torque Ripple Signal Processing

Generally, the torque measurements are non-stationary and interfered with high-frequency noises from measurement sensors, inverter and environment. From the torque ripple measurement waveform shown in Fig. 4-3 (grey curve), it can be seen clearly that the measured torque ripple waveforms are full of sharp distortions. In order to obtain the correct torque ripple information, those electromagnetic noises should be filtered at the



Figure 4-2. Experimental setups for PMSM flux linkage variation monitoring. (a) Lab-designed universal motor controller. (b) Dyno and test motors setup.

first stage. Conventional Fourier Transform does not work well to achieve the result with non-stationary signal, because its function basis is infinite trigonometric which lead to the constant time-frequency resolution, Wavelet transforms is chosen in this section for its advantages as representing finite decaying function basis to match those signals that have discontinuities and sharp peaks, and for accurately deconstructing and reconstructing finite, non-periodic and/or non-stationary signals. Wavelet is selected as Daubechies-4 in this paper based on the simulation results. During experiments, the sampling frequency f_s is set to 2,000 Hz. The bandwidth of the wavelet transform is1,000 Hz. The sensitivity of the proposed techniques is not affected by the frequency selection, because it is determined by Nyquist law.

Following the proposed approach in Fig. 4-1, the filtered torque measurement of the PMSM is shown in purple in Fig. 4-3. It also shows that the ratio of electromagnetnoise decreases by 15% when the proposed wavelet filter is employed to the healthy PMSM.



Figure 4-3. Measured torque ripple from a healthy SPMSM motor with wavelet transforms under test at 200 r/min with 15 Nm output torque.

4.4.3 Validation on Flux Linkage Variation with VKF-OT

In the experiment, the proposed approach is validated with a constant nominated load at varying operation speed. The load torques is provided by the connected dynoma as 20 Nm for the test PMSM. The lab-designed motor drive for test motor controls the PMSM to operate at the rotational speed from 0 to 250 r/min. Three groups of experiments were carried out. In the first group, the healthy motor was operated with speed change from 250 r/min to 50 r/min and the torque data was measured during this interval. Then in the second group, with the PM flux linkage decrease, the tested motor was operating under the artificial flux linage variation condition 1, which is residual 83% of initial flux linkage, with speed varying from 250 r/min to 50 r/min. In the third group, the tested motor was controlled to change the speed from 250 r/min to 50 r/min under flux linkage variation condition 2, with residual 67% of healthy motor flux linkage value. Following the proposed flux linkage variation monitoring flowchart in Fig. 4-1, the first, second and third characteristic orders of torque ripple from those two flux linkage variation groups were defined and tracked as illustrated in Figs. 4-4 and 4-5. The envelopes have been calculated by tracking each order of harmonic component of torque ripple by means of VFK-OT algorithm. It can be seen from Fig. 4-5(a) that with the intentional PM flux linkage variation deterioration, the output torque ripple increases compared with Fig. 4-3 and Fig. 4-4(a).

Consequently, the amplitudes of the tracked 1st, 2nd, and 3rd torque ripple orders under 67%

residual flux linkage variation condition 2, which are shown in Fig. 4-4(b), are greater than those amplitudes from 83% residual flux linkage variation under condition 1. Experimental results shown in Figs.4- 4 and 4-5 corroborate the statement made in (2) which express that the torque ripple is effected prominently by the PM flux linkage variation in the air-gap.

Though there are apparent differences in first and second order amplitude at each frequency band under demagnetization conditions, they cannot be used directly because the vector array contains at least 1,000 elements. A computationally efficient indicator should be selected to simplify the computation. In this way, the proposed method can be implemented on-line due to its efficiency.

4.4.4 Feature Indicator Extraction using VKF Order Tracking

It is observed that the tracked characteristic orders in Figs. 4-4 and 4-5 are disperse and result the difficulties to compare the flux linkage variation levels under different conditions.

Therefore, it is necessary to quantify them by extracting the feature characters from the orders. Since torque ripple order energy mirrors the torque ripple fluctuation ratio, it can be extracted as the monitoring factor to indicate the PM flux linkage variation. Hence, the order energy is defined as the feature indicator in this paper by being calculated with wavelet transforms algorithm.

For the extracted i^{th} order x(t) from (4.3) in section II, the continuous wavelet transforms can be expressed as (4.9):

$$W_{x}(a,b) = \frac{1}{2\sqrt{a}} \int_{R} A_{a,b}(t) \exp\left[i\Phi_{a,b}(t)\right] dt$$
(4.9)

where

$$\begin{cases} A_{a,b}(t) = a(t)A_{\psi}\left(\frac{t-b}{a}\right) \\ \Phi_{a,b}(t) = \varphi(t) - \varphi_{\psi}\left(\frac{t-b}{a}\right) \end{cases}$$
(4.10)



Figure 4-4. Experimental results of PMSM under 83% residual flux linkage variation with speed from 250 r/min. (a) Torque ripple after filtering. (b) Tracked 1st, 2nd, and 3rd orders of torque ripple.



Figure 4-5. Experimental results of PMSM under 67% residual flux linkage variation with speed from 250 r/min to 50 r/min. (a) De-noised torque ripple measurement. (b) Tracked 1st, 2nd, and 3rd orders of torque ripple.

where $\Psi(t)$ is the square-integrable function or mother wavelet, *a* is the scale, *b* is translation parameter, A_{Ψ} is the real component, and $\overline{\tilde{\psi}}\left(\frac{t-b}{a}\right)$ is the conjugate of $\tilde{\psi}\left(\frac{t-b}{a}\right)$.

The torque ripple order energy can be obtained from (4.11) due to its equidistant characteristics.

$$\begin{cases} \int_{R} |x(t)|^{2} dt = \frac{1}{C_{\psi}} \iint_{R} |W_{x}(a,b)|^{2} \frac{\mathrm{d}a \,\mathrm{d}b}{a^{2}} \\ C_{\psi} = \int_{R} \frac{|\hat{\psi}(\omega)|^{2}}{|\omega|} d\omega < \infty \end{cases}$$

$$(4.11)$$

where C_{Ψ} is the permitting condition.

Since $|W_f(a,b)|^2/(C_{\Psi}a^2)$ can be taken as the energy density function on plane (a,b), (11) can be rewritten as:

$$\begin{cases} \int_{R} |x(t)|^{2} dt = \frac{1}{C_{\psi}} \int_{R} a^{-2} E(a) da \\ E(a) = \int_{R} |W_{x}(a,b)|^{2} db \end{cases}$$
(4.12)

where E(a) is scale-wavelet energy spectrum which indicates the torque ripple order energy variation following with scale changes.

In the torque ripple order wavelet energy spectrum, scale *a* is no longer a constant and varies continuously along with ripple order line. Thus the torque ripple order energy down with a certain order line $a_r(b)$ is defined by (4.13).

$$\widetilde{E}[a_r(b)] = \int_R \left| W_f[a_r(b), b] \right|^2 db$$
(4.13)

where $\tilde{E}[a_r(b)]$ indicates the order energy which reflects the torque ripple order value with the certain order line.

Therefore, the results of torque ripple order energy can be obtained by following the above steps, and shown in Fig. 4-6. The ripple order en ergy, extracted from torque ripple orders, exactly represents the flux linkage variation. It can be seen clearly that the energies

extracted from the 1st torque ripple order show the similar amplitudes, but the 2nd and 3rd order energies, which manifest different values in different iteration vector, can be taken as the feature indicators.



Figure 4-6. Torque ripple order energy illustration from VKF-OT. (a) Under 83% residual flux linkage. (b) Under 67% residual flux linkage variation.

4.5 PMSM Flux Linkage Estimation by Using DBN

It is observed from Fig. 4-6 that the characteristic order energies from the 2nd and 3rd torque ripple order can reflect the PM flux linkage variation well, thus both them can be chosen as the flux linkage monitoring indicators. Since the dynamics Bayesian network algorithm is employed in this paper to estimate the flux linkage variation, two system inputs will lead to the large computation and reduce the system efficiency. Hence, the energy from the 3rd torque ripple order is selected as the monitoring indicator in this study.

Dynamic Bayesian networks is a Bayesian Network that extends standard Bayesian networks with the concept of time. It can model the relationships between multiple time

series in the same model, and also different regimes of behavior, since time series often behave differently in different contexts. Thus, it is possible to estimate the flux linkage variation along with the motor operation time [97]. Compared with other statistic model, DBN has exponentially fewer parameters and faster computation speed, and therefore it is can be integrated in the motor control system with limited training data. The DBN algorithm applied in this paper is that found in the [98].

According to DBN theory, the flux linkage can be estimated in a DBN with *T* time slices. In each time slice, the parameters are static and Hidden Markov method (HMM) can be applied to it. The number of DBN states is written as *N*. In this paper, there is one feature indicator, so the number of states is one, that is N=1. In the proposed model, there is only one observation that reflects the variation of the flux linkage, that is feature indicator, so M=1.

The initial state distribution is shown as $\pi = (\pi_1, \pi_2, \dots, \pi_k)$. According to Bayesian prior probability assumption, if the event or the probability of event is unknown, the uniform distribution in interval (0,1) can be taken as the event prior probability because it has equal opportunity at interval. The flux linkage variation states are divided into 100 equal parts from 0 to 100% in this study. Therefore, in the DBN model, $\pi_i = P(q_0 = i) \sim U(0,1)$, K=100 and $p(q_0 = i) = \frac{1}{k} = 0.001$. The state transition probability distribution is represented as $A = (a_{ij})_{K*K}$. Each element a_{ij} means the probability of the next time step flux linkage value obtained from the current flux linkage value.

$$a_{ij} = P(q_t = S_j | q_{t-1} = S_i) = P(FLV_{j:t} | FLV_{i:t-1})$$
(4.14)

According to the Bayes rule,

$$a_{ij} = P(FLV_{j:t} | FLV_{i:t-1}) = \frac{P(FLV_{j:t}, FLV_{i:t-1})}{P(FLV_{i:t-1})}$$
(4.15)

$$A = \left(\frac{P(FLV_{j:t}, FLV_{i:t-1})}{P(FLV_{i:t-1})}\right)_{K^*K}$$
(4.16)

The observation symbol probability distribution is determined by $B = (b_{jk})_{K*L}$. Each element

 b_{jk} is the probability of feature indicator k when flux linkage is in state j [98]. The torque ripple order energy is divided into M equal classes from 0 to 4 J (internal 0.04 J). Thus L=100.

$$b_{ik} = P\left(E_{k:t} \mid FLV_{j:t}\right) = \frac{P\left(E_{k:t}, FLV_{i:t}\right)}{P\left(FLV_{j:t}\right)}$$
(4.17)

$$B = \left(\frac{P(E_{k:t}, FLV_{j:t})}{P(FLV_{j:t})}\right)_{K^*L}$$
(4.18)

After the above five steps, the DBN model parameters $\lambda = (\pi, A, B)$ are determined. Once the energy indicator observation sequence $O=(y_1, y_2, \dots, y_T)$ is obtained, flux linkage variation ratio can be computed by the procedures [19]. By applying the indicator values from the 3rd torque ripple order with the given flux linkage variation ratios to DBN model, the relation between PM flux linkage and energy indicator can be estimated as in Fig. 4-7. Consequently, the PM flux linkage variation ratios can be calculated based on the initial flux linkage value. With the given flux linkage result, the PM flux linkage monitoring results can be compared with the conventional method which used online parameter estimation with the recursive LS (RLS) method [99]. Table 4-2 presents that result obtained from the proposed flux linkage monitoring method is more precise.



Figure 4-7. Flux linkage monitoring from an artificially reduced magnet PMSM with 20 Nm at speed change from 250 r/min to 50 r/min.

| | Proposed | RLS | Measured |
|----------------------|----------|-------|----------|
| Flux linkage (Wb) | 0.435 | 0.462 | 0.415 |
| Variation Ratio (%) | 64.93 | 0 | 61.94 |
| Estimation error (%) | 4.8 | 11.32 | |

TABLE 4-2 Flux Linkage Variation Monitoring Result of the PMSM at Operation with 250 $$\rm R/MIN, 20\,nm$

4.6 Conclusion

A novel torque ripple-based approach is developed and validated for online PM flux linkage monitoring under nonstationary conditions. In general, there are high-frequency electromagnetic noise in the torque measurement from torque transducer. In order to eliminate those noise from inverter, measurement, and current and obtain the exact torque, wavelet transforms were employed to process the torque data. Then the torque ripple order can be tracked from the de-noised torque by applying VKF order tracking which is able to extract the characteristic orders of torque ripple and the torque ripple variation ratio. Moreover, monitoring feature indicator, which was extracted as the order energy from the 3rd torque ripple order, was applied as the system input to the DBN algorithm to estimate the flux linkage variation by referring the indicator values. The experimental results have demonstrated that the proposed approach is able to monitor the flux linkage variation during PMSM nonstationary operation. The future study will focus on the robustness and feasibility related concerns of the proposed approach for real EV applications.

CHAPTER 5

MULTI–SENSOR FUSION BASED PERMANENT MAGNET DEMAGNETIZATION DETECTION IN PERMANENT MAGNET SYNCHRONOUS MACHINES

5.1 Introduction

When a PMSM is operating, the PM rotor flux linkage de-creases as the temperature rises. However, the rotor PM flux linkage is usually considered as constant in PMSM controller design. The actual PM flux linkage fluctuation may lead to unstable torque output, and thus, have an effect on EV performance. Moreover, when motor internal temperature exceeds the material critical point, the PM flux density cannot restore to the original remnant flux density and result in permanent demagnetization, which may lead to failure and reduce the motor performance [100], [101]. Hence, on-line PM flux linkage monitoring and demagnetization detection are critical to ensure high–performance from a PMSM drive.

In order to detect demagnetization, a precise analysis of demagnetization characteristics is necessary. Researchers have studied demagnetization characteristics from different perspectives. Speed harmonics are explored in [102] for PM flux linkage estimation. Position–offset–based parameter estimation was used in [103] to obtain the accurate PM flux linkage. Kalman filter was used in [104] to observe the PM flux link-age/temperature using dq–axis equations. Torque with inductance in [105] was studied to understand the flux linkage reduction in PMSM. However, most of the demagnetization detection techniques are based on single sensor diagnosis such as analysis of stator current [106], acoustic noise [107], or output torque [108]. Nonetheless, single sensor demagnetization detection has inherent uncertainties due to fault models and motor operating environments. Hence, multi–sensor information fusion is an effective method to address such uncertainties and improve demagnetization detection accuracy and control stability.

This chapter proposes a novel method to integrate multiple sensor information to enhance the performance and reliability of the PM demagnetization detection by using acoustic noise and torque. At first, the relationships between PM flux linkage and torque and noise are analyzed to demonstrate that the acoustic noise and torque are dependent on PM flux linkage variations. Then, both measured acoustic noise and torque information are processed by wavelet transforms to eliminate the effect of background electromagnetic interferences and to extract the feature values respectively. The expert system is developed to reduce the dimension of extracted feature vector. The extracted features form both noise and torque are combined in the decision level fusion to predict the demagnetization ratio based on Bayesian network algorithm. The pro-posed multi–sensor fusion based demagnetization detection approach is experimentally verified on a laboratory PMSM drive system. The contributions of this paper lie in the following aspects: 1) the impact of rotor demagnetization feature incompleteness and ambiguity can be eliminated with the combination of Bayesian fusion algorithm; and 2) the pro-posed approach is independent of motor parameters and its performance is not influenced by the machine parameters variation.

5.2 Analysis of Relationship among Rotor Flux Density and Torque Ripple and Acoustic Noise

In EV application, PMSMs are driven by the voltage source inverter (VSI) with PWM switching frequency f_s . When demagnetization occurs, the distorted PM flux linkage combined with VSI harmonic components, may cause disturbances in motor performances including both output torque and acoustic noise.

The deviation component of the output torque is expressed in (5.1) using the d-q transformation [109].

$$T_{r} = T_{c} + P\left\{\frac{1}{2}\left[i_{dq}^{*}\right]^{T} \frac{d\left[\phi_{dq}\right]}{d\theta_{e}} + \left[i_{dq}^{*}\right]^{T} \frac{d\left[\psi_{dq}\right]}{d\theta_{e}}\right\}$$
(5.1)

where *P* is the number of the pole pairs, i_{dq} is the armature current vector, θ_e indicates rotor position, ψ_{dq} represents the PM flux, and Φ_{dq} is armature current flux. From (1), it can be observed clearly that the PM flux variation disturbances in the PM flux density distribution magnify torque ripples noticeably at frequency $(\lambda \pm \xi/P)f_s$ [9].

On the other hand, when a PMSM is fed with ideal sinusoidal current, the radial force is the major exciting force as in (5.2) [110]:

$$P_r(\alpha, t) = B^2(\alpha, t)/2\mu_0$$
(5.2)

where P_r is the radial force, α is the stator space angle. μ_0 is the vacuum permeability, and *B* is the air gap flux density. Where h_i is the harmonic current number, $B_{s,hi}$ is the flux density caused by harmonics, and ω_s is switching speed. The rotor flux density considering VSI and the relevant harmonics can be rewritten as:

$$\begin{cases} B(\alpha,t) = B_r(\alpha,t) + B_s(\alpha,t) + B_{s,h_i}(\alpha,t) \\ B_{s,h_i}(\alpha,t) = \mu_{\alpha} \sum_{h_i} \sum_{j=1}^{\infty} A_{s,h_i} \cos[jp \,\alpha - h_i(\omega + \omega_s)t] \end{cases}$$
(5.3)

Then the relationship between acoustic noise frequencies fed with VSI and motor speed can be obtained as (5.4) [111]:

$$N = \left\{ \left(2k-1\right)\left(\frac{\omega_s}{\omega} \pm 1 \pm h_i\right) \frac{np}{60}, 2k\left(\frac{\omega_s}{\omega} \pm 1 \pm h_i\right) \frac{np}{60}, \left|h_m - h_l\right| \frac{np}{60} \right\}$$
(5.4)

where ω_s is switching speed, ω is the electrical rotor speed, k is the integer, p is the number of pole pairs, and n is rotation speed, h_m and h_l belong to the range { $(2k-1) \omega_s/\omega$, $2k\omega_s/\omega$ }. It can be seen that certain frequency $(2k\pm 1\pm h_i) \omega_s/\pi$ can be spotted in the noise spectrum, which is produced by VSI, f_s , harmonic components and saturation effects. Acoustic noise is evidently increased by the demagnetization fault disturbances in the air–gap flux density distribution. The increase of the noise amplifies the sideband at frequency $(2k\pm 1\pm h_i) \omega_s/\pi$ [111].

Based on the analysis above, both the torque and acoustic noise are influenced by the PM flux linkage variation during demagnetization. Therefore, it is feasible to analyze either output torque or acoustic noise for diagnosing PM demagnetization individually. This chapter integrates both of them into accurate demagnetization detection.

In practice, when PM demagnetization occurs, the armature current under closed-loop control is compensated to maintain the constant output torque. However, to detect the demagnetization through current increase is not easy because the current change can be resulted from various sources such as resolver angle error, current sensor error, and eccentricity. Those cases may enlarge the current in the same way as demagnetization. Thus in this paper, demagnetization is particularly studied by using torque and acoustic information. With above discussion, torque ripple and acoustic noise are available to reveal

the PM demagnetization throughout all motor operation conditions, especially when current detection fails during PM saturation or under flux weakening control. However, it should be noted that current based detection is easy and accurate during motor normal operation.

5.3 Multi-sensor Information Fusion Based Demagnetization Detection

Multi–sensor information fusion technology is based on the idea that sensors with different information have complementary characteristics and results in more accurate estimation than a single source. The multi–sensor fusion method can effectively improve the robustness of diagnostic decision–making. The information can be fused at different levels such as signal–level, feature–level and decision–level. As for a –regular–sized PMSM in EV, there is not much choice in terms of sensor accuracy or feature extraction. So, in this paper, decision–level fusion is more suitable and efficient and hence a Bayesian network based fusion method is implemented.

During motor operation, the rotor magnet demagnetization distorts the magnetic flux distribution resulting in noise, vibrations and torque ripple in the machine. In order to use those information from different sensors as the demagnetization indexes, a demagnetization detection model is proposed and shown in Fig. 5-1. Though there exits relationship between the torque ripple and acoustic noise, this coupling relationship can help to increase the information redundancy during demagnetization detection. The detailed procedure is explained as follows.

5.3.1 Torque and Acoustic Noise Signal Pre-process

As discussed in section II, both output torque and acoustic noise contain the motor operating status information which can then be used to determine demagnetization. However, the measured torque and noise signals from individual sensors are non-stationary and are generally disturbed by the high–frequency noises from operators, position measurement, current measurement, inverter and flux linkage harmonics. It can be observed from Fig. 5-1 that the measured torque and noise waveforms are distorted. To eliminate or reduce the electromagnetic noises and interferences, the initial signals should be filtered first. Since the conventional time–frequency domain algorithm does not work well to achieve the result with those signals due to the constant time–frequency resolution,

wavelet packet transforms (WPT) are used on the torque and acoustic noise measurements filtering. WPT has advantages over conventional filter for representing functions, which comprise of non–stationary signals. The torque and noise waveforms meet the principles well. For that reason, it is expected to filter the initial torque and acoustic noise measurements by using WPT. The example of filtered torque measurement processing is shown in Fig.5-2.



Figure 5-1. Flowchart of multi-sensor based demagnetization detection model.


Figure 5-2. Measured torque ripple from a healthy PMSM with wavelet transforms under test at 1,500 rpm with 15 Nm output torque.

5.3.2 Feature Value Extraction

After obtaining the filtered signals, the hidden useful information should be extracted for further analysis. In general, signals contain feature values in time domain, frequency domain and time–frequency domain. Features in time domain reflect the statistical summary of the signal waveform, while features in frequency domain focus on signal power or energy characteristics with the signal frequency changes. Time–frequency analysis combines both. Since different feature values have different sensitivity to demagnetization status, in this paper, seven feature values are extracted from noise signals in both time and frequency domain as sound fluctuation, sound loudness, sound roughness, articulation index, HHT instantaneous frequency, FFT spectrum and power spectrum density, are chosen from [9] for output torque measurement. They represent the signal energy value with the certain ridge line and the total signal energy respectively. The signal energy $\tilde{E}[a_r(b)]$ down with a certain ridge line $a_r(b)$ is defined is defined in (5.5) [108]:

$$\widetilde{E}[a_r(b)] = \int_{R} \left| W_f[a_r(b), b] \right|^2 db$$
(5.5)

where a is the scale and b is translation parameter. Thereafter, those nine feature values can be used in the further process.

5.3.3 Eigenvector Size Reduction for Multi–Sensor Signals

From section III.B, there are two signal measurements containing nine feature values, which means the dimension of eigenvector is up to nine. In general, large feature information may complicate the calculation and then lengthen the computation time. Hence, the process to reduce the eigenvector size from noise sensor should be implemented. In this paper, multi–attribute expert decision–making algorithm is applied to select the related feature value with most significant weight to improve the calculation efficiency.

Assume that in this paper, the expert decision-making group is made of 4 experts D=(d_1 , d_2 , d_3 , d_4), and the weight of each expert d_k is written as λ_k , where $0 \le \lambda_k \le 1$, k=1, 2, 3 and 4, and $\sum \lambda_k=1$. The decision-making group, which consists of the seven feature value extracted from noise measurements, is defined as $F=(f_1, f_2, \dots, f_n)$, $n=1, 2, \dots, 7$, in which f_1 , f_2, \dots, f_n indicate sound fluctuation, sound loudness, sound roughness, articulation index, HHT instantaneous frequency, FFT spectrum and power spectrum density, respectively. The decision-making attribution set is presented as $C=(c_1, c_2, \dots, c_m)$. The weight of each attribution c_j from set *C* is denoted as w_j , where $0 \le w_j \le 1$, j=1, $2, \dots, m$ and $\sum w_j = 1$. Let each decision maker d_k specify the initial weights concerning the importance of each criterion c_j for each of those 7 extracted feature value f_i , then the evaluation matrix of the feature values can be generated as $A_k=(a_{ij})_{nm}$.

Hereafter, the ranking marks for each feature value marked by each expert can be obtained as $x_k(i) = \sum (a_{ij})_k w_j$ based on the initial expert weight and attribution weight. The final marks for each feature value ranking from expert group is denoted as $x_0(i) = \sum x_k(i) \lambda_k$. Following the above calculation, the group decision–making rank is iterated as $x_0 = (5.803, 7.762, 6.405, 4.852, 6.385, 4.839, 7.437)$. Consequently, when the threshold is set as 6.4, the three characteristics, which are sound loudness, sound roughness, and sound power spectrum density, are selected as the feature values from noise signals. Combined with 2 feature values from the torque signal, the dimension of eigenvector is 5, which is almost half of initial size 9.

5.3.4 Bayesian Network Based Multi-sensor Fusion

According to the multi–sensor information fusion theory, the selected 5 feature values from noise sensor and torque transducer, can be taken as multi–source information from different

sensors, based on which the diagnosis sampling set can be created. Then Bayesian parameter estimation algorithm is applied to fuse that multi–source information on decision–level and to launch a demagnetization detection model G based on the maximum posteriori estimation value.

The basis of Bayesian parameter estimation fusion theory is the Bayesian equation. Let X_1 , X_2, \dots, X_N present the signal measurements from N sensors. The target of information fusion theory is to estimate the real value of demagnetization state Y from X_1, X_2, \dots, X_N according to certain estimation criteria function Z(X). Assume that the state of measured demagnetization sample at a certain time is $Y=\{Y_1, Y_2, \dots, Y_m\}$, and the feature values from sensors are written as $X=\{X_1, X_2, \dots, X_n\}$. The measurement model of the feature information is denoted as X=f(Y)+v, where f(Y) is the function relationship between X and Y, and v is the random noise. For each feature value X_i , the estimation value of state Y is $Y^n(X_i)$, and the loss function is defined as $L[Y^n(X_i), Y]$. According to the Bayesian estimation theory, the expectation of loss function C is

$$R = E\left\{L\left[\hat{Y}(X_i), Y\right]\right\}$$

= $\int dX_i \bullet P(X_i) \int dY \bullet P(Y|X_i) L\left[\hat{Y}(X_i), Y\right]$ (5.6)

where $P(X_i)$ is the distribution probability of feature information, and $P(Y|X_i)$ is the posterior probability of state *Y*. To satisfy the minimal risk estimation criterion, there should be

$$\frac{\partial R}{\partial Y}\Big|_{Y=\hat{Y}(X_i)} = 0 \tag{5.7}$$

Thus, the fusion value of *n* sensors is presented as (5.8):

$$\hat{Y}_{opt}(X_1, X_2, \dots, X_n) = \max_{\hat{Y}} P(Y | X_1 X_2 \dots X_n)$$
(5.8)

Hereafter, the multi–sensor information fusion problem converts to find the posterior probability P(Y|X) of state *Y* and the corresponding maximum posterior estimation value. Then the maximum posterior probability estimation value, which is the reasoning result from information fusion and Bayesian network, can be obtained as:

$$\hat{Y}_{opt}(X_1, X_2, \cdots, X_n) = \alpha \max_{\hat{Y}} \left[\prod_{i=1}^n P(X_k) \right]$$
(5.9)

where $\alpha = 1/P(X_1 X_2 \cdots, X_n)$. Then the demagnetization state can be detected according to the corresponding state Y_j to the maximum posterior probability estimation value from (9).

In this paper, let the 5 selected feature values consist a feature information space set $Y = \{Y_1, Y_2, Y_3, Y_4, Y_5\}$, and the demagnetization level states is divided into 8 states (health 0%, 10%, 20%, …, 70% residual flux linkage) and denoted as $D = \{DEC(0), DEC(1), DEC(2), DEC(3), DEC(4), DEC(5), DEC(6), DEC(7)\}$. From (5.8), the fusion value of 5 sensor features information can be written as (5.10):

$$\hat{Y}_{opt}(Y_1, Y_2, \dots, Y_5) = \max_{\hat{Y}} P(D|Y_1Y_2 \dots Y_5)$$
(5.10)

In order to determine the relationship between Y and D, and to quantify the causal relationship among the random variables, a Naïve Bayesian network classifier [12] is created in Fig. 5-3. According to the Bayesian network classifier theory, the feature vectors are assumed to be mutually conditional independent, and each attribution node is related to demagnetization nodes.

That assumption reduces the complexity of the network and decrease the computation. By deriving (5.10) with (5.9), (5.10) can simplified as (11), which is the detection model in Fig. 5-2.

$$\hat{Y}_{opt}(Y_1, Y_2, \dots, Y_5) = \alpha \max_{\hat{Y}} \left[\prod_{i=1}^5 P(Y_i | D) \right]$$
(5.11)

5.4 Validation for Proposed Demagnetization Model

In order to validate the performance of the proposed demagnetization detection model, a laboratory 12.5 kW PMSM shown in Fig. 5-4 is employed with machine rating and parameters listed in Table I. The test motor was controlled by a lab–designed motor controller. There are two major steps to perform the validation.



Figure 5-3. Naïve Bayesian Network Classifier to detect rotor demagnetization.

The first step is to determine the tested motor PM flux linkage variation. The motor was operating at 3,000 RPM, then the dyno was controlled to provide a load to the test PMSM. Next the motor was kept operating for 2 hours. During this period, the current, voltage, torque, and temperature were read in real time from the motor drive serial port. When the temperature is increased to a pre–set degree (60-180°C), the test was stopped. By using the dyno motor drive, the back EMF value of the PMSM under test can be recorded at that moment. The back EMF is proportional to the PM flux linkage, thus PM flux linkage value as a function of the temperature under different loading conditions value can be determined.

The second step is to test the motor both with the microphone and torque transducer. As described in step 1, the tested motor ran at 0-3,000 r/min and then the dyno was controlled to produce torque 0–40 Nm respectively as loads to the tested motor. The two motors had been kept running until the motor drive LED signaled that the temperature reached the 60-180°C, which indicates the PM flux reduced to 100-40% residual. Then, the acoustic noise and output torque at that moment were measured and processed.



Figure 5-4. Experimental setups for PMSM demagnetization detection validation.

During experiments, step 2 was conducted in two groups. In group 1, the PMSM was operating at the rated speed 3,000 RPM and the load was controlled to rise from 0-40 Nm step by step. In the second group, the dyno was controlled to give a constant 40 Nm load, but the tested motor was controlled to operate at different speeds from 0 to 3,000 r/min in stages.

Based on the above two test steps, the PM demagnetization condition can be created by referring to the motor internal temperature during the experiments, and the acoustic noise and torque at that moment can be measured and analyzed in the further procedures.

During validation, 40 samples were selected for each demagnetization state. For example, in order to calculate the posterior probability of demagnetization state 3 DEC(3) (30% magnet loss), the procedures in section III are applied to obtain the 5 feature values based on the measurement when motor is running at internal temperature 170°C with flux linkage 0.095 Wb·T. According to (11), α =8.65x10⁻¹⁸, and the posterior probability of DEC(0)– DEC(7) is calculated and presented in Table II, from which the maximum posterior probability estimation value is $Y^{\wedge}_{opt}(Y_1, Y_2, Y_3, Y_4, Y_5)$ =0.6241. Thus, the demagnetization state is determined as DEC(3), which is around 30% magnetization loss. Same steps can



Figure 5-5. Comparison of demagnetization detection among three methods using one common feature value.



Figure 5-6. Fusion based detection result compared with noise based method.



Figure 5-7. Results comparison for demagnetization detection validation.

be repeated to detect the demagnetization states from the noise and torque signal measurements.

In order to compare with the previous detection method, noise–based, torque–based, and fusion–based validation were conducted respectively in Fig. 5-5. Figure 5-6 demonstrates that the proposed detection method is more precise to the true value than the previous method. Moreover, results under different operation conditions in Fig. 5-7 validate the accuracy of proposed method.

For the motor with different parameters, the proposed approach needs to be trained by using the corresponding information before it can be applied to this motor. In other words, offline training of the proposed approach is critical to the proposed approach to ensure the performance of the proposed approach for different motors.

5.5 Conclusion

This chapter presented a non-invasive approach to detect the PM demagnetization based on multi-sensor fusion. Signals from two sensors are measured and pre-processed individually. Then fusion method is employed to detect the PM demagnetization. The experimental results demonstrate that the proposed method is able to identify and detect the demagnetization states. From the results comparison among existing noise-based method, torque-based method and the proposed fusion-based method [109]-[111], multisensor fusion method is more accurate than the other two methods, even when the motor is running under different operating conditions. The validation also proves that different information sources are able to complement each other based on the multi-sensor fusion theory. Moreover, the quantitative mapping relationship between demagnetization states and the feature information can be built successfully by using Bayesian network. Hence, system uncertainty can be reduced, and accuracy and reliability can be improved.

To improve the demagnetization detection efficiency and accuracy, extra research efforts on the relationship between the current (feature) and demagnetization as one more fusion information need to be investigated in the future work.

CHAPTER 6 CONCLUSIONS AND FUTURE WORK

6.1 Conclusions

In this thesis, comprehensive permanent magnet demagnetization detection methods have been proposed for PMSMs, in which the torque ripple resulting from the magnetic variation and acoustic noise are included. Detection have been done from two variables acoustic noise and torque ripple.

In order to utilize the acoustic noise to monitor the PM flux variation, a flux based acoustic noise model is proposed to demonstrate that demagnetization will induce acoustic noise containing abnormal frequency. The selected seven objective and psychoacoustic indicators are proposed to evaluate the acoustic noise of healthy and demagnetized PMSMs under different speed and load conditions. With back propagation neural network (BPNN), PM flux status can be monitored and the demagnetization thus can be estimated through acoustic noise data.

Torque ripple based method proposes a torque ripple based rotor flux linkage detection model considering electromagnetic noises. This model employs the wavelet transforms (CWT), wavelet ridge spectrum, torque ripple energy extraction, and Grey System Theory (GST). It reveals the torque variation and eliminate the effect of electromagnetic interferences as well as facilitate the detection of demagnetization ratios and torque ripple energy pulsations caused by demagnetization. After demagnetization occurs, a current regulation strategy is proposed to minimize the torque ripples induced by PM demagnetization, which contributes to making the approach feasible to interior PMSM (IPMSM).

Moreover, different data mining method is also used to analyze the torque ripple caused by the demagnetization as Vold-Kalman filtering order tracking (VKF-OT) and dynamic Bayesian network (DBN). VKF-OT is introduced to track the order of torque ripple of PMSM running in unsteady state. DBN is employed to the train data and to estimate the flux linkage during motor operation.

Since acoustic noise and torque ripple are totally different physical measurement, there are complementary relationship between them. Thus Bayesian network based multi-sensor information fusion is then proposed to detect the demagnetization ratio from the extracted features and tested as more accurate due to the system reluctance. Moreover, the proposed controller does not involve much computation, which is critical for practical implementation, and it does not require accurate information of the test machine, so extending it to other machines can be easily achieved.

In summary, comprehensive PM demagnetization model have been proposed by considering different sensor measurement. Machine learning based demagnetization detection approaches have been developed and evaluated on a laboratory PM machine under transient and steady state operations, varying speeds, temperatures and loading conditions.

6.2 Future Work

More efforts are required to further improve the performance of demagnetization detection. The future work can be focused on:

(1) Though this thesis used both noise and torque information, the noise signal is sometimes affected by torque ripple. Thus considering more information fusion would be more accurate;

(2) Compared to the vibration and noise, the information of torque amplitude decreasing when open-loop control or armature current increasing when closed-loop control are more likely to be detected and calculated

(3) Demagnetization detection under sensorless motor control can be investigated.

(4) Considering diagnosing demagnetization for six-phase permanent magnet synchronous machines.

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