Data-driven fault diagnosis in the converter system

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IN THE CONVERTER SYSTEM**

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SCHOOL OF ELECTRICAL & ELECTRONIC ENGINEERING

2019

DATA-DRIVEN FAULT DIAGNOSIS IN THE CONVERTER SYSTEM

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A thesis submitted to the Nanyang Technological University
in partial fulfillment of the requirement for the degree of
Master of Engineering

2019

Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

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Supervisor Declaration Statement

I have reviewed the content and presentation style of this thesis and declare it is free of plagiarism and of sufficient grammatical clarity to be examined. To the best of my knowledge, the research and writing are those of the candidate except as acknowledged in the Author Attribution Statement. I confirm that the investigations were conducted in accord with the ethics policies and integrity standards of Nanyang Technological University and that the research data are presented honestly and without prejudice.

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Authorship Attribution Statement

This thesis contains material from one paper published in the following peer-reviewed journal(s) where I was the first and/or corresponding author.

Several contents of chapter 2, 3 are published in Y. Xia, B. Gou, and Y. Xu, "A new ensemble-based classifier for IGBT open-circuit fault diagnosis in three-phase PWM converter," *Protection and Control of Modern Power Systems*, vol. 3, no. 1, Nov. 2018.

The contributions of the co-authors are as follows:

- Xia Yang conceived of the study, participated in its design, carried out the programming test and drafted the manuscript.
- Dr. Gou Bin generated the database and participated in the design of the study.
- Dr. Xu Yan participated in its design and coordination and helped to draft the manuscript.
- All authors read and approved the final manuscript.

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Table of Contents

Statement of Originality	Error! Bookmark not defined.
Supervisor Declaration Statement	Error! Bookmark not defined.
Authorship Attribution Statement.....	Error! Bookmark not defined.
Acknowledgements.....	iv
Table of Contents.....	v
Summary.....	vii
List of Figures.....	ix
List of Tables	xi
List of Abbreviations	xii
Chpater 1 Introduction.....	1
1.1 Background and Motivation.....	1
1.2 Major Contributions of the Thesis	8
1.2.1 Feature Extraction and Selection.....	8
1.2.2 Hybrid Ensemble Learning	8
1.2.3 Sliding Window Classifier	9
1.2.4 Sensor Fault Tolerant Control	9
1.3 Organization of the Thesis	10
Chpater 2 System Description and Fault Labelling	11
2.1 Description of The Converter System.....	11
2.1.1 Mathematical Model of Three-phase inverter	12
2.2.2 Mathematical Model of Single-Phase Rectifier	13
2.2 IGBT Open-Circuit Fault Analysis.....	14
2.2.1 Single IGBT Fault	15
2.2.2 Double IGBTs Fault in the Same Arm.....	15
2.2.3 Double IGBTs Fault in Different Arms.....	16
2.2.4 Labels of IGBT Fault Types.....	17
2.3 Sensor Fault Analysis.....	19
Chpater 3 Data-driven Methodology for IGBT Open-Circuit Fault Diagnosis	22
3.1 General Methodology Configuration	22
3.2 Feature Extraction and Selection	23
3.2.1 Frequency-Domain Feature Extraction Using FFT	23
3.2.2 Frequency-Feature Selection Using RELIEFF.....	25
3.3 Randomized Hybrid Ensemble Learning.....	27

3.3.1 Random Vector Functional Link Neural Network	28
3.3.2 Extreme Learning Machine	29
3.3.3 Hybrid Ensemble Learning	31
3.4 Online Sliding-Window Classifier.....	32
3.4.1 The Design of Sliding-Window Classifier	32
3.4.2 Accuracy-Time Tradeoff based on MOP	36
3.5 Simulation and Experimental Validation	38
3.5.1 Database Generation and Model Building	38
3.5.2 Multi-objective Optimization Result.....	42
3.5.3 Experimental Validation.....	43
Chpater 4 Data-driven Methodology for Sensor Fault Diagnosis and Fault-Tolerant Control 48	
4.1 Methodology Configuration.....	48
4.2 Design of Fault Diagnosis and Fault-Tolerant Control Scheme	49
4.2.1 Extreme Learning Machine based on Regression Problem.....	49
4.2.2 NARX Modelling and Training	50
4.2.3 Design of Fault Diagnosis and Fault-Tolerant Control	53
4.3 Simulation Results	54
4.3.1 Simulation Model Building.....	54
4.3.2 Parameters Tuning.....	55
4.3.3 Prediction Results and Analysis	56
Chpater 5 Conclusions and Future Works	63
5.1 Conclusions.....	63
5.2 Future Works.....	65
Author's Publication.....	67
Bibliography	68

Summary

With the development of modern transportation, the induction motor system is widely applied in the practical industry. In the electrical motor system, the converter system is an essential part but usually it is susceptible to electrical faults such as humidity, device aging, or high power stress. For certain high-speed drive systems, those faults are fatal due to the high power and high voltage. The electrical fault also leads to heavy economic penalties from unit failure and maintenance costs. Therefore, condition monitoring and fault diagnosis are significantly attracted attention.

Based on the converter topology, the transistor is one of the core components. As the advance of semiconductor technology, insulated gate bipolar transistor (IGBT) becomes the mainstream in the application of transistors. IGBT has the merits of low on-resistance, high switching frequency, but it is also prone to fail due to abnormal conditions. Generally, IGBT faults can be classified into two types: open-circuit fault and short-circuit fault. As open circuit usually may not be detected immediately and cause a hidden threat to the system, this thesis proposes a novel data-driven fault diagnosis for IGBT open-circuit fault.

Based on the literature review, existing methods which consider the diagnostic time are hardly found. Therefore, the sliding-window classifier is designed to reduce the diagnostic time under the premise of reliable accuracy. Moreover, the hybrid ensemble learning scheme is developed based on two randomized learning algorithms: Extreme Learning Machine (ELM) and Random Vector Functional Link (RVFL). This hybrid ensemble learning improves the learning diversity and the ability of generalization. Owing to the randomized learning, the offline learning process is greatly simplified and the online computational burden is also released. Finally, to find optimal parameters in the diagnostic model, a multi-objective optimization problem (MOP) framework is developed, aiming to achieve the tradeoff between time and accuracy. After the design of this fault diagnosis method, the experimental validation is implemented to verify the feasibility and effectiveness of the proposed method.

Apart from IGBT open-circuit faults, the sensor fault is also an important issue in the converter of the high power drive system. Double closed loop control is an ordinary method used in the converter system to regulate the signal and ensure unity power factor operation. In the control loop, sensors are required to measure and feedback real-time

voltage or current value. However, device aging, or surrounding interference always results in sensor failure. The unexpected failure may affect the converter working condition by the deviant feedback signal and even cause serious damage to power device. Therefore, this thesis proposes a data-driven fault diagnosis for current sensor fault, and a fault-tolerant control strategy with a similar principle.

In most existing sensor fault diagnosis methods, the problem is normally solved by model-based methods, which always suffers from modeling uncertainty. In this thesis, the predicted model is built by the data-driven method. The ELM regression algorithm is used to extract the mapping knowledge embedded in the historic database. Moreover, in order to simplify the data structure and increase computational efficiency, the NARX model is designed based on the mathematical model. By monitoring the residual between the predicted value and measured value, the diagnostic decision can be made based on the faulty threshold. Once the fault flag is given, the predicted value will take place of faulty sensor signal, forming the fault-tolerant control. By the simulation, the proposed method is realized with reliable feasibility and effectiveness.

All the proposed methods have been verified using Matlab R2017a/Simulink or dSpace MicroLabBox simulator. The data-driven method programming is realized with the s-function module based on c++ language in Simulink.

List of Figures

Fig 1.1 Percentage of response hits for different kinds of causes.....	2
Fig 1.2 Percentage of response hits for different types of power device.....	2
Fig 1.3 Schematic of the model-based fault diagnosis	4
Fig 1.4 Schematic of the signal-based fault diagnosis.....	5
Fig 1.5 Schematic of the data-driven fault diagnosis	5
Fig 2.1 The structure of the back-to-back converter system	11
Fig 2.2 Topology of converter system when T_1 is under open-circuit fault	15
Fig 2.3 Three-phase output current when T_1 is under open-circuit fault.....	15
Fig 2.4 Topology of converter system when T_1 , T_4 are under open-circuit fault	16
Fig 2.5 Three-phase output current when T_1 , T_4 are under open-circuit fault.....	16
Fig 2.6 Topology of converter system when T_1 , T_6 are under open-circuit fault	17
Fig 2.7 Three-phase output current when T_1 , T_6 are under open-circuit fault.....	17
Fig 3.1 Framework of the proposed method.....	23
Fig 3.2 Harmonic magnitude of i_a with open-circuit fault occurred in T_1	25
Fig 3.3 RELIEFF weight assigned to frequency domain components with open-circuit fault occurred in T_1	27
Fig 3.4 Network structure of RVFL	28
Fig 3.5 Network structure of ELM	29
Fig 3.6 Offline training structure of hybrid-ensemble learning scheme.....	31
Fig 3.7 Structure of online sliding-window fault diagnosis	32

Fig 3.8 ELM output nodes value when G_j equals to (a) 4.4081 (high credibility) (b) 3.0035 (low credibility)	35
Fig 3.9 Decision-making mechanism in online sliding-window scheme	36
Fig 3.10 RELIEFF results for frequency components	40
Fig 3.11 ELM parameters tuning curve for the 1st classifier	41
Fig 3.12 Derived POFs of parameters optimization	42
Fig 3.13 Experimental Setup	43
Fig 3.14 Experimental results when (a) T_3 is under open-circuit fault (b) t_3 , fault occurs (c) T_1, T_3 are under open-circuit fault (d) t_3 , fault occurs	45
Fig 4.1 The proposed methodology scheme	49
Fig 4.2 ELM learning based on NARX model	51
Fig 4.3 The proposed sensor fault diagnosis and fault-tolerant control	53
Fig 4.4 Validation test for ELM with different numbers of hidden nodes	56
Fig 4.5 The grid side current prediction of the drive system in traction mode.....	57
Fig 4.6 Fault tolerant control for stuck sensor fault of grid-side current sensor.....	59
Fig 4.7 Fault tolerant control for gain sensor fault of grid-side current sensor	62

List of Tables

Table I. Labels of fault types	17
Table II. Data acquisition	38
Table III. Parameters of power drive system.....	38
Table IV. Parameter selection result in the sliding-window classifier	41
Table V. Selected Prato Front Point for experiment.....	42
Table VI. Test results for the proposed methodology	42
Table VII. Parameters of the simulation system.....	54
Table VIII. Parameters of the converter	54
Table IX. Prediction Evaluation	56

List of Abbreviations

PWM	Pulse Width Modulation
IGBT	Insulated Gate Bipolar Transistor
POF	Pareto Optimal Front
SCADA	Supervisory Control And Data
SVM	Support Vector Machine
BN	Bayesian Network
SSM-SVM	Spherical-Shaped Multiple-class Support
PEMFC	Polymer Electrolyte Membrane Fuel Cell
RVFL	Random Vector Functional Link
ELM	Extreme Learning Machine
MOP	Multi-objective Optimization Problem
SVPWM	Space Vector Pulse Width Modulation
FFT	Fast Fourier Transform
DFT	Discrete Fourier Transform
ANN	Artificial Neural Network
MOGA	Multi-Objective Genetic Algorithm
ADT	Average Diagnostic Time
ADA	Average Diagnostic Accuracy
NARX	Nonlinear Auto Regressive Exogenous
RMSE	Root Mean Solution Error
AE	Absolute Error
RE	Relative Error

Chapter 1 Introduction

1.1 Background and Motivation

Increasing modern transportation requirement stimulates rapid development of motor drive system. The converter fed traction motor drive system has been a popular approach applied in practical drive system for its high, reliable performance, low cost and simple control structure.

However, due to several abnormal conditions, like bad environments, heavy loads, and system transients, hardware parts in the drive system always experience progressive performance degradation. Fig 1.1 illustrates the distribution of power device failure causes surveyed by [1]. The first three label – “environment,” “system transient” and “heavy load/overload”, are selected by around 26%-27% of the responders. Apart from that, the “Others” option contains two factors: component design/manufacturing and power/thermal cycles. Among those power devices in the system, power semiconductor is a core part of this drive system, which is also one of the most fragile components. With the technological development of the semiconductor, insulated gate bipolar transistor (IGBT) becomes the mainstream in the industrial application of power converter [1] [2], as demonstrated in the survey result Fig 1.2. Owing to low on-resistance, relatively fast switching speeds, IGBT is applied to adjust the frequency and shape of the output ac voltage of converter, but due to several abnormal conditions mentioned above, IGBTs may easily fail and any IGBT failure can cause a great degradation of the whole system.

Fig 1.1 Percentage of response hits for different kinds of causes

Fig 1.2 Percentage of response hits for different types of power device

Conventionally, IGBT faults can generally be classified as open-circuit and short-circuit fault [3]. Short-circuit condition is usually caused by high thermal or electrical stress. An upheaval of system voltage and current is always raised by short-circuit fault, which brings an eternal injury of system. However, short-circuit fault is normally protected by mature hardware system, which is reliable in practical application. As a result, the short-circuit condition may last an extremely short period and the system

would be shut down immediately. On the other hand, the open-circuit fault may not be detected immediately and leads to the secondary fault, which greatly degrades the working performance. Especially in the high power electric system, like traction motor or wind turbine converter system, when open-circuits occur, the security will be threatened and fault-tolerant control may not be useful to handle those high power systems. Therefore, a more reliable way is to ascertain faulty parts of the system, to implement the timely maintenance and adjustment. Based on that, it is essential to detect and locate the faulty IGBTs in a short time interval, to provide sufficient time for system reaction.

Apart from IGBT faults, sensor fault is also a challenging problem in the converter system. Due to device aging, mechanical vibration, or surrounding interference, unexpected failures always occur in the sensors, which may lead to an erroneous feedback value in the control loop. Consequently, sensor faults may greatly degrade the working performance of the converter, even lead to serious deterioration to power equipment.

Traditionally, the *model-based method* was the mainstream in fault diagnosis area [4]–[11]. For this method, the principle is to build the model of the practical system. By monitoring the consistency between measured outputs and predicted model outputs, this methodology can implement fault diagnosis with a great capacity of robustness and generalization [12]. Especially, the observer method is one of the most popular model-based methods. In [8], a robust observer method has been propose for sensor fault diagnosis. For open-circuit faults occurred in electrical traction drive system, [9] presents another model-based methodology, using the mixed logical dynamic model and residual generation. In [10], three independent observers for voltage source inverters (VSI) are integrated, taking *a*-phase, *b*-phase, and *c*-phase current as inputs. The observers are capable to detect and localize the faults, and switch the system to tolerant vector control mode when only one healthy sensor is available. By establishing a state observer,

insulated gate bipolar transistor (IGBT) open-circuit faults in the modular multilevel converter (MMC) can be detected and located in [11]. After certain faulty sub-modules (SM) are identified, these SMs are bypassed and the remaining SMs are reconfigured to provide continuous operation. The experimental result shows a great effectiveness and accuracy of this proposed model. However, the model-based method always suffers from modelling difficulty and model parameter uncertainties. To compensate this drawback, the *signal-based method* is developed in the industrial practice with respect to systems which are hard to establish mathematical models [13]–[18]. The signal-based method extracts signal feature, and makes final decision by the signal symptom. In the literature [16], the magnetic component voltage signals are measured and based on switch gate-driver signals, characteristics of switch open-circuit/short-circuit faults can be detected in a short period. On the other hand, this signal processing consumes plenty of time, and the fluctuation of loads has a great impact on the method performance [12]. The diagnosis flow charts of model-based, signal-based methods are depicted in Fig 1.3, 1.4.

Fig 1.3 Schematic of the model-based fault diagnosis

Fig 1.4 Schematic of the signal-based fault diagnosis

Based on the advance of artificial intelligence and data-analytic technology, a novel fault diagnosis methodology called knowledge-based method is proposed in recent years [19]-[25]. This method extracts the mapping relationship embedded into the historical database so it is also called *data-driven method*. Without building a complicated model or checking signal patterns, data-driven method has a great capacity of generalization [26]. In the data training/learning process, machine learning techniques are always used. As shown in Fig 1.5, with the training and learning of historic data, the consistency between the observer behavior of the operating system and the knowledge base is then checked, leading to a diagnostic decision with an aid of classifier. Nowadays, data-driven techniques are finding more chances in online applications as the supervisory control and data acquisition (SCADA) system and smart meters are commonly installed in today's industrial systems, leading to a large amount data available.

Fig 1.5 Schematic of the data-driven fault diagnosis

In recent years, several data-driven methods have been investigated in fault diagnosis area. In [20], two output line-to-line voltage signals are collected as historic database for open-circuit fault diagnosis in PMSM drive system. Fast Fourier Transform, Principle Component Analysis (PCA) are used to reduce the dimensions of samples, and faults are

detected and diagnosed using Bayesian Network (BN). Although this method has a high accuracy regardless of the influence of signal noise and bias, feature selection method PCA has ambiguous physical significance in fault diagnosis. Based on the similar principle, reference [19] uses PCA to extract faulty features and applies multiclass relevance vector machine (mRVM) to identify the system operation statuses. Besides, [21] developed a novel learning algorithm based on Support Vector Machine (SVM), named *Spherical-Shaped Multiple-class Support Vector Machine* (SSM-SVM) for *polymer electrolyte membrane fuel cell systems* (PEMFC) system fault diagnosis. In [22], a statistical time-domain feature extraction method is used to generate fault features and support vector machine (SVM) is applied to classify different types of sensor faults based on the generated features. Moreover, the data-driven method has been widely applied into the power system security and stability assessment [27]-[31]. Based on our work, this approach has been used in open-circuit fault diagnosis preliminarily [32]. Although those data-driven methods have effectively improved and facilitated power device fault diagnosis, a series of problems exist in conventional learning algorithm such as low learning speed, unreliable diagnostic accuracy and especially unfit for online application.

Traditionally, fault diagnosis is performed using a fixed diagnostic window, and relatively little research has been carried out, focusing on diagnostic time. Motivated by the relationship between sampling window and accuracy, this thesis proposes a sliding-window classifier for faster fault detection and location. The classification in this sliding-window scheme is created in order to get faster fault diagnosis as well as evaluate the credibility of the output. A decision mechanism is then designed to achieve the time-accuracy tradeoff and hence, the right output can be appropriately achieved in an early stage.

Furthermore, two major concerns in data-driven methods are the inputs and learning algorithm selection. In most existing data-driven methods [19] [20], the PCA method is used to extract signal features as the input. However, due to the lack of solid physical

meaning, PCA may not be reliable enough at online stage. In this thesis, to achieve more significant inputs, FFT is used to extract the frequency domain signal and RELIEFF algorithm [33] is used to select most important frequency components. On the other hand, conventional data-driven methods usually adopt or revise single traditional algorithm, like BN, SVM. However, the drawbacks of those algorithms, such as low learning speed and unreliable accuracy, always lead to the unfeasibility in real-time diagnosis. In order to improve the learning performance, a novel hybrid ensemble learning strategy is proposed in this thesis, consisting of two emerging technologies, Extreme Learning Machine (ELM) [34] and Random Vector Functional Link (RVFL) network [35]. Those two algorithms both belongs to randomized learning methods. Compared to traditional methods, randomized learning methods have faster training speed and simple computationally mechanism. In addition to fit in comprehensive working conditions, multiple options of model parameters are provided for the operators by a MOP framework.

For sensor fault diagnosis methods, the observer-based method is widely used in the system as a representative model-based method. In [36], an extended Kalman filter (EKF) is designed as an observer to detect and isolate all the sensor faults for interior permanent-magnet synchronous motors (IPMSM) drives. Comanescu [37] proposes a sliding model observer for the flux magnitude by a modified model in the rotating reference frame, which can be used in both a sensorless design and sensor fault diagnosis.

Generally, most existing data-driven methods have a promising accuracy at offline testing stage, but they always suffer from the large size of samples and the computational burden, leading to the unfeasibility in real-time application. Conventionally, the data-driven fault diagnosis scheme is always constructed as a multi-classification framework, which may increase the complexity of the diagnostic algorithm. Furthermore, a few sensor fault diagnosis methods for the single-phase PWM rectifier are found in the literature review, especially in the area of data-driven methods.

To overcome those mentioned inadequacies, this thesis proposes a novel data-driven method for current sensor faults of single-phase rectifier in high power drive systems. Instead of the multi-classification problem, the proposed method develops a grid-side current prediction framework based on the regression algorithm. ELM is applied to extract the mapping relationship knowledge in the database, due to the fast learning speed and computationally efficient mechanism. Based on the regression framework, an efficient data structure, nonlinear autoregressive exogenous model (NARX), is designed, and the data size decreases greatly compared with the multi-classification framework [38]. Finally, by the prediction of grid-side current, the residual signal is generated as the diagnostic proof, and the faults are detected, diagnosed using a designed decision-making scheme. Once a fault flag is generated by the diagnosis method, the predicted signal replaces the faulty signal to keep the system in a reliable working condition, which forms the fault-tolerant control.

1.2 Major Contributions of the Thesis

Main contributions are explained as follows:

1.2.1 Feature Extraction and Selection

For open-circuit fault diagnosis, the input of data-driven methods is an important issue which has a decisive impact on the diagnostic performance. By the original simulated and experimental three-phase currents, it is difficult to classify different modes. Therefore, this thesis adopts FFT to extract the frequency domain signal of sampled currents. Moreover, to release the computational burden and clarify faulty features, RELIEFF algorithm is used to select most important components among FFT results. By the process including feature extraction and selection, the input is simplified and defined as several significant frequency components.

1.2.2 Hybrid Ensemble Learning

According to those methods in the literature review, traditional learning techniques are

widely used, such as BN, SVM. However, those algorithms always suffer from excessive learning time and unreliable accuracy, may leading to the unfeasibility in real-time diagnosis. To overcome the inadequacy, the hybrid ensemble learning consisting of ELM and RVFL is proposed in this thesis. Those two algorithms both belongs to randomized learning methods, having merits of faster training speed and computationally efficient mechanism. Moreover, by combination of two algorithms, the learning diversity is further improved, which enhances the generalization ability in learning process. Therefore, this hybrid ensemble learning has a better performance than single algorithm learning.

1.2.3 Sliding Window Classifier

Based on the literature review, little literature investigates the consuming time in fault diagnosis process. Enlightened by the relationship between sampling window and accuracy, a sliding-window classifier is proposed in this thesis. With help of the decision-making mechanism, the credible output is achieved with relatively short time, and the incredible result can be distinguished and delivered to the next window with more inputs information. Therefore, with this sliding-window classifier, the diagnostic time is significantly reduced in the premise of ensuring the accuracy.

1.2.4 Sensor Fault Tolerant Control

In most existing fault diagnosis methods, a few works with regard to the single-phase PWM rectifier are found in the literature review, especially in the area of data-driven methods. This thesis designs a sensor fault diagnosis method and a fault-tolerant control based on grid-side current prediction framework. By utilizing NARX model and ELM regression algorithm, the prediction model is greatly simplified. Owing to the simple data structure and efficient computational mechanism, the method is validated as a feasible approach in the practical application.

1.3 Organization of the Thesis

The following of the thesis is organized as follows:

Chapter 2 briefly introduces the converter system structure. Then IGBT open-circuit fault and sensor fault analysis is reviewed in details.

Chapter 3 presents the data-driven methodology for IGBT open-circuit fault. Firstly, randomized learning algorithms are introduced and then a hybrid ensemble learning scheme is developed based on those algorithms. Secondly, a sliding-window classification model is proposed, including a designed decision-making mechanism and a MOP framework.

Chapter 4 investigates the sensor fault diagnosis and fault-tolerant control for single-phase rectifier. With the introduction of NARX model, a signal prediction methodology is designed for fault diagnosis and fault-tolerant control.

Chapter 5 makes several main conclusions of this thesis and suggests some possible future research directions.

Chapter 2 System Description and Fault Labelling

2.1 Description of The Converter System

Fig. 1 illustrates a back-to-back converter of the ac drive system. The topology of the back-to-back converter consists of a single-phase rectifier on the grid-side and a three-phase inverter on the motor-side. u_N and i_N are the grid voltage and the catenary current. L_N and R_N are the winding leakage inductance and resistance. u_{ab} is the rectifier input voltage. L_2 , C_2 are the series resonant circuit inductance and capacitance. C_d is the dc-link capacitance. The three-phase inverter topology is a full-bridge circuit consisting of IGBT (T_1 - T_6) with corresponding antiparallel connected diodes. The single-phase rectifier also consists of IGBT (S_1 - S_4) with corresponding antiparallel connected diodes. The IGBTs are controlled by corresponding gate signals. i_a , i_b , i_c are three-phase load current or stator current of the induction motor. The IGBT switching patterns are determined by space vector pulse width modulation (SVPWM) strategy. In this model, the converter uses dc voltage, three-phase currents and motor speed for converter feedback control.

Fig 2.1 The structure of the back-to-back converter system

As mentioned above, although short-circuit faults are usually very destructive, industrial gate drivers always have standard function for short-circuit protection. When detecting such overcurrent caused by short-circuit, standard protection system, such as fuse and disconnecting switch, will shut down the system immediately. On the other hand,

open-circuit faults will lurk for a long period to cause the secondary fault, which may lead to system degradation. As a result, it is crucial to develop practical diagnostic method for open-circuit faults [18].

2.1.1 Mathematical Model of Three-phase inverter

To describe the three-phase converter mathematically, when converter works in normal working condition, due to the star-connection of circuit, the sum of three-phase load current (voltage) in the stator is zero, as follows:

$$u_{an} + u_{bn} + u_{cn} = Z_a i_a + Z_b i_b + Z_c i_c = 0 \quad (2-1)$$

In (2-1), u_{an}, u_{bn}, u_{cn} are three-phase voltages in the induction motor stator. i_a, i_b, i_c are three-phase load currents. Based on Kirchhoff's law, the equation set (2-2) can be obtained by:

$$\begin{cases} u_{an} = u_{ao} - u_{no} \\ u_{bn} = u_{bo} - u_{no} \\ u_{cn} = u_{co} - u_{no} \end{cases} \quad (2-2)$$

$$u_{no} = u_{an} + u_{bn} + u_{cn} = \frac{1}{3}(u_{ao} + u_{bo} + u_{co}). \quad (2-3)$$

With the optimal switch function of:

$$S = \begin{cases} 1 & \text{the upper transistor is closed} \\ -1 & \text{the lower transistor is closed} \end{cases} \quad (2-4)$$

three-phase output voltage can be expressed based on switch commands and U_{dc} as:

$$\begin{cases} u_{ao} = S_a \cdot \frac{U_{dc}}{2} \\ u_{bo} = S_b \cdot \frac{U_{dc}}{2} \\ u_{co} = S_c \cdot \frac{U_{dc}}{2} \end{cases} \quad (2-5)$$

based on (2-3) (2-5), u_{no} can be redefined as:

$$u_{no} = \frac{U_{dc}}{6} (S_a + S_b + S_c) \quad (2-6)$$

Based on the mentioned analysis, the calculation matrix of three-phase voltage can be obtained as follows:

$$\begin{bmatrix} u_{an} \\ u_{bn} \\ u_{cn} \end{bmatrix} = \frac{U_{dc}}{6} \begin{bmatrix} 2 & -1 & -1 \\ -1 & 2 & -1 \\ -1 & -1 & 2 \end{bmatrix} \begin{bmatrix} S_a \\ S_b \\ S_c \end{bmatrix} \quad (2-7)$$

2.2.2 Mathematical Model of Single-Phase Rectifier

Based on the topology of a single-phase rectifier illustrated in Fig. 1, the continuous state space model of the single-phase PWM rectifier is described as:

$$u_N = L_N \frac{di_N}{dt} + R_N i_N + u_{ab} \quad (2-8)$$

The switching function is defined as:

$$S = \begin{cases} 1 & \text{the upper transistor is closed} \\ -1 & \text{the lower transistor is closed} \end{cases} \quad (2-9)$$

Then the input voltage of rectifier, u_{ab} , is expressed as:

$$u_{ab} = (S_a - S_b) \cdot U_{dc} \quad (2-10)$$

By substituting (2-10) into (2-8), the mathematical model of single-phase PWM rectifier is obtained as:

$$\dot{i}_N = A i_N + B u_N + C (S_a - S_b) U_{dc} \quad (2-11)$$

where coefficients A , B , and C are defined as: $A = -R_N / L_N$, $B = 1 / L_N$, and $C = -1 / L_N$. Moreover, S_a , S_b are dependent on the PWM command signals of switches.

Based on the model, it can be deduced that when the rectifier parameters are fixed, grid side current i_N relates to grid voltage u_N , dc-link voltage U_{dc} , and PWM command signals.

Therefore, for grid-side current prediction process, the inputs can be determined as those values. Instead of mathematical model, the data-driven approach is used in model building, which will be discussed in details in Chapter 4.

2.2 IGBT Open-Circuit Fault Analysis

When power switch fault breaks down, switch function will change, leading to the distortion of converter output voltage. Therefore, the stator current in the induction motor will distort referring to output voltage. By Park's Transformation, output voltages of (2-7) are transformed as:

$$\begin{bmatrix} u_\alpha \\ u_\beta \end{bmatrix} = \sqrt{\frac{1}{6}} U_{dc} \begin{bmatrix} 1 & -\frac{1}{2} & -\frac{1}{2} \\ 0 & \frac{\sqrt{3}}{2} & -\frac{\sqrt{3}}{2} \end{bmatrix} \begin{bmatrix} S_a \\ S_b \\ S_c \end{bmatrix} \quad (2-12)$$

$$\begin{cases} \dot{i}_{s\alpha} = \left(-\frac{R_s}{\sigma L_s} - \frac{1}{\sigma T_r}\right) i_{s\alpha} - \omega_r i_{s\beta} + \frac{1}{\sigma L_s T_r} \psi_{s\alpha} + \frac{1}{\sigma L_s} \omega_r \psi_{s\beta} + \frac{1}{\sigma L_s} u_{s\alpha} \\ \dot{i}_{s\beta} = \omega_r i_{s\alpha} + \left(-\frac{R_s}{\sigma L_s} - \frac{1}{\sigma T_r}\right) i_{s\beta} - \frac{1}{\sigma L_s} \omega_r \psi_{s\alpha} + \frac{1}{\sigma L_s T_r} \psi_{s\beta} + \frac{1}{\sigma L_s} u_{s\beta} \\ \dot{\psi}_{s\alpha} = -R_s i_{s\alpha} + u_{s\alpha} \\ \dot{\psi}_{s\beta} = -R_s i_{s\beta} + u_{s\beta} \end{cases} \quad (2-13)$$

$$\sigma = 1 - \frac{L_m^2}{L_s L_r} \quad (2-14)$$

$$T_r = \frac{L_r}{R_r} \quad (2-15)$$

where, σ is magnetic leakage factor; T_r is rotor electromagnetic time constant; $i_{s\alpha}$, $i_{s\beta}$ are motor stator currents in α axis, β axis, respectively; $u_{s\alpha}$, $u_{s\beta}$ are motor stator voltages in α axis, β axis, respectively; $\psi_{s\alpha}$, $\psi_{s\beta}$ are motor stator magnetic linkage in α axis, β axis, respectively; R_s , R_r , L_s , L_r , L_m , and ω_r refer to motor stator equivalent resistance, rotor equivalent resistance, stator leakage inductance, rotor leakage inductance, mutual inductance and motor speed, namely [39].

2.2.1 Single IGBT Fault

When the upper switch is in open-circuit fault (e.g. T_1), as shown in the Fig 2.3, the dc bus current i_{dc} cannot flow through T_1 , where Z_a , Z_b and Z_c are equivalent load resistances. In this converter topology, the stator winding of traction motor is in star connection and without grounded neutral. Consequently, the sum of three-phase currents maintains zero. When T_1 breaks down, i_a will be negative, and i_b , i_c will be added with positive dc component. The electromagnetic torque of the induction motor is reduced and pulsed strenuously. Therefore, the waveform of three-phase currents is distorted which is plotted as Fig 2.4.

Fig 2.2 Topology of converter system when T_1 is under open-circuit fault

Fig 2.3 Three-phase output current when T_1 is under open-circuit fault

2.2.2 Double IGBTs Fault in the Same Arm

When both IGBTs in the same phase (e.g. T_1 , T_4) are under open-circuit faults, as

depicted in Fig 2.5, the dc bus current i_{dc} would insert into the induction motor only through phase C or B. Therefore, i_a keeps around zero with slight fluctuation, and i_b , i_c are opposite. This fault mode also includes T_3T_6 , T_5T_2 faults. In this fault circumstance, converter output current will be distorted and in the serious asymmetry, leading to that motor electromagnetic torque falls in strenuous pulsation.

Fig 2.4 Topology of converter system when T_1 , T_4 are under open-circuit fault

Fig 2.5 Three-phase output current when T_1 , T_4 are under open-circuit fault

2.2.3 Double IGBTs Fault in Different Arms

When T_1 , T_6 are under open-circuit faults, i_{dc} can insert into motor only through two paths: T_3 - T_4 / T_2 , T_4 - T_3 / T_5 . Based on that, i_a will keep negative and i_b will keep positive. Consequently, the amplitude of i_c increases and waveform of currents distorted with serious dissymmetry. It is easy to degrade the winding of traction motor, which seriously affects the safety and stability of traction drive system.

Fig 2.6 Topology of converter system when T_1 , T_6 are under open-circuit fault Fig 2.7 Three-phase output current when T_1 , T_6 are under open-circuit fault

2.2.4 Labels of IGBT Fault Types

For single switch open-circuit fault, there are 6 types of faults. For double switches open-circuit fault, there are 15 types of faults. Considering both healthy and faulty working condition, there are 22 labels totally. Each label refers to an operation status of the converter, as listed in the Table I. For the label of each phase, “1” refers to normal working situation, “2” refers to the upper switch open-circuit fault, “3” refers to the lower switch open-circuit fault, and “4” stands for both switches in this phase are in open-circuit fault. To take the discussed situation above as examples, labels (2, 1, 1), (4, 1, 1), (2, 3, 1) stand for that T_1 open-circuit fault, $T_1 T_4$ double open-circuit fault, and $T_1 T_6$ double open-circuit fault respectively, referring to fault labels 2, 10, 12 namely.

Table I. Labels of fault types

Fault Type	Label A	Label B	Label C	Fault Label
The Normal State	1	1	1	1
T ₁ Open-circuit	2	1	1	2
T ₂ Open-circuit	1	1	3	3
T ₃ Open-circuit	1	2	1	4
T ₄ Open-circuit	3	1	1	5
T ₅ Open-circuit	1	1	2	6
T ₆ Open-circuit	1	3	1	7
T ₁ &T ₂ Open-circuit	2	1	2	8
T ₁ &T ₃ Open-circuit	2	2	1	9
T ₁ &T ₄ Open-circuit	4	1	1	10
T ₁ &T ₅ Open-circuit	2	1	2	11
T ₁ &T ₆ Open-circuit	2	3	1	12
T ₂ &T ₃ Open-circuit	1	2	3	13
T ₂ &T ₄ Open-circuit	3	1	3	14
T ₂ &T ₅ Open-circuit	1	1	4	15
T ₂ &T ₆ Open-circuit	3	1	3	16
T ₃ &T ₄ Open-circuit	3	2	1	17
T ₃ &T ₅ Open-circuit	1	2	2	18
T ₃ &T ₆ Open-circuit	1	4	1	19
T ₄ &T ₅ Open-circuit	3	1	2	20
T ₄ &T ₆ Open-circuit	3	3	1	21
T ₅ &T ₆ Open-circuit	1	3	2	22

According to Table I, there are 22 operation states of the converter, including normal status and faulty status. In order to classify open-circuit fault labels simultaneously, this research work presents a data-driven method based on the aforementioned analysis, where inputs are current trajectories, outputs are fault labels in Table. I.

Conventionally, several learning algorithms are used in the relationship mapping extraction, such as artificial neural network (ANN), decision tree (DT), support vector machine (SVM), and Bayesian Network (BN), which were popular approaches in most cases. However, these traditional learning algorithms are based on time-consuming solutions of an optimization objective function or iteratively adjustment of network parameters. Thus, most conventional algorithms above often suffer from excessive training/tuning time.

In this research work, two novel and promising learning methodologies, named

Random Vector Functional Link (RVFL) network, and Extreme Learning Machine (ELM) respectively, are applied for the data knowledge mapping extraction. To improve the diagnostic performance, a hybrid ensemble model is designed to combine two algorithms' advantages. Moreover, a sliding-window online structure is proposed with hybrid ensemble model to achieve a diagnostic earliness in online stage.

2.3 Sensor Fault Analysis

Apart from IGBT open-circuit fault, sensor fault is also one of the main concerns in this thesis. Generally, there are four common types of sensor faults according to the sensor measurement output: stuck fault, drift fault, gain fault, and noise fault, which are expressed mathematically in (2-16) - (2-19).

$$i(t) = \begin{cases} i_0(t), & 0 \leq t \leq t_0 \\ K_1, & t \geq t_0 \end{cases} \quad (2-16)$$

$$i(t) = \begin{cases} i_0(t), & 0 \leq t \leq t_0 \\ i_0(t) + K_2, & t \geq t_0 \end{cases} \quad (2-17)$$

$$i(t) = \begin{cases} i_0(t), & 0 \leq t \leq t_0 \\ A \cdot i_0(t), & t \geq t_0 \end{cases} \quad (2-18)$$

$$i(t) = \begin{cases} i_0(t), & 0 \leq t \leq t_0 \\ i_0(t) + n(t), & t \geq t_0 \end{cases} \quad (2-19)$$

where $i(t)$ refers to the output signal of the current sensor, $i_0(t)$ refers to the output signal of the normal working state, K_1 and K_2 are the constant parameters, $n(t)$ is a Gaussian noise signal, and t_0 is the time moment when sensor faults occur. The sample currents under different scenarios of sensor faults are shown in Fig 2.9. When the sensor fault occurs, the actual signal and desired signal will have deviation. A data-driven method based on current prediction is developed to generate desired signal. With the signal residual, the fault diagnostic decision can be made.

(a)

(b)

(c)

(d)

(e)

Fig 2.9 Plots of samples of normal and faulty signals (a) normal sample (b) stuck fault sample (c) drift fault sample (d) noise fault sample (e) gain fault sample

Chapter 3 Data-driven Methodology for IGBT Open-Circuit Fault Diagnosis

3.1 General Methodology Configuration

In this thesis, a data-driven methodology for IGBT open-circuit fault diagnosis is proposed. As discussed above, with regard to different scenarios of faults, the fault locations and fault types are concluded as 22 fault labels. The inputs are three-phase load currents and the output is the fault label. The flowchart of the proposed fault diagnosis method is plotted in Fig 3.1. Data from historic database is used to train and test the offline diagnostic model. To generate the database containing a large volume of current data, the reliable tool, MATLAB/Simulink, is used to simulate different working condition and collect three-phase current signals. In order to fit in real-time application, the frequency domain signals are extracted by FFT, and most important features are selected by RELIEFF. Furthermore, instead of conventional learning technologies, two promising learning algorithms, ELM and RVFL, form a hybrid ensemble learning scheme to extract the mapping relationship between features and corresponding labels. For further improvement, a MOP framework is formulated to solve the tradeoff problem between diagnostic accuracy and time. This MOP aims to find optimal sets of parameters in the diagnostic model. For the online application stage, operators can empirically select suitable parameter setting for the model. Moreover, instead of the fixed sampling window of most existing methods, a sliding-window classifier is designed at the online stage. Based on a credibility decision-making mechanism, incredible outputs are circular diagnosed with more input information and credible outputs are obtained in the early stage. Therefore, in the premise of ensuring accuracy, the diagnostic time is significantly reduced.

Fig 3.1 Framework of the proposed method

3.2 Feature Extraction and Selection

Traditionally, most existing fault diagnosis methods directly use original sampled signal as inputs, but for data-driven methods, this may increase computational burden or overlap the diagnostic process. In order to simplify the samples, FFT is used in this research to extract frequency domain components, and RELIEFF is then used to select most significant features among those components. Note that such feature extraction and selection are implemented at the offline stage.

3.2.1 Frequency-Domain Feature Extraction Using FFT

To describe the faulty features more clearly, many techniques can be adopted in feature extraction, such as FFT, Discrete Wavelet Transform (DWT) and Short-Time Fourier Transform (STFT) [25]. In this research work, FFT is adopted based on the test that it is able to extract faulty features in frequency-domain without redundant calculating burden.

For a sampled three-phase current $i(n)$, in sampling process, N of $i(n)$ consists of a sampled current sequence $\{i(1), \dots, i(N)\}$. Fourier analysis converts a signal from its

original domain to a representation in the frequency domain and vice versa. An FFT computes the DFT and produces exactly the same result as evaluating the DFT definition directly; the most important difference is that FFT has much higher speed. The DFT is defined by the formula below:

$$F(k) = \sum_{n=0}^{N-1} i(n)e^{-i2\pi kn/N}, \quad k = 1, \dots, N-1 \quad (3-1)$$

where $F(k)$ is the output in frequency-domain. In this study, for original current signals, FFT is used to implement signal preprocessing. It is noted that when open-circuit fault occurs in T_1 or T_4 , the magnitude spectrum is same, which cannot be distinguished. Similarly, the open-circuit faults of T_3 and T_6 , T_5 and T_2 , also lead to the same magnitude spectrums. To handle this problem, the phase information of dc component $F(0)$ is included in magnitude spectrum. To exemplify, for T_1 and T_4 open-circuit faults, after phase information added, their dc components have a phase deviation of π . Hence, to extract the phase information of the dc component, the different characteristics of these faults are separated, which can differentiate between these cases. To identify the meaning of frequency spectrum, $F(0)$ indicates the dc component of sampled current sequence and the second output $F(1)$ indicates the fundamental components. Other outputs $F(k)$ refer to the corresponding harmonic components.

Fig 3.2 Harmonic magnitude of i_a with open-circuit fault occurred in T_1

From FFT results shown in Fig 3.2, rough waveform shapes are similar, which means most of those components are redundant. Therefore, it is unnecessary to include every frequency component because there are several certain components which are able to determine the working state. On the other hand, to include every component, it will overlap the mapping knowledge extraction instead. Based on that, a feature selection methodology named RELIEFF is applied for representative frequency components selection.

3.2.2 Frequency-Feature Selection Using RELIEFF

The dimension of variables is still high after FFT extraction, which brings a burden to include every feature for fault diagnosis. RELIEFF is a technique that reduces the dimensionality of a dataset consisting of huge volume of variables, while retaining original characteristics of dataset as much as possible. RELIEFF is an instance-based algorithm [40]. It statistically evaluates the quality of features according to the how well their values distinguish among instances near each other. It not only considers the difference in features' values and classes, but also the distance between instances. Therefore, significant features can gather similar instances and be far apart from dissimilar ones. The original RELIEFF is to iteratively update the weight for each feature by:

$$W[X]^{i+1} = W[X]^i - \text{diff}(X, D_i, H) / N + \text{diff}(X, D_i, M) / N \quad (3-2)$$

where X refers to a feature, D_i is the instance sampled in the i -th iteration, H is the nearest instance from the same class as D_i while M is the nearest instance from the different class with R_i (called nearest miss), and N is the number of sampled instances guaranteeing the value of weights in the range of $[-1,1]$. Function diff calculates the difference between the values of feature X for two instances R and R' :

$$diff(X, R, R') = \frac{|value(X, R) - value(X, R')|}{\max(X) - \min(X)} \quad (3-3)$$

From the statics point of view, the weight of feature X is an approximation of the difference of probabilities:

$$W[X] = P(\text{diff. value of } X \mid \text{nearest inst. from diff. class}) - P(\text{diff. value of } X \mid \text{nearest inst. from same class}) \quad (3-4)$$

For this thesis, open-circuit fault diagnosis is one of forms of multi-classification problem. To deal with multi-class problems, RELIEFF can be modified with the following weight updating equation:

$$W[X]^{i+1} = W[X]^i - \sum_{j=1}^k diff(X, R_i, H_j) / (N \cdot k) + \sum_{C \neq \text{class}(R_i)}^k \left[\frac{prior(C)}{1 - prior(\text{class}(R_i))} \cdot \sum_{j=1}^k diff(X, R_i, M_j(C)) \right] / (N \cdot k) \quad (3-5)$$

where C is a class label, function *prior* is to calculate the prior probability of a class and k is a user-defined parameter. Rather than find the nearest H and M , (3-5) finds k sets of nearest H and M to average their contribution in updating the weight [41]. By doing so, the probability of miss estimation can be reduced and function *prior* is able to separate each pair of classes. The introduction of $P(C)$ leads to estimating the ability to separate each pair classes. Fig 3.3 depicts frequency component RELIEFF weights [41].

For open-circuit fault diagnosis in this research work, there are hundreds of components in frequency spectrum. However, to identify certain open-circuit faults, dc, fundamental and several harmonic components are always capable to determine the fault mode. Therefore, the dimension of original frequency spectrums is too high to implement subsequent learning process. By utilizing RELIEFF algorithm, components with high weight value are selected as input data and so the dimension can be reduced to release the burden of large data size. Furthermore, RELIEFF eliminates the accidental noise

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disturbance to focus on certain frequency components.

Fig 3.3 RELIEFF weight assigned to frequency domain components with open-circuit fault occurred in T_1

3.3 Randomized Hybrid Ensemble Learning

According to the principle of the proposed method discussed above, it is significant to select the learning algorithm among plenty of machine learning techniques. In order to fit in online application, the learning speed of algorithm is bound to be fast with reliable accuracy. Consequently, two randomized learning methodologies, RVFL and ELM, are selected in this research work. However, while those algorithms are developed with outstanding performance, accuracy and learning speed still need improvement to match the practical requirement. Thus a hybrid ensemble learning model is proposed in this chapter.

3.3.1 Random Vector Functional Link Neural Network

Fig 3.4 Network structure of RVFL

RVFL is a novel randomized learning and was proposed in [42]. As the structure of RVFL illustrated in Fig 3.4 [35], RVFL has direct link between input and output layers.

For a dataset consisting of N instances $(\mathbf{x}_i, \mathbf{r}_i)$, where $\mathbf{x}_i = [x_1, \dots, x_M]^T$, $\mathbf{r}_i = [r_1, \dots, r_P]^T$. The actual output vector $\mathbf{t}_i$ is mapped as:

$$\mathbf{t}_i = \mathbf{d}_i^T \boldsymbol{\beta} \quad (3-6)$$

In Equation. (3-6), $\boldsymbol{\beta}$ indicates the output weight vector and $\mathbf{d}_i$ indicates hidden layer output and input features integrated vector. The weights from the input layer to the hidden nodes are randomly selected within appropriate domain, normally $[0,1]$, to guarantee that the activation function is not saturated all the time. Assuming that the network has J hidden nodes, there are totally $(K+J)$ nodes connected to output layer, thus $\boldsymbol{\beta}$ consists of $(K+J)$ weight vectors. The RVFL learning process can be described as the minimization of the quadratic error E :

$$E = \frac{1}{2P} \sum_{i=1}^P (\mathbf{t}_i - \boldsymbol{\beta}^T \mathbf{d}_i)^2 \quad (3-7)$$

Since the input, direct link weights and biases are generated randomly, the conventional iterative tuning process is skipped, and thus ELM demonstrates

exceptionally faster learning speed over other learning approaches, such as back-propagation (BP) network and support vector machine (SVM). Benefited from the direct link between input and output layers, the randomness generated in estimation can be regularized. With this designed structure, for mapping both linear and nonlinear relationships, especially multi-classification problem, RVFL have a relatively robust and stable performance.

3.3.2 Extreme Learning Machine

Fig 3.5 Network structure of ELM

ELM was proposed in [34] by Huang and has been utilized in engineering problems. Fig 3.5 illustrates the structure of ELM. The relationship between actual output t_i and x_i can be modeled mathematically by:

$$t_i = \sum_{j=1}^N \beta_j \cdot g(\omega_j \cdot x_i + b_j) \quad (3-8)$$

where ω_j refers to the weight vector between input layer and the j^{th} hidden node, β_j refers to the weight between hidden nodes and output layer, b_j refers to bias of hidden nodes, and N denotes the number of hidden nodes. (3-7) can be simplified as:

$$\mathbf{H}\boldsymbol{\beta} = \mathbf{T} \quad (3-9)$$

where $\mathbf{H}$ indicates the hidden layer output matrix. At training stage, the input weight and

bias are generated randomly like RVFL. Then β can be analytically obtained by matrix calculation, using Moore-Penrose inverse pseudo inverse, as:

$$\beta = \mathbf{H}^{-1}\mathbf{T} \quad (3-10)$$

In this research work, to realize the fault diagnosis, ELM is applied as a classification mode[43] [44]. Firstly, when ELM deals with the binary classification case, the output function is expressed as [45]:

$$f_N(\mathbf{x}) = \text{sign}(\mathbf{H}(\mathbf{x})\beta) \quad (3-11)$$

where f_N is the final output function. $\mathbf{H}$ refers to a feature mapping matrix. For the multi-classification case, the number of output nodes equals to the total number of class labels. The final classification result is the index number of the output node with the highest output value. The decision mechanism of multi-classification can be expressed as:

$$\text{label}(\mathbf{x}) = \arg \max_{i \in \{1, 2, \dots, m\}} f_i(\mathbf{x}) \quad (3-12)$$

where m is the total number of output nodes, $f_i(\mathbf{x})$ is the i th output, from ELM classifier output set $f(\mathbf{x})=[f_1(\mathbf{x}), \dots, f_m(\mathbf{x})]$ [45]. Different from RVFL, ELM lacks the direct link between input and output layers so it has a faster learning speed, both for categorical classification and numeric prediction.

3.3.3 Hybrid Ensemble Learning

Fig 3.6 Offline training structure of hybrid-ensemble learning scheme

Compared with traditional learning algorithms, ELM and RVFL show much faster learning speed as well as better generalization capacity without excessive learning time. However, those randomized learning methods always suffer from classification errors. The randomly selected input weight is the main cause of this robustness inadequacy in learning process. In practical application, the problem can affect system as a disturbance. To reduce the impact of aggregated variance, a workable solution is to combine a number of individual learners and determine the result by a decision mechanism. The solution is called ensemble learning. By doing so, ensemble learning tends to reduce the error of randomized learning.

Although ensemble learning is a relatively effective solution, considering unique but limited advantages, a single learning algorithm may not fully extract the mapping relationships embedded among the training data. Therefore, it is advisable to combine multiple learning methods to further improve learning performance. This method is called hybrid ensemble learning. In this thesis, ELM and RVFL are combined to develop

a hybrid ensemble learning scheme. Fig. 3.6 illustrates the structure of hybrid ensemble learning. To compensate their respective drawbacks, two algorithms form a synthesis as a hybrid ensemble scheme. With multiple learning algorithms, the learning diversity is further improved. Moreover, each learning process in hybrid ensemble leaning involves randomness of parameters, which can improve the generalization ability of the learning model.

3.4 Online Sliding-Window Classifier

A dynamic online classifier based on sliding-window scheme is proposed in this chapter. This sliding-window classifier can greatly reduce the consuming time without sacrificing the diagnostic accuracy. Furthermore, in order to study the tradeoff between accuracy and time, a MOP framework is investigated.

3.4.1 The Design of Sliding-Window Classifier

Fig 3.7 Structure of online sliding-window fault diagnosis

To implement open-circuit fault diagnosis with high accuracy and speed, this study also develops a sliding-window structure [46], as shown in Fig. 3.7. Sliding-window

classifier starts with a short time window, which refers to the less sampling data. In the first classifier, a result is generated and passed to a credibility judgment mechanism. If sub-result is judged as a credible one, the classifier is able to draw the result as the final output. On the other hand, if the result is considered to be incredible, the classification process will convert to the next ensemble classifier which uses a wider time window. As time window becomes wider, it carries more waveform data. This procedure will continue until a credible result is obtained or the maximum allowable classification time is reached.

To complete the sliding-window scheme, the definition of credibility should be proposed. As discussed above, ELM/RVFL multi-classification rule is concluded as:

Rule of ELM(RVFL) multi-classification

Given a ELM(RVFL) and a test set $\mathbf{x}$ of $P \times Q$ size, where P is the total number of features of each instance, Q is the number of instances,

$$\text{If } f_{jd}(\mathbf{x}) = \operatorname{argmax}(f_{jk}(\mathbf{x}))(1 \leq k \leq m)$$

$$\text{output}_j = d$$

End

where m is the number of classification label and the number of output nodes as well, output_j refers to the result of the j th sample, $f_{jk}(\mathbf{x})$ refers to the output value of the k^{th} output node for the j^{th} instance, $j=1,2,\dots,Q$.

As introduced above, the ELM/RVFL classification rule is to find the output node with the maximum value. To evaluate if the result is credible, it is rational to evaluate if the maximum value is an outlier, which in statistics defines an instance point that is distant from other instances. Grubbs' outlier test was published by Frank. E. Grubbs in 1950 [47]. For m output node values $\{o_1, \dots, o_m\}$, the outlier evaluation is defined by:

$$G = \frac{|\max(o_j) - \mu|}{\sigma} \quad (j = 1, 2, \dots, m) \quad (3-13)$$

$$\sigma = \sqrt{\frac{1}{m-1} \sum_{j=1}^m |o_j - \mu|^2} \quad (3-14)$$

where G refers to the outlier evaluation value, μ denotes the mean, and σ denotes standard deviation of output nodes value, respectively. As shown in the Fig 3.8(a), if the maximum value is an outlier, the credibility G is high and the result is classified as a credible output. On the contrast, if the maximum value has a little deviation with other node values, the credibility G is low and the result is considered as an incredible output, as shown in the Fig 3.8(b) [48]. Assume the α th output node has the maximum value ($1 \leq k \leq m$). The credibility evaluation rule is defined as:

$$\begin{cases} \text{If } G > \tau, y_i = \alpha \text{ (credible sub-output)} \\ \text{If } G \leq \tau, y_i = 0 \text{ (incredible sub-output)} \end{cases}$$

where y_i is the sub-output of the i th single classifier and τ refers to the threshold in the credibility evaluation. Based on a hybrid ensemble learning consisting of X ELMs and Y RVFLs, $(X+Y)$ sub-outputs can be obtained. Assume ρ sub-outputs are evaluated as credible ($y_i \neq 0$) and α is the label with the most frequency. Therefore, the ensemble decision mechanism is described by:

$$\begin{cases} \text{If } \rho \leq \frac{X+Y}{2}, \text{ classification is incredible} \\ \text{Else if } \begin{cases} \alpha = 0, \text{ classification is incredible} \\ \alpha \neq 0, y = \alpha \end{cases} \end{cases}$$

where y is the final output of the diagnosis. If the classification is evaluated as incredible, a sliding-window classifier will switch to a wider time window and implement diagnostic process circularly. To conclude, the whole decision-making mechanism flow chart is illustrated in Fig 3.9.

(a)

(b)

Fig 3.8 ELM output nodes value when G_j equals to (a) 4.4081 (high credibility) (b) 3.0035 (low credibility)

Fig 3.9 Decision-making mechanism in online sliding-window scheme

3.4.2 Accuracy-Time Tradeoff based on MOP

Based on the proposed sliding-window classifier for open-circuit fault diagnosis, several parameters should be appropriately determined, such as ELM, RVFL credibility threshold, the number portion of learners in hybrid ensemble learning scheme. Those parameters are significant for classification performance. To exemplify, when the credibility threshold is high, the final output can be more accurate and reliable. However, the cost of high accuracy is to undergo several circles of sliding-window classifiers, which greatly increases diagnostic time. To study the tradeoff between classification accuracy and decision time, a multi-objective optimization problem (MOP) is developed.

Based on this MOP, the tradeoff relationship is optimally balanced and interpreted figuratively. Based on previous discussion, this tradeoff issue can be described as a MOP problem as

$$\text{Objective : } \min_{\mathbf{x}}(f_1(\mathbf{x}), f_2(\mathbf{x})) \quad (3-15)$$

$$\mathbf{x} = [N_{ELM} / N_{RVFL}, \sigma_{ELM}, \sigma_{RVFL}] \quad (3-16)$$

$$f_1(\mathbf{x}) = \sum_{i=1}^m t_i N_i / \sum_{i=1}^m N_i \quad (3-17)$$

$$f_2(\mathbf{x}) = -A \times 100\% \quad (3-18)$$

$$\begin{aligned} \text{Constraints : } N_{ELM} &\in (0, 200), \\ N_{RVFL} + N_{ELM} &= 200, \\ \sigma_{ELM} &\in (3.5, 4.5), \\ \sigma_{RVFL} &\in (3.5, 4.5). \end{aligned}$$

To simplify two objectives, f_1 is defined as *Average Diagnosis Time* (ADT) and f_2 is defined as *Average Diagnosis Accuracy* (ADA). $\mathbf{x}$ is the decision variable vector with three elements. In (3-17), t_i refers to diagnostic time of the i th classifier, N_i refers to the credible instance number of the i th classifier and m is the number of classifiers in sliding-window scheme. N_{ELM} , N_{RVFL} refer to the numbers of ELM, RVFL in hybrid ensemble learning and, σ_{ELM} , σ_{RVFL} denote to the credibility thresholds of ELM, RVFL classifier.

Based on the MOP introduced, multi-objective genetic algorithm (MOGA) is utilized to solve this problem [49]. In the proposed scheme, although time and accuracy are employed as two final objectives, accuracy should take the opposite value because MOGA converts optimization to a minimization problem. By doing so, this tradeoff issue turns into multi-objective minimization by mathematical expression [50] [51].

Different from single-objective optimization, MOP has more than one solution to meet two or more objectives optimization. Always, a set of optima can be achieved, called *Pareto set*. The Pareto set of MOP consists of all decision solutions for which the

corresponding objective target cannot be improved in any dimension. Those solution vectors are called *Pareto optimal*. Mathematically, the rule of Pareto optimality can be defined as follows: Consider two solution vectors $a, b \in X$ in a minimization problem. If

$$\forall i \in \{1, 2, \dots, n\}, f_i(a) \leq f_i(b) \wedge \exists j \in \{1, 2, \dots, n\}, f_j(a) < f_j(b),$$

a is said to dominate b , where f_i refers to the i th optimization objective. If vectors are not dominated by any others, those vectors are called non-dominated. In the entire optimization search space, all optimal non-dominated vectors comprise *Pareto optimal front* (POF).

3.5 Simulation and Experimental Validation

In order to verify the feasibility and efficiency of the proposed methodology, the real-time experiment is conducted.

3.5.1 Database Generation and Model Building

Table II. Data acquisition

Simulation parameters in data collection	
DC-link ripple voltage	100 (1:100/1 V)
Reference speed	100 (1:100/1 rad/s)
Reference load torque	100 (21:120/1 N·m)
Open-circuit fault type	21

Table III. Parameters of the drive system

Comment	Value
DC-link voltage U_{dc}	700 V
Stator resistance R_s	0.435Ω
Stator leakage inductance	4mH
Rotor resistance R_r	0.816Ω
Rotor leakage inductance	2mH
Mutual inductance L_m	69.31mH
Rated speed n_{rate}	2,000(r/min)
Rated output power P_{rate}	11kW
Number of the pole pairs	2

To propose an effective open-circuit fault classifier, a comprehensive database is the basic foundation. The database generally consists of numerous working conditions that include various faulty features as inputs and the simulated faulty labels as outputs. So the amplitude of 100Hz ripple voltage in dc-link varies from 1 to 100 V with the interval of 1 V, the reference speed varies from 1 to 100 rad/s with the interval of 1 rad/s, and the reference load torque varies from 21 to 120 N·m with the interval of 1 N·m, by collection of different types of fault states. The database and parameters are summarized in Table II, Table III respectively.

Based on the above mechanism, 2500 sampled points around fault point are collected for each instance under the sampling frequency of 10 kHz. Including 22 types of labels listed in Table. I, 6600 sets of data are collected by the mentioned simulation model. Such a data-collection method implements the comprehensiveness of database, leading to offline training burden reduction and online accuracy improvement. After collecting those datasets, 80% are trained for offline diagnostic model and 20% are used for testing. For sliding-window scheme, the interval of time windows is defined as one cycle and the maximum width of time window is five cycles. In this work, the set of 500 sampled points can be approximately considered as one cycle of output current. Therefore, as three-phase current in one cycle, the original data is collected as the form of 3×500 .

After original data acquisition, FFT is used to convert the signal into frequency-domain. The Fastest Fourier Transform in the West (FFTW) is adopted in this research work for a list of merits, such as arbitrary-size transform, fast transforms of purely real input or output data and portable to any platform with a C compiler, which is advantageous for experimental setup. By FFTW, original three-phase original data (3×500) is transformed into frequency-domain form as candidate features (3×250) and for convenience of data processing, the three-phase form is transformed into one-dimensionality form as 1×750 . Among the 750 candidate features, representative components are further selected by the RELIEFF algorithm which estimates the ability of each frequency components to

distinguish instances from different feature values and target classes. The RELIEFF function used in this research work, has been packaged in Matlab R2017a Statistics and Machine Learning Toolbox. By this feature selection method, each candidature is assigned an importance weight ranging in $[-1,1]$, where a positive weight value means the feature can distinguish the instance, while a negative weight value refers to that the feature overlaps the instance. The bar graph of feature weight is shown in Fig 4.1. With the help of figure and weight value data, 30 frequency components with high positive weights are selected as the training and testing data.

In learning process, for single ELM and RVFL, several parameters are properly tuned to guarantee a reliable learning performance. Given different activation function searching patterns (Triangular basis, sine, sigmoid, radial basis, and hard-limit) and neuron nodes, as shown in Fig. 4.2, test accuracy will reach a maximum value within a specific hidden node range and genetic algorithm is also applied in this tuning process to select appropriate parameters. To exemplify, in the 1st sliding-window classifier, the optimal hidden node ranges for ELM is $[1300, 1400]$, and the Sine function is chosen as valid activation function. For other ELMs and RVFLs in sliding-window classifiers, the optimal activation function and hidden node range also are determined by this tuning process, as listed in Table IV.

Fig 3.10 RELIEFF results for frequency components

Fig 3.11 ELM parameters tuning curve for the 1st classifier

Table IV. Parameter selection result in the sliding-window classifier

The order of the sliding-window classifier	Single classifier type	Hidden node range	Activation function
1	RVFL	[1700,1800]	sin
	ELM	[1200,1300]	sin
2	RVFL	[700,800]	tribas
	ELM	[600,700]	sig
3	RVFL	[600,700]	tribas
	ELM	[500,600]	sig
4	RVFL	[600,700]	tribas
	ELM	[500,600]	sig
5	RVFL	[500,600]	tribas
	ELM	[500,600]	tribas

3.5.2 Multi-objective Optimization Result

Fig 3.12 Derived POFs of parameters optimization

Table V. Selected Prato Front Point for experiment

ADT	ADA
1.052 cycles	99.035%

Table VI. Test results for the proposed methodology

k th	C_k	A_k	M_k	$A_{overall}$	R_k
0	-	-	-	-	1100
1	1048	98.95%	11	98.95%	52
2	45	100%	0	98.99%	7
3	7	100%	0	99.00%	0

In sliding-window classifier performance validation, the solution set of POF is generated as plotted in Fig. 4.3 and extreme Pareto Front points are labeled. Based on the curves, single RVFL ensemble has a stable result but a relatively poor performance in test accuracy. By comparison with single ELM ensemble, hybrid ensemble has a better performance due to the more convex POF curve. Hybrid ensemble has a lower ADT than single ELM ensemble in best ADT case with a little sacrifice in accuracy, and has the same accuracy of 100% in best ADA case but with a higher ADT.

In real-time fault diagnosis, the accuracy always serves as the fundamental index in

methodology evaluation and diagnostic earliness is also essential when system undergoes a faulty state. The proposed hybrid ensemble scheme extends and optimizes the range of ADA, ADT. In practical application, operators can select parameters from the Pareto Front solution set based on requirement empirically.

To verify the optimization result, 1100 datasets are used in the testing. By the variation of dc-link voltage, reference speed, and reference load torque, those new datasets of all fault labels are collected. Under the condition that satisfies the test accuracy beyond 99%, the Pareto point listed in Table. V is used as the compromise solution, based on the offline generated POF solution set. The test results are summarized in Table. VI, where C_k refers to the number of instances which deliver a credible result in the k th classifier, A_k refers to the accuracy of the k th classifier, M_k refers to the number of misdiagnosis, $A_{overall}$ denotes to the diagnostic accuracy of all instances, and R_k denotes to the instance number remaining for next classifiers. In the test, the overall accuracy reaches 99.00%. Furthermore, the whole test is finished after the 3rd cycle, and the 2nd, 3rd classifier implement diagnosis with 100% accuracy. As a result, the ADT is 1.054 cycles. To be concluded, the proposed method is able to diagnose the open-circuit faults accurately with high reliability and anti-interference.

3.5.3 Experimental Validation

Fig 3.13 Experimental Setup

(a)

(b)

(c)

(d)

Fig 3.14 Experimental results when (a) T_3 is under open-circuit fault (b) t_3 , fault occurs
(c) T_1, T_3 are under open-circuit fault (d) t_3 , fault occurs

Based on the model building and parameters optimization, the proposed diagnosis methodology is implemented in the simulation model. As tested in the simulation model, once open-circuit fault occurs, the simulation model diagnoses the accurate label by the cost of extremely short time. In addition, to verify the further feasibility in practical application, the experimental validation is implemented. The simulation and

experimental platform parameters are detailed in Table III. The validation of the proposed fault diagnosis method is conducted under the Pareto point listed in Table. V.

The experimental platform comprises a controller to generate command signals of IGBTs, a dSPACE MicroLabBox simulator, and a computer as a real-time control interface. The open-circuit faults of switches are simulated by disabling corresponding gate signals. In order to achieve a unity power factor operation, a proportional integrator (PI) controller and a proportional resonant (PR) controller are installed at the rectifier-side in the external, inner control loop respectively. Space vector pulse width modulation (SVPWM) and indirect field-oriented control are applied in the inverter-side control to ensure good dynamic responses of motor speed. The training model has been debugged and loaded in advance. In experimental setup, current data is collected with sampling frequency of 10 kHz and injected into the diagnostic model. The number of sampling points for each cycle is determined by frequency which is also obtained from control topology.

The experimentally measured result when an open-circuit fault is in IGBT T_3 is shown as Fig. 4.5, where the traces above are load current trajectories, and the trace below is the fault label flag. The induction motor is in constant-torque/speed operation before t_1 . At t_1 moment, the induction motor begins to brake, motor speed decreasing from 69 rad/s to 65 rad/s. Then, the system load torque drops from 100 N·m to 80 N·m at t_2 moment. It is clear that the diagnostic methodology shows reliability and robustness, regardless the operation of the induction motor and the fluctuation of load torque. In addition, due to the inductive load, the output current contains not only inherent low-order odd harmonics caused by circuit and control topology, but also high-order odd harmonics from power switch characteristic. This diagnostic model also gets rid of influence from harmonics with no misdiagnosis. Generally, when the induction motor converter system is under normal working state, the diagnostic model outputs label 1, as listed in Table. I. As shown in the Fig. 4.5(a), T_3 open-circuit fault is introduced at t_3 . In Fig. 4.5(b), it is shown that

the fault label flag switches to the right diagnostic result, label 4, only after one cycle with approximately 25ms. Similarly, as shown in the Fig. 4.5 (c) (d), double IGBTs open-circuit fault (T_1 , T_3 open-circuit fault) is also diagnosed as the accurate result, label 9, within a short time period. After the methodology diagnoses the open-circuit fault, the system immediately shuts the working state.

From the dynamic experimental process, it can be concluded that the proposed diagnostic methodology is independent of the fluctuation of motor speed, load torque. Furthermore, the diagnostic process costs quite short time with high accuracy of fault type and location, which reserves sufficient time to manage operation. Therefore, by the experimental validation, the proposed data-driven is rapid and reliable for real-time practical application.

Chapter 4   Data-driven Methodology for Sensor Fault Diagnosis and Fault-Tolerant Control

4.1 Methodology Configuration

With regard to the sensor fault, most existing methods are developed based on the model-based principle since it has fast speed and reliable accuracy, but its performance highly depends on the modelling details and parameters uncertainty. Moreover, this method also suffers from the complexity of model building and the difficulty of parameter estimation. In the literature, most methods consider the fault diagnosis as the classification problem which brings computational burden. This thesis develops a predictive method for sensor fault diagnosis, fault-tolerant control based on the data-driven approach. Similar with the model-based methods, data-driven method extracts the mapping relationship between inputs and targets but has efficient computational mechanism and higher generalization ability. The proposed method is based on the signal prediction framework by the regression algorithm. The method adopts ELM to predict the current signal. To improve the prediction model and reduce the error, NARX model is used to develop an online data structure. With the decision-making mechanism based on the residual analysis, the fault flag is given and a fault tolerant control will come into use to guarantee the normal working condition. The general methodology scheme is shown in the Fig 4.1.

Fig 4.1 The proposed methodology scheme

4.2 Design of Fault Diagnosis and Fault-Tolerant Control Scheme

To diagnose those sensor faults, a data-driven method is proposed for current sensor faults in this thesis. ELM is used to predict the grid-side current, and NARX model is utilized as prediction structure. By evaluating the residual between measured and predicted value, a diagnostic result is achieved, and once a fault flag is generated, the predicted signal takes place of sensor signal to implement the feedback control.

4.2.1 Extreme Learning Machine based on Regression Problem

ELM was proposed in [34] by Huang and has been widely utilized in theoretical studies and practical problems. Fig 3.5 depicts the structure of ELM. For a database of N' arbitrary instances $(\mathbf{x}_i, \mathbf{t}_i)$, where $\mathbf{x}_i \in \mathbf{R}^n$ and $\mathbf{t}_i \in \mathbf{R}^m$, the output function of ELM is

$$\mathbf{t}_i = \sum_{j=1}^N \boldsymbol{\beta}_j \cdot g(\boldsymbol{\omega}_j \cdot \mathbf{x}_i + b_j), \quad i = 1, 2, \dots, N' \quad (4-1)$$

where $\boldsymbol{\omega}_j$ refers to the weight vector between input layer and the j^{th} hidden node, $\boldsymbol{\beta}_j$ refers

to the weight between hidden nodes and output layer, b_j refers to bias of hidden nodes, and N denotes the number of hidden nodes. Therefore, (4) can be written in a compact form:

$$\mathbf{H}\boldsymbol{\beta} = \mathbf{T} \quad (4-2)$$

where $\mathbf{H}$ indicates the hidden layer output matrix. At training stage, the input weight and bias are generated. Then $\boldsymbol{\beta}$ is analytically obtained by matrix calculation, using the minimal norm least square method:

$$\boldsymbol{\beta} = \mathbf{H}^\dagger \mathbf{T} \quad (4-3)$$

$$\mathbf{H}^\dagger = \mathbf{H}^T (\mathbf{H}\mathbf{H}^T)^{-1} \quad (4-4)$$

where $\mathbf{H}^\dagger$ is the Moore-Penrose inverse pseudo inverse of $\mathbf{H}$.

Since the input weights and bias of ELM are randomly selected, the parameter tuning process of conventional algorithms is skipped. Consequently, ELM demonstrates faster learning speed than other learning approaches, such as SVM, and back-propagation learning. Moreover, ELM retains high accuracy in regression problems as illustrated in [44]. In this thesis, regarding online prediction task that requires high computational speed and reliable accuracy, ELM is an optimal approach to form the machine learning scheme.

4.2.2 NARX Modelling and Training

This sensor fault diagnosis is based on signal predication. Conventionally, signal prediction always suffers from computational errors and massive data size. To overcome those drawbacks, this thesis develops a dynamic prediction model based on NARX.

Fig 4.2 ELM learning based on NARX model

As depicted in Fig 4.2, the NARX model is proposed to improve prediction accuracy. Since feedback links existing in the model, NARX model contains updating past information and can build the autoregressive model. NARX model is suitable for modeling the nonlinear dynamical systems being commonly used in time series modeling. NARX is an important class of discrete-time nonlinear systems that can be mathematically represented as:

$$\begin{aligned} T(t) &= f[\mathbf{T}(t-1); \mathbf{u}(t-1)] \\ &= f[T(t-1), T(t-2), \dots, T(t-d_T+1); u(t-1), u(t-2), \dots, u(t-d_u+1)] \end{aligned} \quad (4-5)$$

where $\mathbf{T}$, $\mathbf{u}$ are the target vector and the feature vector namely, d_T , d_u refer to the delayed step of the target, feature vectors. The nonlinear mapping f is generally unknown and always extracted by the machine learning technique. In Fig 4.2, z^{-1} denotes a time delay of one samples. With the NARX model, a multistep prediction of the grid side current is

proposed as:

$$\begin{aligned}\hat{i}_{sA}(t) &= f[i_{sA}(t-1), i_{sA}(t-2), U_d(t-1), U_d(t-2), \\ &\quad u_s(t-1), u_s(t-2), \mathbf{PWM}(t-1)] \\ \mathbf{PWM} &= [s_1, s_2, s_3, s_4]\end{aligned}\quad (4-6)$$

where i_{sA} is the grid side current signal in phase A, U_d refers to the dc-link voltage, u_s refers to the grid side voltage, and $\mathbf{PWM}$ denotes the rectifier switch command signal vector.

By the reliable simulation tool, Matlab R2017a/Simulink, a series of grid side current signal has been collected. Based on the NARX model, the collected current signal is transformed into the training form as shown in the (4-7). In (4-7), the first column refers to the regression target, and following columns refers to training features. Based on this data structure, ELM is used to extract the mapping knowledge relationship among this matrix. Similar as the model-based method, this data-driven method focuses on building the model between input features and current targets. This method has a similar principle but uses the data-driven approach. Therefore, the modeling process is more efficient, and this model is more robust against comprehensive scenarios.

$$\left[\begin{array}{c|ccccccc} i_{sA}(3) & i_{sA}(2) & i_{sA}(1) & U_d(2) & U_d(1) & u_s(2) & u_s(1) & \mathbf{PWM}(2) \\ i_{sA}(4) & i_{sA}(3) & i_{sA}(2) & U_d(3) & U_d(2) & u_s(3) & u_s(2) & \mathbf{PWM}(3) \\ \vdots & \vdots & & & & & & \\ i_{sA}(t-1) & i_{sA}(t-2) & i_{sA}(t-3) & U_d(t-2) & U_d(t-3) & u_s(t-2) & u_s(t-3) & \mathbf{PWM}(t-3) \\ i_{sA}(t) & i_{sA}(t-1) & i_{sA}(t-2) & U_d(t-1) & U_d(t-2) & u_s(t-1) & u_s(t-2) & \mathbf{PWM}(t-2) \end{array} \right] \quad (4-7)$$

4.2.3 Design of Fault Diagnosis and Fault-Tolerant Control

Fig 4.3 The proposed sensor fault diagnosis and fault-tolerant control

At online application stage, the NARX model is built as (14). When a predicted value is achieved, the current residual can be described as:

$$\tilde{i}_{sA} = \hat{i}_{sA} - i_{sA} \quad (4-8)$$

where i_{sA} is an actual feedback value in the control loop. After the residual value is calculated, the result is delivered to the decision-making mechanism, as follows:

$$\begin{cases} |\tilde{i}_{sA}| > \sigma, \text{ sensor fault exists} \\ |\tilde{i}_{sA}| \leq \sigma, \text{ no sensor fault} \end{cases} \quad (4-9)$$

where σ is the threshold value to diagnose sensor faults. Based on this decision-making process, when the sensor fault occurs, the faulty system can be detected, and a fault flag

can be generated immediately. To protect the system from erroneous feedback value into control loop, the predicted signal will take place of the current sensor signal to keep the normal working state, which forms as a fault tolerant control. Fig 4.3 illustrates the flowchart of the proposed method.

4.3 Simulation Results

To verify the proposed methodology, an AC-DC-AC back-to-back converter system is simulated.

4.3.1 Simulation Model Building

The simulation model is conducted by MATLAB(R2017a)/Simulink and simulation parameters are given in Table VII and Table VIII. In order to achieve a unity power factor operation, a proportional integrator (PI) controller and a proportional resonant (PR) controller are installed at the rectifier-side in the external, inner control loop respectively. SVPWM and indirect field-oriented control are applied in the inverter-side control to ensure good dynamic responses of motor speed.

Table VII. Parameters of the simulation system

Parameter	Value
RMS grid voltage u_N	1550V
Traction winding leakage L_N	2.3mH
Traction winding resistance R_N	0.068 Ω
DC-link voltage U_{dc}	2700V-3600V
DC-link capacitance C_d	3mF
Series resonant circuit inductance L_2	0.603mH
Series resonant circuit capacitance C_2	4.56mF
Rectifier switching frequency f_R	350Hz
Highest inverter switching frequency f_I	500Hz

Table VIII. Parameters of the converter

Parameter	Value
Stator resistance R_s	0.1065 Ω
Stator leakage inductance L_{1s}	1.31mH
Rotor resistance R_r	0.0663 Ω
Rotor leakage inductance L_{1r}	1.93mH

Mutual inductance L_m	53.6mH
Rated voltage U_r	2700kV
Rated speed n_r	4100r/min
Rated frequency f_r	138Hz
Rated output power P_r	562kW
Rated slip frequency s_r	0.04

4.3.2 Parameters Tuning

In this test, the current prediction process is defined as regression problem in ELM. For ELM learning, the number of hidden layer nodes and activation function are required to be tuned properly. This thesis uses *root mean square error* (RMSE) to assess the regression performance of ELM, defined as:

$$\text{RMSE} = \sqrt{\frac{1}{N_t} \sum_{i=1}^{N_t} (t_i - f(x_i))^2} \quad (4-10)$$

where N_t is the number of regression instances, t_i is the desired target of each instance, and $f(x_i)$ is the prediction output of ELM. The lower RMSE means the higher prediction accuracy.

As shown in Fig 4.4, given different activation function searching patterns (Triangular basis, sine, sigmoid, and radial basis) and neuron nodes, test RMSE will reach a minimum value within a specific hidden node. In this case, the optimal hidden node ranges for ELM is [200, 300], and the sigmoid function is chosen as valid activation function.

Fig 4.4 Validation test for ELM with different numbers of hidden nodes

4.3.3 Prediction Results and Analysis

In this test, several working scenarios are simulated, and the simulation data is collected to verify the prediction method. To evaluate the prediction performance quantitatively, the absolute error (AE) and the relative error (RE) are applied in this thesis:

$$AE = |i_{real} - i_{predict}| = \tilde{i}_{sA} \quad (4-11)$$

$$RE = \frac{|i_{real} - i_{predict}|}{i_{real}} \times 100\% \quad (4-12)$$

The grid side current prediction result is illustrated in Fig. The prediction process is introduced into the simulation model at 7.5s. As shown in the Fig 4.5, in the normal working condition of system, the grid side current signal can be accurately as the prediction begins. Similarly, for the braking mode of system, the real and predicted current signal are tested. From the figure, the real signal and predicted signal are almost coincident. To verify the robustness of prediction, different working conditions are introduced in this simulation by changing the system parameters. The prediction evaluation results are summarized in Table IX. The average AE and RE are 0.2646A and 0.1586%, which indicate that the proposed method can accurately predict the current sensor signal.

Table IX. Prediction Evaluation

Evaluation parameters	System working mode	
	Traction	Braking
Average AE	0.2646A	1.2595A
Average RE	0.1586%	0.2497%
Maximum AE	4.4286A	43.9004A

(a) The grid side current prediction result

(b) The prediction error

Fig 4.5 The grid side current prediction of the drive system in traction mode

To verify the fault tolerant control, the stuck sensor fault is introduced to occur in the system, and the diagnostic threshold σ is define as 50A. To be specific, when the difference between predicted and feedback value equals or exceeds 50A, the predicted value will take place of feedback value, guaranteeing the control loop running as normal. In the test, the stuck value is defined as 1000A, and once the fault occurs, predicted and feedback signal begin to deviate. When the difference reaches the threshold, the fault tolerant control takes over the system. As plotted in the Fig 4.6, the performance of this fault tolerant control is validated to be an effective and reliable method. For stuck sensor fault, the residual threshold is set as 50 A. Because the stuck sensor fault can cause a substantial change of the working system, the threshold is usually defined as a high value.

(a) stuck sensor faulty signal

(b) load current signal without fault tolerant control

(c) predicted current signal with fault tolerant control

(d) residual signal

(e) load current signal with fault tolerant control

Fig 4.6 Fault tolerant control for stuck sensor fault of grid-side current sensor

On the other hand, for gain stuck sensor fault, when the threshold value is 10 A, as shown in the Fig 4.7 (b), the grid-side current signal will reconstruct after a palpable interval. When the threshold changes to 5 A, like Fig 4.7 (e) shows, the system will recover rapidly. Therefore, the threshold value has a great impact on the performance of this fault tolerant control.

(a) gain sensor faulty signal

(b) load current signal without fault tolerant control

(c) predicted current signal with fault tolerant control when current threshold is 10A

(d) residual signal when current threshold is 10A

(e) predicted current signal with fault tolerant control when current threshold is 5A

(f) residual signal when current threshold is 5A

(g) load current signal with fault tolerant control

Fig 4.7 Fault tolerant control for gain sensor fault of grid-side current sensor

Chapter 5 Conclusions and Future Works

5.1 Conclusions

The widespread application of power electronics technology has reshaped traditional industrial system into power electronics based industrial system. Although being advantageous in modern industry, a large scale of deployment of power electronics converter faces the risk of faults by numerous causes. Especially in high power drive system, which has been widespread in public transportation system, any breakdown even irregularity would interrupt the whole working system. Therefore, fault diagnosis of the converter system should be addressed in the leading place. From the perspective of fault types, short-circuit fault can be protected by the standard protection system but open-circuit fault is always latent for a long period, leading to the degradation of working system and the secondary fault. Based on that, this research work focuses on power switch open-circuit fault diagnosis in the induction motor converter system.

Apart from IGBT open-circuit faults, the sensor fault is also an important issue in this area. Due to the device aging or surrounding interference, unexpected failure may occur in the sensors, which leads to the erroneous feedback value into the control loop and degrades the working performance. This thesis also focuses on the data-driven method for sensor fault diagnosis and fault-tolerant control.

To conclude those works above, five main points can be drawn:

- (1) The mathematical expression of stator currents and three-phase output voltages has been deduced in the aforementioned work, as a proof of fault analysis. By analyzing three main types of IGBT open-circuit faults and three-phase output current waveforms achieved from simulation, it is used as the basis of fault diagnosis methodology design. Consequently, a summary of open-circuit fault labels is proposed, including normal working state, single IGBT fault, and double IGBT faults.

- (2) To describe certain open-circuit faults more effectively and accurately, FFT is utilized to transform time-domain data into frequency domain. In order to select the most representative frequency components and fully preserve faulty features, RELIEFF algorithm is served as the tool of feature selection. 30 features are selected as training data features from 750 frequency components, which also greatly attenuates calculation burden in data relationship mapping.
- (3) Owing to characteristic merits of randomized learning, ELM and RVFL network are used to design the learning model. In order to combine fast learning speed of ELM and stable performance of RVFL, a hybrid ensemble model has been proposed in this research. It consists of certain numbers of ELM and RVFL, which is able to compensate each other's learning performance. What's more, in order to realize the earliness of online diagnosis, a sliding-window structure has been designed. With the novel definition of credibility, a decision-making mechanism is designed to classify credible sub-result and incredible result. By tuning and implementing this result determination, the sliding-window classifier is able to show great performance that the confidential decision of faulty state will be made dynamically in the early stage.
- (4) To further improve the diagnostic performance, a MOP framework is investigated to optimize the tradeoff problem between accuracy and time. By model parameter optimization, a solution set of POF has been achieved, which would be provided for system operators as a set of practical options empirically.
- (5) To diagnose the grid-side current sensor fault, a signal prediction framework is proposed. Based on the ELM regression algorithm, a NARX prediction model is designed, which is a dynamic model to simplify the data structure. By monitoring the consistency between measured signal and predicted signal, the signal residual can be generated to make the diagnostic decision. When the residual exceeds the threshold, the fault flag is given and the predicted value will take place of the faulty

sensor signal, forming a fault-tolerant control and guarantee the normal working condition.

An experimental prototype of the proposed data-driven fault diagnosis methodology has been constructed in the laboratory. Experimental results obtained from this prototype clearly demonstrate the feasibility and superiority of the proposed hybrid-ensemble sliding-window diagnostic model. For the methodology with regard to sensor faults, the simulation validation is implemented. The simulation results verify the high accuracy of predication and the effectiveness of proposed fault-tolerant control.

5.2 Future Works

This thesis discusses the research work of the data-driven method for IGBT open-circuit fault and sensor fault. Although the testing performance is promising, there still exist several areas to be compensate:

- (1) In the topology of the back-to-back converter system, the single-phase rectifier is an equivalently important part, which determines the quality of dc-link voltage. However, there are little literatures focusing on the open-switch fault of the single-phase rectifier. The next work is to apply the data-driven method into open-switch fault diagnosis in the single-phase rectifier.
- (2) For sensor fault diagnosis, the proposed method is able to implement fault-tolerant control, but the fault still exists and needs to be handled. The method in this thesis only detects the fault, without determining the fault type and location. Therefore, the future work will focus on the investigation of signal residuals, to define the sensor fault type.
- (3) In the sensor fault tolerant control, several threshold values are defined. However, this threshold value has a great impact on the performance of this fault tolerant control. In this thesis, the threshold is defined empirically. In the future, it is necessary to find a theory-based approach to define the value. Especially for the drift

fault and gain fault, the transient process is not obvious like stuck sensor fault. The working system changes gradually which cannot be detected immediately by this diagnostic method. Therefore, the mechanism of threshold decision still needs to be investigated.

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2. **Y. Xia**, B. Gou, and Y. Xu, "A new ensemble-based classifier for IGBT open-circuit fault diagnosis in three-phase PWM converter," *Protection and Control of Modern Power Systems*, vol. 3, no. 1, Nov. 2018.
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