Intelligent System based Facility Monitoring and Fault Diagnosis of Power Generators

by

Zhong Jianhua

MSc in Electromechanical Engineering

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Faculty of Science and Technology
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Abstract

Intelligent System based Facility Monitoring and Fault Diagnosis of Power Generators

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The malfunction of critical equipment in industries, such as gearbox in power generator enterprise, may present a significant environmental and financial risk. The motivation of this thesis comes from the requirements of a local company, the Companhia de Electricidade de Macau, S.A. (CEM), which was established in 1972 and has become the major supplies of electricity in Macau. The important equipment is Turbo Compound System (TCS) in the Coloane Power Station. Diagnosis of potential faults in TCS of Macau power station is the key of ensuring electrical power supply to consumers. Development a proper monitoring and fault diagnosis technique to prevent malfunction and fault of machine during operation is necessary.

The facility fault in rotating gearbox machinery can be resulted by various failure types, including single component level errors, structural failure in system level, and compounded failures with multiple errors coexisted simultaneously. At the main time, the acquisition of various gearbox failure patterns from real power generator for training the diagnosis system is impractical. This thesis proposes a machine learning method based condition monitoring and fault diagnosis methodology to monitor the status of machinery in real time and avoid the uncontrolled failure.

To analyze the TCS system in laboratory environment, a simulated power transmission system with concentration on gearbox subsystem has been developed, which could be adjusted to run on nine failure conditions. To preprocess the raw fault vibration signal which is in high dimensional scale and with noise, a two stage data preprocessing method is proposed. Firstly, the features of raw data are extracted through the wavelet packet transform and time-domain statistical features computation. To further optimize the feature set, feature selection via sensitivities ranking is carried out using two approaches: the compensation distance evaluation technique (CDET) for optimal features selection, and kernel principal components analysis (KPCA) to obtain principal component features. The point distributions of various failure types in each stage demonstrate the effect on dimension reduction and accuracy improvement.

The preprocessed features are analyzed by intelligent classifiers. The thesis compares the performance of support vector machines with artificial neural networks. To examine the performance of intelligent classifiers, two case studies are carried out by combining different preprocess and classifier, where the KPCA output is used by SVMs and CDET is linked with ANNs. The experimental results show that the both combination models could reach high diagnosis accurate rate for simultaneous fault. It also found that the WPT+TDSF+CDET+ANNs framework is robust to be less sensitive to the environment noise when the training and testing are carried out in different date acquired in different time. It is believed that the proposed method has the potential to be applied in related industries with gearbox system.

TABLE OF CONTENTS

LIST OF FIGURES iv
LIST OF TABLES vii
ACKNOWLEDGEMENTS ix
CHAPTER 1: INTRODUCTION 1
1.1 Introduction of machine condition monitoring and fault diagnosis 1
1.2 Fundamental steps of condition monitoring and fault diagnosis methodology 2
1.3 Advantages and disadvantages of condition monitoring 4
1.4 Requirements from local industries 6
1.5 Research objectives 7
CHAPTER 2: LITERATURE REVIEW FOR ROTATING MACHINERY FAULT DIAGNOSIS 8
2.1 Literature review 8
2.2 Review the fault feature extraction techniques 11
2.2.1 Short time fourier transforms analysis 11
2.2.2 Wavelet transforms analysis 12
2.2.3 Wavelet Packet Transforms analysis 15
2.3 Review the fault feature selection techniques 16
2.4 Review of intelligent fault diagnostic techniques 18
2.4.1 Support vector machines for fault diagnosis 19
2.4.2 Artificial neural networks for fault diagnosis 21
2.5 Other methods for machine faults diagnostic 22
2.6 Summary 24
CHAPTER 3: CONSTRUCTION OF EXPERIMENT FRAMEWORK 27
3.1 Gearbox system introduce 27
3.2 Framework of experiment 28
3.3 Design of gearbox system 29

3.3.1 Gearbox functions requirement and technical requirement 29
3.3.2 Selection of gear types 30
3.3.3 Gearbox design and parameters calculation 33
3.4 manufacture of gearbox system 37
3.4.1 Different between the stabile gears and movable gear 37
3.4.2 Gears process by High-frequency quenching 37
3.4.3 Gear's box part 38
3.5 Selection of vibration sensor 39
3.5.1 Operational theory of two-axis and three-axis sensor 40
3.5.2 Performance comparison of two types sensor 41
CHAPTER 4: METHODOLOGY 43
4.1 Analysis method for condition monitoring and fault diagnosis 43
4.2 Support vector machines (SVMs) 44
4.2.1 Support vector machines for two-class problems 44
4.2.2 Support vector machines for multi-class classification 48
4.3 Artificial neural networks (ANNs) 48
4.3.1 Principle of back-propagation 48
4.4 Feature extraction techniques 50
4.4.1 Time-domain statistical features 50
4.4.2 Wavelet Transform 51
4.5 Feature selection techniques 56
4.5.1 Compensation distance evaluation technique 56
4.5.2 Kernel Principal component Analysis 58
CHAPTER 5: EXPERIMENTS AND ANALYSIS 60
5.1 Experiment setup for multiple failure types 60
5.2 Raw data collection in various system condition 61
5.2.1 Normal condition 61
5.2.2 Structural failure 61
5.2.3 Singular component failure 63
5.2.4 Combined failure 65

5.3 Data acquisition 67
5.4 Extraction of fault features 67
5.4.1 Fault frequency decomposes by WPT 67
5.4.2 Fault feature calculation by TDS 68
5.5 Method I: Kernel principal components analysis for SVM 69
5.5.1 Principal component feature extract by KPCA 69
5.6 Method I: Experimental result and discussion 72
5.6.1 Kernel function and parameters of SVM 72
5.6.2 Performance of SVM classifiers 74
5.6.3 Experimental results of kpca for SVM 78
5.7 Method II: Compensation distance evaluation technique for BP 78
5.7.1 Compensation distance evaluation technique 78
5.7.2 Training and testing for BP 81
5.7.3 Normalization 81
5.8 Method II: Experimental result and discussion 82
5.8.1 Experimental results of CDET for BP 89
5.9 Summary 90
CHAPTER 6: CONCLUSION AND FUTURE WORK 92
6.1 Conclusion 92
6.2 Originalities and contributions of research 93
6.3 Future and further development 93
REFERENCES 95
VITA 101

LIST OF FIGURES

Figure 1-1 Fundamental steps of condition monitoring and fault diagnosis methodology 3
Figure 2-1 Gear ordinary fault examples 9
Figure 2-2 Different condition gear fault examples 9
Figure 2-3 Gear fault diagnosis examples 10
Figure 2-4 Gear fault diagnosis for electric motor 10
Figure 3-1 Gearbox of automatic structure 27
Figure 3-2 Turbo Compound System of Coloane Power Station 28
Figure 3-3 Simulated Turbo Compound System Model in CAD/CAM Lab 28
Figure 3-4 Spur gear 30
Figure 3-5 Helical gear 30
Figure 3-6 Herringbone gear 31
Figure 3-7 Straight Bevel gear 31
Figure 3-8 Spiral Bevel gear 31
Figure 3-9 Worm gear 32
Figure 3-10 Internal gear 32
Figure 3-11 Gears distribution design 33
Figure 3-12 Different status rotational speed 34
Figure 3-13 Gearbox assembly drawing and tolerance requiring 35
Figure 3-14 Right-view of 3D- gearbox 36
Figure 3-15 Left-view of 3D-gearbox 36
Figure 3-16 Stabile gears by high-frequency 37
Figure 3-17 Movable gears by high-frequency 37
Figure 3-18 High-frequency quenching 38
Figure 3-19 Box of gear assembly drawing and tolerance requiring 39
Figure 3-20 Inner structure of the sensor 40
Figure 3-21 Functional Block Diagram of ADXL311 41

Figure 3-22 Functional Block Diagram of ADXL330 41
Figure 4-1 Fault diagnosis based on machine learning method 44
Figure 4-2 Classification of two classes by SVM 45
Figure 4-3 Structure of back-propagation neural network 49
Figure 4-4 Demonstrations of (a) Wave and (b) Wavelet 51
Figure 4-5 Different wavelet families 52
Figure 4-6 Time-frequency window of wavelet transform 54
Figure 4-7 Four - level wavelet reconstruction tree 55
Figure 4-8 Three levels decomposition of wavelet pack transforms 56
Figure 4-9 Selecting index l for dimensionality reduction using KPCA 59
Figure 5-1 Experiment gear faults 60
Figure 5-2 Normal condition and vibration signal diagram of time-domain 61
Figure 5-3 Unbalance defect and vibration signal diagram of time-domain 62
Figure 5-4 Looseness defect and vibration signal diagram of time-domain 62
Figure 5-5 Misalignment defect and vibration signal diagram of time-domain 63
Figure 5-6 Chipped tooth defect and vibration signal diagram of time-domain 64
Figure 5-7 Tooth broken defect and vibration signal diagram of time-domain 64
Figure 5-8 Tooth crack defect and vibration signal diagram of time-domain 65
Figure 5-10 Gear crack combine with chipped tooth fault vibration signal diagram of time-domain 66
Figure 5-9 Gear tooth broken and chipped tooth fault vibration signal diagram of time-domain 66
Figure 5-11 Processing of feature extraction 68
Figure 5-12 Point distribution of raw data under various failure conditions 70
Figure 5-13 Point distribution of extracted features under various failure conditions 70
Figure 5-14 Point distribution of KPCA under various failure conditions 70
Figure 5-15 Raw data predict testing classification 75
Figure 5-16 Extraction feature data predict testing classification 76
Figure 5-17 Feature selection predict testing classification 77

Figure 5-18 Feature selection when threshold set 0.3 79
Figure 5-19 Point distribution of raw data under various failure conditions 80
Figure 5-20 Point distribution of extracted features under various failure conditions 80
Figure 5-21 Point distribution of CDET under various failure conditions 80
Figure 5-22 Accuracy versus threshold from Table 5-9 83
Figure 5-23 Accuracy versus number of test from table 5-10 85
Figure 5-24 Accuracy versus number of hidden layer nodes from Table 5-11 87
Figure 5-25 Accuracy versus number of times training from Table 5-12 89

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LIST OF TABLES

Table 2-1 Literature classification 8
Table 2-2 Description of method performance 25
Table 2-3 Different methods for condition monitoring and fault diagnosis 26
Table 3-1 Performance of each gears 32
Table 4-1 Formulation for used in kernel functions 48
Table 4-2 Definition of the selected statistical features in time-domain 51
Table 4-3 Reconstruction signal contain frequency band 56
Table 5-1 Description of each fault condition of gearbox 60
Table 5-2 Number of the extraction feature in different WPT level 67
Table 5-3 Prediction accuracy of three different types kernel function 71
Table 5-4 SVM classification under different setup parameters used raw data 73
Table 5-5 SVM classification under different setup parameters used kernel principal components features 73
Table 5-6 Confusion matrix for SVM under raw D_{TRAIN} based on $D_{TESTING}$, *Polynomial* kernel with $C = 10$ and $d=4$ 75
Table 5-7 Confusion matrix for SVM under raw $D_{WT\text{-}TRAIN}$ based on $D_{WT\text{-}TESTING}$, *Polynomial* kernel with $C = 10$ and $d=4$ 76
Table 5-8 Confusion matrix for SVM under raw $D_{KPCA\text{-}TRAIN}$ based on $D_{KPCA\text{-}TESTING}$, *Polynomial* kernel with $C = 10$ and $d=4$ 77
Table 5-9 Performance comparisons with the ANN with different threshold using 10-feature formulas in Panel 1-4 82
Table 5-10 Performance comparisons with the ANN accuracy range test using 10-feature formulas in panel 4 84
Table 5-11 Performance comparisons with the ANN with different hidden layer nodes using 10-feature formulas in Panel 4 86
Table 5-12 Performance comparisons with the ANN with different times of training using 10-feature formulas in Panel 4 88

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