

UNIVERSITY OF TECHNOLOGY SYDNEY
Faculty of Engineering and Information Technology

**INTELLIGENT FAULT DIAGNOSIS OF
RECIPROCATING COMPRESSOR USING
DEEP LEARNING METHODS**

by

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REQUIREMENTS FOR THE DEGREE

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Certificate of Authorship/Originality

I, Ying Zhang certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of requirements for a degree except as fully acknowledged within the text.

I also certify that the thesis has been written by me. Any help that I have received in my research work and the preparation of the thesis itself has been acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis. This research is supported by the Australian Government Research Training Program.

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Abstract

Fault diagnosis of reciprocating compressors (RCs) based on vibration signals plays a vital role in guaranteeing a high operating reliability in RCs. Conventional maintenance schemes, which are carried out on a regular basis, can lead to unnecessary maintenance and shutdowns. Online health monitoring can monitor the working conditions of RCs continuously and provide more specific information, thus allowing the RC to be maintained as needed.

This PhD research focuses on the development of effective fault diagnosis methods using deep learning methods, thereby greatly advancing traditional health condition monitoring methods. Most traditional data-driven methods analyze the operating conditions using shallow models, which are incompetent at obtaining more confident results. To overcome this problem, a novel scheme based on deep learning models is proposed and applied to RC fault diagnosis. Traditional fault diagnosis methods select and extract features of raw signal with expertise and fuse them with shallow models. However, these methods cannot analyze the characteristics of signal in depth and thus degrade the performance of health monitoring. Deep learning methods are introduced in this research to calculate more representative features self-adaptive from the RC signals to improve fault diagnosis performance. As most fault diagnosis methods are based on vibration signals being the single information source, they cannot reflect the RC operating condition comprehensively. In this research, multi-source signals are collected and analysed for fault diagnosis. A scheme fusing multi-source information is proposed, as well as an auto-denoising network for denoising RC signals self-adaptively.

This PhD thesis consists of seven chapters. Chapter 1 provides research background. Chapter 2 presents a literature review. Chapter 3 proposes a method using intrinsic vibration feature fusion and a Grassmann manifold-based similarity. Chap-

ter 4 introduces the method of RC fault diagnosis using mode isolation-convolutional deep belief networks. Chapter 5 presents the intelligent fault diagnosis method using an optimized convolutional deep belief network. Chapter 6 proposes a novel ensemble empirical mode decomposition-convolutional deep belief network for RC fault diagnosis, and chapter 7 presents the conclusion and discusses future research in this area.

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List of Publications

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- J-2. **Zhang Y.**, Ji, J.C. and Ma, B., 2020. Reciprocating compressor fault diagnosis using an optimized convolutional deep belief network. *Journal of Vibration and Control*, p.1077546319900115.
- J-3. **Zhang, Y.**, Ji, J.C. and Ma, B., 2020. Fault diagnosis of reciprocating compressor using a novel ensemble empirical mode decomposition-convolutional deep belief network. *Measurement*, vol. 156, p.107619.
- J-4. Ma, B., Zhao, Y., **Zhang, Y.**, Jiang, Q.L. and Hou, X.Q., 2019. Machinery Early Fault Detection Based on Dirichlet Process Mixture Model. *IEEE Access*, 7, pp.89226-89233.
- J-5. **Zhang, Y.**, Ji, J.C., Use of intrinsic vibration feature fusion and a Grassmann manifold-based similarity for intelligent fault diagnosis of a reciprocating compressor, *IEEE Transactions on Industrial Informatics*. [Under review]
- J-6. **Zhang, Y.**, Ji, J.C., Wei, D.B., Wear and fatigue analysis of support ring of reciprocating compressor using a deep belief network-conditional random field method. [Submitted]

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Contributor	Statement of Contribution	Thesis Chapter
Ying Zhang	Literature review, Conceptualization, Methodology, Validation, Investigation, Manuscript Writing- Original Draft. Overall contribution: 80%	Chapter 4
Jinchen Ji]Conceptualization, Manuscript Writing- Review & Editing, Supervision. Overall contribution: 20%	

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Contents

Certificate	ii
Acknowledgments	v
List of Publications	vi
List of Figures	xiv
List of Tables	xvi
Abbreviation	xvii
1 Introduction	1
1.1 Background	1
1.2 Research objectives	3
1.3 Thesis organization	4
2 Literature review	6
2.1 Fault diagnosis based on the traditional methods	6
2.2 Feature dimension reduction	8
2.3 Feature extraction by deep learning methods	10
2.4 Signal denoising	11
2.5 Multi-source information fusion	14
2.6 Summary	15
3 Intelligent fault diagnosis using intrinsic vibration feature fusion and a Grassmann manifold-based similarity	17

3.1	Introduction	17
3.2	Proposed method	20
3.2.1	Empirical mode decomposition	21
3.2.2	High-dimensional feature extraction and feature vector reconstruction	22
3.2.3	Deep belief networks	23
3.2.4	Grassmann manifold-based similarity	25
3.3	Experimental verification and analysis	27
3.3.1	Data description	27
3.3.2	RC fault diagnosis using the proposed method	29
3.3.3	Parameter analysis and method evaluation	31
3.4	Conclusion	32
4	Intelligent fault diagnosis using mode isolation-convolutional deep belief networks	35
4.1	Introduction	35
4.2	Preliminary	37
4.2.1	Sparse filtering	37
4.2.2	Traditional CDBN	39
4.3	The Proposed method	39
4.3.1	General procedure of the proposed method	39
4.3.2	Mode isolation-convolutional deep belief network	41
4.4	Experimental verification and analysis	46
4.4.1	Data description	46
4.4.2	Fault diagnosis by the proposed method	47

4.4.3	Parameter analysis	49
4.4.4	Performance evaluation and comparison	50
4.5	Conclusion	55
5	Intelligent fault diagnosis using an optimized convolutional deep belief network	56
5.1	Introduction	56
5.2	Preliminary	58
5.2.1	Probabilistic out	58
5.3	The proposed method	59
5.3.1	Optimized convolutional deep belief network	59
5.3.2	General procedure of the proposed method	61
5.4	Experimental verification and analysis	62
5.4.1	Data description	62
5.4.2	Fault diagnosis by the proposed method	62
5.4.3	Parameter analysis	65
5.4.4	Method comparison and performance evaluation	67
5.5	Conclusions	68
6	Intelligent fault diagnosis using a novel ensemble empirical mode decomposition-convolutional deep belief network	70
6.1	Introduction	70
6.2	Proposed method	72
6.2.1	General framework	72

6.2.2	Ensemble empirical mode decomposition-convolutional deep belief network	73
6.2.3	Probabilistic committee machine	76
6.3	Experimental verification and analysis	78
6.3.1	Data description	78
6.3.2	Feature learning by the EEMD-CDBN	81
6.4	Evaluation of the proposed method	84
6.4.1	Comparison of denoising methods	84
6.4.2	Comparison of deep learning methods	85
6.4.3	Effectiveness of the PCM	86
6.5	Conclusion	86
7	Conclusion and future work	91
7.1	Conclusion	91
7.2	Future work	92
	Bibliography	94

List of Figures

2.1	Convolution of CDBN	11
2.2	Operation of CDBN	12
3.1	Schematic of the proposed method	21
3.2	The DBN structure	24
3.3	Schematic of RC structure	27
3.4	Faults of RC	28
3.5	EMD results	30
3.6	DBN feature visualization	32
3.7	Confusion matrix	33
3.8	The relationship between output dimension and accuracy	34
4.1	Framework of the proposed method	40
4.2	Diagram of transfer path on the RC	41
4.3	The relationship among fault excitation, transfer paths and acquired data	42
4.4	Raw signals and compressed signals via sparse filtering	47
4.5	Isolated mode data	48
4.6	Features calculated by MI-CDBN	50
4.7	The accuracy of fault diagnosis	51

4.8	Fault diagnosis performance with various compressed data lengths . . .	52
4.9	Accuracy of fault diagnosis with various α	52
5.1	Framework of the proposed method	60
5.2	(a)Raw signals, and (b)compressed signals	63
5.3	Principal components of unsupervised feature	64
5.4	Confusion matrix of diagnosis accuracy	65
5.5	Comparison of generalization error	66
5.6	The relationship between generalization error and λ	67
5.7	The relationship between the accuracy and \hat{p}_0	68
6.1	Framework of the proposed method	72
6.2	Schematic of the EEMD-CDBN method	73
6.3	Probabilistic committee machine	74
6.4	Schematic diagram of the RC and the sensor layout on a cross-section	79
6.5	Locations of Sensors	80
6.6	Examples of raw signals: (a) displacement of piston rod, (b) vibration of cylinder, (c) vibration of crankcase.	81
6.7	The EEMD of cylinder signal	88
6.8	The EEMD of crankcase signal	88
6.9	Cylinder signal denoising	89
6.10	Crankcase signal denoising	89
6.11	Confusion matrix	90

List of Tables

3.1	Extracted features	23
3.2	Date description	29
3.3	Parameter setting of the DBN	31
3.4	Method evaluation	34
4.1	Parameter setting of the MI-CDBN	49
4.2	Comparison of data compression methods	51
4.3	Comparison of deep learning methods	53
4.4	Comparison of the state-of-the-art methods	54
5.1	Comparison of pooling methods	67
6.1	Parameters of the EEMD-CDBN	83
6.2	Comparison of denoising methods	83
6.3	Comparison of deep learning methods	84
6.4	Comparison with the PCM-based and conventional methods	84

Abbreviation

RC - Reciprocating Compressor

EMD - Empirical Mode Decomposition

IMF - Intrinsic mode function

PCA - Principal Component Analysis

KPCA - Kernel Principal Component Analysis

DBN - Deep Belief Network

GM - Grassmann manifolds

RBM - Restricted Boltzmann Machines

SVD - Singular Value Decomposition

SVM - Support Vector Machine

TD - Time-domain

FD - Frequency-domain

CNN - Convolutional Neural Network

CDBN - Convolutional Deep Belief Network

LDA - Latent Dirichlet allocation

AE - Auto Encode

CS - Compressed Sensing

SF - Sparse Filtering

CRBM - Convolutional Restricted Boltzmann Machine

ANN - Artificial Neural Network

EEMD - Ensemble Empirical Mode Decomposition

CC - Correlation Coefficient

WT - Wavelet Transforms

PCM - Probabilistic Committee Machine

GPC - Gaussian Process Classifier

EM - Expectation Maximization

MI - Mode isolation

GMM - Gaussian mixture model

p-V - Pressure-volume