DEVELOPMENT OF MULTI-FAULT DIAGNOSIS STRATEGIES FOR ROTATING MACHINES

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Development of Multi-fault Diagnosis Strategies for Rotating Machines

by

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Dedicated to My Family and Advisors

Certificate

This is to certify that the thesis entitled **"Development of Multi-fault Diagnosis Strategies for Rotating Machines"**, submitted by **Mr. Rismaya Kumar Mishra** to the Indian Institute of Technology Delhi, for the award of the degree of **Doctor of Philosophy**, is a record of the original, bonafide research work carried out by him under our supervision and guidance. The thesis has reached the standards, fulfilling the requirements of the regulations related to the award of the degree. The results contained in this thesis have not been submitted in part or in full to any other university or institute for the award of any degree or diploma to the best of our knowledge.

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Abstract

Rotating machines are the backbone of industries which deteriorate during operation. It leads to production loss, downtime, supply chain disruption, etc. To mitigate these problems, different maintenance strategies have been used, among which predictive maintenance provides the most effective solution. It involves continuous monitoring of rotating components and detecting incipient faults through data-driven approaches like signal processing and Machine Learning (ML). The signal processing approach involves experts' intervention for fault identification. In the Industrial Revolution 4.0, smart factories are designed by automating the machines. Human intervention causes delays during the fault diagnosis in such applications. Therefore, ML-based solutions are adopted rapidly, which gives accurate and real time decisions by mitigating human errors.

The fault diagnosis of rotating machines is a challenging task. In this work, three major problems are identified. It is found that most of the research on rotating machine diagnosis is done by considering single faults. But, the occurrence of a single fault is not a likely scenario in the industrial environment. A fault generated in one component of a system propagates to another, as components are interconnected. So, the strategy developed for single-fault diagnosis cannot detect multi-faults. There is a need for developing methods for multi-fault diagnosis. Besides that, the fault information of all components is not identified by all the sensors. So, when a different type of component is involved, various sensor modalities are used to identify the faults. A strategy developed by considering one sensor modality does not perform efficiently with another. Therefore, there is a need to find a generalised solution that can work with the data of any sensor modality. Lastly, methodologies that are developed under constant speed conditions, are not practical, and do not perform well under speed fluctuation. So, a method that can work in any speed conditions needs to be developed.

To tackle these issues, an effort is made in this work to develop a robust diagnosis strategy for bearing, motor, mechanical unbalance and shaft misalignment multi-fault that is compatible with different sensor modalities and can perform irrespective of speed conditions. Initially, the multi-fault diagnosis of a single component is carried out on a bearing test rig using signal decomposition methods. Moreover, the focus is given to select the best domain for multi-fault diagnosis. This work also involves the analysis of a

streamlined approach that gives efficient results with less computational time. Thereafter, the number of components is increased, and a system-level analysis having different faulty components is diagnosed on another test rig. The work involves the sensitivity analysis of different sensor modalities such as vibration, acoustic and current for multi-fault diagnosis. Eventually, a strategy for a generalised strategy is tested that can perform with the balanced or imbalanced data of different sensor modalities.

Further, to deal with the problem of speed fluctuation, a multi-fault diagnosis strategy is analysed, where an extensive evaluation is done with different speed profiles like constantly accelerated, constantly decelerated, speed fluctuation, speed variation with different ramp rates, etc. In the last section of this work, a robust strategy is developed by implementing a sensor fusion-based multi-fault diagnosis approach. The developed strategy not only gives decisions by considering the information of different sensor modalities but also works in any speed conditions. The strategy will be helpful in diagnosing multi-faults efficiently in different industrial machines and can be used for maintenance planning.

सार

घूर्णन यन्त्र उद्योगों की रीढ़ हैं जो संचालन के दौरान खराब हो जाती हैं। इससे उत्पादन में कमी, आपूर्ति श्रृंखला में व्यवधान और उद्योगों बंद आदि होता है। इन समस्याओं को कम करने के लिए, विभिन्न रखरखाव रणनीतियों का उपयोग किया गया है, जिनमें से पूर्वानुमानित रखरखाव सबसे प्रभावी समाधान प्रदान करता है। इसमें घूर्णन यंत्रो की निरंतर निगरानी और संकेत परिवीक्षण और मशीन लर्निंग (एमएल) जैसे विवरण-संचालित तरीकों के माध्यम से शुरुआती दोषों का पता लगाना शामिल है। संकेत परिवीक्षण दृष्टिकोण में दोष पहचान के लिए विशेषज्ञों का हस्तक्षेप शामिल है। औद्योगिक क्रांति 4.0 में, यंत्रो को स्वचालित करके बुद्धिमान कारखानों को निर्माण किया गया है। मानवीय हस्तक्षेप ऐसे अनुप्रयोगों में दोष निदान के दौरान देरी का कारण बनता है। इसलिए, एमएल-आधारित समाधान तेजी से अपनाए जाते हैं, जो मानवीय त्रुटियों को त्यागकर सटीक और वास्तविक समय में निर्णय देते हैं।

घूर्णन यंत्रो की दोष निदान एक चुनौतीपूर्ण कार्य है। इस कार्य में, तीन प्रमुख समस्याओं की पहचान की गई है। यह पाया गया है कि घूर्णन यंत्रो की दोष निदान पर अधिकांश शोध एकल दोषों पर विचार करके किया जाता है। लेकिन, औद्योगिक वातावरण में एकल दोष की घटना एक संभावित परिदृश्य नहीं है। यन्त्र के एक घटक में उत्पन्न दोष दूसरे तक फैलता है, क्योंकि घटक आपस में जुड़े होते हैं। इसलिए, एकल-दोष निदान के लिए विकसित रणनीति बहु-दोषों का पता नहीं लगा सकती है। बहु-दोष निदान के लिए तरीके विकसित करने की आवश्यकता है। इसके अलावा, सभी घटकों की दोष जानकारी सभी संवेदी उपकरण द्वारा पहचानी नहीं जाती है। इसलिए, जब एक अलग प्रकार का घटक शामिल होता है, तो दोषों की पहचान करने के लिए विभिन्न संवेदी उपकरण तौर-तरीकों का उपयोग किया जाता है। एक संवेदी उपकरण तौर-तरीके पर विचार करके विकसित की गई रणनीति दूसरे के साथ कुशलता से काम नहीं करती है। इसलिए, एक सामान्यीकृत समाधान खोजने की आवश्यकता है जो किसी भी संवेदी उपकरण तौर-तरीके के विवरण के साथ काम कर सके। अंत में, स्थिर गति की स्थितियों के तहत विकसित की गई पद्धतियां व्यावहारिक नहीं हैं, और गति में उतार-चढ़ाव के तहत अच्छा प्रदर्शन नहीं करती हैं। इसलिए, एक ऐसी विधि विकसित करने की आवश्यकता है जो किसी भी गति की स्थिति में काम कर सके।

इन मुद्दों से निपटने के लिए, इस कार्य में बेयरिंग, मोटर, यांत्रिक असंतुलन और शाफ्ट मिसलिग्न्मेंट बहु दोष के लिए एक मजबूत निदान रणनीति विकसित करने का प्रयास किया गया है जो विभिन्न संवेदी उपकरण तौर-तरीकों के अनुकूल है और गति की उतार चढ़ाव स्थिति के बावजूद प्रदर्शन कर सकता है। प्रारंभ में, संकेत अपघटन विधियों का उपयोग करके बेयरिंग परीक्षण रिग पर एकल घटक का बहु दोष निदान किया गया है। इसके अलावा, बहु दोष निदान के लिए सर्वोत्तम डोमेन का चयन करने पर ध्यान दिया जाता है। इस कार्य में एक सुव्यवस्थित दृष्टिकोण का विश्लेषण भी शामिल है जो कम अभिकलनात्मक समय के साथ कुशल परिणाम देता है। इसके बाद, घटकों की संख्या में वृद्धि की जाती है, और विभिन्न दोषपूर्ण घटकों वाले सिस्टम-स्तरीय विश्लेषण का निदान दूसरे परीक्षण रिग पर किया गया है।

इसके अलावा, गति में उतार-चढ़ाव की समस्या से निपटने के लिए, एक बहु दोष निदान रणनीति का विश्लेषण किया गया है, जहाँ विभिन्न गति जैसे लगातार त्वरित, लगातार मंद, गति में उतार-चढ़ाव, विभिन्न रैंप दरों के साथ गति भिन्नता आदि के साथ व्यापक मूल्यांकन किया गया है। इस कार्य के अंतिम भाग में, संवेदी उपकरण संलयन-आधारित बहु दोष निदान दृष्टिकोण को लागू करके एक मजबूत रणनीति विकसित की गई है। विकसित रणनीति न केवल विभिन्न संवेदी उपकरण तौर-तरीकों की जानकारी पर विचार करके निर्णय देती है, बल्कि किसी भी गति की स्थिति में भी काम करती है। यह रणनीति विभिन्न औद्योगिक यंत्रो में बहु दोष का कुशलतापूर्वक निदान करने में सहायक होगी और इसका उपयोग रखरखाव योजना के लिए किया जा सकता है।

Contents

List of Figures

List of Tables

Abbreviations

ADC	Analog to Digital Convertor
AE	Acoustic Emission
AI	Artificial Intelligence
AM	Angular Misalignment
ANN	Artificial Neural Network
BD	Ball Defect
BRB	Broken Rotor Bar
CBD	Combined Bearing Defect
CD	Cage Defect
CLM	Component-Level Multi-fault
CNN	Convolutional Neural Network
CWT	Continuous Wavelet Transform
DAQ	Data Acquisition System
DBCNN	Dual Branch Convolutional Neural Network
DCNN	Deep Convolution Neural Network
DT	Decision Tree
DWT	Discrete Wavelet Transform
ELM	Element Level Multi-fault
EMD	Empirical Mode Decomposition
FB	Faulty Bearing
FM	Faulty Motor
FMB	Faulty Motor with Bearing Defect
FMR	Faulty Motor with Broken Rotor Bar
FSST	Fourier Synchrosqueezing Transform
HB	Healthy Bearing
HM	Healthy Motor
HML	Horizontal Misalignment
HT	Hilbert Transform
IEEE	Institute of Electrical and Electronics Engineers
IF	Instantaneous Frequency
IR	Inner Race

IRT	Infrared Thermography
kNN	k-Nearest Neighbour
LSTM	Long Short-Term Memory
MCSA	Motor Current Signature Analysis
MF	Multi-fault
MFS	Machinery Fault Simulator
MIS	Misalignment
ML	Machine Learning
MM	Mixed Multi-fault
NI	National Instruments
OR	Outer Race
OEM	Original Equipment Manufacturer
PM	Parallel Misalignment
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analysis
RBF	Radial Basis Function
RD	Roller Defect
RF	Random Forest
SLM	System-Level Multi-fault
ST	Synchrosqueezing Transform
STFT	Short Time Fourier Transform
SVM	Support Vector Machine
TF	Time-frequency
UNB	Unbalance
VA	Vibration Analysis
VML	Vertical Misalignment
WASIF	Wavelet Assisted Stacked Image Fusion
WT	Wavelet Transform
WSST	Wavelet Synchrosqueezing Transform
WVD	Wigner Ville Distribution

Symbols

a	Position parameter
a_p	Percentage overlapping
$a(t)$	Instantaneous amplitude
$A_m(t)$	Approximation coefficients
b	Scale parameter
D_c	Input signal column dimension
$D_m(t)$	Detailed coefficients
D_R	Input signal row dimension
F_c	Filter column dimension
F_s	Sampling rate
F_R	Filter row dimension
$g(n)$	Wavelet filter
H	Hilbert transform
$h(f)$	Hilbert envelope spectrum
$h(n)$	Scaling filter
j	Constant
k	Constant
l	Sample length
M	Number of segments
m	Window size
n	Constant
N_c	Segment generation in column shifting
N_l	Length of signal
N_R	Segment generation in row shifting
N_T	Total number of segments generated
$P_{j,k}(t)$	Scaling function
r	Reset value
S'	Normalised value
S_a	Sigmoid activation function
S_c	Column shifting value
$S_{j,k}(t)$	Wavelet function

S_{max}	Maximum value
S_{min}	Minimum value
S_R	Row shifting value
S_v	Value to be normalised
t	Time parameter
T	Maximum iteration
T_a	tanh activation function
$x(t)$	Input signal
$z(t)$	Analytic signal
θ	Instantaneous phase
ε	Constant
τ	Translation parameters
ω	Frequency value