

# **SOME ASPECTS OF CONDITION MONITORING OF TRANSFORMER AND WIND ENERGY CONVERSION SYSTEM (WECS)**

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**SOME ASPECTS OF CONDITION MONITORING  
OF TRANSFORMER AND WIND ENERGY  
CONVERSION SYSTEM (WECS)**

by

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**Submitted**

**in fulfilment of the requirements of the degree of Doctor of Philosophy**

**to the**



**INDIAN INSTITUTE OF TECHNOLOGY DELHI**  
**OCTOBER 2018**

*Dedicated to*  
*My Parents, Daughters & Wife*

## **CERTIFICATE**

This is to certify that the thesis entitled, “**Some Aspects of Condition Monitoring of Transformer and Wind Energy Conversion System (WECS)**” being submitted by **Mr. Hasmat** for the award of the degree of **Doctor of Philosophy** is a record of bonafide research work carried out by him in the Department of Electrical Engineering of Indian Institute of Technology Delhi.

Mr. Hasmat has worked under my guidance and supervision and has fulfilled the requirements for the submission of this thesis, which to our knowledge has reached the requisite standard. The results obtained herein have not been submitted to any other University or Institute for the award of any degree.

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# ABSTRACT

The research work presented in this thesis discusses various complex issues associated with condition monitoring of wind energy conversion system (WECS). The aim of this dissertation research is to develop nonintrusive condition monitoring and fault detection (CMFD) approaches for WECS. In this thesis, four different key components of WECS have been used for condition monitoring and fault diagnosis purpose which are the key element in the WECS: 1) Condition monitoring of wind turbine generating system (WTGS), 2) Condition monitoring of gearbox, 3) Condition monitoring of bearing and 4) Condition monitoring of step-up transformer used for grid integration.

Generally, WTGS is under downtime condition for 3 to 10 days/year due to the components failures, which can be accounted to yaw system failure, structure failure, hydraulic and brakes failure, gearbox failure, sensors failure, drive train failure, control system failure, electric system failure, generator failure, blades/hub/pitch failure, and other failure. The failure due to imbalance indifferent mechanical structure also creates major faults in WTGS. The imbalance faults in blades, shaft, furl and aerodynamic asymmetry are the common imbalance faults in WTGS. The proposed approach uses only PMSG (permanent magnet synchronous generator) current signatures that have already been utilized by the protection and control system of WTGS, no additional mechanical sensors are required. However, there are challenges in using current measurements for CMFD of WTGS. First, it is a challenge to extract WTGS fault signatures from non-stationary current measurements, due to the variable-speed operating conditions of WTGS. Moreover, the useful information in current measurements for CMFD of WTGS usually has a low signal to noise ratio, which makes the CMFD difficult. For this, EMD



(empirical mode decomposition) and wavelet transform based on an appropriate signal processing technique have been proposed. Second, it is a challenge to select the most relevant input variables to the classifier for CMFD of WTGS. For this, the J48 algorithm and PCA algorithm based an appropriate feature selection technique have been proposed. The third, it is a challenge to find out the suitable technique for imbalance fault classification of WTGS. For this, a comparative study of six different artificial intelligence (AI) techniques (i.e., MLP, SVM, PSVM, ELM, GEP and MFQL) has been proposed to find out the suitable AI approach for CMFD of WTGS.

Gearbox is used in the WECS to enhance the rotation speed of the main shaft connected with the generator which is used to generate the electrical power if the generator is not a PMSG. Therefore, condition monitoring of gearbox has become more important for proper functioning of WECS. An unexpected fault of the gearbox may cause huge economic losses, even personal injury. So, probably failure diagnosis is an important process in the preventive maintenance of gearbox which avoids serious damage if defects occur in one of the gears during operation condition. Therefore, for early detection of the defects, AI-based an approach for gearbox fault diagnosis has been proposed in this dissertation by using vibration signals. The proposed approach overcomes the problems of feature extraction, feature selection and accuracy of fault diagnosis in the area of CMFD of the gearbox.

There are various places in WECS where bearings are utilized such as in main shafts, yaw drive, pitch bearings, generators, and gearboxes (if used). Bearing failure may occur due to defects in its inner race, outer race or the rolling elements. To prevent such breakdown, an advance condition monitoring system has been proposed in this dissertation for CMFD of WECS. To carry out the monitoring, the feature extraction, attribute selection and fault classification techniques are proposed for the CMFD of bearing.

Each WTGS in a WECS is equipped with a step-up transformer, which steps up turbine generator output voltage from a few hundred volts to the collector system's medium voltage distribution levels. These wind turbine step-up transformers are failing at an alarming rate and developers and operators of utility-scale wind farm projects are scrambling to identify the most likely causes for this widespread failure. Therefore, an accurate fault diagnosis is important in transformers for ensuring quality power supply with minimum disturbances of WECS. The dissolved gas analysis (DGA) has been widely used as a tool for transformer fault condition interpretation but it required personal experiences than mathematical modelling. Therefore, in this dissertation, an AI-based CMFD approach has been proposed to overcome the problem of conventional DGA interpretation, as well as proposed approach, solves the problem of selection of most relevant attributes, which are used as an input variable to the six different AI approaches.

The proposed approaches have extensively been tested on computer simulations and experiments for a PMSG based WTGS, gearbox, bearings and step-up transformer used in WECS and detailed discussions on each case study results have been presented. The results on test systems (i.e., direct-drive WTGS, gearbox, bearing and transformer) illustrate the effectiveness of the proposed approaches and provide insights into the nature of the problem.

## सार

अनुसंधान इस शोध में प्रस्तुत काम विभिन्न जटिल पवन ऊर्जा रूपांतरण प्रणाली (WECS) की स्थिति निगरानी के साथ जुड़े मुद्दों पर चर्चा की। इस शोध प्रबंध अनुसंधान के उद्देश्य nonintrusive स्थिति निगरानी और गलती का पता लगाना (CMFD) विकसित करने के लिए WECS.In इस शोध के लिए दृष्टिकोण है, 1) पवन टरबाइन उत्पादन प्रणाली की दशा की निगरानी (WTGS), 2) गियरबॉक्स की दशा की निगरानी, 3) की दशा की निगरानी: चार WECS के विभिन्न प्रमुख घटक स्थिति निगरानी और गलती निदान जिस उद्देश्य के WECS में प्रमुख तत्व हैं के लिए इस्तेमाल किया गया है असर और 4) स्टेप-अप ग्रिड एकीकरण के लिए इस्तेमाल किया ट्रांसफार्मर की दशा की निगरानी।

आम तौर पर, WTGS घटक विफलताओं, जो प्रणाली की विफलता, संरचना विफलता, हाइड्रोलिक ब्रेक और विफलता, गियरबॉक्स विफलता, सेंसर की विफलता, ड्राइव ट्रेन की विफलता, नियंत्रण प्रणाली की विफलता रास्ते से हटना करने हिसाब किया जा सकता है की वजह से 3 से 10 दिनों के लिए / वर्ष डाउनटाइम शर्त के तहत है, बिजली प्रणाली की विफलता, जनरेटर विफलता, ब्लेड / हब / पिच विफलता, और अन्य विफलता। असंतुलन उदासीन यांत्रिक संरचना की वजह से विफलता भी WTGS में प्रमुख दोष पैदा करता है। ब्लेड में असंतुलन दोष, शाफ्ट, मोड़ना और वायुगतिकीय विषमता आम असंतुलन हैं WTGS में दोष। प्रस्तावित दृष्टिकोण केवल PMSG (स्थायी चुंबक तुल्यकालिक जनरेटर) का उपयोग करता है वर्तमान हस्ताक्षर कि पहले से ही WTGS के संरक्षण और नियंत्रण प्रणाली द्वारा उपयोग किया गया है, बिना किसी अतिरिक्त यांत्रिक सेंसर की आवश्यकता है। हालांकि, वहाँ cMFD के लिए वर्तमान माप का उपयोग करने में चुनौतियां हैं की WTGS। सबसे पहले, यह चर गति ओपेरा की वजह से, गैर स्थिर वर्तमान माप से WTGS गलती हस्ताक्षर निकालने के लिए एक चुनौती है WTGS की टिंग की स्थिति। इसके अलावा, WTGS की CMFD के लिए वर्तमान माप में उपयोगी जानकारी आमतौर पर शोर अनुपात, जो CMFD कठिन बना देता है के लिए एक कम संकेत है। इस के लिए, ईएमडी (अनुभवजन्य मोड अपघटन) और एक उचित सिग्नल प्रोसेसिंग के आधार पर बदलने तरंगिका तकनीक प्रस्तावित किया गया है। दूसरा, यह WTGS की cMFD के लिए वर्गीकारक लिए सबसे अधिक प्रासंगिक इनपुट चर का चयन करने के लिए एक चुनौती है। इस के लिए, J48 एल्गोरिथ्म और पीसीए एल्गोरिथ्म आधारित कोई उचित विशेषता चयन तकनीक प्रस्तावित किया गया है। तीसरा, यह है एक चुनौती WTGS के असंतुलन गलती वर्गीकरण के लिए उपयुक्त तकनीक पता लगाने के लिए। इस के लिए, छह अलग कृत्रिम बुद्धि (AI) तकनीक (यानी, MLP, SVM, PSVM, एल्म, GEP और MFQL) का एक तुलनात्मक अध्ययन को खोजने के लिए प्रस्तावित किया गया है बाहर WTGS की cMFD के लिए उपयुक्त ऐ दृष्टिकोण।

गियरबॉक्स जनरेटर जो बिजली उत्पन्न करने के लिए करता है, तो जनरेटर एक PMSG नहीं है प्रयोग किया जाता है के साथ जुड़ा हुआ मुख्य शाफ्ट की घूर्णन गति को बढ़ाने के लिए WECS में प्रयोग किया जाता है। इसलिए, गियरबॉक्स की स्थिति निगरानी WECS के समुचित कार्य के लिए और अधिक महत्वपूर्ण हो गया है। गियरबॉक्स की एक अनपेक्षित गलती का कारण हो सकता बड़ा आर्थिक नुकसान, यहां तक कि व्यक्तिगत चोट। तो, शायद विफलता निदान जो गंभीर क्षति से बचा जाता है, तो दोष आपरेशन हालत दौरान गियर में से एक में होते हैं गियरबॉक्स की निवारक अनुरक्षण में एक महत्वपूर्ण प्रक्रिया है। इसलिए, दोष का जल्दी पता लगाने के लिए, ऐ आधारित गियरबॉक्स गलती निदान के लिए एक दृष्टिकोण कंपनी संकेतों का उपयोग करके इस शोध प्रबंध में प्रस्तावित किया गया है। प्रस्तावित दृष्टिकोण की cMFD के क्षेत्र में सुविधा निष्कर्षण, सुविधा चयन और गलती निदान की सटीकता की समस्याओं पर काबू पा गियरबॉक्स।

जहां बीयरिंग मुख्य शाफ्ट, विचलन ड्राइव, पिच बेयरिंग, जनरेटर में के रूप में ऐसी उपयोग किया जाता है WECS में विभिन्न स्थानों, और गियरबॉक्स (यदि प्रयोग किया जाता) कर रहे हैं। इसके भीतरी दौड़ में दोष, बाहरी जाति या रोलिंग तत्वों की वजह से असर विफलता हो सकती है। इस तरह के टूटने को रोकने के लिए एक अग्रिम हालत निगरानी प्रणाली WECS की cMFD के लिए इस शोध प्रबंध में प्रस्तावित किया गया है।, निगरानी, सुविधा निष्कर्षण बाहर ले जाने का श्रेय चयन और गलती वर्गीकरण तकनीक असर की cMFD के लिए प्रस्तावित कर रहे हैं करने के लिए।

एक WECS में प्रत्येक WTGS एक स्टेप-अप ट्रांसफार्मर, जो कलेक्टर सिस्टम के मध्यम वोल्टेज वितरण के स्तर के लिए कुछ सौ वोल्ट से टरबाइन जनरेटर उत्पादन वोल्टेज कदम के साथ सुसज्जित है। ये पवन टरबाइन स्टेप-अप ट्रांसफार्मर एक चौंकाने वाली दर और डेवलपर्स पर असफल रहे हैं और उपयोगिता पैमाने पर पवन खेत परियोजनाओं के ऑपरेटर्स इस व्यापक विफलता का सर्वाधिक संभावित कारणों की पहचान के लिए पांव मार रहे हैं। इसलिए, एक सटीक गलती निदान WECS की न्यूनतम गड़बड़ी के साथ गुणवत्ता बिजली की आपूर्ति सुनिश्चित करने के लिए ट्रांसफार्मर में महत्वपूर्ण है। भंग गैस विश्लेषण (DGA) व्यापक रूप से ट्रांसफार्मर गलती हालत व्याख्या के लिए एक उपकरण के रूप में इस्तेमाल किया गया है, लेकिन यह गणितीय मॉडलिंग से निजी अनुभवों की आवश्यकता है। इसलिए, इस शोध प्रबंध में, एक ऐ आधारित cMFD दृष्टिकोण पारंपरिक डीजीए व्याख्या की समस्या है, साथ ही प्रस्तावित दृष्टिकोण से उबरने के लिए प्रस्तावित किया गया है, सबसे अधिक प्रासंगिक गुण है, जो छह के लिए एक इनपुट चर के रूप में उपयोग किया जाता है के चयन की समस्या का हल विभिन्न ऐ दृष्टिकोण।

प्रस्तावित दृष्टिकोण बड़े पैमाने पर कंप्यूटर पर परीक्षण किया गया है simulati

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## List of Symbols

$Q$	Reactive Power
$P$	Active Power
$R_{ext}$	variable resistance
$CO_2$	Carbon Dioxide,
$CO$	Carbon Monoxide
$CH_4$	Methane
$C_2H_2$	Acetylene
$C_2H_6$	Ethane
$H_2$	Hydrogen
$C_2H_4$	Ethylene
$O_2$	Oxygen
$N_2$	Nitrogen
$^{\circ}C$	Degree Centigrade
$rad/s$	Speed
$Watt - w$	Power
Nm	Torque
$Pe$	Electric Power
$Te$	Electric Torque
$W$	Rotating Speed
$y(t)$	Time Domain Signal
$E$	Energy
$\tau$	Error Penalty
$w$	Weight And Bias
$(\tau)$	Learning Rate
$(b)$	Bias
$e_m(t)$	Upper Envelope



$e_i(t)$	Lower Envelope
(%)	Percent
$e$	mse Error
$t$	Temperature
$D1$ and $D2$	Energy Discharge of low and high energy
$T1-T3$	Thermal Faults
$f_1$	Thermal Fault (<150°C)
$f_2$	Thermal Fault (150-300°C)
$f_3$	Thermal Fault (300-700°C)
$f_4$	Thermal Fault (>700°C)
$f_5$	Partial Discharge (PD) of low energy (LE) (PD1)
$f_6$	PD of high energy (HE) (PD2)
$f_7$	LE discharge (D1)
$f_8$	HE discharge (D2)
( $s$ )	Processing time

# Acronyms

<b>ACI</b>	American Concrete Institute
<b>ADAMS</b>	Automatic Dynamic Analysis of Mechanical Systems
<b>AdjBIMs</b>	Blade imbalance
<b>AI</b>	Artificial Intelligence
<b>ANN</b>	Artificial Neural Network
<b>ASME</b>	The American Society Of Mechanical Engineers
<b>ASTM</b>	The American Society Testing And Materials
<b>AWEA</b>	American Wind Energy Association
<b>BDFIG</b>	Brushless Doubly Fed Induction Generator
<b>bior</b>	Bi-orthogonal wavelets
<b>BPitch</b>	Aerodynamic asymmetry
<b>BS</b>	British Standards
<b>BS</b>	British Standard
<b>CCA</b>	Canonical Correlation Analysis
<b>CCP</b>	Common Coupling Point
<b>CI</b>	Computational Intelligence
<b>CM</b>	Condition Monitoring
<b>CMFD</b>	Condition Monitoring and Fault Diagnosis
<b>coif1</b>	Coiflets wavelets
<b>CS</b>	Cognitive System
<b>CSA</b>	Canadian Standard
<b>CW</b>	Control Winding
<b>db</b>	Daubechies wavelets
<b>DEL</b>	Damage Equivalent Load
<b>DFIG</b>	Doubly Fed Induction Generator
<b>DGA</b>	Dissolved Gas Analysis
<b>dmey</b>	Discrete approximation of Meyer wavelet
<b>DNV-GL</b>	Det-Norske Varitas-Germanischer Lloyd
<b>DOFs</b>	Degrees of Freedom

<b>DT</b>	Decision tree
<b>ELM</b>	Extreme Learning Machine
<b>EMD</b>	Empirical Mode Decomposition
<b>ET</b>	Expression Tree
<b>FAST</b>	Fatigue, Aerodynamic, Structure, Turbulence
<b>FB</b>	Frequency Band
<b>FFT</b>	Fourier transform
<b>FIST</b>	Facilities Instructions, Standards, and Techniques
<b>FQL</b>	Fuzzy Q Learning
<b>GA</b>	Genetic Algorithm
<b>gaus</b>	Gaussian wavelets
<b>GEP</b>	Gene Expression Programming
<b>GP</b>	Genetic Programming
<b>haar</b>	Haar wavelet
<b>HAWT</b>	Horizontal Axis Wind Turbine
<b>HVG</b>	High Voltage Generator
<b>IEC</b>	International Electrotechnical Commission
<b>IEEE</b>	Institute of Electrical And Electronics Engineers
<b>IG</b>	Induction Generators
<b>IM</b>	Iterative Method
<b>IMF</b>	Intrinsic Mode Function
<b>IMS</b>	Intelligent Maintenance System
<b>IS</b>	Indian Standard
<b>ISO</b>	International Organization For Standardization
<b>J48</b>	Java implementation of the C4.5 decision tree algorithm
<b>LSC</b>	Load-Side Converter
<b>MCSA</b>	Machine Current Signature Analysis
<b>MD</b>	Mass Density
<b>mexh</b>	Mexican hat wavelet
<b>meyr</b>	Meyer wavelet
<b>MFQL</b>	Modified Fuzzy Q Learning

<b>morl</b>	Morlet wavelet
<b>MSC</b>	Machine-Side Converter
<b>MW</b>	Mega Watt
<b>NACU</b>	National Association of Cement Users
<b>NacYaw</b>	Control errors of yaw system
<b>NF</b>	No fault
<b>NN</b>	Neural Network
<b>NREL</b>	National Renewable Energy Laboratory
<b>NTM</b>	Normal Turbulence Models
<b>OM</b>	Orthogonalization Method
<b>OPM</b>	Orthogonal Projection Methods
<b>OSIG</b>	OptiSlip Induction Generator
<b>PCA</b>	Principle Component Analysis
<b>PMIG</b>	Permanent Magnet Induction Generator
<b>PMSG</b>	Permanent-Magnet Synchronous Generator
<b>PNN</b>	Probabilistic-NN
<b>PSD</b>	Power spectral density
<b>PSVM</b>	Proximal Support Vector Machine
<b>PW</b>	Power Winding
<b>rbio</b>	Reversed Bi-orthogonal wavelets
<b>RMS</b>	Root Mean Squared
<b>ROC</b>	
<b>RotFurl</b>	Rotor furl imbalance
<b>RSC</b>	The Rotor-Side Converter
<b>SCIG</b>	Squirrel Cage Induction Generator
<b>SFRA</b>	Sweep Frequency Response Analysis
<b>SG</b>	Synchronous Generator
<b>SNR</b>	signal to Noise Ratio
<b>SRB</b>	Spherical-Roller Bearings
<b>SRG</b>	Switched Reluctance Generator
<b>STD</b>	Standard Deviation

<b>STFT</b>	Short-Time Fourier Transform
<b>SVD</b>	Singular Value Decomposition
<b>SVM</b>	Support Vector Machine
<b>sym</b>	Symlets wavelets
<b>TailFurl</b>	Tail furl imbalance
<b>TFG</b>	Transverse Flux Generator
<b>TRB</b>	Tapered Roller Bearing
<b>UL</b>	American safety consulting and certification company
<b>VA</b>	Apparent Power
<b>VAWT</b>	Vertical Axis Wind Turbine
<b>WECS</b>	Wind Energy Conversion System
<b>WEKA</b>	Waikato Environment for Knowledge Analysis
<b>WRIG</b>	Wound Rotor Induction Generator
<b>WRSG</b>	Wound-Rotor Synchronous Generator