IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

Impact Factor: 7.301

Volume 3, Issue 1, September 2023

Emerging a Novel Approach for Fault Diagnosis and Detection in Power Systems using Machine Learning Techniques -a Review Paper

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Abstract: *Condition monitoring and fault diagnosis plays a vital role in extending the lifespan of any equipment. Diagnosing faults at right time is crucial in life saving appliances and applications. Fault diagnosis for any equipment or system involves handling of large voluminous data, which is far beyond human computing capability. So deploying automatic fault diagnosis approaches would be an intelligent solution that has opened the gates for Artificial Intelligence (AI), Data Mining and Machine Learning algorithms. This work reviews the Machine Learning based fault diagnosis algorithms and models in detecting bearings, pumps and power transformer faults. A performance comparison of the models is presented based on their accuracy of fault diagnosis. This analysis also critiques the models with possible scope for improvement. The inferences from the analysis limelight the need for development of Extreme Learning (EL) models that are less dependent on explicit feature sel.*

Keywords: Bearings, Condition Monitoring (CM), Fault Diagnosis, Machine Learning, Power Transformers, Pumps

I. INTRODUCTION

Fault diagnosis is a generic term that explains the process of finding the deviation of any system or a component of a system from its normal operational profile. A comprehensive Condition Monitoring (CM) is continuous surveillance of the system which involves sequence of activities such as system monitoring, fault detection, fault diagnostics and fault prognostics. The condition monitoring of the equipment is performed quantitatively by assessing some of the critical variables. When the variables being monitored and observed values are abnormal, then it is an indication of occurrence of fault in the machinery which can be termed as fault detection. When a fault is detected, a diagnostic module is immediately activated so as to identify and characterize the fault. It is vital to characterize the fault because each fault will contribute to the failure of the system in its own unique way. After identifying the potential fault, the prognostic model will predict the probability of failure distribution from the current and past environmental and usage, conditions, past and current operational sensor data, and historical failure data [1]. Condition monitoring involves assessing the characteristic properties of the systems either continuously or in regular time intervals and the result must be expressed as a quantitative value. Fault detection is finding the variables that are crosses their bound values [2][32]. Fault identification is checking the values of related variables. Sometimes the variables are fused or combined to assess the system. Prognostics involve the sequence of recovery actions to make the plant to regain its safe state [3]. Manual condition monitoring of equipment is a tiresome process that demands more manpower. Apart from inaccuracies, the human intervention in condition monitoring of complex systems that operate in hazardous environments is a serious threat to life and properties. Two types of condition monitoring strategies are followed to avoid or to reduce these overheads: physical models and data-driven approaches [4]. Physical model: The physical models of complex systems can be constructed by exploiting the physical relations of the systems and its associated variables. This approach makes many assumptions in building the physical model of the systems thus limiting its applicability in the real time systems [5]. Data Driven approaches: This approach is also known as data mining or machine learning approach, uses the historic data obtained from the system to learn about the system and model its behaviour [6]. The models that are developed through this approach take the advantage of the availability of large volume of data thus tuning the condition monitoring models for enhanced accuracy [4]. The data driven approaches are broadly classified into two sub divisions

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namely statistical methods and artificial intelligence methods [7]. The statistical methods involve the use of many mathematical and statistical approaches. The artificial intelligence methods like Artificial Neural Network (ANN), Support Vector Machines (SVM) [33], Genetic Algorithms (GA), Principle Component Analysis (PCA), Expert System models are gaining more significance in fault diagnosis and health monitoring because of the rapid development in the field of machine learning. The researchers have geared up their work in exploring the possibilities of extending machine learning algorithms in almost all domains. Notable works have been done in deploying machine learning algorithms for better fault diagnosis in mechanical and electrical machineries. There is definitely a gap in knowledge transfer between diverse communities in engineering discipline.

1.1 Fault Diagnosis in Bearings

Bearings in mechanical machinery are responsible for reducing the wear and tear caused due to shaft rotation. There is wide usage of bearings in mechanical, automobile and textile industry which leads to its enormous production. So there is an impulsive need for fault diagnosis of these bearings in the production line. The literature shows the improvisations in every aspect of the fault diagnosis. So the incremental progress could not be picked up. Relevance Vector Machines (RVM) and Support Vector Machines (SVM) are deployed by Achmad Widodo et al. after performing component analysis of the signals from the acoustic emission sensor [8]. The features are directly extracted from the signals and thus scaled down using the Principle Component Analysis (PCA). The localized errors are diagnosed by SVM using RBF kernel and integrating Sequential Minimal Optimization (SMO) for fixing the classification hyperplane. The performance of both RVM and SVM models with PCA and Independent Component Analysis(ICA) is measured. The testing error for RVM and SVM with ICF is as low as 2.04%. Since the features are directly extracted from the acoustic signals, there is a possibility of missing out more prominent features. The feature engineering is also a notable field in AI. It has become the chief research interest because of its dominance in performance of the algorithm. Feature selection and parameter tuning by nature inspired algorithms has tremendously improved the performance of the many algorithms in different disciplines. Expending this fact, Xiaoyuan Zhang et al. designed a novel hybrid model that optimizes the parameters of SVM using Barebones Particle Swarm Optimization and Differential Evolution (BBDE) [9]. Another novelty in feature selection is given by Ben Ali et al. [10] by employing Intrinsic Mode Functions (IMFs). IMFs are extracting using mathematical analysis of energy entropy from the vibration signal data method that combined the empirical mode decomposition with collected from NSF I/UCR Center for Intelligent Maintenance Systems (IMS). This data is then processed by the neural network. This work also proposes Health Index (HI) metric, which indicates the degree of wear on the bearing because of degradation. The method gives an accuracy of 93% and it can act as a prognostic method to predict the lifetime of the equipment. The mathematical feature selection may not be economic in terms of computational costs. Machine learning has taken a big leap after the introduction of Extreme Learning machines (ELM) which softens the feature selection and parameter optimization in machine learning algorithms. An intelligent method that employs a self- adaptive Local Mean Decomposition (LMD) and Single Valued Decomposition (SVD) enabled Extreme Learning Network (ELM) is framed by Ye Tian et al. [11] for diagnosing the bearing faults from Case Western Reserve University 6205-2RS JEM SKF dataset. The ELM is known for its non-dependency on activation functions. It is actually a generic extension of Single Layered Feed Forward Neural Network (SLFN). The signals are decomposed into Product Functions (PFs) of envelop signals and frequency modulated signals. The PFs form the features for ELM. Similarly the features of SVD namely the singular values are trained using the ELM. A comparative study is made between these methodsin terms of feature coincidence. Then the trained model istested validate against SVM and BP network in terms of manpower, accuracy and running time. The results of the study indicated that ELM out- perform the other two with average accuracy of 99% and average running time in the order of 0.1 seconds. The SVM also offers tough competition to the ELM but the BP suffers from more computational time. This method could be generalised to fit to rotating machinery components like shafts and there is definitely great scope for investigation of new modelling techniques

1.2 Leakage Detection in Pumps

The leakage in pumps is a common phenomenon when the pump wears out. So detection of faulty pumps will save energy and resources. This section describes the major works done in fault diagnosis of pumps. PengXu et al. studied

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the performance applying Artificial Neural Network (ANN) in the leakage detection of suck rod pumps in Jiangsu oilfield, China [19]. The study is done with five classes of dynamometer cards each representing one competitive layer of neurons. The self- organized winning neuron's weight is modified by the Kohonen rule [20]. The classification accuracy of the proposed method is 99.9% which is more than the back propagation network. This method selects the right input neuron using the Kohonen rule that attempts to improve the network's accuracy. In real time systems, the competitive layers may increase drastically affecting the computing time. Decision trees naturally select the most prominent feature which is analogous to competitive layers in neural networks. The extensive literature on fault diagnosis using decision trees with proper pruning proves to be one of the optimal solutions. This is supported by Sakthivel et al. through a fault diagnosis model for monoblock centrifugal pump that used Top Down Inductive Decision Tree (TDIDT) with pessimistic pruning [21]. The statistical features namely mean, maxima, minima, kurtosis, variance and skewness are measured from the vibrational data. The feature selection is done by entropy and information gain at each branching point. Decision trees are always excellent solutions for developing models with continuous data like vibrations. The test data indicates classification accuracy of 100%but when presented with real world data, the algorithm produces 99.7%. This method is simple but when the trees are not pruned, it may lead to an overfitting model. Advanced tree pruning methods may reduce the tree size drastically. This method may suffer from bas convergence when the dataset is large with unprocessed features. A better approach for feature extraction is proposed by Muralidharan et al. [22], was employed in leakage detection for centrifugal pump using stationary wavelet transforms. The representative signals for of the healthy pump are recorded and the defective pumps were isolated by comparing them with healthy signals. J48 algorithm is used for feature selection as well as for classification. The WEKA implementation of the J48 along with Stationary Wavelet transformation shows classification accuracy of 93.84%. Tree pruning mechanism could be integrated inside the model to avoid overfitting. Most of the works in fault diagnosis are based on data emanating from single source. A more generic model should be supported by multisource information, which would naturally avoid biasing.

1.3 Analysis of Machine Learning Algorithms for Fault Diagnosis

The literary works on bearing fault diagnosis has shown its developments in all phases namely feature selection, parameter tuning and modelling. A brief comparative study will clearly indicate the significant progression of the fault diagnosis. The Table I summarizes the performance of Machine Learning methods in the fault diagnosis of bearings. Fig 1. shows the comparative study of the models using in diagnosing bearing faults. Deep learning networks proves to be a promising solution for fault diagnosis of bearings as the models deploying neural networks and extreme learning machines offers better result. The classification accuracy of all the methods is almost same. But there substantial difference between every model in terms of other metrics like computation cost, Remaining Useful Life (RUL) etc. Though the classification accuracy of unsupervised Neural Network is relatively low, it is a good approach for fault diagnosis of unlabelled big data. The fault diagnosis of the discussed algorithms need not be confined only to bearings. There is a wide scope in health monitoring of various equipment such as hydraulic breaks, avionic instruments, gear boxes and rotating machineries

II. CONCLUSION

The field of condition monitoring and fault diagnosis is a wide area of research which is now progressing rapidly by deploying intelligent methods. New inventions and advanced machine designing demands zero-hardware defect. Many models and frameworks are built to detect faults and have been validated against benchmark datasets. The field of AI springs as paramount way to diagnose faults.

REFERENCES

[1] Report on Advanced Surveillance, Diagnostic and Prognostic Techniques in Monitoring Structures, Systems and Components in Nuclear Power Plants, No: NP-T-3.14.

[2] E. Zio, F. Di Maio, M. Stasi, A data-driven approach for predicting failure scenarios in nuclear systems, Annals of Nuclear Energy, Vol. 37, 2015, pp. 482-491.

[3] E. Zio, Diagnostics and Prognostics of Engineering Systems: Methods and Techniques, Chapter 17, Engineering Science Reference, USA.

[4] J.P. Ma and J. Jiang, Applications of fault detection and diagnosis methods in nuclear power plants: A review, Progress in Nuclear Energy, Vol. 53, 2011, pp.255-266.

[5] Fan Li, May, Dynamic Modeling, Sensor Placement Design, and Fault Diagnosis of Nuclear Desalination Systems, The University of Tennessee, Knoxville, 2001.

[6] Mark Schwabacher, A Survey of Data-Driven Prognostics, Infotech Aerospace Conferences, 2015.

[7] Enrico Zio, Francesco Di Maio, Marco Stasi, A data-driven approach for predicting failure scenarios in nuclear systems, Annals of Nuclear Energy, Elsevier Masson, Vol.37, 2011,pp.482- 491.

[8] XiaojieGuo, Liang Chen, ChangqingShen, Hierarchical adaptive deep convolution neural network and its application to bearing fault diagnosis, Journal of Measurements, Vol.93, 2016, pp. 490-502.

[9] ZhenPeng, Lifeng Wu, Beibei Yao and Yong Guan, Fault Diagnosis from Raw Sensor Data Using Deep Neural Networks Considering Temporal Coherence, Article from sensors, 2017.

[10] Ben Ali, Nader Fnaiech, LotfiSaidi, Brigitte Chebel-Morello, FarhatFnaiech, Application of empirical mode decomposition and artificial neural network for automatic bearing fault diagnosis based on vibration signals, Journal of Applied Acoustics, Vol. 8, 2015,pp. 15-27.

[11] Xiaoyuan Zhang a,n, DaoyinQiub,c, Fuan Chen, Support vector machine with parameter optimization by a novel hybrid method and its application to fault diagnosis, Journal of Neurocomputing, Vol.149, 2014, pp. 641-651.

[12] MengGan, Cong Wang n, Chang'an Zhu, Construction of hierarchial diagnosis network based on deep learning and its application in the fault pattern recognition on rolling element bearings, Journal on Mechanical Systems and signals. Vol.72, 2016, pp.94-102,

[13] Ye Tian, Jian Ma, Chen Lu, Zili Wang, Rolling bearing fault diagnosis under variable conditions using LMD-SVD and extreme learning machine, Journal of Mechanics and Machine Theory, Vol. 90, 2015, pp.175-186.

[14] Yaguo Lei, Member, Jing Lin, Saibo Xing, Steven X. Ding, An Intelligent Fault Diagnosis Method Using Unsupervised Feature Learning Towards Mechanical Big Data , IEEE Transactions on Industrial Electronics, Vol. 63, 2016, pp.3137 – 3147.

[15] Marco Fagiani , Stefano Squartini, Leonardo Gabrielli, Marco Severini and Francesco Piazza, A Statistical Framework for Automatic Leakage Detection in Smart Water and Gas Grids, Journal of Energies, Vol.9, 2016.

[16] Wei Zhang, Chuanhao Li, GaoliangPeng ,Yuanhang Chen, Zhujun Zhang, A deep convolutional neural network with new training methods for bearing fault diagnosis under noisy environment and different working load , Journal of Mechanical Systems and Signal Processing, Vol.100, 2017, pp. 439-453.

[17] Ioffe, C. Szegedy, Batch normalization: Accelerating deep network training by reducing internal covariate shift, 2015.

[18] N. Srivastava, G.E. Hinton, A. Krizhevsky, I. Sutskever, R. Salakhutdinov, Dropout: a simple way to prevent neural networks from overfitting, Journal of Machineries, Vol.15, 2014, pp. 1929–1958.

[19] V. Muralidharan, V.Sugumaran, GauravPandey, Fault Diagnosis of Monoblock Centrifugal Pump using Stationary Wavelet Fatures and J48 Algorithm, International Journal of Production Technology and Management, Vol.1, 2011, pp. 0976 – 6383.

[20] Kohonen T, Self-organized formation of topologically correct feature maps, Journal of Biol. Cyber, Vol. 43, 1982, pp. 59–69.

[21] BaopingCai, Yonghong Liu, Qian Fan, Yunwei Zhang, Zengkai Liu, Shilin Yu, RenjieJi, Multisource information fusion based fault diagnosis of ground-sourceheat pump using Bayesian network, Journal of Applied Energy, Vol.114, 2014, pp.1-9.

[22] V. Muralidharan, V.Sugumaran, GauravPandey, Fault Diagnosis of Monoblock Centrifugal Pump using Stationary Wavelet Fatures and J48 Algorithm, International Journal of Production Technology and Management, Vol.1, 2011, pp. 0976 – 6383.

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[23] BaopingCai, Yonghong Liu, Qian Fan, Yunwei Zhang, Zengkai Liu, Shilin Yu, RenjieJi, Multisource information fusion based fault diagnosis of ground-sourceheat pump using Bayesian network, Journal of Applied Energy. Vol. 114, 2014, pp.1-9.

[24] Feng Jia, Yaguo Lei, Jing Lin, Na Lu, Deep neural networks: A promising tool for fault characteristic mining and intelligent diagnosis of rotating machinery with massive data, Journal of Mechanical Systems and Signal Processing, 2015.

[25] V. Muralidharan and V. Sugumaran, A Comparative Study between Support Vector Machine (SVM) and Extreme Learning Machine (ELM) for Fault Detection in Pumps, Indian Journal of Science and Technology, Vol.9, 2016, pp. 0974-6846

[26] Mohamad-Ali Mortada, SoumayaYacout, AouniLakis, Fault diagnosis in power transformers using multi-class logical analysis of data, Journal of Intelligent Manufacturing, Vol.25, 2013,pp. 1429–1439. [27] Ms.Aparna R. Gupta, V. R. Ingle, Dr. M. A. Gaikwad, LS-SVM Parameter Optimization Using Genetic Algorithm To Improve Fault Classification Of Power Transformer, International Journal Of Engineering Research and Application, Vol. 2, 2012, pp.1806-1809.

[28] Mohamad-Ali Mortada, SoumayaYacout, AouniLakis, Fault diagnosis in power transformers using multi-class logical analysis of data, Journal of Intelligent Manufacturing, Vol.25, 2013, pp. 1429–1439. [29] Frank, A., & Asuncion, A., UCI machine learning repository, 2010 http://archive.ics.uci.edu/ml.

[30] HazleeAzilIllias, Wee Zhao Liang, Identification of transformer fault based on dissolved gas analysis using hybrid support vector machine-modified evolutionary particle swarm optimisation , PLOS ONE, Vol. 13, 2018,pp. 1-15.

[31] Ghunem RA, Assaleh K, El-hag AH, Artificial neural networks with stepwise regression for predicting transformer oil furan content, IEEE Transactions on Dielectrics and Electrical Insulation, Vol.19, 2012, pp. 414-420.

[32] S.Sharanya, Revathi Venkataraman, An intelligent Context Based Multi-layered Bayesian Inferential predictive analytic framework for classifying machine states, Journal of Ambient Intelligence and Humanized Computing, https://doi.org/10.1007/s12652-020-02411-2, 2020.

[33] S. Sharanya, S. Karthikeyan, Classifying malicious nodes in vanets using Support Vector Machines with modified fading memory, ARPN Journal of Engineering and Applied Sciences, vol. 12, No. 1, 2017, pp. 171-176