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An Approach on MCSA-Based Fault Detection Using Discrete Wavelet Transform and Fault Classification Based on Deep Neural Networks

Muhammad Zuhaib[1], Faraz Ahmed Shaikh[2], Usman Ahmed Shaikh[3], Asadullah Soomro[4]
[1]Department of Electrical Engineering, (PNEC), National University of Science and Technology, Pakistan, zaibkamboh123@gmail.com
[2]Department of Electrical Engineering, Nazeer Hussain University, (NHU), Pakistan, faraz.ahmed@nhu.edu.pk
[3]Department of Electrical Engineering, University of Engineering and Technology, Pakistan, usman_ahmed4u@yahoo.com
[4]Department of Electrical Engineering, Institute of Business Administration (IBA), Pakistan, assadsoomro4@gmail.com

ABSTRACT

This paper presents a novel approach on motor current signature analysis (MCSA) for broken Rotor Bar fault and High Contact Resistance fault using stator current signals as an input from the three phases of Induction motors. Discrete Wavelet Transform is preferred over the Fast Fourier Transform (FFT). Fast Fourier Transform (FFT) converts signals from time domain to frequency domain on the other hand Discrete Wavelet Transform (DWT) gives complete three-dimensional information of the signal, frequency, amplitude, and the time where the frequency components exist. In wavelet analysis, the signal is converted into scaled and translated version of mother wavelet, which is very irregular so cannot be predicted. Hence, mother wavelets are more appropriate for predicting the local behavior of the signal including irregularities and spikes. In this research features are extracted using DWT and then features are trained in Deep NN sequential model for the purpose of classification of the faults. In this research, MATLAB software has been used for building the motor model in Simulink environment and PyCharm software is used to implement Deep NN for getting accuracy and classification results. This research helps in early detection of the faults that assists in prevention from unscheduled downtimes in industry, economy loss and production loss as well.

Key words: Fault diagnosis; MCSA; DWT; Deep Neural Network.

1. INTRODUCTION

Reliable operation and working of Induction motors is an important topic because of their widespread usage in industries, however, they are like other rotating machines and are open to many different faults. Since past decades, fault diagnostics and condition monitoring have been an area of interest for many researchers and been challenging research topic. Motor failure will cause unwanted downtime and expenses of repairs [1]. According to IEEE survey report about the electrical and mechanical faults of Induction motors, it was found that there appear 42% Bearing faults, 28% Stator faults, 8% faults in the rotor, and remaining 22% are other faults [2]. For prevention from these faults, these faults are detected on early stages [3] and a strategy for early indication of the occurrence of faults is investigated in this research. Moreover, many different types of faults have been studied and investigated in the past including stator winding faults, bearing faults [4], broken rotor bar faults [5] and, eccentricity related faults using different algorithms and methods likewise, ANN for classification purpose and stator current and rotor speed, FFT, MCSA, Hormonic Spectrum methods of signals. However, this research is focused on Deep NN implementation for the classification purpose because in practice deep learning is obviously very successful at various prediction tasks.

1.1 The proposed research methodology is shown in the figure 1 given: First, motor model is designed in MATLAB Simulink environment, and the faults under study are created for experimental purpose and data is acquired for both cases, Healthy and Fault induced cases, and furthermore, features are extracted using wavelet transform and the features are feed to deep NN for fault detection and classification purpose.

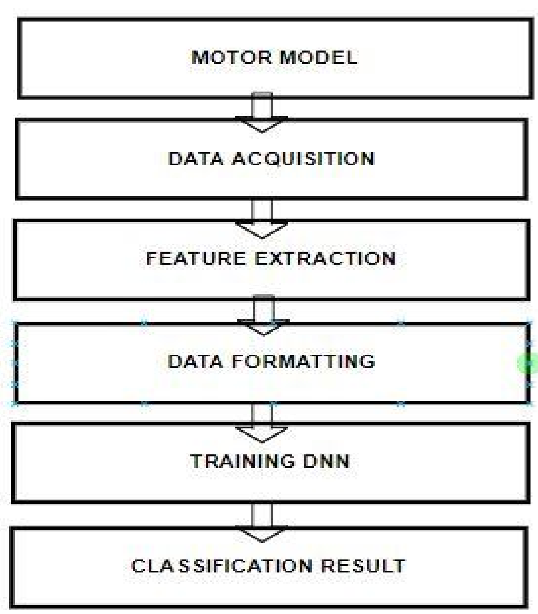

Figure 1: Propose Methodology of the Research

Many fault detection methods have been proposed so far including motor current signature analysis (MCSA), noise and vibration monitoring and temperature measurements. Motor Current Signature Analysis is advantageous over other diagnosing methods. Other methods require expensive sensors, on the contrary motor current signature analysis requires cheap and simple current sensors. In this research, 5.4HP(4KW) - 400V 50Hz, 1430 RPM Induction motor is designed in MATLB Simulink Environment and High Contact Resistance fault, and Rotor Bar faults have been induced and are investigated in this research. Induction motor torque and current are affected when the fault appears. The torque equation is given, and the current values are disturbed from normal values as the fault appears in the system.

$$\tau = T_{loss} + T_{sh} \tag{1}$$

$$T_{sh} = \frac{P_{out}}{\omega} \tag{2}$$

$$\omega = \frac{2\pi N}{60} \tag{3}$$

Since N= 1430, P_{out} = 4000 watts and so $\omega = 149.67 rad/sec$ and T_{sh} or $T_L = 4000w/149.67$ = 26.72 N-m

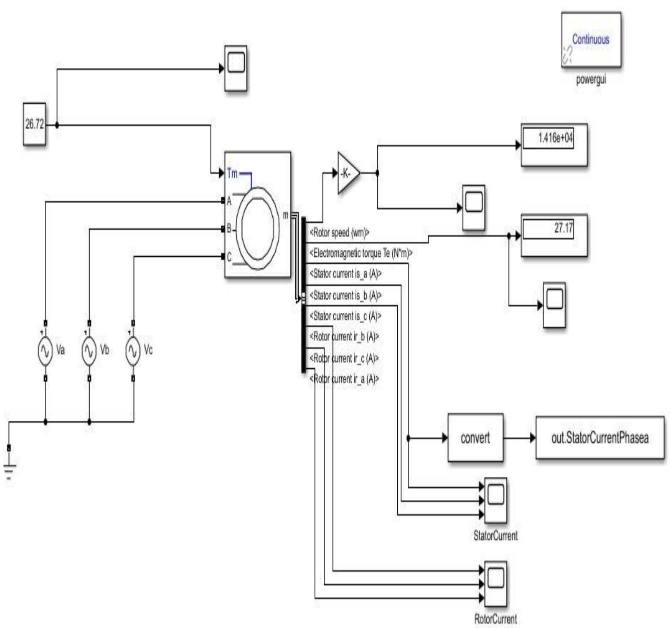

Figure 2: Healthy Motor Model Designed in MATLAB Simulink Environment.

2. MOTOR CURRENT SIGNATURE ANALYSIS

The current monitoring-based techniques assist in detecting almost all types of faults including Rotor Bar Faults and High Contact Resistance Faults. Condition monitoring systems require process signals generated by machine under operation [6],[7]. The MCSA [8-13] is considered as a simple, reliable, and easier. For determination of the existence of the fault, the measured stator current data is analyzed in the frequency domain. When fault appears, the fault modifies the harmonic content of the supply current. MCSA detects the harmonic content and provides potential information and precise analysis based on the detection of the specific current sideband harmonics by means of the Discrete Wavelet Transform (DWT). Other fault indicators include flux, stator line voltages and electromagnetic torque etc., but in this research stator current indicator is investigated.

3. DISCRETE WAVELET TRANSFORM

DWT assists in selecting the subsets of scales (a) and positions (b) of the mother wavelet $\psi(t)$.

$$\psi(a,b) = 2^{\frac{a}{2}}\psi(2^{-\frac{a}{2}}(t-b)) \tag{4}$$

Choosing scales and positions are based on powers of two, which are called dyadic scales and positions {$a_j = 2^{-j}$; b j, k= 2^{-i}k} j and k are integers here. Equation (4) shows that it is possible to build a wavelet for any function by dilating a function $\psi(t)$ with a coefficient 2^j and translating the resulting function on a grid whose interval is proportional to 2^{-j}. With the help of DWT features are extracted and Deep NN is trained using these features. The aim of extracting features is to get relevant information for further processing. DWT provides series of coefficients, approximation and detail coefficients, low frequency feature points and high frequency feature points respectively [14].

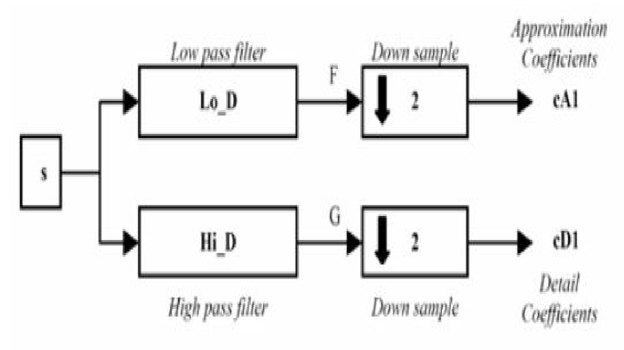

Figure 3: DWT representation for Approximation and Detail Coefficients.

DWT for the Healthy Motor and Fault induced Motors is shown in the figures given below. Wavelet 'db4' is preferred here and uptill level 5, the detail coefficients and approximation coefficients are shown in the figures.

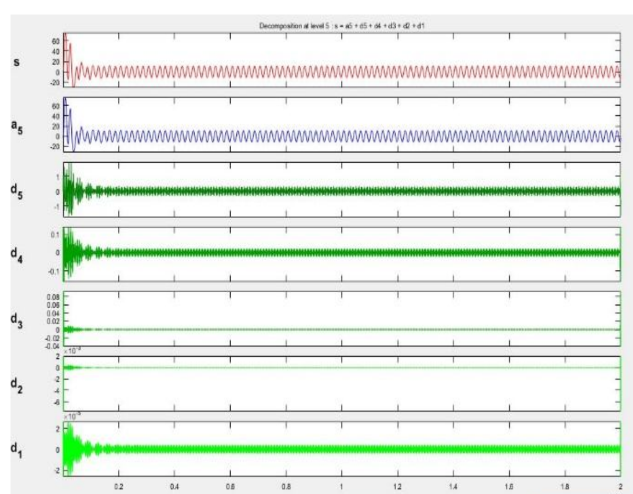

Figure 4: Discrete Wavelet Transform for the Healthy motor uptill level-5 is shown.

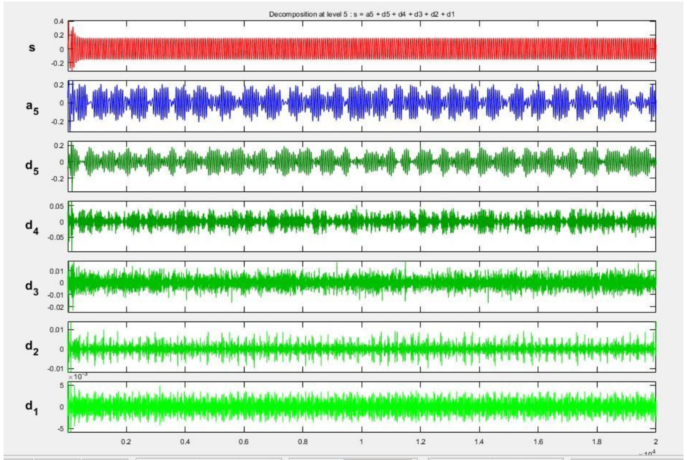

Figure 5: Discrete Wavelet Transform for the Fault induced motor (HCR fault) uptill level-5 is shown.

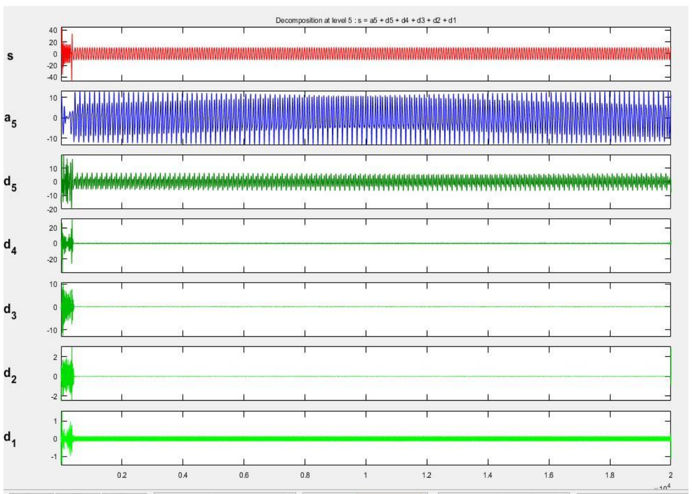

Figure 6: Discrete Wavelet Transform for the Fault induced motor (Rotor Bar fault) uptill level-5 is shown.

From the above figures it is concluded that when fault appears in motors, the variance in coefficients is observed as compared to the coefficients of the healthy motor.

4. Deep Neural Network

A deep NN is an ANN with multiple hidden layers in between the inputs and output layers. Neural Network has been successfully used and is suitable for fault detection [15,16,17,18]. DNNs can model complex non-linear relationships. Steps to be followed in this research are:

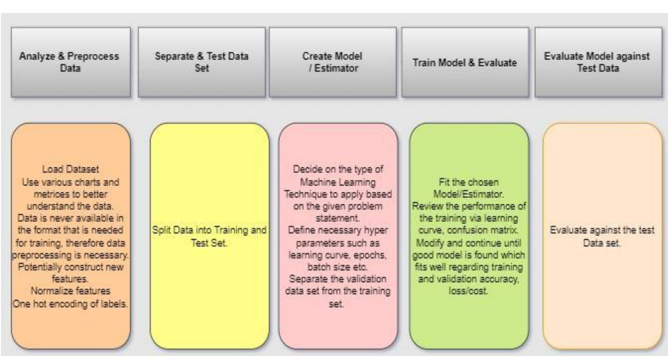

Figure 7: Proposed Methodology for the Deep Neural Network.

Moreover, using deep NN multiple faults can be classified. In this research 24 different motors data is obtained at different time intervals. In that healthy motor data and fault induced motor data is combined to get complete dataset. In this research 14 motors data have been taken for training and remining motors data has been considered for testing purpose. Before training the Deep NN, first, data has been converted to time-sliced representation, and reshaped the multi-dimensional tabular data so that can be accepted by Keras. Furthermore, split up the data into training, validation, and test set. After all, defined the deep NN model in Keras and validated the performance of DNN against tests data set using confusion matrix. In this research, 200 dense layers are taken, and sequential model is trained with softmax activation function.

5. Results and Discussion

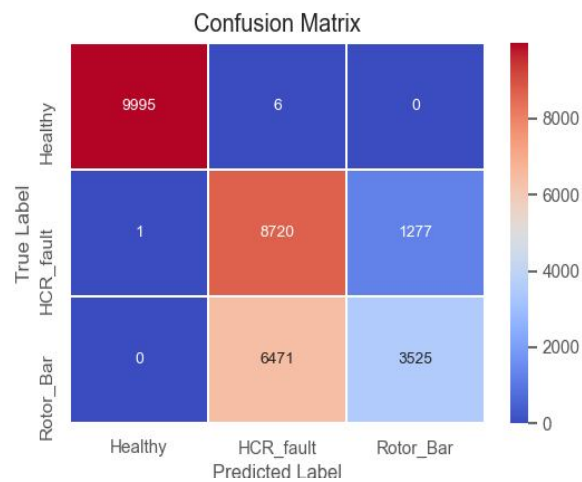

Figure 8: Confusion Matrix

	precision	recall	f1-score	support
0.0	0.94	1.00	0.97	18774
1.0	0.49	0.11	0.17	14538
2.0	0.59	0.90	0.72	19505
accuracy			0.72	52817
macro avg	0.67	0.67	0.62	52817
weighted avg	0.69	0.72	0.66	52817

	precision	recall	f1-score	support
0.0	1.00	1.00	1.00	10001
1.0	0.57	0.87	0.69	9998
2.0	0.73	0.35	0.48	9996
accuracy			0.74	29995
macro avg	0.77	0.74	0.72	29995
weighted avg	0.77	0.74	0.72	29995

Figure 9: Precision Model Results.

From the result obtained, it can be found that precision model is good for predicting Healthy (0.0) and Rotor Bar fault (2.0). The accuracy obtained for the training data is 72% and the test data accuracy obtained is 74%, this means that our model can generalize well for the data that has not been seen yet by the model. Above results are obtained using PyCharm software.

6. CONCLUSION

Form the research it is concluded that the DNN model can help in finding multiple faults classification and if the number exceeds more than five faults at the same time, the model can predict well and can provide good results. The DWT has been implemented to get the features particularly RM features are obtained at level-9 for this research and are fed as an input to the Deep Neural Network. Result can be improved by changing the model and tunning the hyper parameters and by retraining the algorithm multiple times as the method is based on iterative approach. However, the work is still carried out to get more accurate results and research is being done for improving accuracy so that optimum results are obtained. Different models like CNN and some other strategies will be followed to achieve the target.

REFERENCES

[1] T. Han, B.-S. Yang, W.-H. Choi, and J.-S. Kim, “Fault diagnosis system of induction motors based on neural network and genetic algorithm using stator current signals,” International Journal.

[2] Benbouzid, M.E.H. A Review of Induction Motors Signature Analysis as a Medium for Faults Detection, IEEE Transactions on Industrial Electronics, vol. 47, no. 5 (October 2000), pp. 984-993.

[3] Motor Reliability Working Group. Report of large motor reliability survey of industrial and commercial installations Part I, and II, IEEE Transactions on Industry Applications, vol. IA21, no. 4 (July 1985), pp. 853-872.

[4] M.Y. Chow, P.M. Mangum, S.O. Yee, A neural network approach to real-time condition monitoring of induction motors, IEEE Trans. Ind. Electron. 38 (6)(1991) 448–453.

[5] R.R. Schoen, B.K. Lin, T.G. Habetler, J.H. Schlag, S. Farag, An unsupervised, on-line system for induction motor fault detection using stator current monitoring, IEEE Trans. Ind. Appl. 31 (6) (1995) 1280–1286.

[6] Sin, M.L., Soong, W.L., Ertugrul, N. Induction machine on-line condition monitoring and fault diagnosis – A survey, Australasian Universities Power Engineering Conference (AUPEC '03), Christchurch (New Zeeland), 2003.

[7] Negrea, M.D. Electromagnetic flux monitoring for Detecting faults in electrical machines, Ph.D. Dissertation, Department of Electrical and Communications Engineering, Helsinki University of Technology, Espoo (Finland), 2006.

[8] M.E.H. Benbouzid, “A Review of Induction Motors Signature Analysis as a Medium for Faults Detection,” IEEE Trans. on Ind. Electronics, vol. 47, no. 5, Oct. 2000, pp. 984-993

[9] Neelam Mehala and Ratna Dahiya, "Motor Current Signature Analysis and its Applications in Induction Motor Fault Diagnosis", International Journal of Systems Applications, Engineering & Development, vol. 2, no. 1, 2007.

[10] Alan Miletic and Mirko Cettolo, "Frequency Converter Influence on Induction Motor Rotor Faults Detection Using Motor Current Signature Analysis – Experimental Research", Symposium on Diagnostics for Electric Machines, Power Electronics and Drives, Atlanta, GA, USA, 24-26 August 2003.

[11] Ruiming Fang and Hongzhong Ma, "Application of MCSA and SVM to Induction Machine Rotor Fault Diagnosis", Proceedings of the 6th World Congress on Intelligent Control and Automation, June 21 - 23, 2006, Dalian, China.

[12] Chiara Boccaletti, Claudio Bruzzese, Onorato Honorati and Ezio Santini, "Rotor Bars Breakage in Railway Traction Squirrel Cage Induction Motors and Diagnosis by MCSA Technique Part II: Theoretical Arrangements for Fault-Related Current Sidebands", SDEMPED 2005– International Symposium on Diagnostics for Electric Machines, Power Electronics and Drives, Vienna, Austria, 7-9 September 2005.

[13] A Alwodai, F Gu and A D Ball, "A Comparison of Different Techniques for Induction Motor Rotor Fault Diagnosis", 25th International Congress on Condition Monitoring and Diagnostic Engineering, IOP Publishing, Journal of Physics: Conference Series 364, 012066, 2012

[14] S. H. Kia, H. Henao, and G.-A. Capolino, “Diagnosis of broken-bar fault in induction machines using discrete wavelet transform without slip estimation,” IEEE Trans. Ind. Applicat., vol. 45, no. 4, pp. 1395–1404, July/Aug. 2009.

[15] A. Elnozahy, K. Sayed and M. Bahyeldin, "Artificial Neural Network Based Fault Classification and Location for Transmission Lines," 2019 IEEE Conference on Power Electronics and Renewable Energy (CPERE), Aswan, Egypt, 2019, pp. 140-144, doi: 10.1109/CPERE45374.2019.8980173.

[16] Mori, H., Aoyama, H., Yamanaka, T., & Urano, S. (n.d.). A fault detection technique with preconditioned ANN in power systems. IEEE/PES Transmission and Distribution Conference and Exhibition. doi:10.1109/tdc.2002.1177570.

[17] S. Sornmuang and J. Suwatthikul, "Detection of a motor bearing shield fault using neural networks," SICE Annual Conference 2011, Tokyo, Japan, 2011, pp. 1260-1264.

[18] M. J. Fuente and C. Represa, “A Comparative Study of Neural Networks Based Approach for Fault Detection”, 3rd IFAC Symposium, Kingston Upon Hull, UK 26-28 August 1997.