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Research Article

Winding Fault Detection in Motor Using Near Infra-Red Sensor Signal Based Dywt and Tdywt Analysis

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ABSTRACT

Introduction: Runtime monitoring of the stator and rotor windings of asynchronous motors is essential for early detection of faults. Early fault detection enables rapid recovery and prevents severe operational failures during critical stages. Rotor winding faults can lead to turn-to-turn faults, which in turn increase fault current, thermal stress, and the temperature of the motor windings. If inter-turn insulation faults are not identified promptly, they can escalate to rotor bending and coil burning. However, continuous surveillance of motor windings and insulation during operation is challenging.

Objectives: This study aims to develop a more effective fault detection mechanism for asynchronous motors by addressing the limitations of traditional monitoring methods. The goal is to enhance the accuracy and reliability of fault diagnosis, particularly for rotor winding faults and inter-turn insulation failures, during motor operation.

Methods: The proposed approach utilizes Near-Infrared (NIR) sensor-based analysis in conjunction with signal processing through two different wavelet transform techniques: dyadic and transverse dyadic wavelet transforms. These methods are used to analyse signals collected from the motor in real-time.

Results: The analysis demonstrated a notable improvement in fault detection accuracy compared to traditional diagnostic methods. The use of NIR sensors with dyadic and transverse dyadic wavelet transforms enhanced the sensitivity and effectiveness of runtime monitoring, making it more reliable for early fault identification in asynchronous motor windings.

Conclusions: Mi tempus imperdiet nulla malesuada. Magna fermentum iaculis eu non diam phasellus vestibulum. Consectetur adipiscing elit duis tristique sollicitudin nibh sit amet commodo. Elit scelerisque mauris pellentesque pulvinar. Et malesuada fames ac turpis egestas maecenas pharetra convallis posuere. Elementum integer enim neque volutpat ac tincidunt vitae semper.

Keywords: Asynchronous Motor, Rotor Winding Faults, Real-time Monitoring, Motor Fault Diagnosis, Predictive Maintenance, Electrical Machine Health Monitoring.

INTRODUCTION

Identification of insulation and winding defects in the stator and rotor during operation in electric motors normally detected through smell, or dismantling them. Coil-to-coil and phase-to-phase short circuit faults occur when a motor is running with winding and insulation problems. Unbalanced and differential flux radiation are caused by winding insulation and coil problem in motors. During the running condition of the motor, NIR sensor monitors the motor windings. Near Infra-Red (NIR) sensor is fixed in air gaps of motor.

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The Researchers applied various methodologies to analyse the defects at various motor conditions such as harmonic analysis [1], isolation forest and frequency response analysis [2], DCNN method-based model for broken rotor detection [3], Chan lee et al. experimented a DL approach-based method under different varying state of operations [4]. Ruhan pontes et al. proposed an adaptive estimation method for detecting stator winding faults [5]. Zara masoumi et al. used eigen value analysis for anomaly detection in motors which also focusses on air gap eccentricity [6]. Subashish Sarkar developed RIO based method to detect online, the stator insulation defect in AC motors [7]. Thang thun vo et al. utilized deep learning approach-based attention technique for faulty load condition in armature coil [8]. Manar abdelmaksoud et al. diagnosed faults using convolutional neural network mechanism for individual and multiple datasets [9]. Ankur Srivastava et al. did performance evaluating analysis for faults at various load states using dynamic state estimation [10]. Ma'd el-dalahmeh et al. detected deformity in motors using decomposition method and Hilbert huay transform. It is designed in such a way that it self-updates the errors into the database [11]. R. Senthilkumar et al. proposed a combination of HT and ANN based early-stage broken bar fault identification which detailed the defective baars at an earlier stage [12]. Minh-Quang Tran et al. reported a robust correction scheme for flaw recognition with effective IOT with the DL approach [13]. Similarly, many approaches were done by the researchers, NRR Signal analysis with different wavelets and have translational invariance, which causes artefacts & appear during the reconstruction of the signal, which never detect the stator winding fault of below 3cm. In this study, for prediction of the fault in stator winding of 3 cm, DyWT is applied. The DyWT has a mother wavelet with a quadratic spline for low frequency signal enhancements, reconstruction, and accurate NRR signal representation. In addition, lifting property of DyWT reconstructs vanishing instances of the signal. DyWT is a redundant frame expansion and overcomes orthogonal wavelet transform shortcomings. DyWT provides multi-resolution analysis of the NRR signal. DyWT define through dail coefficients and approximation coefficients.

PROBLEM STATEMENT

Even though these methods are efficient, they have certain drawbacks which is overcome by our proposed method. In this study, shift invariance and translation of signals are detected accurately using the DyWT and TDyWT analysis. The motor winding and insulation fault are diagnosed by placing a Near Infra-Red sensor in the air gap region between the rotor and the stator. Infrared (NIR) sensor ray is directed to the flux generated by them & detects and diagnoses problems in winding and insulation in asynchronous motor.

METHODOLOGY

The work flow of the proposed model is depicted as in **Figure 1.** The various operating conditions such as loaded, and other faulty conditions are monitored and the signals from the NIR sensor which is placed between the air gap region of the motor windings are accessed as Near-infrared Residual signals. They are then processed and analysed two waveforms such as the dyadic and transverse dyadic wavelet transforms, thereby detects the motor winding faults in an improved accuracy range of detection when compared to the traditional methods which

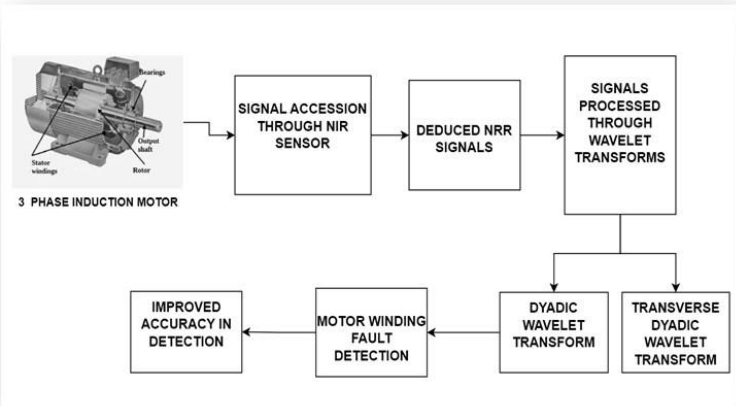

Figure 1. Schematic block diagram of the developed system

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provides less accuracy. Spectral subtraction involves considering the extraction of signals from the NIR sensor which is shown in **Figure 2.** and the received signals are analysed using fault feature extraction method as to detect the accuracy of fault detection using wavelet transforms, DyWT and TDyWT. Flaws in the stator/rotor winding can be detected using the spectral component of the photo diode signal.

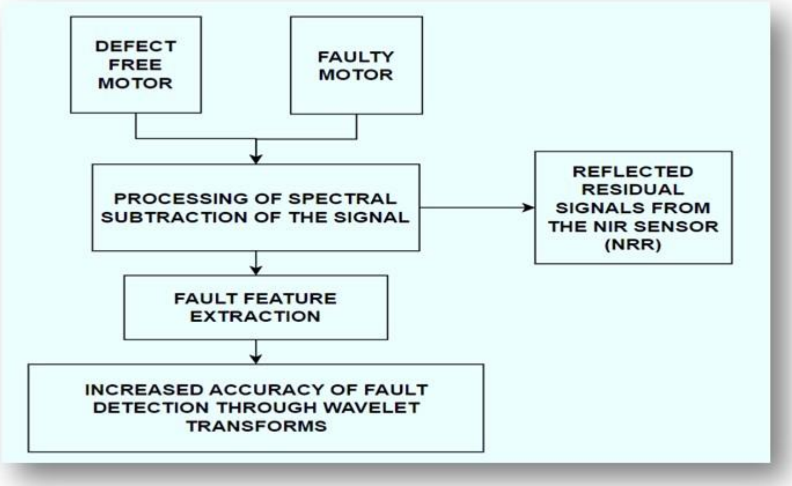

Figure 2. Processing of Spectral subtraction of the signal from healthy and faulty motor for detection of accuracy

Magnetic flux causes these faults which is coming from the motor air gap region. The spectral subtraction, on the other hand, results in remnant noise in the signal. This causes the fault feature signal to be distorted. Hence, the signal must be processed using DYWT, TDyWT in order to ensure accurate fault diagnosis. Let us discuss the wavelet transforms suggested in this study.

DYADIC ALGORITHM

In Dyadic wavelet transform, the design of vanishing moments is of higher number. Inclusion of Lifting construction of spline dyadic wavelet filters can be made with arbitrary vanishing moments. DyWT relates the class of redundant frame expansions of signals that shows translation invariance (overcoming the shortcoming of orthogonal wavelet transforms) and better multi-resolution analysis abilities. The DyWT decomposes one-dimensional signal concerning translated and dilated wavelets. The translational invariance in traditional wavelet transform overcome by the Equation (1),

$$\{(n),\{s(n)\}m\in[1,M]\}neZ \quad (1)$$

Where, (n)=s*ϕm(n) represents narrow band information in NRR signal and the signal narrow band information is represented by SMs(n)=s*m(n). The DyWT implementation includes a wavelet function, fast filter bank, and reconstruction filter. Fast filter bank with breakdown and rebuilding filters. The decomposition filter and reconstruction filter make up the fast filter bank. The filters meet the requirement.

DYADIC - DISADVANTAGES IN FAULT DETECTION

Selecting a low threshold value ensures fewer false alarms; however, the trade-off is that less of the co-channel interference between stator & rotor winding fault flux signal. The fundamental drawback of sampled dyadic wavelet transforms for signal recognition is non-translation. A uniform sampling of a dyadic wavelet transform is difficult for signal analysis, so the Transverse Dyadic Wavelet transforms are applied to NRR Signal.

TRANSVERSE DYADIC WAVELET TRANSFORM

Transverse Dyadic Wavelet Transform (TDyWT) is introduced to overcome the drawbacks of DyWT. DyWT is more complex to perform. It requires more memory to store the result. Interpretation of results is more difficult.

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Confusion arises in the usage of bases (frequency, location) for multiple faults In TDyWT, during decomposition, Haar wavelet transform is used and during decomposition Burt 5x7 wavelet is used for the better resolution of low frequency NRR signal. When the (time) is not necessary, DyWT is a disadvantage. The Haar wavelet is applied during decomposition. Haar wavelet has the reversible property. Additional information is obtained from TDyWT processed signal the reversible characteristic extracts shapes & edges in signal, which is a challenge in other transforms. In Bio-orthogonal wavelet family, removes unnecessary data points signal and frees up memory. The split phase, which involves dividing odd and even data points, is the initial step. The predict phase, in which the odd data is anticipated from the even data points, is the second step. The update phase, which is used to update the even set during the wavelet coefficient, is the third stage the dyadic wavelet transform is defined by Equation (5.1)

$$Wf(u,2^i) = \int_{-\infty}^{+\infty} f(t)\,\frac{1}{\sqrt{2}}\psi\left(\frac{t-u}{2^i}\right)dt = f*\bar{\psi}_{2^i}(u) \tag{2}$$

with
$$\bar{\psi}_{2^i}(t) = \psi_{2^i}(-t) = \frac{1}{\sqrt{2^i}}\psi\left(\frac{-t}{2^i}\right) \tag{3}$$

The family of dyadic wavelets is a of $L^2(R)$. Sequences of wavelets and scaling functions that are ordered both in time and frequency & create the set of basic functions. The sequences acquired by the operations of digital filtering and down sampling, which are the coefficients to functions in reflecting the underlying continuous processes. The TDyWT changes window to provide correct temporal and frequency resolutions.

EXPERIMENTAL STUDY

A typical winding failure is shown in **Figure.3**

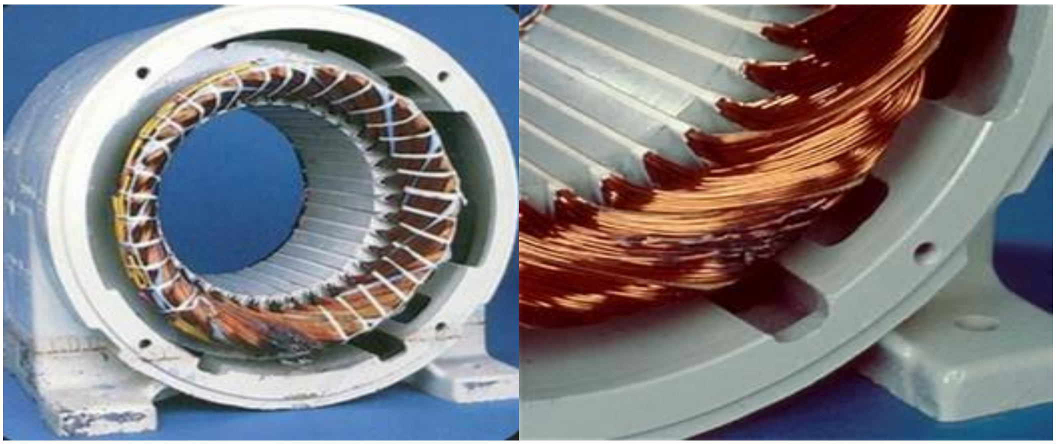

Figure 3. Winding defects in Induction motor

A simple winding fault is shown as a real time induction motor in **Figure 3. Figure 4(a)** Shows the Experimental setup of NRR signal acquisition. **Figure 4(b)** shows NIR sensor located towards in shaft left Side in motor and **Figure 4(c).** shows the NIR sensor located below motor shaft region.

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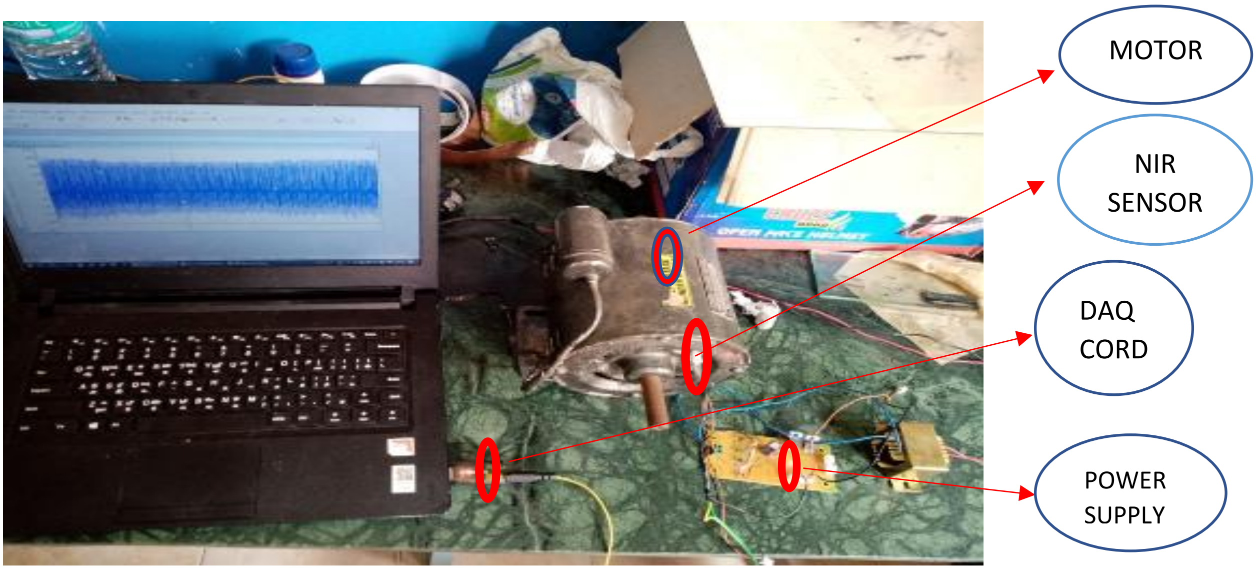

Figure 4. (a)Experimental setup of NRR signal acquisition

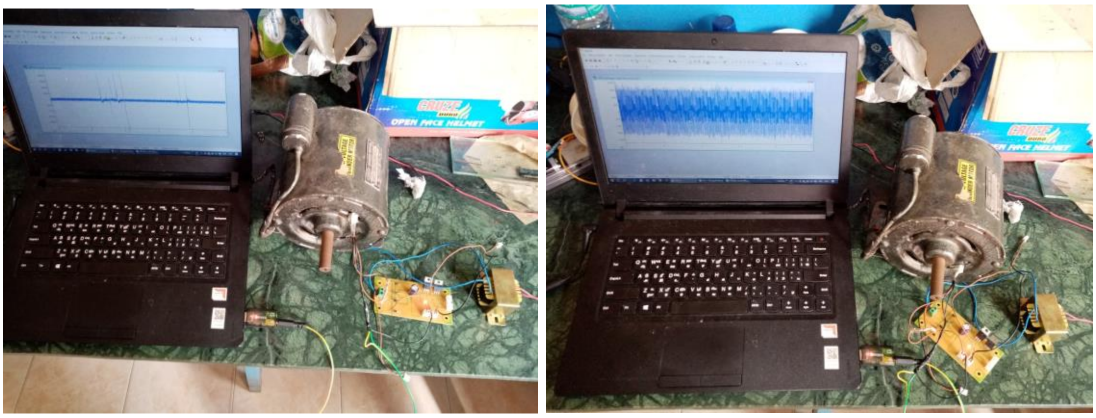

Figure 4(b). NIR sensor located towards in shaft left Side in motor and

4(c). Below motor shaft region

RESULTS AND DISCUSSION

Figure 5. Representation shows DyWT processed output signal for the acquired input signal with overload, stator and rotor winding fault in motor during acquisition of signal. **Figure 6.** Representation DyWT processed signal with high speed and rotor winding fault signal. **Figure 7.** shows DyWT processed signal for low speed and transient fault signal. **Figure 8.** DyWT processed signal with transient Fault. **Figure 9.** to **Figure 15.** shows the different combination of TDyWT and their processing signals with different faults conditions.

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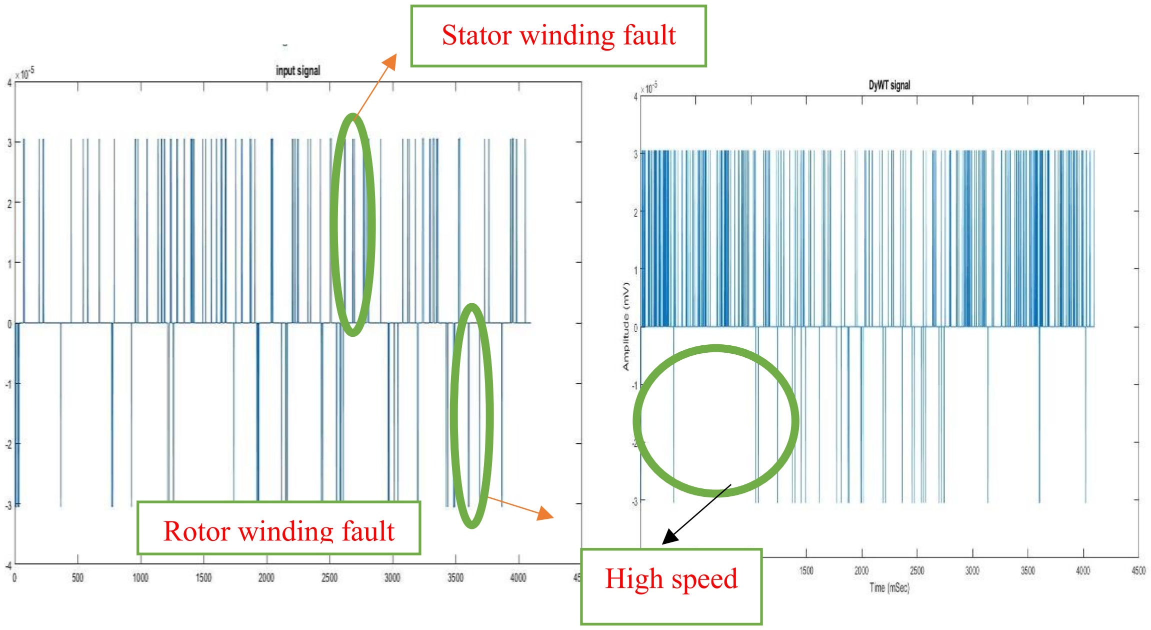

(Figure 5) **(Figure 6)**

Figure 5. **DyWT processed signal with overload, and stator & rotor winding faults in signal and**
Figure 6. **DyWT - processed high speed and rotor winding fault signal**

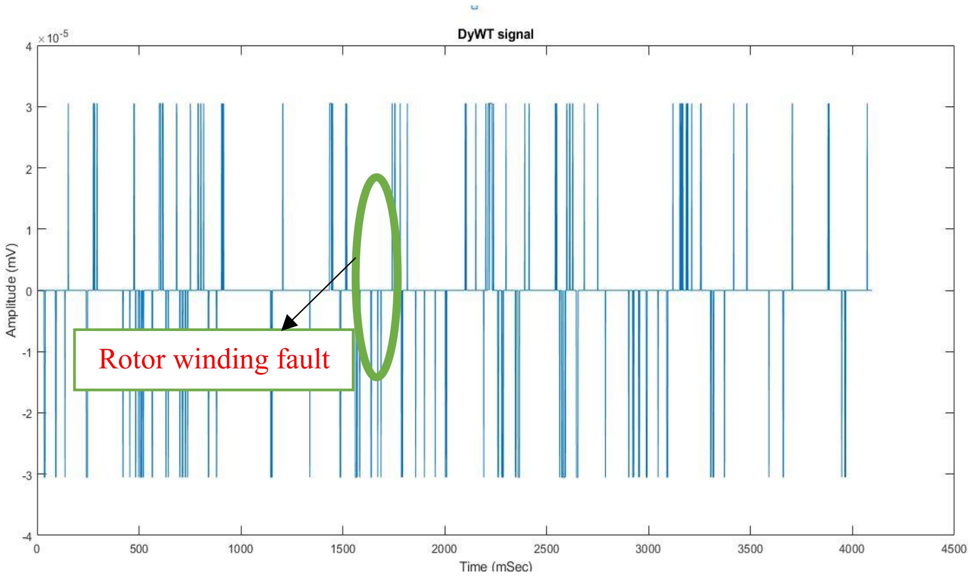

Figure 7. **DyWT processed signal with low speed and transient fault signal**

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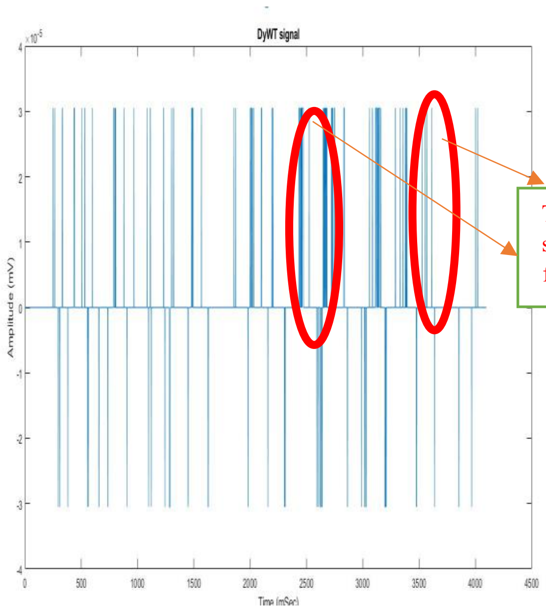
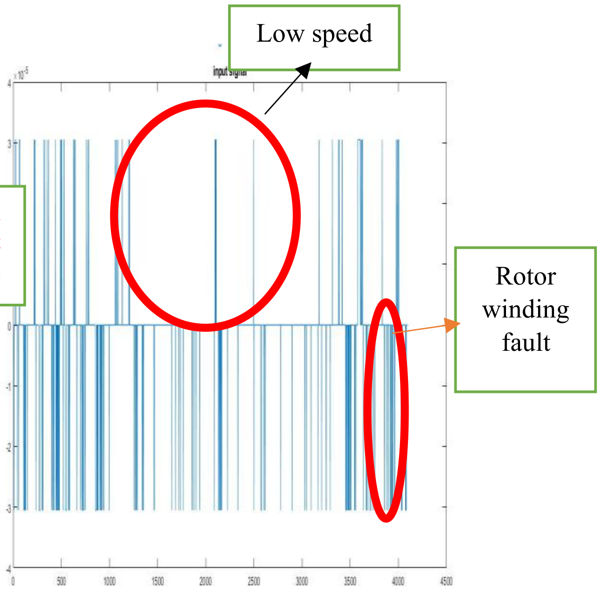
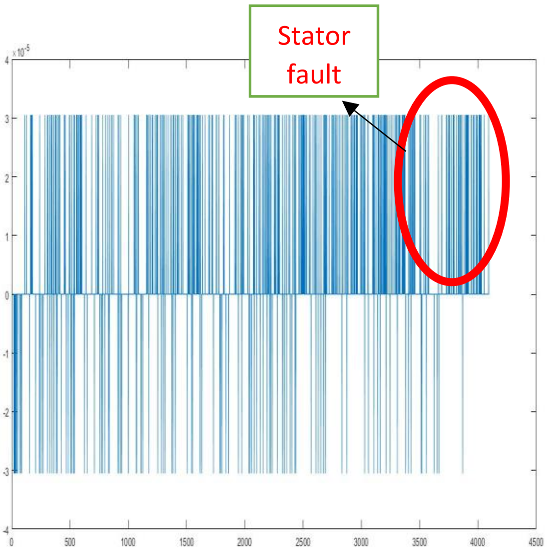


(Figure. 8)



(Figure.9)

Figure 8 & 9. DyWT - processed signal with only transient fault. DyWT Processed signal with slow speed & rotor winding fault



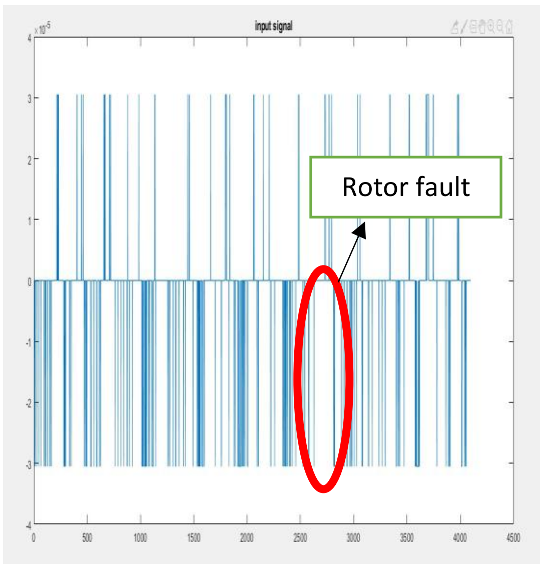


Figure 10. Raw signal with high speed and stator fault and Figure 11. With slow speed and armature fault

The DyWT is performed based on the Haar wavelet during the decomposition and during reconstruction Haar wavelet is applied however, the different combination of induced faults such as and stator/ rotor winding fault signals are analyzed. The stand deviater & Kurtosis show difference in their range for all the major faults. More than 3 faults in a motor and their signals are overlapped with winding faults. The Table 1. shows the statistical value comparison of NRR signal processed with DyWT transform.

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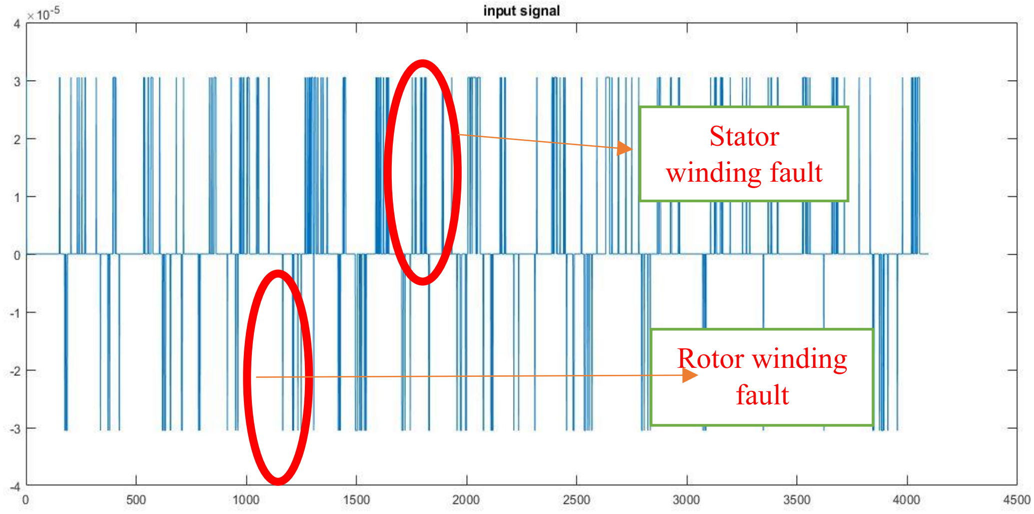
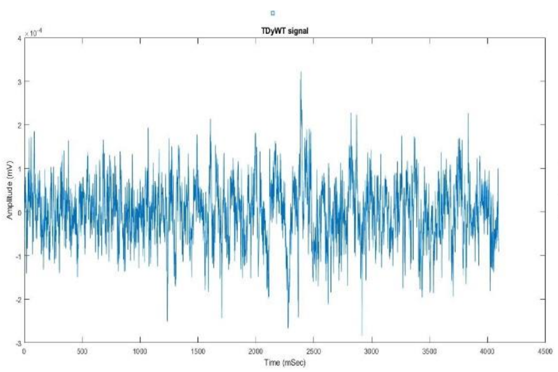


Figure 12. **DyWT Processed signal in normal speed with stator & rotor winding fault.**

Table 1. Comparative analysis of NRR signal Processed with Dyadic Wavelet transform for winding and insulation fault

	NRR signal (Haar X Haar)					
	Fault free condition	**Motor operated at the loaded state**	**Stator insulation fault**	**Stator winding fault**	**Armature insulation faulty detection**	**Rotor winding fault**
Mean	20.5334	20.1158	-0.456583	2.40374	-0.952193	0.05123102
Standard Deviation	**535.367**	**304.167**	**256.763**	**4199.583**	**388.850**	**259.735**
Variance	278910	51464	34080.2	207494	60488.6	51361.4
Skewness	0.35557	2.40574	-0.20743	26.3117	22.4383	0.466705
Kurtosis	**3.17748**	**39.5588**	**22.681**	**5683.95**	**1677.32**	**20.1757**



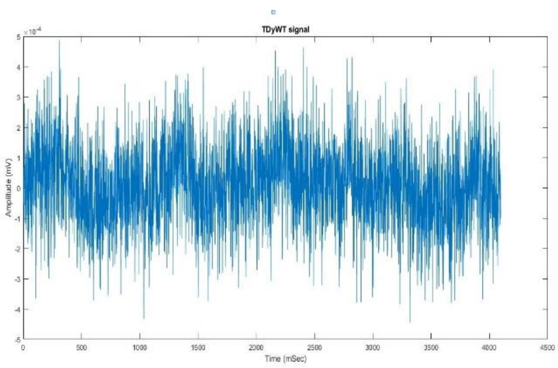


Figure 13. TDyWT- processed signal with Slow speed and rotor winding fault (Burt-5x7 X Haar-detalp **) and Figure 14. With slow speed and stator winding fault (**Burt-5x7 X Haar-detalp)

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The following wavelet transforms are used for the TDyWT such as (i)Burt-5x7 (ii) Haar-detalp (iii)CDF-9X7 (iv)LeGall-5x3 (v)LeGall-5x3 deltalp.

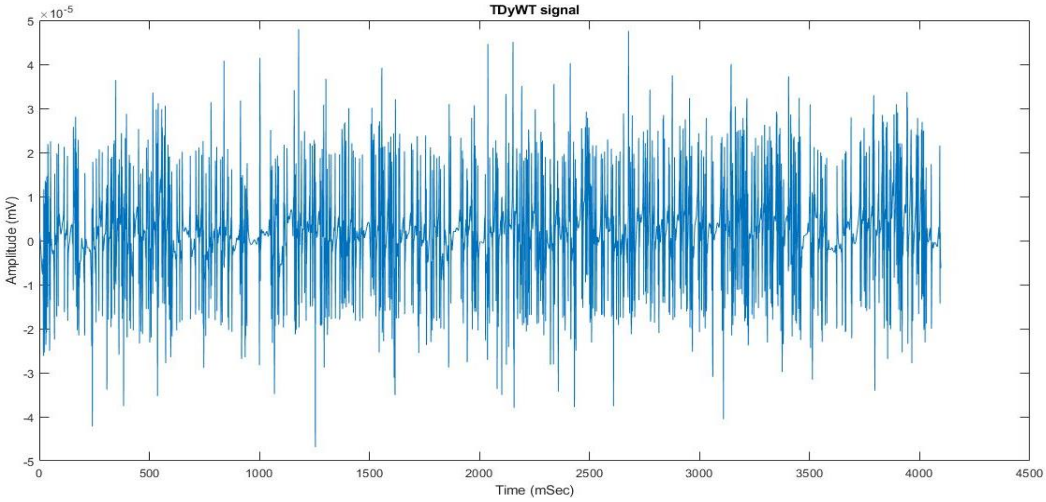

Figure 15. TDyWT processed signal with Highly transient and stator insulation fault (Burt-5x7 X Haar-detalp)

Table 2. Statistical comparison of NIR Reflected Residual signal Processed with Transverse Dyadic wavelet transform for winding and insulation fault

	NRR signal					
	Defect free state	**Operation of motor at loaded condition**	**Insulation fault of stator**	**Stator winding fault**	**Insulation fault of Rotor**	**Armature coil defect**
Mean	19.5335	19.1158	-0.496583	3.40374	-0.552193	0.04123102
SD	**535.637**	**304.068**	**256.367**	**4199.385**	**388.705**	**259.537**
Variance	278910	51464	34080.2	207494	60488.6	51361.4
Skewness	0.35557	2.40574	-0.20743	26.3117	22.4383	0.466705
Kurtosis	**3.17748**	**39.5588**	**22.681**	**5683.95**	**1677.32**	**20.1757**

Table 2. shows the TDyWT transformed processed NRR signal statistical values, for different faults in motor. The dyadic disadvantages are overcome by using transverse dyadic algorithm. The comparison between the two wavelet transforms is shown in **Table 3** as shown below.

Table 3. Comparison of transforms and performance accuracy

Transform	**Decomposition X Reconstruction**	**Performance in winding and insulation fault % accuracy (Winding faults in different Motors)**
DyWT	Haar X Haar	81
	Burt 5x7 X Burt 5x7	87
	CDF_9x7 X CDF_9x7	78
TDyWT	Haar X Burt 5x7	71
	CDF_9x7 X Burt 5x7	67
	Haar X CDF_9x7	83

Results obtained show performance analysis of accuracy in implementing the wavelet transforms as in **Figure 16**. It outwits the traditional method of fault detection.

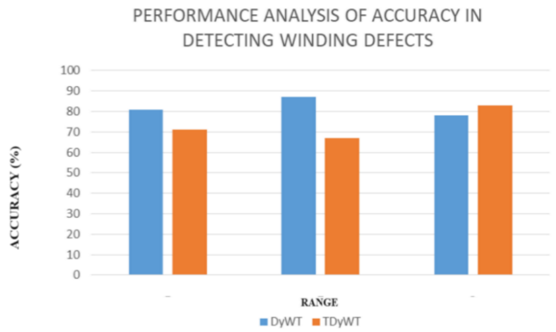

Figure 16. Performance analysis of accuracy for the developed study

CONCLUSION

In this paper, the winding fault with the dyadic transform, and Transverse dyadic wavelet transform is analysed through NRR signal from the induction motor fault. The fundamental drawback of dyadic wavelet transforms in motor winding fault detection is that the non- translate signals. The problem of translation in dyadic wavelet transforms is solved through the Transverse dyadic wavelet transform for winding fault detection. In TDyWT, scaling functions inextricably linked to the filters, and the exact specifications of the filters and functions provide temporal and frequency resolution. This study consolidated the overall analysis of NRR Signal using both the wavelets which improved accuracy comparing traditional mechanisms. Machine learning algorithms can used in feature for motor break-even point analysis.

DECLARATIONS

DATA OBTAINABILITY

Available on request.

FUNDING

No external funding is provided.

DECLARATION OF INTEREST

No conflicts of interest.

CONTRIBUTIONS

All authors have equally contributed towards the study.

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