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Induction Motor Voltage Variation and Fault Adaptation in Submarines

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

Induction motors are critical components in submarine systems, powering propulsion and auxiliary machinery under challenging operational conditions. These motors, however, are susceptible to faults such as voltage disturbances and mechanical anomalies that can compromise performance and operational safety. This research investigates the fault adaptation mechanisms for induction motors in submarine scenarios by integrating wavelet decomposition for fault detection and undervoltage relays for fault adaptation and mitigation. Wavelet transform analysis is employed to detect transient faults, specifically voltage disturbances occurring between 0.3 and 0.7 seconds. The system identifies fault characteristics in real-time using the high-resolution capabilities of discrete wavelet transforms, allowing precise localization and classification of anomalies. An undervoltage relay, integrated into the system, adapts to the fault condition by tripping the motor at 0.54 seconds to prevent prolonged exposure to damaging voltage dips. The study utilizes

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MATLAB/Simulink to model and analyze a 7.5 kW, 400 V, 1440 RPM induction motor operating under realistic submarine conditions. For fault identifications, twelve different scenarios are examined: Three phase to ground fault, three phase fault, double line to ground fault (AB-G), double line to ground fault (AC-G), double line to ground fault (BC-G), line to line fault (A-B), line to line fault (A-C), line to line (B-B) fault, single line to ground fault (A-G), single line to ground fault (B-G), single line to ground fault (C-G), and no faults. Also, for fault adaptation using under-voltage relay, two different scenarios are simulated for reference purpose: single line to ground and three phase to ground. Simulation results demonstrate the effectiveness of the wavelet-based detection in identifying faults early and the relay's timely intervention to protect the motor. These findings highlight the viability of integrating wavelet decomposition and adaptive relay mechanisms to enhance the resilience of induction motors in submarines.

Keywords: Induction motors; wavelet; faults detection; undervoltage relays; simulation.

1. INTRODUCTION

Induction motors are vital components of submarine propulsion systems and auxiliary machinery due to their robustness, efficiency, and reliability (Thongam et al. 2013, Liang 2019, Bassham 2003). However, these motors operate in highly challenging environments, including high-pressure conditions, limited cooling capabilities, and variable loads, which can increase their susceptibility to faults such as rotor bar damage, bearing failures, and insulation breakdowns. Adapting to and mitigating such faults is critical to ensure uninterrupted submarine operations, especially given the limited accessibility for repairs during missions (Schauder 1989).

Fault dictation and adaptation in induction motors within submarines involves the integration of advanced diagnostic and predictive maintenance systems (Bindi et al. 2023). For instance, (Delgado-Arredondo et al. 2017) propose a methodology for detecting faults in induction motors in steady-state operation based on the analysis of acoustic sound and vibration signals. (Gangsar & Tiwari 2020, Udoh et al. 2024, Abunike et al. 2021) uses signal-based condition monitoring techniques for fault detection and diagnosis of induction motors. Induction Motors Fault Diagnosis Using Finite Element Method was carried out in (Liang et al. 2019, Faiz et al. 2009). The use of artificial intelligence methods for condition monitoring and fault diagnosis of rolling element bearings for induction motor was propose in (AlShorman et al. 2020, Nkan et al. 2023). Similarly, (Kim et al. 2023, Okoro et al. 2022) further advance to induction motor fault diagnosis using support vector machine, neural networks, and boosting methods.

Traditional approaches like preventive maintenance often fall short in addressing unforeseen faults or operational stresses, leading to unexpected downtimes. Modern methodologies leverage condition monitoring systems that analyze parameters like vibration, temperature, and current signatures in real-time. For instance, motor current signature analysis (MCSA) is widely used to detect anomalies by identifying characteristic frequency components associated with specific faults (Bhole & Ghodke 2021, Mehala & Dahiya 2007, Sakhalkar & Korde 2017, Kalaskar & Gond 2014, Rafaq et al. 2020, Sonje & Munje 2012). Similarly, Wavelet transform has emerged as a promising solution for fault detection in induction motors due to its ability to decompose signals into time-frequency domains, enabling precise detection of transient and localized disturbances. Studies in (Bessous et al. 2018, Siddiqui & Giri 2012) propose a diagnosis of bearing defects in induction motors using discrete wavelet transform. Similarly, (Jimenez et al. 2007, Diji et al. 2013, Sunday et al. 2024) advance to fault detection in induction motors using Hilbert and Wavelet transforms. However, its application in submarine-specific induction motor fault detection remains underexplored. Current research lacks frameworks tailored to address voltage disturbances and non-stationary signal patterns arising from the unique operational demands of submarines.

In recent years, artificial intelligence (AI) and machine learning (ML) have further revolutionized fault diagnosis and adaptation. Techniques such as autoencoders, neural networks, and decision-support systems have been employed to model non-linear relationships in motor operations and distinguish between normal and fault conditions with high accuracy. These frameworks allow for the early detection of faults, enabling submarines to transition from reactive repairs to predictive maintenance strategies, which reduce operational risks and extend equipment lifespans.

Previous studies have explored the use of autoencoders in various applications, including an LSTM autoencoder for real-time pipeline leak detection using accelerometer signals and a framework for the identification of corrosion in hydropower facilities, achieving over 80% true positive detection (Spandonidis et al. 2022, Fera & Spandonidis 2024, Ekpo 2012). Recent studies have shown that autoencoders effectively identify damage in electric motors. A comparative analysis found that MLP autoencoders outperformed MLP, CNN, and LSTM architectures in detecting damage from vibration signals, achieving an AUC of 99.11% (Okpo et al. 2020, Okpo et al. 2023, Etim et al. 2024, Nkan & Okpo 2016). Additionally, research developed a hybrid health indicator using current and vibration signals to monitor bearings and stator windings in motors, demonstrating excellent performance across various load conditions (Husebø et al. 2020). CNN autoencoders were also used for the rapid identification of electrical damage in induction motors, achieving over 95% accuracy. Research carried out in (Riveiro et al. 2018, Bassey et al. 2024) shows the unsupervised methodology which proved to be an advantageous in sectors such as maritime, where instances of, damage data are frequently limited.

Digital twin technologies are also being integrated into submarine systems to simulate real-time operational conditions of induction motors (Madusanka et al. 2023, Okpo et al. 2019, Diji et al. 2013, Olatunbosun et al. 2014). These virtual replicas enable engineers to test fault scenarios and implement adaptive controls without risking actual hardware. Such technologies provide significant insights into system performance under varying conditions, aiding in the development of more resilient systems.

Despite these advancements, there are challenges in implementing fault adaptation systems in submarines. These include the need for high-fidelity sensors, data storage limitations, and computational constraints in confined spaces. Overcoming these barriers requires continued research into lightweight and efficient diagnostic tools tailored for maritime applications.

To bridge these gaps, this research work focuses on development of robust fault detection and protection framework for induction motors in submarine applications by integrating wavelet-based signal analysis and undervoltage relay mechanisms, ensuring early detection, accurate diagnosis, and timely mitigation of faults under challenging operational conditions. The study also focuses on enhancing motor reliability and operational continuity while addressing the specific challenges of non-stationary fault signals and voltage disturbances unique to submarine environments.

This paper is organized as follows. Section 2 outlines the overall methodology of wavelet-based signal analysis and undervoltage relay mechanisms. Section 3 details the simulation model for the motor, while Section 4 presents the validation results of the model. Section 5 concludes with the key findings of the research.

2. SIGNAL ANALYSIS METHOD—WAVELET TRANSFORM (WT)

The detection components installed in the motor, such as acceleration transducer, bearing resistance temperature detector (RTD), winding temperature sensor in the stator slot, partial discharge couplers, etc., can immediately control the running status of the unit and can immediately shut down for maintenance when the motor is abnormal. In the past, when the motor fails, experienced equipment maintenance engineers must make preliminary judgments before repairing the motor. The motor is often affected by the harsh operating environment and the noise interference, which makes maintenance engineers misjudge. Therefore, in recent years, there have been many signal analysis studies on the fault detection of electrical machinery. Common methods include fast Fourier transform by frequency and energy, and wavelet transform by frequency, energy, and time, as a reference for maintenance engineers to determine the types of failure.

Wavelet transform (WT) uses a mother wavelet to do the proper translation and scaling to match the signal which will be decomposed. The theory is extended from Fourier transform and it has the capability of multiple resolution analysis (Nichoga et al. 2010). WT can be divided into continuous wavelet transform (CWT) and discrete wavelet transform (DWT).

2.1 Continuous Wavelet

WT uses the oscillating waveform of a mother wavelet with finite length or fast attenuation to represent the signal. The mother wavelet has the following characteristics:

1. The integral is zero

$$\int_{-\infty}^{\infty} \psi(t)dt = 0 \quad (1)$$

2. Limited energy

$$\int_{-\infty}^{\infty} |\psi(t)|^2 dt < \infty \quad (2)$$

Compared to the Fourier transform, CWT can construct the time–frequency signal. CWT lets any function f(t) expanded by mother wavelet ψ(t), which is composed of a scaling function and displacement function, shown in (3), and CWT is shown in (4).

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \quad (3)$$

$$CWT_{a,b} = \int_{-\infty}^{\infty} f(t)\psi_{a,b}(t)dt \quad (4)$$

where a is the scaling function, b is the displacement function, and $\frac{1}{\sqrt{a}}$ is the normalization factor.

2.1.1 Discrete wavelet transform

DWT is used to discretize the scaling function a and displacement function b of the mother wavelet, that is, it is limited to a regularly distributed discrete point, thereby reducing the complexity of CWT. Therefore, making (4) discretize, and letting a = $a0^m$, b = $a0^m b0$, t = kT, where k, m, and n are all integers, T is defined as a time unit, and it will get the DWT, shown in (5). To consider the conversion efficiency, a0 = 2 and b0 = 1 are usually chosen, which is a dyadic orthonormal wavelet transform.

$$DWT_{(m,n)} = \frac{1}{\sqrt[m]{a0}}\sum_k f(k)\psi\left(\frac{k-na0^m b0}{a0^m}\right) \quad (5)$$

2.1.2 Multiple resolution analysis

Multiple resolution analysis (MRA) was proposed by Mallat (Huang et al. 2006). The equation is shown in (6). MRA decomposes the original signal into detail coefficients and approximation coefficients with a scaling function φ(t) and wavelet function ψ(t), shown in (7) and (8), and then reconstructed in different resolution layers, where the scaling function can be regarded as a low-pass filter, and the wavelet function can be regarded as a high-pass filter.

$$f(t) = \sum_k C_k\phi_k(t) + \sum_j \sum_k d_{j,k}\,\psi_{j,k}(t) \quad (6)$$

$$\phi(t) = \sqrt{2}\sum_k h(k)\phi_k(2t-k) \quad (7)$$

$$\psi(t) = \sqrt{2}\sum_k g(k)\phi_k(2t-k) \quad (8)$$

where h(k) and g(k) are low-pass and high-pass filter coefficients, respectively. The schematic diagram of MRA is shown in Fig. 1, where $dj\ and\ aj$ are the detail coefficient and approximate coefficient, and↓2 means the bandwidth sampling rate is halved.

2.2 Wavelet Decomposition Algorithm

A wavelet is a mathematical function used to decompose a signal into components of different frequency bands while retaining time information. Unlike Fourier transform, which only analyzes signals in the frequency domain, wavelet transform provides a time-frequency representation, making it ideal for analyzing non-stationary signals. Faults in induction motors submarine produce transient signals, such as sudden changes in current or voltage. Wavelets effectively detect these changes due to their localized nature in both time and frequency.

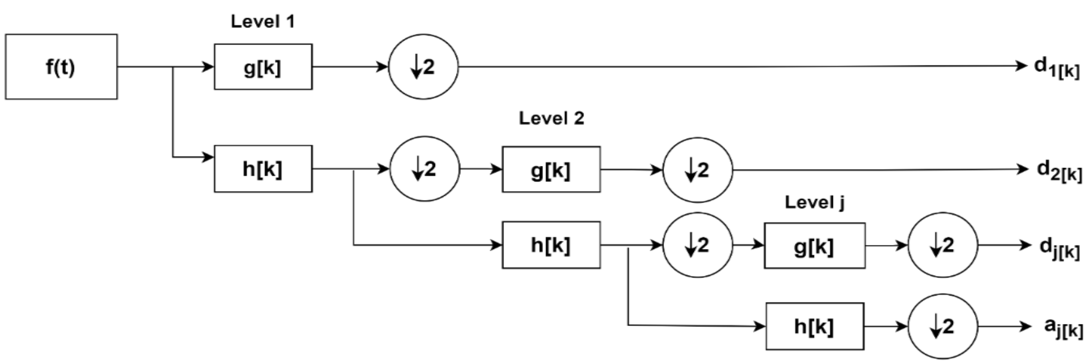

Fig. 1. Schematic diagram of multiple resolution analysis (MRA) (Lee & Cheng 2020)

The proposed fault detection algorithm leverages in this research work are wavelet transforms which will enable us to analyze the transient characteristics of current signals from the three-phase induction motor. Using the Daubechies wavelet (db4), this algorithm decomposes phase and ground current signals into detail coefficients that capture high-frequency transients caused by faults. By computing the maximum coefficients and comparing them to a predefined threshold, the algorithm effectively identifies and classifies faults such as single-line-to-ground, line-to-line, and three-phase faults. A flowchart representation of the algorithm demonstrates its logical structure, and its performance is validated through simulations of various fault conditions in MATLAB/Simulink. The results confirm the algorithm's accuracy and robustness, making it a reliable tool for real-time motor protection. The flow chart of the wavelet decomposition algorithm is shown in Fig. 2.

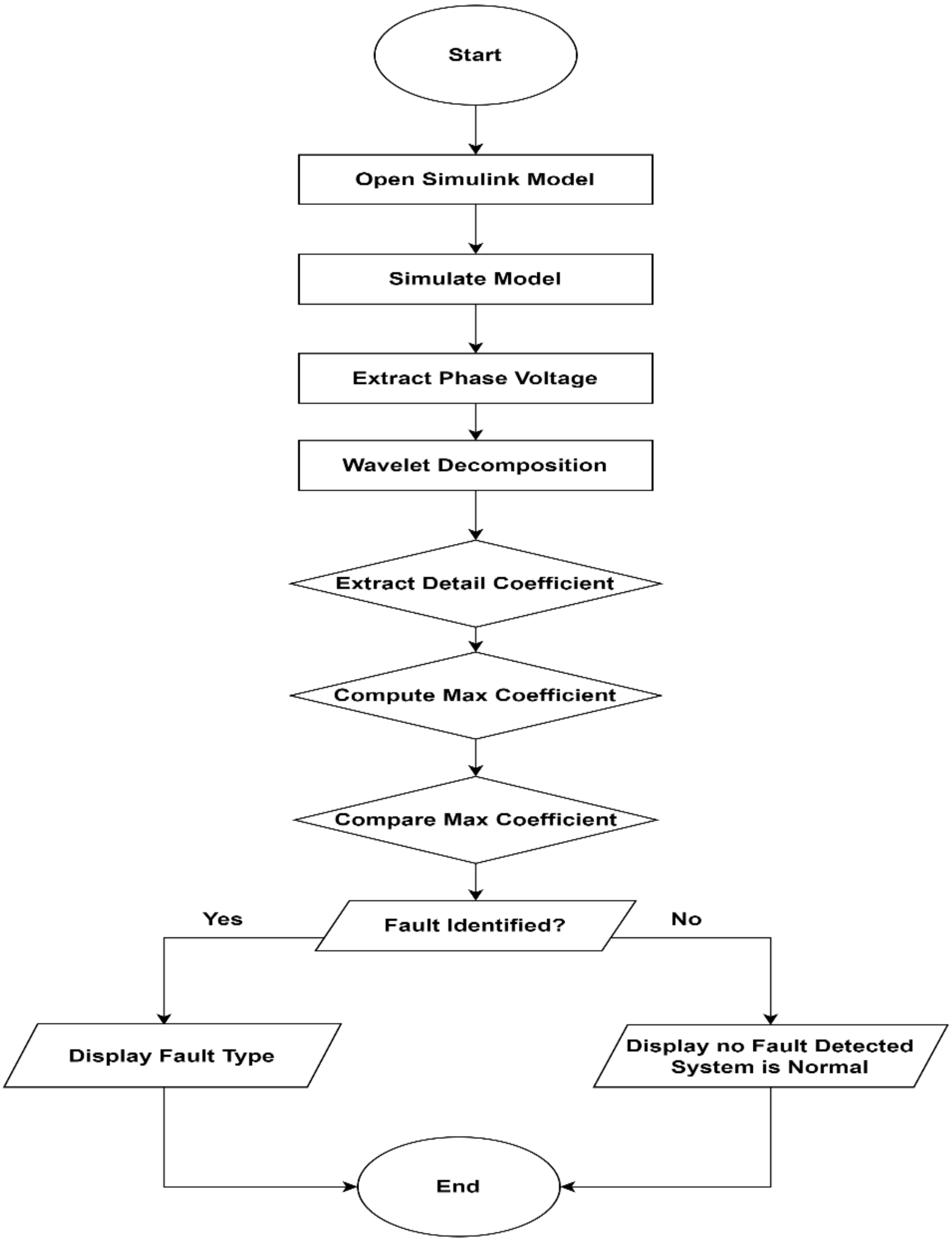

Fig. 2. Flow chart of wavelet decomposition algorithm

3. SIMULATION TEST CASE

The framework proposed in this research work is to evaluate whether the wavelet decomposition can detect stator winding damage in induction motors. In practice, the experimental analysis of electromechanical systems under normal and damaged operation conditions is not always possible due to the need to damage the equipment. To address the above-mentioned problem, a 3-phase low-voltage squirrel-cage motor is simulated using MATLAB Simulink. The simulation model utilized a 7.5 kW, 3-phase squirrel-cage induction motor (IM) and a fault block to replicate faulty operations. Fig. 3 displays the finalized model, while Table 1 outlines the key components, including the IM and fault block.

The selection of the 3-phase squirrel-cage motor is based on its extensive use in various electromechanical systems, including maritime applications. The model is developed to simulate the operation of the induction motor alongside a fault block specifically inject fault to the induction motor. The detailed specifications of the induction motor are outlined in Table 1, while Fig. 3, illustrates the simulation setup within the MATLAB workspace. The focus of the fault analysis is on the stator winding during a short-circuit event. The Simulink 3-phase fault block is capable of simulating two types of faults: phase-to-phase and phase-to-ground short circuits. Specifically, for fault detection and identification, twelve different scenarios are examined: Three phase to ground fault, three phase fault, double line to ground fault (AB-G), double line to ground fault (AC-G), double line to ground fault (BC-G), line to line fault (A-B), line to line fault (A-C), line to line (B-B) fault, single line to ground fault (A-G), single line to ground fault (B-G), single line to ground fault (C-G), and no faults. Also, for fault adaptation using under-voltage relay, two different scenarios are simulated for reference purpose: single line to ground and three phase to ground. Additionally, the level of damage, indicated by the resistance, is a crucial factor. The literature (Zoeller et al. 2017, Chaves& Oswaldo 2012) suggests that lower resistance indicates a severe insulation failure, representing a complete interturn short circuit, whereas higher resistance can produce similar malfunctions that are more challenging to detect.

The simulation is conducted over 1 s, utilizing a sampling of 0.2 $p.u$ voltage drop to capture the speed and torque of the induction motor as applicable to maritime sector. The choice of a 20% undervoltage variation for fault simulation in this study is grounded in its practical relevance to real-world operational scenarios and its ability to effectively replicate common faults in induction motor applications, particularly in demanding environments like submarines. In many cases, voltage drops of 10%–20% are used to simulate moderate to severe undervoltage conditions that can significantly affect motor performance. Severe voltage drops would result in more dramatic motor performance issues, such as significant torque reductions, motor stalling, or even insulation failure. While the faults are easier to detect, the system’s ability to adapt to such severe conditions might be compromised, possibly resulting in irreparable damage before the protection mechanisms engage. The relay would trip faster, and the wavelet analysis would show more intense and frequent transients.

Table 1. Motor simulation details and specs

Number	Parameters	Value
1	Input power of the motor	7.5Kw
2	Motor input voltage	400V
3	Frequency	50Hz
4	Motor speed	1440 RPM
5	Mechanical power	7.5Kw
6	Stator resistance	0.7384Ω
7	Stator inductance	0.003045 mH
8	Rotor resistance	0.7402Ω
9	Rotor inductance	0.003045 mH
10	Mutual inductance	0.1241H
11	Inertia(J)	0.0343 (kg.m^2)
12	Friction factor(F)	0.000503 $(N.m.s)$
13	Number of pole pair	4
14	Initial condition	10000000

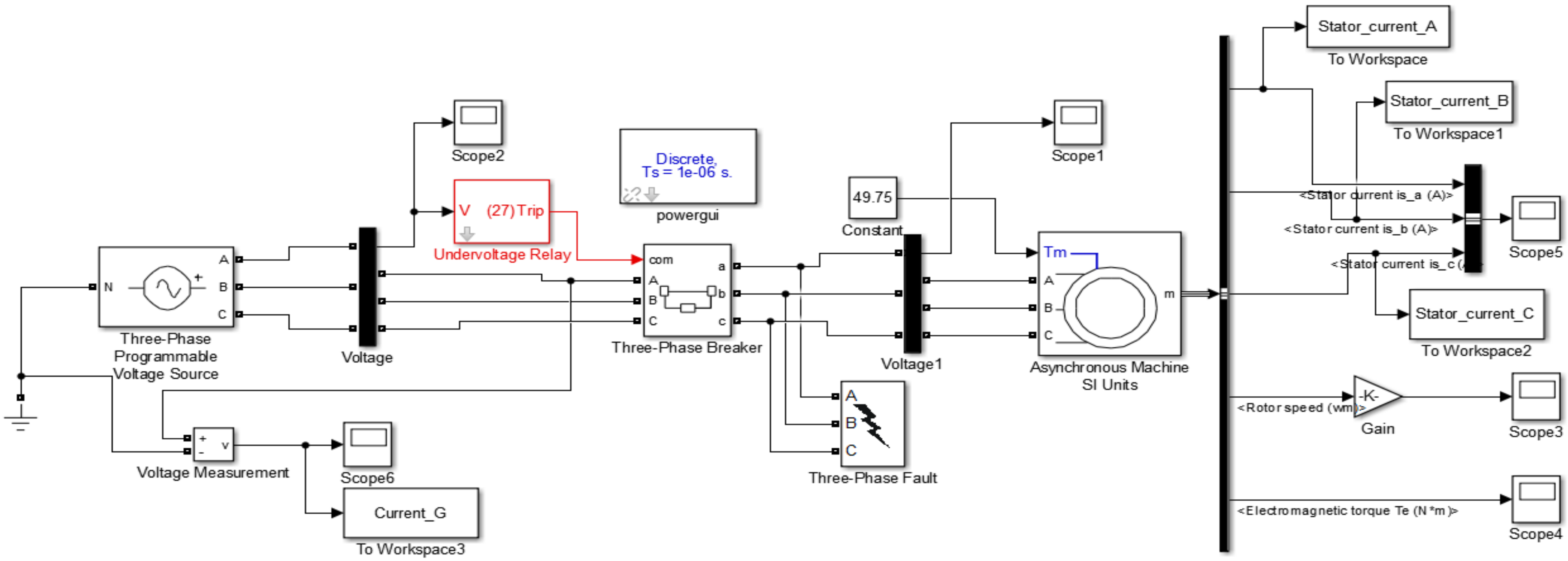

Fig. 3. Simulation setup as represented in MATLAB's workspace

4. NO FAULT ANALYSIS

For an induction machine supplied directly with the motor rated voltage, we can visualize the rotor speed, electromagnetic torque in Fig. 4.

As seen in Fig. 4. a, we have a normal transient state at the rotor speed; the speed start from zero (0 RPM) and move to the motor rated speed which is about 1440 (RPM) and maintain a stable output waveform without any distortion in the speed. As seen in Fig. 4. b, we have a normal transient state at the electromagnetic torque; however, at start, the electromagnetic torque experiences an increase of 2 to 2.5 the rated torque before it stable at 0.1 seconds and maintain a stable transient state till 1 second without any distortion.

4.1 Single Line to Ground (A-G) with 20% Under-Voltage Variation

Single line to ground fault (A-G) with 20% under-voltage variation introduces an unbalanced condition, they by impacting the motor's performance and causing asymmetric magnetic flux in the stator, which in turn affects the rotor speed, electromagnetic torque. In other for the induction motor to adapt to the fault, an under-voltage relay is connected to the motor to disconnect it from the supply. Fig. 5a, and 5b present the simulation result with 20% under-voltage variation and Fig. 5c, and 5d shown the adaptation simulation result.

As seen in Fig. 5a, the voltage drops in a single phase cause the rotor speed to experiences a slight reduction and distortion in the output waveform. The fault occurs at 0.3 second till 0.7 seconds, this weakens the overall magnetic field strength, causing the motor to lose some synchronism and slip slightly more than it would under balanced conditions.

As seen in Fig. 5b, electromagnetic torque becomes uneven and less stable leading to fluctuation and vibrations in the torque.

It can be seen in Fig. 5c, and 5d how the relay trip at 0.54 seconds, they by adapting to the fault scenarios also protecting the motor from damage.

4.2 Three phase to ground fault with 20% Under-Voltage Variation

The fault in this scenario occurs simultaneously across all three phases to ground representing a balanced but reduced voltage condition, this affects the motor performance differently than single-phase voltage drops. The system is analyzed up to the 0.54-second mark, when the under-voltage relay adapts to the fault by disconnecting the motor.

As seen in Fig. 6a the fault occurs across all three phases, this causes the rotor speed decrease but remains relatively stable compared to single-phase faults. Since the voltage reduction is balanced, the motor experiences less fluctuation in speed and can maintain a controlled, albeit lower, speed.

As seen in Fig. 6b the torque reduction is more uniform but lacks the severe oscillations seen in single-phase faults, as all three phases contribute equally to torque production. However, the torque output is insufficient to fully meet the load demand due to the lower power input, causing a steady but diminished torque level.

It can be seen in Fig. 6c, and 6d, how the motor adapts to the fault upon relay activation at 0.54 seconds by disconnecting it from the power supply they by bringing its rotor speed and torque to zero.

4.3 Wavelet Fault Identification Analysis

For fault identification analysis with wavelet, the selection of the Daubechies wavelet (db4) in this research was primarily motivated by its superior ability to capture transient, non-stationary signals, which are typical of fault-induced disturbances in induction motors. Table 2 present the specific reasons and comparative justifications for choosing db4 over other wavelets:

The maximum value of detailed coefficients of all the phases and ground voltage for different fault identification using wavelet decomposition algorithm are presented in Table 3.

Table 3 already summarizes the wavelet coefficients effectively, providing insights into the signal decomposition across different levels. For the simulated 20% undervoltage, detection times cluster around 0.3 to 0.7 seconds, with distinct deviations in both high- and low-frequency wavelet coefficients. This detection time vary slightly depending on the duration of the fault and waveform characteristics.

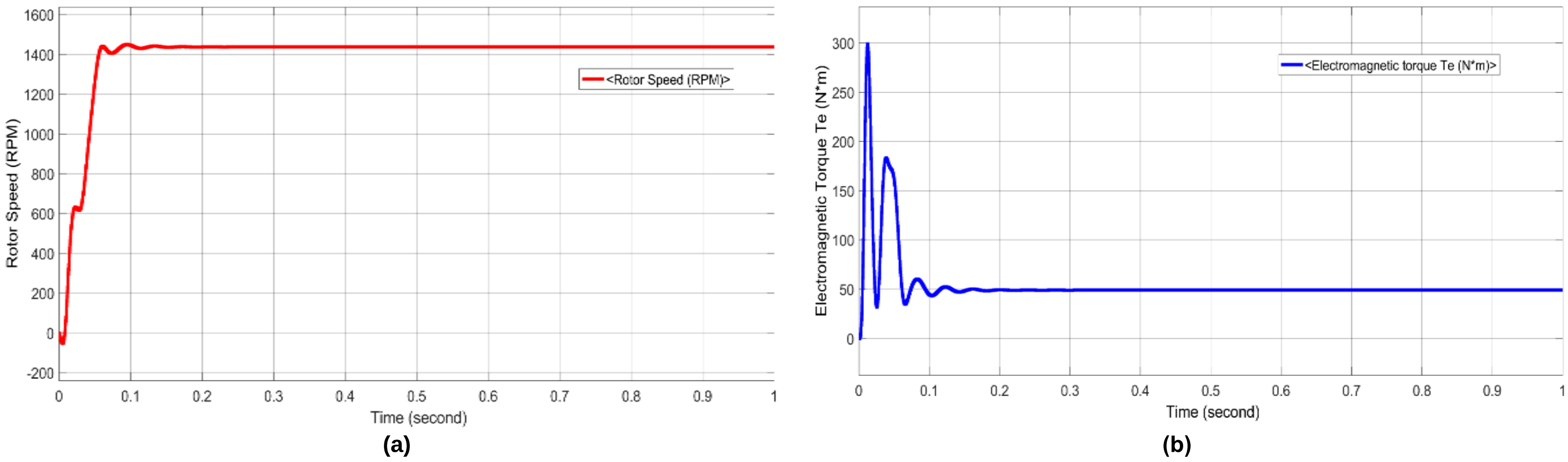

Fig. 4. (a) Rotor speed simulation result at no fault. (b) Electromagnetic torque simulation result at no fault

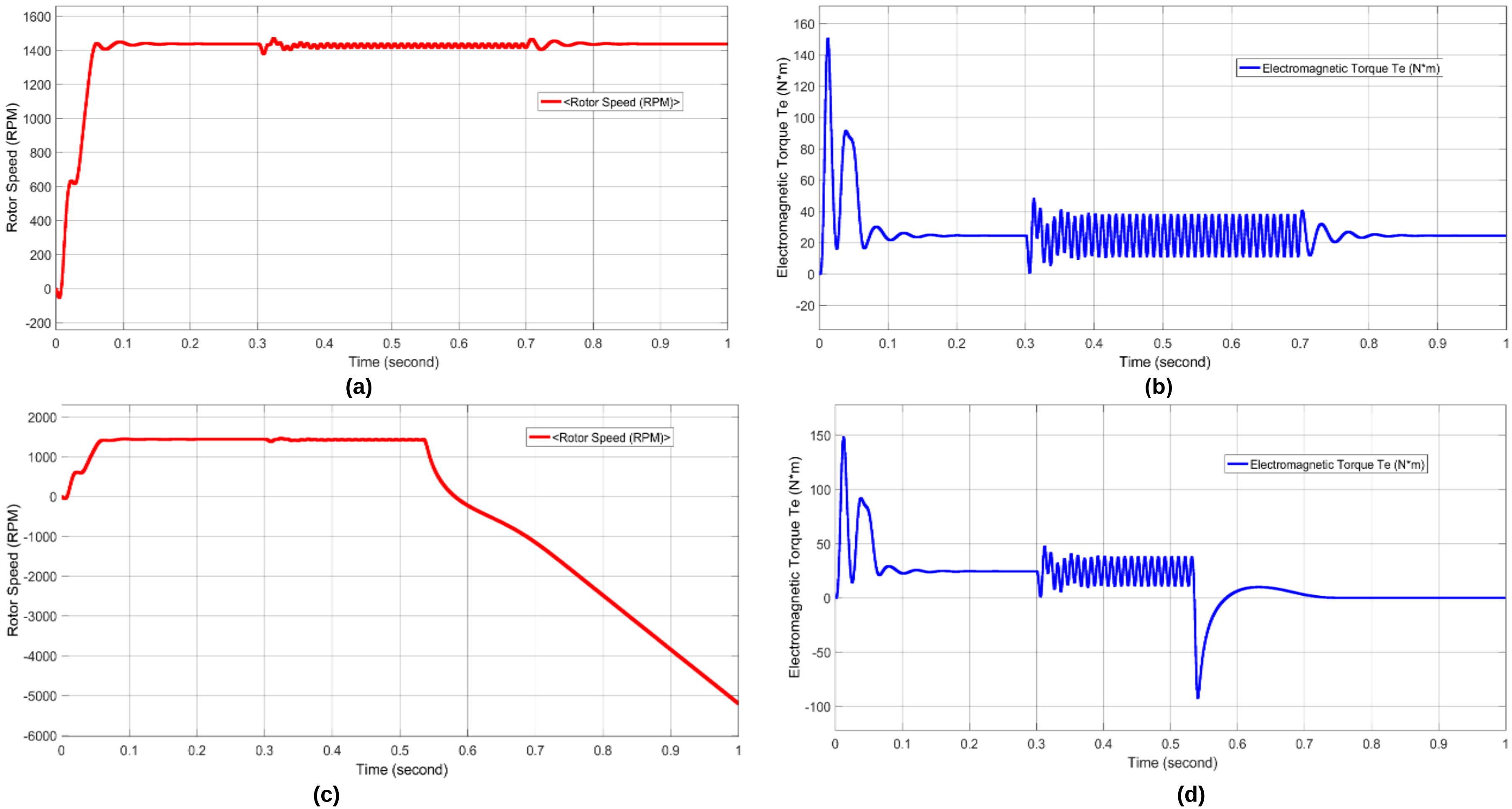

Fig. 5. (a) Rotor speed simulation result at single line to ground fault. (b) Electromagnetic torque simulation result at single line to ground fault. (c) Rotor speed simulation result at single line to ground fault with relay. (d) Electromagnetic torque simulation result at single line to ground fault with relay

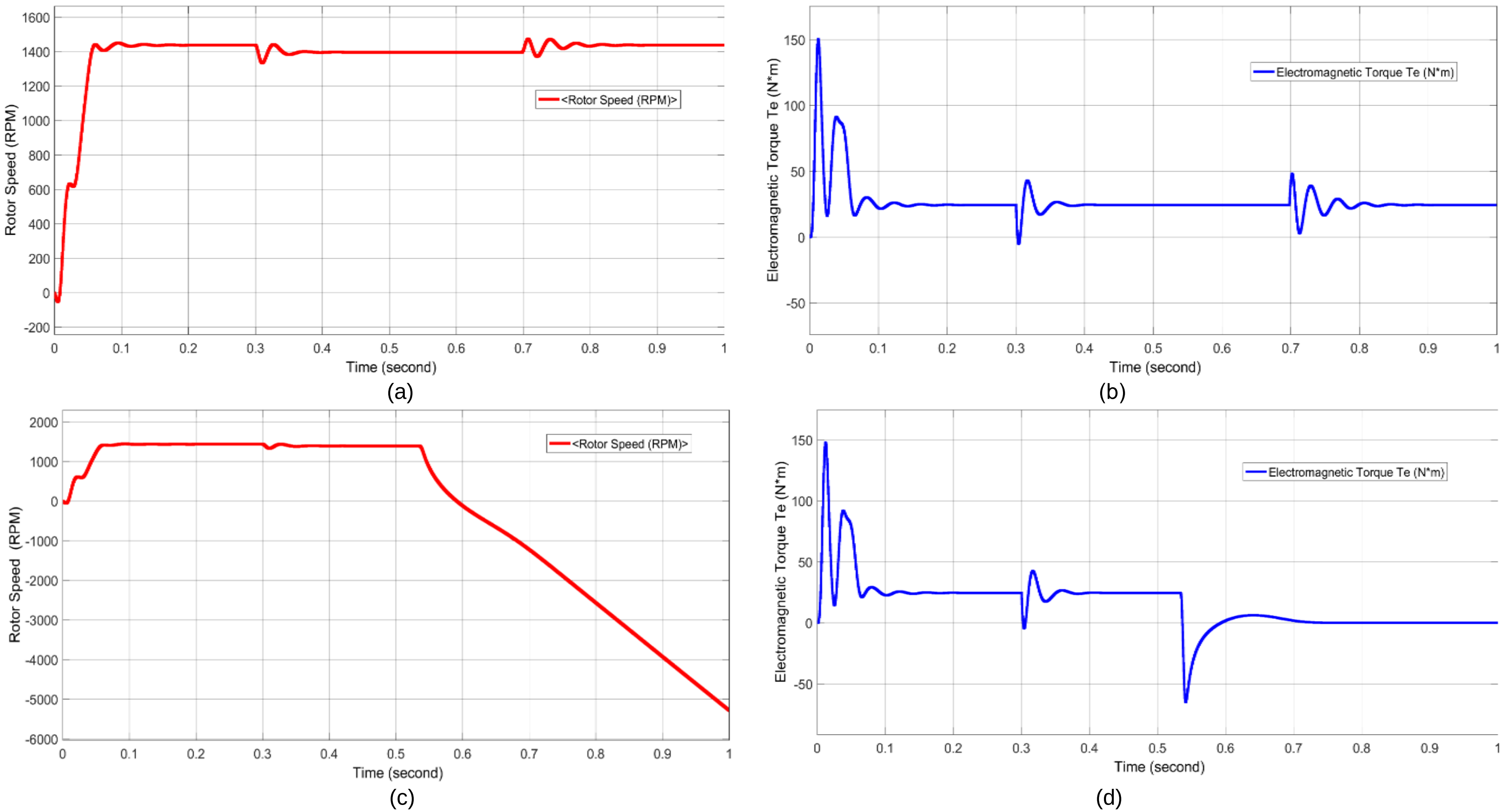

Fig. 6. (a) Rotor speed simulation result at three lines to ground fault. (b) E lectromagnetic torque simulation result at three lines to ground fault. (c) Rotor speed simulation result at three lines to ground fault with relay. (d) Electromagnetic torque simulation result at three lines to ground fault with relay

Table 2. Comparative analysis of daubechies wavelet and other wavelet

Wavelet Type	Strengths	Weaknesses	Comparative Notes
Haar	Simple, fast, good for step-like signals	Poor frequency resolution	Unsuitable for smooth, transient signals
Symlet (sym4)	Symmetry, good for image processing	Higher computational complexity	Similar to db4 but less efficient for faults
Coiflet (coif4)	Good frequency localization	Higher computational requirements	db4 offers similar results with lower effort
Morlet/Mexican Hat	Excellent frequency analysis, continuous wavelet	Computationally intensive, not discrete	Overkill for motor fault analysis
Daubechies (db4)	Balanced time-frequency, localized, robust for faults	Slightly less intuitive interpretation	Optimal for transient signal fault detection

Table 3. Maximum coefficients for different fault identification using daubechies wavelet decomposition algorithm

Type of Fault	Max. coefficient of phase A current	Max. coefficient of phase B current	Max. coefficient of phase C current	Max. coefficient of Ground B current
Three phase to ground fault	1.6097e+07	1.6025e+07	1.6097e+07	1.6024e+07
Three phase faults	1.6097e+07	1.6025e+07	1.6097e+07	0.0094
Double line to ground (AB-G)	1.0796e+07	1.1332e+07	119.5264	1.2652e+07
Double line to ground (AC-G)	1.9807e+07	135.5646	1.9739e+07	1.9393e+07
Double line to ground (BC-G)	103.9857	1.1725e+07	1.1478e+07	1.1619e+07
Line to line (AB)	1.0802e+07	1.0363e+07	119.5264	0.0094
Line to line (AC)	1.3363e+07	135.5620	1.3443e+07	0.0204
Line to line (BC)	103.9857	1.0725e+07	1.0847e+07	0.0051
Single line to ground (A-G)	1.3523e+07	103.9844	119.5264	1.4187e+07
Single line to ground (B-G)	103.9857	1.1024e+07	119.5264	1.1253e+07
Single line to ground (C-G)	103.9857	103.9844	1.4099e+07	1.5023e+07
No faults	103.9857	103.9844	104.9264	104.9355

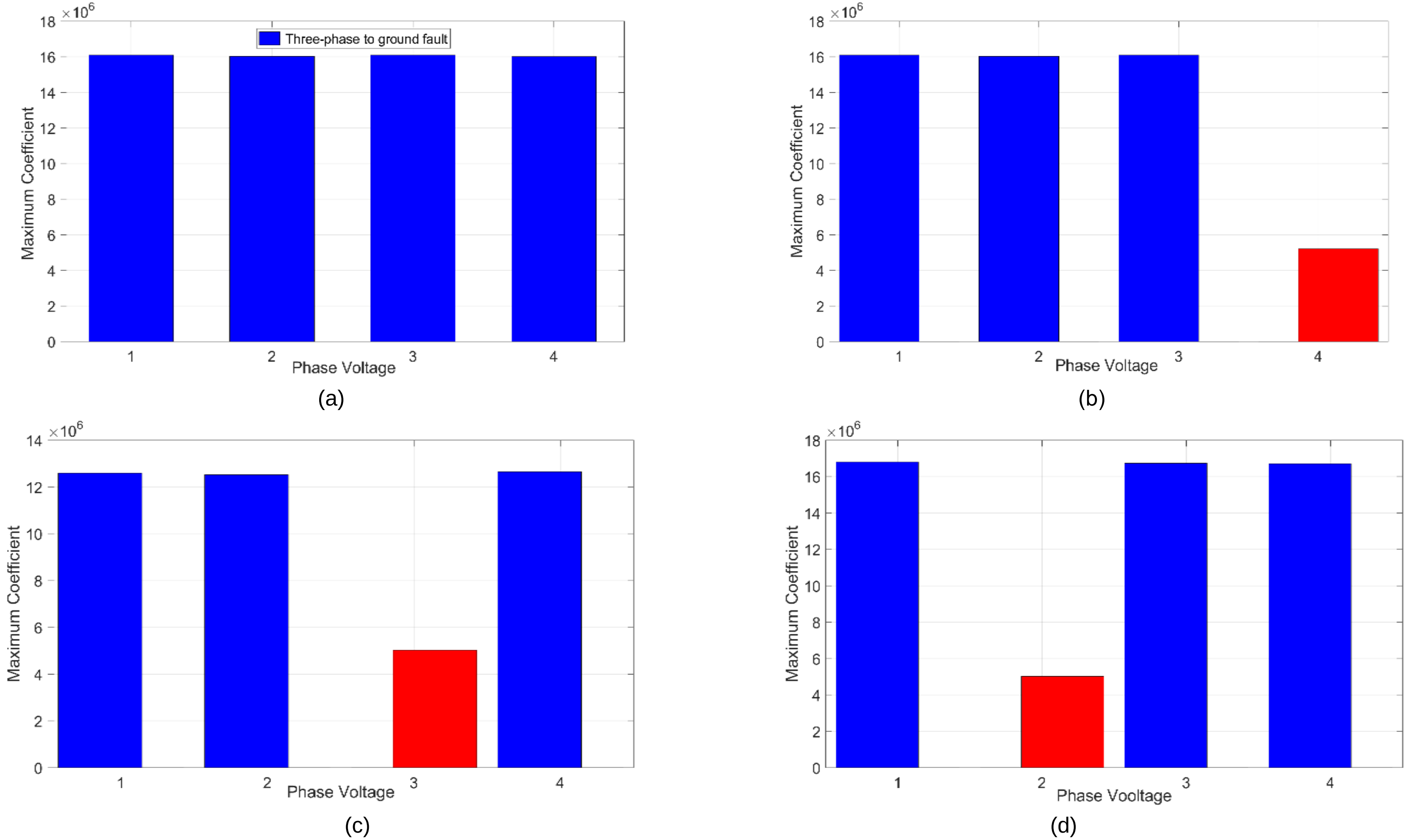

Fig. 7. (a) three phase to ground fault. (b) three phase fault (c) phase A-B to ground fault. (d) phase A-C to ground fault

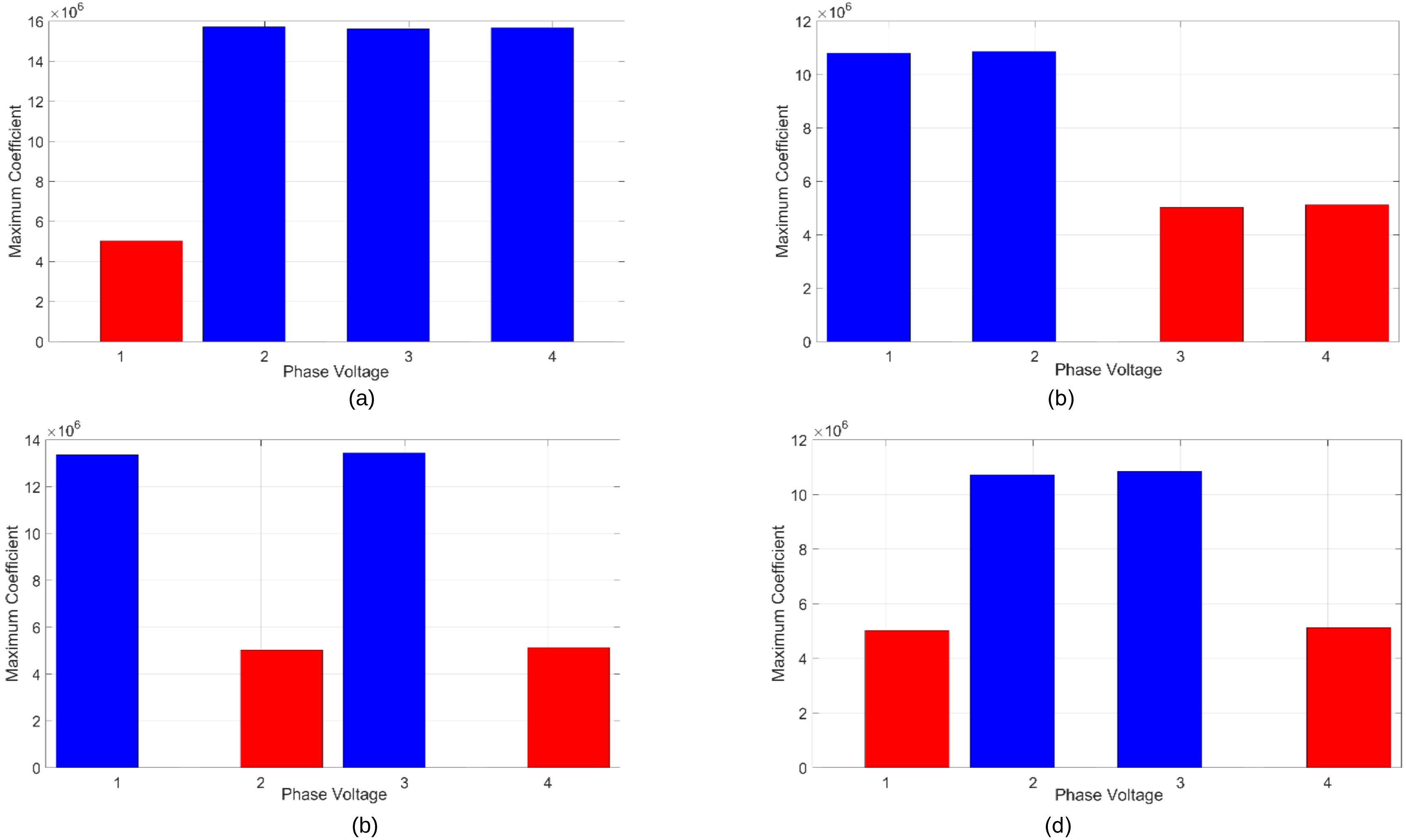

Fig. 8. (a) phase B-C to ground fault. (b) line A-B fault (c) line A-C fault. (d) line B-C to fault

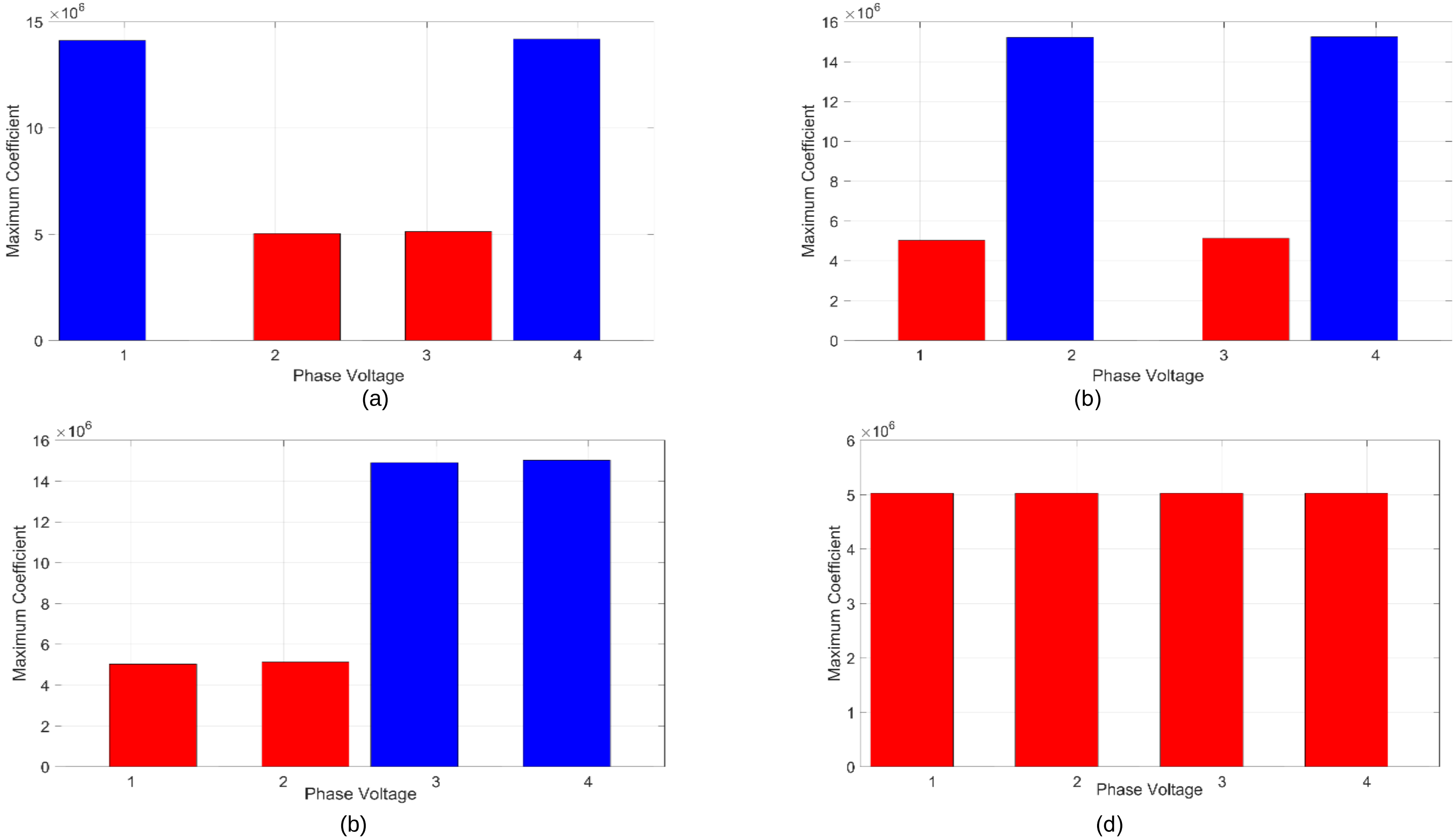

Fig. 9. (a) phase A to ground fault. (b) phase B to ground fault (c) phase C fault to ground fault. (d) no fault

As seen in Fig. 7a, when the fault occurs in all the three phases to ground, the coefficient in all the three phases to ground are very high.

As seen in Fig. 7b, when the fault occurs in three phases only, the coefficient in phase A, B, C are very high while ground coefficient is low.

As seen in Fig. 7c, when the fault occurs in line A-B to ground, the coefficient in phase A-B, and ground are very high while phase C coefficient is low.

It can be seen in Fig. 7d, when the fault occurs in line A-C to ground, the coefficient in phase A-C, and ground are very high while phase B coefficient is low.

As seen in Fig. 8a, when the fault occurs in phase B-C to ground, the coefficient in phase B-C to ground are very high while phase A coefficient is low.

As seen in Fig. 8b, when the fault occurs in phase A and B, the coefficient in phase A-B is very high while phase C and ground coefficients are low.

As seen in Fig. 8c, when the fault occurs in line A-C, the coefficient in phase A-C, are very high while phase B and ground coefficients are low.

It can be seen in Fig. 8d, when the fault occurs in line B-C, the coefficient in phase B-C is very high while phase A and ground coefficients are low.

As seen in Fig. 9a, when the fault occurs in phase A to ground, the coefficient in phase A to ground are very high while phase B and C coefficient is low.

As seen in Fig. 9b, when the fault occurs in phase B to ground, the coefficient in phase B to ground are very high while phase A and C coefficients is low.

As seen in Fig. 9c, when the fault occurs in phase C to ground, the coefficient in phase C to ground are very high while phase A and B coefficients is low.

It can be seen in Fig. 9d, when no fault occurs in the system, all the phase to ground coefficient are normal and equal.

5. CONCLUSION

This research successfully integrates wavelet decomposition and undervoltage relay mechanisms to develop a robust fault detection and protection framework for induction motors, specifically addressing the unique challenges of submarine environments. The proposed approach leverages the ability of wavelet transform analysis to detect transient, non-stationary faults with high precision, ensuring early diagnosis of critical issues like voltage disturbances. Additionally, the undervoltage relay's adaptive functionality ensures timely motor protection, tripping at a critical threshold of 0.54 seconds to prevent prolonged damage and operational failures.

The MATLAB/Simulink-based simulation of a 7.5 kW, 400 V, 1440 RPM induction motor validates the effectiveness of this methodology under demanding operational conditions. Results demonstrate that this approach significantly minimizes downtime, enhances motor reliability, and extends the operational lifespan of induction motors. Such improvements are especially critical for submarine applications, where operational continuity is paramount, and access for maintenance and repairs is limited.

Despite the widespread adoption of induction motors in submarine systems, existing fault detection methods, such as motor current signature analysis (MCSA) and vibration-based monitoring, often fall short in addressing transient and localized disturbances in the highly variable conditions of submarine environments. By addressing these limitations, this study bridges a critical gap in current research and offers a tailored solution for the fault detection and protection of induction motors in submarines.

The findings justify the adoption of wavelet-based signal analysis and undervoltage relay mechanisms as a practical and effective approach for improving fault tolerance and operational resilience in marine applications. This framework provides a foundation for future advancements in marine fault management systems, paving the way for more reliable, efficient, and adaptive submarine operations.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during writing or editing of this manuscript.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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