MJSAT

Malaysian Journal of Science
and
Advanced Technology

journal homepage: https://mjsat.com.my/

Revolutionizing Motor Health: IoT-Driven Detection of Electrical Abnormalities in Three-Phase A.C. Induction Motors

Alex Kok Bin See[*1], and Jed Jian Yao Ong[1]

[1] *School of Engineering, Ngee Ann Polytechnic, Singapore.*

KEYWORDS

Induction Motor
IoT Monitoring System
Non-Invasive Technique
Single Phasing Analysis
Vibration Measurements

ARTICLE HISTORY

Received 11 November 2023
Received in revised form 29 November 2023
Accepted 3 December 2023
Available online 4 December 2023

ABSTRACT

This paper presented a comprehensive investigation into the detection of electrical abnormalities in a 3-phase alternating current (AC) induction motor (IM) rated at 1.5 kW under simulated single phasing and overloading test conditions. The findings from data analysis on electrical abnormalities simulated physically on an IM were reported, employing a non-invasive technique. The data logging and control were designed using an industrial-grade graphical system design software, LabVIEW, and NI PXIe-1071 embedded controller hardware. A novel combination of in-situ on-line current measurements, infrared temperature detection, and 3-axes micro-electro-mechanical systems (MEMS) accelerometers were utilized for measurements. An internet of things (IoT) monitoring system of IM to any electrical abnormalities is described. Experimental results suggested that an IM subjected to single phasing experienced observable z-plane vibration, with a standard deviation of 0.24 G. For overload tests (at 50 Hz and 30 Hz) on the Induction Motor (IM) according to the National Electrical Manufacturers Association (NEMA) standard, the percentages of heating were calculated as 103.98 percent and 109.67 percent, respectively. No significant increase in z-plane vibrations was observed.

1. INTRODUCTION

Induction motors (IMs) are commonly used in many industries. The prevalent adoption of IM across diverse industries underscores their pivotal role, especially within the increasing upsurge of industrial automation, where they amplify production efficiency and resource optimization. In this dynamic context, the realm of electrical machines condition monitoring (EMCM) is pivotal and offers many advantages. Some of the key benefits are included as follows:

- Improved reliability: condition monitoring helps identify issues in electrical machines before they lead to complete failure. This proactive approach minimizes unexpected downtime and enhances overall system reliability.
- Increased efficiency: by monitoring machine performance and identifying inefficiencies or abnormal behaviours, operators can take corrective actions to optimize energy consumption.
- Cost savings: early detection of potential problems allows for timely maintenance and repairs, reducing the need for costly emergency repairs or replacements. This can result in significant cost savings over time.
- Extended equipment lifespan: regular monitoring and maintenance can extend the operational lifespan of electrical machines, reducing the frequency of replacements and associated capital expenses.
- Safety: Monitoring can help identify safety hazards such as overheating or insulation degradation, reducing the risk of accidents and ensuring a safer working environment.
- Data-driven insights: condition monitoring generates a wealth of data that can be used for predictive maintenance, trend analysis, and process optimization. This data-driven approach can lead to more informed decision-making.
- Reduced downtime: scheduled maintenance based on condition monitoring data can be planned during periods of lower demand, minimizing production downtime and

*Corresponding author:
E-mail address: Alex Kok Bin See <alex_see@np.edu.sg>.
https://doi.org/10.56532/mjsat.v3i4.212
2785-8901/

disruptions. Many asset owners in industries uses IM for extended long hours, it is crucial to be able to control, monitor the motors, while being able to diagnose and predict any upcoming potential faults.

Narwade et al [1] postulated that early fault detection in IM can significantly reduce the cost of maintenance and the risk of unexpected failures by allowing the early detection of potentially catastrophic faults. As in [2], this paper presents a novel approach for detecting electrical faults in induction motors using the Gabor transform and current spectral analysis. As in [3], the authors used a bio-flexible, lead-free piezoelectric sensor for vibration analysis and an infrared thermopile for non-contact temperature measurement. The data is transmitted via Wi-Fi to a monitoring station that intervenes to detect anomalies. The diagnosis of the motor condition is realized using an artificial neural network (ANN) algorithm implemented on the microcontroller. In [4], the authors propose a machine learning strategy based on algorithms to learn the characteristics from vibration signal's frequency distribution.

Shnibha et al. [5] introduced an enhanced method for monitoring the condition of three-phase induction motors, emphasizing vibration analysis only to improve accuracy and reliability. Mahami et al. [6] explored the utilization of infrared thermography imaging and ensemble learning techniques for induction motor condition monitoring. This approach aims to elevate the precision and efficiency of monitoring practices by incorporating advanced technologies. Krikor and Numan [7] delved into on-line current-based condition monitoring and fault diagnosis of three-phase induction motors. The study focuses on developing a method for assessing motor health through the analysis of current patterns, offering insights into potential faults and facilitating effective online monitoring.

Boudiaf et al. [8] introduced a real-time diagnosis method for three-phase induction machines using an Arduino-Uno card based on Park's circle method. The authors focus on leveraging the capabilities of Arduino-Uno to implement an effective real-time diagnostic system for induction machines, specifically employing Park's circle method for analysis. Rajamany et al. [9] addressed the detection of stator interturn short circuit faults in induction motors through the utilization of artificial neural networks (ANNs). The authors propose a method that analyzes line current sequence components to identify stator interturn short circuit faults. The use of ANNs enhances the accuracy and efficiency of fault detection in induction motor stators.

There are different types of faults in IM. They are broadly classified into two groups, namely mechanical and electrical fault. A detailed classification has been provided elsewhere by other researchers such as by Djagarov et al [10]. Furthermore, there are three main groups of fault detection and diagnosis (FDD) methods namely, model-based, signal-based and data-based methods which are described.

In this paper, the key motivation is to ensure that measurements data should be kept simple, minimum and analysis could be obtained instantly from the measurement readings. Inference should be made to provide an accurate and succinct indication of the potential faults in the shortest possible time. This research is important because many research papers presented complex detection algorithms and requires processing time which may hinder early detection and arresting of any electrical abnormalities of IM and thus alerting the operator to take immediate corrective actions to prevent further damage to the IM subjected to electrical faults.

This paper describes a signal-based approach for the detection of electrical abnormalities in three-phase AC IM by an automated computer-control system. A physical prototype was purposefully designed, developed, and built for experimental testing. Variable speed drive (VSD) sets were used for control of the IMs under tests. LabVIEW was used to send command/control signals to the VSD and the measurements were logged real-time and displayed on the program. LabVIEW was utilised as a powerful tool to perform data acquisition and analysis after measurements were extracted from the various sensors. Using a non-invasive approach, the electrical signal parameters including in-situ online supplied current, motor's external surface temperature, 3-axes vibrations were measured under different experimental tests. Two main experimental type of tests were conducted in this work, namely single phasing experiment and overloading experiment. No load tests were initially conducted to obtain baseline electrical parameters measurements for comparison purposes.

The field of fault detection and analysis in IMs presents researchers with intricate challenges arising from the complex nature of these electromechanical systems and the diverse operational conditions they are subjected to. IMs exhibit a remarkable degree of complexity due to their intricate interplay of various components and parameters, rendering accurate modeling a formidable task. Additionally, the advent of multiclass and multi-fault scenarios further compounds the challenges faced by researchers. The occurrence of multiple fault types concurrently requires further development work capable of accurately detecting, classifying, and distinguishing between distinct faults in a dynamically changing environment.

After literature review, the authors postulated that an extensive computer-control automated system with IoT capability has not been reported in the literature to date, and at the time of this writing. It is believed this IoT system with combined in-situ experimental measurements involving online phase currents, external motor's surface temperature and vibration has not been reported anywhere. Little is known about the specific effects combining underlying temperature rise, vibration and current increase as a result of single phasing or overload conditions in 3-phase IMs, prompting the need for further investigation. Research setup and results presented will add to the body of knowledge to the existing research related to detection of electrical abnormalities in 3-phase IMs.

2. LITERATURE REVIEW

In [11] this paper focuses on the development of an intelligent diagnostic system for AC motors, employing techniques such as artificial intelligence or machine learning for continuous monitoring. Similarly, as in [12] this paper explores the Internet of Things (IoT) and covers its architectures, communication protocols, and applications. While the specific domains differ, both papers share a common theme of leveraging advanced technologies to enhance efficiency, reliability, and performance in their respective contexts. Amanuel et al [13] explores an approach for fault detection in three-phase induction motors. The proposed method centers around a vibration frequency approach only, incorporating a fine-tuned factor to enhance the accuracy of fault detection. The paper provides insights into the design and implementation of this methodology, aiming to improve the reliability and efficiency of fault detection systems for three-phase induction motors. The details of the fine-tuned factor and the overall methodology are discussed, offering valuable contributions to the field of motor fault diagnostics. In [14], this study explores the application of the Kohonen Self-Organising Map as a tool for identifying and diagnosing faults in 3-phase induction motors. The paper discussed the methodology, experimental setup, and findings related to the effectiveness of this approach. The goal is likely to contribute valuable insights into fault detection techniques for induction motors, offering potential applications in industrial settings. As in [15]-[16], these two papers authored by A.H. Bonnett and G.C. Soukup provides an in-depth understanding of the NEMA motor-generator standards for three-phase induction motors. In their first paper, it covers key aspects and updates within the standards, with a focus on three-phase induction motors. The second paper, published at the IEEE Industry Applications Magazine, it extended the discussion on NEMA standards for three-phase induction motors. They provided further insights, updates, and practical applications of the standards outlined in the earlier paper. Collectively, these two papers contribute a comprehensive overview of NEMA standards, offering valuable information for professionals in the industry seeking a detailed understanding of the standards governing three-phase induction motors.

Thermal impact, degradation and protection of IM as a result of voltage imbalances and overloading have been reported. In the research paper as in [17], the review comprehensively addresses fault diagnosis in three-phase industrial induction motors. Covering a range of fault-related aspects, the paper explores various diagnostic techniques, methodologies, and technologies employed in identifying and preventing faults in these motors. The authors aim to provide a valuable resource for researchers, engineers, and practitioners involved in the maintenance and reliability of industrial induction motors. Ginacinski [18] reported in the study, the impact of voltage unbalance, overvoltage, and undervoltage conditions on the temperature and lifespan of the windings in an IM. The research includes experimental investigations to assess the thermal impact of different voltage disturbances. Measurements of winding temperature were conducted under various voltage unbalance, overvoltage, and undervoltage scenarios. This research presents empirical results that show the correlation between voltage disturbances and winding temperature. It also provides insights into how the combination of voltage unbalance, overvoltage, and undervoltage contributes to accelerated aging and reduced lifespan of the machine. Another research paper that focuses on enhancing the lifespan of electric motors by implementing improved overload protection based on an updated thermal model was presented by Ransom and Hamilton [19]. All three papers emphasize the significance of extending the lifespan and enhancing the reliability of electrical machines, particularly IMs. Each paper recognizes the importance of assessing and mitigating the thermal impact on electrical machines, specifically the temperature rises within these machines. All three research papers included experimental validation to test the effectiveness of their proposed methods and models. Real-world testing and measurements are conducted to verify the accuracy of temperature predictions and protection strategies. These three research papers share common objectives related to enhancing the reliability and lifespan of electrical machines, with a specific focus on monitoring and mitigating thermal impact. They propose protection strategies, utilize experimental validation, and emphasize the importance of IEEE standards in their research.

This research paper by Kersting [20] examines the causes and effects of unbalanced voltages when supplying power to an IM. It investigates the various factors that lead to voltage imbalances in three-phase systems and their consequences on the performance of IMs. In [21], Anwari and Hiendro introduced a new unbalance factor to assess the performance of three-phase IMs under conditions of both under- and overvoltage unbalance. The study provides a novel method for evaluating motor performance in the presence of voltage imbalances, contributing to the understanding and optimization of motor operations. To further serve researchers in better understanding of the power quality issues of supplying power to IM and other electrical machineries, the IEEE Standard 1159-2019 [22] would be a valuable resource for professionals in the electrical and power industries, offering guidance on how to effectively monitor and manage electric power quality to ensure the reliable and efficient operation of electrical systems and equipment.

Another research article by Tallam et al [23] serves as an important resource for researchers and engineers in the field of electrical machines and industrial applications. It offers an in-depth survey of methods for detecting stator-related faults in IMs, providing insights into the strengths and limitations of various diagnostic approaches. Most current review and reported by researchers at the time of this writing included a Canadian researcher, Liang [24] reported about the criticality of condition monitoring for the reliable operation of electrical submersible IMs especially in the oil and gas industries. It allows for the early detection of incipient faults, correct diagnosis, and the prevention of machine failures. By taking measurements from a motor and extracting features from the recorded time series signals, the motor's condition can be classified as either healthy or faulty. This helps to prevent costly downtime and repairs, and ensures that industrial processes run smoothly and efficiently. In summary, this research article provides valuable insights into temperature estimation and vibration monitoring for IMs, with a specific focus on their applicability in electrical submersible motors. It underscores the importance of proactive motor health monitoring to enhance reliability and performance in challenging industrial applications.

With the evolution of machine learning (ML) and fault detection in IMs, there is a growing body of research papers in this field at the time of this writing. Kumar and Hati [25] and Ciaburro [26] reviewed and reported machine fault detection methods based on ML algorithms. Other researchers, Barcelos and Cardoso [27] proposed and introduced a new approach based on fractional wavelet denoising and a deep learning algorithm to perform a bearing damage diagnosis from stator current. Gonzalez-Jimenez et al. [28] highlight the challenge of data availability and propose the use of simulation-based data generation. Their article presents a ML based fault diagnosis strategy to help maintenance assistants on identifying faults in the power connections of induction machines.

Benbouzid [29] reviews the use of signature analysis in detecting faults in IMs. It explores the application of various techniques to analyse motor operation and detect potential faults by analysing the motor's electrical and mechanical signatures.

Neelam Mehla and Ratna Dahiya [30] presented an approach for condition monitoring of IMs using motor current signature analysis (MCSA). Their study focuses on utilizing MCSA to detect and diagnose faults in IMs, contributing to improved motor maintenance and reliability. These recent article [31]-[36] discusses various techniques for detecting faults in electric motors by measuring physical variables and other techniques. Research articles [37]-[39] examined and reported on motor current signature and vibration analysis (MCVA) techniques in analysing and detecting faults in IM.

A voltage imbalance occurs when the voltage magnitudes within a three-phase system are unequal and/or have a phase angle difference of 120 degrees as reported elsewhere. The degree of voltage imbalance can be quantified using the voltage unbalance percentage (%UNB) as outlined in the IEEE standards 1159. From the outline and details, the postulated formula is given as follows:

$$\% \text{ UNB} = (V_{neg}/V_{pos})\times 100\% \quad (1)$$

where V_{neg} is the magnitude negative sequence component of the voltage and V_{pos} is the magnitude of the positive sequence of the voltage.

Conversely, mechanical overload arises when motors experience torque levels surpassing their designated operating conditions, resulting in elevated current consumption. This heightened current flow leads to the generation of excessive heat within the stator insulation. Overload is quantifiable as the current magnitude that surpasses the motor's nominal value. Typically, the extent of overload (% OVL) can be computed as shown in equation (2), where I is the measured current signal and Io is the current found on the nameplate of the motor:

$$\% \text{ OVL} = ((I-I_o)/I_o)\times 100\% \quad (2)$$

Most research papers surveyed reported the use of temperature, current or vibration measurements and analysis separately. In this proposed system, the objective is to design, develop, and implement an automated computer-controlled system for integrated fault detection in IM. It addresses single phasing and overloading conditions using collective/combined temperature, current and vibration measurements through signal-based analysis approach.

3. METHODS

In this section, the authors will provide an overview with an emphasis on the three main classifications of fault diagnosis and detection (FDD) methods. Different fault detection and diagnosis methods are generally discussed. Different categories of IMs are based on the following:

- Rotor constructions
- Number of phases
- Starting methods
- Speed control

Special Features:

1. Low cost
2. Requires little maintenance.
3. Good speed regulation
4. High efficiency
5. Good heat regulation
6. Small and lightweight
7. Explosion proof

3.1 Faults classification in 3-phase IMs

Faults in an IM can be further categorised into internal and external faults.

a. Internal Fault

1. Air-gap eccentricity
2. Inter turn short circuit
3. Imperfections in the stator core
4. Broken rotor bar
5. Bearing faults

b. External Fault

1. Single phasing
2. Unbalanced voltage
3. Voltage sag
4. Voltage swell
5. Mechanical overload
6. Short circuit
7. Abnormal speed

3.2 Classifications of fault detection and Diagnosis

There are three main classification of fault diagnosis and detection (FDD) methods. They are namely, model-based analysis, signal-based analysis and data-based analysis.

A. Model-Based Analysis

Model-based analysis method uses mathematical models based on the theoretical knowledge to exemplify the normal operation conditions of IM. Assumptions are made and it does not account for disturbances and uncertainties while avoiding impractical and complex modelling, therefore it might not be as accurate.

B. Signal-Based Analysis

Signal-based analysis stems from measured readings. The readings are extracted and processed to evaluate the conditions of the IM. However, there must be data that include faults acquired previously to correctly implement fault diagnosis. The three most commonly used analysis are as follows: time-domain analysis, frequency-domain analysis and time-frequency analysis.

- Time-Domain Analysis

Time-domain FDD methods are carried out through checking peculiar changes in the readings extracted from the collection of data along with time. It involves simple calculations to determine the condition of the IM but the accuracy of the analysis might be jeopardized due to its low sensitivity. For instance, noise produced might be collected in the data resulting in unreliable information.

- Frequency-Domain Analysis

There are faults that provides frequency information in various spectra due to the resulting periodic vibrations of mechanical forces and airgap spacing. Fast Fourier Transform (FFT) is frequently used to conduct frequency-domain analysis [40] – [41]. There are some prominent drawbacks such as spectral leakage, low resolution, and long measurement periods. The drawbacks are discussed elsewhere by researcher, Lee et al [42] who examined the mechanical vibration analysis and the vibration frequencies occurring at the stator far exceeds the rotor. Benbouzidi et al [43] investigated the use of Fourier and wavelet analysis tools and this research addresses the issue of fault localization, aiming to determine the physical location of the fault within the motor. This is achieved by analyzing the spatial distribution of fault-related information in the stator current signals.

- Time-Frequency Analysis

Time-frequency analysis is suitable for dealing with moving signals. This method has a more accurate determination of the condition of IM from the collected readings as it uses continuous spectral analysis with short time intervals, and it is complex in computing.

C. Data-based Analysis

Based on data analysis, data are read and the treatment of signals to identify the characteristics on relevant application based on patterns recognition. Other data-based analysis includes empirical models such as using process data; statistical methods, artificial intelligence, artificial neural network and fuzzy logic methods have been widely reported elsewhere.

In this work, signal-based approach of fault detection and analysis was performed, using an IM based on rotor construction was chosen for ease of conducting the various experimentations. Two 3-phase rated 50 Hz squirrel case IMs of 175 W and 1.5 kW were utilized in this project.

3.3 Current transducer and 3-axes MEMS accelerometers

A current transducer is a device that converts current into a proportional industrial standard electrical signal. Current transducer is prevalent and essential in many industries due to its non-invasive, isolation ability and does not directly connect in series to the existing "live" circuit under measurements. As there are many other devices placed in any single industry, there might be a possibility of interferences which might reduce the accuracy of the measurement signal, thus using a current transducer will remove the interferences. Due to the conversion function, it can transform any non-standard electrical current to industrial standard electrical signal, which eases the usage of terminal equipment use. It can work for long distances, and it has in-built safety function.

The industry standard electrical signal can be in the form of current or voltage depending on the customization. The brand and model in used is LEM AC current transducer AT-B420L, a split core type for measurement of AC waveforms currents with galvanic separation between primary circuit and secondary circuit. The looped powered output of 4-20 mA is proportional to the RMS value of the primary current. with ambient operating temperature range -20 °C to +60 °C. With measurement error current of $< \pm 1.5\%$ and linearity error is $< \pm 0.5\%$ of the primary nominal 5A RMS value. The transducer is considered suitable for this research experimentation work.

The current transducer has four main segments, namely: sensitive components, conversion components, conversion circuits and power circuit. The measured electrical parameter transmits into the sensitive component, it would pass into the conversion component which results in small current signal. The small current signal will pass through the conversion circuit to give an output based on the specifications selected in the industry standard electrical signal. Both the conversion component and circuit are powered by the power circuit.

A 3-axes MEMS accelerometer (AKF394) from Rion Technology was used for this project. The accelerometer is an industrial grade sensor which was used for vibration testing impact and other fields such as in high-speed railway fault detection. The accelerometer uses a digital interface RS485 with Modbus protocol for communications. Selectable range of baud rates are available using this device. It's a non-invasive sensor, which is versatile, accurate and highly sensitive. After much research, it was found to be relevant and highly suitable for this measurement and monitoring research application.

3.4 Data acquisition module

A brand and model known as ADAM 6017+ Data acquisition Module (DAQ) was used to convert the analogue signals captured from the current transducer into digital values. The DAQ is linked to a router for capturing of "real-time live" data to the main program at high throughput. In addition, an industrial embedded controller from National instruments, a PXIe-1071 controller was utilized for this work.

3.5 Temperature parameter measurements

A pyromini USB model CALEX PMU21 with temperature range -20 °C to +1000 °C , accuracy of ±1°C was utilized for this work. Infrared (IR) temperature sensor transmits an infrared energy beam focused by lens onto a surface to detect the surface temperature at the exterior of the IM at the chassis area as depicted in Figure 7, labeled position 4. The reflected beam converts the energy received to an electrical signal that can be displayed in temperature units. The communication protocol in used was the Modbus RTU.

A thermal imager model FLUKE TiS55+ was utilized to verify the accuracy, precision and reliability of the CALEX PMU21 temperature sensor. By employing the thermal imager, TiS55+, a comparison and cross-reference the temperature readings were obtained from the sensor with the corresponding thermal images. This method or approach had successfully enabled the assessment of the consistency and precision of the on-situ temperature sensor, ensuring its performance aligns with the desired specifications, to an accuracy of ±0.1°C variation.

3.6 Programming and software design

In this work, LabVIEW with appropriate device drivers, Modbus RTU and Modbus TCP/IP libraries were used for the main program and the data analysis program. The system overview or architecture is depicted and shown in Figure 1. The main program consists of an interactive user-friendly page/interface, for the user to monitor the real-time "live" data acquired from the various sensors and vary the speed of the motor by controlling the frequencies of the different variable speed drives set based on the Nidec Unidrive M700 series. Figure 2 depicts the image of the LabVIEW front panel design of the main program which interacts with the user/operator. Figure 3 depicts the image of the LabVIEW front panel design to vary the speed of the motor by controlling the different Variable Speed Drives set based on the Nidec M700 Series. Figure 4 depicts the image of the LabVIEW front panel design of the real time measurements.

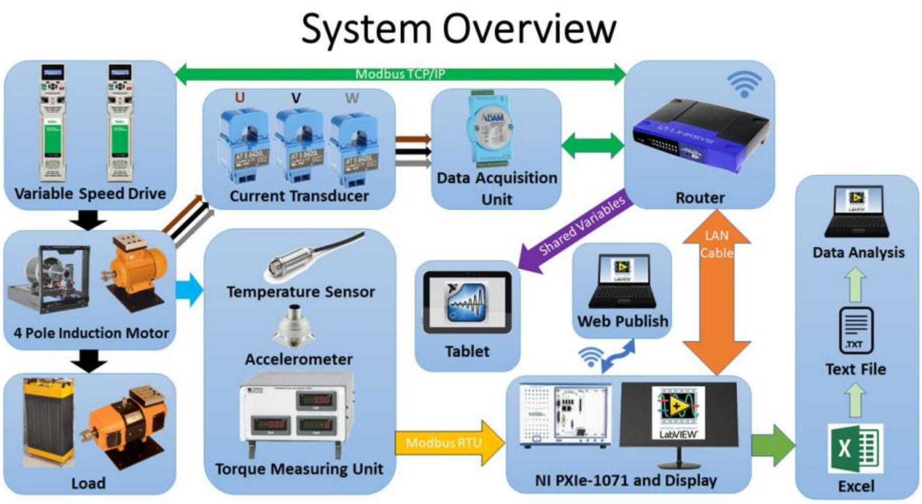

Fig. 1. System Overview

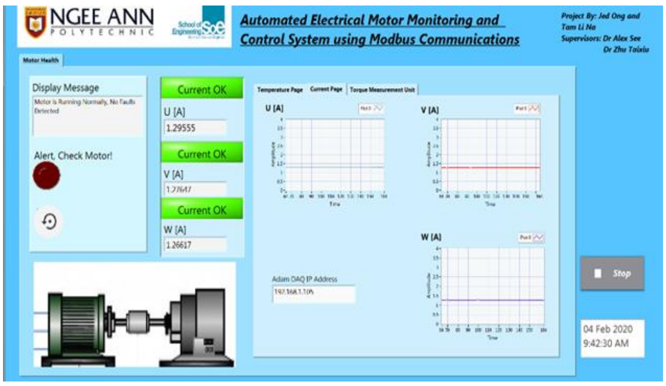

Fig. 2. Front Panel of Main Program in LabVIEW

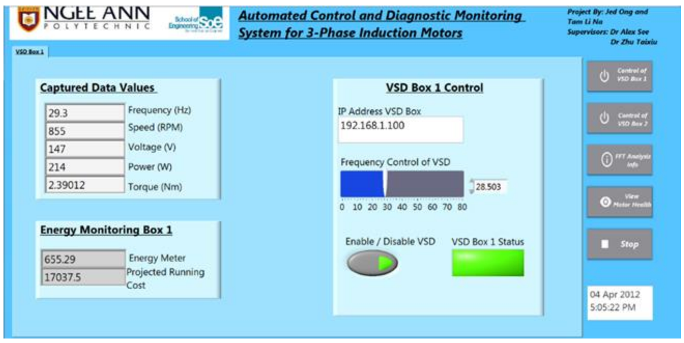

Fig. 3. Front Panel of Main Program to control Nidec M700 (VSD Box 1 Control Page

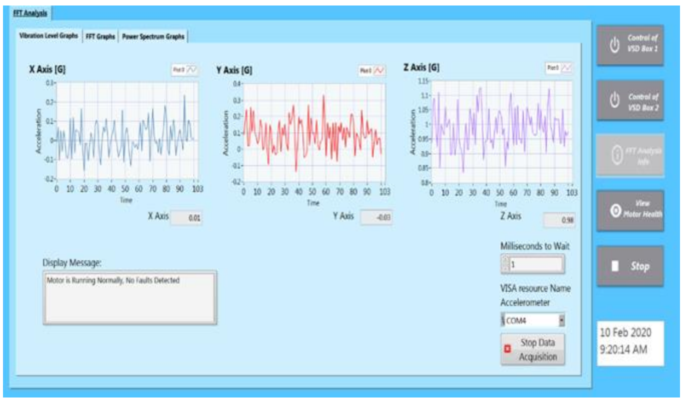

Fig. 4. Front Panel of Main Program depicting real-time measurements

3.7 Data Logging and Data Analysis

Data logging refers to the collection of measured data using LabVIEW. LabVIEW is used for the collection of data and the data collected is saved in Microsoft Excel sheet. The parameters collected are the magnitude of the current in amperes, the magnitude of the temperature in degree Celsius and the level of vibration measured in G. Subsequently, these excel files would be converted to tab delimited files, also known as "txt" file manually. These .txt files were transferred into the data analysis program where it would allow the user/operator to offline perform further analysis on the motor tested.

3.8 Web publishing and IoT applications

The main LabVIEW program allows operator to view measurement data remotely. The advanced measurement data used shared variables in LabVIEW, where the data on the main program could be viewed on NI Data Dashboard application which could be downloaded from the App Store or through the internet by using the Web Publishing feature in LabVIEW. Hence, the system is well-suited for use with IoT applications. As mentioned earlier in the introduction section, the advancement of this automated computer-based using IoT approach has not been reported anywhere else in the literature to date at the time of this writing. This system is considered to be novel and applicable for industrial automation in a scalable manner and possibly deployable at various manufacturing plants. It is believed that this measurement system will be applicable and relevant for industrial applications.

4. RESULTS

4.1 Experimental setup

The experimental configuration was meticulously designed and composed of essential components, as visually depicted in Figures 6 and 7. These components collectively formed a comprehensive system to investigate and monitor the operational characteristics of a 3-phase squirrel cage IM for the experimental tests conducted. At the heart of the experiment is the 3-phase squirrel cage , with a power rating of 415 V, 3.55 A, and 1.5 kW. The setup incorporated 3 current transducer the AT-B420L which are used to measure the individual phases of the motor – U, V and W. The readings obtained from the current transducer are acquired via the ADAM 6017+ Data Acquisition Module which converts the analog signals from the current transducer into digital values for data logging purposes. To assess the motor's thermal conditions, an infrared temperature detector was integrated into the setup. Lastly, the 3-axes MEMS accelerometer is used to measure the vibrations level of the motor under test conditions as stipulated in this paper.

4.2 Test environment

All tests were conducted within a controlled laboratory environment, maintaining an ambient temperature ranging from 23°C to 25°C based on the experimental setup as shown in Figure 6. This ensured consistent testing conditions throughout the experiments.

4.3 Test phases and conditions

The experimental investigation encompassed three pivotal test phases which are listed below namely: normal no-load operating condition, single-phasing condition, and overloading tests. The three phase supplied currents are denoted by U, V and W phases. These electrical current parameters were measured values in RMS quantities.

4.4 Normal no load operating condition

Firstly, the motor operated with magnitudes of the three phase currents (U, V, and W) maintained below the rated current of 3.55 A. The motor was operated at frequencies of 20 Hz and 60 Hz, with the resistor load bank disconnected from the motor. The line current, the vibrations level of the motor was observed to be stable as shown from Figure 9 to 14.

4.5 Single phasing test

Secondly, the procedure for conducting the single phasing test involves activating the dedicated single phasing switch. This specialized control circuit serves the purpose of disconnecting one of the phases in the supplied line to the 3-phase A.C. IM. Specifically, the "W" phase of the motor is linked to this single-phase switch, which is intentionally designed for executing the test. By intentionally disconnecting the "W" phase, the previously balanced interplay among the three phases is disrupted. It's important to note that in a healthy 3-phase system, the phases are typically 120 degrees apart in terms of voltage and phase angle.

Consequently, this deliberate disconnection of the "W" phase results in an alteration of the supplied voltage to the motor. The absence of one phase causes the voltage distribution to become skewed, leading to an uneven distribution of power within the motor. This deviation from balanced operation triggers an immediate response from the remaining two phases. In an effort to compensate for the reduced power input due to the disconnected phase, the currents in these two phases undergo an increase.

To perform the single phasing test, the IM is set to operate at a frequency of 30 Hz. This specific frequency is chosen to assess the motor's response to the deliberate disruption of the phases. The test duration spans a period of 3 minutes, during which various measurements are taken to closely observe the effects of single phasing on the behaviour and performance of the induction motor.

4.6 Overload test

Lastly, the overload test of the IM. The overload test necessitated connecting the motor to a resistor load bank. The overload test was conducted at two frequencies, 30 Hz and 50 Hz. The resistor load bank is adjusted from 0 ohms (the minimum resistance) to the maximum resistance of 132 ohms. Once the load was set to the maximum resistance, the motor line current will exceed the rated current on its nameplate, hence the IM will become overloaded as a result. Measurements were also taken for the readings captured to observe the effect of overloading on the IM.

4.7 Block diagram of the experimental approach

In the block diagram in Figure 5, it illustrates the approach taken for the experimental approach. The parameters acquired during the tests encompassed the magnitude of current in amperes (RMS values), temperature in degrees Celsius (°C), and vibration levels measured in G (acceleration units in meters per second squared) for the X, Y and Z axis. These datasets were recorded and subsequently converted into tab-delimited "txt" files for further analytical processing. The datasets obtained from the single phasing and overload test and then compared with the normal condition after further processing of the datasets.

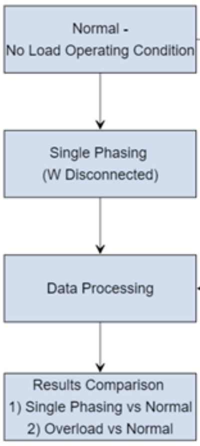

Fig. 5. Block diagram of experimental approach

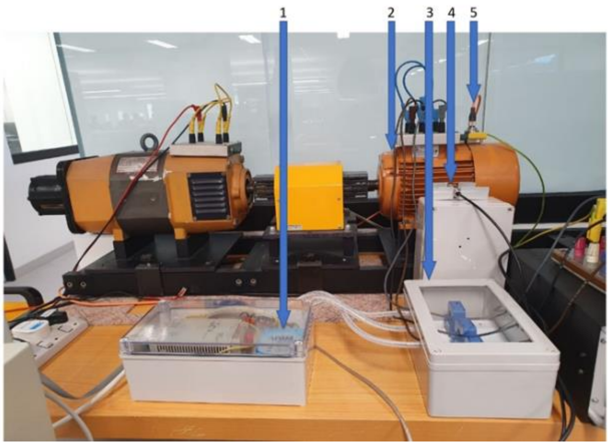

Fig. 6. Experimental set-up

Fig. 7. Photograph of the 3-phase IM full system setup in a laboratory environment with controlled ambient temperature well kept at between 23°C to 25°C

Table 1. Legends for experimental setup

Number	Name
1	Data acquisition module, Adam 6017+ DAQ x 1 unit
2	Induction motor, squirrel cage, 415V, rated 3.55A, 1.5kW@50 Hz x 1 unit
3	LEM current transducers, AT-B420L x 3 units
4	Infrared temperature sensor, PMU21 x 1 unit
5	3-axes MEMS Accelerometers, AKF394 x 1unit

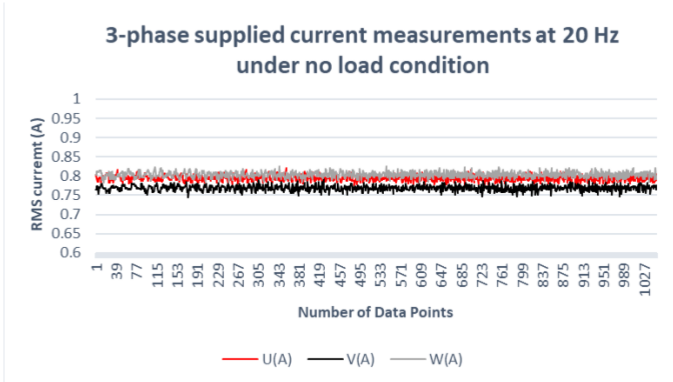

Fig. 8. On-line current measurement of the IM at 20 Hz with no load

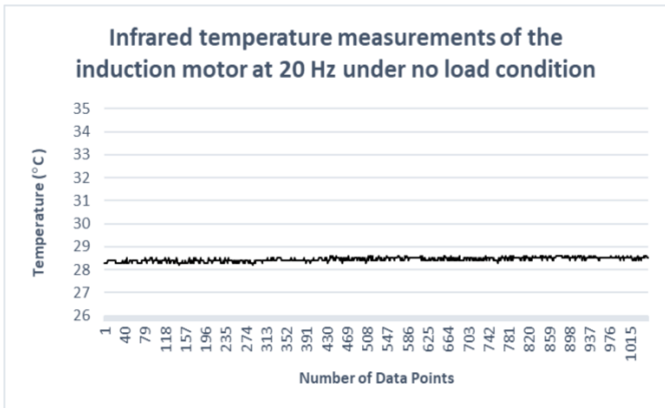

Fig. 9. Infrared temperature measurements of the IM at 20 Hz with no load

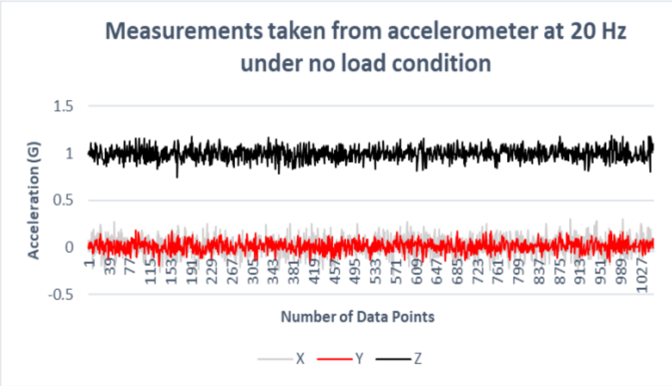

Fig. 10. 3-axes MEMS accelerometer measurements of the IM at 20 Hz with no load

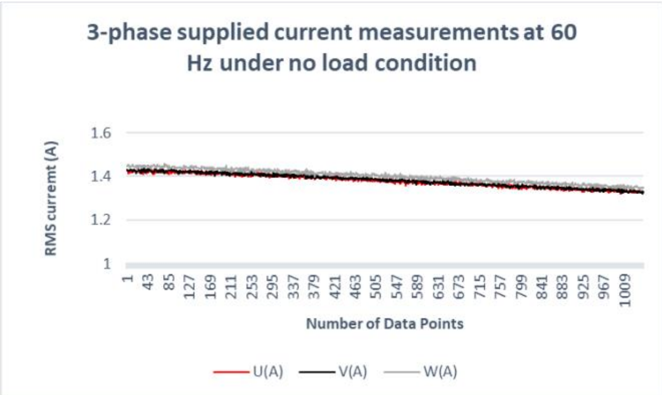

Fig. 11. On-line currents measurements of the IM at 60 Hz with no load

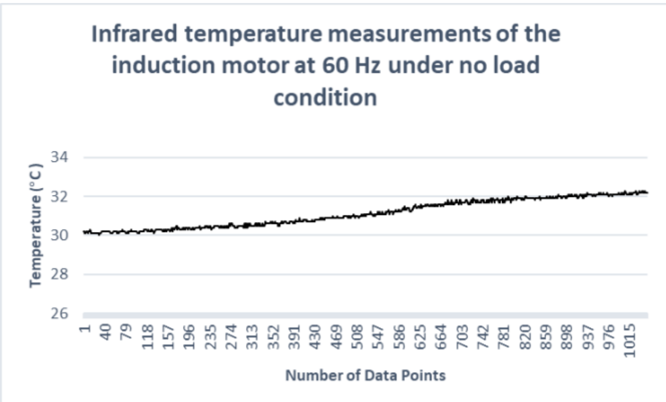

Fig. 12. Infrared temperature measurements of the IM at 60 Hz with no load

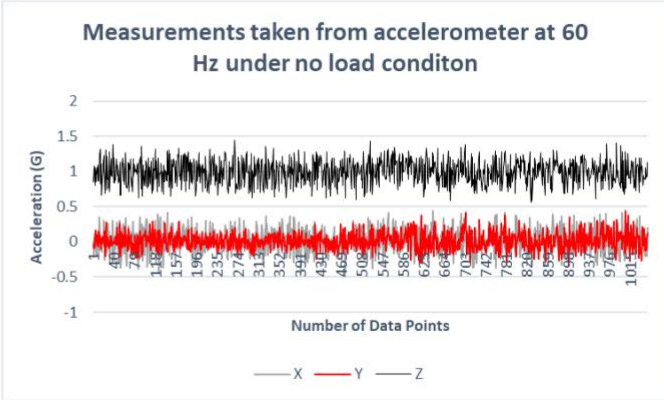

Fig. 13. Measurements of the 3-axes MEMS accelerometer under no load test at 60 Hz

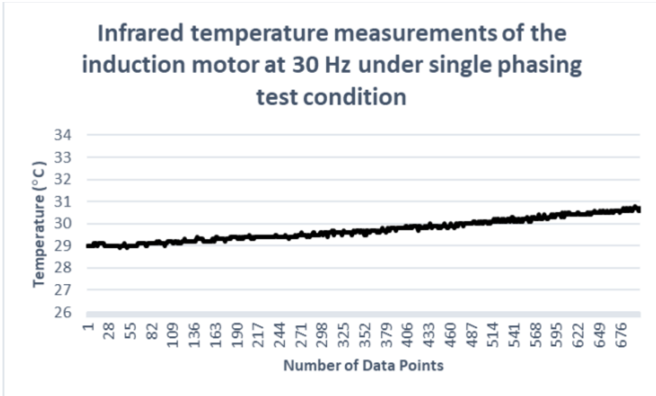

Fig. 14. Infrared temperature measurement of the IM at 30 Hz under single phasing test

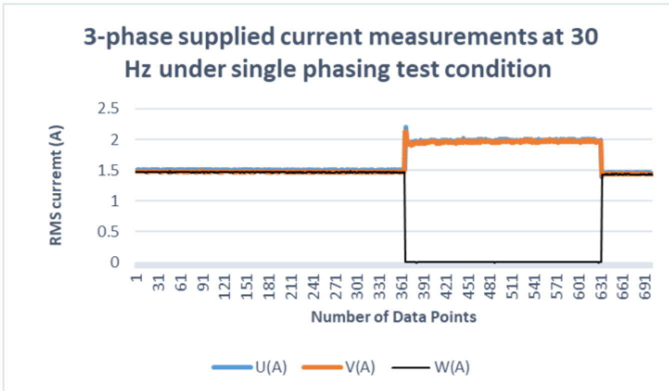

Fig. 15. Measurements of the 3-phase currents under single phasing test at 30 Hz.

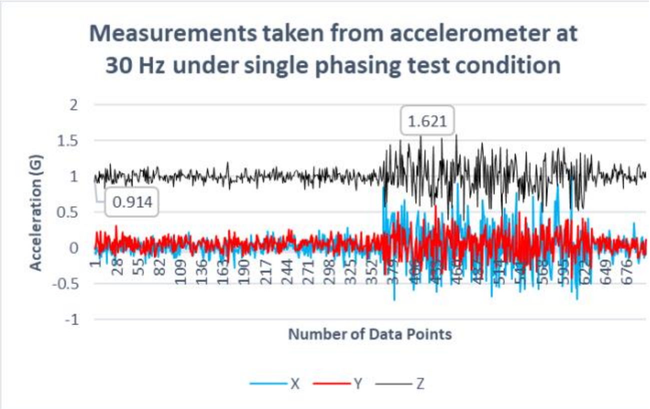

Fig. 16. Measurements of the 3-axes MEMS accelerometer under at 30 Hz under single phasing test

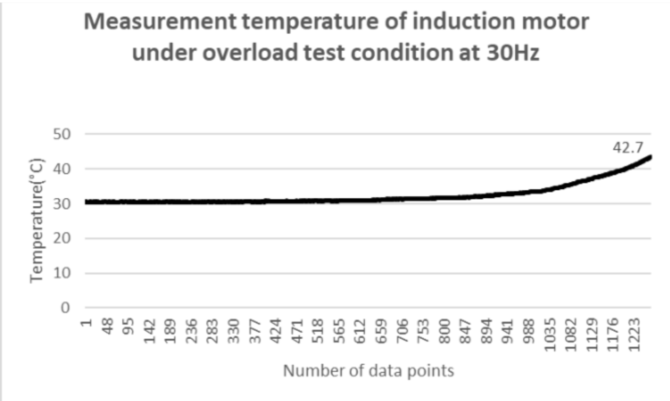

Fig. 17. Infrared temperature measurement of the IM at 30 Hz for overload test

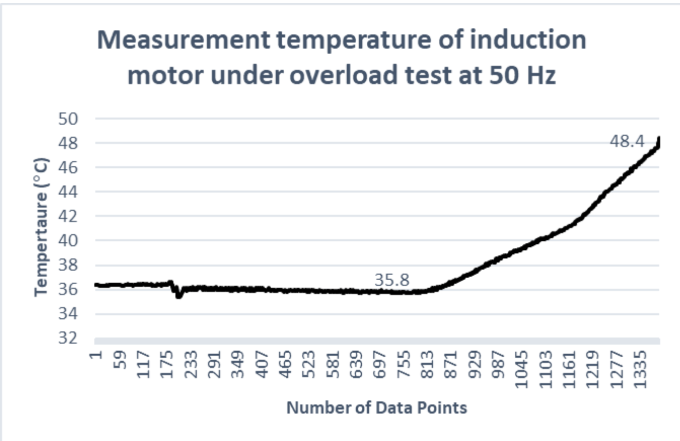

Fig. 18. Infrared temperature measurement of the IM at 50 Hz for overload test

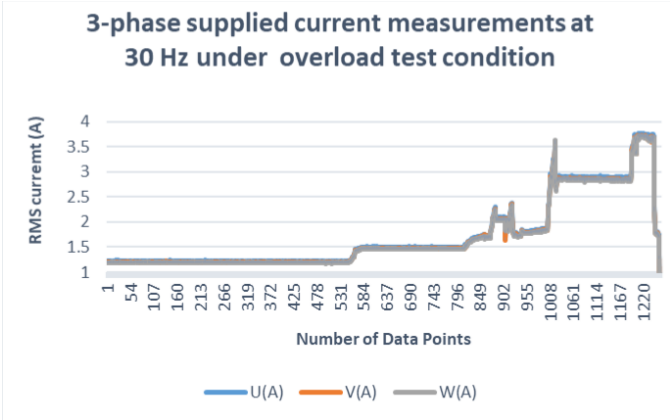

Fig. 19. Measurements of the 3-phase currents for overload test at 30 Hz

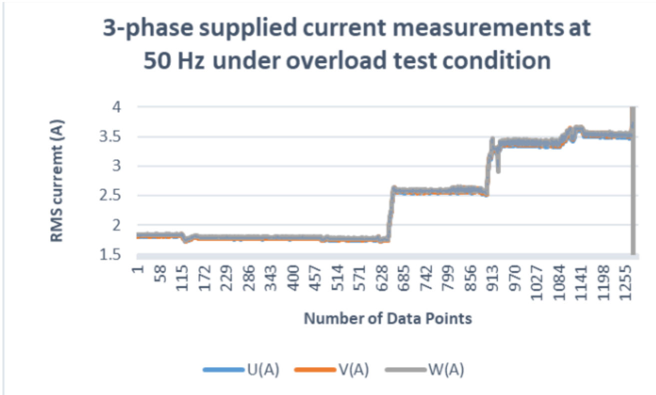

Fig. 20. Measurements of the 3-phase currents for overload test at 50 Hz

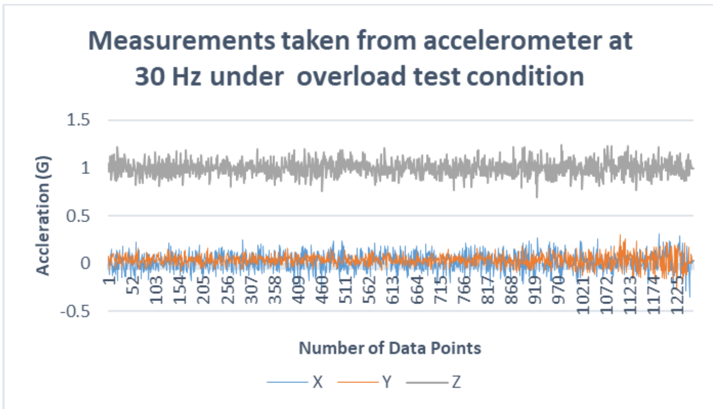

Fig. 21. Measurements of the 3-axes MEMS accelerometer under at 30 Hz for overload Test

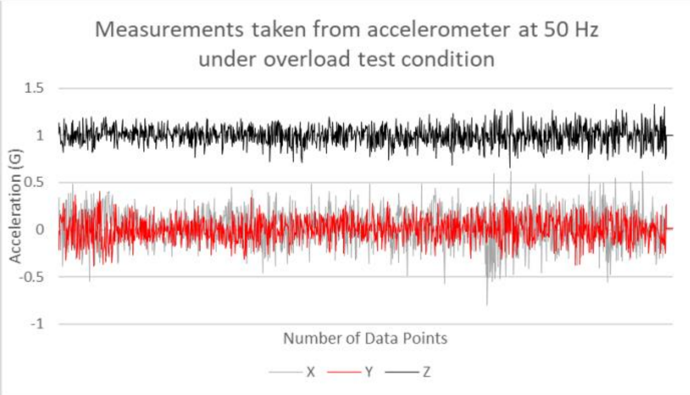

Fig. 22. Measurements of the 3-axes MEMS accelerometer under at 50 Hz for overload test

5. RESULTS

5.1 No Load Test

To establish baseline experimental results, IM experiments were conducted at 20 Hz and 60 Hz with no load. These experimental electrical parameters were measured using the sensors that were specified earlier in section 3-5. Modbus RTU and Modbus TCP/IP communications enable measurement data to be logged and commands to be sent to the VSD drive controller respectively.

The motor was running at a frequency of 20 Hz and 60 Hz respectively under no load conditions. For Figure 8 to Figure 10, data were collected over 1024 data points when the motor was running at a frequency of 20 Hz. The average RMS current calculated was 0.8A, average infrared temperature measurement was 31.1°C and the Z-plane's highest measured average accelerometer measured value was 0.995G with a standard deviation value of 0.172G.

Similarly, for Figure 11 to Figure 13, data were collected for over 1015 sample data points, when the no load test is conducted when the IM is running at 60 Hz. The average RMS current calculated was 0.8036A, average infrared temperature measurement was 28.44°C and the Z-plane's highest measured average accelerometer measured value was 0.995 G with a standard deviation value of 0.069G.

5.2 Single Phasing Test

For the single phasing test, it was conducted when the motor was running at 30 Hz. One of the phases of the motor, namely W phase was disconnected, it was observed that the motor start to heats up from the operating temperature of 29 °C to 31°C as shown Figure 14 with over 700 sample data points collected at 1 sample per second during the test. In Figure 15, the graphs show that in phase 'W', the current dropped to 0A when single phasing occurs while the remaining two phases increases as it needs to 'compensate' for the 0A current flowing in phase 'W'.

In Figure 16, it shows the data of the level of vibration measured in G from the accelerometer. It was observed when the single phasing simulated fault occurred, the level of vibrations measured on the X, Y, Z axis/plane increased significantly as compared to the normal readings captured when there is no loading on the motor.

5.3 Overloading Test

Figure 17 shows the graph of the temperature of the motor when the motor is running at 30 Hz during the overload test. The resistance from the load bank is increased gradually till it maximum, where the motor becomes overloaded.

The heating rate of the motor during the overload test can be calculated using the following equation determined by National Electrical Manufacturers Association (NEMA) standard, already cited in the references. The equation (3) is given as shown, where I is the current at voltages higher than the rated current, and the Irated is the rated current of the motor's nameplate.

$$\% \text{ heating} = (I/I_{rated})^2 \times 100 \tag{3}$$

Observation that the motor started to heat up and this is shown by the steep gradient from 30°C to 44°C over 1400 sample data points collected when the motor was operating during the overloading test. The overload test was also conducted when the motor runs at 50 Hz. Initially the starting temperature of the motor was observed to be at 36.4°C, and as the resistance from the load bank increases till the motor is overloaded, the motor heats up rapidly to 48.4°C. This is depicted and shown in Figure 18. A significant temperature increases by 12°C.

In Figure 19 and 20 show the graphs of the line current of the motor recorded during the overloading test. Since the rated current is 3.55A, and the current that exceeds and rise above this value will consider the IM to be operating at overload condition.

In Figure 21 and 22, the graphs show the accelerometer measurements during the overloading test conducted at 30 Hz and 50 Hz. Measurements reveal no significant increase in the 3-axes MEMS accelerometers' G-readings. The Z-plane accelerometer measurements revealed a calculated standard deviation of 0.078 G at 30 Hz. The Z-plane accelerometer measurements revealed a calculated standard deviation of 0.12 G at 50 Hz. A summary of the experimental findings and tabulated results is depicted in Table 2.

5.4 Comparative Study

In an extensive and insightful comparative research study conducted by Gonzalez et al [44], a deliberate manipulation of the line voltage in a motor phase was orchestrated to induce varying levels of voltage imbalance. The results of this study unveiled a noteworthy discovery: a voltage imbalance of 7.91% yielded a consistent and significant thermal elevation of 4 °C during steady-state operational conditions. These findings exhibited a remarkable congruence with outcomes observed in experiments simulating the single phasing test. In our simulated test scenario, intentional disconnection of the motor's W-Phase through the activation of a single phasing switch led to an abrupt temperature surge, evidenced by temperature recordings across more than 700 data points within 3 minutes. This surge caused the temperature to escalate sharply from 29 °C to 31 °C. Additionally, Gonzalez et al conducted an array of overload tests, systematically subjecting the motor to a range of overload percentages. These tests unveiled a consistent pattern in the thermal profiles. Notably, a rapid temperature surge characterized by a steep gradient was consistently observed, closely mirroring the response exhibited in the overloading.

Table 2. Summary of experimental findings and observations

Experiment	Measurements and observations		
	On-line current Measurement	***Temperature measurement***	***Vibration levels measurement***
No Load (20 Hz)	Current readings measured between the range from 0.75 to 0.8A	Surface temperature at 28°C.	Standard deviation of Z-plane accelerometer reading is 0.069 G. **No abnormality**
No Load (60 Hz)	Current readings measured between the range from 1.34 to 1.44 A	Surface temperature measured between 30.1 to 32.2 °C	Standard deviation of Z-plane accelerometer reading is 0.172 G. **No abnormality**
Single phasing (30 Hz)	W-phase current reading at 0 A. U and V phases currents between the range from 1.5 to 2.0 A	Surface temperature heated up from 28.0 to 31.0°C	Standard deviation of Z-plane accelerometer reading at 0.24G. **Significant increase in vibration was observed**
No Load (60 Hz)	Current readings measured between the range from 1.34 to 1.44 A	Surface temperature measured between 30.1 to 32.2 °C	Standard deviation of Z-plane accelerometer reading is 0.172 G. **No abnormality**
Overloading tests (30 and 50 Hz)	Line currents readings increase for both tests and the current exceeded 3.55A	At 30 Hz, surface temperature heated up from 30.0 to 44.0°C. **Heating rates** calculated to be at 109.67%. At 50 Hz, surface temperature heated up from 36.0 to 48.0°C. **Heating rates** calculated to be at 103.98%. According to NEMA's standard.	Standard deviation of Z-plane accelerometer reading at 0.078G. **No significant increase in vibration was observed.**

tests, highlighting a profound similarity in the thermal response of the motor.

In contrast to Gonzalez et al 's primary focus was on thermal profiles, the scope of the current research expanded beyond their study. While Gonzalez et al investigated the implications of voltage imbalance and thermal response. Our research investigated deeper by incorporating additional dimensions of analysis, specifically targeting vibration characteristics. This innovative approach involves the integration of MEMS accelerometers to capture vibration data generated by the motor during various operational scenarios. These vibration measurements provided a wealth of supplementary insights that can augment our understanding of the motor's behaviour. The MEMS accelerometer proves to be an invaluable device in our investigation, allowing us to discern intricate vibrational patterns in response to different perturbations. This data, when subjected to advanced signal processing techniques such as Fast Fourier Transform (FFT), can be harnessed to extract meaningful signatures and frequency spectra. The approach taken for this investigation extends beyond thermal effects and into the realm of vibration, allowing for a more comprehensive framework to delve into the motor's response. when single phasing or overloading occurs, allowing enhanced motor diagnostic to potentially detect such faults in the process.

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5.5 Limitations of this Study

In this study, one limitation is the placement of the infrared temperature sensor. The surface temperature at the exterior of the IM's chassis was measured through the use of pyromini USB model CALEX PMU21 described in section 3.5. This sensor was placed at the chassis area of the IM, although ideally, the stator windings inside the IM should be monitored. However, in view of the practicality and safety of the investigative study, it was not practical and accessible to place temperature sensor inside the yoke structure within the stator windings. In experimental results, we would expect that the actual measured temperature readings of the stator windings to be higher than our measurement result. As a result, we would further consider different suitable and appropriate mounting locations on the stator winding for temperature sensor installation. This should be a spot/location where temperature fluctuations are representative of the overall winding temperature. We will consider and avoid areas with direct airflow or other factors that could cause temperature anomalies. The second limitation is about the placement of the vibration sensor axial measurements, the MEMS accelerometer should be positioned on the motor drive bearings, with the accelerometer mounted directly to the machine housing through drilled and tapped holes. Due to practical and safety issues, no physical attempt was made to drill or alter the IM's existing setup.

6. CONCLUSION AND FUTURE WORK

This paper has presented the findings of simulated single phasing power supplies faults and overloading tests on the IM using non-invasive techniques. The main program designed for the IM's system has the potential to perform three major functions – firstly the ability to control the IM using commands sent through LabVIEW program via the VSD controller. Secondly, the system can perform combined in-situ online measurements and monitor of the operating conditions of the IM, where it could be implemented in a setting such as in a factory production line using an IoT approach.

Further, from the data analysis of the single phasing tests within the given duration, the experimental results seem to suggest that vibrations measurement readings are more observable, detectable with calculated standard deviation of 0.24 G.

For overloading tests at 30 Hz and 50 Hz, vibrations measurements were less prominent with the Z-plane accelerometer measurements revealed a calculated standard deviation of 0.078 G and 0.12 G at 30 Hz and 50 Hz respectively. The percentage of heating within the stator windings were calculated to be at 103.98% to 109.67% for 50 Hz and 30 Hz respectively. In general, overloading tests on IM will cause the internal stator windings to experience a rise in temperature which will have long term detrimental effects on the motor's health. One such detrimental effect is specific to the insulation degradation of the stator windings.

In conclusion, this experimental research work has been deemed to have contributed to the body of literature in the detection of electrical abnormalities in 3-phase AC IM using an IoT approach through an automated computer control system. For the current research, the usage of variable speed drive (VSD) does provide convenience and accuracy in relation to the configuration of setting and operating frequencies. However, the use of VSDs can introduce harmonic currents and voltages into the electrical system. These harmonics can cause distortion in the power supply and potentially affect other connected equipment, leading to efficiency losses and possible system instability. For future work considerations, the authors would like to perform a measurement comparison using traditional 3-phase power 230V supplies versus VSD supplies at different frequencies.

ACKNOWLEDGEMENT

The authors would like to extend gratitude for the financial and technical support from the School of Engineering, Ngee Ann Polytechnic. In particular, the authors would like to thank the technical staff, Mr How Sek Thong, Mr Wong Yu Cheong and Mr Yong Saw Soon for their technical and installation support and mechanical fabrication of the parts.

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