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Research Article

A Web-Based Smart Real-Time Motor Control Center (MCC) Monitoring and Analytics System for Early Detection of Motor Anomalies in Muara Karang Power Plant

Prisma Riashuda Prakosa[1], Jasmine Aulia[1*]
[1] PLN Nusantara Power, UP Muara Karang
***Email:** jasmine.aulia@plnnusantarapower.co.id

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Abstract: This study proposes a comprehensive web-based real-time monitoring and analytics framework for 380V Motor Control Center (MCC) assets at PLTGU Block 1 Muara Karang, addressing the challenge of early identification of motor performance degradation under variable operational conditions. The system integrates a multi-layer architecture comprising sensor-level data acquisition, a real-time processing pipeline, and an analytics layer incorporating statistical modelling, multivariate trend assessment, and anomaly scoring algorithms. An Early Warning System (EWS) is implemented using hybrid rule-based and data-driven thresholds, enabling automated detection of abnormal operating patterns. A historical knowledge engine supports Work Planning and Control (WPC) by modeling temporal degradation signatures, enabling structured diagnostic interpretation and follow-up maintenance actions. The framework further incorporates an event-streaming notification mechanism through Telegram API for low-latency dissemination of contextualized alerts. Validation under field operation demonstrates successful detection of early-stage faults, including a bearing defect in motor 88BT GT1.2 identified before crossing critical failure limits. These interventions prevented unit trips and reduced risk of cascading failures. Experimental results indicate improvements in detection accuracy, diagnostic efficiency, and operational reliability. The proposed framework exhibits strong scalability potential for fleet-wide deployment across PLN's induction motor systems.

Keywords: Motor Control Center, anomaly detection, real-time monitoring, predictive analytics, reliability engineering, power generation systems.

1. Introduction

Induction motors operating at 380 VAC are essential components in power generation facilities, as they support a wide range of auxiliary systems that directly affect unit continuity and overall plant reliability. Their operational integrity is therefore crucial in maintaining high availability and preventing unexpected outages [1]. Routine maintenance programs—including weekly Preventive Maintenance (PM) and Predictive Maintenance (PdM)—are widely implemented to mitigate equipment failure risks [2]. However, the effectiveness of these conventional approaches remains limited for motors located in areas with restricted physical access, where direct inspection and condition

measurements cannot be performed optimally [3].

Historical Work Order (WO) data from 2019 to 2023 indicate several trip incidents involving motor 88BT GTG 1.2, triggered by protective relay activation. Similar studies have shown that disturbances in medium- and low-voltage induction motors can lead to significant operational consequences, including derating and full unit trips, which may compromise both plant performance and power system stability [4], [5]. These conditions demonstrate the vulnerability of essential 380 V motors at PLTGU Block 1 Muara Karang and the importance of enhanced fault detection and reliability improvement measures.

Given these challenges, there is a clear need for maintenance strategies that extend beyond periodic inspection. Recent research highlights the importance of continuous monitoring, data-driven diagnostics, and real-time anomaly detection to identify degradation patterns before reaching critical failure thresholds [6], [7]. Developing an integrated monitoring and analytics system therefore presents a promising solution to overcome the limitations of conventional maintenance methods and strengthen early detection capabilities for critical motor assets.

2. Materials and methods

2.1. System Block Modeling

The system developed in this study is a Centralized Online Monitoring System designed to acquire, process, and transmit real-time electrical parameters of three-phase induction motors in GTG Block 1 at UP Muara Karang in Figure 1. Continuous measurement of voltage, current, power variables, power factor, frequency, energy, and motor efficiency supports early fault detection and enhances system reliability [8], [9], while historical datasets enable performance evaluation and data-driven diagnostics [10].

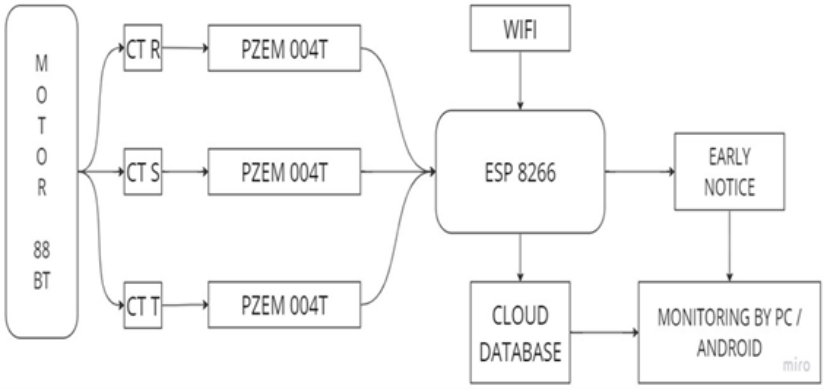

Figure 1. Diagram Block of Smart Real-Time Motor Control Center

The architecture comprises three components: a data acquisition module, a communication and processing module, and a web-based monitoring platform. Current Transformers (CTs) serve as primary sensors due to their accuracy and protection suitability [11], and their outputs are processed by the PZEM-004T module using internal ADC sampling [12]. Measurements are transmitted to the ESP8266 microcontroller, which performs local computation and Wi-Fi communication, making it suitable for industrial IoT applications [13], [14].

Powered by a regulated 5 VDC supply, the ESP8266 firmware manages threshold settings, data formatting, and communication protocols. Threshold values follow established standards for voltage imbalance, current imbalance, and motor protection [15], [16] and drive the Early Warning

System (EWS) for anomalies such as current surges, voltage sags, phase imbalance, or power quality deterioration [17].

All data are stored in a backend database and visualized through a ThingsBoard-based dashboard supporting real-time telemetry, alarms, and device management [18]. Historical trending and automated notifications further improve coordination between operations and maintenance teams [19]. Operating continuously 24/7, the system generates long-term datasets essential for fault diagnosis and predictive maintenance. Such real-time monitoring architectures are widely recognized as core components of Condition-Based Maintenance (CBM) and Predictive Maintenance (PdM) strategies [20], [21].

2.2. Integration of System Block Modeling with Electrical Monitoring Equations

The system block model described in Section 3.1 is designed not only to collect real-time electrical parameters but also to perform analytical computations that directly relate to key motor health indicators. These indicators—current unbalance, voltage unbalance, voltage drop, and overcurrent—are computed within the data processing layer using the measurements provided by the CT sensors and the PZEM-004T energy meter. The derived parameters are then evaluated against international standards, such as ANSI C84.1-1995, IEEE Std. 45-2002, and the National Electrical Code (NEC), to determine abnormal or unsafe operating conditions.

1. Current Unbalance Analysis

The CT sensors supply phase-current readings (Ia, Ib, Ic) to the PZEM-004T. The system computes the percentage of current deviation and compares it against the allowable limit (≤5% per ANSI C84.1, with a monitoring threshold of 3%). Current unbalance is used as an early indicator of insulation degradation, bearing faults, or unequal load distribution. When the unbalance exceeds the threshold, the ESP8266 triggers an anomaly flag for the Early Warning System (EWS).

2. Voltage Unbalance Analysis

The PZEM-004T also measures phase voltages (Va, Vb, Vc). The microcontroller calculates the voltage unbalance percentage (UB%) using:

$$V_a - V_{av} = \text{Maximum Deviation}$$
$$V_b - V_{av} = \text{Maximum Deviation}$$
$$V_c - V_{av} = \text{Maximum Deviation}$$
$$UB\% = \frac{\text{Maximum Deviation}}{V_{av}} \times 100$$

IEEE Std. 45-2002 specifies that voltage unbalance should not exceed 3%, and the system setting is conservatively limited to 2%. These values are embedded into the ESP8266 firmware as thresholds for automated classification of motor health states.

3. Voltage Drop Monitoring

Using real-time current (I), resistance (R), reactance (X), and power factor (cosφ) values, the system computes line-to-neutral and line-to-line voltage drops:

$$V_d(L-N) = RI\cos(\phi) + XI\sin(\phi)$$
$$V_d(L-L) = \sqrt{3}[RI\cos(\phi) + XI\sin(\phi)]$$

The NEC allows a voltage drop of up to 5% on feeders (with recommended design at 3%). These equations help identify wiring degradation, loose terminals, and overload conditions. When detected, the web interface highlights abnormal trends and records them in the historical database for diagnostic analysis.

4. Overcurrent Detection

The nominal current reference is computed by:

$$I_{Nominal} = \frac{P}{\sqrt{3} \cdot V \cdot \cos \phi \cdot \mu}$$

The system sets the overcurrent threshold at 125% of Full Load Current (FLC), in accordance with MCC protection practices. If real-time current exceeds this limit, the EWS issues an instant notification, automatically forwarded via the integrated platform (e.g., Telegram alert).

2.3. Specification of Smart Real-Time Motor Control Center

The design of a centralized smart online monitoring system requires a structured engineering approach to ensure accuracy, reliability, and compatibility with existing industrial equipment. The initial step involves determining the key electrical parameters based on the characteristics of the monitored induction motor and the available measurement sources. The selected parameters—voltage (V), load current (I), motor operating frequency (Hz), measurement variables, and environmental conditions—must comply with industrial standards and be synchronized with the testing equipment available in the Electrical Workshop of Block 1, Muara Karang Power Plant.

The system utilizes an input voltage of 220 VAC, which is rectified to a stable 5 VDC to supply the microcontroller. Based on the motor specification indicating a nominal current of 28.3 A, a Current Transformer (CT) with a maximum capacity of 100 A is selected to ensure measurement tolerance, avoid saturation, and maintain linearity under fluctuating loads. Measurement variables are determined using the motor nameplate data, which then become the basis for firmware logic and web-based dashboard development. Environmental considerations—such as temperature, humidity, insulation class, and installation constraints—are integrated to ensure long-term operational durability under power plant conditions, consistent with best practices in motor condition monitoring [21], predictive maintenance frameworks [22], and IoT-based energy systems [23].

Table 1. Summarizes the primary specifications used in the design of the Smart Real-Time Motor Control Center

Parameter	Value
Supply Voltage	220 V
Maximum Measured Current	100 A
Measured Variables	V, I, Hz, pF, Wh, Var, VA, Watt
Ambient Temperature	–40°C to 85°C
Relative Humidity	≤ 90% at 40°C
Frequency	50–60 Hz
Insulation Thermal Class	Class B (130°C)
Insulation Resistance	>1000 MΩ
Winding Resistance	42 Ω
Software Platform	ThingsBoard
Access Device Compatibility	All (PC / Android)
Mechanical Dimensions	10 × 10 × 4 cm

2.5. Web Desain of Smart Real-Time Motor Control Center

In this stage, the web platform employed is ThingsBoard, an open-source Internet of Things (IoT) platform designed for device management, telemetry acquisition, and web-based data visualization [24]. ThingsBoard functions as a centralized monitoring server supporting standard IoT communication protocols, including MQTT, HTTP, and CoAP, enabling seamless integration with the sensing devices implemented in the induction motor monitoring system at GTG Block 1 [25]. The platform also supports remote monitoring and control, allowing continuous observation of electrical parameters as long as the device remains connected to the internet. Its user-friendly interface, compatibility with smartphones and web browsers, and capability for multi-user access make it suitable for operational and maintenance workflows in industrial environments [26].

The web monitoring dashboard operates when the device appears in an active state, enabling real-time acquisition of telemetry data such as voltage, current, power, and power factor. When operational anomalies occur, the Early Warning System (EWS)—configured through the ThingsBoard rule engine—automatically triggers notifications according to predefined threshold logic [27]. All telemetry stored in the backend server can be exported in Excel (.xlsx) format for external analysis. Additionally, the system applies a configurable data retention policy; in this study, historical data are retained for 30 days, which meets the operational monitoring requirements of induction motors operating in GTG Block 1 at UP Muara Karang [28].

3. Results and discussion

3.1. Sensor Accuracy Testing

The sensor accuracy test was performed to evaluate the precision and stability of the current-sensing subsystem integrated into the monitoring device. The sensing element utilized in this study is a Current Transformer (CT) installed on each phase of the three-phase induction motor. The CT output represents the primary current and is processed by the measurement module before being transmitted to the microcontroller.

The objective of this test is to validate the sensor readings by comparing them with reference measurements obtained using a true-RMS clamp meter, which serves as the industrial-standard benchmark. The testing procedure consisted of the following steps:

1. Applying incremental load currents to the motor phase under test.
2. Recording the measured current values generated by the CT and processed by the monitoring system.
3. Measuring the actual current values using a calibrated true-RMS clamp meter.
4. Computing the absolute error and percentage error for each measurement point.

The percentage measurement error was calculated using the standard accuracy evaluation formula:

$$\text{Error (\%)} = \frac{|\ I_{measured} - I_{actual}\ |}{I_{actual}} \times 100\%$$

where:

$I_{measured}$= current value obtained from the CT-based monitoring system

I_{actual}= reference current measured by the true-RMS clamp meter

The test results, as illustrated in Table 2 and Table 3, indicate that the monitoring system demonstrates high measurement accuracy. The average current measurement error was 0.25%, while the average voltage measurement error was 0.20%. The maximum observed error across all measured parameters was 0.39%, which is significantly below the allowable tolerance for industrial

motor monitoring applications.

Table 2. Sensing of Current

Actual Arus (R)	Actual Arus (S)	Actual Arus (T)	CT Arus (R)	CT Arus (S)	CT Arus (R)	Error sensor
21,3	21,7	21,6	21,2	21,6	21,5	0,39
21,1	21,4	21,3	20,9	21,4	21,3	0,36
21,0	21,4	21,4	20,9	21,4	21,3	0,25
21,1	21,4	21,4	21,0	21,4	21,4	0,20
21,0	21,4	21,4	20,9	21,4	21,3	0,19
20,9	21,4	21,3	20,9	21,3	21,3	0,22
20,9	21,3	21,3	20,9	21,3	21,3	0,11
20,9	21,4	21,3	20,9	21,3	21,2	0,19
20,9	21,3	21,2	20,8	21,3	21,2	0,22
20,7	21,2	21,1	20,7	21,1	21,1	0,25
20,8	21,3	21,1	20,7	21,2	21,0	0,19
20,9	21,3	21,2	20,8	21,3	21,2	0,24
20,8	21,3	21,2	20,8	21,2	21,1	0,25
20,9	21,2	21,3	20,8	21,2	21,2	0,32
20,8	21,3	21,2	20,8	21,2	21,2	0,27
20,9	21,3	21,2	20,8	21,2	21,1	0,30
20,7	21,1	21,2	20,6	21,1	21,1	0,27
20,8	21,2	21,1	20,7	21,2	21,0	0,29
20,7	21,2	21,3	20,7	21,2	21,2	0,25
20,7	21,2	21,2	20,6	21,1	21,2	0,30
					Error	**0,25**

Table 3. Sensing of Voltage (L-N)

Actual Tegangan (R)	Actual Tegangan (S)	Actual Tegangan (T)	Sensing Tegangan (R)	Sensing Tegangan (S)	Sensing Tegangan (R)	Error sensor
223,75	225,65	223,85	223,7	225,6	223,8	0,02
223,58	225,7	223,7	223,5	225,6	223,6	0,03
223,85	226	224,5	223,8	225,9	224,0	0,10
224,0	226,0	225,0	223,9	225,9	224,0	0,18
224	226,5	224,3	223,8	225,9	223,9	0,18
223,75	225,75	223,8	223,7	225,7	223,3	0,09
224,2	225,68	223,8	223,6	225,6	223,4	0,16
224,2	226	223,8	223,6	225,6	223,4	0,21
223,6	225,8	223,8	223,1	225,3	223,5	0,19
223,8	226	224	223,5	225,6	223,5	0,18
223,7	226,4	223,7	223,2	225,2	223,3	0,31
224	225,8	224,3	223,5	225,5	223,6	0,22

223,5	226,2	224,1	223,0	225,6	223,6	0,24
223,7	225,6	223,8	223,2	225,0	223,1	0,27
223,7	225,5	223,7	223,0	225,0	223,0	0,28
223,5	226	223,4	223,0	225,2	222,8	0,28
224	225,8	224	223,4	225,3	223,3	0,27
223,7	226	224	223,1	225,0	223,0	0,39
223,9	225,5	223,5	223,5	225,4	223,4	0,09
223,8	225,6	223,8	222,9	224,8	222,9	0,39
					Error	**0,20**

Further validation through direct comparison between CT readings and clamp-meter measurements showed no significant deviation across all tested operating conditions. These results confirm that the sensing subsystem provides reliable, accurate, and repeatable measurements, making it suitable for continuous motor condition monitoring and early anomaly detection within a predictive maintenance framework.

3.2. Data Analysis of Smart Real-Time Motor Control Center

After the installation of the centralized smart online monitoring system on the PCC GTG 1.2 panel for the 88BT motor, real-time acquisition of electrical parameters was conducted through the web-based dashboard. The monitored parameters include line voltage (V), line current (A), active power (W), reactive power (VAR), apparent power (VA), frequency (Hz), power factor (p.f), and energy consumption (Wh). The objective of this monitoring stage is to obtain continuous real-time data for evaluating the operational condition of the 88BT motor under actual field conditions.

Data acquisition was performed from 7 October 2023 at 24:00 to 15 October 2023 at 24:00. The CT-based current and voltage measurements were sampled at 1-minute intervals, controlled by the ESP8266 firmware. Over the 7-day observation period, the system generated 61,109 total data entries, stored in the database and visualized on the monitoring dashboard in Figure 2.

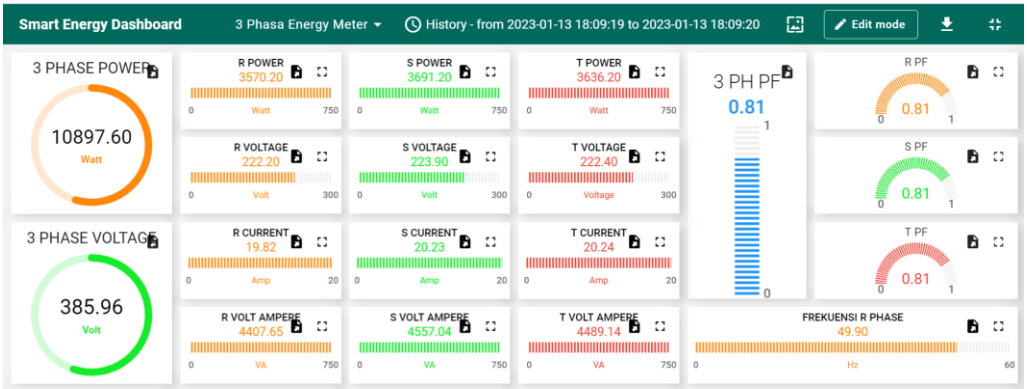

Figure 2. Dashboard of Smart Real-Time Motor Control Center

3.2.1. Voltage Analysis

The system records per-phase L–N and three-phase voltages in real time to assess supply stability. The 20 HP motor is rated at 380 V. The monitoring results indicate fluctuating voltage levels throughout the observation period. The maximum measured voltages were 227.88 V (R), 229.90 V (S), and 228.40 V (T), while the minimum voltages were 218.42 V (R), 220.46 V (S), and 217.73 V (T). The average voltages across phases were 222.99 V (R), 225.14 V (S), and 223.63 V (T) in Figure 3.

Voltage variations were primarily influenced by generator load changes. Increased load reduces generator flux, slightly decreasing rotational speed and resulting in voltage sag—consistent with synchronous generator operating principles. Based on the 7-day trend, the voltage unbalance remained at 0.5%, well below the ANSI limit of 3%, confirming acceptable supply quality.

Figure 3. Graph of Voltage (R-S-T)

3.2.2. Current Analysis

Current monitoring is critical as current imbalance and overload significantly affect motor lifespan. The maximum recorded current values were 23.7 A (R), 24.3 A (S), 24.3 A (T), measured on 10 November 2023 at 03:15 in Figure 4. These values remain below the motor's rated current of 28.3 A. Zero-current periods occurred during scheduled RSH (Reserve Shutdown) conditions, typically between 01:00–06:00 daily.

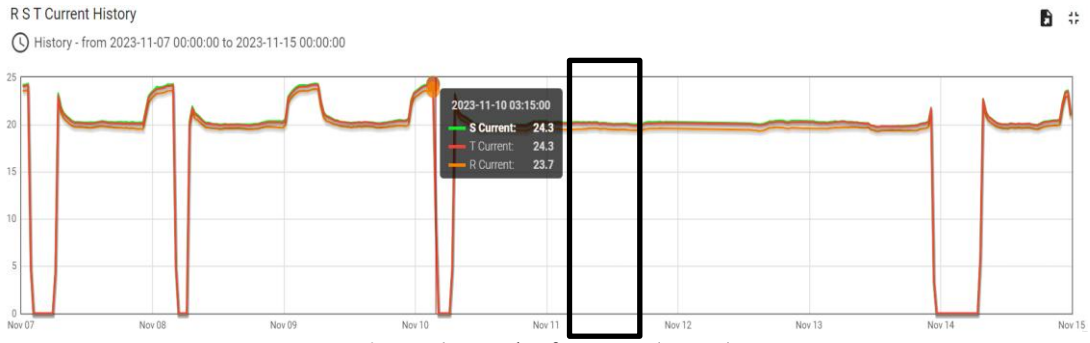

Figure 4. Graph of Current (R-S-T)

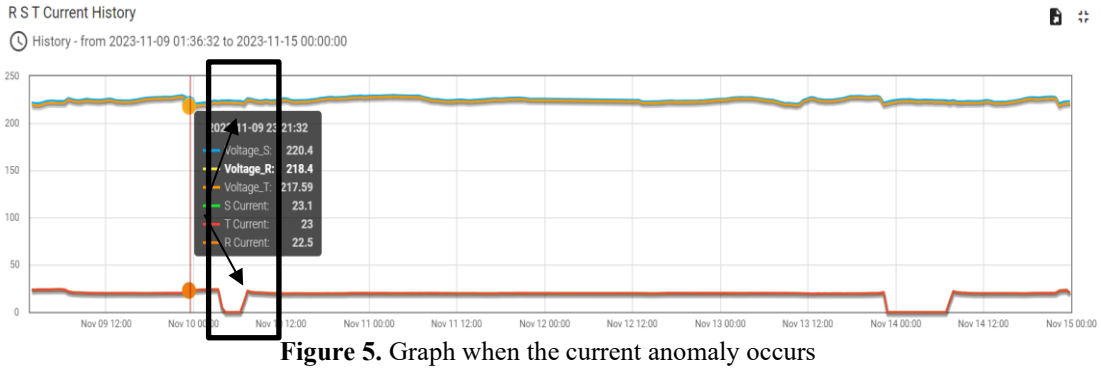

Figure 5. Graph when the current anomaly occurs

Based on Figure 5, the motor current exhibits a direct dependency on variations in the supply voltage. When the system voltage decreases, a corresponding increase in phase current is observed. This behavior aligns with induction motor theory: a reduction in stator voltage lowers the air-gap flux density, thereby reducing electromagnetic torque and increasing slip. The increased slip subsequently elevates both magnetizing and load current. At the anomaly point, the voltage dropped to 218.4 V (R), 220.4 V (S), and 217.59 V (T), while the current increased to 22.5 A (R), 23.1 A (S), and 23 A (T). This fluctuation pattern consistently occurred between 23:00 and 02:00. Despite the current rise, no overheating symptoms were detected; the motor body temperature remained within normal limits, and the bearing temperature stabilized at 48°C. The unbalanced current analysis yielded an average value of 1.08%, well below the ANSI maximum threshold of 3%, indicating that the current imbalance remained within a safe operational range.

3.2.3. Frequency Analysis

The motor operates at a nominal frequency of 50 Hz, corresponding to a synchronous speed of 1500 rpm. The observed frequency variation was minimal, with maximum values of 50.01–50.02 Hz and minimum values of 49.93–49.92 Hz, resulting in an average of 49.97 Hz in figure 6. These fluctuations fall within acceptable limits and do not impact motor performance or torque generation.

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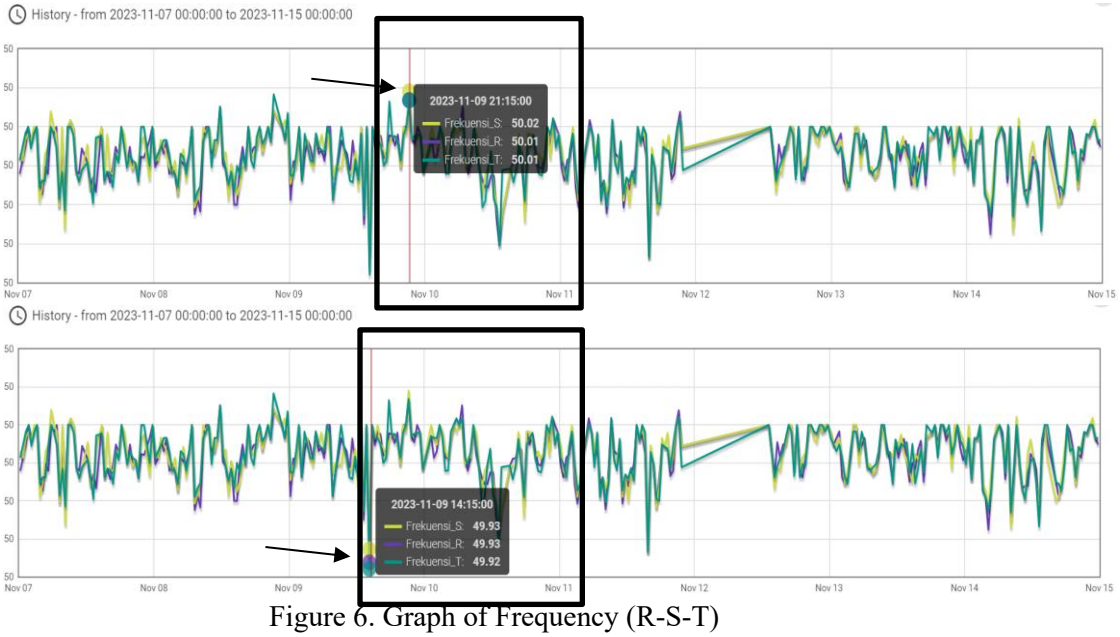

Figure 6. Graph of Frequency (R-S-T)

3.3. Early Warning System

The acquired data were evaluated by the embedded Early Warning System configured in the monitoring platform. Throughout the observation period (7–15 November 2023), no abnormal events were detected. All measured parameters remained within the allowable ranges specified on the motor nameplate and IEC/ANSI standards. Notifications generated by the EWS display real-time status and alerts; however, no critical alarms occurred, indicating stable and safe motor operation.

Figure 7. Notification regarding current conditions on the 88BT Motor GT 1.2

4. Discussion

Future enhancement of this monitoring system will prioritize the integration of Artificial Intelligence to advance its capability beyond real time measurement and basic anomaly detection. The planned system will utilize supervised learning to recognize known fault signatures such as phase imbalance, bearing degradation, rotor bar defects, and insulation issues based on historical labeled data. In parallel, unsupervised learning methods will identify new or unexpected patterns by detecting clusters and deviations in long term operational behavior.

When an abnormal condition is detected, the Artificial Intelligence module will not only identify the most probable fault source but also generate actionable maintenance recommendations. These include corrective steps, troubleshooting options, and risk-reduction strategies. To support

field personnel, the system will also provide preparation guidelines detailing required Personal Protective Equipment, tools, consumables, and manpower.

Through continuous learning, the platform will evolve into an intelligent decision support system that enhances diagnostic accuracy, streamlines maintenance planning, and strengthens PLN's roadmap toward predictive maintenance.

5. Conclusion

The design, implementation, and evaluation of the Centralized Smart Online Monitoring system for the three-phase induction motor at GTG Block 1 demonstrate that the platform is capable of performing continuous 24-hour real-time acquisition and monitoring of electrical parameters without generating data anomalies while fully adhering to the applicable operational standards. Measurement validation confirms high system accuracy, with an average current measurement error of 0.25%, an average voltage error of 0.20%, and a maximum deviation of 0.39%, thereby verifying that the deployed current-transformer (CT) sensors are suitable for precision monitoring applications.

Operational trend analysis further indicates that a recurring voltage depression within the 23:00–02:00 time window leads to a corresponding rise in motor current, consistent with established electromagnetic behavior of induction motors under reduced stator voltage. All primary measured variables—including an average frequency of 49.97 Hz, average phase voltages of 222.99/225.14/223.63 V (R/S/T), an average motor current of 21.33 A, and a power factor of 0.84—remain within nominal operational limits, confirming stable motor performance throughout the monitoring interval.

Additionally, no alarm states or anomaly indicators were recorded by the early-warning subsystem during the monitoring period (7–15 November 2023), confirming that the 88BT motor operated within safe and normal boundaries. The implementation of the centralized monitoring architecture provides measurable operational benefits, including multi-parameter real-time monitoring capability, IoT-enabled system integration for improved diagnostics, availability of comprehensive historical datasets for analytical evaluation, early notification of potential disturbances, and enhanced efficiency in energy-audit and reliability-assessment processes.

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