

Design and implementation of a low-cost Arduino-based three-phase electrical monitoring and reporting system

Idoko Livinus Akor ^{1,*}, Adoyi Ene Helen ¹, Adah John Ejeh ¹, Agbese Echo Agbese ², Ojinu Ojima Joel ¹ and Adoyi Patrick ¹

¹ Department of Electrical/Electronic Engineering Technology, Benue State Polytechnic Ugbokolo, Benue State, Nigeria.

² Department of Electrical/Electronic Engineering, Federal Polytechnic Wanune, Benue State, Nigeria.

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Abstract

Three-phase electrical systems are extensively adopted in industrial, commercial, and institutional environments due to their high efficiency and ability to support heavy electrical loads. Continuous and real-time monitoring of these systems remains a significant challenge, particularly in developing regions, small-scale industries, and educational laboratories. Traditional monitoring approaches are largely manual and reactive, making them ineffective at detecting transient faults such as voltage imbalance, phase failure, and overcurrent at an early stage. This study presents the design and implementation of a low-cost, Arduino-based three-phase electrical monitoring and reporting system capable of real-time data acquisition, fault detection, and remote user notification. The system integrates ZMPT101B voltage sensors and ACS712 current sensors with an Arduino Mega 2560 microcontroller to measure key electrical parameters RMS voltage, RMS current, active power, apparent power, and power factor across all three phases. Processed data is displayed locally on a 20×4 I2C LCD and transmitted remotely via a SIM900/SIM800L GSM module through SMS alerts. Experimental testing validated the system's performance, recording voltage measurement errors of less than 0.4% and current errors of approximately 1.5%. The fault detection module successfully identified all simulated anomalies including over-voltage, under-voltage, phase imbalance, and phase failure within 500 milliseconds, achieving a 100% local detection rate. The GSM reporting subsystem attained an overall SMS delivery success rate of 98% with an average latency of 5.8 seconds. These results demonstrate that the proposed system provides a practical, reliable, and cost-effective alternative to expensive commercial power analyzers, making it well-suited for educational institutions, workshops, and small-scale industries.

Keywords: Three-Phase Monitoring; Arduino Mega 2560; Real-Time Fault Detection; GSM Reporting; ZMPT101B; ACS712; Power Quality Monitoring

1. Introduction

Electrical energy is a fundamental requirement in modern society, particularly in industrial, commercial, and institutional environments where continuous and reliable power supply is essential. Among the various forms of electrical power distribution, three-phase power systems are the most widely adopted due to their superior efficiency, balanced power delivery, and ability to support heavy electrical loads. These systems are extensively utilized in industries, workshops, laboratories, and large-scale facilities where equipment such as motors, compressors, and other high-power machines are operated. Their capability to deliver constant power with reduced energy losses has established them as the standard in contemporary electrical installations (Kumar et al., 2020; Ullah et al., 2023; Schirmer & Mporas, 2023).

* Corresponding author: Idoko Livinus Akor.

Despite their widespread adoption, effective monitoring of three-phase electrical systems remains a significant challenge, particularly in developing regions and small-scale industrial environments. In many cases, monitoring practices are still carried out manually, which introduces inefficiencies and increases the likelihood of human error. Manual approaches limit the ability to detect abnormal operating conditions such as voltage imbalance, phase failure, and excessive power consumption in real time. Consequently, the absence of reliable monitoring systems often leads to increased power losses, reduced operational efficiency, and potential damage to electrical equipment (Gopinath et al., 2020; Iqbal et al., 2020).

Recent advancements in smart grid technologies and the Internet of Things (IoT) have provided new opportunities for enhancing electrical monitoring systems. Modern monitoring solutions are capable of acquiring electrical parameters such as voltage, current, power, and frequency in real time, while simultaneously transmitting this data for analysis and decision-making. Studies have demonstrated that IoT-based monitoring systems significantly improve energy efficiency and enable early fault detection before critical system failures occur (Bhavani et al., 2022; Ullah et al., 2023; Mudaliar & Sivakumar, 2020). These capabilities support continuous system observation and facilitate proactive maintenance strategies, thereby improving overall system reliability.

The development of low-cost monitoring systems using microcontrollers has gained considerable attention in recent years. Platforms such as Arduino are widely adopted due to their affordability, ease of programming, and flexibility in interfacing with sensors and communication modules. Several studies have demonstrated that Arduino-based systems can effectively perform real-time data acquisition and transmission for monitoring applications (Mudaliar & Sivakumar, 2020; Syafrudin et al., 2018). These systems are particularly suitable for educational institutions and small-scale industries where access to high-cost monitoring equipment is limited.

However, despite these technological advancements, many small-scale industries, workshops, and educational laboratories continue to rely on traditional and reactive monitoring methods. Previous studies have identified the lack of real-time monitoring as a major contributor to inefficiency in electrical systems, particularly in developing regions (Ullah et al., 2023; Gopinath et al., 2020). Furthermore, many advanced monitoring solutions require sophisticated hardware and proprietary software, making them unsuitable for small-scale applications (Bhavani et al., 2022; Mudaliar & Sivakumar, 2020).

In response to these challenges, this study focuses on the design and development of a three-phase monitoring and reporting system using Arduino components, with the aim of improving system reliability, enhancing fault detection, and supporting efficient energy management. The system integrates ZMPT101B voltage sensors, ACS712 current sensors, a 20×4 LCD display, and a SIM900/SIM800L GSM module with an Arduino Mega 2560 microcontroller to achieve real-time measurement, fault detection, and remote notification. This study ultimately contributes to improving operational safety and energy efficiency in small-scale industrial and educational environments.

2. Literature Review

2.1. IoT-Enabled Monitoring Systems

IoT-based monitoring systems have been widely adopted due to their ability to provide real-time data acquisition, remote accessibility, and improved system visibility. Mazhar et al. (2023) demonstrated that real-time monitoring significantly improves energy efficiency and operational awareness through continuous data visualization. The system however, relied on complex architectures and high computational resources, limiting its applicability in low-cost environments. Ullah et al. (2023) developed an IoT-based monitoring framework for electrical substations, enabling dynamic load management, though the study did not fully address latency issues in data transmission.

Syafrudin et al. (2018) proposed a real-time IoT monitoring platform for industrial applications using big data technologies, demonstrating scalability and responsiveness, though the complexity of the infrastructure makes it unsuitable for small-scale or educational applications. Barbosa et al. (2024) designed a low-cost IoT-based monitoring system for photovoltaic systems, achieving real-time measurement of electrical parameters, with performance dependent on communication stability. Overall, while IoT-enabled systems provide powerful monitoring capabilities, their reliance on complex infrastructure limits their suitability for simple, low-cost applications.

2.2. Fault Detection Techniques

Fault detection is a critical function in electrical monitoring systems, as early identification of abnormal conditions can prevent equipment damage and improve system reliability. Durodola et al. (2023) explored the use of machine learning

models for predictive fault detection in industrial systems, demonstrating high accuracy in identifying early signs of equipment failure. Singh et al. (2025) developed a deep learning-based framework combining edge and cloud computing for proactive power management and anomaly detection. Although these approaches offer high accuracy, they require significant computational resources, making them unsuitable for implementation on low-cost microcontrollers.

In contrast, simpler fault detection techniques based on threshold analysis and parameter comparison have been widely used in embedded systems. These methods involve defining acceptable operating limits and detecting deviations that indicate abnormal conditions. While less sophisticated than machine learning models, threshold-based approaches provide reliable performance for real-time fault detection in resource-constrained systems, as demonstrated in several Arduino-based implementations (Mudaliar & Sivakumar, 2020; Barbosa et al., 2024).

2.3. Low-Cost Embedded Monitoring Systems

The development of low-cost embedded monitoring systems has gained significant attention, particularly in applications where affordability and accessibility are critical. Mudaliar and Sivakumar (2020) developed an Arduino-based energy monitoring system capable of measuring electrical parameters and displaying real-time data, demonstrating the feasibility of using low-cost hardware for effective monitoring, although the system lacked advanced fault detection capabilities. Barbosa et al. (2024) further demonstrated that low-cost monitoring systems can achieve acceptable accuracy and performance when properly designed, though sensor limitations and environmental conditions can affect performance.

2.4. Advanced Monitoring Techniques

Beyond conventional monitoring approaches, several studies have explored advanced techniques such as artificial intelligence (AI), Non-Intrusive Load Monitoring (NILM), and digital twin technologies. Çimen et al. (2021) applied deep neural networks in residential microgrids, achieving high accuracy in load identification. Gowrienganthan et al. (2023) extended NILM techniques to three-phase systems using ensemble learning, improving disaggregation accuracy. Abdullahi et al. (2024) developed a digital twin framework for predictive maintenance, improving real-time condition assessment. Despite these advantages, such systems are highly complex and resource-intensive, limiting their suitability for small-scale or low-cost applications.

2.5. Summary of Reviewed Studies

Table 1 Summary of Reviewed Studies on Electrical Monitoring Systems

No.	Author(s)	Approach	Key Contribution	Limitation
1	Mazhar et al. (2023)	IoT + Machine Learning	Enhances real-time monitoring and improves energy efficiency	High complexity and lack of standardization
2	Ullah et al. (2023)	IoT-based monitoring system	Improves load management and operational efficiency	Latency in control response not fully addressed
3	Syafudin et al. (2018)	IoT + Big Data analytics	Handles large-scale real-time sensor data effectively	Complex infrastructure and high implementation cost
4	Barbosa et al. (2024)	Low-cost IoT data acquisition	Provides affordable real-time voltage and current monitoring	Performance depends on network stability
5	Çimen et al. (2021)	NILM + Deep learning	Achieves high accuracy in load identification	Sensitive to smart meter data quality
6	Mari et al. (2022)	NILM-based analysis	Enables anomaly detection and energy management	Difficulty detecting low-power devices
7	Gowrienganthan et al. (2023)	Ensemble learning (NILM)	Improves load disaggregation in three-phase systems	Complexity in overlapping phase signals
8	Schirmer & Mporas (2023)	NILM system review	Provides classification and evaluation of NILM methods	Poor transferability across environments
9	Durodola et al. (2023)	Machine learning for fault detection	Enables early detection of equipment failure	Requires large datasets for training

10	Singh et al. (2025)	Deep learning + IoT	High accuracy in predictive monitoring and grid optimization	High computational cost and hardware requirements
11	Rosati et al. (2022)	Decision Support System (ML-based)	Improves predictive maintenance performance	Limited interpretability of models
12	Abdullahi et al. (2024)	Digital twin technology	Enhances real-time condition monitoring and asset utilization	Complex implementation and lack of standardization
13	Pech et al. (2021)	Intelligent sensor systems	Supports predictive maintenance and fast response time	Large data volume overwhelms processing systems
14	Narayana et al. (2024)	IoT sensor networks	Improves real-time monitoring stability	High power consumption for continuous operation
15	Forhad et al. (2024)	Sensor-based monitoring system	Provides accurate real-time parameter measurement	Requires frequent sensor calibration

From Table 1, it is evident that existing monitoring systems either rely on complex and resource-intensive architectures or provide limited functionality in low-cost implementations. This highlights the need for a simplified, cost-effective system that integrates real-time monitoring, fault detection, and reporting within a single platform. This study addresses this gap by developing an Arduino-based three-phase monitoring and reporting system that prioritizes affordability, simplicity, and real-time performance while maintaining reliable fault detection capabilities.

3. Methodology

3.1. System Architecture and Block Diagram

The system block diagram illustrates the five basic units constituting the design: the power supply unit, sensor unit, control unit, input unit, and output unit. Each unit was designed and tested in isolation before integration into a single unified system. The core of the system is built around the Arduino Mega 2560 microcontroller, which interfaces with ZMPT101B voltage sensors, ACS712 current sensors, a 20×4 LCD display module, a 4×4 matrix keypad, and a SIM900/SIM800L GSM module for remote communication. The complete hardware integration enables high-frequency sampling of three-phase AC signals, real-time parameter computation, local data visualization, and remote fault notification.

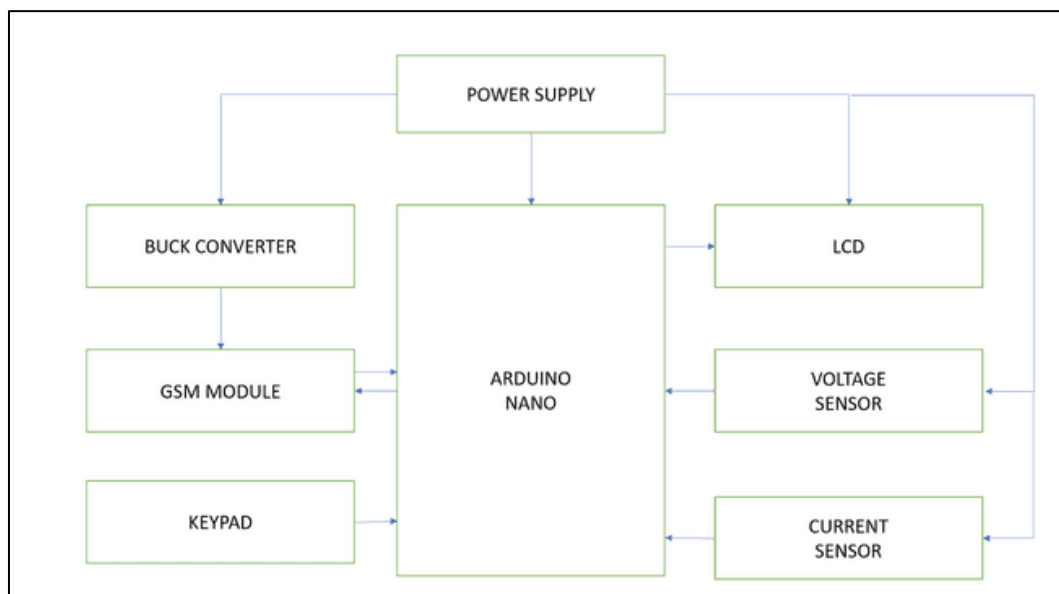


Figure 1 System Block Diagram

3.2. Hardware Components

The successful implementation of the proposed system required the selection of hardware components that are compatible, cost-effective, and suitable for real-time three-phase monitoring. The Arduino Mega 2560 was adopted as the central controller due to its expanded number of input/output pins and multiple serial communication ports, which are advantageous for handling several sensors and the GSM module simultaneously. The hardware components used for the implementation are as follows:

- Arduino Mega 2560; Central processing and control unit
- ZMPT101B Voltage Sensor Units (×3); Phase voltage measurement
- ACS712 Current Sensor Units (×3); Phase current measurement
- 20×4 LCD Display with I2C Adapter; Local data visualization
- 4×4 Matrix Keypad Module; User input and threshold configuration
- GSM Module (SIM800L/SIM900); Remote SMS fault reporting
- Power Supply Unit; Multi-rail DC regulation (5V and 3.3V)

3.3. Power Supply Unit Design

The power supply unit consists of a 240V/18V AC, 50 Hz step-down transformer, rectifier, filter, and voltage regulator. The conversion process involves four main stages: step-down transformation, full-wave rectification, capacitive filtering, and multi-stage voltage regulation. The 240V/50 Hz AC supply is stepped down to 18V AC, which is then rectified and regulated to provide stable 12V, 5V, and 3.3V DC rails for the system components.

A full-wave bridge rectifier using four IN4007 diodes was employed to convert the 18V AC to a pulsating DC output. The peak voltage is calculated as:

$$V_{peak} = \sqrt{2} \times V_{rms} = \sqrt{2} \times 18 = 25.46$$

A 1000 μ F/25V electrolytic capacitor was selected for filtering, maintaining peak-to-peak ripple at approximately 10% of the peak voltage. The 5V rail (LM7805) powers the Arduino Mega, sensors, and LCD, while a buck converter provides the 3.3V rail required by the GSM module.

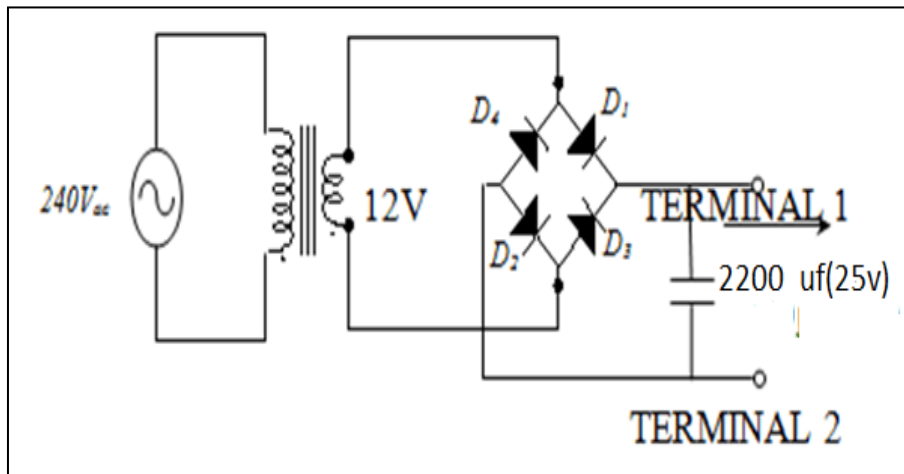


Figure 2 Full-Wave Bridge Rectifier Circuit

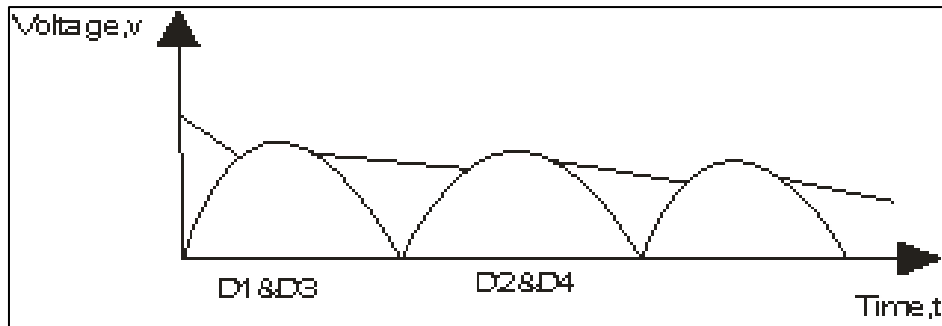


Figure 3 Rectified and Filtered Output Waveform

3.4. Voltage and Current Sensing Units

The ZMPT101B voltage sensor detects, monitors, and measures AC phase voltage levels, utilizing a voltage divider circuit and outputting an analog signal proportional to the stepped-down AC phase voltage. It was selected for its compactness, wide dynamic range, high accuracy, and non-saturable characteristics, making it a reliable solution for continuous AC voltage monitoring. Three ZMPT101B sensors are connected in parallel across the Red (R), Yellow (Y), and Blue (B) phases relative to the neutral line.

The ACS712 current sensor employs Hall-effect technology for precise AC and DC current measurement up to $\pm 20A$, outputting a proportional analog voltage. Key benefits include high accuracy, a linear response, and galvanic isolation between the high-current and low-voltage sides, enhancing safety and reducing noise. Three ACS712 sensors are connected in series with the individual phase lines feeding the load. Both sensor types interface directly with the Arduino Mega's 10-bit ADC channels.

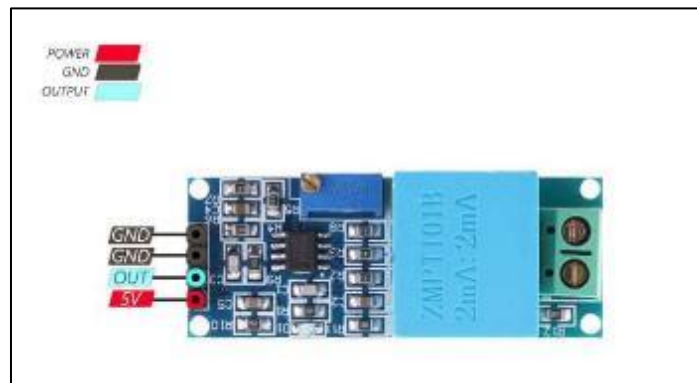


Figure 4 ZMPT101B Voltage Sensor Module

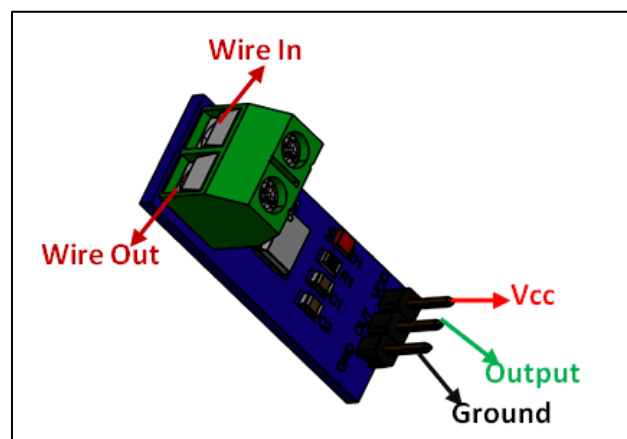


Figure 5 ACS712 Current Sensor Module

3.5. GSM Communication Module and Keypad

The GSM module (SIM800L/SIM900) serves as the primary remote reporting gateway, enabling the system to transmit real-time electrical metrics and fault alerts to remote mobile devices via SMS. It communicates with the Arduino Mega through a UART serial interface using standard AT commands, operating within a voltage range of 3.7V to 4.2V. The module is capable of formatting phase voltages, currents, and status messages into a single SMS string dispatched to a pre-configured recipient, ensuring facility managers receive instantaneous updates regardless of internet availability.

The 4×4 matrix keypad provides a user input interface for navigating display menus, setting voltage thresholds, and inputting contact numbers for SMS alerts. It operates on a scanning principle, requiring only eight digital I/O pins to manage 16 individual inputs, using a keypad library that handles debouncing for accurate key registration.



Figure 6 SIM900 GSM Module



Figure 7 4×4 Keypad Module

3.6. System Circuit Diagram and Simulation

The complete system circuit diagram integrates the sensing units, Arduino Mega 2560, keypad, LCD display, GSM communication module, and power supply stages into a single operational system. During development, the circuit was first simulated in the Proteus Design Suite to verify correct interconnection, signal flow, and logic behavior before practical implementation through breadboard prototyping and final hardware assembly.

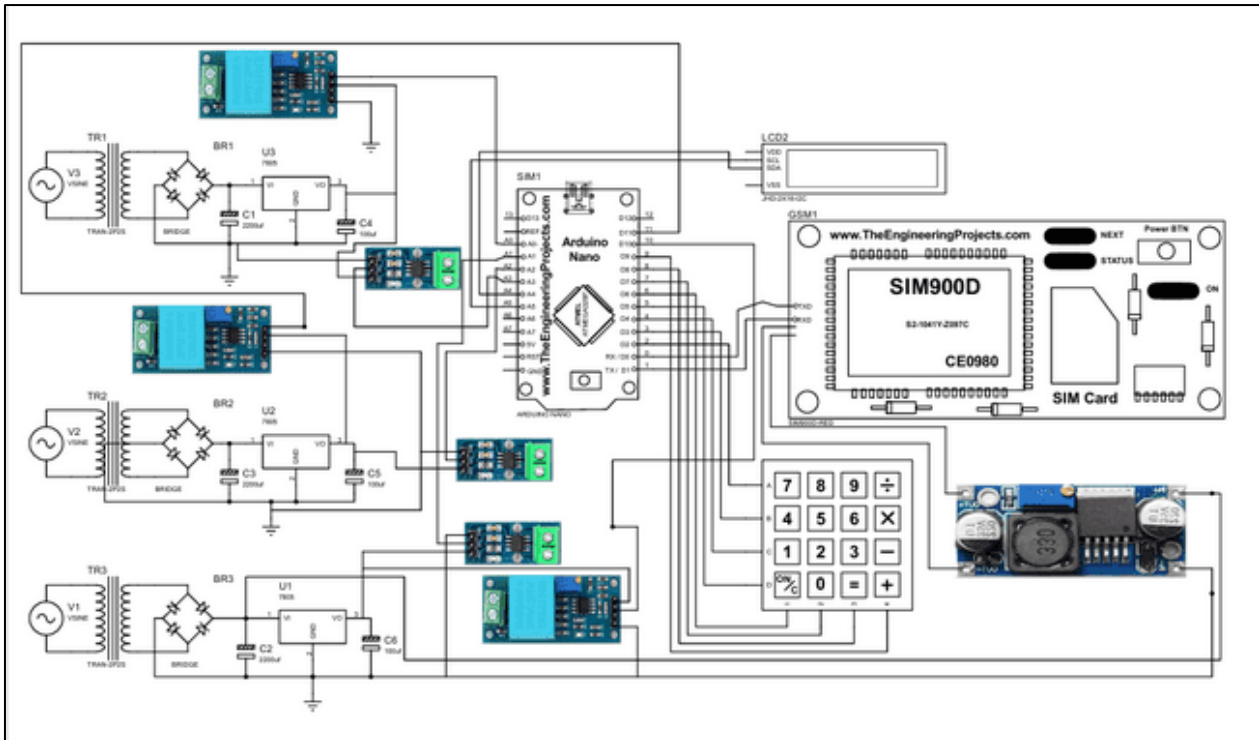


Figure 8 Complete System Circuit Diagram

3.7. Software Architecture and Development

The software was developed using the Arduino Integrated Development Environment (IDE) and written in C++. The software architecture follows a modular and layered design comprising three core layers: the Hardware Abstraction Layer, the Processing and Logic Layer, and the Reporting/Output Layer.

The Hardware Abstraction Layer handles low-level signal acquisition from the ACS712 and ZMPT101B sensors, managing sampling frequency and bias offsets necessary for AC waveform capture. The Processing and Logic Layer executes RMS and active power calculations, zero-crossing detection, and threshold-based comparative analysis for fault identification. The Reporting and Output Layer coordinates I2C communication for the LCD and manages UART serial protocols for the GSM module, allowing alert thresholds to be updated via the keypad without disrupting the continuous monitoring loop.

The fault detection algorithm compares measured parameters against predefined safety thresholds. A fire alert function $F(V, I)$ is defined as:

$$F(V, H) = \{1, \text{if } V_{\text{phase}} < 200V \text{ OR } V_{\text{phase}} > 250V \text{ OR } I_{\text{phase}} > 5.0A \text{ OR } |\Delta V| > 10\%; 0 \text{ otherwise}\}$$

where V represents phase voltage, I represents phase current, and ΔV represents voltage variance between phases. The system flowchart is presented in Figure 9.

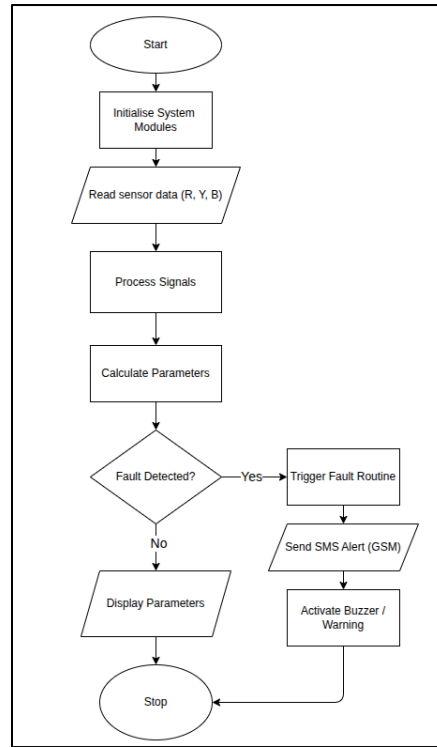


Figure 9 System Operational Flowchart

4. Results and Discussion

4.1. Experimental Setup

To rigorously evaluate the performance and reliability of the developed three-phase monitoring and reporting system, a series of experimental tests were conducted within a controlled electrical machines laboratory. The system was interfaced with a standard 415V (line-to-line) / 240V (line-to-neutral) 50 Hz three-phase power supply. Testing was conducted using a variable three-phase resistive load bank and a 1.5 kW three-phase induction motor to introduce inductive characteristics and real-world power factor variations.

For benchmarking purposes, sensor readings from the Arduino Mega 2560 were compared against a Fluke 87V True-RMS Digital Multimeter for phase voltage verification and a Fluke 376 FC True-RMS Clamp Meter for phase current measurement. Safety precautions including isolation transformers and proper grounding were strictly observed throughout testing.

4.2. Calibration and Accuracy Analysis

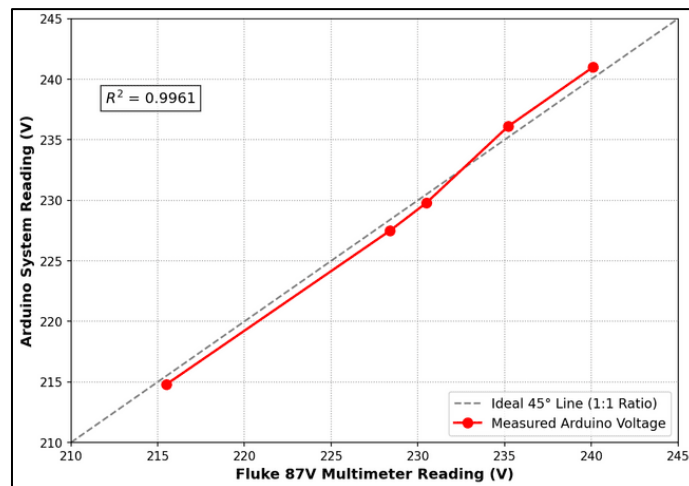
4.2.1. Voltage Sensor (ZMPT101B) Calibration and Validation

The ZMPT101B voltage sensor outputs an analog signal proportional to the stepped-down AC phase voltage. During testing, the system voltage was varied using a three-phase variac to observe sensor linearity across the three phases. The absolute percentage error was calculated as:

$$\text{Percentage Error (\%)} = \left[\frac{|\text{Standard Value} - \text{Measured Value}|}{\text{Standard Value}} \right] \times 100$$

Table 2 Calibration and Error Analysis of Phase Voltages (Line-to-Neutral)

Phase	Fluke 87V Multimeter (V)	Arduino System Reading (V)	Absolute Error (V)	Percentage Error (%)
Red (R)	230.50	229.80	0.70	0.30%
Yellow (Y)	235.20	236.10	0.90	0.38%
Blue (B)	228.40	227.50	0.90	0.39%
Red (R)	240.10	241.00	0.90	0.37%
Yellow (Y)	215.50	214.80	0.70	0.32%

**Figure 10** Voltage Calibration Linearity Curve (Line Graph)

The results indicate that the ZMPT101B sensors, coupled with the Arduino's ADC, exhibit a maximum percentage error of less than 0.4%. This high degree of accuracy comfortably meets the standard requirements for educational and small-scale industrial monitoring.

4.2.2. Current Sensor (ACS712) Calibration and Validation

Measuring AC current via the Hall-effect ACS712 sensor presents challenges due to sensitivity to external electromagnetic interference and inherent zero-current noise. A software-based low-pass filter and zero-crossing detection algorithm were implemented to mitigate these effects. The system was tested under varying load conditions ranging from 1.0A to 5.0A.

Table 3 Calibration and Error Analysis of Phase Currents

Load Condition	Fluke Clamp Meter (A)	Arduino System Reading (A)	Absolute Error (A)	Percentage Error (%)
Light Load	1.50	1.53	0.03	2.00%
Medium Load	3.20	3.15	0.05	1.56%
Heavy Load	4.85	4.91	0.06	1.23%
Heavy Load	5.50	5.44	0.06	1.09%

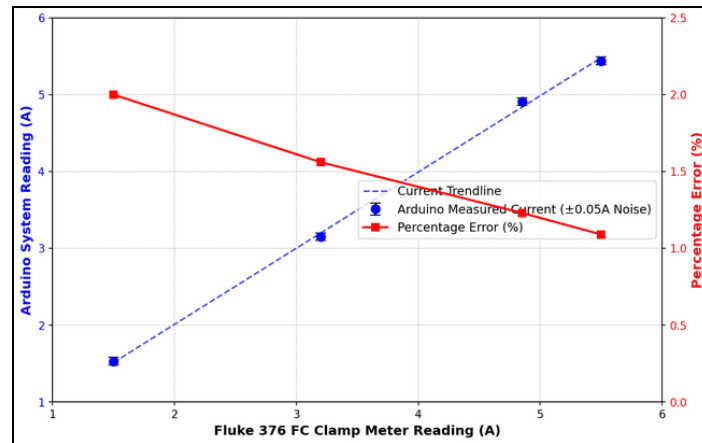


Figure 11 Current Measurement Accuracy and Error Tracking

The current calibration results yield an average error of approximately 1.47%. The slightly higher error margin at lighter loads is typical for the ACS712 sensor due to ADC quantization steps; however, this error diminishes as load increases. Overall, these results confirm that the hardware and software architectures successfully fulfill the objective of accurately acquiring critical electrical parameters.

4.3. System Performance under Normal Operating Conditions

Table 4 Real-Time Logging of Phase Parameters under a Balanced Inductive Load

Parameter	Red Phase (R)	Yellow Phase (Y)	Blue Phase (B)	Average / Total
RMS Voltage (V)	230.20	229.50	231.00	230.23 (Avg)
RMS Current (A)	2.15	2.18	2.12	2.15 (Avg)
Apparent Power (VA)	494.93	500.31	489.72	1,484.96 (Total)
Active Power (W)	420.69	420.26	421.16	1,262.11 (Total)
Power Factor (Cos θ)	0.85	0.84	0.86	0.85 (Avg)

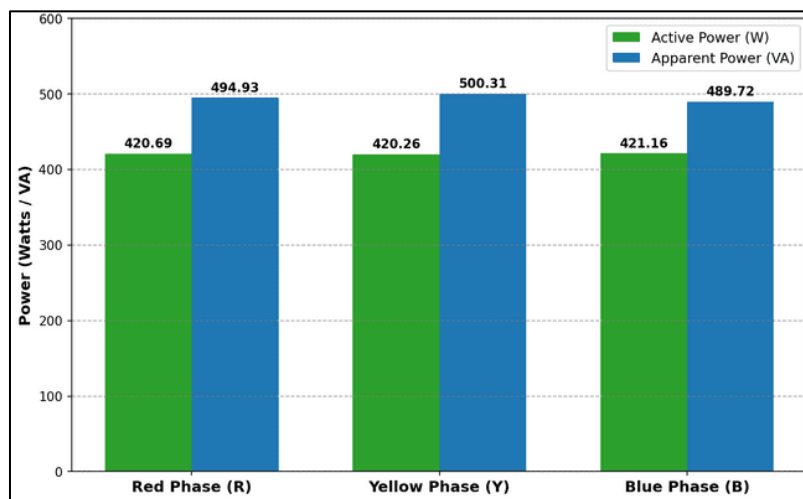


Figure 12 Power Consumption Distribution across Three Phases

The integrated system was evaluated under normal, fault-free operating conditions using a balanced 1.5 kW three-phase induction motor operating under steady mechanical load. The microcontroller's algorithm successfully executed continuous sampling of AC waveforms, calculating RMS voltage, RMS current, apparent power, active power, and power

factor for each phase. Active power was derived by computing the average of the instantaneous product of voltage and current over multiple AC cycles, inherently accounting for phase shift caused by the inductive load.

The data demonstrates that the system accurately captures natural variations in real-world three-phase supplies while confirming the balanced nature of the load. The calculated power factor values (averaging 0.85) are highly consistent with typical lagging characteristics of a standard induction motor, validating the efficiency of the software architecture and the reliability of the microcontroller-based platform.

4.4. Fault Detection Capabilities and Responsiveness

The system's threshold-based fault detection logic was subjected to a series of controlled, simulated electrical faults. Predefined safety thresholds for the 240V nominal phase voltage were set as follows: Under-Voltage ($< 200V$), Over-Voltage ($> 250V$), Overcurrent ($> 5.0A$), Phase Imbalance ($> 10\%$ voltage variance between phases), and Phase Failure ($< 50V$ on any active phase line).

Under-voltage and over-voltage scenarios were simulated using a three-phase variac. Phase failure was simulated by physically disconnecting the Blue phase, which the voltage sensor instantaneously registered as $0V$, triggering accurate categorization as Phase Failure rather than a general power outage. Phase imbalance was simulated by loading a single phase with a heavy resistive load, causing a localized voltage sag; the software's comparative analysis algorithm successfully detected the variance exceeding the 10% tolerance threshold.

Table 5 Summary of Simulated Faults, Thresholds, and System Response Metrics

Fault Type	Programmed Threshold	Injected Condition	Test	Detection Status	Local (LCD/Buzzer)	Latency
Under-Voltage	$V_{\text{phase}} < 200V$	R-Phase dropped to $190V$		Successful	< 300 ms	
Over-Voltage	$V_{\text{phase}} > 250V$	Y-Phase raised to $255V$		Successful	< 300 ms	
Overcurrent	$I_{\text{phase}} > 5.0A$	B-Phase loaded to $5.8A$		Successful	< 400 ms	
Phase Imbalance	$> 10\%$ variance	R= $210V$, Y= $240V$, B= $240V$		Successful	< 300 ms	
Phase Failure	$V_{\text{phase}} < 50V$	B-Phase disconnected ($0V$)		Successful	< 250 ms	

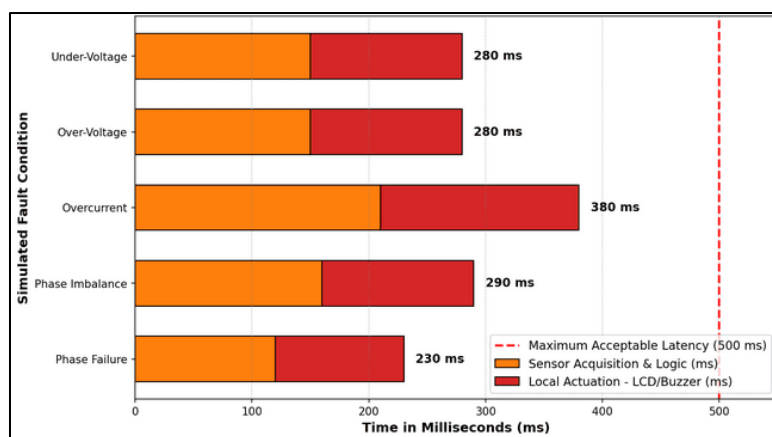


Figure 13 System Latency Flow for Fault Detection and Reporting

The results confirm a 100% success rate in detecting all simulated anomalies, with local processing and display latencies remaining well under 500 milliseconds. This demonstrates that the low-cost microcontroller approach does not compromise functional safety, successfully fulfilling the research objective of identifying transient faults and preventing gradual system degradation.

4.5. GSM Communication and Reporting Analysis

The SIM800L/SIM900 GSM module was programmed to dispatch a concatenated SMS upon detection of any fault, containing the fault type, affected phase(s), and instantaneous voltage and current values. To evaluate reliability and latency, a total of 50 simulated fault events (10 per fault category) were triggered, with delivery time measured from LCD update to SMS receipt on the configured mobile device.

Table 6 SMS Delivery Success Rate and Latency across Varying Signal Strengths

Network Signal Strength (CSQ Range)	No. of Test SMS Dispatched	Successful Deliveries	Delivery Success Rate (%)	Average Delivery Latency (Seconds)
Excellent (20 - 31)	20	20	100%	3.5
Good (10 - 19)	20	20	100%	5.2
Poor (0 - 9)	10	9	90%	12.4
Overall System Average	50	49	98%	5.8

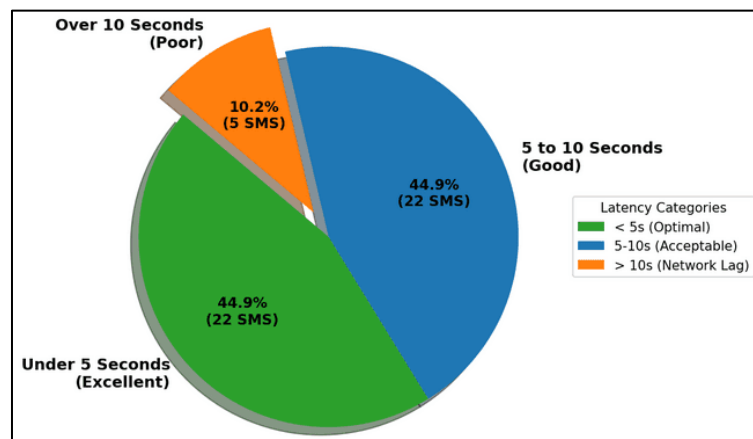


Figure 14 SMS Delivery Latency Distribution

The empirical data indicates a highly reliable remote reporting mechanism, with an overall SMS delivery success rate of 98%. Under normal network conditions (CSQ > 10), facility managers receive a detailed diagnostic text message within an average of 3 to 5 seconds after fault detection. The single failed delivery during the poor signal test was attributed to a complete momentary network drop. This SMS-based approach prioritizes reliability and operates entirely independently of local internet outages, ensuring that facility managers receive critical fault alerts regardless of geographical proximity to the installation.

5. Discussion

The results obtained from experimental testing strongly validate the efficacy of deploying a low-cost, Arduino-based architecture for three-phase electrical monitoring. The integration of ZMPT101B and ACS712 sensors yielded exceptional accuracy, with voltage measurement errors below 0.4% and current errors stabilizing around 1.5% under functional loads. This directly addresses the research gap identified in the literature review regarding the high cost and complexity of commercial power analyzers, demonstrating that small-scale industries and educational institutions can reliably monitor critical electrical parameters without prohibitive financial investments.

The fault detection capabilities underscore the practical application of Cyber-Physical Systems (CPS) theory. The ability of the microcontroller to continuously sample physical electrical signals, execute mathematical comparative logic, and actuate a local response within 500 milliseconds proves that lightweight edge-computing platforms are capable of managing real-time industrial constraints. The implementation of the GSM-based reporting module further elevates the system from a localized digital meter to an active, resilient diagnostic tool, achieving a 98% SMS delivery success rate with an average latency under six seconds.

6. Conclusion

This study successfully designed and implemented a functional, reliable, and low-cost three-phase electrical monitoring and reporting system using an Arduino Mega 2560 microcontroller. By leveraging accessible sensing modules, the ZMPT101B voltage sensor and ACS712 current sensor, the project demonstrated that near-industrial measurement accuracy is achievable without the prohibitive financial barriers associated with commercial power analyzers, recording error margins of less than 0.4% for voltage and 1.5% for current.

The study conclusively demonstrated the critical value of automated, real-time fault detection. The system's edge-computing architecture successfully eliminated the inefficiencies and human errors inherent in manual monitoring practices by consistently detecting severe electrical anomalies, including phase failure, phase imbalance, and over/under-voltage within 500 milliseconds. The highly dependable GSM-based SMS alerting mechanism ensured that facility managers receive immediate fault notifications regardless of internet availability, achieving a 98% delivery success rate with an average latency of 5.8 seconds.

This research bridges a critical gap in electrical systems management for small-scale industries, workshops, and educational laboratories, proving that affordable embedded systems, when engineered with robust software algorithms and proper hardware isolation, are viable, industrially relevant solutions. The developed system enhances operational safety, promotes efficient energy management, and extends the lifespan of expensive three-phase electrical machinery.

Future work should consider integrating IoT and cloud-based data logging using Wi-Fi-enabled platforms such as the ESP32, incorporating machine learning algorithms for predictive fault detection, implementing NILM techniques for load disaggregation, and integrating hardware tripping mechanisms to enable automatic power disconnection upon critical fault detection.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

- [1] Abdullahi, I., Longo, S., & Samie, M. (2024). Towards a distributed digital twin framework for predictive maintenance in industrial internet of things (IIoT). *Sensors*, 24(8). <https://doi.org/10.3390/s24082663>
- [2] Athanasiadis, C., Doukas, D., Papadopoulos, T., & Chrysopoulos, A. C. (2021). A scalable real-time non-intrusive load monitoring system for the estimation of household appliance power consumption. *Energies*, 14(3). <https://doi.org/10.3390/en14030767>
- [3] Barbosa, A., Mubarak, H., Mohammadi, F., Sanjari, M. J., & Saif, M. (2024). A real-time IoT-based data acquisition and monitoring system for photovoltaic applications. In 2024 3rd International Conference on Power Systems and Electrical Technology (PSET). <https://doi.org/10.1109/pset62496.2024.10808965>
- [4] Bhavani, N., Kumar, R., Panigrahi, B., Balasubramanian, K., Arunsundar, B., Abdul-Samad, Z., & Singh, A. (2022). Design and implementation of IoT integrated monitoring and control system of renewable energy in smart grid. *Sustainable Computing: Informatics and Systems*. <https://doi.org/10.1016/j.suscom.2022.100769>
- [5] Çimen, H., Çetinkaya, N., Vasquez, J., & Guerrero, J. (2021). A microgrid energy management system based on non-intrusive load monitoring via multitask learning. *IEEE Transactions on Smart Grid*. <https://doi.org/10.1109/tsg.2020.3027491>
- [6] Durodola, O. M., et al. (2023). Machine learning for fault detection in industrial electrical systems: A review. *Journal of Industrial Engineering*.
- [7] Fortuna, L., & Buscarino, A. (2022). Non-intrusive load monitoring. *Sensors*, 22(17). <https://doi.org/10.3390/s22176675>
- [8] Gopinath, R., Kumar, M., Joshua, C. P. C., & Srinivas, K. (2020). Energy management using non-intrusive load monitoring techniques—State-of-the-art and future research directions. *Sustainable Cities and Society*. <https://doi.org/10.1016/j.scs.2020.102411>

- [9] Gowrienganthan, B., Kiruthihan, N., Rathnayake, K., Kiruthikan, S., Velmanickam, L., Kumarawadu, S., & Wanigasekara, C. (2023). Deep learning based non-intrusive load monitoring for a three-phase system. IEEE Access. <https://doi.org/10.1109/access.2023.3276475>
- [10] Iqbal, H. K., Malik, F. H., Muhammad, A., Qureshi, M. A., Abbasi, M. N., & Chishti, A. R. (2020). A critical review of state-of-the-art non-intrusive load monitoring datasets. Electric Power Systems Research. <https://doi.org/10.1016/j.epsr.2020.106921>
- [11] Jiang, Y., Yin, S., Dong, J., & Kaynak, O. (2021). A review on soft sensors for monitoring, control, and optimization of industrial processes. IEEE Sensors Journal. <https://doi.org/10.1109/jsen.2020.3033153>
- [12] Kumar, N. M., Chand, A. A., Malvoni, M., Prasad, K. A., Mamun, K., Islam, F., & Chopra, S. S. (2020). Distributed energy resources and the application of AI, IoT, and blockchain in smart grids. Energies. <https://doi.org/10.3390/en13215739>
- [13] Mari, L., et al. (2022). NILM-based anomaly detection for energy management. Energy and Buildings.
- [14] Mazhar, T., Irfan, H., Haq, I., Ullah, I., Ashraf, M., Al Shloul, T., Ghadi, Y., Imran, & Elkamchouchi, D. H. (2023). Analysis of challenges and solutions of IoT in smart grids using AI and machine learning techniques: A review. Electronics. <https://doi.org/10.3390/electronics12010242>
- [15] Mudaliar, M., & Sivakumar, N. (2020). IoT based real time energy monitoring system using Raspberry Pi. Internet of Things. <https://doi.org/10.1016/j.iot.2020.100292>
- [16] Narayana, T. L., Venkatesh, C., Kiran, A., Babu, C. J., Khan, S. B., Almusharraf, A., & Quasim, M. T. (2024). Advances in real time smart monitoring of environmental parameters using IoT and sensors. Heliyon, 10, e28193. <https://doi.org/10.1016/j.heliyon.2024.e28195>
- [17] Pech, M., et al. (2021). Intelligent sensors for predictive maintenance in industrial settings. IEEE Transactions on Industrial Informatics.
- [18] Pereira, L., & Nunes, N. (2018). Performance evaluation in non-intrusive load monitoring: Datasets, metrics, and tools—A review. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery. <https://doi.org/10.1002/widm.1265>
- [19] Rafiq, H., Manandhar, P., Rodriguez-Ubinas, E., Qureshi, O. A., & Palpanas, T. (2024). A review of current methods and challenges of advanced deep learning-based non-intrusive load monitoring (NILM) in residential context. Energy and Buildings. <https://doi.org/10.1016/j.enbuild.2024.113890>
- [20] Schirmer, P., & Mporas, I. (2023). Non-intrusive load monitoring: A review. IEEE Transactions on Smart Grid. <https://doi.org/10.1109/tsg.2022.3189598>
- [21] Singh, K., et al. (2025). Deep learning and IoT for predictive power system optimization. IEEE Access.
- [22] Syafrudin, M., Alfian, G., Fitriyani, N. L., & Rhee, J. (2018). Performance analysis of IoT-based sensor, big data processing, and machine learning model for real-time monitoring system in automotive manufacturing. Sensors. <https://doi.org/10.3390/s18092946>
- [23] Ullah, Z., Rehman, A., Wang, S., Hasanien, H. M., Luo, P., Elkadeem, M., & Abido, M. (2023). IoT-based monitoring and control of substations and smart grids with renewables and electric vehicles integration. Energy. <https://doi.org/10.1016/j.energy.2023.128924>
- [24] Zoha, A., Gluhak, A., Imran, M., & Rajasegarar, S. (2012). Non-intrusive load monitoring approaches for disaggregated energy sensing: A survey. Sensors. <https://doi.org/10.3390/s121216838>