JOURNAL OF RENEWABLE ENERGY AND SMART GRID TECHNOLOGY

Vol. 20, No. 2, July-December 2025

Development of a Data-driven Energy Monitoring System for Power Consumption and Power Quality Monitoring

Owen Kwong-Hong KEE[1], Keh-Kim KEE[1*], Ching Yee YONG[1], Ramli Rashidi[1], Tzu Hsiung LO[2]

[1]School of Engineering and Technology, University of Technology Sarawak, Sibu 96000, Malaysia
[2]Sarawak Energy Berhad (SEB), Kuching 93050, Malaysia
***Corresponding author's email**: kkkee@uts.edu.my

Article info:

Received: 23 August 2025
Revised: 15 October 2025
Accepted: 4 November 2025
DOI:
10.69650/rast.2025.263660

Keywords:

Smart Metering
IoT
Energy Monitoring
Fog-Cloud
Power Quality
Rule-Based System

ABSTRACT

The rapid growth of global electricity demand and the widespread adoption of non-linear loads have intensified power quality (PQ) concerns, revealing critical limitations of existing energy metering solutions. These systems lack real-time monitoring, data granularity, and analytical capabilities necessary for advanced energy and power quality management. This paper presents the design, development, and validation of the Data-Driven Energy Monitoring System (DDEMS), an IoT-based platform integrating smart metering, edge computing, and hybrid analytics for real-time PQ assessment and energy management. The system combines low-cost sensors such as PZEM-004T, ZMPT101B and SCT-013, incorporated with an ESP32 microcontroller to measure key electrical parameters, and classify PQ events using a cloud-based rule-based engine which compliance with IEEE 1159 and IEC 61000-4-30 for power quality standards. Experimental validation was conducted on DDEMS against the calibrated Lovato DMG800 power multimeter and Fluke 437-II demonstrated its accuracy with overall system measurement errors at 1.24% of mean absolute percentage error (MAPE). Furthermore, the system successfully identified and categorized PQ disturbances into four severity levels, enabling timely mitigation the issues such as supply voltage fluctuations, harmonic distortions, and poor power factors. A subsequent 90-day field deployment in residential settings confirmed the system's reliability, and a web-based dashboard facilitating energy optimization with power quality monitoring. DDEMS addresses key limitations of existing solutions by offering a cost-effective, scalable alternative to expensive PQ analyzers while maintaining high accuracy and real-time capabilities. The system's modular architecture and successful real-world implementation highlight its potential for widespread adoption in smart energy management applications.

1. Introduction

1.1 Background and motivation

The global energy sector is in the midst of significant transformation driven by escalating electricity demand, the integration of distributed renewable resources, and the widespread adoption of non-linear loads (NLLs). Despite the growth in renewables, fossil fuels remained the dominant sources, amounting to 62% of global electricity generation in 2022 [1]. The extensive reliance on non-renewable energy resources not only accelerates their depletion but also contributes significantly to environmental degradation and climate change. These pressing concerns have intensified the need for intelligent, data-driven energy management solutions that can optimize consumption, reduce waste, and seamlessly integrate renewable sources in smart grids [2].

In 2024, worldwide electricity consumption reached an estimated 30,856 TWh while residential and commercial sectors collectively responsible for 42% of this total demand [3]. This surge is compounded by ubiquitous and widespread adoption of the non-linear loads such as variable speed drive (VSD), switched-mode power supply (SMPS) in computers and Internet of Things (IoT) devices, LED lighting and electric vehicle (EV) chargers. These devices draw current in short, non-sinusoidal pulses, and injecting harmonic currents back into the power grid. The proliferation of NLLs has led to more frequent power quality (PQ) issues, including voltage fluctuations, voltage and current harmonic distortion, voltage sags and swells, and phase imbalances [4]. The economic impact of poor PQ issues is severe, estimated to cause annual losses in the billions of US dollars for industries worldwide due to equipment malfunctions, premature failure, reduced operational efficiency, production downtime, and increased energy costs [5].

IoT paradigm, characterized by the integration of low-cost sensors, edge computing, and cloud-based analytics, has proven to be a transformative force across numerous domains beyond energy systems. For instance, in precision agriculture, IoT-assisted context-aware systems have demonstrated remarkable efficacy. These systems leverage sensor networks to monitor soil conditions and microclimates, enabling data-driven recommendations for fertilizer application [6], reclaiming saline soils through context-aware evapotranspiration monitoring [7], and optimizing water usage via intelligent models for reference evapotranspiration [8]. The success of these systems in providing robust and real-time decision support using an architecture comprising sensing, edge processing, and cloud analytics underscores the viability and scalability of the IoT framework for solving complex, data-intensive problems. This reinforces the potential of applying a similarly structured, data-driven approach to the challenges of energy monitoring and power quality management.

1.2 Limitations of existing solutions

Conventional electromechanical energy meters and smart meters are fundamentally inadequate for addressing the challenges in advanced energy and power quality management. Their primary limitations include:

(a) Lack of real-time PQ monitoring: They are designed primarily for billing purposes based on kWh accumulation. They lack capability to monitor, record, or alert PQ disturbances in real-time [6]
(b) Insufficient data granularity: They typically provide data at intervals of 15 minutes or longer, which is too coarse to capture transient PQ events like sags or swells that can occur and resolve within milliseconds or cycles [7]
(c) Absence of advanced analytics: They lack computational capability such as harmonic analysis, waveform capture, or event classification, which are essential for diagnostic and detection purposes [8]

While specialized, high-fidelity power quality analyzers are available to fill this gap, their high costs (typically exceeding $5,000 per unit) and frequently proprietary architectures render them impractical for widespread and scalable deployment, particularly in residential and small-to-medium commercial settings [9]. Prior research into IoT-based energy monitoring systems has made considerable progress. Numerous prototypes leveraging platforms such as Arduino, Raspberry Pi and ARM-based computation have been proposed. However, these often suffer from critical shortcomings:

(a) High cost or complexity: Many systems integrate expensive, high-precision measurement chipsets or require complex sensor arrays without cost-competitiveness and ease of deployment. [10], [11]
(b) Limited parameter set: Many prototypes focus on fundamental parameters (V, I, P) but omit critical PQ indices such as Total Harmonic Distortion factor (THD) and individual harmonic components [12].
(c) Laboratory-bound validation: Proposed mechanisms or models for fault detection or load disaggregation often demonstrate high accuracy in controlled lab environments but fail to generalize reliably under the noisy, variable conditions of real-world deployments [13], [14].

Furthermore, the evolution towards data-driven systems introduces two critical, often overlooked challenges: data complexity and data privacy. The acquisition of high-frequency waveform data for harmonic analysis, as performed in this study, generates complex, high-dimensional datasets. Managing this complexity requires robust computational frameworks to ensure efficient processing and model reliability, a challenge echoed in other fields dealing with intricate data, such as the evaluation of model dependence for classifying complex medical images [15]. Simultaneously, the continuous collection of fine-grained energy consumption data presents a significant privacy risk, as it can reveal detailed patterns of occupant behavior. While existing energy monitoring systems frequently overlook this, the broader IoT domain has seen a push towards privacy-preserving and decentralized architectures to mitigate such risks [16]. An ideal system must therefore address not only measurement accuracy but also the computational demands of complex data and the imperative of protecting user privacy.

1.3 Proposed solution and contributions

To overcome these challenges, this paper introduces the Data-Driven Energy Monitoring System (DDEMS), a holistic, affordable and robust IoT-based solution that integrates multi-sensor data acquisition, edge computing, cloud data storage and analytics, and a rule-based power quality analytics engine for comprehensive power consumption and PQ monitoring.

The system utilizes a selected suite of low-cost sensors including the PZEM-004T for high-accuracy measurement of fundamental electrical parameters (V, I, P, Q, PF etc.), a SCT-013 non-invasive current transformer for capturing current waveforms in harmonic analysis, and a ZMPT101B voltage sensor for detailed voltage waveform analysis. An ESP32 microcontroller serves as the central processing unit (CPU) which performs initial data processing and real-time Fast Fourier Transform (FFT) computations at the edge to enable rapid detection of power quality issues. The processed data is transmitted to a cloud platform, where a rule-based PQ Advisor is deployed to evaluate PQ measurement against IEEE 1159 and IEC 61000-4-30 thresholds for both immediate detection power quality events and provide mitigations to remedy issue [17], [18]. The PQ Advisor provides not only detection but also actionable insights and mitigation recommendations

This research makes several key contributions. First, it presents a cost-effective hardware design that integrates multiple sensors for comprehensive power data analytics and power quality monitoring. Second, it introduces optimized rule-based algorithms that significantly simplified the detection and classification of power quality issues and severity as compared to existing solutions. Finally, the system has been rigorously validated in real-world environments, demonstrating high accuracy in detecting electrical disturbances while reducing energy costs. The remainder of this paper is structured as follows: Section 2 details the system architecture and methodology. Section 3 presents experimental results and discussion. Finally, Section 4 concludes the paper and suggests future work.

2. Materials and Methodology

2.1 System architecture overview

The Data-Driven Energy Monitoring System (DDEMS) is architected on a multi-layer fog-cloud IoT framework, as illustrated in Fig. 1. The hierarchical design optimizes data flow, computational efficiency, and scalability by distributing tasks across five distinct layers, namely the Physical Layer, the Fog Computing Layer, the Network Layer, the Cloud Computing layer, and the Application Layer. The multi-layer approach enables real-time monitoring of both power consumption and power quality while maintaining scalability for large-scale deployments. The conceptual design and physical implementation diagram of DDEMS are depicted in Fig. 1 (a) and (b), respectively [19].

The physical layer is the foundation of the DDEMS system which comprises several physical sensors responsible for acquiring raw analog data from the electrical system. The key sensors in this layer include a PZEM-004T Power Module to measure fundamental parameters (V_{rms}, I_{rms}, P, Q, PF and Frequency), a ZMPT101B Voltage Sensor to acquire high-fidelity analog output proportional to the AC voltage waveform for detailed analysis, and a SCT-013 non-invasive current transformer used to acquire AC current waveform for current harmonic analysis.

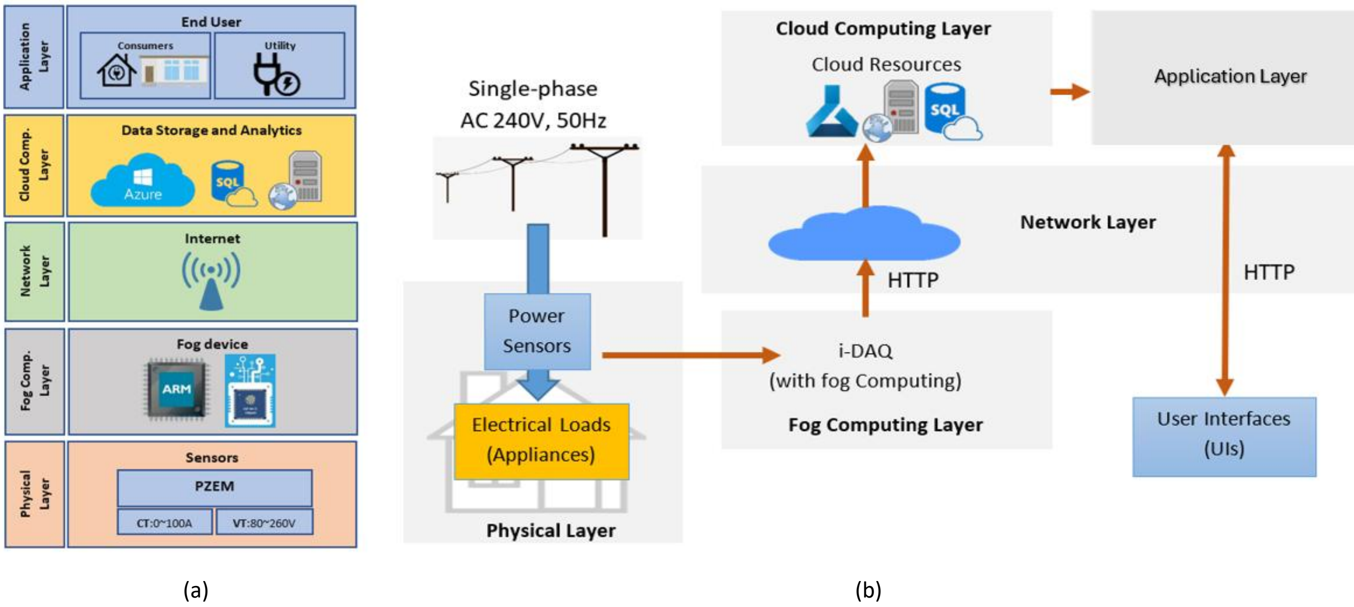


Fig. 1 The design of the DDEMS system, (a) conceptual layered architecture, (b) implementation diagram.

The fog computing layer is positioned at the edge of the network with an intelligent data acquisition (i-DAQ) unit to handle lightweight data storage and computation of the power data collected by the physical layer [20]. It is built around an ESP32 microcontroller. Its critical functions include Data Acquisition, Signal Processing and Data Preprocessing. This layer reads analog signals from sensors via ESP32's Analog-to-Digital Converter (ADC). Signal Processing aims to perform real-time computations including RMS conversion, power calculation and a windowed Fast Fourier Transform (FFT) on the current waveforms to compute harmonic components and total harmonic distortion factor (THD). With Data Preprocessing function, this layer encapsulates the processed data into a structured format for efficient transmission, and minimizing bandwidth usage and latency for critical alert by reducing the raw data volume sent to the cloud.

The cloud computing layer offers extensive data storage and advanced computing capabilities required for long-term analytics. It is hosted on a virtual private server (VPS) running Ubuntu Server 20.04 LTS. This layer hosts several integrated services:

- A Web Server running Apache with PHP 8.1 to handle incoming HTTP requests from the i-DAQ units.
- A MySQL Database Server (version 8.0) for structured storage of all historical time-series data and event logs. The database is configured with daily automated backups to a secure, off-site location.
- A Rule-based Engine for the PQ Advisor, implemented as a set of PHP scripts, which continuously evaluates incoming data packets against predefined rules based on IEEE/IEC standards.
- RESTful Application Programming Interfaces (APIs) to facilitate structured communication between the database, the web front-end, and potential third-party services.

The network layer serves as the communication bridge between fog and cloud computing layers. The primary protocol used is Wi-Fi (IEEE 802.11) for its ubiquity and high data rate in indoor environments. The ESP32's integrated Wi-Fi shield handles the connection. Data is transmitted to the cloud server using Hypertext Transfer Protocol (HTTP) POST requests with encapsulated JSON payloads, ensuring reliable and standardized data exchange [21].

The final layer is the application layer, which manages all application processes using the information from the cloud computing layer. This layer consists of a responsive, web-based portal accessible via any modern web browser on desktops, tablets, or smartphones. Its functions include:

(a) Real-time data visualization: Displaying live values of all parameters through gauges, charts, and graphs.
(b) Historical data analysis: Providing tools for viewing trends over custom time periods (hours, days, weeks).
(c) PQ Advisor: Presenting rule-based PQ monitoring for all detected PQ events with their severity level and sending SMS alerts for critical events.
(d) Benchmarking and reporting: Allowing users to compare current consumption against previous periods to identify savings and generate reports.

This multi-layer approach effectively distributes the workload. Time-sensitive processing is handled at the edge (fog computing layer), while resource-intensive storage and complex analytics are managed in the cloud, creating a scalable, efficient, and responsive system suitable for large-scale deployments. The fog-cloud architecture of DDEMS is fundamentally designed for scalability and robustness. Scalability is achieved through distributed edge processing, where each i-DAQ unit operates autonomously, preventing a linear increase in cloud computational load with additional units. The cloud layer's web and database servers can be scaled horizontally to manage increased data influx. To ensure stability during network outages, the ESP32 microcontroller implements a local data buffering system on its internal flash storage. Processed data packets are stored locally if the cloud is unreachable and are transmitted once connectivity is restored, preserving data integrity.

2.2 Acquisition of power parameters

The intelligent Data Acquisition (i-DAQ) unit is the main hardware of DDEMS. Fig. 2 illustrates the simplified block diagram of the i-DAQ unit which consists of power sensors (SCT-013 and ZMPT101B), signal conditioning circuit, an ESP32 microcontroller with built-in Wi-Fi shield, and PZEM-004T power module to acquire and streamline electrical data for uploading to the cloud platform for data storage, monitoring, and computation. The acquired data includes Voltage (V), Current (A), Real Power (W), Reactive Power (Q), Energy (kWh), Power Factor (%), Frequency (Hz), current harmonics, and Total Harmonic Distortion factor (THD).

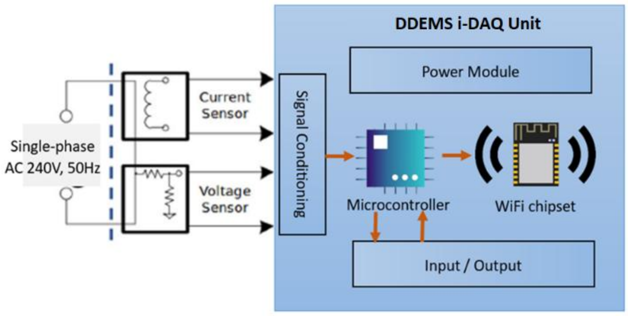


Fig. 2 Simplified block diagram of i-DAQ unit of the DDEMS.

For the acquisition of power parameters from the local grid, the system utilizes the PZEM-004T power module, which provides ±0.5% accuracy for voltage (80-260V range), current (0-100A), and power measurements (0-23kW) [22]. It has built-in RS485 with Modbus communication protocol to communicate with external devices for data exchange purposes. To provide an interface between the PZEM-004T (RS485) and the ESP32, an RS485-to-TTL converter module is essential. This module is based on a MAX485 chip to translate the electrical signaling standards. The connection diagram of the interfacing module is shown in Fig. 3 [23].

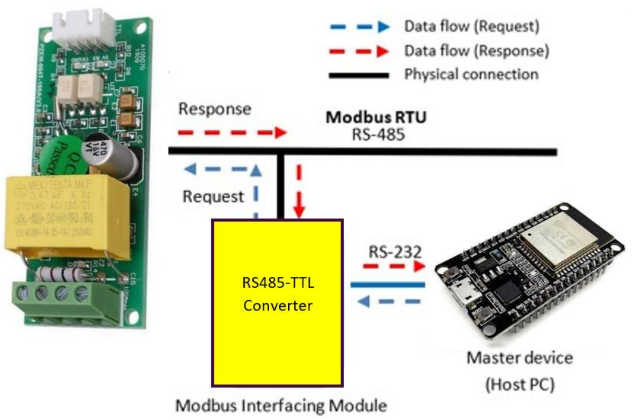


Fig. 3 Interfacing module for Modbus RS485 Communication Protocol.

2.3 Acquisition of current harmonics

The widespread use of non-linear loads (NLLs) such as switched-mode power supplies (SMPS), power converters and inverters, induction ovens and battery chargers, has degraded the power quality of low voltage (LV) distribution grid networks. These NLLs generate harmonics that distort the sinusoidal waveforms of supply voltage and current [24], [25], while these harmonics can be analyzed by using Fourier Series (FS) and its Fast Fourier Transform (FFT) algorithm. Any periodic signal function *f(t)* can be represented as a sum of a DC term, along with the amplitudes and frequencies of its sinusoidal components (harmonics), as shown in Equation (1):

$$f(t) = \frac{a_0}{2} + \sum_{n=1}^{\infty} a_n cos\, n\omega_0 t + b_n sin\, n\omega_0 t \qquad (1)$$

where:

- *f(t)* is the instantaneous value of the periodic signal at time t
- $a_0/2$ is the average value or the DC component of the signal,
- *n* is the harmonic order (a positive integer: 1, 2, 3,…)
- a_n *and* b_n are the Fourier coefficients representing the amplitudes of the cosine and sine components of the n-th harmonic, respectively,
- ω_0 is the fundamental angular frequency, defined as $\omega_0 = 2\pi f_o$, f_o is the fundamental power system frequency [26].

Due to the half-wave symmetrical nature of sinusoidal wave distortion around the average center line of the waveform, odd harmonics (3rd, 5th, 7th, etc.) tend to be dominant in the distortion waveform, while even harmonics are typically minimal [27]. In many scenarios, higher-order harmonics are indeed smaller in magnitude and can be considered negligible compared to lower-order harmonics [28]. This is particularly true when dealing with systems involving non-linear loads like power electronics whereby as the harmonic order increases (i.e., the frequency increases), the amplitude of the harmonic components generally decreases [28].

The total harmonic distortion factor (THD) is a key metric quantifying the distortion present in the signal. It is defined as the ratio of the root-sun-square of all harmonic components to the fundamental frequency component [29], as expressed in Equation (2).

$$THD = \frac{\sqrt{\sum_{h=2}^{n} (I_h)^2}}{I_1} \times 100\% \qquad (2)$$

where:

- *THD* is the Total Harmonic Distortion factor (expressed as a percentage),
- I_1 is the RMS value of the fundamental frequency component (e.g., 50 Hz current),
- I_h is the RMS value of the *h*-th harmonic component,
- h is the harmonic order (an integer starting from 2 for the 2nd harmonic),
- n is the highest harmonic order considered in the calculation.

Current harmonics refer to distortions in the current electrical waveform caused by non-linear loads, which can affect the performance of electrical systems [30]. Current harmonic acquisition is performed using the SCT-013 non-invasive current sensor coupled with a custom signal conditioning circuit that includes a 22Ω burden resistor and analog-to-digital converter to measure current harmonics of the power quality. Fig. 4 illustrates acquisition circuit of current signal for harmonics from SCT-013 current sensor. The sensor's output is a small current proportional to the measured current, which is then converted into a voltage using a burden resistor. The embedded firmware in ESP32 MCU implements a real-time processing pipeline featuring separate tasks for data acquisition, FFT computation, and communication. The harmonic analysis algorithm employs a windowed FFT with a sampling rate of 2.0kHz, optimized to minimize memory usage while capturing harmonics up to the 13th order and its THD.

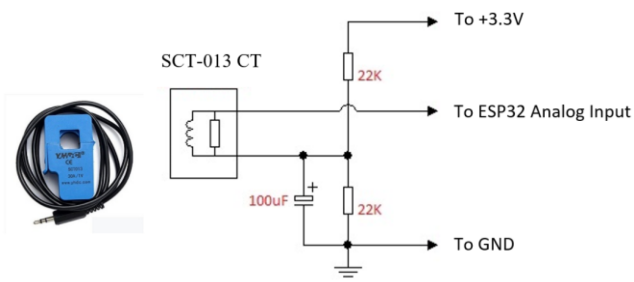


Fig. 4 Signal conditioning circuit for current harmonic acquisition from SCT-013 non-invasive current sensor.

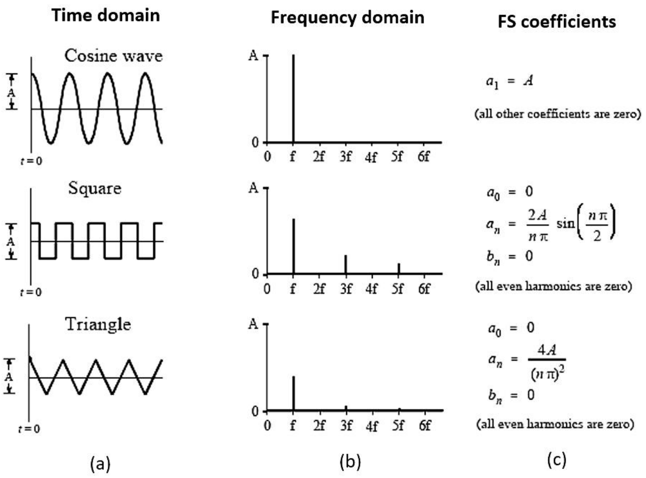


Fig. 5 Fourier series of various types of signals in (a) time-domain, (b) frequency-domain, (c) FS coefficients.

Through the application of the Fourier Series and its FFT algorithm, time-domain signals such as cosine waves, square waves, and triangle waves can be effectively represented in the frequency domain for harmonics acquisition [31]. The FS coefficients obtained from the Fourier analysis provide insights into the amplitudes of frequency components including fundamental frequency and harmonics, which can be visually depicted in Fig. 5.

Among three signal waveforms, the cosine wave is a simple waveform comprising a single sinusoid frequency, i.e., fundamental frequency f [32]. Conversely, the square and triangle waves are classified as complex waveforms, consisting of multiple sinusoids that include the fundamental frequency and its odd harmonics. Both square and triangle waves exhibit positive and negative cycles, displaying half-wave symmetry with respect to the zero axis. Consequently, these waveforms exclusively possess odd harmonics according to Fourier theorems, while the magnitudes of even harmonics are minimal and can be neglected [32].

As per the Fourier theorems, the square wave exhibits harmonic magnitudes expressed as a percentage relative to the fundamental frequency and follows the order of $1/n$, where n represents the harmonic order. This results in harmonics magnitudes (in %) for 1^{st}, 3^{rd} and 5^{th} orders are 100%, 33.3%, and 20.0%, respectively. In contrast, the magnitudes of harmonics in the triangle wave are characterized by an order of 1/n^2, leading to percentages of 100%, 11.1%, and 4.0% for the first three orders of odd harmonics [33].

2.4 Web-based DDEMS Portal

Data analytics and Power Quality Monitoring of DDEMS are implemented by using a web-based DDEMS Portal for various functions such as data storage, information retrieval, remote monitoring of power parameters, data trending and visualization. The front-end portal is developed using HTML, CSS, JavaScript (with Chart.js for graphing), and PHP. It provides a dynamic and user-friendly interface for visualizing the data stored in the MySQL database server. Key features include:

(a) Real-Time Gauges: Displaying live electrical values of V, I, P, Q, F, PF, THD and harmonics.
(b) Time-Series Charts: Interactive graphs allow users to zoom and pan through historical data for any electrical parameter.
(c) Data Analytics: Dashboards for daily, weekly, and monthly energy consumption, including benchmarking tools to compare against previous periods.

Fig. 6 The Web-based DDEMS Portal showing real-time monitoring dashboard.

(d) PQ Advisor Dashboard: A dedicated panel providing an at-a-glance view of the current status of each key PQ parameter, color-coded by severity level (e.g., Green for Level 0, Yellow for Level 1, Orange for Level 2, Red for Level 3).

The portal integrates APIs that facilitates communication between DDEMS i-DAQ unit, backend servers, and third-party cloud servers. The web-based DDEMS Portal provides graphical user interface (GUI) which can be accessed via uniform resource locator (URL) address using a web browser or mobile handphone. The snapshot of GUI of the Web-based DDEMS Portal is depicted in Fig. 6.

2.5 Rule-based PQ Advisor

On the other hand, the Power Quality (PQ) Advisor is a classification system that involves identifying and categorizing disturbances in electrical signals that can affect the performance and safety of power supply systems. Table 1 shows the general PQ severity levels and its impact. The PQ Advisor adopts a rule-based engine that evaluates measurements against IEEE 1159 and IEC 61000-4-30 thresholds for both immediate detection power quality events and providing mitigations to remedy issues.

This approach was selected for its computational efficiency, transparency, and direct alignment with regulatory frameworks. The rule sets are pre-programmed in PHP scripts residing on the cloud server and are executed on every data packet received from the i-DAQ unit. The system evaluates four critical power quality parameters: supply voltage, system frequency, total harmonic distortion for current (THDi) [34], and power factor (PF). For each parameter, measurements are categorized into one of four severity levels (Level 0 to Level 3), which describe the operational condition and potential impact on the electrical system, as outlined in Table 1.

Table 1 PQ Severity Levels and its Impacts.

Level	Severity	Impact
Level 0	No disturbance	Nominal / optimum operation; no mitigation required
Level 1	Minor disturbance	In monitoring stage. May affect sensitive equipment
Level 2	Moderate disturbance	Require corrective action(s). Likely to trip or damage devices
Level 3	Major disturbance	Need to take action immediately. Trip or damage devices

Table 2 The proposed rule-based PQ classification with its severity level, parameter ranges, technical description and impacts.

PQ Parameter	Class/Label	Classification Level	Typical Range	Description	Impact
Supply Voltage [35]	Normal Supply	Level 0: Normal	207 – 253 V (within ±10%)	Continuous	Overall, in perfect condition. No action required
	Undervoltage / Overvoltage	Level 1: Minor Deviation	195 – 206 V or 254 – 264 V	Sustained (>1 min)	May affect sensitive electronics, slight efficiency loss
	Transient Events	Level 2: Voltage Sag/Swells	70 – 194 V (sag) or 265 – 300 V (swell)	10 ms – 1 min Sag (Dip) (10–90% of nominal) Swell (>110% of nominal)	Flickering, device malfunction, tripping risks
	Deep Sag / Surge / Interruption	Level 3: Severe Deviation	< 70 V or > 300 V	Instantaneous to several seconds Voltage drops to < 10% of nominal	Equipment damage, system shutdown, safety concerns
System Frequency	Normal Frequency Nominal 50Hz (in Malaysia)	Level 0: Normal	49.5 – 50.5 Hz (within ±0.5 Hz)	Within acceptable variation	Overall, in perfect condition. No action required
		Level 1: Minor Deviation	49.0 – 49.49 Hz or 50.51 – 51.0 Hz (i.e., ±0.5 – ±1.0 Hz)	Slight imbalance, possibly transient)	Monitor; sensitive devices may trip
		Level 2: Significant Deviation	48.0 – 48.99 Hz or 51.01 – 52.0 Hz (i.e., ±1.0 – ±2.0 Hz)	Potential frequency stability concern	Appliance malfunction, protection activation
		Level 3: Severe Deviation	< 48.0 Hz or > 52.0 Hz (> ±2.0 Hz)	Grid instability or fault condition	Serious equipment damage risk
Harmonics (THDi) [27]	Low Harmonics	Level 0: Acceptable	THDi < 5%	THD < 5% (IEEE Std 519 limit)	Overall, in perfect condition. No action required
	Moderate Harmonics	Level 1: Moderate distortion	5% ≤ THDi < 8%	Waveform close to pure sine wave	Monitor; may cause minor heating effects
	High Harmonics	Level 2: Poor distortion	8% ≤ THDi < 15%	Acceptable distortion for residential settings	Affects efficiency, higher loss
	Severe Harmonics	Level3: Severe distortion	THDi ≥ 15%	High distortion from multiple non-linear loads	Overheating, malfunction, tripping risks
Power Factor (PF) [34]	Good PF	Level 0 PF >0.95	PF ≥ 95%	Efficient power usage, Resistive or well-compensated loads	Overall, in perfect condition. No action required
	Moderate PF	Level 1: PF in 0.85–0.95	PF in 85%–95%	Acceptable but slightly inefficient, Mild inductive loads	Monitor periodically
	Poor PF	Level 2: PF in 0.70 – 0.84	70% ≤ PF < 84%	Significant reactive power, uncompensated inductive loads, CFLs, AC compressors	Energy waste and billing penalty possible, increased line losses, voltage drops, transformer stress
	Very Poor PF	Level 3: < 070	PF < 70%	Highly inefficient, mostly reactive or non-linear Heavy inductive/capacitive loads	Severe losses; correction required Increased line losses, voltage drops, transformer stress

It is important to acknowledge the inherent limitations of a rule-based system. Its performance is fundamentally constrained by the completeness and precision of the pre-defined rules. While highly effective for classifying well-defined, standard-based disturbances, it may exhibit rigidity when confronted with novel, complex, or overlapping PQ events that are not explicitly captured in the rule matrix. Furthermore, unlike adaptive machine learning models, it lacks the ability to learn from new data or identify subtle, complex patterns in the signal that may precede a fault or indicate a non-standard type of distortion. Table 2 shows the proposed rule-based PQ classification with its severity level, parameter ranges, technical description and impacts.

2.6 Cybersecurity Considerations

The IoT architecture of DDEMS, which transmits sensitive energy consumption and power quality data from the edge to the cloud, necessitates a robust cybersecurity framework to protect against unauthorized access, data breaches, and manipulation. This subsection outlines the potential vulnerabilities and the specific security mechanisms implemented to mitigate them.

A primary point of vulnerability identified in the system is the Network Layer, where data is transmitted from the ESP32-based i-DAQ unit to the cloud server using HTTP with JSON payloads. While HTTP is simple and widely supported, it is inherently unsecured, making communication susceptible to eavesdropping and data tampering if left unprotected. An attacker on the same local network could potentially intercept data packets to infer user behavior or inject malicious data to disrupt monitoring and analytics.

To address these vulnerabilities, the following security measures have been implemented:

(a) Data-in-Transit Encryption: All HTTP communication between the i-DAQ unit and the cloud server is secured using Transport Layer Security (TLS) 1.2 protocol. The ESP32 firmware is configured to establish a secure HTTPS connection, ensuring that all JSON payloads containing electrical measurements are encrypted end-to-end. This prevents eavesdropping and guarantees data integrity during transmission.

(b) Authentication and Access Control: To prevent unauthorized devices from posting data to the cloud server, a token-based authentication mechanism is employed. Each i-DAQ unit is pre-provisioned with a unique access token (a long, random string). This token must be included in the header of every HTTP POST request. The cloud server's PHP API validates this token before accepting any data for processing and storage. This effectively protects against spoofing and unauthorized data injection.

3. Results and Discussion

The performance and validity of the DDEMS were assessed through a rigorous three-stage evaluation strategy. The validation of FFT algorithm is conducted to verify its accuracy of harmonic acquisition against theoretical data derived from Fourier theorems. Experimental laboratory testing used DDEMS i-DAQ unit to conduct cross measurements verification of electrical data against calibrated Lovato DMG800 power multimeter and Fluke 437-II as reference [36]. Field evaluation involved 90-days of continuous operation across the selected residential buildings with diverse load profiles. It confirms the system's reliability, with real-time alerts and a web-based dashboard facilitating energy optimization and power quality monitoring.

3.1 Validation of FFT algorithm

To validate the accuracy of harmonics acquisition using the FFT algorithm, the computed harmonics readings (i.e., the order of harmonics and magnitudes) are compared against theoretical data derived from Fourier theorems. An experimental setup is configured, comprising a laboratory-based signal generator, a monitoring PC, and DDEMS's i-DAQ unit which incorporates a built-in fog computing device (i.e., ESP32 microcontroller). The FFT algorithm computation is then executed with the experiment set up to compute the harmonic contents of the test signal generated by the signal generator, as illustrated in Fig. 7.

This comparative analysis serves to assess the accuracy and reliability of the acquired harmonic data from FFT algorithm computation against theoretical expectations. Three test signals are used in this experiment, namely cosine wave, square wave and triangle. The amplitudes of theoretical (from Fourier Series) are tabulated and compared to the computed ones for different harmonics, in Table 3. It is for the purpose of accuracy validation of harmonics acquisition by the DDEMS system.

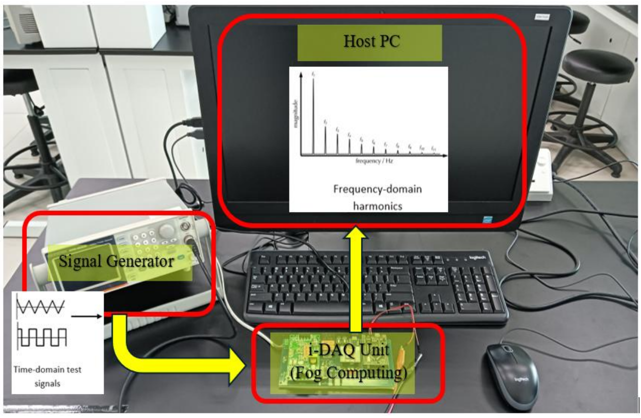


Fig. 7 Experiment set up to verify the accuracy of harmonics acquisition based on FFT computation.

The table presents the theoretical and practical harmonic values for sine, square, and triangle waves, along with the respective errors. For the sine wave, the fundamental harmonic (f_1) theoretically has 100% amplitude, while all higher-order harmonics (f_3, f_5, f_7, f_9) are expected to be 0%. However, practical results show minor deviations at higher harmonics, with small percentages such as 0.69% for f_3 and 0.45% for f_5. These slight discrepancies could be attributed to noise or imperfections in the signal acquisition process, resulting in negligible errors.

For the square wave, the theoretical values show the presence of odd harmonics (f_3, f_5, f_7, f_9) with specific percentages (e.g., 33.33% for f_3 and 20.00% for f_5). The practical results closely match the theoretical values with minimal errors, such as 0.17% for f_3 and 0.18% for f_5, indicating accurate harmonic acquisition. Similarly for the triangle wave, the theoretical harmonic amplitudes decrease significantly for higher-order odd harmonics, such as 11.11% for f_3 and 4.00% for f_5. Practical results align well with theoretical values but exhibit slight errors, such as 0.39% at f_3 and 0.18% at f_5, which may be due to system limitations or minor inaccuracies during signal processing.

Overall, the results demonstrate that the harmonic acquisition process is highly reliable, with errors remaining minimal across all waveforms. Minor deviations observed in practical results could be attributed to hardware imperfections, or signal processing limitations.

3.2 Cross-Verification of Acquired Electrical Data with Multiple Reference Instruments

To thoroughly validate the measurement accuracy of the DDEMS i-DAQ unit and address the need for cross-verification, we conducted a comparative analysis against two calibrated reference instruments: the Lovato DMG800 power multimeter and a Fluke 437-II Power Quality and Energy Analyzer. Lovato DMG800 power multimeter is a high-precision instrument widely recognized in industry, which is highly comparable in measurement accuracy to the Fluke 437-II for advanced power quality analysis. Fig. 8 illustrates the measurement setup of Lovato DMG800 power multimeter.

Table 3 Validation result of harmonics acquisition by DDEMS's i-DAQ unit.

Harmonics	cosine wave			Square wave			Triangle wave		
	Theory (in %)	Practical (in %)	Error (in %)	Theory (in %)	Practical (in %)	Error (in %)	Theory (in %)	Practical (in %)	Error (in %)
f_1	100.0	100.00	0	100.00	100.00	0	100.00	100.00	0
f_3	0.0	0.69	0.69	33.33	33.16	0.17	11.11	11.50	0.39
f_5	0.0	0.45	0.45	20.00	19.82	0.18	4.00	4.18	0.18
f_7	0.0	0.40	0.40	14.28	14.07	0.21	2.04	1.86	0.18
f_9	0.0	0.16	0.16	11.11	10.99	0.12	1.23	1.11	0.12

Table 4 Measurement results of selected electrical appliances with DMG800 and DDEMS.

Feature	Resistive Load			Inductive Load					
	LED Light Bulb 70W			Fluorescent Light 45W			Compact Fluorescent Light (CFL) 24W		
	DMG800 / Fluke 437-II (Avg.)	DDEMS	Error (%)	DMG800 / Fluke 437-II (Avg.)	DDEMS	Error (%)	DMG800 / Fluke 437-II (Avg.)	DDEMS	Error (%)
Vrms (V)	245.55	244.7	-0.35	245.22	245.1	-0.05	245.75	245.3	-0.18
Irms (A)	0.283	0.28	-1.06	0.311	0.32	2.89	0.17	0.18	5.88
P (W)	68.45	68.8	0.51	44.5	44.4	-0.22	26.95	25.2	-6.49
PF (%)	98.8	99	0.20	60.2	60	-0.33	62.6	62	-0.96
F (Hz)	50	49.9	-0.20	50.03	50	-0.06	50.02	50	-0.04
THD (%)	3.81	3.87	1.57	10.46	10.4	-0.57	80.9	81.5	0.74

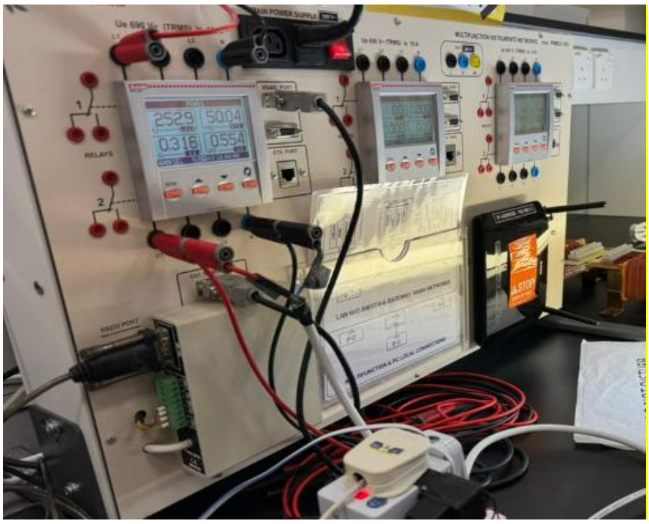


Fig. 8 Measurement setup showing DDEMS validation against Lovato DMG800 power multimeter.

The metric used for the evaluation is the Mean Absolute Percentage Error (MAPE), calculated as per Equation (3).

$$MAPE = \left(\frac{1}{N}\sum\frac{\bar{Y} - Y_{ref}}{Y_{ref}}\right) \times 100\% \qquad (3)$$

where

- N is the total number of observations or data points,
- $\bar{Y}$ is the value measured by the DDEMS system,
- Y_{ref} is the reference value measured by the calibrated Lovato DMG800 and Fluke 437-II.

MAPE is a simple metric and dimensionless index in which a lower MAPE indicates better performance of measurement. A MAPE of 10% means that the average deviation between the predicted value and the actual values was 10%, regardless of whether the deviation was positive or negative. However, it is suggested that the performance is acceptable if MAPE is between 10-20% [37].

Three electrical appliances with different load characteristics, i.e., an LED light (70W, largely resistive), a Fluorescent Light (45W, inductive with ballast), and a Compact Fluorescent Light (CFL, 24W, non-linear), were selected for this test. The results, comparing DDEMS measurements to both reference devices, are presented in Table 4. For this validation, N=10 samples were collected for each parameter under steady-state conditions to ensure a statistically significant comparison. The overall system MAPE of 1.24% represents the average of the individual MAPE values calculated for voltage, current, power, and power factor across all three test appliances.

Table 5. Analysis of whole-house energy consumption (kWh).

Day	Utility Meter Reading (kWh)	DDEMS Reading (kWh)	Absolute Error (kWh)	Relative Error (%)
1	1250.5	1251.2	0.7	0.06
7	1388.7	1389.9	1.2	0.09
14	1520.1	1521.8	1.7	0.11
21	1655.3	1657.1	1.8	0.11
30	1790.6	1792.5	1.9	0.11

The results demonstrate a strong correlation between the DDEMS and both reference instruments. The measurements for voltage, power, power factor, frequency, and THDi show minimal deviations. High errors were observed for the low-power CFL load in current measurement (+5.88%) and active power (P) measurement (-6.49%), which can be attributed to the highly distorted current waveform and the resolution limit of the PZEM-004T module when measuring very low power levels. The overall MAPE for the three appliances was 0.65%, 0.69% and 2.38%, respectively, resulting in a grand mean MAPE of 1.24%. This cross-verification confirms that the DDEMS provides highly accurate and reliable measurements comparable to established, high-cost industry instruments.

To validate the system's performance in its primary application of whole-house monitoring, a separate comparative analysis was conducted during the field deployment. The cumulative active energy (kWh) recorded by the DDEMS system was compared against the readings from the terraced house's utility-grade energy meter. The comparison was performed over 30 consecutive days, with readings taken from both meters at the same time each day. The results of this analysis are presented in Table 5.

As shown in Table 5, the DDEMS system demonstrated excellent agreement with the utility meter over the one-month period. The relative error in cumulative energy consumption remained consistently around 0.1%, which is well within an acceptable range for energy monitoring applications and confirms the high accuracy of the PZEM-004T module at typical household load levels. This real-world validation confirms that while the DDEMS may have reduced precision for very low-power, individual appliances, it performs with high accuracy for its intended purpose of monitoring aggregate household energy consumption.

Table 6 provides a comparative analysis of the proposed DDEMS against established commercial power quality analyzers and recent academic cloud-based prototypes across six key metrics. The primary differentiator for DDEMS is its exceptional cost-effectiveness, with a unit cost of approximately $120 that is much lower than commercial alternatives. This is achieved while maintaining highly competitive performance, evidenced by an accuracy (MAPE) of 1.24%, which is close to the industry standard.

Table 6 Comparison of DDEMS to Commercial Power Quality Analyzers and recent academic prototypes.

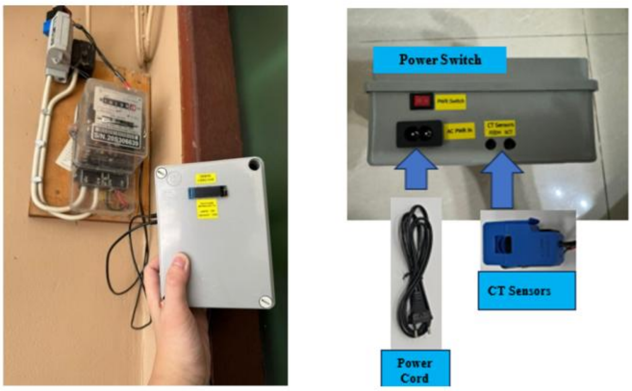
Feature / Metric	Proposed DDEMS	Commercial PQ Analyzers (Fluke 437-II, Hioki PW3390)	Recent Academic Prototypes (Cloud-based)
1. Cost per Unit	~$120	$5,000 – $10,000	Varies, but typically low (component cost)
2. Deployment Model	Distributed, Scalable Networks	Standalone, Single-point measurement	Often centralized or cloud-dependent
3. Accuracy (MAPE)	1.24% (Highly Comparable)	< 1.0% (Industry Standard)	Varies; often comparable to DDEMS
4. Key Architectural Advantage	Fog-Layer (Edge) Processing	On-device processing	Cloud-based processing
5. Real-Time Processing Latency	< 100 ms (Edge-based FFT)	< 100 ms (On-device)	> 2 seconds (Due to cloud communication latency)
6. PQ Event Detection Latency	~95% reduction vs. cloud-only	Minimal (On-device)	High (Baseline for comparison)

Architecturally, DDEMS employs a distributed and scalable network model, contrasting with the standalone, single-point deployment of commercial meters and the centralized nature of many academic prototypes. Its key innovation lies in its Fog-Layer (Edge) processing, which enables significant performance advantages. This edge-based architecture facilitates real-time processing latencies of under 100ms and vastly outperforms the counterparts. Consequently, DDEMS achieves a dramatic ~95% reduction in PQ event detection latency compared to cloud-only systems. In summary, the table positions the DDEMS as a unique solution that combines the low cost of academic prototypes with the high performance of commercial systems, enabled by its strategic use of edge computing.

3.3 Field evaluation of DDEMS

The practical deployment and long-term reliability of the DDEMS system were evaluated through a 90-day field trial in the selected residential buildings with diverse load profiles. One of the selected sites was a 2-storey terraced house with 2,000 square feet area located in Sibu town of Sarawak, Malaysia. The DDEMS i-DAQ unit is connected to a SCT-013 non-invasive current sensor clamped around the live conductor of the incoming mains of power supply. This placement enables DDEMS to capture and monitor the electrical power parameters of the terraced house. The unit was powered independently and connected to the home's Wi-Fi network. Fig. 9 shows (a) the deployment of the DDEMS and (b) the prototype of DDEMS i-DAQ unit with CT sensors.

Data Analytics with Benchmarking function is a core component of the DDEMS Portal. It provides real-time insights into critical electrical parameters and overall energy consumption within a user-friendly and visually intuitive interface. It also assesses the long-term reliability and stability of the system outside a controlled laboratory environment.



(a) (b)

Fig. 9 Field deployment of DDEMS: (a) snapshot of installation at the residential mains, (b) prototype of DDEMS i-DAQ unit with current transformer sensor

Fig. 10 depicts the DDEMS portal which features several key navigation tabs, including (a) Time-series Charts for visualizing energy usage trends and identifying anomalies, (b) daily consumption trend in kW unit, which is averaged from previous week data, and (c) benchmarking of daily consumption (versus previous week data) for comparing current performance with historical data. These tools collectively enable users to perform effective energy analysis, track efficiency, and support decision-making for energy optimization and fault detection.

Over the 90-day period, the system demonstrated remarkable robustness:

(a) Uptime: The i-DAQ unit maintained a consistent Wi-Fi connection, successfully transmitting data packets at the configured interval (every 15 seconds) with a measured uptime of 99.4%.

(b) Data Integrity: The cloud database successfully received and stored over 1.5 million individual data points without corruption. The structured JSON payload and HTTP POST protocol proved to be a reliable method for continuous data transmission. Throughout the 90-day deployment, no security incidents or unauthorized access attempts were detected, validating the effectiveness of the implemented cybersecurity measures.

(c) Hardware Stability: No hardware failures occurred. The ESP32 microcontroller and all sensors operated within expected temperature ranges and showed no signs of performance degradation, validating the design choices for component selection and power supply regulation.

This proven reliability is a critical factor for user trust and adoption, demonstrating that the DDEMS is not merely a prototype but a viable product for sustained operation.

On the other hand, the field deployment also acquired a rich dataset of real-world power quality. The power quality (PQ) Advisor engine is used to process this continuous stream of data, and its dashboard provides a real-time evaluation of power quality conditions including supply voltage, power factor, system frequency and total harmonic distortion factor (THD), as depicted in Fig. 11 (a)-(d). The results have identified Level 0 (Normal) or good conditions for supply voltage, power factor and system frequency. However, it has identified Level 3: Severe Harmonics, indicating significant distortion that can lead to equipment overheating, malfunction, or tripping, as depicted in Fig. 9 (d). The PQ levels range from Level 0 (Good) to Level 3 (Critical), with higher levels indicating more severe harmonic distortion. Visual indicators and alert icons help users quickly assess system health and take appropriate action to maintain power quality and reliability.

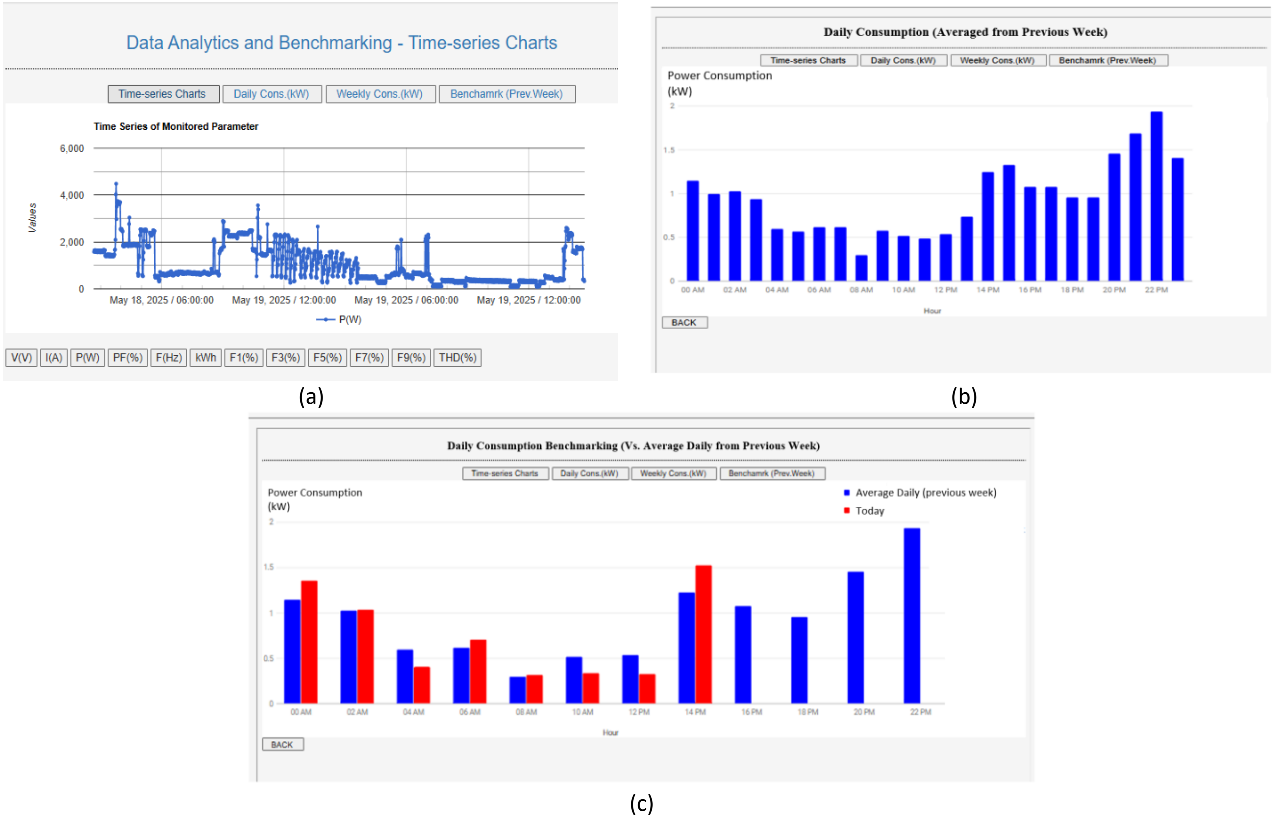


Fig. 10 Data Analytics and Benchmarking of DDEMS Portal (a) Real-time time-series charts, (b) Daily consumption in kW (averaged from previous week data) and Consumption Pattern, (c) Benchmarking of daily consumption (versus previous week data).

Fig. 11 Snapshots of Power Quality (PQ) Advisor for (a) supply voltage, (b) power factor, (c) frequency, and (d) total harmonic distortion factor (THD).

The results over the monitoring period were revealing:

(a) Supply Voltage (Fig. 9(a)): The supply voltage was exceptionally stable, consistently measured between 238V and 245V, well within the Level 0 (Normal) range defined by the standard (207V - 253V for a 230V system). No voltage sags, swells, or interruptions were detected, indicating a robust local grid infrastructure at the site location.

(b) Power Factor (Fig. 9(b)): The overall household power factor typically varied between 0.85 and 0.98, often residing in Level 0 (Good) or Level 1 (Moderate). The dips into the moderate range were correlated with the operation of inductive loads like refrigerator and air conditioner compressors without power factor correction. This suggests a potential opportunity for economic savings through targeted power factor correction, which could reduce reactive power charges if levied by the utility.

(c) System Frequency (Fig.9(c)): The grid frequency was remarkably stable, fluctuating between 49.95 Hz and 50.05 Hz, consistently classified as Level 0 (Normal). This is a testament to the excellent regulation by the regional grid operator.

(d) Total Harmonic Distortion factor for current (THDi) (Fig. 9(d)): This was the most significant finding. The THDi was consistently measured above 15%, often reaching 20-25%, triggering a persistent Level 3: Severe Distortion alert. This high level of distortion is indicative of a high penetration of non-linear loads within the household. Modern electronics like LED TVs, computer power supplies, smartphone chargers, and the CFLs and LED lights themselves are the primary culprits.

4. Conclusion

The complete design, development and validation of the Data-Driven Energy Monitoring System (DDEMS) presented in this study to address critical challenges in power consumption monitoring and power quality (PQ) assessment. By integrating low-cost sensors, ESP32 microcontroller for edge computing, and a rule-based engine of PQ Advisor, DDEMS offers a cost-effective, scalable, and accurate solution for real-time energy management and PQ detection. Key achievements of this work include:

(a) High accuracy and reliability: Experimental validation of DDEMS against the calibrated Lovato DMG800 power multimeter demonstrated exceptional measurement accuracy, with a Mean Absolute Percentage Error (MAPE) of 1.24% for key electrical parameters such as voltage, current, power, power factor and harmonic distortion. This confirms the system's capability to perform comparably with high-cost specialized industry-standard instruments.

(b) Comprehensive PQ monitoring: DDEMS successfully classified PQ disturbances into severity levels (Level 0 to Level 3) based on industrial IEEE 1159 and IEC 61000-4-30 standards, enabling timely detection of issues such as voltage fluctuations, harmonic distortions, and poor power factors. The rule-based PQ Advisor provided actionable insights, enhancing system reliability and safety.

(c) Real-world deployment: The system was rigorously tested in residential settings over 90 days, proving its robustness in diverse load conditions. The web-based portal facilitated real-time data visualization, anomaly detection, and benchmarking, empowering users to optimize energy usage and reduce costs.

(d) Future potential: The modular architecture of DDEMS allows for further enhancements, such as integrating machine learning for predictive analytics or expanding its application to industrial and commercial environments.

In conclusion, DDEMS represents a significant advancement in smart energy monitoring, combining affordability, accuracy, and real-time analytics to address global energy challenges. Its successful deployment underscores its potential to contribute to sustainable energy management and improved power quality in modern electrical systems.

4.1 Limitations and Future Work

While the 90-day residential deployment validated the DDEMS's core accuracy and reliability, this study has limitations that outline a clear path for future work. A primary constraint is the single-site evaluation in a stable grid environment, which does not represent the diverse power quality (PQ) issues found in industrial settings, weak rural grids, or networks with high renewable penetration. Furthermore, the system’s current design for single-phase systems limits its application in three-phase commercial and industrial settings.

A key limitation is the lack of impact quantification. While the system identified issues like high harmonic distortion, it did not quantify the resulting energy losses or the environmental footprint of the hardware itself. Finally, interoperability with broader building and grid management systems remains an open challenge. To address these limitations, a structured future roadmap is proposed:

1. System Expansion: The hardware and software will be extended to support three-phase measurements and critical metrics like phase imbalance.
2. Broader Validation: A multi-phase deployment plan includes geographical expansion into industrial, urban, and weak grid areas, alongside collaborations with utilities to monitor feeders with high solar PV penetration.
3. Value and Impact Quantification: An integrated Energy Saving Quantification (ESQ) module will be developed to calculate avoidable losses from PQ issues, providing users with direct savings estimates. A comprehensive Life Cycle Assessment (LCA) will also be conducted to evaluate the system's environmental footprint.
4. Enhanced Interoperability and Intelligence**:** Future versions will integrate standardized communication protocols such as Modbus and BACnet for seamless data exchange. Machine learning for predictive maintenance and load forecasting remains a key long-term goal to evolve the DDEMS into a universally robust and value-driven energy management solution.
5. Accelerated Life Testing for Drift Characterization: A key future study will involve subjecting multiple DDEMS units to accelerated life testing. This will allow us to empirically model long-term measurement drift and identify the dominant aging mechanisms of critical components, such as the current transformer core and voltage sensor.

This structured approach to broader validation demonstrates our commitment to evolving the DDEMS from a proven prototype into a universally robust and adaptable solution for smart energy management across the diverse landscape of global electrical grids.

Acknowledgements

This work is fully funded by the UTS Research Grant (Project ID: UTS/RESEARCH/<3/2023/07>(01)) of the University of Technology Sarawak. The authors would like to thank the Centre of Research and Development (CRD) of UTS for its support. Special thanks to Sarawak Energy Berhad (SEB) for the sponsorship of the Idea Powering Programme in this project.

References

[1] Vedanarayanan, V., Vibhakar, C., Sujaatha, A., Chavda, J. K., Karthik, M., Pramila, P. V. and Raghavan, I. K., Utilization of sustainable resources for promoting energy efficiency in environment using smart technologies. *International Journal of Photoenergy.* (2022) 6711300, doi: https://doi.org/10.1155/2022/6711300.

[2] Pandiyan, P., Saravanan, S., Usha, K., Kannadasan, R., Alsharif, M. H. and Kim, M. K. Technological advancements toward smart energy management in smart cities. *Energy Reports*. 10 (2023) 648–677, doi: https://doi.org/10.1016/j.egyr.2023.07.021.

[3] International Energy Agency. *World energy outlook 2023,* OECD Publishing, 2023, doi: https://doi.org/10.1787/827374a6-en.

[4] Islam, S., Muyeen, S. M., Iqbal, A., Bakhsh, F. I. and Ben-Brahim, L., Effect of battery storage based electric vehicle chargers on harmonic profile of power system network, current scenario and future scope. *Journal of Energy Storage*. 131 (2025) 117563, doi: https://doi.org/10.1016/j.est.2025.117563.

[5] Beleiu, H. G., Beleiu, I. N., Pavel, S. G. and Darab, C. P., Management of power quality issues from an economic point of view. *Sustainability*. 10 (2018) 2326, doi: https://doi.org/10.3390/su10072326.

[6] Khan, A. A., Faheem, M., Bashir, R. N., Wechtaisong, C. and Abbas, M. Z., Internet of things (IoT) assisted context aware fertilizer recommendation. *IEEE Access*. 10 (2022) 129505–129519, doi: https://doi.org/10.1109/ACCESS.2022.3228160.

[7] Khan, A. A., Nauman, M. A., Bashir, R. R., Jahangir, R., Alroobaea, R. and Binmahfoudh, A., Context aware evapotranspiration (ETs) for saline soils reclamation. *IEEE Access*. 10 (2022) 110050–110063, doi: https://doi.org/10.1109/ACCESS.2022.3206009.

[8] Bashir, R. N., Khan, F. A., Khan, A. A., Tausif, M., Abbas, M. Z., Shahid, M. M. A. and Khan, N., Intelligent optimization of reference evapotranspiration (ETo) for precision irrigation. *Journal of Computational Science*. 69 (2023) 102025, doi: https://doi.org/10.1016/j.jocs.2023.102025.

[9] HIOKI E.E. CORPORATION (Hioki). *Power quality analyzers, power loggers | FAQ,* <https://www.hioki.com/sg-en/support/faq/pqa#anc-5592> (n.d.).

[10] Alahakoon, D. and Yu, X., Smart electricity meter data intelligence for future energy systems: A survey. *IEEE Transactions on Industrial Informatics*. 12 (2016) 425–436, doi: https://doi.org/10.1109/TII.2015.2414355.

[11] Stjelja, D., Kuzmanovski, V., Kosonen, R. and Jokisalo, J., Building consumption anomaly detection: A comparative study of two probabilistic approaches. *Energy and Buildings*. 313 (2024) 114249, doi: https://doi.org/10.1016/j.enbuild.2024.114249.

[12] Rind, Y. M., Raza, M. H., Zubair, M., Mehmood, M. Q. and Massoud, Y., Smart energy meters for smart grids, an internet of things perspective. *Energies*. 16 (2023) 1974, doi: https://doi.org/10.3390/en16041974.

[13] Rafiq, H., Manandhar, P., Rodriguez-Ubinas, E., Ahmed Qureshi, O. and Palpanas, T., A review of current methods and challenges of advanced deep learning-based non-intrusive load monitoring (NILM) in residential context. *Energy and Buildings*. 305 (2024) 113890, doi: https://doi.org/10.1016/j.enbuild.2024.113890.

[14] Mozaffari, M., Doshi, K. and Yilmaz, Y., Real-time detection and classification of power quality disturbances. *Sensors*. 22 (2022) 7958, doi: https://doi.org/10.3390/s22207958.

[15] Kujur, A., Raza, Z., Khan, A. A. and Wechtaisong, C., Data complexity based evaluation of the model dependence of brain MRI images for classification of brain tumor and Alzheimer's disease. *IEEE Access*. 10 (2022) 112117–112133, doi: https://doi.org/10.1109/ACCESS.2022.3216393.

[16] Khan, A. A., Driss, M., Boulila, W., Sampedro, G. A., Abbas, S. and Wechtaisong, C., Privacy preserved and decentralized smartphone recommendation system. *IEEE Transactions on Consumer Electronics*. 70 (2024) 4617–4624, doi: https://doi.org/10.1109/TCE.2023.3323406.

[17] Van den Broeck, G., Stuyts, J. and Driesen, J., A critical review of power quality standards and definitions applied to DC microgrids. *Applied Energy*. 229 (2018) 281–288, doi: https://doi.org/10.1016/j.apenergy.2018.07.058.

[18] Yan, Y., Chen, K., Geng, H., Fan, W. and Zhou, X. A review on intelligent detection and classification of power quality disturbances: Trends, methodologies, and prospects. *CMES - Computer Modeling in Engineering and Sciences.* 137 (2023) 1345–1379, doi: https://doi.org/10.32604/cmes.2023.027252.

[19] Kee, K. K., Rashidi, R., Kee, O. K. H., Han, A. B., Patrick, I. Z. and Bawen, L. M., Context-aware self-powered intelligent soil monitoring system for precise agriculture. *International Journal of Electrical and Computer Engineering (IJECE)*. 15 (2025) 1123–1131, doi: https://doi.org/10.11591/ijece.v15i1.pp1123-1131.

[20] Sabireen, H. and Neelanarayanan, V. A review on fog computing: Architecture, fog with IoT, algorithms and research challenges. *ICT Express*. 7 (2021) 162–176, doi: https://doi.org/10.1016/j.icte.2021.05.004.

[21] Mudaliar, M. D. and Sivakumar, N., IoT based real time energy monitoring system using Raspberry Pi. *Internet of Things*. 12 (2020) 100292, doi: https://doi.org/10.1016/j.iot.2020.100292.

[22] Sushma, N., Suresh, H. N., Mohana, L. J. and Santhosh Kumar, K. B., Experimental investigation on wireless integrated smart system for energy and water resource management in Indian smart cities. *Results in Engineering*. 23 (2024) 102687, doi: https://doi.org/10.1016/j.rineng.2024.102687.

[23] Zheng, Y., Development of a ubiquitous industrial data acquisition system for rotogravure printing press. *Journal of Networks*. 6 (2011) 1543–1548, doi: https://doi.org/10.4304/jnw.6.11.1543-1548.

[24] Rustemli, S., Satici, M. A., Şahin, G. and van Sark, W., Investigation of harmonics analysis power system due to non-linear loads on the electrical energy quality results. *Energy Reports*. 10 (2023) 4704–4732, doi: https://doi.org/10.1016/j.egyr.2023.11.034.

[25] Eroğlu, H., Cuce, E., Mert Cuce, P., Gul, F. and Iskenderoğlu, A., Harmonic problems in renewable and sustainable energy systems: A comprehensive review. *Sustainable Energy Technologies and Assessments.* 48 (2021) 101566, doi: https://doi.org/10.1016/j.seta.2021.101566.

[26] Fischer-Cripps, A. C. *Newnes interfacing companion.* Newnes, 2002.

[27] Michalec, Ł., Jasiński, M., Sikorski, T., Leonowicz, Z., Jasiński, Ł. and Suresh, V., Impact of harmonic currents of nonlinear loads on power quality of a low voltage network–review and case study. *Energies*. 14 (2021) 3665, doi: https://doi.org/10.3390/en14123665.

[28] Nuñez-Ramírez, V., Guerrero-Rodríguez, N., Batista-Jorge, R. O., Mercado-Ravelo, R., Ramírez-Rivera, F. A., Ferreira, J. A. and Ramos-Ciprian, R. D., Harmonic distortion caused by non-linear household loads: Measurement and modelling. *Results in Engineering*. 25 (2025) 104483, doi: https://doi.org/10.1016/j.rineng.2025.104483.

[29] Qi, H. and Zhao, C., Research and implementation of harmonic detection and current compensation technology in active power filter in *Chinese Control Conference (CCC).* (2016), 10008–10012, doi: https://doi.org/10.1109/CHICC.2016.7554938.

[30] MyElectronicHome. *Arduino House current limit system (SCT-013-030)*, https://myelectronichome.altervista.org/blog/en/too-much-current-detector-absorbed-from-the-house-made-with-arduino-and-sct-013-020-or-013-030-sct/> (n.d.).

[31] Munson, D. C. *Reference Data for Engineers: Radio, Electronics, Computer, and Communications.* 9th edn., Newnes, 2002, doi: https://doi.org/10.1016/B978-075067291-7/50009-1.

[32] Grami, A. in *Introduction to digital communications: Fundamental aspects of digital communication,* Ch. 2, Academic Press, (2016) 11–39, doi: https://doi.org/10.1016/B978-0-12-407682-2.00002-8.

[33] Electronics Tutorials. *Harmonics and harmonic frequency in AC circuits,* <https://www.electronics-tutorials.ws/accircuits/harmonics.html> (n.d.).

[34] Thentral, T. M. T., Palanisamy, R., Usha, S., Bajaj, M., Zawbaa, H. M. and Kamel, S. Analysis of power quality issues of different types of household applications. *Energy Reports*. 8 (2022) 5370–5386, doi: https://doi.org/10.1016/j.egyr.2022.04.010.

[35] Joga, S. R. K., Naidu Surisetti, S. S. M., Karri, S., Jalaluddin, S., Madhu, K. and Shiva, J. Detection and classification of changes in voltage magnitude during various power quality disturbances. in *2023 4th International Conference for Emerging Technology (INCET).* (2023), 1-6, doi: https://doi.org/10.1109/INCET57972.2023.10170211.

[36] Lovato Electric. *DMG800 | Energy meters and power analyzers,* <https://catalogue.lovatoelectric.com/gl_en/DMG800/snp> (n.d.).

[37] Chang, Y. F., Lin, C. J., Chyan, J. M., Chen, I. M. and Chang, J. E., Multiple regression models for the lower heating value of municipal solid waste in Taiwan. *Journal of Environmental Management.* 85 (2007) 891–899, doi: https://doi.org/10.1016/j.jenvman.2006.10.025.