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A Data-Driven Energy Monitoring System with Machine Learning for Enhanced Power Quality and Appliance Recognition in Smart Grids

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ABSTRACT - The escalating global demand for electricity, coupled with the proliferation of non-linear loads, presents significant challenges to power quality (PQ), grid stability and energy efficiency. Conventional smart meters often lack the capability for granular, real-time PQ monitoring and advanced analytics. This paper presents the design, development, and validation of a novel Data-Driven Energy Monitoring System (DDEMS) that integrates Internet of Things (IoT) architecture with machine learning to address these limitations. The proposed system features a low-cost IoT data acquisition (i-DAQ) unit capable of measuring a comprehensive suite of electrical parameters, including voltage, current, power, energy, and crucially, harmonic distortion up to the 13th order. Acquired data is processed through a five-layer IoT architecture (Physical, Fog, Network, Cloud, Application) to a cloud platform. Five machine learning classifier models were constructed and compared for their performance including Decision Tree, Random Forest, Logistic Regression, Naïve Bayes and Neural Network, for non-intrusive load monitoring of appliance recognition. Furthermore, a rule-based PQ advisor engine is implemented to classify power quality events include voltage sags, swells, harmonic distortion according to severity levels based on standards like IEEE 1159 and IEC 61000. System validation against a calibrated power multimeter showed a high degree of accuracy, with mean absolute percentage errors for key parameters typically below 1%. For appliance recognition, the Random Forest model achieved 100% accuracy, precision, recall, and F1-score, outperforming other tested algorithms. Deployed in a real residential setting, the DDEMS provides a robust, scalable, and intelligent platform for real-time energy management, proactive PQ diagnostics, and support for smart grid applications like demand-side management (DSM), contributing to a more sustainable and reliable electrical infrastructure.

INTRODUCTION

The global energy sector is undergoing significant changes due to the escalating electricity demand, the push for decarbonization, and the growing adoption of distributed energy resources and widespread nonlinear loads. The world's heavy reliance on fossil fuels amounting to 62% of global energy use in 2022 [1]. This contributes to environmental degradation, while the ever-increasing demand, particularly in rapidly urbanizing nations like Malaysia. In 2024, worldwide electricity consumption hit 30,856 TWh, with residential and commercial users responsible for 42% of this demand [2]. Utility companies such as Sarawak Energy Berhad (SEB) face immense pressure to ensure efficient and reliable energy distribution [2].

A critical shortcoming in current electricity infrastructure is the limitation of conventional and even modern digital smart meters. While an improvement over analog predecessors, these meters are often

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insufficient for the evolving needs of smart grids and Industry 4.0. They frequently lack the ability to provide real-time, granular data on power quality (PQ) parameters include harmonics and total harmonic distortion (THD) factor, which is essential for comprehensive monitoring, advanced energy management, and electrical fault detection [3 - 6]. The proliferation of non-linear loads such as variable speed drives, LED lights and SMPS, exacerbates PQ issues and leading to waveform distortion, equipment overheating, reduced efficiency, and potential safety hazards [7].

The integration of Internet of Things (IoT) technologies offers a pathway to overcome these limitations. IoT-enabled smart meters can measure a vast array of parameters, enabling transparency for consumers and providing utilities with the data needed for grid optimization [6]. Furthermore, machine learning (ML) presents an opportunity to transform this data into actionable intelligence, from identifying individual appliances so-called non-intrusive load monitoring (NILM) to predicting faults and classifying PQ events [8 - 10].

This paper proposes a novel Data-Driven Energy Monitoring System (DDEMS) that synergizes IoT and ML to create a comprehensive solution for modern energy challenges. The main contributions of this work are:

1. The design and implementation of a low-cost, IoT-based data acquisition unit (i-DAQ) for high-resolution measurement of electrical parameters including harmonics.
2. The development and benchmarking of multiple ML classifier models for accurate appliance recognition.
3. The creation of a rule-based PQ advisory system for automatic classification and severity assessment of power quality issues.
4. The full integration and validation of the system in a real residential environment, demonstrating its efficacy for smart grid applications.

LITERATURE REVIEW

The shift towards intelligent energy systems has spurred significant research into smart metering. Early work focused on basic remote metering and automated billing using ubiquitous cellular networks like GSM. These meters perform periodic data transmission, eliminating manual reads but offering no real-time insight or analytical value [11]. The proliferation of the Internet of Things (IoT) catalyzed a revolution, enabled by low-cost, programmable microcontrollers (MCUs) like Arduino and the ESP8266/ESP32 series. These platforms allowed researchers to integrate voltage and current sensors including ACS712 and ZMPT101B, and push data to cloud services for basic real-time visualization and historical tracking [12; 13]

For instance, Hasan et al [12] demonstrated a system using an ESP8266 and ACS712 sensor to monitor power consumption and visualize it on a smartphone via the ThingSpeak platform. Similarly, Ahammed et al. [13] used an Arduino Uno with a PZEM-004T sensor module to transmit data to cloud servers including Firebase database for data storage. These studies proved the viability of low-cost IoT for energy monitoring but were limited to measuring fundamental parameters like voltage (V), current (I), and active power (P), lacking any capability for sophisticated PQ assessment.

Subsequent research focused on overcoming range and scalability limitations. Studies explored Low-Power Wide-Area Network (LPWAN) technologies like LoRaWAN, ideal for distributed monitoring across large areas like campuses or distribution grids [14]. Lavric et al. [14] proposed an architecture using LoRa-enabled sensor nodes with a Raspberry Pi gateway, highlighting the trade-off between long-range, low-power communication and the bandwidth required for high-frequency PQ data. While effective for scalar data transmission, such systems are not suited for the high-fidelity waveform analysis essential for harmonics detection.

Fast Fourier Transform (FFT) is an algorithm that decomposes a complex time-domain waveform into its constituent frequency components, allowing for the calculation of key indices like harmonics and total harmonic distortion (THD) factor [15]. Research has successfully implemented this on various hardware. Leccese [16] developed a dedicated PQ analyzer using a Raspberry Pi. Dhaou et al. [17] designed a Zigbee-based mesh network of sensors capable of measuring THD and capturing voltage sag events, effectively addressing distributed monitoring.

However, a common limitation persists: these advanced PQ monitors often operate as standalone, specialized instruments. They are frequently built on more expensive platforms or lack integration with

higher-level analytics like machine learning, limiting their role to data collection rather than intelligent diagnosis. Wang et al. [18] presented a comprehensive cloud-based framework using ensemble models for both NILM and fault detection. However, such systems typically rely on data from external commercial smart meters, which often lack the necessary sampling rate for detailed harmonics analysis and create a dependency on proprietary infrastructure.

In the domain of machine learning (ML), previous efforts have applied algorithms like Decision Trees and Neural Networks to NILM, achieving high accuracy in disaggregating loads from aggregate power data [19; 20]. Other studies have utilized ML for predictive maintenance and fault detection within power systems [21; 22].

A review of the literature, summarized in Table 1, reveals a significant gap: few systems successfully integrate comprehensive PQ monitoring (especially harmonics), advanced ML analytics (like NILM and PQ classification), and smart grid support functions into a single, low-cost, user-friendly platform. Most existing solutions address only one or two of these aspects. This work aims to bridge this gap by proposing a unified DDEMS framework.

Table 1. Summary of prior research as compared to the proposed DDEMS system.

Ref.	Sensors	MCU/Platform	Communication	PQ Monitoring	ML Support	Smart Grid Support
[12]	ACS712	ESP8266	WiFi	No	No	No
[13]	PZEM-004T	Arduino Uno	WiFi	Basic	No	No
[14]	PZEM-004T	Raspberry Pi, LoRa	LoRaWAN	Basic	No	No
[17]	ZMPT101B, SCT-013	Raspberry Pi	Zigbee	Basic	No	No
[18]	(Data from Utility Meter)	Cloud-based	Ethernet	Limited	Yes (NILM, Faults)	Yes
Proposed	PZEM-004T, SCT-013	ESP8266, RPi	WiFi/Ethernet	Advanced (Harmonics, THD, Events)	Yes (NILM, PQ Class.)	Yes (Dashboard, Alerts)

MATERIALS AND METHODOLOGY

The development of the Data-Driven Energy Monitoring System (DDEMS) followed a structured approach, integrating hardware design, data acquisition, cloud infrastructure, and machine learning model development. The overall methodology is based on multi-layered IoT architecture and the flow of data from physical sensors to intelligent applications, as depicted in Figure 1 (a) and (b), respectively.
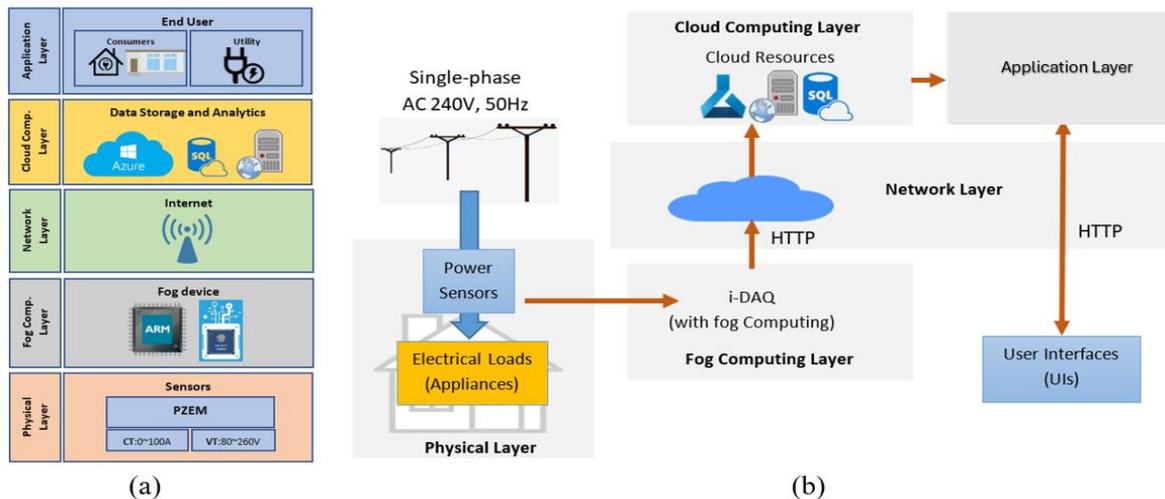

(a)   (b)

Figure 1. High-level architecture of the proposed DDEMS, illustrating the five-layer IoT model, (a) conceptual layered architecture, (b) implementation diagram

System Architecture Overview

The DDEMS is built upon a five-layer IoT architecture model:

1. **Physical Layer:** Comprises the sensors responsible for acquiring raw electrical data from the power line including the PZEM-004T power module and the SCT-013 non-invasive current transformer.
2. **Fog Computing Layer:** Consists of the ESP8266 microcontroller, which performs initial data processing, computation of harmonics via windowed FFT algorithm (2.0 kHz sampling rate), and temporary data buffering at the network edge.
3. **Network Layer:** Handles wireless communication (Wi-Fi) to transmit the processed data securely to the cloud platform in JSON format via HTTP POST requests at 20-second intervals.
4. **Cloud Computing Layer:** Provides extensive data storage (MySQL database), historical analysis, and hosts the machine learning models for advanced analytics.
5. **Application Layer:** Delivers the user interface via a web portal, enabling real-time monitoring, data visualization, remote control, and access to ML-driven insights such as appliance recognition and PQ advisories.

This layered architecture ensures a scalable, secure, and efficient pipeline from data acquisition to user application.

Hardware Design and Data Acquisition

The intelligent data acquisition (i-DAQ) unit, shown in Figure 2, integrates power sensors, signal conditioning, and a microcontroller with a built-in Wi-Fi shield. The acquired and streamlined electrical data are uploaded to the cloud platform for data storage, monitoring and computation.
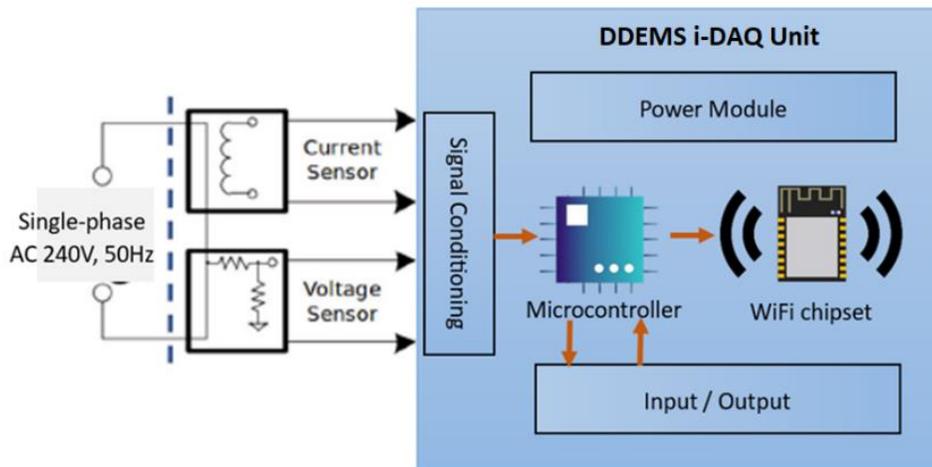

Figure 2. Simplified block diagram of i-DAQ unit of the DDEMS

The PZEM-004T power module provides ±0.5% measurement accuracy for voltage (80-260V range), current (0-100A), and power measurements (0-23kW) [23]. It has built-in RS485 with Modbus communication with the external device for data exchange purposes. To ensure communication between PZEM-004T Power Module and ESP32 MCU, an interfacing module for Modbus Communication Protocol is essential. It consists of an RS-485-to-TTL Modbus Converter which connects between PZEM-004T Power Module and ESP32 MCU, as depicted in Figure 3 [24].
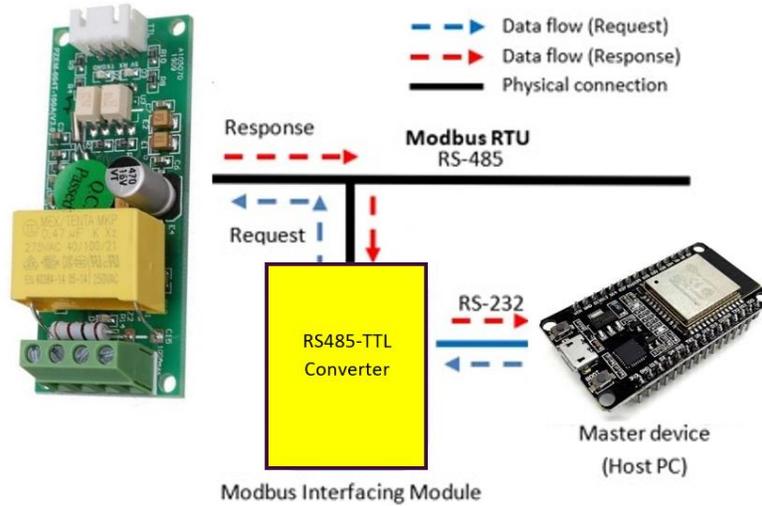
Figure 3. Interfacing module for Modbus RS485 Communication Protocol

Current harmonics refer to distortions in the electrical current waveform caused by nonlinear (NL) loads, which can affect the performance of electrical systems [25]. The widespread use of NL loads has degraded the PQ of low voltage (LV) distribution networks by generating harmonics that distort the sinusoidal waveforms of current and voltage [26; 27], while these harmonics can be analyzed by using Fourier Series and its Fast Fourier Transform (FFT) algorithm. In this work, the harmonics and total harmonic distortion (THD) factor are acquired by using SCT-013 current transformer (CT) sensor. Figure 4 illustrates acquisition of current signal for harmonics from SCT-013. The sensor's output is a small current proportional to the measured current, which is then converted into a voltage using a burden resistor [28].
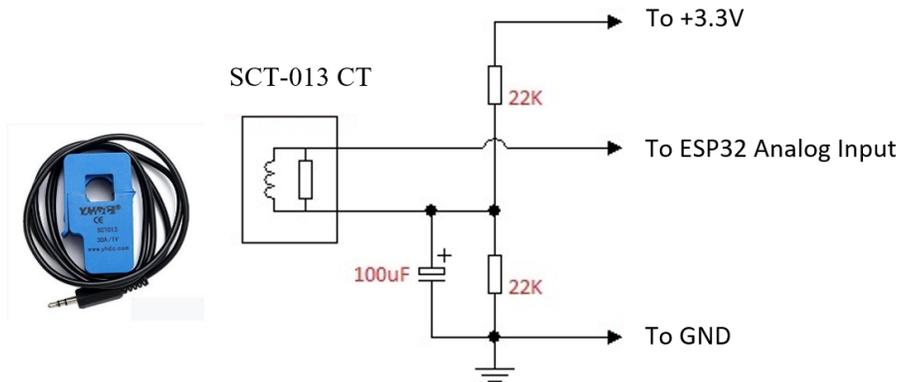

Figure 4. Acquisition of current signal for harmonics from SCT-013 Current Sensor

The embedded firmware in ESP8266 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 decompose the current signal into its fundamental and harmonic components (up to the 13th harmonic). THD was calculated as per Equation (1):

$$THD = \frac{\sqrt{\sum_{h=2}^{n}(I_h)^2}}{I_1} \times 100\% \tag{1}$$

where I_1 is the RMS value of the fundamental current and I_h is the RMS value of the hth harmonic.

Machine Learning Modelling Procedure

The workflow for developing the appliance recognition model followed a standard supervised learning pipeline, as shown in Figure 5. The process begins with data acquisition, which is followed by a pre-processing phase that purifies the raw sensor data to remove noise, handle missing values, and normalize measurements. Feature extraction for identifying relevant parameters of the electrical signals, such as rms current and voltage, power factor, harmonics and THDi [29]. After the relevant features are extracted from the data, the dataset gets partitioned into the training and testing datasets to enable an unbiased evaluation of the performance of the models. The training dataset gets used to train various machine learning and deep learning models, to enable them to learn typical load patterns and spot anomalies or irregular patterns. With the training process complete, the testing dataset is used to evaluate the models and determine their prediction potential.
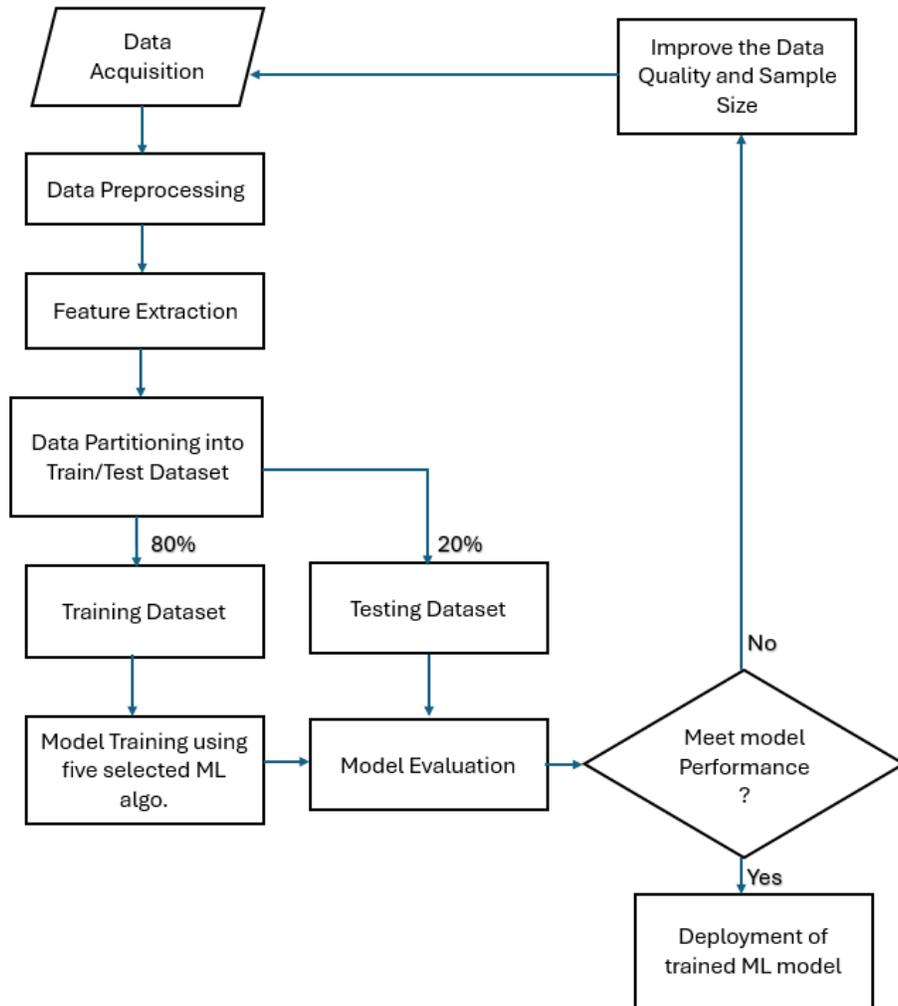

Figure 5. Flowchart of the machine learning modelling procedure for appliance recognition.

(1) Data Acquisition
A comprehensive dataset is essential for training the machine learning models for appliance recognition. Eight common residential electrical appliances were selected, covering a range of power ratings and load types (resistive, inductive, non-linear): LED Light, Refrigerator, Incandescent Bulb, Air-Conditioner, Standing Fan, Microwave Oven, LED TV, and a Mini PC. The technical specifications for these appliances are detailed in Tables 2.

Table 2. Technical specifications of eight selected electrical appliances

Label	Appliance name	Shortform	Specifications	Rate watt (W)
1	LED Light	LED	Philips, 30W	30W
2	Refrigerator	Fridge	Sharp, Model SJ-P49N-SL	500W
3	Bulb (Incandescent)	Bulb	Philips,	60W
4	Air-conditioner	Air-cond	Mitsubishi, GR Series	1.5HP
5	Standing Fan	Fan	Khind, Model KB404	60W
6	Microwave Oven	Oven	Sharp, Model R207EK	800W
7	LED TV	TV	Samsung UA50AU	145W
8	Mini PC	PC	Mini PC (i-7 Intel chipset)	100W

Each appliance was operated individually, and the i-DAQ unit captured 50 sets of measurements for each. Each data point consisted of a 13-dimensional feature vector F as shown in Equation (2):

$$F=\{\ Vrms,\ Irms,\ P,\ Q,\ PF,\ F,\ THD, f_3, f_5, f_7, f_9, f_{11}, f_{13} \} \qquad (2)$$

This resulted in a labelled appliance dataset of 5,200 instances. The measured parameter statistics (mean and standard deviation) for the appliances are detailed in Tables 3.

(2) Data Preprocessing
Following data acquisition, the acquired data is undergoing data preprocessing and feature extraction stages. The acquired dataset was imported into Python using the Pandas library. The preprocessing stage involved handling missing values, normalizing the numerical features to a common scale using StandardScaler, and encoding the target appliance labels. All the procedures were programmed in Python script under PyCharm's IDE software.

Furthermore, the raw current waveform underwent a feature extraction process. This critical step transforms the high-dimensional raw data into a lower-dimensional, informative set of parameters that uniquely characterize the operational signature of each appliance.

(3) Data Partitioning
The dataset was partitioned into input features (X) and target values (Y), and subsequently into training dataset (80%) (X_train, Y_train) and testing dataset (X_test, Y_test), to ensure unbiased evaluation of the model performance.

Table 3. The measurements of electrical appliances

Device / Parameters	LED	Fridge	Bulb	Air-cond	Fan	Microwave Oven	LED TV	Mini PC
V_{rms} (V)	240.06±0.15	244.96±1.66	239.29±0.11	239.26±0.23	241.10±0.74	236.57±1.83	242.94±0.10	237.84±0.09
I_{rms} (A)	0.21±0.07	1.45±0.02	0.28±0.01	5.63±0.56	0.22±0.01	5.92±0.08	0.34±0.01	0.25±0.07
P (W)	25.31±7.61	209.25±3.88	65.93±0.06	1125.25±215.97	52.76±0.29	1312.75±25.38	75.08±0.26	33.26±10.08
Q (VAR)	26.13±8.32	285.24±3.50	0.50±0.01	323.54±112.12	6.32±0.07	486.84±20.05	34.20±0.10	29.56±8.63
PF (%)	49.89±0.52	59.15±0.59	99.90±0.01	72.71±8.72	97.79±0.43	93.76±0.44	91.00±0.00	54.73±2.02
F (Hz)	49.95±0.05	49.95±0.03	50.02±0.03	49.97±0.05	49.99±0.04	50.01±0.01	49.98±0.005	49.94±0.05
THD (%)	10.36±18.40	7.63±0.81	11.04±4.09	35.69±6.48	9.72±2.72	33.20±6.54	5.98±0.12	3.69±0.27
f_3 (%)	7.48±12.48	6.95±0.49	7.27±2.31	25.72±7.14	3.57±1.23	31.09±5.84	5.48±0.07	3.06±0.31
f_5 (%)	3.80±12.48	1.63±0.24	6.16±2.25	17.10±2.73	5.04±1.18	9.93±3.80	2.38±0.06	1.70±0.10
f_7 (%)	3.22±7.25	2.27±0.26	4.65±1.93	17.15±0.45	5.78±1.28	5.02±0.88	0.21±0.07	0.59±0.14
f_9 (%)	3.39±7.50	0.58±0.20	5.46±1.93	4.95±1.75	4.41±0.88	2.76±0.80	0.84±0.09	0.72±0.12
f_{11} (%)	0.26±0.03	0.11±0.01	1.31±0.40	0.12±0.01	0.10±0.03	1.03±0.02	0.21±0.03	0.12±0.02
f_{13} (%)	0.08±0.01	0.04±0.02	0.43±0.01	0.03±0.02	0.03±0.02	0.13±0.01	0.09±0.01	0.08±0.02

(3) Model Training and Selection

There are numerous options of ML algorithms available for developing multiclass classification modelling in PyCharm IDE. However, the choice of algorithms is made depending on the specific characteristics of the available dataset and the performance requirements. For instance, Neural Networks (NN) can be effective for large datasets due to their capacity to learn complex patterns, while simpler models like Decision Tree (DT) may perform well with smaller datasets. In terms of model performance, there is a trade-off between accuracy and speed. If real-time applications with speed requirement, simpler models like Decision Trees (DT) may be preferred over more complex models that require more computation.

Five distinct ML classification algorithms were selected for a comparative analysis to identify the best performer for the given dataset and task. The comparison of these ML classification algorithms is tabulated in Table 4.

Table 4. Comparison of 5 selected ML classification algorithms

ML Algor.	Characteristics	Complexity	Strengths	Weaknesses	Use Cases
DT [30]	Sequential decision trees	Moderate	Handles non-linear and complex relationships, and high accuracy with low bias	Overfitting problem, dense computation, and sensitive to noisy data	Fraud detection, customer churn, image classification
RF [31] [32]	Ensemble of randomized decision trees	Moderate	Robust to noise, handle high-dimensional data, good accuracy with low bias and low variance.	Less interpretable, may require tuning	Classification, regression, feature ranking, diverse domains
LR [33]	Linear binary classification	Low	Interpretable, computationally efficient, suitable for linear data	Limited to linear data, may underperform for complexity, fewer expressive capabilities	Medical diagnosis, credit scoring, social sciences
NB [34]	Probabilistic classifier based on Bayes' Theorem	Low	Simple, fast, and efficient. Handle high-dimensional data but require little training data.	Strong assumption of feature independence. Poor performance if the assumption is violated.	Text classification medical diagnosis, simple recommendation systems
NN[35]	Deep learning with interconnected layers	High	Captures intricate patterns, handles various data types and non-linear transformation	Computationally intensive, prone to overfitting	Image recognition, NLP, recommendation, complex data relationships

(4) Model Evaluation

The trained models were evaluated on the unseen testing set using a suite of performance metrics such as accuracy, recall rate, precision rate, and F1-score. The calculation formulae are shown in Equation (3)-(6).

- **Accuracy:** The proportion of total correct predictions.

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \tag{3}$$

- **Precision:** The proportion of true positive predictions among all positive predictions.

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

- **Recall:** The proportion of true positives identified correctly among all actual positives.

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

- **F1-Score:** The harmonic mean of precision and recall.

$$F1 - Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{6}$$

Where *TP* denotes true positive, *TN* means true negative, *FP* means false positive,
and *FN* means false negative.

Rule-Based Power Quality Classification

Alongside the ML model, a deterministic, rule-based PQ advisor was developed. This system classifies power quality based on predefined thresholds derived from international standards like IEEE 1159 and IEC 61000-4-30. The rules evaluate four key parameters:

1. **Supply Voltage:** Classified as Normal, Undervoltage/Overvoltage, Sag/Swell, or Severe Deviation/Interruption based on percentage deviation from the nominal 240V.
2. **Power Factor (PF):** Classified as Good (PF ≥ 0.95), Moderate (0.85 ≤ PF < 0.95), Poor (0.70 ≤ PF < 0.85), or Very Poor (PF < 0.70).
3. **Current THD (THD-i):** Classified as Acceptable (THD < 5%), Moderate (5% ≤ THD < 8%), Poor (8% ≤ THD < 15%), or Severe (THD ≥ 15%).
4. **System Frequency (F):** Classified as Normal Deviation (within ±0.5 Hz), Minor, Significant, and Severe Deviation (> ±2.0 Hz)

This advisor provides immediate, interpretable alerts to users about the state of their power quality and recommends mitigation actions. The classification rules and severity levels are detailed in Table 5.

Table 5. The proposed rule-based PQ classification with severity levels, parameter ranges, and impacts.

PQ Parameter	Class/Label	Classification Level	Typical Range	Description	Impact
Supply Voltage [36]	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 (±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 (±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) [37]	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 nonlinear loads	Overheating, malfunction, tripping risks
Power Factor (PF) [38]	Good PF	Level 0	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 consumption 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 nonlinear Heavy inductive/capacitive loads	Severe losses; correction required Increased line losses, voltage drops, transformer stress

Web-based DDEMS Portal and Rule-based PQ Advisor

Data analytics and Power Quality Monitoring 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 portal is constructed using hypertext preprocessor (PHP), MySQL database, and it integrates APIs that facilitates communication between DDEMS, backend systems, 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 Figure 6.
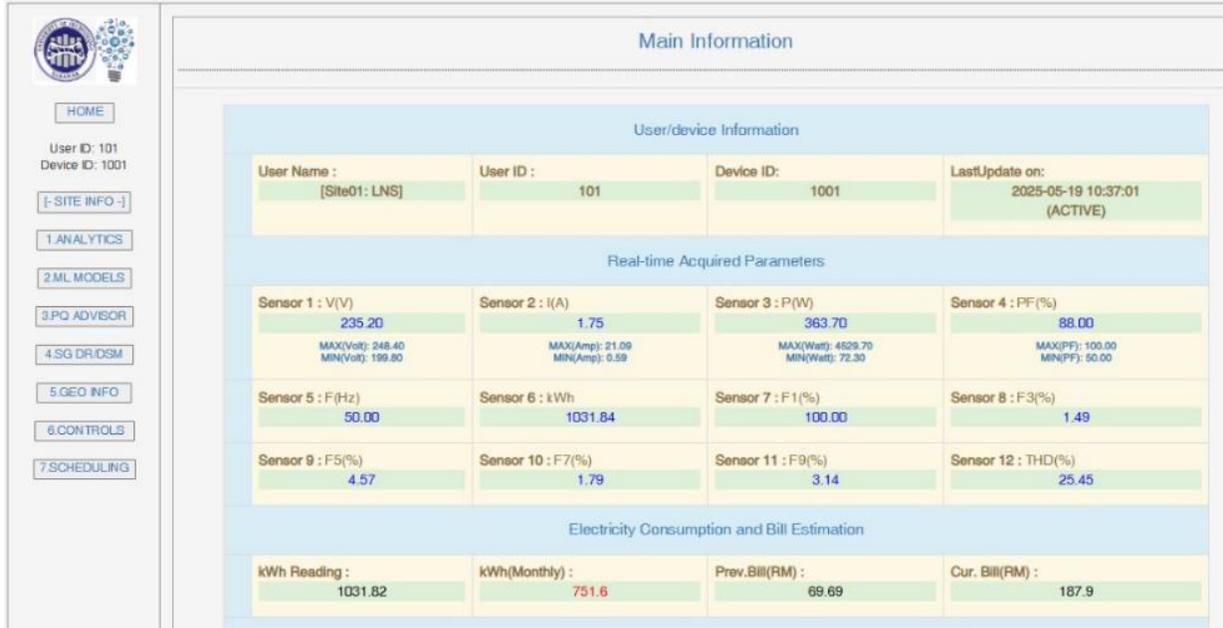
Figure 6. The Web-based DDEMS Portal

RESULTS AND DISCUSSION

This section presents the experimental results of the Data-Driven Energy Monitoring System (DDEMS), validating its hardware accuracy, evaluating the performance of the developed machine learning models, and demonstrating the functionality of the integrated system. Field evaluation involved 90-days of continuous operation across 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. It confirms the system's reliability, with real-time alerts and a web-based dashboard facilitating energy optimization and power quality monitoring.

Validation of Measurement Accuracy

The accuracy of the i-DAQ unit's measurements was rigorously validated against a calibrated Lovato DMG800 industrial power multimeter. Three appliances with distinct load characteristics were tested: a resistive load (70W LED Bulb), an inductive load (45W Fluorescent Light), and a non-linear load (45W Compact Fluorescent Light - CFL). The Mean Absolute Percentage Error (MAPE) was used for evaluation by using Equation (7).

$$MAPE = \left(\frac{1}{N} \sum \frac{\bar{Y} - Y_{ref}}{Y_{ref}} \right) \times 100\% \qquad (7)$$

Where N is the number of observations, Y_{ref} is the reference data value, and
$\bar{Y}$ is the average data measured by the sensor.

The results, presented in Table 6, demonstrate that the DDEMS achieves high measurement accuracy. Errors for voltage, current, and power were consistently below 1% for resistive and inductive loads. The slightly higher error for current (+4.65%) and power (-8.15%) on the non-linear CFL load is attributed to the complex current waveform. Crucially, the THD measurement error remained below 1.1% across all loads, validating the effectiveness of the implemented FFT algorithm. The overall MAPE for the three loads was 1.24%, confirming the suitability of the low-cost DDEMS hardware for reliable residential energy monitoring.

Table 6. Measurement accuracy comparison between DDEMS i-DAQ unit and Lovato DMG800 reference meter.

| Feature | Resistive Load | | | Inductive Load | | | | | |
| | LED Light Bulb 70W | | | Fluorescent Light 45W | | | Compact Fluorescent Light (CFL) 45W | | |
	DMG800	DDEMS	Error (%)	DMG800	DDEMS	Error (%)	DMG800	DDEMS	Error (%)
Vrms (V)	245.60	244.70	-0.36	245.6	245.30	-0.41	245.6	245.20	-0.16
Irms (A)	0.282	0.290	+2.84	0.315	0.320	+1.59	0.172	0.18	+4.65
P (W)	68.30	68.90	+0.88	44.5	44.4	-0.22	27	24.80	-8.15
Q (VAR)	10.68	9.82	-8.05	58.58	60.76	+3.72	34.17	31.38	-8.16
PF (%)	98.80	99.00	+0.20	60.4	60.00	-0.4	62.50	62.00	-0.5
F (Hz)	50.00	49.9	-0.2	50.05	50.00	0.0	50.04	50	-0.08
THD	3.90	3.87	-0.77	10.40	10.60	+1.92	80.7	81.10	+0.49
f_3 (%)	10.00	9.9	-0.10	9.80	9.76	-0.04	60.30	60.90	+0.60
f_5 (%)	2.50	2.30	-0.20	2.20	2.30	+0.10	30.20	29.7	-1.00
f_7 (%)	1.20	1.10	-0.10	1.20	1.40	+0.20	25.30	25.90	+0.60
f_9 (%)	0.80	0.90	+0.10	0.40	0.50	+0.10	22.20	21.80	-0.40
f_{11} (%)	0.60	0.70	+0.10	0.20	0.30	+0.10	10.50	10.80	+0.30
f_{13} (%)	0.20	0.20	0.00	0.10	0.2	+0.10	6.40	5.90	-0.50

Performance of Appliance Recognition Models

The labelled dataset of 5,200 instances from eight appliances was used to train and test five machine learning classifiers, namely Decision Tree (DT), Random Forest (RF), Naïve Baye (NB), Logistic Regression (LR), and Neural Network (NN). The models were evaluated based on accuracy, precision, recall, F1-score, and computation time to determine the most suitable algorithm for real-time deployment. The results are summarized in Table 7.

Table 7. Comparative performance of machine learning models for appliance recognition.

Model	Accuracy (%)	Precision	Recall	F1-Score	Computation Time (ms)
LR	56.12	0.45	0.58	0.48	94
DT	97.23	0.95	0.95	0.97	16
NB	98.42	0.98	0.98	0.98	0.1
RF	100.00	1.00	1.00	1.00	219
NN	27.30	0.11	0.34	0.12	160

- **Superior Performance of Ensemble Methods:** The **Random Forest (RF)** classifier demonstrated flawless performance, achieving 100% accuracy, precision, recall, and F1-score. This is because the ensemble nature of RF, which builds multiple decorrelated decision trees and aggregates their results, effectively handles potential non-linearities and complex feature interactions in the appliance signature data, minimizing overfitting and maximizing generalization.
- **Speed vs. Accuracy Trade-off: Naïve Bayes (NB)** was the fastest algorithm, with near-instantaneous training time (0.1ms), and achieved a very high accuracy of 98.42%. This makes it an excellent candidate for scenarios where computational resources are extremely limited. The **Decision Tree (DT)** model also performed excellently (97.23% accuracy) with very low computation time (16ms), offering a good balance between interpretability and performance.
- **Poor Performance NN:** The **Neural Network (NN)** models performed poorly (27.3% accuracy), likely because they require a larger dataset to learn the complex decision boundaries

separating the appliance classes effectively. Their default configurations were insufficient for this specific task.

System Deployment and Functionality

The fully integrated DDEMS was deployed and validated in a residential setting for 90-day deployment. The system successfully demonstrated its core functionalities:

1. **Real-time Monitoring and Data Logging:** The i-DAQ unit reliably sampled and transmitted data to the cloud database. The web portal (accessible at http://myseb.genesys.com.my/) provided real-time visualization of all electrical parameters (Figure 3a).
2. **Data Analytics and Benchmarking:** The portal featured interactive dashboards for analyzing historical energy consumption trends, comparing weekly usage, and identifying peak demand periods (Figure 3b).
3. **Machine Learning Integration:** The deployed Random Forest model was accessible through a prediction interface. Users receive instant appliance recognition results, successfully identifying active loads like fans, refrigerators, and air conditioners.
4. **Power Quality Advisory and Alerting:** The rule-based PQ advisor automatically classified real-time power quality events. For instance, it successfully identified "Level 3: Severe Harmonics" conditions caused by multiple non-linear loads (Figure 4a). Furthermore, the system's HTTP API-driven notification bot sent immediate alerts to users via the web portal (Figure 4b), enabling proactive responses to potential issues.

Field evaluation of DDEMS

The practical deployment of DDEMS system was accomplished with 90 days of field evaluation across the selected residential buildings with diverse load profiles. One of the selected sites was a 2-storey terraced house with 2,000 square feet located in Sibu town of Sarawak, Malaysia. The DDEMS i-DAQ unit is connected to a current transformer (CT) sensor clamped on the live cable of the incoming utility power supply. This placement enables DDEMS to capture and monitor the electrical power parameters of the terraced house. Figure 7 shows (a) the deployment of the DDEMS and (b) the prototype of DDEMS i-DAQ unit with CT sensor.
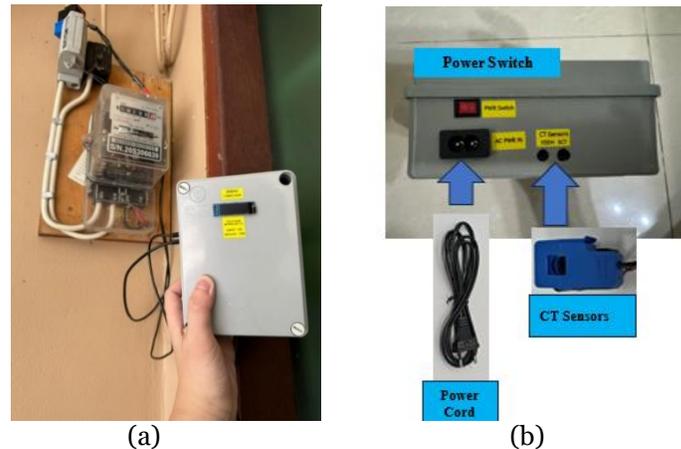

(a)   (b)

Figure 7. The Deployment of DDEMS to the Terraced House (a) Snapshoot of Actual Deployment, (b) Prototype of DDEMS i-DAQ unit with CT sensor

Data Analytics and Benchmarking 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. Figure 8 depicts the DDEMS portal which features several key navigation tabs, including Time-series Charts for visualizing energy usage trends and identifying anomalies, daily consumption (kW) for data trending of usage patterns, weekly consumption (kW) analysis, and a daily consumption benchmarking (versus previous week) tab 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.
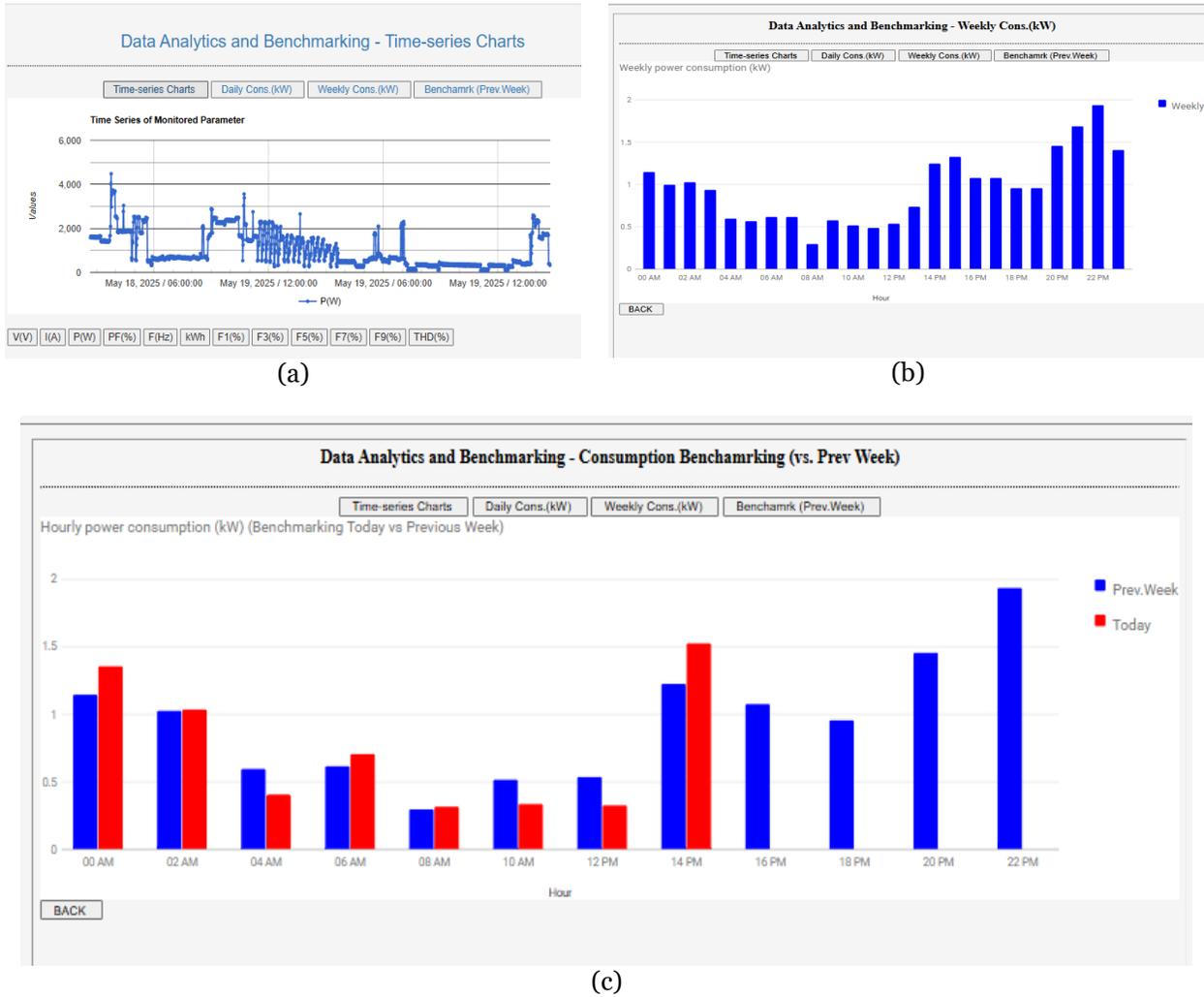

(a)

(b)

(c)

Figure 8. Data Analytics and Benchmarking of DDEMS Portal (a) Real-time Time-series charts, (b) Daily consumption (kW) and Consumption Pattern, and (c) Daily Consumption (benchmarking versus previous week)

The Power Quality (PQ) Advisor Dashboard of the DDEMS provides a real-time evaluation of power quality conditions including supply voltage, power factor, system frequency and total harmonic distortion (THD) as depicted in Figure 9 (a)-(d). The system has identified Level 3: Severe Harmonics, indicating significant distortion that can lead to equipment overheating, malfunction, or tripping. 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.
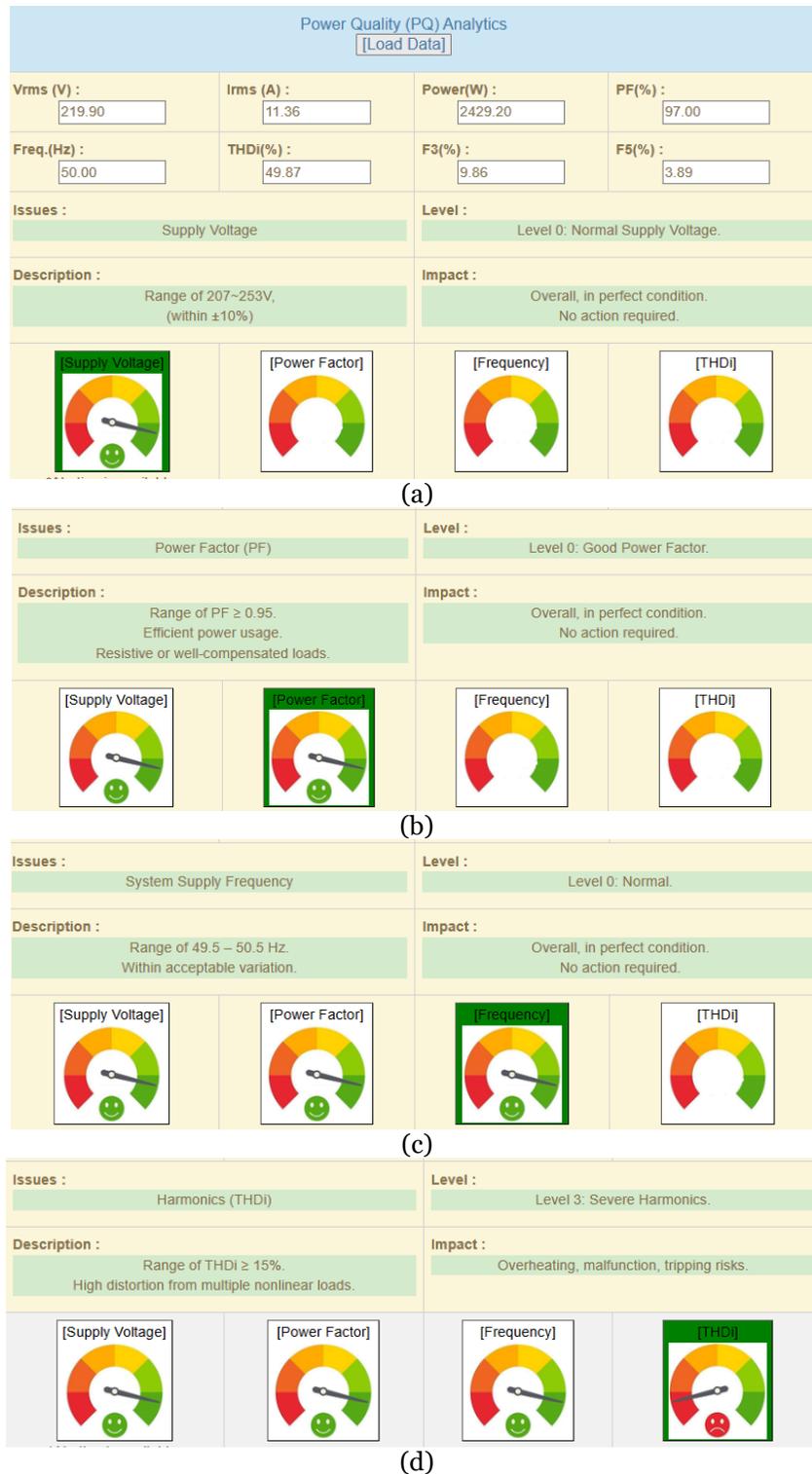
(a)

(b)

(c)

(d)

Figure 9. Snapshoot of Power Quality (PQ) Advisor for (a) supply voltage, (b) power factor, (c) frequency, and (d) total harmonic distortion (THD)

CONCLUSION

This research successfully designed, developed, and validated a comprehensive Data-Driven Energy Monitoring System (DDEMS) that integrates Internet of Things (IoT) technology and machine learning to address modern energy management challenges. The system was built upon a robust five-layer IoT architecture, utilizing low-cost, readily available components to create an intelligent Data Acquisition (i-DAQ) unit capable of measuring a comprehensive suite of electrical parameters—including voltage, current, power, energy, power factor, frequency, harmonics, and Total Harmonic Distortion (THD)—with accuracy validated to be within 5% of an industrial-grade power multimeter.

A central contribution of this work is the successful development and comparative analysis of multiple machine learning models for appliance recognition. Among the algorithms tested include Decision Tree, Naïve Bayes, Support Vector Machine, Neural Network, and Random Forest. The Random Forest classifier demonstrated superior performance, achieving perfect classification metrics, i.e., 100% accuracy, precision, recall, and F1-score. This ensemble-based Random Forest classifier proved to be the most robust and reliable for discerning individual appliance load signatures from aggregated energy data. Furthermore, a rule-based power quality advisor was implemented to automatically classify disturbances according to international standards, providing users with actionable insights and real-time alerts for issues such as voltage variations, poor power factor, and excessive harmonic distortion.

Deployed as a fully functional cloud-based platform, DDEMS demonstrates practical applicability through real-time data visualization, historical analytics, and remote access via a web portal. This integration of accurate hardware sensing, cloud computing, and advanced machine learning analytics provides a holistic solution that transcends the capabilities of traditional smart meters to support the core objectives of smart grids and Industry 4.0.

In conclusion, this study makes a significant contribution to the field of smart energy systems by providing a scalable, cost-effective, and intelligent platform that empowers consumers with detailed insights into their energy consumption and power quality health. The DDEMS effectively supports the core objectives of smart grids and Industry 4.0, promoting energy efficiency, enabling predictive maintenance, and enhancing overall grid stability through data-driven decision-making.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

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