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Monitoring Energy and Power Quality of the Loads in a Microgrid Laboratory Using Smart Meters

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Abstract: Microgrids are local energy production and distribution networks that can operate independently when disconnected from the main power grid thanks to the integration of power generation systems, energy storage units and intelligent control systems. However, despite their advantages, the optimal energy management of real microgrids remains a subject that requires further investigation. Specifically, an effective management of microgrids requires managing a large number of electrical variables related to the power generated by the microgrid's power supplies, the power consumed by the loads and the aspects of power quality. This study analyzes how we can monitor different variables, such as the active power, reactive power, power factor, total harmonic distortion and frequency in the loads of a microgrid, using high-precision power meters. Our empirical study, conducted using a functional microgrid comprising a hybrid wind–solar power system and several household appliances, demonstrates the feasibility of using low-cost and high-performance power meters with IoT functionality to collect valuable power quality and energy consumption data that can be used to control the microgrid operation.

Keywords: energy data analysis; energy management; microgrids; power quality; smart homes; smart meters

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1. Introduction

The traditional electrical grid cannot cope with the new challenges of the world in terms of reliable, efficient and clean energy [1]. In fact, the exponential expansion of distributed generation systems in some areas evidences the tendency toward the decentralization of electric networks. These transformations are driven by digital and green transition policies [2], which require a faster adoption of technology. Considering that energy saving and the reduction in the use of natural resources have direct impacts on life and humanity, the smart grids [3] emerge as a new paradigm that promotes greater efficiency, enhanced security, and increased reliability. This is achieved through real-time monitoring of electricity usage and the implementation of control strategies aimed at reducing energy waste and improving system efficiency. Smart grids likewise work with the joining of sustainable power sources and electric vehicles, contributing to a more sustainable future by reducing greenhouse gas emissions [4].

Smart cities, smart homes and microgrids are completely interconnected ideas. A smart city [5] incorporates technological solutions from a wealth of urban data in order to improve residents' personal satisfaction and urban management. An effective approach for smart cities to achieve this goal is the implementation of microgrids [6]. Microgrids are self-contained energy systems capable of operating independently from the main power grid. They can use overflow energy created inside the microgrid and feed it into the main grid during periods of low energy consumption within the microgrid. Moreover, smart homes are important components of smart cities, as they employ modern technology and automation to improve energy consumption and waste.

The management and control of microgrids require monitoring the status of various components of the system. A pivotal part is upgrading energy effectiveness by providing detailed, real-time information on electricity consumption [7–10]. These advanced devices not only provide accurate measurements of electricity consumption, but also enable the implementation of algorithms for the optimal operation of the microgrid [10]. For instance, non-intrusive load monitoring (NILM) techniques are commonly employed to identify the energy consumption patterns of specific appliances and to detect the operational state (on/off) of devices by analyzing the overall power consumption [11,12]. These data enable households to receive personalized advice on improving their electrical consumption management [13]. Therefore, the use of smart metering infrastructure in combination with efficient management systems contributes to creating a more sustainable and efficient urban environment, while making it possible to incorporate important data for strategic energy planning and urban development decision-making [6].

This paper outlines the process of monitoring energy and power quality data in a microgrid using advanced smart meters with IoT capabilities. The proposed framework is validated through a real case study. Section 2 gives an overview of recent trends about smart cities and microgrids, with particular focus on measuring electrical variables in microgrids using smart meters. Section 3 describes how the proposed framework is able to monitor a set of home appliances (loads) when they are switched on/off to obtain energy consumption and power quality measures in a microgrid. Section 4 presents the outcomes acquired in the experimental study, while Section 5 outlines the main conclusions and suggests future research directions.

2. Related Work

A microgrid [14] can be characterized as a limited-scale electrical network that can work freely or in relation to the higher-power lattice, utilizing nearby age sources (for example, environmentally friendly power frameworks) and energy stockpiling frameworks. One of the vital advantages of microgrids in smart cities is their energy dependability and versatility. By producing and disseminating power at the neighborhood level, usually using renewable energy sources, microgrids can continue to provide electric capacity during framework blackouts. Moreover, microgrids can likewise assist with decreasing energy costs by improving energy utilization and diminishing power demand on the grid. This may result in financial savings for utilities as well as consumers, as well as reducing the energy consumed during peak demand on the electric grid. Of course, the energy generated in the microgrid and not consumed by the loads can be stored in the storage systems or, alternatively, sent to the grid.

The integration of microgrids in smart cities is driven by the need for reliable and smart energy, electricity networks and the transformation of urban infrastructure. Smart cities [15,16] have evolved towards more sophisticated ecosystems [17]. The widespread use of renewable energy sources and the progressive implementation of energy storage systems are just a few examples. Additionally, the creation of intelligent transportation systems further exemplifies this trend. Another key element for the development of smart cities is determined by the continuous deployment of smart homes [18]. These are homes equipped with electronic devices and appliances that can communicate with each other and with the control system, allowing customers to better control their energy consumption and expenses [19]. Smart homes in microgrids also enable homeowners to generate their own power using renewable energy sources and utilize it to operate home appliances.

Efficient energy management in microgrids has become a highly relevant topic for researchers worldwide. For example, some studies have proposed heuristic optimization algorithms to optimize the schedule of home appliances [20]. In different cases, the point is to give an essential structure to adjust the organic market variance for RES-based microgrids in a detached region [21] to such an extent that the foundation expected to carry out the proposed technique is connected with building a checking station furnished with a large number of PCs and sensors expected to apply NILM calculations. The improvements, advantages, and lacking features of smart grid communication methods have also been analyzed in the literature [22]. Some authors have demonstrated that unsupervised methods can achieve the same range of uncertainty as supervised NILM algorithms while saving money on the acquisition of labeled data [13]. In [23], a hierarchical design is introduced that requires no prior information or general models of individual loads. Furthermore, AI strategies have additionally been applied to examine the adaptability of power utilization in private structures [24]. In addition, the cyber and physical structures of the hardware and software in a smart grid determine the security requirements [25] and are important in guaranteeing secure measurement, communication and control [26].

To deal with the information in microgrids, smart meters and energy management systems are used. Smart meters are often used to measure energy consumption and the power quality variables of various loads, including household devices [9]. The relevant features of a smart meter are the sampling frequency and the electrical measurements it is capable of calculating [27]. Many investigations have proposed different smart metering infrastructures to be used in microgrids [28]. For instance, some authors have proposed multi-objective energy management systems with smart energy meters that allow for the storage of data on energy generation and battery loads as well as information about the appliances, in order to investigate the end-user's energy use habits [29].

3. Monitoring Electrical Variables Using Smart Meters

3.1. Framework Description

The framework proposed here for monitoring and examining energy data at the loads of a microgrid is divided into several steps:

- Number and type of smart meters: The first step is to determine the type and number of smart meters to be installed in the microgrid. One option is to employ an intrusive load monitoring (ILM) approach [30], which involves the use of low-end power meter gadgets that straightforwardly measure every gadget's energy utilization. Smart plugs communicate with the smart meter to transmit real-time energy consumption data. However, deploying many smart meters can be prohibitively expensive due to the potentially large number of loads in the microgrid [31]. As an alternative, NILM techniques [32,33] often involve using a single meter to measure power generation and another meter to measure overall demand across multiple appliances. The proposed framework enables the application of NILM methods [34] for different purposes. For example, the data obtained can be used for load disaggregation, i.e., separating the energy usage of specific appliances from the total household energy usage [35]. Therefore, it is essential to consider high-precision, low-cost smart meters for this purpose. In our study, the openZmeter is used [7,36], which is capable of measuring important variables, including, but not limited to current, voltage, power (active, reactive and apparent), power factor, energy consumption, harmonics up to the 50th order, total harmonic distortion, frequency, etc.
- Installation of the smart meters: Considering that our aim is to conduct measurements on the loads within the microgrid, an openZmeter device is utilized for monitoring these loads. For instance, Figure 1 illustrates how the openZmeter captures energy data from home appliances at a single point, which is then transmitted to a computer that will process the data received. With this, homeowners can access and view energy consumption data at any time and receive alerts if any of the parameters are out of normal range through a web page or mobile application linked to the smart meter. Furthermore, the openZmeter can also be employed to monitor the power generated by renewable energy sources.
- Data processing: The data collected by the smart meter can then be processed and displayed using visualization tools to provide real-time and historical energy consumption and power quality statistics [37]. Such visual data simplify complex information into intuitive visuals, aiding homeowners in understanding energy usage patterns, spotting peak demand periods, and identifying wasteful areas. Such visual insights

assist homeowners in optimizing energy usage within small-scale microgrids by adjusting device settings, turning off devices when not in use or replacing outdated appliances with newer, more energy-efficient models. Managing control within large microgrids typically requires the implementation of advanced procedures, including artificial intelligence methods [38].

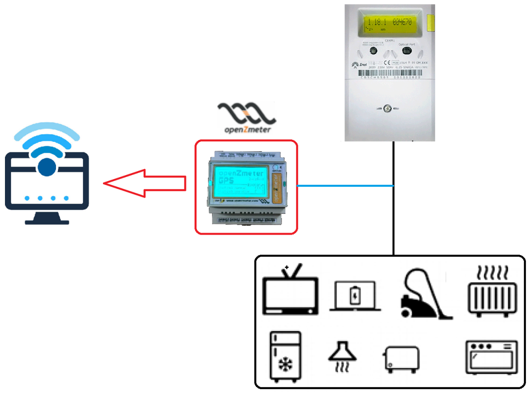


Figure 1. Measuring electrical variables in home appliances using the openZmeter.

3.2. Differences with Other Studies

Recent studies have analyzed the use of metering infrastructures to monitor electrical variables in microgrids. However, many of these studies are limited in their findings compared to our framework. This is either due to the measuring of a smaller number of electrical variables, primarily focusing on power quality data, using devices with limited accuracy, or having a less versatile interaction system between the device and users.

On the one hand, empirical studies often analyze a limited number of variables. For example, the authors of [39] present a method to optimize consumption to improve power quality and security levels in electrical systems while considering economic costs. However, only information regarding active power (W) and cost (monetary units) is provided. Similarly, the authors of [40] modeled a smart metering system in a microgrid, but the empirical study focused on analyzing the energy that flows between loads and renewable energy systems. Other investigations have proposed using a smart meter with voltage, transformer and microcontroller units equipped with embedded communication modules to measure current, voltage, power factor, harmonics and frequency [41]. In [23], a method is presented to infer load signatures of different home appliances based on active and reactive power measurements, but no information is provided about the specifications of these meters. Furthermore, other researchers have analyzed demand response in microgrids by coordinating data measured by smart meters and distributed superconducting magnetic energy storage units [39], but the empirical results are focused on the study of active power flows.

On the other hand, most of the devices used have limited measurement and communication capabilities compared to the openZmeter. For instance, the digital power meter used in [42] provides voltage values in the range of [50 V–350 V] (while the openZmeter can safely measure up to 1000 V), and current values in the range of [10 mA–15 A] (whereas the maximum current measured by the openZmeter is 50 A) [7]. Additionally, the smart meter described in [42] allows for communication via USB I/O and 100 Mbps Ethernet interfaces. In [28], a metering infrastructure is presented that enables the measurement of voltage, current and frequency, using wired and wireless communication interfaces (such as Wi-Fi, IEEE 802.15.4 and LoRa) to transfer the measurements to a central unit. The access to the graphical interface of the openZmeter allows direct access to the measurements via the web, regardless of the end-user's location.

4. Results

The experimental study was carried out in the laboratory microgrid of the University of Almería (Spain) (latitude: 36°49′45′′ N, longitude: 2°24′28′′ W). Almería is one of the locations in Europe with long hours of daylight (more than 3000 h annually) [43]. Figure 2 shows the main elements of the microgrid. Firstly, Figure 2a shows the generation system that consists of two solar tracker systems with 3600 watts capacity each. Three wind turbines (model Wind 13+, manufactured by the Spanish brand Bornay) can also be connected to the microgrid. The energy generated and not consumed is stored in batteries for later use (see Figure 2b). The arrangement of loads in the microgrid incorporates several home appliances like fridges, refrigerators, ovens, electronic devices, etc. (see Figure 2c,d). These devices harness energy from renewable sources or batteries, in addition to the building's own electrical connection.

Figure 2. (**a**) Photovoltaic solar trackers; (**b**) power electronics and storage systems; (**c**,**d**) loads (home appliances).

Although the aim of this paper is to monitor the loads (home appliances), the openZmeter device is capable of gathering real-time data on other parts of the microgrid. For example, Figure 3 shows the energy generated by the photovoltaic system within one week, where it can be observed that solar intensity varies periodically, as indicated by the recurring patterns.

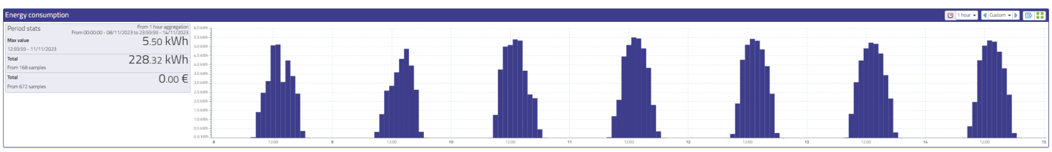


Figure 3. Energy produced by renewable sources in the microgrid.

Focusing on load analysis, most published articles tend to focus on measuring active power, although various authors have proposed the analysis of reactive power as part of future work [28], which is a critical variable in real systems [44]. In fact, some recent surveys have highlighted the importance of maintaining a balance between active and reactive power to ensure power quality in microgrids [45].

The electrical power that is converted into useful work (light, motion or heat) is called active or real power and is measured in watts (W). Reactive power (volt-ampere reactive, VAR) is the power consumed by motors and transformers to create and maintain magnetic fields, but performing no useful work. Therefore, it is also important to reduce the reactive power, since it allows us to improve the power factor and, therefore, to reduce the energy losses and improve efficiency. Figure 4 shows the active and reactive power measured by the openZmeter during the experiment. It is evident that both variables experience a significant increase when certain home appliances are switched on. Figure 5 shows a breakdown of the active and reactive power consumed by different household appliances, where each data point represents a measurement taken every 200 ms. As depicted, heating element loads (such as the oven and water heater) appear to be nearly purely resistive and therefore only absorb a small amount of VARs, whereas other appliances (like the vacuum cleaner and kitchen hood) absorb substantial amounts of reactive power.

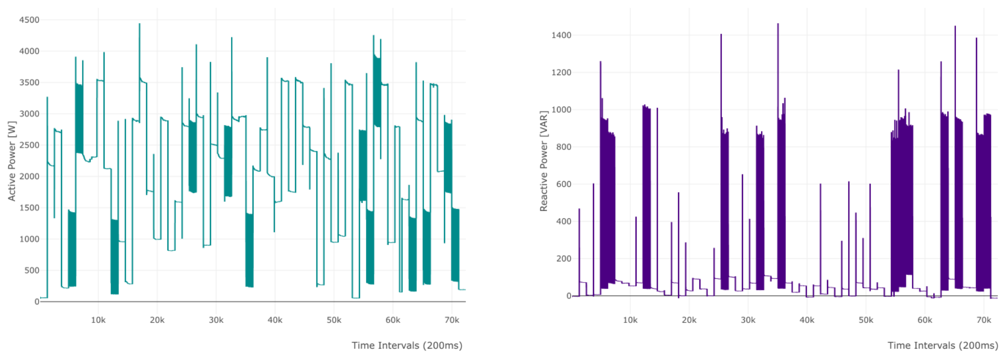


Figure 4. (**a**) Active power and (**b**) reactive power during the experiments.

Furthermore, the openZmeter is capable of capturing power quality data, as per the EN50160 power quality standard, which is of significant importance in the microgrid context. For instance, Figure 6 illustrates the frequency variation within the microgrid relative to the standard 50 Hz frequency (commonly observed in Spain and many other electricity systems worldwide). It is evident that the frequency remains close to—but slightly below—the reference value for most of the experiment duration.

The openZmeter is capable of collecting data on other power quality variables, such as total harmonic distortion (THD), in terms of current and voltage. THD numerically represents the harmonic distortion present in a signal, and its presence can lead to issues such as increased current, excessive heat, and other inconveniences that could cause damage to equipment and systems. Figure 7a displays the THD of the voltage during the experiment, where it can be observed that the values are below 2.5%. Meanwhile, Figure 7b illustrates that the THD of the current is sometimes higher than 50%.

Table 1 shows the minimum, maximum, mean and standard deviation of different electrical variables measured by openZmeter during the experiment. As it can be observed, active power varies according to the home appliances connected in each instance, with an average of 1911.88 watts. Reactive power varies from negative values (caused by capacitive loads) to high positive values (inductive loads). It is shown that the average power factor is close to 1 due to the presence of several purely resistive loads, but in some periods, it decreases significantly due to the activation of reactive loads (inductive or capacitive). In reference to the frequency, the mean value is 49.99 Hz, which is very close to the reference value (50.00 Hz). Finally, THD(v) values are lower than THD(i), as is usual in most electrical installations.

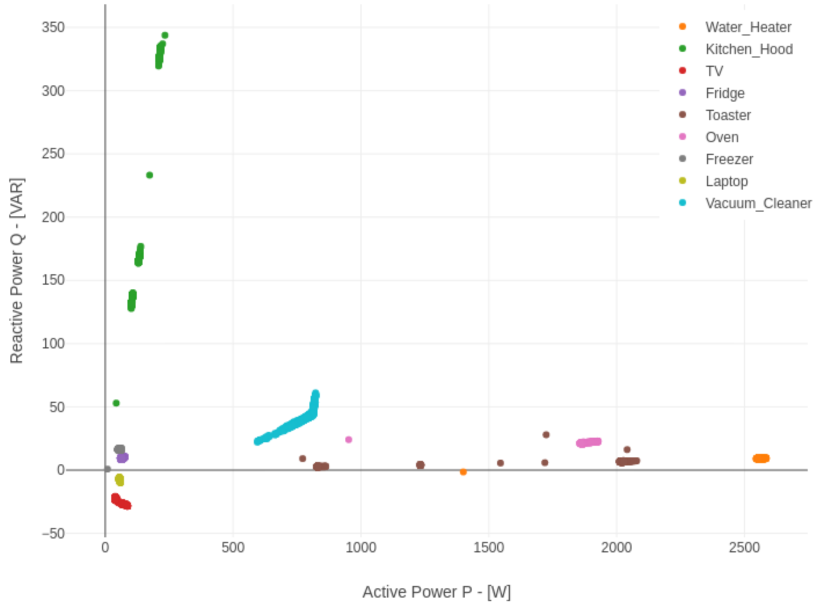
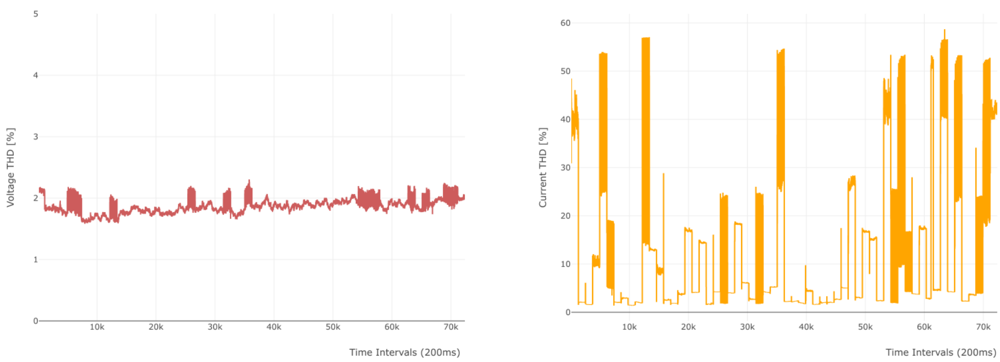


Figure 5. Active and reactive energy measured for each home appliance.

Figure 6. Frequency measured during the experiment.



(a) (b)

Figure 7. (**a**) Voltage THD and (**b**) current THD measured during the experiments.

Table 1. Statistical values obtained during the experiment.

	Active Power [W]	Reactive Power [VAR]	Power Factor [0–1]	Frequency [Hz]	THD(v) [%]	THD(i) [%]
MIN	45.71	−16.01	0.20	49.94	1.58	1.38
MAX	4445.29	1464.03	1.00	50.04	2.30	58.70
MEAN	1911.88	80.06	0.98	49.99	1.87	11.56
STD	1094.46	142.20	0.06	0.02	0.12	13.61

5. Conclusions

An efficient management of microgrids requires collecting and analyzing data on energy consumption and power quality. Smart meters are key instruments for gathering real-time data on energy usage, generation and power quality attributes. These measurements aid in optimizing energy distribution and ensuring the seamless operation of smart city infrastructure. This paper outlines the process of monitoring energy data in microgrids using a smart meter with IoT functionalities capable of measuring voltage, current, power (active, reactive, apparent), power factor, harmonics in voltage and current up to 50th order, THD in voltage and current, or frequency, among other parameters. An empirical study has been performed in a real microgrid that incorporates a combination of wind and solar power generation, a battery storage system and various home appliances.

The findings illustrate that the smart meter is capable of collecting, processing and displaying data from various components of the microgrid. Specifically, smart meters offer valuable insights into both power generation and energy consumption within the microgrid. Homeowners and microgrid operators can utilize this information to gauge energy production against demand, devise strategies to reduce energy consumption and costs, and thereby mitigate carbon emissions. Additionally, smart meters provide real-time measurements of power quality parameters, offering insights into the electrical supply's quality. These data serve to identify and rectify any power quality issues that could potentially damage appliances, result in energy wastage and ensure the microgrid's reliability and resilience. In summary, the utilization of low-cost high-precision smart meters in microgrids presents a cost-effective and accurate solution for energy consumption and power quality monitoring, complemented by versatile connectivity features.

As part of our future work, we plan to expand our measurements beyond the loads to include other components of the microgrid, such as batteries. Additionally, we will examine the ways to manage high-dimensional data using machine learning and prediction techniques [46,47], including soft computing and other advanced techniques [48,49], with the aim of improving energy management by leveraging information measured from power supplies, storage systems and energy loads within the microgrid.

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