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ADAPTIVE ENERGY MONITORING AND MANAGEMENT SYSTEM FOR ELECTRICAL NETWORKS USING REAL-TIME SENSORS AND RASPBERRY PI

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Summary

This work proposes a system that performs continuous, real-time monitoring using on sensor networks, enabling the early detection of faults in the electrical system. The main objective is to prevent short circuits, breakdowns, and other issues associated with inadequate installations by analysing electrical variables such as voltage and current. This is achieved through the implementation of Raspberry Pi-type equipment, programmed with Python, which enables data collection and real-time processing. The data comes from distribution boards and electrical equipment that are in a critical phase, to obtain favourable measurements that can be processed in real time. This results in an innovative, high-impact solution that identifies anomalies proactively, effectively, accurately, and quickly, optimizing the maintenance process and significantly reducing downtime. The most conclusive results of the work are based on the measures taken, which allowed the load to be redistributed more evenly between the phases, considerably reducing negative sequence currents (35%) and voltage drop from 1.8% to 1.2%, which in turn translates into a significant decrease compared to other works with the same structure. In which a difference of 0.6% can be seen between the generated model and its results, compared to another research.

Keywords: Raspberry Pi, python, power factory, electrical panels, electrical circuits.

1. INTRODUCTION

The expansion of rural, urban and commercial areas has caused the demand for energy to increase, this increase poses many challenges such as maintaining reliable and stable electrical power with respect to time. To maintain stability in an electrical infrastructure, monitoring systems are being implemented that are currently becoming a priority when installing or expanding electricity grids [1].

Therefore, there is an axis of continuous monitoring and control that is fundamental within the process, and which is a pillar within the research work that I derive in this article, in this context, the use of fast and reliable communication technologies plays a crucial role. In recent years, it has been possible to implement specific technology such as wireless sensor networks that allows the rapid transmission of data from equipment to computer centers. This information received is interpreted through data analysis, which facilitates the detection and resolution of possible problems indicated by alarms generated, such as overloads, electrical leaks, short circuits and failures in the power supply [2].

The main objective is to be able to detect in a timely manner even the most critical faults such as heating in the conductors due to high temperatures, insulation failures, short circuit due to the collision of line to line of the system, among other possible faults to be detected in real time, thanks to constant monitoring within the system in which work is being done [3].

Technology offers a variety of communication options, seeking to guarantee between 90 - 95% availability and reliability of data reception, allowing continuous and accurate monitoring of the electrical system. This facilitates the early detection of potential problems and the adoption of corrective measures quickly and efficiently, thus minimizing response times to critical situations [4, 5].

The main challenge of this research work is the need to quickly and reliably detect faults in the electrical system, reducing response time and minimizing interruption time in the electricity supply, in addition to diagnosing the network, facilitating the identification of faults and helping maintenance decision-making. Whether they are corrective or preventive in nature. This contributes to maintaining the continuity of business operations, optimizing resources, avoiding economic losses, ensuring the correct supply of energy and strengthening competitiveness in commercial sectors that contribute to economic development.

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However, production sectors account for approximately 40% of energy consumption, to achieve existing environmental objectives and to have better energy quality it is necessary to reduce consumption in all types of buildings, carry out energy quality studies and implementing new strategies to mitigate long-term failures of electrical systems [6]. Thus, energy reduction strategies are becoming increasingly important due to electricity costs and growing environmental awareness. The industrial sector of the United States represents 31% of electricity consumption, this in 2010 increasing electricity costs [7]. Most research does not give much detail on how data is obtained for analysis; therefore, strategy development becomes an industry standard [8].

The Internet of Things (IoT) is one of the fastest-growing fields benefiting emerging and developing socio-economic areas. The field of IoT expands in all domains such as medicine, industry, transportation, education, mining, among others [9]. The IoT enables intercommunication between hardware and software equipment to facilitate large-scale automation and data analysis, driving the development of general-purpose applications [10].

To address these challenges, it is proposed to use a combination of low-cost equipment and rapid implementation. The Raspberry Pi [11], as a minicomputer based on the Linux operating system, has been expressly built as a highly flexible and powerful device that is low cost compared to traditional computers and is a great tool for research and development of monitoring of external variables [12]. The signals from the sensors connected to an Arduino Uno will be captured and transmitted through a board ESP8266 to the IoT through Blynk, which is a platform that helps share sensor information through a wireless network, managing to identify and exchange information through the internet [13].

Electrical systems are subject to energy variations due to electrical phenomena that are made up of structures of many passive and active elements [14]. For this reason, the structure of electrical circuits will be analyzed using DigSilent Power Factory software, which will allow simulating and identifying problems such as voltage drops, overloads and imbalances in the electrical system [15].

Advanced technologies in electrical monitoring also facilitate the implementation of predictive systems that anticipate grid failures, which is crucial for planning and maintenance [16]. The ability to anticipate failures helps reduce electrical circuit downtime and minimizes costs when performing unexpected maintenance, in addition to the implementation of IoT platforms allows the collection and analysis of a large batch of data to improve real-time decision-making [17].

Finally, this study combines solid theoretical principles with their practical implementation in a real electrical distribution environment. This approach enables continuous monitoring of operating conditions and facilitates the timely detection of abnormal behaviors that may compromise system stability. By integrating electronic sensing devices, embedded processing units, and IoT-based communication technologies, the proposed system provides a reliable platform for real-time supervision and energy management in electrical networks.

1.1. Main contributions and innovation of this work

Although the hardware components employed in this work are based on commercially available and low-cost technologies, the contribution of this research is not limited to system integration. The main innovation lies in the development of an analytical and architectural framework that transforms these devices into an intelligent monitoring solution capable of supporting real-time analysis and decision-making.

The intelligence of the proposed system does not stem from complex artificial intelligence models or deep learning techniques. Rather, it is based on a simple yet effective adaptive statistical approach that allows the system to adjust its decision thresholds automatically according to real-time operating conditions. By continuously calculating the mean and standard deviation of the aggregated power within a moving time window, the system updates its anomaly limits dynamically, without relying on fixed predefined values. This self-adjusting capability enables the monitoring framework to adapt naturally to changing load behaviors and operational variability, offering a practical and computationally efficient solution that can be reliably implemented on low-cost edge devices such as the Raspberry Pi.

In particular, the proposed system introduces a distributed edge fog cloud architecture that enables data acquisition at the sensor level, local processing on the Raspberry Pi, and cloud-based storage and visualization. This organization reduces communication delays and allows faster responses compared to conventional centralized approaches.

Additionally, a time series-based anomaly detection strategy is implemented to identify irregular consumption patterns, voltage disturbances, and potential faults. This method relies on statistical indicators such as moving averages and adaptive thresholds, allowing abnormal events to be detected automatically without the need for complex or expensive equipment.

The system also incorporates power-quality assessment tools, including harmonic analysis, total harmonic distortion estimation, and flicker evaluation, which are integrated into a single analytical workflow to provide a comprehensive view of grid performance.

Finally, the proposed framework is designed to be scalable and easily transferable to other contexts. Although validated in a commercial facility, it can be deployed in industrial plants, campuses, microgrids, or other distributed energy environments where low-cost and flexible monitoring solutions are required.

The remainder of this paper is organized as follows. Section 2 presents the materials and methods, Section 3 describes the analysis and results, and the final sections discuss the conclusions and future works.

2. MATERIALS AND METHODS

The prototype and system for energy monitoring consists of five key components. Current and voltage are counted through dedicated sensors capable of converting environmental variables into electrical variables. The acquisition of this data is done using a Linux-based minicomputer that is Raspberry Pi, a low-cost computer and a processing necessary for this project that will allow capturing and processing the data in real time. The data obtained is controlled and managed to ensure accuracy and consistency in collection. In addition, the monitoring is cloud-based using Internet of Things technology, with communication managed through a REST (Application Programming Interface Representational State Transfer) API [18].

Arduino Uno is an electronic board based on ATMEGA328 that will be responsible for taking the readings of the current sensor that previously its voltage was conditioned and amplified to be taken by analog input. This is done because Arduino Uno has more precision when it comes to acquiring an analog signal where the voltage resolution is smaller, in this case the voltage obtained from the amplified analog current sensor is from 0 to 1V depending on the resolution of the sensor the signal can be calibrated in programming [19].

The non-invasive current sensor model SCT-013 is used to obtain the amperage values that pass in a conductor without the need to make a direct electrical connection, the working principle is the transformation of current, the current that flows in a conductor is transformed into a proportional alternating current signal. This sensor is a popular choice for energy monitoring projects due to its ease of use, safety, and accuracy [20].

The SCT-013 sensor, with a measurement range of up to 100A depending on the model, offers an analog voltage output proportional to the measured current. This non-invasive sensor attaches directly to the conductor, eliminating the need to interrupt the power grid. The sensor ZMPT101B uses a voltage transformer that reduces the magnitude to a safe voltage level for measuring in electronic equipment, this transformation principle helps ensure safe measurement without the risk of damaging hardware equipment. Given the implementation of a real-time monitoring system, it is possible that electricity consumption will be reduced by 15% [21].

The low-cost, ESP8266-capacity Wi-Fi module allows electronic projects to be connected to the internet network. This module includes a microcontroller for processing capacity and Wi-Fi communication interface, which is an advantage when carrying out projects with Internet of Things connectivity. This programming module has compatibility with different protocols and can work autonomously, that is, it does not require extra maintenance at the time of installation. Figure 1 corresponds to the design of the prototype for current and voltage acquisition [22].

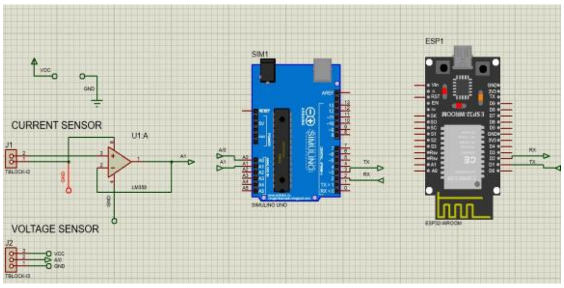

Fig. 1. Voltage and current data acquisition design and data acquisition circuit design

The Raspberry Pi processes the collected data in real time to save it in a database necessary for energy analysis. This device captures information from sensors and connected devices, then processes and organizes them using the Python programming language, displaying the analysis in graphs and parameters obtained. Thanks to its ability to handle multiple tasks simultaneously, the Raspberry Pi also facilitates the implementation of advanced analysis algorithms, thus allowing for a more detailed and accurate interpretation of energy data.

The data previously scaled and processed using the Arduino hardware platform was sent to an MQTT (Message Queuing Telemetry Transport) platform of the Internet of Things. In this case, Blynk IoT is used, a platform that provides a REST API method, allowing communication with any web platform that makes an HTTP GET (Hypertext Transfer Protocol) request. The Raspberry Pi executes a Python script to make such a request, receiving the data in JSON (JavaScript Object Notation) format.

Once the data is acquired, it is sent to a database in PhpMyAdmin at 5-minute intervals, so the information collected includes voltage, current, and power measurements in a transmission line, located on the distribution board of a shopping mall. This data is essential for the monitoring and analysis of the electrical system, ensuring an efficient and reliable energy supply. Figure 2 shows the data acquisition and analysis design using a Raspberry Pi and Figure 3 the full diagram of the real-time energy monitoring prototype.

Fig. 2. Data acquisition design and analysis

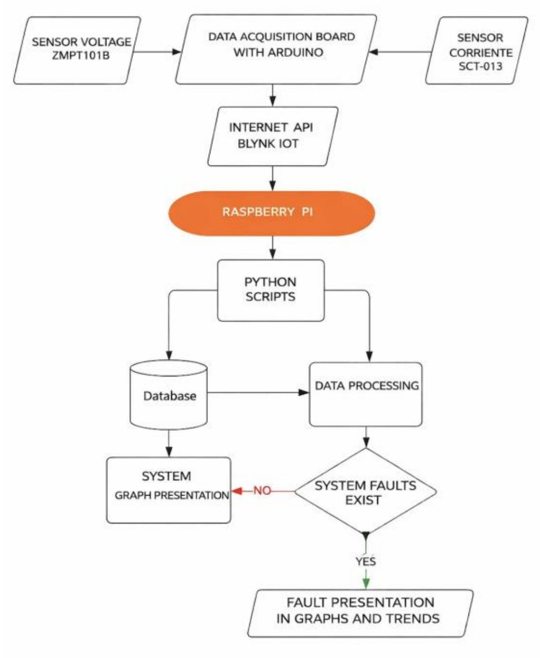

Fig. 3. Data acquisition and analysis design.

The formulas given represent how current and voltage vary over time within an electrical system. These mathematical expressions allow us to model the behavior of electrical signals, where both current and voltage oscillate in a sinusoidal manner. By measuring these signals, it is possible to calculate power consumption based on variations in current time and voltage that the system's sensors traverse. This information is key to carrying out accurate energy analysis, facilitating the management and optimization of energy consumption in electrical installations and is represented by [23]:

$$i(t) = I_{max} \cos(\omega t + \theta_i) \quad (1)$$

Where:

$i(t)$ is the instantaneous current at time t (A)

I_{max} is the maximum amplitude (A).

ω is the angular frequency (rad/s).

t is the time in which the current is measured in seconds (s).

θ_i is the phase angle of the current (rad).

$$v(t) = v_{max}\, cos(\omega t + \theta_v) \quad (2)$$

Where:

$v(t)$ is the instantaneous voltage at time t (V).

v_{max} is s the peak voltage amplitude (V)..

ω is the angular frequency (rad/s), $\omega = 2\pi f$.

t is the time (s).

θ_v is the phase angle of the voltage (rad).

The average power of a cycle with period T is given by [8]:

$$P = \frac{1}{T}\int_0^T v(t)\, i(t) dt = V_{rms}\, I_{rms}\, cos(\theta_v - \theta_i) \quad (3)$$

Where:

P is the average (active) power over one complete cycle (W).

$v(t)$ is the instantaneous voltage at time t (V).

i(t) is the instantaneous current at time t (A).

T is the period of the signal (s).

V_{rms} is the root mean square voltage.

I_{rms} is the root mean square current.

θ_i is the phase angle of the current (rad).

θ_v is the phase angle of the voltage (rad).

2.1. Harmonic analysis in the electrical network

The Fast Fourier transform (FFT) was used to detect harmonics in the power grid and analyze frequencies given current, power, and voltage data. FFT converts these given signals in the time domain to the frequency domain, allowing us to detect how the different frequencies are distributed allowing us to obtain total harmonic distortion (THD). This made it possible to evaluate the quality of the power supply and to be able to adjust and optimize the performance of the electrical circuits. In turn, FFT allows the signal to be broken down into frequency components, identifying possible faults in the electrical system.

$$\mathrm{X(k)} = \sum_{n=0}^{N-1} x(n) e^{-j2\pi kn/N} \quad (4)$$

Where:

X(k) is the discrete Fourier transform (DFT) of the signal at frequency index k.

$x(n)$ is the discrete-time signal sample at index n.

$\mathrm{j} = \sqrt{-1}$ is the imaginary number.

k is the frequency index.

N is the total number of samples

n is the time index

The formula for THD is:

$$THD = \frac{\sqrt{\sum_{n=0}^{N-1} H_n^2}}{H1} \quad (5)$$

Where:

$H1$ is the component fundamental.

H_n is harmonic component of the signal.

The formula for total harmonic distortion (THD) is calculated by obtaining the square root of the sum of the squares of the amplitudes of all harmonics, divided by the amplitude of the first fundamental harmonic. Using a Python script, the voltage, current and power signal was sampled every 0.001 seconds, this for the analysis at high frequencies, while for low frequencies the sampling was performed every 3 minutes. This approach ensures accurate evaluation of both high and low frequency components.

2.2. Grid Failure Analysis Using Time Series

Time series measurements of voltage $\mathrm{v}(t)$, current $\mathrm{i}(t)$, and instantaneous power $\mathrm{p}(t)$ were analyzed to assess grid stability and detect abnormal operating conditions. Voltage fluctuations were quantified using the short-term flicker index P_{st}, which characterizes variations that may affect human visual perception and lighting quality.

$$P_{st} = \frac{1}{T}\int_0^T (\frac{\Delta v(t)}{V_{nom}})^2\, dt \quad (6)$$

Where:

$\Delta v(t)$ is the instantaneous voltage deviation from the nominal value (V).
V_{nom} is the nominal system voltage (V).
T is the observation period (s)

Additionally, the daily load profile $L(t)$ was evaluated to identify peak demand conditions. The peak demand P_{max} was defined as the maximum instantaneous power recorded during the observation interval. To detect potential grid failures, statistical deviations of voltage and current signals from their historical averages were analyzed. Significant departures from normal behavior, together with abrupt changes in power trends over time, were classified as anomalies that may indicate overloads, unbalanced loads, or incipient electrical faults.

2.3. Power factory system simulation

For an electrical system where there is an external grid that feeds a transformer from 13kV to 0.24kV of low voltage, and a main bus that is derived into two secondary bars to feed the loads, a circuit with loads that unbalance the voltage level is simulated [24].

When uneven or unbalanced loads are connected in a commercial circuit network, the electrical system can experience voltage variations, such as spikes in one phase and dips in another, affecting the performance and stability of the system. The purpose of the simulation is to represent this phenomenon of voltage imbalance and then implement a solution that stabilizes the system and prevents loads from causing variations, improving the quality of the energy supplied [25].

2.4. Analysis of trends, graphs and faults in the electrical network

For the trend analysis of an electrical grid, voltage and current data were collected and processed with the aim of identifying patterns over time. The analysis was reinforced with graphs that presented the variations of parameters such as power and consumption.

Line graphs were used to observe trends and detect possible anomalies, which facilitated decision-making. In addition, fault analysis was reinforced in the detection, classification and rapid location of faults, allowing efficient solutions to be implemented and improving the reliability of the electrical system [26].

2.5. Data analysis libraries in Python

Several libraries were used in the design of the program made in Python for interaction with the Blynk IoT API and the due processing of the sensor data. Request is the library that allows HTTP requests to be made in real time, while MySQL. Connectors allow remote connection to a database from the program. NumPy was used for numerical calculation and time series analysis. For graphical display of the analyzed voltage, current, and power data. The SciPy. Ft library allowed the analysis to be performed in the frequency domain using the Fast Fourier Transform (FFT), while Scipy.signal.find_peaks which is a SciPy library allowed detecting peaks in the signals that in this case those peaks indicate faults or overloads in the electrical system. Date Time and time delta managed the dates that the program saved in the database when the signals were collected, allowing the sampling times to be obtained, and finally Threading is a library that allowed code executions to be carried out in different task threads, improving the efficiency of the program.

2.6. Preparation of data acquisition equipment

The energy monitoring system was designed to measure, transmit and process voltage and current data in real time. Commercial and low-cost sensors compatible with the Arduino Uno controller were used, the values collected were sent to the Blynk IoT platform that allows integration with the acquisition center, sending data to the database and energy analysis of the samples collected with Raspberry Pi.

The central acquisition unit shown in Figure 4 consists of an Arduino Uno that collected the data from the voltage and current sensors in Alternating (AC) signal, and which were converted into direct current (DC) signals. The voltage sensor that was connected to the Phase and Neutral of the outlet (Figure 4a), its DC output was connected to an Arduino Analog input receiving a voltage of 0 to 5 VDC, this signal was scaled with a library that allows to obtain the average signal (RMS) of the voltage for presentation in the main program.

The current sensor is placed on one of the transmission lines in the main circuit as shown in Figure 4c, previously conditioned using an LM358 op-amp to raise the voltage converted by the sensor to a signal connected to the analog input and that can be interpreted by Arduino Uno. The data collected by Arduino Uno was sent by serial communication to the module ESP8266 which received the data and sent to the Blynk IoT platform thanks to its ability to connect to the internet through Wi-Fi, allowing remote monitoring in real time.

Arduino Uno and ESP8266 were connected with serial communication as shown in Figure 4a, since ESP8266 has only one analog input and its reading range is from 0 to 1V which complicated at least reading a sensor with the ESP8266 module by taking into account that the voltage and current sensor are sensors that send analog values from 0 to 5V, therefore the connections of the sensors were made on an Arduino Uno, and to send these values to real-time monitoring, ESP8266 was used to process the data and send it to the Blynk IoT platform.

Blynk IoT was used as it offers ease of configuration and an intuitive interface for real-time monitoring. Thanks to the cross-platform connection, connectivity between the ESP8266 module and Raspberry Pi was achieved quickly and securely using the REST API, it did not require further configuration unlike other platforms where it is more complicated to work with services, and its

API is available in the platform's documentation, with the advantage of only placing the id of the element which in this case is the id of the current, voltage and power, and the project token to make HTTP requests from Raspberry Pi.

The capacity of Raspberry Pi as shown in Figure 4b, allowed this study to be carried out reliably, the first Python script allowed communication with Blynk IoT that served as an effective intermediary facilitating the transmission of signals that were sent to a SQL database in an orderly manner with timestamps, a second Script downloaded the SQL data, ordered and processed them using the aforementioned libraries and the analysis of the electrical network was carried out, allowing to obtain as a result graphs and relevant values that served to evaluate and give conclusions in an analytical way of the monitoring system.

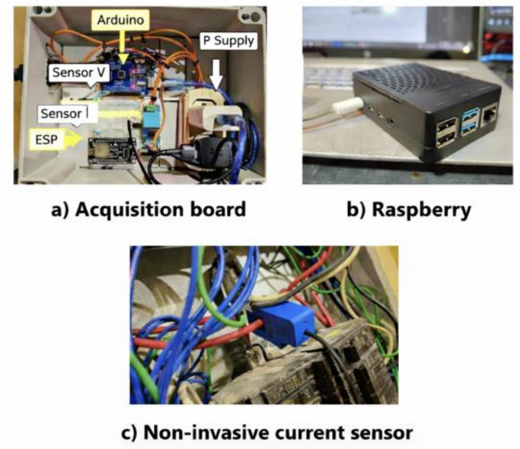

Fig. 4. Module assembly from the acquisition board to the current sensor

For the analysis using Python, 2 scripts were created, SAVE_SQL.py HTTP GET requests to the Blynk IoT API were made to obtain the current voltage values. The power was obtained by multiplying the voltage and current value, at the time of the request it is saved to SQL including the time and date. While the script is running, perform this data saving action. The second script Graphs_FP.py obtained the stored data by SQL query by creating the lite of date data and voltage and current data so that they can be graphed and analyzed. The Flicker index calculation is performed by dividing the calculation of the standard deviation and the meaning of the voltage values whose formula in Python is: flicker index = np.std (voltages)/np.mean (voltages).

The maximum and minimum values were calculated using the max () and min () function for voltage, current and power, the average values were also obtained using the np.mean () function which were then saved in variables to be graphed along with the timestamps. For the calculation of failures, the analysis of significant changes with respect to a moving average was used, defining the moving average as a window at 10, that is, the average of each set of 10 consecutive power values was calculated. The formula: moving_average_power = np.convolve (powers, np.ones (window_moving_average)/window_moving_average, mode = 'same'), calculates the moving average (np.converve ()) of the power series using convolution with a uniform window (np.ones ( )) the value 'same' ensured that the output of power values is the same input size.

The result moving_average_power is taken to calculate the changes with respect to the moving average where the difference between each power value and the moving average of powers is calculated by taking the absolute values of this calculation, the function in Python for this calculation is:

power_changes = np.abs (np.array (powers [moving_average_window//2: len (powers) - moving_average_window //2]) - moving_average_power [moving_average_window //2: len (moving_average_power) - moving_average_window //2]).

The fault threshold was defined using the standard deviation of the power change values (power_changes) to measure the average variability of the changes. From this it was obtained that for power change values that exceed the fault threshold will be unusual changes indicating the existence of possible faults, this threshold is calculated with the formula: failure_threshold = np.mean (power_changes) + 3*np.std (power_changes).

Finally, the values of power change with respect to the fault threshold are listed by performing a data tour that contains the indices in power changes that represent the possible failures indicating that there were unusually large changes with respect to the moving average using the formula: failure_indices = [i for i, change in enumerate (power_changes) if change > failure_threshold].

The load profile was calculated by hours of the day by initializing a dictionary to store the average power values of each hour and then iterated through each hour from 0 to 23 hours to finally put the indices together and present them graphically in the results, the ANOVA statistical analysis helped to determine the ratio of variance between the consumption groups in the hours of the day, the Python function to get the values of the hourly power groups is: f_statistic, p_value = stats.f_oneway (*hourly_powers).

The values of this script generate an array of data that are then adjusted with timestamps for presentation in the graphs as shown in the results from Figure 9 to Figure 14, also to present numerical data on the analysis performed in the Python script.

The main objective of this project is the development of a monitoring system for electricity grids that allows efficient energy management. To achieve this, a prototype has been designed that uses the versatility of the Raspberry Pi as the central brain, combined with a variety of sensors to collect real-time data on electricity consumption.

The methodology used in this work is based on an experimental approach, where a physical prototype was built and tests were carried out to validate its operation and performance. Through iterative design, both the system's hardware and software were refined.

The heart of the system is the Raspberry Pi, a small single-board computer that is responsible for processing the data from the sensors, communicating with the cloud and storing the information. Sensors, specifically current and voltage sensors, are responsible for acquiring electrical data. These sensors were chosen because of their accuracy, low cost, and ease of integration with the Raspberry Pi. To ensure communication between the different components, the MQTT protocol, a lightweight and efficient protocol for IoT, was used. The collected data is stored in a cloud database, which allows it to be accessed from anywhere and perform real-time analysis.

The data flow begins with the acquisition of data by the sensors. This data is sent to the microcontroller (Arduino or ESP8266) in charge of preprocessing the information and sending it to the Raspberry Pi. The Raspberry Pi, in turn, processes the data, stores it in the database, and sends it to the cloud platform. Before storing the data, a filtering and cleaning process is carried out to eliminate possible errors or noise. In addition, redundancy mechanisms were implemented to ensure data integrity.

For data analysis, the Python programming language, along with libraries such as Pandas, NumPy and Matplotlib, is used through various analyses, including the visualization of the data in the form of graphs, the calculation of descriptive statistics and the identification of patterns. These analyses made it possible to evaluate the performance of the system and detect possible anomalies in electricity consumption.

The results obtained show that the developed system can monitor electricity consumption accurately and reliably. The data collected made it possible to identify consumption patterns and detect possible opportunities for energy savings. However, some limitations were identified, such as the accuracy of the sensors at high frequencies and the Raspberry Pi's processing capacity for large volumes of data.

Thus, this work presents an energy management system based on Raspberry Pi that offers a viable and efficient solution for monitoring power grids. The results demonstrate the viability of this technology for applications in the field of energy efficiency. However, further research is required to address the identified limitations and improve the performance of the system.

Furthermore, the incorporation of machine learning techniques is planned to enhance system intelligence. Data driven models will be developed to forecast energy consumption patterns, detect incipient faults, and optimize energy management decisions through predictive and adaptive control strategies.

To mathematically describe the electrical behavior of the monitored system, a simplified power aggregation model is defined as:

Model Equation 1:

$$P(t) = \Sigma_{i=1}^{N} V_i(t) I_i(t)$$

Where:

$P(t)$ is the total instantaneous power at time t (W).

$I_i(t)$ is the instantaneous current measured at node i (A).

$V_i(t)$ is the instantaneous voltage measured at node i (V).

N is the total number of monitored sensing nodes.

This formulation enables real-time estimation of total power consumption by aggregating multi-sensor measurements, providing a scalable analytical model applicable to distributed monitoring architectures in commercial, industrial, or microgrid environments.

This formulation allows the total power consumption to be estimated in real time by combining the measurements collected from the different sensing nodes. In practical terms, this provides a clear picture of the overall behavior of the electrical network and makes the system easy to adapt to different contexts, such as commercial facilities, industrial plants, or small microgrids.

In addition to estimating energy consumption, it is also necessary to interpret these measurements to identify abnormal operating conditions. For this reason, an additional processing stage was incorporated to analyze the signals automatically and detect irregular patterns in the data.

2.7. Intelligent anomaly detection strategy

Rather than relying solely on fixed alarm thresholds, the proposed system incorporates a data-driven approach to identify anomalies directly from time-series measurements. The objective is to detect unusual behavior in voltage, current, or power signals without requiring constant supervision or specialized equipment.

First, the signals are smoothed using a moving average calculated over a sliding time window. This average represents the normal operating condition of the system within that interval. In addition, the variability of the aggregated power signal is quantified through its standard deviation, enabling a dynamic characterization of system behavior.

Based on these statistical indicators, an adaptive decision threshold is defined as.

The adaptive threshold is defined as:

$$T_f = \mu_P + k\sigma_P \quad (7)$$

Where:

μ_P represents the mean aggregated power within the observation window, σ_P is the corresponding standard deviation, and k is a sensitivity coefficient. An anomaly event is triggered whenever the instantaneous aggregated power exceeds this adaptive limit.

This strategy enables the monitoring framework to adjust automatically to normal load variations while still detecting significant deviations. Consequently, false alarms are reduced, and the system becomes more robust under fluctuating operating conditions. The adaptive nature of the method enhances scalability and facilitates its deployment across diverse electrical environments without requiring manual recalibration. The current behavior during the monitoring period is shown in Fig. 5.

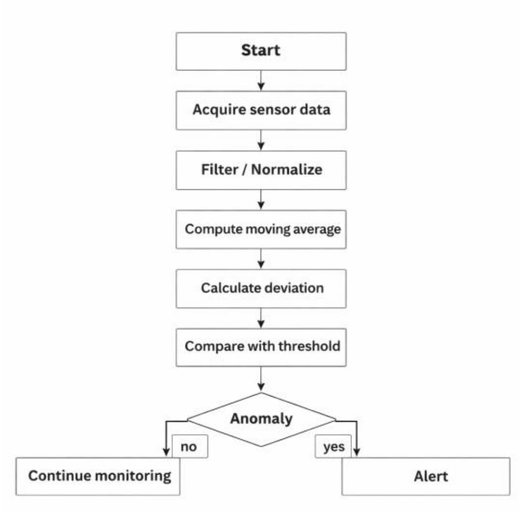

Fig. 5. Current graph during the monitoring period (A)

3. ANALYSIS AND RESULTS

3.1. Voltage measurement and data storage

Blynk IoT is used to obtain real-time data and access it through the REST API that the platform provides, the data is displayed on the platform graphically using two-gauge type meter widgets corresponding to voltage (V) and current (A), and a Label configured to indicate the power (W) as indicated in Figure 6 below.

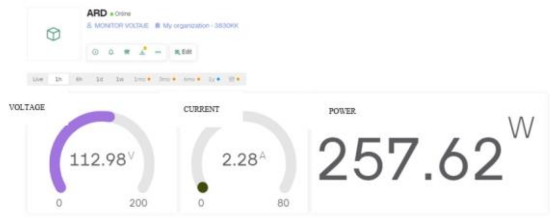

Fig. 6. Dashboard Blynk IoT.

The collected data for 6 days is stored in a MySQL database via phpMyAdmin. Using Python, this data is processed to generate voltage, current, and power graphs. MySQL. Connector was used to connect to the database, NumPy to handle the data arrays, and matplotlib to visualize the results. The resulting graphs illustrate the values measured over time, also indicating the low and high maximum peaks.

In Figure 7 you can see a peak voltage Max of 118.68V while a peak of low voltage was located at 107.70V.

In the same way, the current graph in Figure 8 shows that there was a maximum current peak at 36.40A and a minimum of 0.53A, the power that has a direct relationship with the current has a maximum peak of 4088.11W of consumption, refers to the use of appliances with a high energy demand.

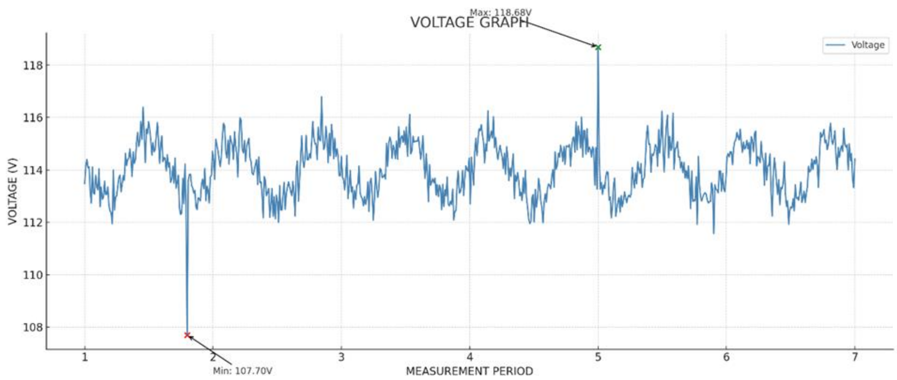

Fig. 7. Graph Voltage (V)

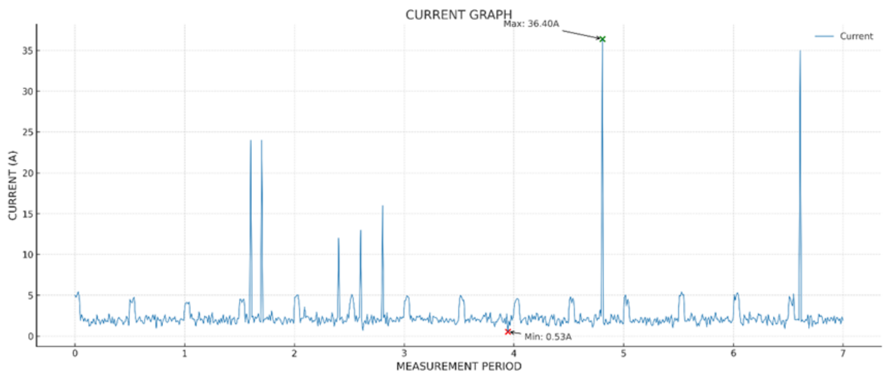

Fig. 8. Current Graph (A)

The average voltage of 113.84V with a range between 107.70V and 118.68V shows a variability in the electrical system. The average of 113.84 V indicates the typical voltage level during the analysis as shown in Figure 9. The 11V difference between the maximum and minimum suggests fluctuations in voltage. A wide range can signal potential problems in the stability of the electricity supply. There are problems in electrical distribution if the range of variability is mostly considerable with the average range measured.

The average current of 2.62 A, compared to the maximum of 36.40 A and the minimum of 0.53 A, suggests a wide variability in electric charge. This could be due to equipment that draws a lot of current at specific intervals or system problems, poor distribution of load, or faulty connections. To investigate, it is useful to analyze the pattern of current consumption over time, identify times of high demand, and check the electrical installation for problems by monitoring the system in real time.

3.2. Power trends

Power trend analysis is also obtained to graphically help identify anomalous changes in energy consumption where a change in consumer behavior is evident over time. The detection of 29 faults when comparing the measured power with the mobile power indicates that there is considerable variability in energy consumption. The graph is presented in Figure 10.

To interpret these faults, it is crucial to carry out the physical review of the electrical installation, identifying the specific times when the deviations occurred. This will help determine if there are problems with equipment, loose connections, or irregularities in the power supply. The solution could involve adjustments to the electrical system, corrective maintenance, or replacement of faulty components to improve the stability and efficiency of the electrical system.

The analysis of load per hour of day is calculated from the average power given for each hour of the day, which results in a demand that grows from 12:00 p.m. to 11:00 p.m., having as a peak demand 693 Watts consumed in the hours that can be reviewed according to Figure 11.

Power changes are calculated with the absolute differences between the power series and its moving average to detect faults or significant changes. The fault threshold is defined as the mean of the power changes plus three times its standard deviation. The results obtained from the Flicker calculation, peak demand, date and time of the maximum peak demand recorded and number of possible failures are shown in Figure 12.

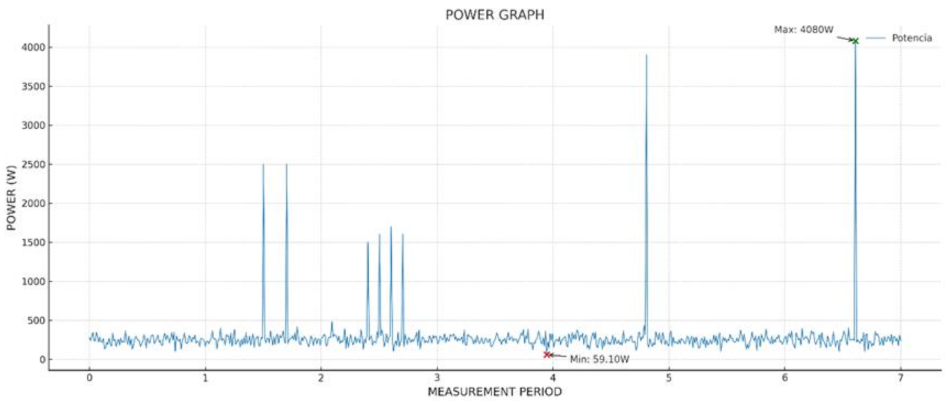

Fig. 9. Power Graph (W)

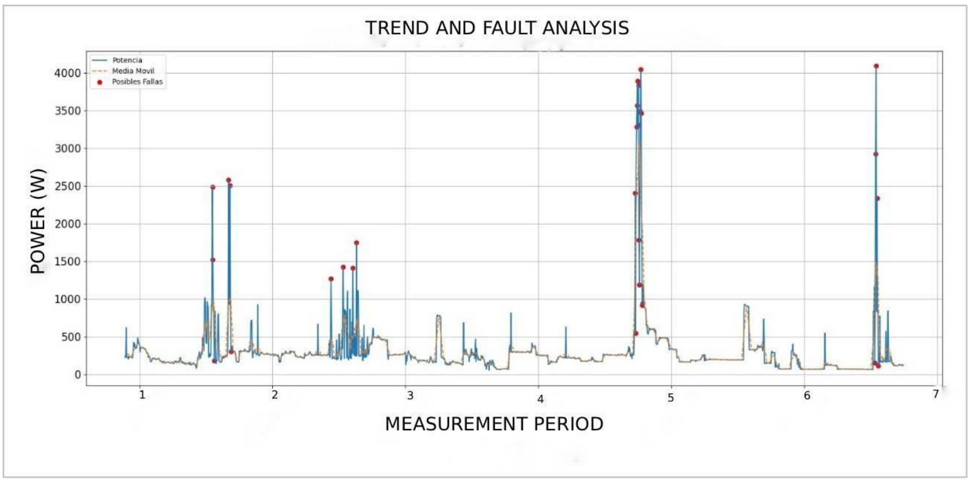

Fig. 10. Power trend analysis chart

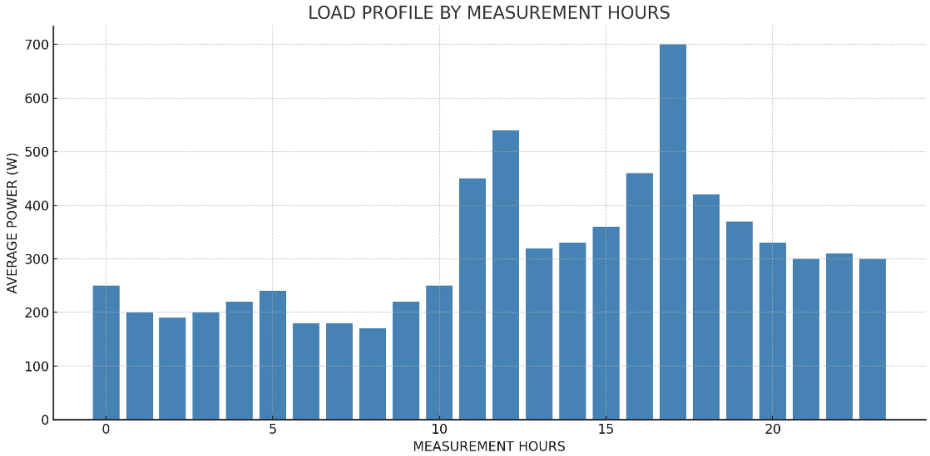

Fig. 11. Load profile graph by hours of the day

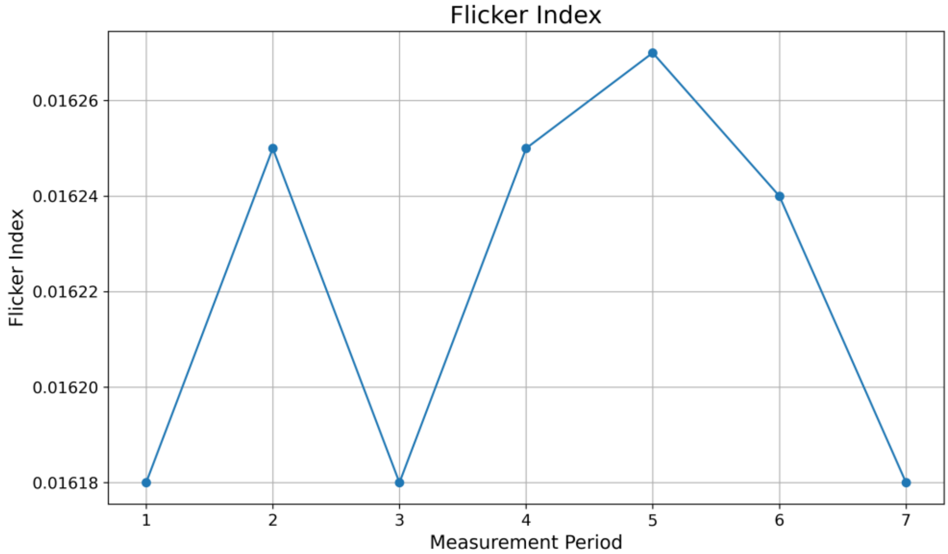

Fig. 12. Flicker Index

The Flicker index, or flicker index, is a quantitative measure that tells us the perception of fluctuation or flicker in a light source. The higher the Flicker index, the greater the observer's perception of flickering. The Flicker Index located at 0.02 (Figure 11) indicates that the voltage fluctuation is at a very low level therefore the electrical circuit in this sampling does not detect flickering of lights, the power quality is optimal at this point. The calculation corresponds to the ratio of the standard deviation of the voltage to the mean voltage.

The peak of maximum demand recorded was detected at 4088,109 W corresponding to the maximum demand where a high consumption is evidenced corresponding to an event recorded on 2024-06-25. This high consumption is evident as a critical point in the system's load. 29 possible voltage reading faults were detected, which can be attributed to a poor distribution in the main circuit. Specifically, a transmission line is receiving load from electric heaters, motors, and other devices, which is not balanced with respect to the adjacent line, this lack of balancing causes fluctuations in voltage, resulting in voltage surges and drops when connecting equipment that unbalances the voltage signal.

3.3. ANOVA analysis

Analysis of variance, or ANOVA, is an invaluable statistical tool when it comes to comparing the means of more than two groups. In the context of an energy monitoring system, its usefulness is revealed in multiple facets. Let's imagine that we want to know if the electricity consumption of a building varies significantly between the different seasons of the year. The ANOVA (Analysis of Variance) allows us to compare the average consumption for summer, autumn, winter and spring, and to determine if there is a statistically significant difference between them. Thus, the ANOVA makes it possible to compare the average consumption for summer, autumn, winter and spring, and to determine if there is a statistically significant difference between them. Beyond this simple application, ANOVA can be used to evaluate the effectiveness of different energy-saving measures.

The ANOVA analysis results in F statistics of 9.48, this value indicated the ratio of variance between the hours of the day. A high F value suggests that there is more variability between hours than within them, which specifically differences in the means. A p-value of 2.56x10^31 indicated a very low value compared to the commonly used significance level of 0.05. Given this value, it was estimated that the probability that the observed differences between the means are due to chance is practically zero.

Next, it can be inferred that the ANOVA analysis, which allows correlating and studying, is the level of failures that can occur according to the variance of the hours of the day, in addition, to verify the impact of the seasons of the year on these failures, in order to study in a meaningful way and with solid bases, the aspects involved in the occurrence of these failures. Thus, when carrying out this study, it is convinced that there are specific failures due to related elements that are determinant from the variance. This analysis is a fundamental process within the work, and its greatest contribution lies in identifying factors that can generate failures, associated with levels of variability with respect to external elements that cannot be fully controlled by the electrical network, such as the time of arrival of the work, the use of certain electrical appliances and others.

The results are interpreted by identifying that there are significant differences between the power averages at different times of the day, this means that energy consumption is not constant throughout the day and varies every hour, then it is possible to identify the peak hours of demand and which appliances cause a higher consumption and corroborate the analysis with the result seen in Figure 12.

A simulation is created in Power Factory as evidence of the biggest problem in the main voltage distribution circuit of a shopping center which is the imbalance of the loads that cause voltage peaks generating possible failures to the system, the basic elements of Power factory are used to perform the simulation with a load whose Active power is above 5 MW (Mega Watts) assuming that there was a considerable expansion of loads that may include installations of air conditioning units, installation of motors, among others, the Power Factory circuit is included in the following figure with the additional load problem 4 IMBALANCE.

Given this simulation in Figure 13 whose bars are in imbalance when configuring one of the loads went from 5MW to 10 MW, with the other loads
being low in comparison, the results of the following Table 1 are obtained.

The results indicate the voltage drop due to the imbalance of the loads produced by an expansion in the electrical circuit when placing load 4 which generates an energy imbalance resulting in a voltage drop of 0.24KV to 0.21KV shown in Figure 14, a deterioration in the voltage profile due to the concentration of high load in a single node. This imbalance observed in the simulation is also observed in the physical distribution circuit analyzed with Raspberry Pi in Python and that produces risks of overheating and degradation of the main transformer.

The analysis indicates that the system will not be able to adequately support the increase in demand without having voltage failures, in response to these results it is proposed to implement a new transformer and distribute the load 4 that produces imbalance to this new node, the transformer must also be able to support the growth in demand in case of expansion.

Therefore, the loads are distributed by installing a new transformer that can cover the current demand, thus leaving 5MW in load 4 IMBALANCE in the current circuit and 5MW in the new transformer, this due to the growth that can be the installations of air conditioning plants, equipment necessary for each commercial premises, acquisition of new technologies whose loads increase electricity consumption.

Given the solution by installing the new transformer, the busbars no longer produce the voltage imbalance when one of the loads is in maximum demand, thus managing to distribute the loads within a complex of commercial premises and alleviating voltage fluctuations before taking further corrective measures. The results are shown in Table 2 below.

Table 1. Load voltages

Name	Grid	Nom.L-L Volt.kV	UI Magnitude kV	At magnitude p.u.	In the Angle deg
Bar1	Grid	13.8	13.8	1.0	0
Bar2	Grid	0.24	0.2166	0.9027	-24.1291
Bar3	Grid	0.24	0.2166	0.9027	-24.1291
Bar4	Grid	0.24	0.2166	0.9027	-24.1291

Table 2. Load voltages before corrective actions

Name	Grid	Nom.L-L Volt.kV	UI Magnitude kV	At magnitude p.u.	In the Angle deg
Bar1	Grid	13.8	13.8	1.0	0
Bar2	Grid	0.24	0.2166	0.9027	-24.1291
Bar2(1)	Grid	0.24	0.2166	0.9027	-24.1291
Bar3	Grid	0.24	0.2166	0.9027	-24.1291
Bar4	Grid	0.24	0.2166	0.9027	-24.1291

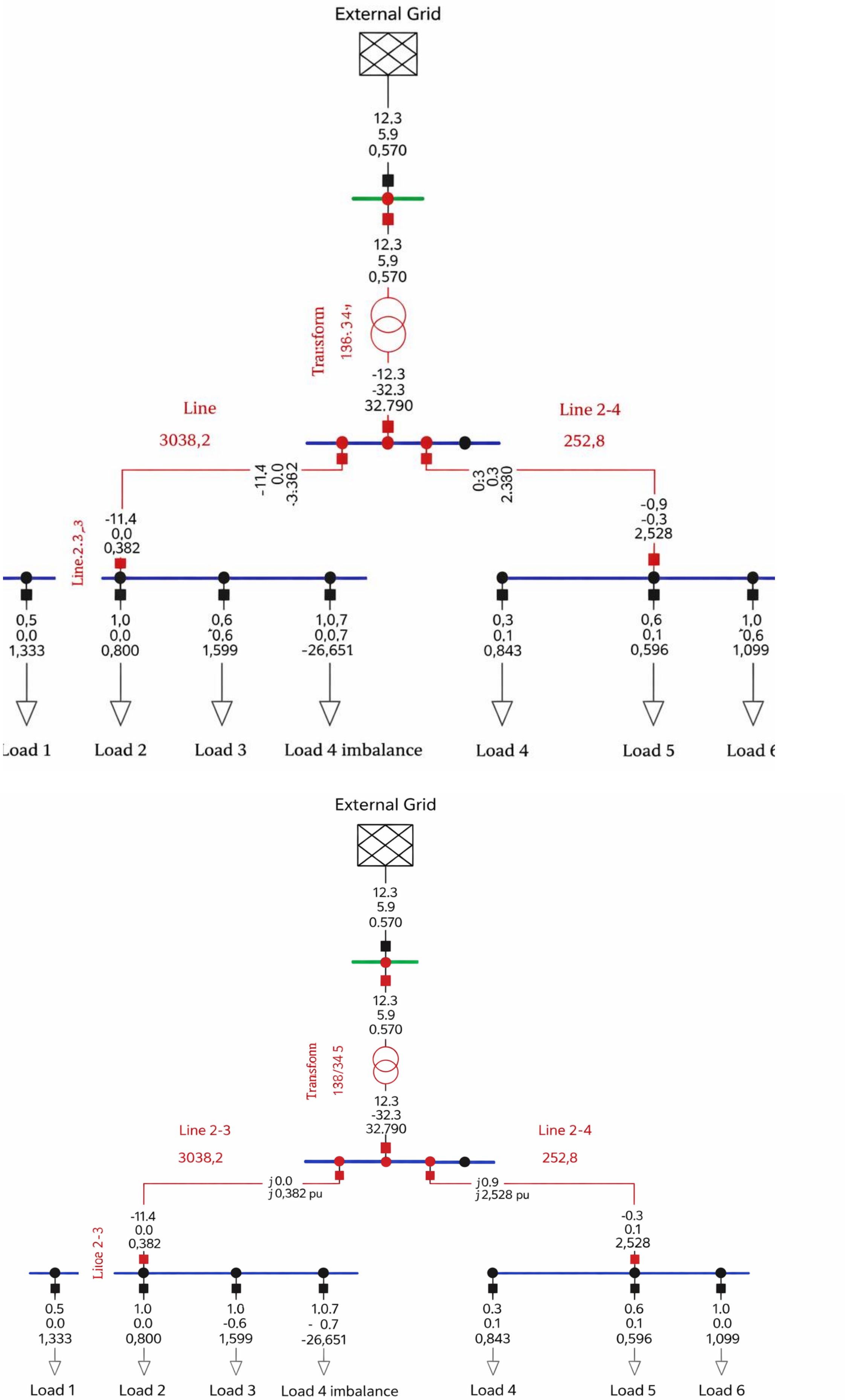

Fig. 13. PF Load Simulation

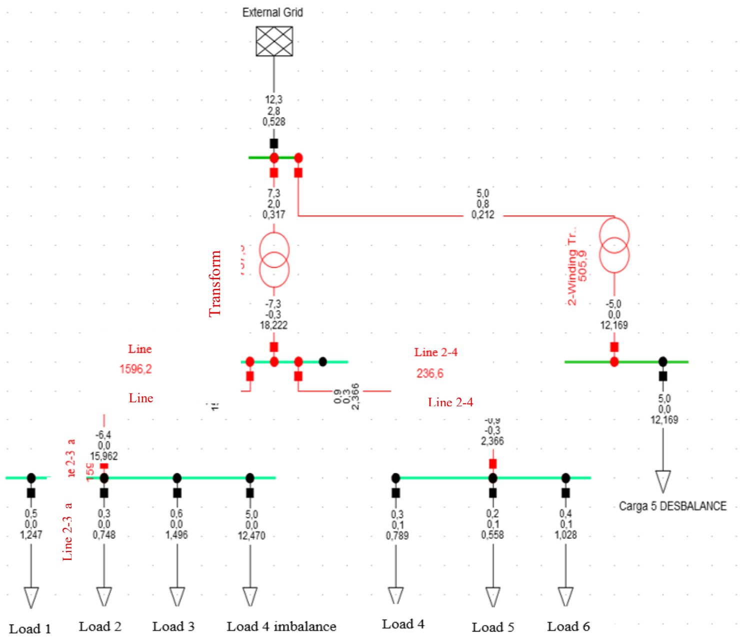

Fig. 14. PF Load Solution Simulation

Finally, we obtain Table 3 of loads already distributed correctly, considering the possible increase in loads in the electrical system of a shopping center, simulating the real problem of voltage fluctuation and its proper distribution. This redistribution stabilized voltage fluctuations in the system by ensuring levels within operating limits and preventing overheating at the nodes.

A detailed simulation was carried out in Power Factory to model the impact of a load imbalance on an electrical distribution system. The simulated system, representative of a grid, was subjected to an unbalanced load by introducing a single-phase load of 10 MW in one of the phases. To ensure the accuracy of the simulation, real network data such as topology, line impedances, and load curves were used.

The 1.8% imbalance in the load generated a series of adverse consequences in the system. Negative sequence currents increased significantly, which could lead to overheating in electrical conductors and equipment. In addition, a voltage drop was observed in the most loaded phase, affecting the operation of sensitive equipment. Transformer losses also increased due to circulating currents.

To mitigate the effects of the imbalance, an engineering solution was implemented: the addition of a new transformer at a strategic point in the network, about 20 meters from the main source. This measure allowed the load to be redistributed more evenly between the phases, considerably reducing negative sequence currents (35%) and voltage drops from 1.8% to 1.2%. The simulation results showed a substantial improvement in the quality of the power supplied from 88% to 95.7%.

To evaluate the effectiveness of the proposed solution, the results of the simulation were compared with the energy quality standards established by current regulations, they were also compared with the work carried out by Román, Mora and Londoño [30]. Those who state in their thesis who had a maximum error of 1.6%, so it is determined that the model presented is of high reliability. The results demonstrated that the modified system meets regulatory requirements, thus ensuring a reliable and efficient power supply.

The analysis of the simulation results allowed valuable conclusions and recommendations for future studies to be drawn. It is suggested to implement continuous system monitoring to Evaluate the evolution of the load balance and the effectiveness of the measures implemented. It is also interesting to explore the incorporation of distributed generation sources, such as solar panels or wind turbines, and to analyze their impact on load balancing. Optimizing transformer location and developing advanced control algorithms also represent promising areas for future research.

In summary, the study demonstrates the importance of maintaining an adequate load balance in an electrical system. Simulation in Power Factory has been a fundamental tool to evaluate the effects of the imbalance and the effectiveness of the corrective measures implemented. The results obtained, verifying that the level of voltage failures was reduced by 0.6%, or in such a case, in comparison, the work addressed with the proposed model, a comparison was obtained where the result of 1.2 is significantly lower than the 1.6% also proposed, which derives in a contribution to scientific knowledge in the field of power quality and offers valuable recommendations for the improvement of the electrical systems of distribution.

Table 3. Charging powers

Name	Grid	Terminal Busbar	At magnitude p.u.	Active Powe MW	Reactive Power Mvar	Apparent Power Mvar	Power Factor
Load1	Grid	Bar3	0.9655	0.5	0	0.5	1
Load2	Grid	Bar3	0.9655	0.3	0	0.3	1
Load3	Grid	Bar3	0.9655	0.6	0	0.6	1
Load4	Grid	Bar4	0.9655	0.3	0.1	0.3162	0.9487
Load4 IMBALANCE	Grid	Bar3	0.9655	5	0	5	1
Load5	Grid	Bar4	0.9655	0.2	0.1	0.2236	0.8944
Load5 IMBALANCE	Grid Grid	Bar2(1)	0.9884	5	0	5	1
Load6	Grid	Bar4	0.9655	0.4	0.1	0.4123	0.9701

5. DISCUSSION

Power distribution systems in commercial, industrial, and institutional facilities often face voltage stability problems that may affect their normal operation. Voltage drops, imbalances, and even blackouts are common challenges in electrical infrastructures where load demand changes throughout the day [27]. Maintaining voltage levels within acceptable limits is essential to guarantee system reliability and avoid operational interruptions [28]. Although this study was validated in a shopping mall, the challenges identified are not exclusive to this type of facility. Similar conditions can be found in many modern electrical installations.

Improving power quality has become increasingly important due to the growth of nonlinear loads and high-demand equipment. Poor load distribution, harmonic distortion, and peak demand conditions can gradually deteriorate electrical systems if they are not monitored properly [29]. In this context, continuous monitoring provides valuable information that supports better maintenance planning and operational decisions.

While the experimental validation was carried out in a commercial shopping center, the monitoring approach presented in this work is not limited to this specific environment. The proposed system is based on real-time measurement, statistical analysis of electrical variables, and a modular hardware structure. These elements can be applied in other contexts such as industrial plants, university campuses, hospitals, residential complexes, or small microgrids. The main contribution of the work lies in demonstrating that a low-cost and adaptable monitoring structure can provide meaningful electrical analysis in different types of installations [30].

The statistical analysis also helps to identify other problems such as Total Harmonic Distortion or THD by identifying the presence of non-linear loads such as electronic equipment, power supplies, variable speed drives that introduce harmonics, in large shopping centers the situation becomes critical when the energy demands are not analyzed, producing visual distortion in lighting, damage to equipment in commercial premises, among others [31]. Is another important aspect in modern electrical systems, especially where electronic devices, variable-speed drives, and power converters are widely used [20].

Harmonics can cause overheating, reduced equipment lifespan, and energy inefficiencies. The integration of harmonic analysis into the monitoring process allows early identification of abnormal conditions and supports corrective measures such as load redistribution or the installation of filters [32].

The results obtained from the case study show measurable improvements in voltage stability after load redistribution, including a reduction in voltage deviation compared to related works. Although the validation scenario was specific, the methodology used to detect imbalances and evaluate corrective actions can be replicated in other electrical systems facing similar operational challenges [33].

The implementation of a real-time monitoring system supports sustainable and efficient energy management across diverse electrical infrastructures by enabling early detection of operational deviations and performance losses. Through timely identification and correction of inefficient consumption patterns, energy waste can be reduced, thereby lowering the carbon footprint and minimizing environmental impact. Furthermore, optimizing equipment operation contributes to extending its service life and reducing maintenance costs, ultimately improving overall system reliability [34].

The statistical time-series analysis applied in this work also opens the possibility for future improvements. While advanced predictive techniques were not implemented in this study, the monitoring structure can serve as a basis for incorporating more advanced forecasting or optimization tools in future developments [35].

It is important to recognize some limitations. Raspberry Pi-based systems may face processing constraints in large-scale deployments with very high data volumes [36]. However, due to the modular and distributed nature of the architecture, the system can be expanded gradually according to the needs of the installation.

6. CONCLUSIONS

Electrical analysis shows voltage and current fluctuations, which can suggest problems in the stability of the electrical circuit. With the calculation of average voltages and the ranges obtained in this article, voltage variability was defined is significant, which in the long term can be a power quality problem. These fluctuations measured over time can be linked to improper load distribution or faulty connections in the internal electrical circuit.

The analysis of average current and maximum peaks obtained reinforces the hypothesis that the energy demand is variable caused by intermittency in equipment that requires high levels of current for its operation. The graphs reinforce the study by obtaining power trends where 29 possible failures are reflected, which requires that the electrical network physically in the facilities be reviewed to identify and perform corrective maintenance.

Additionally, thanks to the analysis of Flicker indicates that there are no problems with flickering of luminaires despite voltage fluctuations, the power quality is not affected in terms of visual stability of luminaires and is optimal for lighting. However, peak demand peaks were detected, indicating a simultaneous use of high-consumption equipment such as electric stoves, air conditioners, motors, and electric heaters.

This study focuses on understanding and reducing the factors that can affect the stability of electrical systems in modern power distribution networks. It proposes practical and adaptable solutions, such as load balancing and power factor correction, which can be applied in different types of electrical installations beyond the specific case analyzed. The results of Power Factory. They validate the hypotheses raised in the analysis of voltage fluctuations, showing the need to improve the distribution of loads or implementation of a new transformer that supports the demand.

Other road solutions for the handling of loads within a shopping center given the simulation of a distribution circuit (where the power of the simulation loads was increased to make large-scale problems more visible), is the use of voltage regulators, use of capacitors for reactive power compensation for power factor correction in places where the use of reactive loads is identified, harmonic filters due to the amount of electronic equipment contained in shopping centers, review of the wiring system and the real-time monitoring proposed in this topic to identify demand problems in the electrical system.

The benefits of having real-time energy monitoring are that its adoption will reduce the risk of electrical failures, also to identify when the electrical system requires expansion, reducing operating costs and to carry out preventive maintenance instead of corrective maintenance that raises operating and investment costs.

It is estimated that with the advent of artificial intelligence, energy monitors will be able to predict future scenarios and provide a much deeper analysis without the need for more complex measurement and computing equipment, thus improving energy efficiency, energy and money savings. The electricity system can also be significantly improved by implementing renewable energies such as solar panels to give better stability to the electricity system at peak demand.

The implementation of a Raspberry Pi-based real-time monitoring system in shopping malls has revealed the critical importance of power quality in these environments. Voltage fluctuations and current spikes detected indicate stability issues in the electrical system and underscore the need for more proactive energy management.

The rapid response capability of this system allows emerging problems to be identified and addressed before they become major failures. Not only does this extend the life of electrical equipment, but it also reduces the operating costs associated with repairs and replacements. By detecting irregular demands and scheduling preventive maintenance, shopping centers can optimize their energy consumption and minimize service interruptions.

To further improve power quality and energy efficiency, several complementary measures can be implemented. Load balancing, installation of harmonic filters and capacitors, and optimization of power factors are effective strategies to reduce total harmonic distortion and improve system stability. In addition, integrating renewable energy, such as solar panels, can help reduce reliance on the power grid and lower energy costs.

Artificial intelligence can play a critical role in optimizing monitoring systems. By analyzing large volumes of historical data, machine learning algorithms can identify consumption patterns, predict failures, and optimize equipment operation. This allows for more proactive and efficient energy management.

Future research may focus on developing more advanced and scalable monitoring systems. The integration of IoT sensors, the utilization of low-power communication technologies, and the implementation of cloud platforms can enable wider coverage and greater data processing capacity.

The data obtained in this study validates the initial hypothesis about the importance of energy quality in shopping centers. The voltage fluctuations and current spikes detected demonstrate the need to review and improve the electrical infrastructure of these buildings. By identifying critical points in the grid, it is possible to implement corrective measures to ensure a reliable and efficient electricity supply.

In conclusion, real-time monitoring of power quality in shopping malls is an essential tool to improve energy efficiency, reduce operating costs, and ensure environmental sustainability. By combining technologies such as Raspberry Pi, artificial intelligence, and renewable energy, it is possible to create intelligent and adaptable energy management systems that meet the needs of modern shopping malls.

The benefits of this technology extend beyond shopping centers and can be applied to a wide range of sectors, from industry to the residential sector. By encouraging the adoption of more efficient energy management practices, you contribute to building a more sustainable and resilient future.

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