

Internet of Things (IoT) Based Power Quality Monitoring System

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ARTICLE INFO

Article history:

Received 21 February 2025
Received in revised form 23 August 2025
Accepted 23 September 2025
Available online 30 October 2025

Keywords:

Power quality; Internet of Things (IoT);
disturbances; monitoring system,
Simulink

ABSTRACT

Every electrical network experience various power quality disturbance that necessitates meticulous planning, preparation, measurement, and, most crucially, the ability to promptly identify issues as they arise. Currently, the system faces limitations in remote data access and experiences delays in identifying disturbances due to the manual analysis required once disturbances are detected. The objective of this research is to integrate IoT technology to enhance the system by enabling real-time remote data access and automated classification of disturbances. The methodology of this project involves three main stages: first, generating power quality disturbance signals using Simulink software; second, developing a disturbance classification system on Arduino; and finally, designing and implementing a monitoring system on Arduino using ThingSpeak as the IoT component. The results demonstrate the successful detection and classification of the tested power quality disturbances by the developed monitoring system.

1. Introduction

Power quality (PQ) refers to the measurement of electrical power signals produced, typically assessed using a PQ analyzer to evaluate the quality of supplied power and detect any disturbances [1]. In recent times, the nature of electrical loads has become more complex due to increased use of power electronic equipment, leading to deviations from typical sinusoidal voltage waveforms [2]. Power quality disturbances are defined as any alterations in the power waveform (voltage and current) that disrupt the smooth operation of electrical equipment [3]. Industries, heavily reliant on electrical machinery, frequently encounter such issues, which can have significant economic implications.

Some types of power quality disturbances include voltage sag, voltage swell, interruption, harmonic, spike and many others [4,5]. This paper will only focus on four common types of disturbances which are voltage sag, voltage swell, transient and interruption which have been monitored by the proposed project. Voltage sag is a decrease in RMS voltage magnitude and normally

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<https://doi.org/10.37934/ard.146.1.105119>

lasts between 0.5 and ten cycles within the customers' premises; it is the most prevalent type of power quality disturbance [6]. It is typically caused by factors such as sudden load increases, faults, or starting large equipment [7].

Next is the voltage swell, which is an increase in RMS voltage magnitude over a short duration cycle. It may occur because of energizing a large capacitor bank or de-energizing a large load [8]. Mitigation strategies include using voltage regulators, surge protectors, and proper system design to minimize their occurrence and impact [9].

A transient is a disturbance that involves a sudden, large change in either current or voltage. It can even reach thousands of volts and amperes, even in a low voltage system [10]. This disturbance occurs only for a short period but can still cause significant damage to the equipment or system involved. This disturbance is often caused by external factors such as lightning strikes, power surges, electromagnetic interference, or switching events [11].

Lastly is the interruption. An interruption refers to a sudden and temporary loss of electrical power supply to a system or equipment [12]. Interruptions can occur due to various factors such as faults in the power grid, equipment failures, or planned maintenance activities [13]. These disruptions can lead to downtime, data loss, or damage to sensitive equipment.

Ensuring good power quality is essential for the reliable operation and longevity of connected electrical loads [14]. Poor power quality can lead to failures or reduced efficiency, necessitating higher maintenance costs associated with installation and operation [15]. Therefore, prioritizing power quality management is crucial for maintaining efficient industrial operations and minimizing associated expenses.

By using the correct power quality monitoring device, various problems can be analyzed and solved without excessive spending on troubleshooting power quality disturbances [16]. Despite advancements in power system technology, the devices available in the market lack the implementation of Internet of Things (IoT) technology. Integrating IoT into power quality monitoring systems can provide real-time data that is accessible remotely by users [17]. When disturbances occur and data are not classified promptly by the system, it can lead to delays in resolving the disturbance.

Rahul and Bharat Choudhary developed a hybrid approach that combines machine learning and deep learning, utilizing regression models like Extreme Gradient Boosting, CatBoost, Light Gradient Boosting, and LSTM neural networks [18]. This method achieves an impressive average accuracy of approximately 99.51% across six power quality event classes. However, the use of boosting models and convolutional neural networks can introduce complexity in terms of implementation and understanding.

Rahul, M. Gangadharappa, and Ashwani Kharola employed a deep learning approach using transfer learning with seven pre-trained CNN architectures [19]. Their method utilizes regularization techniques to achieve superior accuracy and faster training/testing times compared to existing CNN models. Validated through laboratory experiments, the approach demonstrates high accuracy in classifying various power disturbances. While leveraging transfer learning for improved performance and real-world applicability, the method's complexity and resource-intensive nature pose challenges in terms of implementation.

Mohamed Ali *et al.*, [20] combined wavelet scattering feature extraction with LSTM techniques to effectively identify and classify power quality issues using synthetic disturbance signals in MATLAB simulations. This approach enables efficient feature extraction for time series analysis and achieves automatic identification and categorization of power quality problems. Despite its versatility, the method's effectiveness depends on the quality and quantity of training data, and its implementation is technically complex.

Vishakha Pandya et al. proposed an innovative algorithm combining the Stockwell Transform, Hilbert Transform, and PQ-index for detecting and classifying power quality disturbances, achieving over 99% efficiency. This method outperforms previous studies based on the Stockwell Transform and rule-based decision trees. While the approach is highly effective, its implementation is complex due to the multiple steps involved and the need for appropriate threshold selection for PQ-index, H-index, and ST-index.

This paper presents the development of an IoT-based power quality monitoring system to address the challenges of real-time data access and automated disturbance classification in electrical networks. Current systems face limitations due to manual data analysis, causing delays in identifying power quality issues. The proposed solution integrates IoT technology to facilitate real-time remote monitoring and automatic classification of disturbances. The methodology involves generating power quality disturbance signals using Simulink, developing a disturbance classification system on Arduino, and implementing a monitoring system using ThingSpeak for cloud-based data management. Simulations in Simulink produce various disturbance signals, which are transmitted to the ThingSpeak cloud and processed by Arduino. The monitoring system, incorporating ESP32, LEDs, buzzer, and an LCD, successfully detected and classified selected power disturbances such as transients, voltage sags, voltage swells, and interruptions. The results indicate high accuracy in disturbance detection and classification demonstrating the system's effectiveness in real-time power quality monitoring.

2. Methodology

In this section, the workflow of the project is described in a more comprehensive way to help with understanding of the project. Figure 1 shows the flowchart of the project. The project started with designing the circuit model for each disturbance using Simulink. There are three circuit models that were constructed to simulate the disturbance signals. Firstly, a model of energization of capacitor bank to simulate the transient signal was created. Next, the model of three-phase load switching simulated the voltage swell signal meanwhile; to simulate the voltage sag, a model of energization of three phase heavy load was constructed.

For simulation of interruption, a permanent three-phase fault was modelled. After that, the constructed models were integrated with ThingSpeak. A block function of ThingSpeak output was added to send the data from Simulink to ThingSpeak cloud. After the integration of the two components was successful, the project continued with building the classification system for disturbance signals in Arduino. The system created was then evaluated whether the results obtained were correct or not.

After the classification system worked well for all four disturbances, the hardware configuration was installed on a breadboard. The hardware used are ESP32, LCD I2C, LED and Buzzer. Once the hardware monitoring system ran as expected, all the system was integrated. The inputs from Simulink were simulated and the values were sent to ThingSpeak cloud. Then, the ESP32 read the value. If there is a disturbance presented in the system, the monitoring system in ESP32 will send the signal to LED and Buzzer module to alert the user. After that, the LCD will display the per-unit value and also the type of disturbance that occurred. Finally, the data was gathered, and analysis was performed.

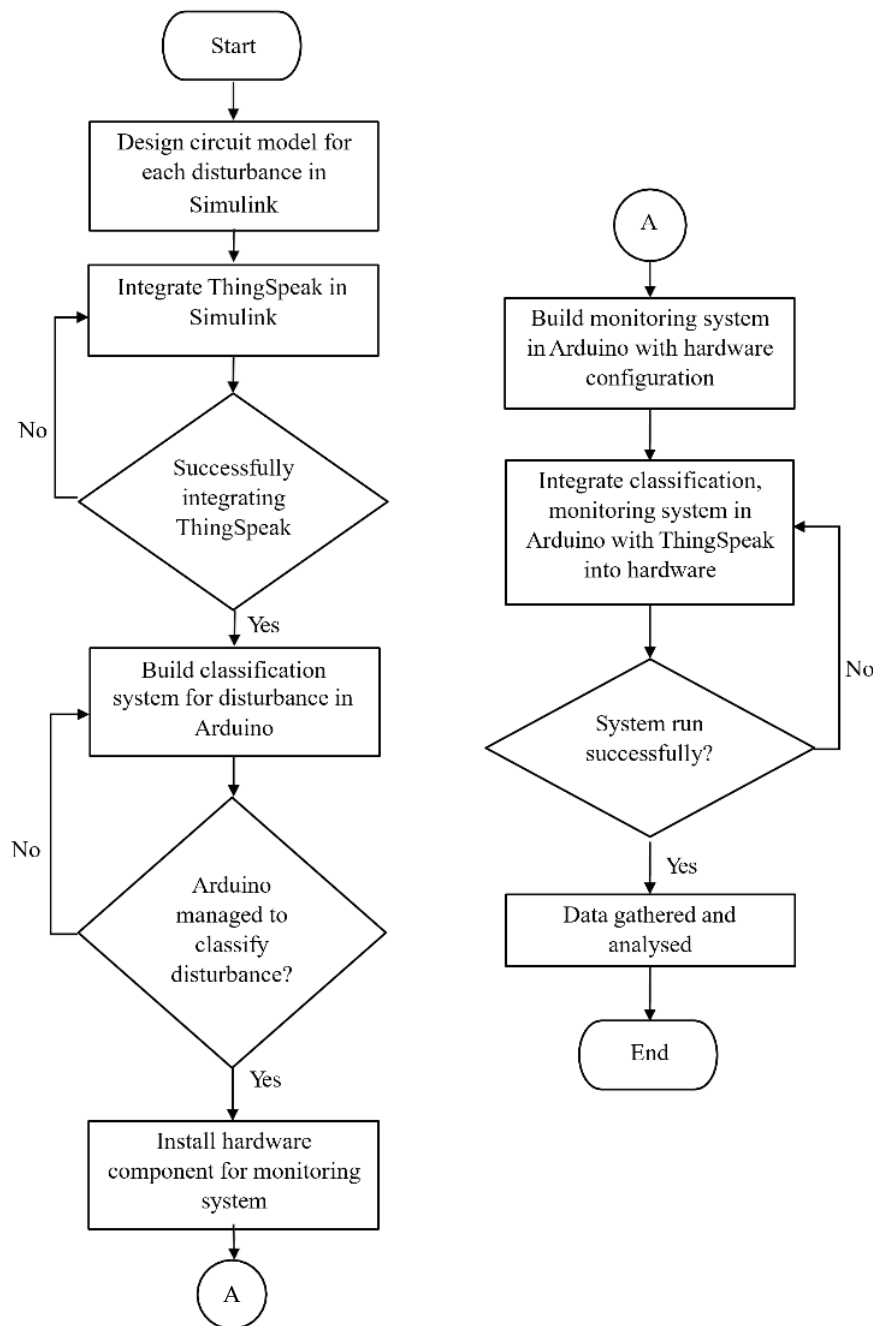


Fig. 1. Overall project flowchart

2.1 Designing Circuit Models for Generating Disturbance Signals

Matlab Simulink had been used to construct the circuit to generate the disturbance signals. Figure 2 shows the flowchart of generation of the power quality disturbances. Some of the components used to generate the disturbance signals are such as three-phase source, three-phase circuit breaker, RL load, capacitor, universal bridge, three-phase fault, and three-phase transformer. The model needs to be constructed based on the desired type of disturbance signals. The capacitor bank model (Figure 3) was used to simulate transient, three-phase large load model was used to simulate voltage sag and swell (Figure 4). Lastly, the permanent three-phase fault was used to simulate interruption (Figure 5). After constructing the circuit model, the parameters for each component need to be

initialized together with the duration of the disturbance. The parameters for all the circuit models together with the durations are listed in Table 1, Table 2 and Table 3.

After setting up the parameters, the simulation of the circuit models was run. The checking was made whether the simulated signals met the expectation according to the correct disturbance signals. Then, the signals were ready to be used as the input data for Arduino.

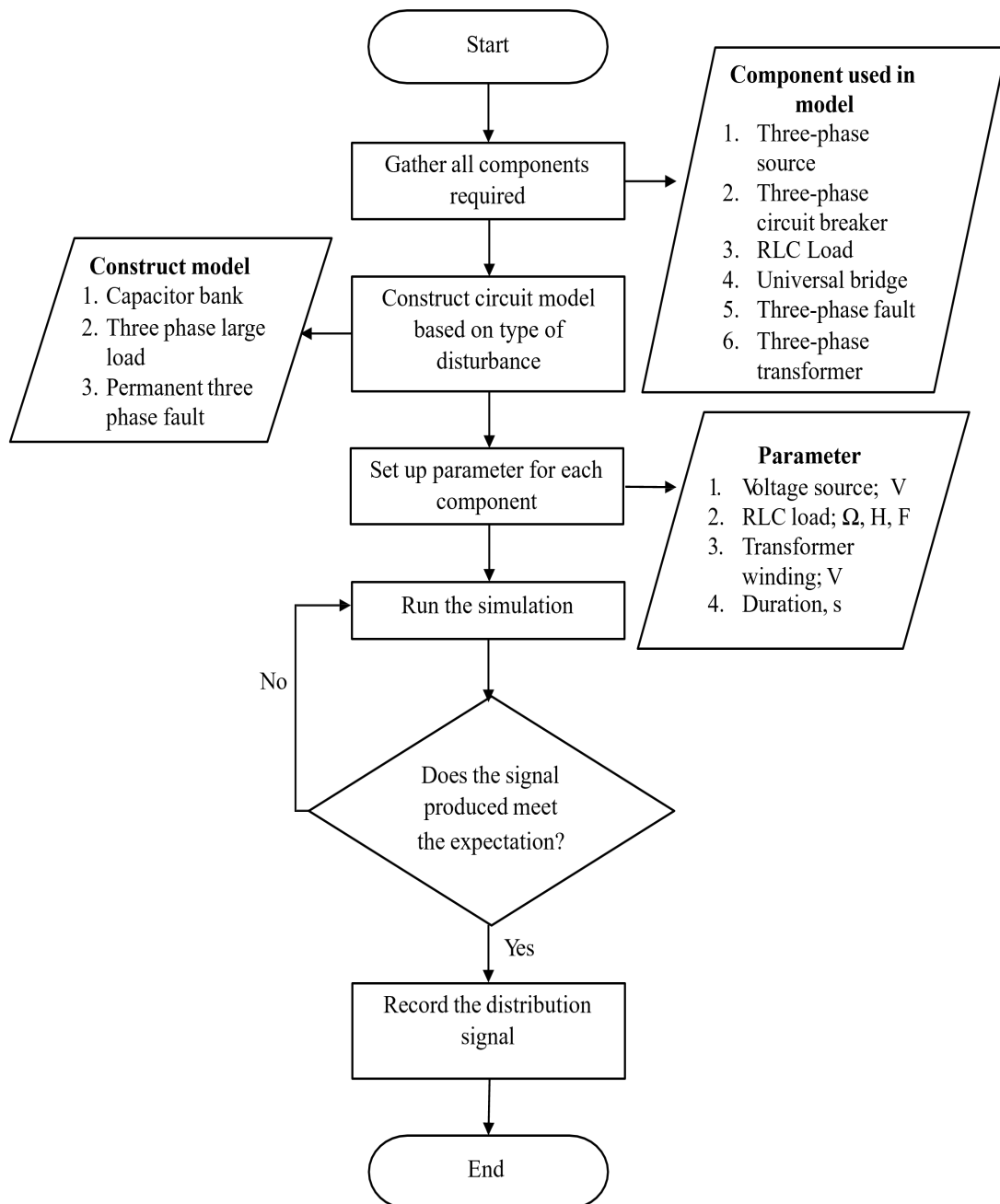


Fig. 2. Flowchart of designing circuit models for generating disturbance signals

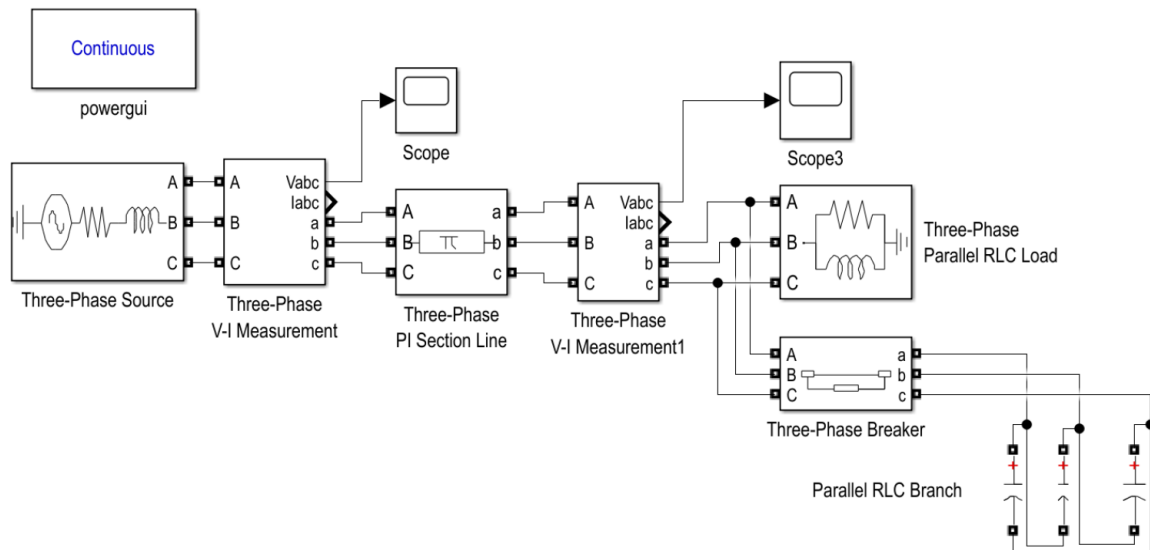


Fig. 3. Circuit model of capacitor bank to simulate transient

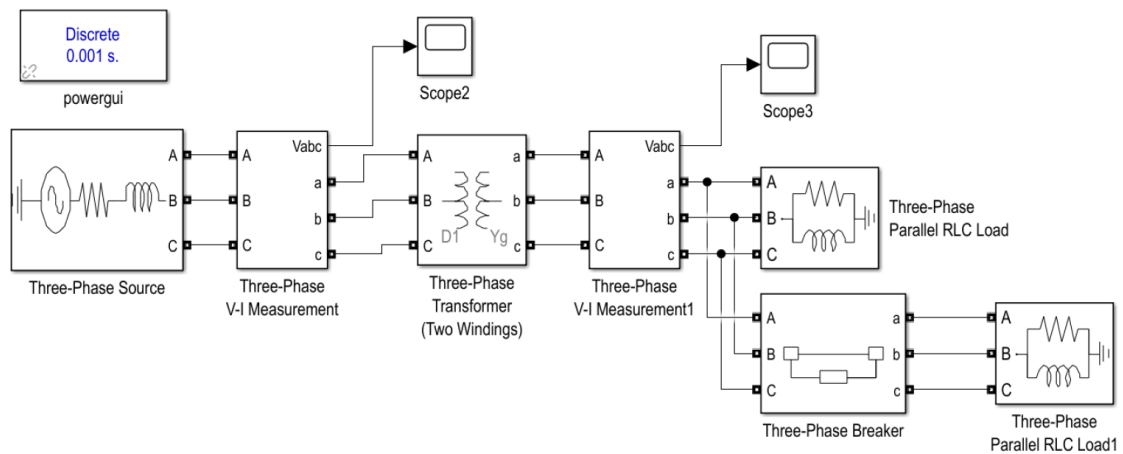


Fig. 4. Circuit model of three-phase large load to simulate voltage sag and voltage swell

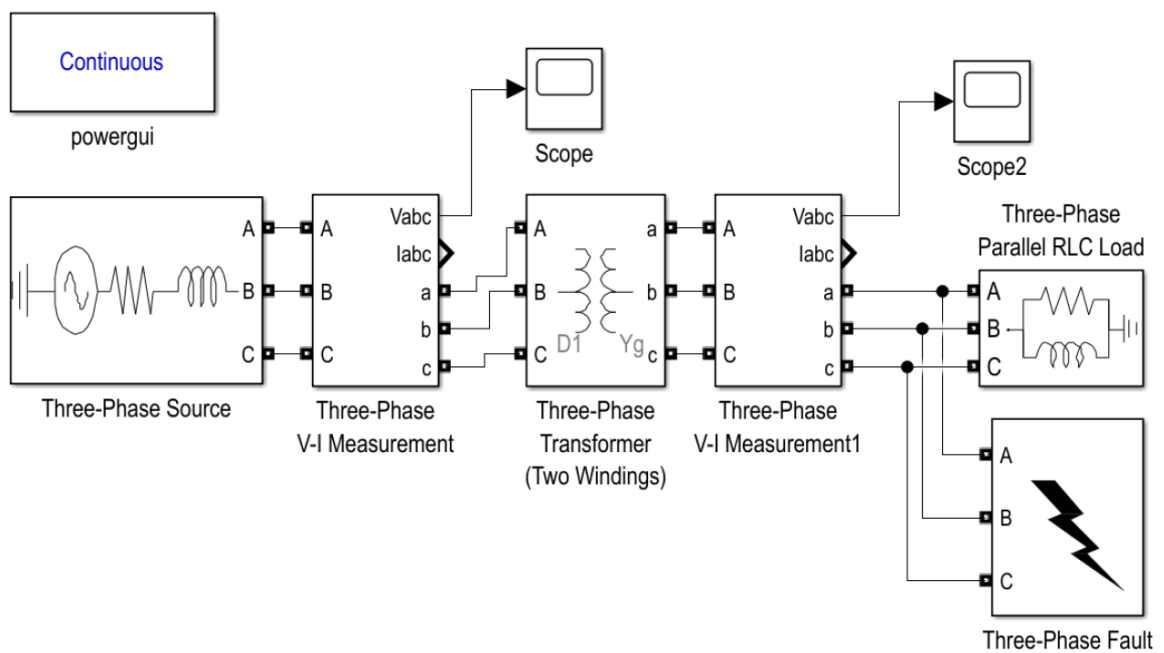


Fig. 5. Circuit model of permanent three-phase fault to simulation interruption

Table 1

Parameters for circuit model of capacitor bank

Component	Value
Three-phase Voltage Source	132 kV
Frequency	50 Hz
Load Active Power	10 MW
Load Reactive Power	5 MVar
Capacitor Bank	30 MVar

Table 2

Parameters for circuit model of three-phase large load

Component	Value
Three-phase Voltage Source	132 kV
Frequency	50 Hz
Delta-Wye Transformer	132 kV / 220 kV
1 st Load Active Power	10 MW
1 st Load Reactive Power	5 MVar
2 nd Load Active Power	40 MW
2 nd Load Reactive Power	10 MVar

Table 3

Parameters for circuit model of three-phase fault

Component	Value
Three-phase Voltage Source	132 kV
Frequency	50 Hz
Delta-Wye Transformer	132 kV / 220 kV
Load Active Power	10 MW
Load Reactive Power	5 MVar

2.2 Classifying the Disturbance Signals

After creating the disturbance signal circuit models, the next step was to develop the disturbance classification system using per-unit values. First, the ThingSpeak output block was included in every Simulink circuit model to integrate the model with the ThingSpeak cloud. After ThingSpeak was successfully integrated with Simulink, the classification system was developed in Arduino. Before building the classification system, the per-unit values for the disturbance limits were configured to be used in the system. Table 4 shows the per-unit values for each disturbance.

Table 4

Per-unit value for each disturbance

Type of Disturbance	RMS Value (pu)
Voltage Sag	0.1 to 0.9 pu
Voltage Swell	> 1.1 pu
Interruption	0 pu
Transient	> 2 pu

Further, the Wi-Fi connection between the Arduino IDE and the ESP32 board was set up and tested to ensure stability and usability. A read function from ThingSpeak was incorporated to fetch data from the ThingSpeak cloud, written in Simulink. The output value was then compared to the value in Simulink to ensure proper communication between Simulink, ThingSpeak, and Arduino. After the data from ThingSpeak has been verified, the classification system was built. The system includes an

"if-else" conditional statement in Arduino, with conditions based on the per-unit values. After several runs of test, and the system produced the expected output, it proceeded with the development of the monitoring system. Figure 6 illustrates the workflow for classifying the disturbance signals.

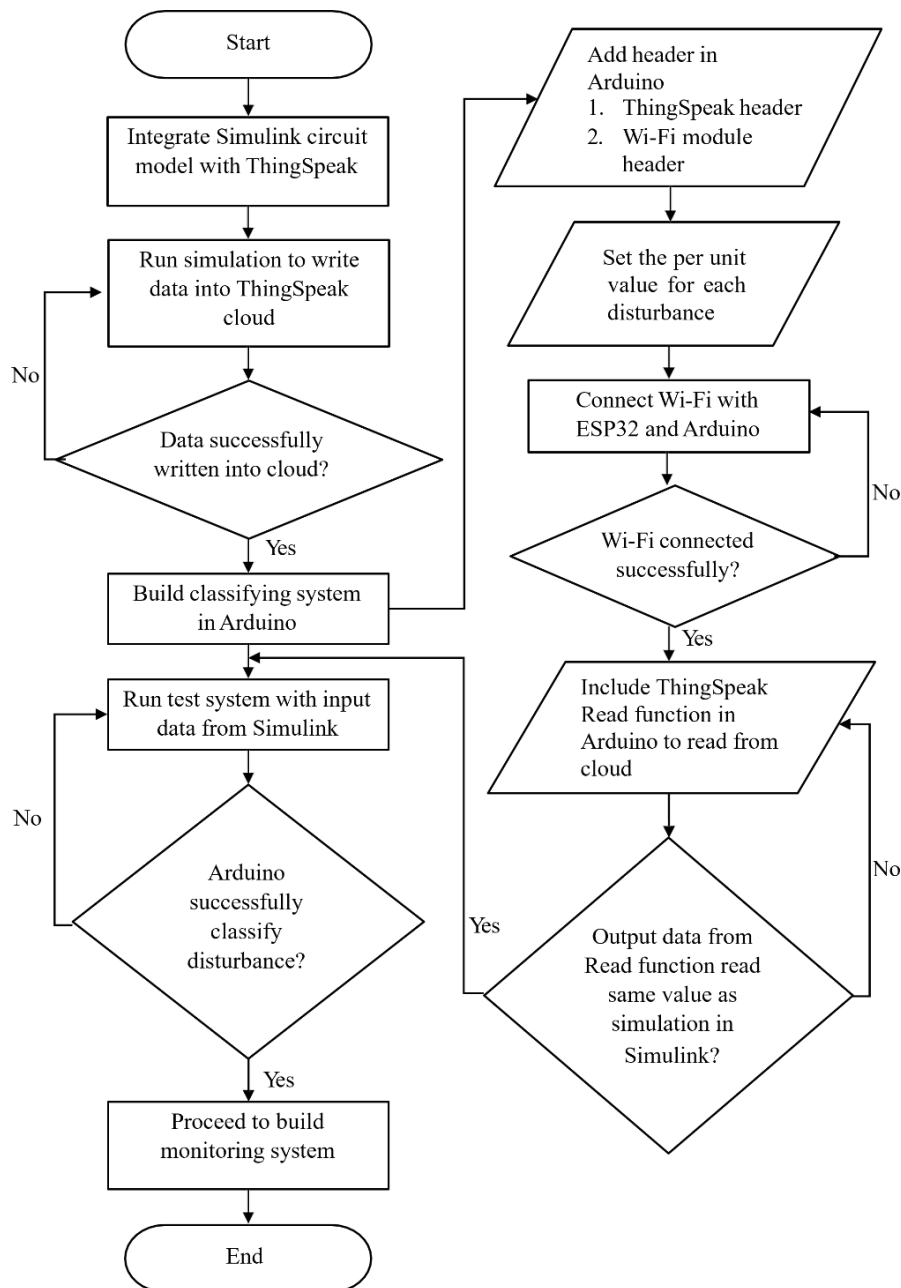


Fig. 6. Flowchart of disturbance signals classification

2.3 Building the Monitoring System in Arduino Hardware

The final step involves building the hardware component of the monitoring system and the flowchart is shown in Figure 7. This system was developed in the Arduino IDE, continuing from the classification system. Initially, the hardware components, including the LED, a buzzer module, and an I2C LCD, were connected to the ESP32 on a breadboard for testing. The monitoring system in Arduino employed the same "if-else" statements as the classification system. The conditions are set such that when a disturbance is detected, the LED and buzzer activate to alert the user, and the LCD will display the type of disturbance identified by the system. After the coding was completed, it was uploaded

and run on the ESP32 microcontroller. Figure 8 shows the overall connection of the IoT based power quality monitoring system.

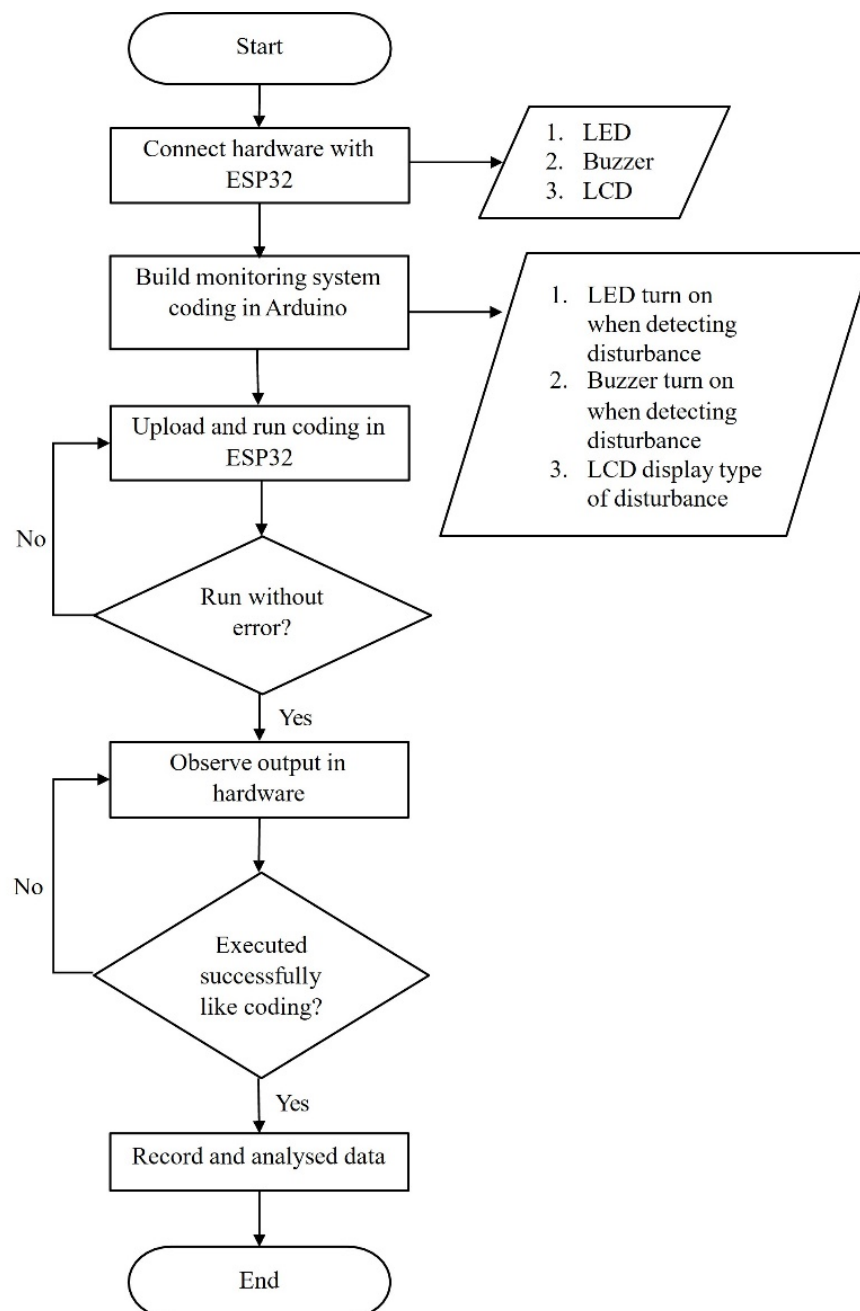


Fig. 7. Flowchart of building monitoring system in Arduino hardware

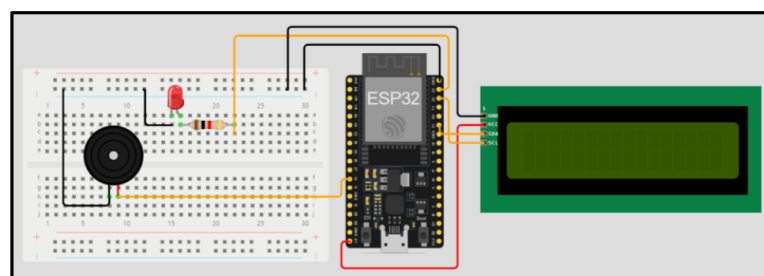


Fig. 8. Overall hardware connection of the IoT monitoring system

Figure 9 shows the flowchart for the data collection process for the overall power quality disturbance monitoring system. First, the circuit model is simulated to obtain the per-unit value at the output, which is then will be written to the ThingSpeak cloud for storage. Each new simulation updates this value in the cloud. Once the ThingSpeak cloud stores the updated value, Arduino reads it to classify the type of disturbance detected. The monitoring system in Arduino then uses this value to display the disturbance type and alert the user if a disturbance occurs, activating the hardware components such as LEDs and buzzers accordingly.

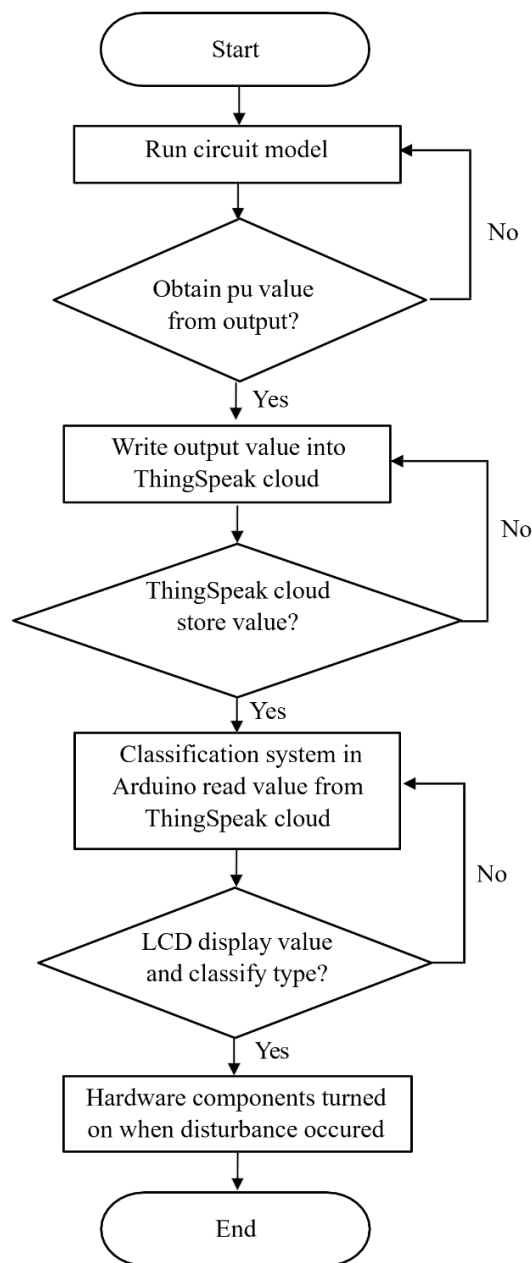


Fig. 9. Flowchart of data collection process for overall power quality disturbance monitoring system

3. Results and Discussion

In this section, the results from all methods executed are discussed and analyzed.

3.1 Simulation Results from Generated Disturbance Waveforms

There are several constructed circuit models which represent the selected disturbances for this research. The disturbances are transient, voltage swell, voltage sag and interruption. The analysis made for this method was based on observing the voltage value during disturbance and the duration of the disturbance. From these two magnitudes, it can help to detect and classify the type of disturbance that occurred.

The transient voltage disturbance signal was simulated from a circuit model of energization of capacitor bank. Figure 10 shows the simulated transient voltage disturbance signal. From the figure, there are 3 parts of the signal. The first part is the normal condition which is before energization of the capacitor bank. The second part is during the energization of capacitor bank which caused the transient to occur (sudden increase of voltage for a certain period). Lastly, the third part is the part where the disturbance stopped and decreased in voltage. The disturbance occurred for about 0.05 seconds which is the duration of a transient signal (momentary disturbance).

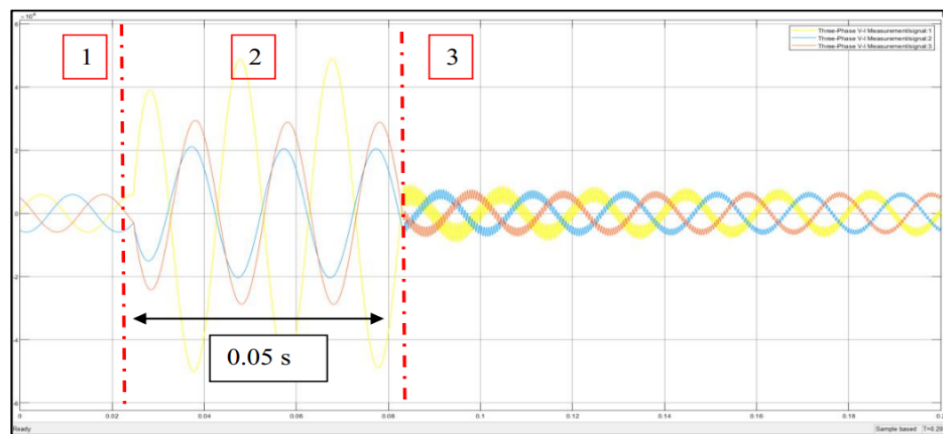


Fig. 10. Generated transient voltage disturbance

The voltage sag disturbance was simulated from the model of large load switching. Figure 11 shows the generated voltage sag signal. The voltage sag occurred due to the energization of a very large load. From the figure, the voltage magnitude decreased when the large load was energized. The duration of the sag is 0.05 seconds which is momentary. The voltage dropped to almost 0 V during the disturbance.

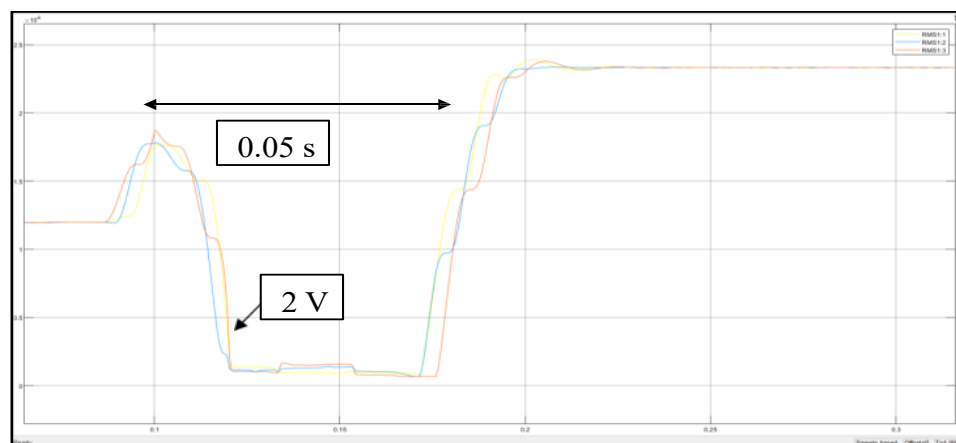


Fig. 11. Generated voltage sag disturbance

The voltage swell disturbance also was simulated from the model of large load switching. Figure 12 shows the generated voltage swell signal. The voltage swell occurred because of the de-energization of a very large load. From the figure, the swell of voltage is clearly formed. The duration of swell is 0.08 seconds which is momentary. The voltage value increased to 25 kV during the disturbances.

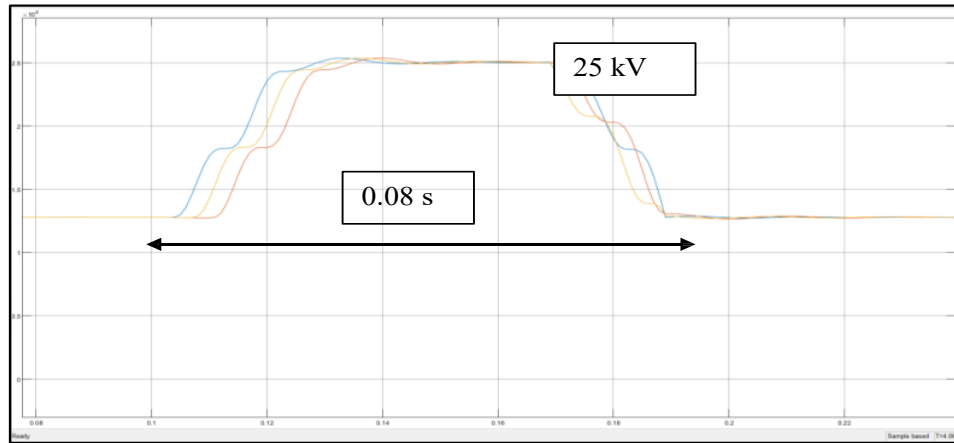


Fig. 12. Generated voltage swell disturbance

The interruption disturbance was simulated from the model of permanent three-phase fault. Figure 13 shows the generated interruption signal. The three-phase fault was the cause for the interruption. The disturbance occurred for 0.05 seconds, and the voltage value is completely 0 V during the disturbance.

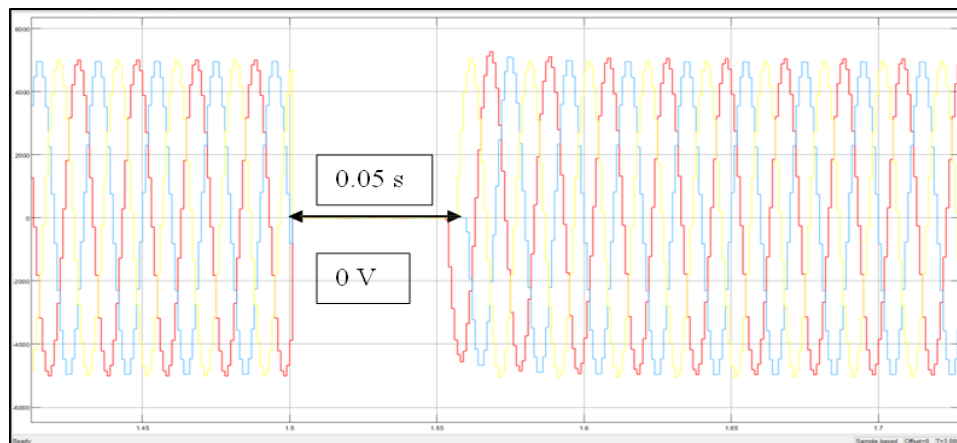


Fig. 13. Generated interruption disturbance

3.2 Results from ThingSpeak

ThingSpeak acts as the bridge for the whole system as it connects Simulink model and Arduino hardware through its cloud. All the output values from disturbance models can be found in ThingSpeak. Figure 14 shows the output values from the running of all four disturbance models which were simulated separately. The value was checked after every simulation whether it tally with the simulation in Simulink.

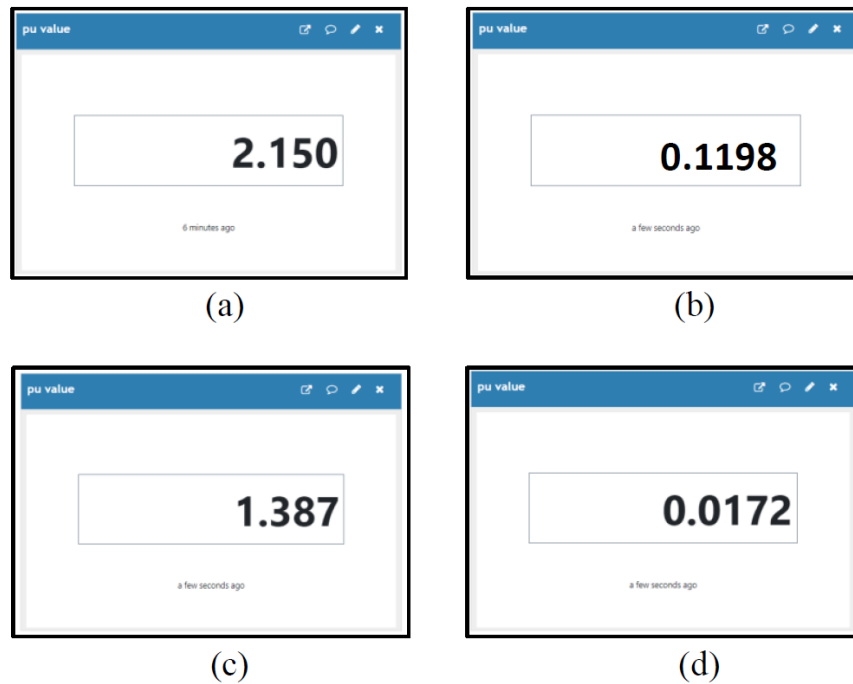


Fig. 14. ThingSpeak Outputs for the Simulation of the Different Disturbance Models;(a)Transient, (b) Voltage Sag, (c) Voltage Swell and (d) Interruption

Table 5 compared the output value displayed in Simulink and ThingSpeak cloud to see the accuracy of value transferred to the cloud. The accuracies for all types of disturbances are 100%, which means the value from Simulink successfully written in ThingSpeak cloud without error.

Table 5

Comparison of output between Simulink models and ThingSpeak

Type of Disturbance	Output from Simulink (pu)	Output from ThingSpeak (pu)	Accuracy (%)
Transient	2.15	2.150	100
Voltage Sag	0.1198	0.1198	100
Voltage Swell	1.387	1.387	100
Interruption	0.01724	0.0172	100

3.3 Results from Hardware

Hardware components that were observed and analysed are LCD, LED, and buzzer. When any disturbance detected, LED and buzzer are expected to turn ON and LCD will display the per unit value of the disturbance and will display the type of disturbance occurred. Table 6 shows the comparison between the output from ThingSpeak with the output from hardware. For transient, the value obtained at ThingSpeak is slightly different compared to LCD value in terms of rounding off the numbers. For voltage sag and voltage swell, both have the same values between ThingSpeak and LCD. But for interruption, the LCD display the value as 0.0000 while the value from ThingSpeak display 0.0172. This happened because the value is too small for Arduino and be rounded up as 0. Overall, all the output values achieved 100% of accuracy. This shows that the integration of IoT and the whole system is well synchronized.

Table 6

Comparison between output from ThingSpeak with output from Hardware

Type of Disturbance	Output from ThingSpeak (pu)	Output from LCD (pu)	Accuracy (%)	LCD Display
Transient	2.150	2.1579	100	
Voltage Sag	0.1198	0.1198	100	
Voltage Swell	1.387	1.3871	100	
Interruption	0.0172	0.0000	100	

4. Conclusion

This paper details the development of an IoT-based power quality monitoring system aimed at enhancing real-time data access and automatic classification of power systems disturbances. Traditional methods often suffer from delays in identifying and addressing power quality issues due to manual analysis, underscoring the need for automated systems. By integrating Simulink for disturbance signal generation, ThingSpeak for cloud-based data management, and Arduino for real-time classification and alerting, the study successfully demonstrated high accuracy in detecting and classifying various disturbances such as transient, voltage sag, voltage swell, and interruption. The system effectively utilized per-unit values to categorize disturbances. This approach not only streamlines monitoring processes but also lays groundwork for future advancements in IoT-driven power quality management systems.

Acknowledgement

The authors would like to acknowledge the support from the Faculty of Electrical Engineering & Technology and Center of Excellence for Renewable Energy (CERE), Universiti Malaysia Perlis (UniMAP) for partially funding this project.

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