An Enhanced Edge Computing Technique for Detection of Voltage Fluctuation in Grid-tied Renewable Energy

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Abstract: - Renewable energy sources (RES) such as solar photovoltaic and wind are becoming the most attractive power generation options in many nations. Even while high penetration seems likely, power quality anomalies such as voltage fluctuation, harmonics, and frequency fluctuation associated with RES hinder seamless integration. The variability and unpredictability of these sources create the most oddities. In grid-tied renewable energy, monitoring power quality efficiently is crucial. Power grid monitoring solutions in related literature use sensor-based cloud and edge computing techniques. The existing systems struggle with excessive latency when delivering large amounts of generated data to the cloud. To fill this gap, a new approach for the detection and localization of voltage fluctuation is proposed in this study. The approach integrated three techniques namely; feed-forward neural network (FFNN), Stockwell transform, and anomaly-aware edge computing to detect and locate voltage fluctuation in a GtRE. Using MATLAB/Simulink, virtual emulation of a modified IEEE 33 Bus and a GtRE representing a section of Ado Ekiti (in Nigeria) low-voltage distribution grid are carried out for data generation and system evaluation. Feature extraction was carried out in a Python IDE using Stockwell transform. The voltage fluctuation events are detected and localized based on the extracted features using the trained FFNN model deployed and evaluated within three microcontroller-based computing devices. The proposed approach integrated anomaly-aware with edge computing to send only voltage data that are considered abnormal to a dedicated data center for visualization and storage. Performance evaluation of the proposed technique on the simulated GtRE demonstrates a significant decrease of 98% and 90% in latency when compared to cloud computing and conventional edge computing respectively. Comparison of the proposed approach to two closely related solutions in literature also demonstrates a 50% and 92.5 % reduction in latency. The contribution of the study is the reduced latency and minimal bandwidth utilization achieved by the implementation of the developed technique.

Key-Words: - Power grid, renewable energy, voltage fluctuation, neural network, edge computing, latency.

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1 Introduction

Fossil fuel-based power plants have major contributions to greenhouse effects which cause global climate change. The use of such plants has been declining globally over the past few decades, [1]. Emissions of carbon dioxide and nitrogen oxide from fossil fuels have great influence on climate, [2]. Apart from the effects of the conventional power system generation on climate, the motivation to consider renewable energy sources (RES) is derived from other factors such as rising demand for electricity and energy poverty, [3]. Alternative power generation resources such as solar and wind are often environmentally friendly and have advanced technologically, with the capability to generate electrical power without contributing to carbon footprint or having any adverse effects on people or animals, [3], [4]. The integration of the RES into the utility grid has led to the development of various Distributed Generation (DG) technologies as part of solutions to foster the implementation of the "Paris Agreement" to maintain global temperatures below 2 ^{0}C and 80%

carbon foot-print elimination by the year 2050, [5], [6].

Grid-tied renewable energy (GtRE), if carefully implemented, has a positive impact on the stability of the power system, [6], [7]. One of the most recent developments in the power distribution system is the distributed generation (DG), which offers a decentralized approach to power grid architecture, [8]. DG involves producing a considerable amount of power close to the distribution network, with renewable generators as typical examples, [9], [10], [11]. Distributed generation has benefits that include: lower power loss, greater voltage support, peak shaving, increased system efficiency, stability, and dependability, [10], [12]. Meanwhile, the technical challenges of GtRE from certain sources such as solar photovoltaic and wind turbines are critical power quality issues, [11]. According to [13], [14], power quality (PQ) is how closely the parameters of a power supply system such as voltage, frequency, and waveform adhere to the predetermined standards which operate end-user equipment appropriately.

Renewable energy sources have gained a lot of attention lately due to their ability to address issues like the rising need for electricity, air pollution, and the subsequent difficulties caused by global warming. The inherent characteristics of these renewable energy sources namely, fluctuations in wind speed and solar radiation have a big impact on power quality, dependability, and safety. Low PQ levels therefore run the risk of causing motor failure, line overheating, imprecise metering, early device aging, and disruptions in communication circuits. In addition to renewable energy sources, PQ anomalies (PQAs) caused by heavy interference to grid voltages and currents can also result from the operation of electronic appliances and equipment.

"The concept of powering and grounding sensitive equipment in a matter that is suitable to that equipment's operation" is how the IEEE defines PQ. A PQA is defined as any variation in voltage or current over a certain period from its nominal values. PQAs are defined as a temporary deviation from the nominal magnitude and/or frequency components. The voltage fluctuation caused by the integration of renewable energy sources, including solar photovoltaic, is the main focus of this study. One of the main problems with power quality that arises from RES integration with the grid is voltage fluctuation which is primarily caused by the intermittency of renewable energy sources, [15].

The rest of this section provides a brief background of the power quality anomaly under investigation and the detection technique. The subsequent sections of this study are structured as follows: section two provides a concise overview of the power quality issues associated with grid-tied renewable energy. Section three provides comprehensive information regarding the methodologies and approaches utilized to address the identified issue. Section four presents the outcomes attained by the proposed solution and also includes a comparative analysis with other techniques and solutions. The study is concluded in section five with recommendations on possible adaption of the proposed technique.

1.1 Voltage Fluctuation

Voltage fluctuation is the variance in voltage amplitude from the nominal value. According to IEEE standards, it is a repeated voltage fluctuation with a magnitude of 0.9 to 1.1 pu, [15], [16], [17]. It is produced by sources whose output power varies over time. Voltage fluctuation is one of the key issues of power quality that emerges when RES are integrated with the grid. The significant prevalence of intermittent, uncontrollable RES is the main cause of voltage fluctuation. Voltage flicker is the major effect of voltage fluctuations. According to [15], [18] voltage fluctuations can be described using two metrics, short-term flicker severity and long-term flicker severity. Although, there are other inherent grid factors capable of causing voltage fluctuations, but are particularly heightened by renewable energy, which hurts power quality if not effectively monitored.

Voltage may increase (swell) or decrease (sag) more than usual when there is an excess of renewable energy in certain locations. A power system phenomenon known as voltage sag causes the nominal RMS voltage to drop between 10% to 90% for small intervals of time, lasting from 0.5 cycles to 1 minute, [16], [17]. A voltage sag is defined by the IEC 61000-4-30 standard as a transient drop in the RMS voltage of 10% or more just below the rated system voltage during a period of 1/2 cycle to 1 minute [15]. The reverse of voltage sag is the voltage swell. In [19], voltage swell is defined as a brief rise in RMS voltage of 10% or more that lasts for up to one minute and occurs just over the rated system voltage, [20]. All appliances connected to electrical power that has unstable voltage are susceptible to damage. Such power supply hurts the efficiency and proper operation of electrical and electronic appliances.

1.2 Edge Computing

The advent of the Internet of Things (IoT) has created a plethora of opportunities for complicated real-time systems. Industry 4.0 aims to process sensor data for practical applications using digital technologies, [20]. A distributed computing paradigm called edge computing places applications closer to data sources such as local edge servers and Internet of Things devices. This proximity to data sources provide significant benefits, such as quicker insights, enhanced response times, and increased bandwidth availability. Implementation of edge computing and IoT techniques requires machine learning integration, [21]. For voltage signal data, a time series prediction model such as a feed forward neural network (FFNN) is required.

The feed-forward neural network is classified as one of the two main categories of artificial neural networks, [22], [23], distinguished by how information is transmitted between its layers. The flow of the model is characterized as unidirectional, indicating that information within the model progresses solely in one way. This progression occurs from the input nodes, passing through any hidden nodes, and ultimately reaching the output nodes. Feed-forward networks are trained by the utilization of the backpropagation approach.

2 Power Quality Challenges of Grid-Tied Renewable Energy

The infrastructures for conventional power grids were designed to handle energy produced from conventional sources. Technologies behind these infrastructures can adjust their output to achieve an energy balance between supply and demand at all times to ensure the stability and reliability of the power grid. Due to the high penetration of RES like solar and wind, the operators in the power sector are worried about the stability of the grid, the quality of the power, and voltage regulation, [6], [11].

Three power quality challenges are prominent in renewable energy systems such as; voltage fluctuation, harmonics, and frequency fluctuation, [6], [16], [24]. Additionally, in the case of grid-tied RE, voltage and frequency changes may result from inherent power grid problems. Voltage and frequency, as specified by the IEEE Standard 519-2022 in [25], are the two key factors to consider when evaluating the power quality of RES (PV and wind systems). Deviation of these parameters creates power quality problems. These problems can be discussed from two perspectives: The renewable energy perspective and the power grid perspective.

This study focuses on the effective detection of voltage fluctuation in GtRE. According to IEEE standards, voltage fluctuation is a repeated voltage fluctuation with a magnitude of 0.9 to 1.1 pu, [15]. It is produced by sources whose output power varies over time. Voltage fluctuation is one of the key issues on power quality that emerges when RES are integrated with the grid. The significant prevalence of intermittent, uncontrollable RES is the main cause of voltage fluctuation.

A typical mathematical representation of voltage fluctuation is presented in Equation 1. All appliances connected to electrical power that has unstable voltage are susceptible to damage. Such power supply hurts the efficiency and proper operation of electrical and electronic appliances.

$$V(1\varphi) = \frac{2\mathrm{I}(\mathrm{R}\cos\theta + \mathrm{X}\sin\theta)}{1000} L \quad (1)$$

where I is load current, R is wire resistance, X is wire impedance, L is wire length, θ is phase angle and 1φ is single phase.

3 Methods

3.1 System Overview

The proposed edge computing approach for monitoring power quality anomalies (voltage fluctuation) in grid-tied renewable energy (GtRE) is a four-layered system presented in Figure 1. In the first layer, the simulation of a GtRE is carried out using MATLAB/Simulink. This layer is designed and configured to generate data of normal voltage, and voltage fluctuations required to train and validate the feed-forward neural network (FFNN) model. Also, this layer is equally designed to generate data needed to evaluate the deployed edge computing system. The second layer is the sensor layer which directly obtains voltage fluctuation data from the simulated grid for onward transmission to the edge computing (EC) layer. In the third layer, the EC device performs four functions; feature extraction using Stockwell Transform, voltage fluctuation detection, voltage fluctuation location, and voltage fluctuation severity screening. The fourth layer is the cloud layer, where visualization of events monitoring takes place.

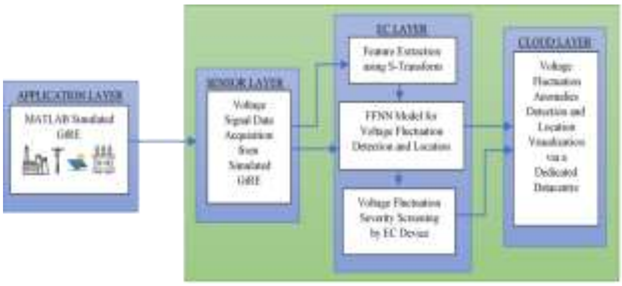

Fig. 1: System Overview

3.2 System Requirement

The system utilized hardware devices and software programs. A Laptop Computer running on 64-bit Microsoft Windows 10 Pro operating system (Intel corei7 CPU at 2.7GHz, with installed 16GB RAM, and 256GB SSD) played host to the software programs and the user interface for the model development.

Neural Network tools in MATLAB R2023a (version 9.14.0.2206163) were used to run the code extracted from the feed forward neural network model which was implemented using Replit Python IDE (version 0.3.2) running on Python 3.10. MATLAB was used to model the modified IEEE 33-bus test feeder (a benchmark network) which was used to simulate voltage signal datasets for model training. Also, MATLAB was used to simulate grid-tied renewable energy (solar) where the developed system is evaluated. The edge computing devices are comprised of simulated voltage sensors and microcontrollers managed by a Raspberry pi 2 (b+). The Raspberry pi microcontroller is responsible for running the output weight of the edge-based neural network model and sending the captured data to the developed cloud platform. The cloud-based platform was designed using Java graphical user interface framework, to visualize the system performance.

3.3 Data Collection

Related literature on power quality anomalies in grid-tied renewable energy was explored. This study focused majorly on the most prominent power quality anomaly in grid-tied renewable energy (GtRE) which is voltage fluctuation. Training datasets of voltage fluctuation were generated from the simulated modified IEEE 33 Bus network using algorithmic codes. Data of normal voltage signals and fluctuated voltage signals were obtained from the simulated grid. The measured line voltages were collected and saved at the output side of the power system. 10000 data of voltage signals were collected and labeled.

Additionally, to obtain the large number of datasets required in training and validating the feed-forward neural network model, voltage fluctuation signals were derived from the grid by inducing certain random noise to alter the simulated mathematical model presented in equation 2, the simulated random noise model is presented in equation 3.

$$V = A * \sin(2\pi f t + \varphi) \tag{2}$$

$$Vr = V + 10 * randn\ (size(V)) \tag{3}$$

where V is the voltage at time t, A is the amplitude, f is the frequency, φ is the phase and $randn$ is the induced random noise.

In this study, an alternate current (AC) voltage of 230v is considered as nominal voltage with a tolerance range of +6% and -13%. This is by IEEE Standard 1547 of 2022, [26]. A voltage fluctuation signal is considered as any voltage signal outside the tolerance range.

3.4 Data Feature Extraction

Feature extraction is a commonly employed methodology in data analysis that aims to condense a voluminous input dataset into a set of pertinent features. Dimensionality reduction is employed to convert extensive input data into more compact and relevant clusters for subsequent analysis. Within the field of machine learning, feature extraction refers to the systematic procedure of converting diverse forms of data, such as signal, textual, or visual information, into numerical features that are amenable for utilization in machine learning algorithms. In this study, Stockwell Transform (S-Transform) is used to extract useful numerical features from the voltage signals generated using equation 4, before feeding the dataset into the feed-forward neural network model. The S-Transform algorithm was developed in this study utilizing the Python programming language.

The development of the S-Transform as a time-frequency distribution for the analysis of geoscience data occurred in 1994, [22]. According to [22], the S-Transform can be considered a broader form of the short-time Fourier transform (STFT), as it encompasses the continuous wavelet transform while also addressing certain limitations associated with it. Firstly, it should be noted that modulation sinusoids exhibit a fixed relationship about the time axis. This characteristic allows for the localization of scalable Gaussian window dilations and translations within the S-Transform. Furthermore, it is worth noting that the S transform does not suffer from the issue of cross-terms, making it a more effective method for achieving signal clarity compared to the Gabor transform, [22]. The S-Transform, adopted from [27] can be expressed comprehensively, elucidating its connection to other time-frequency transforms, including the Fourier, short-time Fourier, and wavelet transforms as shown in equation 4.

$$S(\tau,f)=\int_{-\infty}^{\infty} h\,(t)\mid f\mid \frac{2}{\sqrt{2}}e^{-\frac{t-(\tau)^2 f^2}{2}}e^{-j2\pi f t}dt \qquad (4)$$

where τ (tau) is time location, t is time, f is frequency, h(t) is signal concerning time.

3.5 Description of the Studied Power Grids

Due to the adverse effects of voltage fluctuations on other loads connected to the same network as the disruptive load, and the constraints of technical feasibility, the only viable method for experimental verification was through simulation. The IEEE 33-bus test system is the first studied network in this study, the network, adopted from [28] is depicted in Figure 2. The network is modeled in MATLAB/Simulink environment. The modified 33-bus test system is adapted from the IEEE 33-bus test system. The modified system integrates photovoltaic (PV) systems of 0.5MW each at three busses (11, 18, and 22). The modified network is designed for a base frequency of 50 Hz and a nominal voltage of 13.8 kV at the substation. The substation transformer at bus 1 has a capacity of 3 MW.

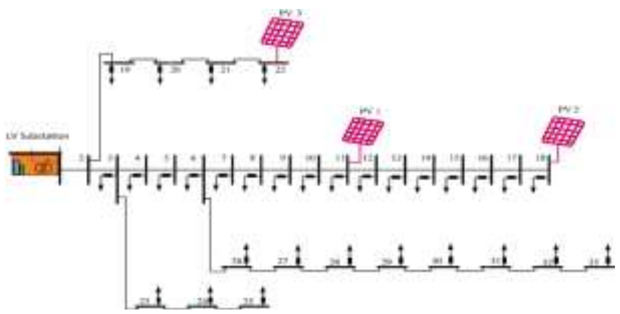

Fig. 2: Line diagram of IEEE 33-bus test system, [28]

The primary focus of this study is mainly on low-voltage networks, because voltage fluctuations most often occur in them. The majority of the low-voltage networks in Nigeria are radial topologies with branches. The second studied power grid is a section of Ado Ekiti low-voltage distribution grid. Ado Ekiti is a city in the South Western region of Nigeria. A MATLAB simulation was conducted to model the grid with a base frequency of 50 Hz and a voltage of 11kV for secondary distribution. Three-phase consumers were represented with a nominal voltage of 415V, while single-phase customers were represented with a nominal voltage of 230V. The system incorporates 0.5MW photovoltaic (PV) systems at each bus in the network.

3.6 Description of the Trained FFNN Model

The trained feed-forward neural network (FFNN) model was implemented using Python and Keras library with the TensorFlow backend engine. FFNN is considered in this study due to its ability to model complex non-linear relationships, which are often present in power systems. Another great feature of FFNN is its ability to adapt to new data, making it suitable for voltage fluctuation prediction where certain parameters may change over time. Also, FFNN is potent in handling inherent noise in input data, which is natural with voltage fluctuations, [29].

MATLAB is used to create the simulated time series dataset. Using an initial learning rate of 0.001, the model is trained with the aid of an Adam optimizer.

The adaptive learning rate is employed to progressively reduce the learning rate by a factor of 0.1 until learning ends. The total number of epochs used in the training process is 200 with a batch size of 25. This study exploits the capability of FFNN to reshape data into brief fixed-length segments and analyze the time sequence of the simulated sensors. The Holdout method of cross-validation was adopted with training and validation split of 80 to 20 respectively.

Feed-forward neural network is a type of artificial neural network characterized by the absence of loops among nodes. This particular neural network architecture is commonly referred to as a multi-layer neural network, as it exclusively propagates information in a forward direction. During the process of data flow, input nodes receive data, which subsequently traverse via hidden layers, and ultimately escape through output nodes. There are no available links inside the network that can be utilized to transmit information from the output node. The multi-layer feed forward neural network is presented in Figure 3. X1, X2, Xn represent the external source input signal which represents the voltage fluctuation signals. Every input variable's synaptic weight is represented by W1, Wn which permits the appraisal of their importance to the model's performance.

As shown in Figure 3, the network has three layers, input, hidden, and output layers. In the input layer, the neurons receive incoming voltage fluctuation signals and subsequently transmit them to the next layer within the network. It is imperative that the feature or attribute numbers inside the voltage signal dataset correspond to the number of neurons present in the input layer. The hidden layers of a neural network consist of several neurons that perform further processing on the input voltage signal before transmitting it to the subsequent layer (output). The weights of this network are continuously changed to enhance its voltage fluctuation predictive capabilities. The output layer simply represents the predicted voltage fluctuation events.

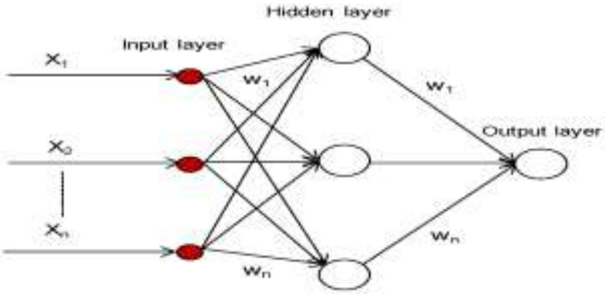

Fig. 3: The Simplified FFNN Architecture

3.7 Description of the Edge Computing System

Three model-based computing devices were deployed on a raspberry pi microcontroller to run the FFNN algorithm for voltage fluctuation detection in GtRE. The first computing device is configured to represent Cloud Computing (CC), and the second computing device is configured to represent Edge Computing (EC). The third computing device is configured to represent Enhanced Edge Computing (EEC), which is the solution that is being proposed in this study. Each computing device is designed to communicate with the simulated voltage sensors deployed to specific busses on the studied power distribution grid. The algorithm for CC was developed to transfer data from sensors, directly to a cloud platform. The algorithms for EC and EEC devices were developed to work within three layers, the first is sensor layer, the second is edge computing layer and the third is cloud layer.

In EEC, a voltage fluctuation-aware algorithm is introduced to capture and send only data considered by the trained model to be anomalies. Data from the sensors are processed within the edge computing layer, anomaly events are transmitted to the cloud layer which comprises of a dedicated Java-based graphical user interface. The algorithm of the cloud layer is programmed to perform adaptive deletion schemes on data streams. The architecture of the EEC system is shown in Figure 4.

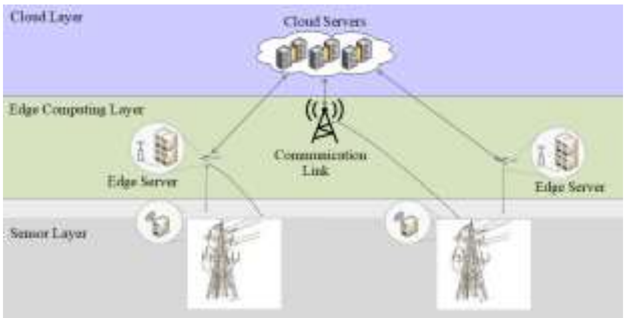

Fig. 4: Enhanced Edge Computing Architecture

3.8 System Implementation

The implementation of the entire system is depicted in the flowchart presented in Figure 5. The chart explicitly shows the various stages of the process from data acquisition to the final deployment of the edge-based neural network model for voltage fluctuation detection in GtRE.

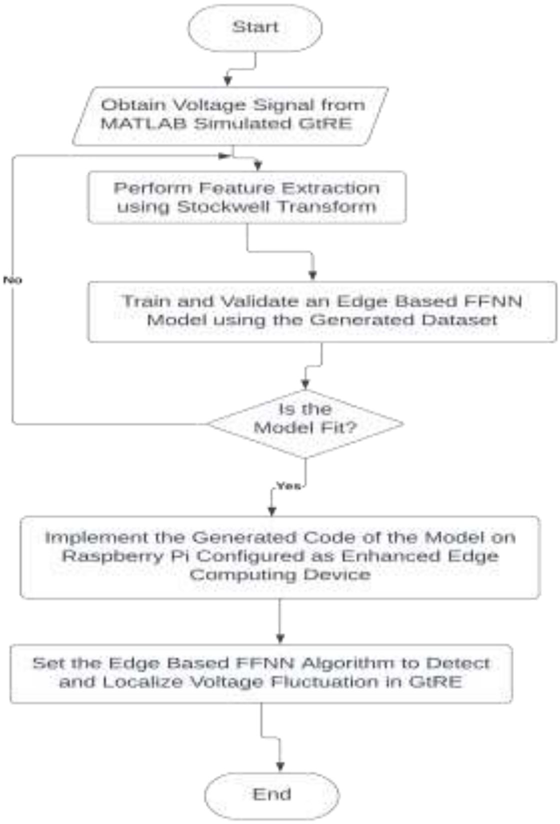

Fig. 5: System Implementation Flowchart

3.9 System Evaluation

Voltage fluctuation detection is typically considered in this study as a classification task rather than a regression task. In general machine learning, classification tasks are about predicting a discrete label, while regression tasks are about predicting a continuous quantity. In the case of voltage fluctuation detection, the task is to detect whether a fluctuation has occurred or not, which can be represented as two classes, 'fluctuation' and 'no fluctuation'. Performance metrics are crucial for evaluating the effectiveness of the developed model. For a voltage fluctuation detection task using a Feed-Forward Neural Network (FFNN), which is a binary classification problem, the following metrics were considered as defined in [30].

3.9.1 Detection Accuracy

This is the most intuitive performance measure. It is simply a ratio of correctly detected voltage fluctuation events to the total events. Equation 5 was programmed in the FFNN algorithm to carry out voltage fluctuation detection accuracy (DA) rate.

$$\mathrm{DA} = \frac{Number\ of\ Correct\ Prediction}{Total\ Events} * 100 \quad (5)$$

3.9.2 Precision

Precision (P) looks at the ratio of correct positive detections to the total detected positives. It answers the question of what proportion of positive voltage fluctuations classification was correct. Equation 6 was programmed in the FFNN algorithm to carry out voltage fluctuation detection precision rate.

$$P = \frac{True\ Positive}{True\ Positive + False\ Positive} * 100 \quad (6)$$

3.9.3 Recall (Sensitivity)

Recall (R) calculates the ratio of correct positive voltage fluctuation detections to all observations in the actual voltage fluctuation class. It answers the question of what proportion of actual voltage fluctuations were detected correctly. Equation 7 was programmed in the FFNN algorithm to carry out voltage fluctuation detection recall rate.

$$R = \frac{True\ Positive}{True\ Positive + False\ Negative} * 100 \quad (7)$$

3.9.4 F1 Score

The weighted average of Precision and Recall constitutes the F1 Score. It attempts to strike an equilibrium between recall and precision. The FFNN algorithm was configured to perform voltage fluctuation detection with an F1 score using Equation 8.

$$F1 - Score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (8)$$

3.9.5 Latency

In this study, the latency of all assignments is represented by 'L' which is used to determine the overall delay time in data transfer from the edge sensors to the cloud platform. L comprises four components: the interval separating data capture and transfer to the edge server, the delay in assignment queuing, the time taken by the edge to conduct operations, and the potential time required for the edge server to transmit data to the cloud. The mathematical expression of L, adopted from [31] and [32] is presented in equation 9.

$$L = \frac{\sum_{i=1}^{n} x_{i,j}(s_j/b_{i,j} + t_{ej} + s_j/v_e + s_j/b_{ej}p_i)}{n} \quad (9)$$

where "n" denotes sets of monitoring sensors. Set "x" delegate the connection between edge devices and the edge server. The set "e" represents the collection of peripheral servers, while "e_j" denotes each edge server within the distribution grid. The data magnitude produced by each monitoring sensor is denoted as "s_j", while "p_i" represents the likelihood that the edge sensors will detect a voltage fluctuation. The term "edge conducting rate" (v_e) refers to the number of frames that can be processed by each edge server within one second. The unit of time expressed in seconds is "t". The bandwidth of the uplink from every peripheral server In the cloud, "E_j" is denoted by the symbol "b_{ej}". The bandwidth of upstream is "$b_{i,j}$".

4 Results

4.1 Voltage Signal Generation Output

Voltage signals within the tolerance range of +6% to -13% of the nominal voltage of 230V, at a frequency of 50 Hz, were regarded as normal voltage signals, whereas voltage signals outside the tolerance range were regarded as voltage fluctuation signals. Figure 6 is an example of the normal voltage signal waveforms generated by the simulated grid without renewable energy integration, whereas Figure 7 is an example of the voltage fluctuation signal waveforms generated from the simulated grid when solar energy is integrated.

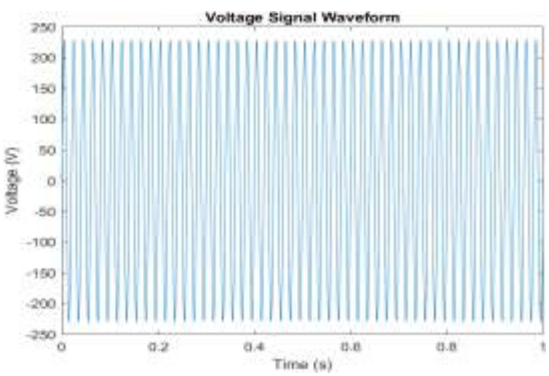

Fig. 6: Sample of normal voltage waveform from grid without solar integration

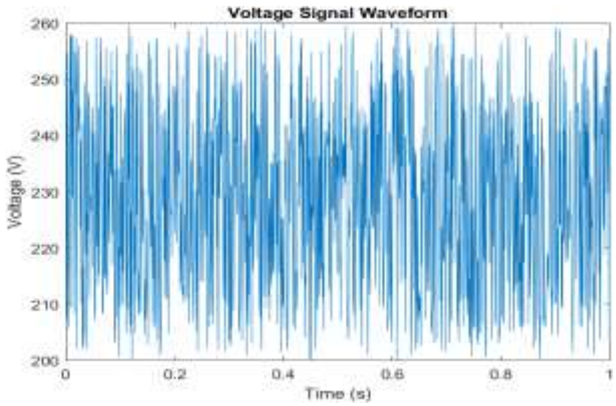

Fig. 7: Sample of fluctuated voltage waveform from GtRE

4.2 Model Training and Validation

The training and validation of the FFNN model gives a promising result on precision, recall, and the f1-score with the attainment of an average of 92% and 94% for each of the three metrics programmed in the algorithm with equations 6, 7, and 8. The training and validation results are shown in Table 1. Figure 8 illustrates the curve depicting the accuracy of the model during both the training and validation phases as a function of the epoch. During the 25th epoch, there was a significant increase in accuracy, and the optimal fit was obtained beginning at epoch 150. The curve in Figure 9 illustrates the progression of model training and validation loss over multiple epochs. The decline in loss commenced during the 25th epoch, and by the 150th epoch, the loss had diminished to a near-zero level.

Table 1. Model Training and Validation Scores.

Metrics	Training Score (%)	Validation Score (%)
Recall	90	94
Precision	92	92
F1-Score	94	96

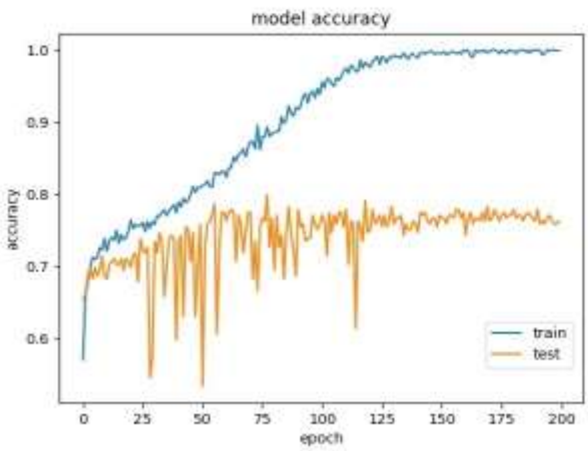

Fig. 8: The accuracy curve of the model

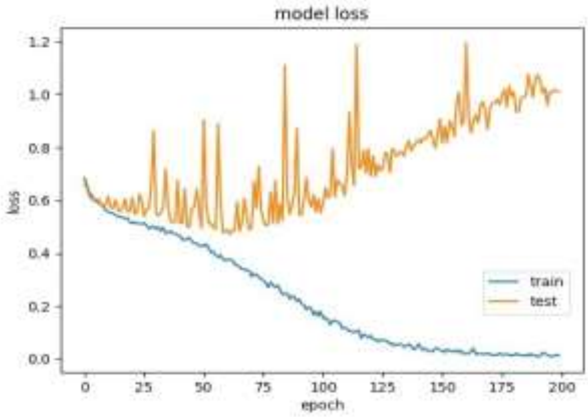

Fig. 9: The loss curve of the model

4.2.1 The FFNN Test

The test of the FFNN model gives a promising result on accuracy with the attainment of an average of 96% for detection accuracy programmed in the algorithm with equation 5. The detection accuracy results are shown in Table 2.

Table 2. FFNN Detection Accuracy Results.

Events	Number of Signal Samples	Number of Correct Prediction	Number of Wrong Prediction
Voltage Sag	500	482	18
Voltage Swells	500	480	20
Interruption	500	481	19
Flicker	500	484	16
Normal	500	478	22

4.3 Comparison of Enhanced Edge Computing with Other Computing Techniques

Table 3 illustrates the time taken by the three computing devices to transfer data of voltage fluctuation events from certain buses on the network, to the cloud platform. The results of enhanced edge computing demonstrate a significant decrease of 98% and 90% in latency when compared to cloud computing and conventional edge computing respectively.

Selected screenshots of the computing model curves as logged on the web platform are presented in Figure 10, Figure11 and Figure12. The vertical axis represents the voltage signal while the horizontal axis represents data transfer delay.

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Table 3. Comparison of the three computing devices concerning data transfer delay for selected buses.

Buses	Cloud Computing Transmitted Time (Seconds)	Edge Computing Transmitted Time (Seconds)	Enhanced Edge Computing Transmitted Time (Seconds)
Bus 3	120s	40s	2s
Bus 4	125s	30s	1s
Bus 6	133s	32s	1s
Bus 7	140s	38s	1s
Bus 8	137s	37s	2s
Bus 9	138s	32s	1s
Bus 10	138s	39s	1s
Bus 11	129s	38s	2s
Bus 17	130s	40s	1s
Bus 30	136s	32s	2s

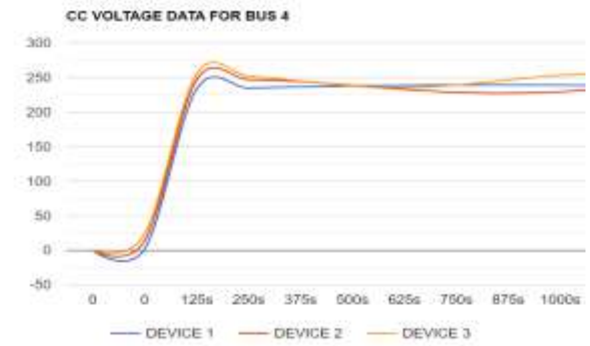

Fig. 10: Bus 4 Cloud Computing Curve

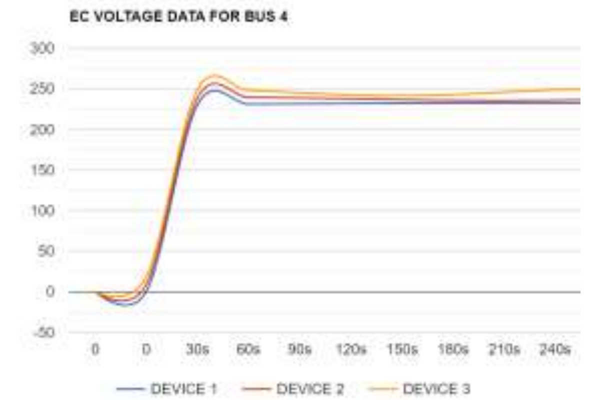

Fig. 11: Bus 4 Edge Computing Curve

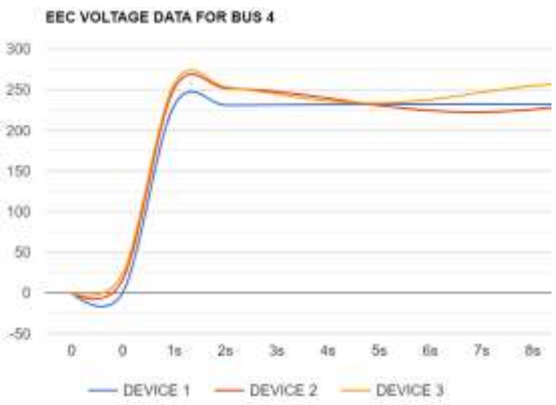

Fig. 12: Bus 4 Enhanced Edge Computing Curve

It is evident from the bus 4 curves that the data transfer delay for the proposed enhanced edge computing technique offered the shortest time of 1second in comparison with an average of 32 seconds offered by edge computing and an average of 125 seconds offered by cloud computing.

4.4 Comparison of Latency and Detection Accuracy of Selected Edge Computing Techniques

Table 4 illustrates the latency and detection accuracy recorded with selected Edge Computing Techniques in related literature as compared with the proposed Enhanced Edge Computing Techniques. The proposed edge computing technique outperformed the existing solutions by offering latency reduction of 50% and 92.5% when compared with the performance of the two related solutions.

Table 4. Comparison of Latency and Detection Accuracy of Selected Edge Computing Techniques.

Technique Used	Input Signal Considered	Average Latency Recorded (s)	Detection Accuracy (%)
Edge Computing [33]	Sensor Data	20	84
Edge Computing [34]	Voltage Signal	3	94.5
Proposed Enhanced Edge Computing	Voltage Signal	1.5	96

5 Conclusion

This study examines the application of an enhanced edge computing technique for monitoring voltage fluctuations in grid-tied renewable energy. Significant emphasis was placed on guaranteeing that the system functions with the least possible delay. The methodology employed a combination of three techniques: feed-forward neural network (FFNN), Stockwell transform, and anomaly-aware edge computing, to identify and localize voltage fluctuations in a GtRE.

The trained FFNN's output weight is deployed as three computing devices on a microcontroller, allowing it to identify and localize voltage fluctuation occurrences based on extracted attributes. The proposed solution used edge computing and anomaly-aware operations to send only anomalous voltage data to a designated data center for storage and presentation. The performance evaluation of the developed technique on the simulated GtRE reveals a significant reduction in latency when compared to cloud computing and conventional edge computing.

Adoption of the proposed technique will result in improved power quality monitoring in GtRE. The developed technique is not limited to monitoring voltage fluctuation in GtRE, it can be adapted to monitor other power quality anomalies. In addition, the technique can also be adapted to other power-related events such as monitoring the rate or quality of power generation from hydrogen-powered fuel cells, and monitoring of the rate of charging of electric vehicle energy storage systems.

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Conflict of Interest

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