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Advanced Edge Computing Framework for Grid Power Quality Monitoring of Industrial Motor Drive Applications

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***Abstract*—In large-scale industrial machine applications (IMAs) during condition monitoring, all sensor devices can produce raw data up to 15TB of data/week. Transmitting these large high-frequency data sets to the cloud to closely monitor the operational environment and make decisions is not feasible for two reasons : (a) bandwidth and latency issues and (b) higher cost of data transfer and storage. Condition monitoring applications usually extract critical features from raw high frequency sensor signals and discard raw data to mitigate this issue. The computation is carried out on an edge device near to the application hardware and the role of the cloud/remote server is limited to receiving fault types, features, and monitoring. Therefore, this paper proposes an intelligent data capturing methodology with an edge-cloud framework for grid power quality monitoring of the IMAs that only triggers and transmits datasets to the cloud if the raw datasets contain any grid events and/or grid side anomalies. Using dSPACE, grid emulation is carried out virtually. Feature extraction using Short Term Fourier Transform (STFT) is done in the edge device and grid events are detected based on features. The proposed methodology is configured to send raw grid voltage data and features in the Microsoft Azure-based cloud that contain at least one abnormal grid event. Thus, the proposed approach of this paper limits the space requirement in the cloud by 95%, saves data transmission costs, and enables the cloud to run predictive maintenance algorithms.**

***Index Terms*—Cloud, Edge computing, power quality, condition monitoring, Internet of Things, STFT**

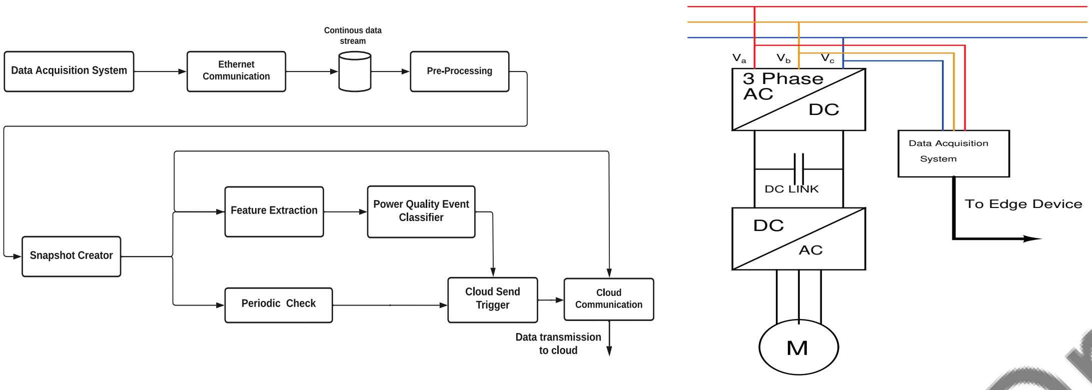
I. Introduction

The emergence of Internet of Things (IoT) has opened a multitude of possibilities for real-time complex systems. The smart industry or industry 4.0 [1] envisions to use digital technologies for processing sensor data for useful applications. Condition monitoring and predictive health maintenance are major application areas in electromechanical systems. The key enabling digital technologies are edge computing, big data analysis, machine learning, 4G/5G communication, and cloud computing. Traditionally sensor-cloud based approaches were used in IoT setups. Due to the increasing demand in real-time monitoring of systems to capture events of ms range, the traditional approach falls short in terms of latency and bandwidth. To mitigate these issues edge computing has emerged as the most promising technology in recent times [2]. An efficient edge-cloud communication strategy is needed to use digital technologies to the fullest possibilities.

Industrial motor drives suffer due to undesirable variations in the input voltage of the 3-phase grid power supply, often leading to a loss of production and quality issues [3]. The variation in voltage, magnitude, shape, and frequency is a result of switching on/off of high loads, grid faults, and capacitor bank switching [4]. The increasing usage of power electronics converters also contributes to the existing power quality (PQ) issues. PQ problems can cause equipment failure, data/memory loss, and protection/relay failure [5]. Good PQ is essential for reliable and continuous operation of industrial machines [6]. Monitoring power quality is a necessary pre-condition for the development of countermeasures [7].

Monitoring of PQ requires grid voltage and current sensors to measure 3-phase voltage and current (Vab, Vbc, Vca, Ia, Ib, Ic), which are sampled at high frequency (typically from 2kHz - 10kHz) to obtain useful information. As a typical industrial setup will contain a fleet of power electronics drives, the amount of data generated will be very high. It is not feasible to send the data from a remote location to the cloud to be processed due to cost and reliability issues associated with data transfer. Processing and computing data on the edge (near to the system) and sending data to the cloud as and when required is the best solution.

Data reduction techniques such as filtering, compression, pattern detection, and deduplication are being applied at the edge device to reduce data transmission. [8]. This paper proposes an advanced framework consisting of Edge-Cloud computational functionality to efficiently monitor IMAs, and implemented in Python. Raw sampled data is processed on the edge to monitor faults/events in real-time. Raw data and calculated features are sent to the cloud intelligently. The framework is applied to power quality problems for IMA setups. Section II describes the details of the proposed framework. Section III details the application-specific PQ event detection methodology. In section IV the proposed framework is tested virtually with dSPACE and an edge PC. Section V provides the concluding remarks.



(a) Edge Device Software Architecture (b) Industrial Motor Drive Setup

Fig. 1: Software and Hardware Setup

II. Framework Configuration

The proposed digital framework in Figure 1a depicts the software architecture on the edge device. The IMA setup is shown in figure 1b, which is supplied from a 3-phase power supply. The IMA setup is virtually emulated in real-time hardware using Simulink and dSPACE. The edge device handles real-time data processing,condition monitoring, and communicates with the cloud, which receives data to run complex algorithms for predictive maintenance. The framework can be described as follows

- **Sensor Data Reception:** The sensor data from data acquisition hardware (DAQ) is received through Ethernet communication protocol.
- **Pre-Processing:** The data integrity is checked. Also, filtering could be implemented if necessary. The received data is stored in a FIFO (First-in-First-out) queue for further processing.
- **Snapshot Creator:** The continuous stream of raw sensor data is divided into fixed time length sampled data (Snapshot). Along with raw data, a snapshot also contains sensor information, sampling frequency, calculated features, and fault status. For the application of PQ monitoring, snapshot time is 3s with 4kHz sampling.
- **Feature Extraction:** This block extracts useful features from the raw data, which will be used by classification and detection algorithms. Popular feature calculation methods are FFT (Fast Fourier Transform), STFT (Short Time Fourier Transform), Wavelet transform (WT), and S-transform [9]. In this paper, STFT is used for feature extraction.
- **Power Quality Event Classifier:** This function implements the classifier algorithm to detect PQ events. If an event is detected, it triggers the program to send data to cloud. This paper implements a decision tree(DT) for the classification problem.
- **Periodic Check:** This block gives a trigger to send data to cloud periodically even when no PQ event is detected. The frequency of trigger can be varied dynamically as per requirement and communication from the cloud. It is an essential feature, as during initial operation the cloud can request a high amount of snapshots and once the cloud has enough data-sets, the periodic checker can be set to a high value to reduce data transmission.
- **Cloud Communication:** This function sends snapshots to the cloud with inputs from the event classifier and the periodic checker. The extracted features are always sent for each snapshot.

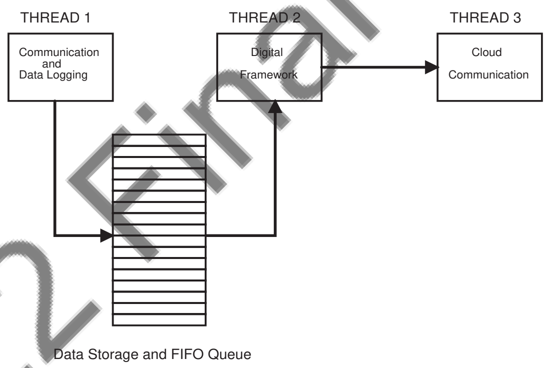


Fig. 2: Python Implementation

Figure 2 shows the multi-threading software implementation strategy. Three threads run in parallel in Python to keep the edge computing in real-time. Thread 1 runs the communication with DAQ and logs the data in a FIFO queue. Thread 2 takes the data from the FIFO queue for snapshot creation, feature extraction, and classification. Thread 2 also specifies which snapshots are to be sent to the cloud. Thread 3 takes the specified snapshot from thread 2 and sends it to the cloud. Thread 3 adds an advantage to the system, as during an internet communication failure, the PQ detection algorithm could still run in real-time, and data can be sent to cloud once internet connection is resumed.

III. Power Quality Disturbances

The importance of PQ monitoring is increasing due to the significant growth of interest in smart grid, distributed

TABLE I: Power Quality Events [10]- [11]

Category	Spectral Information	Equation	Parameters
Voltage Sag	Duration : 10ms - 3s	$V_{peak}(1-\alpha(u(t-t_1)-u(t-t_2)))sin(\omega t-\phi)$	$0.1 \leq \alpha \leq 0.9$, u: step function t_1, t_2: Start,End time
Voltage Swell	Duration: 10ms-3s	$V_{peak}(1+\beta(u(t-t_1)-u(t-t_2)))sin(\omega t-\phi)$	$0.1 \leq \beta \leq 0.8$ u: step function t_1, t_2: Start,End time
Voltage Interruption	Duration: 10ms-3s	$V_{peak}(1+\gamma(u(t-t_1)-u(t-t_2)))sin(\omega t-\phi)$	$0.9 \leq \gamma \leq 1.0$ u: step function t_1, t_2: Start,End time
Flicker	Spectrum: Upto 9kHz	$V_{peak}(1+\lambda sin(\omega_f t))sin(\omega t-\phi)$	$0.05 \leq \lambda \leq 0.1$ $f_f \in [8Hz, 25Hz], \omega_f = 2\pi f_f$
Harmonics	Spectrum: Upto 9kHz	$V_{peak}(sin(\omega t-\phi)+\sum_{n=3}^{7}\alpha_n sin(n\omega t-\upsilon_n))$	$0.05 \leq \alpha_n \leq 0.15$ $-\pi \leq \upsilon_n \leq \pi$

generation, usage of power electronics equipment, and integration of renewable energies [4]. IEEE 1159, IEC 61000-4-30 and EN50160 present power quality indices [10], [12], [13]. IEEE 1159 standard details the definition of various power quality events. This paper considers the PQ events described in Table I. The equations in Table I are used to synthesize the waveforms for the DT training. All the parameter variations are considered while generating the training data set.

A. *Waveform Analysis with Short Time Fourier Transform*

STFT is a common method to evaluate time-varying waveform distortions [14]. The non-stationary nature of PQ disturbances makes STFT a useful tool for analysis. STFT applies a moving window of a fixed length to the signal and performs Fourier Transform to obtain both time and frequency information. The discrete STFT for a signal $x[n]$ is

$$X(m,k) = \sum_{n=-\infty}^{\infty} x[n]w[n-m]e^{-j2\pi kn/N} \tag{1}$$

where w is the window function, m is the position of the window, $k\omega_0$ refers to discrete frequency and ω_0 is the frequency resolution of applied Fourier transform. The time and frequency resolution of STFT is fixed as the window length is selected in advance. The overlap between two consecutive windows also affects the time resolution of the output. STFT returns Fast Fourier Transform (FFT) coefficients for each window. The time and frequency resolution of STFT is

$$\Delta t = \frac{N - N_o}{F_s} \qquad \Delta f = \frac{F_s}{N} \tag{2}$$

where F_s is the sampling frequency of the data, N is the window length on which FFT is performed and N_o is the number of sample overlap. For the extraction of features STFT is performed with $N = 256$ and $N_o = 216$ resulting in $\Delta t = 10ms$ and $\Delta f = 15.62Hz$. Figure 3 shows the STFT output data for various power quality disturbances. It is evident from Figures 3b, 3d, 3f, 3h that low frequency FFT coefficients varies when there is a momentary sag/swell/interruption/flicker in the voltage. Figure 3j shows the STFT for low frequency harmonic disturbances.

B. *Feature Extraction from STFT Data*

It is evident from the STFT graph that a few frequency components of the STFT output matrix are most useful for detection of disturbances. The frequencies 46.8Hz ($a3$), 62.5Hz ($a4$) and 156.2 Hz ($a10$) are considered for extracting the features. The sag/swell/interruption/flickering could be observed using $a3$ and $a4$ and harmonics could be observed on $a10$ output. Figure 4 shows the variation of the selected frequency coefficients with respect to the snapshot time. The graph for voltage interruption is not given in the figure, as interruption behaviour of features is similar to voltage sag. The statistical data for the time-varying FFT coefficient is used as features. The final feature used for DT training are

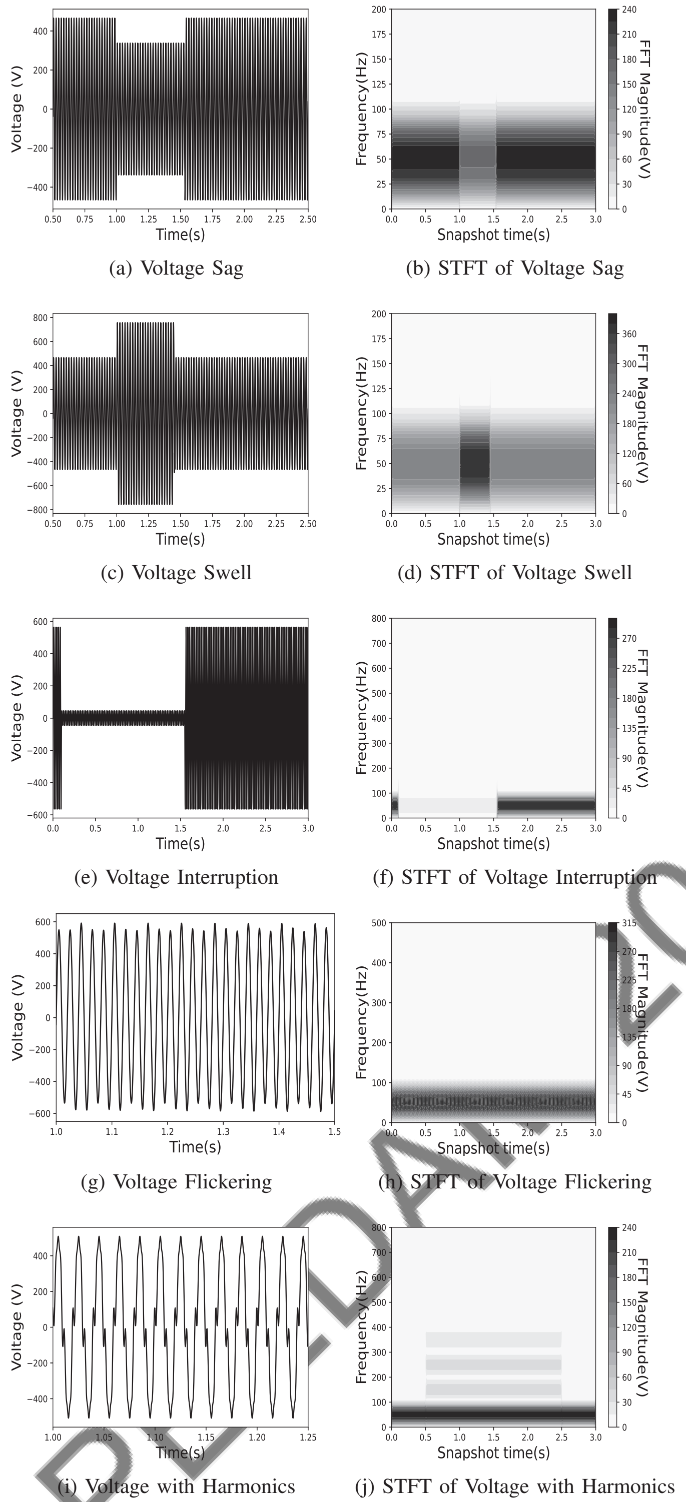
1) *a3*: Minimum, Variance, Kurtosis, Skewness
2) *a4*: Variance, Kurtosis, Skewness
3) *a10*: Mean Value

C. *Decision Tree Classifier*

DTs are a non-parametric supervised learning method used for classification problems. The model predicts the target variable by learning simple decision rules from a feature set [15]. The DT has nodes, where each node represents a test based on feature value, and each branch of a node represents a distinct outcome of the test. DT is a white-box model. It is highly interpretable through proper visualization. This makes it very attractive for real-time deployment. DT has been successfully applied to PQ event classification problem in [16] with Hilbert Transform. The total data-set consists of 678 3-phase voltage snapshot. The *normal* 3-phase supply snapshot is added with white noise, and acceptable frequency variation. 70% of the data is used for training purpose and 30% is used for testing. The formulated DT is shown in Figure 5. The validation accuracy is 98%. Table II lists the output of the decision tree validation.

TABLE II: Decision Tree Validation Test Result

PQ Event	Number of Test Sample	Number of Prediction
Normal	46	46
Sag	56	*57*
Swell	54	*53*
Interruption	16	16
Flicker	11	11
Harmonics	46	46



(a) Voltage Sag (b) STFT of Voltage Sag

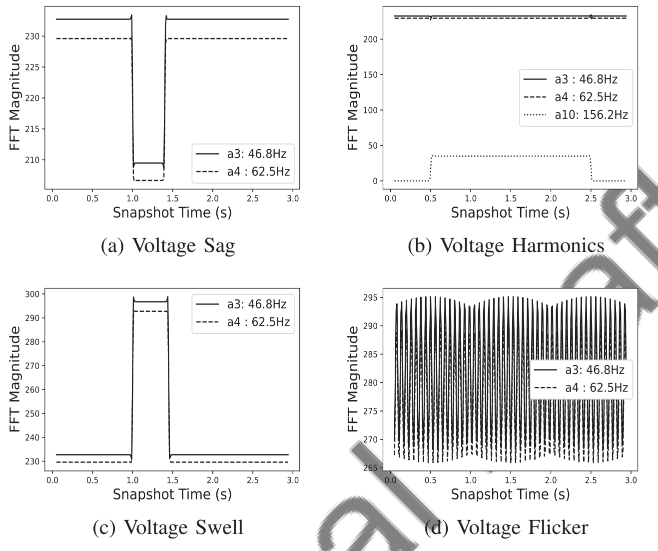
(c) Voltage Swell (d) STFT of Voltage Swell

(e) Voltage Interruption (f) STFT of Voltage Interruption

(g) Voltage Flickering (h) STFT of Voltage Flickering

(i) Voltage with Harmonics (j) STFT of Voltage with Harmonics

Fig. 3: STFT for Various Power Quality Disturbances



(a) Voltage Sag (b) Voltage Harmonics

(c) Voltage Swell (d) Voltage Flicker

Fig. 4: Frequency coefficients (a3,a4,a10) of STFT for PQ Event

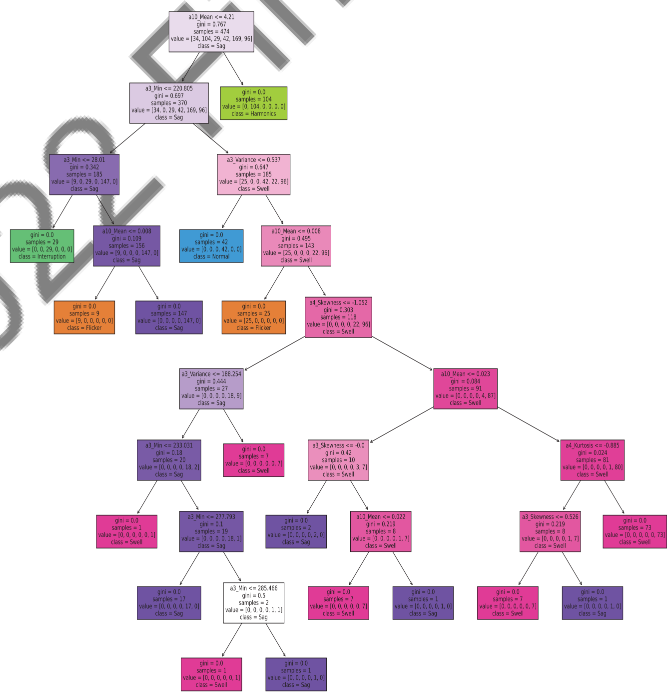


Fig. 5: PQ Event Decision Tree Classifier

IV. RESULTS

The software framework is implemented in Python environment. The snapshot is created using a user-defined class. Snapshot uses NumPy array for storing raw sensor data and dictionary for storing data such as sensor information, signal name, and sampling frequency. STFT feature extraction algorithm is developed on top of FFT, and the DT is implemented using the sklearn Python module. The testing data is generated by taking random parameters for different power quality events. The 3-phase power supply is simulated in real-time hardware in dSPACE and data is sent to edge device through Ethernet. Figure 6 shows the result of the virtual test. It shows the graph of the detected PQ event with respect to the received snapshot number. The red dots in the figure are the snapshots that will be sent to cloud. The periodic checker is set to 1-

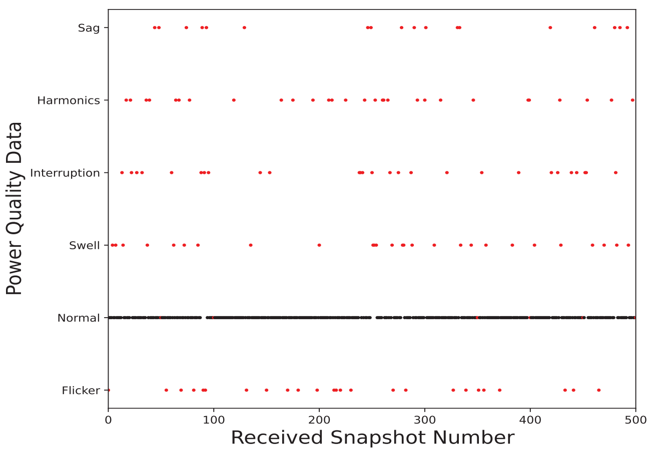


Fig. 6: PQ Event Classification Results

minute, so snapshots are sent to cloud periodically after every 20 snapshots even when there is no abnormal PQ detection.

For a single snapshot with a length of 3s, the raw sensor data size is 288KB and feature set data size is 0.2KB. For a 24hour time duration, the total sensor data size would be around 8GB. Assuming that 50 grid event occurs in a day, the total data transmission size in 24 hours is the sum of the periodic transmission (each minute interval), the 50 Snapshots of the PQ event, and the feature set of 24 hours. The total data transmission using the proposed framework is 424.68MB, which is 94.8% less than the sensor data size of 8GB.

V. Conclusion

The usage of the proposed edge computation framework is not limited to condition monitoring and anomaly detection. Applications, where edge computing is used to monitor local electromechanical systems, can use the framework to effectively communicate with the cloud. Data reduction techniques focus to minimize the amount of raw data that is being sent to the cloud for further processing but the framework intelligently filters out redundant snapshots using a classification algorithm at the edge. The paper demonstrates the application of the proposed software framework to power quality monitoring and implements STFT and DT algorithm for classification purposes, which resulted in approximately 95% reduction of transmitted data in comparison to the only cloud-based framework.

Future work will improve upon the proposed software framework to establish communication from cloud to edge and update the edge device software such as periodic checker, classification algorithm, and snapshot time. Future work also includes implementation of real-time PQ event detection and testing with the industrial drive. The feature sets will be optimized to include all the possible abnormal PQ events that can be detected by keeping the sampling time pragmatic with low-cost edge device.

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References

[1] Aceto, G., Persico, V., & Pescapé, A. (2019). A Survey on Information and Communication Technologies for Industry 4.0: State-of-the-Art, Taxonomies, Perspectives, and Challenges. In IEEE Communications Surveys and Tutorials (Vol. 21, Issue 4, pp. 3467–3501). Institute of Electrical and Electronics Engineers Inc. https://doi.org/10.1109/COMST.2019.2938259

[2] Hafeez, T., Xu, L., & McArdle, G. (2021). Edge intelligence for data handling and predictive maintenance in IIoT. IEEE Access, 9, 49355–49371. https://doi.org/10.1109/ACCESS.2021.3069137

[3] Prudenzi, A., Falvo, M. C., & Mascitelli, S. (2008). Power quality survey on Italian industrial customers: Paper industries. IEEE Power and Energy Society 2008 General Meeting: Conversion and Delivery of Electrical Energy in the 21st Century, PES. https://doi.org/10.1109/PES.2008.4596463

[4] Beniwal, R. K., Saini, M. K., Nayyar, A., Qureshi, B., & Aggarwal, A. (2021). A critical analysis of methodologies for detection and classification of power quality events in smart grid. IEEE Access, 9, 83507–83534. https://doi.org/10.1109/ACCESS.2021.3087016

[5] Thapar, A., Saha, T. K., & Dong, Z. Y. (2004). Investigation of power quality categorisation and simulating it's impact on sensitive electronic equipment. 2004 IEEE Power Engineering Society General Meeting, 1, 528–533. https://doi.org/10.1109/PES.2004.1372855

[6] Hunter I. Power quality issues – a distribution company perspective. Power Engineering Journal 2001;15(2):75–80.

[7] Azam, M. S., Tu, F., Pattipati, K. R., & Karanam, R. (2004). A dependency model-based approach for identifying and evaluating power quality problems. IEEE Transactions on Power Delivery, 19(3), 1154–1166. https://doi.org/10.1109/TPWRD.2003.822537

[8] Pioli, L., Dorneles, C. F., de Macedo, D. D. J., & Dantas, M. A. R. (2022). An overview of data reduction solutions at the edge of IoT systems: a systematic mapping of the literature. Computing. https://doi.org/10.1007/s00607-022-01073-6

[9] Saini, M. K., & Kapoor, R. (2012). Classification of power quality events - A review. International Journal of Electrical Power and Energy Systems, 43(1), 11–19. https://doi.org/10.1016/j.ijepes.2012.04.045

[10] Committee of the IEEE Power, D., & Society, E. (2009). IEEE Recommended Practice for Monitoring Electric Power Quality IEEE Power & Energy Society.

[11] Igual, R., Medrano, C., Arcega, F. J., & Mantescu, G. (2018). Integral mathematical model of power quality disturbances. Proceedings of International Conference on Harmonics and Quality of Power, ICHQP, 2018-May, 1–6. https://doi.org/10.1109/ICHQP.2018.8378902

[12] Testing and Measurement Techniques-Power Quality Measurement Methods, International Electrotechnical Commision Standard IEC 61000-4-30, 2003

[13] Voltage Characteristics of Electricity Supplied by Public Distribution System, European Standard EN 50160, 2010.

[14] Baghzouz, Y., Burch, R. F., Capasso, A., Cavallini, A., Emanuel, A. E., Halpin, M., Imece, A., Ludbrook, A., Montanari, G., Olejniczak, K. J., Ribeiro, P., Rios-Marcuello, S., Tang, L., Thallam, R., & Verde, P. (1998). Time-varying harmonics: Part I - Characterizing measured data. IEEE Transactions on Power Delivery, 13(3), 938–944. https://doi.org/10.1109/61.686996

[15] 1.10. Decision Trees — scikit-learn 1.0.2 documentation. (n.d.). Retrieved March 9, 2022, from https://scikit-learn.org/stable/modules/tree.html

[16] Saini, R., Mahela, O.P. and Sharma, D., 2018, December. An algorithm based on hilbert transform and rule based decision tree classification of power quality disturbances. In 2018 IEEE 8th Power India International Conference (PIICON) (pp. 1-6). IEEE.