"The Rise of Tech and the Question of Power" A Review on Detection and Classification of Multiple Power Quality Disturbances

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***Abstract*—Every single device responds differently to each disturbance, in addition, electrical devices themselves, at times, cause PQ disturbance. Recent studies are focussed on signal processing and classification method of PQ disturbances. The aim of the study is to find the best combination method of classifying multiple PQ disturbances. 80 papers were reviewed in this study. The papers are grouped into several categories related to signal processing and classification method. In this study, an Excel spreadsheet was used to outline the strengths and the weaknesses of the classification methods disscussed in the papers. It is found that the close similarity of characteristic hinders quality detection of PQ disturbance and secondly, previous researchers have chosen limited features extraction hence the lack of information for performing detection. Therefore, a development of modified methodologies is needed in improving the robustness in features extraction and better performance of PQ disturbances classifier. For future studies, it is suggested to focus on Stockwell Transform and Support Vector Machine combination in the methodology.**

***Index Terms*—Power quality, power quality disturbance, signal processing, features extraction, classification technique.**

I. Introduction

POWER system includes power generation, transmission line, and lastly, distribution [1]. Power system has been improved parallel to the development of countries and the manufacturing of electrical machines [2], [3]. In the last a few decades, electrical machines have reduced in size, yet are more efficient [4], [5]. The reduction in size requires these machines to utilize more power electronic devices such as integrated circuits.

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The size reduction is in accordance with the economic competition for products in terms of supply continuity, voltage quality and commercial services [6]. Power quality is an important aspect of a power system. This is very important in demonstrating the efficiency of the power system. Initially, PQ disturbances affecting the electricity supply were considered acceptable.

However, it is now considered a problem to users as the concern falls on both the equipment itself as well as the electricity consumption [7]. This is so as PQ disturbances can lead to malfunctions of equipment as well as affecting the power quality hence resulting in high electricity consumption. The growth of electrical equipment which does not achieve the outlined specification can give rise to the possibility of disturbances to occur. Besides, the use of power electronic devices and non-linear load usually lead to more complex problems in power quality in terms of poor power factor and unstable voltage [8]–[10].

For many years, studies on power quality (PQ) disturbance detection and classification have been published and the field of the study is growing. An accurate detection of PQ disturbance is necessary for precise classification and further mitigation process [3], [11]–[13]. The challenge is more complex due to the growth of technology, which has become a concern when it comes to better PQ.

The characteristics of the electricity at any point in an electrical system, considering a few parameters such as voltage, current, frequency, or waveform (including phase shifted), are known as PQ [13]–[15]. Originally, the waveform of power is a perfect sinusoidal which operates at 50Hz rated frequency, with rated voltage of, for example, 0.4kV, 11kV, 22kV, 33kV, 132kV, 275kV, and 500kV. Distribution system is expected to be capable of conveying quality power to end user. Therefore, researchers are working to find ways to mitigate the PQ problems to minimize the impact of PQ disturbances [16], [17]. Voltage sag, voltage swell, harmonics, momentary interruption, flicker, notch, spike, and transient are disturbance phenomena in power line [18], [19]. To make matters more complex, two or more disturbances can occur simultaneously and they could also take place together with or without noisy environment. These combinations are known as multiple disturbances [20], [21]. These disturbances may cause problems related to PQ, leading to product lifetime reduction, malfunction, stability problems, and equipment failure [2], [22]. The economic value is a strong reason for the need to overcome PQ disturbance problems.

There are two steps to improve PQ. First, recognizing the behaviour of each disturbance by analysing the signal, and secondly, classifying the disturbances using techniques or algorithm. These need to be considered so that characterization and classification of disturbances from raw data can be done.

As per discussed, the present paper aims to uncover techniques for detection and classification of PQ disturbance. The reason behind these are to get better insights for better mitigation of PQ disturbance.

II. DISTURBANCE IN PQ

Every single device responds differently to each disturbance, in addition, electrical devices themselves, at times, cause PQ disturbance. Voltage waveforms can reduce, increase, fluctuate, or distort due to controlled or uncontrolled conditions [23]. This will affect the system such as blinking lamp, unintended trip, and reverse rotation of motors.

There are two classifications for PQ disturbance, which is stationary (e.g. harmonics, inter-harmonics, and flicker) and non-stationary PQ disturbance (e.g. transient, notches, and impulsive waveforms) [24]. Stationary means has a constant variance independent of time and non-stationary are unpredictable data. Basically, the most affected party, when it comes to PQ disturbance, are the end users. However, service providers and manufacturers also need to play their role in providing a quality and safe environment in the using of electricity.

Most power networks, multiple disturbances may appear concurrently and most are superposition (individual PQ disturbance may take place simultaneously with another disturbance and they may occur non-linear to each other) [25], [26]. Due to the complex disturbances, multiple disturbances become an interesting and focused area compared to single PQ disturbance. Another challenge in multiple PQ disturbances is the unexpected possibility of disturbance contributing to the growth in the study perspective. Therefore, in classification techniques, focus should be given on improvements in terms of high rate of recognition, flexibility and consistency [7]. A few weaknesses are found in the existing techniques. Fourier Transform (FT) didn't perform well in extracting PQ disturbance features which are mostly non-stationary signals due to its reliance on the resolution of the window size and it is not suitable to obtain the values of amplitude and frequency due to leakage. Short-Time Fourier Transform (STFT) suffers from inadequate transient signal description due to a fixed window size. Wavelet Transform (WT) capabilities on the other hand, are often significantly degraded in actual practice in noisy environments.

III. SINGLE DISTURBANCE

The Single disturbance is an occurrence where only one PQ disturbance is taking place at the specific time. Examples of single PQ disturbance are discussed according to IEEE standard 1159 [27], including:

A. Sag

A sudden reduction in magnitude is known voltage sag or dip. The occurrence is common in the electric use which is caused by Root Means Square (RMS) reduction due to the reduction of the AC line voltage of 10% to 90% of the nominal line-voltage at certain power frequencies in the period of half of a cycle to 1 minute. Switching on a heavy load, large induction motor starting, or transformer energization are example events causing voltage sag.

B. Swell

Swell is a condition caused by the increase in RMS caused by AC line voltage increment of 110% to 180% of the nominal line-voltage at a certain power frequency in the period of half cycle to 1 minute. Switching off a heavy load and large capacitor bank are examples of causes of voltage swell.

C. Transient

Transient mainly occurs in switching events or due to environmental effects. This may be due to the changes in polarity or due to the condition of the waveform, being in additive or subtractive state. Transient occurs when a voltage or current undergoes a sudden change in the power system. Transients is a short-term event in which, the characteristics are determined by resistance, capacitance, and inductance of the power system network at a certain point. The main characteristic defining transient is the peak amplitude, the increase time, the decrease time, and the oscillation frequency.

D. Interruption

Interruption is a reduction in line-voltage or current of less than 10% percent of the nominal in the duration of half cycle to 1 minute. The failure of the control relay or protection technique, equipment, or any other systems could contribute to interruption.

E. Notch

A steady state phenomenon is known as notch. Notch is a periodic supply of voltage caused by power electronic devices such as converters, rectifiers, or universal bridges. This happens due to current commutation from one phase to another.

F. Flicker

A variation of the input voltage sufficiently over time allowing visual observation of the change in intensity of the electric light source is called flickering. Quantitatively, flicker may manifest as there are changes in voltage over the nominal.

G. Harmonics

Harmonic is a condition where a component's frequency in multiplication of the fundamental frequency at certain peak points. Harmonic is divided into several types, which are Triplen Harmonics, Zero-Sequence Harmonics, Inter-Harmonics, and Subharmonic. Power electronic devices or non-linear loads are the main cause of harmonics.

H. Noise

Noise is self and mutual inductances. Electrical noise is an unwanted electrical signal that produces an unwanted effect on the circuit of the control system in which it occurs.

IV. Multiple Disturbances

Multiple disturbance is a combination of two or more disturbances (with or without noise) occurring simultaneously at the same point [28]–[30]. A few combinations were discussed (e.g. Sag with Oscillatory Transient, Oscillatory transient with Swell, Sag with Notching with Oscillatory Transient, Harmonics with Notch with Swell, and Notch with Oscillatory Transient with Sag with Harmonic) [5],[22],[23].
PQ disturbances are results of heavy load switching, use of power electronic devices, non-linear loads, and line faults [3]. Computers, workstations, and programmable logic controller (PLC) are examples of sensitive equipment prone to miss operation and susceptible to damage if PQ disturbance occurs.
Lightning strikes causes trips as multiple PQ disturbances such as voltage sag and transient occur during its events [33], [34]. The change in the lifestyle also provide impact to the power quality [35]. In concordance to this, the multiple PQ disturbance could occur due to the growth in electrical appliances users. The situation leads to the occurrence of voltage sag with harmonics. The growth of heavy industry, oil and gas industry, and manufacturing are resulted from foreign direct investment and the government policy [36]–[39]. Hence, this results in multiple PQ disturbance such as transient with harmonics as this is always the problem with industrial equipment.

Multiple PQ disturbances come in combinations. With multiple possible combinations of PQ disturbance and a close characteristic of each other, multiple disturbances become more complex in the detection stage, also known as features extraction. Studies conducted had to filter the multiple disturbances repeatedly with a combination of few techniques to get a good feature for excellent use in the classification step. Encoder-Decoder Temporal Convolutional Neural Network (EDTCNN) consists of a number of temporal convolutional layers, maximum pooling layers, and fully connected layers in architecture. Twenty nine classes were classified in which, eight of them being single disturbances and the rest being multiple disturbances [29]. This is quite complex as twenty-nine classes (a large number) were introduced. This is, however, beneficial as high number of single and multiple disturbances can be predicted. More so, this study reveals a result with high levels of noises (20dB to 40dB).

Change Detection Filter Technique (CDFT) was used in the detection method in [40]. This seems easier in extracting features than EDTCNN by proposed parameters with eight indices were considered. These include energy, entropy, root mean square, mean, standard deviation, kurtosis, variance, and maximum peak as classes used. Only six single disturbances and 2 multiple disturbances were discussed in this paper.

Multiple Window Time Window (MWT) spectrum estimation is presented to investigate the Time Frequency analysis (TF) in [41]. MWT is more reliable in extracting features when compared to EDTCNN and CDFT. This is because by analyzing the local power and local frequency comprehensively, identification of any PQ disturbance can be achieved more precisely. In the study, four feature statistics are used to describe the properties of each PQ disturbance (DP = minimum level of the local power, SP = the symmetry of the probability distributions of the local power, HP = autocorrelation characteristics of the local power, and Hf = the and local frequency). This method requires only four feature statistics reflecting the relatively fast in term of computational time.

V. Signal Processing for Features Extraction

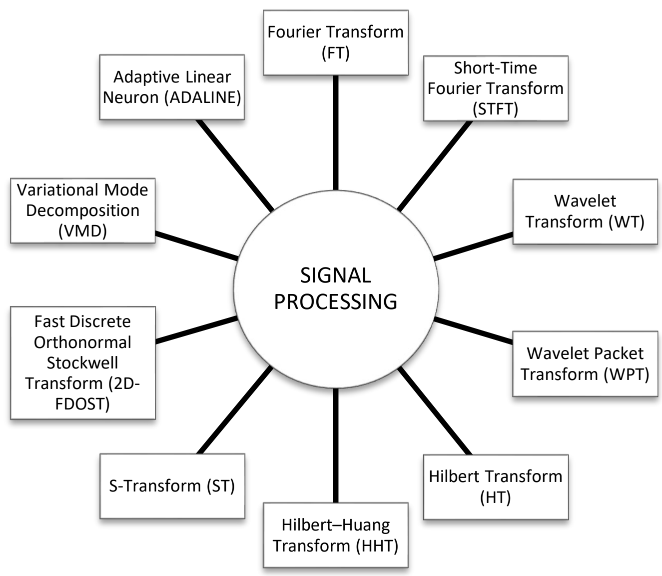

Fig. 1: Signal Processing Methods.

Raw data can be analyzed, modified, and synthesized by signal processing (SP) [42]–[45]. SP will be utilized to extract the raw data to a suitable feature for a selected classification technique. Figure 1 shows the common methods among researchers for SP include Fourier Transform (FT), Short-Time Fourier Transform (STFT), Wavelet Transform (WT), Wavelet Packet Transform (WPT), Hilbert Transform (HT), Hilbert–Huang Transform (HHT), S-Transform (ST), Fast Discrete Orthonormal Stockwell Transform (2D-FDOST), Variational Mode Decomposition (VMD), and Adaptive Linear Neuron (ADALINE).

The Hilbert-Huang Transform (HHT), is proposed based on the energy generated by each disturbance, a distorted waveform is decomposed into eight levels of intrinsic mode functions [46]. Each PQ disturbance has its uniqueness extracted sub signal symbolized as a very important fingerprint for the classification process, considering that these disturbances are considered a short term variation. The main factor in feature extraction is analyzing the original distorted power signal to produce an instantaneous amplitude and instantaneous frequency for the targeted disturbance. Great feature extraction processer called empirical mode decomposition (EMD) is found in HHT resulting in HHT to be able to perform frequency of effective time method for analyzing and detecting the non-stationary signals. In EMD, a non-stationary signal in time domain can be decomposed into an array of sub-signals. Other than that, EMD has the ability to separate the attached frequency to each PQ disturbance and the mean value of these envelopes is zero. Besides that, HHT assimilates the advantages of various Wavelet Transform resolutions, and overcomes the difficulty of selecting wavelet bases. On the other hand, due to end effect and mode mixing that comes with HHT in predicting the number of Intrinsic Mode Functions (IMF), HHT is also considered to be complex. Adding to its complexity, HHT also has no supporting mathematical theory prone to low access, and is sensitive to noise.

The Variational Mode Decomposition (VMD) is also proposed in a study [47]. VMD is more robust to noise, making it better than HHT as it is able to isolate high frequency signals. PQ signal can be decomposed into different modes which is diverse in spectrum. The starting and ending point of a PQ disturbance can be identified as VMD introduces higher level modes. The duration of PQ event can also be measured by choosing the appropriate threshold. However, VMD also suffers from complexity due to the mode features (e.g. Mode Central Frequencies (Mcfs), Relative Mode Energy Ratios (Rmers), Instantaneous Amplitude (IA), and Number of Zero Crossings (Zcs)) which need to be considered in discriminating PQ disturbances effect.

Arithmetic mean, geometric mean, harmonic mean, standard deviation, skewness, and kurtosis are statistical properties for time frequency basis presented in [48] for feature extraction stage based on 2D Fast Discrete Orthonormal Stockwell Transform (2D-FDOST). Two types of feature vectors were chosen which are energy-based (energy, entropy, and log-energy entropy) and 2D-signal processing (homogeneity). By calculating the amplitude and phase matrices, the feature vector was created in the 2D-FDOST result. The 2D-FDOST advantage is it is less complex in calculating the feature extraction stage compared to 1D Transformation as proposed by [11], [29] and K-Nearest Neighbour (KNN) from machine learning methods which provides genetic diversity with less complex calculation of fitness function. However, the result shown is as good as 1D-signal processing method. 2D-FDOST however, although not as complex as 1D-signal processing method, still suffers from the complexity as HHT and VMD and is still time-consuming.

ADALINE is used in extracting signals from noisy environments, model identification, and linearizing nonlinear problems [52]. Harmonics estimation is assumed based on the Fourier series. This is considering that the sum of all harmonic component is the fundamental frequency, and the amplitude and phase angles are unknown. The performance using ADALINE is compared to VMD [31], and VMD provides a better result for double disturbances in noisy environment, where ADALINE shown 86.23%, meanwhile VMD shown 99%, in average. However, ADALINE also has a drawback as it is time consuming and it becomes more challenging when it comes to troubleshooting.

The less time-consuming technique is Stockwell Transform (ST). ST results in a two-dimension matrix with complex elements presented in a size of $N \times M$ matrix elements with a selected power frequency. A data window of the selected number of cycles simulates the disturbance. In the result, their magnitudes and frequencies in their duration of test characterize these disturbances [22], [53], [54].

Among all of the techniques, ST is the most powerful signal processing method in extracting features in single or multiple PQ disturbances as mentioned by [11], [34]. ST provide the solution to overcome the drawbacks on FT and STFT, in which they cannot adequately analyse transient phenomenon due to fixed window sizes. Besides that, ST fixes the problem of the presence of electrical noise in WT, Continous Wavelet Transform (CWT), Discrete Wavelet Transform (DWT) which significantly affect the performance. In addition, ST acts as an extension of WT covering the major drawbacks in WT. The major drawbacks of WT are the inability to select an appropriate mother wavelet for different PQ disturbances and the difficulty to fix the number of levels of decomposition. WT is also not suitable in the analysis of high-frequency signals with relatively narrow bandwidth. ST has the capabilities to solve problems faced in other methodologies as it is easy to structure and requires minimal computational complexity.

VI. CLASSIFICATION ALGORITHM

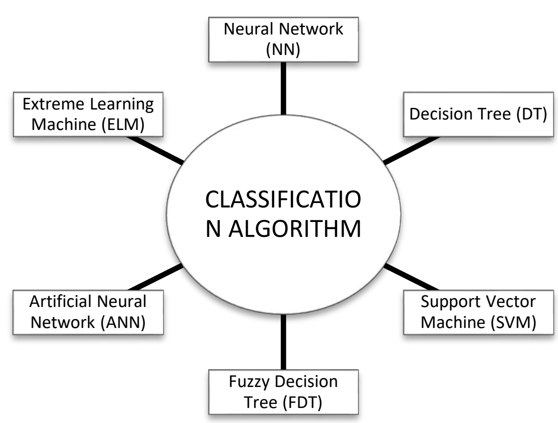

Fig. 2: Types of Classification Algorithm

After extracting the features, the second step is to recognize by classifying the type of single or multiple disturbances in PQ. This step is known as classification technique. Each of the disturbances has its own characteristics which will be figured out in this stage. Figure 3 shows a block diagram of the journey for the detection and the classification of PQ disturbances.

The most common methods to classify the disturbance signal, as can be observed in Figure 2 are Neural Network (NN), Decision Tree (DT), Support Vector Machine (SVM), Fuzzy

Decision Tree (FDT), Artificial Neural Network (ANN), and Extreme Learning Machine (ELM).

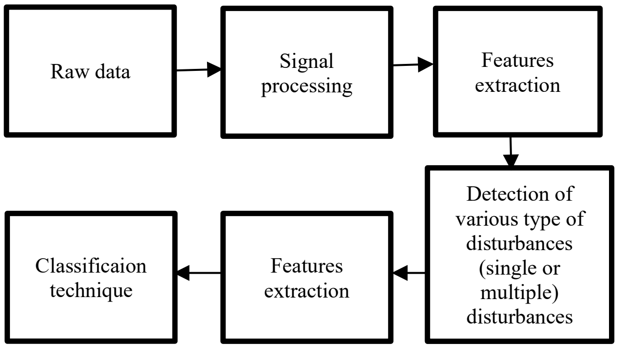

Fig. 3: Block diagram of steps for detection and classification of PQ disturbances.

Feedforward Neural Network (FFNN) was proposed in [56]. Through four outputs, it indicates a parameter of each of disturbance, whether it is single or multiple disturbances. By setting the neuron outputs, the disturbance exists if the value is one, and no disturbance found if the value is zero. To force the output to either one or zero, a threshold of 0.5 is chosen.

A different approach was taken by [46] where FFNN is based on multiplying inputs with their weights. Seven PQ disturbances were extracted where each one of the events has its own neural. The results of features solve the issues in the database, hence solving other problems in learned results.

Experimental results are faster to acquire and are more accurate in disturbance classification when employing ELM [57] compared to FFNN. Also known as a single hidden layer network, ELM is good at generalizing capabilities and has a fast learning capacity. Due to the random determination of hidden biases and the input weights, more hidden neurons are required. This reflected the sufferings in determining suitable hidden biases and input weights, in order to get a solid performance.

DT is applied in [31] as a method for classification of PQ disturbances. It is able to separate noise from disturbance features while detecting the existence of single or multiple disturbances independently. Based on center frequency with a tolerance band of ±5Hz, detection can be done on stationary features. This center frequency can also determine the fundamental frequency and mode decomposition error even in strong noise level conditions. For suitability in flicker detection, the frequency is narrowed down to ±2Hz. DT methods reveal cumulative errors in the process of the iterative classification of all disturbances.

DT based on Perceptron's and Bayesian classifier is also presented in[58]. The possibility of the proposed method was to classify twenty classes of multiple and isolated disturbances. DT is also proposed in [12] mentioning that it splits the training data with the maximum possible distinction via a large number of nodes. The optimal tree obtained according to the node splitting is always guided by certain metrics.

SVM is a learning algorithm which is used in solving regression problems and small sampling data classification [59]. The nonlinear classification via the introduction of kernel function is the main idea of SVM. To construct the optimal classification of hyper plane in the space, the interval between the positive and the negative samples is made to obtain the maximum value.

Based on the study, SVM is chosen for classification method. In high dimensional spaces, SVM performance is better compared to NN. The strength of SVM is caused by the kernel trick. With an appropriate kernel function, complex problem or non-linear data can be solved efficiently. In addition, SVM is a stable model, where a little change to the data does not affect the performance of SVM. Moreover, SVM is faster in training and robustness to noise.

VII. SIGNAL PROCESSING AND CLASSIFICATION ALGORITHM FOR MULTIPLE DISTURBANCES

There are two steps to be taken before the types of disturbance can be identified. The first step is signal processing or features extraction which is to extract the relevant features and to identify the detection threshold for classification from the voltage signals (with or without noise) and PQ disturbances [60], [61]. Researchers must use a strong signal processing tool as feature extraction is the most important part in the detection and classification of different types of disturbance. The next step is the classification method. This is employed to extract and classify the PQ events' characteristics. The review of the studies reveals that signal processing can be combined to yield some advantages and better results for methods discussed. The studies discussed certain combinations such as ADALINE and Feedforward Neural Network (FFNN), S-transform and a Rule-Based Decision Tree (RBDT) and ANN, S-transform and Multi-Resolution Analysis (MRA), Variational Mode Decomposition and Decision Tree, and Time Frequency Analysis (MWT) and Decision Tree. Table 1 presents a combination of signal processing and classification algorithm, with advantages outlined in the paper.

TABLE I
COMBINATION OF SIGNAL PROCESSING AND CLASSIFICATION ALGORITHM

No.	Combination of signal processing classification method	Advantages	Disadvantages
1	ADALINE and Feedforward Neural Network (FFNN) [52]	The use of NNs allows obtaining good results in noisy environments due to the high immunity to noise of an NN. The methodology can be easily expanded for three-phase power systems.	Training and testing is time consuming. Linear nature of ADALINE may result in inaccurate predictions
2	S-transform and a Rule-Based Decision Tree (RBDT) and ANN [22]	Features extracted from contours of the S-matrix are effectively used for the automatic classification of the PQ	ST Suffers from mode mixing problem, huge calculation complexity and

		disturbances. The ANN and rule-based decision tree, is an effective and intelligent technique for the PQ monitoring instruments.	excessive dependence to power quality signals.
3	S-transform and Multi-Resolution Analysis (MRA) [62]	The proposed approach using S-transform can effectively be applied to detect various operational events and assess the PQ in a hybrid power system with RE penetration.	Very dependence to power quality signals and suffer to map a given function into an appropriate subspace before starting an MRA
4	Variational Mode Decomposition and Decision Tree. [31]	The potential ability of VMD technique to accurately estimate amplitudes, frequencies and phases of the fundamental, harmonic and interharmonic, and flicker components under mixture of other non-sinusoidal PQ disturbances, in both noise-free and noisy scenarios. The VMD with decision-tree based algorithm is an effective and efficient method for detection and classification of single and mixed PQ disturbances under noise-free and noisy environments.	Suffer to mode mixing problem. DT suffer to very sensitive to the training set and sensitive to noise. DT also suffer to fragmentation problem causes partitioning of the data into smaller fragments.
5	Multiple Window Time Window (MWT) and Decision Tree. [41]	The feature-extraction algorithm can acquire the target statistics of different PQ disturbances using TF analysis. the proposed method requires only four feature statistics, and the computational cost is relatively small, and it also has implications for conquering the challenges faced in modern smart grids.	DT suffer to very sensitive to the training set and sensitive to noise. DT also suffer to fragmentation problem causes partitioning of the data into smaller fragments.
6	Histogram of Oriented Gradients and Support Vector Machine. [63]	Has less processing time since this technique can be applied to multiple events occurring at same time. All the events have been generated synthetically as per IEEE standards so the results obtained are highly reliable.	SVM suffer on selection on appropriate kernel and its parameters and expose to multiclass problems.
7	Variational Mode Decomposition (VMD) and Fischer liear discriminant analysis (FDA) and Reduced Kernel Extreme Learning Machine (RKELM). [47]	Computationally RKELM is much efficient, and has a faster response, with lowest training time, for almost all the multiclass power system disturbances. KELM has better generalisation capability than basic ELM. The most important point in KELM is that volatility does not occur in it.	Suffer to high training time and difficult to choose the best kernel function for better result in classification.
8	Fast S-Transform (FST) and Extreme Learning Machine (ELM). [64]	The statistical based features of the FST amplitude matrix remain more observable and logical. ELM has the ability for online PQ disturbances classification automatically.	Suffer to select discriminative features that can describe, detects and recognizes the main characterization of the disturbed signals for better efficiency.
9	Variational Mode Decomposition (VMD) and Random discriminative projection extreme learning machine for multi-label learning (RDPEML. [65]	The RDPEML could achieve better classification performance compared with several state-of-the-art multi-label algorithms, but with far lower computational costs (training time).	Suffer to high training time and difficult to choose the best kernel function for better result in classification.
10	Tunable-Q wavelet transform (TQWT) and Multiclass support vector machines (MSVM). [14]	Excellent decomposition, less number of features and computationally efficient.	Suffer to tuning of Q and r is decided on the basis of interharmonics present near fundamental frequency

ST and SVM are the combination of technique chosen for next study. An advantages of ST will give a good result in extracting data [66]. With good extraction features, it is hoped that each interruption may show different behaviors, in terms of output waves or other forms of output, that are expected to be found in the future. Based on ST results, SVM will classify the disturbances. Finally, to confirm this combination is better than other combinations, comparisons with other techniques are taken into account, based on the papers that have been published.

VIII. CONCLUSION

This paper deals with a review on past studies on detection and classification of PQ disturbances in the electrical power system. The main objective of this paper is to provide a comprehensive understanding on papers cited, focusing on the methodologies on features selection and classification methods. Despite the number of papers published in this area in the recent years, the researcher is still interested to venture in this field even though it has been a widely discussed in publications as there are still rooms for improvements. This is due to the concern of PQ among manufacturers and users in which it is still growing.

In the case of multiple PQ disturbances, the close similarity of characteristic hinders quality detection of PQ disturbance [67]. Here, a few modifications can be made. First, signal processing creates a border distortion at the starting and the ending in the result. A few modifications can be made in the signal processing technique to minimize the border distortion especially in ST results as it has never been done before [68]–[71]. Secondly, previous researchers have chosen limited features extraction hence the lack of information for performing detection [72]–[74]. Here, more numbers need to be considered to resolve confusions in acquiring a solid and consistent result in PQ disturbance detection. However, dealing with a large number of features are time consuming and requires complicated algorithms in the classification process. Alternatively, this problem can be resolved by employing statistical science such as analysis of variance (ANOVA), which can reduce the convolution process [75]–[77]. Lastly, the mitigation process can be done easily if the location of occurrence of PQ disturbance is identified [78]–[80]. If the source location of PQ disturbance can be detected, equipment contributing to PQ disturbances can be identified and the mitigation process can be performed more accurately, without interfering with the operations of other equipment.

Therefore, for future venture, the development of modified methodologies based on ANOVA is needed in improving the robustness in features extraction and better performance of PQ disturbances classifier as it would provide a more comprehensive inclusivity of features of signal processing.

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REFERENCES

[1] M. Guarnieri, "Electricity in the age of enlightenment," *IEEE Industrial Electronics Magazine*, pp. 60–63, 2014.

[2] E. G. Ribeiro *et al.*, "Real-time system for automatic detection and classification of single and multiple power quality disturbances," *Measurement (Lond)*, vol. 128, pp. 276–283, 2018, doi: 10.1016/j.measurement.2018.06.059.

[3] R. K. Beniwal, "Generation of single and multiple power quality disturbances using MATLAB/Simulink," *Internasional Journal of Engineering, Science and Mathematics*, vol. 6, no. 4, pp. 10–15, 2017.

[4] N. Ullah *et al.*, "Modeling and assessing cyber resilience of smart grid using Bayesian network-based approach : a system of systems problem," *J Comput Des Eng*, vol. 7, no. 3, pp. 352–366, 2020, doi: 10.1093/jcde/qwaa029.

[5] Q. Wu, Y. Cao, H. Wang, and W. Hong, "Machine-learning-assisted optimization and its application to antenna designs : opportunities and challenges," *China Communications*, vol. 17, no. 4, pp. 152–164, 2020.

[6] T. Gómez and J. Rivier, "Distribution and power quality regulation under electricity competition. A comparative study," *Proceedings of International Conference on Harmonics and Quality of Power, ICHQP*, vol. 2, pp. 462–468, 2000, doi: 10.1109/ICHQP.2000.897723.

[7] S. Khokhar, A. A. M. Zin, A. S. Mokhtar, and N. Zareen, "Automatic pattern recognition of single and multiple power quality disturbances," *Australian Journal of Electrical and Electronics Engineering*, vol. 13, no. 1, pp. 43–53, 2016, doi: 10.1080/1448837X.2015.1092932.

[8] E. Kaufhold, J. Meyer, and P. Schegner, "Measurement framework for analysis of dynamic behavior of single-phase power electronic devices," in *18th International Conference on Renewable Energies and Power Quality (ICREPQ'20)*, 2020, vol. 18, pp. 494–499.

[9] Ł. Michalec and M. Jasi, "Impact of harmonic currents of nonlinear loads on power quality of a low voltage network – review and case study," *Energies, MDPI, Open Access Journal*, vol. 14, no. 12, 2021.

[10] J. Hern, A. Romero, J. Meyer, and A. Mar, "Impact of nonlinear lighting loads on the neutral conductor current of low voltage residential grids," *Energies, MDPI, Open Access Journal*, vol. 13, no. 18, 2020.

[11] S. A. Deokar and L. M. Waghmare, "Integrated DWT-FFT approach for detection and classification of power quality disturbances," *International Journal of Electrical Power and Energy Systems*, vol. 61, pp. 594–605, 2014, doi: 10.1016/j.ijepes.2014.04.015.

[12] U. Singh and S. N. Singh, "A new optimal feature selection scheme for classification of power quality disturbances based on Ant Colony Framework," *Applied Soft Computing Journal*, vol. 74, pp. 216–225, 2019, doi: 10.1016/j.asoc.2018.10.017.

[13] O. P. Mahela and A. G. Shaik, "Power quality recognition in distribution system with solar energy penetration using S-transform and Fuzzy C-means clustering," *Renew Energy*, vol. 106, pp. 37–51, 2017, doi: 10.1016/j.renene.2016.12.098.

[14] K. Thirumala, M. Siva Prasad, T. Jain, and A. C. Umarikar, "Tunable-Q Wavelet Transform and Dual Multiclass SVM for online automatic detection of power quality disturbances," *IEEE Trans Smart Grid*, vol. 9, no. 4, pp. 3018–3028, 2018, doi: 10.1109/TSG.2016.2624313.

[15] K. Thirumala, Shantanu, T. Jain, and A. C. Umarikar, "Visualizing time-varying power quality indices using generalized empirical Wavelet Transform," *Electric Power Systems Research*, vol. 143, pp. 99–109, 2017, doi: 10.1016/j.epsr.2016.10.017.

[16] O. P. Mahela, B. Khan, H. H. Alhelou, S. Tanwar, and S. Padmanaban, "Harmonic mitigation and power quality improvement in utility grid with solar energy penetration using distribution static compensator," *IET Power Electronics*, vol. 14, no. 5, pp. 912–922, 2021, doi: 10.1049/pel2.12074.

[17] A. Y. Solanki and Dr. S. R. Vyas, "A review on power quality enhancement using custom power devices," *International Research Journalof Enginering and Technology (IRJET)*, vol. 8, no. 2, pp. 287–290, 2021.

[18] Rahul and B. Choudhary, "An advanced genetic algorithm with improved Support Vector Machine for multi-class classification of real power quality events," *Electric Power Systems Research*, vol. 191, pp. 1–11, 2021, doi: 10.1016/j.epsr.2020.106879.

[19] R. Saini, O. P. Mahela, and D. Sharma, "Detection and classification of complex power quality disturbances using Hilbert Transform and rule based Decision Tree," in *8th IEEE Power India International Conference, PIICON 2018*, 2018, vol. 1680, pp. 1141–1147. doi: 10.1109/POWERI.2018.8704427.

[20] K. Wang and Y. Xi, "A new method of power quality disturbance classification based on deep belief network," *J Phys Conf Ser*, vol. 1827, no. 1, pp. 1–8, 2021, doi: 10.1088/1742-6596/1827/1/012021.

[21] Abdullah, M. U. Khan, S. Aziz, A. Usman, and T. Jalil, "Soft computing approach for classification of complex power quality events," *2021 International Conference on Artificial Intelligence, ICAI 2021*, pp. 223–228, 2021, doi: 10.1109/ICAI52203.2021.9445264.

[22] R. Kumar, B. Singh, D. T. Shahani, A. Chandra, and K. Al-Haddad, "Recognition of power-quality disturbances using S-Transform-Based ANN classifier and rule-based Decision Tree," *IEEE Trans Ind Appl*, vol. 51, no. 2, pp. 1249–1258, 2015, doi: 10.1109/TIA.2014.2356639.

[23] W. Grycan, B. Brusilowicz, and M. Kupaj, "Photovoltaic farm impact on parameters of power quality and the current legislation," *Solar Energy*, vol. 165, pp. 189–198, 2018, doi: 10.1016/j.solener.2018.03.016.

[24] H. Liu, F. Hussain, Y. Shen, S. Arif, A. Nazir, and M. Abubakar, "Complex power quality disturbances classification via curvelet transform and deep learning," *Electric Power Systems Research*, vol. 163, no. 2018, pp. 1–9, 2018, doi: 10.1016/j.epsr.2018.05.018.

[25] D. D. Ferreira, J. M. D. Seixas, and A. S. Cerqueira, "A method based on independent component analysis for single and multiple power quality disturbance classification," *Electric Power Systems Research*, vol. 119, pp. 425–431, 2015, doi: 10.1016/j.epsr.2014.10.028.

[26] S. Dalai, D. Dey, B. Chatterjee, S. Chakravorti, and K. Bhattacharya, "Cross-Spectrum analysis-based scheme for multiple power quality disturbance sensing device," *IEEE Sens J*, vol. 15, no. 7, pp. 3989–3997, 2015, doi: 10.1109/JSEN.2014.2377775.

[27] IEEE Power and Energy Society, *EEE Std 1159TM-2019: Recommended Practice for Monitoring Electric Power Quality*, vol. 2019. 2019.

[28] Y. Shen, H. Wu, G. Liu, H. Liu, H. Zhang, and W. Xia, "Study on identification of power quality disturbances based on compressive sensing," *Proceedings of the World Congress on Intelligent Control and Automation (WCICA)*, vol. 11, pp. 5550–5555, 2015, doi: 10.1109/WCICA.2014.7053664.

[29] M. Mohammadi, M. Afrasiabi, S. Afrasiabi, and B. Parang, "Detection and classification of multiple power quality disturbances based on Temporal Deep Learning," in *2019 IEEE International Conference on Environment and Electrical Engineering and 2019 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe)*, Jun. 2019, pp. 1–5. doi: 10.1109/EEEIC.2019.8783378.

[30] X. Shi, H. Yang, Z. Xu, X. Zhang, and M. R. Farahani, "An Independent Component Analysis classification for complex power quality disturbances with Sparse Auto Encoder features," *IEEE Access*, vol. 7, pp. 20961–20966, 2019, doi: 10.1109/ACCESS.2019.2898211.

[31] P. D. Achlerkar, S. R. Samantaray, and M. Sabarimalai Manikandan, "Variational Mode Decomposition and Decision Tree based detection and classification of power quality disturbances in grid-connected distributed generation system," *IEEE Trans Smart Grid*, vol. 9, no. 4, pp. 3122–3132, 2018, doi: 10.1109/TSG.2016.2626469.

[32] Y. Deng, H. Jia, P. Li, X. Tong, and F. Li, "A Deep Learning method based on long short term memory and Sliding Time Window for type recognition and time location of power quality disturbance," in *2018 Chinese Automation Congress (CAC)*, Nov. 2018, pp. 1764–1768. doi: 10.1109/CAC.2018.8623810.

[33] M. A. Bahari, Z. A. Baharudin, T. Sutikno, A. I. A. Rahman, M. A. M. Hanafiah, and M. Ibrahim, "An analysis of manual and autoanalysis for submicrosecond parameters in the typical first lightning return stroke," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 23, no. 3, pp. 1451–1457, 2021, doi: 10.11591/ijeecs.v23.i3.pp1451-1457.

[34] K. Nazri, C. L. Siow, and C. Gomes, "Lightning safety awareness level in Malaysia," *Research Synergy Foundation*, pp. 1–8, 2021.

[35] N. A. Ismail, "The rising cost of living among B40 households in penang state : does lifestyle matter ?," *Malaysian Journal Of Consumer And Family Economics*, vol. 27, no. 2011, pp. 25–43, 2021.

[36] "Foreign direct investment and manufacturing growth : the malaysian experience," *International Business Research*, vol. 1, no. 3, pp. 83–90, 2008.

[37] Y. Go, L. Lau, and K. Yii, "Does energy efficiency affect economic growth ? Evidence from aggregate and disaggregate levels," *Energy & Environment*, vol. 31, no. 6, pp. 983–1006, 2019, doi: 10.1177/0958305X19882395.

[38] A. Samsi, N. Abdullah, and L. H. Eam, "Malaysian Economic Transformation Programme (ETP) and pattern of job flows in manufacturing sector : 2005-2015," *Journal of Critical Reviews*, vol. 7, no. 5, pp. 144–150, 2020.

[39] M. Rosli and F. Kari, "Malaysia ' s National Automotive Policy and the performance of Proton ' s foreign and local vendors Malaysia ' s National Automotive Policy and the performance of Proton ' s foreign and local vendors," *Asia Pacific Business Review*, vol. 14, no. 1, pp. 103–118, 2008, doi: 10.1080/13602380701661044.

[40] Kanche Anjaiah, "An Advanced signal processing based multiclass power quality disturbance detection and classification technique for grid connected solar PV farm," *International Journal of Innovative Technology and Exploring Engineering (IJITEE)*, vol. 8, no. 9, pp. 876–896, 2019.

[41] T. Zhong, S. Zhang, G. Cai, and N. Huang, "Power-quality disturbance recognition based on time-frequency analysis and decision tree," *IET Generation, Transmission and Distribution*, vol. 12, no. 18, pp. 4153–4162, 2018, doi: 10.1049/iet-gtd.2018.5780.

[42] S. Wu, S. Member, P. Russhard, R. Yan, S. Member, and S. Tian, "An adaptive on-line blade health monitoring method : from raw data to parameters identification," *IEEE Trans Instrum Meas*, vol. 69, no. 5, pp. 2581–2592, 2020, doi: 10.1109/TIM.2020.2967111.

[43] A. Khosla, P. Khandnor, and T. Chand, "A comparative analysis of signal processing and classification methods for different applications based on EEG signals," *Integr Med Res*, vol. 40, no. 2, pp. 649–690, 2020, doi: 10.1016/j.bbe.2020.02.002.

[44] M. H. Conde, "Raw Data Processing For Practical Time-of-Flight Super-Resolution," in *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2021, pp. 1650–1654.

[45] H. Su, Q. Liu, and J. Li, "Boundary effects reduction in Wavelet Transform for Time-frequency Analysis 2 boundary effects in the time- frequency signal analysis using Wavelet scalogram," *WSEAS Transactions on Signal Processing*, vol. 8, no. 4, pp. 169–179, 2012.

[46] S. Alshahrani, M. Abbod, and G. Taylor, "Detection and classification of power quality disturbances based on Hilbert-Huang transform and feed forward neural networks," *2016 51st International Universities Power Engineering Conference, UPEC 2016*, pp. 1–6, 2017, doi: 10.1109/UPEC.2016.8114075.

[47] T. Chakravorti and P. K. Dash, "Multiclass power quality events classification using variational mode decomposition with fast reduced kernel extreme learning machine-based feature selection," *IET Science, Measurement & Technology*, vol. 12, no. 1, pp. 106–117, 2018, doi: 10.1049/iet-smt.2017.0123.

[48] S. Karasu and Z. Saraç, "Investigation of power quality disturbances by using 2D discrete orthonormal S-transform, machine learning and multi-objective evolutionary algorithms," *Swarm Evol Comput*, vol. 44, no. 2019, pp. 1060–1072, 2019, doi: 10.1016/j.swevo.2018.11.002.

[49] O. P. Mahela and A. G. Shaik, "Recognition of power quality disturbances using S-transform based ruled decision tree and fuzzy C-means clustering classifiers," *Applied Soft Computing Journal*, vol. 59, pp. 243–257, 2017, doi: 10.1016/j.asoc.2017.05.061.

[50] M. V. Reddy and R. Sodhi, "A rule-based S-Transform and AdaBoost based approach for power quality assessment," *Electric Power Systems Research*, vol. 134, pp. 66–79, 2016, doi: 10.1016/j.epsr.2016.01.003.

[51] H. Erişti, Ö. Yildirim, B. Erişti, and Y. Demir, "Automatic recognition system of underlying causes of power quality disturbances based on S-Transform and Extreme Learning Machine," *International Journal of Electrical Power and Energy Systems*, vol. 61, pp. 553–562, 2014, doi: 10.1016/j.ijepes.2014.04.010.

[52] M. Valtierra-Rodriguez, R. De Jesus Romero-Troncoso, R. A. Osornio-Rios, and A. Garcia-Perez, "Detection and classification of single and combined power quality disturbances using neural networks," *IEEE Transactions on Industrial Electronics*, vol. 61, no. 5, pp. 2473–2482, 2014, doi: 10.1109/TIE.2013.2272276.

[53] S. Jamali, A. R. Farsa, and N. Ghaffarzadeh, "Identification of optimal features for fast and accurate classification of power quality disturbances," *Measurement (Lond)*, vol. 116, no. 2018, pp. 565–574, 2018, doi: 10.1016/j.measurement.2017.10.034.

[54] M. Fais, A. Ghani, A. F. Abidin, N. S. Hannoon, and U. T. Mara, "Real time detection and classification of single and multiple power quality disturbance based on embedded S- Transform algorithm in Labview," *2017 International Symposium on Industrial Engineering and Operations Management (IEOM)*, pp. 280–289, 2017.

[55] M. Meena, O. P. Mahela, M. Kumar, and N. Kumar, "Detection and classification of power quality disturbances using Stockwell Transform and rule based Decision Tree," in *2018 International Conference on Smart Electric Drives and Power System (ICSEDPS)*, Jun. 2018, pp. 227–232. doi: 10.1109/ICSEDPS.2018.8536064.

[56] M. Valtierra-Rodriguez, R. De Jesus Romero-Troncoso, R. A. Osornio-Rios, and A. Garcia-Perez, "Detection and classification of single and combined power quality disturbances using neural networks," *IEEE Transactions on Industrial Electronics*, vol. 61, no. 5, pp. 2473–2482, 2014, doi: 10.1109/TIE.2013.2272276.

[57] R. Ahila, V. Sadasivam, and K. Manimala, "An integrated PSO for parameter determination and feature selection of ELM and its application in classification of power system disturbances," *Applied Soft Computing Journal*, vol. 32, pp. 23–37, 2015, doi: 10.1016/j.asoc.2015.03.036.

[58] E. G. Ribeiro, G. L. Dias, B. H. G. Barbosa, and D. D. Ferreira, "Real-time system for automatic classification of power quality disturbances," *Proceedings of International Conference on Harmonics and Quality of Power, ICHQP*, pp. 908–913, 2016, doi: 10.1109/ICHQP.2016.7783405.

[59] Z. Liquan, G. Meijiao, and W. Lin, "Classification of multiple power quality disturbances based on the improved SVM," *Proceedings of the 2017 International Conference on Wireless Communications, Signal Processing and Networking, WiSPNET 2017*, pp. 2625–2628, 2018, doi: 10.1109/WiSPNET.2017.8300239.

[60] O. Cortes-Robles, E. Barocio, A. Obushevs, P. Korba, and F. R. S. Sevilla, "Fast-training feedforward neural network for multi-scale power quality monitoring in power systems with distributed generation sources," *Measurement (Lond)*, vol. 170, 2021, doi: 10.1016/j.measurement.2020.108690.

[61] Y. Liu, T. Jin, M. A. Mohamed, and Q. Wang, "A novel three-step classification approach based on time-dependent spectral features for complex power quality disturbances," *IEEE Trans Instrum Meas*, vol. 70, 2021, doi: 10.1109/TIM.2021.3050187.

[62] A. G. Shaik and O. P. Mahela, "Power quality assessment and event detection in hybrid power system," *Electric Power Systems Research*, vol. 161, pp. 26–44, 2018, doi: 10.1016/j.epsr.2018.03.026.

[63] R. Kapoor, R. Gupta, L. H. Son, S. Jha, and R. Kumar, "Detection of power quality event using histogram of oriented gradients and Support Vector Machine," *Measurement (Lond)*, vol. 120, pp. 52–75, 2018, doi: 10.1016/j.measurement.2018.02.008.

[64] L. Samal, D. Samal, and B. Sahu, "Recognition and classification of multiple power quality disturbances with S-Transform and Fast S-Transform using ELM based classifier," *2018 2nd International Conference on Data Science and Business Analytics (ICDSBA)*, pp. 180–185, 2018, doi: 10.1109/ICDSBA.2018.00039.

[65] C. Zhao *et al.*, "Novel method based on Variational Mode Decomposition and a Random Discriminative Projection Extreme Learning Machine for multiple power quality disturbance recognition," *IEEE Trans Industr Inform*, vol. 15, no. 5, pp. 2915–2926, 2019, doi: 10.1109/TII.2018.2871253.

[66] K. Nandi, A. K. Das, R. Ghosh, S. Dalai, and B. Chatterjee, "Hyperbolic window S-Transform aided Deep Neural Network model-based power quality monitoring framework in electrical power system," *IEEE Sens J*, vol. 21, no. 12, pp. 13695–13703, 2021, doi: 10.1109/JSEN.2021.3071935.

[67] I. Sekhar, S. Pravat, K. Rout, and S. Mishra, "An optimal extreme learning-based classification method for power quality events using fractional Fourier transform," *Neural Comput Appl*, vol. 33, pp. 4979–4995, 2020, doi: 10.1007/s00521-020-05282-y.

[68] M. Hadas-Dyduch, "Nonlinear alleviation of edge effects in the context of minimizing prediction errors," *Int J Econ Finance*, vol. 10, no. 2, p. 161, 2018, doi: 10.5539/ijef.v10n2p161.

[69] I. Domuta and T. P. Palade, "Sliding DFT and zero padding," *2019 42nd International Conference on Telecommunications and Signal Processing, TSP 2019*, pp. 154–157, 2019, doi: 10.1109/TSP.2019.8769076.

[70] S. H. Asman, M. A. T. M. Yusoh, and A. F. Abidin, "The application of S-Transform to reduce border distortion effect based on window length," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 9, no. 1, pp. 177–182, 2018, doi: 10.11591/ijeecs.v9.i1.pp177-182.

[71] A. Nguyen, S. Choi, W. Kim, S. Ahn, J. Kim, and S. Lee, "Distribution padding in Convolutional Neural Networks," *2019 IEEE International Conference on Image Processing (ICIP)*, pp. 4275–4279, 2019.

[72] O. P. Mahela, B. Khan, H. H. Alhelou, P. Siano, and S. Member, "Power quality assessment and event detection in distribution network with wind energy penetration using Stockwell Transform and Fuzzy clustering," *IEEE Trans Industr Inform*, vol. 16, no. 11, pp. 6922–6932, 2020, doi: 10.1109/TII.2020.2971709.

[73] E. Aker, M. L. Othman, V. Veerasamy, and I. Aris, "Compensated transmission line using discrete," *Energies, MDPI, Open Access Journal*, vol. 13, no. 14, 2020.

[74] R. Kaushik, O. M. P. Mahela, and S. Member, "A hybrid algorithm for recognition of power quality disturbances," *IEEE Access*, vol. 8, no. December 2020, pp. 229184–229200, 2020, doi: 10.1109/ACCESS.2020.3046425.

[75] A. Rahman and A. S. Ahmar, "Relationship between learning styles and learning achievement in mathematics based on genders," *World Transactions on Engineering and Technology Education*, vol. 15, no. 1, pp. 74–77, 2017, doi: 10.26858/wtetev15i1y2017p7477.

[76] K. Daud, A. F. Abidin, and H. S. Nagindar Singh, "ANOVA based feature analysis and selection in power quality disturbances identification," *Applied Mechanics and Materials*, vol. 793, pp. 510–515, 2015, doi: 10.4028/www.scientific.net/amm.793.510.

[77] K. Daud, A. F. Abidin, H. S. Nagindar Singh, and M. N. Mohd Hussain, "Classification of power quality disturbance based on Continuous S-Transform-Windowing Technique (CST-WT) and ANOVA as a feature selection," *Applied Mechanics and Materials*, vol. 785, pp. 368–372, 2015, doi: 10.4028/www.scientific.net/amm.785.368.

[78] H. Zhang, Y. Sun, Z. Lei, B. Zhang, and Y. Zhang, "Study of power quality disturbance location based on MUDW," in *Proceedings 2018 Chinese Automation Congress, CAC 2018*, 2019, pp. 97–100. doi: 10.1109/CAC.2018.8623155.

[79] P. E. T. Martins, M. Oleskovicz, A. L. D. S. Pessoa, and I. De Moura Faria, "Optimized allocation of power quality monitors in distribution systems considering fault location," in *Proceedings of International Conference on Harmonics and Quality of Power, ICHQP*, 2018, pp. 1–6. doi: 10.1109/ICHQP.2018.8378928.

[80] Y. Deng, H. Jia, P. Li, X. Tong, and F. Li, "A Deep Learning Method based on Long Short Term Memory and Sliding Time Window for type recognition and time location of power quality disturbance," in *Proceedings 2018 Chinese Automation Congress, CAC 2018*, 2019, pp. 1764–1768. doi: 10.1109/CAC.2018.8623810.