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Research challenges in real-time classification of power quality disturbances applicable to microgrids: A systematic review

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A R T I C L E I N F O

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A B S T R A C T

Microgrids with distributed renewable energy sources are especially sensitive to power quality disturbances. To mitigate the effects of distortions, they must first be detected and classified. Automatic classification of power quality disturbances has been extensively studied. However, real-time classification is yet to be investigated. Real-time classification is especially important in microgrids as they include a large number of subsystems. This paper presents a critical systematic review focused specifically on real-time applications. For this review, 809 papers were identified and the most cited papers of each year were analyzed in detail, i.e., a total of 134 papers were analyzed. Studies on all types of power systems were considered as their distortions can be observed in microgrids. These studies were categorized into three groups depending on their real-time abilities, and a comprehensive analysis to examine key items was performed. Subsequently, the research challenges in real-time operation were identified, i.e., extracting a reduced number of discriminant features with minimal processing, achieving a balance between classification accuracy and computational complexity, using datasets with more types of disturbances, including more types of combined disturbances, using real data to validate the classifiers, distributing public comprehensive datasets, embedding classifiers in dedicated hardware, improving the performance of real-time classification systems, conducting objective real-time analyses in physical devices, and setting a common evaluation framework to objectively compare real-time operations. These research challenges

Abbreviations: Acc, Accuracy; ADALINE, Adaptative linear element; ADC, Analog-to-digital converter; ALU, Arithmetic logic unit; AMD, Advanced micro devices; ATP, Alternative transients program; BP, Bagging predictor; Combd, Combined; CPU, Central processing unit; CT, Clarke transform; CWT, Continuous wavelet transform; CVC, Common vector classifier; DR, Decision rule; DT, Decision tree; DSP, Digital signal processor; DAG-SVM, Directed acyclic graph support vector machine; DHT, Discrete Hilbert transform; DWT, Discrete wavelet transform; DG, Distributed generation; DDWT, Discreet dyadic wavelet transform; DRST, Double-resolution Stockwell transform; DTW, Dynamic time warpping; EMTDC, Electromagnetic transients including direct current; EMTP, Electromagnetic transients program; EMD, Empirical mode decomposition; EEMD, Ensemble empirical mode decomposition; E, Euclidean norm; ELM, Extreme learning machine; Feat, Feature; FM-DWT, Fast match-dynamic time warping; FDST, Fast discrete Stockwell transform; FF-NN, Feed forward neural network; FPGA, Field-programmable gate array; FT, Fourier transform; FRFT, Fractional Fourier transform; FmA, Frequency maximum amplitude; FF, Fundamental frequency; FCM, Fuzzy C-mean; GB, Gigabyte; GHz, Gigahertz; GPRS, General packet radio service; GPU, Graphical processing unit; GT, Gabor transform; GWT, Gabor-Wigner transform; HDL, Hardware description language; HMM, Hidden Markov model; HHT, Hilbert-Huang transform; HT, Hilbert transform; HST, Hyperbolic Stockwell transform; IA, Instantaneous amplitude; IF, Instantaneous frequency; IMF, Intrinsic mode function; I/O, Input / Output; k-NN, k-Nearest neighbor; Lab, Laboratory setup; LVQ, Learning vector quantization; LS-SVM, Least square support vector machine; LHD, Lower harmonic distortion; LUT, Look up table; MB, Megabyte; MHz, Megahertz; MO-DWT, Maximal overlap discrete wavelet transform; MED, Minimum euclidean distance; MFMM, Modified fuzzy min-max clustering; MST, Modified Stockwell transform; MTD-NN, Modified time-delay neural network; MLP, Multilayer perceptron; MRA, Multiresolution analysis; MG-ST, Multiresolution generalized Stockwell transform; MSVM, Multi support vector machine; NN, Neural network; OPA, Orthogonal polynomial approximation; OpenCL, Open computing language; PSO, Particle swarm optimization; PC, Personal computer; PLC, Power line communications; PQ, Power quality; PSCAD, Power systems computer-aided design; PCA, Principal component analysis; PNN, Probabilistic neural network; RBF, Radial basis function network; RAM, Random access memory; RT, Real-time; RTDS, Real-time digital simulator; RMS, Root mean squared; RMSE, Root mean squared error; SOLAR, Self-organizing learning array; STFT, Short time Fourier transform; SNR, Signal-to-noise ratio; Simul, Simulated; SPWVD, Smoothed pseudo Wigner-Ville distribution; SSD, Sparse signal decomposition; SD, Standard deviation; S-matrix, Stockwell-matrix; ST, Stockwell transform; BNT, Supervised balanced neural tree; SVM, Support vector machine; Synth, Synthetic; TLBN, Three-level multiply connected Bayesian network; TBM, Threshold-based method; TF, Time frequency; TFST, Time–frequency-scale transform; THD, Total harmonic distortion; TmA, Time maximum amplitude; TTT, Time-time transform; Tx, Transmission; μC, Microcontroller; VMD, Variational mode decomposition; VHDL, VHSIC hardware description language; WT, Wavelet transform; WP, Wavelet packet; WBELM, Weighted bidirectional extreme learning machine; WD, Wigner distribution; WD-FT, Windowed discrete Fourier transform.

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must be tackled to obtain a viable, accurate, fast, low-cost, and embeddable power quality classification system that facilitates the inclusion of distributed renewable energy sources in microgrids.

1. Introduction

A "distributed energy system" refers to a system in which energy conversion units are placed close to energy consumers [1]. Flexibility, locality, and networking are key aspects of the distributed systems that are considered to overcome the challenge of sustainable development. In addition, distributed energy systems are environmental friendly owing to the absence of large power plants and long transmission lines [1]. The work of Alanne and Saari [1] concluded that distributed energy systems are ultimately a good option for sustainable development. These systems are the core of microgrids. A microgrid is a group of interconnected distributed generation (DG) units, loads, and distributed storage units that operates as a single controllable entity with respect to the main grid [2]. Microgrids provide a solution for the reliable integration of distributed energy systems [3]. They are perceived by the main grid as a single element that responds to control signals [4]. Microgrids can operate while being connected to the main electrical grid or while in island mode. The DG units integrated in microgrids typically include renewable energy sources, i.e., solar and wind powers; additionally, small hydro, biomass, biogas, and geothermal powers are also common [5]. According to Hatziargyriou et al. [6], "they can substantially reduce carbon emissions, thereby contributing to the commitments of most developed countries to meet their greenhouse gas emission reduction targets or otherwise substantially reduce their carbon footprints."

Microgrid operation suffers from certain major challenges. One such challenge is the maintenance of power quality (PQ) in the microgrid [7]. This is primarily due to the deep presence of intermittent renewable energy sources and power electronic interfaces, which are sources of PQ distortions [8]. The most common PQ distortions are sags, swells, interruptions, oscillatory transients, spikes, harmonics [9], flickers, and notches. It is common that several disturbances occur simultaneously (combined distortions) [10,11]. An inferior PQ has devastating effects on the operation of microgrids, such as incorrect functioning of electronic controls, erratic operation of grid equipment, damage of sensitive loads, loss of efficiency of the power system, tripping of protection devices, electromagnetic interferences, overheating of all cables and equipment, errors in measurements, and data losses [12–14].

Microgrids must guarantee PQ when operating in both grid-connected and islanded modes. The PQ must also be controlled during the transition from both modes. This is particularly important in the terminals of critical loads, distributed power sources, and at the point of common coupling with the grid [8]. When there is a PQ issue, mitigation actions must be undertaken. Kalair et al. [15] reviewed several harmonic mitigation techniques, such as linear reactors, passive and active harmonic filters, isolation transformers, K-factor transformers, phase shifting transformers, and multiple pulse rectifiers. Several studies have dealt with PQ mitigation methods [16,17]. For example, Mahela and Shaik [18] implemented a distribution static compensator with battery energy storage system to address the PQ issues.

To adopt proper mitigation actions, the PQ issues must first be identified and specific types of distortions that have occurred must be determined. Therefore, the classification of PQ distortions is required and it must be performed automatically and in real time. The requirement for real-time PQ classification is especially relevant in microgrids owing to the large number of subsystems involved in its functioning [19, 20]. Real-time PQ detection helps to master microgrid operation, guiding the decision-making process pertaining to the entire energy system [21]. For instance, PQ distortions influence the operation of intermittent renewable energy sources, inverter controllers, automatic switching between operation modes (islanded or grid-connected) [21], batteries, electric vehicle charging devices [22], solid state switches, transformers [23], and microgrid multi-energy systems (power-to-heat or power-to-gas system, among others) [19]. Rapid PQ detection is essential for instantly changing the operating conditions to prevent microgrid malfunction in any of its multiple subsystems [24]. Therefore, it performs a relevant role in microgrid centralized or distributed control, which must be performed in real time [25,26].

The classification of PQ distortions has been extensively studied [27]. An automatic PQ classifier starts with the segmentation of the original electrical signal to obtain several signal cycles. Then, these segmented signals are subjected to a feature extraction process. As features extracted from the time-domain signals are generally not sufficiently discriminative, a signal processing technique must be applied to the time-domain signals to extract discriminative features. These features are then used in a machine-learning classifier to determine the type of PQ disturbance [28]. Generally, classifiers must be previously trained with a labeled dataset of disturbances. To measure the performance of the classification systems, accuracies of the classifiers are calculated using test datasets. PQ classification systems must operate online at the same speed, at least, at which the electrical signals are generated [29]. However, performing accurate real-time classification is not an easy task (Fig. 1). Therefore, PQ classification is still an open research topic, whose importance has grown owing to the utilization of microgrids that include intermittent renewable energy sources [30].

As this is a relevant, unsolved problem, there are several studies on this subject. Several reviews have already been published. Granados-Lieberman et al. [31] and Saini and Kapoor [32] analyzed the signal processing techniques applied to electrical signals in the preprocessing step and the intelligent techniques used to determine the classifications, among other minor aspects. The primary conclusion of both these reviews was that most methodologies proposed led to an increase in the required computational resources. This limited the online performance and implementation in technological platforms. However, the reviews did not include any specific analysis regarding the computation load in the examined studies. Other reviews on this topic were published by Khokar et al. [33] and Mittal [34] with a similar structure and conclusion. The studies of Mahela et al. [27], Khokhar et al. [35], Mishra [36], and Ahsan et al. [37] are the most recent reviews on this topic, to the best of our knowledge. These reviews also described the strategies adopted by different studies regarding the stages of a PQ classifier: segmentation, feature extraction, and classification. All authors agreed in their conclusion that the remaining focus in PQ research should be on real-time operation. Similar to the previous studies, these papers analyzed PQ classification from a broad perspective without focusing specifically on real-time operation.

In this work, we present a new literature review that covers the gaps detected in existing reviews:

o First, this review is focused on real-time operation. This is an important difference with respect to previous reviews that did not include the computation time or complexity of the studies. The existing reviews highlighted real-time operation as the most important remaining research effort. This is especially important in microgrids owing to the large number of control systems that must operate in real time [24]. Thus, a review focused on this aspect may be useful for researchers in this field. The organization of the sections pertaining to the results and critical discussion provides relevance to real-time operation. Papers considered in this review may or may not include renewable energy sources as all the existing research in automatic PQ classification may be applicable to renewable systems. The basic types of PQ distortions that are described in the IEEE Standard 1159 [10] are also present in microgrids [19,28]; therefore, any study that classifies those disturbances may be of interest to researchers in this field.

o Second, this review is systematic, which implies that objective selection criteria were used. None of the published surveys were systematic. The search results of this review can be replicated if the same search procedure is applied. To the best of our knowledge, this is the first systematic review on this topic. Owing to space restrictions, the complete analyses are included in Appendices A and B. Additionally, contrary to existing surveys that focused primarily on the description of existing studies, an extensive critical discussion section is included, identifying the future research challenges of real-time automatic PQ classification. In addition, a non-systematic analysis of studies was also performed in the category most related to real-time operation (Section 3.3), which had fewer papers. Thus, several recent studies were incorporated, extending the perspective of the primary article topic.

The rest of this paper is organized as follows: Section 2 describes the search procedure and categorizes the identified studies based on their real-time abilities; Section 3 presents the results of the review, analyzing the most relevant items of real-time PQ classification; Section 4 discusses the research challenges identified in this field based on the results of the review work; finally, Section 5 draws certain conclusions.

2. Methods

2.1. Search procedure

To identify the most relevant papers in the field of automatic PQ classification, a set of systematic searches were conducted on the *Web of Science*. Different search criteria were considered using the following combinations of title keywords: 1) "power + quality + classification," 2) "power + quality + analysis," 3) "disturbance + classification," 4) "power + quality + characterization," 5) "power + quality + identification," 6) "power + quality + recognition," and 7) "power + quality + monitor." These keywords were selected as they are relevant to the topic. Fig. 2 shows the number of papers obtained in each search. From the obtained studies, those related to the field of automatic classification of PQ distortions were selected. This led to 809 studies. They were grouped according to the publication year (Fig. 2) and sorted based on the number of citations. The searches were completed in August 2018, except for the years 2017 and 2018, for which the searches were repeated in May 2019; further, for the year 2019, the searches were performed in April 2020 to obtain all possible studies (the publication of certain studies in the scientific repositories often suffers from delays).

Fig. 3 represents the total number of papers identified on this topic in each year since the beginning of the research. As the total number of papers obtained on this topic is significant, 15% of the most cited papers in each year were considered for this study and analyzed in detail. This led to a total of 134 studies, distributed as shown in Fig. 2. Three more papers were added because of the revision process of this article [38–40]. The results of this analysis are presented in Section 3 (Results). This analysis is completed in Appendices A and B owing to space constraints.

2.2. Classification of the studies

As this review focuses on real-time classification of PQ distortions, the studies were categorized into three different groups depending on the computation time information included in them. These groups were: 1) studies that did not consider the computation times, 2) studies that considered the computation times while using a regular personal computer (PC), and 3) studies that embedded the classifiers in dedicated hardware.

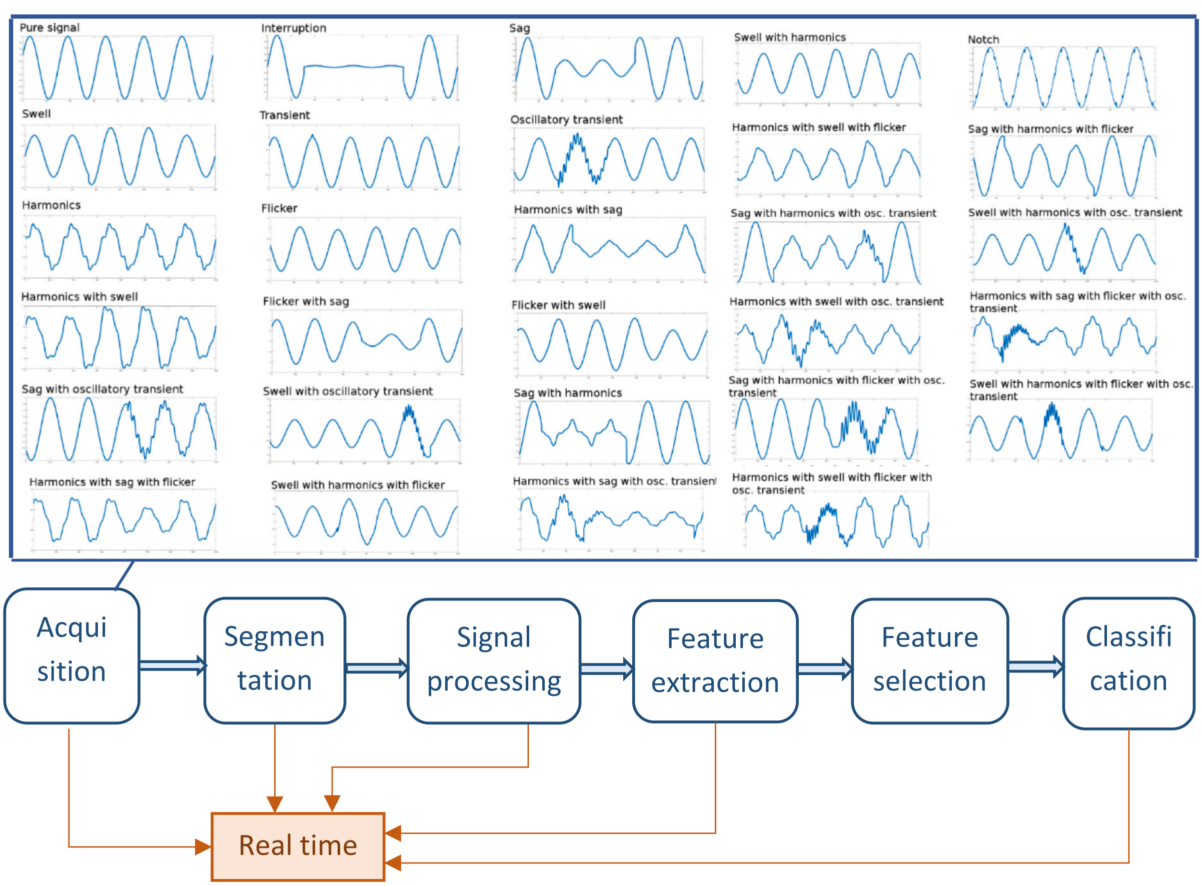

Fig. 1. Overview of the structure of a power quality (PQ) classification system, highlighting the blocks involved in the real-time operation.

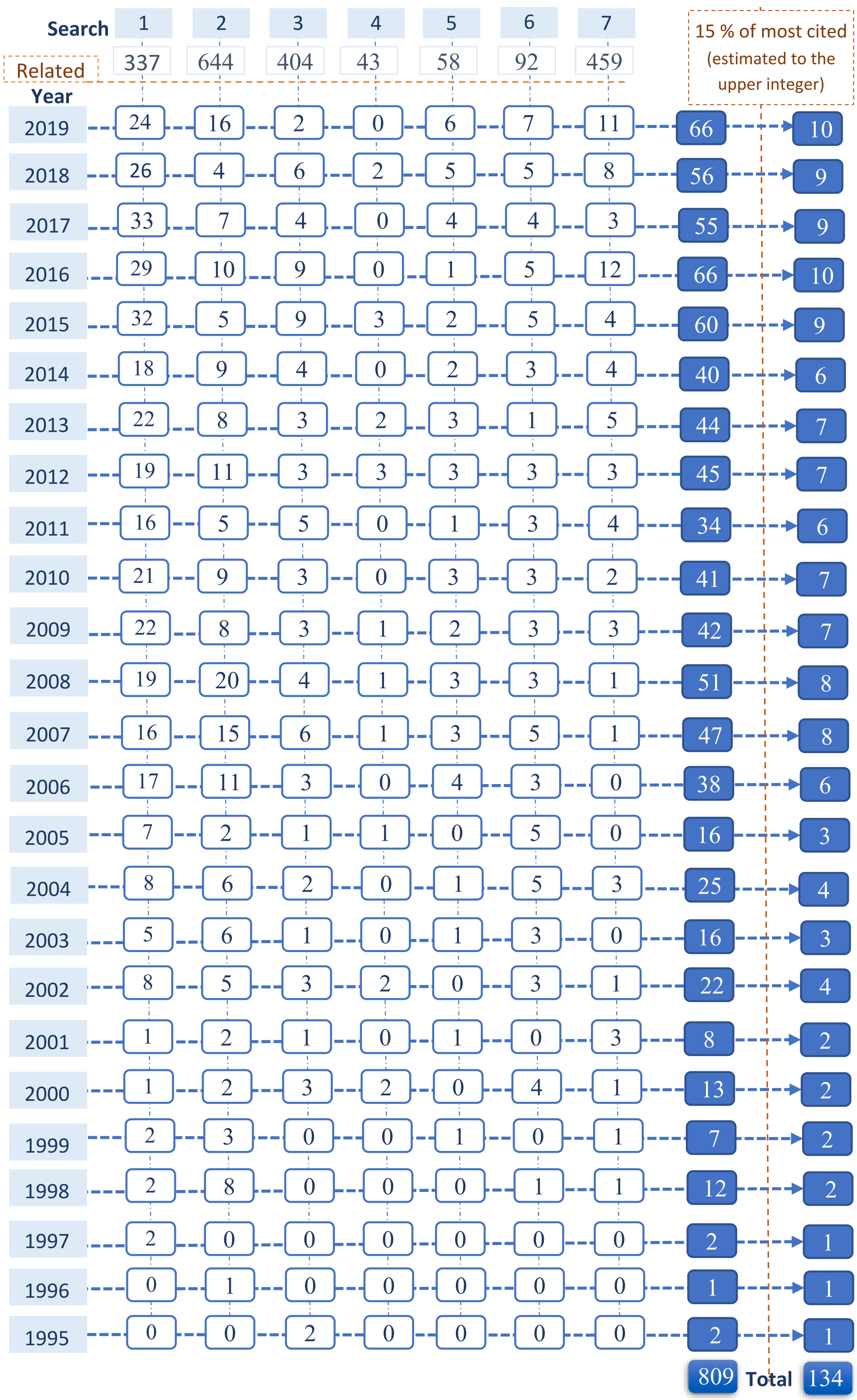

Fig. 2. Number of papers obtained as a result of the systematic searches and the selection criteria.

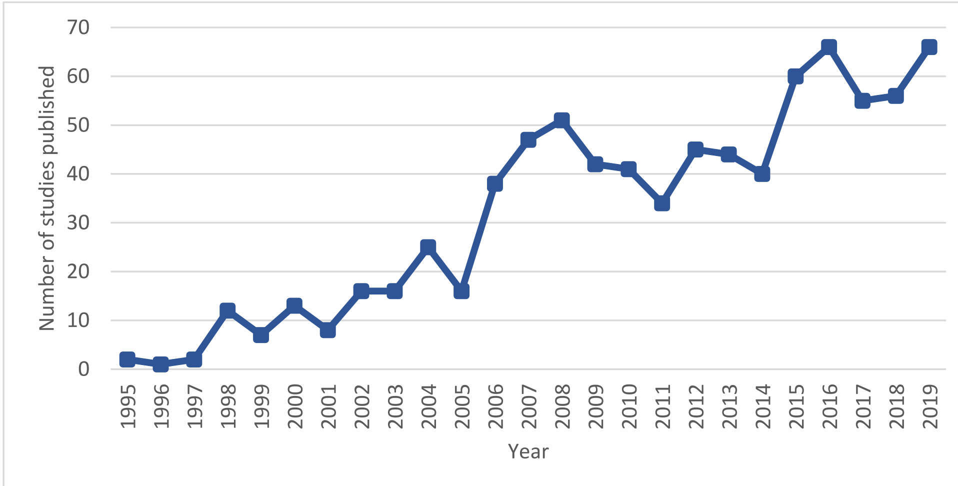

Fig. 3. Estimation of the number of studies published per year in the field of automatic classification of PQ distortions since the beginning of the research.

A set of items were extracted for each study. These items were selected as they are relevant for the development of real-time PQ classifiers. The analysis of these items for studies of the different categories is presented in Section 3. The items considered were:

- **Signal processing**: This includes the techniques used to transform the original time-domain electrical signals to facilitate the extraction of discriminant features. Certain techniques considered in the studies are (for the sake of simplicity, equations are presented for the continuous signals, although the processing is discrete):
  - o Fourier transform (FT): It decomposes a time-domain signal into its constituent frequencies [41].
  - o Short time FT (STFT): The STFT divides the electrical signal into shorter segments of the same length and computes the FT on each segment independently (Equation (1)). Thus, certain time resolutions can be obtained (determined by the segment length).

$$STFT(\tau,f) = \int_{-\infty}^{\infty} v(t)w(t-\tau)e^{-j2\pi ft}dt, \tag{1}$$

where t indicates time, f is frequency, $v(t)$ is the time-domain voltage signal to be processed, τ is the length of the segment (in time units), which is the time of the spectral location, and w is the window function used to create the segments.

  - o Wavelet transform (WT): The STFT provides a fixed time-frequency resolution, showing no adaptation based on the characteristics of the signal. The WT overcomes this by providing high time resolution for high frequencies and high frequency resolution for low frequencies. To achieve this, continuous (CWT) (Equation (2)) or discretized wavelet transform (DWT) is performed.

$$WT(a,b) = \int_{-\infty}^{\infty} v(t)\psi^{*}_{ab}(t)dt, \tag{2}$$

where ψ is a time-frequency domain function called "mother wavelet," a is the scaling factor that dilates or compresses signal ψ, and b is the shifting value (a time value) that shifts signal ψ. Further technical details are available in Ref. [42].

  - o Multiresolution analysis (MRA): WT is the basis of MRA. MRA represents the voltage signal at different resolution levels. To obtain the resolution levels, a mother wavelet (scaled and shifted) is used. Thus, sets of detail and approximation coefficients (D_j and A_j, respectively) are obtained for each decomposition level j in such a way that the original voltage signal can be reconstructed from them (Equation (3)). The coefficients contain time-frequency information of the voltage signal.

$$v(t) = \sum_{j=1}^{l} D_j + A_l, \tag{3}$$

where l is the number of decomposition levels [43].

  - o Stockwell transform (ST) [44]: The ST is similar to the STFT but with a variable window. It is also an extension of WT. It allows frequency dependent resolution by using a scalable localizing Gaussian window [45] (Equation (4)).

$$ST(\tau,f) = STFT(\tau,f) = \int_{-\infty}^{\infty} v(t)\frac{|f|}{\sqrt{2\pi}}e^{-\frac{(\tau-t)^2f^2}{2}}e^{-j2\pi ft}dt \tag{4}$$

  - o Empirical mode decomposition (EMD): This method is used to decompose a given signal into intrinsic mode functions (IMFs), each of which can generally be associated to a physical meaning of the signal [46].
  - o Ensemble EMD (EEMD): EMD can suffer from a mode mixing problem (the same IMF includes oscillations with disparate time scales or oscillations with the same time scales are sifted into different IMFs). EEMD allows a better scale separation using a noise-assisted algorithm [47].
  - o Hilbert transform (HT): The HT is defined as a convolution with the function $1/\pi t$. The HT allows the creation of an "analytic signal" $v_A(t)$:

$$v_A(t) = v(t) + j\hat{v}(t), \tag{5}$$

where $v(t)$ is the signal to be processed and $\hat{v}(t)$ is its HT. The "analytic signal" is complex valued and can be expressed as:

$$v_A(t) = A(t)e^{j\psi(t)}, \tag{6}$$

where $A(t)$ is the instantaneous amplitude and $\psi(t)$ is the instantaneous phase. Therefore, the values of amplitude and phase can be obtained as functions of time. Further technical details are available in Ref. [48].

  - o Hilbert–Huang transform (HHT): It merges EMD with HT. The IMFs obtained when applying EMD are transformed with the HT to obtain instantaneous frequency data. If the instantaneous frequency of each IMF is represented as a function of time, it is possible to obtain a time-frequency representation of the original signal (Hilbert spectrum). Further technical details are available in Ref. [49].

o Variational mode decomposition (VMD): This method decomposes a time-domain voltage signal into a discrete number of subsignals (modes). Each mode is required to be mostly compact around a center pulsation w_k, which is determined along with the decomposition. This method was proposed to overcome the limitations of EMD [50].

o Clarke transform (CT) [51]: It transforms the time-domain voltage signals of a three-phase system $(v_R(t), v_S(t), v_T(t))$ to different components $(v_\alpha(t), v_\beta(t), v_0(t))$ in two stationary axes. This transformation can achieve the reduction of dimensionality as the three-phase voltage signals are "projected" onto two stationary axes. The projection matrix is:

$$\begin{bmatrix} v_\alpha(t) \\ v_\beta(t) \\ v_0(t) \end{bmatrix} = \frac{2}{3} \begin{bmatrix} 1 & \frac{-1}{2} & \frac{1}{2} \\ 0 & \frac{\sqrt{3}}{2} & \frac{-\sqrt{3}}{2} \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \end{bmatrix} \begin{bmatrix} v_R(t) \\ v_S(t) \\ v_T(t) \end{bmatrix} \tag{7}$$

o Gabor–Wigner transform (GWT): On the one hand, the Gabor transform (GT) is a particular case of the STFT [52]. The time-domain voltage signal is first multiplied by a Gaussian function centered in the time under analysis. Then, the FT is applied to the resulting signal. Thus, more weight is given to a particular time t (Equation (8)). On the other hand, the Wigner distribution (WD) is a time-frequency analysis tool based on autocorrelations and the FT (Equation (9)) [53]. The GWT combines the GT with WD (Equation (10)), providing a time-frequency representation tool that overcomes some of the individual limitations of the two transforms (avoiding the cross-term problem while maintaining clarity) [54].

$$GT(\tau,f) = \int_{-\infty}^{\infty} v(t) e^{-\pi(t-\tau)^2} e^{-j2\pi f t} dt, \tag{8}$$

$$WD(\tau,f) = \int_{-\infty}^{\infty} v\left(\tau+\frac{t}{2}\right) v^*\left(\tau+\frac{t}{2}\right) e^{-j2\pi f t} dt, \tag{9}$$

$$GWT(\tau,f) = G(\tau,f) \quad W(\tau,f), \tag{10}$$

where $GT(\tau,f)$, $WT(\tau,f)$, and $GWT(\tau,f)$ indicate the GT, WT, and GWT, respectively, for time τ and frequency f; v is the voltage signal in the time domain.

o Principal component analysis (PCA): It is a dimensionality reduction method that converts a set of data associated with several correlated variables into a new set of data associated with uncorrelated variables. These uncorrelated variables are the principal components. For each principal component, a number, called eigenvalue, can be calculated. This number represents the "amount of variance" associated with the principal component. By removing the data associated with the principal components with lower eigenvalues, a reduction in dimensionality can be obtained without losing considerable information [55].

o Other methods: Other methods include symmetrical components [56], time-time transform (TTT) [57], Walsh transform [58], morphological operations [59], sparse signal decomposition (SSD) [60], Kalman filter [61], and quadratic transform [62].

- **Classification**: There are several classification methods that are used to determine the types of PQ distortions. Some of the techniques considered in the studies are:

o Threshold-based method (TBM)/decision rule (DR): The classification is based on whether an unknown pattern is above or below a given threshold or fits a set of rules.

o Decision tree (DT): DTs are supervised classifiers composed of a set of nodes or rules in a hierarchical structure [63].

o Neural network (NN) classifier: This involves a set of algorithms to recognize patterns. They are inspired by the human brain. Certain possible NN classifiers are (those used in the studies analyzed in Section 3): probabilistic NNs (PNNs), multilayer perceptron (MLP), adaptive linear element (ADALINE), learning vector quantization (LVQ), radial basis function (RBF) network, supervised balanced neural tree (BNT), self-organizing learning array (SOLAR), and extreme learning machine (ELM) [64].

o Support vector machine (SVM): SVM is a supervised classifier that performs classification by determining the hyperplane that maximizes the margin between the classes [65].

o Fuzzy-based classifier: This is characterized by the use of fuzzy sets or fuzzy logic at some stage of the training or operation [66].

o Hidden Markov model (HMM): HMM includes a collection of hidden states connected by transitions with a visible output. The output is dependent on the state [67].

o k-nearest neighbor (k-NN): This is a supervised classifier that assigns an unknown pattern to the majority class among the k-nearest neighbors [68].

o Other methods: Other methods include Bayes rules [69], dynamic time warping (DTW) [70], and quadratic classifiers [71].

- **Number of features**: The number of features extracted to perform the classification is considered. If an optimal set of features was selected in the studies, that value was included in the analysis.
- **Features**: This indicates the description of the specific features extracted that were fed to the classifiers. For space constrains, this information is included in Appendix B.
- **Number of types of disturbances**: This indicates the total number of disturbance types subjected to classification.
- **Type of dataset**: This indicates the methods used for generating or registering the PQ distortions. Possible types identified in this paper are as follows:

o Synthetic: Disturbances are generated from mathematical models through a numerical computing software.

o Simulated: Disturbances are generated from simulations of power systems. Events that cause PQ distortions are induced during power system simulations. Then, the associated PQ disturbances are retrieved.

o Laboratory setup: One or more laboratory setups are mounted to induce PQ distortions. Then, the real signals with the PQ distortions are registered through an acquisition system.

o Real grids: PQ distortions are recorded directly from real grids using an acquisition setup.

o Public dataset: Real disturbances are obtained from existing databases of signals with PQ distortions.

- **Combined distortions**: It was also determined whether or not studies considered combined PQ distortions (signals with more than one distortion in them).
- **Noise**: It was determine whether or not studies quantified the effect of different signal-to-noise ratios (SNRs) of the disturbances on classification accuracy.
- **Software/Hardware**: The specific software and hardware used to perform the classification were considered:

o MATLAB: It is the most popular numerical computing environment with a programming language.

o Simulink: It is a block diagram programming environment that supports modeling, simulation, testing, and analysis of systems.

o Laboratory Virtual Instrument Engineering Workbench (LabVIEW): Developed by National Instruments, it is a systems engineering software with access to hardware and data insights with a visual programming language.

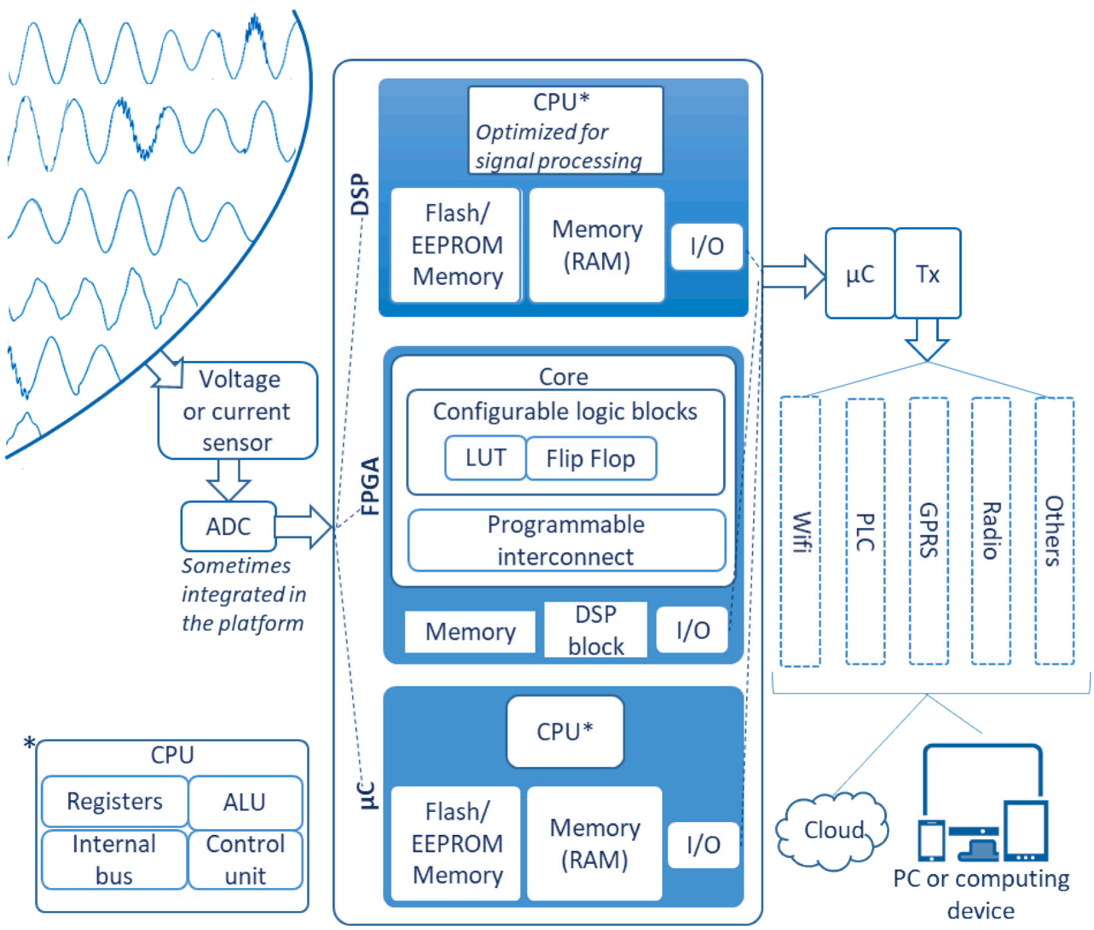

Fig. 4. Structure of a typical embedded system for PQ classification. Meaning of acronyms not previously introduced: LUT (look-up table), Tx (transmission), ALU (arithmetic logic unit), I/O (input/output), CPU (central processing unit), GPRS (general packet radio service), PLC (power line communications).

Table 1
Analysis of the studies that did not consider computation times (Category 1).

				Disturbances						
Study	Signal processing	Classification[1]	No. of feat.[2]	No. of types[3]	Dataset[4]	Combd[5]	Noise[6]	Software	Acc. (%)[7]	Real-time qualitative analysis
Mahela 2020 [38]	ST, FT	–	–	10 events	Lab	Y	–	MATLAB, WTViewer	–	–
Mahela 2020 [39]	ST, FT	Fuzzy C-means (FCM) clustering	3	4/4/1 events	Simul/Lab/ Real	–	–	MATLAB/ Simulink/RTDS	–	Real-world implementation was validated with RTDS
Hafiz 2019 [86]	MRA	DT, SVM, Naïve Bayes, k-NN, NN, ELM, PNN	99	13	Synth and Lab (mixed)	Y	Y	MATLAB	99.85	Computational complexity of WT was acceptable
Huang 2019 [87]	Optimal multiresolution fast ST	Rotation forest	15	16/3	Synth/Real	Y	Y	MATLAB	99.5	Low computational complexity method suitable for FPGA
Shi 2019 [88]	Independent component analysis	Spare autoencoder and softmax	–	7 (single)	Synth	Y	N	–	98.61	–
Shaik 2018 [40]	ST, FT	DR	4	9/9 events	Simul/Lab	Y	–	MATLAB/ Simulink/RTDS	–	Real-time results (RTDS) close to simulated results
Luo 2018 [89]	Fast Discrete ST	Three-level multiply connected Bayesian network (TLBN)	–	48/-	Synth/Lab/ Public	Y	Y	MATLAB	98.98	Strategies reduced the computational complexity of TLBN
Liu 2018 [90]	Singular spectrum analysis Curvelet Transform	Deep convolutional NN	–	30/30	Synth and Simul/Public	Y	Y	MATLAB, PSCAD/EMTDC	99.52	Algorithm more suitable for offline operation
Kapoor 2018 [91]	-	SVM	2	11	Synth	Y	N	–	94.02	Achieved processing time reduction
Ma 2017 [92]	-	Deep learning TBM (for some)	–	7	Synth	Y	Y	MATLAB	99.75	–
Mahela 2017 [93]	ST	FCMs clustering initialized by DT	6	9	Synth	N	Y	MATLAB/RTDS	99.6	Classifiers have low computational burden
Morales 2017 [95]	-	–	7	3	Real	N	N	–	–	Some calculations online, others offline
Wang 2017 [96]	ST with a feature oriented width factor	PNN	4	8	Synth	Y	Y	–	99.26	PNN faster training than MLP
Upadhyaya 2016 [97]	Maximal Overlap (MO) DWT (MRA)	SVM, DT	21	10/3	Synth/Real	Y	Y	MATALB	96.67	MO-DWT suitable tool for RT
Biscaro 2016 [98]	DWT (MRA)	Fuzzy-ARTMAP NN	16	–	Simul	–	N	–	93.4	Fast algorithms
Abdoos 2016 [99]	VMD ST	SVM	13	8	Synth	Y	Y	–	99.66	The algorithm can be used for real-time monitoring
Kumar 2015 [100]	ST	DT and NN	6	12/3	Synt/Lab	Y	N	MATLAB	99.9	–
Huang 2015 [101]	Multiresolution generalized ST (MGST)	DT	6	13	Synth	Y	Y	MATLAB	98.38	Future reduction of MGST computation burden
Liu 2015 [102]	EEMD	rank-WSVM	11	47/9/4	Synth/Simul/ Real	Y	Y	MATLAB/RTDS	100	EEMD more computationally efficient than wavelet-based methods

Note: The analysis for studies published before 2015 [103–162] is included in Appendix A (Table A.1).
Note: The analysis of the features, detailed performance, and hardware used for all studies is included in Appendix B (Table B.1).
[1] If several classifiers are separated by a comma, it implies that they were applied independently.
[2] Number of features: If an optimum set of features was selected, that value is provided.
[3] $No_1/No_2/ \ldots /No_n$: No_n (number of types of disturbances included in the *n*-type of dataset, which is indicated in the next column-). Symbol "-" implies that the number could not be determined. For instance: "48/- | Synth/Lab/Public" means that the synthetic dataset includes 48 types of disturbances, while the number for the rest of datasets could not be determined.
[4] Synth (Synthetic), Lab (Laboratory setup), Simul (Simulated), Public (Public/existing dataset). If, instead of "/" symbol, the word "and" appears, it implies that the data of both types are combined in a single dataset.
[5,6] Combined distortions (Combd), Yes (Y), No (N).
[7] Highest classification accuracy.

o Electromagnetic transients program (EMTP).
o Electromagnetic transients including DC (EMTDC): This software simulates time-domain instantaneous responses of electrical systems. It can be used with a graphical user interface called power system computer-aided design (PSCAD) [72].
o Alternative transients program (ATP): It is a software for digital simulation of transient phenomena of electromagnetic and electromechanical nature [73]
o Real-time digital simulator (RTDS): It simulates electromagnetic transients in real time [74].
o Digital processor: A device used to perform signal processing, feature extraction, and/or classification. It includes possible types are regular PCs, microcontrollers (μCs), digital signal processors (DSPs), and field programmable gate arrays (FPGAs).
o Programming languages: These include C++, VHSIC hardware description language (HDL).

- **Performance**: This is determined by the best value of classification accuracy (Acc) provided in the studies. The accuracy is calculated according to Equation (11).

$$Acc\ (\%) = \frac{Number\ of\ samples\ correctly\ classified}{Total\ number\ of\ samples} \cdot 100 \tag{11}$$

- **Real-time analysis**: The meaning of real time in the current paper shares many aspects with the concept of real-time digital signal processing [75,76] in which an analog signal is digitized using an analog-to-digital converter (ADC) and then the discretized values are processed by a digital system. Fig. 4 illustrates a typical schematic of a PQ classifier.

For achieving real-time classification, the time devoted to data acquisition and processing must be lower than the sampling period. For the purpose of disturbance detection, it is reasonable to think that this restriction must be considered as an average throughput value, with certain occasional delays being acceptable.

By considering a computer just as a machine that executes instructions sequentially, microelectronic technology has reduced delays at the transistor level, which has demonstrated a direct influence in the frequency of sequential logic, and thus of microprocessors [77]. There are also certain guidelines to optimize high-level programming languages, for instance C++ [78].

DSPs are variants of microprocessors that utilize a Harvard architecture, with separated memory spaces for data and program. They are optimized for typical signal processing operations [75]. For embedded systems, μCs are also very popular. They include not only a central processing unit (CPU) and memory but also input/output peripherals for use in control and instrumentation systems.

However, considering a computer as a sequential machine is not accurate and the performance improvement over the previous years is primarily owing to the hardware parallelism of the current computers [77], i.e., symmetric multiprocessors, multithreaded processors, and chip multiprocessors. General purpose languages also offer the possibility to program parallel applications. Another step toward parallelism is the use of graphical processing units (GPUs), whose original purpose was to allow fast 3D rendering and video processing. They contain hundreds to thousands of parallel processor cores on a single integrated circuit. With the advent of development tools compute unified device architecture (CUDA) [79], open computing language (OpenCL) [80]), GPUs can be used for general purpose computing [77]. They are widely used for the implementation of NNs [81].

Yet another technology that allows higher parallelism is that of FPGAs [76]. The basic FPGA architecture is composed of several logic units and synchronous registers. Any digital circuit can be implemented on them depending on its size. They can be customized to any particular purpose at a very low level and several applications such as filtering, cross-correlation, and finite-difference physical modeling can be easily incorporated in FPGAs [76]. For digital signal processing applications, manufacturers include internal random-access memory (RAM), multipliers, and specialized blocks. Besides parallelism, algorithms for which fixed-point data types are sufficient can also be implemented in FPGAs, with an additional speed increase. A current trend is the combination of CPU and FPGA modules. FPGAs have also been used to implement complex classifiers like NNs or SVMs [82,83]. The design of FPGAs can be performed through HDLs or, more recently, using high-level languages (Xilinx Vivado high-level synthesis [84], MATLAB HDL coder [85]).

This review gathered information about hardware and software implementation details as explained above, as well as processing times, when published, or else the qualitative conclusions:

o **Real-time qualitative analysis**: This indicates the primary conclusions reflected in the studies regarding the real-time operation of the proposed classification systems.
o **Real-time quantitative analysis**: This considers the specific processing times provided in the studies to assess the real-time operation of classification systems.

3. Results

This section presents the results of the study structured in the three categories indicated in Section 2. The items selected (Section 2.2) were analyzed for studies in each category. Owing to space constraints, the analysis is presented in Appendices A and B.

3.1. Studies not considering computation times

Table 1 lists the analysis of the studies that did not provide computation times to assess the real-time performance of the classification systems. The percentage of studies that belong to this category is 57.5%.

The first step in a PQ classifier is to process the input electrical signal to extract the discriminant features. In relation to the signal processing techniques, the MRA obtained from the DWT is the most used technique to automatically classify PQ distortions [86,97,98,108,110,112,113,115,118–122,132,135–139,141,145–147,151–155,158]. It was used in more than one-third of the analyzed studies. This was the first technique used for this purpose. The ST was also applied in a considerable number of studies [38–40,87,89,93,94,96,99–101,105,106,114,116,117,123,125,126,140,142–144,148,159,160], although it was only introduced later (in 2003). However, recent years have witnessed a growing trend in the use of this technique, contrary to the trend detected in the use of the MRA. Other signal processing techniques that were used in a minority of studies are FT [38–40,111,115,117,122,128,129,138,139,152,156], EEMD or EMD [102–104], HT [103,104], STFT [149,156], VMD [99], GWT [109,113], CT [130,134], quadratic transform [154], Prony analysis [156], orthogonal polynomial approximation (OPA) [157], smoothed pseudo Wigner–Ville distribution [113], singular spectrum analysis [90], or Kalman filter [162]. Once signals are processed, discriminant features must be extracted. Standard deviation and the energy of the signals were the most used features. Other widely used features were mean, maximum, and minimum values. Total harmonic distortion [163] or the calculation of the difference between two values were also used frequently.

While considering the classification techniques, NNs in their different forms [86,90,92,96,98,100,103,108,116,118,121,124,132,134,136,143,145,146,148,157,159,160], DTs [86,93,97,100,101,106,125,126,141], and SVMs [86,91,97,99,102,110,112,119,120,122,126,128,129,134,137,148,159] were the preferred classifiers. More than half of the studies used one of these three techniques. Other less common methods were fuzzy systems [39,93,94,98,104,105,107,111,114,140,145,162], Bayes classifier [120,131], k-NN [86,130,146,151], and HMMs [106,138], among others. Only a limited number of

Table 2
Analysis of the studies that considered computation times in a regular personal computer (Category 2).

Study	Signal processing	Classification[1]	No. feat.[2]	Disturbances: No. types[3]	Dataset[4]	Combd[5]	Noise[6]	Hardware	Acc. (%)[7]	Real-time analysis: Qualitative	Quantitative
Qiu 2019 [164]	Modified ST	Parallel stacked sparse autoencoder and softmax	250	12/7	Synth/Lab	Y	Y	GTX 1060 GPU	99.46	Online monitoring	5.1 ms (synth)/8.7 ms (real)
Zhao 2019 [165]	VMD	ELM-based	–	47/15	Synth/Lab	Y	Y	Intel core i7, 3.5 GHz	95.11	System with low computational cost	0.7633 s
Deng 2019 [166]	-	Deep learning (bidirectional gated recurrent unit)	–	96/13	Synth/Lab	Y	Y	Intel i7	100	Parameters of classifier determines in real time	0.34 s
Thirumala 2019 [167]	Empirical-WT adaptive filtering	Multiclass SVM	6	15/3	Synth/ Real	Y	Y	Intel Core i5, 3.1 GHz, 4 GB RAM	95.56	Online detection achievable in DSP or FPGA	0.027 s (16 classes)
Singh 2019 [168]	ST-TTT	DT, k-NN, SVM	13	15/7	Synth/Lab	Y	Y	Intel core i3, 3.40 GHz	99.93	High-speed multicore processor required for real-time analysis	0.0834 s
Wang 2019 [19]	-	Deep convolutional NN	–	16/8/8	Synth/ Simul/ Real	Y	Y	GPU (NVidia GTX 1060)	100	Smaller model required for embedded devices	0.45 s (5000 samples)
Jamali 2018 [169]	FT, STFT, WT, ST, TTT, HT	k-NN, NN, SVM, DT, Naïve Bayes, linear discriminant analysis	8	16/16	Synth/ Simul	Y	Y	–	100	ST and WT computational complexity higher than HT, STFT. Decreases sampling frequency to increase speed.	Signal processing, feature extraction, and classification: 2.301 s (noiseless/6.4 kHz/ synth)
Singh 2018 [170]	ST TTT	DT	26, Synth	14/7	Synth/Lab	Y	Y	Intel Core i3-4130, 3.40 GHz, 8 GB RAM	99.93	Computation time optimized in feature selection	Training and testing: 0.1949 s (synth), 0.081 s (real) NSGA-II computational complexity: $O(NP^2)$
Chakravorti 2018 [171]	VMD	Reduced Kernel ELM (RK-ELM)	45, no select.	15/15	Synth/Lab	Y	N	Two Duo processors, 2.94 GHz, 2 GB RAM	98.82	RK-ELM computationally efficient	0.0274 s (training)
Achlerkar 2018 [172]	VMD	DT	4	13	Synth/ Simul/ Public	Y	Y	RTDS	97.5 to 100	Embed in the future. VMD could be implemented in real time	VMD-DT: 190 ms
Singh 2017 [173]	Time–frequency-scale transform (TFST)	DT, SVM, bagging predictor (BP)	18	14/7	Synth/Lab	Y	Y	–	99.63	Optimal design would save computational time	TFST computational complexity: O(N log N)
Kubendran 2017 [174]	ST	DT	6	23	Synth	Y	Y	–	98.55	Potential for online classification	Computation of signals in the order $O(N^2 \log N)$
Singh 2017 [175]	Fractional FT (FRFT)	DT, BP	9	14/8	Synth/Lab	Y	Y	Intel core i3-4130, 3.40 GHz	99.93	FRFT-DT for real-time analysis FRFT-BP parallel processing	FRFT-DT (pure signal): 0.2187 s (training), 0.0156 s (testing)
Khokhar 2017 [176]	MRA	PNN	9	16/16	Synth/ Simul	Y	Y		99.875	PNN is faster than MLP and RBF	Classification: 0.1762 s (nine features)
Garousi 2016 [177]	MRA	TBM and MLP	11	17	Synth	Y	Y	i3, 2.26 GHz, 4 GB RAM	99.57	Computational time reduced with parallel NN	Recall time: 7.353 ms (five parallel networks)
Lopez_ Ramirez 2016 [178]	EMD	MLP	15	8/8	Synth/Lab	Y	Y	–	100	–	Signal processing, feature extraction, classification: 210 ms (12-cycles)
Kumar 2016 [179]	Symmetrical components	DR	6	8/4	Synth/Lab	N	N	i5, 2.4 GHz/DSP-dSpace 1104	–	Implemented online	Average lapse time: 0.031 s (symmetrical components, 10 cycles)
Zhang 2016 [180]	Modified ST (MST)	ELM	4	14	Synth	Y	Y	–	100	MST-ELM faster than MST-Back-propagation NN and MST-SVM	Classification: 0.029 s (ELM), 33.90 s (Back-propagation NN), 0.516 s (SVM)
		–	–		Synth/Lab	Y	Y		–		

(*continued on next page*)

Table 2 (*continued*)

Study	Signal processing	Classification[1]	No. feat.[2]	Disturbances: No. types[3]	Dataset[4]	Combd[5]	Noise[6]	Hardware	Acc. (%)[7]	Real-time analysis: Qualitative	Quantitative
Camarena 2016 [181]	Down sampling fused to EMD			7/more than 3				Quad-core, 2.2 GHz, 8 GB RAM		Down sampling-EMD faster than EEMD	Down sampling and EMD: 0.1775 s
Ferreira 2015 [182]	Filters	MLP and TBM. Combination using logic AND	13	17/-	Synth/ Public	Y	Y	–	over 97	Reduced computational complexity	For window of 1024 samples 29,901 additions, 39,129 multiplications
Manikandan 2015 [183]	SSD with overcomplete hybrid dictionaries	Hierarchical DT	13	32 (among all)	Synth/ Simul/Lab	Y	Y	AMD E350 CPU, 1.60 GHz, 2 GB RAM	82.67 to 100	SSD computation time high	Signal processing: 1.98–7.65 s
Ahila 2015 [184]	DWT	Particle swarm optimization (PSO) ELM	6	10	Synth	Y	N	Pentium duo core, 2.88 GHz, 3 GB RAM	97.6	Online classification	PSO-ELM: 0.0936 s (six features)
Aneesh 2015 [185]	VMD Empirical-WT (comparison)	SVM	8	5	Synth	Y	N	Core i5, 2.50 GHz, 4 GB RAM	100	Empirical-WT faster than VMD	1918.37 s (VMD), 943.14 s (EWT)
Kanirajan 2015 [186]	MRA	RBF-NN with PSO (to update the weights)	7	19/4	Synth/ Public	Y	Y	–	97.85	Potential real-time application	0,08 s (RBF-NN testing)
Seera 2015 [187]	-	Clustering: modified fuzzy min-max clustering NN (MFMM-NN)	12	21	Real	–	N	Intel Core i5, 2.50 GHz, 4 GB RAM	72 to 92	MFMM longer computational times	MFMM: 1.13 s–7.89 s

Note: The analysis of studies published before 2015 [188–211] is included in Appendix A (Table A.2).
Note: The analysis of the features, detail performance, and software used for all studies is included in Appendix B (Table B.2).
1,2,3,4,5,6,7 Refer to the footnotes of Table 1.

studies combined two or more classifiers [92,93,100,106,111,118,120,124,126,136,143,160].

For the PQ distortions considered in the previous studies, it was determined that 49% of works considered combined distortions while 33% modeled simple distortions exclusively. The remaining 18% of studies not only classified PQ distortions, but also events that cause PQ distortions [38–40,94,110,115,120,128,129,133–135,137,149,152,156,157]. A little more than half of the works considered the study of the effect of noise on classification performance. Most authors (65%) opted to model synthetic PQ distortions. Simulations of power systems to capture PQ distortions were used in one-third of the studies [39,40,90,94,98,102,105,106,110,114,117–119,123,126,129,134,138,141,144,148–150,154,156,157,159,162]. The use of real signals to perform the classification based on laboratory setups [38–40,86,89,100,120,126,133,135,148,159,161] or real-world electrical grids [39,87,95,97,102,106,117,118,127–129,136,137,145,150,156,158] was adopted in 13% and 21% of the studies, respectively. The use of public datasets of PQ distortions was a minority option [89,90,131,162]. Certain studies identified both PQ distortions and the events that caused those disturbances. This was the case of the works of Mahela et al. and Shaik [38,40] that assessed the PQ in grids with renewable sources.

The software tool used to conduct the studies was in most cases MATLAB. Other authors selected EMTP/ATP [110,117–119,149,150,156,157], PSCAD/EMTDC [90,138,141], Simulink [39,40,94,106,123,148,159,162], or even RTDS [39,93,94,102]. However, these platforms were not prevalent. Thirty-two % of the studies did not provide details regarding the tool used to obtain the performance of the classification systems. Accuracies were in general significantly high (above 90% in nearly all studies). Fifty-seven % of studies reported performances above 98% [86–90,92,93,96,99–102,104–108,110–112,114–119,122,124–126,131,133–138,140,148,150,159,160,162] and eleven % of studies declared 100% accuracy [102,118,119,131,133,135,150,160].

While considering the real-time operation of the classifiers, 69% of the studies considered this in relation to time execution [39,40,86,87,89–91,93–99,101,102,104–106,108,110–113,115–121,124,125,129–136,138,139,141,143,145–149,151,153,155,156,160,162]. This indicates the importance of the computational load in this field. Several studies highlighted that the systems proposed had the potential to operate online. This was more a future desire than a fact based on the study results as no evidence was provided. A wide set of studies also compared the computational load of different PQ signal processing techniques and classifiers. However, following the results provided (Table 1), it was difficult to determine whether the classification systems can operate in real time.

3.2. Studies considering computation times in a regular personal computer

Table 2 lists the analyses performed for classification systems pertaining to PQ distortions and provides data on computation times to assess the degree of real-time operation. Computation times were measured using regular PCs. Similar to the previous category, the MRA [169,176,177,186,189,192,196,197,199,203,205,208,211] and ST [164,168–170,174,180,189,193,194,206,207,210] were the prevalent techniques. The FT is the third most used technique [169,175,201,204]. Certain studies that applied it were considerably recent. This may be because the real-time execution of the classifiers is a relatively new requirement in this field. The initial studies focused more on providing high classification accuracies without paying much attention on processing time. Other signal processing methods that were subjected to a time analysis in a PC environment are EMD [178,181], HT [169,200], EEMD [200], VMD [165,171,172], symmetrical components [179], SSD [183], TTT [168–170,210], and Walsh transform [201], among others. However, these methods were not extensively adopted.

Most studies that included computation analysis classified distortions using NN structures [19,164,169,176–178,182,186–189,193,194,

Table 3
Analysis of the studies that embedded the classifiers in dedicated hardware (Category 3).

				Disturbances						Real-time analysis	
Study	Signal processing	Classification[1]	No. feat.[2]	No. type[3]	Dataset[4]	Combd[5]	Noise[6]	Hardware	Acc. (%)[7]	Qualitative	Quantitative
Sahani 2019 [212]	HHT with reduced samples	Type of NN	6	15/15	Synth/Lab	Y	Y	Xilinx Virtex-5 FPGA embedded processor	99.81	Online operation with vast unused FPGA area	0.014 s
Ribeiro 2018 [213]	Notch filter	Neuro tree and Bayesian classifier	6	20/-	Lab/Public	Y	Y	National Instruments compact reconfigurable I/O FPGA	97.8	Real-time system (FPGA detection, LabVIEW classification)	Computational complexity (classification): 7188 sums, 11,285 multiplications, three activation functions
Sahani 2018 [214]	HHT	Weighted bidirectional ELM (WBELM)	12	16/16	Synth/Lab	Y	Y	DSP (TMS320C6713)/PC i3 – 3220, 3.3 GHz, 4 GB RAM	99	HHT-WBELM operates in real time	190 ms (DSP, detection, and classification) 19.8 s (PC, testing)
Li 2016 [215]	Double-resolution ST (DRST)	Directed acyclic graph-SVM (DAG-SVM)	10	8/4	Synth/Lab	Y	Y	DSP (TMS320VC674) + advanced reduced instruction set computing machine	99.3	DRST-DAG-SVM advantage in real time	DRST-DAG-SVM: 13.4 ms
Borges 2016 [216]	TD and FFT	NN and DT	16	8/4	Synth/Real	Y	Y	µC TM4C1294NCPDT	99.3	Quick response, even with low-cost hardware	Feature extraction: 0.8532 ms; NN: 0.040 ms; DT (worst case): 0.0360 ms
He 2013 [217]	ST modified with dynamics, FFT	DT	5	10/-	Synth/Lab/Real/Public	Y	Y	DSP FPGA	–	real-time ability	ST modified with dynamics: 1.27/500 s; Signal processing (10 cycles): 0.03–0.08 s
Zhang 2011 [218]	TD and DFT	DT	5	9/9	Synth/Lab	Y	Y	DSP FPGA	99	real-time requirements are satisfied	DSP: 90–120 ms (10 cycles)
Radil 2008 [219]	TD and morphological operations	TBM	5	7/7/7	Synth/Lab/Real	N	N	DSP	–	Suitable for real-time monitoring	20% faster than WT
Ramos 2007 [220]	TD and morphological operations	TBM	2	7	Real	N	N	ADSP-21369 at 266 MHz	–	DSP performs processing in real time	121.6 ms (3 s of data, DSP)

Note: The analysis of the features, detailed performance, and software used for all studies is included in Appendix B (Table B.3).
[1,2,3,4,5,6,7] Refer to the footnotes of Table 1.

196–199,202–204,209–211], i.e., PNN, MLP, or LVQ, among others. Several studies also proposed DTs [168–170,172–175,183,206,208], although this technique was less common than NNs. NNs are more time demanding. Therefore, it is appropriate to perform a computation time analysis. It is also important to highlight that it is common to observe studies that combine two or more classification techniques [177,182,188,194,195,197,201,202,205,208,211]. The percentage of studies adopting this approach is significantly higher than those in Category 1. This may be because the use of several techniques has an impact on computation time that cannot be ignored.

While considering the PQ distortions included in the simulations, 81% of the authors considered combined distortions. The effect of noise on classification performance was examined by 69% of the studies. While considering the method in which distortions were generated or registered, 81% of the studies modeled synthetic signals. It is important to highlight that 62.5% of the studies included several sets of distortions obtained by different methods, with the modeling of synthetic signals using a laboratory or real-world electrical distortions being the most common approach. With respect to the types of distortions, the average number for the synthetic datasets (15.2) was significantly higher than that for the simulated (9.7), laboratory (8.7), and real (7.8) datasets.

Studies in this category also operated the algorithms mostly in MATLAB to obtain the performance and operation time of the classifiers. As runtime is completely influenced by the processors, RAM, and processing frequency, it is essential to know the specific hardware elements used to perform computing. It is to be noted that 65.5% of the studies included information regarding the hardware elements [19,164–168,170,171,175,177,179,181,183–185,187–189,192,194,195,198,199,203,205–207,209–211], while the rest did not provide details. The lack of this information does not permit contextualizing of execution times and comparing them with those of other studies. In Table 2, it is possible to observe that the execution times referred to particular processors.

Several papers highlighted the real-time abilities of the studies[164,171,172,174,175,179,184,186,189,190,193,196–198,201,207–209,211]. However, most times this was proposed as future line of work than a conclusion derived from the studies. Other authors mentioned that their methods could operate in real time if parallel processing was applied [168,175,177,205] or the methods are embedded in a DSP or FPGA [19,167,172,188,194,199,206]. Again, this was proposed as a future line of work. A set of studies compared the computational loads of the signal processing techniques and classification methods [19,164,165,167–169,175,176,180,181,183,185,187,191,192,195,200,201,204,210]. While considering the specific time data that was provided, most studies provided computation times measured using a particular computer [19,164,165,167–169,171,172,175–181,183–190,192–208,210,211], while a smaller set of studies included the computation complexity of the methods, which was independent of the computer used [170,173,174,182,191]. The time periods provided were not always of the entire classification system. Frequently, they were provided only for the signal processing technique or classifier. Sometimes, training times were provided instead, which is not an interesting metric to determine the real-time execution of the classifiers as they can be trained offline. In certain cases, it was not possible to determine what was included in the times provided (only processing, only classification, number of signal cycles processed, etc.). The last column of Table 2 lists the specific results for each study.

3.3. Studies embedding the classifiers in dedicated hardware

Table 3 lists the results of the analysis performed for studies that embedded the classification systems in dedicated hardware devices (such as μCs, DSPs, FPGAs) to achieve real-time execution. The number of studies identified in this category was significantly lower than in Categories 1 and 2.

In relation to the signal processing methods, it is worth highlighting that most studies considered the features in the time domain directly [216,218–220]. This increased the computation speed of the system as no previous processing was required. A set of studies performed the FT [216–218], which is one of the fastest signal processing techniques. The ST was also used but with a particular scheme based on processing only key frequency points to reduce the computational complexity [215]. The HHT was adopted in two studies [212,214]. The works in this category did not use other signal processing methods such as MRA, GT, or CT, which require an extensive set of resources. Therefore, a significant difference can be observed with respect to the signal processing methods used in the classification systems of the previous categories (Sections 3.1 and 3.2). This difference also appears in the extracted features, as the calculation of time intervals and root mean square values are the most common features. This may be a consequence of the direct use of the signals in the time domain.

The extracted features were inputted into DTs [216–218] or threshold-based classifiers [219,220]. Contrary to the previous categories, NNs [212,213] and SVMs [215] were not prevalent. When embedding the systems in hardware platforms, authors opted for efficient simple classifiers, although the most recent studies included more

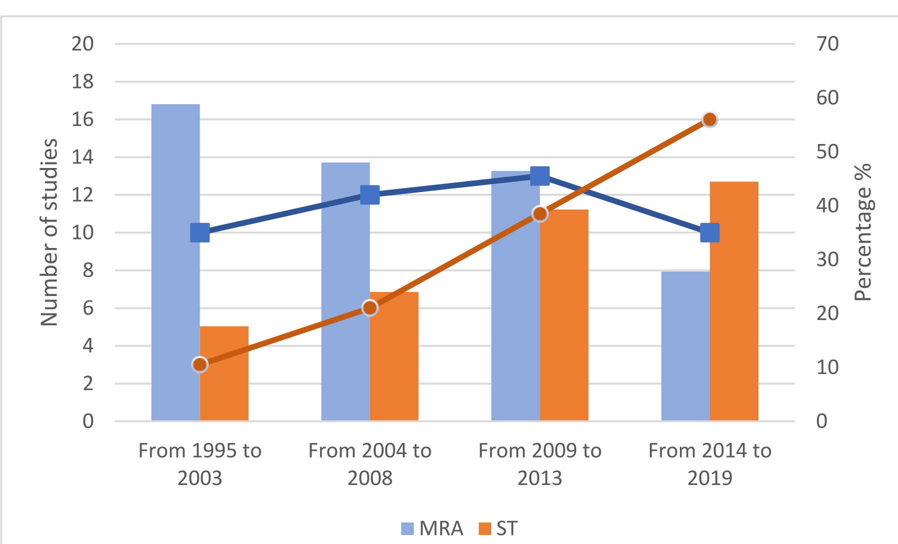

Fig. 5. Use of multiresolution analysis (MRA) and Stockwell transform (ST) as signal processing techniques in studies of Categories 1 and 2. The line graphs (left axis) represents the total number of studies in the periods under analysis that used MRA and ST. The bar graphs (right axis) represent, for each period, the percentage of studies that used MRA and/or ST with respect to the total number of most common signal processing techniques (MRA, ST, Fourier transform, empirical mode decomposition, Hilbert transform, and Hilbert–Huang transform) used in all studies published in that periods.

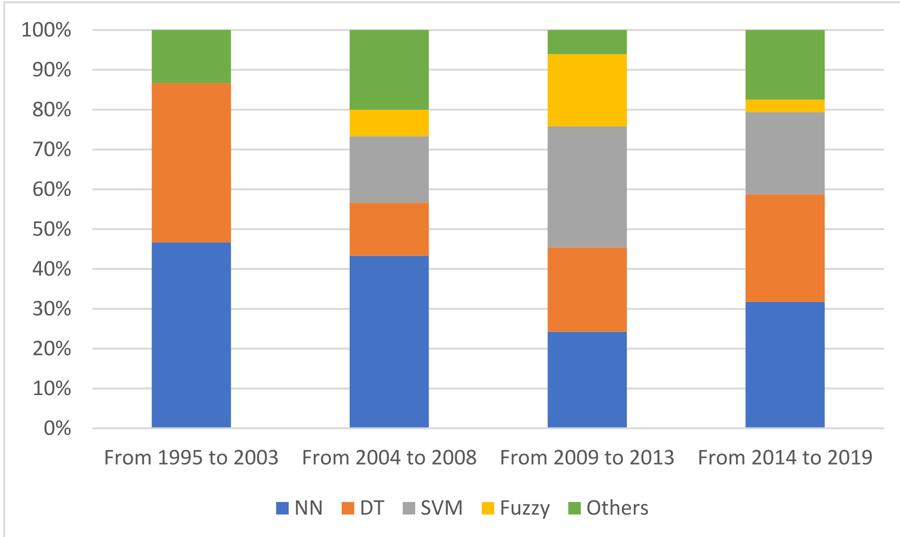

Fig. 6. Distribution of classifiers in studies published in different time periods for Categories 1 and 2 (Percentages of studies using particular classifiers with respect to the total number of classifiers used in the studies published in a given period).

complex techniques [213,214].

While considering the method for generating or recording the data, all studies that included classifiers embedded in dedicated hardware captured real signals from either laboratory setups [212–215,217–219] or real grids [216,217,219,220]. This percentage of studies is significantly higher than in the previous categories. However, the use of synthetic signals was also a common approach [212,214–219]. None of the studies opted to simulate power systems. Most studies also considered combined distortions and performed noise studies [212–218].

To conduct the real-time classification, most studies selected DSPs [214,215,217–220] or FPGAs [212,213,217,218]. They were preferred over µCs [216]. This may be because µCs have limited signal-oriented computation capabilities, which are insufficient for most applications. For the initial prototyping of the algorithms, MATLAB was again the prevalent tool [212,214,215,218,219]. Further, in general, high accuracies were obtained (almost all of them demonstrated accuracy above 95%, which is an acceptable value). However, 33% of the studies did not provide details on this aspect. This percentage is significantly higher than that in Categories 1 and 2. This might indicate that the integration of PQ classifiers is still an open line of research.

While considering the real-time operation of the systems, all studies stated that online operation was achieved with hardware platforms [212–220], i.e., DSPs, FPGAs, or µCs. However, there is less consensus on the runtimes provided to test the real-time execution. Certain studies focused only on signal processing, while others provided the processing times for the entire system. A reduced number of studies included the individual times associated with signal processing and classification [216,217]. Others provided the computational complexity [213]. In general, all presented times showed a real-time operation of the classifiers.

In addition to the studies listed in Table 3, several papers that focused on embedding the classification systems were also recently published. Although they do not satisfy the selection criteria, they are briefly discussed for their relevance to the topic. The paper presented by Santos et al. [221] presented an FPGA that computed a Hilbert filter to extract discriminant features and classify the most common types of PQ distortions. The FPGA operated under 25% of its available resources. It required 7862 adaptive logic modules of the total available 32,070 modules, 8% of the total pins, 30 out of 87 DSP blocks, and 1% of the total memory units. Similarly, the work of Martinez et al. [222] presented a classification system based on high-order statistics and a NN in an FPGA. It used 36% of the available logic elements, 18% of the registers, and 46% of the memory. A NN was also the classifier selected by Lopez-Ramirez et al. [223] to be implemented on two platforms (Xilinx Virtex-6 and Altera DE3) using 33–34% of the available programmable logic, 43-32% of the memory, and with maximum operating frequencies of 66 and 77 MHz. Response time (signal processing and classification) was less than 3 ms for a 200 ms window signal. In another study, an ADALINE NN was embedded in a Spartan 3 A XC3SD1800A DSP processor by Garanayak et al. [224]. The work of Yildirim et al. [225] used an FPGA to perform data processing and transmit the result to a server using User Datagram Protocol/Internet Protocol communication. Other FPGA-based studies can be obtained in Ref. [226,227].

Another set of works used DSPs to embed the PQ classification systems. The work of Babu et al. [228] implemented the ST and a simple DT to classify 11 types of distortions with an accuracy of up to 99.2%. The paper estimated the number of additions and multiplications required for the processing. Meanwhile, Huang et al. [229] and Zaid et al. [230] used the DSP TMS320F28335 and STM32F429-DISCO µC hardware platforms, respectively, to monitor the PQ of the grid. The transmission of the data to a storage or display unit was performed through general packet radio service (GPRS) [229] or WiFi [230] communication. Dalai et al. [231] introduced a classification system that could be implemented in any general purpose µC for embedded applications. The system was tested on the PIC24F series µC with a 16-bit data bus operating at 16 MHz. Similarly, a DR classifier of PQ distortions implemented in a PIC18F452 µC was described in the work of Kiranmai et al. [232]. Meanwhile, Guerrero et al. [233] used an ATmega328 µC in their PQ monitoring system. The operating frequency was 20 MHz and the processed data were transmitted through radio (433 MHz or 2.4 GHz).

4. Discussion

In this section, different research challenges in this field are critically discussed. They are based on the analysis presented in Section 3.

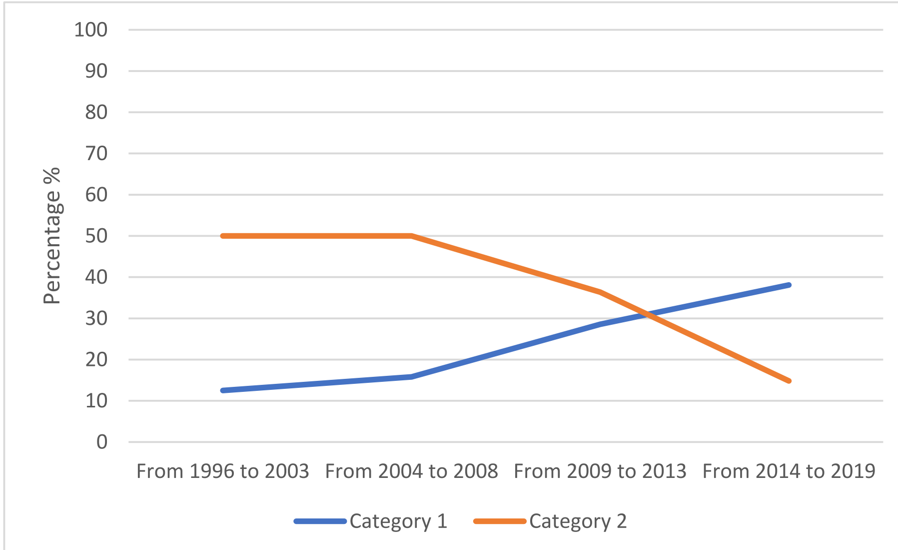

Fig. 7. Percentage of studies including more than one classifier in cascade with respect to the total number of studies under analysis for the selected period (in years). Data provided for Category 1 (blue) and Category 2 (orange). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

4.1. Research challenges in relation to real-time signal processing, feature extraction, and classification methods

Extracting discriminant features with little processing

A trend was observed in the studies of Categories 1 and 2 where ST was used as the signal processing technique. This was the most extensively used method in studies published between 2014 and 2018, culminating a growing trend that started several years ago, as can be observed in Fig. 5. The utilization of the second most used technique, MRA, has been constant over time. This contrasts with the signal processing methods primarily used in the studies of Category 3, in which the FT was predominantly performed with no processing (direct use of signals in the time domain). Therefore, a significant difference can be observed among categories in relation to signal processing. Sophisticated signal processing techniques such as ST, MRA, EMD, and HHT obtain discriminant features of the distortions. However, they are usually time-consuming processes and less appropriate for real-time systems embedded in low-cost hardware. This may be the reason why methods with minimal computational loads were embedded in the hardware. However, the extracted features may have limited discriminant capabilities. A future research challenge is to obtain discriminant features without sophisticated signal processing methods or to increase the speed of the signal processing methods to achieve real-time PQ classification.

Using a reduced number of features

The average number of features considered in the studies in Categories 1, 2, and 3 are 12, 18.1, and 7.4, respectively. The inclusion of more features may improve the classification accuracy; however, it increases the computational load in two ways, i.e., more calculations are required to obtain the features and more time is used by classifiers to process them. Those studies that were predominantly focused on

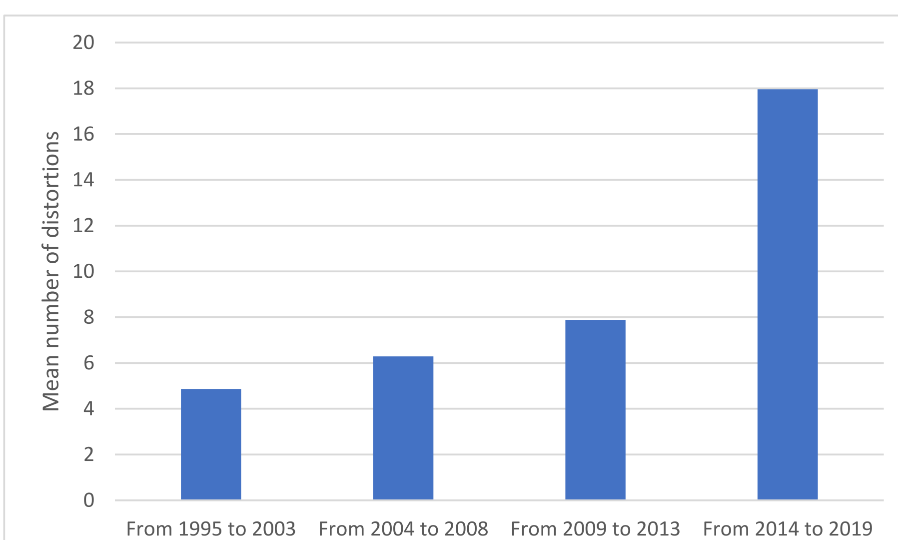

Fig. 8. Mean number of different types of distortions considered by the studies in four time periods.

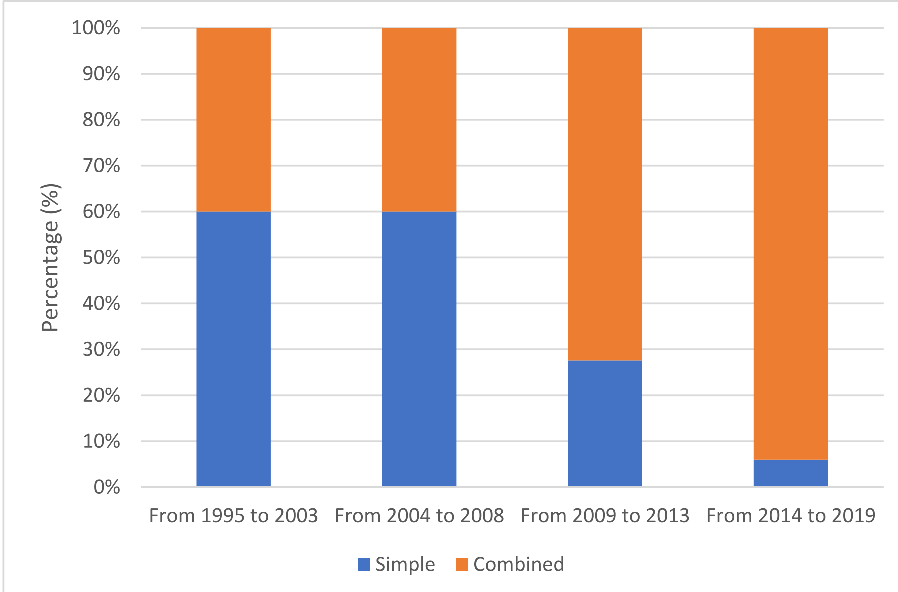

Fig. 9. Percentage of studies considering only simple distortions (blue) or combined distortions (orange) with respect to the total number of studies that included this information in four time periods. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

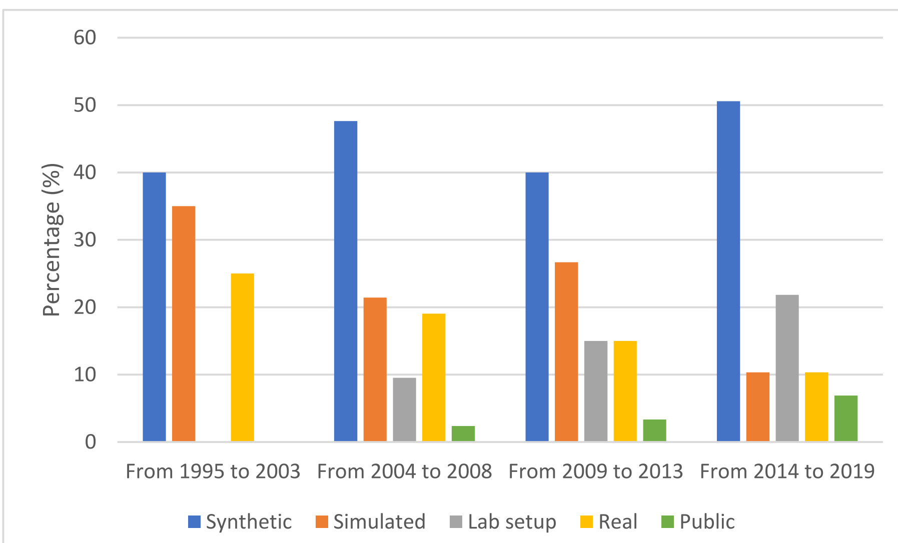

Fig. 10. Percentages of use of each type of dataset (synthetic, simulated, laboratory setup, real grids, and public dataset) with respect to the total number of datasets for four different time periods.

providing high classification accuracy (Categories 1 and 2) used, on average, more features than those that were more focused on the real-time operation (Category 3). Therefore, a future research challenge is to reduce the number of features without compromising the classification performance. This implies extracting more discriminant features.

Achieving high classification performance with computationally simple classifiers

A gap was detected between the studies that implemented the classification systems in regular PCs (Categories 1 and 2) and those that used embedded hardware platforms (Category 3). The first two groups used more advanced classifiers (Fig. 6), while, in Category 3, simple DRs were mostly adopted. The second approach is suitable for real-time operation, but the classification capabilities are limited when considering the types of distortions to be detected, classification of combined distortions, system performances, etc. A research challenge is to integrate sophisticated classifiers into affordable hardware platforms or to achieve the classification results of sophisticated methods with computationally efficient classifiers.

Aligning the trend toward the use of several classifiers with real-time implementation

A trend pertaining to the use of several classifiers in cascade was identified for Category 1, while it was not observed in Categories 2 and 3 (Fig. 7). Therefore, the studies that focused less on real-time classification have proposed classifiers that are more complex. The use of several classifiers in cascade can improve the classification accuracy; however, this increases the computational complexity. Thus, a future research challenge is to integrate several classifiers in cascade into low-cost hardware while achieving real-time operation.

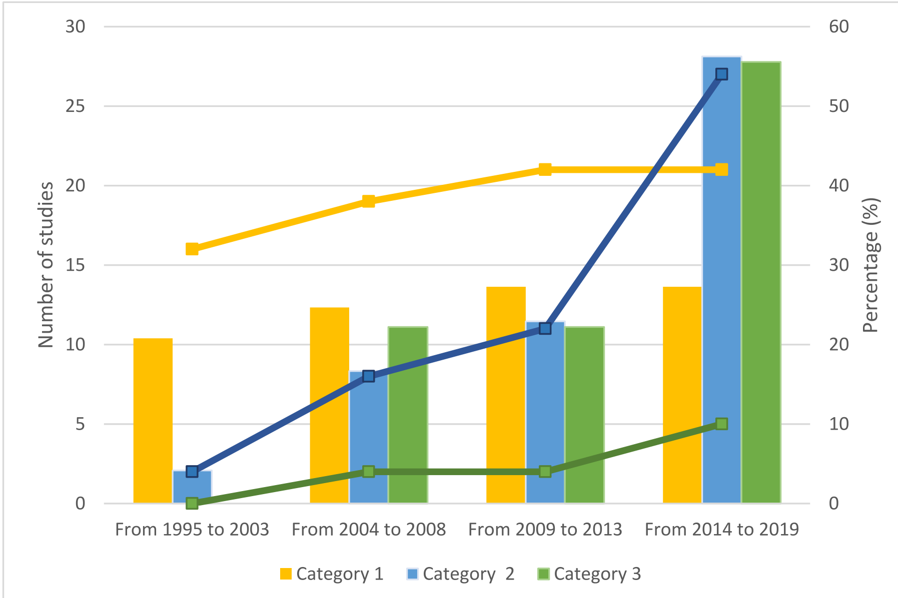

Fig. 11. Number of studies in each category for different time periods (line graphs, left axis) and percentage of studies in each category for a time period with respect to the total number of studies in the category (bar graphs, right axis). For instance, 50% of the studies in Category 2 were published between 2014 and 2018.

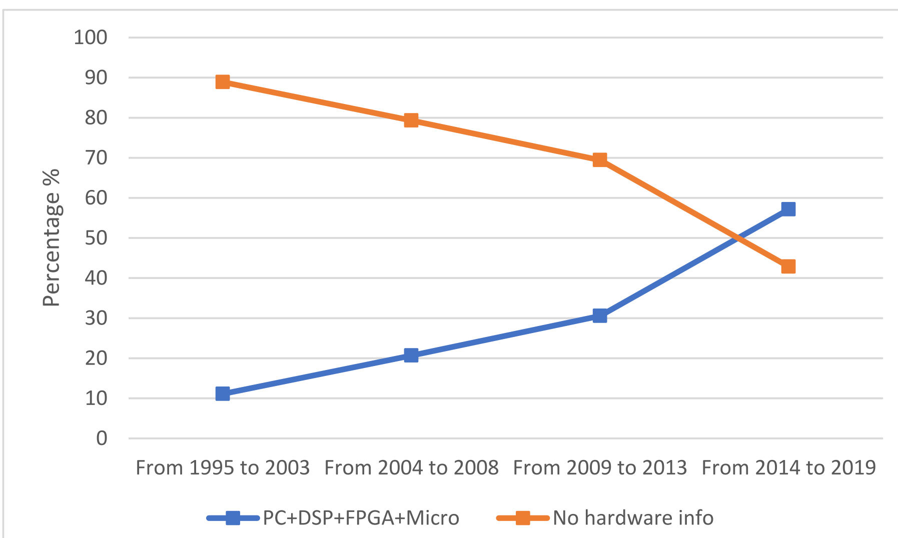

Fig. 12. Percentage of studies including and excluding any kind of hardware information (PC, digital signal processors, field programmable gate array, and microcontrollers) for four different time periods.

4.2. Research challenges pertaining to test datasets for real-time classification

Including more types of distortions in real-time classifiers

A clear trend of the inclusion of more types of distortions in the classifiers was detected. Fig. 8 shows the average number of distortion types for all categories as a function of the publication year. A growing trend can be observed as the average value is 18 in the last five years under analysis. This contrasts with the average value for studies embedding the classifiers in dedicated hardware, i.e., 11.1 types of distortions. Testing more types of distortions usually requires more features and more complex signal processing methods and classifiers, which leads to an increase in computation times. Therefore, a future research challenge is to include more types of distortions in the real-time systems without increasing the computational load.

Expanding the types of combined distortions

Several studies considered combined distortions. A growing trend in this regard can be observed in the analysis of Fig. 9. However, the combined distortions included in most studies were reduced to “sag with harmonics” and “swell with harmonics.” Studies that considered other combined distortions are significantly limited. Therefore, the inclusion of different types of combined distortions is a future research effort. This is especially challenging for the real-time implementation of classifiers as their classification may affect computation times significantly.

Including real distortions

Most studies used synthetic signals to test the PQ classifiers. This fact was observed in the first period that was analyzed and has remained consistent over time. It is also a fact that more recent studies focused less on the simulation of power systems to record simulated distortions. In the first period analyzed (from 1995 to 2003), this option was considered by 35% of the studies, while in the last period analyzed, this percentage fell to 10.3% (Fig. 10). The use of real-world distortions has

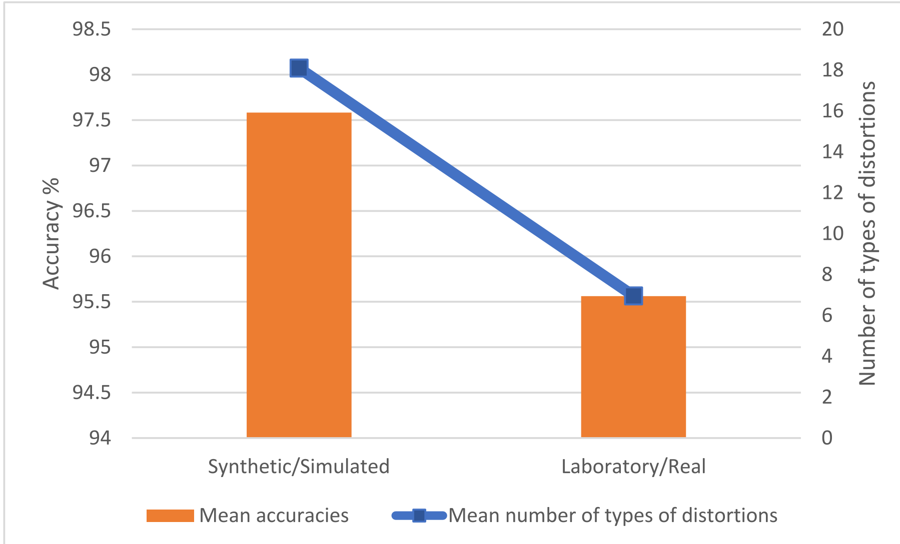

Fig. 13. Mean accuracy values (bar graphs, left axis) and mean number of the types of distortions (line graph, right axis) provided by the studies that independently tested the classifier using both synthetic or simulated data and laboratory or real data. Only studies providing data on the number of distortions and accuracies are included.

never been the primary trend. A research challenge is to test the classifiers using real data from real grids. However, recording real data is a difficult task. Distortions occur occasionally and many hours of grid monitoring is required to register a few of them. However, even if continuous grid monitoring was performed, it would be very unlikely that all possible types would be registered to have a complete dataset. Moreover, the number of repetitions of each type may be insufficient to train and test a classifier. Another added difficulty is the categorization of distortions to particular types. This process usually has to be performed by human experts following PQ standards and recommendations. However, sometimes the types of distortion may not be clear, especially if the signal contains more than one type simultaneously.

The percentage of studies that used real distortions increased significantly in the hardware-implementation category. This may be because the studies in this category included comprehensive evaluations of the classifiers. However, only a few types of distortions were considered and with a low number of repetitions, which was insufficient at most times for training a classifier; therefore, training was required to be performed using synthetic data. Another future research challenge is to implement an integral real-time classifier that is trained and tested using real data.

Adopting public datasets

The use of public datasets is rare in existing studies. Although the number of public datasets has grown in recent years, it is still limited [234–239]. There are significant differences in the datasets pertaining to the types of distortions, number of samples, labeling of the data, and tools to access them. The limited number of public repositories is especially significant as approximately one-quarter of the studies have captured real signals from laboratory setups or real grids. However, their data have not been publicized in most cases. A future research challenge is to generalize the sharing of real data of PQ distortions with the research community. Datasets should include as many types of distortions and repetitions as possible including combined ones. The registration conditions should also be included, and distortions should be labeled according to existing standards or recommendations [240].

Comparing different studies objectively

It is difficult to objectively compare classification performances and execution times among studies as there are significant variations in the types and number of distortions. Several studies used synthetic data. However, the equations used to generate the distortions have significant differences. The work of Igual et al. [241] highlighted this fact and presented an integral model of PQ distortions that is publicly available to any interested researcher. However, the most popular public datasets [234–236,239] are not widely used. As test conditions are different, it is not possible to ensure fair comparisons. A future research challenge is to standardize the test conditions.

4.3. Research challenges in relation to classification performance, hardware, and real-time analyses

Increasing embeddability of classifiers

An emerging trend on the inclusion of computational load and computation times in the PQ classification studies was detected (Categories 2 and 3). The use of embedded hardware devices was not considered in the first period that was analyzed, while the last period included considerably more studies with hardware implementations. Studies considering real-time analysis in computers (Category 2) have become the primary trend (Fig. 11). However, embedding the classifiers in dedicated hardware is a challenging task and the number of studies that adopted this approach is still low. There is still considerable room for improvement pertaining to this point, especially regarding the use of low-cost hardware. The use of low-cost μCs or DSPs is a challenge as their computation capabilities are limited. This requires the use of more efficient signal processing techniques and classifiers to maintain an acceptable level of performance. This should be the focus of future research.

Facing the growing interest for real-time operation

Fig. 12 shows the percentage of studies that include and exclude any kind of information regarding the processing characteristics of the hardware used to perform the computations. In the last 10 years, a clear trend in the inclusion of computers, DSPs, FPGAs, and μCs has been observed. This is because the real-time operation of the classification systems has gained research interest. However, there is still scope for growth as half the studies analyzed in the last period (from 2014 to 2018) did not contain information pertaining to this point. If this trend continues, it is likely that the real-time operation of the classifiers will be the core part of the research in the subsequent years.

Improving performance in more real-time focused studies

As a result of this review, it was identified that accuracy values were lower when the classification was obtained using data from laboratory setups or real grids. This is especially relevant as the types of distortions considered in a lab or real dataset were less than those considered in the synthetic case in nearly all studies. Fig. 13 shows a comparison of the mean accuracies and mean number of distortions for the classifiers tested using both synthetic/simulated and real data (laboratory setups or real grids) [97,102,106,118,126,159,170,173,175,178,188,192, 205–207,214–216]. The decrease in performance observed when the classifiers were tested using real data may be because the mathematical equations used to obtain synthetic distortions did not accurately reflect the real distortions. In addition, as the number of real disturbances is significantly limited, classifiers are trained using synthetic data. Therefore, when they are tested using real data, the performance values deviate from the synthetic case.

All the studies that included some type of hardware implementation of the classification systems performed the tests using real data (obtained from laboratory setups or real grids) [95,179,213–220]. This shows that these studies were more focused on the real deployment of the classifiers than on experimental studies. Therefore, the performances provided by these studies may reflect the real-world performance of the classifiers in a better manner, thereby showing that the classification accuracies in real-world contexts (mean value of 94.4%) are still far from 100%.

Performing objective analysis of real-time operation

On the one hand, it is common to identify studies that state that their systems are suitable for a real-time operation without providing any specific analyses that support this fact. On the other hand, there are studies that present time analyses, although they do not identify the computing unit in which the computations were performed. Therefore, future studies should conduct objective real-time tests. A future challenge is to present the conclusions on real-time performance based on evidence and reproducible data.

Performing time analysis in embedded hardware

In the context of smart grids, the automatic classification of PQ distortions should be executed in embedded hardware. However, most studies utilized a PC environment to perform time analysis. This is useful for obtaining an orientation of the time performance of the systems; however, it has the disadvantage that its real-world implementation is not tested. A research challenge is to implement the classification systems in dedicated hardware and provide a complete time analysis of system performance. Only a limited number of studies have faced this challenge [213–220]. However, several PQ distortions, signal processing techniques, and classifiers presented in Section 3 were not tested on dedicated hardware. Therefore, this is a remaining research effort.

Defining a common evaluation framework for real-time operation

A requirement for a common framework to evaluate the degree of real-time operation of automatic classifiers of PQ distortions was detected. Significant differences were identified in the methods used for computing the computational load of the classification systems. Several studies did not provide information on the number of cycles used for the calculations, signal frequency, or specific hardware used, which are factors that have a direct influence on the processing time. Other studies did not clarify whether signal processing, feature extraction, and classification were all included in the time periods that were provided. A set of studies indicated the time used to train the classifiers but not the test times. Further, there were studies that included computation complexities instead of providing computation times. In conclusion, there is no common framework for evaluating the real-time operation. This results in difficulty in comparing studies objectively. A future research challenge is to propose a framework for the evaluation of the real-time abilities in automatic PQ classification.

5. Conclusion

Automatic PQ classification in real time is a remaining research effort. Hundreds of research studies on this topic were published following a growing trend that has intensified in recent years due to the inclusion of renewable energy sources in microgrids. This paper has presented the first review on real-time PQ classification. From a set of systematic searches, 809 studies were identified and 134 were analyzed in detail. The ST and MRA were used in 61.2% of the studies, demonstrating their popularity in signal processing in the non-real-time studies. NNs in their different forms were the preferred classifiers as 38.1% of the studies incorporated them. DTs or simple DRs were more common in real-time systems. The mean number of features extracted was 13.9, although it was much lower in embedded classifiers (7.4 features). The average number of distortions classified was 18 in the last period that was analyzed (from 2014 to 2019). Ninety-four % of the studies considered combined distortions. This contrasts with the mean value of 6.7 distortions considered between 1995 and 2013. In this period, the percentage of studies that classified combined distortions was 53.6%. While considering the methods through which the distortions were obtained, 71.6% of the studies simulated them synthetically, which was the primary trend. The percentage of studies that used real distortions from real grids is still moderate (23.1%) and did not increase over time. Classification accuracies were higher in the studies that used synthetic or simulated signals (mean value of 97.6%), while they were lower in studies based on laboratory setups or real grids (mean value of 95.6%). The information regarding the computational load or computation times of PQ classifiers was included in 60.4% of the studies in the last period that was analyzed (from 2014 to 2019). This percentage decreased to 30.9% for the previous years (from 1995 to 2013).

As a result of these critical analyses, several research challenges were identified. We detected the requirement for signal processing methods and classifiers with sufficient computation efficiency to be embedded in low-cost hardware. In addition, we observed that future research should focus on including more types of disturbances and more combinations among them in the hardware implementation of the classifiers. A requirement was detected for the use of real datasets in the tests. In this regard, public datasets of real disturbances with a large number of types, repetitions, and labeled data can facilitate the work of researchers in this field. This would also allow overcoming one of the primary research problems, i.e., the fair comparison of performances. Additionally, improving accuracies in real-time classification is required. Performance values were still low in comparison with non-real-time studies. Another research challenge is to evaluate the real-time abilities of the classifiers in physical hardware. Conducting more objective real-time analyses is also required. The proposal of a common framework to evaluate the real-time operation would help to achieve this purpose. In the previous studies, each author performed a customized test; therefore, it is not possible to objectively compare the computational load of different classification systems. Finally, owing to this review, we identified a growing trend in research focusing on real-time operation, despite this still being an open topic. Further research is required for the development of a viable, accurate, fast, low-cost, and embeddable PQ classification system, which is a crucial step to improve the integration of distributed renewable energy sources into the grid.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Table A.1
Analysis of the studies published before 2011 that did not consider computation times (Category 1).

Study	Signal processing	Classification[1]	No. of feat.[2]	Disturbances				Software	Acc. (%)[7]	Real-time qualitative analysis
				No. of types [3]	Dataset[4]	Combd[5]	Noise[6]			
Biswal 2014 [103]	HHT	BNT	2	8	Synth	Y	N	–	97.9	–
Shukla 2014 [104]	EMD HHT	Fuzzy Product Aggregation Reasoning Rule-based classif.	9	9	Synth	Y	Y	MATLAB	98	Strategies provided for efficient computation
Deokar 2014 [115]	DWT (MRA) FFT	Rule based system	3	15	Synth	Y	Y	MATLAB	99	Potential for on-line applications
Ray 2014 [126]	Hyperbolic ST (HST)	DT and SVM	10	3/3/6	Lab/Lab/Simul	Y	Y	–	99.5	–
Eristi 2013 [137]	DWT (MRA)	Least Square-SVM (LS-SVM)	17	5 events	Real	–	Y	MATLAB	98.88	–
Ray 2013 [148]	ST	Modular PNN (MPNN), SVM, LS-SVM	10	9/6/6	Lab/Lab/Simul	N	Y	MATLAB/Simulink	98.33	LS-SVM and MPNN lesser computational burden
Mohanty 2013 [159]	ST	Modular PNN, SVM	12	4/4	Simul/Lab	–	Y	MATLAB/Simulink	99	–
Huang 2012 [160]	ST, TD	PNN and DR	3	8	Synth	Y	Y	MATLAB	100	Feature selection reduces computation time
Tse 2012 [161]	Frequency-shifting DWT via HT	–	–	6/2	Synth/Lab	N	N	–	–	–
Abdelsalam 2012 [162]	DWT Kalman filter	Fuzzy expert system	3	7/-	Simul/Public	Y	Y	MATLAB/Simulink	98.71	Hybrid technique computationally simple
Biswal 2012 [105]	Fast ST (dyadic scaling, band pass filter)	FCMs	4	9	Simul	Y	Y	MATLAB	99.8	Proposed processing reduces processing time
Hasheminejad 2012 [106]	ST	DT structure of HMM	–	7/2	Simul/Real	Y	Y	MATLAB Simulink	98.14	HMM can operate online
Pires 2011 [107]	3D space referential	Neuro-fuzzy classf.	2	6	Synth	Y	N	–	99.71	–
Masoum 2010 [108]	DWT (MRA)	Wavelet network	8	16	Synth	Y	Y	–	98.18	Fast algorithm
Cho 2010 [109]	GWT	–	–	7	Synth	Y	N	MATLAB	–	–
Eristi 2010 [110]	Wavelet MRA	SVM	9	6 events	Simul	–	Y	EMTP/ATP	99.71	Potential for on-line classification
Hooshmand 2010 [111]	Windowed discrete FT (WD-FT) WT	Two fuzzy systems (detection/classification)	8	16	Synth	Y	Y	MATLAB	98.5	Low computational burden
Eristi 2010 [112]	WT (MRA)	SVM	14	7	Synth	Y	Y	MATLAB	99.43	SVM and MRA computationally simple. Potential for on-line classification
Szmajda 2010 [113]	GT, Discreet Dyadic WT (DDWT), Smoothed Pseudo Wigner-Ville Distribution (SPWVD), New GWT	–	–	3	Synth	N	N	–	–	GT, SPWVD and GWT suitable for off-line. DDWT for RT
Biswal 2009 [114]	Generalized ST (modified Gaussian window)	FCMs clustering	2	9	Simul	Y	N	MATLAB	90 to 100	–
Uyar 2009 [116]	ST	MLP	4	8	Synth	Y	Y	MATLAB	99.67	Potential for on-line classification
Nguyen 2009 [117]	WD-FT ST	DR	6	10	Synth and Simul and Real	Y	N	EMTP	99.64	Strategy in DR to make them computationally efficient
Oleskovicz 2009 [118]	WT (MRA)	Five NNs	3	5/2	Simul/Real	N	N	ATP	100	Five ANNs with single outputs reduce training time
Ekici 2009 [119]	WT (MRA)	SVM	6	5	Simul	N	Y	ATP/MATLAB	100	Training of ANN is slower than SVM
Gunal 2009 [120]	WT (MRA) Spectrum analysis (power spectral density)	Bayes classifier and SVM	19	4 events	Lab	–	N	–	85.83	Feature selection: Sequential forward floating selection and Plus-l takeaway-r fair computational load
Uyar 2008 [121]	WT (MRA)	MLP	13	6	Synth	Y	Y	MATLAB	96	Data size reduction for efficiency. Potential for on-line classification
Hu 2008 [122]		Weighted SVM	5	5	Synth	N		MATLAB	98.4	–

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Table A.1 (*continued*)

Study	Signal processing	Classification[1]	No. of feat.[2]	Disturbances: No. of types [3]	Dataset[4]	Combd[5]	Noise[6]	Software	Acc. (%)[7]	Real-time qualitative analysis
	WT (MRA) DFT									
Gargoom 2008 [123]	ST	DR	2	5/2	Synth/ Simul	N	N	MATLAB/ Simulink	–	–
Kaewarsa 2008 [124]	Multi-WT	LVQ (multiple) and a voting scheme	–	5	Synth	N	N	MATLAB	98.03	Low usage time
Zhao 2007 [125]	ST	DT	5	10	Synth	Y	Y	MATLAB	99.7	ST quickly calculated (FFT and convolution theorem). Potential for online classification
Senroy 2007 [127]	HH method based on masking signal	–	–	2/-	Synth/Real	N	N	–	–	–
Axelberg 2007 [128]	FFT RMS values	SVM	72	5/5	Synth/Real	N	N	MATLAB	95.9	–
Bollen 2007 [129]	Segmentation, FT (spectrogram), RMS values	Rule based expert system, SVM	72	9/5 events	Real/Real and Simul	–	N	MATLAB	97	RMS sequence downsampled before to reduce computational cost
Gargoom 2007 [130]	CT (component vectors unified) Discrete HT (DHT)	k-NN	2	8	Synth	Y	N	–	89.2	CT has faster processing time than ST and MRA
Ribeiro 2007 [131]	Second order notch filter	Bayes detection rule based on the maximum likelihood criterion	2	7/-	Synth/ Public	N	Y	–	~100	Fast, simple and efficient
He 2006 [132]	WT (MRA)	SOLAR	11	6	Synth	Y	Y	MATLAB	94.93	Long wavelet filters or decomposition levels have larger computational cost
Gerek 2006 [133]	20th-order Elliptic notch filter	Quadratic classifiers along each cumulant order	6	2 events	Lab	–	N	–	100	Cumulant calculation could be in real-time even with microcontrollers
Janik 2006 [134]	Space phasors (CT)	SVM, RBF networks	–	5 dist/4 events	Synth/ Simul	N	Y	MATLAB	97.5 to 100	Complex phasors reduce computational effort
Gerek 2006 [135]	WT (MRA) Spectrum analysis 50 Hz notch filter	Covariance-based subspace classifier (“common vector classifier”)	7	4 events	Lab	–	N	–	100 (2 class)	Computational complexity of the CVC lower. Data-acquisition with programmable digital filters can operate in real-time
Lira 2006 [136]	DWT (MRA)	Three/six MLPs, “winner-takes-all” method to ensemble results	10 to 188	5	Real	N	N	MATLAB	99.3	Applying PCA provides ANN faster learning
Abdel-Galil 2005 [138]	DWT (MRA) FT	HMM	–	5/5	Synth/ Simul	N	N	EMTDC/ PSCAD/ MATLAB	98	Algorithms to speed up HMMs (similar performance to NN). Potential for online classification
Chen 2005 [139]	FT, WT (MRA), TD	–	9	–	–	N	N	–	–	Advanced signal processing achievable by improvement in computing resources
Chilukuri 2004 [140]	ST	Fuzzy logic-based classf.	6	7	Synth	N	Y	MATLAB	99.28	–
Abdel-Galil 2004 [141]	WT (MRA)	DT	11	6/6	Synth/ Simul	Y	N	EMTDC/ PSCAD	90.4	Potential for online classification
Dash 2003 [142]	ST	–	–	5	Synth	N	Y	MATLAB	–	–
Lee 2003 [143]	ST	Feed Forward (FF)-NN, PNN and final DR	4	10	Synth	Y	Y	MATLAB	95.33	Quick network. Three-dimensional reduces training time
Dash 2003 [144]	ST	Rule-based classifier	3	6	Simul	Y	Y	–	97	–
Huang 2002 [145]	WT (MRA)	Neural-fuzzy-based classifier	–	13	Real	N	N	–	93.3	Removing redundancies and simplifying reduces computation cost of NN. Potential for online classification
	WT (MRA)		15	5	Synth	Y	Y	MATLAB	95.83	

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Table A.1 (*continued*)

Study	Signal processing	Classification[1]	No. of feat.[2]	Disturbances: No. of types [3]	Dataset[4]	Combd[5]	Noise[6]	Software	Acc. (%)[7]	Real-time qualitative analysis
Gaouda 2002 [146]		Minimum Euclidean Distance (MED), k-NN, NN								k-NN requires more computation time than MED (worse performance)
Gaouda 2002 [147]	WT (MRA)	DR	13	7	Synth	Y	Y	–	–	Fast online classification required
Jurado 2002 [149]	STFT WT	–	–	2 events	Simul	–	N	EMTP/ATP/ MATLAB	–	STFT with a dyadic structure may be slower than wavelets
Yang 2001 [150]	DWT Denoising technique	–	–	3/2	Simul/Real	N	Y	EMTP/ATP/ MATLAB	100	–
Gaouda 2001 [151]	WT (MRA)	31(k)-NN	15	5	Synth	Y	Y	MATLAB	95.83	k-NN enables online monitoring (certain classes). On-line classification possible
Santoso 2000 [152]	TD, WT (MRA), FT	Rule-based expert system	23	3 events	–	–	N	–	–	–
Gaouda 1999 [153]	WT (MRA)	DR	–	5	Synth	N	N	MATLAB	–	DWT requires less computational time than CWT
Poisson 1999 [154]	CWT, MRA, Quadratic transform	–	3	4	Simul	N	N	–	–	–
Angrisani 1998 [155]	CWT DTWT (MRA)	–	–	3	Synth	N	Y	–	–	Wavelet with few vanishing moments minimizes computation
Meunier 1998 [156]	FT, WT, Prony analysis	–	–	2 events	Simul and Real	–	N	EMTP/ MATLAB	–	Prony analysis heavy. Wavelets, STFT, and FT more computationally efficient
Lee 1997 [157]	OPA	LVQ	7	7 events	Simul	N	Y	EMTP	97.1	–
Santoso 1996 [158]	WT (MRA)	–	–	4	Real	N	N	–	–	–

[1,2,3,4,5,6,7] See the footnotes of Table 1

Table A.2
Analysis of the studies published before 2011 that considered computation times in a regular personal computer (Category 2).

Study	Signal processing	Classification[1]	No. of feat.[2]	Disturbances: No. of types [3]	Dataset[4]	Combd[5]	Noise[6]	Hardware	Acc. (%)[7]	Real-time analysis: Qualitative	Quantitative
Valtierra-Rodriguez 2014 [188]	TD, ADALINE NN (to obtain the spectrum per sample)	ADALINE and FF-NN	22	96/3	Synth/Lab	Y	Y	Intel Pentium Dual Core, 2.2 GHz	+90	Real-time can be achieved with DSP or FPGA.	46.5 ms (half frequency)
Hajian 2014 [189]	Hyperbolic ST MRA	Multi SVM (MSVM)/ PNN/k-NN (using PSO)	26	7/-	Synth/Real	Y	Y	Intel Core 2 Due T9600, 2.8 GHz, 4 GB RAM	99.77	Feature selection suitable for RT	Feature selection algorithm for MSVM (twenty features, noiseless): 10.934 ms
Ozgonenel 2013 [200]	EEMD with HT	SVM	10	8/-	Synth/Real	N	N	–	100	SVM: polynomial kernel computationally worse than RBF kernel	10.686 s (SVM with RBF Kernel)
Dehghani 2013 [205]	TD MRA	HMM and Dempster-Shafer algorithm (final decision)	18	15/3	Simul/Real	Y	Y	2.67 GHz, 4 GB RAM	99.46	Real-time classification possible with parallel processing	Less than 1 s
Biswal 2013 [206]	Fast discrete ST (FDST)	Automated DT	6	13/13	Synth/Lab	Y	Y	Intel Core 2 Duo, 4 GHz, 4 GB RAM	98.8	FDST can be implemented in real-time DSP	FDST: 3.2 ms using dyadic scaling (614 sample points)
Rodríguez 2012 [207]	ST	DR	6	10/10/7	Synth/ Simul/Real	Y	Y	Pentium Dual-Core, 2.50 GHz	99.5	Algorithm works in RT	71 ms (5 cycles)
Eristi 2012 [208]	MRA TD	SVM (event) and DT (disturbance)	10	3 dist., 5 events	Real	N	N	–	98.51	Faster classification	One event (3-cycles): 0.9196 s (feature extraction), 0.0269 s (SVM test)
		PSO-PNN	22	6	Simul	Y	N		–		–

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Table A.2 (*continued*)

Study	Signal processing	Classification[1]	No. of feat.[2]	Disturbances: No. of types [3]	Disturbances: Dataset[4]	Disturbances: Combd[5]	Disturbances: Noise[6]	Hardware	Acc. (%)[7]	Real-time analysis: Qualitative	Real-time analysis: Quantitative
Huang 2011 [209]	Chaos Synchronization-based detector							Pentium-IV, 2.4 GHz, 480 MB RAM		Promising result for future RT	
Lee 2011 [210]	ST TTT	Adaptive PNN, MLP, k-NN	5	10/10	Synth/ Simul	Y	Y	Intel Pentium Dual-Core, 2.7 GHz, 2.0 GB RAM	98.1	Runtime can improve with PNN-based feature selection	Adaptive PNN: 1.43 s (ten cycles)
Decanini 2011 [211]	DWT (MRA)	Fuzzy-ARTMAP NN	5	8/-	Synth/ Simul	Y	N	Intel Core 2 Duo, 2.93 GHz, 4 GB RAM	99.66	High computing performance	Disturbance detection: 2.9 ms (seven cycles)
Ji 2011 [190]	Phase space	DR	5	7/-	Synth/ Simul	Y	Y	–	100	Suitable for online application	Classification: 2.7–0.012115 ms
Zygarlicki 2010 [191]	Reduced Prony's method	–	–	2	Synth	N	N	–	–	Computational complexity of Reduced Prony similar to DFT	Computational complexity: N^2 complex multiplications, N(N-1) complex additions
Panigrahi 2009 [192]	DWT (MRA)	Fuzzy k-NN	16	10/10	Synth/Lab	Y	Y	IBM 3.0 GHz, 256 MB RAM	96.33	Larger feature sets rise computation time	Classification 1-fold (1000 data training/100 testing): 63.3 ms (Sixteen features)
Mishra 2008 [193]	ST	PNN	4	10	Synth	Y	Y	–	98.64	PNN with four features reduces time	Testing: 0.002 s (PNN)
Bhende 2008 [194]	ST	Modular NN	4	10	Synth	Y	N	Pentium IV, 2.6 GHz	95.5	Potential hardware implementation for online application	Detect disturbance: 0.687 s
Lin 2008 [195]	WT	MSVM	–	7	Simul	Y	Y	Pentium IV, 256 MB RAM	99	WT-MSVM is fast	WT-MSVM (testing) < 0.35 s
Monedero 2007 [196]	MRA TD	Four MLPs	22	Above 9/0	Synth and Lab/Real	Y	N	–	70 to 100	Real-time prototype developed	Below 46 ms (100 ms time window)
Reaz 2006 [197]	DWT (MRA)	NN and Fuzzy Logic	–	5	Synth and Lab and Real	N	N	–	98.19	VHDL model speed-up	Classification: 0.016 ms
Lin 2005 [198]	WT	PNN	–	6	Simul	Y	Y	Pentium III, 128 MB RAM	–	Decreased processing time	WT-PNN (training): 0.11 s Recalling time: 0.11–0.17 s
Gaing 2004 [199]	WT (MRA)	PNN	14	6	Simul	N	N	Pentium III 550, 256 MB RAM	90	Suitable for real-time processing in digital recorder	For 70 training samples: 0.04 s (learning), 0.39 s (recall)
Youssef 2004 [201]	FFT Walsh Transform	Fast Match-DTW (FM-DTW) and nearest neighbor rule	–	5	Synth	N	Y	–	97.3	FM-DTW reduces computational effort	Savings of 66.6% in computational times by applying FM to DTW
Santoso 2000 [202,203]	WT (MRA)	DR and multiple NNs with output combination	–	5	Real	N	N	150 MHz PC	98.5	Training takes considerable time	Training: less than 1 h.Testing: 1.6–1.9 s (one disturbance)
Ghosh 1995 [204]	Windowed Discrete FT	FF-NN, Modified Time-delay NN (MTD-NN)	8	5	Simul	Y	Y	–	93	Training time for MTD-NN is 1.5 times faster than FF-NN	MTDNN (training): up to 1 h (2 hidden layers)

[1,2,3,4,5,6,7] See the footnotes of Table 1

Appendix B.

Table B.1
Analysis of the features extracted, performance details and hardware used for studies that did not consider computation times (Category 1).

Study	Features	Performance details	
Mahela 2020 [38]	ST plots and THD in voltage and current	–	**Hardware** Intel Core i5, 2.60 GHz
Mahela 2020 [39]	1) Mean and 2) SD of the absolute value of the ST matrix, and 3) maximum deviation of the ST matrix with respect to the mean	Simulated and Real-time results closed	**Hardware** RTDS of OPAL-RT. Laptop Intel Core i5, 2.60 GHz
Hafiz 2019 [86]	1)-99) Eleven statistical functions for each of the 8 detail decomposition levels and one approximation level	99.85 (DT)/99.5 (SVM)/98.01 (Naïve Bayes)/98.15 (ELM)/98.45 (NN)/96.6 (k-NN)	
Huang 2019 [87]	1) Minimum and 2) SD of the Frequency maximum Amplitude (FmA)-plot, 3) Minimum, 4) mean and 5) SD of the minimum of each row of the ST matrix, 6) min and 7) SD of the mean of each row of the ST matrix, 8) maximum, 9) minimum, 10) sum of maximum and minimum, 11) subtraction of maximum and minimum, 12) mean, 13) SD of the SD of each row of the ST matrix, 14) minimum and 15) SD of the RMS of each row of the ST matrix	99.5 (Synth)/- (Real)	
Shi 2019 [88]	Auto selected (not specified)	98.61	
Shaik 2018 [40]	1) Kurtosis of sum absolute values curve from the ST matrix, 2) maximum value of variance of ST matrix, 3)-4) THD in voltage and current	Simulated and Real-time results closed	
Luo 2018 [89]	Derived from the maximum value of the basic frequency row	98.98 (Synth)/89.08 (Data)/86.83 (Lab)	
Liu 2018 [90]	–	Combined: 99.52 (Synth and Simul)/99.04 (Data)	
Kapoor 2018 [91]	1) Kullback–Leibler divergence, 2) SD	94.02	
Ma 2017 [92]	The signal feeds the classifier directly	99.75	
Mahela 2017 [93]	1) Number of peaks in the FmA-plot, 2) mean, 3) SD and 4) variance of absolute values of S-matrix, 5) energy content of S-contour, 6) maximum deviation of S-matrix	99.6 (MATLAB)/98.33 (RTDS)	**Hardware** Intel Core i5, 2.60 GHz, 4 GB RAM, running a RTDS of OPAL-RT
Mahela 2017 [94]	From the S-matrix: 1) mean, 2) SD (amplitude), 3) variance, 4) maximum deviation (amplitude)	–	Intel Core i5, 2.60 GHz, 4 GB RAM, running a RTDS of OPAL-RT
Morales 2017 [95]	1) RMS value of voltage and current signals, 2) power factor, 3) active power, 4) apparent power, 5) THD, 6) total RMS value (of the 3 phases jointly), 7) voltage imbalance estimator	–	Xilinx_ FPGA Spartan6 (XC6SLX16)
Wang 2017 [96]	From the Time maximum Amplitude (TmA)-plot: 1) minimum amplitude, 2) summation of the maximum and minimum From the FmA-plot: 3) subtraction of the maximum and minimum for frequencies above four times the line frequency 4) SD of time-amplitude plot determined by the frequency that has maximum amplitude in S-matrix matrix above the frequency of 200 Hz	99.26	
Upadhyaya 2016 [97]	1)-7) Energy, 8)-14) SD and 15)21) entropy of 7 levels of detail coefficients	DT: 96.67 (Synth)/95.64 (Real)	**Hardware** Core i5, 2.40 GHz
Biscaro 2016 [98]	1)-8) Voltage wavelets indices obtained from detail and approximation coefficients. 9)-16) Complement of those indices	93.4	
Abdoos 2016 [99]	**ST** - > From magnitude contour: 1) SD and 2) Energy. From frequency contour: 3) SD and 4) Energy. From phase contour: 5) SD. From contour levels 1–5: 6)-10) energy **VMD** -> 11)-13) SD, 14)-16) energy and 17)-19) maximum absolute value of three modes, (13 optimal features selected)	99.66	
Kumar 2015 [100]	From the frequency-amplitude vector: 1) number of peaks From the TmA-vector: 2) minimum, 3) maximum, 4) mean, 5) skewness, 6) kurtosis	99.9 (Synth)	
Huang 2015 [101]	The extent of energy 1) falling and 2) rising in 1/4 cycle, 3) SD and 4) normalizing factor of amplitude of fundamental frequency (FF), 5) maximum value of average amplitude of every frequency in middle frequency area, 6) modified energy of high frequency area	98.38	
Liu 2015 [102]	1)-11) Standard energy differences between each IMF (decomposition level of EEMD is 11) and the corresponding of the normal signal (sine wave)	92.8 (Synth)/97.3 (Simul)/100 (Real)	
Biswal 2014 [103]	From HT: 1) SD, 2) entropy	97.9	
Shukla 2014 [104]	From the Hilbert array (three IMFs obtained): 1)-3) energy, 4)-6) SD of the magnitudes, 7)-9) SD of the phase	98	**Hardware** dSpace DS1103
Deokar 2014 [115]	From MRA: 1) percentage average energy entropy of squared detailed coefficients at 10 levels From FT: 2) magnitude of 3-times FF coefficient, 3) sum of magnitudes of all coefficients excluding the fundamental	99	
Ray 2014 [126]	From magnitude/phase contour: 1)-2) energy, 3)-4) SD, 5)-6) mean, 7)-8) skewness, 9)-10) kurtosis	98 (Real/DT)/99.5 (Simul/HST with DT)	
Eristi 2013 [137]	From approximation coefficients: 1)-3) mean, 4) SD, 5) skewness, 6) kurtosis, 7)-8) RMS, 9)-11) energy, 12)-13) Shannon entropy, 14)-17) norm entropy	98.88	
Ray 2013 [148]	From TmA-plot: 1) energy, 2) mean, 3) SD 4) skewness, 5) kurtosis From phase contour: 6) energy, 7) mean, 8) SD, 9) skewness, 10) kurtosis	98.33 (LS-SVM, Wind data)	
Mohanty 2013 [159]	From the Stockwell (S)-matrix: 1)-3) SD, 4)-6) energy, 7)-8) mean, 9)-10) skewness, 11)-12) kurtosis	SVM: 99 (Simul)/98.2 (Lab)	

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Table B.1 (*continued*)

Study	Features	Performance details
Huang 2012 [160]	From the TmA-plot: 1) amplitude factor From the FmA-plot: 2) SD in the high frequency area above 100 Hz 3) The minimum of the maximum amplitudes in all cycles of the disturbance sample	100
Tse 2012 [161]	–	–
Abdelsalam 2012 [162]	1) Amplitude of the FF (obtained from the estimated state variables of the Kalman filter) 2) Slope of the fundamental amplitude 3) SD of the means of the harmonics normalized to the mean of the fundamental	98.71 (Simul)
Biswal 2012 [105]	1) Variance, 2) normalized value of the maximum deviation, 3) energy, 4) mean	99.8
Hasheminejad 2012 [106]	1) Maximum amplitude curve, 2) SD curve, 3) FF-amplitude curve	98.14 (Simul) 90.24 to 98 (Real)
Pires 2011 [107]	1)-2) Two normalized total error signals obtained from the eigenvalues of two phase voltage signals	99.71
Masoum 2010 [108]	From different levels of detail coefficients: 1)-4) ratio of SD to mean value, 5)-7) maximum absolute value From approximation coefficients: 8) mean absolute value	98.18
Cho 2010 [109]	–	–
Eristi 2010 [110]	1)-8) Energies of eight detail and 9) one approximation levels of three-phase signals (energies of the 3 phases combined)	99.71
Hooshmand 2010 [111]	1) Amplitude of the FF component, 2) phase angle shift, 3) THD, 4) number of maximums of the absolute value of wavelet coefficients, 5) energy of the wavelets coefficients, 6) number of zero-crossings of the missing voltage, 7) LHD, 8) number of peaks of the RMS value	98.5 (single) 96.75 (combined)
Eristi 2010 [112]	1)-6) Log-energy entropy, 7) crest factor, 8)-9) energy, 10)-11) Shannon entropy, 12) SD, 13)-14) kurtosis	99.43
Szmajda 2010 [113]	–	–
Biswal 2009 [114]	1) Variance, 2) normalized values	90 to 100
Uyar 2009 [116]	From the Time Frequency (TF)-contour: 1) SD of contour having the largest frequency amplitude From the TmA-plot: 2) mean, 3) amplitude factor From the Frequency-SD-plot: 4) mean of square root	99.67
Nguyen 2009 [117]	1) Amplitude of the FF of the signal, 2) phase angle shift, 3) oscillation number of the missing voltage of each cycle, 4) SD of the maximum absolute value of each column in the S-transform matrix, 5) number of cycles in a waveform that have THD greater than a threshold value, 6) factor that compares maximum and minimum amplitude values of the input signal with respect to an ideal reference signal	99.64
Oleskovicz 2009 [118]	1)-3) Mean of energies of different detail levels	91.03 (Simul/MLP)/100 (Real/RBF)
Ekici 2009 [119]	1)-6) Energies of detail coefficients of 6 levels	100
Gunal 2009 [120]	1)-4) maximum and 5)-8) minimum values of the detail coefficients of four levels in a time-window, 9) reciprocal proportion of the signal energy corresponding to the FF in relation to the remaining energy at all other frequencies, 10)-19) extrema of statistical parameters (maximum and minimum of variance, third and fourth central cumulate, skewness and kurtosis), (different subsets selected)	85.83 (Bayes classifier, 8 features)
Uyar 2008 [121]	1)-13) Variations in norm entropy of 12 detail and 1 approximation coefficients with respect to an ideal pure signal	96
Hu 2008 [122]	1) Total energy entropy, 2) amplitude of the fundamental component, 3) THD, 4) number of peaks of the wavelet package coefficients, 5) oscillation number of the missing voltage	98.4
Gargoom 2008 [123]	1)-2) Maximum and minimum values of the energies of the IF	–
Kaewarsa 2008 [124]	–	98.03
Zhao 2007 [125]	1) Number of main frequencies (peaks in FmA-curve), 2) whether or not there is a peak: 2) near the FF and 3) near a high-frequency component in the SD-curve, 4) mean of FF-Amplitude-curve, 5) degree of the sag, interruption, or swell	99.7
Senroy 2007 [127]	–	–
Axelberg 2007 [128]	For each phase of a three-phase system: 1)-60) 20 RMS values, 61)-69) 2nd, 5th and 9th harmonics magnitude, 70)-72) THD	95.9 (real for training, synthetic for testing)
Bollen 2007 [129]	**SVM** - > For each phase of a three-phase system: 1)-60) RMS values (equally distance sampling), magnitudes of 61)-63) 2nd, 64)-66) 5th, and 67)-69) 9th harmonics, 70)-72) THD with respect to the magnitude of power system FF component	97 (Rule-based system)/96.1 (Real/SVM)
Gargoom 2007 [130]	From the space vectors of the CT: 1) mean, 2) SD From the module of the analytical signal of the HT (envelope of the original signal): 1) mean, 2) SD (2 features per classifier)	89.2 (k-NN with DHT)
Ribeiro 2007 [131]	1)-2) High order statistics	+95 (Synth)/~100 (Data)
He 2006 [132]	1)-10) Energy of detail coefficients at each decomposition level, 11) energy of approximation coefficients	94.93
Gerek 2006 [133]	Cumulant 1)-3) maxima and 4)-6) minima for moment orders of 2–4	100 (6 dimensional)
Janik 2006 [134]	–	SVM: 97.5 to 100 (Synth)/85.42 to 100 (Simul)
Gerek 2006 [135]	1) Spectral harmonics, 2)-6) 2nd, 3rd, 4th central cumulant extrema, 7) skewness maxima	100 (2 classes)
Lira 2006 [136]	–	99.3 (six NNs)
Abdel-Galil 2005 [138]	–	WT: 98 (Synth)/96.5 (Simul)
Chen 2005 [139]	1) RMS value, 2) shape of the distortion, 3) balanced or unbalanced three-phase system, 4) magnitude and 5) phase of harmonics, 6) amount of phase shift jump between begin and end (of the distortion), 7) magnitude and 8) energy of wavelet coefficients, 9) dominant frequency	–

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Table B.1 (*continued*)

Study	Features	Performance details	
Chilukuri 2004 [140]	1)-3) SD of three contours, 4) amplitude factor, 5) first peak of the first TF contour, 6) duration between two peaks of first contour	99.28	
Abdel-Galil 2004 [141]	1)-11) Normalized energy at different resolution levels	90.4	
Dash 2003 [142]	SD of the TF representation	–	
Lee 2003 [143]	1) SD of the lowest ST contour that is above the normalized FF, 2) amplitude factor, 3) SD of the amplitude versus time graph derived from the S-matrix for frequencies above twice the normalized FF, 4) THD	95.33	
Dash 2003 [144]	1) SD of the lowest ST contour that is above the FF, 2) SD of the amplitude versus time curve obtained from the S-matrix (above the FF), 3) amplitude factor	97	
Huang 2002 [145]	MRA coefficients. RMS and similarity analysis	93.3	
Gaouda 2002 [146]	Difference between analyzed signal and pure signal in relation to energy distribution of 1)-13) detailed levels and 14) approximation level, 15) duration of the distortion	95.83 (k-NN)	
Gaouda 2002 [147]	1)-13) Difference between analyzed and pure signal in relation to energy of coefficients at different resolution levels	–	
Jurado 2002 [149]	–	–	
Yang 2001 [150]	–	100 (Simul)	**Hardware** PC-586
Gaouda 2001 [151]	Difference between analyzed signal and pure signal in relation to energy distribution of 1)-13) detailed levels and 14) approximation level, 15) duration of the distortion	95.83	
Santoso 2000 [152]	From WT coefficients: 1)-4) maximum and 5)-6) average value of squared coefficients, 7) count of impulse number, 7) small oscillating wave duration From FT: 8)-18) magnitude of harmonics, 19) oscillation frequency in current From time domain: 20) overvoltage, 21) voltage change and slope, 22) oscillation frequency in voltage and 23) polarity of the voltage step	–	
Gaouda 1999 [153]	SD at different resolution levels of detail coefficients	–	
Poisson 1999 [154]	From CWT: 1) magnitude of 50 Hz signal, 2) time of sharp signal changes and 3) transient events From MRA: 1) time of sharp signal changes, 2) transients From quadratic transform: 1) magnitude of 50 Hz signal, 2) harmonic content, 3) time of sharp signal changes	–	
Angrisani 1998 [155]	Duration, amplitude and oscillation frequency	–	
Meunier 1998 [156]	–	–	
Lee 1997 [157]	1)-6) Integration of bispectra of differences between the normalized original signal and its approximation after applying PCA, 7) power value of the signal	97.1	
Santoso 1996 [158]	–	–	

Table B.2
Analysis of the features extracted, performance details and software used for studies that considered computation times in a regular personal computer (Category 2).

Study	Features	Performance details	Software
Qiu 2019 [164]	Auto selected (not specified)	99.46 (Synth)/94.8 (Real)	MATLAB
Zhao 2019 [165]	Difference in energy between the submodes of the signal and that of the undistorted sinusoidal	89.6 (Synth)/95.11 (Lab)	MATLAB
Deng 2019 [166]	Auto selected (not specified)	>98 (Synth)/100 (Lab)	MATLAB/Python
Thirumala 2019 [167]	1) Absolute peak-to-peak difference of signal magnitude, 2)-3) RMS of instantaneous amplitude of fundamental frequency and total instantaneous amplitude, 4) THD mean, 5) maximum of THD, 6) maximum of total instantaneous distortion factor	95.56 (16 classes)/88.48 (21 classes)	MATLAB
Singh 2019 [168]	From ST matrix: 1)-3) mean, mean of column-wise standard deviation and mean of row-wise maximum, 4)-6) sum of maximum and minimum of column-wise minimum, column-wise mean, column-wise root mean square, 7)-9) SD of column-wise root mean square, row-wise minimum and row-wise standard deviation, 10)-11) difference between maximum and minimum of row-wise mean and row-wise standard deviation, 12) THD of row-wise mean From real TT matrix: 13) RMS of diagonal elements	99.93(Synth)/98.57 (Lab)	MATLAB
Wang 2019 [19]	Automatically extracted (not specified)	99.96 (Synth)/100 (Simul)	PSCAD/EMTDC
Jamali 2018 [169]	From ST: 1) kurtosis, 2) skewness and 3) SD of 50-Hz contour, 4) minimum of 150-Hz contour From WT: 5) maximum, 6) THD and 7)-8) energy-entropy of different frequency nodes	DT-Random Forest: 100 (Synth)/ 98.33 (Simul)	EMTP
Singh 2018 [170]	Synthetic case: 1)-2) THD, 3)-7) max + min, 8)-13) max − min, 14)-18) mean, SD, 19)-23) RMS, 24)-26) Root Mean Squared Error (RMSE)	99.93 (Synth)/98.57 (Real)	MATLAB
Chakravorti 2018 [171]	From the modes: 1)-4) median versus mean, 5)-8) median and mean difference, 9)-12) mode energy ratio, 13)-16) energy, 17)-20) entropy, 21)-24) SD, 25)-28) variance, 29)-32) kurtosis, 33)-36) skewness, 37)-45) mode correlation-based feature selection. Then, optimum set selected	98.82	MATLAB
Achlerkar2018 [172]	1) Relative mode energy ratio, 2) center frequency of mode, 3) number of zero-crossings, 4) instantaneous amplitude (IA)	97.5 to 100	MATLAB
Singh 2017 [173]	From absolute S-matrix: 1)-6) maximum and 7)-12) minimum (matrix, SD –rows and columns-, variance –rows and columns-, first row), 13)-14) SD at first level rows and columns, 15) amplitude at first level rows, 16) squared sum, 17) histogram parameter, 18) mean	SVM: 99.63 (Synth)/98.57 (Lab)	MATLAB
Kubendran 2017 [174]	From FmA-plot: 1) number of peaks From SD-plot: whether or not there is a peak near the 2) fundamental and 3) high-frequency component From FF-amplitude plot: 4) number of peaks, 5) mean, 6) degree of the amplitude drop or increase	98.55	MATLAB
Singh 2017 [175]	1) Variance, 2) average power, 3) SD, 4) RMS, 5) peak to RMS ratio, 4) mean frequency, 5) SNR, 6) THD	BP: 99.93 (Synth)/97.3 (Lab)	MATLAB
Khokhar 2017 [176]	From detail coefficients: 1)-2) energy, 3)-4) skewness and 5)-6) RMS of two levels, 7) entropy and 8) kurtosis of one level Approximation coefficients: 9) kurtosis	99.875 (Synth)/98.625 (Simul)	MATLAB PSCAD/EMTDC
Garousi 2016 [177]	From detail coefficients: 1)-4) ratio of SD of absolute values of levels from 1 to 3, from 4 to 6, from 7 to 8 and from 9 to 12 in relation to their mean of absolute values, 5)-7) absolute value of maximum value of three levels and 8) energy of first level. Approximation coefficients: 9) absolute value of maximum value and 10) energy. 11) Effective value of voltage	99.57	MATLAB
Lopez_ Ramirez 2016 [178]	1)-5) Kurtosis, 6)-10) skewness and 11)-15) entropy of five IMFs	100	MATLAB
Kumar 2016 [179]	From Negative symmetric component: 1) duration from which it is non-cero, 2) number of zero-crossings. From Positive-sequence components peak contour: 3) number of zero crossings, 4) average magnitude, 5) maximum and 6) minimum values	–	MATLAB
Zhang 2016 [180]	From TmA-plot: 1) difference between the maximum (or minimum) and the normal value, 2) SD FmA-plot: 3)-4) SD in two frequency intervals	100	MATLAB
Camarena 2016 [181]	–	–	MATLAB
Ferreira 2015 [182]	High-order statistics: 1)-9) second-order and 10)-12) fourth-order cumulants. 13) RMS of the fundamental component	above 97 (Synth)/86.2 (Public)	–
Manikandan 2015 [183]	From detail: 1) maximum value of the RMS envelope, 2) peak polarity, 3) number of isolated events, 4) time of occurrence of events, 5) autocorrelation of detail signal From approximation: 6) minimum, 7) maximum, 8) mean value and 9) SD of the RMS envelope of the amplitude, 10) mean value and 11) SD of the RMS envelope during the detected event, 12) duration of the event, 13) frequency value	82.67 to 100	MATLAB
Ahila 2015 [184]	From detail coefficients: 1)-6) energy at different decomposition levels	97.6 (PSO-ELM)	MATLAB
Aneesh 2015 [185]	From three IMFs: 1)-12) sines and 13)-24) cosines of four statistical parameters (variance, kurtosis, median and range)	100 (VMD-SVM)	MATLAB
Kanirajan 2015 [186]	1) SD, 2) variance, 3) norm, 4) median, 5) absolute deviation and 6) mean absolute deviation of transformed signals 7) Energy at each decomposition level. (2 features selected with optimal performance)	97.85	MATLAB
Seera 2015 [187]	For each phase of a 3-phase system: 1)-3) voltage harmonics, 4)-6) current harmonics, 7)-9) voltage THD, 10)-12) current THD	Cophenic Correlation Coefficient scores (clustering): 72 to 92	MATLAB
Valtierra-Rodriguez 2014 [188]	From time domain: 1)-20) vertical and horizontal histograms (10 density functions per histogram). From ADALINE spectrum: 21) RMS, 22) THD	+90 (Synth)/~80 (Lab)	MATLAB
Hajian 2014 [189]	From HST: 1)-2) means, 3)-5) SD, 6)-12) energies, 13)-16) areas, 17) amplitude factor From MRA: 18)-20) means of entropies, 21) SD, 22) minimum value, 23)-24) mean, 25) energy	99.77 (MSVM)	MATLAB

(*continued on next page*)

Table B.2 (*continued*)

Study	Features	Performance details	Software
	From time domain: 26) skewness, 27) kurtosis, 28)-30) moments of different order, 31) RMS (26 optimum features selected, noiseless)		
Ozgonenel 2013 [200]	From Instantaneous Frequency (IF) and IA: 1)-2) mean, 3)-4) SD, 5)-6) singular values, 7)-8) maxima, 9)-10) minima	100	–
Dehghani 2013 [205]	For each phase of a 3-phase system: 1)-15) normalized values of energies of different detail coefficients, 16)-18) normalized values of RMS voltage	99.46 (Simul)/96 (Real)	PSCAD/EMTDC
Biswal 2013 [206]	From the TF-matrix: 1) maximum and 2) minimum amplitude, 3) total energy, 4) maximum SD (amplitude), 5) autocorrelation of the absolute value (frequency), 6) amplitude at contour level 1 (amplitude)	98.8 (Synth)/96.9 (Lab)	MATLAB
Rodríguez 2012 [207]	1) Mean and 2) minimum of FF contour, 3)-5) energies of 3rd, 5th and 7th harmonic contours, 6) sum of energy from 600 to 1600 Hz contours	99.5 (Synth) 98.5 (Simul)/93.8 (Real)	–
Eristi 2012 [208]	For event classification: 1)-10) sum of the root square values of the energies for each 9 detail and 1 approximation coefficients of all three phases For disturbance classification: RMS value of time domain signal	98.51 (events)	MATLAB
Huang 2011 [209]	1)-22) Dynamic error equation	–	MATLAB
Lee 2011 [210]	From the ST-Absolute-matrix, Time Characteristic Curves, or Frequency Characteristic Curves: 1)-5) THD, 6)-17) the sum of maximum and minimum, 18)-29) the difference between maximum and minimum, 30)-39) mean, 40)-51) SD, 52)-61) RMS, 62) RMSE for the diagonal elements of TT matrix. (from 5 –noiseless- to 10–20 dB SNR- optimal features selected)	MLP: 98.1 (Synth)/89.9 (Simul)	MATLAB/Simulink
Decanini 2011 [211]	1)-5) Mean entropy of detail and approximation coefficients removing the normal operation values	99.66 (Synth)	–
Ji 2011 [190]	From the Euclidian norm (E) of the xy plane: 1) duration, 2) magnitude, 3) whether there are additional pairs satisfying a condition, 4) whether there are beginning and ending pairs of equal intervals over one quarter of a cycle, 5) SD of E and the values of the xz plane	100 (Synth)	MATLAB/PSCAD
Zygarlicki 2010 [191]	–	–	–
Panigrahi 2009 [192]	For nodes of the 4th decomposition level: 1)-3) mean, 4)-8) kurtosis, 9) skewness 10)-12) SD, 13) entropy, 14)-16) energy	96.207 (Synth)/96.33 (Lab)	MATLAB
Mishra 2008 [193]	From maximum values of each column of the S-matrix: 1) SD, 2) energy From maximum values of each row of the S-matrix: 3) SD From phase contour: 4) SD	98.64	MATLAB
Bhende 2008 [194]	From the maximum magnitude of the S-matrix at each sample: 1) SD, 2) energy From the frequency contour: 3) SD From the phase contour: 4) SD	95.5	MATLAB
Lin 2008 [195]	Output of the WT.	99	MATLAB
Monedero 2007 [196]	From each level (7 levels) of the detail coefficients: 1)-7) integral, 8)-14) RMS value of the waveform of the coefficients, 15)-21) maximum of the absolute values of the coefficients. 22) RMS value of the voltage signal	+89 (Synth)/70 to 100 (Lab)	LabVIEW/MATLAB/C++
Reaz 2006 [197]	Approximation and detail coefficients considered directly	98.19	COMTRADE, PSCAD, ATP and MATLAB/VHDL
Lin 2005 [198]	WT output directly	–	MATLAB
Gaing 2004 [199]	1)-13) Energy of coefficients of 13 level decomposition, 14) disturbance duration (obtained from 1st level MRA)	90	MATLAB
Youssef 2004 [201]	Vector quantization is applied to the output of the signal processing techniques	97.3 (FFT), 96.8 (Walsh Transform)	MATLAB
Santoso 2000 [202,203]	For sags and interruption: local voltage minima and maxima from the time domain signal For the rest of disturbances: MRA output directly	98.5 (sag-interruption), 92.3 (rest)	–
Ghosh 1995 [204]	From current waveforms: 1)-4) four sets of harmonics grouped together From voltage waveforms: 5) 3rd harmonic, 6) high frequency components 7) normalized peak, 8) RMS	93 (MTDNN)	EMTP/PlaNet software on Sun Workstation platform (for NN)

Table B.3
Analysis of the features extracted, performance details and software used for studies that embedded the classifiers in dedicated hardware (Category 3).

Study	Features	Performance details	Software
Sahani 2019 [212]	From three IMFs: 1–3) Instantaneous mode energy, 4–6) Instantaneous mode Renyi entropy	99.81 (Synth)/99.29 (Lab)	MATLAB/Simulink with Xilinx system generator soft.
Ribeiro 2018 [213]	1)-5) Second-order cumulants from the error signal, 6) RMS of original signal minus filtered signal	97.8 (Lab)	LabVIEW
Sahani 2018 [214]	From the Hilbert array (three IMFs): 1)-3) SD of magnitude, 4)-6) energy, 7)-9) Shannon-entropy, 10)-12) SD of phase	99 (Synth)/95.5 (Lab)	MATLAB, Code Composer Studio
Li 2016 [215]	1)-6) Three maximum amplitude peaks of the frequency characteristic curve and their 3 corresponding frequencies. 7)-9) Three duration values of the time characteristic curve	99.3 (Synth)/+80 (Lab)	MATLAB
Borges 2016 [216]	Time domain: 1) harmonic mean, 2) SD, 3) mean deviation, 4) kurtosis, 5) entropy, 6) Shannon entropy, 7) Rényi entropy, 8) RMS, 9) peak value, 10) max-min difference Frequency domain: 11) THD, 12) magnitude of fundamental, 13) 2nd, 14) 3rd, 15) 4th, and 16) 5th harmonic	NN: 96.03 (Synth)/99.3 (Real)	–
He 2013 [217]	1) Mean value of fundamental amplitude, 2) sum number of Dynmax and Dynmin of fundamental curve, 3) THD, 4) number of Dynmax of high frequency component curves, 5) amplitude of the point indicated by 2), when 2) is 1	–	
Zhang 2011 [218]	1) RMS value of the fundamental component, 2) variation rate of RMS value, 3) oscillation number of the RMS values, 4) THD, 5) LHD	99 (Synth)	MATLAB
Radil 2008 [219]	1) Magnitude of processed signal, duration 2) over or 3) between given thresholds, 4) minimum and 5) maximum values	–	MATLAB
Ramos 2007 [220]	1) Duration of the disturbance and 2) RMS value	–	–

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References

[1] Alanne K, Saari A. Distributed energy generation and sustainable development. Renew Sustain Energy Rev 2006;10:539–58. https://doi.org/10.1016/j.rser.2004.11.004.

[2] Fu Q, Hamidi A, Nasiri A, Bhavaraju V, Krstic SB, Theisen P. The role of energy storage in a microgrid concept: examining the opportunities and promise of microgrids. IEEE Electrif Mag 2013;1:21–9. https://doi.org/10.1109/MELE.2013.2294736.

[3] Hirsch A, Parag Y, Guerrero J. Microgrids: a review of technologies, key drivers, and outstanding issues. Renew Sustain Energy Rev 2018;90:402–11. https://doi.org/10.1016/j.rser.2018.03.040.

[4] Force IT, Olivares CDE, Mehrizi-sani A, Etemadi AH, Cañizares CA, Iravani R, et al. Trends in microgrid control. IEEE Trans Smart Grid 2014;5:1905–19.

[5] U.S. Department of Energy. Renewable energy: distributed generation policies and programs | department of energy n.d. https://www.energy.gov/eere/slsc/renewable-energy-distributed-generation-policies-and-programs. [Accessed 11 July 2019].

[6] Hatziargyriou N, Asano H, Iravani R, Marnay C. Microgrids: an overview of ongoing research, development, and demonstration projects. IEEE Power Energy Mag 2007;5:78–94. https://doi.org/10.1109/MPAE.2007.376583.

[7] Salam AA, Mohamed A, Hannan MA. Technical challenges on. Micro 2017;3:587–94. https://doi.org/10.21647/icctest/2017/49027.

[8] Basak P, Chowdhury S, Halder Nee Dey S, Chowdhury SP. A literature review on integration of distributed energy resources in the perspective of control, protection and stability of microgrid. Renew Sustain Energy Rev 2012;16:5545–56. https://doi.org/10.1016/j.rser.2012.05.043.

[9] Grady WM, Gilleskie RJ. Harmonics and how they relate to power factor. EPRI Power Qual. Issues Oppor. Conf 1993:1–8. San Diego.

[10] IEEE. IEEE recommended practice for monitoring electric power quality, vol. 2009; 2009. https://doi.org/10.1109/IEEESTD.2009.5154067.

[11] Kannan A, Kumar V, Chandrasekar T, Rabi BJ. A review of power quality standards, electrical software tools, issues and solutions. Proc - 2013 Int Conf Renew Energy Sustain Energy, ICRESE 2013 2014. https://doi.org/10.1109/ICRESE.2013.6927794. 91–7.

[12] Ms Ankita A, Yeotikar SBM. An Overeview on power quality issues in power systems. Int Res J Eng Technol e-ISSN 2016;3:581–4.

[13] Olikara K. Power quality issues , impacts , and mitigation for industrial customers, vol. 8. Power-Wp002a-En; 2015.

[14] Pepermans G, Driesen J, Haeseldonckx D, Belmans R, D'haeseleer W. Distributed generation: definition, benefits and issues. Energy Pol 2005;33:787–98. https://doi.org/10.1016/j.enpol.2003.10.004.

[15] Kalair A, Abas N, Kalair AR, Saleem Z, Khan N. Review of harmonic analysis, modeling and mitigation techniques. Renew Sustain Energy Rev 2017;78:1152–87. https://doi.org/10.1016/J.RSER.2017.04.121.

[16] Moreno-Muñoz A. Power quality: mitigation technologies in a distributed environment. Springer Science & Business Media; 2007.

[17] Singh B, Chandra A, Al-Haddad K. Power quality: problems and mitigation techniques. Wiley; 2015.

[18] Mahela OP, Shaik AG. Power quality improvement in distribution network using DSTATCOM with battery energy storage system. Int J Electr Power Energy Syst 2016;83:229–40. https://doi.org/10.1016/J.IJEPES.2016.04.011.

[19] Wang S, Chen H. A novel deep learning method for the classification of power quality disturbances using deep convolutional neural network. Appl Energy 2019;235:1126–40. https://doi.org/10.1016/J.APENERGY.2018.09.160.

[20] Chakravorti T, Patnaik RK, Dash PK. Detection and classification of islanding and power quality disturbances in microgrid using hybrid signal processing and data mining techniques. IET Signal Process 2018;12:82–94. https://doi.org/10.1049/iet-spr.2016.0352.

[21] Li P, Gao J, Xu D, Wang C, Yang X. Hilbert-Huang transform with adaptive waveform matching extension and its application in power quality disturbance detection for microgrid. J Mod Power Syst Clean Energy 2016;4:19–27. https://doi.org/10.1007/s40565-016-0188-5.

[22] van der Kam M, van Sark W. Smart charging of electric vehicles with photovoltaic power and vehicle-to-grid technology in a microgrid; a case study. Appl Energy 2015;152:20–30. https://doi.org/10.1016/J.APENERGY.2015.04.092.

[23] Muscas C. Power quality monitoring in modern electric distribution systems. IEEE Instrum Meas Mag 2010;13:19–27. https://doi.org/10.1109/MIM.2010.5585070.

[24] Shi W, Li N, Chu C, Gadh R. Real-time energy management in microgrids. IEEE Trans Smart Grid 2017;8:228–38. https://doi.org/10.1109/TSG.2015.2462294.

[25] Colson CM, Nehrir MH. Comprehensive real-time microgrid power management and control with distributed agents. IEEE Trans Smart Grid 2013;4:617–27. https://doi.org/10.1109/TSG.2012.2236368.

[26] Abrishambaf O, Faria P, Gomes L, Spínola J, Vale Z, Corchado JM. Implementation of a real-time microgrid simulation platform based on centralized and distributed management. Energies 2017;10. https://doi.org/10.3390/en10060806.
[27] Mahela OP, Shaik AG, Gupta N. A critical review of detection and classification of power quality events. Renew Sustain Energy Rev 2015;41:495–505. https://doi.org/10.1016/j.rser.2014.08.070.
[28] Igual R, Medrano C, Schubert F. Evaluation of automatic power quality classification in microgrids operating in islanded mode. 13th IEEE PowerTech; 2019.
[29] Shen Y, Abubakar M, Liu H, Hussain F. Power quality disturbance monitoring and classification based on improved PCA and convolution neural network for wind-grid distribution systems. Energies 2019;12:1280. https://doi.org/10.3390/en12071280.
[30] Bagheri M, Nurmanova V, Abedinia O, Salay Naderi M. Enhancing power quality in microgrids with a new online control strategy for DSTATCOM using reinforcement learning algorithm. IEEE Access 2018;6:38986–96. https://doi.org/10.1109/ACCESS.2018.2852941.
[31] Granados-Lieberman D, Romero-Troncoso RJ, Osornio-Rios RA, Garcia-Perez A, Cabal-Yepez E. Techniques and methodologies for power quality analysis and disturbances classification in power systems: a review. IET Gener, Transm Distrib 2011;5:519. https://doi.org/10.1049/iet-gtd.2010.0466.
[32] Saini MK, Kapoor R. Classification of power quality events - a review. Int J Electr Power Energy Syst 2012;43:11–9. https://doi.org/10.1016/j.ijepes.2012.04.045.
[33] Khokhar S, Zin AAM, Mokhtar AS, Ismail NAM, Zareen N. Automatic classification of power quality disturbances: a review. Proceeding - 2013 IEEE Student Conf Res Dev SCOReD 2013 2015:427–32. https://doi.org/10.1109/SCOReD.2013.7002625.
[34] Mittal D. Classification of power quality disturbances in electric power system: a review. IOSR J Electr Electron Eng 2012;3:6–14. https://doi.org/10.9790/1676-0350614.
[35] Khokhar S, Zin AABM, Mokhtar ASB, Pesaran M. A comprehensive overview on signal processing and artificial intelligence techniques applications in classification of power quality disturbances. Renew Sustain Energy Rev 2015;51:1650–63. https://doi.org/10.1016/j.rser.2015.07.068.
[36] Mishra M. Power quality disturbance detection and classification using signal processing and soft computing techniques: a comprehensive review. Int Trans Electr Energy Syst 2019;29:e12008. https://doi.org/10.1002/2050-7038.12008.
[37] Ahsan MK, Pan T, Li Z. A three decades of marvellous significant review of power quality events regarding detection & classification. J Power Energy Eng 2018. https://doi.org/10.4236/jpee.2018.68001. 06:1–37.
[38] Mahela OP, Khan B, Alhelou HH, Tanwar S. Assessment of power quality in the utility grid integrated with wind energy generation. IET Power Electron 2020.
[39] Mahela O, Khan B, Haes Alhelou H, Siano P. Power quality assessment and event detection in distribution network with wind energy penetration using Stockwell transform and fuzzy clustering. IEEE Trans Ind Informatics 2020;1. https://doi.org/10.1109/TII.2020.2971709.
[40] Shaik AG, Mahela OP. Power quality assessment and event detection in hybrid power system. Elec Power Syst Res 2018;161:26–44. https://doi.org/10.1016/J.EPSR.2018.03.026.
[41] Jbj Fourier. Théorie analytique de la chaleur (in French). Paris: Firmin Didot, père et fils; 1822.
[42] Naik CA, Kundu P. Power quality index based on discrete wavelet transform. Int J Electr Power Energy Syst 2013;53:994–1002. https://doi.org/10.1016/j.ijepes.2013.06.024.
[43] Mallat S. A theory for multiresolution signal decomposition: \uppercase{t}he wavelet representation. IEEE Trans Pattern Anal Mach Intell 1989;11:674–93. https://doi.org/10.1109/34.192463.
[44] Stockwell RG, Mansinha LLRP. Localization of the complex spectrum: the S transform. IEEE Trans Signal Process 1996;44:998–1001. https://doi.org/10.1109/78.492555.
[45] Wang Y. The tutorial: S transform. 2010.
[46] Fosso OB, Molinas M. Method for mode mixing separation in empirical mode decomposition, vols. 1–7; 2017.
[47] Gaci S. A new Ensemble empirical mode decomposition (EEMD) denoising method for seismic signals. Energy Procedia 2016;97:84–91. https://doi.org/10.1016/j.egypro.2016.10.026.
[48] Jayasree T, Devaraj D, Sukanesh R. Power quality disturbance classification using Hilbert transform and RBF networks. Neurocomputing 2010;73:1451–6. https://doi.org/10.1016/j.neucom.2009.11.008.
[49] Zhang Rui, Zhu Run-xia, Wang Tian-bo. The application of Hilbert-Huang transform in power quality detection? Proc. 2013 2nd Int. Conf. Meas. Inf. Control 2013;2:983–6. https://doi.org/10.1109/MIC.2013.6758124.
[50] Dragomiretskiy K, Zosso D. Variational mode decomposition. IEEE Trans Signal Process 2014;62:531–44. https://doi.org/10.1109/TSP.2013.2288675.
[51] Duesterhoeft WC, Schulz MW, Clarke E. Determination of instantaneous currents and voltages by means of alpha, beta, and zero components. Trans Am Inst Electr Eng 1951;70:1248–55. https://doi.org/10.1109/T-AIEE.1951.5060554.
[52] Gabor D. Theory of communication. J Inst Eng Electron Part I Gen 1946;93:429–57. https://doi.org/10.1049/ji-1.1947.0015.
[53] Wigner E. On the quantum correction for thermodynamic equilibrium. Phys Rev 1932;40:749–59. https://doi.org/10.1103/PhysRev.40.749.
[54] Pei S, Ding J. Relations between gabor transforms and fractional fourier. IEEE Trans Signal Process 2007;55:4839–50. https://doi.org/10.1109/TSP.2007.896271.
[55] Abdi H, Williams LJ. Principal component analysis. WIREs Comput Stat 2010;2:433–59. https://doi.org/10.1002/wics.101.
[56] Blackburn JL. Symmetrical components for power systems engineering. 1993. New York, NY, USA.
[57] Pinnegar CR, Mansinha L. A method of time–time analysis: the TT-transform. Digit Signal Process 2003;13:588–603. https://doi.org/10.1016/S1051-2004(03)00022-8.
[58] Ahmed N, Rao KR. Walsh-hadamard transform BT - orthogonal transforms for digital signal processing. In: Ahmed N, Rao KR, editors. Berlin, Heidelberg: Springer Berlin Heidelberg; 1975. p. 99–152. https://doi.org/10.1007/978-3-642-45450-9_6.
[59] Gautam S, Brahma S. Overview of mathematical morphology in power systems — a tutorial approach. 2009. IEEE Power Energy Soc. Gen. Meet. PES '09; 2009. p. 1–7. https://doi.org/10.1109/PES.2009.5275190.
[60] Chen L, Zheng D, Chen S, Han B. Method based on sparse signal decomposition for harmonic and inter-harmonic analysis of power system. J Electr Eng Technol 2017;12:559–68. https://doi.org/10.5370/JEET.2017.12.2.559.
[61] Mostafa MA. Kalman filtering algorithm for electric power quality analysis: harmonics and voltage sags problems. 2007. Large Eng. Syst. Conf. Power Eng. 2007:159–65. https://doi.org/10.1109/LESCPE.2007.4437371.
[62] Makarov YV, Hill D, Hiskens I. Properties of quadratic equations and their application to power system analysis. Int J Electr Power Energy Syst 2000;22:313–23. https://doi.org/10.1016/S0142-0615(99)00041-1.
[63] Breiman L, Friedman JH, Olshen RA, Stone CJ. Classification and regression trees. Belmont: Wadsworth; 1984.
[64] Ding S, Zhao H, Zhang Y, Xu X, Nie R. Extreme learning machine: algorithm, theory and applications. Artif Intell Rev 2015;44:103–15. https://doi.org/10.1007/s10462-013-9405-z.
[65] Cortes Corinna, Vapnik VN. Support-vector networks. Mach Learn 1995;20:273–97. https://doi.org/10.1023/A:1022627411411.
[66] Zimmermann H-J. Practical applications of fuzzy technologies. Norwell, MA, USA: Kluwer Academic Publishers; 1999.
[67] Rabiner LR, Juang BH. An introduction to hidden Markov models. IEEE Acoust Speech Signal Process Mag 1986:4–16.
[68] Cover TM, Hart PE. Nearest neighbor pattern classification. IEEE Trans Inf Theor 1967;13:21–7. https://doi.org/10.1109/TIT.1967.1053964.
[69] Bollen MHJ, Yu-Hua Gu I. Signal processing of power quality disturbances. Institute of Electrical and Electronics Engineers, Inc.; 2005.
[70] Senin P. Dynamic time warping algorithm review. 2008.
[71] Tharwat A. Linear vs. quadratic discriminant analysis classifier: a tutorial. Int J Appl Pattern Recognit 2016;3:145. https://doi.org/10.1504/IJAPR.2016.079050.
[72] Manitoba Hydro International. PSCAD n.d, https://hvdc.ca/pscad/. [Accessed 12 July 2019].
[73] European EMTP-ATP Users Group. n.d, https://www.emtp.org/. [Accessed 12 July 2019].
[74] Real time digital power system simulator. RTDS Technologies Inc. n.d. https://www.rtds.com/. [Accessed 12 July 2019].
[75] Kuo SM, Lee BH, Tian W. Real-time digital signal processing: fundamentals, implementations and applications. third ed. John Wiley & Sons, Ltd; 2013.
[76] Pfeifle F. Real-time signal processing on field programmable gate array hardware. In: Bader R, editor. Springer handb. Syst. Musicol. Berlin, Heidelberg: Springer Berlin Heidelberg; 2018. p. 385–417. https://doi.org/10.1007/978-3-662-55004-5_20.
[77] Stallings W. Computer organization and Architecture : designing for performance. 10th editi. Pearson; 2016.
[78] Guntheroth K. Optimized C++: proven techniques for heightened performance. first ed. O'Reilly Media, Inc.; 2016.
[79] NVIDIA. Cuda. 2020. https://developer.nvidia.com/cuda-zone. [Accessed 6 May 2020].
[80] NVIDIA. OpenCL (open computing language). 2020. https://developer.nvidia.com/opencl. [Accessed 6 May 2020].
[81] Feng X, Jiang Y, Yang X, Du M, Li X. Computer vision algorithms and hardware implementations: a survey. Integration 2019;69:309–20. https://doi.org/10.1016/j.vlsi.2019.07.005.
[82] Shawahna A, Sait SM, El-Maleh A. FPGA-based accelerators of deep learning networks for learning and classification: a review. IEEE Access 2019;7:7823–59.
[83] Song X, Wang H, Wang L. FPGA implementation of a support vector machine based classification system and its potential application in smart grid. 2014 11th Int. Conf. Inf. Technol. New Gener. 2014:397–402.
[84] Xilinx. Vivado high-level synthesis. 2020. https://www.xilinx.com/products/design-tools/vivado/integration/esl-design.html. [Accessed 6 May 2020].
[85] MathWorks. Hdl. Coder 2020. https://es.mathworks.com/products/hdl-coder.html.
[86] Hafiz F, Swain A, Naik C, Abecrombie S, Eaton A. Identification of power quality events: selection of optimum base wavelet and machine learning algorithm. IET Sci Meas Technol 2019;13:260–71. https://doi.org/10.1049/iet-smt.2018.5044.
[87] Huang N, Wang D, Lin L, Cai G, Huang G, Du J, et al. Power quality disturbances classification using rotation forest and multi-resolution fast S-transform with data compression in time domain. IET Gener, Transm Distrib 2019;13:5091–101. https://doi.org/10.1049/iet-gtd.2018.5439.
[88] Shi X, Yang H, Xu Z, Zhang X, Farahani MR. An independent component analysis classification for complex power quality disturbances with sparse auto encoder features. IEEE Access 2019;7:20961–6. https://doi.org/10.1109/ACCESS.2019.2898211.

[89] Luo Y, Li K, Li Y, Cai D, Zhao C, Meng Q. Three-layer bayesian network for classification of complex power quality disturbances. IEEE Trans Ind Informatics 2018;14:3997–4006. https://doi.org/10.1109/TII.2017.2785321.

[90] Liu H, Hussain F, Shen Y, Arif S, Nazir A, Abubakar M. Complex power quality disturbances classification via curvelet transform and deep learning. Elec Power Syst Res 2018;163:1–9. https://doi.org/10.1016/j.epsr.2018.05.018.

[91] Kapoor R, Gupta R, Son LH, Jha S, Kumar R. Boosting performance of power quality event identification with KL Divergence measure and standard deviation. Measurement 2018;126:134–42. https://doi.org/10.1016/j.measurement.2018.05.053.

[92] Ma J, Zhang J, Xiao L, Chen K, Wu J. Classification of power quality disturbances via deep learning. IETE Tech Rev 2017;34:408–15. https://doi.org/10.1080/02564602.2016.1196620.

[93] Mahela OP, Shaik AG. Power quality recognition in distribution system with solar energy penetration using S-transform and Fuzzy C-means clustering. Renew Energy 2017;106:37–51. https://doi.org/10.1016/j.renene.2016.12.098.

[94] Mahela OP, Shaik AG. Recognition of power quality disturbances using S-transform based ruled decision tree and fuzzy C-means clustering classifiers. Appl Soft Comput 2017;59:243–57. https://doi.org/10.1016/j.asoc.2017.05.061.

[95] Morales-Velazquez L, de Jesus Romero-Troncoso R, Herrera-Ruiz G, Morinigo-Sotelo D, Osornio-Rios RA. Smart sensor network for power quality monitoring in electrical installations. Measurement 2017;103:133–42. https://doi.org/10.1016/j.measurement.2017.02.032.

[96] Wang H, Wang P, Liu T. Power quality disturbance classification using the S-transform and probabilistic neural network. Energies 2017;10. https://doi.org/10.3390/en10010107.

[97] Upadhyaya S, Mohanty S. Localization and classification of power quality disturbances using maximal overlap discrete wavelet transform and data mining based Classifiers**Sponsor and financial support acknowledgment goes here. Paper titles should be written in uppercase and lower. IFAC-PapersOnLine 2016;49:437–42. https://doi.org/10.1016/j.ifacol.2016.03.093.

[98] Bíscaro AAP, Pereira RAF, Kezunovic M, Mantovani JRS. Integrated fault location and power-quality analysis in electric power distribution systems. IEEE Trans Power Deliv 2016;31:428–36. https://doi.org/10.1109/TPWRD.2015.2464098.

[99] Abdoos AA, Khorshidian Mianaei P, Rayatpanah Ghadikolaei M. Combined VMD-SVM based feature selection method for classification of power quality events. Appl Soft Comput J 2016;38:637–46. https://doi.org/10.1016/j.asoc.2015.10.038.

[100] Kumar R, Singh B, Shahani DT, Chandra A, Al-Haddad K. Recognition of power-quality disturbances using S-Transform-Based ANN classifier and rule-based decision tree. IEEE Trans Ind Appl 2015;51:1249–58. https://doi.org/10.1109/TIA.2014.2356639.

[101] Huang N, Zhang S, Cai G, Xu D. Power quality disturbances recognition based on a multiresolution generalized S-transform and a PSO-improved decision tree. Energies 2015;8:549–72. https://doi.org/10.3390/en8010549.

[102] Liu Z, Cui Y, Li W. A classification method for complex power quality disturbances using EEMD and rank wavelet SVM. IEEE Trans Smart Grid 2015;6:1678–85. https://doi.org/10.1109/TSG.2015.2397431.

[103] Biswal B, Biswal M, Mishra S, Jalaja R. Automatic classification of power quality events using balanced neural tree. IEEE Trans Ind Electron 2014;61:521–30. https://doi.org/10.1109/TIE.2013.2248335.

[104] Shukla S, Mishra S, Singh B. Power quality event classification under noisy conditions using EMD-based de-noising techniques. IEEE Trans Ind Informatics 2014;10:1044–54. https://doi.org/10.1109/TII.2013.2289392.

[105] Biswal B, Behera HS, Bisoi R, Dash PK. Classification of power quality data using decision tree and chemotactic differential evolution based fuzzy clustering. Swarm Evol Comput 2012;4:12–24. https://doi.org/10.1016/j.swevo.2011.12.003.

[106] Hasheminejad S, Esmaeili S, Jazebi S. Power quality disturbance classification using S-transform and hidden Markov model. Elec Power Compon Syst 2012;40:1160–82. https://doi.org/10.1080/15325008.2012.682250.

[107] Pires VF, Amaral TG, Martins JF. Power quality disturbances classification using the 3-D space representation and PCA based neuro-fuzzy approach. Expert Syst Appl 2011;38:11911–7. https://doi.org/10.1016/j.eswa.2011.03.083.

[108] Masoum MAS, Jamali S, Ghaffarzadeh N. Detection and classification of power quality disturbances using discrete wavelet transform and wavelet networks. IET Sci Meas Technol 2010;4:193–205. https://doi.org/10.1049/iet-smt.2009.0006.

[109] Cho S, Jang G, Kwon S. Time-frequency analysis of power-quality disturbances via the gabor-wigner transform. IEEE Trans Power Deliv 2010;25:494–9. https://doi.org/10.1109/TPWRD.2009.2034832.

[110] Erişti H, Demir Y. A new algorithm for automatic classification of power quality events based on wavelet transform and SVM. Expert Syst Appl 2010;37:4094–102. https://doi.org/10.1016/j.eswa.2009.11.015.

[111] Hooshmand R, Enshaee A. Detection and classification of single and combined power quality disturbances using fuzzy systems oriented by particle swarm optimization algorithm. Elec Power Syst Res 2010;80:1552–61. https://doi.org/10.1016/j.epsr.2010.07.001.

[112] Erişti H, Uçar A, Demir Y. Wavelet-based feature extraction and selection for classification of power system disturbances using support vector machines. Elec Power Syst Res 2010;80:743–52. https://doi.org/10.1016/j.epsr.2009.09.021.

[113] Szmajda M, Górecki K, Mroczka J. Gabor transform, SPWVD, gabor-wigner transform and wavelet transform - tools for power quality monitoring. Metrol Meas Syst 2010;17.

[114] Biswal B, Dash PK, Panigrahi BK. Power quality disturbance classification using fuzzy C-means algorithm and adaptive particle swarm optimization. IEEE Trans Ind Electron 2009;56:212–20. https://doi.org/10.1109/TIE.2008.928111.

[115] Deokar SA, Waghmare LM. Integrated DWT–FFT approach for detection and classification of power quality disturbances. Int J Electr Power Energy Syst 2014;61:594–605. https://doi.org/10.1016/j.ijepes.2014.04.015.

[116] Uyar M, Yildirim S, Gencoglu MT. An expert system based on S-transform and neural network for automatic classification of power quality disturbances. Expert Syst Appl 2009;36:5962–75. https://doi.org/10.1016/j.eswa.2008.07.030.

[117] Nguyen T, Liao Y. Power quality disturbance classification utilizing S-transform and binary feature matrix method. Elec Power Syst Res 2009;79:569–75. https://doi.org/10.1016/j.epsr.2008.08.007.

[118] Oleskovicz M, Coury DV, Felho OD, Usida WF, Carneiro AAFM, Pires LRS. Power quality analysis applying a hybrid methodology with wavelet transforms and neural networks. Int J Electr Power Energy Syst 2009;31:206–12. https://doi.org/10.1016/j.ijepes.2009.01.012.

[119] Ekici S. Classification of power system disturbances using support vector machines. Expert Syst Appl 2009;36:9859–68. https://doi.org/10.1016/j.eswa.2009.02.002.

[120] Gunal S, Gerek ON, Ece DG, Edizkan R. The search for optimal feature set in power quality event classification. Expert Syst Appl 2009;36:10266–73. https://doi.org/10.1016/j.eswa.2009.01.051.

[121] Uyar M, Yildirim S, Gencoglu MT. An effective wavelet-based feature extraction method for classification of power quality disturbance signals. Elec Power Syst Res 2008;78:1747–55. https://doi.org/10.1016/j.epsr.2008.03.002.

[122] Hu GS, Zhu FF, Ren Z. Power quality disturbance identification using wavelet packet energy entropy and weighted support vector machines. Expert Syst Appl 2008;35:143–9. https://doi.org/10.1016/j.eswa.2007.06.005.

[123] Gargoom AM, Ertugrul N, Soong WL. Automatic classification and characterization of power quality events. IEEE Trans Power Deliv 2008;23:2417–25. https://doi.org/10.1109/TPWRD.2008.923998.

[124] Kaewarsa S, Attakitmongcol K, Kulworawanichpong T. Recognition of power quality events by using multiwavelet-based neural networks. Int J Electr Power Energy Syst 2008;30:254–60. https://doi.org/10.1016/j.ijepes.2007.07.003.

[125] Zhao F, Yang R. Power-quality disturbance recognition using S-transform. IEEE Trans Power Deliv 2007;22:944–50. https://doi.org/10.1109/TPWRD.2006.881575.

[126] Ray PK, Mohanty SR, Kishor N, Catalão JPS. Optimal feature and decision tree-based classification of power quality disturbances in distributed generation systems. IEEE Trans Sustain Energy 2014;5:200–8. https://doi.org/10.1109/TSTE.2013.2278865.

[127] Senroy N, Suryanarayanan S, Ribeiro PF. An improved hilbert-huang method for analysis of time-varying waveforms in power quality. IEEE Trans Power Syst 2007;22:1843–50. https://doi.org/10.1109/TPWRS.2007.907542.

[128] Axelberg PGV, Gu IYH, Bollen MHJ. Support vector machine for classification of voltage disturbances. IEEE Trans Power Deliv 2007;22:1297–303. https://doi.org/10.1109/TPWRD.2007.900065.

[129] Bollen MHJ, Gu IYH, Axelberg PGV, Styvaktakis E. Classification of underlying causes of power quality disturbances: deterministic versus statistical methods. EURASIP J Appl Signal Process 2007;2007. https://doi.org/10.1155/2007/79747.

[130] Gargoom AM, Ertugrul N, Soong WL. Investigation of effective automatic recognition systems of power-quality events. IEEE Trans Power Deliv 2007;22:2319–26. https://doi.org/10.1109/TPWRD.2007.905424.

[131] Ribeiro MV, Marques CAG, Duque CA, Cerqueira AS, Pereira JLR. Detection of disturbances in voltage signals for power quality analysis using HOS. EURASIP J Appl Signal Process 2007;2007:59786. https://doi.org/10.1155/2007/59786.

[132] He H, Starzyk JA. A self-organizing learning array system for power quality classification based on wavelet transform. IEEE Trans Power Deliv 2006;21:286–95. https://doi.org/10.1109/TPWRD.2005.852392.

[133] Gerek ON, Ece DG. Power-quality event analysis using higher order cumulants and quadratic classifiers. IEEE Trans Power Deliv 2006;21:883–9. https://doi.org/10.1109/TPWRD.2006.870989.

[134] Janik P, Lobos T. Automated classification of power-quality disturbances using SVM and RBF networks. IEEE Trans Power Deliv 2006;21:1663–9. https://doi.org/10.1109/TPWRD.2006.874114.

[135] Gerek ON, Ece DG, Barkana A. Covariance analysis of voltage waveform signature for power-quality event classification. IEEE Trans Power Deliv 2006;21:2022–31. https://doi.org/10.1109/TPWRD.2006.877102.

[136] Lira MMS, de Aquino RRB, Ferreira AA, Carvalho MA, Lira CABO. Improving disturbance classification by combining multiple artificial neural networks. 2006. IEEE Int. Jt. Conf. Neural Netw. Proc. 2006:3436–42. https://doi.org/10.1109/IJCNN.2006.247347.

[137] Erişti H, Yıldırım Ö, Erişti B, Demir Y. Optimal feature selection for classification of the power quality events using wavelet transform and least squares support vector machines. Int J Electr Power Energy Syst 2013;49:95–103. https://doi.org/10.1016/j.ijepes.2012.12.018.

[138] Abdel-Galil TK, El-Saadany EF, Youssef AM, Salama MMA. Disturbance classification using Hidden Markov Models and vector quantization. IEEE Trans Power Deliv 2005;20:2129–35. https://doi.org/10.1109/TPWRD.2004.843399.

[139] Chen S. Feature selection for identification and classification of power quality disturbances. IEEE Power Eng. Soc. Gen. Meet. 2005:2301–6. https://doi.org/10.1109/pes.2005.1489187.

[140] Chilukuri MV, Dash PK. Multiresolution S-transform-based fuzzy recognition system for power quality events. IEEE Trans Power Deliv 2004;19:323–30. https://doi.org/10.1109/TPWRD.2003.820180.

[141] Abdel-Galil TK, Kamel M, Youssef AM, El-Saadany EF, Salama MMA. Power quality disturbance classification using the inductive inference approach. IEEE

Trans Power Deliv 2004;19:1812–8. https://doi.org/10.1109/TPWRD.2003.822533.
[142] Dash PK, Panigrahi BK, Panda G. Power quality analysis using S-transform. IEEE Trans Power Deliv 2003;18:406–11. https://doi.org/10.1109/TPWRD.2003.809616.
[143] Lee IWC, Dash PK. S-transform-based intelligent system for classification of power quality disturbance signals. IEEE Trans Ind Electron 2003;50. https://doi.org/10.1109/TIE.2003.814991. 800–5.
[144] Dash PK, Panigrahi BK, Sahoo DK, Panda G. Power quality disturbance data compression, detection, and classification using integrated spline wavelet and S-transform. IEEE Trans Power Deliv 2003;18:595–600. https://doi.org/10.1109/TPWRD.2002.803824.
[145] Huang Jiansheng, Negnevitsky M, Nguyen DT. A neural-fuzzy classifier for recognition of power quality disturbances. IEEE Trans Power Deliv 2002;17:609–16. https://doi.org/10.1109/61.997947.
[146] Gaouda AM, Kanoun SH, Salama MMA, Chikhani AY. Pattern recognition applications for power system disturbance classification. IEEE Power Eng Rev 2002;22:69–70. https://doi.org/10.1109/MPER.2002.4311687.
[147] Gaouda AM, Kanoun SH, Salama MMA, Chikhani AY. Wavelet-based signal processing for disturbance classification and measurement. IEE Proc Generat Transm Distrib 2002;149:310–8. https://doi.org/10.1049/ip-gtd:20020119.
[148] Ray PK, Mohanty SR, Kishor N. Classification of power quality disturbances due to environmental characteristics in distributed generation system. IEEE Trans Sustain Energy 2013;4:302–13. https://doi.org/10.1109/TSTE.2012.2224678.
[149] Jurado F, Saenz JR. Comparison between discrete STFT and wavelets for the analysis of power quality events. Elec Power Syst Res 2002;62:183–90. https://doi.org/10.1016/S0378-7796(02)00035-4.
[150] Yang Hong-Tzer, Liao Chiung-Chou. A de-noising scheme for enhancing wavelet-based power quality monitoring system. IEEE Trans Power Deliv 2001;16:353–60. https://doi.org/10.1109/61.924810.
[151] Gaouda AM, Kanoun SH, Salama MMA. On-line disturbance classification using nearest neighbor rule. Elec Power Syst Res 2001;57:1–8. https://doi.org/10.1016/S0378-7796(00)00120-6.
[152] Santoso S, Grady WM, Powers EJ, Lamoree J, Bhatt SC. Characterization of distribution power quality events with Fourier and wavelet transforms. IEEE Trans Power Deliv 2000;15:247–54. https://doi.org/10.1109/61.847259.
[153] Gaouda AM, Salama MMA, Sultan MR, Chikhani AY. Power quality detection and classification using wavelet-multiresolution signal decomposition. IEEE Trans Power Deliv 1999;14:1469–76. https://doi.org/10.1109/61.796242.
[154] Poisson O, Rioual P, Meunier M. New signal processing tools applied to power quality analysis. IEEE Trans Power Deliv 1999;14:561–6. https://doi.org/10.1109/61.754104.
[155] Angrisani L, Daponte P, D'Apuzzo M, Testa A. A measurement method based on the wavelet transform for power quality analysis. IEEE Trans Power Deliv 1998;13:990–8. https://doi.org/10.1109/61.714415.
[156] Meunier M, Brouaye F. Fourier transform, wavelets, Prony analysis: tools for harmonics and quality of power. 8th Int. Conf. Harmon. Qual. Power. Proc. 1998;1:71–6. https://doi.org/10.1109/ICHQP.1998.759842.
[157] Lee JS, Lee CH, Kim JO, Nam SW. Classification of power quality disturbances using orthogonal polynomial approximation and bispectra. Electron Lett 1997;33:1522–4. https://doi.org/10.1049/el:19971028.
[158] Santoso S, Powers EJ, Grady WM, Hofmann P. Power quality assessment via wavelet transform analysis. IEEE Trans Power Deliv 1996;11:924–30. https://doi.org/10.1109/61.489353.
[159] Mohanty SR, Ray PK, Kishor N, Panigrahi BK. Classification of disturbances in hybrid DG system using modular PNN and SVM. Int J Electr Power Energy Syst 2013;44:764–77. https://doi.org/10.1016/j.ijepes.2012.08.020.
[160] Huang N, Xu D, Liu X, Lin L. Power quality disturbances classification based on S-transform and probabilistic neural network. Neurocomputing 2012;98:12–23. https://doi.org/10.1016/j.neucom.2011.06.041.
[161] Tse NCF, Chan JYC, Lau W, Lai LL. Hybrid wavelet and Hilbert transform with frequency-shifting decomposition for power quality analysis. IEEE Trans Instrum Meas 2012;61:3225–33. https://doi.org/10.1109/TIM.2012.2211474.
[162] Abdelsalam AA, Eldesouky AA, Sallam AA. Characterization of power quality disturbances using hybrid technique of linear Kalman filter and fuzzy-expert system. Elec Power Syst Res 2012;83:41–50. https://doi.org/10.1016/j.epsr.2011.09.018.
[163] Khan N, Abas N. Comparative study of energy saving light sources. Renew Sustain Energy Rev 2011;15:296–309. https://doi.org/10.1016/J.RSER.2010.07.072.
[164] Qiu W, Tang Q, Liu J, Teng Z, Yao W. Power quality disturbances recognition using modified S transform and parallel stack sparse auto-encoder. Elec Power Syst Res 2019;174:105876. https://doi.org/10.1016/j.epsr.2019.105876.
[165] Zhao C, Li K, Li Y, Wang L, Luo Y, Xu X, 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 Ind Informatics 2019;15:2915–26. https://doi.org/10.1109/TII.2018.2871253.
[166] Deng Y, Wang L, Jia H, Tong X, Li F. A sequence-to-sequence deep learning architecture based on bidirectional GRU for type recognition and time location of combined power quality disturbance. IEEE Trans Ind Informatics 2019;15:4481–93. https://doi.org/10.1109/TII.2019.2895054.
[167] Thirumala K, Pal S, Jain T, Umarikar AC. A classification method for multiple power quality disturbances using EWT based adaptive filtering and multiclass SVM. Neurocomputing 2019;334:265–74. https://doi.org/10.1016/j.neucom.2019.01.038.
[168] Singh U, Singh SN. A new optimal feature selection scheme for classification of power quality disturbances based on ant colony framework. Appl Soft Comput 2019;74:216–25. https://doi.org/10.1016/j.asoc.2018.10.017.
[169] Jamali S, Farsa AR, Ghaffarzadeh N. Identification of optimal features for fast and accurate classification of power quality disturbances. Measurement 2018;116:565–74. https://doi.org/10.1016/j.measurement.2017.10.034.
[170] Singh U, Singh SN. Optimal feature selection via NSGA-II for power quality disturbances classification. IEEE Trans Ind Informatics 2018;14:2994–3002. https://doi.org/10.1109/TII.2017.2773475.
[171] Chakravorti T, Dash PK. Multiclass power quality events classification using variational mode decomposition with fast reduced kernel extreme learning machine-based feature selection. IET Sci Meas Technol 2018;12:106–17. https://doi.org/10.1049/iet-smt.2017.0123.
[172] Achlerkar PD, Samantaray SR, Sabarimalai Manikandan M. Variational mode decomposition and decision tree based detection and classification of power quality disturbances in grid-connected distributed generation system. IEEE Trans Smart Grid 2018;9:3122–32. https://doi.org/10.1109/TSG.2016.2626469.
[173] Singh U, Singh SN. Detection and classification of power quality disturbances based on time–frequency-scale transform. IET Sci Meas Technol 2017;11:802–10. https://doi.org/10.1049/iet-smt.2016.0395.
[174] Puliyadi Kubendran AK, Loganathan AK. Detection and classification of complex power quality disturbances using S-transform amplitude matrix–based decision tree for different noise levels. Int Trans Electr Energy Syst 2017;27:e2286. https://doi.org/10.1002/etep.2286.
[175] Singh U, Singh SN. Application of fractional Fourier transform for classification of power quality disturbances. IET Sci Meas Technol 2017;11:67–76. https://doi.org/10.1049/iet-smt.2016.0194.
[176] Khokhar S, Zin AAM, Memon AP, Mokhtar AS. A new optimal feature selection algorithm for classification of power quality disturbances using discrete wavelet transform and probabilistic neural network. Measurement 2017;95:246–59. https://doi.org/10.1016/j.measurement.2016.10.013.
[177] Rahmati Garousi M, Reza Shakarami M, Namdari F. Detection and classification of power quality disturbances using parallel neural networks based on discrete wavelet transform. J Electr Syst 2016;12:158–73.
[178] Lopez-Ramirez M, Ledesma-Carrillo L, Cabal-Yepez E, Rodriguez-Donate C, Miranda-Vidales H, Garcia-Perez A. EMD-based feature extraction for power quality disturbance classification using moments. Energies 2016;9:1–15. https://doi.org/10.3390/en9070565.
[179] Kumar R, Singh B, Shahani DT. Symmetrical components-based modified technique for power-quality disturbances detection and classification. IEEE Trans Ind Appl 2016;52:3443–50. https://doi.org/10.1109/TIA.2016.2536665.
[180] Zhang S, Li P, Zhang L, Li H, Jiang W, Hu Y. Modified S transform and ELM algorithms and their applications in power quality analysis. Neurocomputing 2016;185:231–41. https://doi.org/10.1016/j.neucom.2015.12.050.
[181] Camarena-Martinez D, Valtierra-Rodriguez M, Perez-Ramirez CA, Amezquita-Sanchez JP, de Jesus Romero-Troncoso R, Garcia-Perez A. Novel downsampling empirical mode decomposition approach for power quality analysis. IEEE Trans Ind Electron 2016;63:2369–78. https://doi.org/10.1109/TIE.2015.2506619.
[182] Ferreira DD, de Seixas JM, Cerqueira AS. A method based on independent component analysis for single and multiple power quality disturbance classification. Elec Power Syst Res 2015;119:425–31. https://doi.org/10.1016/j.epsr.2014.10.028.
[183] Manikandan MS, Samantaray SR, Kamwa I. Detection and classification of power quality disturbances using sparse signal decomposition on hybrid dictionaries. IEEE Trans Instrum Meas 2015;64:27–38. https://doi.org/10.1109/TIM.2014.2330493.
[184] Ahila R, Sadasivam V, Manimala K. An integrated PSO for parameter determination and feature selection of ELM and its application in classification of power system disturbances. Appl Soft Comput 2015;32:23–37. https://doi.org/10.1016/j.asoc.2015.03.036.
[185] Aneesh C, Kumar S, Hisham PM, Soman KP. Performance comparison of variational mode decomposition over empirical wavelet transform for the classification of power quality disturbances using support vector machine. Procedia Comput Sci 2015;46:372–80. https://doi.org/10.1016/j.procs.2015.02.033.
[186] Kanirajan P, Kumar VS. Power quality disturbance detection and classification using wavelet and RBFNN. Appl Soft Comput 2015;35:470–81. https://doi.org/10.1016/j.asoc.2015.05.048.
[187] Seera M, Lim CP, Loo CK, Singh H. A modified fuzzy min–max neural network for data clustering and its application to power quality monitoring. Appl Soft Comput 2015;28:19–29. https://doi.org/10.1016/j.asoc.2014.09.050.
[188] Valtierra-Rodriguez M, de Jesus Romero-Troncoso R, Osornio-Rios RA, Garcia-Perez A. Detection and classification of single and combined power quality disturbances using neural networks. IEEE Trans Ind Electron 2014;61:2473–82. https://doi.org/10.1109/TIE.2013.2272276.
[189] Hajian M, Foroud AA. A new hybrid pattern recognition scheme for automatic discrimination of power quality disturbances. Measurement 2014;51:265–80. https://doi.org/10.1016/j.measurement.2014.02.017.
[190] Ji TY, Wu QH, Jiang L, Tang WH. Disturbance detection, location and classification in phase space. IET Gener, Transm Distrib 2011;5:257–65. https://doi.org/10.1049/iet-gtd.2010.0254.
[191] Zygarlicki J, Zygarlicka M, Mroczka J, Latawiec KJ. A reduced prony's method in power-quality analysis-parameters selection. IEEE Trans Power Deliv 2010;25:979–86. https://doi.org/10.1109/TPWRD.2009.2034745.
[192] Panigrahi BK, Pandi VR. Optimal feature selection for classification of power quality disturbances using wavelet packet-based fuzzy k-nearest neighbour

algorithm. IET Gener, Transm Distrib 2009;3:296–306. https://doi.org/10.1049/iet-gtd:20080190.
[193] Mishra S, Bhende CN, Panigrahi BK. Detection and classification of power quality disturbances using S-transform and probabilistic neural network. IEEE Trans Power Deliv 2008;23:280–7. https://doi.org/10.1109/TPWRD.2007.911125.
[194] Bhende CN, Mishra S, Panigrahi BK. Detection and classification of power quality disturbances using S-transform and modular neural network. Elec Power Syst Res 2008;78:122–8. https://doi.org/10.1016/j.epsr.2006.12.011.
[195] Lin W, Wu C, Lin C, Cheng F. Detection and classification of multiple power-quality disturbances with wavelet multiclass SVM. IEEE Trans Power Deliv 2008;23:2575–82. https://doi.org/10.1109/TPWRD.2008.923463.
[196] Monedero I, Leon C, Ropero J, Garcia A, Elena JM, Montano JC. Classification of electrical disturbances in real time using neural networks. IEEE Trans Power Deliv 2007;22:1288–96. https://doi.org/10.1109/TPWRD.2007.899522.
[197] Reaz MBI, Choong F, Mohd-Yasin F. VHDL modeling for classification of power quality disturbance employing wavelet transform, artificial neural network and fuzzy logic. Simulation 2006;82:867–81. https://doi.org/10.1177/0037549707077782.
[198] Lin C-, Tsao M-. Power quality detection with classification enhancible wavelet-probabilistic network in a power system. IEE Proc Generat Transm Distrib 2005;152:969–76. https://doi.org/10.1049/ip-gtd:20045177.
[199] Zwe-Lee Gaing. Wavelet-based neural network for power disturbance recognition and classification. IEEE Trans Power Deliv 2004;19:1560–8. https://doi.org/10.1109/TPWRD.2004.835281.
[200] Ozgonenel O, Yalcin T, Guney I, Kurt U. A new classification for power quality events in distribution systems. Elec Power Syst Res 2013;95:192–9. https://doi.org/10.1016/j.epsr.2012.09.007.
[201] Youssef AM, Abdel-Galil TK, El-Saadany EF, Salama MMA. Disturbance classification utilizing dynamic time warping classifier. IEEE Trans Power Deliv 2004;19:272–8. https://doi.org/10.1109/TPWRD.2003.820178.
[202] Santoso S, Powers EJ, Grady WM, Parsons AC. Power quality disturbance waveform recognition using wavelet-based neural classifier. II. Application. IEEE Trans Power Deliv 2000;15:229–35. https://doi.org/10.1109/61.847256.
[203] Santoso S, Powers EJ, Grady WM, Parsons AC. Power quality disturbance waveform recognition using wavelet-based neural classifier. I. Theoretical foundation. IEEE Trans Power Deliv 2000;15:222–8. https://doi.org/10.1109/61.847255.
[204] Ghosh AK, Lubkeman DL. The classification of power system disturbance waveforms using a neural network approach. IEEE Trans Power Deliv 1995;10:109–15. https://doi.org/10.1109/61.368408.
[205] Dehghani H, Vahidi B, Naghizadeh RA, Hosseinian SH. Power quality disturbance classification using a statistical and wavelet-based Hidden Markov Model with Dempster–Shafer algorithm. Int J Electr Power Energy Syst 2013;47:368–77. https://doi.org/10.1016/j.ijepes.2012.11.005.
[206] Biswal M, Dash PK. Detection and characterization of multiple power quality disturbances with a fast S-transform and decision tree based classifier. Digit Signal Process 2013;23:1071–83. https://doi.org/10.1016/j.dsp.2013.02.012.
[207] Rodríguez A, Aguado JA, Martín F, López JJ, Muñoz F, Ruiz JE. Rule-based classification of power quality disturbances using S-transform. Elec Power Syst Res 2012;86:113–21. https://doi.org/10.1016/j.epsr.2011.12.009.
[208] Erişti H, Demir Y. Automatic classification of power quality events and disturbances using wavelet transform and support vector machines. Gener Transm Distrib IET 2012;6:968–76. https://doi.org/10.1049/iet-gtd.2011.0733.
[209] Huang C-H, Lin C-H, Kuo C-L. Chaos synchronization-based detector for power-quality disturbances classification in a power system. Power Deliv IEEE Trans 2011;26:944–53. https://doi.org/10.1109/TPWRD.2010.2090176.
[210] Lee C, Shen Y. Optimal feature selection for power-quality disturbances classification. IEEE Trans Power Deliv 2011;26:2342–51. https://doi.org/10.1109/TPWRD.2011.2149547.
[211] Decanini JGMS, Tonelli-Neto MS, Malange FCV, Minussi CR. Detection and classification of voltage disturbances using a Fuzzy-ARTMAP-wavelet network. Elec Power Syst Res 2011;81:2057–65. https://doi.org/10.1016/j.epsr.2011.07.018.
[212] Sahani M, Dash PK. FPGA-based online power quality disturbances monitoring using reduced-sample HHT and class-specific weighted RVFLN. IEEE Trans Ind Informatics 2019;15:4614–23. https://doi.org/10.1109/TII.2019.2892873.
[213] Ribeiro EG, Mendes TM, Dias GL, Faria ERS, Viana FM, Barbosa BHG, et al. Real-time system for automatic detection and classification of single and multiple power quality disturbances. Measurement 2018;128:276–83. https://doi.org/10.1016/j.measurement.2018.06.059.
[214] Sahani M, Dash PK. Automatic power quality events recognition based on Hilbert Huang transform and weighted bidirectional extreme learning machine. IEEE Trans Ind Informatics 2018;14:3849–58. https://doi.org/10.1109/TII.2018.2803042.
[215] Li J, Teng Z, Tang Q, Song J. Detection and classification of power quality disturbances using double resolution S-transform and DAG-SVMs. IEEE Trans Instrum Meas 2016;65:2302–12. https://doi.org/10.1109/TIM.2016.2578518.
[216] Borges FAS, Fernandes RAS, Silva IN, Silva CBS. Feature extraction and power quality disturbances classification using smart meters signals. IEEE Trans Ind Informatics 2016;12:824–33. https://doi.org/10.1109/TII.2015.2486379.
[217] He S, Li K, Zhang M. A real-time power quality disturbances classification using hybrid method based on S-transform and dynamics. IEEE Trans Instrum Meas 2013;62:2465–75. https://doi.org/10.1109/TIM.2013.2258761.
[218] Zhang M, Li K, Hu Y. A real-time classification method of power quality disturbances. Elec Power Syst Res 2011;81:660–6. https://doi.org/10.1016/j.epsr.2010.10.032.
[219] Radil T, Ramos PM, Janeiro FM, Cruz Serra A. PQ monitoring system for real-time detection and classification of disturbances in a single-phase power system. IEEE Trans Instrum Meas 2008;57:1725–33. https://doi.org/10.1109/TIM.2008.925345.
[220] Ramos P, Radil T, Janeiro F, Cruz Serra A. DSP based power quality analyser using new signal processing algorithms for detection and classification of disturbances in a single-phase power system. Proc. IMEKO TC4 Symp. 2007;2:433–8.
[221] Santos-Hernandez JA, Valtierra-Rodriguez M, Amezquita-Sanchez JP, Romero-Troncoso RDJ, Camarena-Martinez D. Hilbert filter based FPGA architecture for power quality monitoring. Measurement 2019;147:106819. https://doi.org/10.1016/J.MEASUREMENT.2019.07.047.
[222] Martinez-Figueroa GDJ, Morinigo-Sotelo D, Zorita-Lamadrid AL, Morales-Velazquez L, Romero-Troncoso RDJ. FPGA-based smart sensor for detection and classification of power quality disturbances using higher order statistics. IEEE Access 2017;5:14259–74. https://doi.org/10.1109/ACCESS.2017.2732726.
[223] Lopez-Ramirez M, Cabal-Yepez E, Ledesma-Carrillo LM, Miranda-Vidales H, Rodriguez-Donate C, Lizarraga-Morales RA. FPGA-based online PQD detection and classification through DWT, mathematical morphology and SVD. Energies 2018;11. https://doi.org/10.3390/en11040769.
[224] Garanayak P, Panda G. An adaptive linear neural network with least mean M-estimate weight updating rule employed for harmonics identification and power quality monitoring. Trans Inst Meas Contr 2017;40:1936–49. https://doi.org/10.1177/0142331217695402.
[225] Yildirim O, Eristi B, Eristi H, Unal S, Erol Y, Demir Y. FPGA-based online power quality monitoring system for electrical distribution network. Measurement 2018;121:109–21. https://doi.org/10.1016/J.MEASUREMENT.2018.02.058.
[226] Sahani M, Dash PK. Automatic power quality events recognition using modes decomposition based online P-norm adaptive extreme learning machine. IEEE Trans Ind Informatics 2020;16:4355–64. https://doi.org/10.1109/TII.2019.2945822.
[227] Parimala KV, Nisha KCR, Nemichandran. FPGA based power quality monitoring using FFT method for single phase power metering. 2016. Int. Conf. Emerg. Technol. Trends 2016:1–6. https://doi.org/10.1109/ICETT.2016.7873744.
[228] Babu PR, Dash PK, Swain SK, Sivanagaraju S. A new fast discrete S-transform and decision tree for the classification and monitoring of power quality disturbance waveforms. Int Trans Electr Energy Syst 2014;24:1279–300. https://doi.org/10.1002/etep.1776.
[229] Huang G, Xu X, Yin Q, Zhang K. A mobile power quality monitoring terminal based on DSP and ARM. 2016 3rd. Int. Conf. Inf. Sci. Control Eng. 2016:1208–12. https://doi.org/10.1109/ICISCE.2016.259.
[230] Zaid MM, Nauman M, Rahim M, Malik MU. Dsp based energy monitoring with online daq system. Acta Tech Corviniensis - Bull Eng 2018;11:59–64.
[231] Dalai S, Chatterjee B, Dey D, Chakravorti S, Bhattacharya K. Rough-set-based feature selection and classification for power quality sensing device employing correlation techniques. IEEE Sensor J 2013;13:563–73. https://doi.org/10.1109/JSEN.2012.2219144.
[232] Asha Kiranmai S, Jaya Laxmi A. Hardware for classification of power quality problems in three phase system using Microcontroller. Cogent Eng 2017;4:1386364. https://doi.org/10.1080/23311916.2017.1386364.
[233] Guerrero-Rodríguez J-M, Cobos-Sánchez C, González-de-la-Rosa J-J, Sales-Lérida D. An embedded sensor node for the surveillance of power quality. Energies 2019;12. https://doi.org/10.3390/en12081561.
[234] IEEE Power and Energy. IEEE 1159.2 working group: test waveforms n.d. http://grouper.ieee.org/groups/1159/2/testwave.html. [Accessed 12 October 2019].
[235] IEEE Power and Energy Society. IEEE 1159.3 PQDIF Task Force. n.d, http://grouper.ieee.org/groups/1159/3/. [Accessed 12 October 2019].
[236] Kittredge K, Sabin D, Todd B. Publicly accessible online power quality monitoring databases. CIRED - Open Access Proc J 2017;2017(3):828–31.
[237] Florencias-Oliveros O, Espinosa-Gavira MJ, González de la Rosa JJ, Agüera-Pérez A, Palomares-Salas JC, Sierra-Fernández JM. Real-life Power Quality Sags 2017. https://doi.org/10.21227/H2K88D.
[238] Florencias-Oliveros O, Espinosa-Gavira MJ, Gonzalez de la Rosa JJ, Aguera-Perez A, Palomares-Salas JC, Sierra-Fernandez JM. Real-life Power Quality Transients 2017. https://doi.org/10.21227/H2Q30W.
[239] Spavieri G, Ferreira RTM, Fernandes RAS, Lage GG, Barbosa D, Oleskovicz M. Laboratorial essays of polypropylene and all-film power capacitors. 2017. https://doi.org/10.1016/j.asoc.2017.02.017.
[240] IEEE Power and Energy Society. IEEE recommended practice for power quality data interchange format (PQDIF). 2019.
[241] Igual R, Medrano C, Arcega FJ, Mantescu G. Integral mathematical model of power quality disturbances. Proc. Int. Conf. Harmon. Qual. Power, ICHQP 2018; 2018– May. https://doi.org/10.1109/ICHQP.2018.8378902.