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Categorization Method of Power Supply Quality Events Using Rule-Based Decision Trees, Combining Traditional Indices With Higher-Order Statistics

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ABSTRACT

This letter presents a novel method for power quality event detection using higher-order statistical indicators and rule-based decision trees. The method achieves up to 90% efficiency in the most challenging cases and excels in hybrid event classification, increasingly common in modern grids. Its simplicity enables fast execution and real-time applicability, making it a robust complement to traditional visualization tools.

1 | Introduction

Power quality (PQ) refers to the characteristics that the electrical supply must satisfy to ensure stable operation and reliability of sensitive electronic devices. Different methodologies, such as wavelet transform and short-time Fourier transform, have been widely studied for PQ characterization. However, techniques such as higher-order statistics (HOS) hold potential for further research to enhance signal characterization and integration into measurement systems. Despite the limited knowledge of the behaviour of fifth-order statistics onward for signal processing, HOS has been shown to facilitate event detection due to their immunity to Gaussian noise and require low computational load and execution time [1–4].

Artificial intelligence (AI) is increasingly applied to event classification since AI techniques are very versatile: In addition to being applied in countless fields from the electrical power grid to healthcare [5], AI techniques such as neural networks or fuzzy logic serve purposes such as load forecasting, fault detection and diagnosis, and PQ assessment in electrical grids [6, 7]. Among AI techniques, decision trees are particularly advantageous due to their simplicity, efficiency in real-time applications, and robustness against noise [8].

This letter contributes an innovative method for PQ event classification using HOS and decision trees. We propose the feature extraction from two different datasets (Dataset #1 and Dataset #2), elaborated using a MATLAB tool [9] and a signal generator, respectively. These datasets differ in origin, sampling frequencies, durations and event types (simple or hybrid). The feature extraction uses third- to sixth-order statistics, as these HOS are sensitive to changes in the shape of the sinusoidal signal, crest factor (CF), signal-to-noise ratio (SNR) and signal-to-noise and distortion ratio (SINAD). These indicator values are analysed using a rule-based decision tree, with behavioural patterns established for each event. The method's efficiency is evaluated by the number of events correctly detected. The main objective is to provide an algorithm for manipulating power quality data and enhancing event classification, complementing visualization tools and offering a more robust approach than traditional methods.

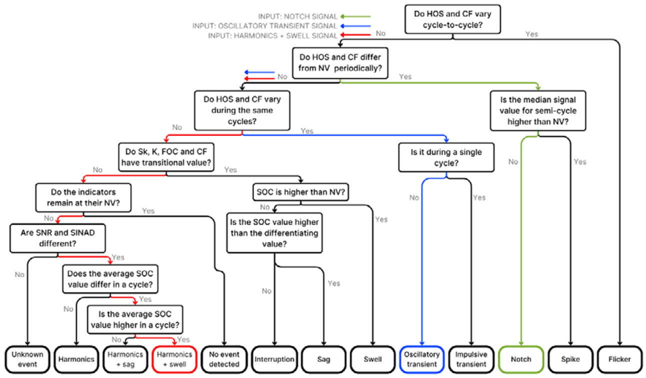

FIGURE 1 | Decision tree scheme method for power quality event classification. A swell + harmonics signal (red), an oscillatory transient signal (blue) and a notch signal (green) are included as examples of decision processes. NV, nominal value.

2 | System's Inputs

The indicators, chosen as characteristic features and measured per cycle, are presented below. In Figure 2, feature #1 is represented as F1, and so on.

i. Skewness (Sk): The nominal value (NV in Figure 1) of Sk for a 50-Hz signal is zero. In Equations (1)–(4), x_j is a sample register measured from 1 to sample size, N, and σ corresponds to standard deviation.

$$\mathrm{Sk}(x) = \frac{1}{N}\sum_{j=1}^{N}\left[\frac{x_j - \bar{x}}{\sigma}\right]^3 \quad (1)$$

ii. Kurtosis (K): K nominal value is 1.5 for 50-Hz signals.

$$K(x) = \frac{1}{N}\sum_{j=1}^{N}\left[\frac{x_j - \bar{x}}{\sigma}\right]^4 \quad (2)$$

iii. Fifth-order statistic (FOS): FOS nominal value for a 50 Hz signal is zero.

$$\mathrm{FOS}(x) = \frac{1}{N}\sum_{j=1}^{N}[x_j - \bar{x}]^5 \quad (3)$$

iv. Sixth-order statistic (SOS): SOS nominal value for a 50 Hz signal is 0.3125.

$$\mathrm{SOS}(x) = \frac{1}{N}\sum_{j=1}^{N}[x_j - \bar{x}]^6 \quad (4)$$

v. Crest factor: CF nominal value for a 50 Hz signal is 1.4142. In Equation (5), V_{peak} is the maximum value of the signal, and V_{rms} is its root mean square (RMS) value.

$$\mathrm{CF} = \frac{V_{\mathrm{peak}}}{V_{\mathrm{rms}}} \quad (5)$$

vi. SNR, measured per signal: In Equations (6) and (7), P_{S} is signal power, P_{N} is noise power, and P_{D} is distortion power.

$$\mathrm{SNR} = 10 \times \log\left(\frac{P_{\mathrm{s}}}{P_{\mathrm{N}}}\right) \quad (6)$$

vii. SINAD, measured per signal.

$$\mathrm{SINAD} = 10 \times \log\left(\frac{P_{\mathrm{s}} + P_{\mathrm{N}} + P_{\mathrm{D}}}{P_{\mathrm{N}} + P_{\mathrm{D}}}\right) \quad (7)$$

Key points from the pre-established behaviour patterns when measuring cycle-by-cycle include:

Under interruption, sag and swell: Features #1–3 and #5 deviate from nominal values only at the start and end cycles, acquiring the named transitional values. However, feature #4 differs throughout the event, proportional to amplitude: In the presence of a swell, feature #4 value rises; when the amplitude decreases under a sag or interruption, so does feature #4. For sags and interruptions, an experimental value, based on lab results, named differentiating value of 3.12×10^{-7} is established: If feature #4 acquires a value lower than the differentiating value, the event is classified as an interruption; otherwise, as a sag.

Under transients, features #1–5 differ from their nominal values during the entire disturbance.

Under harmonics, the values obtained by features #6 and #7 differ from each other. For hybrid events, feature #4 detects if there is also the presence of sag (decreasing) or swell (increasing), in addition to harmonics.

Under notch and spike, features #1–5 differ from their nominal values while remaining constant between cycles; feature #5 is also measured per semi-cycle since its nominal value is independent on the cycle start point, and its variations indicate the presence of notch (decreasing) or spike (rising). Features #1–5 differ from the nominal value and vary between cycles under flicker.

Dataset #1 includes flicker, harmonics, impulsive and oscillatory transients, interruption, notch, sag, spike, swell and sag and swell with harmonics. These events have been prepared through the tool proposed by Machlev et al. [9]. These signals have been randomly produced by groups of events. As additional robustness of the method, authors incorporate real signals for specific events in Dataset #2. Both datasets are shown in Table 1, where the number of signals used for event is specified.

3 | System Description

Once features' characteristics are extracted from 30% of the signals of Dataset #1, behavioural patterns are obtained, thus developing a first scheme of the decision tree shown in Figure 1. After developing the classification code for Dataset #1 signals and its testing on 100% of the signals, Dataset #2 has been added to the research for testing. As can be seen, the algorithm returns 13 different results: the event types, the non-existence of events and an additional category named "Unknown event"—when no predefined behaviour pattern is followed.

The order of decision nodes in the scheme has posed a challenge for adjusting the algorithm and, therefore, reducing unknown events. These variations between both values have caused authors to have to prioritize the best detection of some events over

TABLE 1 | Datasets for calibration and testing the proposed decision tree.

	Dataset description	PQ event	Number of events
Dataset #1 Origin: MATLAB	Sampling frequency: 3.2 kHz. Signals' duration: 0.2 s. Authors' elaboration through reference [7].	Flicker	100
		Harmonics	100
		Impulsive transient	100
		Interruption	100
		Notch	100
		Oscillatory transient	100
		Sag	117
		Spike	100
		Swell	100
		Sag + harmonics	100
		Swell + harmonics	100
		No event	100
Dataset #2 Origin: Signal's generator	Sampling frequency: 20 kHz. Signals' duration: from 0.3 to 22 s. Authors' elaboration.	Sag	500
		Interruption	100
		Swell	100
		Impulsive transient	80

others. For this purpose, two criteria have been followed: first, the improvement ratio of the percentage of detection of one event compared with the decrease of another one. If this criterion is not differentiating, then the frequency of appearance of these events in real signals is considered, prioritizing the most common of them. See an example: If a change in the algorithm would improve notch detection by 5%, harming sag detection by 1%, the change would be applied. However, if the improvement in notch and perjury in sag detection were in both cases 1%, then the change would not be applied as the appearance of sags in real signals is more frequent in real life.

Figures 1 and 2 show three examples of events: swell + harmonics, oscillatory transient and notch. The hybrid event (swell with harmonics) is framed in red, with its path through the algorithm highlighted (Figure 1). The oscillatory transient is highlighted in blue, and the notch behaviour is framed in green. All features are extracted cycle-by-cycle (shown in Figure 2) from the full signal and then processed using the decision tree.

For the hybrid signal swell + harmonics, features #2 and #5 do not vary cycle-by-cycle, and variations below 10^{-15} for features #1 and #3 are considered negligible on the algorithm (notice the exception in the second cycle with transitional values), but they do differ from the nominal value due to the harmonic component. This fact causes the algorithm to not consider transitional values in the second cycle. The variation between features #6 and #7 exposes the harmonic presence, and the significant increase in feature 4 during five cycles highlights the presence of a swell.

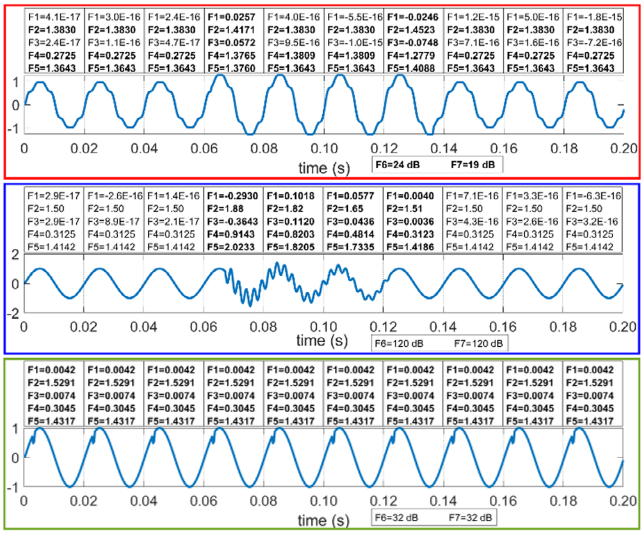

FIGURE 2 | Events included as examples in Figure 1: swell + harmonics in red, oscillatory transient in blue and notch in green.

Related to oscillatory transient, features remain at their nominal values. Notice that, although the nominal value for features #1 and #3 are apparently nil, this is displayed with orders lower than 10^{-15}. Under transients, the features change throughout the event, both with respect to the value acquired in previous and subsequent cycles and with respect to the nominal. Feature alterations greater than one cycle, that is, four cycles, are indicative of an oscillatory transient.

For a notch event, features remain at a constant value and different from the nominal value. Feature #5 is measured for semi-cycle, and an average value lower than the nominal reflects the presence of a notch.

4 | Results

The proposed decision tree processes the signals from both datasets. Table 2 shows the detection percentage by each type of event, for each dataset and for both datasets. Table 2 presents the detection percentages for each event type across individual and combined datasets. The method outperforms previously tested approaches, such as boxplots, with detection improvements of up to 50%. Additionally, the proportion of signals classified as "unknown event" is highlighted, as these represent cases where detected events do not conform to any pre-established behaviour pattern. Such results typically correspond to events that are only partially captured within the signal.

To evaluate computational efficiency, the algorithm's execution time was measured for every 1000 signal data points, a mid-range value chosen for clarity and comparability across datasets. The average execution time for Dataset #1 is 1.20 s per 1000 points, while for Dataset #2, it drops to 0.36 s, demonstrating significant speed differences.

TABLE 2 | Accuracy of the rule-based decision tree detecting each type of event.

PQ event	Detection in Dataset #1 (%)	Detection in Dataset #2 (%)	Detection in both datasets (%)	Detected as "Unknown event" (%)
Flicker	100	–	100	0
Harmonics	100	–	100	0
Impulsive transient	99	96.25	97.78	2.22
Interruption	91	90	90.50	5
Notch	90	–	90	0
Oscillatory transient	90	–	90	0
Sag	94.87	91.20	91.90	7.29
Spike	98	–	98	0
Swell	91	98	94.50	0.50
Sag + Harmonics	98	–	98	0
Swell + Harmonics	100	–	100	0
No event	100	–	100	0

5 | Conclusion

Indeed, the method for classifying electrical disturbances from rule-based decision trees exhibits more than acceptable behaviour based on the input characteristic features, selected with the criterion of combining traditional indicators with HOS. Only using the former would significantly reduce the effectiveness rate of the algorithm. On the other hand, the method is very simple to implement in control and instrumentation units, which therefore makes its online implementation not only possible but also practical for real-time power quality monitoring. Likewise, since it is based on basic programming elements, its computational speed is high, ensuring efficient operation in scenarios requiring immediate response. For all these reasons, the methodology and the associated decision algorithm outperform machine learning systems based on neural networks.

Author Contributions

P.R.C. took the roles of conceptualization, data curation, formal analysis, investigation, methodology, project administration, resources, validation, visualization, and writing—original draft and review and editing. O.F.O. took the roles of conceptualization, data curation, supervision, validation, visualization, and writing—review and editing. J.J.G.R. took the roles of conceptualization, supervision, validation, visualization, and writing—review and editing.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data are available upon request from the authors.

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