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Evaluation of wavelet-based feature extraction methods for detection and classification of power quality disturbances

Aldo Vinicio Rico-Medina, Enrique Reyes-Archundia *, Jose A Gutiérrez-Gnecchi, Marco V Chávez-Báez, Juan C Olivares-Rojas and Maria del C García-Ramírez

National Technological of Mexico, Technological Institute of Morelia, Morelia, México.

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Abstract

The appearance of Power Quality Disturbances can cause serious damage to the utility grid. Their detection and identification are two of the major problems related to the improvement of Power Quality. This paper presents an evaluation of different combinations of wavelet-based features for the detection and classification of eight types of Single Power Quality Disturbances. A set of disturbances was generated in MATLAB through their mathematical models. The detection stage was performed using Multiresolution Analysis. The extracted features were normalized by Z-score to serve as input to four different classifiers: Multilayer Perceptron, K-Nearest Neighbors, Probabilistic Neural Network, and Decision Tree. The combination of Shannon Entropy and Log-Energy Entropy was found the best with the highest accuracy in all cases. Furthermore, the normalization stage has an impact on classification as it improves accuracy regardless of the classifier used. This fact makes it possible to reduce the computational expense by using only two types of features without compromising the accuracy.

Keywords: Power Quality Disturbances; Wavelet-Based Features; Detection; Classification

1. Introduction

Power Quality improvement is one of the major concerns nowadays. The term Power Quality refers to the set of parameters and properties that describes power supply in terms of magnitude, continuity, symmetry, frequency and waveform. The interest over this topic has led to the development of new equipment and electronic devices for its measurement and control [1].

Among the main factors that affect Power Quality are the recent population growth, which implies an increase in supply demand, as well as the use of traditional and obsolete utility grids [2]. Some other causes can include the incorporation of renewable energies, the use of new switching devices and non-linear loads, aside from environmental factors [3].

One of the main consequences of poor Power Quality is the appearance of disturbances in the waveform of power supply signals known as Power Quality Disturbances (PQD). The detection and identification of these disturbances is vital in order to determine many of the possible anomalies in equipment and systems before any decisions are made [4]. This process can be divided into three main stages: signal processing, feature extraction and classification [5].

Several techniques and methods have been proposed for the detection of PQDs. Most of them involve the use of mathematical tools in order to obtain some information from their waveform such as Stockwell Transform, Wavelet Transform, Kalman Filters, Hybrid Techniques, among others. This information is generally optimized by feature

* Corresponding author: Enrique Reyes-Archundia

extraction methods in order to reduce it dimensionally so that it can serve as optimal input for a classifier, e.g., Neural Networks, Support Vector Machines, Bayesian Classifiers, Fuzzy Logic, and some others [6].

Wavelet Transform has been described as an appropriate tool for the analysis of signals with small discontinuities and abrupt changes in their waveforms, as is the case of PQDs [7]. Most of the related works involve the use of a large set of features for classification purposes, however, the selection of a suitable subset of features, both in terms of accuracy and computational performance, remains a research challenge [8].

This paper presents an evaluation of different combinations of wavelet-based features for detection and classification of eight types of Single Power Quality Disturbances including: Sag, Swell, Interrupt, Harmonics, Flicker, Notching, Oscillatory Transients and Impulsive Transients. A set of disturbances was generated in MATLAB through their mathematical models. Detection stage was performed using Multiresolution Analysis (MRA). The mother wavelet used was Daubechies 4 (db4) at nine resolution levels. Feature vector formation was performed using different feature extraction methods such as Energy, Mean, Standard Deviation, Skewness, Shannon Entropy, RMS, Kurtosis, Log-Energy Entropy and Peaks Difference. These vectors served as inputs to four kinds of classifiers: Multilayer Perceptron (MLP), K-Nearest Neighbors (KNN), Probabilistic Neural Network (PNN) and Decision Tree (DT), in order to find an appropriate combination of features in terms of accuracy and computational expense.

2. Detection and classification

2.1. Data set generation

Power Quality Disturbances are deviations in the waveform of power supply signals, i.e., any variation in the magnitude of both current and voltage within a given time interval regarding to their nominal values [6]. This topic has been a concern in power grids over the last decades and nowadays with the incorporation of new smart girds and smart meters [4]. The appearance of PQDs involves a momentary increase or decrease in magnitude, presence of harmonics, interruptions, and transients, among others. PQDs can be classified as single or complex depending on the number of disturbances present in the signal, as well as short-term, long-term or stationary if they are present over the entire time. The main single disturbances that affect Power Quality are Sag, Swell, Interrupt, Harmonics, Flicker, Notching, and Oscillatory Transient and Impulsive Transient, from which the other complex disturbances are made [8]. Their behavior can be described through mathematical models, such as those shown in Table 1 [9]. Also, their typical parameters are regulated by the IEEE 1159-2009 standard [10].

For this work, a data set of synthetic disturbances was generated in MATLAB. The signals have a sampling frequency of 10 kHz, with a duration of 0.5 s, considering a line frequency of 60 Hz. The amplitude of the signals is represented in per-unit values (PU) and the time in seconds (s). Each type of disturbance has 500 examples, whose parameters were randomly determined, so the data set consist of 4,000 examples stored as a comma-separated value file, in which each row represents a different PQD, and the columns correspond to the samples of such signal.

2.2. Wavelet transform and multiresolution analysis

The Wavelet Transform (WT) is a signal processing technique that can provide local information about a signal in both the time and frequency domains. It can be applied on signals in steady-state, as well as non-steady-state with sudden changes, abrupt contours, and discontinuities [11], as is the case of Power Quality Disturbances.

Wavelet Transform engages both the Discrete Wavelet Transform (DWT) and the Continuous Wavelet Transform (CWT), however, the latter provides inefficient and redundant information, so the use of DWT is more appropriate as it decrease the computational expense. The DWT can be represented though equation (1), where m and n are known as scale and translation factors, respectively. On the other hand, $f(k)$ is the discrete version from a continuous signal, and ψ is the mother wavelet to use [12].

$$DWT(m,n) = a_0^{-m/2} \sum_k f(k)\psi\left(\frac{n-kb_0a_0^m}{a_0^m}\right) \quad \text{..........(1)}$$

Table 1 Main Disturbances, Their Mathematical Models and Typical Parameters

PQD	Mathematical Model	Parameters
Ideal	$V(\omega t) = Asin(\omega t)$	$\omega = 2\pi f$ $f =$ line frequency
Sag	$V(\omega t) = A\left(1 - \alpha\left(u(t-t_1) - u(t-t_2)\right)\right)\sin(\omega t)$	$0.1 \leq \alpha \leq 0.9$ $T < t_2 - t_1 < 9T$
Swell	$V(\omega t) = A\left(1 + \alpha\left(u(t-t_1) - u(t-t_2)\right)\right)\sin(\omega t)$	$0.1 \leq \alpha \leq 0.8$ $T < t_2 - t_1 < 9T$
Interrupt	$V(\omega t) = A\left(1 - \alpha\left(u(t-t_1) - u(t-t_2)\right)\right)\sin(\omega t)$	$0.9 \leq \alpha \leq 1$ $T < t_2 - t_1 < 9T$
Harmonics	$V(\omega t) = A\left(\sin(\omega t) + \sum_{n=1}^{3} \alpha_{2n+1}\sin(n\omega t)\right)$	$0.05 \leq \alpha_3 \leq 0.15$ $0.05 \leq \alpha_5 \leq 0.15$ $0.05 \leq \alpha_7 \leq 0.15$ $\sum\alpha_i^2 = 1$
Flicker	$V(\omega t) = A(1 + \alpha\sin(\beta t))\sin(\omega t)$	$0.1 \leq \alpha \leq 0.2$ $\beta = 2\pi f_c$ $5Hz \leq f_c \leq 10Hz$
Notching	$V(\omega t) = A(\sin(\omega t) - sign(\sin(\omega t))\sum_{n=0}^{9} k\left(u(t-(t_1 - 0.02n)) - u(t-(t_2 - 0.02n))\right)$	$0.1 \leq k \leq 0.4$ $0 < t_1, t_2 < 5T$ $0.01T \leq t_2 - t_1 \leq 0.05T$
Oscillatory Transient	$V(\omega t) = Asin(\omega t) + \left(\alpha e^{\frac{t-t_1}{\tau}}\left(u(t-t_1) - u(t-t_2)\right)\right)\sin(\omega_n t)$	$0.1 \leq \alpha \leq 0.8$ $0.5T \leq t_2 - t_1 \leq 3T$ $8\ ms \leq \tau \leq 40\ ms$ $\omega_n = 2\pi f_n$ $300\ Hz \leq f_n \leq 900\ Hz$
Impulsive Transient	$V(\omega t) = A\left(1 + \sum_{n=1}^{k} \alpha\left(u(t-(t_1 + T*n)) - u(t-(t_2 + T*n))\right)\right)\sin(\omega t)$	$k =$ number of impulses $0.1 \leq \alpha \leq 1$ $0.05T \leq t_2 - t_1 \leq 0.06T$

DWT can be interpreted as a decomposition of a given signal into two different signals, a detailed and a smoothed version. This concept is known as Multiresolution Analysis (MRA), in which the original signal is passed through a pair of complementary high-pass and low-pass filters, so that the information about its high and low-frequency components is stored into a series of coefficients called detail and approximation coefficients, cD and cA, respectively [13]. MRA can be applied multiple times as shown in figure 1, the first decomposition is applied over the original signal, S, while the subsequent decompositions are applied over the previous approximation coefficients. Each decomposition is called a resolution level. The detail and approximation coefficients of the first resolution level are designated as cD_1 and cA_1, in this way, the detail and approximation coefficients of the n-th resolution level are designated as cD_n and cA_n.

WT also represents how closely a given signal resembles to a specific wavelet function, so the choice of the latter is a very important aspect. There are several wavelet families and functions, so different approaches can be performed using different wavelets. In this sense, Daubechies 4 function (db4) is one of the most widely used functions because it shares several of the characteristics that PQDs also present [6], so it was chosen for this work.

Since each resolution level contains information about a certain frequency range, then the greater the number of resolution levels, the more information that can be obtained, but this also implies the increase of the computational expense [14]. So, the key is decomposing the signals into a large enough number of levels to obtain relevant information, without affecting computational performance. For this work, the signals were decomposed into nine resolution levels.

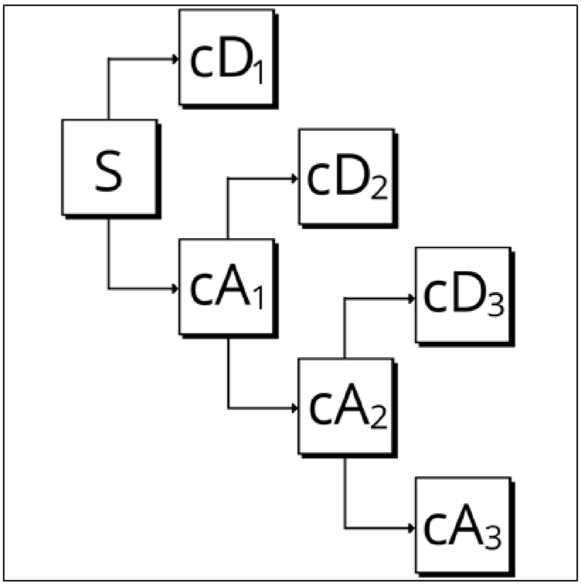

Figure 1 Multiresolution Analysis Process (Taken and modified from [12])

2.3. Wavelet-based feature extraction

The coefficients obtained from the MRA contain relevant information from the analysis of the waveform of the signals, however, they can be impractical, so the objective is to reduce it dimensionally by using feature extraction methods preserving its distinctive characteristics [15].

There are several feature extraction methods from the detail and approximation coefficients resulting from the application of the DWT to the signals. These features are kwon as wavelet-based features [16]. Table 2 shows some of these methods, as well as their mathematical definition, where $C_{i,j}$ are the N coefficients of the i-th resolution level.

Using only two or three features is enough to obtain a good accuracy in the classification [17], so for this work a combination of two different features was carried out, which gives 20 data for the classification, i.e., 10 for each one, corresponding to the 9 levels of detail coefficients and the last level of approximation coefficients.

Feature selection was performed by checking all the possible combinations, with the combination of Shannon Entropy and Log-Energy Entropy being the one that obtained the highest accuracy. The equations (2) and (3) show the data for the classification, where F_{1cD_n}, F_{1cA_n} and F_{2cD_n}, F_{2cA_n} represent two different extracted features of the detail and approximation coefficients, respectively.

$$F_{1PQD} = \left[F_{1cA_n}, F_{1cD_n}, \ldots, F_{1cD_2}, F_{1cD_1}\right] \quad \ldots\ldots\ldots..(2)$$

$$F_{2PQD} = \left[F_{2cA_n}, F_{2cD_n}, \ldots, F_{2cD_2}, F_{2cD_1}\right] \ldots\ldots\ldots\ldots.(3)$$

Due to the training data has a large variation, the feature vector of each disturbance was extracted using the features of an ideal sinusoidal signal as reference, as shown in equation (4), where F_{1Sin} and F_{2Sin} correspond to the extracted features of this ideal signal.

$$\Delta_{PQD} = \left[F_{1PQD}, F_{2PQD}\right] - \left[F_{1Sin}, F_{2Sin}\right] \ldots\ldots\ldots.(4)$$

Table 2 Wavelet-Based Feature Extraction Methods

Energy	$E_i = \sum_{j=1}^{N} \lvert C_{i,j} \rvert^2$
Mean	$\mu_i = \frac{1}{N}\sum_{j=1}^{N} C_{i,j}$
Standard Deviation	$\sigma_i = \sqrt{\frac{1}{N}\sum_{j=1}^{N} \left(C_{i,j} - \mu_i\right)^2}$
Skewness	$SK_i = \sqrt{\frac{1}{6N}\sum_{j=1}^{N} \left(\frac{C_{i,j} - \mu_i}{\sigma_i}\right)^3}$
Shannon Entropy	$SE_i = -\sum_{j=1}^{N} C_{i,j}^2 \log\left(C_{i,j}\right)^2$
RMS	$RMS_i = \sqrt{\frac{1}{N}\sum_{j=1}^{N} C_{i,j}^2}$
Kurtosis	$KRT_i = \frac{N}{24}\left(\frac{1}{N}\sum_{j=1}^{N} \left(\frac{C_{i,j} - \mu_i}{\sigma_i}\right)^4 - 3\right)$
Log-Energy Entropy	$LOE_i = \sum_{j=1}^{N} \log\left(C_{i,j}^2\right)$
Peaks Difference	$PK_i = \max\left(C_{i,j}\right) - \min\left(C_{i,j}\right)$

The feature vector of each disturbance was normalized by Z-score in order to obtain a new range of values closer to each other, which in turn improves the classification process [18]. The normalization through Z-score is shown in the equation (5), where χ corresponds to the data to normalize, μ to its mean and σ to its standard deviation. This normalization provides to the data the properties of a normal distribution, i.e., a mean of zero and a standard deviation equal to one [19].

$$Z = \frac{\chi - \mu}{\sigma} \text{...........(5)}$$

Each of the normalized vectors are finally the inputs for the classifiers, in addition, a binary coded target matrix was used, so that a value of 1 means that it belongs to the class and 0 the opposite case.

2.4. Classification

- For the classification, four types of classifiers were trained. The parameters of each classifier were iteratively evaluated in order to choose those that provided the best performance in the classification. The classifiers used were:
- Multilayer Perceptron (MLP) with 12 neurons in the hidden layer and Softmax as the activation function.
- K-Nearest Neighbors (KNN) with $K = 3$.
- Probabilistic Neural Network (PNN) with a spread of the radial basis function (smoothing factor σ) equal to 0.002.
- Decision Tree (DT).

The validation was performed by using K-Fold cross validation method, in which the data is separated randomly in K subsets such that one of them is used for the validation whereas the remaining $K-1$ subsets are used for training. The performance is subsequently evaluated based on the accuracy average after K rounds of training and validation [20]. For this work $K=10$ was taken, so of the 4,000 available examples, 3,600 were used for training and 400 for validation in each round. The accuracy was obtained from the equation (6).

$$Accuracy = \frac{No.\ of\ correctly\ classified}{Total\ data} \times 100\% \ldots\ldots\ldots (6)$$

3. Results

The proposed method was proved in simulation using the synthetic disturbances generated as a comma-separated values file and evaluating its performance through K-Fold. Table 3 shows the accuracy of each classifier regarding a specific combination of features, in such way that all possible combinations were checked. All combinations were normalized by Z-score. The highest accuracy was obtained from the combination of Shannon Entropy and Log-Energy Entropy. Table 4 shows the accuracy of classifiers in each round for that specific combination, the last row represents the average after all rounds. The KNN, PNN and DT classifiers presented a very similar performance, with an accuracy greater than or equal to 99% in each round. On the other hand, MLP classifier presented the lowest accuracy.

A comparison of the results obtained in other literature works and the proposed method is shown in Table 5. In all cases, the detection is based on MRA at different resolution levels. In the same way, the table shows the feature extraction method as well as the classifier used for the classification of different types of PQDs and their respective accuracy in simulation.

For example, in [17] different combinations of features were analyzed for the detection and classification of 8 types of single and 2 types of complex disturbances from the application of MRA at 6 resolution levels in MATLAB. Such combinations include the use from 1 to 9 different features including: Energy, Mean, Standard Deviation, Skewness, Shannon Entropy, RMS, Kurtosis, Log-Energy Entropy and Norm-Entropy. All combinations were tested through various classifiers such as Support Vector Machine (SVM), Decision Tree (DT) and Random Forest (RF). The results suggest that using a combination of 2 or 3 features is enough to obtain a good result in the classification, thus, for the case of 2 features, the combination of Shannon Entropy and Log-Energy Entropy provided a high accuracy for the SVM and RF classifiers, being 97.24% and 98.38%, respectively, whereas for DT classifier, the combination of Energy and Log-Energy Entropy was the one that provided the highest accuracy with 97.40%.

In [21] the use of Mean, Maximum and Minimum values, Variance, Standard Deviation, Mode, Median, Kurtosis, Shannon Entropy and Energy was proposed for the classification of 5 types of single disturbances. For this, the signals were decomposed into 7 resolution levels through MRA. For the classification, two types of classifiers were trained, a K-Nearest Neighbors (KNN) and Naïve Bayesian classifier (NB) in MATLAB. The results show an accuracy of 97.91% and 92.22% for the KNN and NB classifiers, respectively.

Table 3 Accuracy for Each Combination of Features

Combination		**Accuracy**			
		MLP	**KNN**	**PNN**	**DT**
Energy	Mean	89.4%	92.7%	88.825%	92.125%
Energy	Std. Deviation	88.85%	93.2%	88.925%	92.85%
Energy	Skewness	90%	90.625%	80.3%	90.35%
Energy	Shannon Ent.	94.25%	97.225%	88.3%	96.675%
Energy	RMS	89.775%	93.175%	88.625%	92.7%
Energy	Kurtosis	91.05%	88.275%	85.675%	88.675%
Energy	Log-Energy Ent.	96.175%	99.25%	85.675%	88.675%
Energy	Peaks Diff.	90.6%	93.375%	87.375%	92.125%
Mean	Std. Deviation	93.875%	93.025%	70.075%	90.925%

Mean	Skewness	63.775%	63.275%	61.6%	67.875%
Mean	Shannon Ent.	84.85%	93.025%	87.375%	93.3%
Mean	RMS	93.9%	92.95%	69.425%	91.775%
Mean	Kurtosis	71.05%	70.375%	69.85%	73.75%
Mean	Log-Energy Ent.	90.775%	95.325%	95.175%	95.275%
Mean	Peaks Diff.	91.325%	89.875%	74.2%	88.925%
Std. Deviation	Skewness	79.1%	69.675%	67.6%	76.4%
Std. Deviation	Shannon Ent.	85.2%	92.85%	87.225%	93.55%
Std. Deviation	RMS	92.65%	92%	76.375%	91.7%
Std. Deviation	Kurtosis	73.4%	71.375%	70.475%	78.8%
Std. Deviation	Log-Energy Ent.	90.65%	95.475%	95.075%	94.85%
Std. Deviation	Peaks Diff.	94.1%	92.55%	75.375%	91.75%
Skewness	Shannon Ent.	87.375%	91.925%	81.95%	91.425%
Skewness	RMS	79.775%	69.825%	67.475%	76.325%
Skewness	Kurtosis	72.675%	71.375%	69.65%	75.275%
Skewness	Log-Energy Ent.	90.875%	95.65%	95.225%	95.2%
Skewness	Peaks Diff.	88.45%	77.55%	74.6%	81.2%
Shannon Ent.	RMS	85.65%	92.825%	87.325%	93.2%
Shannon Ent.	Kurtosis	92.55%	90.35%	86.835%	90.65%
Shannon Ent.	Log-Energy Ent.	98.25%	99.65%	99.6%	99.475%
Shannon Ent.	Peaks Diff.	85.475%	93.55%	86.7%	93.725%
RMS	Kurtosis	73.25%	71.4%	70.2%	78.35%
RMS	Log-Energy Ent.	90.25%	95.45%	95.225%	94.925%
RMS	Peaks Diff.	94.25%	92.075%	75.425%	91.75%
Kurtosis	Log-Energy Ent.	94.2%	96.525%	96%	94.875%
Kurtosis	Peaks Diff.	80.4%	72.15%	72.05%	81.325%
Log-Energy Ent.	Peaks Diff.	90.375%	95.55%	95.35%	96.025%

On the other hand, in [22] a feature selection algorithm known as Artificial Bee Colony (ABC) was proposed for the detection and classification of 7 types of single and 6 types of complex disturbances based on Energy, Shannon Entropy, Standard Deviation, Kurtosis, Skewness and RMS extraction at 8 resolution levels. The algorithm focuses on the selection of optimal features for the classification from a larger set of them, at the same time that it allows establishing the optimal spread parameter for a Probabilistic Neural Network (PNN). The results of PNN classifier were compared with other classifiers such as Multilayer Perceptron (MLP) and Radial-Basis Function Neural Network (RBF), obtaining and accuracy of 98.25%, 95.25% and 96.625% in each case. The selected features were normalized by Min-Max method and the ABC algorithm was carried out in simulation through PSCAD.

In [23] a comparison of the performance of different classifiers such as K-Nearest Neighbors (KNN), Decision Tree (DT), Support Vector Machine (SVM), Naïve Bayesian classifier (NB) and Random Forest (RF) is proposed from the extraction of Mean, Standard Deviation, Skewness, Kurtosis, Crest and Form Factors, Shannon and Log-Energy Entropy of 8 types of single disturbances decomposed into 9 resolution levels through MRA in MATLAB. Despite obtaining a low accuracy, the results suggest that additional feature selection methods could improve the classification.

Table 4 Accuracy for Each Round K

Round	MLP	KNN	PNN	DT
1	97.5%	99%	99%	99%
2	99%	99.75%	99.75%	100%
3	98.25%	100%	100%	100%
4	97.25%	99.75%	100%	99.5%
5	98.5%	99.75%	99.25%	99.25%
6	98.75%	100%	99.75%	99%
7	98.25%	99.75%	99.75%	100%
8	98.5%	99.75%	99.75%	99.25%
9	97.5%	99.25%	99.25%	99.5%
10	978.5%	99.5%	99.5%	99.25%
Average	98.25%	99.65%	99.6%	99.475%

With the proposed method it can be evidenced that, from the decomposition of the signals into 9 resolution levels, the extraction of Shannon and Log-Energy Entropy results in an appropriate combination for the classification of 8 different types of single disturbances. Furthermore, data normalization has an impact on classification as it provides a higher accuracy regardless of the classifier used. This fact makes it possible to reduce the computational expense by using only two different types of features without compromising accuracy.

Table 5 Comparison with Other Proposed Works

Reference	Detection	Resolution levels	Feature extraction	Normalization	Classification	Type of Signals	No. of PQD	Environment	Accuracy
[17]	DWT/MRA	6	E, SE, LOE	–	SVM DT RF	Synthetic	8 single and 2 complex	Simulation	97.24% 97.40% 98.30%
[21]	DWT/MRA	7	$\mu, \sigma^2, \sigma, KRT, SE, E,$ $Max, Min, Mode, Median$	–	KNN NB	Synthetic	5 single	Simulation	97.91% 97.22%
[22]	DWT/MRA	8	$E, SE,$ $\sigma, KRT,$ SK, RMS	Min-Max	PNN MLP RBF	Synthetic	7 single and 6 complex	Simulation	98.625% 95.25% 96.625%
[23]	DWT/MRA	9	$\mu, \sigma,$ $SK, Crest\ Factor,$ $KRT, Form\ Factor,$ SE, LOE	–	KNN DA NB DT SVM RF	Synthetic	8 single	Simulation	76.32% 72.45% 75.13% 78.13% 79.13% 81.75%
Proposed	DWT/MRA	9	SE, LOE	Z-score	MLP KNN PNN DT	Synthetic	8 single	Simulation	98.25% 99.65% 99.6% 99.475%

4. Conclusion

In this work, a methodology for the evaluation of different combinations of wavelet-based features for the detection and classification of eight types of simple disturbances was proposed. The combination of Shannon Entropy and Log-Energy Entropy was the one that provided the highest accuracy. The fact of using only two different features allows to reduce the computational expense required, likewise, data normalization by Z-score significantly improves the classification results, providing them the attributes of a normal distribution. In this sense, the classifiers that obtained the highest accuracies were PNN and KNN, which shows that these classifiers are particularly effective for this type of application. Then the DWT results in a powerful tool for the analysis of anomalous signals with sudden changes in their waveform, as is the case of Power Quality Disturbances.

Compliance with ethical standards

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Disclosure of conflict of interest

The Authors confirm that the content of this manuscript has no conflict of interest.

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