

# Detection and classification of disturbances in the islanded micro-grid by using wavelet transformation and feature extraction algorithm

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**Abstract:** Digital signal processing (DSP) methods have been used by many researchers for detection and classification of transient disturbances because of their fast and powerful abilities to recognise waveform distortions. However, some DSP methods such as the wavelet transformation (WT) show less accuracy when applied to noisy real data. In this study, disturbance features are extracted in the wavelet domain based on the WT levels. Moreover, a new feature extraction algorithm namely normalised Renyi entropy with the signal energy is applied. This algorithm has been proven to be effective and robust for noisy signals. However, their application in power systems has not yet been tested. Using a laboratory setup of an islanded micro-grid, experimental results validate the efficacy of the wavelet-based normalised Renyi entropy in the detection and classification of four disturbance types (voltage sag, interruption, harmonics, mixture of harmonics and sag).

## 1 Introduction

Power quality (PQ) has become a challenging concern in power system operation due to the increasing penetration of distributed generations. Fast and accurate detection and classification of any PQ disturbances are required to maintain the system stability, especially for the islanded micro-grids, which face worse situations during the disturbances [1].

The PQ indices in concordance with the required standards are used in illustrating the undesirable impact of electrical disturbances. The electrical disturbances are abnormalities in voltage or current that present variations in magnitude or root-mean-square (rms) values with respect to nominal value during an interval time. Depending on the thresholds of these features, the IEEE standard 1159 [2] and the European standard EN 50160 [3] categorise these disturbances as shown in Table 1.

Variations in load, switching phenomena, power electronic devices, charging of transformer and use of non-linear loads can cause PQ problems [4]. Various methods such as wavelet transformation (WT), S-transform (ST), hyperbolic S-transform and time-time transform are studied to detect and classify PQ disturbances [5, 6]. The research indicates that most of the digital signal processing algorithms can efficiently detect and classify all PQ disturbances occurring under noise-free scenarios. However, some algorithms like WT and ST fail to detect the disturbances in the presence of noises and harmonics. And some algorithms return a large amount of data, which makes the detection to slow down heavily. In this case, the feature extraction algorithm is proposed.

A well-established feature extraction technique can reduce the time series, and can help remove the influence of noises and harmonics. PQ disturbances under different operating conditions can be classified by extracting features using WT/ST/HS-transform followed by the selection of optimal features [7]. Other features including signal energy, standard deviation of signals and rms value of signals are also applied for PQ detection and classification [8, 9].

Renyi entropy is one of the feature extraction algorithms that have been tested [10]. However, only the normal Renyi entropy is considered, and the test is done in time domain only by using the raw signals. Thus, a new feature extraction algorithm namely normalised Renyi entropy with the signal energy is applied in this paper, and this algorithm is achieved in time-frequency domain by combining the wavelet transformation with the new normalised Renyi entropy. Both single and multiple disturbances including voltage sag, interruption, harmonics, harmonics + sag are involved. All disturbance signals are collected from a laboratory setup of an islanded micro-grid which consists of a wind turbine, photovoltaic panel and battery storage.

## 2 Methodology and algorithm

### 2.1 Wavelet transformation

The WT was first introduced at the beginning of the 1980s by Morlet, who used it to evaluate seismic data [11, 12]. Since then, various types of wavelet transformations have been developed, and many other applications have been found. It is a tool that decomposes data or functions or operators into different frequency components, and then studies component with a resolution matched to its scale. The WT of a signal evolving in time depends on two variables: scale (or frequency) and time. Wavelets provide a tool from time-frequency localisation [13].

Equation (1) shows the general form of the wavelet transformation  $W(\tau, d)$

$$W(\tau, d) = \int_{-\infty}^{\infty} x(t)w(d, t - \tau) dt \quad (1)$$

where  $x(t)$  is the signal analysed and  $t$  is the amount of time shift.

**Table 1** Specification of PQ disturbances

| Disturbances type | Duration     | Amplitude, pu | Spectral content |
|-------------------|--------------|---------------|------------------|
| flicker           | >0.5 cycle   | 0.9–1.1       | <25 Hz           |
| harmonic          | steady state | 0–0.2         | 0–5 kHz          |
| transients        | ns–ms        | 0–8           | 5 kHz–5 MHz      |
| sag               | >0.5 cycle   | 0.1–0.9       | —                |
| swell             | >0.5 cycle   | 1.1–1.8       | —                |
| interruption      | >0.5 cycle   | <0.1          | —                |
| notch/spike       | steady state | —             | —                |
| noise             | steady state | 0–0.01        | broadband        |

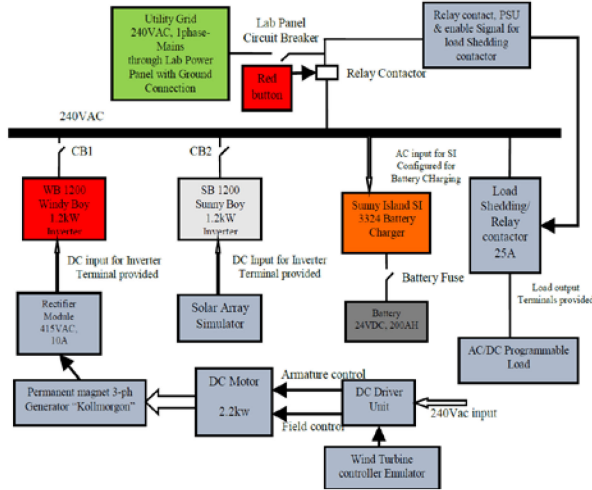


Fig. 1 Arrangement of micro-grid system

Table 2 Detection results of PQ disturbances

| Power disturbances | Detection accuracy, % |     |
|--------------------|-----------------------|-----|
|                    | SVM                   | KNN |
| sag                | 100                   | 100 |
| interruption       | 100                   | 100 |
| harmonics          | 100                   | 100 |
| hamonics + sag     | 100                   | 100 |

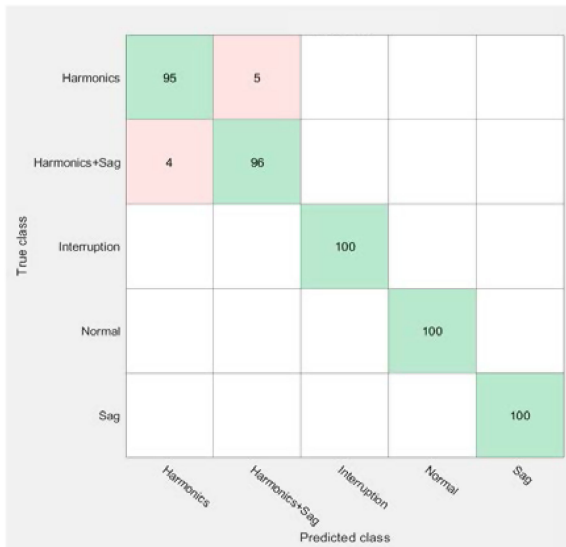


Fig. 2 Classification results with SVM

## 2.2 Normalised Renyi entropy

The Renyi entropy is useful for classification of non-stationary signals because of its sensitivity to the number of signal components, their time duration, bandwidth and their amplitude ratio [14].

The time-frequency Renyi entropy is defined as

$$\text{TFRE} = \frac{1}{1-\alpha} \log_2 \left( \sum_{n=1}^N \sum_{m=1}^M \rho^\alpha[n, m] \right) \quad (2)$$

where  $\alpha > 0$  and  $\alpha \neq 1$ .

This time-frequency Renyi entropy has the problem by the fact that zero-mean cross-terms cannot be detected. In order to convert the distribution to the unity signal energy case, the normalised Renyi entropy with the signal energy is proposed.

The equation of this normalised algorithm is expressed as below:

$$\text{TRFE}_x = \frac{1}{1-\alpha} \log_2 \left( \frac{\sum_{n=1}^N \sum_{k=1}^K \rho x^\alpha(n, k)}{\sum_{n=1}^N \sum_{k=1}^K \rho x(n, k)} \right) \quad (3)$$

with  $\alpha > 0$  and  $\alpha \neq 1$ . Different values have been trialled by the authors to find the optimal choice and the  $\alpha = 0.5$  is chosen for use in this paper.

This kind of normalisation is important for comparison of various distributions, or the same distribution when it is not energy unbiased, by definition [15].

## 3 Detection of power disturbance

Disturbances including voltage sag, interruption, harmonics, harmonics + sag are detected by using the normalised Renyi entropy here. All single and multiple disturbances, minor and large disturbances or short-term and continuous disturbances are involved by choosing these four types of PQ events. All data used is collected from the islanded micro-grid laboratory setup. Hundred samples are collected for each type of disturbance. The arrangement for this experimental setup is shown in Fig. 1. The voltage sag transients are triggered by changing the load demand of the system. The voltage interruption is created by switching the power off. The harmonic signals are collected when connecting a 300 Hz non-linear load to the islanded micro-grid.

In the detection part, each type of disturbance is trained and tested one by one with the normal voltage signal (signal collected without any disturbances). The objective of this part is to test whether the signals with power disturbances can be separated from normal signals. The raw signals are firstly analysed by the WT with six levels decomposition, and the WT coefficients are then used as the input of normalised Renyi entropy for feature extraction. The results are trained and tested by classifiers. In order to ensure the accuracy of training results, both support vector machine (SVM) and K-nearest neighbours (KNN) are used. The  $k$ -fold cross-validation method is used. All data are randomly separated into five equal-sized subsets. Of these five subsets, a single subset is retained as the validation data for testing, and the remaining four subsets are used as training data. The cross-validation process is then repeated five times, with each of the subsets being used exactly once as the validation data. The five results from the subsets are then averaged to produce the final outcome.

The result of detection is shown in Table 2.

The detection accuracy of each type of disturbance is 100%, when either SVM or KNN is used. The results indicate that the normalised Renyi entropy shows perfect performance for disturbances detection. All of the disturbances are successfully identified. The efficiency of this normalised algorithm is proved by high detection accuracy.

The algorithm will also be applied in the next section to test its performance for classifying these four types of disturbances.

## 4 Classification of power disturbance

The algorithm is extended to classify all different disturbances when they are trained together. The objective is to test if the normalised Renyi with the signal energy can clearly classify different types of disturbances. Figs. 2 and 3 show the classification accuracy for four types of disturbances with SVM and KNN.

A better result is found when the SVM is applied. Signals under normal condition and disturbances like voltage sag and voltage interruption are completely classified from others. The mix-up happened between harmonics signals and harmonics + sag signals. The classification accuracy of harmonics signals is 95%, with 5% is classified as harmonics + sag. Similarly, for harmonics + sag signals, 96% of this disturbance is correctly identified; however, 4% is mixed with the harmonics signals. These results are acceptable since the accuracy is still above 90%.

Signals under normal condition, voltage sag and voltage interruption are also clearly classified when the KNN is used. The problem still arises from the harmonics and harmonics + sag signals. The classification accuracy of harmonics signals is 95%,

|            |               |                 |               |              |        |     |
|------------|---------------|-----------------|---------------|--------------|--------|-----|
| True class | Harmonics     | 95              | 5             |              |        |     |
|            | Harmonics+Sag | 12              | 88            |              |        |     |
|            | Interruption  |                 |               | 100          |        |     |
|            | Normal        |                 |               |              | 100    |     |
|            | Sag           |                 |               |              |        | 100 |
|            |               | Harmonics       | Harmonics+Sag | Interruption | Normal | Sag |
|            |               | Predicted class |               |              |        |     |

Fig. 3 Classification results with KNN

which is same as the result when SVM is used. The accuracy of harmonics + sag is 88% in this case, which is relatively low. Hence, the KNN is not recommended for data training when the normalised Renyi with the signal energy is applied.

## 5 Conclusion

This paper investigates the detection and classification of single and multiple disturbances in an islanded micro-grid. The disturbances data are collected from the micro-grid laboratory setup, which contain more noises and harmonics.

The wavelet transformation and normalised Renyi entropy with the signal energy are applied as the time-frequency algorithm and the feature extraction algorithm.

The results indicate that the wavelet-based normalised Renyi entropy has a high efficiency in detecting disturbances in an islanded micro-grid. All four types of disturbances including voltage sag, voltage interruption, harmonics and harmonics + sag are successfully identified. The detection accuracy achieved is 100%.

The results also demonstrate that this algorithm can be used for disturbance classification, especially when the SVM is used for data training. The normal voltage signals, voltage sag and interruption signals are completely classified from others. Mis-

classification only occurs between harmonics signals and harmonics + sag signals. Nevertheless, the accuracy is still higher than 95% which is acceptable.

The results of classification accuracy with KNN show worse performance. However, the normal voltage signals, voltage sag and interruption signals are still 100% classified. The classification accuracy of harmonics signals is 95%, with 88% for harmonics + sag signals. Hence, KNN is not recommended for classification of sag signals with harmonics.

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