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A Novel Methodology for Power Quality Disturbances Detection and Classification in Industrial Facilities

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The industrial facilities inject noise to the power line. Concerning this issue, researchers are focusing their effort on developing new techniques for analyzing the power quality of the power net. This work presents a novel methodology for power quality disturbances detection and classification based on the Harris hawks optimization algorithm and discrete wavelet transforms decomposition of the signal.

Keywords: Classification, Discrete wavelet transform, Harris hawks optimization, Optimization, Power quality analysis

Introduction

A healthy power net is critical for the continuous manufacturing industry[1]. For this reason, there is a concern on power quality (PQ) monitoring for the power lines that feed these facilities.[2,3] Most PQ analysis solutions are based in detecting and classifying PQD events by using features of power signals or certain transformation of them. Methods developed have used the d-q transform[4], the continuous wavelet transform[5,6], the wavelet packet transform[7,8], the S-transform[9,10], the empirical mode decomposition[11] and the discrete wavelet transform[12–14] as the base for the extracting features from the signal to analyze. While, regarding to classification techniques, support vector machine[15] (SVM), artificial neural network[16] (ANN), particle swarm optimization[17] (PSO), genetic algorithms (GA)[18] and ant colony framework (ACF)[19] have been studied as well. Recently, novel methodologies have emerged for example using convolutional neural networks (CNN).[20] Meta-heuristic optimization algorithms have been used for fitting synthetic to raw power signals as GA combined with particle swarm optimization (PSO)[21] or differential evolution (DE).[22]

In this paper, a novel hybrid methodology for PQD detection and classification is proposed. The work use an optimization method known as Harris hawks optimization (HHO) and DWT decomposition of the signal takes place for obtaining features that allow classifying the remaining transient PQD. The proposed methodology is validated with synthetic power signal dataset and real power signals from the industry.

Experimental Details

Harris Hawks Optimization (HHO)

Harris hawks optimization algorithm[23] is a meta-heuristic optimization technique. It is nature-inspired in the hunting behavior of Harris hawks, where a family of hawks prey for a rabbit, whose energy decreases over time as it tries to escape. The goal is to minimize the distance from the hawks to the rabbit in order to optimize the function. At first, the energy of the rabbit is high, after that, there is a first exploitation phase, where the rabbit tries to escape jumping and the hawks encircle it. Finally, at the last exploitation phase, the rabbit is so much exhausted that has not enough energy to escape and the prey is completed.

Discrete Wavelet Transform Algorithm (DWT)

The algorithm of discrete wavelet transform[24] is used for decomposing a signal by the use of filters repeatedly. Where, for each step (level), there is a low-pass and a high-pass filtering process that results in the approximation and detail coefficients respectively. With it resulting in a higher number of features that can be extracted in order to feed a subsequent classification algorithm as support vector machine (SVM), a decision tree (DT) or a probabilistic neural network (PNN).

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Power Quality Disturbances Detection and Classification

The proposed methodology is based primarily on HHO and DWT. The complete methodology can be divided in two stages, at a first stage the steady PQD are characterized, while at a second stage the transient PQD are analyzed as well. Firstly, the voltage signal for a phase of the power line is acquired by a signal acquisition system, whose sampling frequency can be as high as the resolution of the system needed. In counterpart, because of high frequency content, as transient power quality disturbances and higher order harmonic content, a trade-off must be carried out. In this implementation, a sampling frequency of 10 kHz is used. Secondly, the steady PQD detection block adjust with the aid of HHO the raw power signal to a synthetic power signal whose frequency and phase matches the fundamental sine-wave by reducing the sum of squares error (SSE) using the sine wave mathematical model. The function to minimize, e, is shown in Eq. (1). In this function $x(t)$ represents the captured sample point at time t, f_1 is the estimated fundamental frequency and ϕ_1 is the estimated radial phase for the fundamental sine wave. After this optimization is performed, amplitude is estimated for each half cycle for detecting sag, swell, interruptions and flickers of the fundamental frequency and harmonic content as well by application of HHO too, resulting in $A_h(t)$. This results in a synthetic power signal whose amplitude is defined by half cycles, expressed as $s(t)$ in Eq. (2).

$$e = \sum_{t\in T}(x(t) - \sin(2\pi f_1 t + \phi_1))^2 \quad \dots (1)$$

$$s(t) = \sum_{h\in\mathscr{H}}(A_h(t)\sin(2\pi h f_1\, t + \phi_1)) \quad \dots (2)$$

Thirdly, the transient PQD detection block is used to assess whether the power signal is affected by transient phenomena or not. In this case, the transient PQD that are detected by the system are: impulsive transients and oscillatory transients. In this step, a transient extraction system is used, a signal $a(t)$ is calculated by using the difference between the synthetic signal from the last block and the raw signal as shown in Eq. (3). Immediately after, the level 4 DWT is extracted from the signal. After that result is obtained, an absolute threshold for certain ε is applied over it, resulting in an indicator function $I_\varepsilon(t)$, shown in Eq. (4). Disturbances signatures are extracted by isolating the time ranges where, $I_\varepsilon(t) = 1$. As the last step, a smoothing of this signature is performed and the number of zero-crossings is used for discrimination between the classes, the classification of transient PQD takes place. When the number of zero-crossings is less than 18 the disturbance is classified as an oscillatory transient, otherwise it is classified as an impulsive transient. Examples of the signatures for each kind of disturbance can be seen in Fig. 1, where, the previously described behaviors of the transient PQD are shown.

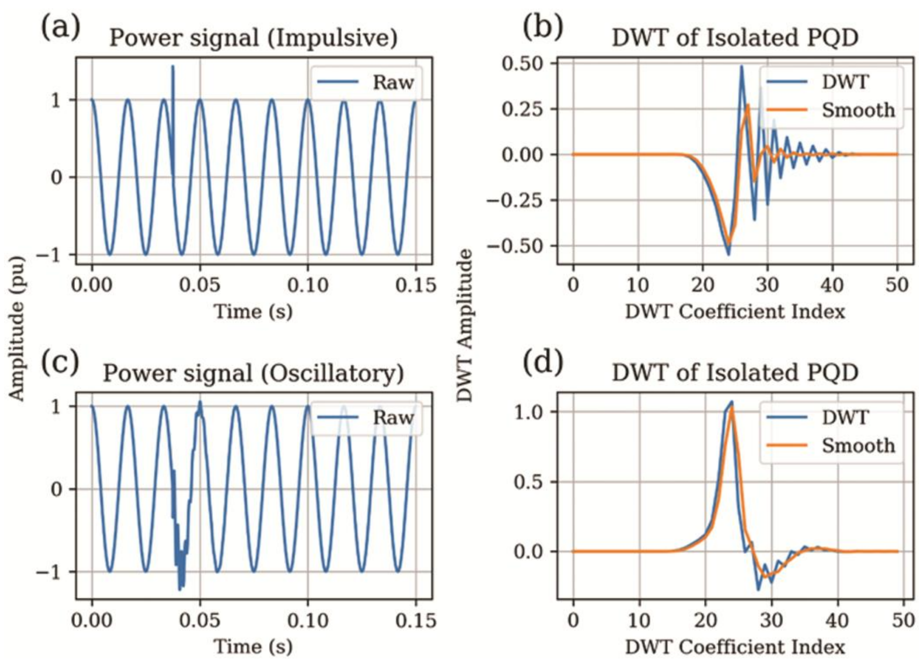

Fig. 1 — (a) Power signal of an impulsive transient; (b) DWT of isolated impulsive transient; (c) Power signal of an oscillatory transient; (d) DWT of isolated oscillatory transient

$$a(t) = x(t) - s(t) \quad \dots (3)$$

$$I_\varepsilon(t) = \begin{cases} 1, if\ |W_4(t)| > \varepsilon \\ 0, otherwise \end{cases} \quad \dots (4)$$

Test Bench for Synthetic Power Signals

A series of experiments have been developed to validate the proposed methodology. As a theoretical approach, a bank of synthetic power signals has been generated. Where, for each one of them, a set ofone or more power quality disturbances is present. The synthetic signals have been generated by the complete mathematical model described in a recent publication[25], taking values for the parameters in the ranges shown in it. Testbench power signals are divided in two groups: steady PQD power signals and transient PQD power signals, as the nature of the methodology requires a different validation for each one of them.

For the steady PQD power signals validation, a data bank of signals containing sag, swell, interruption, flicker and harmonic content is generated. After that, an estimation of the power signal parameters is performed by the methodology, leading to an estimated power signal. The relative sum of squares error is taken as an indicator in order to evaluate how the methodology performed; its formula is presented in Eq. (5). In this equation, $x(t)$ represents the estimation of the raw acquired signal $s(t)$. As values of this indicator approach zero a better fit is obtained, elsewhere, when values of this indicator approach one, a worse fit is obtained. As a result of the testbench execution, a RSSE of 0.06% is obtained for flicker, 1.52% for harmonic content of third, fifth and seventh order, 2.79% for interruption, 0.26% for sag of 3.6% for swell. It can be seen that the algorithm behaves reasonably well for every kind of steady PQD.

$$RSSE(x,s) = \frac{\sum_t \left(x(t) - s(t)\right)^2}{\sum_t s(t)^2} \quad \dots (5)$$

After the generation of steady PQD power signals, the transient PQD classification block needs to be validated. Having this a goal, synthetic signals containing oscillatory transient disturbances and impulsive transient disturbances are generated. The methodology computes the signal of fourth-level DWT decomposition, extracts the PQD by using an absolute threshold, smooths them and classifies them by the number of zero-crossings found. A correct classification of 92.2% in the cases for the impulsive transient, while, on the other hand, classification accuracy for the oscillatory transient obtained is 94%. Based on these results, it could be affirmed that the present methodology behaves as expected when tackling with steady and transient PQD.

Industrial Real Power Signal

A real signal sampled from the power lines of an industrial environment present in the IEEE Workgroup database is used as input for the proposed methodology. Using descriptive analysis, the signal seems to contain a sag disturbance, where the amplitude of the sine wave has decreased over 14%. This PQD could lead to malfunction of sensitive digital equipment as micro-processor control systems, what could lead to a stoppage of the production in some part of the plant. The steady PQD analysis of the proposed methodology is performed by using HHO, giving as result the Fig. 2. After measuring the signal decomposition obtained by the optimizer, average amplitude of 86.42 pu is obtained for the fundamental sine-wave, while harmonic content amplitude is under 0.5 pu for each one of the analyzed orders (three, five and seven).

Results and Discussion

The outcome of the analysis for the real power signal agrees with the assumptions made. It can be seen in Fig. 2 as the fitting signal adjusts itself reducing its amplitude in the range between 0.1 and 0.5 seconds. Moreover, the sag effect in the amplitude of the fundamental sine wave in this range is estimated to be over 81%.

The observed results clearly demonstrate the validity of the proposed methodology for real power signals added to the theoretical results shown two sections before. The key principal advantages of the proposed methodology are its reliability, taking into account that no filters are used for isolating frequencies, and its simplicity at implementation, where there exists only HHO and DWT as the main algorithms and no other computational demanding classic techniques, as FFT or Wavelet decomposition, are used.

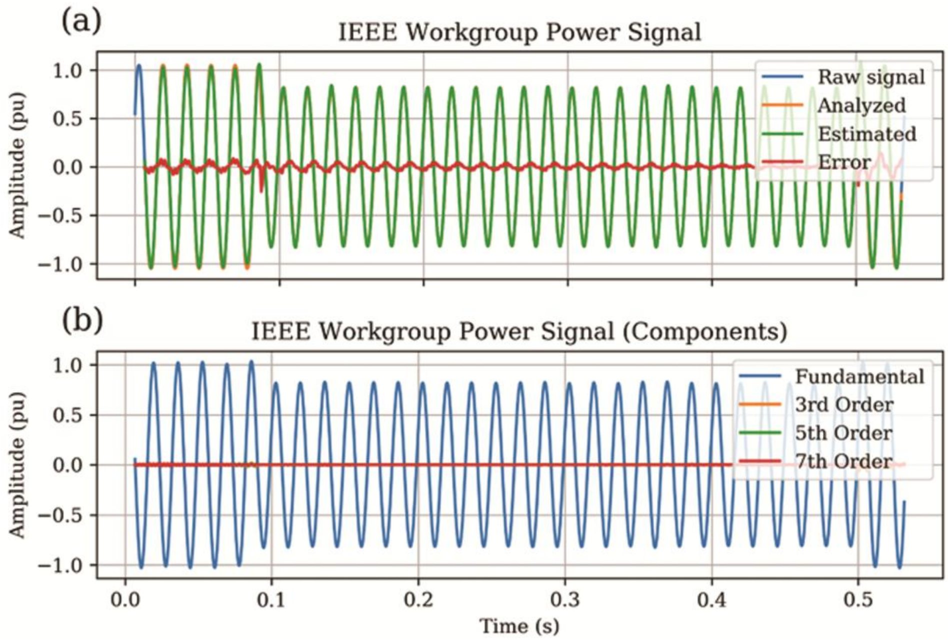

Fig. 2 — (a) Real power signal from IEEE Workgroup, estimated signal by the proposed methodology and estimation error; (b) Real power signal decomposition into fundamental sine-wave and harmonic content of order 3, 5 and 7

Conclusions

To sum up, it has been shown that the proposed methodology is able to characterize and classify steady and transient PQD that are present in power signals. Moreover, it accomplishes the characterization task with the help of a state-of-the-art meta-heuristic optimization algorithm (HHO). Nevertheless, there are hyper-parameters in the optimization algorithm that need to be refined in order to achieve a more efficient implementation for this research area. Added to this, it must be said that in this case there was no need on implementing any intelligent algorithm for the binary classification, as the signal smoothed zero-crossings turned out to be a valuable feature. Future research will aim to obtain an intelligent method that allows a full characterization of the signal in an on-line process.

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