Detector of Power Quality Disturbance Signal with Random Phase Offset

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Abstract The wavelet- or wavelet packet-based power quality disturbance (PQD) signal detection is highly sensitive to random phase offset owing to their shift-variant characteristics, which has not yet been well discussed in the literature. In this letter, we newly define the wavelet packet transform modulus (WPTM), introduce the two WPTM metrics (MV and RMS) with an optimum factor \( k \) modifying conventionally defined universal threshold, and present a WPTM-based PQD detector using those metrics that is robust against severe channel conditions with random phase offset. Simulation results verify that the presented method greatly reduces false edge detection rate (FER) (< 10%), while maintaining a high detection rate (DR), when compared to existing wavelet- or wavelet packet-based methods.

key words: wavelet packet transform modulus (WPTM), power quality disturbance (PQD) detector, random phase offset

Classification: XYZ (choose one from Table II)

1. Introduction

Currently, owing to the increasing use of high-precision equipment and facilities, power quality disturbance (PQD) issues within the power grid are a major concern [1-5]. For the PQD detection, the wavelet transform (WT) and wavelet packet transform (WPT) have been more favorably used than the short-term Fourier transform (STFT), Hilbert–Huang transform (HHT), and so on [6-25]. However, WT and WPT are highly sensitive to random phase offset \( \varphi_m \) (uniformly distributed \( \sim U[0, 2\pi] \)) owing to their shift-variant wavelet characteristics [26]. Thus, existing WT- and WPT-based detection schemes have large false edge detection rates (FERs), especially for the PQDs with random phase offset, but this has not yet been well discussed in the literature [26, 27].

The wavelet transform modulus (WTM) is often used to detect or localize the discontinuities of transient signals as images [15-24]. In this letter, we newly introduce wavelet packet transform modulus (WPTM) that enjoys a large degree of freedom for the detection of PQD. We also propose an WPTM-based PQD detector with a modified threshold using the optimum “\( k \)” factor, which is robust against severe PQD channel conditions like low signal-to-noise ratio (SNR) and random phase offset. Via simulation, we evaluate the proposed scheme in terms of double edge detection allowing reliable PQD localization, rather than conventional single edge detection [26]. Simulation results prove that the presented scheme greatly reduces FER while maintaining a higher detection rate (DR) over such severe PQ channels (see Table II & III), when compared to existing wavelet- or wavelet packet-based schemes [15, 28].

2. Wavelet packet transform modulus (WPTM) and WPTM-based metrics

In this section, we first define the WPTM and then derive WPTM-based metrics like majority voting (MV) and root-mean-square (RMS) that enjoy a large degree of freedom and retain the PQD transient (high-frequency) characteristics well.

Assume that we construct an admissible tree for the input signal \( x[i] \) with all of the \( l \)th level wavelet packets \( \psi^k \) (where the level index \( l = 0, \ldots, L \) and the packet index \( k = 0, \ldots, 2^l - 1 \)) that can be represented with \( 2^l \) elementary wavelets \( \psi^k[:]: \psi^k[i - r] = \frac{1}{\sqrt{2^l}} \psi^k \left[ \frac{-r}{2^l} \right], \)

\( i = 0, \ldots, 2^l - 1 \) and \( r = 2^ln \) denotes the translation index.

Then, the corresponding wavelet packet coefficients (WPCs) of \( x[i] \) become

\[ W^k_l = \{ x[i] \mid n = 1, \ldots, N \}, \]

where \( W^k_l = (x[i], \psi^k[i - r]) = \sum_{n=-\infty}^{\infty} x[i] \psi^k[i - r] \),

\( x[i] = \sum_{k=0}^{N} \sum_{n=-\infty}^{\infty} x[i] \psi^k[i - r] \psi^k[i - r], \)

\( P = 2^l - 1, \) and \( N \) is the size of WPC.

Then, we can see that most of the PQD transient (high-frequency) components of the input signal \( x[i] \) can be defined with all WPCs besides the approximation (\( W^0_0 \)). Hence the wavelet packet coefficient (WPC) matrix \( W_k \) of \( x[i] \) can be approximately expressed with \( P \) WPCs as follows:

\[ W_k = \begin{bmatrix} W^1_0 & \cdots & W^{P}_0 \\ \vdots & \ddots & \vdots \\ W^1_P & \cdots & W^{P}_P \end{bmatrix} = \begin{bmatrix} W^1_0[1] & \cdots & W^1_0[N] \\ \vdots & \ddots & \vdots \\ W^P_0[1] & \cdots & W^P_0[N] \end{bmatrix}. \]

In the letter, for the PQD feature detection, we define the WPTM \( \mathbf{M} \) with the WPC matrix \( \mathbf{W}_k \) as follows:
\[ M = \{ M[n] = f([W_1^1[n]], [W_1^2[n]], \ldots, [W_1^P[n]]) | n = 1, \ldots, N \}. \quad (3) \]

In the presented scheme, we can use the following WPTM-based RMS metric
\[ M = \{ M_{rms}[n] | n = 1, \ldots, N \}, \quad (4) \]
where \( M_{rms}[n] = \sqrt{\frac{1}{P} \sum_{p=1}^{P} |W_p^1[n]|^2} \).

Or we can use the WPTM-based MV metric, where each packet has a flag that is enabled (’1’) if the sample value of the packet is larger than a threshold (note that the MV metric has relatively higher complexity than the RMS metric). And, in the MV-based detection step, the PQD edge detection checkers are enabled if the accumulated (summed) value of \( P \) flags is greater than and equal to \( \lceil P/2 \rceil \), where \( \lceil \cdot \rceil \) denotes the ceiling function.

As you can see in Table I, MV metric has relatively higher DR than RMS metric. However, the former one has higher complexity and FER than the latter one. To reduce this FER, we propose the modified threshold using \( k \) factor (see Table I), which will be discussed in detail in next section.

3. Proposed PQD detector

As seen in Fig. 1, the proposed scheme consists of the following two steps: Step 1. De-noising — the noise using WTM is removed, and Step 2. PQD detection — PQD is detected using WPTM with the modified threshold \( TH_M \) (see (8)) where an optimum factor \( k \) is assigned according to the used metric type. Throughout this letter, we assume that the PQD signal is corrupted by Gaussian noise.

![Image](image.png)

Fig. 1. Block diagram of proposed PQD detector.

For more reliable and precise PQD localization, the presented scheme employs double edge detection (even there is some performance degradation) instead of the conventional single edge detection [27, 29]. For this double edge detection, we employ two edge checkers (front and back) and decide that a PQD event is occurred only if both checkers are “ON” in the detection step (Step 2). In the de-noising step (Step 1), a five-coefficient Daubechies’s wavelet filter (DB5) is used for the removal of noise from the input signal \( x[i] \). And, in the detection step (Step 2), a three-coefficient Daubechies’s wavelet filter (DB3) is used for the wavelet packet decomposition (WPD). For the de-noised input signal \( x_d[i] \), in Step 2, we first apply WPD to \( x_d[i] \) to obtain WPCs \( W_p^l \) \((p = 1, \ldots, P)\). For the WPD, we need to select “cost function” that determines the cost value of each node (indicating each WP sub-band) in the binary tree as the optimal representation basis of the input signal. Among several possible choices of the cost function, such as \( l \)-norm, Shannon entropy (SE), and log energy, we choose the SE of coefficient of sub-band \( S \), which is calculated as follows [30]:
\[ SE(S) = -\sum_i S_i log(S_i) \].

Conventional wavelet- (W-Den.) or wavelet packet-based denoising (WP-Den.) schemes often use the universal threshold \( TH_D \) [31]
\[ TH_D = \sigma_a \sqrt{2 \log |N|} \],
where the parameter \( \sigma_a \) is the median of the corresponding metric \( M \) (in the case of MV metric, it will be replaced with WPCs \( W_p^l \), where \( p = 1, 2, \ldots, 2^l - 1 \)), i.e.,
\[ \sigma_a = \text{med}(M) \]

The PQD feature detection is surely dependent upon random characteristics of the PQ signal. In particular, the PQD DR is highly sensitive to random phase offset
\[ \varphi_m = (\tau_m \mod T) \times 2\pi/T \],
where \( T \) is the sampling time and \( \varphi_m \sim U[0, 2\pi) \) is assumed to be uniformly distributed and \( \tau_m \sim U[0, T) \) specifies the delay offset of the starting \((m = 1)\) or ending \((m = 2)\) edge points of the PQD. Fig. 2, where assuming the MV (majority voting) metric is used, shows the average DR curves of a sag signal (assuming SNR = 40 dB) along the phase offset axis; note that DR goes to 0% at around \( \varphi_m \approx \pi/2 \) or \( 3\pi/2 \). It clearly shows the direct effect of the random phase offset \( \varphi_m \) to the performance indices.

![Image](image.png)

Fig. 2. Detection rate versus random phase offset (assuming SNR = 40dB)

| Table I. MV versus RMS metrics |
|--------------------------------|
| Complexity | Higher | Lower |
| Strength | Higher DR | Lower FER |
| \( k \) factor | 1.4 | 1.1 |

To avoid a high FER, we also employ a modified threshold with the “\( k \)” factor that is dependent upon the used metric. An optimal value of \( k \) that would maximize the estimated DR with low FER (< 10%) is obtained via simulation (see Table I). The factor “\( k \)” could be higher (or lower) depending on the used metric type, such that FER is adequately suppressed while maintaining a high DR value. The modified threshold \( (TH_M) \) of the proposed scheme is
determined with the value of \( k \) as follows:
\[
TH_M = k \sigma_d \sqrt{2 \log |N|}.
\] (8)

The proposed PQD feature detection procedure using RMS metric is summarized with pseudo-code (we omit the MV metric for the space and simplicity) as follows.

**PQD detector:**
1. **De-noising**
   Remove the noise from input signal \( x \) using WTM.

2. **PQD Detection**
   - Determine \( k \) value depending on the used metric type.
   - Derive the WP matrix \( W_k \) of the de-noised input signal \( x_d \).
   - all observation window (size = \( N \) samples)
   - Save detection points
   - ‘detection fail’

In our presented procedure, after the WTM-based de-noising step (Step 1), the PQD detection step (Step 2) is processed, where the \( k \) value is assigned according to metric type that determines the threshold \( TH_M \) in (8) (see Table I). In this detection step, double edge detection is assumed. In Step 2, for the determined (and saved) detection points \( DP[t] \) with \( th = TH_M \), the PQD “detection success” flag is enabled, i.e., \( C_{det} = 1 \), only if both detection points indicating the start and end edges are “1” (ON), i.e., \( DP[t_{str}] \) & \( DP[t_{end}] = 1 \). Otherwise, the detection flag fails (“detection fail”, i.e., \( C_{det} = 0 \). The PQD FER flag is enabled, i.e., \( C_{false} = 1 \), when any one of the rest of points becomes “1” even if \( C_{det} = 1 \) — this process is omitted in the pseudocode for simplicity.

### 4. Simulation results

Via simulation, we verify that the proposed WPTM-based scheme has better detection performance than the conventional schemes [15, 27, 31], especially for a random PQD signal with uniformly distributed phase offset \( \varphi_m \) (simply “Random PQD”).

It is also noticeable that the proposed method may greatly reduce FER while maintaining a high DR value. Hence, the proposed scheme could be more robust against random PQD signal conditions than existing schemes.

In Table II, we compare the double edge-based detection performance between existing wavelet-correlation-based detection schemes (WC-Det [15]), wavelet-denosing schemes (W-Den [28, 31]), and proposed schemes. For the simulated PQD, we assume a sag signal with 80 \( % \) pu or a swell signal with 120 \( % \) pu under Gaussian noise channels with SNR = 35 dB or 40 dB. Table II shows that there is not much difference in terms of DR between existing and proposed schemes in the case of “Fixed PQD” (where a fixed phase offset \( \varphi_m \approx 0 \) or \( \pi \) is assumed). However, in the case of “Random PQD” (where assuming uniformly-distributed random phase offset: \( \varphi_m \sim U[0,2\pi] \)), the proposed scheme has superior DR compared to existing schemes, owing to its robustness against random channel conditions. For instance, for the 1.2 \( pu \) swell signal (or 0.8 \( pu \) sag signal), the proposed RMS scheme has 7.1 to 9.4 \( % \) (or 4.0 to 9.6 \( % \) higher) DR than W-Den and 34 \( % \) (or 17.6 \( to 32.6 \) \( % \) higher) DR than W-Den.

**Table II.** Double edge-based performance of fixed/random PQD (DR \( [%] \)) between proposed and conventional schemes, where 80 \( % \) pu (sag) or 120 \( % \) pu (swell) signal under SNR = 35 dB or 40 dB is assumed.

|                  | Fixed PQD  | Random PQD |
|------------------|------------|------------|
|                  | SNR = 35 dB| SNR = 40 dB|
| Prop. (MV)       | 100        | 90         | 90         |
| Prop. (RMS)      | 100        | 90.4       | 93.2       | 93.8       |
| WC-Det.          | 100        | 76.8       | 76.4       | 80.2       |
| W-Den.           | 89.5       | 43.9       | 47.8       | 64.3       | 72.2       |

For the case of “random PQD” signal conditions, Table III compares the performance results between the proposed and existing schemes (WP-Den [27], WC-Det, and W-Den), where the results of single edge-based detection (only start or end) and double edge-based detection (both start and end) are separately shown and compared each other. In particular, WP-Den [27] is the same type of WP-based scheme as our scheme, but uses an interscale or intrascale correlation metric. As mentioned earlier, double edge detection is worse in terms of performance than single edge detection, but would be more feasible for the PQD localization. For this simulation, voltage sag signal samples with 80 \( % \) pu and SNR = 45 dB are generated.

From Table III, we can observe that in the case of single-edge, existing schemes retain a high DR (at least 89 \( % \)) but have a large FER (> 52 \( % \)). Note that in the case of double-edge, WC-Det and W-Det have further degraded DR (80 to 83 \( % \) and FER (56 to 72 \( % \)). And WP-Den maintains a good DR (97 \( % \)) but has worse FER (89 \( % \)). On the contrary, the proposed MV scheme (assuming \( k = 1.4 \)) has high DR (> 95 \( % \)) while maintaining low FER (< 6 \( % \)), whether it is either double-edge or single-edge. Furthermore, it should be
noted that the proposed RMS scheme even with a universal threshold (where $k = 1$) significantly reduces FER (13.8% for single-edge and 14.3% for double-edge) compared to existing schemes. Therefore, we can confirm that the proposed scheme is superior to existing wavelet- or wavelet packet-based schemes over Gaussian noise channels with random phase offset.

| Table III. Single-edge-based and double-edge-based performance of random PQD (DR/FER [%]) of proposed and conventional schemes, where a sag signal with 80% pu under SNR = 45 dB is assumed. |
|---------------------------------------------------------------|
| **Prop. with: TH$_{av}$ (MV) | single-edge  | double-edge |
|---------------------------------|-------------|-------------|
| 96.8 / 5.6                     | 95.0 / 4.0  |
| Prop. with: TH$_{av}$ (RMS)    | 95.4 / 3.9  | 93.5 / 4.5  |
| Prop. with: TH$_{av}$ (RMS)    | 96.6 / 13.8 | 94.4 / 14.3 |
| WP-Den. [27]                   | 97.6 / 88.9 | 96.8 / 89.1 |
| WC-Det. [15]                   | 92.3 / 70.7 | 82.7 / 71.4 |
| W-Den. [28, 31]                | 89.9 / 52.6 | 80.4 / 56.2 |

5. Conclusion

We have presented an WPTM-based PQD detection scheme with a modified threshold that is robust against random PQD channels. Via simulation, we have proved that the presented scheme is superior to existing wavelet- or wavelet packet-based schemes, especially in terms of DR & FER.

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