Power Quality Feature Modelling of Waveform Disturbances for Distribution System Diagnosis

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Abstract. This paper presents a Power Quality (PQ) modelling and filtering processes for the distribution system disturbance recognition learning. typical PQ waveforms with mathematical applications and gathered field data are applied to our models. The process has modules to obtain the waveforms of incipient failures or abnormal operations, trouble condition waveforms in the distribution system through feature extraction and trigger condition techniques. In this regard, we found that proposed extraction criteria of determination rules can interact suitably with our parameter update method to detect and containing the waveforms. Therefore, the recurring analysis can classify the event conditions and ensures disturbance and fault recognitions which containing the waveform information.

1. Introduction

Power Quality (PQ) monitoring to control are emerging issues in perspective of the real-time intelligent power distribution networks. Distributed energy resources (DERs) has become widespread and other bi-directional power sources can lead us to a new environment for the future distribution power system operation as well. Including renewable resources that have grid connection capabilities claim that the necessity of multi directional power flow operations especially in the network management aspect. One of the reasons that the PQ has become an emerging issue is to avoid equipment damage and to determine the cause of the disturbances from newly using power network installations. Essentially, PQ can be used to measure and evaluate the state of distribution system corresponding to effects, stability, abnormal equipment operation, and even fault conditions [1].

In recent years, engineers and researchers in the field of power quality, power system protection, and equipment testing have realized that useful information can be extracted from the waveforms. For the purpose of the equipment condition monitoring including DERs, the methodology to analyse the waveform-type power disturbance data and extract information has attracted a good interest from industry and academia recently [2]. The waveform signature and the feature study have concurrently been conducted with the aim of improving the distribution networks with respect of the system state prediction [3].

With respect to PQ data analytics, the primary goal is to share the signatures of various equipment failures so that researchers can develop appropriate algorithms to identify equipment abnormality. Equipment failures and system faults are infrequently occurred and that possibly be observed from the voltage and current waveforms associated with the devices and locations [4]. The acquired data, however, is not always sufficient to determine the exact nature of problems [5].

In order to make sense of waveform data available, many approaches have been made to model disturbances, classify, and estimate the waveforms [6]. In this regard, we modelled typical PQ

waveforms with mathematical applications and used gathered field data to our models. For three phase meters which measure both voltage and current waveforms, the data is minimum 8 times much including neutral and binary data.

More practical solutions developed in recent years are to store waveform data as long as an PQ event occurs at which particular cycles and samples are allocated or to use more signal processing methods such as frequency transformed data compression and sparse signal decomposition methods. These applied techniques provide signal and feature insights for the PQ recognitions as well [7]-[9]

Thus, our objective is analysing PQ data with respect to monitoring, discriminating, and evaluating the waveform of power disturbances to ensure the system preventative system failure protections and complex system problem estimations. Suggested signal filtering techniques are used for the field waveform noises and feature extractions. Using extraction and learning classification techniques in this paper, we focus on interactive modelling methods to suitably verify the PQ disturbances in this paper. The waveform features and further learning analytic basis are proposed as well [10], [11].

2. Modelling waveforms of disturbances

As short-term and long-term duration of waveforms contain certain information of the system state. Accordingly, voltage and current measurements in field devices at monitoring locations are treated by control, and operation systems such as Distribution Management System (DMS) and Power Quality Management System (PQMS). The systems are basically operating on monitoring acceptable voltage, current, frequency levels and conditionally obtaining intentional waveforms. In practical applications, the system attempts to improve the reliability and quality of distribution network operating conditions as to providing empirical and practical criteria to acquire power quality waveforms.

The steady state components of voltage and current waveforms $w(t)$ with the magnitude of A (p.u.) are modelled as sampling duration having certain cycles of the device performances. Therefore, the ideal state of single phase waves which has angular velocity $\omega = 2\pi f_n$ with the nominal operating frequency $f_n = 60 Hz$ is:

$$w(t) = A \cdot \sin\{\omega t + \delta(t)\} + \eta(t) \tag{1}$$

where, t is the time instant as sampled signals; $\delta(t)$ is the disturbance phase angle; $\eta(t)$ is the modelled noise denoted by the estimated uniform distribution function where $p(\gamma) = 1/(b-a)$ with the parameter (detection set) $\gamma, a \le \gamma \le b$; and the ranges a and b are upper and lower outliers respectively of DMS and PQMS systems (sampled) because of measurement errors and piled up (superposition) noises from the field device. The magnitude of the signal is selectively decided as $A = 1 \pm [u(t-t_1) - u(t-t_2)] \cdot \gamma$ with respect to disturbance signal types that are modelled and generated. t_1 and t_2 represent a lapse of the disturbance duration determined with estimated PQ signal characteristics. Our mathematical model uses general standard criteria based on the PQ signals and the representative disturbance waveforms referenced by IEEE-1159-2009 PQ standard [12, 13]. Through consistently modifying parameters, the actual distribution line signals which are common PQ disturbances are determined as sag, swell, interruption, flicker, oscillation, notch, spike, and harmonics. In addition to the waveform generation, the proposed model has feedbacks and update processes so that the model varies in accordance with newly obtained data and improve the signal identification ability on its own. Accordingly, the modelled wave generation parameters are incorporated into randomize processes within the PQ criteria after obtaining learning weight from the actual event signals. Real distribution line event waveforms obtained from the field devices are combined with the dataset and the proposed model. The data contains not only PQ waveforms and disturbances but also system fault and operation-related waveforms such as temporary / permanent faults, inrush / switching operations, and incipient fault waveforms as illustrated in Fig. 1(a)-(c).
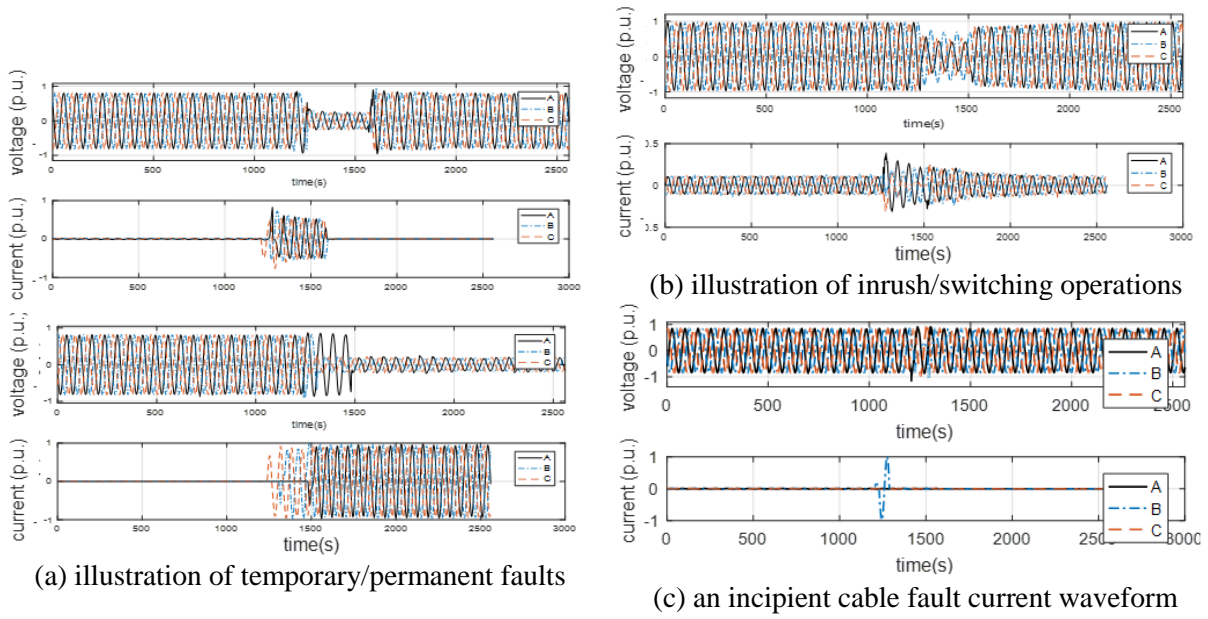
(b) illustration of inrush/switching operations

(a) illustration of temporary/permanent faults

(c) an incipient cable fault current waveform

Figure 1. Types of field event waveforms for signal feature variations.

In accordance of the waveform acquiring scheme, various types of measurements (e.g., voltage, current, switch status, temperature, and oil level) are recorded in the field at the distribution transformer and feeder devices. Further studies will have combined to the conventional data to make state inference of predictive fault detections.

3. Waveform pre-processing

PQ event signals are detected and identified by means of real time measurement and calculation processes as sampled waveforms. The processes have modules to obtain the waveforms of incipient failures or abnormal operations, trouble condition waveforms in the distribution system through feature extraction and trigger condition techniques. We found that proposed trigger and extract criteria of determination rules interact suitably with our parameter update method to detect and containing the waveforms so that the recurring analysis can classify the event conditions.

3.1. Symmetrical component processing

Since the distribution line operate in the balanced state of three phases, the PQ disturbances disrupt the synchronization therefore the distortion occurs concurrently. Symmetrical components are primarily used in the power system analysis in terms of evaluating the unbalanced state phasors of the balanced three phase system. The approach is to extract unbalances of the phase angles in the vaguely scattered event signals compared with other phases, currents, and voltages. Moreover, due to the real-time measurement burdens on the line devices, we minimize data by extracting a single phase symmetrical value instead. Simultaneity of the disturbance phase and other steady states is derived as an index of disturbance trigger conditions. We use $v_d^-(t)$, $\vec{i}_d^-(t)$ of the negative sequence components where the disturbance phases (or certain any phase) $d \in a, b, c$ and $v_{abc}^{-,+}(t)$, $\vec{i}_{abc}^{-,+}(t)$ of three phase of sequence states to estimate disturbances because these components represent differences of each phase and only returns near zero values in the steady state otherwise. The negative sequence component matrix is obtained as follows:

$$\mathbf{v}_{a,b,c}^- = \begin{bmatrix} v_a^-(t) \\ v_b^-(t) \\ v_c^-(t) \end{bmatrix} = \frac{\sigma^c}{3} \begin{bmatrix} 1 & \alpha_2 & \alpha_1 \\ \alpha_1 & 1 & \alpha_2 \\ \alpha_2 & \alpha_1 & 1 \end{bmatrix} \cdot \begin{bmatrix} v_a(t) \\ v_b(t) \\ v_c(t) \end{bmatrix}$$

(2)

where, $\alpha = e(j \cdot 2\pi / 3)$ is the Fortescue operator. Here, as it is a frequency domain, the angle can shift into the time domain concept based on the time-dependent variables [14].

The α is converted as a time shifting operator by calculating the of samples in a third of cycle samples as $1/3f$ at a determined sampling frequency f. This is a domain change process from frequency domain of $e^{j2\pi}/3$ to $1/3$ sampling rate for the digital measurements and the measurements are subsequently scaled and normalized when the waveforms are acquired by the field devices. The normalization parameter σ^c is determined as:

$$\sigma^c = \begin{cases} 1 & \text{modelled} \\ \dfrac{v_r}{\lambda_2^c} \cdot \lambda_m^c & \text{field obtained} \end{cases}, \tag{3}$$

where v_a^r represents the rating ratio value; λ_2^c and λ_m^c are the secondary value ratio and the channel multiplier of COMTRADE (Common format for Transient Data Exchange for power systems) format waveform [15] respectively when it comes to the field obtained waveforms. In addition to that, the sum of negative sequence components $v_t^{abc-} = (v_t^{a-} + v_t^{b-} + v_t^{c-})/3$ is applied for the magnitude of distortions for the saved events.

The Phase calculation is based on the phase locked loop (PLL) modulation with real-time phase shifts. Despite of the fact that sequence components are decomposed successfully obtained, actual samplings are usually not separable by exact 1/3rd of samples that makes sequence component noises. We handle the noise and gaps following feature extraction steps such as additional filtering.

3.2. Signal filtering (smoothing / de-noising)
The noise especially on field measured waveforms has a particular measurement error which occurred by following reasons. One is due to measurement errors from the installed field devices (like switches) using potential and current transformers which have physical (hardware) accuracy limitation that related with sensor performances.

The other one is calculation deviations by PLL, even though the problem can deal with increasing the samples for the measurement cycle, the three phases signal basically make separating deviation by phase shifting on the symmetrical calculations. The PLL phase shifting is not exactly be separated by 1/3rd cycle of the nominal frequencies due to sampling can be archived typically 64 ~ 128 samples in field devices and that are not the times of thirds. The noises are normally recognizable when tracking the waveform patterns since majority of overlapped data is not generally in steady state. When it comes to symmetrical negative sequences, the frequencies are distinctively different near the zero region so that if we shrink the filter based on statistical signal process methods, the noises can be eliminated except the waveform features are mostly remained smoothly.

We suggest the filter that updated intermittently for cancelling the sampling noises using the histogram based analysis. The noise smoothing was achieved by generating a cumulate filter proposed in this paper which is similar to opposite Gaussian mask of negative symmetrical values. Thus, if we treat signal $h(t)$ as a negative sequence value of $\mathbf{v}_{a,b,c}^-$ with disturbance phase $v_d^-(t)$, then $h(t)$ apparently has a detecting characteristic in which the unbalance exists, otherwise the values are zero. Therefore, the $h(t)$ has majority values of zero except the disturbance, and the noises for the histogram analysis, the zero values are not necessary so that we can filter the sampling noises. The histogram that has bins with commonly used Square root rule and Sturges (Sequence value histogram) method as:

$$b = \begin{cases} \lceil \sqrt{h(t)} \rceil, & \text{square root} \\ \lceil 1 + \log_2 h(t) \rceil, & \text{sturges,} \end{cases} \text{ where, } h(t) \neq 0, \tag{4}$$

where, the braces indicate the ceil function and Sturges method implicitly assumes an approximately normal distribution. From the histogram, we can model a statistical distribution of quantified histogram $H(h)^b$ with b bin levels at a set of the region. The relation is given between the measured

value and distribution and the noise can be perceived with applying threshold at which the number of $H(h)^b$ considerably exceeds the expected distribution. The gaussian fitting is derived as the histogram stochastic signal $p(b) \sim N(\mu, \sigma^2)$ for normal distribution and the upper, under thresholds are

$$\delta^{under} = H(h)^{axis}_{first},$$
$$\delta^{upper} = H(h)^{axis}_{last},$$
$$\text{where,} \quad H(h)^b > C \cdot p(b). \tag{5}$$

If histogram $H(h)^b$ frequencies exceed the probability fitting value, the points where criteria with the weight parameter C are applied to the filtering range starting from the first value to the last exceed point. Consequently, the filtering conditions are reflected on time series waveform symmetrical values as shown in Fig. 2, and the filtered values $h(t)_F$ are obtained as follows:

$$h(t)_F \begin{cases} 0, & \delta^{under} < h(t) < \delta^{upper} \\ h(t), & \text{otherwise} \end{cases} \tag{6}$$
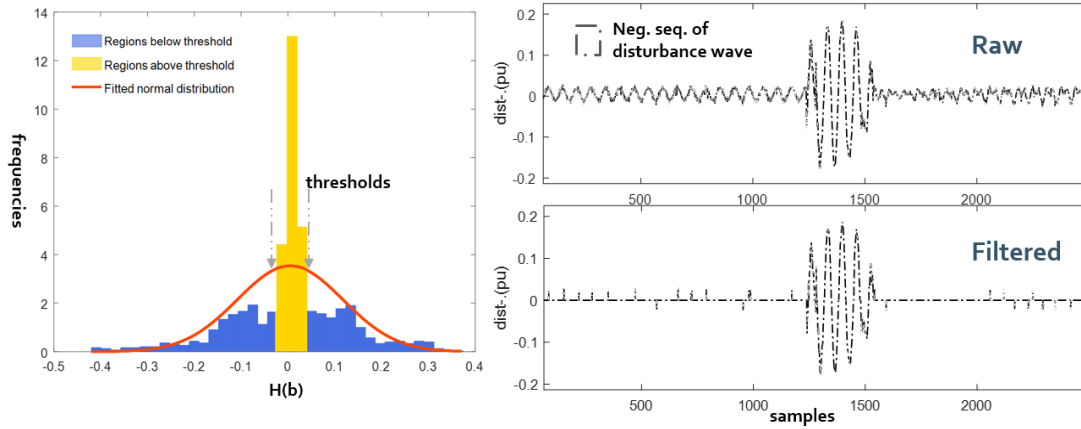

Figure 2. Illustration of the sequence value histogram and the applied noise filtering example

4. Feature extraction models and trigger conditions for waveforms

PQ waveforms illustrate diverse pattern on dense samplings which closely sustaining 60Hz speed in real time. Accordingly, the waveform need to be transformed to classify the noticeable disturbances so that the extracted features are used for PQ detection and for triggering the signal measurement previously at the field devices. In addition, we suggest criteria for the feature extractions to discover desired signal from the patterns. When we detect changing points of the unbalanced signal as disturbance occurring, proposed triggering condition assists to acquire the waveforms for the further signal learning processes. Some of basic features are derived to measure the grouped features as following Table 1 for the further pattern recognition processes.

Table 1. Features of converted waveforms

Features	Equation
1-norm (magnitude)	$f_1 = \omega_1 \cdot \left\| h(t)_F \right\|_1, \ \forall t$
Signal deviation	$f_2 = \omega_2 \cdot \sum_{t=1}^{T} \left(h(t)_F - \bar{h}_F \right)^2, \ \forall t$
Disturbance duration	$f_3 = \omega_3 \cdot \sum_{t=1}^{T} \left| \text{sign} \left(h(t)_F \right) \right|, \ \forall t$
Zero crossing counts	$f_4 = \sum_{t=1}^{T} \left| \text{sign} \left(h(t-1)_F \right) - \text{sign} \left(h(t)_F \right) \right| \cdot \omega_4, \ \forall t$

Furthermore, we combine features which readily represents the distinctive feature regions as per PQ waveform of extracted signals. Therefore, the features with respect to the type of PQ pattern are determined as:

$$f_E^m = (f_1 + f_3) / \sigma_s^m$$
$$f_E^f = \sigma_s^f \cdot (f_2 + f_4)$$

(7)

Consequently, the triggering conditions are determined in accordance with feature criteria of desired power quality signals. measuring devices consistently solves following values whether the signal would exceed the trigger condition in which we consistently have set for sparingly occurred disturbances.

5. Results

Our model suggests the PQ feature extraction processes with regard to the waveform modelling and field obtain PQ data by means of waveform signal processes. The waveform of selected 8 disturbances are modelled with randomized parameters of IEEE-1159 PQ ranges. The range, parameters and weights are updated regarding field waveform obtained. Along with voltages, currents have same process to obtain the waveform features, the voltage is normalized apart from some of ratings and filters. For the reason that changing loads are causing the distortion in the voltage waveform, the different patterns can be obtained from the current variation as shown in Fig. 3 and Fig 4.
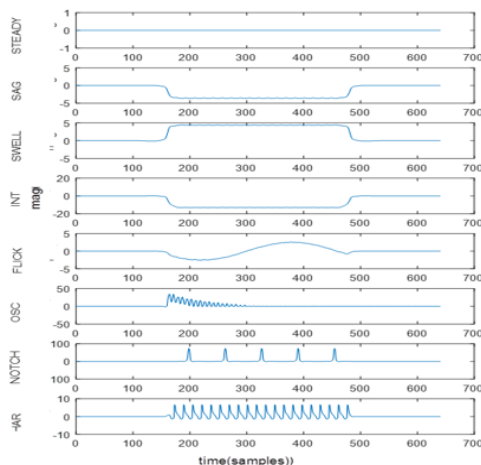

Figure 3. Filtered symmetrical component values (Neg.) of modelled PQ waveforms.
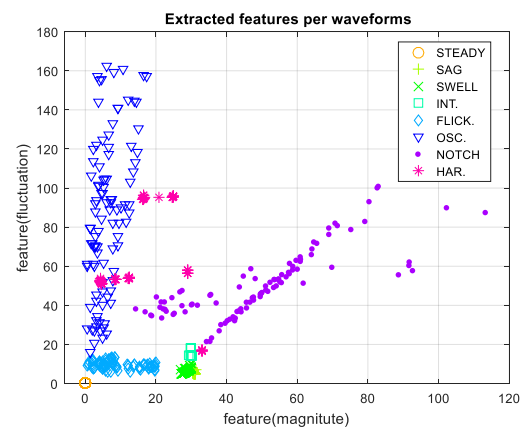

Figure 4. Extracted signal features of modelled PQ waveforms.

6. Conclusion

PQ disturbances in the voltage and current waveforms indicate different types of patterns and variations. The modified technique based on the symmetrical components in time domain was proposed in this paper for the PQ disturbance detections and classification. Our method is based on the fact that obtained waveforms from the suggested trigger conditions contain potential information for abnormality detections. The extracted features will sequentially be applied to estimation and recognition learning modules of further studies.

7. References

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