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Identifying Microgrid Disturbances Using Independent Component Analysis

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Abstract—This paper focuses on the identification of islanding and power quality (PQ) disturbances in microgrids using signal processing techniques such as wavelet transform (WT) and independent component analysis (ICA). WT is known to be a suitable approach for detecting various disturbances such as PQ events, islanding, transients and harmonics due to better multi-resolution analysis. However, it is observed that WT is susceptible to increased noise levels or transients in the voltage signal extracted at the point of common coupling (PCC). Therefore, ICA is proposed to find the significant components of the voltage signal which will help in identifying the disturbances more accurately. A comparative analysis, both qualitative and quantitative, is presented in this paper to demonstrate the superior detection capabilities of the proposed ICA approach when compared with the WT approach under noisy scenarios. The proposed technique is validated in real time using OPAL-RT's OP5600 to demonstrate its feasibility for practical applications.

Index Terms—Identification, independent component analysis, islanding, power quality, wavelet transform.

I. INTRODUCTION

Power quality (PQ) disturbances in microgrids may be caused by factors such as interfacing converters, intermittent renewable energy resources and switching operations. To maintain microgrid stability, PQ issues need to be identified and mitigated quickly. Moreover, grid-connected microgrids may become islanded due to disturbances in the upstream grid which may lead to large deviations in the system parameters [1]. Irrespective of whether an islanding or a PQ disturbance occurs, the signal frequency varies with respect to time. Consequently, it is necessary to estimate and extract both time and frequency information from the signal. Fourier Transform (FT) is one possible option to obtain the frequency information from the signal. However, it is incapable of extracting the time information which plays an important role in the detection process [2]. In order to extract explicit information about the frequency with time localization, Short-Time Fourier Transform (STFT) [3] has been employed for detecting disturbances. STFT provides time-frequency resolution which helps in detecting disturbances. For a variety of non-stationary PQ disturbances like transients, flickers and harmonics, STFT may not be able to track disturbances present in the voltage/current signal since it uses a fixed-size window. Hence, it is imperative that the window size is adaptive and varies with the changing signal frequency. Consequently, the

WT approach was proposed to provide time-frequency multi-resolution analysis with an adaptive window size which varies inversely with the varying signal frequency [4]–[6]. Furthermore, some researchers have investigated the potential of using hybrid wavelet and Fourier transforms for analysing harmonics in power systems [7]. The hybrid combination has proven to be effective in monitoring transients and harmonics present in the voltage signal. Frequency and spectral estimations of signals with harmonics and inter-harmonics have been reported in previous works for PQ analysis [8], [9]. The authors of [10] performed disturbance analysis in the time-frequency domain and showed in their experimental studies that WT performs better than STFT. Detection of voltage sags and transient disturbances are done using WT and recursive algorithms. The advantage of WT is that it does not assume that the power system signal is either stationary or periodic [11], [12]. Change detections during disturbances are achieved by decomposing the signal simultaneously into time and frequency planes [13]. The simulated voltage disturbance detection approach was introduced using WT with decision making techniques [14]. Adaptive wavelet network (AWN) [15] was proposed to analyse PQ disturbances generated synthetically. WT was also used online for classifying PQ disturbances using the nearest neighbourhood technique to reduce the complexity [16].

It has been observed that WT fails to identify disturbances when noise levels in the voltage signal increase. Denoising the signal could improve WT performance at the cost of higher detection times. To overcome this, ICA [17], [18] is proposed in this paper as an efficient technique for detecting islanding and PQ disturbances accurately even under noisy conditions. ICA is based on finding the linear transformation of latent variables which are statistically independent and non-Gaussian. This characteristic of ICA is explored in this paper to identify islanding and PQ disturbances. In addition, statistical features like standard deviation (SD) and energy are extracted under different PQ and islanding disturbance conditions for supporting disturbance detection. These values are calculated for normal, disturbance as well as noisy conditions. To distinguish between islanding and PQ disturbances, these values are compared to establish a threshold value. If the SD and energy values are greater than their respective thresholds, islanding is detected. Conversely, if they are less than their respective thresholds, PQ disturbances are detected.

To demonstrate and validate the viability of the proposed approach, some case studies are performed in real time using OPAL-RT's OP5600.

This paper is organized as follows: Section II presents the microgrid system model. This is followed by a description of different detection techniques in Section III. The proposed detection methodology is explained in Section IV followed by simulation results and discussions in Section V. Finally, some concluding remarks are presented in Section VI.

II. SYSTEM CONFIGURATION

The microgrid (MG) system considered in this paper comprises a wind turbine generator, a photovoltaic system, a fuel cell and a hydrogen storage system. Individual elements are connected to their respective DC or AC buses through interfacing power converters as shown in Fig. 1. Some of the power at the DC bus is converted to hydrogen gas and stored for use by the fuel cell depending on the load demand. The system is designed such that a decrease in power output from one source is compensated by an increase in the power output from other sources. This enhances the reliability of the power supply. The AC bus in Fig. 1 is treated as the PCC from where the voltage waveforms are extracted for processing using either WT or ICA to identify the normal and disturbance operating conditions. Various PQ disturbances are created in the MG by switching loads. Islanding disturbances are created by isolating the MG suddenly due to faults in the upstream network. These disturbances are identified by WT or ICA based on suitable threshold values. The threshold values for disturbance detection are selected by comparing performance indices such as SD and energy for noiseless and noisy operating scenarios. The MG components are modelled using MATLAB/Simulink wherein the different parameter values are derived from [1], [4].

Figure 1: Block diagram of MG configuration.

III. PQ/ISLANDING DISTURBANCE DETECTION TECHNIQUES

A. Wavelet Transform (WT)

WT is a modification of STFT and is designed to provide time-frequency multi-resolution analysis with an adaptive win-

dow which varies inversely with frequency [4]- [5]. Continuous wavelet transforms (CWTs) may be helpful for simulation studies but are not feasible for real time applications. Consequently, discrete wavelet transform (DWT) which reduces the computational complexities of CWT, has been proposed for real time applications. In DWT, the time and frequency scale information of a real time digital signal is obtained using a set of low-pass and high-pass digital filtering techniques. DWT-based multi-resolution analysis decomposes the voltage signal into different levels which consist of one-half of band low pass filters and one half band high pass filters as shown in Fig. 2.

Figure 2: Decomposing a signal using DWT.

The process of decomposition continues till all the frequency components are filtered out. During each level of decomposition, the frequency range is halved and the number of samples is reduced by down sampling so that the frequency information is retained. The down sampling is done to reduce the size of the transformed coefficients without losing any disturbance and frequency information in the original signal. The sampling frequency considered in this paper is 5kHz. Daubechies (db) is used as the mother wavelet for the analysis [6]. The voltage signal at PCC is passed through a series of low and high pass filters for four levels of decomposition to extract information about different frequency bands. Based on testing for different mother wavelet and decomposition levels, db4 is observed to provide the best possible results for the detection of islanding and PQ disturbances. By extracting the voltage signal at PCC as $v(t)$, the CWT can be expressed as:

$$CWT(v, p, q) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} v(t) \psi^* \left(\frac{t-q}{p} \right) dt \quad (1)$$

where p and q represent the scaling (dilation) and translation (time shift) parameters respectively and ψ is the wavelet function. The DWT of the voltage signal in discrete samples is given by:

$$DWT(v, p, q) = \frac{1}{\sqrt{p_0^m}} \sum_k v(k) \psi^* \left(\frac{n - kp_0^m}{p_0^m} \right) dt \quad (2)$$

where p and q in CWT equation are replaced by p_0^m and q_0^m ; k and m are integers. Now, after decomposition of the voltage signal $v(t)$, the approximate $c_j(k)$ and detail $d_j(k)$ coefficients are represented as follows [6]:

$$c_j(k) = \sum_{m=-\infty}^{\infty} c_{j+1}(m) h(m-2k) \quad (3)$$

$$d_j(k) = \sum_{m=-\infty}^{\infty} c_{j+1}(m)h_1(m-2k) \quad (4)$$

WT decomposes the signal based on dilation and translation of wavelets. The original signal is recovered after the decomposition and synthesis processes, without losing any actual information.

B. Independent Component Analysis

ICA is an efficient tool for processing a large amount of data with non-Gaussian characteristics. It can extract hidden intrinsic features present in high-dimensional data. Using ICA, a multivariate signal can be decomposed into sub-components which are statistically independent and non-Gaussian in characteristic [17]. It is a modified version of the conventional blind source separation (BSS) methodology used in speech processing. ICA works accurately in the non-deterministic modelling of source signals [17]- [18]. To achieve this, the following assumptions are made: (i) source signals are statistically independent (ii) one of the source signals is Gaussian in nature and (iii) number of observations M is greater than the number of sources N .

ICA can be modelled by employing different statistical methodologies such as: (i) maximization of non-gaussianity (ii) minimization of mutual information (iii) maximum likelihood estimation and (iv) tensorial property. In this paper, it is designed based on the first technique because of its property of extracting significant components which are independent and non-Gaussian. This helps in detecting islanding and PQ disturbances in microgrids. Usually, ICA follows the BSS methodology to estimate the input sources from a mixture of them. Blind in this context means that the input sources in the mixture are initially unknown. ICA transforms the input data to independent sources to recognize their characteristics for making them ready for any signal analysis. This concept has been popular in various applications such as speech processing and bio-medical signal processing [18].

C. ICA estimation by maximization of non-Gaussianity

To perform BSS, the non-Gaussianity in the form of negentropy $N(y)$ is estimated based on differentiating the normalized entropies. To obtain mutual information between the sources, $N(y)$ is maximized. This measures the mutual information between independent input random variables. The negentropy values of these variables are always greater than zero [17].

$$N(y) = E(y_{\text{gauss}}) - E(y) \quad (5)$$

The differential entropy E of a random vector y with density $p_y(\eta)$ is defined as:

$$E(y) = - \int p_y(\eta) \log p_y(\eta) d\eta \quad (6)$$

In these equations, negentropy is measured by estimating the probability function of the unknown input source signals using the following expression:

$$N(y_i) = N(H(w_i^T x)) = [H\{G(w_i^T x)\} - H\{G(y_{\text{gauss}})\}]^2 \quad (7)$$

Here, H is the statistical expectation and G is a non-quadratic function. Consider a linear mixture of n input variable $x_1, \dots, x_n$ which can be expressed as a linear combination of n mutually independent random components $s_1, \dots, s_n$ with the help of mixing coefficients $a_1 \dots a_n$:

$$x_j = a_1 s_1 + a_2 s_2 + \dots + a_n s_n \quad \forall j \quad (8)$$

$$x = \sum_{i=1}^n a_i s_i \quad (9)$$

It is assumed that each input variable x_j and every independent component s_i is a random variable rather than a time varying signal with zero-mean value. Using matrix notations, the random input vector x consists of the input mixture $x_1, \dots, x_n$; random vector s consists of independent components $s_1, s_2, \dots, s_n$ and the column matrix A contains mixing coefficients $a_1, a_2, \dots, a_n$. In matrix form, this is expressed as follows:

$$x = As \quad (10)$$

This statistical model expressed in the above equation is treated as the ICA model formulation. Here, the model is generative and the independent components are latent variables which cannot be observed directly. The unknown matrix x can be estimated by evaluating A and s using linear combination. It is assumed initially that the components are statistically independent and are non-Gaussian in nature [17]. Now, by estimating the matrix A , the inverse matrix $W = A^{-1}$ can be computed to extract the independent components $s_1, s_2, \dots, s_n$. Thus, the following equation can be expressed:

$$s = Wx \quad (11)$$

IV. PROPOSED DETECTION METHODOLOGY

This section describes the methodology used for the detection and identification of islanding and PQ disturbances. The MG model described in Section II is developed using MATLAB/Simulink. Different PQ disturbances are created by switching linear or non-linear loads in the MG. Islanding events are created by suddenly isolating the grid from the MG with the wind turbine, solar PV and fuel cell systems still supplying power to the local load. The different types of disturbances considered in this paper are presented in Table I. It is observed that these disturbances distort the voltage signal at the PCC. The distorted voltage signal extracted from the PCC is processed using WT and ICA to identify the type of disturbance. The detection procedure using WT is presented in the flowchart shown in Fig. 3. As shown in Fig. 3, the signal extracted from the PCC is passed through WT to obtain the detail coefficient as a function of time. Performance indices such as SD and energy are calculated for different disturbances and compared with the selected threshold values for identification purposes.

Similarly, the algorithm for detecting islanding and PQ disturbances using the proposed ICA technique is described below. Any abrupt change in the voltage profile at the PCC of the MG is recognized by ICA using the flowchart shown in Fig. 4. The ICA index is evaluated for the detection objective

TABLE I: Descriptions of Different Disturbances

Class	Islanding/PQ disturbance details
C1	Islanding disturbance
C2	Sag due to increase in load at PCC
C3	Swell due to, decrease in at PCC
C4	Harmonics due to connection of non-linear load at PCC
C5	Momentary Interruption due to faults and isolation of resources from load at PCC
C6	Transients due to load switching and transformer energisation at PCC
C7	Flicker due to continuous load change at PCC
C8	Combined swell with harmonics
C9	Combined sag with harmonics
C10	Combined harmonics with momentary interruption
C11	Combined swell with harmonics followed by 3-ph fault

through the following steps: i) The data for islanding and PQ disturbances is extracted from the voltage signal at the PCC of the MG. ii) The data is pre-processed to remove redundant information thereby minimizing the complexity and computational burden. This is done based on de-correlation of unwanted data by removing second order dependencies [17]. iii) This step is used for whitening the data to reduce the dimension for minimizing the data size and extracting the significant feature data. iv) The principal data components are evaluated and the processing is proceeds to the next stage. v) In this step, the independent components are evaluated by using the fixed point iteration methodology [17]- [18]. vi) This step involves the separation of the matrix W_f along with independent components, s_f of the voltage signal data extracted from the PCC. The independent variables x_f are obtained from the signal. vii) The ICA index is evaluated using the following equation:

$$Index_{proposed}(k) = (normalised(abs(W_f(k) * x_n(k) - s_f(k)))^2) \quad (12)$$

The disturbance is identified when $Index_{proposed}(k)$ is greater than the index threshold value, $(Index_{proposed})_{threshold}$. The index threshold value, $(Index_{proposed})_{threshold}$ is selected by comparing the index values for normal and different disturbance operating conditions.

V. SIMULATION RESULTS AND DISCUSSION

This section presents results from the simulation studies performed to detect islanding and PQ disturbances in the MG shown in Fig. 1. Different PQ disturbances such as voltage sag, swell, interruption, harmonics, transients, flickers and their combinations are created in the MG under linear/non-linear load switching and fault conditions. The system parameters for the simulation studies are taken from literature [1], [4]. The case studies under different operating conditions are represented in the following sub-sections.

A. Detection of single event power quality disturbances

Power quality disturbances such as voltage sags, swells and notches are created to test the detection capabilities of WT and ICA respectively. The voltage signal at PCC is extracted and passed through WT and ICA for detecting the disturbance. First, a voltage notch is generated in the voltage profile by sudden load switching. The detection results using WT and

Figure 3: Flowchart for detection of disturbances using WT.

Figure 4: Flowchart for detection of disturbances using ICA.

ICA are shown in Fig. 5a. The 3-phase voltage signal with a notch at about 80s is shown in the first graph of Fig. 5a. Phase B of the 3-phase voltage signal is shown in the second graph of Fig. 5a. The third and fourth graphs show the ICA index and WT detail coefficient respectively when the phase B signal is processed. They clearly display a spike at the point of disturbance (at 80s), thereby identifying the instance of notch in the voltage signal. To test the efficacy of the proposed technique, synthetic noises of different levels are added into the voltage signal at the PCC. From the analysis, it is observed that the detection of disturbances in the voltage signal is greatly affected when the noise levels rise above 25-dB. To demonstrate this effect, a notch with 25-dB noise is generated and processed using WT and ICA. The voltage signals along

Figure 5: Detection of notch using WT and ICA with (a) no-noise (b) 25-dB noise.

with detection results using the performance coefficient or index are shown in Fig. 5b. It is observed from the simulation results that the ICA detects the notch instance even though there is some noise in the ICA index whereas WT is unable to identify the instance of notch in the voltage profile. This clearly suggests that WT is fully affected while ICA is only partially affected by the presence of noise. It is also clear that ICA is relatively more efficient in detecting the PQ disturbance under noisy conditions.

Similarly, a voltage swell is created by suddenly decreasing the loads at PCC. The voltage signals and detection coefficients or indices are shown in Fig. 6a. As there is no noise in the voltage signal, both WT and ICA can detect the swell event without any difficulty. The superior detection capability of the proposed ICA technique is demonstrated by adding 25-dB noise to the voltage signal extracted at the PCC. The corresponding simulation results are shown in Fig. 6b. Similar to the earlier case study, WT completely fails to detect the swell event in the presence of noise while ICA easily detects the same swell event despite the presence of noise.

B. Detection of multiple events power quality disturbances

The detection capabilities of WT and ICA in the presence of back-to-back disturbances are compared in this section. To

Figure 6: Detection of swell using WT and ICA with (a) no-noise (b) 25-dB noise.

create consecutive disturbances, the load is first decreased. This is followed by a three-phase fault. The disturbances caused by these actions are reflected in the voltage profile shown in Fig. 7a. The presence of non-linear loads also injects harmonics in the voltage waveform. This waveform is passed through WT and ICA and the detail coefficient and index are shown in Fig. 7a. It is observed that ICA effectively tracks the harmonics and swell followed by fault. This is reflected in the ICA index shown in the third graph. It is also observed that the voltage signal harmonics are tracked in the index profile where the magnitude increases or decreases at the corresponding swell due to load reduction and sag due to faults. It is observed that the WT is unable to detect the disturbances caused due to the presence of harmonics in the voltage signal. To test the efficacy of the ICA approach, 25-dB noise is added to the voltage signal. The noisy signal is then processed using ICA and WT and the results are shown in Fig. 7b. It is observed that the disturbances are tracked to some extent by ICA while WT does not identify the three different types of disturbances present simultaneously in the voltage profile.

C. Detection of disturbances in OPAL-RT

This section demonstrates the practical applicability of the ICA approach through real-time simulations performed using OPAL-RT's OP5600. The results of this case study are shown in Fig. 8. The PC has a 32-bit Windows 7 operating system with Xilinx v10.1 and MATLAB 2013a. A model of the MG described in Fig. 1 is built using MATLAB/Simulink

Figure 7: Detection of simultaneous swell and fault with harmonics using WT and ICA with (a) no-noise (b) 25-dB noise.

and is tested in OP5600 with the objective of detecting disturbances. The sag in the voltage signal is generated by suddenly increasing the load demand at about 9.05s and is detected using the ICA technique. It is observed from Fig. 8b that the sudden decrease in voltage magnitude by about 60% is characterized by a corresponding decrease in the envelope produced by ICA. Similarly, a swell in the PCC voltage is obtained by a sudden decrease in load demand at about 9.24s. This voltage swell, shown in Fig. 8c, is detected and effectively characterized by an increase in the ICA index. The results obtained from this real-time simulation support the simulation results presented in previous sections which were obtained using MATLAB.

D. Discriminations of islanding and PQ disturbances

This section describes the methodology used to distinguish islanding events from PQ disturbances. The voltage signal extracted at the PCC under islanding or PQ disturbance conditions is processed using WT and ICA to estimate the WT detail-coefficient and ICA index. Performance indices (PIs) such as SD and energy are calculated for different cases using statistical formulae and their values are presented in Table II. By comparing the SD and energy values for islanding and PQ disturbances under no-noise and 25-dB noise conditions, a threshold value of 10 is selected. When the

(a)

(b)

(c)

Figure 8: Detection of disturbances in OPAL-RT (a) set-up of real time digital simulator OP5600 (b) sag (c) swell.

PIs are greater than the threshold value, the disturbance is recognized as an islanding event. Otherwise, if the PIs are less than the threshold value, the event is identified as a PQ disturbance. While the exact type of PQ disturbance cannot be identified, this method helps in distinguishing islanding events from PQ disturbances. The following section describes how a feature plot can be used for identifying different types of PQ disturbances and islanding events through clustering.

E. Identification of power quality disturbances using feature plots

Once the disturbances are detected using WT and ICA, the next step is to identify the type of event occurring in the MG. For this, the PCC voltage signal is passed through WT and ICA to calculate the detail coefficient and index respectively. From these profiles, SD and energy are calculated. Different PQ events are considered for the determination of a feature matrix which is used to draw feature plots by taking the feature data for all 11 types of PQ disturbances. The feature plot efficiently clusters different groups of PQ disturbances thereby identifying individual events. This helps in identifying

TABLE II: Comparison of Performance Indices for ICA

Class	No noise		With 25-dB noise	
	SD	Energy	SD	Energy
C1	14.456	15.251	18.782	24.056
C2	0.569	1.657	2.044	3.782
C3	1.826	2.456	3.345	4.263
C4	1.562	2.142	4.231	5.826
C5	0.453	0.942	1.362	2.928
C6	2.824	4.435	4.625	6.261
C7	1.262	2.618	3.271	4.864
C8	1.027	3.228	3.286	5.285
C9	0.953	1.837	2.482	4.065
C10	0.873	1.764	2.165	3.556
C11	2.837	3.886	4.877	7.853

Figure 9: Identification of different class of PQ disturbances using feature plot.

the type of disturbances occurring in the MG. In the feature plot shown in Fig. 9, it is observed that the disturbances from class 1 to class 11 are clustered accurately at different locations. This suggests that the different types of disturbances are distinguished from each other based on the feature data being clustered using the feature plot.

VI. CONCLUSION

This paper presented the detection of islanding and PQ disturbances using WT and ICA under different operating conditions. Voltage signals were extracted at PCC under different operating conditions and were passed through the signal processing techniques to detect the disturbances. WT detected disturbances effectively except when the input voltage signal contained noise or harmonics. ICA could easily identify islanding and PQ disturbances under all operating conditions including when the input voltage signal contained noise. Performance indices such as SD and energy were estimated for all disturbances to detect the disturbances. Based on the comparison of PIs under no-noise and 25-dB noise conditions, a threshold of 10 was selected which distinguished the islanding from the PQ disturbances. Moreover, disturbance detection using the ICA technique proposed in this paper was tested in real time using OPAL-RT's OP5600, thereby validating the practical applicability of the offline MATLAB simulation results. Different types of disturbances were identified based on clustering in feature plots. Based on the results of various case studies performed in this paper, it may be concluded that the ICA technique provides better performance when compared to WT for all operating scenarios.

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