## T. Radil<sup>1</sup>, P. M. Ramos<sup>1,2</sup>, F. M. Janeiro<sup>1,3</sup>, A. Cruz Serra<sup>1,2</sup>

 <sup>1</sup> Instituto de Telecomunicações Portugal, e-mail: tomas.radil@lx.it.pt
 <sup>2</sup> Technical University of Lisbon Depeartment of Electrical and Computer Engineering Portugal, e-mail: pedro.ramos@lx.it.pt, acserra@ist.utl.pt
 <sup>3</sup> Universidade de Évora Departamento de Física Portugal, e-mail: fmtj@uevora.pt

# DSP BASED POWER QUALITY ANALYZER FOR DETECTION AND CLASSIFICATION OF DISTURBANCES IN A SINGLE-PHASE POWER SYSTEM

This paper describes the prototype of a power quality analyzer designed for real-time detection and classification of disturbances that occur in a single-phase power system. The standalone DSP-based analyzer implements previously developed algorithms for detection and classification of power quality disturbances such as transients, waveform distortions, sags, swells and interruptions. Its performance was verified during long term monitoring of the power system.

Keywords: power quality, event detection, mathematical morphology, digital signal processor

#### 1. INTRODUCTION

Reliable and real-time monitoring of the quality of electric power has become an important task in recent years and a major concern for its consumers, manufacturers and distributors. Several methods for detection and classification of power quality (PQ) disturbances that occur in a power system were presented. As far as the detection of transients and similar disturbances is concerned, these methods usually rely on some time-frequency representation of the power system's voltage signal such as the wavelet transform [1] or the short time Fourier transform [2]. The wavelet transform, which is the mostly used method, requires a significant amount of computational power since decomposition of the input signal up to the 6<sup>th</sup> level is usually required for reliable detection of disturbances [3].

The computational burden represented by the wavelet transform led to the development of a new and simpler detection method [4]. The proposed method was implemented in a PC-based measuring set-up and its ability to detect and subsequently classify a wide range of PQ disturbances was verified during long term monitoring of the power system [5]. This paper describes the improved version of the algorithm that removes some of the weak points of its predecessor (e.g. limitations in the frequency range of detected disturbances or in determination of the disturbance's duration) and its implementation in a standalone DSP based prototype of a PQ analyzer.

#### 2. METHOD FOR DETECTION AND CLASSIFICATION OF DISTURBANCES

The disturbances that occur in a power system can have significantly different parameters. The method for disturbance detection has to deal with wide ranges of frequencies, magnitudes and durations of disturbances. In Table 1 the ten most common categories of disturbances encountered in a single-phase power system are presented [6].

With respect to the different nature of individual disturbances, the categories of disturbances were divided into two groups, so that an optimized detection and classification method tailored to deal with the particularities of the respective disturbances can be applied to each category. The first group of disturbances includes: transients, harmonics, interharmonics, notching and noise. The second group includes: sags, swells, interruptions, undervoltages and overvoltages (in [6] they are called short and long duration variations).

-			
Category	Spectral content	Typical duration	Typical magnitude
Transient	up to 5 MHz	ns – ms	0 – 8 pu
Harmonics	0 – 5 kHz	steady state	0 – 0.2 pu
Interharmonics	0 – 6 kHz	steady state	0 – 0.02 pu
Notching		steady state	
Noise	broad-band	steady state	0 – 0.01 pu
Sag		0.5 cycle – 1 min	0.1 – 0.9 pu
Swell		0.5 cycle – 1 min	1.1 – 1.8 pu
Interruption		> 0.5 cycle	< 0.1 pu
Undervoltage		> 1 min	0.8 – 0.9 pu
Overvoltage		> 1 min	1.1 – 1.2 pu

Table 1. Categories of PQ disturbances and their typical parameters as defined in [6] and [8].

The detection and classification method implemented in the prototype of the PQ analyzer consists of three stages as presented in Fig. 1. In the first stage, which is common to both groups of disturbances, the normalization of the input voltage signal is performed. The normalization makes the disturbance detection (namely the selection of the threshold levels) independent of the used voltage transducer's output range and enables *e.g.*, to introduce correction of the gain of the analyzer's input signal conditioning circuit. After this stage, the signal flow splits into two branches where each branch handles one of the two groups of disturbances.



Fig. 1. Block diagram of the disturbance detection and classification method.

#### 2.1. Transients and waveform distortions

The detection of transients and waveform distortions (such as harmonics, interharmonics, notching and noise) is based on a digital high-pass filter that filters out the component with the fundamental frequency and leaves the component of the normalized voltage that contains eventual disturbances. The algorithm employs a  $6^{th}$  order IIR elliptic filter with cut-off frequency at 100 Hz, gain in the pass-band equal to 0 dB and 80 dB attenuation in the stop band. Figure 2 shows a detail of the filter's amplitude frequency characteristic.



Fig. 2. Amplitude frequency characteristic of the digital high-pass filter.

The output signal of the high-pass filter  $u_{HP}$  can be directly used for disturbance detection using thresholding with a predefined threshold level. However, to simplify the detection task (*e.g.*, by eliminating multiple crossings of the threshold level that belong

to a single disturbance) the signal  $u_{\rm HP}$  is processed using mathematical morphology operation called closing [7].

Morphology operations are used for processing of discrete signals (mainly images) based on the signal's shape. Each output sample of a morphology operation depends on the corresponding input sample and the samples in its neighborhood, which is defined by a function called structuring element. The closing operation used by the proposed method consists of two other morphology operations that employ the same structuring element. The closing of a function u using a structuring element s is defined as dilation of u using s followed by erosion using s:

$$u \bullet s = (u \oplus s) \ominus s. \tag{1}$$

In case of the proposed method, the signal u is a vector of voltage signal's samples with length  $N_{\rm U}$ . The structuring element s is a binary vector (vector of ones) whose length  $N_{\rm S}$  defines the size of the neighborhood used in the calculation of closing. In such case, the dilation and erosion can be defined as

$$(u \oplus s)[n] = \max\{u[n-m]\} \quad \forall s[m] \neq 0, \ m \in S, \ n-m \in U$$
(2)

and

$$(u \ominus s)[n] = \max\{u[n+m]\} \quad \forall s[m] \neq 0, \ m \in S, \ n+m \in U,$$
(3)

respectively, where

$$S = \begin{cases} \{-(N_S - 1)/2, ..., (N_S - 1)/2\} & N_S \text{ odd} \\ \{-(N_S - 2)/2, ..., N_S/2\} & N_S \text{ even} \end{cases}$$
(4)

and

$$U = \{1, ..., N_U\}.$$
 (5)

For such signals u and s, the calculation of each output sample of the dilation and erosion is reduced to calculation of the maximum and minimum value, respectively, of the signal u within the neighborhood defined by the structuring element s.

The proposed method applies the closing operation to the absolute value of the signal  $u_{textrmHP}$  and the employed structuring element s is a vector with the length equal to 2.5 times the length of the voltage signal's nominal period

$$u_{\text{MORPH}} = |u_{\text{HP}}| \bullet s. \tag{6}$$

The result of the closing operation  $u_{\text{MORPH}}$  is an envelope of the signal  $|u_{\text{HP}}|$  as depicted in Fig. 3. In this figure, the formation of the signal  $u_{\text{MORPH}}$  by successively applying the dilation and erosion operations is shown. For each operation, four steps (four positions of the structuring element *s*) are shown. For explanatory purposes the

structuring element in this example is shorter than the one used by the proposed method. In each step of the dilation operation, an output sample is calculated as the maximum value of the input samples that are within the structuring element (*i.e.* that are on the positions where the value of the structuring element is one). The position of the output sample is defined by the so called origin of the structuring element (in Fig. 3 it is the sample in the middle shown with the gray background). The procedure to calculate the erosion is the same, only this time the minimum values are calculated.



Fig. 3. Formation of the  $u_{\text{MORPH}}$  signal using the closing operation.

A disturbance is detected when the signal after closing  $u_{\text{MORPH}}$  exceeds a predefined threshold level *Morph\_THR*. The method then proceeds to the classification stage where the type of the disturbance and its parameters (magnitude and duration) are determined. The classification is based on the typical parameters of disturbances [6] and uses the signals  $|u_{\rm HP}|$  and  $u_{\rm MORPH}$ . When the duration of the disturbance in the  $u_{\text{MORPH}}$  signal (the duration is the time between the crossing of the *Morph\_THR* level and the return of the  $u_{\text{MORPH}}$  signal below this threshold level) is longer than 2.5 times the nominal signal's period (50 ms in case of 50 Hz power systems) the disturbance is classified as a waveform distortion. Otherwise, the signal  $|u_{\rm HP}|$  is once again processed using the closing operation. This time, the structuring element is only 4 ms long (1/5)of the voltage signal's period in case of 50 Hz power systems). The shorter structuring element enables the detection of potential multiple transients that are close together (because of the long structuring element used to obtain the  $u_{MORPH}$  signal, transients that are close together might appear as a single disturbance in  $u_{\text{MORPH}}$ ). After the closing operation, the crossings of the *Morph\_THR* level are detected and the amplitude and duration of individual transients are determined.

#### 2.2. Short and long duration variations

The detection process of the disturbances from the second group (sags, swells, interruptions, undervoltages and overvoltages) follows the recommendations of power quality standards [6, 8] and is based on the detection of variations of the voltage signal's RMS value. The RMS value is calculated over one period of the power system's voltage and refreshed every half-period

$$u_{\rm RMS}(j) = \sqrt{\frac{1}{N} \sum_{i=(j-1)N/2}^{(j+1)N/2-1} U_{\rm NORM}^2(i)},$$
(7)

where N is the number of samples per period; j = 1, 2, ..., 2p - 1 and p is the number of periods in the analyzed segment of data.

The disturbance detection is done by comparing the  $u_{RMS}$  values with two threshold levels:  $RMS_THR+$  which is above the nominal RMS value of the power system and  $RMS_THR-$  which is below the nominal value. In the classification stage, the category of the disturbance and its magnitude and duration are determined. Figure 4 shows typical parameters (duration and RMS value) of short and long duration variations as specified in [6]. The proposed method classifies events whose RMS value exceeds 1.1 pu as swells or overvoltages (based on their duration). Events with RMS value between 0.1 pu and 0.9 pu are marked as sags or undervoltages (again, based on the event's duration). Events with RMS voltage below 0.1 pu are classified as interruptions. DSP based power quality analyzer for detection...



Fig. 4. Disturbance duration vs. voltage RMS value characteristics of typical short and long duration PQ disturbances as defined in [6].

### 3. DSP BASED PQ ANALYZER

The described method for detection and classification of PQ disturbances was implemented in the prototype of a power quality analyzer. The analyzer (see Fig. 5) is designed for monitoring of a single-phase 230 V/50 Hz power system.



Fig. 5. Block diagram of the PQ analyzer.

The analyzer is based on a floating-point digital signal processor (DSP) ADSP 21369 that performs all the processing required by the proposed method. The DSP also controls the acquisition process. The analyzer is equipped with closed-loop Hall effect voltage (LEM LV 25 P) and current (LEM LA 25 NP) transducers. The input voltage range is  $\pm$  700 V and the input current range is  $\pm$  8.5 A.

The output signals of the transducers are amplified in the signal conditioning circuit and digitized using analog-to-digital converters (ADC). The ADCs are 16 bit, 100 kS/s, successive approximation converters AD7683. In the PQ analyzer, the sampling rate of the ADCs is set to 50 kS/s. The selection of the sampling rate follows from the bandwidth of the used transducers (the bandwidth of the voltage transducer is approximately 10 kHz) and is a compromise between required memory and the range of disturbance's frequencies that can be analyzed. Although the bandwidth of the selected voltage transducer is not sufficient to measure all PQ disturbances (*e.g.*, high frequency transients) is enough for detection of many common disturbances such as sags, swells, interruptions, waveform distortions caused by harmonic distortion or transients that result from capacitor switching [9].

The ADCs are connected to one of the DSP's serial ports (SPORT). The DSP generates all necessary control signals for the ADCs: the chip select signal (CS) and sampling clock (CLK). The sampling clock is derived from the DSP's internal precision clock generator which provides a stable and low-jitter clock signal that operates the ADCs at 50 kS/s.

In the DSP, an interrupt driven function reads the data from the ADCs and stores them in a buffer in the internal memory. Because the DSP contains an insufficient amount of internal memory (the DSP contains 64k words of memory while the algorithm requires 150 000 words just to store data of one channel), the samples to be analyzed have to be stored in an external memory. When the buffer in the internal memory is full, its content is moved to the DSP's external SDRAM memory using direct memory access (DMA). In the external memory, a 3 second (150 000 samples per channel) frame of data is built. Only when the whole frame is acquired, the DSP starts to process the acquired samples. Application of the DMA enables the DSP to process the previously acquired data frame while acquiring a new frame. The external memory is a 128Mb synchronous DRAM with 32 bit word length (*i.e.*, 4M words) running at 133 MHz.

Only the voltage signal is used in the detection and classification process. The signal from the current channel can be used e.g. for further analysis of the conditions during a disturbance and for identification of its cause.

The results of the detection and classification process (type of detected disturbance, its parameters and the time of its occurrence together with the corresponding voltage and current waveforms) are stored on a Secure Digital (SD) memory card connected to the DSP via SPI interface. The stored data can be transmitted to a PC using the prototype's USB 2.0 (full speed) interface for further analysis and storage. However, the PC is not required for the analyzer's operation.

The analyzer's power supply contains a rechargeable back-up battery which powers the analyzer during sags and interruptions.

# 4. IMPLEMENTATION OF THE DETECTION AND CLASSIFICATION METHOD

All the computations are performed with single-precision (32 bit) floating point number format. This number format provides optimal performance since it is the DSP's native format and has sufficient precision for the required calculations. Formats with smaller word-width do not have sufficient precision to *e.g.* adequately implement the IIR filter.

Some parts of the method, such as the digital filter, are implemented using library functions that are supplied with the DSP's development environment. However, some less common functions, such as the mathematical morphology operations, are not included in these libraries and had to be implemented. The closing operation (6), according to its definition, is implemented using two other morphology operations: dilation  $\oplus$  and erosion  $\oplus$ 

$$u_{\text{MORPH}} = |u_{\text{HP}}| \bullet s = (|u_{\text{HP}}| \oplus s) \ominus s.$$
(8)

The dilation and erosion are implemented using the van Herk-Gil-Werman algorithm [10, 11]. Both dilation and erosion using this algorithm require  $3-4/N_S$  comparison operations per each sample of the processed signal [12]. Although there are more efficient algorithms for the calculation of the dilation and erosion or directly of the closing (*e.g.* [12]), the memory requirements of such implementation and the limitations of the employed DSP have to be taken into account. The amount of DSP's internal memory is usually very limited and although DSPs can work with large amounts of external memory, access to it is significantly slower than the access to the internal memory which may render algorithms with big memory requirements inefficient.

Table 2 shows an overview of typical computational requirements of individual parts of the proposed method when processing a 3 seconds long (150 000 samples) frame of acquired signals. The times shown in Table 2 were achieved using an ADSP 21369 running at 266 MHz; the processed data were stored in SDRAM memory with a 133 MHz clock.

The total time required to detect and classify disturbances in a 3 second frame of data shows that the proposed method is suitable for real time operation and can be used for on-line detection of disturbances. Its performance leaves space for the addition of new features not yet implemented in the current version of the PQ analyzer, such as detection of flicker, voltage unbalance or calculation and logging of instantaneous active and reactive power. The selected DSP also enables to extend the PQ analyzer for the monitoring of three-phase power systems.

The time required to execute some parts of the method (especially the classification), of course, depends on the actual signal being processed and the number of disturbances it contains. The values shown in Table 2 correspond to a signal that contained 1 interruption, 3 transients and 1 waveform distortion.

Method's part	Time required			
Transients and waveform distortions				
IIR filter, absolute value	42.2 ms			
Closing	20.7 ms			
Detection (thresholding)	22.2 ms			
Classification	24.0 ms			
Short and long duration variations				
RMS calculation	12.4 ms			
Detection (thresholding)	52 μs			
Classification	18 µs			
TOTAL	121.6 ms			

Table 2. Computational requirements of the proposed detection and classification method for a 3 second frame (150 kS).

### 5. MEASUREMENT RESULTS

Two prototypes of the analyzer were constructed and installed on two sites in Portugal (in Lisbon and in Évora) where they monitored the local condition of the power system. The *Morph\_THR* threshold was set to 0.12 pu, the *RMS\_THR*+ was set to 1.1 pu and the threshold *RMS\_THR*- was adjusted to 0.9 pu. The summary of the disturbances detected during the 7 months long monitoring is shown in Fig. 6. These graphs show the type and range of parameters of the disturbances used to verify the proposed method and its implementation. In the course of monitoring, 77 sags and undervoltages, 18 interruptions and over 19 000 transients and 3 500 waveform distortions were detected. Note that in case of waveform distortions the indicated magnitude represents the maximum deviation from a pure sine signal during the disturbance. Therefore, it includes all the spurious frequencies and not just harmonics as in case of total harmonic distortion, which is often used to describe this type of disturbances.



Fig. 6. Summary of detected disturbances: a) transients and waveform distortions; b) sags, undervoltages and interruptions.

Figure 7 shows examples of some of the detected disturbances. In Fig. 7a an example of a transient is shown (duration 2 ms; magnitude 0.52 pu). Figure 7b depicts a waveform distortion. Only part of the disturbance is shown: the duration of the whole disturbance is 421 ms, its magnitude is 0.18 pu. An example of a sag is shown in Fig. 7c (duration 311 ms; the voltage dropped down to 0.18 pu). Finally, an interruption with 115 ms duration is depicted in Fig. 7d.



Fig. 7. Examples of detected disturbances.

### 6. CONCLUSIONS

The designed prototype of a power quality analyzer implements the improved version of the previously developed new detection and classification algorithms [4, 5]. For the purposes of the method, the PQ disturbances were divided into two groups and different algorithms are used in each group. For transients and waveform distortions, digital filtering and mathematical morphology operation closing are applied. Disturbances from the second group (*e.g.* sags, swells and interruptions) are detected and classified using the voltage RMS value. The mathematical morphology operations are usually used in image processing. This paper shows that they can represent a useful and efficient tool also in power quality measurements.

The analyzer is based on a digital signal processor ADSP 21369. The analyzer is able to perform all the required processing in real-time and is therefore suitable for on-line monitoring of the power system. The performance of the analyzer was verified during long term monitoring of a single-phase 230 V/50 Hz power system. Although the analyzer was designed for monitoring of a single-phase power system, the proposed method is efficient enough to enable extension for real-time monitoring of three phase

power systems even with the currently used DSP. Besides performing the processing the described algorithm in two more channels, the computational power of the selected DSP and the efficiency of the proposed algorithm enable to add other measurements typical for three-phase system such as the measurement of voltage unbalance.

#### ACKNOWLEDGEMENTS

Work sponsored by IT/LA/318/2005 and by the Portuguese national research project reference POSC/EEA-ESE/57708/2004 entitled "Fast and accurate power quality measurements using analog to digital converters and digital signal processing techniques".

#### REFERENCES

- 1. Santoso S., Powers E. J., Grady W. M., Hofmann P.: *Power quality assessment via wavelet transform analysis*. IEEE Trans. Power Del., vol. 11, no. 2, pp. 924–930, April 1996.
- Wang M., Rowe G. I., Manishev A. V.: Classification of power quality events using optimal timefrequency representations, theory and application. IEEE Trans. Power Del., vol. 19, no. 3, pp. 1496–1503, July 2004.
- 3. He H., Starzyk J. A.: A self-organizing learning array system for power quality classification based on wavelet transform. IEEE Trans. Power Del., vol. 21, no. 1, pp. 286–295, January 2006.
- Matz V., Radil T., Ramos P., Serra A. C.: Automated Power Quality Monitoring System for On-line Detection and Classification of Disturbances. IEEE Instrumentation and Measurement Technology Conference IMTC, 2007, Warsaw, Poland, May 2007.
- Radil T., Matz V., Janeiro F. M., Ramos P., Serra A. C.: On-line Detection and Classification of Power Quality Disturbances in a Single-phase Power System. International Conf. on Power Engineering, Energy and Electrical Drives – Powereng, Setúbal, Portugal, pp. 713–718, April 2007.
- IEEE Std. 1159–1995, IEEE Recommended Practice for Monitoring Electric Power Quality. The Institute of Electrical and electronics Engineers, Inc., New York, December 1995.
- 7. Serra J.: Image Analysis and Mathematical Morphology, volume 1. Academic Press, 1982.
- 8. *IEC 61000-4-30 Electromagnetic compatibility: Testing and measurement techniques Power quality measurement methods.* IEC, 2003.
- Forti M., Millanta L.: Power-Line Impedance and the Origin of the Low-Frequency Oscillatory Transients. IEEE Trans. on EMC, vol. 32, no. 2, pp. 87–97, May 1990.
- Van Herk M.: A fast algorithm for local minimum and maximum filters on rectangular and octagonal kernels. Pattern Recognition Letters 13, pp. 517–521, July 1992.
- 11. Gil J. Y., Werman M.: Computing 2-D min, median and max filters. IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 15, no. 5, pp. 504–507, May 1993.
- 12. Gil J. Y., Kimmel R.: *Efficient Dilation, Erosion, Opening, and Closing Algorithms*. IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 24, no. 12, pp. 1606–1617, December 2002.