DSP Based Power Quality Analyzer using New Signal Processing Algorithms for Detection and Classification of Disturbances in a Single-phase Power System

Pedro M. Ramos[1,2], Tomáš Radil[2], Fernando M. Janeiro[2,3], A. Cruz Serra[1,2]

[1] *Department of Electrical and Computer Engineering, Instituto Superior Técnico, Technical University of Lisbon, IST, Av. Rovisco Pais 1, 1049-001 Lisbon, Portugal*
Phone: +351-218418485; Fax: +351-218418472, e-mail: pedro.ramos@lx.it.pt, acserra@ist.utl.pt
[2] *Instituto de Telecomunicações, Av. Rovisco Pais 1, 1049-001 Lisbon, Portugal*
e-mail: tomas.radil@lx.it.pt
[3] *Universidade de Évora, Departamento de Física, Rua Romão Ramalho, nº. 59, 7000-671 Évora, Portugal, Phone: +351-266745300; e-mail: fmtj@uevora.pt*

Abstract- 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 previously developed algorithm for disturbance detection and classification was improved and implemented in a standalone DSP based analyzer. Its performance was verified during long term monitoring of the power system.

I. Introduction

Reliable and real-time monitoring of quality of electric power has become an important task in recent years and a major concern for consumers, manufacturers and distributors of the electric power. 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^{th} 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.

II. 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. Table 1 shows the ten most common categories of disturbances encountered in a single-phase power system [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).

Table 1. Categories of PQ disturbances and their typical parameters.

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

The detection and classification method implemented in the prototype of the PQ analyzer consists of three stages (Figure 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. After this stage, the signal flow splits into two branches, each branch handles one of the two groups of disturbances.

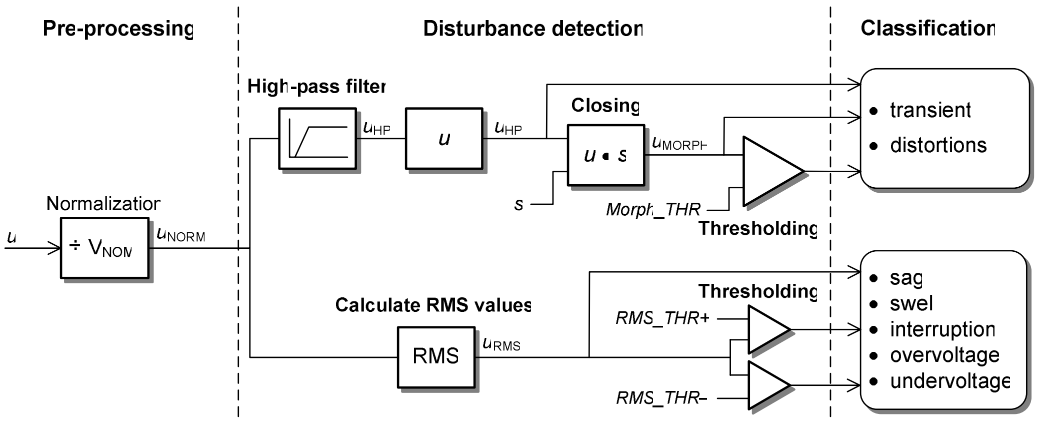

Figure 1. Block diagram of the disturbance detection and classification method.

A. 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 fundamental frequency and leaves the component of the normalized voltage that contains eventual disturbances. The algorithm employs a 6th order IIR elliptic filter with cut-off frequency at 100 Hz, gain in the pass-band equal to 1 and 80 dB attenuation in the stop band.

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_{HP} is processed using mathematical morphology operation called closing [7]. Closing is applied to the absolute value of the signal u_{HP} and the employed structuring element s is a binary vector (vector of ones) with the length equal to the 2.5 times the length of the voltage signal's period

$$u_{MORPH} = |u_{HP}| \bullet s \ . \quad (1)$$

A disturbance is detected when the signal after closing u_{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 $|u_{HP}|$ and u_{MORPH}. When the duration of the disturbance in u_{MORPH} signal (the duration is the time between the crossing of the *Morph_THR* level and the return of the u_{MORPH} signal below this threshold level) is longer than 50 ms the disturbance is classified as a waveform distortion. Otherwise, the signal $|u_{HP}|$ 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). The shorter structuring element enables to distinguish potential multiple transients that are close together (because of the long structuring element used to obtain u_{MORPH} signal, transients that are close together might appear as a single disturbance in u_{MORPH}). After the closing operation, the crossings of the *Morph_THR* level are detected and the parameters of individual transients are determined.

B. Short and long duration variations

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

$$u_{\mathrm{RMS}}(j)=\sqrt{\frac{1}{N}\sum_{i=(j-1)N/2}^{(j+1)N/2-1}u_{\mathrm{NORM}}^{2}(i)} \tag{2}$$

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.

III. 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 Figure 2) is designed for monitoring of a single-phase 230 V/50 Hz power system.

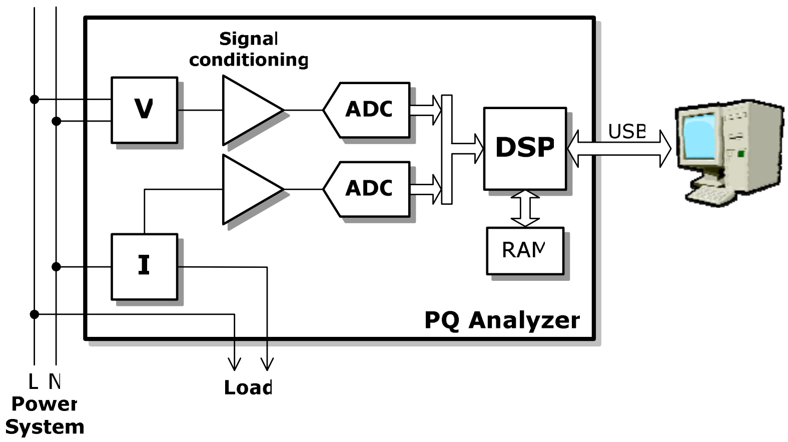

Figure 2. Block diagram of the PQ analyzer.

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 ±700 V; input current range is ±8.5 A.
The output signals of the transducers are 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.
The ADCs are connected to the DSP using its serial port. 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 insufficient amount of internal memory, 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) long frame of data is built. Only when the whole frame is acquired, the DSP starts to process the acquired samples. Application of DMA enables the DSP to process previously acquired frame of data while acquiring new frame.

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 in the DSP's external memory from where they can be transmitted to PC for further analysis and storage. However, the PC is not required for the analyzer's operation. The prototype is equipped with USB 2.0 (full speed) interface.

IV. 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 a 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 DSPs 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 (used in (1)), according to its definition, is implemented using two other morphology operations: dilation $\oplus$ and erosion $\ominus$:

$$u_{\mathrm{MORPH}} = |u_{\mathrm{HP}}| \bullet s = \left(|u_{\mathrm{HP}}| \oplus s\right) \ominus s \,. \quad (3)$$

The dilation and erosion are implemented using the van Herk-Gil-Werman algorithm [8][9]. Although there are more efficient algorithms for the calculation of the dilation and erosion or directly of the closing (e.g. [10]), 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 drive algorithms with big memory requirements inefficient.

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

Table 2. Computational requirements of the proposed detection and classification method.

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**

The total time required to detect and classify disturbances in a 3 second long 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 including new features not yet implemented in the

current version of the PQ analyzer, such as detection of flicker or calculation and logging of instantaneous active and reactive power. The selected DSP also enables to extend the PQ analyzer for monitoring of three-phase power systems.
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. Times shown in Table 2 are valid for a signal that contained 1 interruption, 3 transients and 1 waveform distortion.

V. 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, 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 are shown in Figure 3. In the course of monitoring, 77 sags and undervoltages, 18 interruptions and over 19 000 transients and 3 500 waveform distortions were detected.

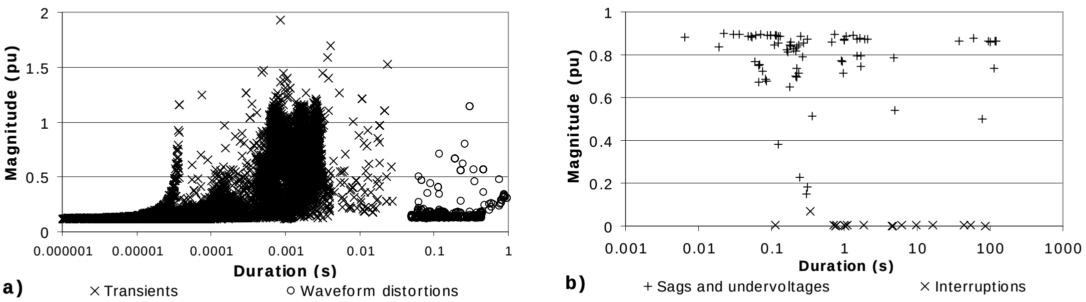

Figure 3. Summary of detected disturbances: a) transients and waveform distortions; b) sags, undervolatges and interruptions.

The following figures show examples of some of the detected disturbances: in Fig. 4a an example of a transient is shown (duration 2 ms; magnitude 0.52 pu); Fig. 4b 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. 4c (duration 311 ms; the voltage dropped down to 0.18 pu) and, finally, an interruption with duration of 115 ms is depicted in Fig. 4d.

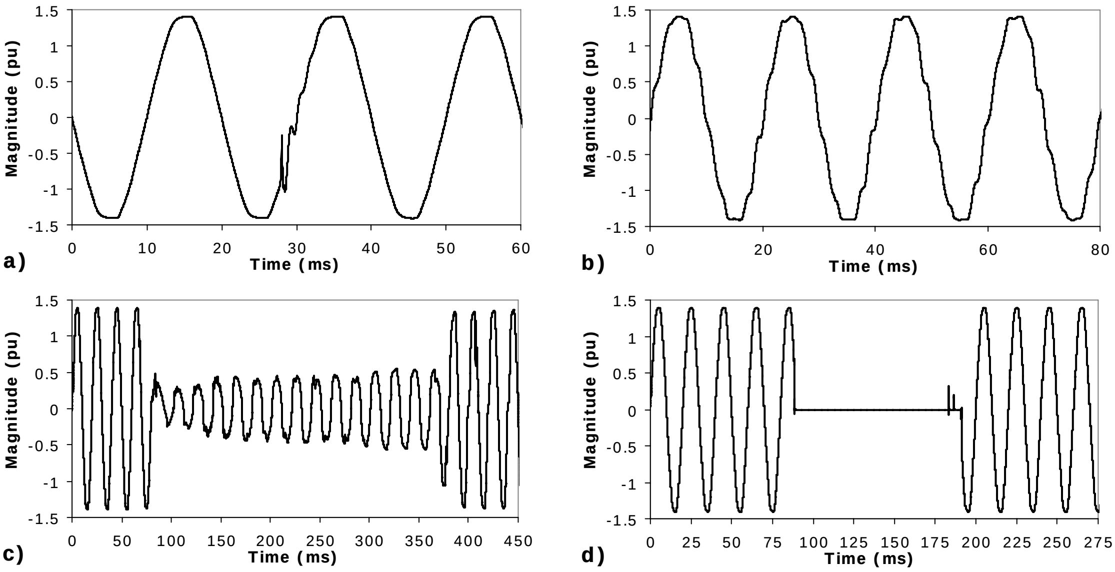

Figure 4. Examples of detected disturbances.

VI. Conclusions

The designed prototype of a power quality analyzer implements the improved version of the new detection and classification method. 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 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.

Acknowledgement

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] S. Santoso, E. J. Powers, W.M. Grady, P. Hofmann, “Power quality assessment via wavelet transform analysis,” *IEEE Trans. Power Del.*, vol. 11, no. 2 pp. 924–930, Apr. 1996

[2] M. Wang, G. I. Rowe, A. V. Manishev, “Classification of power quality events using optimal time-frequency representations, theory and application,” *IEEE Trans. Power Del.*, vol. 19, no. 3, pp. 1496–1503, July 2004

[3] H. He, J. A. Starzyk, "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, Jan. 2006

[4] V. Matz, T. Radil, P. Ramos, A. C. Serra, “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

[5] T. Radil, V. Matz, F. M. Janeiro, P. Ramos, A. C. Serra, “On-line Detection and Classification of Power Quality Disturbances in a Single-phase Power System”, I*nternational Conf. on Power Engineering, Energy and Electrical Drives - Powereng*, Setúbal, Portugal, pp. 713–718, April 2007

[6] “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] J. Serra, *Image Analysis and Mathematical Morphology*, volume 1. Academic Press, 1982

[8] M. van Herk, “A fast algorithm for local minimum and maximum filters on rectangular and octagonal kernels,” *Pattern Recognition Letters* 13, pp. 517–521, July 1992

[9] J. Y. Gil, M. Werman, “Computing 2-D min, median and max filters,” *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 15, no. 5, pp. 504–507, May 1993

[10] J. Y. Gil, R. Kimmel, “Efficient Dilation, Erosion, Opening, and Closing Algorithms,” *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 24, no. 12, pp. 1606–1617, Dec. 2002