VIRTUAL INSTRUMENT FOR POWER QUALITY ASSESSMENT

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Abstract - The paper presents a Virtual Instrument (VI) for Power Quality (PQ) events monitoring and analysis designed in LabView. The instrument is designed to detect harmonics, interharmonics, dips, swells and unbalance and it also performs a distortion classification prior to the identification step. The harmonics and interharmonics are detected with high accuracy using a time domain technique based on linear algebra. Dips and swells are identified using the wavelet technique and the unbalance analysis is based on the symmetrical components method. Timefrequency representations (TFR) are obtained for distortion classification by performing the Stockwell Transform (ST) and they are fed to a pattern recognition system.

The normal operation limit is previously established on empirical expert knowledge and then a few measurements are performed on an experimental rig. The measurements reveal the accuracy of the instrument and its high online analysis performance.

Keywords: distortions analysis, time-frequency representations, self organising maps.

1. INTRODUCTION

Electric power quality is a term that has gained more importance over the years. The increasing use of sensitive and non-linear loads, the deregulation of utilities, and the increased interconnections in power systems has led to an increased need to solve and prevent power quality problems [1]. Dugan [2] defined power quality as "Any power problem manifested in voltage, current, or frequency deviations that results in failure or malfunction of customer equipment." Power quality results in equipment malfunction and premature failure and has financial consequences on utilities grids, their customers and suppliers of load equipment. Thus, monitoring power quality has become a necessity for fast identification and correction power quality problems. Signal processing methods for power quality analysis comprise Fourier Transform (FT), Park's Vector Approach, Kalman filters and time-frequency analysis methods such as Short Time Fourier Transform (STFT), Wavelet Transform (WT) and Stockwell Transform (ST).

Stationary signals are those whose statistical properties do not change with time while the characteristics of non-stationary signals vary with time [3]. Fourier Transform (FT) determines the spectral components of a signal without providing the times at which the different frequency components occurred. FT produces a time-averaged spectrum which is inadequate to track the changes in signal magnitude, frequency and phase with time. Thus, non-stationary signals are better processed in the time-frequency plane by using techniques like STFT, WT and ST.

For non-stationary signals like power quality disturbance signals, where the frequency content change with time, STFT has got a fixed resolution over the time-frequency plane and does not recognize the signal dynamics properly due to the limitation of a fixed window width chosen a priory [4,5].

WT is incapable of providing accurate results under noise conditions [5]. Moreover, if an important disturbance frequency component is not precisely extracted by the WT, the classification accuracy using artificial intelligence techniques may be limited [4]. Also, there is an absence of phase information in WT and the time-scale plots provided by WT are difficult to interpret [3].

Therefore ST which combines the elements of STFT and WT and which performs multiresolution timefrequency analysis is a better candidate for power quality distortion classification.

Time-frequency representations are then analysed with a self-organising map that extracts key features for each distortions.

The paper continues to describe the power quality analysing system where the harmonics and interharmonics are studied with a novel time-based parametric method.

Voltage dips are monitored by the means of the WT and the RMS method for dip amplitude computation.

The paper also analysis the flicker effect and transients. The first is studied with a method that extracts the modulating component parameters from the spectral estimation algorithm used for interharmonics estimation and the second is extracted from the ST time-frequency representations.

In the last decades power quality analysis became a very important issue in power systems so the necessity of accurate parameters measurement has grown in importance too [6]. Virtual instrumentation will play an important role among the power quality monitoring systems. The main advantage is that it is much cheaper than the standard equipment and it is much more flexible.

2. VIRTUAL INSTRUMENTATION

In the recent years, analysis of electromagnetic distortions in power systems requires a significant volume of data and knowledge. Therefore, using computers, new analysis methods and artificial intelligence techniques became a necessity.

The virtual instrument developed in this paper was designed in LabView and it drives a PCMCIA data acquisition board (DAQ-NI-6008). Fig. 1 shows the instrument organization where part a describes the input options followed a sampling action (Fig. 1. b.).

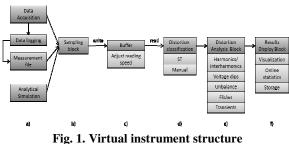


Fig. 1. Virtual instrument structure

The influx of data can be inserted either in an analytic way, for testing purposes, from the acquisition card (Fig. 2.) or from a previously made recording.

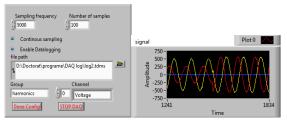


Fig. 2. Data aquisition subroutine

LabView environment is very efficient for data aquisition. It offers all the necessary functions to develop a data aquisition virtual routine.



Fig. 3. Virtual buffer

First, a smart buffer was programmed (Fig. 3). This buffer performs a very accurate data synchronization (Fig. 1.c.) with the acquisition card and the desired reading speed can also be adjusted.

A brief description of the block d performs a distortion classification based on the Stockwell transform and self-organizing maps prior to the distortion analysis found in block e. The last block (Fig. 1.f.) is the user interface of the instrument where the results and statistical data can be visualized.

3. DISTORTION CLASSIFICATION

At present more and more power electronic elements and nonlinear load are used in industry application which brings heavy pollution to power network. The correct classification of power disturbance is the premise and basis of the power quality analysis and evaluation.

3.1. Time-frequency analysis

S Transform, developed by Stockwell, is a powerful time-frequency multi-resolution analysis signal processing tool. ST provides a time-frequency representation (TFR) with a frequency dependent resolution. The window width varies inversely with frequency and thus, ST produces high time resolution at high frequency and high frequency resolution at low frequency as presented in Fig. 4.

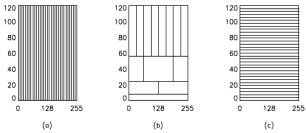


Fig. 4. The resolution of time frequency space when the signal is viewed: a) as a time series, having precise time resolution, and no frequency resolution. b) in the ST representation, having frequency dependent resolution. c) as a spectrum, having no time

resolution, and precise frequency resolution.

The ST of a discrete time series h[kT] is given by:

$$S\left[jT,\frac{n}{NT}\right] = \sum_{m=0}^{N-1} H\left[\frac{m+n}{NT}\right] e^{-\frac{2\pi^2 m^2}{n^2}} e^{\frac{i2\pi mj}{N}}$$
(1)

where *j*, *m* and n = 0, 1, ..., N-1 [7].

In this work, four single commonly occurring PQ disturbances namely voltage dip, harmonics, transient and flicker, as well as the pure sinusoidal waveform are considered. The following plots show some of the essential information that can be obtained from the modified ST.

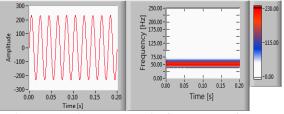


Fig. 5. Pure sine wave and its feature waveforms

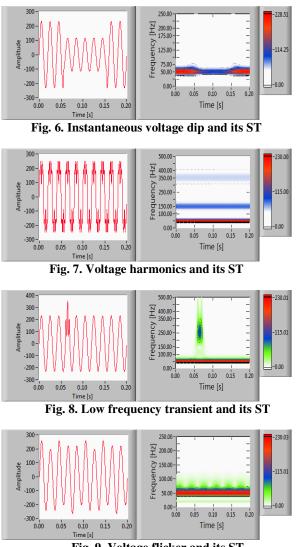


Fig. 9. Voltage flicker and its ST

From the ST, the time-frequency, time-amplitude and frequency-amplitude plots can easily be obtained. These plots enable the detection, localization and visual classification of PQ disturbances.

3.2. Self-organising maps (SOM)

The features required for PQ disturbance classification are extracted from the S-matrix. The features extracted are used to train a self-organizing map that allows automatic distortion classification. In this work, three features are extracted and they are:

1) Standard deviation (SD) of the data set comprising the elements of maximum magnitude from each column of the S-matrix.

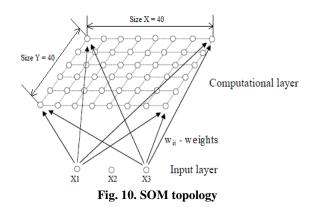
2) Energy of the data set comprising the elements of maximum magnitude from each column of the S-matrix.

3) Mean of the data set constituting the elements of maximum magnitude from each row of the S-matrix.

Clustering techniques come under the concept of competitive learning. Clustering is one of the most important unsupervised training techniques. Basically it is a process by which objects that are closely related to each other are grouped. Similar objects form groups and they are dissimilar from other groups.

a) SOM architecture

In this paper the topology of the SOM network is a 40x40 neurons lattice and 3 input vector space as shown in Fig. 10



b) SOM algorithm

The self-organization process involves four major components:

Initialization: All the connection weights are initialized with random values scaled between 0 and 1. Fig. 11 rescales the weights on the interval 0-255 and plots them on an RGB color map for better visualization.

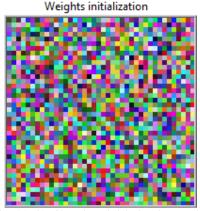


Fig. 11. 40x40 weight initialization lattice

Competition: For each input pattern the neurons compute their respective values of a *discriminant function* which provides the basis for competition. The particular neuron with the smallest value of the discriminant function is declared the winner.

Cooperation: The winning neuron determines the spatial location of a topological neighborhood of excited

neurons, thereby providing the basis for cooperation among neighboring neurons.

Adaptation: The excited neurons decrease their individual values of the discriminant function in relation to the input pattern through suitable adjustment of the associated connection weights, such that the response of the winning neuron to the subsequent application of a similar input pattern is enhanced.

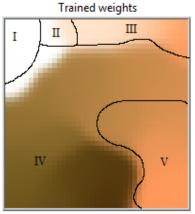


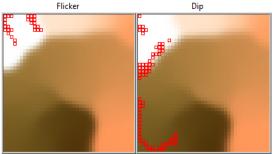
Fig. 12. SOM weights after 1000 cycles

Cycle by cycle the weights are updated until an optimum distribution is reached. This distribution (Fig. 12.) delimitates separate areas corresponding to each distortion:

Zone I – pure signal Zone II – subharmonic region Zone III – harmonics region Zone IV – changes in RMS (dips) Zone V – transients region

c) SOM testing

Once an optimum distribution map was achieved, testing can be performed using analytically created distortions.



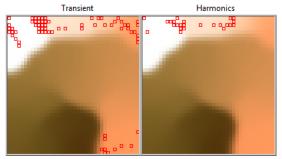


Fig. 13. SOM testing

The signal considered in this paper has 10 fundamental cycles sampled at 5000Hz, therefore, the total length of the analysis window is 1000 samples. Computing the S-matrix and extracting the three corresponding features, the input vector size will be 3x500 so it will plot 500 hits on the SOM map.

Signals shown in Fig. 5-9 were used and since they contain different distortions, they correspond to different regions on the map (Fig. 13). This feature allows accurate distortion classification.

4. DISTORTIONS ANALYSIS

As soon as the distortions are classified by the selforganizing maps, the instrument triggers the corresponding analysis subroutine.

4.1. Harmonics and interharmonics analysis

The real-time performance of a spectral estimation algorithm depends not only on its computational efficiency but also on its ability to obtain accurate estimates from short signal segments. Here, the system estimates harmonics and interharmonics with a time based method, assessing a parametric model of the signal as in equation (1) where y(t) represents the sampled signal and n(t) the noise.

$$y(t) = \sum_{i=1}^{M} A_i \exp(j\omega_i t) + n(t); \ 0 \le t \le T$$
(2)

The parametric model of is written in matrix form and following a strict linear algebra algorithm, the instrument performs spectral estimation.

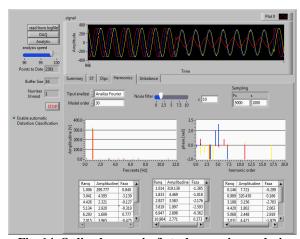


Fig. 14. Online harmonics/interharmonics analysis subroutine

The instrument approximates the frequency, magnitude and phase of the harmonics/interharmonics, on each phase, every 10 cycles of fundamental. The front panel of the online subroutine in presented in Fig. 14.

4.2. Dips analysis

There are various methods of dips analysis in the current literature. The classic method is based on a RMS plot of the signals every half-cycle, other methods require a high amount of computational time as the recursive methods like the Kalman filters. However, these methods seem to have problems in noisy conditions and long response times for control purposed. The subroutine developed implements the wavelet transform for fast initial and final time of dip computation while the amplitude of the sag is computed according to the classic RMS method.

The wavelet transform is described as:

$$W(\tau,d) = \int_{-\infty}^{\infty} h(t)w(t-\tau,d)dt$$
(3)

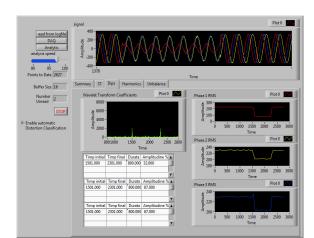


Fig. 15. Online dips analysis subroutine

Fig. 15. shows the front panel of the online dips analyser subroutine under real operation conditions. It displays the three phase sampled signal acquired from the power systems, a plot of the wavelet coefficients and the dips parameters on each phase.

4.3. Flicker effect analysis

Current standards present the flicker analysis implying a filter cascade that extracts the modulating waveform frequency and amplitude. The last two blocks in Fig. 16. compute the flicker parameters, respectively the long and short term flicker.

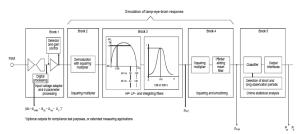
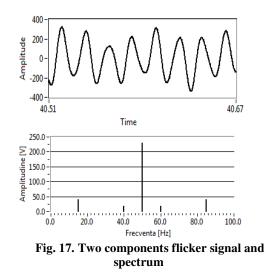


Fig. 16. Flicker meter functional scheme - IEC 61000-4-15

The drawback of the method imposed by the IEC standard is the wide analysis window that it requires. Signals in power systems are time-variable and a stationary requirement of 500 cycles is almost impossible to achieve in real operation conditions. The method proposed here replaces the filter cascade method with a spectral pairing method. It has been observed that the flicker effect produces a particular spectral pattern. The modulating component lies around the fundamental, seen as a pair of subharmonics – interharmonics components (Fig. 17.).



Using the method developed under the interharmonics analysis block, these components can be carefully extracted from the 10 cycles.

4.4. Transients analysis

Transient analysis has been an issue for a very long time as the phenomena is very short and hard to accurately detect and measure. Classic methods like the ones implying the Fourier transform fail due to severe spectral leakage and therefore, time-frequency analysis is the best tool to locate such distortions in frequency and time.

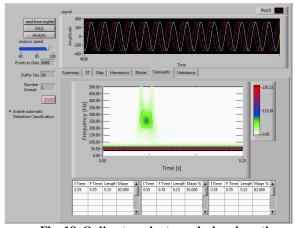


Fig. 18. Online transients analysis subroutine

The LabView system developed (Fig. 18.) collects the transient's information from the ST's time-frequency representations since the transform provides a very good time-frequency resolution and it is computed in the distortions classification step anyway.

5. CONCLUSION

This paper describes a virtual instrument designed to analyse the most common power quality disturbances.

In this work, an S-Transform based process is proposed for power quality disturbances recognition. Thus it is suitable for an online power quality disturbance classification system where a very large number of waveforms can be captured and analysed in a very short time interval.

The S-transform performs multiresolution analysis on a time varying signal as its window width varies inversely with frequency. This gives high time resolution at high frequency and high frequency resolution at low frequency. Since power quality disturbances make the power signal a nonstationary one, the S-Transform can be applied effectively. Together with the self-organising maps, the system performs a distortion classification in just a few milliseconds. This preidentification reduces the computational effort since the whole system doesn't analyse the signal for distortions that are not present.

Harmonics and interharmonics are computed with a model based algorithm in time. It can approximate with high accuracy the real harmonics or interharmonics even if their frequencies are very close. Based on simple principle, the same algorithm is effectively used to extract the flicker modulation waveform frequency and amplitude parameters.

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REFERENCES

- [1]. Kennedy, B.W., *Power Quality Primer*. New York: McGraw-Hill, 2000.
- [2]. Dugan, R.C. et al., *Electrical Power Systems Quality*. 2nd ed. USA: McGraw-Hill, 1996.
- [3]. George, N.V., S transform: Time Frequency Analysis and Filtering. Thesis (MTech). National Institute of Technology Rourkela, 2009.
- [4]. Chikuri, M.V. and Dash, P.K. Multiresolution S-Transform-Based Fuzzy Recognition System for Power Quality Events. IEEE Transactions on Power Delivery, 19(1), pp. 323-330, 2004.
- [5]. Samantaray, S.R., Power System Events Classification using Pattern Recognition Approach. International Journal of Emerging Electric Power Systems, 6(1), pp. 1-16, 2006.
- [6]. Gheorghe, D., Chindriş, M., Cziker, A., Vasiliu, R. B., Online Power Systems Harmonics/Interarmonics Analysis , Conferința Internațională MPS 2011, editția a IV-a, 17-20 Mai, Cluj-Napoca, România
- [7]. Stockwell, R.G., S-Transform Analysis of Gravity Wave Activity from a Small Scale Network of Airglow Imagers. Thesis (PhD). The University of Western Ontario, 1999.
- [8]. Stockwell, R.G., Mansinha, L., *Localization of the Complex Spectrum: The S Transform*. IEEE Transactions on Signal Processing. 44(4), pp. 998-1001, 1996.
- [9]. Reddy, J.B., Power System Disturbance Recognition Using Wavelet and S-Transform Techniques. International Journal of Emerging Electric Power Systems. 1(2), pp. 1-14., 2004.
- [10].Gheorghe, D., ş.a., Signal Analysis in Polluted Power Networks, CIE 2010, 27-28 May 2010, Oradea, Romania.
- [11].Portnoff, M.R., *Time-frequency representation of digital signals and systems based on short-time fourier analysis.* IEEE Transactions on Acoustics, Speech, and Signal Processing, 1980.
- [12].Bollen, M., Signal Processing of Power Quality Disturbances, IEEE Press Series on Power Engineering, ISBN-13 978-0-471-73168-9, United States, 2006.
- [13].Neumann, T., Feltes, C., Erlich, I. Development of an Experimental Rig for Doubly-Fed Induction Generator based Wind Turbine, IEEE Transactions on Signal Processing, MEPS, September 20 - 22, 2010, Wroclaw, Poland
- [14].Ouibrahim, H., Matrix pencil approach to direction finding, IEEE Transactions on Acoustics, Speech and Signal Processing, Aprilie 1988, pp. 610-612.
- [15].Gantmacher, F.R., *Theory of Matrices*, Vol. 1, New York, 1960.
- [16].Hanzelka, Z., Bien, A., Perturbații de tensiune: Măsurarea nivelului de flicker, AGH University of Science and Technology, Octombrie 2005
- [17].Gheorghe, Şt., ş.a. Monitorizarea calității energiei electrice, Editura Macarie, Târgovişte, 2001
- [18].***IEC 61000-4-15 Ed.1: Electromagnetic compatibility (EMC) - Part 4- 15: Testing and measurement techniques -

In the last part, the ST is used again for transient analysis.

Flickermeter - Functional and design specifications, Noiembrie 2002.

- [19].*** Ghid de Aplicare Calitatea Energiei Electrice, Armonici Interarmonici, <u>http://www.sier.ro/</u>
- [20].Barros, J., A virtual measurement instrument for electrical power quality analysis using wavelets, Measurement 42, 2009, pp. 298–307.
- [21].Gheorghe, D., Cziker, A., Vasiliu, R. B., Estimarea semnalelor interarmonice în sisteme electroenergetice, Masa Rotundă – Calitatea Energiei Electrice, 30 Noiembrie, Bucureşti, România.