Differential Evolution Implementation for Power Quality Disturbances Monitoring using OpenCL

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***Abstract*—This article presents a new methodology to implement a computational parallel scheme based on Differential Evolution (DE) algorithm through the use of Graphical Processing Units (GPU). A system application in which it is possible to perform an online monitoring of Power Quality Disturbances (PQD) in electric grids is presented as a case study, where a fitting of the parameters of a mathematical model is performed through this technique. Hyper-parameter optimization of the parallel Differential Evolution algorithm is performed for the assigned fitting function. As a result of this parallel implementation, a speed-up of 37 times compared with the serial implementation is achieved by using a single low budget GPU. The work presented shows a significant speed and accuracy improvement compared with Micro-Genetic Algorithm for Power Quality Analysis (MGA-PQA) technique.**

***Index Terms*—evolutionary computation, parallel programming, parallel processing, power quality, power system faults.**

I. INTRODUCTION

Nowadays, parallel computation techniques allow to obtain an improvement on computation time and the processing of wide data sets. As a large number of computation cores exist, processing time can be diminished when an initial complex task can be decomposed into independent simpler subtasks assigning a processor core to each one, executing them simultaneously. Computational intensive tasks as meta-heuristic optimization algorithms[1]–[4] that were used to taking a significant amount of time for computational expensive evaluation functions, are processed more efficiently by the use of parallel computing scheme allowing their implementation to obtain on-line systems. Different parallel systems architectures as multi-core central processing units (CPU) and graphics processing units (GPU) are present these days in nearly every personal computer, while infrastructure as a service (IaaS) servers specifically built for this purpose can be easily accessed by Google Cloud Platform and Amazon Web Services.

The meta-heuristic algorithms are used to obtain an approximate solution to a problem whose exact resolution method is unknown, where the classic algorithms are ineffective, or where it is very expensive to apply due to its computational time and resources needed. Differential Evolution (DE) is a technique within meta-heuristic algorithms, which allows obtaining an estimation for the solution of a multi-parametric continuous optimization problem. This technique is based on the evolution of a population through mutation and crossover operations between its agents, leading to a new population whose best agent score is equal or better for each new generation. Due to the population nature that DE has, this algorithm allows being directly implemented in a parallel computing environment taking the developers to an application able to solve multi-parametric optimization problems in a sped-up way by minimizing the impact on the resources consumption that its serial implementation implies. Particularly, an application in which this work will focus is given in a mathematical model fit to an electric signal containing power quality disturbances, a problem in power quality.

Power quality (PQ) is a research area focused on studying disturbances appearing in electric signals at power lines. Because now many key processes from the continuous manufacturing industry, commerce and services are dependent on the electric supply, this research area has increased its popularity. The continuous monitoring and conditioning of the power line signals prevent fails that would lead to significant losses [5], which can be economical in the case of the continuous manufacturing industry or fatal in a hospital building. In the PQ field, various disturbances can appear at voltage electric signals such as constant amplitude variations, harmonic contents, and flickers. Different sources responsible for causing disturbance events are present with a considerable portion of them because of customer loads [6]. These can cause harmonic content (due to nonlinear loads), poor power factor (due to highly inductive loads), flicker (due to arc furnaces), transients (due to device switching) and others. Power quality monitoring and conditioning should be considered for economic benefits. For example, a present disturbance like harmonic content at the power line could lead to a reduction of a 30% of life expectancy of a capacitor [7]. Because sampling frequency necessary for obtaining a valid signal for the power quality analysis is by the range of 6 kHz to 8 kHz [8], the quantity of data generated is very large. So, an on-line fitting process on a mathematical model which represents the various

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disturbances that can appear in the electric signal has not been studied yet. In the literature simplifications are taken in the actual model implementations, for instance, by declaring the fundamental wave frequency as a constant to get solutions in a shorter time. However, through this way, real power signals are not adequately adjusted. Nowadays, the online monitoring of power signals is a tendency where the monitoring system response delay is reduced to be able to detect and quantify power quality disturbances in a fast and accurate way [9]–[12]. The reported methods for the mathematical model adjustment focused on PQD detection are widely computational expensive. Regarding the meta-heuristic techniques, these could be used for the power quality analysis. Therefore, it would be desirable to develop a methodology which has a parallel distributed computational cost as well as an on-line implementation.

The contribution of this paper is the development of a new methodology based on differential evolution for a mathematical model fitting of power quality disturbances. Parallel implementation is achieved through the use of GPU. A mathematical model that describes power quality disturbances in an electric voltage signal is used as the case study. Parallel implementation of this new methodology leads to an on-line signal parameters estimation for high-frequency sampled signals. Validation is run for synthetic and real power signals and a comparison is performed with MGA-PQA method [13]. The outcome of this study represents a significant advance in power quality field.

II. Related Work

Recently, parallel implementations of meta-heuristic algorithms have been published [14]–[19]. They are known to be a computational intensive task, as well, development of GPU based solutions for signal processing [20], [21] and FPGA based ones [22]–[24] show that parallel programming fits at the Signal Processing applications empowering researchers with the fastest tools for their experiments, situating the solutions at the area of High-Performance Computing (HPC).

The use of evolutionary algorithms (EA) as a multi-parametric optimization algorithms is instantiated at signal processing research area [25]–[27], where differential evolution (DE) has been used for feature subset selection in conjunction with other artificial intelligence classification algorithms [28]–[31] to obtain the input variable set that maximizes the classification process accuracy. The idea of DE comes from genetic algorithms (GA), which follows the idea of principles of evolution. This algorithm has been studied extensively and new variants are being published recently [32]. In the predictive maintenance area, DE is used for obtaining an estimation of uncertain ranged bearing-related physical values [33]. Examples are shown in the literature where a meta-heuristic algorithm is used in conjunction with other techniques for solving optimization problems [34]–[36].The monitoring and the identification of the power quality disturbances present in power lines must be performed. Different methods were recently published where the estimations of the phase offset ϕ_1 and the fundamental frequency f_1 are done in separate processes (or even considered fixed as in the standards) [11], [13], [37]–[39]. The accuracy of the results is acceptable for test cases presented at those studies but an improvement is needed for these methodologies by using a full time-dependent parametric model, in order to obtain a higher accuracy at Power Quality Disturbances detection and characterization. The EN 50160 standard [40] specifies a nominal frequency of 60Hz (50Hz for Europe) with deviations (using measuring periods of 10s) of $\pm 1\%$ over a year and $\pm 6\%$ for each measuring period at interconnected systems. Given that, the frequency may vary over time, the decision of estimating frequencies at a calibration stage that only runs once or fixating it at the standard nominal frequency leads to a self-imposed lower-bound at fitting error. Mathematical models for signals with Power Quality Disturbances where the frequency value is taken as a function of time has been presented lately [41], [42], these works present the most complete modelization. However, the frequency and the phase are fixed at a posterior step because of the complexity of the model presented and the computing time needed to manage signal processing with it. This error is aggravated during harmonic content parameters estimation because of the nature of their frequency being a multiple of the fundamental one [43], [44]. Also, an incorrect frequency filter band could lead to attenuation of these important disturbances. Having the correct phase and frequency of the fundamental waveform and the harmonic content ensures the accuracy of the power quality diagnostic tool because of the flexibility to adapt the synthetic signal to the real one and it has not been done before. Considering the aforementioned, there is a need on developing an on-line robust methodology capable of providing these parameters accurately for reaching the best fitting of the PQ parameterized model with the minimal computational resources required, and in the lowest time, though a parallel structure, compared with the current solution based on the micro-genetic algorithm power quality analysis (MGA-PQA) proposed in [13]. The present work introduces a new methodology that performs PQD detection and characterization considering a parametric mathematical model where the frequency and the phase offset are considered as time-dependent variables and their values are estimated with accuracy at first. The proposed approach is based on two main techniques. A combination of both makes up a more accurate fitting: DE and moving root mean squared (MRMS). DE algorithm has been parallelized using OpenCL, and a flexible parallel C++ library has been developed for future implementations of the algorithm. The algorithm has been studied considering different variants of it and internal parameters tuning for the sinusoidal waveform fitting with the aim of obtaining the configuration that minimizes the number of generations computed for reaching a goal relative squared error (RSE) ε. The MRMS technique detects the voltage sag and the voltage swell for each half cycle by the use of a precise number of points defined by the previous DE block output.

A parallel implementation has been done for a power quality event classifier leading to a greater event detection accuracy, lowering misclassification rate as a consequence, even for a mixture of PQD events. The electric events detected and characterized are voltage sag, voltage swell, flicker, harmonic content and disturbance mixture. A statistical study on the outcomes obtained was accomplished to prove the goodness of the methodology proposed, by using randomly generated voltage power signals. A comparison was performed with the MGA-PQA methodology, which considers the frequency and the phase values as time-invariant, by using real power signal data from a hospital in Spain and from the IEEE 1159.2 working group database, where the proposed methodology returns faster and more accurate results.

III. Methods

A. Differential Evolution algorithm

DE algorithms [45]–[47] are a family of evolutionary algorithms designed to solve optimization problems by using a population-based approach. The algorithm is iterative, at an initial step a population matrix $\boldsymbol{X}^{0} = \left[x^{0}_{a,p}\right]_{A\times P}$ containing A different agents, where each one of them has P parameters, the dimensions of the problem, is randomly generated by using a random variable following a normalized $\mathcal{U}(0,1)$ distribution. The use of random values allows to avoid the grid search and locates the initial population in certain solutions, that if they are close enough to the global solution, they will converge to it. These parameters are randomly distributed as the classical way that it is done for genetic algorithms [48], [49]. In this study, $P=2$ is defined, as the set $\{\omega_1, \phi_1\}$ will be estimated, $x^{g}_{a,1} \equiv x^{g}_{a,\omega}$ and $x^{g}_{1,2} \equiv x^{g}_{a,\phi}$ are equivalents.

The stop conditions of the algorithm indicate when it has already finished the computation and must return a result. A certain number of maximum generations G is defined. A generation counter increases at each iteration of the algorithm's main loop starting at 0 where a check of the goal condition is performed in the beginning.

In the main loop a population $\boldsymbol{X}^{g}$ previously defined, a matrix of neighbors $\boldsymbol{N}^{g} = \left[n^{g}_{a,\lambda}\right]_{A\times\Lambda}$ is generated, Λ is dependent on the strategy (or scheme) selected. A population $\boldsymbol{Y}^{g} = \left[y^{g}_{a,p}\right]_{A\times P}$ is created by crossover and mutation. A selection is done by pairs, where each agent $x^{g+1}_{a,*}$ of $\boldsymbol{X}^{g+1}$ will be equal to the best of the agents $\left\{x^{g}_{a,*}, y^{g}_{a,*}\right\}$, using the fitting function value of the agents for the comparison. Once the stop condition is reached, the best agent is returned as the best fit solution found. A flowchart of the algorithm is shown in Fig. 1.

The schemes used in the study are presented and the new trial parameter expression is shown for each one of them. The differential process is the core of the proposed methodology and the factor $F \in (0,1]$ determines the behavior of the crossover (graduates how much noticeable is the change at the parameters).

The name of the strategies is defined by considering the used crossover technique and the count of neighbors pairs used at this stage. The *DE/Rand/N* and *DE/Best/N* sets are the family of strategies analyzed in this research, where a vector of unique neighbors is created for each agent, taking $n^{g}_{a,1}$ as the agent with the lowest score in the main population when using *Best* strategies. The parameter N in the strategy name refers to how many pairs of agents are appended to the vector, leading to $\Lambda = 1 + 2N$ as the cardinality of the vector of neighbors for each agent. For the p-th parameter, the trial parameter w of the agent a at generation g is calculated as shown in (1).

$$w = \kappa(1) + \sum_{\lambda=2}^{\Lambda}\left((-1)^{\lambda} F\kappa(\lambda)\right), \kappa(\lambda) = x^{g}_{\left(n^{g}_{a,\lambda}\right),p} \tag{1}$$

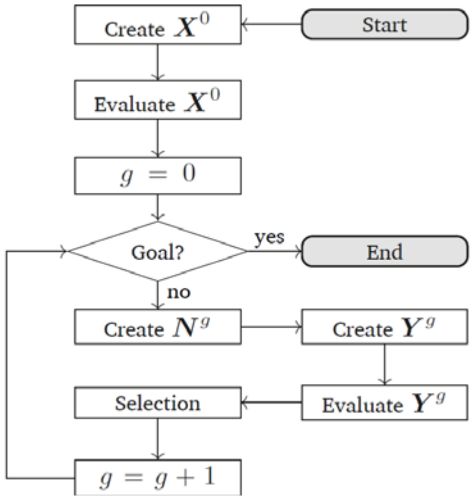

Figure 1. DE algorithm flowchart

For each a-th agent of the main population at generation g a crossover process is done. A randomly selected parameter is fixed where the index of the parameter is δ which is taken from a discrete uniform distribution $\mathcal{U}(1,P)$. For each parameter $p \neq \delta$, a random c is generated using an $\mathcal{U}(0,1)$ if $c \le C$ with C being the crossover probability. Then, the trial parameter w is generated as described in the equation (1) and as the last step $y^{g}_{a,p} = \min\{1, \max\{0, w\}\}$, else $y^{g}_{a,p} = x^{g}_{a,p}$. When F is multiplied by an observation of a $\mathcal{U}(0,1)$ variable for each parameter and the agent of the population in the crossover stage the strategy is named with a * mark at the end of its name (*DE/Best/N** and *DE/Rand/N**).

B. Analytical study of the sinusoidal waveform definition

A study of the sinusoidal waveform definition needs to be done for the selection of the optimization method that will be used with the aim of obtaining an approximate solution.

Given a signal $r(t)$ based on a sinusoidal waveform, with the formula shown in (2), it is necessary to obtain a synthetic signal $\hat{r}(t)$ that minimizes the error.

$$r(t) = \alpha \sin(\omega t + \phi) \tag{2}$$

The error is described in the integral part of (3) for a given standard sine wave. This expression must be converted to its discrete form to work with it.

$$\hat{r}(t) = \operatorname{argmin}_{x(t)} \int_{I_w} \left(x(t) - r(t)\right)^2 dt \tag{3}$$

The equation (4) shows the objective function to optimize by using s as the sampling rate and $\boldsymbol{r}$ as the raw signal data vector, with r_p as its p-th component, and $I_w = \left[I_{w,s}, I_{w,e}\right)$ as the time interval where the waveform parameters are estimated and $\gamma(I_w)$ is the interval of discrete sample indexes corresponding to I_w. The parameters ω and ϕ are defined as the frequency and the phase offset of the waveform, respectively, and t is a variable representing time.

$$\hat{r}(t) = \operatorname{argmin}_{x(t)} \sum_{p\in\gamma(I_w)} \left(x\left(\frac{p}{s}\right) - r_p \right)^2 \quad (4)$$

The objective function has local minimum points at $\mathcal{F}$ as expressed in (5). So, an adequate constraint set must be defined to obtain a solution.

$$\mathcal{F} = \begin{Bmatrix} \omega = \omega_1, \phi = \phi_1 + 2n\pi, n \in \mathbb{Z} \\ \omega = -\omega_1, \phi = -\phi_1 + 2n\pi - \pi, n \in \mathbb{Z} \end{Bmatrix} \quad (5)$$

The equation (6) specifies a definition of the constraints $\mathcal{K}$ created for the resolution, where $\omega_0^* = 2\pi f_0^*$ relates to the standard fundamental frequency as described in [40]. A deviation of $\pm 6\%$ is selected to comply with the frequency specification. A $\phi \in [0, 2\pi)$ constraint was added for phase offset because of the cyclic property that sine wave function possesses in $x(t)$.

$$\mathcal{K} = \begin{Bmatrix} (0.94)\omega_0^* \le \omega \le (1.06)\omega_0^* \\ 0 \le \phi < 2\pi \end{Bmatrix} \quad (6)$$

A filled contour plot of the objective function is shown in Fig. 2 where the RSE between the real and the estimated signal, calculated by applying the equation (7) and by using $\bar{\boldsymbol{r}}$ as the mean of the raw signal data mean (must be equal to zero for this methodology), measures waveform fitting.

$$\text{RSE} = \frac{\sum_p \left(\boldsymbol{r}_p - \hat{\boldsymbol{r}}_p \right)^2}{\sum_p \left(\boldsymbol{r}_p - \bar{\boldsymbol{r}}_p \right)^2} \quad (7)$$

The RSE goes from 0 to infinity where a lower index value corresponds to a better fit. The minimum value is reached at (60Hz, π radians) as expected.

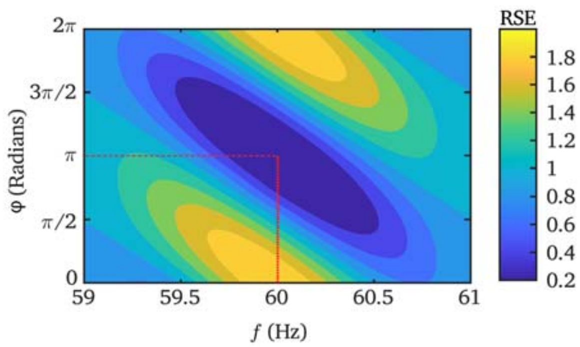

Figure 2. Objective function contour plot for f_1 (60Hz, π rads)

The DE algorithm will find out the optimization problem solution stated by (4), using (5) and (6) as constraints. This particular algorithm was chosen because it is able to solve optimization problems with multiple continuous variables as the present problem, whereas its population nature makes its implementation in parallel a straightforward process. Furthermore, recent evidence reveals the prevalence of meta-heuristic algorithms for solving this kind of problem, as particle swarm optimization (PSO) in [34], gravitational search algorithm (GSA) in [35] and harmony search (HS) in [36].

C. Micro-genetic algorithm for power quality analysis

A methodology focused on power quality disturbances detection and measuring named as Micro-genetic algorithm for power quality analysis (MGA-PQA) has been studied in [13]. This methodology will be used for comparison purposes with the proposed methodology.

The approach presented in the article is based on the use of low population size genetic algorithms for parameter estimation. Mathematical model fitting by using MGA is performed at different steps of the methodology showing results that outperform the PSO and classical methodologies.

IV. Methodology

In this section, the proposed methodology is described and the system implementation is presented. The system shown in Fig. 3 is proposed as an online power quality event classifier, where the characterization of sag, swell, flicker and harmonic content can be done. Furthermore, unbalance and asymmetries between phases [50] can be accomplished with no extra steps. The proposed approach is also able to determine if an unknown disturbance is present at the system because of the fitting error that distinct DE blocks may return. The simplicity of the methodology which is mainly based on DE blocks, band-pass filters and moving RMS blocks is a key point for the ease of its implementation.

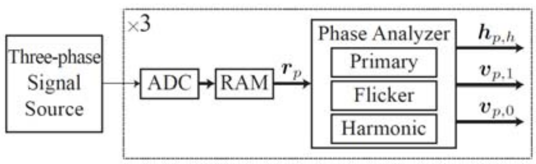

Figure 3. Main block diagram of the system

The presented block diagram is designed for a three-phase signal which is most common at continuous manufacturing industry, a different diagram could be built for being used in two-phase systems where the multiplicity of the components in the acquisition and analysis modules is changed. The methodology takes a raw stationary voltage power signal which is composed of three phases, this is sampled through ADC systems and the data is stored in a Random-Access Memory (RAM) using a sampling rate s, after certain number of samples a window phase signal data vector $\boldsymbol{r}_p$ is obtained for each phase p. These vectors $\boldsymbol{r}_p$ are submitted to the analysis module where fundamental signal estimated waveform parameters $\{\hat{\omega}_{p,1}, \hat{\phi}_{p,1}\}$ and moving RMS of the signal are calculated. Harmonic content characterization is conducted where moving RMS $\boldsymbol{h}_p$ of each of them is obtained. Moreover, flicker characterization is performed, where its moving RMS, $\boldsymbol{v}_{p,0}$, is taken as the result. Once all outputs of the analysis module are calculated, different thresholds are applied to accomplish with the event detection.

A. Phase Analyzer module

An extended description of the Phase Analyzer is needed in order to understand the proposed methodology. This module is the main block of the methodology, where the logic of the method is contained, it is shown in Fig. 4. In the Primary module, a band-pass filter is needed in order to attenuate frequencies far from the fundamental frequency. Once applied, the resulting signal $\boldsymbol{r}_{p,1}$ is taken as input for a DE block and the system proceeds to an estimation of $\{\omega_{p,1}, \phi_{p,1}\}$ parameter set. The Moving RMS by a half fundamental cycle sliding window (with $\pi / \hat{\omega}_{p,1}$ as length) of the raw phase signal data (formerly $\boldsymbol{v}_{p,1}$) is performed. A threshold analysis is performed at $\boldsymbol{v}_{p,1}$ where for each value $v \in \boldsymbol{v}_{p,1}$ a sag is present if $0.1\text{pu} \le v \le 0.9\text{pu}$, a swell is present if $1.1\text{pu} \le v \le 1.8\text{pu}$ and an interruption is present if $v < 0.1\text{pu}$. This method allows an accurate detection and characterization for these voltage variation disturbances by each half of a period or more as the standard claims [8]. There is no need for syncing by using phase offset because moving RMS does the calculation independently of it.

A flicker module is present at the phase analyzer. The primary module output signal is filtered by a band-pass in order to erase frequencies outside the flicker expected range. A DE block proceeds with the estimation of flicker parameters $\{\hat{\omega}_{p,0}, \hat{\phi}_{p,0}\}$. By obtaining an estimated frequency close to the search lower bound could be a sign of flicker absence. Otherwise, a flicker effect correction must be done at $\boldsymbol{v}_{p,1}$ to avoid detecting flicker cycles as voltage sags and voltage swells (because it can be seen as voltage falling and voltage rising, continuously). A moving mean is used to center the filtered signal at 0V. The Moving RMS by a half flicker cycle sliding window is calculated (formerly $\boldsymbol{v}_{p,0}$) using last step output. A flicker present at the time window analyzed lead to a DC signal at $\boldsymbol{v}_{p,0}$.

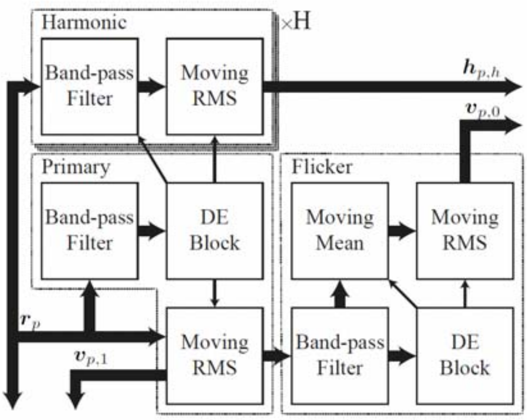

Figure 4. Phase Analyzer block diagram

The harmonic modules are implemented as well, where each one of them performs the analysis of one harmonic, by receiving the raw phase signal $\boldsymbol{r}_p$ and returning a moving RMS signal $\boldsymbol{h}_{p,h}$, from Fig. 4 harmonic content modules are replicated H times with H being the number of harmonic content to analyze. This module composition leads to a linear growth of the system architecture taking the number of harmonic content orders to analyze as the parameter. A threshold is set for harmonic module output signal $\boldsymbol{h}_{p,h}$ to show the presence of harmonic content. There is the need of having the fundamental frequency estimation done before analyzing harmonic content, the reason is that this method relies on it for creating the harmonic filter and moving RMS sliding window. A flowchart of the process performed at phase analyzer block is shown at Fig. 5.

B. Differential evolution parameters estimation block

The most compute expensive part of the methodology is the DE parameters estimation block. Given that the fitting function evaluation shown in (7) is computationally expensive when the sampling frequency of the signal is high (≥ 8 kHz), summed up to the presence of this block at different parts of the system. A study has been directed for reducing the computation time required for fitting waveform signals.

Because DE is a generation-based algorithm, the lowest number of generations needed to obtain a fit, whose sum of square errors (SSE) is expected to be lower than certain ε is desired. This goal could be reached by increasing the population size or by modifying the random generation of the initial agents. The first approach is discarded because of a not efficient use of the computational resources would be done. Given that signals present at the system are not supposed to change over time and similar frequencies between the last processed time window signal and the current one is expected, DE modules are designed in a way that feedback of the best agent found at last time window is stored for using it at the creation of the new initial population.

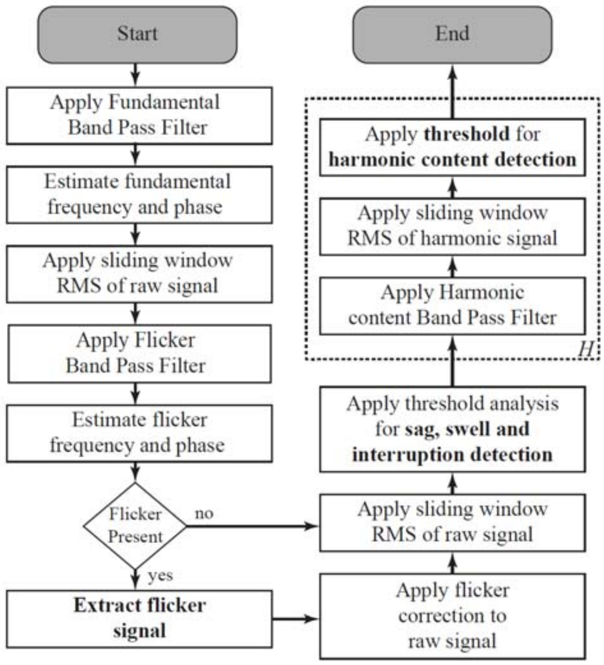

Figure 5. Flowchart of Phase Analyzer block

A study was driven in the DE block for waveform fitting, where different parameters of the algorithm were tuned to achieve a better fit in fewer generations. The results of the study by population size are summarized in Table I where each test case is defined using a population size, a mutation strategy, a crossover probability C and a differential factor F. Each line represents the minimum generations, g^{ε}, needed to reach the lower bound defined as $\varepsilon = 0.005$ (0.5%

mean square error). The phase shift, Φ, is defined as the sum of the mean and the standard deviation of the MSE for that row using 100 samples per each. The table shows that for 25 agents as population size test case (*DE/Best/3*,1,0.25*) with 20 as the generations needed using 3 pairs of neighbors (and the best agent) for the mutation strategy, for all the population sizes tested the case (*DE/Best/1*,1,0.25*) appears at the top in the first or the second position. This case will be named the general optimum configuration.

Also, a comparison is done between a serial and a parallel GPU OpenCL implementation (both present at the C++ library developed in this study), where parallel implementation shows a significant difference of running time required for 80 generations. Tests were run defining 200 agents as population size for the general optimum configuration, (Best,1,1,0.25,1), a mean speed-up of up to 37 times is reached when using the GPU parallel implementation. In Fig. 6 is shown that, this speed-up will probably increase for larger window sizes.

The maximum parallel implementation throughput is achieved by the subdivision of the process in independent tasks, taking advantage of the fact that computation of the population scores is an independent process between agents.

TABLE I. GENERATIONS NEEDED BY DE CONFIGURATION TO ACHIEVE $\varepsilon < 0.5\%$ RSE

Pop. Size	Strategy	C	F	g^{ε}	Φ (%)
25	DE/Best/3*	1	0.25	20	0.43317
25	DE/Best/1*	1	0.25	24	0.42089
25	DE/Best/1	0.75	0.25	24	0.44026
50	DE/Best/1*	1	0.25	9	0.31885
50	DE/Best/2*	1	0.25	9	0.49077
50	DE/Best/3*	1	0.25	9	0.4943
100	DE/Best/1*	1	0.25	5	0.35433
100	DE/Best/2*	1	0.25	6	0.30329
100	DE/Best/1*	0.75	0.25	6	0.37286
200	DE/Best/1*	1	0.25	3	0.46988
200	DE/Best/2*	1	0.25	4	0.32843
200	DE/Best/3*	1	0.25	4	0.46404

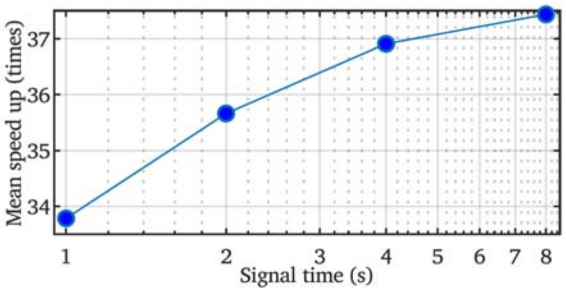

Figure 6. Speed up by window size by the use of a Tesla K80 GPU on Amazon Web Services Elastic Cloud Computing

V. VALIDATION USING SYNTHETIC POWER SIGNALS

To test the validity of the methodology in a simulated environment a synthetic power signals battery of tests is performed.

Detection of PQDs using larger windows is done with a gain of accuracy in disturbance classification compared with the MGA-PQA methodology proposed in [42] where a fixed standard frequency is taken.

For each test case a synthetic signal that contains a set of PQD is generated, after that, MGA-PQA and proposed methodology are both applied using the raw signal as input. Using the output fit from each methodology the error values are calculated by using (7) and (8).

$$\Delta(r,\hat{r}) = \max_k |r_k - \hat{r}_k| \tag{8}$$

Synthetic signals were created by using the mathematical model shown in [51], analysis and reconstruction of each signal are done by the MGA-PQA and the proposed methodology. These tests have run taking 60 Hz and 59.7 Hz as the fundamental frequency and the next disturbances present for each test: 0.6pu sag, 1.2pu swell, 20 Hz and 0.3pu flicker, harmonic content of third and ninth order with an amplitude of 0.1pu and 0.2pu respectively. A signal with a 0.6pu sag, 20 Hz and 0.2pu flicker and fifth order harmonic content of 0.1pu is analyzed at 60 Hz fundamental frequency as well.

The tracking error comparison is done by using maximum absolute difference, which is calculated as shown in (8) using $\boldsymbol{r}$ as the raw signal and $\hat{\boldsymbol{r}}$ as the reconstructed estimated signal, which is the output of the proposed methodology based on DE. The results of the fitting quality by both methodologies are summarized in Table II.

The disadvantage of analyzing a signal using a fixed frequency at the model is noticeable even more when analyzing high order harmonic content, because the error of the fundamental frequency is multiplied so automated analysis is now possible under these uncertain conditions.

Analysis of the signal with a combination of disturbances shows that a flicker is detected, a correction at the signal RMS must be done to detect the sag component. After the correction is done, the sag is detected correctly independently from the flicker as two distinct events as shown in Fig. 7. The proposed methodology is able to extract the flicker as well.

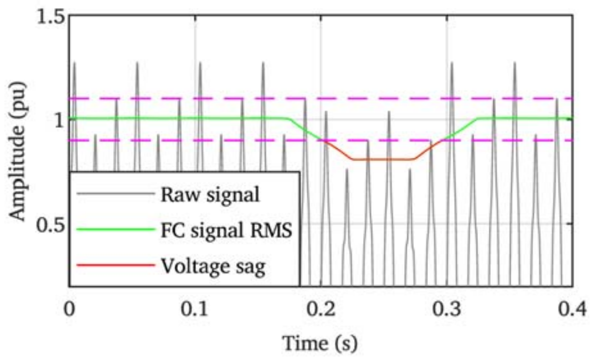

Figure 7. Flicker corrected RMS analysis of mixed signal

A study has been driven to analyze the importance of using good fixed frequency parameter in the MGA-PQA method. A synthetic 60Hz sine waveform is generated, and the RSE is calculated for different fixed frequencies set for the MGA-PQA method. The results of the study can be seen in Fig. 8. The results reveal the important use of the correct fixed frequency parameter for the estimation of the waveform. Furthermore, real power signals are not constant in frequency, what leads to an estimation of this parameter for each window.

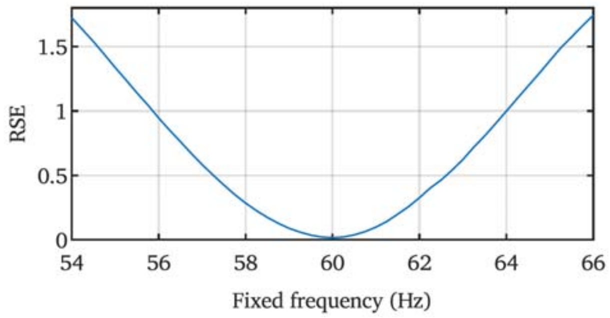

Figure 8. RSE for different fixed frequencies set for the MGA-PQA method on a 60Hz sine waveform

TABLE II. RESULTS OF SYNTHETIC SIGNALS TESTS

Test Signal	Method	60 Hz Δ (%)	60 Hz RSE (%)	59.7 Hz Δ (%)	59.7 Hz RSE (%)
Sag	MGA-PQA	**29.355**	**0.306**	38.599	5.145
	Proposed	30.718	0.3132	**32.171**	**0.283**
Swell	MGA-PQA	**13.385**	**0.0863**	38.894	4.259
	Proposed	14.196	0.091	**13.418**	**0.099**
Flicker	MGA-PQA	11.49	0.439	45.553	5.069
	Proposed	**7.866**	**0.31**	**8.183**	**0.308**
Harm. content	MGA-PQA	6.677	0.05	52.801	7.644
	Proposed	**2.238**	**0.01**	**0.268**	**0**
Mixed	MGA-PQA	20.248	0.666	33.314	2.491
	Proposed	**17.25**	**0.178**	**15.898**	**0.219**

Test Signal	Method	59.4 Hz Δ (%)	59.4 Hz RSE (%)	58.8 Hz Δ (%)	58.8 Hz RSE (%)
Sag	MGA-PQA	42.089	4.981	69.756	16.234
	Proposed	**32.828**	**0.601**	**31.07**	**0.587**
Swell	MGA-PQA	75.381	17.698	117.41	50.342
	Proposed	**15.179**	**0.103**	**15.204**	**0.105**
Flicker	MGA-PQA	80.565	17.332	118.64	48.953
	Proposed	**8.337**	**0.309**	**8.429**	**0.309**
Harm. content	MGA-PQA	83.32	19.71	109.26	50.065
	Proposed	**0.419**	**0**	**0.853**	**0**
Mixed	MGA-PQA	54.203	6.126	76.811	17.814
	Proposed	**14.96**	**0.229**	**13.639**	**0.222**

VI. VALIDATION USING REAL POWER SIGNALS

With the purpose of validating the proposed methodology in a real environment after it has been validated with synthetic signals, real power signals are being processed by the implementation of the system: a signal from IEEE and another from a hospital in Spain.

With the aim of comparing the proposed methodology and MGA-PQA methodology, the raw signal has been given to each of these methods. After a fit is obtained for each methodology, errors are calculated by using (7) and (8).

A. Laboratory power signal from IEEE

With the aim to provide a standard signal, a real power signal from the IEEE 1159.2 Working Group database, phase B from wave 1 in their dataset, was used to validate the proposed method showing an accurate detection for disturbances sag and harmonic content.

In Fig. 9.a it could be seen that the signal shows a disturbance between 0.3-0.4 seconds, normalized RMS falls to 24.75% with the proposed methodology and a sag is detected as shown in Fig 9.b. No flicker has been detected at the signal so no correction is needed for the signal normalized RMS. In Figure 9.c tracking error is present as shown for the MGA-PQA methodology and the proposed methodology showing a result of $\Delta = 21.009\%, RSE = 0.578\%$ for the proposed methodology and $\Delta = 39.562\%, RSE = 1.749\%$ for the MGA-PQA methodology. Harmonic content is estimated by the proposed method, an amplitude of $5.82\% \pm 0.87\%$ is estimated for the third order, $3.44\% \pm 0.38\%$ for the fifth order, $2.46\% \pm 0.28\%$ for the seventh order and $0.38\% \pm 0.1\%$ for the ninth order.

Because of this signal is generated under a controlled environment, its frequency is about to 60Hz; at the fundamental waveform DE block, a frequency of 59.9521 Hz is estimated. By the use of a longer time window, the MGA-PQA is expected to fail at voltage sag estimation if the disturbance is present at some point where the phase offset difference of the waveform generated by the fixed frequency method and the fundamental waveform is relatively high in magnitude.

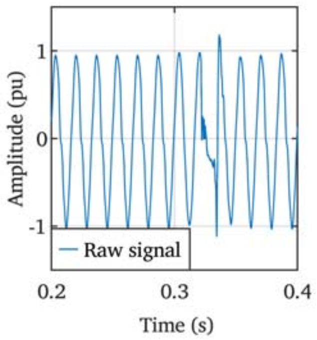

Figure 9. a. Raw signal

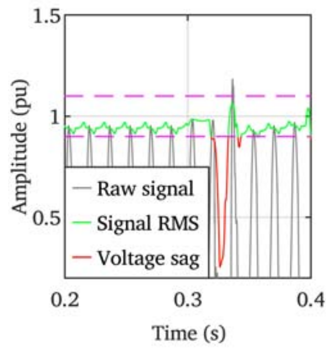

Figure 9. b. RMS analysis

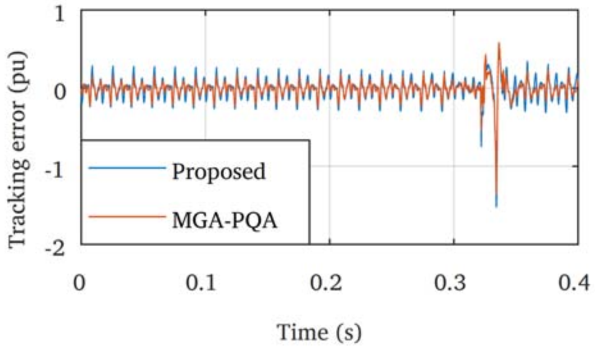

Figure 9. c. Tracking error

Figure 9. IEEE Working Group signal analysis by the proposed method

B. Power signal from a hospital in Spain

Having as a goal to provide a second real power signal test, a sanitary facility study has been done. The analysis of an uncontrolled environment power signal obtained by a proprietary acquisition system from a hospital at Valladolid, Spain, has been accomplished. Having in mind that this signal was acquired in Spain the fundamental frequency is expected to be 50 Hz, estimation by the proposed methodology solved it as 50.0209 Hz. The raw signal is shown in Fig. 10.a. A voltage sag is detected by the proposed methodology in 0.16-0.24 seconds time range as shown in Fig. 10.b. The tracking error of the MGA-PQA methodology and the proposed methodology could be seen in Fig 10.c where the proposed methodology tracking error seems lower compared with the other methodology, confirmed by the numerical results of $\Delta = 21.009\%, RSE = 0.57828\%$ for the proposed methodology and $\Delta = 39.562\%, RSE = 1.735\%$ for the MGA-PQA methodology.

Harmonic content is analyzed by the proposed methodology showing an amplitude of $1.12\% \pm 0.28\%$ for the third order, $0.49\% \pm 0.11\%$ for the fifth order, $0.36\% \pm 0.07\%$ for the seventh order and $0.52\% \pm 0.05\%$ for the ninth order respectively.

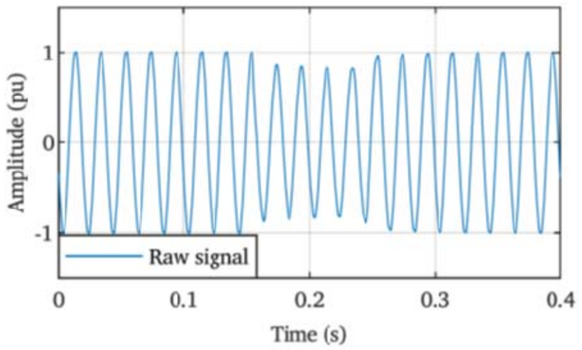

Figure 10. a. Raw signal

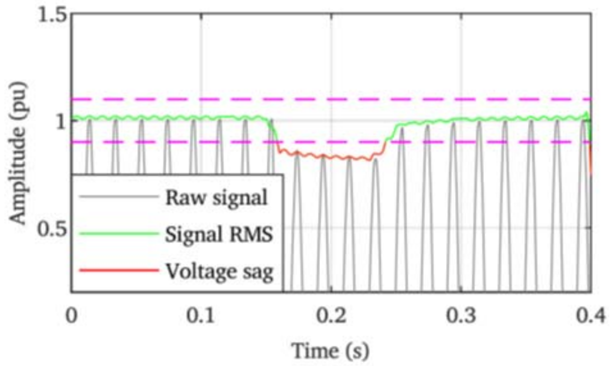

Figure 10. b. RMS analysis

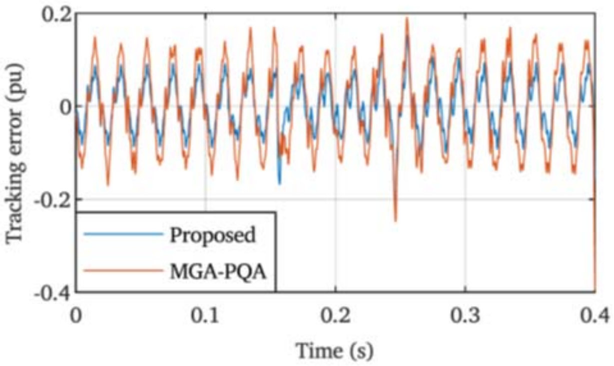

Figure 10. c. Tracking error

Figure 10. Hospital signal analysis by the proposed method

VII. Discussion and Analysis

An analysis of the results of the previous section is needed. In this section, analysis and discussion of the results is performed.

In section IV.B a group of strategies for DE are presented. These strategies are studied where using DE/Best/1* as the mutation strategy shows generally more favorable results for high population sizes, where only 3 generations are needed to obtain a 0.16% RSE for a population of 400 agents with no previous information of the signal. The number of generations needed is expected to decrease when initial population parameters are distributed centered on last window values. A new statistical distribution based on a constrained normal distribution is presented for this process.

A test suite has been performed showing the mean and the standard deviation of maximum absolute difference (Δ) and RSE by the use of the MGA-PQA methodology and the proposed methodology using 60 Hz standard. Also, fundamental frequencies deviations of $-0.5\%, 1\%$, and 2% were tested. Ten iterations per configuration are run, where a configuration is represented by a synthetic signal generated: a sag with amplitude in the range of $(0.8, 0.9)$ pu and a length in the range of $(0.05, 0.10)$ s, a swell with amplitude in the range of $(1.1, 1.2)$ pu and a length in the range of $(0.05, 0.10)$ s, a flicker with a frequency in the range of $(10, 20)$ Hz and an amplitude in the range of $(0.2, 0.3)$ pu, a 3rd harmonic content with an amplitude in the range of $(0.05, 0.10)$ pu, a 9th harmonic content with an amplitude in the range of $(0.05, 0.10)$ pu and a combination of the sag, flicker and 9th harmonic content described before. The results of this test suite are shown in Table III.

For each test-case 100 signals were generated. After applying the proposed methodology and the MGA-PQA methodology on each one, a fit is obtained. The error vector is calculated by using (7) and (8). Average and standard deviation of the errors vector are calculated for each methodology.

Table III. Results of the Test Suite Performed

Test signal	Method	60 Hz Δ (%)	RSE (%)
Sag	MGA-PQA	12.37±2.117	0.09±0.017
	Proposed	**11.04±3.183**	**0.04±0.031**
Swell	MGA-PQA	**10.28±1.411**	**0.07±0.004**
	Proposed	13.77±6.136	0.11±0.236
Flicker	MGA-PQA	18.43±1.25	1.08±0.189
	Proposed	**9.4±0.956**	**0.42±0.077**
3rd H.	MGA-PQA	6.14±0.998	0.04±0.008
	Proposed	**0.54±0.015**	**0±0**
9th H.	MGA-PQA	5.65±1.032	0.04±0.008
	Proposed	**0.47±0.007**	**0±0**
Mixed	MGA-PQA	18.79±1.909	1.08±0.101
	Proposed	**14.14±4.883**	**0.45±0.107**
Test signal	**Method**	**59.7 Hz Δ (%)**	**RSE (%)**
Sag	MGA-PQA	37.77±0.989	4.78±0.152
	Proposed	**10.24±2.216**	**0.04±0.03**
Swell	MGA-PQA	38.76±1.672	4.65±0.157
	Proposed	**12.09±2.905**	**0.03±0.015**
Flicker	MGA-PQA	47.95±0.801	5.73±0.153
	Proposed	**9.06±1.111**	**0.39±0.083**
3rd H.	MGA-PQA	45.84±1.854	4.9±0.117
	Proposed	**0.18±0.029**	**0±0**
9th H.	MGA-PQA	38.88±1.563	5.14±0.16
	Proposed	**0.32±0.008**	**0±0**
Mixed	MGA-PQA	49.51±1.454	6.39±0.272
	Proposed	**15.04±3.236**	**0.48±0.07**
Test signal	**Method**	**59.4 Hz Δ (%)**	**RSE (%)**
Sag	MGA-PQA	68.44±0.838	17.51±0.444
	Proposed	**11.57±4.426**	**0.07±0.125**
Swell	MGA-PQA	69.19±0.928	16.49±0.59
	Proposed	**12±4.823**	**0.08±0.153**
Flicker	MGA-PQA	88.01±1.213	18.01±0.314
	Proposed	**8.91±1.114**	**0.37±0.089**
3rd H.	MGA-PQA	75.33±1.543	17.36±0.117
	Proposed	**0.24±0.035**	**0±0**
9th H.	MGA-PQA	72.02±1.16	17.28±0.115
	Proposed	**0.25±0.032**	**0±0**
Mixed	MGA-PQA	92.01±1.335	18.5±0.631
	Proposed	**14.44±3.72**	**0.5±0.099**

The proposed methodology shows more accurate results compared with the MGA-PQA methodology even when using 58.8 Hz as the fundamental frequency.

Differences between the MGA-PQA methodology and the proposed methodology presented in section IV lead to different results. By using the MGA-PQA methodology a DE parameter search is conducted for each half cycle, using zero crossings as the indicator, resulting in a peak amplitude value. The assumption of the standard frequency presence at the fundamental waveform could drive to a low accuracy signal fitting where PQD could not be detected and characterized. A fundamental frequency difference for a 60Hz standard, a 5% difference, has shown a high loss of accuracy in the previous fixed frequency method, showing an interruption when a flicker is present. Through the frequency and the phase estimation of the signal fundamental waveform by time window, a new level of stability is reached where the proposed methodology adapts itself effectively to real power signals in an automated way. The results obtained from the analysis of synthetic and real power signals are as they were expected to be, given that frequency search space is compliant with valid fundamental waveform frequency range.

Given that harmonic content frequencies are multiples of the fundamental waveform frequency a precise estimation of the last one must be performed in order to design and calculate the total harmonic distortion (THD). As the order of the harmonic content grows error does as.

VIII. Conclusions

After the assessment of the results presented in this research, several conclusions are reached. These conclusions are related to the parallel implementation of the algorithm and the use of DE as a method for fitting the PQD mathematical model used.

In conclusion, current research presented a new methodology based on a parallelization scheme for minimizing the computational resources that the computationally intensive technique of definition evolution requires. This parallel structure allows a decrease in a significant amount the processing time by applying calculations in parallel structures at high speed diminishing the computational effort by the use of hardware dedicated to graphics processing through CUDA and OpenCL libraries. Nevertheless, the architecture introduced shows simplicity as one of its characteristics in an open architecture.

The presented methodology uses differential evolution as its main module for its construction. Through the implementation of libraries that allow the use of graphics processing units, a parallelization of this technique is reached. As a consequence of the computational scheme shift, the result of this case study, a complete mathematical model fitting of a signal, is a speed-up of 37 times. Demonstrating the power in the use of both techniques together, leading to a minimization of the resources needed for the processing.

The implementation of the methodology in the case study leads to an on-line monitoring power quality system with high accuracy in the measurement of power disturbances. This new methodology has been validated through tests using synthetic and real power signals, which contain different types of disturbances such as isolated and mixed. A remarkable improvement has been obtained compared with the MGA-PQA methodology, reaching a precision gain of 5% for signals whose fundamental wave frequency is equal to the fixed standard and a precision gain of 69% when dealing with signals whose fundamental wave frequency differs by 1% from the standard frequency.

It has been demonstrated that the proposed methodology is capable of making a considerable contribution to the scope of power quality monitoring. Computation of evaluation function values in the differential evolution algorithm has been accelerated by the use of parallel computing obtaining an on-line power quality monitoring system as a result. The future aims for using parallel computing along with meta-heuristic and artificial intelligence algorithms. The compound of these techniques would illuminate the various uncertainties that are currently present in the field of power quality.

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