

# Identification of harmonics origin in distribution networks using minimum number of power quality analyzers and genetic algorithms

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This paper presents a novel approach to identify harmonics origin in distribution networks. The technique first collects measurements from networked power quality analyzers installed at key locations, and using the genetic algorithm as a search methodology, it can deduce the most probable event that generates the obtained data profile. A case study proved the validity of the proposed identification algorithm.

يقدم هذا البحث طريقة جديدة لتحديد مصدر التوافقيات في شبكات التوزيع. تقوم الطريقة علي جمع القياسات من أجهزة تحليل جودة الطاقة المتصلة ببعضها و المركبة في أماكن قياسية، ثم يستخدم أسلوب الخوارزم الجيني كطريقة بحث عن المصدر الذي ينتج مجموعة قياسات مشابهة للقياسات التي تم الحصول عليها. هذا و قد تم تطبيق الطريقة علي شبكة قياسية و أثبتت النتائج فاعليتها و تم تحديد مصدر التوافقيات بنجاح.

**Keywords:** Harmonics, Power quality, Distribution network, Genetic algorithms

## 1. Introduction

Power Quality (PQ) is an important concern for both utilities and customers. PQ variations such as momentary interruptions, voltage sags, capacitor switching transients, and harmonic distortion can impact customer operations, causing equipment malfunctions and significant cost in lost production and downtime. Electric utilities must be able to characterize and assess the system performance at all levels. This performance information must be available in a form that customers can use to evaluate the impacts on their processes and to evaluate the economics of PQ improvement alternatives. The performance information should also be shared throughout the utility so that problem areas can be identified and solutions implemented. The increased concern for PQ has resulted in significant advances in monitoring equipment that can be used to characterize disturbances and PQ variations.

Although the trend is towards permanent PQ monitoring for ongoing identification of possible PQ problems and to continuously characterize the system PQ performance, we

still do not have PQ monitors in every facility nor in every circuit. Consequently, when a power quality event occurs that causes a concern to certain customer, the question that always arise, who is the origin for the disturbance, the utility, the neighbouring facility, or the customer himself. This brought up the need for analysis tool to conclude the origin and type of the disturbance from the data provided from the PQ analyzers installed in key locations of the system .

This paper describes a genetic algorithm technique that upon triggering of PQ event, it uses harmonic load flow equations to calculate the harmonic voltages and currents at networked PQ analyzer locations due to certain events, and compare it with the recorded data. The most probable events that may have happened can then be identified.

## 2. Proposed technique

If the harmonics generated by the non-linear loads are reasonably independent of the voltage distortion level in the ac system, the derivation of the harmonic sources can be decoupled from the analysis of harmonic

penetration and a direct nodal solution is possible. A separate system admittance matrix is generated for each frequency of interest. Having appropriate parameters for system components at required frequencies, it is straightforward to build up the system fundamental and harmonic frequency admittance matrices [1].

The system harmonic voltages are calculated by direct solution of the linear equation

$$[I_h] = [Y_h][V_h] \quad \text{for } h \neq 1. \quad (1)$$

Where  $[Y_h]$  is the system admittance matrix,  $I_h$ , and  $V_h$  are the injected currents and bus voltages vectors at harmonic order  $h$ .

The injected currents at most buses will be zero, since the sources of the harmonics considered are the nonlinear loads. Therefore, the system equations can be reduced to a system with only buses at which harmonic injection occurs [2]. The reduced matrix equation is

$$\begin{bmatrix} I_j \\ \dots \\ I_n \end{bmatrix} = \begin{bmatrix} Y_{jj} & \dots & Y_{jn} \\ \dots & \dots & \dots \\ Y_{nj} & \dots & Y_{nn} \end{bmatrix} \begin{bmatrix} V_j \\ \dots \\ V_n \end{bmatrix}. \quad (2)$$

Where  $j$  to  $n$  are the injection points.

The first phase of the analysis is a conventional load flow study on the power system neglecting all harmonics sources. The second phase employs the above technique on each individual harmonics. The principle of the superposition is then used to obtain bus voltages (3), and the simple Kirchoff's law is used to obtain current flows (4).

$$V_n = \sqrt{\sum_{h=1}^{25} V_{nh}^2}, \quad (3)$$

$$i_{kh} = (V_{ih} - V_{jh}) Y_{kh}. \quad (4)$$

Where  $i_k$  is the harmonic current through element  $k$ ,  $V_i$ ,  $V_j$  are the voltages across the

element  $k$ , and  $Y_k$  is the admittance of the element  $k$ , all at harmonic  $h$ .

Using the above technique, harmonic load flow analysis can be obtained for each assumed harmonic current injections profile with arbitrary value. Output results contain resultant branch currents, each harmonic voltage at each bus, VTHD at each bus, ITHD at analyzer location, etc.

When an event is flagged, the data is collected from the power system analyzers located at key buses, and compared with the output of the harmonic load flow technique via a search algorithm for the closest data profile to the obtained profile from the analyzers. Possibilities for the occurred event, in priority order, can then be obtained. This is due to the nature of fixed topology and parameters of the distribution system. This idea can also be extended to compare the pre event data with the post event data to conclude vital information that pinpoints the origin of disturbance, or application of similar techniques for other dynamic behaviors like voltage dips due to motor starting for example.

### 3. Genetic algorithms as a search technique

Genetic Algorithms (GA) are search methods based on the principles of natural selection and genetics, so they are highly probabilistic. Genetic Algorithms are robust, in the sense that they solve many types of simple and complex problems and their solutions are more likely to be global optimums.

Genetic algorithms encode each point in a solution into a string which is often a binary bit string called a chromosome; these chromosomes are strings of binary digits 1 and 0. Each point is associated with a "fitness" value that, for maximization, is usually equal to the optimization objective function evaluated at the point. Instead of a single point, GA usually keeps a set of points as a population or gene pool, which then evolved repeatedly toward a better overall fitness value, i.e., evolves to better generations. In each generation, the GA constructs a new population using genetic operators such as crossover and mutation;

members with higher fitness value are more likely to survive and participate in mating (crossover) operations. After a number of generations, the population contains members with better fitness values; this is analogous to Darwinian models of evolution by random mutation and natural selection. GA and their variants are sometimes referred to as methods of population-based optimization that improve performance by upgrading entire populations rather than individual members. Major components of GA include encoding, fitness evaluation, parent selection, crossover operator, and mutation operator [3].

#### 4. Application of GA to harmonics origin identification problem

The harmonics origin identification problem can be considered as an optimization problem where the objective function is to minimize the sum of the squares of the differences between each measured value and the value obtained from the system harmonic load flow solution corresponding to certain event. The objective function is:

$$\begin{aligned} \min J(V_1^1, V_1^3, V_1^5, \dots, V_2^1, \dots, V_n^{11}, V_{THDs}, \\ I_1^1, I_1^3, \dots, I_n^{11}, \dots, I_{THDs}) \\ = \sum_{i=1}^m [z_i - f_i(V_1 \dots V_n, I_1 \dots I_n)]^2 \end{aligned} \quad (5)$$

Where

- $f_i$  : function of the value being measured,
- $J$  : measurements residual,
- $m$  : number of measurements from PQ analyzers,
- $n$  : number of buses, and
- $z_i$  : measurement  $i$ .

Then our problem is how to estimate the best probable event by minimizing the objective function using the genetic algorithms. Usually, only two components of GA are problem dependant, the representation and evaluation functions. Representation is a key genetic algorithm issue because genetic algorithms directly manipulate coded

representations of the problem. Two possible coding methods to represent the state variables were tried, binary encoding and real-number encoding. When binary encoding was tried for a system of six buses, the state variables of that system were thirty harmonic current variables considering the odd harmonic current injected at each bus until the 11th harmonic. To meet the requirement of accuracy, each variable should be represented by a binary string of length 9 in average, which means a chromosome of length 270 in average approximately. Long chromosome resulted in poor performance for genetic algorithms. Moreover, it is time consuming; the program took approximately 32 minutes to reach the optimal solution. Furthermore the solution is not guaranteed, the program fail to reach optimal solution in many runs. Representing the variables by real number strings instead of binary coding can save the coding processing time and get more accurate values of the variables.

Each chromosome is encoded as a vector of real-numbers of the current magnitudes at each bus for each individual odd harmonic till the 11th harmonic. If the number of buses is  $n$ , there will be  $(n \times 5)$  variables represented by the chromosome string. Numbers of zero and non zero current injections can be restricted in the program based on the data received from the analyzers. GA parameters were set as follows [4]:

##### 4.1. Fitness function

Along with the representation scheme, the fitness function is problem dependent. The fitness value is determined from the objective function, and since the problem is minimization problem, the fitness function is given by:

$$\text{Fit}(x) = F_{\max} + F(x)$$

Where  $F(x)$  is the raw fitness function =  $-\mathcal{J}(x)$  (the objective function),  $F_{\max}$  is the largest absolute value of  $F(x)$  in the current population.

#### 4.2. Initial population

The initial population is formed randomly by creating the current variables as real random values in the range.

#### 4.3. Genetic operators

The new population is generated from the old population by applying genetic operators (selection, crossover, and mutation) to the old population. Genetic operators depend on the chosen encoding.

##### 4.3.1. Selection techniques

- *Parent selection:* The parents were selected from the population according to their fitness using the roulette wheel selection technique; the chromosomes with higher fitness values have higher probabilities to be selected as parent.
- *Elitism selection:* This was used in order to preserve the best chromosomes in the new generation if it is not selected through the roulette wheel selection process.
- *Survivor selection:* the new generations were selected from the offsprings by selecting the fittest individuals.

##### 4.3.2. Crossover operator

Arithmetical Crossover was used by linear combination of two vectors.

##### 4.3.3. Mutation operator

Non-uniform Mutation operator was applied to each gene according to mutation probability. The used function is  $\Delta(t,y) = y.r.(1 - t/T)^b$ , where the function  $\Delta(t,y)$  returns a value in the range  $[0, y]$  such that the probability of  $\Delta(t,y)$  approaches 0 as  $t$  increases ( $t$  is the generation number). This property causes the operator to search the space uniformly initially (when  $t$  is small), and very locally at later generations.  $r$  is a random number from  $[0, 1]$ ,  $T$  is the maximum generation number, and  $b$  is a system parameter determining the degree of non-uniformity.

The flowchart for the proposed algorithm is shown in fig. 1.

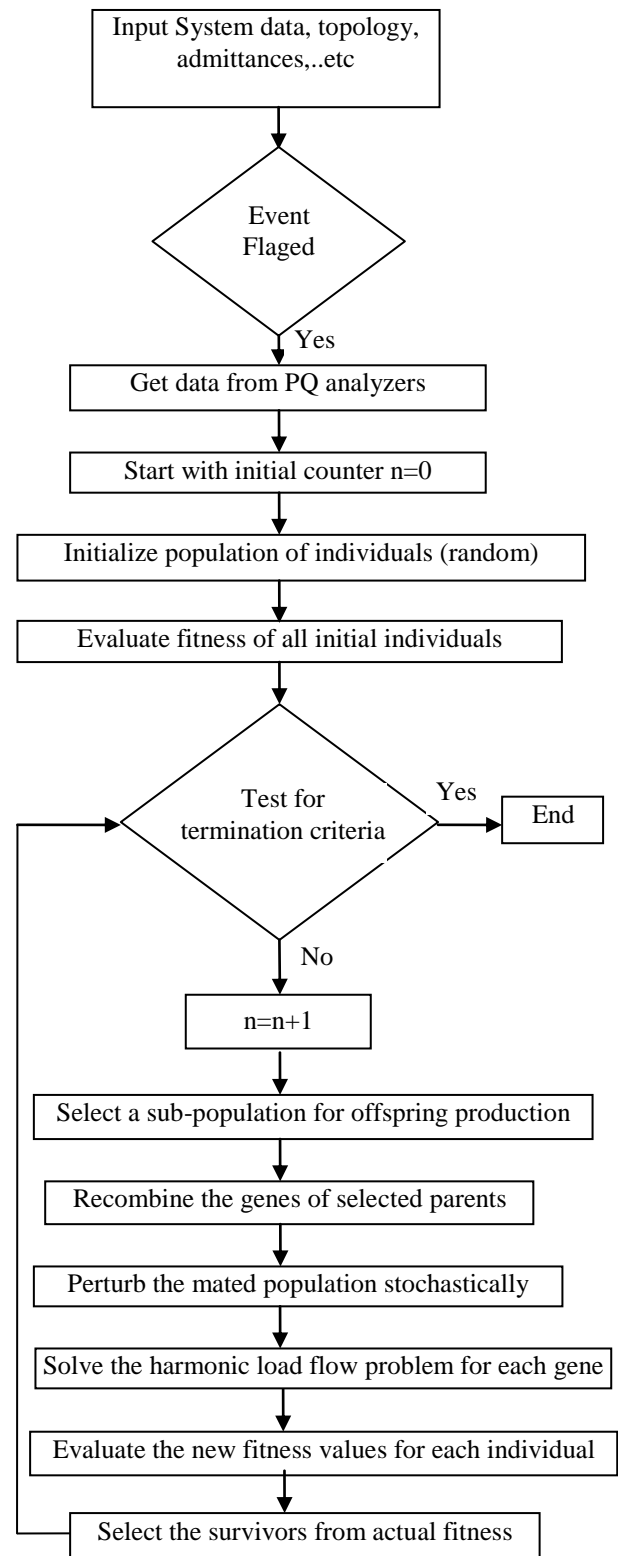


Fig. 1. Proposed algorithm flowchart.

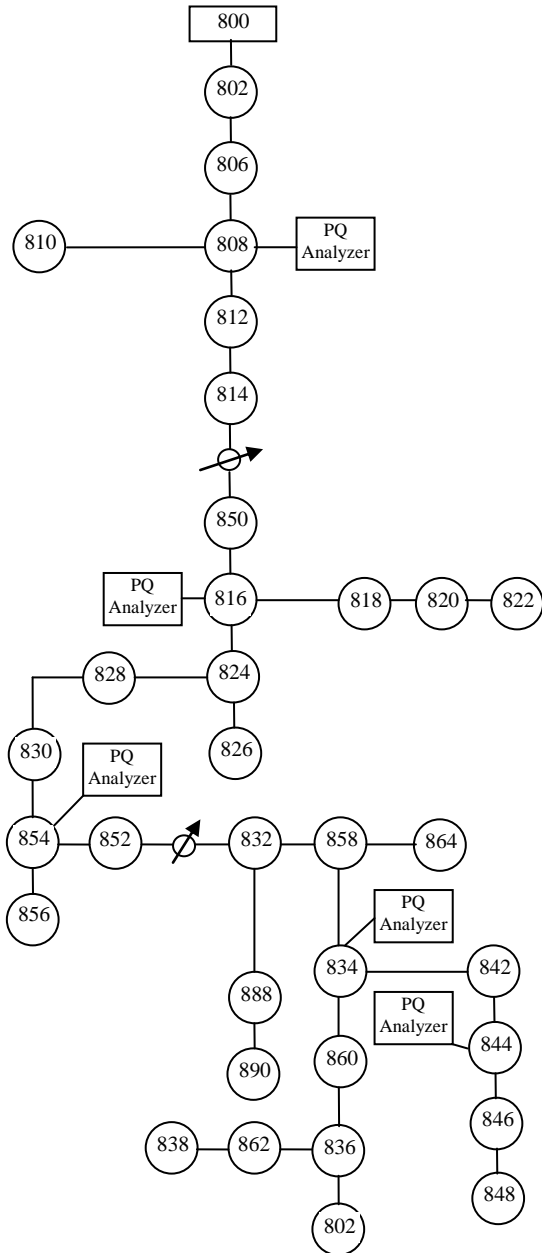


Fig. 2. IEEE 34 bus circuit diagram with installed PQ analyzers locations.

### 5. Case study

The IEEE 34 bus distribution system model [6] was used as a case study. A simulation of arbitrary harmonic input at certain bus was first run, then the simulated output data was used as inputs from the power quality analyzers and the target was to identify the assumed event fig. 2. Harmonic

order data was also used to limit the chromosome size, i.e., if the analyzers read only third harmonic currents, then chromosomes contains only third harmonic elements. Genetic algorithms parameter values were set at the following default values:

- Population size (popsize) = 34
- Maximum generation (maxgen) = 200
- Crossover probability (Pcross) = 0.7
- Mutation probability (Pmut) = 0.04
- The degree of non-uniformity (b) = 2
- Harmonic current values lie between [0.01, 2]

For every case, ten runs were performed to test the algorithm robustness. The experimental result is represented in table 1; the performance is measured by successful identification of the injected harmonic current and its value.

As shown in table 1, with the above parameters, GA converges at high objective function (J) values, and also indicates a wrong origin of the harmonics.

The mutation rate was increased to 0.2 and the degree of non-uniformity to 2.2, in order to help the GA wander freely among local minima at early stages, the algorithm was still not able to converge to the true origin in 8 cases out of the ten table 2, but it was concluded that parameter modification is on the right track. The mutation probability increased to 0.6 and the degree of non-uniformity to 4 after that which gave a satisfying results, this is indicated by small residual deviations and successful identification of the harmonics origin in all ten runs. This is shown in table 3.

Table 1  
Case study 1, third harmonic current injection of 0.4pu at bus 860, GA set with initial parameters

10 different runs	Residual (J)	Output event identification
1	50.45	$F_{860} = 0.55$ pu
2	67.67	$F_{864} = 0.3$ pu
3	81.21	$F_{854} = 0.7$ pu
4	46.1	$F_{840} = 0.6$ pu
5	73.23	$F_{848} = 0.34$ pu
6	39.90	$F_{840} = 0.55$ pu
7	90.16	$F_{890} = 0.4$ pu
8	58.07	$F_{824} = 0.5$ pu
9	66	$F_{820} = 0.2$ pu
10	46.55	$F_{862} = 0.63$ pu

Table 2  
Case study 1, third harmonic current injection of 0.4pu at bus 860, GA set with  $P_{mut}=0.2$ ,  $b=2.2$

10 different runs	Residual (J)	Output event identification
1	76.94	$F_{890}=0.39$ pu
2	49.48	$F_{862}=0.68$ pu
3*	22.45	$F_{860}=0.43$ pu
4	38.43	$F_{836}=0.51$ pu
5	78.32	$F_{890}=0.33$ pu
6*	19.90	$F_{860}=0.38$ pu
7	68.03	$F_{846}=0.38$ pu
8	40.91	$F_{838}=0.67$ pu
9	60.53	$F_{820}=0.31$ pu
10	38.11	$F_{832}=0.5$ pu

Table 3  
Case study 1, third harmonic current injection of 0.4pu at bus 860, GA set with  $P_{mut}=0.2$ ,  $b=2.2$

10 different runs	Residual (J)	Output event identification
1*	19.9	$F_{860}=0.39$ pu
2*	20.1	$F_{860}=0.38$ pu
3*	22.45	$F_{860}=0.42$ pu
4*	25.33	$F_{860}=0.45$ pu
5*	19	$F_{860}=0.36$ pu
6*	19.90	$F_{860}=0.40$ pu
7*	20.5	$F_{860}=0.41$ pu
8*	21	$F_{860}=0.39$ pu
9*	27	$F_{860}=0.36$ pu
10*	28	$F_{860}=0.44$ pu

Population size and max generations limit had an effect on the technique. It was found that the most stable and accurate solution is obtained at population size equal 60 and maximum generation equal 300. This is shown in tables 4 and 5.

Crossover operator found to have no effect on the algorithm. Changing the crossover probability value didn't influence the value of objective function or the identification process. Removing the elitism technique didn't have any effect on the results as well, which indicated robustness. Good initial guess and reduction of harmonic current search space increased the speed of program convergence.

Having tuned the GA parameters, two other combined trial runs were run and successfully identified; this is shown in tables 6 and 7.

Table 4  
Case study 1, third harmonic current injection of 0.4pu at bus 860, population size optimization

Pop size	Average residual (J) over 10 runs	Residual standard deviation over 10 runs
20	39	7.1
30	34	6.3
40	25	4.1
50	22	3.5
60	20.5	2.9
70	30	5.09
80	34	5.8

Table 5  
Case study 1, third harmonic current injection of 0.4 pu at bus 860, generations limit optimization

Maximum number of generations	Average residual (J) over 10 runs	Residual standard deviation over 10 runs
50	69.12	9.9
100	51.4	8.1
200	25	4.1
300	24.9	4
400	26	3.8
500	25.5	4.1

Table 6  
Case study 2, 0.3 pu fifth and 0.2 pu seventh harmonic current injection at bus 844

5 different runs	Residual (J)	Output event identification
1*	23.4	$F_{844}=0.33$ pu $I_{844}=0.21$ pu
2*	20.7	$F_{844}=0.38$ pu $I_{844}=0.22$ pu
3*	28.8	$F_{844}=0.27$ pu $I_{844}=0.19$ pu
4*	18.5	$F_{844}=0.3$ pu $I_{844}=0.18$ pu
5*	29.7	$F_{844}=0.26$ pu $I_{844}=0.29$ pu

Table 7  
Case study 3, 0.34 pu third harmonic at bus 840 and 0.16 pu seventh harmonic current injection at bus 848

5 different runs	Residual (J)	Output event identification
1*	26.5	$F_{840}=0.33$ pu $I_{848}=0.21$ pu
2*	30.1	$F_{840}=0.38$ pu $I_{848}=0.17$ pu
3*	28.4	$F_{840}=0.29$ pu $I_{848}=0.25$ pu
4*	24.35	$F_{840}=0.3$ pu $I_{848}=0.17$ pu
5*	27.2	$F_{840}=0.40$ pu $I_{848}=0.29$ pu

## **6. Conclusions**

A new algorithm for identification of harmonics origin is proposed. The algorithm depends on data collected from networked power quality analyzers and known network topology. It uses GA as optimization method to predict the origin that best produce the closest data profile obtained. Genetic Algorithms parameters tuning is a key factor for technique robustness. The technique was tested via three case studies with different locations and magnitudes, and all the cases were identified successfully.

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Received September 5, 2008

Accepted January 15, 2009