Allocation of Power Quality Monitors by Genetic Algorithms and Fuzzy Sets Theory

C. F. M. Almeida, *Student Member, IEEE*, and Nelson Kagan, *Member, IEEE*

Abstract--**The aim of this article is to present the application of Genetic Algorithms (GA's) and Fuzzy Mathematical Programming in the design of Voltage Sag and Swell monitoring systems for power transmission networks.**

The proposed methodology uses the simulations of different types of short-circuit in many different points of the power system, in order to characterize the system behavior towards the occurrence of voltage sags and swells. Then, different configurations for the monitoring system (number of monitors and buses where they are supposed to be installed) are assessed through GA's.

Two different GA modeling are presented, namely one based on binary vectors, for the decision over the installation of a monitor in a specific bus of the power system and another based on integer vectors, in order to indicate in which buses the monitors should be installed.

The evaluation of the methodology performance for the IEEE 30-buses network is presented, and a comparison between the results achieved and the results from a similar work in the same field is carried out.

Index Terms-- **fuzzy sets theory, genetic algorithms, optimal meter allocation, power quality monitoring, voltage sags and swells.**

I. Introduction

With the new environment of the electrical sector, the need for power quality monitoring systems augmented. Such systems might help in resolving the conflicts between customers and utilities, which could inflict in penalties due to the transgressions over the power quality phenomena limits. It also could be attributed due to the increased competition in the electrical sector, once electricity started to be faced as a commercial product which should be evaluated based not only by its reliability but also by its voltage quality. In other words, utilities providing electrical energy bearing better quality and lower costs have more chances to attract a bigger slice of the market, especially those customers that need something close to the "disturbance free" electricity.

In this context, knowing the disturbances' frequencies of occurrence has become essential for the utilities companies, in order to guarantee the customers' supply in a satisfactory manner. Thus, a methodology that determines the minimal number of power quality meters required to monitor a power network, and that defines the buses where these meters should be installed becomes an interesting and relevant issue.

The optimum power quality monitor allocation model determines the positions where these devices should be installed, in order to maximize the monitored area over the power system that is being studied. Another way to put it would be through considering a given monitor; this should be installed in a bus that would allow it to "observe" the largest possible number of disturbances that may occur in the power network. This "observation" characteristic for a monitor installed in a certain bus in a power network defines the **Observability** concept that is used in this paper. The aim of this concept is to make possible the quantification of the monitoring reach for a given power quality meter installed in a certain bus of the power network, given the possible disturbances that may occur.

On the other hand, the determination of the minimum number of power quality meters aims to establish how many of them are required to monitor a whole power network with the lowest possible **Redundancy**. It means that, on the limit case (where each bus would be monitored by at least one meter), each possible disturbance that may occur in the power network should be "observed" by at least one of the installed monitors.

The determination of the minimum number of monitors and the optimal allocation of them are then linked together, since the minimum number of monitors is reached through the optimal allocation of them, i.e., by installing the monitors in strategic network buses (buses with the highest **Observability** capacities), the number of monitors required is reduced.

The use of GAs (Genetic Algorithms) to formulate the solution for this problem characterizes an interesting alternative, given that the problem consists on determining the most suitable configuration of the monitoring system among the many possibilities for it. Fuzzy Sets Theory provides a convenient framework to evaluate the possible configurations for the monitoring system alternatives. It allows the representation of different objectives (maximization of the **Observability**, minimizing the number of monitors required, minimizing installation costs, etc.), subject to specific constraints (buses where monitors may not be installed, customers that require monitoring, etc.). Such multi-objective optimization problem applied to real power networks cannot be simply solved by using conventional approaches, such as standard linear programming techniques.

The disturbances considered in this paper were short

C. F. M. Almeida is with Enerq – Center for Regulation and Power Quality Studies, University of São Paulo, São Paulo, Brazil (e-mail: carlos.almeida@poli.usp.br).

Nelson Kagan is with the Department of Electrical Engineering, São Paulo University, São Paulo, Brazil (e-mail: nelsonk@pea.usp.br).

duration voltage variations, also known as voltage sags and voltage swells. It might happen when starting heavy motors, energizing power transformers, etc.; or when there are fault occurrences at the customer´s installation or in the power system network. Normally the most severe voltage sags and swells are caused by short-circuits, especially in phase to earth faults. In transmission and subtransmissions systems voltage disturbances can be noticed far away from the point where the fault occurred. They might affect the normal operation of sensitive equipment to the supplying voltage and interrupt industrial processes, thus causing considerable financial losses. This fact makes voltage sags and swells one of the most important causes for consumers' complains.

Short duration voltage variations are very difficult to monitor, since they are caused by random and unpredictable factors, i.e., the main difficulty is not on measuring the disturbances magnitude and duration, but it is about knowing their occurrence frequencies and when they will occur.

The literature suggests the installation of a power quality monitor in each bus of a power system where measuring voltage sags and swells is relevant [1]-[3]. The inconvenient of this approach is the number of devices required, and the capability of the equipment to analyze the large amount of data to be captured. Thus, the evaluation of Power Quality becomes an expensive activity, thus avoiding a widespread installation of monitoring systems.

Therefore, the methodology developed in this paper considers simulations to assess short duration voltage variations due to all possible fault types that may occur as well as considering different points for their occurrence (buses and power lines are considered as possible fault points), in a way to allow the characterization of the power network regarding voltage sags and swells. This characterization considers the power network topology. Through this characterization, it is possible to allocate power quality monitors, in order to enhance the "observed" area as much as possible

II. Genetic Algorithms Applied to the Optimal Power Quality Monitors Allocation Problem

The Optimal Power Quality Monitors Allocation Problem required the development of a specific approach to evaluate alternative configurations for the power quality monitor system. This approach also systematized the search for the best solution. Some specific definitions, presented in this section, were developed to conveniently model the problem and avoid repetitive and complex matrix calculations required to power systems analysis.

A brief description of a Genetic Algorithm (GA) and its fundamental aspects are provided, since the parameters´ configuration directly affects the results for the allocation problem.

The basic genetic algorithm is composed by four main stages:

- draw of an initial population;
- evaluation;
- selection;
- crossing-over and mutation.

Figure 1 shows how these stages are related to each other, which illustrates the GA used in the Power Quality Monitor Allocation problem.

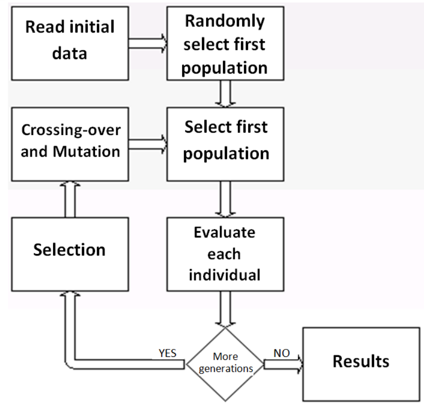

Figure 1 – Basic Genetic Algorithm Flowchart

Basically, it comprises a population of individuals (which are limited sets of possible solutions for a problem) in different phases (generations). In each phase operators are applied to the population, namely Selection, Crossing-over and Mutation, similarly to the biological process of Natural Selection. This is carried out in order to make all individuals evolve in a way to attain the best fitted solution, i.e. a solution that satisfies the problem requirements in the best way.

Thus, each GA individual is formed by a string of bits, which carries information that defines its own features, i.e. parameters related to a possible solution. This is called decoding process that allows the evaluation of the individual or how a possible solution attains the objectives and constraints related to the problem. The GA operators change the individuals in each generation, through the manipulation of the bits in their strings in a suitable way that leads to the convergence of such a process.

The initial population is randomly created and then a loop is performed, where the evaluation, selection and operator applications (Crossing-over and mutation) in each generation are carried out until a convergence criterion is achieved.

More detailed information regarding Genetic Algorithms can be found in [5].

A. Individual Representation in the GA (Allocation-Vector)

The representation of the individuals in the GA is directly related to the solution of the Power Quality Monitor Allocation problem. The codification explicitly indicates the number of power quality meters required to monitor the power network and the buses where they should be installed.

Thus, the *Allocation-Vector* was defined in two different ways, in order to satisfy the solution process presented in this methodology.

A1. Binary Allocation-Vector

The *Binary Allocation-Vector* was defined considering that its dimension should correspond to the number of buses in the power network, i.e., each position in the vector represents a bus in the power network where the monitor could be installed.

The decision towards the installation or not of a monitor in a specific bus is represented by a binary variable, where the 0 indicates that no monitor should be installed in the bus that corresponds to that position and the 1 indicates that a monitor should be installed.

The expression (1) shows the definition of the *Binary Allocation-Vector*:

$$V_{Alloc}(i)=\begin{cases}1, & \text{considering the installation of a monitor on bus } \boldsymbol{i}\\ 0, & \text{considering the installation of no monitor on bus } \boldsymbol{i}\end{cases} \qquad (1)$$

In order to illustrate the Binary Allocation-Vector, Figure 2 shows an example for a 12-bus power network. In this example, the Binary Vector suggests the installation of monitors in buses #1, #3, #5 and #10.

Power Network Buses →

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
1	**0**	**1**	**0**	**1**	**0**	**0**	**0**	**0**	**1**	**0**	**0**

Figure 2 – Example of a *Binary Allocation-Vector*

A2. Integer Allocation-Vector

The *Integer Allocation-Vector* was defined with the number of positions was defined previously. The issue related to the number of required monitors was constrained by the vector's size, similar to the concept defined in [4].

The decision towards the installation or not of a monitor in a specific bus is determined by an integer value in each position of the vector, which corresponds to a specific power network bus. In other words, only buses identified in the positions of the *Allocation-Vector* should have a power quality monitor installed.

Expression (2) shows the definition of the *Integer Allocation-Vector*:

$$V_{Alloc}(i)=n, \text{ considering the installation of monitor } \boldsymbol{i} \text{ on bus } \boldsymbol{n}\text{, and } \boldsymbol{n} \text{ may vary from 1 to the number of busses of the power network} \qquad (2)$$

In order to illustrate the *Integer Allocation-Vector*, Figure 3 shows an example where the maximum number of monitors is 5 (since the vector has five positions), and the solution exhibited suggests the installation of monitors in buses #1, #3, #5 and #10.

It is important to notice that in the *Integer Allocation-Vector* of Figure 3 there is the repetition of bus #3 purposely,

Meters to be allocated →

(1)	(2)	(3)	(4)	(5)
01	**03**	**05**	**10**	**03**

Figure 3 – Example of an *Integer Allocation-Vector*

i.e., that monitors 2 and 5 should both be installed in bus # 3. This implies that in order to completely monitor the power network, there would be necessary only 4 monitors. The maximum value of 5 exceeds the minimum number of monitors that are actually required to monitor the power network with maximum **Observability Degree**, considering the minimum monitoring **Redundancy** (at least one monitor is capable to "observe" each one of the faults that may occur in this power network).

B. Evaluation

The evaluation of each individual is performed through a fitness-function. Regarding the allocation problem, the fitness-function should indicate how much each individual satisfies the problem objectives. In order to accomplish this task, the *Observability Matrix* and *Redundancy-Vector* concepts were defined.

C1. Observability Matrix (OM)

This concept was firstly introduces by [8]–[10]. Basically, in order to characterize the performance of a power network towards the possible occurrences of voltage variations, a *Fault-Voltage Matrix* was defined, which is determined by the values of the fault voltages in each bus, for each simulated fault. This matrix was defined considering that each row relates to a specific fault in the power network, i.e., it refers to a bus or a point in a line of the power network where a specific short-circuit was simulated; and in each column refers to a specific power network bus. So, a voltage value is stored in each matrix position, related to the bus (column) and simulated fault (row).

The *Observability Matrix* is based on the *Fault-Voltage Matrix*. It is obtained by comparing each one of its values to a fixed value (the *Trigger Level* - u_t), which, by the way, corresponds to the voltage magnitude value that will trigger the power quality monitors to store waveforms and characteristics of voltage sags and swells.

Regarding the voltage sag analysis, the *Trigger Level* is adjusted to a suitable value (where u_t ε [0.1pu; 0.9pu]), and the *Fault-Voltage Matrix* elements are compared to the *Trigger Level*. Each element of the *Observability Matrix* is then filled with 0 (zero), when the fault voltage is higher than the *Trigger Level*; and with 1 (one), otherwise. On the other hand, for the voltage swell analysis, the *Trigger Level* is adjusted to a suitable value (where u_t ε [1.1pu; ∞)), and each element of the *Observability Matrix* is filled with 0 (zero), when the fault voltage is lower than the *Trigger Level*; and 1 (one), otherwise.

Expression (3) shows the procedure described in order to compose the *Observability Matrix*, considering the voltage sag analysis. Similarly, expression (4) shows the procedure described in order to compose the *Observability Matrix*, considering the voltage swell analysis.

$$mo_{ij}=\begin{cases}1, & \text{when due to the fault } \boldsymbol{i} \text{ the voltage on bus } \boldsymbol{j}\text{, } v_{ij}\text{, is lower or equal than the } \textit{Trigger Level} \text{ fixed } (\boldsymbol{v_{ii}} \le \boldsymbol{u_t})\\ 0, & \text{when due to the fault } \boldsymbol{i} \text{ the voltage on bus } \boldsymbol{j} \text{ is higher than the } \textbf{\textit{Trigger Level}} \text{ fixed } (\boldsymbol{v_{ij}} >\end{cases} \qquad (3)$$

$$mo_{ij}=\begin{cases}1, & \text{when due to the fault } \boldsymbol{i} \text{ the voltage on bus } \boldsymbol{j} \text{ is higher or equal than the } \textbf{\textit{Trigger Level}} \text{ fixed } (\boldsymbol{v_{ij}} \ge \boldsymbol{u_t})\\ 0, & \text{when due to the fault } \boldsymbol{i} \text{ the voltage on bus } \boldsymbol{j} \text{ is lower than the } \textbf{\textit{Trigger Level}} \text{ fixed } (\boldsymbol{v_{ij}} < \boldsymbol{u_t})\end{cases} \qquad (4)$$

In order to illustrate the procedure described, a *Fault-Voltage Matrix* is considered for a specific 12 bus power network, as shown in Figure 4.

Power Network Buses

Faults Simulated

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
[1]	0.20	0.52	1.00	0.88	0.89	0.89	0.96	0.87	0.96	0.96	0.97	0.91
[2]	0.39	0.27	1.00	0.81	0.86	0.83	0.95	0.80	0.95	0.95	0.96	0.86
[3]	1.00	1.00	0.14	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
[4]	0.75	0.72	0.99	0.49	0.87	0.50	0.94	0.50	0.93	0.93	0.94	0.57
[5]	0.94	0.95	1.00	0.97	0.31	0.97	0.98	0.97	0.98	0.98	0.98	0.98
[6]	0.70	0.67	0.99	0.28	0.83	0.10	0.91	0.32	0.91	0.91	0.92	0.49
[7]	0.97	0.97	1.00	0.98	0.96	0.97	0.51	0.98	0.67	0.74	0.79	0.98
[8]	0.74	0.71	0.99	0.50	0.87	0.53	0.94	0.47	0.94	0.93	0.94	0.59
[9]	0.99	0.99	1.00	0.99	0.99	0.99	0.87	0.99	0.16	0.79	0.85	0.99
[10]	0.97	0.97	1.00	0.98	0.96	0.97	0.75	0.98	0.54	0.49	0.64	0.98
[11]	0.97	0.97	1.00	0.98	0.97	0.97	0.75	0.98	0.52	0.53	0.08	0.98
[12]	0.92	0.90	1.00	0.79	0.96	0.82	0.98	0.80	0.98	0.98	0.98	0.17
[13]	0.98	0.98	1.00	0.98	0.97	0.98	0.82	0.98	0.64	0.67	0.43	0.99
[14]	0.98	0.98	1.00	0.99	0.98	0.98	0.85	0.99	0.67	0.73	0.53	0.99
[15]	0.95	0.95	1.00	0.97	0.89	0.96	0.98	0.97	0.98	0.98	0.98	0.97

Figure 4 – Fault-Voltage Matrix Example

Considering 0.9pu as the Trigger Level, the *Observability Matrix* obtained is shown on Figure 5.

Power Network Buses

Faults Simulated

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
[1]	1	1	0	1	1	1	0	1	0	0	0	0
[2]	1	1	0	1	1	1	0	1	0	0	0	1
[3]	0	0	1	0	0	0	0	0	0	0	0	0
[4]	1	1	0	1	1	1	0	1	0	0	0	1
[5]	0	0	0	0	1	0	0	0	0	0	0	0
[6]	1	1	0	1	1	1	0	1	0	0	0	1
[7]	0	0	0	0	0	0	1	0	1	1	1	0
[8]	1	1	0	1	1	1	0	1	0	0	0	1
[9]	0	0	0	0	0	0	1	0	1	1	1	0
[10]	0	0	0	0	0	0	1	0	1	1	1	0
[11]	0	0	0	0	0	0	1	0	1	1	1	0
[12]	0	0	0	1	0	1	0	1	0	0	0	1
[13]	0	0	0	0	0	0	1	0	1	1	1	0
[14]	0	0	0	0	0	0	1	0	1	1	1	0
[15]	0	0	0	0	1	0	0	0	0	0	0	0

Figure 5 – *Observability Matrix* Example

Thus, one can realize that the results depend on the network performance characterization, which is related to the short duration voltage variations that may occur, i.e., it is related to the aspects considered when composing the *Observability Matrix* (number of fault points, types of short-circuits, fault impedances, and so forth).

C2. Redundancy-Vector

By taking the *Allocation-Vector* and the *Observability Matrix* for a given power network, as described in the previous sections, the *Redundancy-Vector* is then defined through the multiplication of the *Observability Matrix* by the transposed *Allocation-Vector*, as described in expression (5).

$$V_{\mathrm{Red}} = OM \times V^{t}{}_{Alloc} \quad (5)$$

Figure 6 shows the *Redundancy-Vector* obtained by multiplying the *Observability Matrix* in Figure 2 to the *Binary Allocation-Vector* in Figure 1. This vector shows that the proposed allocation does not observe the fault #12, whereas fault #1, #2, #4, #6 and #8 triggers 2 power quality meters.

Faults Simulated

[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]
2	**2**	**1**	**2**	**1**	**2**	**1**	**2**	**1**	**1**	**1**	**0**	**1**	**1**	**1**

Figure 6 – *Redundancy-Vector* Example

Expression (5) is applied to the *Binary Allocation-Vector* only. However, it is used the *Integer Allocation-Vector* in the GA process, as it will be shown in the following sections. So, in the evaluation of the *Allocation-Vector*, one must first convert it from the integer form into the binary form. It is then possible to calculate the redundancies towards the power quality monitoring for each one of the faults considered on the *Observability Matrix*.

C. Application of the Fuzzy Set Theory

In order to model the objectives and constraints related to the problem, the authors realized that the application of the Fuzzy Set Theory would be suitable to determine the GA´s fitness function. Through this approach, the convergence of the GA was not be affected by the values of the objective functions and penalization-function related to the constraints.

The Fuzzy Set Theory can be used in decision problems [7], as it is the case of the allocation problem considered in this paper. Thus, the aim is to determine a solution that satisfies the objectives and the constraints in a symmetrical way. This is done through the application of membership-functions in the description of the problem's objectives and constraints. Basically, these membership-functions describe how each possible solution satisfies the problem.

Regarding the Power Quality Monitor Allocation problem, a membership-function ($\boldsymbol{\mu_{obj}}$) was adopted to describe the objective function, which provides a value that is proportional to the number of monitors suggested by each individual. A membership-function ($\boldsymbol{\mu_{res}}$) was adopted to describe the constraints, which evaluates how the *Redundancy-Vector* performs towards a possible solution (*Allocation-Vector*), considering the unitary redundancy as goal for each fault, i.e. at least one power quality monitor triggers for any given fault. The evaluation of both allocation and redundancy vectors is performed by a decision membership-function ($\boldsymbol{\mu_{dec}}$), which combines the results of objectives and constraints. Expression (6) summarizes the described procedure:

$$\mu_{dec} = \mu_{obj} \otimes \mu_{res} \quad (6)$$

C3. Objective-Function

The objective-function proposed for modeling the problem aims at minimizing the number of allocated monitors, which are given according to the *Allocation-Vector* as shown in expression (7). Figure 7 illustrates the behavior of the function described by the expression (7).

Note that this function is not defined for the interval (-∞, 1[, since the number of monitors to be installed in the power network is, obviously, at least equal to 1.

Where:

$$F_{obj}(x) = \begin{cases} \dfrac{1}{x}, \text{ if } 1 < \boldsymbol{x} < \boldsymbol{IMN} \\ 0, \text{ if } \boldsymbol{IMN} \geq \boldsymbol{x} \end{cases} \quad (7)$$

- ***x***: is the number of allocated monitors, determined by the individual's codification;
- ***IMN***: is the maximum number of monitors considered for the power network, i.e. it is the number of power quality meters that makes the monitoring system unacceptable.

The other reason for choosing the hyperbolic function given in (7) was that this kind of function describes the problem objective very well, with no need for constants or any other algebraic operations.

Besides that, this function provides an interesting behavior in a very simple way. This behavior relates to the fact that by adding a unit (in this case, one monitor) in the function, the result is not as expressive as removing a unit, i.e., considering *f(x)* as the hyperbolic function:

$$\left| f(x+1) - f(x) \right| > \left| f(x) - f(x-1) \right| \quad (8)$$

Thus, it is easy to understand that due to this behavior, the objective-function contributes towards the minimization of the number of monitors required.

C4. Penalization-Function

The constraints regarding the Power Quality Monitor Allocation problem were implemented through the penalization-function in two stages. In the first stage, it was evaluated the minimum redundancy, accordingly with the expression [9]. Figure 8 illustrates the behavior of the function described by the expression [9].

$$F_{pena}(x) = \begin{cases} \dfrac{1}{x - RA} & \text{, if } \boldsymbol{x} > (RA + 1) \\ 1 & \text{, if } (RA - 1) \leq \boldsymbol{x} \leq (RA + 1) \\ \dfrac{-1}{x - RA} & \text{, if } x < (RA - 1) \end{cases} \quad (9)$$

Where:

- ***x***: is the redundancy average for the power quality monitor allocation proposed by an Allocation-Vector;
- ***RA***: is the minimum redundancy defined during the optimal allocation process (i.e., it expresses the minimum number of monitors to monitor each fault).

In order to guarantee that the redundancy was homogeneously distributed for the elements of the Redundancy-Vector, the value provided by the Penalization Function was divided by the number of positions with zeros from the same the Redundancy-Vector. Through this operation, it is avoided that an individual (the Allocation-Vector that was being evaluated by the algorithm) with high redundancy for some faults and zero redundancy for other faults was evaluated as well as an individual with a low redundancy for all faults.

Thus, following the same reasons that led us to choose for a hyperbolic function for the Objective Function, the Penalization Function used in the algorithm is given by expression (10).

$$F_{pena} = \frac{\mu_{res}}{NRZ^{3}} \quad (10)$$

Where:

- ***NRZ***: is the number of positions of the Redundancy-Vector with zeros.

The denominator of the function (10) is powered by 3, so that the impact of this factor in the evaluation is increased. The GA process then tends to produce individuals with fewer or no zeros in their *Redundancy-Vectors*. In other words, the Penalization Function tries to ensure that every simulated fault is monitored.

III. Results

In order to evaluate the performance of the methodology proposed in this paper, it was applied for the IEEE-30 buses network. It was considered 3-phase, 2-phase to ground, single-phase to ground, and single-phase to ground with impedance of 40 Ω faults. The faults were independently simulated at every power network bus and at every 10% of each branch through the simulation and developent enviroment of the research group, namely SINAP. So, a total of 1770 faults were simultaneously considered in this evaluation. Two independently evaluations were carried out. It was considered 200 generations with 100 individuals for both of them. The Crossing-over and Mutation rates were 70% and 5%, respectively.

The methodology proposed in this paper established that the network could be completely monitores by 7 meters in both evaluations. Figure 11 illustrates the *Allocation-Vectors* obtained in each evaluation. In Figure 12 it was shown the positions of the installation sites for the power quality meters. The continuous ellipses indicate the sites suggested through the first evaluation and the dashed ellipses indicate the sites suggested through the second evalutation. In order to allow the comparison between the results achived through the methodology proposed in this paper and the methodology proposed in [10], it was used square dot to indicate the sites suggested in [10].

Observing Figure 12 it is possible to notice that the methodology presented in this paper suggests less power quality meters than the methodology presented in [10] (in [10] it was suggested 10 power quality meters). This reduction in the number of meters required to monitor the network was already expected, since the methodology developend in this papers covers the monitoring of voltage sags and voltage swells only.

It is worthy to mention that the sites suggested in the first evaluation of the proposed methodology were not exactly the same as in the second evaluation. While the first evaluation suggested bus #30, the second evaluation suggested bus #29. This behaviour sugests that th Observability capacity of these buses are equivalent, and that the complete monitoring of the system can be achived through the installation of a power quality meter in any of them.

Meters to be allocated →

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Allocation-Vector from the 1st Simulation:	**14**	**17**	**18**	**02**	**06**	**30**	**19**
Allocation-Vector from the 2nd Simulation:	**17**	**29**	**18**	**14**	**19**	**02**	**06**

Figure 11 – *Allocation-Vectors* obtained for the IEEE-30 buses network

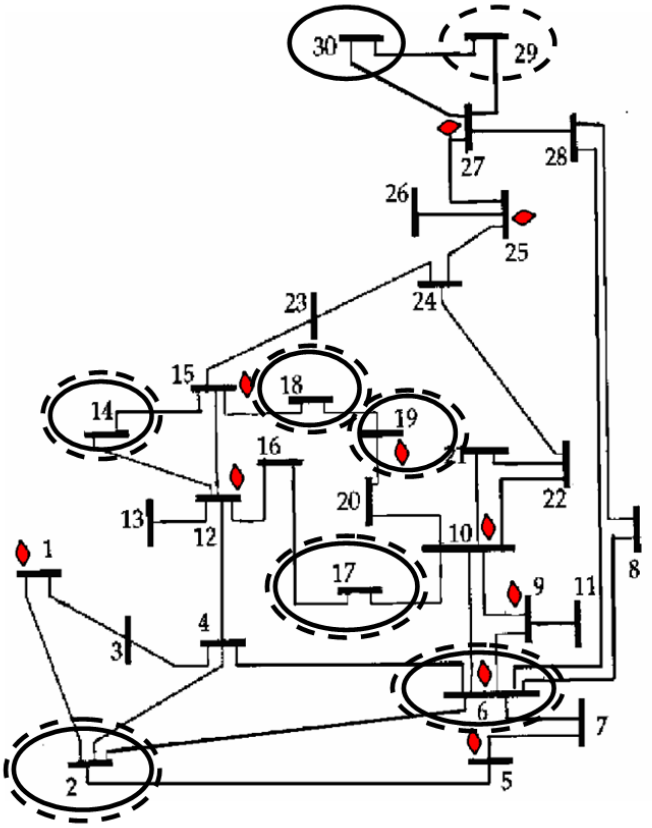

Figure 12 –IEEE 30-buses network, [10]

IV. Conclusions

The proposed methodology showed satisfactory results, which may help the planning engineer towards the acquisition and allocation of power quality monitors. Thus, it is possible to maximize the monitoring capacity in the power network and minimize the acquisition and installation costs in power quality meters.

Considering that the *Allocation-Vector* suggests a possible configuration for the power quality monitors allocation, it was noticed that the position of the power quality meters is not as important as the quantity of monitors, i.e., while the monitors quantity variation is relatively low, the buses where they should be installed may change, due to the different combinations of the **Observability** capacity in each power network bus.

Besides that, the methodology presents a higher potential, once it is flexible enough to take into consideration particular aspects of the allocation problem, such as the need to monitor some specific buses or the difficulties in installing power quality meters at some other buses.

The methodology clearly shows the feasibility to completely monitor power networks without installing power quality monitors at every system bus, i.e., depending on the system´s topological characteristics, some few meters can suffice to characterize the system performance related to short duration voltage variations.

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VII. Biographies

Carlos Frederico M. Almeida was born in São Paulo, Brazil, on December 15th, 1979. He graduated from Polytechnic School, University of São Paulo in 2003. His MSc. degree in 2007 is from Polytechnic School, University of S. Paulo. Currently he is towards the Ph.D. degree at University of Alberta, Canada. His research interests are Power Quality, Power System Planning and Computer Programming.

Nelson Kagan was born in São Paulo, Brazil, on October 8th, 1960. He graduated from Polytechnic School, University of São Paulo in 1982. His MSc. degree in 1988 is from Polytechnic School, University of S. Paulo and his Ph.D. degree was obtained in 1993 in the University of London. He lectures at Polytechnic School, University of S. Paulo since 1983, where he is an Associate Professor. His main areas of interest are Power System Planning and Power Quality.