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Analysis of Fault in Power System Networks Using Modified Sparsity Genetic Algorithm Optimizer

Hachimenum N. Amadi[1], West Sopakiriba Maxwell[2]
Electrical Engineering Department, Rivers State University, Nkpolu - Oroworukwo Port - Harcourt, Nigeria

Abstract:
The Optimal Placement Problem (OPP) presents the need to solve the Phasor Measurement Units (PMU) economy problem as there are always limited budgets available to the power system operators, and it is not always a feasible practice to have a fully observable system. This paper presents the mathematical formulations for optimal PMU placement and the core methodology of the GA based on sparsity using a hypothetical Six Bus Network and an IEEE 14-Bus Network – both networks sourced from materials in the open domain and the approach specifically employs a Genetic Algorithm Optimizer (GA) for the optimal placement and a proposed Modified Sparsity Genetic Algorithm Optimizer (MSGAO) is used in speeding the computational process. Artificial Intelligence applications, MATLAB Simulink program (2022a), and GNU Octave program (8.4.0) are the materials used. Investigations are performed on a case study bus and the results showed that the proposed MSGAO approach is competitive with the standard Genetic Algorithm (GA), and gives a better computational run time with an average run-time improvement (reduction) over the standard GA of about 0.5s. Thus, it will be much better to employ a sparse optimizer approach to the fault localization based on synchronized PMUs.
Keywords: *Average Run-Time, Computational Run Time, Genetic Algorithm, Phasor Measurement Units, Modified Sparsity*

I. Introduction

Just as no human being can survive without the flow of blood, no nation or city can develop without reliable electricity. The developed nations rode on reliable electricity to attain and sustain their present status. Today, they can boast of years of uninterrupted power supply which have helped their industries, utilities, hospitals, schools, etc to make life comfortable for their citizens. This means that, we can comfortably say that no nation can move from an underdeveloped status to becoming a developed nation without reliable electricity; no reliable electricity, no development. Sustainable developments have continued to elude Nigeria as a nation due to lack of reliable electricity (Ibinabo and Ijeoma, 2019).

Electrical energy finds innumerable uses in the home, industry, agriculture, and transport. The demand for electrical power is generally in the increase at a fast rate in economically developing countries like Nigeria. So, the power distribution networks are becoming highly loaded; so, the issue of protection scheme has become a great concern in most of the injection substation power distribution networks. A number of works have been carried out in the area of electric power distribution protection and solutions have been proposed to improve the protection of the distribution network (Ijeoma and Amadi, 2024).

The Optimal Placement Problem (OPP*)* presents the need to solve the PMU economy problem as there are always limited budgets available to the power system operators and it is not always a feasible practice to have a fully observable system (Theodorakatos, 2019). Thus, current trends in research are now directed towards the transition from the use of conventional deterministic solutions to advanced heuristics and meta-heuristics solutions the choice of which is made considering several factors such as the computational efficiency, system observability, computation time, system complexity, etc (Theodorakatos, 2018).

Baldwin *et al* (1993) used the Simulation Annealing (SA) method to find the ideal placements for the PMUs installed in a power network. Their proposed approach further applied methods based on graph theory and a modified bisecting search algorithm to reduce time spent in the identification process, to identify good starting points. On the other hand, a more practicable communication-constrained OPP solution was proposed by Nuqui and Phadke (2005). This approach used the SA and a depth-of-unobservability criterion to support dispersed futuristic placement of PMUs in the power network.

Chakrabarti *et al* (2008) on the other hand proposed a more enhanced Binary Particle Swarm Optimizer (BPSO) approach following earlier studies in Del Valle *et al.,* (2008) that included velocity rule updates in the original PSO and applied this modified version to the solution of the OPP problem. This was intended to ensure a feasible solution space during the Particle Swarm Optimizer (PSO) optimal PMU search operations.

Hachimenum *et al*. (2025) explains that a power distribution unit is a device fitted with multiple outputs designed to distribute electric power, especially to racks of computers and networking equipment located within a data centre. Data centres face challenges in power protection and management solutions. This is why many data centres rely on Protocol Data Unit or Power Distribution Unit (PDU) monitoring to improve efficiency, uptime, and growth. PDUs vary from simple and inexpensive rack-mounted power strips to larger floor-mounted PDUs with multiple functions including power filtering to improve power quality, intelligent load balancing, and remote monitoring and control by LAN or Simple Network Management Protocol (SNMP). This kind of PDU placement offers intelligent capabilities such as power metering at the inlet, outlet, and PDU branch circuit level and support for environment sensors. The newer generation of intelligent PDUs allows for IP consolidation, which means many PDUs can be linked in an array under a single IP address. Next-generation models also offer integration with electronic locks, providing the ability to network and manage PDUs and locks through the same appliance.

In Ghaffarzadeh *et al* (2015) a Binary based PSO (BPSO) is combined with the DEA in a hybridized dual-stage manner, for the solution of the OPP problem. This hybrid solution was an attempt to balance the benefits of crude global search with an intense local search procedure. Their goal was to minimize the cost and number of installable PMUs in the power network.

In Zhou *et al* (2015), dual step micro phasor measurement unit (µPMU) based method is also applied to fault location in an active distribution network. Synchrophasors (µPMUs) are measured at one terminal and candidate locations are found by iterating line segments in a first step. The actual fault location is then found in a second step by a comparison operation of voltage phasors by the PMU at two terminals. They reported a high position accuracy of less than 1% in the traditional or active distribution network.

Micro-PMUs (µPMUs) for distribution systems have been proposed (Abdolahi and Kalantari, 2022) a two-stage programming model is adopted in their proposed solution where in the first stage the optimal µPMUs placement is exploited to minimize system costs, and in the second stage a Taylor Series approximated DSSE model is used to achieve complete state estimation of the power network.

Rajeev and Jose (2022) used the Binary Search Algorithm (BSA) to study the PMU placement problem in the location of faults in power networks. The method uses synchrophasor measurements from multiple locations to pinpoint the faulted location considering about eight different fault cases. They reported an accuracy of within 98% of the line length.

Ahmed *et al* (2022) critically examined the state-of-the-art techniques for optimal placement of PMUs. Their survey covered a large number of conventional techniques such as Linear Programming (LP) for the solution of the PMU OPP, several metaheuristics for solving the OPP such as PSO, ACO, etc, several IEEE power networks and the Polish system network, and several simulation solvers such as MATLAB, TOMLAB, IBM, etc, used in the field. They identified the need to solve the Optimal Placement Problem (OPP) by considering application-based planning, node-breaker model approaches, the use of hybridized optimization techniques in more practical power systems, and the need for robust performance indices.

In Al-Hinai *et al* (2023), multi-objective optimal placement of PMUs for lengthy power lines has been proposed considering a novel localization index called the Fault Location Observability (FLO) used as an additional objective to the Optimal PMU Placement (OPP) objective. Their solution was cast as a Mixed Integer Linear Programming (MILP) problem and applied to both an IEEE 300-bus power network and a case study network of the Oman power grid. Their approach sought to minimize the number of PMUs used in conjunction with maximizing the total number of fault location observable lines using the FLO. The results of their simulations showed an acceptable number of PMUs can be determined while attaining a maximum amount of FLO-indexed lines.

Andic *et al* (2023), proposed the use of a robust Crow Search Algorithm (CSA) for solving the PMU-OPP including as well the optimal Power System State Estimation (PSSE) of an entire power system. They employed the Newton-Raphson (NR) load flow technique to generate benchmark solutions and in turn, used the solution values to define the actual system state variables. They also modeled the PSSE using Weighted Least Square (WLS) and Weighted Least Absolute Value (WLAV) objective function values. In comparison to other heuristics strategies as the Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Artificial Bee Swarm Optimization (ABSO), with their proposed CSA-WLAV approach, they reported better (lowest) Mean Squared Error (MSE) solutions for the IEEE 14, 30 and 57 bus power networks.

In Appasani *et al* (2021), a Microwave Synchrophasor Communication System (MSCS) including a dual-metric Multi-Objective GA MOGA) optimized PMU with Situation Awareness (SA) capabilities. SA considers the propagation delay and processing delay as core metrics to be evaluated and optimized. The MOGA is used to either maximize the minimum SA or the mean SA with or without the inclusion of Zero Injection Buses (ZIB) Their proposed approach has been applied to a real power network located in India. They found out that with the inclusion of ZIB, the system SA is not greatly affected from when without the ZIB but the number of PMUs needed for full system observability is reduced.

Arpanahi *et al* (2023), proposed a novel MILP-WAMS approach to the optimal solution of the OPP. They considered the PMU type and specifications including fixed costs of the PMU and its corresponding channel cost constraints in an objective function formulation. A novel constraint based on the line-wise observability (LWO) criterion was proposed as an extension to the existing constraints utilized in the OPP solution. LWO includes the important functions of restoration management, line model validation/dynamic line rating, transformer model validation, and synchronous generator parameter estimation. When compared to several existing OPP solution techniques, their studies on several IEEE power network buses showed the potential of their proposed solution to attain a global minimum cost and number of PMUs with competitive and/or better results.

Cruz *et al* (2022) proposed a multi-objective optimization non-dominated Pareto solution based on the Variable Neighborhood Search (VNS) algorithm (Mladenović and Hansen, 1997) for solving the OPP in a centralized WAMS power network. Their proposed approach addressed the issues of PMU and communication cost in addition to numerical PMU observability during the State Estimation (SE) process. Their proposed approach has been tested on very large power systems (5771 buses) to conventional power system networks. Simulations considering the constraints of non-loss and loss of PMUs showed that the proposed approach will be better or is competitive with the existing approaches. Also, their simulations showed that the average CPU computational times taken for processing by the proposed approach increase as the size of the network increases but the number of non-dominated solutions is not directly proportional to increases in size.

In Džafić *et al* (2022), the use of MODIFIED Prony's method in Multiple Prony Analytic Method (MPAM) solutions considering discrete-time analytic signals in a synchronized two-terminal fault localization technology has been proposed. The MPAM averages out the resulting fundamental frequency components of a standard PAM at a preset phase angle. Their results showed that in terms of maximum fault location errors during non-outage and outage scenarios, the proposed approach gave better improvements over the classical Prony method and other methods used in the literature.

One of the fundamental challenges in electrical power systems research lies in the need to determine the optimal solution considering a large number of unique solutions to choose from. This presents additional problems particularly due to the fact that no single algorithm is best as the problem domain tested might equally present its own unique set of issues.

The significance of this study lies in the solution of the Phasor Measurement Unit Optimal Placement Problem (PMU-OPP) using global search (Genetic Algorithms – GA) optimization techniques. The research borders on fault localization using PMUs. It concerns the optimal placement of PMUs in power system networks considering the use of dynamic programming strategies based on Artificial Intelligence and applied to IEEE power networks.

II. Materials And Method

This paper presents the mathematical formulations for optimal PMU placement and the core methodology of the GA based on sparsity using a hypothetical Six Bus Network and an IEEE 14-Bus Network – the both networks sourced from materials in the open domain.

Materials:

The following materials were used:

1. Artificial Intelligence applications
2. MATLAB Simulink program (2022a)
3. GNU Octave program (8.4.0)

The data were sourced and collected from open-source data and IEEE benchmarks – IEEE 6 bus and 14 bus power system networks.

Method:

The Optimal PMU Placement (OPP) Problem

The OPP problem is a fundamental one that describes the PMU placement strategy within a power system considering the limitations of costs and system network constraints.

Consider an n bus system with a given PMU placement vector x,

Then,

$$x_i = \begin{cases} 1, & if\ PMU\ is\ installed\ at\ bus\ i \\ 0, & otherwise \end{cases} \tag{1}$$

The objective function for this study is to minimize the total number of PMUs, while the set of constraints are Observability, Sparsity, Reliability and Cost of the PMUs.

A minimum cost may be defined as:

$$\min \sum_{j=1}^{n} w_i * x_i \tag{2}$$

s.t.

$$Ax \geq b \tag{3}$$

Note that:

$$b = [111.........1]^T \tag{4}$$

b = [b1, b2, b3…..bN]T

$$x = [x_1\, x_2.........x_n]^T \tag{5}$$

where,

w_i = Cost associated with the placement of PMU at bus i

b = a unit vector length, transposed

Note that there are some buses that should not hold a PMU as this may violate the full observability rule.

Genetic Algorithm Sparsity Solution Model

The GA sparsity based solution includes a definition of the following key factors:

1)The feature set

2)The fitness function

3)The Selection algorithm

The feature set includes the PMU feature data needed for the fault location analysis, the GA parameters and its associated boundaries i.e. maximum and minimum values for performing an optimal feature optimization operation.

The fitness function describes the procedure for obtaining an optimal (minimal) set of PMU features based on predefined constraints. The fitness function is defined accordingly as:

$$Fitness = \alpha Err + \beta\frac{f}{F} + \gamma\frac{n}{N} \tag{6}$$

Where,

Err = classification error rate from a wrapper PMU feature set

f = number of selected features

F = the total number of features

n = number of PMU units determined by the evaluated GA

N = maximum number of PMU units possible

α, β, γ = the coefficients or weight factors of each classification rate term in the fitness function above.

The selection algorithm used in the proposed system uses a modified sparsity-based roulette wheel selection algorithm (S-RWS) which is generally referred to as the Modified Sparsity Genetic Algorithm (GA) optimizer (MS-GAO).

The computational steps for generating the MS-GAO solution are as follows:

Step1: Sample a population of fitness values from the original fitness value feature set say *P*, as *s* and of size, *N*:

$$P^* = s.*(P) \tag{7}$$

$$N = n(s) \tag{8}$$

Step2: Compute the first mean:

$$\mu_{o(1)} = \frac{\sum(P^*)}{N} \tag{9}$$

Step3: Extract the set of P^* less than $\mu_{o(1)}$ and its corresponding indices:

$$P_z^* = P^* < \mu_{o(1)}, \quad P_z \subset P^*$$
$$z^* = z, \quad \forall z,\, z \in Z \tag{10}$$

Step4: Compute the second mean:

$$\mu_{o(2)} = \frac{\sum\left(P_z^*\right)}{n}, \qquad (11)$$
$$n = n(z), \quad n << N, n \in Z$$

Step5: Repeat Step1-4 for a fixed number of trial runs, say 10 trial runs, and update in a buffer store; compute its mean as:

$$\mu^*_{o(2,i)} \leftarrow \frac{\sum\left(\mu_{o(2,i)}\right)}{n(\mu_{o(2)})} \qquad (12)$$

Step6: Set the fitness selection threshold as:

$$P_{r(th)} = \mu^*_{o(2,i)} \qquad (13)$$

III. Results And Discussion

In this study, the results obtained from the MATLAB Simulink simulations were discussed. The Modified Sparsity Genetic Algorithm Optimizer (MSGAO) implementation on IEEE 6-bus and 14-bus was simulated in MATLAB and the results were shown as Fitness (Cost) Functions. Then the standard Genetic Algorithm (sGA) and the Modified Sparsity Genetic Algorithm Optimizer (MSGAO) were compared based on Classification Efficiency (CE) and their Computational RunTime as simulated in MATLAB and GNU Octave.

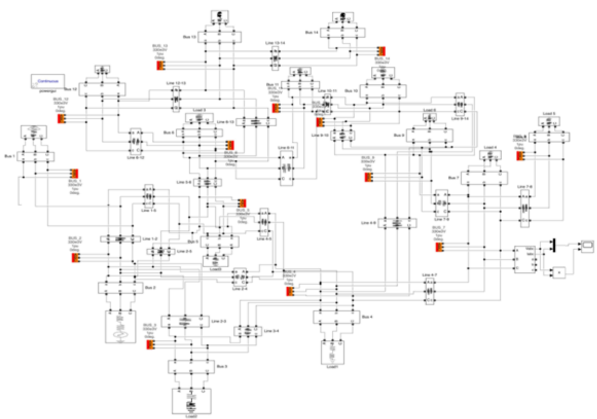

Figure 1: IEEE 14 bus Transmission Network in MATLAB SIMULINK

14 bus IEEE transmission network was simulated in MATLAB Simulink tool to determine the system voltage profile and its behavior in the presence of short circuit.

Simulations considering the IEEE 14-bus Network

The IEEE 14-bus network is a well studied power system used in many researches so it is considered here as well. The results using the full GA solution and the MS-GAO approach are evaluated on the basis of varying sample iterations and the classification efficiency or correctness measure, as simulated in the Main Program using MS-GAO (14-Bus Network).

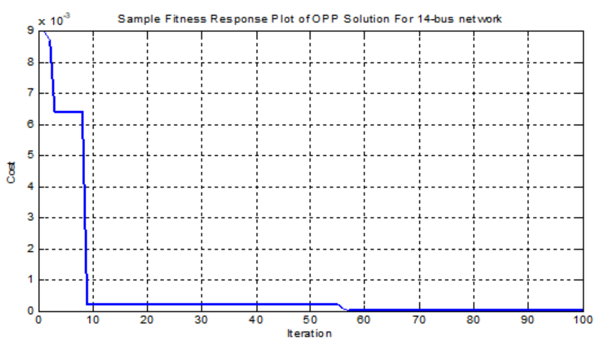

Figure 2: Fitness response of 14bus network – Trial 1 (14-Bus Network)

Fault Analysis:

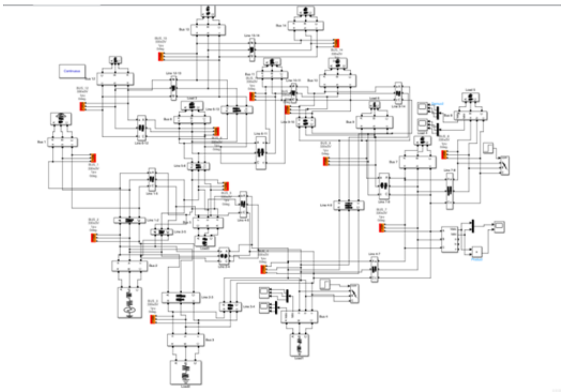

Figure 3: IEEE 14 bus network Modeled in MATLAB Simulink

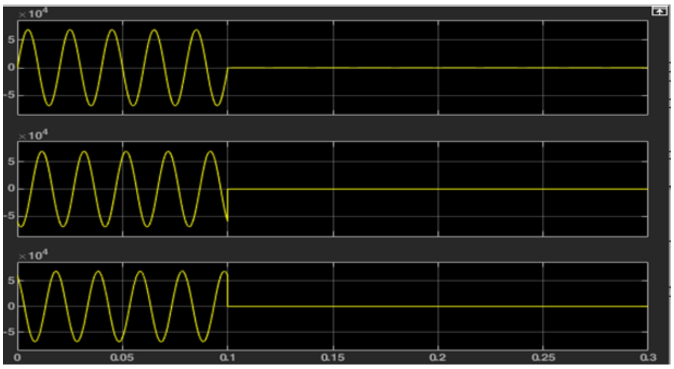

Figure 4: IEEE 14 bus network Voltage Profile of bus 4 under three phase short circuit at 0.1 seconds and cleared at 0.15s

As seen in Figure 4, at fault point, bus voltage dropped to zero.

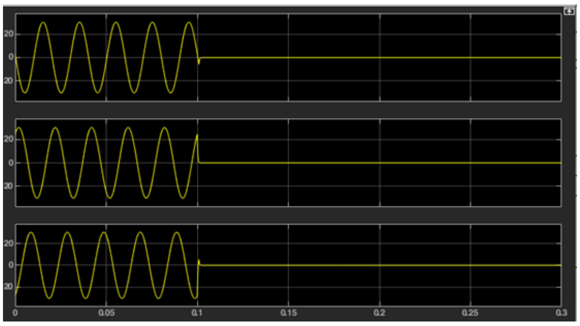

Figure 5: IEEE 14 bus network current Profile of bus 4 under three phase short circuit at 0.1 seconds

The presence of fault leads to voltage drop and system collapse as seen in Figure 5.

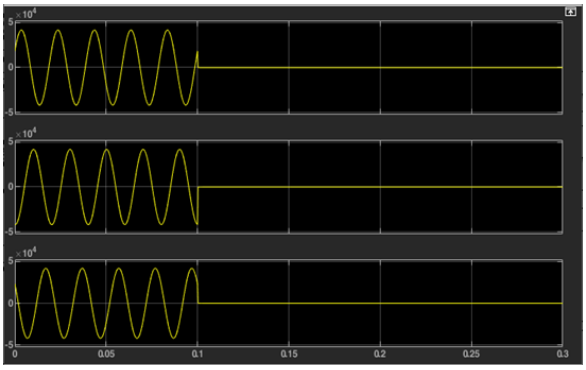

Figure 6: IEEE 14 bus network Voltage Profile of bus 2 under three phase short circuit at 0.1 secs

In Tables 1 to 3, is the result of the simulation, Cost Function (14-Bus Network), showing optimal PMU placement at 5 different trials and at 200, 100 and 50 iterations respectively for the considered approach. It also reports the percent classification efficiency (CE) of MS-GAO as compared with existing full GA.

Table 1: PMU Placement States at 200iters: 1 (PMU) 0 (No PMU)

	Iter 1		Iter 2		Iter 3		Iter 4		Iter 5	
Bus No	Full GA	MS-GAO	Full GA	MS-GAO	Full GA	MS-GAO	Full GA	MS-GAO	Full GA	MS-GAO
1	1	1	0	0	0	0	0	0	1	1
2	0	0	1	1	1	1	1	1	0	0
3	1	1	1	1	0	0	0	0	1	1
4	1	1	0	0	0	0	1	1	1	1
5	0	0	1	1	1	1	0	0	0	0
6	1	1	0	0	1	1	1	1	1	1
7	0	0	0	0	0	0	0	0	0	0
8	1	1	0	0	1	1	0	0	1	1
9	0	0	0	0	0	0	1	1	1	1
10	1	1	0	0	0	0	1	1	1	1
11	0	0	1	1	1	1	0	0	0	0
12	0	0	1	1	1	1	1	1	0	0
13	0	0	1	1	0	0	1	1	1	1
14	1	1	0	0	1	1	1	1	0	0
	%CE: 100		%CE: 100		%CE: 100		%CE: 100		%CE: 100	

As seen in Table 1, both the Full GA and the MS-GAO gave 100% CE. This is most likely due to the use of higher number of iterations (200iters in this case).

Table 2: PMU Placement States at 100iters: 1 (PMU) 0 (No PMU)

	Iter 1		Iter 2		Iter 3		Iter 4		Iter 5	
Bus No	Full GA	MS-GAO	Full GA	MS-GAO	Full GA	MS-GAO	Full GA	MS-GAO	Full GA	MS-GAO
1	1	1	1	1	0	0	1	1	1	1
2	1	1	0	0	1	1	1	1	1	1
3	0	0	1	1	1	1	1	1	0	0
4	1	1	0	0	1	1	0	0	0	0
5	0	0	1	1	0	0	0	0	0	0
6	0	0	1	1	0	0	0	0	1	1
7	1	1	1	1	1	1	0	0	1	1
8	0	0	0	0	1	1	1	1	0	0
9	1	1	1	1	0	0	1	1	1	1
10	0	0	0	0	0	0	1	1	1	1
11	0	0	1	1	0	0	0	0	1	1
12	1	1	1	1	1	1	1	1	0	0
13	0	0	0	0	0	0	1	1	1	1
14	1	1	0	0	0	0	0	0	0	0
	%CE: 100		%CE: 100		%CE: 100		%CE: 100		%CE: 100	

As seen in Table 2, both the Full GA and the MS-GAO gave 100% CE. This may be attributed to the higher number of iterations. In particular, there are some variations in the activated cells where 1 and 0 occurs when compared to the case of 200iters.

Table 3: PMU Placement States at 50iters: 1 (PMU) 0 (No PMU)

	Iter 1		Iter 2		Iter 3		Iter 4		Iter 5	
Bus No	Full GA	MS-GAO	Full GA	MS-GAO	Full GA	MS-GAO	Full GA	MS-GAO	Full GA	MS-GAO
1	1	0	0	1	0	0	0	0	0	0
2	2	1	1	0	1	0	0	1	0	1
3	3	1	1	0	0	1	1	1	1	1
4	4	0	0	0	0	1	1	0	0	1
5	5	1	1	1	0	0	0	0	1	0
6	6	0	0	1	1	1	1	1	0	0
7	7	0	0	1	1	0	0	1	0	0
8	8	1	1	1	1	1	1	1	1	0
9	9	1	1	1	0	1	1	0	1	1
10	10	0	0	0	0	0	0	0	0	0
11	11	1	1	1	1	1	1	0	1	0
12	12	1	1	0	0	0	0	0	1	0
13	13	0	0	0	1	1	1	1	1	1
14	14	1	1	1	1	1	1	1	0	0
	%CE: 100		**%CE: 64.29**		%CE: 100		**%CE: 42.86**		%CE: 100	

As seen in Table 3, both the Full GA is much better than the MS-GAO considering trials 2 for Full GA and trial 4 for MS-GAO. However, both gave 100% CE for the other trials. The presence of reducing CE may be attributed to the lower number of iterations employed (in this case 5iters). Thus, it becomes more challenging for the MS-GAO to give better CE at much lower values of the maximal running iterations.

Discussions considering the IEEE 14-bus Network

From the results shown in Tables 1-3, it is clear that depending on the trial run and iteration setting, the proposed MS-GAO gives equivalent results as standard GA. In particular, the lower iteration setting is more likely to give less accurate CE values as shown in Table 3 (see CE values in bold).

Validation Considering 14-Bus Network

In Table 4, the CE results using the GNU Octave tool compared with the MATLAB tool for the 14 Bus power network and considering 5 different trial runs for default iterations (200iters) are presented.

Table 4: Comparative Performance of Software Tools (5 trials; 14-bus network)

Trials	CE_{MATLAB} (%)	$CE_{OCTAVE-GNU}$ (%)
1	100	100
2	100	100
3	100	100
4	100	100
5	100	100
Mean:	100	100

IV. Conclusion

The OPP presents the need to solve the PMU economy problem as there are always limited budgets available to the power system operators and it is not always a feasible practice to have a fully observable system. One of the fundamental challenges in electrical power systems research lies in the need to determine the optimal solution considering a large number of unique solutions to choose from. This presents additional problems particularly because no single algorithm is best as the problem domain tested might equally present its own unique set of issues. The significance of this study lies in the solution of the Phasor Measurement Unit Optimal Placement Problem (PMU-OPP) using global search (Genetic Algorithms – GA) optimization techniques. The research borders on fault localization using PMUs. It concerns the optimal placement of PMUs in power system networks considering the use of dynamic programming strategies based on Artificial Intelligence and applied to IEEE power networks. This study achieved the mathematical formulations for optimal PMU placement and the core methodology of the GA based on sparsity using a hypothetical Six Bus Network and an IEEE 14-Bus Network – both networks sourced from materials in the open domain. Finally, the Modified Sparsity Genetic Algorithm Optimizer (MSGAO) implementation on IEEE 6-bus and 14-bus was simulated in MATLAB and the results were shown as Fitness (Cost) Functions. Then the standard Genetic Algorithm (sGA) and the Modified Sparsity Genetic Algorithm Optimizer (MSGAO) were compared based on Classification Efficiency (CE) and their Computational Run-Time as simulated in MATLAB and GNU Octave.

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