



# Evolutionary Computing Heuristics of the Optimal Phasor Measurement Units Placement for Fault Location in Power System Networks

Hachimenum N. Amadi<sup>1</sup>, West Sopakiriba Maxwell<sup>2</sup>, Richeal Chinaeche Ijeoma<sup>3</sup>

<sup>1</sup>hachimenum.amadi@ust.edu.ng, <sup>2</sup>sopakiriba.west1@ust.edu.ng, <sup>3</sup>ijeoma.richeal@ust.edu.ng  
Electrical Engineering Department, Rivers State University, Nkpolu - Oroworukwo Port - Harcourt, Nigeria

## ABSTRACT

Power system networks are currently facing an unprecedented surge in demand by consumers of power in addition to the stress facing mostly overhead lines such as line breaks, vandalism, etc. Thus, the need to maintain the demand whilst building much stronger and more resilient networks that can withstand such faults or abuse of power networks more proactively is becoming a core priority. In this paper, the functional methods utilized in the development of PMU-based fault localization considering the Optimal PMU Placement (OPP) problem are presented from the first principles. Furthermore, the Evolutionary Computing (EC) approach which is based on a Modified Sparsity Genetic Algorithm (GA) optimizer (MS-GAO) is presented and validated using a hypothetical Six Bus Network and an IEEE 14-Bus Network – both networks sourced from materials in the open domain. Then the overall architecture of the proposed system is presented and described. Artificial Intelligence applications, MATLAB Simulink program (2022a), and Electrical Transient Analytical Program (ETAP 19.0) were used for modeling, and this result shown in the ETAP software simulations was discussed. The Fault Index was simulated in MATLAB using the approximate Positive Admittance Sequence (aPSA). Also, several IEEE Benchmarks were validated using the MATLAB program. The evolutionary computing heuristics for the Optimal PMU Placement (OPP) were developed and validated numerically as shown in the method.

**Keywords:** Evolutionary Computing, ETAP, Optimal PMU Placement, Power system networks, Modified Sparsity Genetic Algorithm (GA) optimizer

## INTRODUCTION

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 center. Data centers face challenges in power protection and management solutions. This is why many data centers 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.

EC is a generalized form of techniques and a discipline that also includes such techniques as genetic algorithms (Holland, 1975), evolutionary programming (EP) as in Fogel et al., (1966), and evolutionary strategies (ES) as in Rechenberg and Rechenberg, (1973). It is mostly based on the principles of Darwinian (survival of the fittest) evolution which is founded on biological life forms, their characteristic species, and their origin. So by Darwinian evolution, individuals who have good fitness survive while those with bad fitness may die due to the inability to be competitive.

In EC, the GA's were firstly developed to solve discrete and integer based optimization problems, while the EP and ES were developed to solve AI simulation and continuous parameter optimization respectively.

Ever since then, the EC approaches have been loosely based on the GA though it is sometimes referred to in different contexts as an EP or ES.

Irrespective of the EC approach or technique, the basic processes are generally defined as follows:

1. Selection of an initial population randomly
2. Selection of parents based on fitness
3. Production of offspring and parental variants thereof
4. Few individuals are selected based on fitness – determined by the problem

Genetic Algorithms (GA) are evolutionary inspired techniques rooted on human evolution and natural competition Osegi and Enyindah, (2015). It is one of the most powerful computational techniques using in solving a large category of optimization problems.

Historically, GA's may be traced to the works of G.E.P. Box, G.J. Friedman, W.W. Bledsoe, and H.J. Bremermann who all developed evolutionary-inspired algorithms for key application areas such as Mathematical Function Optimization (MFO) and Machine Learning (ML) modeling in 1962, Ingo Rechenberg who introduced the idea of evolution strategies in 1965 but which did not initially include population or crossover features, and then in 1966 when the concept of evolutionary programming were introduced by L.J. Fogel, A.J. Owens and M.J. Walsh in the United States of America.

However, it was not until the arly 1970's that Genetic Algorithm (GA) was invented by Holland with the intent of developing nature inspired adaptive computing systems (Holland, 1975).

In a GA solution, a set of genes or individuals representing a set of feature points are formed initially as a population of candidate solutions to a functional problem in a search (solution) space. Then these features are then iteratively processed in an evolutionary intelligent way over a number of generations (simulation trial runs in computational terms) by the GA solution model to solve the problem.

The Hill Climbing (HC) technique is fundamentally a local search technique that uses the steepest aspect to greedily solve an optimization problem (Russell & Norvig, 2010). The HC can search for the optimal solution faster than a GA search but is not guaranteed to converge. However, with proper specification of the initial conditions and a lucky random trail, it will always return a more accurate or competitive solution to the problem concerning other locally inspired search techniques. Figure 1 shows the concept of HC as it pertains to the solution of a 1-D optimization problem such as a hill-climb where the problem is to find the global maximum.

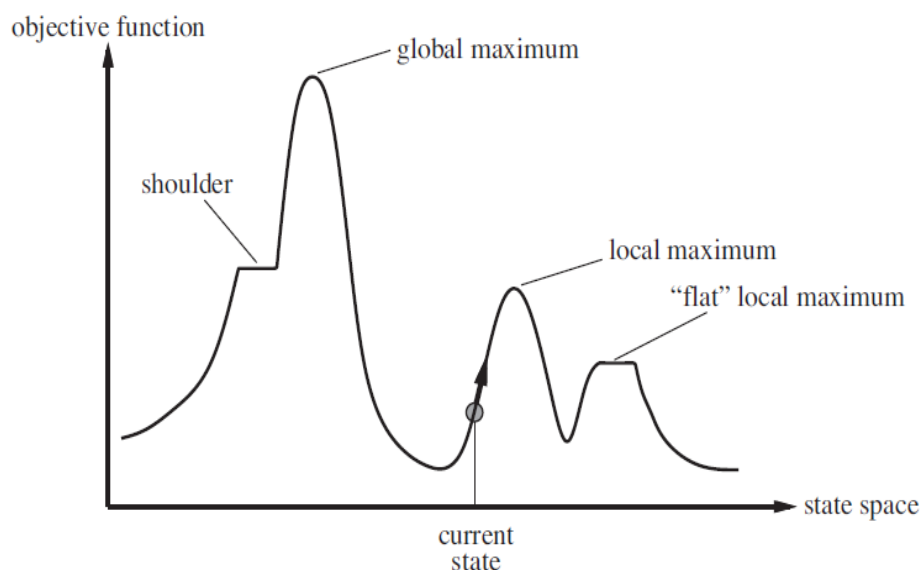


Figure 1: Concept of the HC Technique; Source: Russell & Norvig, (2010)

Considering the Figure 1, it can be seen that the HC algorithm will attempt to modify its current state in order to move towards a more global state which in actual fact is a local state of the next-order.

In this research study, the technique of the HC heuristic is applied to the PMU Optimal Placement Problem (OPP) and localization of faults in power transmission lines. The effective ability of the HC as an alternate but speedy solution to the base evolutionary search techniques used to locate faults in transmission lines will be examined. Phasor Measurement Units (PMUs) also called synchrophasors are a class of power system measurement and monitoring devices that allow for remote connectivity whilst measuring the currents, voltages, and frequency phasors. Figure 2 illustrates the physical architecture of such a device.

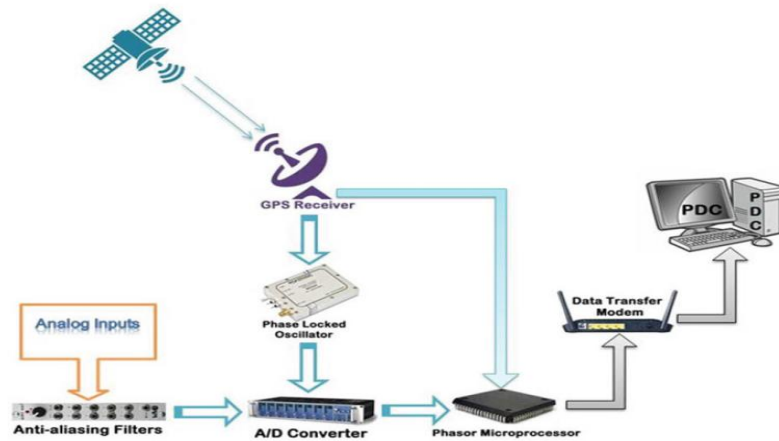


Figure 2: Physical outlay of a Phasor Measurement Unit (PMU)

As a primary remote sensing and monitoring power network device, the primary feature of PMUs lies mostly in their time synchronization among each other in the wide power area network (WPAN). Hence, the sharing of information across the network can be effectively coordinated.

Historically, PMUs were invented by Phadke and his team in the Virginia Tech State University, USA in 1988. This invention can be traced to an earlier development on Symmetrical Component Distance Relay (SCDR) developed in the late 1970's. The PMUs were able to achieve synchronization accuracies of better than or about  $1\mu\text{s}$ .

Ever since then, numerous applications and research on the topic of PMUs started to take place. Some of the key applications include:

- Generalized Steady State Estimation and State Measurements
- Real-time monitoring of dynamic power system phenomena
- Adaptive relaying and out-of-step relaying functions
- Fault Identifications and Localizations
- Voltage Collapse Alarming Systems
- Predicting Voltage Stability Margins
- Data Recording and Visualization Applications
- Etc

Electricity is delivered at a frequency of either 50 or 60 Hz, depending on the region. It is delivered to domestic customers as single-phase electric power. In some countries, as in Europe, a three-phase supply may be made available for larger properties. Seen with an oscilloscope, the domestic power supply in North America would look like a sine wave, oscillating between  $-170$  volts and  $170$  volts, giving an effective voltage of  $120$  volts RMS. Three-phase electric power is more efficient in terms of power delivered per cable used and is more suited to running large electric motors. Some large European appliances may be powered by three-phase power, such as electric stoves and clothes dryers. A ground connection is normally provided for the customer's system as well as for the equipment owned by the utility. The purpose of connecting the customer's system to the ground is to limit the voltage that may develop if high-voltage conductors fall onto lower-voltage conductors which are usually mounted lower to the ground, or if a failure occurs within a distribution transformer.

Xu et al (2015) proposed a graph based unified topology approach for identifying the optimal location and number of PMUs that give a fully observable system. Their proposed approach also obviates the need for a centralized data fusion unit by allowing the independent state estimation in several closely decoupled non-overlapping islands. Using this approach, redundant power flow measurements and effective factors may be computed.

Reddy et al (2015) studied the performance of ILP approach on placement of PMU considering the presence and absence of Zero Injection Bus (ZIB) and with single PMU outages. Their results report a lower PMU count when ZIB is included in the solution process; also considering single PMU outages, the PMU count is increased drastically.

Khajeh et al (2015) proposed a Mixed Integer Linear Programming (MILP) based on a General Algebraic Modelling Software (GAMS) language for minimizing the number of PMUs used in a power network including support for zero-injection bus; however, the approach did not include channel limitation constraints and no optimization of fault location was considered in this study.

Pignati et al (2016) proposed a fully connected PMU-based fault detection and location algorithm based on the real-time Linear Weighted Least Squares State Estimator (LWLS-SE) technique and including Weighted Measurement Residuals (WMRs). Their proposed state estimation fault location approach is robust against the noise effects in the

lines, effectively identifies faulted lines, and gives accuracies that are uniquely independent of the influence of Distributed Generations (DGs).

Zhang et al (2016) proposed a transition resistant scheme for fault localization based on PMU in multi-distribution power networks. They used a mutation detection algorithm for fault point judgement. They reported less than 1% accuracy and precision under different types of faults.

Usman and Faruque (2018) proposed a real time PMU based fault location identification algorithm for a distribution network in the presence of distributed generation - Solar Photovoltaics (PV). Their proposed approach was validated on the IEEE-37 Bus system. Their proposed method was found to improve the overall efficiency by 13% when compared to existing model.

Babu et al (2022) proposed a Non-Linear Programming Genetic Algorithm (NLP-GA) approach for minimizing the number of PMUs used in a power network. Their approach also included support for zero-injection bus; however, the approach did not include channel limitation constraints and no optimization of fault location was considered in this study.

Graph Neural Network (GraphNet) approach is proposed by Lv et al (2022) for minimizing the number of PMUs used in a power network. Their approach did not include support for zero-injection bus; however, the approach did not include channel limitation constraints and N1-contingency constraints and no optimization of fault location was considered in this study.

Cao et al (2022) used the Mixed Integer Linear Programming (MILP) to minimize the cost of installing PMUs in power network. No support was provided for optimizing fault location.

The binary Dragon Fly (BDF) algorithm was proposed by Patel et al (2022) for minimizing the number of PMUs used in a power network. Their approach included support for zero-injection bus; however, the approach did not include channel limitation and N1-contingency constraints and no optimization of fault location was considered in this study.

Abd el-Ghany et al (2022) developed a generalized fault detector and location technique based on the WAN with minimum PMUs installed only at the more needed zones and following a maximum threshold rule to minimize costs. The location based on the intelligent selection of PMUs obviates the requirement for the computation of fault resistances. A WAN Fault Index (FI) based on positive sequence admittances is formulated and proposed for reliable fault location state estimation using optimally installed PMUs and via measurable TL parameters. Using the proposed approach, the authors reported a < 1.03% error in fault location estimation.

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. In this regard, the extended problems of sub-optimization due to local search may be made minimal through global search and additionally, the use of local search based on a modified sparsity-based GA to discover timely solutions. This study also presents important aspects bordering on the research in PMU-based fault localization and particularly presents a concise survey of the recent developments from the conventional models to the state-of-the-art models. In particular, the study findings demonstrate potential applications in the field of evolutionary-inspired Artificial Intelligence (AI) based power systems network planning and design in the context of efficient fault protection systems based on the localization of PMUs.

## MATERIALS AND METHOD

In this paper, the functional methods utilized in the development of PMU-based fault localization considering the Optimal PMU Placement (OPP) problem are presented from the first principles. Furthermore, the Evolutionary Computing (EC) approach which is based on a Modified Sparsity Genetic Algorithm (GA) optimizer (MS-GAO) is presented and validated using a hypothetical Six Bus Network and an IEEE 14-Bus Network – both networks sourced from materials in the open domain. Then the overall architecture of the proposed system is presented and described.

### Materials:

The following materials were used.

1. Artificial Intelligence applications
2. MATLAB Simulink program (2022a)
3. Electrical Transient Analytical Program (ETAP 19.0)

### State Estimation Technique of Faulted Line(s)

Determining the exact faulted line in advance is not possible in practice; thus, state estimation techniques are normally employed Pignati et al., (2016). In this method, a virtual bus voltage state estimator say  $x$ , is computed concerning a corresponding measurement matrix say,  $H$ .

Consider a set of power network buses say,  $D$ .

Also, consider a bus network measurement set say,  $z$  where:

$$z \in \mathfrak{R}^D : D = 3d \cdot 4 \quad (1)$$

The measurement set,  $z$ , is composed of say two phase-to-ground phasors – the 3-d real and imaginary voltage and current phasors as shown in eqn (3.36) and eqn (3.37) respectively:

$$z_V = \left[ \dots, V_{i_{re}}^{a,b,c}, \dots, V_{i_{im}}^{a,b,c}, \dots \right]^T \quad i \in D \quad (2)$$

$$z_I = \left[ \dots, I_{i_{re}}^{a,b,c}, \dots, I_{i_{im}}^{a,b,c}, \dots \right]^T \quad i \in D \quad (3)$$

The measurement model expressions in eqns (2) and (3) may be summarized as in eqn(4) as:

$$z = \left[ z_V, z_I \right]^T \quad (4)$$

Relating measurements with state variables:

$$z = Hx + v \quad (5)$$

where,

$H$  = measurement matrix

$v$  = assumed Gaussian white noise vectors

A further sub-division of  $H$  also allows for the computation of a Linear Weighted Least Squares State estimator (LWLS-SE):

$$H = \begin{bmatrix} H_V \\ H_I \end{bmatrix} \quad (6)$$

The sub-matrix  $H_V$  is derived from eqn (5) and relates the voltage measurements to its corresponding state variables; it comprises of ones and zeros.

The sub-matrix  $H_I$  is derived from the eqns (7) and (8) as follows:

$$I_{i_{re}}^p = \sum_{h=1}^n \sum_{l=1}^3 \left[ G_{ih}^{pl} V_{hre}^l - B_{ih}^{pl} V_{him}^l \right] \quad (7)$$

$$I_{i_{im}}^p = \sum_{h=1}^n \sum_{l=1}^3 \left[ B_{ih}^{pl} V_{hre}^l + G_{ih}^{pl} V_{him}^l \right] \quad (8)$$

And,

$$H_I = \begin{bmatrix} G_{ih}^{pl} - B_{ih}^{pl} \\ B_{ih}^{pl} - G_{ih}^{pl} \end{bmatrix} \quad (9)$$

In the context of maximization-minimization (max-min), the LWLS-SE maximizes a likelihood which is synonymous to a minimization operation in the least error sense.

For the purposes of this study, a modified objective function as shown in eqn (10) is considered:

$$J_{\text{mod}}(x) = \sum_{i=1}^D \frac{\left( z_i - \sum_{h=1}^N H_{ih} x_h \right)^2}{v_{ii} + k_{\text{bias}}} \quad (10)$$

By iterating over several trials and across all candidate network measurement buses, the estimated state variable can be computed as:

$$\hat{x}_{LWLS} = G^{-1} H^T v^{-1} z \quad (11)$$

where,

$$G = H^T v^{-1} H \quad (12)$$

Finally, in order to determine fault position, the Weighted Measurement Residual (WMR) is computed as in

$$WMR^j = \sum_i^D \frac{|z_i - \hat{z}_i|}{\sigma_{z_i}} \quad j \in [1, \dots, m] \quad (13)$$

where,

$$\hat{z}_j = H^j \hat{x}_j \quad (14)$$

The algorithm for identifying the faulted line location is as provided in the following paragraph.

### RESULTS AND DISCUSSION

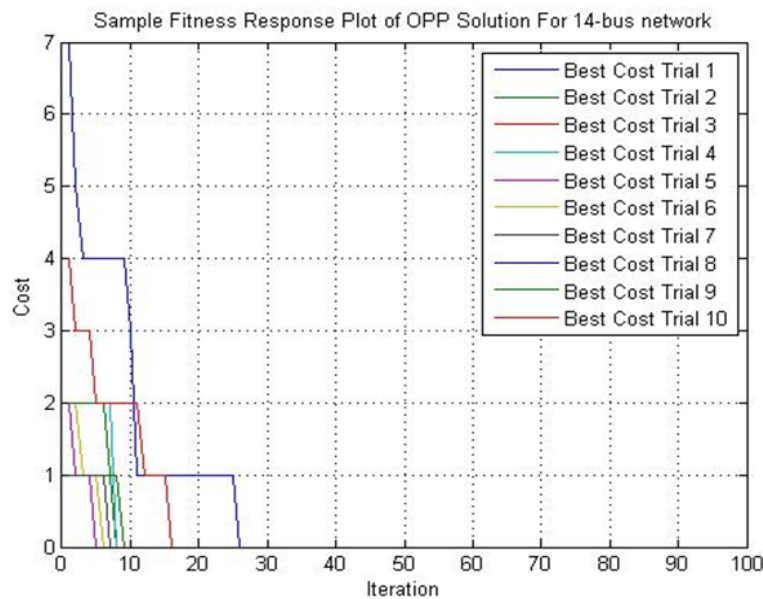
This result shown in the ETAP software simulations was discussed. The Fault Index was simulated in MATLAB using the approximate Positive Admittance Sequence (aPSA). Also, several IEEE Benchmarks were validated using the MATLAB program. The evolutionary computing heuristics for the Optimal PMU Placement (OPP) were developed and validated numerically as shown in the method. Also, simulations of a hypothetical model and an IEEE model including a real-world power system network using the Optimal PMU Placement (OPP) approach are presented. The Modified Sparsity Genetic Algorithm Optimizer (MSGAO) implementation on 14-bus was simulated in MATLAB and the results were shown as Fitness (Cost) Functions. Also, several IEEE Benchmarks were validated using the ETAP program. Fault localization is done using an evolutionary computing technique based on the Genetic Algorithms and a modified version – the Modified Sparsity Genetic Algorithm (GA) optimizer (MS-GAO).

#### Results of 14-Bus Network using the Admittance (aPSA) and GA Model

Table 1 shows the simulation result of Main Program aPSA (14-Bus Network) shows the optimal PMU placement for 14-bus and also considers a total of 10 trial runs. Also shown are the corresponding fitness responses for the 10 trial runs. The parameters for the GA are used in the 6-bus case.

**Table.1:** Solved Optimal PMU Placement at Different Buses (14-bus)

Trial No.	Optimal PMU Bus Locations
1	1, 3, 4, 5, 11, 12
2	1, 3, 4, 5, 11, 12
3	1, 3, 4, 5, 11, 12
4	1, 3, 4, 5, 11, 12
5	1, 3, 4, 5, 11, 12
6	1, 3, 4, 5, 11, 12
7	1, 3, 4, 5, 11, 12
8	1, 3, 4, 5, 11, 12
9	1, 3, 4, 5, 11, 12
10	1, 3, 4, 5, 11, 12



*Figure 3: Fitness response of 14-bus network for 10 different trials*

As can be seen from Figure 3 and considering the various fitness trial (Fit) runs, it will take a maximum of about 27 iterations to attain perfect convergence to the zero point, this is gotten from the simulation result of Main Program aPSA (14-Bus Network Cost Function).

**Table 2:** Time complexity performance (5 trials; 14-bus network)

Trials	t <sub>MATLAB</sub> (s)	T <sub>OCTAVE-GNU</sub> (s)
1	2.1449	11.8784
2	1.8415	9.1898
3	1.8071	9.0017
4	1.8070	12.9601
5	1.3709	14.0941
<b>Mean:</b>	1.7943	11.4248

As can be seen, the performances are roughly similar so this implies that the GNU Octave tool can serve as an alternative cost-free solution for solving the OPP problem. However, in the case of computational run-times, the MATLAB gives a much faster run and is preferred.

**Result Validation in ETAP Software**

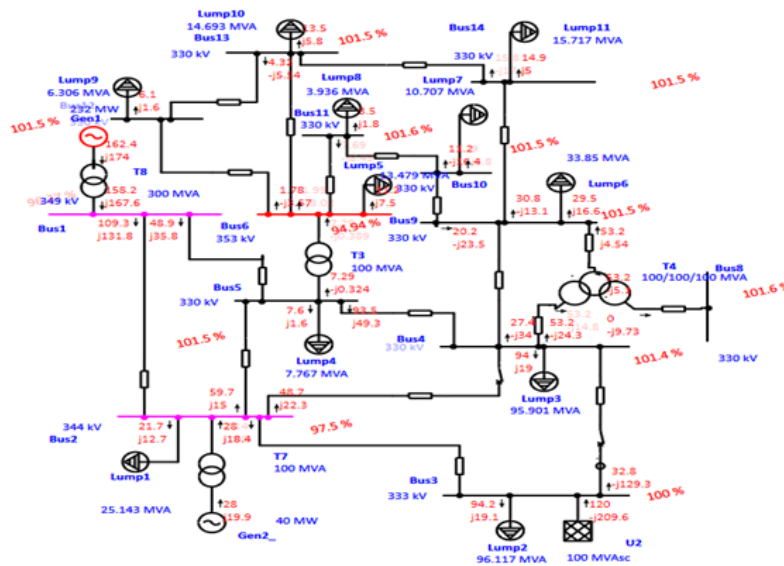


Figure 4: IEEE 14 bus network Modelled in ETAP

In Figure 4, IEEE 14 bus network was modeled and simulated at Steady state in ETAP Environment to validate the result obtained using MATLAB Simulink tool. The network voltage profile on steady state shows that the bus voltages of the network are stable at steady state, with values greater than its threshold values 95%.

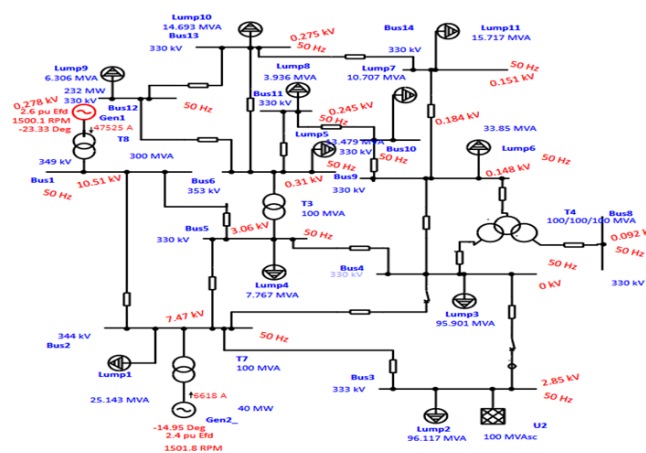


Figure 5: Power Network of IEEE 14 bus with Three Phase Fault at Bus14

Three phase transient fault was applied at bus 4 to validate the effect of fault on the power network

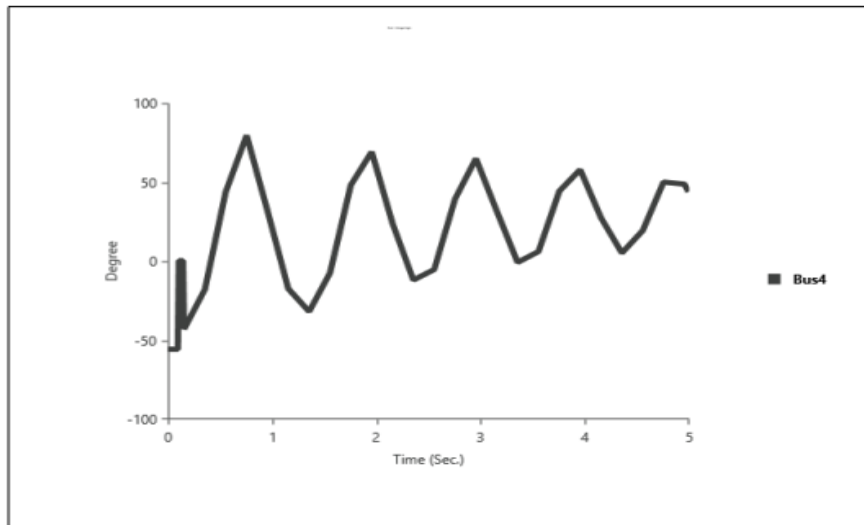


Figure 6: Voltage profile when fault was applied to bus 4 at 0.1s in ETAP

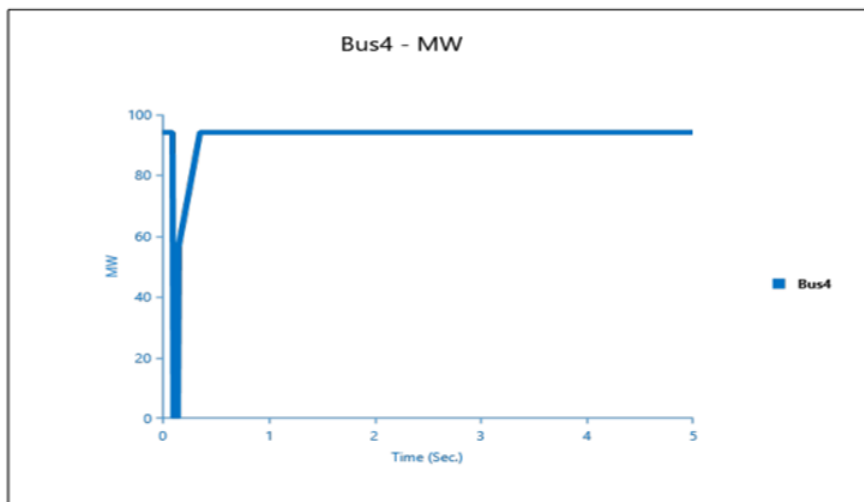


Figure 7: Power profile when fault was applied to bus 4 at 0.1s

The voltage profile of Figure 6 and Power profile of Figure 7 validates the result obtained using MATLAB Simulink tool that the presence of fault reduced the system voltage and power characteristics of the power network. The placement of phasor measurement unit (PMU) at optimum points will enhance the system reliability.

### CONCLUSION

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 center. Data centers face challenges in power protection and management solutions. This is why many data centers rely on Protocol Data Unit or Power Distribution Unit (PDU) monitoring to improve efficiency, uptime, and growth. Determining the exact faulted line in advance is not possible in practice; thus, state estimation techniques are normally employed. In this method, a virtual bus voltage state estimator say  $x$ , is computed concerning a corresponding measurement matrix say,  $H$ . The evolutionary computing heuristics for the Optimal PMU Placement (OPP) were developed and validated numerically as shown in the method. Also, simulations of a hypothetical model and an IEEE model including a real-world power system network using the Optimal PMU Placement (OPP) approach are presented. The Modified Sparsity Genetic Algorithm Optimizer (MSGAO) implementation on 14-bus was simulated in MATLAB and the results were shown as Fitness (Cost) Functions. Also, several IEEE Benchmarks were validated using the ETAP program. Fault localization is done using an evolutionary computing technique based on the Genetic Algorithms and a modified version – the Modified Sparsity Genetic Algorithm (GA) optimizer (MS-GAO).



**REFERENCES**

- [1]. JH Holland, *Adaptation in Natural and Artificial Systems*. University of Michigan Press, Ann Arbor. (2nd Edition, MIT Press, 1992.), 1975.
- [2]. GB Fogel, *Handbook of Natural Computing: Evolutional Programming*, Springer Nature Link, pp. 699-708, 1966.
- [3]. EN Osegi, and P Enyindah, A Smart SMS-SQL Database Management System for Low-Cost Microcontrollers, *African Journal of Computing & ICT*, 8(2), pp. 133-144, 2015. <http://www.ajocict.net/>
- [4]. S Russell, and P Norvig, *Artificial Intelligence: A Modern Approach*, Third Edition, ScienceDirect, 175, pp. 935-937, 2011. DOI: 10.1016/j.artint.2011.01.005
- [5]. T Xu, and T Overbye, Real-time event detection and feature extraction using PMU measurement data. *IEEE International Conference on Smart Grid Communications (SmartGridComm)*, pp. 265-270, 2015.
- [6]. BR Reddy, P. Sujatha, and YS Reddy, Fuzzy Logic and PSO based Hybrid Technique Formulation for Optimal Placement and Sizing of Interline Power Flow Controller'. *Acta electrotechnica et informatica*, 15(1); 50-60, 2015.
- [7]. KG Khajeh, E Bashar, AM Rad, and GB Gharehpetian, Integrated model considering effects of zero injection buses and conventional measurements on optimal PMU placement. *IEEE Transactions on Smart Grid*, 8(2), 1006-1013, 2015.
- [8]. M Pignati, L Zanni, P Romano, R Cherkaoui, and M Paolone, Fault detection and faulted line identification in active distribution networks using synchrophasors-based real-time state estimation. *IEEE Transactions on Power Delivery*, 32(1), 381-392, 2016.
- [9]. L Zhang, A Bose, A Jampala, V Madani, and J Giri, Design, testing, and implementation of a linear state estimator in a real power system. *IEEE transactions on Smart Grid*, 8(4), 1782-1789, 2016.
- [10]. MU Usman, MO Faruque, Validation of a PMU-based fault location identification method for smart distribution network with photovoltaics using real-time data. *IET Generation, Transmission & Distribution*, 12(21), 5824-5833, 2018.
- [11]. R Babu, VK Gupta, K and Subbaramaiah, An Approach to Unravel the Optimal PMU Placement Problem for Full Observability of Power Network in View of Contingencies. *International Journal of System Assurance Engineering and Management*, 13(3), 1170-1186, 2022.
- [12]. Q Lv, Y Chen, K Yuan, L Qin, X Yu, and H Gui, Optimal sensor placement in distribution network based on super resolution network. *Energy Reports*, 8, 1050-1058, 2022.
- [13]. B Cao, Y Yan, Y Wang, X Liu, JCW Lin, AK Sangaiah, and Z Lv, A Multiobjective Intelligent Decision-Making Method for Multistage Placement of PMU in power grid enterprises. *IEEE Transactions on Industrial Informatics*, 2022.
- [14]. CD Patel, TK Tailor, SK Shukla, S Shah, and SN Jani, Steiner Tree-Based Design of Communication Infrastructure With Co-Optimizing the PMU Placement for Economical Design of WAMS. *IEEE Transactions on Instrumentation and Measurement*, 71, 1-11, 2022.
- [15]. HA Abd el-Ghany, IA Soliman, AE ELGebaly, An advanced wide-area fault detection and location technique for transmission lines considering optimal phasor measurement units allocation. *Alexandria Engineering Journal*, 61(5), 3971-3984, 2022.