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# Optimal Placement of Phasor Measurement Units on Shiroro 330kv Grid Network using Binary Grey Wolf Optimization Algorithm

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**ABSTRACT**

Phasor Measurement Units (PMUs) are crucial for improving the control, monitoring, and observability of modern power systems. This research presents an optimal PMU placement strategy for the Shiroro 330 kV grid network using the Binary Grey Wolf Optimization (BGWO) algorithm. The objective is to minimize the number of PMUs required while ensuring full system observability under both normal and contingency conditions. The BGWO algorithm, inspired by the hunting behavior of grey wolves, is a powerful metaheuristic for solving binary optimization problems. Applied to the Shiroro grid, this method demonstrates enhanced observability and system reliability. Compared to other optimization techniques, BGWO achieves higher accuracy and reduced computational time. The simulation results validate the effectiveness of the proposed approach in achieving cost-effective and reliable PMU deployment for the 330 kV network.



## 1. INTRODUCTION

Modern electrical power systems are increasingly complex. This complexity highlights the urgent need for advanced monitoring and control systems to ensure operational efficiency, security, and reliability [1]. The incorporation of advanced measuring techniques is crucial for ensuring system stability and enabling timely reactions to disruptions, as real-time situational awareness is crucial [2]. In this regard, phasor measurement units (PMUs), which provide fast, synchronized measurements of voltage and current phasors throughout the power grid, have become essential elements [3]. Phasor Measurement Units (PMUs) have several advantages over the remote field of conventional Supervisory Control and Data Acquisition (SCADA) systems, which typically consist of Remote Terminal Units (RTUs), Programmable Logic Controllers (PLCs), or Intelligent Electronic Devices (IEDs). The synchronization of PMU measurements in real-time can be ensured by using the Global Positioning System (GPS), thereby obtaining very high-precision data at the source, which allows for real-time, wide-area monitoring and control [4]. By enhancing overall grid observability, these advantages enable operators to make informed decisions that support system resilience and performance [5]. However, financial and technological constraints frequently prevent PMUs from being deployed effectively, necessitating plans on where to position them within the power network [6]. The goal of optimal PMU placement is to minimize the number of PMUs required while maximizing grid observability by utilizing binary grey wolf optimization to achieve the minimum number of PMUs needed. This minimizes implementation costs and ensures effective resource usage [7]. This optimization problem is particularly relevant in developing nations, where the widespread deployment of expensive monitoring equipment is often hindered by financial constraints [8]. Strong monitoring systems are urgently needed in Nigeria, one of Africa's largest economies, as the electricity grid faces numerous challenges, including frequent disruptions and unstable systems [9]. An essential part of Nigeria's power infrastructure, the Shiroro 330 kV grid network is crucial to the production and distribution of electricity [10]. To improve the stability and dependability of this network, which are critical for the socioeconomic development of the area, full observability is required [11]. The optimal PMU placement

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problem (OPP) is a combinatorial optimization challenge that has attracted significant research attention [12]. Several optimization techniques, such as integer linear programming (ILP), particle swarm optimization (PSO), and genetic algorithms (GA), have been applied to solve this problem [13]. Despite their effectiveness, these methods sometimes face issues with convergence speed, solution accuracy, and scalability when applied to large grid networks [14].

The Metaheuristic algorithms are more suitable than conventional methods for optimal PMU placement on the Shiroro 330kV grid because they efficiently handle large, complex, and constrained optimization problems, offer better global search capability, and adapt well to real-world grid topologies. The Grey Wolf Optimization (GWO) algorithm is one such algorithm that imitates the natural hunting patterns of grey wolves. A version of the original GWO algorithm, the Binary Grey Wolf Optimization (BGWO) algorithm is especially well-suited for handling binary decision-making situations such as the OPP [15].

This research proposes an approach that utilizes the BGWO algorithm to deploy PMUs on the Shiroro 330 kV grid network in the most optimal manner. A vital component of Nigeria's transmission system, the Shiroro network requires consistent monitoring to ensure uninterrupted electricity delivery and meet the increasing demand. To reduce the number of PMUs and maintain full system observability in both regular and emergency scenarios, the BGWO algorithm is employed. To improve system robustness, additional restrictions are added to the optimization model, such as zero injection buses and single PMU failures [16].

This study demonstrates the effectiveness of the Binary Grey Wolf Optimization (BGWO) algorithm in minimizing the number of PMUs required for full observability of the Shiroro 330 kV grid network, achieving optimal sensor placement while considering real-world constraints. This approach offers a robust and scalable solution for modern power system monitoring.

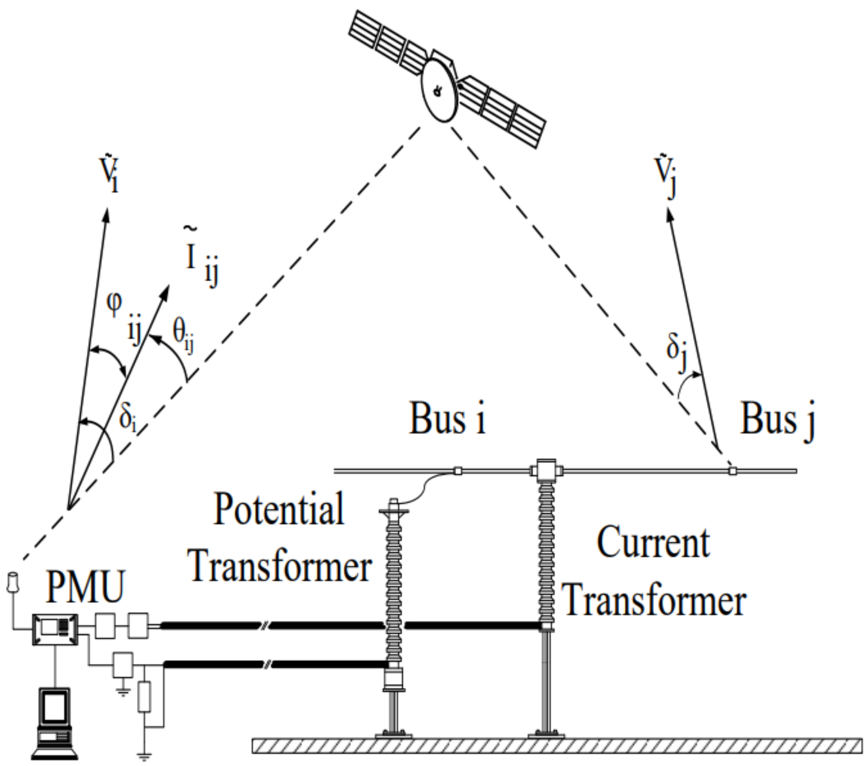


Figure 1. PMU Satellite 1

## 2. REVIEW OF RELATED LITERATURE

The literature on optimal PMU placement emphasizes the critical role of strategically deploying PMUs across power networks to enhance system observability, stability, and real-time monitoring capabilities that are increasingly vital in managing the variability and uncertainty introduced by renewable energy integration and dynamic grid loads, particularly in large-scale transmission systems such as the Shiroro 330 kV network. [17]. Studies have shown that PMUs play a crucial role in real-time monitoring and control, which is essential for resolving issues brought on by the growing integration of renewable energy sources and the requirement for improved grid dependability [18] Binary Grey Wolf Optimization (BGWO) is particularly effective in handling non-linear constraints because of its adaptive hunting behavior and flexible solution encoding, which allow it to efficiently navigate complex, high-dimensional search spaces without relying on gradient information. Unlike traditional optimization methods or even some other metaheuristics, BGWO mimics the social hierarchy and cooperative hunting strategies of grey wolves, enabling a balance between exploration and exploitation. This makes it highly suitable for solving the PMU placement problem, which involves discrete variables, non-linear observability constraints, and practical limitations such as budget and measurement redundancy. Consequently, BGWO emerges as a powerful tool in modern grid management, where the integration of renewable energy and changing load dynamics necessitates robust, constraint-aware, and scalable optimization techniques. These techniques have demonstrated promise in successfully addressing the non-linear limitations related to power system observability and reducing deployment costs [19].

Additionally Recent studies demonstrate significant progress in hybrid optimization techniques, which combine the strengths of multiple algorithms such as integrating BGWO with local search or machine learning methods to improve convergence rates and enhance solution accuracy that utilize BGWO in conjunction with other metaheuristic algorithms to increase convergence rate and accuracy of solutions in intricate situations with changeable grid conditions and multi-dimensional constraints. To assure complete system observability while reducing redundancy and installation costs, for example, researchers have investigated combining BGWO with techniques like Differential Evolution (DE) and Modified Genetic Algorithms (MGA) [20].

Additional research has confirmed that BGWO is a reliable and effective tool for PMU placement in complex power networks, with case studies demonstrating its superiority in minimizing the number of PMUs while ensuring complete system observability. For example, comparative simulations on IEEE 14-, 30-, and 118-bus systems show that BGWO achieves faster convergence, higher observability indices, and reduced computational overhead compared to algorithms like Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) [21].

Furthermore, the use of BGWO has been broadened to take into account dynamic operating conditions, enabling adaptive PMU placement techniques that react to changes in load patterns and grid topology in real-time [21][22].

Furthermore, significant levels of renewable energy integration and growing grid complexity characterize current power systems BGWO is particularly well-suited for handling dynamic grid environments due to several key features: its adaptive social hierarchy-based search mechanism allows for dynamic adjustment between exploration and exploitation phases, which is essential for responding to changes in grid topology, load variations, or renewable energy fluctuations. Additionally, its binary encoding enables efficient modeling of on/off decisions, such as PMU installation. At the same time, its ability to incorporate real-time data streams through fitness function updates makes it highly responsive to evolving grid conditions. [23]. As a result, in current PMU placement research, BGWO has emerged as a top optimization technique that provides a dependable and effective means of improving power system monitoring and control in expansive, dynamic grid environments [21][24].

Modern power systems are characterized by variable demand and generation conditions, and maintaining observability in the face of these conditions requires this adaptability [25].

Communication delays and data transmission reliability significantly impact PMU placement decisions because timely and accurate phasor data are essential for real-time monitoring, fault detection, and state estimation. If PMUs are placed without considering communication constraints, delays, or data losses can compromise observability and reduce the effectiveness of control actions. Therefore, incorporating factors such as latency, bandwidth availability, and network reliability into optimization models ensures that selected PMU locations not only provide electrical coverage but also maintain dependable data delivery [26]. By ensuring that the PMU locations are selected to maximize observability and enable dependable data transfer, these integrations seek to improve the overall performance of innovative grid systems [27][28]. In PMU placement research, the synergy between BGWO and communication reliability considerations provides a promising area that will help create more durable and resilient power networks [29].

Furthermore, chances for further placement strategy optimization exist due to the ongoing development of PMU technology, which includes improvements in sensor capabilities and communication protocols [30][31]. This enables the realization of more intelligent and responsive power systems.

### 2.1. Optimal Power Flow Problem

An Optimal Power Flow (OPF) problem is formulated as a constrained optimization problem, where the objective is to minimize or maximize a specific function (e.g., generation cost, transmission losses) while satisfying power system constraints (e.g., power balance, voltage limits, and line flow limits). The general mathematical statement of the OPF problem is given below:

#### 2.1.1. Objective Function

The primary objective in OPF is to minimize the total generation cost. The total price is typically represented as a quadratic function of the generator power output.

Minimize $C = \sum_{i=1}^{N}(aiP_{Gi}^{2} + biPGi + ci)$ (1)

$P_{Gi}$ is the real power output of generator i

$a_i$, $b_i$, and $c_i$ are the cost coefficients for the quadratic cost curve of generator i, which are obtained from generator cost data.
G is the set of all generators in the system.

#### 2.1.1.1. Power Balance Constraints (Equality Constraints)

The total power generated must equal the total demand plus system losses.
The active and reactive power balance equations represent this.

Active power $\sum P_G = \sum P_D + P_L$ (2)

Reactive power = $\sum Q_G = \sum Q_D + Q_L$ (3)

#### 2.1.1.2. Generator Capacity Constraints (Inequality Constraints)

The real and reactive power outputs of each generator must be within their respective limits.

$P_{Gmin} \leq P_G \leq P_{Gmax}$ (4)

$Q_{Gmin} \leq Q_G \leq Q_{Gmax}$ (5)

#### 2.1.1.3. Voltage Magnitude Limits (Inequality Constraints)

The voltage at each bus must be within specified operational limits.

$V_{min} \leq V_i \leq V_{max}$ (6)

#### 2.1.1.4. Transmission Line Flow Limits (Inequality Constraints)

The power flow through each transmission line must not exceed its thermal capacity.

Active Power Flow Limit $|P_{ij}| \leq P_{ij}^{max}$ (7)

Reactive Power Flow Limit $|Q_{ij}| \leq Q_{ij}^{max}$ (8)

#### 2.1.1.5. System Observability Constraint Subsubsection 1

All system buses must either have a PMU placed on them or be adjacent to a bus with a PMU to ensure full observability.

All of the system's buses must have a PMU placed on them or be adjacent to one in order for full observability to be guaranteed [70]. This restriction is known as:

$x_i + \sum_{j \in N_i} x_j \geq 1 \ \forall_i \in B$ (9)

$N_i$ is the set of neighboring buses connected to bus i.
B is the set of all buses in the power system.

With the use of a PMU on the bus or its nearby buses, this constraint guarantees that each bus $i$ is either directly or indirectly observable.

**2.1.1.6. Redundancy Constraint (Optional)**

Ensures that each bus is observable from at least two PMUs to enhance system reliability in the event of a failure. To enhance system reliability and ensure observability in the event of PMU failure, a redundancy constraint can be implemented. This constraint ensures that each bus is observable from at least two PMUs:

$$x_i + \sum_{j \in N_i} x_j \geq 2 \; \forall_i \in B \tag{10}$$

By guaranteeing that observability is maintained even in the event of a PMU failure, this optional constraint is used to increase robustness and reliability.

**2.1.1.7. Zero-Injection Bus Constraint**

Because of Kirchhoff's Current Law, zero-injection buses—those in which no power is injected or withdrawn—can require fewer PMUs. (KCL) [70]. The following is the formulation of the zero-injection bus constraint:

$$\sum_{j \in N_i} x_j \geq 1 \; \forall_i \in ZIB \tag{11}$$

**2.1.1.8. ZIB represents the set of zero-injection buses**

Without the usage of a PMU, this constraint guarantees that zero-injection buses are visible to at least two nearby buses.

**2.2. PMU Placement Formulation**

The optimal placement of phasor measurement units (PMUs) is formulated as a minimization problem aimed at determining the minimum number of PMUs required to achieve complete system observability while satisfying redundancy and monitoring constraints [69]. A PMU is a smart device in the smart grid that provides real-time synchronized voltage and current measurements. Thus, the entire power network can be observed by the strategic placement of PMU devices. The main objective of the OPP problem is to find the minimum PMUs to achieve full observability of the power system [32]. The objective function (F (x)) for the optimal placement problem is formulated to reduce the number of PMUs as well as to maximize the measurement redundancy and can be represented as follows:

$$F(x) = \min \sum_{i=1}^{N} x_1 + w_1 (M - A' X)^T (M - A' X) + w_2 \times N_{obs} \tag{12}$$

Subject to: $A' X \geq b$

Where N is the total number of bus locations in a network, M is the desired value of measurement redundancy, and Nobs is the number of observable buses. In this study, the weights w1 and w2 were selected through a trial-and-error process, based on the relative importance of each objective in the optimization problem. w1 represents the weight assigned to minimizing the number of PMUs, while w2 corresponds to the weight for ensuring system observability. These weights were fine-tuned to balance the trade-off between reducing PMU count and maintaining full observability, with their values chosen to optimize overall system performance based on simulation results and the specific requirements of the Shiroro 330 kV Parameters A′ The binary connectivity matrix, denoted as A′ is a matrix that represents the connectivity between buses in the power network, where each element Aij indicates whether there is a direct transmission line between bus i and bus j. This matrix is crucial for determining the observability and interactions between different parts of the grid. And is the binary connectivity matrix, and can be defined as follows:

$$A_{ij}' = \begin{cases} 1, & if\ i = j\ or\ i\ is\ connected\ to\ j \\ 0, & otherwise \end{cases} \tag{13}$$

The decision variable vector X consists of binary values x_i, where each x_i represents the placement decision for the PMU at bus i. If x_i=1, it indicates that a PMU is installed at bus i, while x_i= 0 means no PMU is installed at that bus.

$$X_i = \begin{cases} 1, & if\ the\ PMU\ is\ installed\ at\ bus\ i \\ 0, & otherwise \end{cases} \tag{14}$$

The optimal PMU placement (OPP) problem is defined as determining the minimum number of PMUs and their optimal placement locations to make the power system network completely observable. The power system observability is divided into two approaches: the topological observability and the numerical observability. In the topological observability approach, the process is grounded in graph theory. It relies on decoupled modeling, where the power system is represented as a graph with buses as nodes and transmission lines as edges, allowing observability analysis to be conducted using connectivity rather than electrical measurements. An observable network is determined from the existence of a full ranked measurement tree based on the observability rules [32]. The numerical observability approach is based upon the numerical factorization of the Jacobian gain matrix. This approach to determining observability is not suitable for large systems due to the massive matrix manipulation and complexity. In this paper, topological observability is used to analyse the observability of the electrical network.

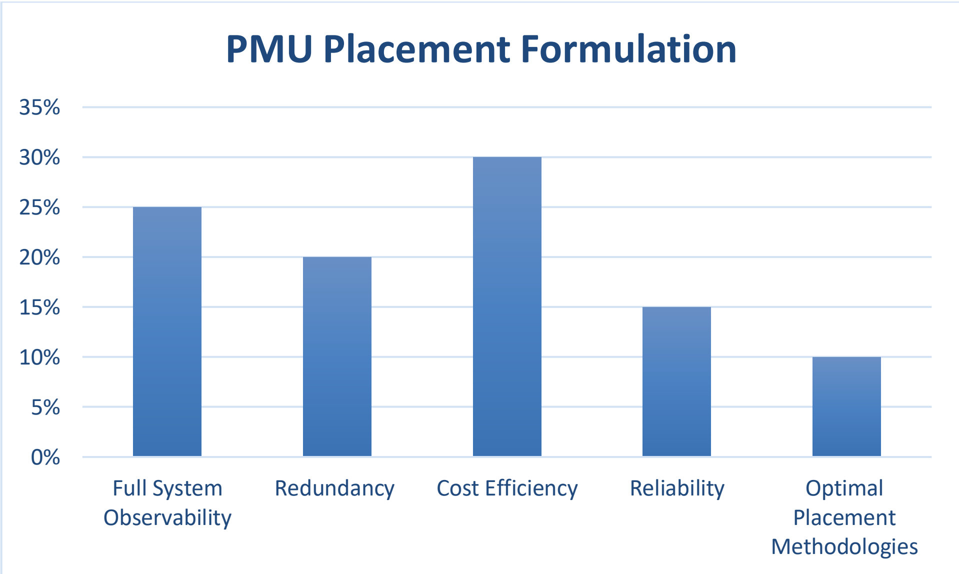


Figure 2. PMU Placement Formulation

### 2.3. PMU Placement Problem with Binary Grey Wolf Optimization (BGWO)

Phasor Measurement Units (PMUs) measure electrical signals synchronously in real-time, thereby enhancing power grid stability, reliability, and monitoring capabilities. Optimizing the placement of PMUs within a power grid, such as Nigeria's Shiroro 330kV Grid Network, is a complex binary optimization issue. The Binary Grey Wolf Optimization (BGWO) method offers a practical solution by efficiently minimizing the number of PMUs needed while ensuring full grid observability, outperforming traditional methods through better handling of non-linear constraints and faster convergence to optimal solutions. This explanation explores the BGWO method, the PMU placement problem, and the related mathematical formulations. This is a binary optimization problem where each bus in the grid either has a PMU (1) or does not (0). The Binary Grey Wolf Optimization (BGWO) algorithm provides an efficient approach to solving this problem by mimicking the hunting behaviors of grey wolves, adapted for binary decision-making.

#### 2.3.1. Grey Wolf Optimization (GWO)

##### 2.3.1.1 Definition

Binary Grey Wolf Optimization (BGWO) is employed in PMU placement due to its robust search capabilities and adaptability to complex, discrete optimization problems commonly encountered in power system observability. Key reasons for using BGWO in PMU optimization include Wolf Optimization (GWO). A nature-inspired metaheuristic algorithm that mimics the social hierarchy and hunting behaviour of grey wolves.

##### 2.3.1.2 Key Components

The leadership hierarchy in GWO mimics the natural social structure of grey wolves, which is divided into four distinct ranks: alpha (α), beta (β), delta (δ), and omega (ω).

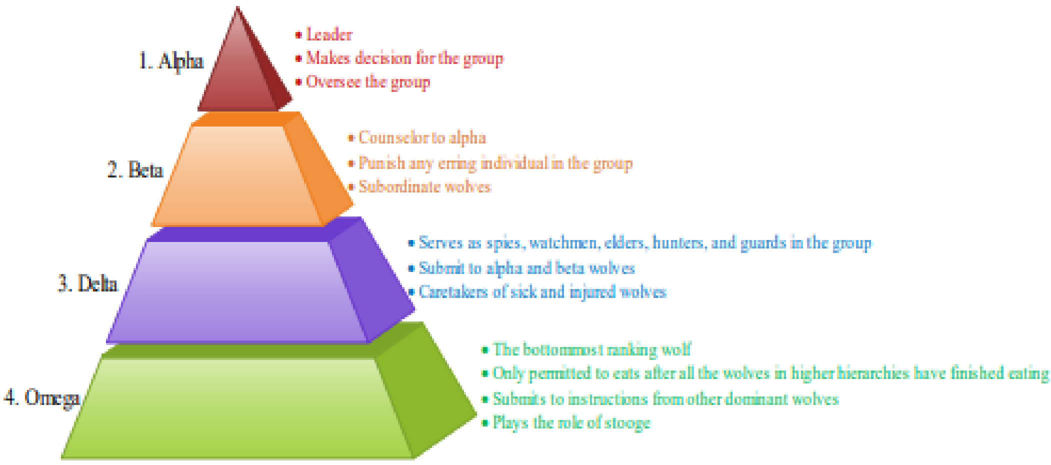


Figure 3. GWO leadership [28]

Hunting mechanism is closely related to the optimization process and serves as a metaphor for how candidate solutions evolve toward the global optimum

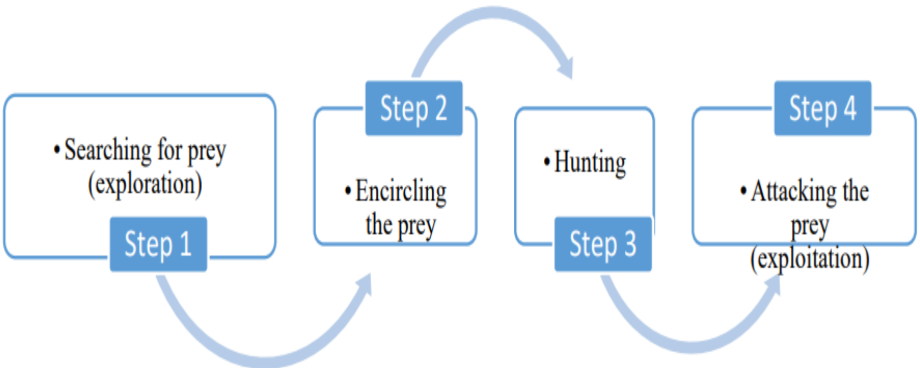


Figure 4. Hunting process [28]

**2.3.1.1. Objective Function**

The primary objective of optimal PMU placement is to minimize the total number of PMUs installed while guaranteeing complete topological observability of the power grid. This involves identifying the smallest set of bus locations where PMUs can be placed so that the entire grid, either directly or indirectly through observability rules, is effectively monitored.

$$min = \sum_{i=1}^{n} x_i \quad (15)$$

Each bus is either equipped with a PMU or connected to at least one bus with a PMU.

$$x_i \in \{0\ ,1\}\ \forall_i = 1,2,\ldots,N \quad (16)$$

**2.3.1.2. Fitness Function Subsubsection 1**

In the optimal placement of PMUs, the fitness function is designed to evaluate each candidate solution by considering two conflicting goals:

1. Minimizing the number of PMUs deployed, and
2. Maximizing the system's observability.

To balance these objectives, two weighting coefficients are introduced:

- α: The weight assigned to minimizing the number of PMUs (cost-efficiency).
- β: The weight assigned to maximizing observability (coverage quality).

$$Fitness = \alpha \times (\sum_{i=1}^{n} x_i) + \beta \times Observability \quad (17)$$

α and β are weighting factors balancing the importance of minimizing PMUs and maximizing observability, respectively.
Observability

$$A' \chi \geq 1 \quad (18)$$

$A' \chi$ →tell how many of each bus's neighbours (including itself) have PMUs.
$A' \chi \geq 1$ means every bus must be covered by at least 1 PMU directly or indirectly.

**2.3.1.3. Observability Calculation**

For a given PMU placement vector X, observability is determined as follows:

$$\text{Observable} = \frac{Number\ of\ Observable\ Buses}{N} \times 100\% \quad (19)$$

Observable buses are those with a PMU or directly connected to a bus with a PMU.

**2.3.1.3.1. Initialization**

Population Setup. In the optimal PMU placement, each potential solution is represented as a binary vector X = $[\chi_1, \chi_2 ..., \chi_n]$, where each element xi∈{0,1} denotes the presence (1) or absence (0) of a PMU at bus i . The initialization process involves generating a population of such candidate solutions randomly to start the optimization. This diverse starting population enables broad exploration of the search space. Population Size (P): Number of candidate solutions.

- Maximum Iterations (T): Termination condition.
- Control Coefficients: Parameters guiding the GWO behaviour.

**2.3.1.3.2. Fitness Evaluation**

Compute Observability

**Fitness Evaluation Steps**

For each wolf ω in the population (i.e., each candidate PMU placement solution represented by a binary vector Xω):

**Input the Placement Vector**

Use the binary vector Xω = $[\chi_1, \chi_2 ..., \chi_n]$, where $\chi_i$ = 1 if a PMU is placed at bus i, and zero otherwise.

**Compute Observability Vector**

Multiply the connectivity matrix A′ with the placement vector and add it to the vector itself: $A' \chi \geq 1$
This reflects which buses are observed either directly or through connected buses.

**Check Observability Condition**

Ensure that all elements of vector X are greater than 0, i.e.,
If Xi>0 for all i, then the system is fully observable.
If not, assign a high penalty (e.g., fitness = ∞).
Count PMUs
If the system is fully observable, compute the fitness as the total number of PMU, Fitness = $\sum_{i=1}^{n} x_i$. The objective is to minimize this value. Return Fitness Value:
If the system is observable, → return the number of PMUs.
If not observable → return an enormous penalty value (e.g., ∞).
Calculate Fitness: Use the fitness function to evaluate each wolf's solution.

$$Fitness_\omega = \alpha \times (\sum_{i=1}^{n} x_i) - \beta \times Observability_\omega \quad (20)$$

**2.3.1.3.3. Identify Leaders**

In the GWO algorithm, the process of hunting prey is metaphorically mapped to solving optimization problems. Here's how:

- Alpha (α): Represents the best solution (lowest fitness value).
- Beta (β): Represents the second-best solution.
- Delta (δ): Represents the third-best solution.
- The rest of the wolves are omega (ω) and update their positions based on the guidance of α, β, and δ.

**2.3.1.3.4. Encircling process**

$$X(t+1) = X_p(t) + A.D \quad (21)$$

$$D = |CX_p(t) - X(t)| \quad (22)$$

$$A = 2ar_1 - a\ ,\ C = 2\ r_1 \quad (23)$$

**2.3.1.3.5. Position Update**

Encircling Prey Equations: Update each wolf's position based on the positions of α, β, and δ wolves.

$$D_\alpha = [\ C_1 \times X_\alpha - X_\omega] \quad (24)$$

$$D_\beta = [\ C_2 \times X_\beta - X_\omega] \quad (25)$$

$$D_\delta = [\ C_3 \times X_\delta - X_\omega] \quad (26)$$

$$X_1 = [\ X_\alpha \times A_1 - D_\alpha] \quad (27)$$

$$X_2 = [\ X_\beta \times A_2 - D_\beta] \quad (28)$$

$$X_3 = [\ X_\delta \times A_3 - D_\delta] \quad (29)$$

$$X_{New} = \frac{X_1 + X_2 + X_3}{3} \quad (30)$$

**2.3.2. Binary grey wolf optimization algorithm**

Binary Grey Wolf Optimization (BGWO) is an adaptation of the standard Grey Wolf Optimization (GWO) algorithm, specifically designed for binary optimization problems, such as the optimal placement of Phasor Measurement Units (PMUs), where decisions are represented as 0s and 1s (e.g., placing a PMU or not). In the Binary Grey Wolf Optimization (BGWO) algorithm, the position of each grey wolf is represented as a binary vector, where each element is either 0 or 1. This binary encoding is crucial for solving discrete optimization problems, such as determining whether to install a PMU at a specific bus in a power grid.

To adapt the continuous position updates from the standard GWO to binary space, BGWO uses a transfer function, typically the sigmoid function (SF), to map real-valued positions to probabilities.

Therefore, Eq. (3.18) can now be updated as Eq. (3.28) as follows. To convert continuous position values into binary decisions in the Binary Grey Wolf Optimization (BGWO) algorithm, the sigmoid transfer function is applied:

$$X(t+1) = \begin{cases} 1 & if\ SF \geq r_3 \\ 0, & otherwise \end{cases} \quad (31)$$

The sigmoid function is a key mechanism that facilitates the binary conversion in BGWO. Mapping continuous position values to a range of 0 to 1 enables the algorithm to make decisions about PMU placement in a smooth and controlled manner, thereby enhancing the accuracy and efficiency of the optimization process. The introduction of randomness through thresholding (using the random value rrr) adds diversity to the search, enabling the algorithm to explore the search space effectively.

$$SF = \frac{1}{1 + e^{-X_{New}}} \quad (32)$$

Where $r_3$ is a random number between [0, 1] and SF is the sigmoid function.

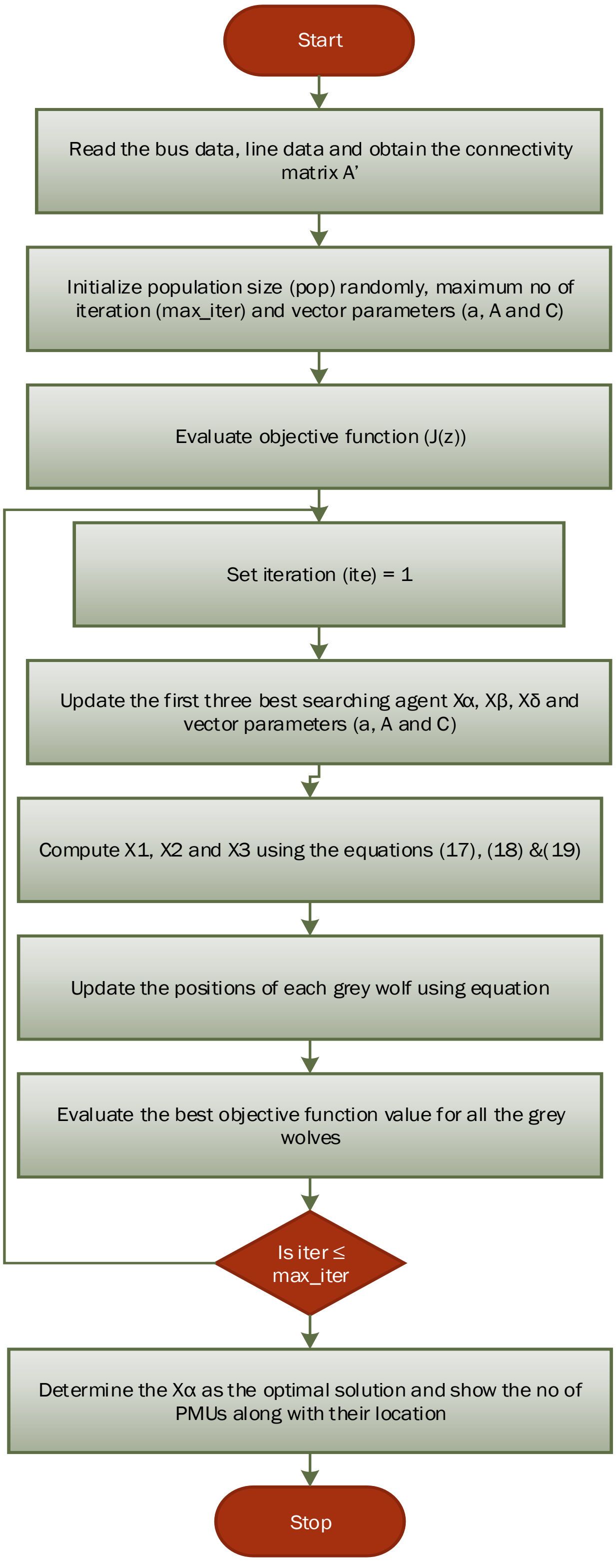


Figure 5. Optimization process [33]

## 3. RESULTS AND DISCUSSION

BGWO's key achievements are minimizing PMUs while ensuring full observability from the foundation of its effectiveness. Additional benefits, such as handling non-linear constraints and adaptability to dynamic grid environments, make it an ideal solution for PMU placement optimization in complex power networks. The result for the Optimal PMU Placement on Buses in the Shiroro 330KV Grid Network of Nigeria using the Binary Grey Wolf Optimization (BGWO) Algorithm is the determination of the least number of PMUs needed to guarantee complete system observability by strategically placing them on key buses, optimizing grid-wide monitoring for enhanced fault detection, stability, and power quality assessment, while minimizing installation, maintenance, and operational costs, accelerating the optimization process through BGWO's computational efficiency, and contributing to improved grid security, adaptability to future upgrades, and better.

### 3.1. BGWO Optimization Result

PS C:\Users\DELL> & "C:/Program Files/Python313/python.exe" c:/Users/DELL/Desktop/SHIRORO.py
Optimal PMU Placement:
PMU Locations (1 indicates PMU placement): [0 1 0 1 0]
Number of PMUs used: 2
PS C:\Users\DELL>

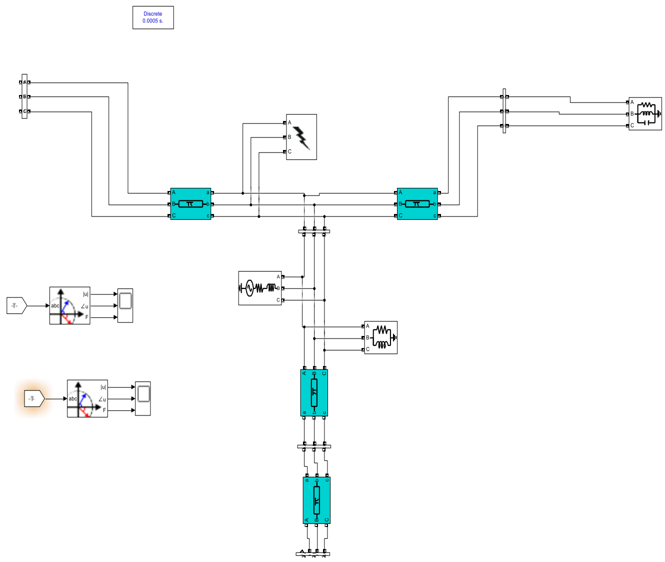

Figure 6. Optimally located for PMU 1

#### 3.1.1. Optimal PMU Placement

The optimization results demonstrate the success of the Binary Grey Wolf Optimization (BGWO) algorithm in identifying the optimal placement of Phasor Measurement Units (PMUs) within the Shiroro 330 kV grid network. The algorithm has effectively computed the best locations for installing PMUs, minimizing the number of units required while ensuring full observability of the entire power system. This optimization process not only reduces installation costs but also guarantees that all critical system buses are monitored, ensuring efficient grid monitoring and control. In the following sections, we will delve into the technical details of the placement results and the key factors contributing to the algorithm's effectiveness.

Table 1. OPP Result Obtained from Proposed BGWO

| Shiroro 330kv Grid Network | Location of PMU | Optimal no of PMUs |
|---|---|---|
| 5-bus | 2, 4 | 2 |

- This array represents different buses in the power system.
- A value of 1 means a PMU is placed at that bus.
- A value of 0 means no PMU is placed at that bus.
- In this case, PMUs are placed at buses 2 and 4 (indexing starts from 0 in Python).

Number of PMUs used: 2"

- This indicates that 2 PMUs are required for complete observability of the power system.

### 3.2. PMU Placement on strategic Buses in MATLAB/Simulink on Shiroro 330kV

#### 3.2.1. PMU Placement on strategic Buses in MATLAB/Simulink with and without fault

Once the PMUs were installed, fault analysis was conducted within the MATLAB/Simulink environment to assess the robustness of the PMU configuration under fault conditions. The simulation considered various fault scenarios, including short circuits, line-to-ground faults, and other disturbances commonly found in power systems.

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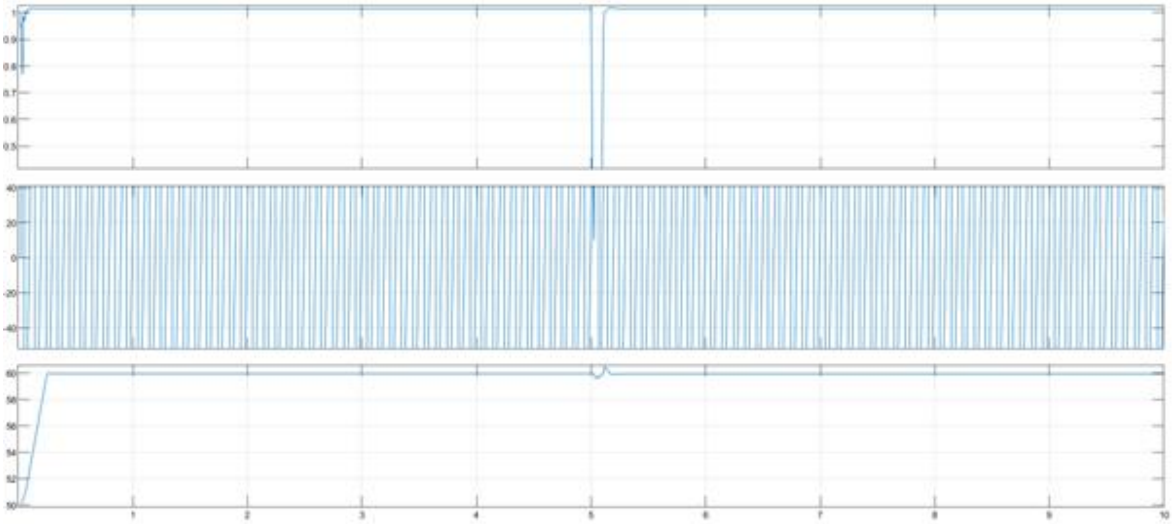

Figure 7. PMU placement with fault

**3.2.1.1. Voltage Magnitude Response (Top Plot)**

- Initially, the voltage is stable at 1 per unit (p.u.), indicating normal operation.
- At t ≈ 5s, there is a sudden dip, suggesting a fault event (e.g., short circuit, line outage).
- PMUs measure the voltage phasor at a bus as

$$V(t) = |V(t)|e^{(-j\theta(t))} \tag{33}$$

where

$|V(t)|$ is the voltage magnitude (in per unit p.u)

$j\theta(t)$= is the voltage phase angle (in radians or degrees)

Fault impact on voltage

At t = 5 seconds, a voltage dip occurs in the system, representing a disturbance such as a fault or sudden load change. This voltage dip impacts the voltage magnitude, phase angle, and frequency of the buses in the following ways:

- Voltage Magnitude:

The disturbance causes a temporary drop in the voltage level at the affected buses. This is typically observed as a sudden decrease in RMS voltage values from nominal (e.g., from 1.0 p.u. to around 0.7–0.8 p.u.), depending on the fault severity.

- Phase Angle:

A fault or disturbance introduces a rapid shift in the voltage phase angle, indicating instability or mismatch in the power flow. The phase angle deviation helps identify where and how the system's synchronism is affected, and PMUs are crucial in capturing this data in real time.

- Frequency:

Frequency is sensitive to power imbalances. During the disturbance, local frequency deviation occurs as the system attempts to stabilize. A dip or surge in frequency is a critical signal of generation-load mismatch, with PMUs detecting even small deviations from the nominal 50 Hz standard.

$$V_{fault} = |V|_{pre\ fault} - \Delta V \tag{34}$$

**3.2.1.2. Phase Angle Response (Middle Plot)**

- The phase angle remains relatively stable before the fault.
- At t ≈ 5s, a sudden shift occurs, meaning there is a disturbance in power flow.
- Oscillations after the fault indicate the system is trying to re-establish synchronization.
- If oscillations are significant or sustained, it could mean generator instability or poorly damped power swings.

The phase angle difference is the angular separation between the voltage phasors of buses i and j.. Phasor Measurement Units (PMUs) provide synchronized real-time measurements of voltage phase angles. By measuring θi and θj directly, PMUs eliminate estimation errors, improving power system observability and control.

$$P_{ij} = \frac{|V_i||V_j}{X_{ij}} \operatorname{Sin}(\theta_i - \theta_j)\, \Delta\, \theta \tag{35}$$

Fault Impact on Phase Angle. During a fault, the power flow equation is disturbed.

$$\Delta P = \frac{|V_i||V_j}{X_{ij}} \cos(\theta_i - \theta_j)\, \Delta\, \theta \tag{36}$$

**3.2.1.3. Frequency Response (Bottom Plot)**

- The frequency starts at 60 Hz, which is the nominal operating frequency of the power grid.
- At t ≈ 5s, there is a deviation in frequency, indicating a power imbalance due to the fault.
- A rapid frequency dip suggests a significant loss of generation or a sudden change in load.
- If the system does not restore frequency to 60 Hz, automatic load shedding or generation adjustments may be required.

Frequency is related to the power systems' rotating machines and is governed by

$$\frac{d\theta}{dt} = 2\pi f \tag{37}$$

The rate of change of frequency is given by

$$\frac{df}{dt} = \frac{P_m - P_e}{2H} \tag{38}$$

Fault impact on frequency

A fault introduces a power imbalance. $P_m \neq P_e$ causing a frequency deviation.

$$F_{fault} = f_{nominal} - \Delta f \tag{39}$$

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**3.2.2. PMU Placement on strategic Buses in MATLAB/Simulink without fault**

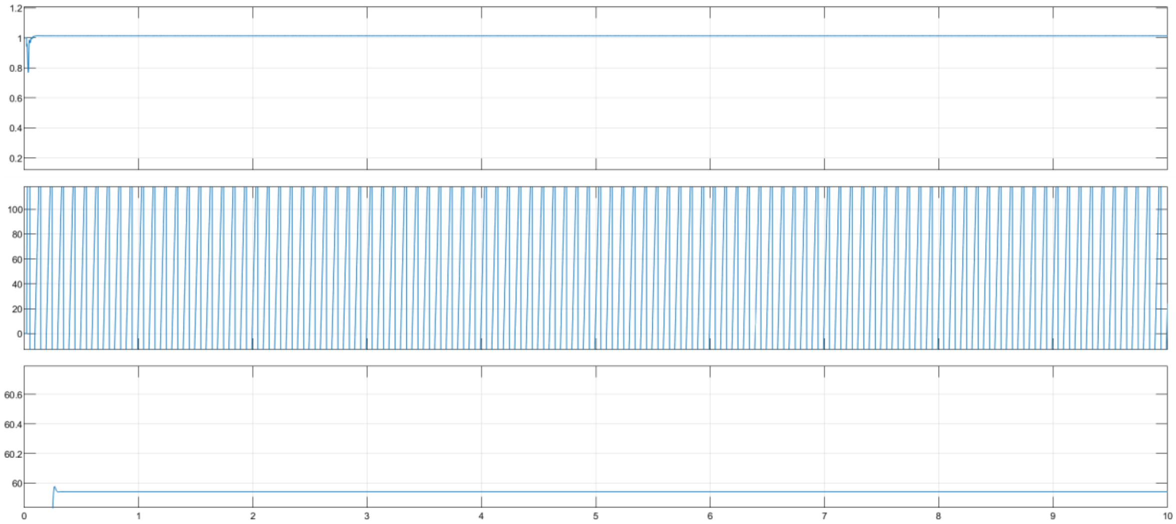

Figure 8. PMU placement on strategic Buses

**Voltage Stability Observation:** Throughout the simulation period, the voltage magnitude at the monitored bus remains nearly constant at approximately 1.0 per unit (p.u.), indicating that the system is operating under stable conditions.

**Normal Operating Benchmark:** In power systems, a voltage magnitude of 1.0 p.u. is considered the nominal or reference value, representing the ideal voltage level without any deviations or disturbances. No visible disturbances, dips, or oscillations are present, indicating a stable voltage profile.

Mathematical Representation:

$$V(t) = |V(t)|e^{-j\theta(t)} \tag{40}$$

where V(t) = 1.0p.U means no voltage sag or fault is occurring.

**3.2.2.1. Phase Angle Response (Middle Graph)**

The phase angle graph demonstrates the system's dynamic response and highlights the critical importance of phase angle stability in maintaining a balanced power flow:

- Initial Oscillation: At the onset of the simulation, the phase angle exhibits a slight transient oscillation, which is typical after a system is subjected to a change, such as a minor disturbance or switching event.
- Stabilization: Shortly after the disturbance, the phase angle settles around a steady-state value, indicating that the system has effectively damped out the oscillations and returned to equilibrium.

PMUs precisely measure these angles in real-time, enabling operators to detect phase instability early and take corrective actions, thereby reinforcing the value of optimal PMU placement. No significant deviation was observed, indicating normal power flow without sudden disturbances.

Mathematical Representation:

$$P_{ij} = \frac{|V_i||V_j}{x_{ij}} \text{Sin}(\theta_i - \theta_j) \tag{41}$$

Since $\theta_i - \theta_j)$ remains stable, power flow is maintained, meaning there is no fault.

**3.2.2.2. Frequency Response (Bottom Graph)**

The frequency response analysis reveals a critical relationship between frequency stability and the balance between mechanical input power and electrical output power of the generators:

- Initial Oscillation: The slight initial frequency oscillation observed is a natural response to transient imbalances between mechanical and electrical power during system disturbances or switching events.

- Stabilization at 50 Hz: The quick return and sustained operation around the nominal 50 Hz frequency indicate that the mechanical input from the turbines and the electrical power demand on the grid are closely matched, reflecting an effective governor response and load balancing mechanism.
- Generator Stability: The absence of significant frequency deviations confirms that the generators are operating within stable conditions, and the automatic control systems are successfully maintaining equilibrium between input torque and electrical load.

Mathematical Representation:

$$\frac{df}{dt} = \frac{P_m - P_e}{2H} \tag{42}$$

Since $\frac{df}{dt} = 0$, mechanical and electrical power are balanced.

## 4. CONCLUSION AND LIMITATION

This study successfully applied the Binary Grey Wolf Optimization (BGWO) algorithm to determine the optimal placement of PMUs on the Shiroro 330 kV grid. The result, which requires only two PMUs for complete observability, demonstrates BGWO's effectiveness in reducing costs and enhancing system reliability. The method supports improved monitoring, fault detection, and scalability for future upgrades, offering a robust solution for grid development in emerging economies. Also significantly enhances system resilience and real-time fault detection during high-voltage disturbances, by simulating the Shiroro grid with and without PMUs using MATLAB/Simulink. The presence of optimally placed PMUs improved voltage stability, phase angle tracking, and frequency response during faults.

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