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Multi-Objective in Mapping the Optimal Distributed Generation Configuration through GWOA to Enhance Grid Performance Reliability

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***Abstract*—In electric power distribution systems, the distance between the load bus and the generating unit significantly affects grid efficiency and reliability, with longer distances causing greater voltage drops. To mitigate this, Distributed Generation (DG) is increasingly being used, generating electricity closer to the point of consumption. Determining the optimal DG location requires advanced metaheuristic methods. This research proposes the Grey Wolf Optimizer Algorithm (GWOA) to determine optimal DG placement, tested on the IEEE 14-bus distribution grid. The method generated two scenarios: In the first scenario, power losses were reduced by 98.1465% for real power and 98.9538% for reactive power compared to the existing conditions, while voltage increased by an average of 0.0127 p.u. for all buses combined. The second scenario also showed a notable voltage increase of 0.0064 p.u. The GWOA method proves to be an efficient and effective solution for DG placement, enhancing system reliability and protecting household electronic devices.**

Keywords: optimal, distributed generation, grey wolf optimizer algorithm, electric, effective

I. Introduction

In the electric power distribution system, the distance between the load bus and the generating unit has a significant impact on the overall efficiency and reliability of the network. The farther the distance, the greater the voltage drop that occurs along the distribution line. It also causes increased energy losses in the form of heat during the transmission process. In addition, this remote configuration often contributes to an increase in Total Harmonic Distortion (THD), which is the system's ability to generate harmonics that can damage the network being used. This also generates heat energy in the network, which directly impacts energy losses during electricity distribution [1].

There is a growing need to cut greenhouse gas emissions and quicken the switch to greener, more sustainable energy sources in the current global environment. The Kyoto Protocol, agreed upon on December 11, 1997, is a first step in addressing that demand [2], [3]. However, the agreement has a weakness, as it is only intended for developed countries. Therefore, in 2015, the agreement under the United Nations Framework Convention on Climate Change (UNFCCC) established the Paris Agreement, which encourages 195 countries around the world to participate in combating climate change [4]. In Indonesia itself, the Indonesian Law No. 16 of 2016, which has been ratified, aims for a reduction of greenhouse gas emissions by 26% through its own efforts and by 41% with assistance from other countries [5]. In addition, the Indonesian government has set a target for Net Zero Emission (NZE) by the year 2060 [6]. These steps aim to reduce environmental impact, enhance national energy security, and promote innovation in renewable energy technology.

To address this challenge, interest in the use of Distributed Generation (DG) is increasing. This technology generates electricity close to the point of consumption. Not only that, DG also supports the diversification and decentralization of the energy system as well as reducing vulnerability to external disruptions. This approach brings significant advantages by reducing energy losses during transmission and lowering voltage drop. In addition, the infrastructure costs associated with the use of networks and cable distribution have become more economical. The role of distributed generation (DG) also serves as a promising solution; this system can be utilized during periods of high electricity demand or when sunlight intensity decreases. This helps to maintain stability and power availability in the electrical grid.

Several vital studies provide deep insights into the methods of DG placement, voltage drop reduction, and

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losses. Optimal Sizing of Distributed Generation using the population-based heuristic approach known as Particle Swarm Optimization (PSO) and New Particle Swarm Optimization (NPSO) for determining the optimal sizing of Distributed Generators in distribution systems by R.V.S.L. Kumari et al. [7]. Rather than utilizing a recursive approach such as power flow, H. Nazaripouya et al. frame the problem by employing the network impedance matrix to generate an analytical solution. The proposed approach utilizes active power control and reactive power control to enhance voltage regulation capabilities in distribution systems [8]. In a unique formulation, R. Chedid and A. Sawwas approach the problem as a multi-objective optimization and apply the Genetic Algorithm (GA) technique to arrive at the ideal configuration [9]. The time domain power flow analysis of the optimized Grid-PV and Grid-PV-BESS systems looks at each bus's voltage profile and annual energy losses. An area reduction technique for DG placement and size optimization has been proposed by Jangkung et al., where this technique is very simple. After the feasible area is determined, several candidate solutions are spread into the feasible area and the best candidate is sought based on its objective function. Then the possible area is reduced, with the best solution being in that area. And so on until the best solution is obtained globally [10]. Thus, these articles can highlight the critical role of DG placement strategies in raising voltage to meet Grid Code standards and minimizing power losses as much as possible.

PSO, GA, Ant Colony Optimization (ACO), Artificial Bee Colony (ABC), and Artificial Neural Network (ANN) are a few popular metaheuristic techniques for mapping Distributed Generation (DG) [11]-[14]. In determining the location with optimal capacity for the DG unit, the use of effective metaheuristic methods is necessary to solve complex optimization problems. However, these methods often face limitations such as premature convergence or getting trapped in local optima, particularly in high-dimensional or non-linear search spaces. This creates a gap in finding a robust, efficient, and accurate algorithm that can ensure a global optimum in DG placement.

The proposed new method will be applied in determining the location of DG in this research, namely the Grey Wolf Optimizer Algorithm Method (GWOA). The algorithm used in the GWOA method was inspired by wolves' natural hunting techniques. Because they are regarded as apex predators, gray wolves occupy the highest position in the food chain. The metaheuristic method is effective in solving complex optimization problems and can assist in determining the most efficient placement strategy for DG.

This study aims to evaluate the effectiveness of the GWOA method in reducing power losses and improving voltage stability in power distribution systems. The strategic placement of DG is expected to enhance voltage profiles and reduce energy losses which can indirectly reduce operational costs. In addition, the proper placement of DG can also directly contribute to improving the reliability and overall performance of the power grid.

The novelty of this work lies in applying GWOA to the IEEE 14-bus distribution system and analyzing its performance under two different placement scenarios. Unlike previous studies, this paper emphasizes the quantifiable improvement in power loss reduction and voltage rise, while also aligning with grid code requirements and supporting national NZE targets. In this study, the proposed penetration in determining the location of DG with an optimal capacity of a maximum of 20% of the peak power of the DG divided by the total grid consumption at peak hours [15]. The method developed in this research is expected to be a pioneer in optimizing the placement of Distributed Generation (DG), whether it is based on conventional power plants or Fixed Renewable Energy. This optimization is not only beneficial for improving the technical and economic efficiency of the electricity distribution network but is also crucial in supporting global policies that promote the transition towards cleaner and more sustainable energy use. With the existence of this method, it is hoped that the integration of DG can be carried out more optimally, thereby accelerating the adoption of renewable energy, reducing carbon emissions, and enhancing the stability and reliability of the overall power system.

Divided into four distinct sections, this paper carefully reveals its findings. At the outset, this chapter provides a comprehensive overview of the various methodologies employed to address the challenges of distributed generation placement for power system reliability. After that, the second part explains the proposed methods in detail, supported by a dataset for rigorous system testing. The third segment delves into the analysis of the simulation results, facilitating further discussion. Finally, the conclusion summarizes the research findings, outlines the in-depth conclusions drawn from the study, and maps potential avenues for future investigation.

II. Research Methods

A. *Multi-Objective Functions*

The Grid Code, in accordance with the Minister of Energy and Mineral Resources Regulation Number 20 of 2020, serves as the basis for the objective function of this research. The allowable nominal range in the electrical distribution system is shown in equation as bellow [16],

$$0.90\, p.u \ \leq\ V_{bus} \leq\ 1.05\, p.u \tag{1}$$

$$\text{Min}\ (l) \tag{2}$$

where V_{bus} is the bus voltage, and l represents the losses after the integration of distributed generation into the grid [17]. This research is expected to meet the established objective function. An electrical system that does not meet the grid code leads to operational failures of the system.

This will directly impact the risk of damage to household electronic equipment.

B. Load Flow Analysis

The most important approach to investigate issues in the operation and planning of power systems is load flow analysis. Without taking into account generating conditions and the transmission network's structure, load flow analysis can give a balanced and stable operating state by determining the steady-state operating conditions with node voltages and branch power flows in the power system [18]. The process of organizing and estimating the amount of real and reactive power that is provided, transmitted, and consumed in an electric power system is known as load flow analysis [19]. This study is the most fundamental of all analyses in electrical systems, after which it can be followed by short circuit analysis and grid system stability analysis. The basis for solving performance equations in power system analysis using a computer, such as load flow analysis, is numerical analysis, including the simultaneous solution of algebraic equations [20]. In load flow analysis, busbars or buses are classified into 3 types. There is a Slack bus with a known scalar value of voltage $|V|$ and phase angle θ as the reference bus, a Voltage Control bus (*PV-bus*) as the generator bus, and a Load bus (*PQ-bus*) where the active and reactive power have already been determined. Establishing the *Y-bus* admittance using input data from transmission lines and transformers is the first stage in doing load flow analysis [21]. The following can be used to write the nodal equations for a power system network that uses the *Y-bus*,

$$I = Y_{bus}V \tag{3}$$

The following nodal equations and can be expressed in general form for the currents flowing in an n-bus system,

$$I_i = \sum_{j=1}^{n} Y_{ij}V_j, \quad \text{for } i = 1,2,3,...,n \tag{4}$$

$$I_i = \sum_{j=1}^{n} |Y_{ij}||V_j| \ \angle\theta_{ij}\delta_j \tag{5}$$

The general equations for the complex power flow supplied to bus-*i* are as follows,

$$P_i + jQ_i = V_i I_i^* \tag{6}$$

$$P_i + jQ_i = |V_i|\angle-\delta_i \sum_{j=1}^{n} |Y_{ij}||V_j|\angle\theta_{ij}\delta_j. \tag{7}$$

Iterative methods are used in the above equation to solve load flow issues. As a result, it is essential to go over the basic versions of several load flow analysis solution techniques, including Newton-Raphson, Gauss-Seidel, and Fast-Decoupled.

In this study, load flow analysis is conducted using the Fast-Decoupled approach. According to Stott and Alsac's 1974 study, the Fast-Decoupled method is an improved technique built upon the simplicity of the Newton-Raphson method [22]. Similar to the Newton-Raphson method, this approach is frequently employed in load flow analysis because it provides fast convergence, dependable findings, and computational simplicity. However, because the Fast-Decoupled approach is an approximation method that relies on multiple assumptions to reduce the Jacobian matrix, it might not work well in some situations, such as high resistance-to-reactance *(R/X)* ratios or heavy loads (low voltage) at some buses. Numerous initiatives and advancements have been made in these circumstances to solve these convergence hurdles. While some of them concentrate on low-voltage buses, others aim for system convergence with a high *R/X* ratio [23], [24]. Considering the IEEE 14-bus test system used in this study, which features a semi-meshed structure and generally moderate R/X ratios (typically < 1), the use of the Fast-Decoupled method remains appropriate. In such configurations, both Fast-Decoupled and Newton-Raphson methods are known to offer efficient and reliable convergence. Although the Backward/Forward Sweep method is often preferred for strictly radial systems with high R/X values, it is less critical in the type of network examined in this research. This approach is a variant of Newton-Raphson, which capitalizes on the high *X: R* ratio-induced weak correlation between $P - \delta$ and $Q - V$. The Jacobian matrix from the Newton-Raphson equations is halved by neglecting the J_2 and J_3 elements. Thus, the equation can be simplified to:

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = \begin{bmatrix} J_1 & 0 \\ 0 & J_4 \end{bmatrix} \begin{bmatrix} \Delta\delta \\ \Delta|V| \end{bmatrix} \tag{8}$$

Expanding (8) resulted in two separate matrices as follows,

$$\Delta P = J_1 \Delta\delta = \left[\frac{\partial P}{\partial \delta}\right]\Delta\delta \tag{9}$$

$$\Delta Q = J_4 \Delta|V| = \left[\frac{\partial P}{\partial |V|}\right]\Delta|V| \tag{10}$$

$$\frac{\Delta P}{V_i} = -B'\Delta\delta \tag{11}$$

$$\frac{\Delta Q}{V_i} = -B''\Delta|V|. \tag{12}$$

The imaginary components of bus admittance, sometimes referred to as susceptance, are *B'* and *B''*. It is preferable to disregard every component associated with the shunt in order to simplify the creation of J_1 and J_4. This will eliminate the need for several inversions and simply allow for a single matrix. As a result, the following equations represent the change in phase angle and voltage magnitude,

$$\Delta\delta = -|B'|^{-1}\frac{\Delta P}{|V|} \tag{13}$$

$$\Delta|V| = -|B''|^{-1} \frac{\Delta Q}{|V|}. \tag{14}$$

C. Grey Wolf Optimizer Algorithm (GWOA)

In 2014, [25] introducing a metaheuristic optimization technique called Grey Wolf Optimization. The idea is derived from the behaviour and hunting methods of grey wolves in nature. The GWO technique consists of three leader wolves named *α, β,* and *δ,* which represent the best solutions to guide the other wolves in searching for the global solution [26]. There are three basic steps to completing the wolf hunt.

1. Encircling

The following equations can be used to build the hunting strategy of grey wolves in the encircling network [27],

$$D = |C \times V_{pr}(t) - V(t)| \tag{15}$$

$$V(t+1) = V_{pr}(t) - A \times D. \tag{16}$$

The prey's location is denoted by V_{pr} in the aforementioned equations, the grey wolf's position vector is located by *V*, and the current iteration is indicated by *t*. The coefficient vectors of *A* and *C* in [25] are found in equations bellow,

$$A = 2 \times A \times r_1 - a(t) \tag{17}$$

$$C = 2 \times r_2. \tag{18}$$

Following completion of the iterations, Equation (19) causes the vector element to decrease from 2 to 0, reflecting the random vectors r_1 and r_2.

$$a(t) = 2 - (2 \times t) / Max_{iter} \tag{19}$$

2. Hunting

This pertains to the mathematical examination of wolves' hunting behavior, wherein it is assumed that *α, β,* and *δ* possess sufficient information to locate the prey. Therefore, other wolves will follow them, keeping in mind the three best solutions offered by the placements of *α, β,* and *δ*. Equations (20) – (22) mention their hunting prowess.

$$\begin{aligned} D_\alpha &= |C_1 \times V_\alpha - V(t)| \\ D_\beta &= |C_1 \times V_\beta - V(t)| \\ D_\delta &= |C_1 \times V_\delta - V(t)| \end{aligned} \tag{20}$$

where Equations (19) and (20) determine C_1, C_2, and C_3.

$$\begin{aligned} V_{j1}(t) &= V_a(t) - A_{j1}(t) D_\alpha(t) \\ V_{j2}(t) &= V_\beta(t) - A_{j2}(t) D_\beta(t) \\ V_{j3}(t) &= V_\delta(t) - A_{j3}(t) D_\delta(t) \end{aligned} \tag{21}$$

$$V(t+1) = \frac{V_{j1}(t) + V_{j2}(t) + V_{j3}(t)}{3} \tag{22}$$

3. Attacking

When the prey stops moving and settles in one spot, the hunting strategy comes to an end. The wolves then launch their attack. Mathematically, this formula can be obtained by reducing the value of a within a given interval. Equation (19) illustrates how the value of an is altered in this model in a range from 2 to 0. The variable value of an in the interval (2, 0) indicates that the searcher's subsequent location can be anywhere between the hunter's current position and the location of the prey. The first three wolves, α, β, and δ, are deemed to have the highest level of fitness in each iteration. Every wolf moves in accordance with the aforementioned stalking, attacking, and surrounding procedures. It is possible to pinpoint the precise location of the prey, which is α's, by repeated iterations. GWOA is effective and applicable to a wide range of situations. There is, however, one disadvantage to GWOA. It is incapable of supporting population diversity. It also has premature convergence and an imbalance between exploration and exploitation. Furthermore, the position regulator equation yields an inefficient solution, even though it is exploitable [28].

D. IEEE 14 Bus Dataset for System Testing

Extensive testing has been conducted to evaluate the suitability and effectiveness of the GWOA Method approach. One important aspect of the evaluation process relates to the careful selection of the dataset used in the testing phase. This dataset was deliberately chosen to facilitate a comprehensive exploration of the reliability and performance of the GWOA Method across various scenarios and conditions. As evidenced by the data presented in Tables 1 and 2 below, the testing utilized a design showcasing a 14-unit bus system configuration sourced from IEEE. The two tables below present data based on 100 MVA. It is believed that the phase angle and voltage magnitude have minimum and maximum limitations of -45 degrees to +45 degrees and 0.90 p.u. to 1.05 p.u., respectively [29].

To maintain consistency with the IEEE 14-bus system standard, several modeling assumptions were adopted in this study. The Distributed Generation (DG) units are modeled as diesel generators, selected for their stability and controllability, particularly in supporting the goal of minimizing system losses and improving voltage profiles. The DGs operate in swing mode within the ETAP simulation environment, allowing dynamic response to load variations. Additionally, reactive power limits, power factor, and the connection interface follow specifications provided in the IEEE 14-bus datasheet. Lastly, the number and placement of DG units, which total four are determined through the optimization process using the Grey Wolf Optimizer Algorithm (GWOA), rather than being set a priori.

E. Pseudocode

The following is the pseudocode for the GWOA

Table 1. Line data

From Bus	To Bus	Line impedance		Half-line charging Susceptance (p.u.)	MVA Rating
		Resistance (p.u.)	Reactance (p.u.)		
1	2	0.01938	0.05917	0.0264	120
1	5	0.05403	0.22304	0.0219	65
2	3	0.04699	0.19797	0.0187	36
2	4	0.05811	0.17632	0.0246	65
2	5	0.05695	0.17388	0.017	50
3	4	0.06701	0.17103	0.0173	65
4	5	0.01335	0.04211	0.0064	45
4	7	0	0.20912	0	55
4	9	0	0.55618	0	32
5	6	0	0.25202	0	45
6	11	0.09498	0.1989	0	18
6	12	0.12291	0.25581	0	32
6	13	0.06615	0.13027	0	32
7	8	0	0.17615	0	32
7	9	0	0.11001	0	32
9	10	0.03181	0.0845	0	32
9	14	0.12711	0.27038	0	32
10	11	0.08205	0.19207	0	12
12	13	0.22092	0.19988	0	12
13	14	0.17093	0.34802	0	12

method to map the optimal DG configuration as seen in Figure 1 and described below.

Initialization:

1. $wolf_{position}$: Array (size = 100 x num_{buses}) - Random initial positions for grey wolves (positions of distributed generators).
2. $wolf_{fitness}$: Array (size = 100) - Fitness values of wolves (initial value calculated based on power losses).
3. $line_{data}$: Data from a network line, including resistance, reactance, MVA, and bus to bus.
4. num_{buses}: The total quantity of buses inside the system.
5. max_{iter}: Maximum iterations (ex: 100).
6. α, β, δ: Wolves with the best, second best, and third best fitness (power loss minimization).
7. a: Control parameter (linearly decreases from 2 to 0 during iteration).

Iterations until convergence:

1. Repeat until maximum iterations is reached:
   a. Calculate $a = 2 - (2 \times current\ iteration / max_{iter})$

Table 2. Transformer data

From Bus	To Bus	Tap Setting (p.u.)
4	7	0.978
4	9	0.969
5	6	0.932

   b. For each wolf (i):
      1) Generate random numbers r_1, r_2
      2) Calculate A_1, C_1, A_2, C_2, A_3, C_3 based on a, r_1, r_2
      3) Update position X_1 using α wolf:
         a) $D_\alpha = |C_1 \times \alpha - wolf_{position}[i]|$
         b) $X_1 = \alpha - A_1 \times D_\alpha$
      4) Update position X_2 using β wolf:
         a) $D_\beta = |C_2 \times \beta - wolf_{position}[i]|$
         b) $X_2 = \beta - A_2 \times D_\beta$
      5) Update position X_3 using δ wolf:
         a) $D_\delta = |C_3 \times \delta - wolf_{position}[i]|$
         b) $X_3 = \delta - A_3 \times D_\delta$
      6) Update $wolf_{position}[i] = (X_1 + X_2 + X_3) / 3$
   c. After updating all wolves' positions:
      1) Calculate the new fitness (total losses) for each wolf position.
      2) Sort wolves based on fitness and update α, β, δ wolves.
   c. Print the best fitness (power loss) at each iteration.

Output:

1. α: The optimal grey wolf position (optimal distributed generator placement).
2. Optimal DG positions: Positions of distributed generators corresponding to the α wolf.
3. Best fitness value: The minimum power loss achieved.

III. Results

The Single Line Diagram (SLD) design is created using the IEEE 14 bus system dataset. Assisted by ETAP software, the condition of the existing network before the installation of the DG can be seen in Figure 2. From Table 3 below, we can see that buses 12 and 14 experience a significant voltage drop under existing conditions. This affects the reliability of the electrical system, and the solution is the installation of DG as a voltage drop reducer. The determination of the DG location will be assisted through the GWOA method. The best configuration will have an impact on increasing the voltage.

The DG configuration is optimized through this GWOA method, resulting in two scenarios in DG mapping. Where scenario 1 involves placing DG at bus 7, 8, 11, and 14. Meanwhile, scenario 2 involves placing DG at bus 1, 2, 8, and 14. This mapping can reduce voltage drops and losses in the electrical system. The optimal DG capacity on each applied bus will be optimized using GWOA.

Table 4 shows the results of the load flow analysis for all conditions, where the total losses of 25.358 MW and 84.501 MVAR in the existing condition are issues that need to be reduced. These losses result in financial losses [30]. Thus, optimizing this electricity efficiency affects operational costs, making them more economical. It also directly enhances the reliability of the system to meet electricity demands effectively.

In the first scenario, optimization was achieved with

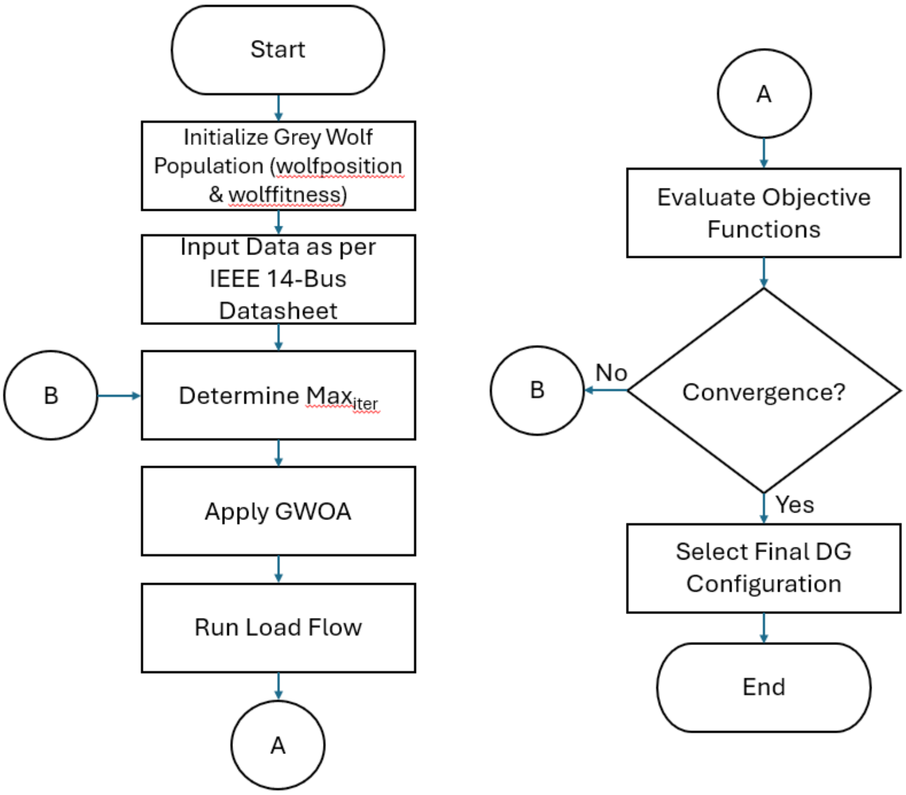

Figure 1. Flowchart for mapping the optimal DG configuration through the GWOA method

the selection of buses 7, 8, 11, and 14. In this scenario, using 100 maximum iterations, we can see in Table 4 below those losses decreased by 98.1465% for real power and 98.9538% for reactive power compared to the existing conditions. Meanwhile, the voltage increased by an average of 0.0127 p.u. for all buses combined. Thus, all buses meet the objective function.

If in this scenario 2 the maximum iterations are set to 50. Thus, the best bus to pair with DG is consistently the 1st, 2nd, 8th, and 14th bus. This result is already significant in increasing the voltage by an average of 0.0064 p.u. for all buses and also reducing losses compared to the existing conditions by 94.7748% for active power and 96.8616% for reactive power. Similar to scenario 1, all the voltages at each bus also meet the objective function according to Equation (1). However, in terms of effectiveness, the voltage profile in the results of scenario 2 is still very far down, especially at bus 14. Therefore, scenario 1 is significantly more feasible to consider.

Table 3. Voltage profiles

Bus ID	Existing Condition (p.u.)	After DG Mapping			
		Scenario1 maxiter=100 (p.u.)	DG Size (kW)	Scenario2 maxiter=50 (p.u.)	DG Size (kW)
BUS-1	1.0000	1.0000		1.0000	152.23
BUS-2	1.0000	1.0000		1.0000	293.88
BUS-3	1.0000	1.0000		1.0000	
BUS-4	0.9954	0.9985		0.9984	
BUS-5	0.9997	0.9999		0.9999	
BUS-6	0.9828	1.0000		1.0000	
BUS-7	0.9963	0.9994	224.13	0.9992	
BUS-8	0.9970	1.0000	468.61	1.0000	648.63
BUS-9	0.9958	0.9999		0.9988	
BUS-10	0.9882	0.9929		0.9927	
BUS-11	0.9777	0.9899	360.23	0.9894	
BUS-12	0.9496	0.9693		0.9667	
BUS-13	0.9512	0.9779		0.9684	
BUS-14	0.9151	1.0000	205.39	0.9242	174.18

The use of max_{iter} = 50 and 100 in both scenarios was based on empirical findings during the optimization process. Iterations below 50 often caused premature convergence and suboptimal DG placement, whereas iterations above 100 led to insignificant improvement in results but noticeably increased computational time. Thus, these iteration bounds were chosen to balance optimization quality with computational efficiency.

To validate the significant loss reductions shown in Table 4, the optimization process was carried out using multiple iterations and objective evaluations based on (1). The comparison between the existing condition,

Table 4. Comparison of losses reduction

Condition	Losses		Reduction Losses (%)	
	Active Power (MW)	Reactive Power (MVAR)	Active Power	Reactive Power
Existing	25.3580	84.5010	-	-
Scenario 1	0.4700	0.8840	98.1465	98.9538
Scenario 2	1.3250	2.6520	94.7748	96.8616

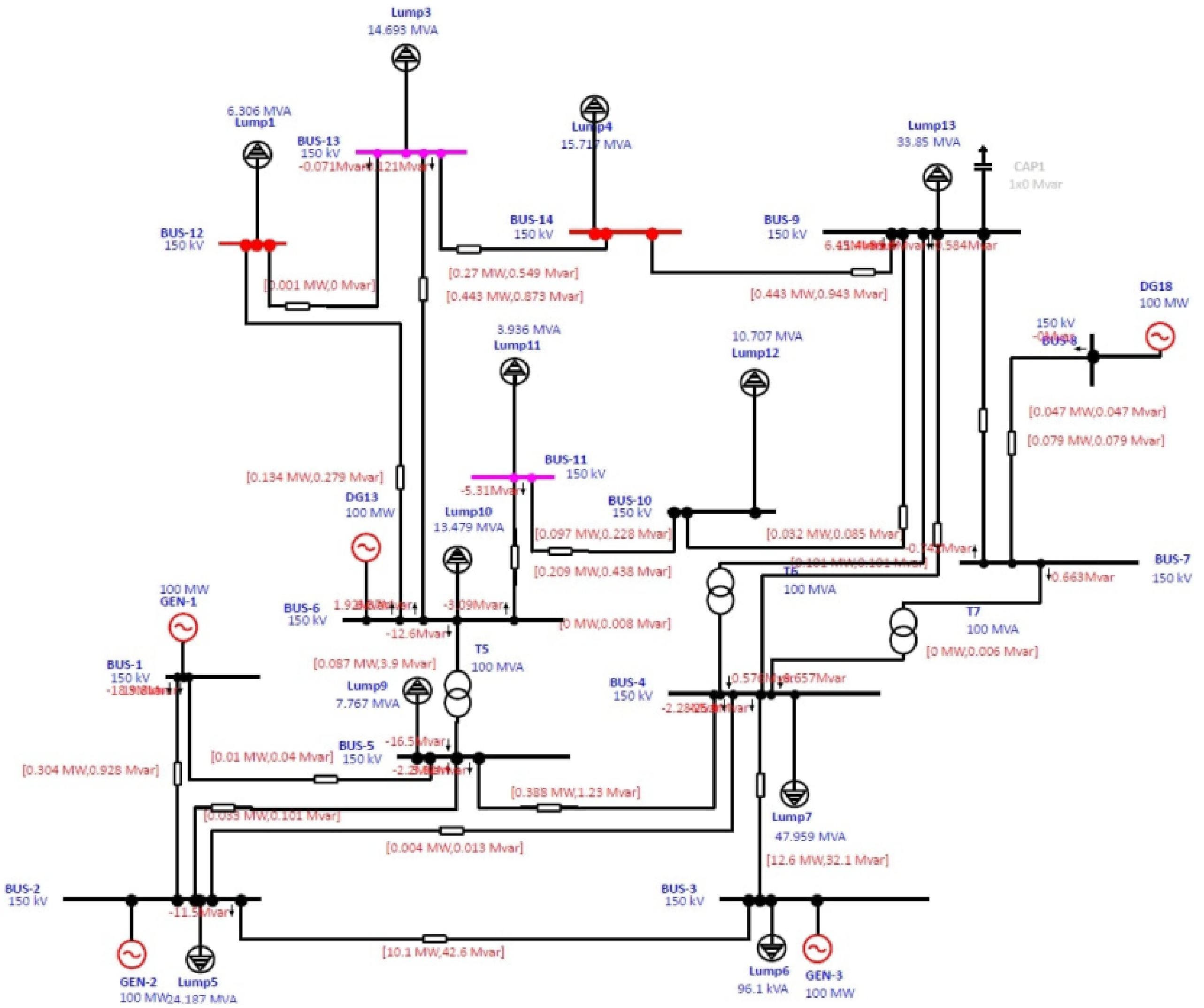

Figure 2. Existing SLD condition

Scenario 1 (max_{iter} = 100), and Scenario 2 (max_{iter} = 50) has been systematically presented in Table 4, including the percentage improvement in both active and reactive power losses. These results were consistently verified through multiple simulation runs using ETAP to ensure convergence accuracy and repeatability of the GWOA outcomes. The use of benchmark IEEE 14-bus data, along with standard voltage and phase angle constraints, further supports the validity of these outcomes under realistic system assumptions.

IV. Discussions

In the existing conditions, significant losses and voltage drops are observed. The voltage drop is quite far from normal conditions, especially on bus 14 which reached 8.49%. The voltage profile on buses 12 and 13 is also relatively low. So, the improvement was made through the installation of DG with optimization by GWOA, a significant improvement in reliability has been achieved. The decrease in voltage drop causes each bus in this electrical system to meet the objective function according to Equation (1), even approaching the normal value (1.0 p.u.) at almost all buses. Specifically for bus 14, the voltage profile becomes 1.0 p.u. in scenario 1. The voltage at buses 12 and 13 also increases to 0.9693 p.u. and 0.9779 p.u. in this scenario.

Power losses in the initial condition reached 25.4 MW and 84.5 MVAR, which became an issue that needed to be minimized. After optimization through GWOA, a load flow analysis was conducted, resulting in an enormous reduction in losses. Scenario 1 provides the minimum possible losses, which is 0.47 MW and 0.88 MVAR, or a reduction of 98.55% from the total losses. Thus, (2) is very well satisfied by this result. This demonstrates the strength of GWOA in optimizing the placement of DG, which ultimately improves the reliability and stability of the electrical system statically.

Optimization through GWOA in this study provides two scenarios. In which scenario 1 is dominated by excellent reduction in losses and voltage drop. Meanwhile, scenario 2 also yields better results than the existing conditions. Although bus-14 still has a lower voltage than the other buses in scenario 2, it already meets the PLN grid code standard [16]. This condition is not considered a violation, but it is acknowledged as an area for further improvement.

This can be fixed by using several power electronic devices (e.g., capacitor banks, voltage regulators, or on-load tap changers) to reduce the voltage drop. So, it will achieve a voltage close to 1.0 p.u. or 100% of the nominal voltage. This will contribute to enhancing system reliability and preventing damage to household electronic equipment.

To ensure the reliability of these significant loss reductions, all simulation results presented in Table 4 were cross-validated through multiple runs using ETAP software with consistent parameters and configurations. The use of a standardized IEEE 14-bus test system further supports the credibility of the findings. Additionally, the compliance of bus voltages with the Regulation of the Minister of Energy and Mineral Resources No. 20/2020, especially the 0.90 to 1.05 p.u. range confirms that, although Bus 14 in Scenario 2 is relatively lower, it remains within the regulatory limits and operationally acceptable. These aspects validate that the proposed scenarios effectively enhance grid performance while highlighting areas that may benefit from future technical improvements.

V. Conclusions

This research uses a multi-objective function to outline the problems around the best placement of DG. Reactive and real power loss minimization are included in the multi-objective function. To formulate the problem, power loss and voltage intervals are based on the PLN Grid Code. The proposed GWOA method in this study provides an effective solution for the placement of DG. The IEEE 14-bus distribution grid is used to assess this method's efficacy. The acquired results demonstrate a discernible decrease in the static system stability's voltage drop, real power loss, and reactive power loss.

The DG operating under scenario 1 has the smallest losses. Meanwhile, the highest average voltage increase is also in scenario 1, which is 0.0127 p.u. for all buses combined. According to the PLN Grid Code's requirements, scenario 1's outcomes are highly satisfactory, making them extremely practical to implement in terms of efficacy. On the other hand, both scenarios achieve that all voltages at each bus also meet the objective function according to (1). Thus, the analysis from this comprehensive study, obtained from the GWOA method with the reported works, shows that the proposed approach is reliable in the placement of DG. Therefore, it validates its use as a planning tool for related studies in the future. In conclusion, the GWOA method can be an efficient and optimal solution for the placement of DG in electrical systems.

In the upcoming work, the proposed project will be expanded to include capacity calculations for installing power electronic devices as a mitigation for far voltage drops. It will also delve into new concepts for planning and scheduling electrical systems with renewable energy sources through distributed generation (DG).

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