A Probabilistic Renewable Energy Allocation Applying Metaheuristics Optimization Methodologies

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Abstract— The optimal installation and size of renewable distributed generation (RDG) in a distribution network has always been challenging for utilities and consumers, considering environmental, economic, and technological factors in order to extract the greatest possible benefits, especially in remote and small areas. In order to maximize their potential benefits, this has prompted the investigation of several techniques for determining their optimal location and size, which minimizes system losses, improves the voltage profile, and enhances system dependability and stability. In this work, an objective function is developed to optimally size two types of RDG using two modern meta-heuristic algorithms for optimal loss reduction in radial power distribution networks. Grey Wolf Optimization (GWO) and Whale Optimization Algorithms (WOA) are tested to minimize the power losses and enhancing the voltage profile of the standard IEEE 69 bus system. The study compares both algorithms for different scenarios of various RDG penetration levels. The obtained results clarifies the superiority of GWO algorithm over WOA in achieving a global optimal solution for minimizing power loss with a small sized RDG.

Keywords—Renewable Energy Resources, Whale Optimizer (WOA), Grey Wolf Optimizer (GWO), Optimal Size, Optimal Location, smart grid

I. Introduction

The conventional power grid's loading has escalated in recent years, prompting the deployment of renewable energy to improve the power grid’s efficiency and performance while meeting the required power demand [1], [2]. Through the use of abundant solar and wind energy, energy efficiency and renewable energy policies can help reduce the demand for fossil-fuel-generated energy (such as natural gas, oil, and coal-fired power plants) [3]. Stand-alone and decentralized systems that use a hybrid combination of photovoltaics (PVs) and wind turbines (WTs) are currently the most promising renewable resources for meeting load demands, especially in remote locations [4]. Unlike conventional electrical networks, decentralized systems are more economical to establish due to the low cost of electrical system infrastructure, reduced emissions, and improved efficiency [5]. With the help of smart grid technology, full utilization of RDG can be achieved for maximized benefits for utility operators and consumers.

Researchers are constantly tackling the problem of renewable sources optimal sizing and placement as it is considered one of the most critical aspects of integrating hybrid renewable energy systems and a major key factor in ensuring operational profitability and maximum yield extraction. Accordingly, a vast number of studies, both theoretical and applied, have been conducted in this field, which employs a variety of optimization techniques. Commonly, optimization algorithms can be classified into analytical, and meta-heuristic (intelligent) techniques [6]. Analytical techniques rely on the development of a mathematical system model, which yields precise results while requiring minimal computing time. However, analytical strategies are appropriate for small and simple systems with a small number of state variables involved. Metaheuristic algorithms on the other hand, add stochasticity to the solution obtained allowing them to explore the search space continuously [7].

Different Metaheuristic techniques have been developed to solve complex power engineering problems such as Particle Swarm Optimizer (PSO), Genetic Algorithms (GA), WOA, and GWO. In [8], authors have compared the performance of Particle Swarm Optimization (PSO) and Simple Genetic Algorithm (SGA) for total energy loss reduction on a 33 bus system. A study using Pathfinder Algorithm (PFA) was carried out in [9] to significantly reduce active power losses and reducing the average voltage deviation when compared to other algorithms. In [10], an Improved Crow Search Algorithm (ICSA) was applied to a hybrid renewable system employing PV/wind /batteries and applying generation uncertainties. The work in [11] used Honey badger algorithm (HBA) to optimally size four different types of RDG units. PSO and Dragonfly algorithms (DA) were employed simultaneously in [12] to achieve maximum savings and an enhance the voltage profile using different types of renewable resources with network reconfiguration. Authors in [13] examined multiple optimization techniques in attempt to find the optimum configuration for maximum loss reduction, where the Whale Optimization Algorithm (WOA) achieved better results among all the tested algorithms. The study in [14] used a Hybrid Fuzzy Equilibrium Optimizer (HFEO) to minimize active power losses by integrating different types of renewable energy resources and combining fuzzy logic with a metaheuristic optimizer leading to better performance with fast convergence speed.

In this paper a comparative study has been performed on radial power distribution system for the purpose of optimally allocating and sizing two renewable resource units (PV/Wind), all while serving the main objective goal of minimizing the total active power losses in distribution systems feeders and without violating the bus voltage profile. Load flow calculation using Backward/ Forward Sweep (BFS) methodology is employed. The study compared the performance of Grey Wolf Optimization (GWO) and WOA applied to the IEEE-69 bus standard system at a variety of penetration levels.

II. Problem Formulation

A standard IEEE-69 bus test system has been considered in this work which comprises 69 nodes, 5 looping lines, with 7 lateral feeders and edges on each branch [15]. Nominally, the system voltage is 12.66 kV, with total connected load of 3802.19 kW and 2694.60 kVAR.

A. *Load Flow Algorithm:*

The proposed method performs a load flow study using the BFS method [16], which is widely regarded as one of the most effective methods for radial distribution system load-flow analysis where power losses for each bus branch and voltage magnitudes at each node are calculated. This method consists of two cycles: a backward sweep and a forward sweep cycle. Backward sweep computes voltage and currents using from the farthest node from the source node, while the forward sweep computes the downstream voltage is calculated from the source node. The flow chart in Fig (1) shows the major steps of the BFS algorithm (1).

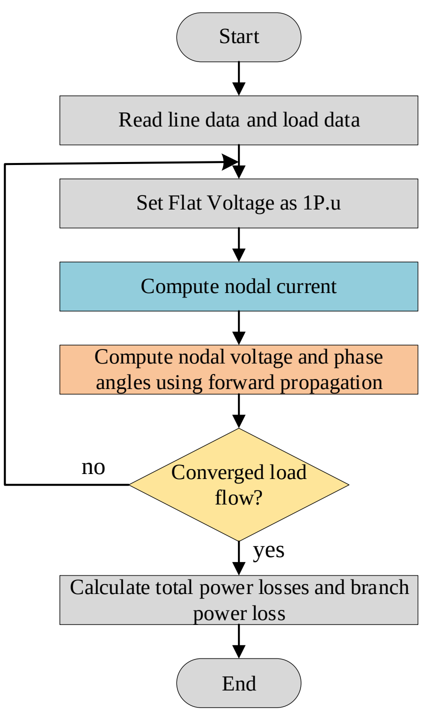

Fig. 1. BFS Work Flow Algorithm

B. *Objective Function:*

This paper aims to optimally size and find RDG location to reduce active power loss in the power network. The problem can be formulated as in (1) to minimize active power loss such that:

$$OF_{object} = Min\ (P_{Total}) \tag{1}$$

Where OF_{object}, P_{Total} represent the main objective goal and the total system active power losses, respectively. Solving the corresponding objective function will help in determining the combined total RDG capacity, location and individual PV/wind capacity.

C. *Technical Constraints:*

The objective function in (1) is subject to several technical constraints which can be described in (9)-(13). These constraints can be divided into:

1) *Location Of Wind/PV*

In order to maximize system stability, the wind/PV position should be close to the loads. Therefore, the RDG placement restriction is considered to begin on the second bus and may be stated as follows (9):

$$Bus_2 \leq Location \leq N \tag{2}$$

Where Bus_2 is the second bus, $Location$ is the renewable energy resource location, and N is indicate the bus number for the IEEE-69 bus system.

2) *Size Of Wind/PV*

To prevent power interruptions, wind/PV sizes and capacities are selected to be not less than or equal to 10 % (penetration level) of total load power as given by (3)

$$0.1P_{Load} \leq Wind/Pv\ (Size) \leq P_{max} \tag{3}$$

Where P_{Load} represent the total system load demand, P_{max} represent the maximum power output from wind/PV units.

3) *Voltage Limit*

In power systems, the permissible amplitude of bus voltages should satisfy the range of $\pm$ 10% for the load busses and $\pm$ 5% for the feeders (RDG units), respectively as specified by (4)- (6)

$$V_{bus-min} \leq V_i \leq V_{bus-max} \tag{4}$$
$$0.9V_{i-bus} \leq V_i \leq 1.1V_{i-bus} \tag{5}$$
$$0.95V_{i-feeder} \leq V_i \leq 1.05V_{i-feeder} \tag{6}$$

Such that $V_{bus-max}$, $V_{bus-min}$, maximum and minimum allowable voltages at buses respectively. V_{i-bus} is the voltage at the bus (i), while $V_{i-feeder}$ represent the feeder voltage.

III. Methodolgy

A. *Grey Wolf Optimizer:*

The Grey Wolf Optimizer (GWO) is a meta-heuristic-based optimization algorithm developed by Mir Jalili and Lewis in 2014 that mimics the natural leadership structure and hunting mechanism of grey wolves [17]. The grey wolf lives in a pack of up to twelve individuals. The algorithm formulation phases to achieve the objective function can be mainly divided into three categories: social hierarchy, encircling the prey, and the hunting phase which will be explained in the following sections.

1) Social Hierarchy

The ranking begins with α and ends with ω. The α of the pack is at the top of the hierarchy and makes all choices regarding hunting and where to stay. The β is the second-highest level in the pack and the α 's subordinate. They reinforce α 's directives and provide feedback to assist it in making sound decisions. The ω members of the pack are expected to simply obey orders given by the α and β, while the γ pack reports to α and β. Accordingly, four types of decision or solutions where α is the best solution, β, γ are considered to be the second (mean) and third best solution respectively, and ω represents the rest of solutions.

2) Encircling Prey

As previously stated, the GWO encircles the prey during the hunt in the second step. The encircling behavior of the GWO can be represented from (7) to (10) as:

$$\vec{D} = |\vec{C}.\vec{X}_p(t) - \vec{X}(t)| \tag{7}$$
$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A}.\vec{D} \tag{8}$$
$$\vec{A} = 2\vec{a}.\vec{r}_1 - \vec{a} \tag{9}$$
$$\vec{C} = 2.\vec{r}_2 \tag{10}$$

Where t is the number of iterations, $\vec{A}$, $\vec{C}$ are coefficient vectors, $\vec{X}_p$ is the position of the prey (best solution), $\vec{X}$ is the current position of the grey wolf.

3) Hunting

The hunting process will start to fetch for the best solutions α , β , γ to reach the objective function and the rest of solution from ω. The first three best solutions obtained so far are saved and oblige the other search agents (including the ω) to update their positions according to the position of the best search agent. The flow chart in Fig. 2. illustrates the GWO process which can follow the relations found from (11) to (15)

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{11}$$
$$\overrightarrow{D\alpha} = |\overrightarrow{C_1}.\vec{X}\alpha - \vec{X}|, \overrightarrow{D\beta} = |\overrightarrow{C_2}.\vec{X}\beta - \vec{X}|, \overrightarrow{D\gamma} = |\overrightarrow{C_3}.\vec{X}\gamma - \vec{X}| \tag{12}$$
$$\vec{X}_1 = \vec{X}\alpha - \vec{A}_1.(\overrightarrow{D\alpha}) \tag{13}$$
$$\vec{X}_2 = \vec{X}\beta - \vec{A}_2.(\overrightarrow{D\beta}), \tag{14}$$
$$\vec{X}_3 = \vec{X}\gamma - \vec{A}_3.(\overrightarrow{D\gamma}) \tag{15}$$

Where $\vec{X}^1, \vec{X}^2, \vec{X}^3, \overrightarrow{D\alpha}, \overrightarrow{D\beta}, \overrightarrow{D\gamma}$ are represented from equations (12) to (15) [18].

B. Whale Optimization Technique:

Mir Jalili and Lewis introduced the Whale Optimizer Algorithm (WOA) in 2016 [19]. The WOA mimics the behavior of whales in their search for food by attacking the prey with spiral bubble nets blown in a specific path. The algorithm is comprised of three phases; encircling the prey, the bubble net hunting phase, and the searching phase.

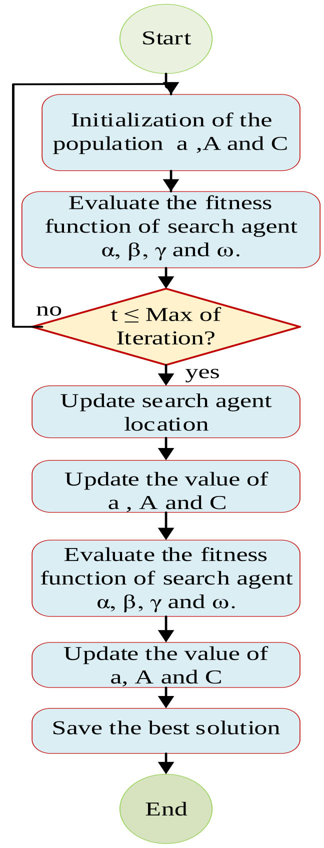

Fig. 2. GWO Flow Chart.

1) Encircling Prey:

Humpback whales encircle their prey, and the manner as it upgrades its location from the initial position can be described using (16)- (19)

$$\vec{X}(t+1) = \vec{X}^*(t) - \vec{A}.\vec{D} \tag{16}$$
$$\vec{D} = |\vec{C}.\vec{X}^*(t) - (t)| \tag{17}$$
$$\vec{A} = 2\vec{a}.\vec{r}_1 - \vec{a} \tag{18}$$
$$\vec{C} = 2.\vec{r}_2 \tag{19}$$

Where $\vec{X}^*$ represents the prey and the best optimized solution, $\vec{X}$ is the position vector of whale and $t$is the current iteration. $\vec{A}$ and $\vec{C}$ are coefficient vectors. $\vec{a}$ linearly reduces from two to zero as the iteration process progresses and $\vec{r}$ is a randomly generated vector in the range of [0,1].

2) Bubble-net hunting method:

There are two mechanisms involved in the hunting phase, the shrinking mechanism and the spiral updating position. In the shrinking mechanism, encircling the prey is achieved by decreasing the value of vector $\vec{A}$, which is determined from the original position and the best whale position. The Spiral mechanism, on the other hand, represents the attacking method and is used to determine the distance between the position of whale and the prey. This process can be represented mathematically by (20) and (21) as:

$$\vec{X}(t+1) = \begin{cases} \vec{X}^*(t) - \vec{A}.\vec{D} & if\ p < 0.5 \\ D'.e^{bl}.cos(2\pi l) + \vec{X}^* & if\ p \geq 0.5 \end{cases} \quad (20)$$

$$D' = \left|\vec{X}^* - \vec{X}(t)\right| \quad (21)$$

Where p is number randomly selected from [0,1], D' is the given distance between the prey and humpback whales, l is a randomly number generated from [-1,1] and b is a constant number.

3) *Searching for Prey:*

To obtain the global optimum solutions, the whale position is updated using a randomly selected whale rather than the best whale as represented in (22) and (23).

$$\vec{D} = \left|\vec{C}.\vec{X}rand - \vec{X}\right| \quad (22)$$

$$\vec{X}(t+1) = \vec{X}rand - \vec{A}.\vec{D} \quad (23)$$

Where $\vec{X}$ is the randomly selected whale of current iteration.

The flow chart in Fig.3. illustrates the whale optimizer process.

IV. SIMULATION RESULTS AND DISCUSSION

The GWO and WOA performance on 69-bus IEEE standard radial distribution systems was investigated to evaluate the performance of the two suggested approaches in addressing RDG unit installation, size, and allocation using two different types of RDG units (Wind/PV). The simulation analysis was carried out using Matlab. As a base case, the total active power losses were calculated using the BFS technique before adding the RDG units. The results showed that the total active power losses are equal to 224.9310 kW without any RDG installed to the system.

In the following investigation, two cases have been analyzed regarding the RDG size using GWO and WOA. In the first case (Case I), the two RDG units (PV/wind) are assumed to have a combined capacity of 3 MW. In the seconds case (Case II), three different penetration levels of percentages of the PV/wind units are studied and power losses are calculated accordingly.

A. *Case Study I:*

In this case, the system under investigation is tested to determine the impact of full penetration of PV and wind units. The RDG units are installed to the test system of capacity 3MW each corresponding to the maximum power that could be obtained from the wind/PV modules. Active power losses were calculated using GWO and WOA, and the corresponding results are shown in Table I. As observed from Table 1, both GWO and WAO produced similar results in terms of active power loss of 785 kW, and with RDG units allocation at bus 11 and 50. Both algorithms reduced the power losses in the network by 65.1% compared to the baseline case without the RDG units installation. In order to determine the fastest converging algorithm, convergence curves for GWO and WOA are depicted in Fig. 4. Depending on the complexity and searching capabilities of each algorithm, converge occurs in a particular time period. Almost every optimization technique strives to find the optimal global solution in a short period of time to avoid divergence at any stage. Fig. 4 illustrates that WOA achieved the optimum and accurate results faster than the GWO.

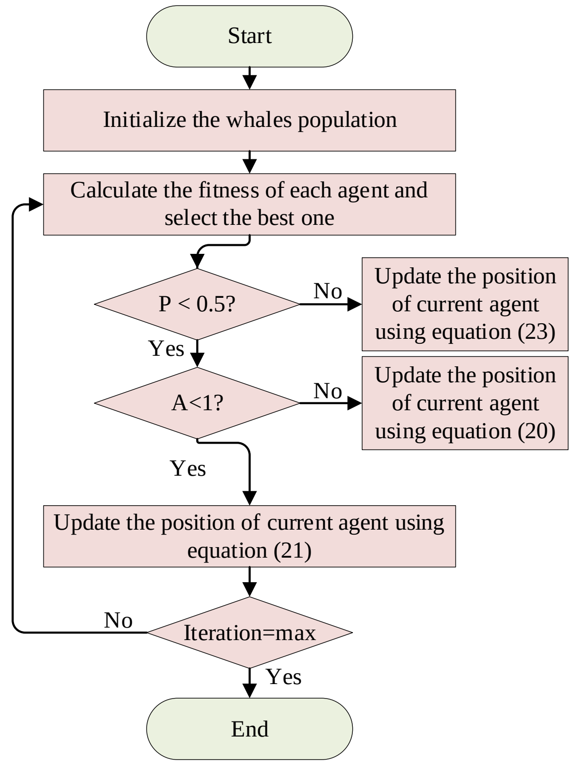

Fig. 3. WOA Flow Chart.

TABLE I. GWO AND WOA RESULTS FOR CASE I

	PV Size (MW)	PV Size (MW)	RDG Location	Power Losses (MW)
Base Case	------	------	------	0.224
GWO	3	3	11,50	0.0785
WOA	3	3	11,50	0.0785

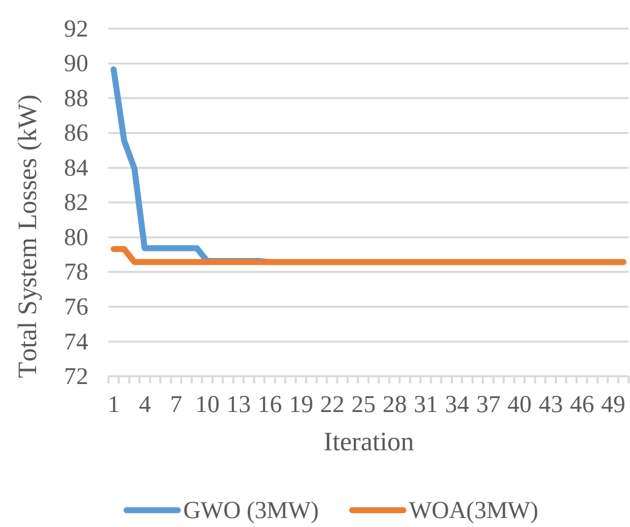

Fig. 4. GWO and WOA Convergence Curves for Case I

B. *Case Study II:*

Due to the intermittent and stochastic nature of the renewable resources [20], it is often recommended that the RDG size should not exceed certain limits in order to reduce the power grid's total dependability on RDGs to avoid possible power outages. For this reason, Case II investigates the performance of GWO and WOA when two RDG units are installed in the test system with different penetration levels, corresponding to three parts representing 10%, 20% and 30% from total system active power. Table 2 shows the results for applying both GWO and WOA for different penetration levels indicating the locations and the total power loss in each part. Part I results at 10% capacity (380 kW) for both wind/PV modules, similar results are obtained for both optimization algorithms with the optimal location of RDG units at bus 53 yielding total power losses of 170 kW. In Part II, 20% capacity is tested for a total capacity of 760 kW from both RDG units. Similar to Part I, both GWO and WOA achieved the same power loss reduction level of 129.5 kW, with RDG units optimally located at bus 50 and 53. Finally, Part III is carried out at penetration level of 1140 kW of RDG units, which corresponds to 30% from total IEEE69 active power is tested. Results demonstrated in Table II show the superiority of the GWO in achieving the most optimal solution in terms of power losses. Compared to 127 kW losses achieved with WOA, the total active power losses with GWO are 102.4 kW if RDGs are placed at bus 50 and 53, with a total size of 570 kW. Fig. 5 and Fig. 6 show the performance of both GWO and WOA in all cases at different possible penetration levels. Convergence curves achieved by both proposed algorithms for the three penetration levels covered in Case II can be found in Fig. 10. In terms of speed in locating the near-optimal minimum solution, WOA reaches the optimum solution with the lowest number of iterations compared to GWO, yet this is achieved at a lower accuracy in optimization results.

Summarizing the results of Table II, Table III shows the percentage reduction in total power losses in both cases studied in this work. It should be noted that the higher RDG penetration level, the more reduction is system losses can be achieved for both algorithms, which is demonstrated in Case I. However, this comes at the cost of installing higher RDG units.

TABLE I. CASE I AND CASE II RESULTS FOR GWO AND WOA

Case	GWO (PV, Wind)		WOA (PV, Wind)		Power Losses (MW)	
	Size (MW)	Location	Size (MW)	Location	GWO	WOA
Base Case	------		------		0.224	
Part I (10%)	0.380	53,53	0.380	53,53	0.170	0.170
Part II (20%)	0.760	50,53	0.760	50,53	0.129	0.129
Part III (30%)	1.140	50,53	1.140	17,53	0.102	0.127

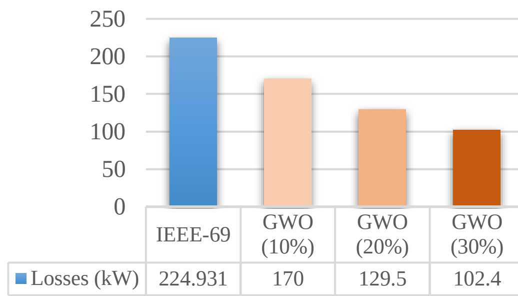

Fig. 5. Case II System Losees with GWO

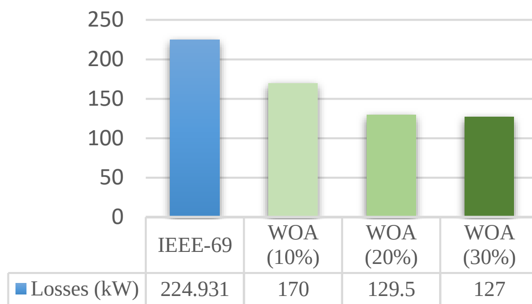

Fig. 6. Case II System Losees with WOA

TABLE II. PERCENTAGE LOSS REDUCTION SUMMARY FOR CASE I AND CASE II

	Case I	Case II-Part I 10%	Case II-Part I 20%	Case II-Part I 30%
Base Case	------	------	------	------
GWO	65.1%	24.5%	42.4%	54.5 %
WOA	65.1%	24.5%	42.4%	43.5 %

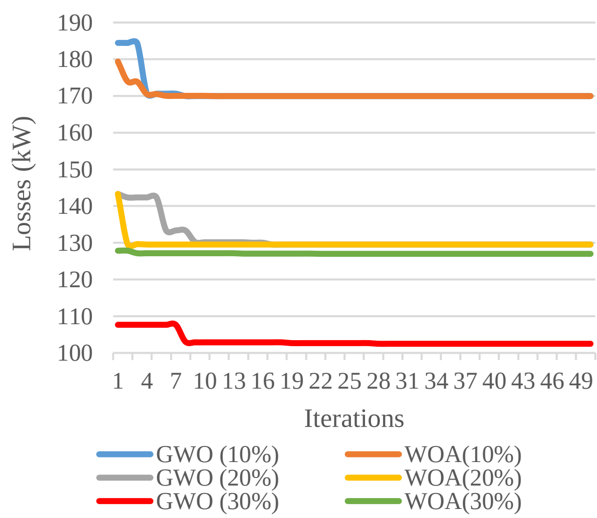

Fig. 7. Convergence Curves for Case I and Case II using GWO and WOA

V. CONCLUSION

Traditional power generation based on fossil fuels is generally regarded as unsustainable over the long term due to the scarcity of non-exhaustible resources and the environmental problems caused by their emissions. Renewable energy resources are thus a viable option for electricity generation if managed appropriately and optimally. This paper presents a comparative study for the optimal probabilistic allocation and sizing of RDG in distribution systems using PV/wind modules. Load flow calculations were implemented using the forward-backward sweep approach. The optimization problem was analyzed using GWO and WOA meta-heuristic algorithms to minimize the system power losses in feeders using different capacities of RDG and different penetration levels. Based on the results, the use of RDG modules helps improve the system efficiency by minimizing the total losses, without the need of installation of fossil fuel-based generation alternatives, which consequently helps is carbon emission reduction. Comparing GWO and WOA performances, the GWO results demonstrate the efficiency and superiority in finding the optimal sizing of PV/wind modules on the distribution network, yet at a slower convergence speed compared to the counterpart.

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