Optimal Allocation of Multiple Distributed Generation Using an Enhanced Whale Optimization Algorithm

John Laurence P. Elambayo
Electrical and Electronics Engineering Institute
University of the Philippines Diliman
Quezon City, Philippines
john.laurence.elambayo@eee.upd.edu.ph

Adonis Emmanuel DC. Tio
Electrical and Electronics Engineering Institute
University of the Philippines Diliman
Quezon City, Philippines
adonis.tio@eee.upd.edu.ph

***Abstract*—The integration of distributed generation (DG) into the distribution system is a complex problem that requires an efficient optimization technique. To maximize benefits while minimizing disadvantages, it is crucial to determine optimal locations and capacities for DG installations. Despite the frequent use of recently developed optimization algorithms, their enhanced counterparts are rarely investigated. Moreover, most research relied on peak loads, which do not accurately reflect real-world demand. We proposed using the enhanced whale optimization algorithm (E-WOA) for optimal DG allocation in a radial distribution system, aiming to minimize power and energy losses. This study also developed representative variable load profiles based on real-world consumption data. The backward/forward sweep algorithm is used for load flow analysis, with the IEEE 33-Bus radial distribution system serving as the test system. The optimization was simulated over 100 independent runs, each with 200 iterations and a population of 50. Results demonstrated that E-WOA effectively solves the optimal DG allocation problem, achieving a power loss of 72.785 kW for three DGs at unity power factor, outperforming the standard WOA and several recent algorithms, and matching the performance of hybrid algorithms. Comparison with WOA across different loading scenarios showed that E-WOA consistently produced higher quality solutions at the cost of slower convergence speeds, longer runtimes, and poor scalability. These suggest E-WOA's limitations in addressing large-scale optimization tasks.**

***Index Terms*—distributed generation, optimal distributed generation allocation, metaheuristic algorithms, radial distribution system, enhanced whale optimization algorithm**

I. Background

The increasing penetration of Distributed Generation (DG) in power systems is a direct response to the numerous challenges in the modern energy landscape. Rising energy demand, environmental concerns, and the necessity for a more resilient and reliable power supply have propelled the widespread adoption of DG technologies. This transition is further driven by declining costs of renewable energy sources, advancements in energy storage solutions, the growing popularity of electric vehicles, increasing fossil fuel prices, and supportive global decarbonization policies [1].

However, integrating DG into power systems can disrupt system dynamics and introduce complications such as reduced system reliability and higher power losses. When properly integrated, DG can offer significant economic benefits, reduced emissions, and other power system advantages. Determining the optimal location and capacity of DG installations through exhaustive brute force methods is feasible for simple, small-scale systems. However, for larger, more complex systems, these methods become computationally expensive, inefficient, and time-consuming.

To address this, many studies have applied intelligent search or metaheuristic algorithms to the optimal DG allocation (ODGA) problem. These algorithms provide more adaptive, efficient, and robust solutions within reasonable time frames. Traditional algorithms like Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) have effectively addressed the challenges in the optimal distributed generaiton allocation (ODGA) problem, but newer algorithms show even greater promise. Among these, the Whale Optimization Algorithm (WOA) has gained popularity due to its simplicity, efficiency, and flexibility. WOA has been effectively used in numerous optimization problems, including ODGA, demonstrating its capability in finding optimal locations and sizes of multiple DGs [2]. Despite its effectiveness, WOA has limitations such as low population diversity, poor exploration capability, and premature convergence. Researchers have sought to improve WOA by incorporating strategies like Lévy Flight to improve exploration and exploitation [3], Adaptive Social Learning to enhance local optimal trapping [4], and multi-population mechanisms to improve population diversity [5].

Recently, an improved variant called the Enhanced Whale Optimization Algorithm (E-WOA) was developed for global optimization and medical feature selection problems. Initial testing indicates its superior performance compared to most improved WOA variants on standard test cases [6]. This improved algorithm may effectively solve the ODGA problem, along with addressing some issues that are hardly explored in the literature.

One such issue in most previous studies is the oversimplification of load modeling, including the consideration of only constant peak load assumptions when solving the optimization problem. Others multiply a constant factor to the peak load of each bus to simulate different load levels, but the load distribution remains the same [2]. Although some studies have used seasonal load profiles, the load distribution of each bus often remains constant across all hours, scaled by a load factor, which does not fully reflect real-world load demand variability [7].

To address this limitation, we develop detailed hourly load profiles that more accurately model real-world load variability, with different total system loads and loading levels for each bus every hour. Using these profiles, we aim to minimize both active power losses (for static loads) and energy losses (for variable loads), while adhering to critical constraints such as voltage limits, current ratings, and DG generation capacities.

Although WOA has been widely used to solve the ODGA problem with constant peak loads, its performance with variable loads remains unexplored. Additionally, the application of the E-WOA to the this problem with both constant and variable loads has not yet been investigated. Given its potential as an effective metaheuristic, E-WOA may better address the increasing challenges in the DG allocation problem.

Thus, this study presents a new application of the Enhanced Whale Optimization Algorithm (E-WOA) to determine the optimal allocation of multiple distributed generators (DGs) within the IEEE 33-Bus radial distribution system (RDS). We use the backward/forward sweep algorithm for load flow analysis, a DG model that generates both active and reactive power, and the developed hourly load profiles to simulate realistic load variability scenarios.

A limitation of this study is the focus on optimizing only a single objective—either minimizing power losses for static loads or minimizing energy losses for variable loads—to evaluate the performance of the optimization algorithms under different load scenarios. While multi-objective optimization is desirable, we adopt a single-objective approach to minimize the uncertainties associated with multi-objective optimization and to provide a clearer evaluation of algorithm performance across various load scenarios.

The rest of this paper is organized as follows: Section II presents the methodology, Section III discusses the results, and Section IV concludes the report and offers recommendations.

II. Methodology

The study uses E-WOA to address the optimal distributed generation allocation problem in a standard distribution system. The study is subdivided into the following steps: data gathering, load profile development, load flow analysis, problem formulation, implementation of the optimization algorithms, the test cases, and the performance metrics.

A. Data Gathering

1) 5-Bus Test System: The 5-bus radial distribution system in Fig. 1 is used to validate the optimization algorithms. The algorithms determine the optimal location and size of a single integrated distributed generator (DG) at a 0.9 power factor, with results compared to a brute force search.

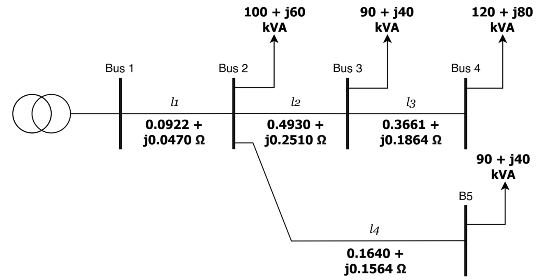

Fig. 1. 5-Bus Radial Distribution System.

2) IEEE 33-Bus System: The IEEE 33-bus radial distribution system in Fig. 2 includes a main 18-bus feeder and three lateral feeders, with a total demand of 3.715 MW active and 2.3 MVAr reactive power. The base voltage is 12.66 kV, and the base MVA is 100. This system is widely used in studies, providing several published results for performance comparison.

3) Variable Load Demand Data: Historical load demand data, obtained from [8], includes half-hour active power demand for 300 houses connected to the Australian grid from 1 July 2012 to 30 June 2013.

B. Development of Load Profiles

Fig. 3 illustrates the development of the load profiles. From the annual demand of 300 houses, load profiles of 9 randomly selected houses are aggregated and assigned across 32 load buses. The pre-processed data is averaged over specific periods for daily and seasonal profiles e.g. in the daily load profile, the load demands are categorized by each hour of the day (hours 1-24) and then averaged per hour. The minimum, median, and maximum system demands for the year generate the low, medium, and peak for the 3-hour load profile, detailed in the Appendices. Three hourly variable load profiles were developed for 3-, 24-, and 96-hour periods, with one peak load profile derived from the 3-hour load profile.

C. Load Flow Analysis

In the optimal distributed generation allocation (ODGA) problem, optimization techniques explore potential DG sizes and sites, while load flow algorithms evaluate these configurations' fitness based on metrics such as losses and reliability. This study uses the backward/forward sweep (BFS)

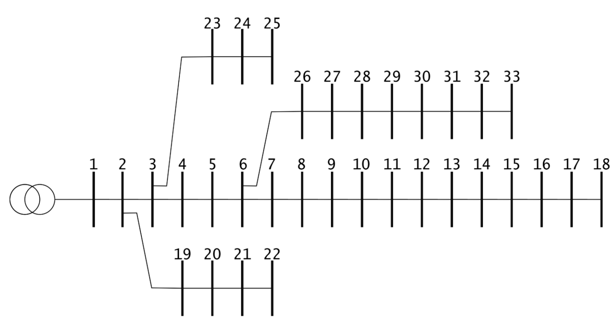

Fig. 2. IEEE 33-Bus Radial Distribution System.

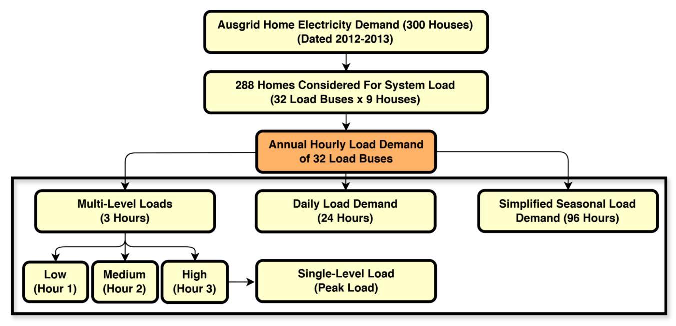

Fig. 3. Load Profile Development Overview.

load flow method [9], which has been validated against the results found in [10].

D. Problem Formulation

1) Objective Function:

a) Minimization of Power Losses: For peak load profiles, the objective function minimizes power losses as shown in (1),

$$PL = \sum_{k=1}^{N_{lines}} |I_k|^2 \times R_k \tag{1}$$

where N_{lines} is the total number of lines or branches, I_k is the line current of line k, and R_k is the resistance of line k.

b) Minimization of Energy Losses: For variable loads, the objective function minimizes energy losses as in (2),

$$EL = \sum_{t=1}^{N_{hours}} P_L^t \Delta t \tag{2}$$

where EL represents the energy loss, P_L^t is the active power loss at the time period t, and t is the time duration of one hour. N_{hours} is the total number of hours considered in the study, equal to 3, 24, and 96 hours.

2) Constraints:

a) Power Balance: Equation (3) ensures no reverse power flows occur,

$$P_{S/S}^t + \sum_{i=1}^{N_{DG}} P_{DG}^t = \sum_{i=1}^{N_{\text{Load}}} P_{\text{Load}}^t + \sum_{i=1}^{N_{\text{Line}}} P_{\text{loss}}^t \tag{3}$$

where $P_{S/S}^t$ is the active power generated by the substation at hour t, P_{DG}^t is the active power generated by a DG, P_{Load}^t is the active power demand, and P_{Loss}^t indicates line losses.

b) Voltage: Post-DG installation bus voltages must fall within the limits in (4),

$$\left|V_i^{min}\right| \leq \left|V_i^{withDG}\right| \leq \left|V_i^{max}\right| \tag{4}$$

where V_i^{min} is ± 0.95 pu and V_i^{max} is ± 1.05 pu.

c) Current: Power lines must not exceed their maximum capacity described in (5),

$$I_i^{withDG} \leq I_i^{max} \tag{5}$$

where I_i^{withDG} is the current on line i in the presence of DGs and I_i^{max} is the maximum current capacity of line i.

d) Power Generation: The generated active power of each DG is constrained between the limits in (6),

$$P_{DG}^{min} \leq P_i^{DG} \leq P_{DG}^{max} \tag{6}$$

where P_{DGmin} is the minimum active power generation limit set to 0 and P_{DGmax} is the maximum active power generation limit for each DG which is equal to the total active power demand of the system (at hour i for variable loads).

e) DG Location: The permissible sites for DG installation are limited by the location of the slack bus (Bus 1) and the total DGs as in (7) and (8),

$$2 \leq DG_{loc} \leq N_{Bus} \tag{7}$$

$$DG_1^{loc} \neq DG_2^{loc} \neq DG_3^{loc} \tag{8}$$

where DG_{loc} represents the potential installation sites for DGs, excluding Bus 1 as it is the slack bus. N_{Bus} denotes the total number of buses. The second equation ensures that each DG is installed on a different bus, indicated by DG_i^{loc}.

E. Optimization Algorithm Implementation

Both WOA and E-WOA are continuous optimizers that process continuous variables. Discrete variables are incorporated using the relaxation method during initialization and before fitness evaluation [11]. Algorithm-specific parameters are retained from their original implementations [6], [12]. Simulations use 200 iterations, a population of 50, and 100 runs. Fig. 4 illustrates the flowchart of E-WOA.

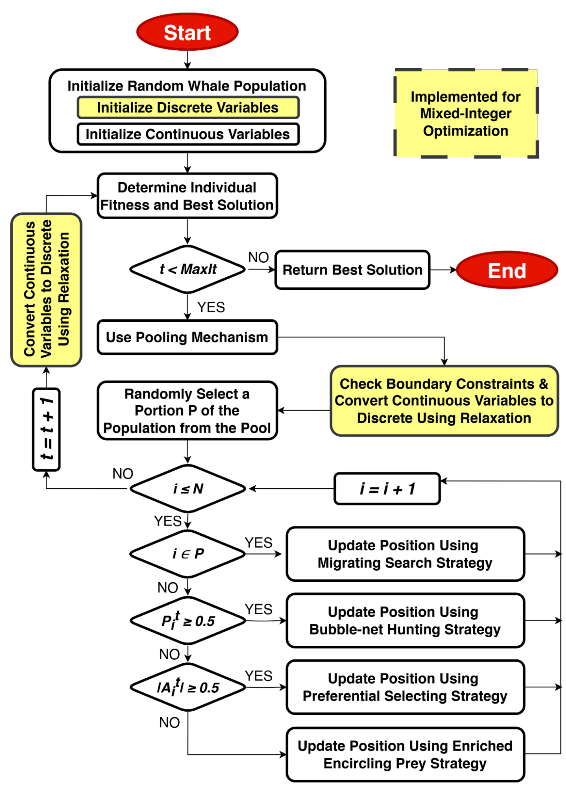

Fig. 4. Enhanced Whale Optimization Algorithm Flowchart.

F. Test Cases

Table I summarizes the test cases which vary in objective functions, load scenarios, numbers of DGs, and test systems.

TABLE I
SUMMARY OF TEST CASES

Test Case	Obj. Func.	Load Profile	No. of DGs	Test System
1	Min. Active Power Loss	Peak Load for Test	Single	5-Bus
2	Min. Active Power Loss	Peak Load (1 Hour)	Multiple	33-Bus
3	Min. Energy Loss	Multi-Level (3 Hours)	Multiple	33-Bus
4	Min. Energy Loss	Daily (24 Hours)	Multiple	33-Bus
5	Min. Energy Loss	Seasonal (96 Hours)	Multiple	33-Bus
A	Min. Active Power Loss	IEEE 33-Bus Peak Load For Comparison	Single/ Multiple	33-Bus

G. Evaluation Metrics

The results for all test cases are evaluated based on objective function values, number of iterations to converge within 200 iterations, runtime, scalability or average runtime with increasing problem size, and number of violations.

III. RESULTS AND DISCUSSION

The optimal solutions are summarized, and a brief discussion on voltage profiles, and convergence characteristics is provided. The last section compares WOA and E-WOA on a set of evaluation metrics.

A. Comparison with Published Results

Table II details the optimal allocation of three DGs. E-WOA and CBGA-VSA achieve the minimum power loss of 72.785 kW. Although E-WOA attains lower power losses than WOA, WOA still outperforms other recent and improved algorithms.

B. Optimal Solutions for Test Cases

The optimal DG locations and sizes for Test Cases 1-5 are summarized in Table III. In Case 1, both WOA and E-WOA achieve identical minimal losses, demonstrating their effectiveness in a simple system. As complexity increases in Cases 2-4, E-WOA consistently achieves lower losses compared to WOA. When the algorithms encounter a constraint violation, they return a large penalty value for that iteration. In Case 5, E-WOA consistently returned this penalty value across 100 independent runs of 200 iterations each, indicating its failure to identify any solutions that met the required constraints. This shows EWOA's potential limitations in handling highly complex systems. In contrast, WOA successfully identifies solutions, highlighting its robustness despite being less effective in simpler cases.

C. Voltage Profiles

Fig. 5 illustrates the voltage profile of the IEEE 33-Bus system for Test Case 3 with increasing loading levels. Both WOA and E-WOA satisfy the voltage constraints of ±5% deviation from 1 pu while allocating the DGs. Although voltage deviation minimization is not part of the objective function, E-WOA, which achieves lower power losses, also improves the voltage profile more effectively than WOA. Ref. [23] notes that minimizing power loss enhances voltage stability, which is related to the improved voltage profile.

TABLE II
OPTIMIZATION RESULTS FOR MULTIPLE DGS IN IEEE 33-BUS SYSTEM AT UNITY POWER FACTOR

Year	Algorithm	DG Location	DG Size (kW)			Power Loss (kW)
			DG1	DG2	DG3	
Base		-	-	-	-	210.9880
2016 [13]	HSA-PABC	14, 24, 30	755.000	1073.000	1068.000	72.8100
2016 [14]	QOSIMBO-Q	13, 24, 30	801.600	1090.600	1054.20	72.8000
2017 [15]	FA	13, 17, 31	623.100	261.300	1012.000	87.8300
2017 [16]	GWO	13, 24, 30	850.020	1103.870	1100.770	73.0600
2018 [17]	CTLBO	13, 24, 30	801.700	1091.300	1053.600	72.7870
2018 [18]	IMOEHO	14, 24, 30	1057.000	1054.000	1741.000	95.0000
2019 [19]	MOCDE	13, 24, 30	801.840	1091.460	1046.580	72.8480
2020 [20]	HHO	14, 24, 30	745.690	1022.690	1135.780	72.9800
2020 [20]	IHHO	14, 24, 30	775.540	1080.830	1066.690	72.7900
2020 [21]	**CBGA-VSA**	**13, 24, 30**	**801.800**	**1091.300**	**1053.600**	**72.7853**
2021 [22]	MRFO	13, 24, 30	788.276	1017.100	1035.300	72.8760
Present	**WOA**	**13, 24, 30**	**799.830**	**1047.810**	**1073.150**	**72.8147**
Present	**E-WOA**	**13, 24, 30**	**801.799**	**1091.315**	**1053.601**	**72.7853**

TABLE III
BEST RESULTS FOR ALL TEST CASES (DGS AT 0.9 POWER FACTOR, 200 ITERATIONS, 100 RUNS)

Case	DG Locations	DG Sizes (kW)			Loss
		DG1	DG2	DG3	
Case 1	*5-Bus Test System With 1 DG at Peak Load*				kW
Base	-	-	-	-	0.358
WOA	4	201.833			0.059
E-WOA	**4**	**201.833**			**0.059**
Case 2	*33-Bus Test System With at Most 3 DGs at Peak Load*				kW
Base	-	-	-	-	169.389
WOA	6, 15, 30	826.965	785.037	722.887	11.311
E-WOA	**6, 15, 30**	**807.596**	**791.401**	**727.083**	**11.307**
Case 3	*33-Bus Test System With at Most 3 DGs Across 3 Loading Levels*				kWh
Base	-	-	-	-	216.017
WOA	6, 15, 30	975.723	760.002	628.851	15.479
E-WOA	**6, 15, 30**	**807.594**	**791.402**	**727.084**	**14.469**
Case 4	*33-Bus Test System With at Most 3 DGs Across 24 Loading Levels*				kWh
Base	-	-	-	-	1598.547
WOA	6, 7, 14	914.943	1037.055	933.643	221.838
E-WOA	**8, 13, 30**	**1094.201**	**889.338**	**867.780**	**168.244**
Case 5	*33-Bus Test System With at Most 3 DGs Across 96 Loading Levels*				kWh
Base	-	-	-	-	3765.261
WOA	**6, 8, 14**	**908.942**	**745.308**	**831.379**	**647.610**
E-WOA	No Solutions Found				

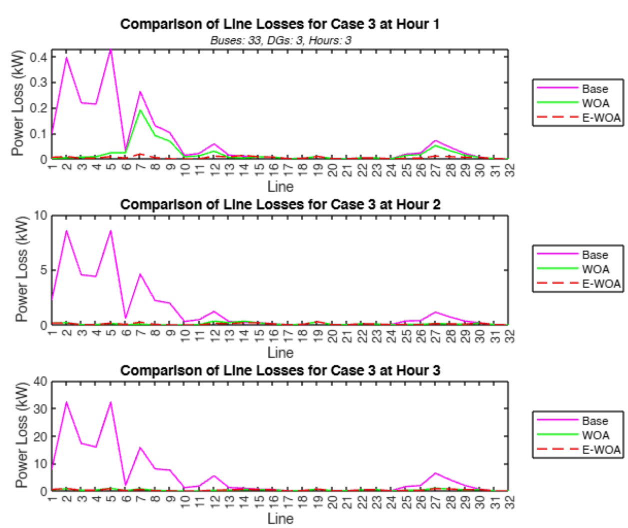

Fig. 5. Comparison of Voltage Profiles for Case 3 for Each Hour.

D. Convergence Characteristics

Fig. 6 compares the best convergence curves of the two algorithms for case 4, showing significant differences. WOA converges quickly but prematurely due to limited exploration in later iterations. In contrast, despite encountering infeasible solutions and starting slower, E-WOA continues improving in later iterations, achieving lower objective function values without premature convergence. This highlights E-WOA's ability to maintain exploration and avoid getting trapped in local optima, although at the cost of slower convergence speed. While this trend is evident in Case 4, in Cases 2 and 3, E-WOA converges faster, retaining the same rough staircase pattern compared to WOA's smooth curve, as detailed in the Appendices.

E. Performance Metrics

1) Objective Function Values: Fig. 7 compares the boxplots of normalized objective function results for both algorithms. E-WOA shows lower variability and median values. Table IV summarizes key performance measures, showing E-WOA's lower mean and standard deviation, suggesting better consistency in finding high-quality solutions in Cases 1-4.

2) No. Iterations to Converge: Fig. 8 compares boxplots of iterations to converge for all cases. Both algorithms have a median of 1 iteration for Case 1. For Cases 2-5, WOA's medians are 99, 103, 113, and 125, while E-WOA's are 54, 108, and 199. Although E-WOA converges faster in Case 2, its convergence speed deteriorates in subsequent cases.

3) Runtime: Fig. 9 compares the boxplots of total runtimes for 200 iterations across 100 runs. In Case 1, runtimes are similar for both algorithms. In Cases 2-4, WOA has lower median and average runtimes highlighting its computational efficiency.

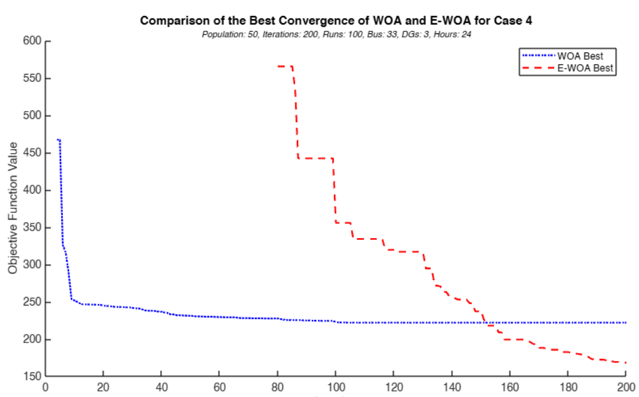

Fig. 6. Comparison of Best Convergence Curves for Case 4.

TABLE IV
COMPARISON OF KEY PERFORMANCE MEASURES OF OBJECTIVE FUNCTION RESULTS

	Mean		Standard Deviation		Minimum	
	WOA	*E-WOA*	*WOA*	*E-WOA*	*WOA*	*E-WOA*
Case 1	0.0589	0.0589	2.53e-15	2.00e-17	0.0589	0.0589
Case 2	14.6446	11.7118	2.5773	1.0800	11.3111	11.3073
Case 3	30.5655	16.2833	5.9251	3.7039	15.4794	14.4691
Case 4	349.2446	257.4618	146.3024	32.8077	221.8375	168.2436
Case 5	917.1043	-	550.9331	-	647.6101	-

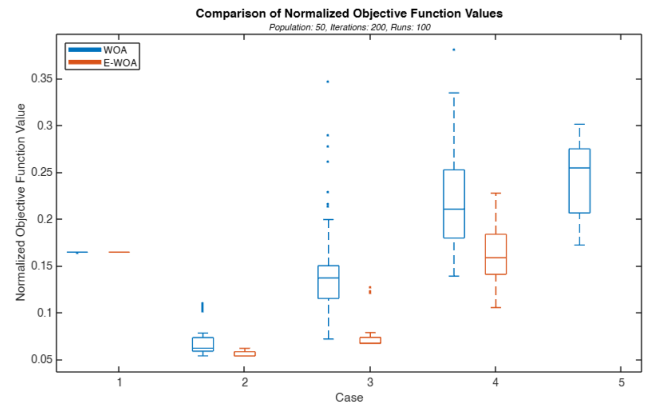

Fig. 7. Box Plot Comparison of the Normalized Objective Function Value Obtained by WOA and E-WOA for Cases 1-5.

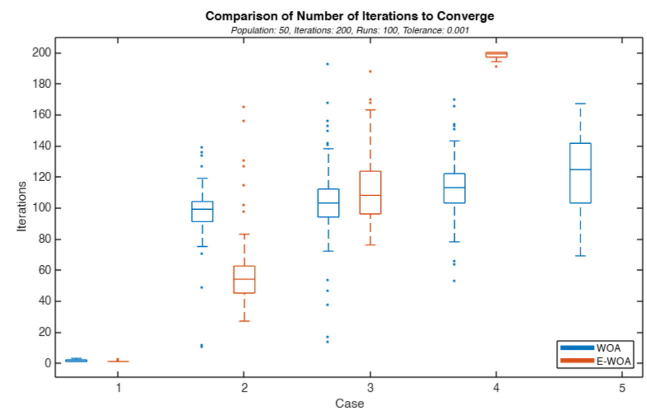

Fig. 8. Box Plot Comparison of Number of Iterations to Converge for 100 Independent Runs.

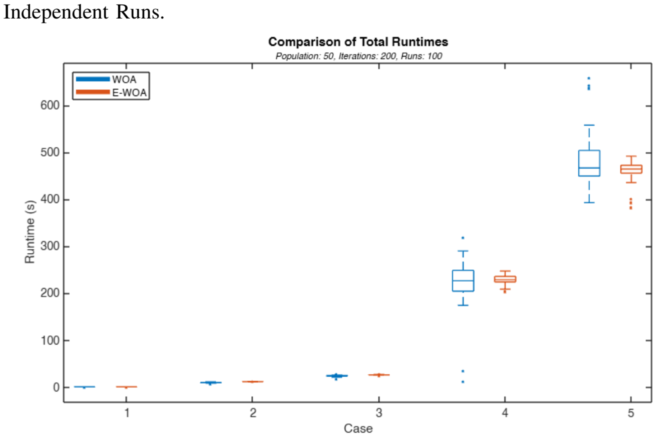

Fig. 9. Box Plot Comparison of Total Runtimes.

4) No. of Constraint Violations: Table V shows that for smaller cases (1 to 3), both WOA and E-WOA consistently find feasible solutions without significant constraint violations. However, in larger cases (4 and 5), E-WOA encounters a higher number of constraint violations, indicating poor performance in navigating larger search spaces, while WOA maintains a lower violation count. Significantly, WOA found feasible solutions in Test Case 5, where E-WOA fails to identify any, revealing the limitations of E-WOA's search strategies in highly complex, large-scale optimization problems compared to WOA.

5) Scalability: Table VI shows a significant increase in average runtimes as the number of variables increases from Case 3 to 5. WOA outperforms E-WOA in average and minimum runtime for Cases 2-4 due to its simpler implementation. Although E-WOA has lower runtimes in Case 5, it is insignificant since it fails to find any feasible solutions. Previous sections reveal E-WOA's limitations in larger cases, including its inability to find feasible solutions in Case 5, higher iterations to converge in Cases 3 and 4, higher average runtimes in Cases 3 and 4, and more iterations with constraint violations in Cases 4 and 5. These results indicate E-WOA's poor potential in handling large-scale and complex problems, demonstrating inferior scalability compared to the standard WOA.

IV. Conclusion

In this study, the Enhanced Whale Optimization Algorithm (E-WOA) was applied to optimally allocate distributed generation units in the IEEE 33-Bus system, focusing on minimizing power losses and accommodating load variations through low-mid-peak, daily, and seasonal load profiles.

The results demonstrate that both WOA and E-WOA are effective in solving the ODGA problem, with E-WOA performing on par with or better than recent improved and hybrid optimization algorithms in finding the global optimum. An in-depth comparison reveals the impact of E-WOA's improved search strategies and population diversity. These enable E-WOA to consistently find high-quality solutions for problems with few variables. However, these enhancements lead to longer runtimes, slower convergence for large problems, worse constraint handling, and poor scalability, failing to find feasible solutions in large-scale problems. While E-WOA outperforms WOA in smaller cases, its advantages diminish as problem complexity increases.

Future research should aim to refine E-WOA for large-scale applications, explore its performance across different electrical system configurations, and incorporate modern load demands and renewable generation profiles to enhance the simulation's practicality and relevance.

TABLE V
Iterations With Violations and Runs With Feasible Solutions

Algorithm	Criteria	Case 1				
		1	*2*	*3*	*4*	*5*
WOA	I.w.V.[a]	0	8	745	**13340**	**17453**
	R.w.F.S.[b]	100	100	99	**42**	**16**
E-WOA	I.w.V.	0	**0**	**1**	17765	20000
	R.w.F.S.	100	100	**100**	17	0

[a]I.w.V. is Iterations with Violations.

[b]R.w.F.S. is Runs with Feasible Solutions.

TABLE VI
Comparison of Key Performance Measures of Objective Function Results

		Case 1	Case 2	Case 3	Case 4	Case 5
Case Specs.	DGs	1	3	3	3	3
	Hours	1	1	3	24	96
Variables	Locations	1	3	3	3	3
	Size/ Dispatch[a]	1	3	9	72	288
	Total	**2**	**6**	**12**	**75**	**291**
Mean (s)	WOA	**0.57**	**9.51**	**23.949**	**223.80**	479.36
	% Inc.		1557%	152%	835%	114%
	E-WOA	0.57	11.61	26.11	228.66	~~**461.01**~~[b]
	% Inc.		1923%	125%	776%	~~102%~~

[a]Dispatch = (No. of DGs) * (No. of Hours).

[b]Average runtime is irrelevant for comparison since no feasible solutions were found.

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