Multi-Objective Optimization of Emissions and Green Accounting Costs in Smart Distribution Networks with Distributed Generation

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Received: 22 July 2025 | Revised: 3 August 2025 | Accepted: 15 August 2025

ABSTRACT

This paper presents a multi-objective optimization framework for Distributed Generation (DG) planning in smart Distribution Networks (DNs), with the aim of minimizing carbon dioxide emissions (CO_2) and Green Accounting Costs (GAC). A hybrid model is formulated to incorporate power flow constraints, lifecycle emission factors, and environmental cost components under a green accounting perspective. To solve the proposed problem, an enhanced Grey Wolf Optimizer (GWO), termed Eco-Aware Multi-Objective Grey Wolf Optimizer (EMOGWO), is developed by introducing environmentally guided leader selection, adaptive convergence control, and a fuzzy-based decision mechanism. The algorithm is tested on the IEEE 33-bus and IEEE 69-bus systems and benchmarked against Particle Swarm Optimization (PSO), Reptile Search Algorithm (RSA), Arithmetic Optimization Algorithm (AOA), and the standard GWO. Simulation results demonstrate that EMOGWO consistently achieves the lowest power loss, emissions, and environmental cost across all cases, while providing the highest Emission Reduction Ratio (ERR) and Green Cost Savings (GCS). The proposed approach offers a practical and effective tool for sustainable DG planning aligned with environmental and economic objectives.

Keywords-Distribution Networks (DNs); green accounting; Carbon Emissions (CE); Distributed Generation (DG); Eco-Aware Multi-Objective Grey Wolf Optimizer (EMOGWO)

I. INTRODUCTION

The increasing integration of environmental and financial considerations into power system planning reflects a paradigm shift in modern energy policy. Among the critical challenges is the simultaneous reduction of carbon dioxide emissions (CO_2) and the internalization of environmental externalities into economic decision-making frameworks. Distributed generation (DG), particularly from renewable sources, plays a pivotal role in this transformation by supporting grid decarbonization, reducing energy losses, and enhancing voltage stability in Distribution Networks (DNs) [1, 2]. However, the deployment of DG also introduces multidimensional impacts that extend beyond traditional power system metrics. Although DG technologies such as photovoltaic and wind systems exhibit negligible operational emissions, their lifecycle emissions, including material processing, transportation, installation, and decommissioning, must be accounted for in holistic sustainability assessments [3]. Concurrently, the emergence of green accounting provides a methodology to assign financial value to environmental impacts, particularly emissions, thereby enabling utilities and regulators to incorporate carbon-related costs directly into planning models [4]. This shift is reinforced by the proliferation of carbon pricing mechanisms, environmental taxation, and Environmental, Social, and Governance (ESG) mandates at national and corporate levels.

Despite this convergence of environmental science and financial accountability, existing DG planning models often omit explicit cost treatment of emissions, focusing instead on power loss or voltage profiles. The environmental cost is typically viewed as an exogenous constraint rather than an endogenous component of the objective function. Moreover, the integration of green accounting principles, such as emission cost penalties, environmental investment amortization, and lifecycle-based emission accounting, into distribution-level optimization remains underexplored in current literature [5].

To address this gap, the present study proposes a multi-objective optimization framework for DG planning in smart DNs that jointly minimizes lifecycle Carbon Emissions (CE) and Green Accounting Cost (GAC). A hybrid model is developed to couple power flow constraints with lifecycle emission data and environmental financial metrics. To solve the resulting complex optimization problem, an enhanced Grey Wolf Optimizer (GWO) is introduced, termed Eco-Aware Multi-Objective Grey Wolf Optimizer (EMOGWO), incorporating adaptive convergence control, environmentally guided leader selection, and decision support. The proposed model aims to:

- Provide a unified formulation integrating power system objectives with financial and environmental accountability.
- Develop a lifecycle-based emission modeling framework applicable to renewable DG technologies.
- Define a green cost function that reflects capital investment, Operation and Maintenance (O&M), and CO_2-related penalties.
- Design a customized EMOGWO algorithm tailored for sustainability oriented DN planning.

By embedding green accounting logic directly into the optimization loop, this approach enables carbon-cost-sensitive grid decisions, offering a practical tool for utilities aiming to balance technical reliability with sustainability targets. The framework is validated on the IEEE 33-bus and IEEE 69-bus test systems, demonstrating superior performance in emission reduction and environmental cost savings compared to existing algorithms.

II. MATHEMATICAL MODELING

This section formulates a multi-objective optimization problem for planning DG in smart DNs under the orientation of green accounting. The goal is to determine the optimal siting and sizing of DG units such that both CE and GAC are minimized, while ensuring technical feasibility and system reliability. The problem is modeled as follows.

A. Problem Formulation

Let $\mathcal{N}$ be the set of buses in the DN and let $\mathcal{L}$ be the set of distribution lines. Let $\mathcal{D} \subseteq \mathcal{N}$ be the subset of candidate buses for DG installation. The objective is to minimize the following two functions:

- Objective 1: Minimize the total CE E^{total} over the planning horizon.
- Objective 2: Minimize the total GAC C_{GA}, including investment, operational, and emission related costs.

$$\min \begin{cases} f_1 = E^{total} & \text{(CE)} \\ f_2 = C_{GA} & \text{(GAC)} \end{cases} \tag{1}$$

The optimization is subject to power flow balance equations, voltage magnitude limits, DG penetration constraints, operational and grid code compliance. The components of this formulation are detailed below.

B. Power Flow and Operational Constraints

We consider a radial DN represented as a graph $G(\mathcal{N},\mathcal{L})$. Power flows are solved using the backward/forward sweep method, capturing voltage drops and line losses.

At each bus $i \in \mathcal{N}$:

- P_i^{load}, Q_i^{load}: active/reactive load demand.
- P_i^{DG}, Q_i^{DG}: active/reactive power injected by DG.
- V_i: voltage magnitude.
- I_{ij}: current magnitude along line ij.
- R_{ij}, X_{ij}: resistance and reactance of line ij.

Power injection at bus i:

$$P_i^{inj} = P_i^{DG} - P_i^{load}, \quad Q_i^{inj} = Q_i^{DG} - Q_i^{load} \tag{2}$$

Power flow equations:

$$P_{ij} = V_i I_{ij} \cos(\theta_{ij}), \quad Q_{ij} = V_i I_{ij} \sin(\theta_{ij}) \tag{3}$$

Voltage drop across line ij:

$$V_j^2 = V_i^2 - 2(R_{ij}P_{ij} + X_{ij}Q_{ij}) + (R_{ij}^2 + X_{ij}^2)I_{ij}^2 \tag{4}$$

Voltage limits:

$$V_{min} \le V_i \le V_{max}, \quad \forall i \in \mathcal{N} \tag{5}$$

C. Carbon Emission Estimation

The total CO_2 emission E^{total} is computed over the time horizon T, combining grid-based and DG-based generation using lifecycle emission factors. Let:

- EF_{conv}: emission factor of conventional energy sources.
- EF_{DG}: lifecycle emission factor of DG.

Then:

$$E^{total} = \sum_{t=1}^{T}(P_t^{conv} \cdot EF_{conv} + P_t^{DG} \cdot EF_{DG}) \qquad (6)$$

where P_t^{conv} and P_t^{DG} are the power supplied by the grid and DG units at time t.

D. Green Accounting Cost Model

The GAC C_{GA} aggregates investment, operational, and environmental penalty components:

$$C_{GA} = C_{inv}^{DG} + C_{op}^{DG} + \lambda \cdot E^{total} \qquad (7)$$

where C_{inv}^{DG} is the DG investment cost, C_{op}^{DG} is the operational and maintenance cost, λ is the cost per unit CO_2 emitted, and $\lambda \cdot E^{total}$ is the environmental cost proportional to emissions.

This composite cost reflects both financial burden and environmental accountability, aligning with sustainability reporting practices.

E. Decision Variables and Constraints

Let $x_i \in \{0,1\}$ be the binary decision variable for DG placement at bus i, and P_i^{DG} be its corresponding size:

- DG siting: $x_i = 1$ (DG installed at bus i).
- DG sizing bounds: $0 \leq P_i^{DG} \leq x_i \cdot P_i^{DG,\max}$.
- Total number of DG units is limited:

$$\sum_{i\in\mathcal{D}} x_i \leq N_{DG}^{\max} \qquad (8)$$

Table I summarizes the notations used in this section for clarity and ease of understanding.

TABLE I. NOTATIONS AND UNITS USED IN THE MODEL

Symbol	Description	Unit
P_L, Q_L	Load demand	kW, kVar
P_{DG}, Q_{DG}	DG output power	kW, kVar
V	Bus voltage magnitude	p.u.
I	Line current magnitude	A
R, X	Line resistance and reactance	Ohm
EF_g, EF_{dg}	Emission factors	kg CO_2, kWh
CE	Total Carbon Emissions (CE)	kg/day
GAC	Green Accounting Cost (GAC)	USD/day
C_{inv}, C_{om}, C_{CO2}	Investment, O&M, carbon cost	USD, USD/kWh, USD/kg
x_i, s_i	DG placement, DG size	– , kW
ERR, GCS	Emission Reduction Ratio (ERR), Green Cost Savings (GCS)	%

III. PROPOSED SOLUTION METHODOLOGY

To effectively solve the multi-objective optimization problem formulated in Section II, minimizing both CE and GAC, this study introduces a tailored metaheuristic framework built upon an improved version of the GWO [6]. The complexity and nonlinearity of the problem, combined with the dual focus on technical performance and environmental accountability, demand a solution technique capable of exploring a wide decision space while balancing conflicting objectives. The proposed EMOGWO algorithm enhances the original GWO [4] by incorporating environmental awareness and adaptive control mechanisms. It is specifically designed for planning DG in smart DNs under green accounting considerations. The algorithm improves search guidance, maintains diversity in the solution set, and supports the extraction of compromise solutions aligned with both engineering constraints and sustainability criteria.

Traditional metaheuristic algorithms such as Particle Swarm Optimization (PSO) [7], Arithmetic Optimization Algorithm (AOA) [8], Reptile Search Algorithm (RSA) [9], and the standard GWO, have demonstrated success in power system planning tasks. However, these approaches often suffer from limitations including premature convergence, limited diversity in multi-objective contexts, and the lack of explicit integration of environmental metrics. To benchmark the performance of EMOGWO, all aforementioned algorithms are implemented under consistent parameter settings and constraints and tested on the IEEE 33-bus and IEEE 69-bus distribution systems. The comparative analysis focuses on their ability to minimize emissions and environmental accounting costs over 30 independent simulation runs for statistical consistency.

A. Overview of Eco-Aware Multi-Objective Grey Wolf Optimizer

EMOGWO builds upon the canonical GWO, a swarm-based metaheuristic inspired by the leadership hierarchy and hunting strategy of grey wolves in nature. While GWO is effective in various single-objective problems, it requires significant adaptation for multi-objective tasks involving conflicting goals such as technical efficiency and environmental responsibility. EMOGWO addresses this by integrating three key strategies:

- Environmental-density-based leader selection.
- Adaptive control of convergence parameters.
- Fuzzy logic for compromise solution extraction.

These enhancements allow the algorithm to explore the Pareto front effectively and select solutions that balance emission reduction with cost minimization.

B. Environmental Enhancements in Eco-Aware Multi-Objective Grey Wolf Optimizer

The EMOGWO algorithm introduces three core improvements to address the limitations of standard GWO in sustainability-oriented applications:

- Environmentally guided leader selection: Instead of relying solely on Pareto dominance ranking, EMOGWO incorporates an environmental density score to guide the selection of leading wolves (α, β, δ). This score combines crowding distance and a carbon efficiency index defined as:

  $$\eta_i = \frac{1}{C_{GA,i} \cdot E_i^{total}} \qquad (9)$$

  A normalized composite score S_i is used to prioritize solutions:

  $$S_i = w_1 \cdot \mathrm{Norm}(D_i) + w_2 \cdot \mathrm{Norm}(\eta_i), \text{ with } w_1 + w_2 = 1$$

  where D_i is the crowding distance of solution i, and $\mathrm{Norm}(\cdot)$ is the min-max normalization function.

- Adaptive convergence control: To balance global exploration and local exploitation, the convergence factor a is dynamically adjusted based on the diversity:

$$a(t) = \begin{cases} a_{max} \cdot \left(1 - \frac{t}{T_{max}}\right), & \text{if diversity}(t) > \varepsilon \\ a_{reset}, & \text{otherwise} \end{cases} \quad (10)$$

  This prevents premature convergence and maintains search adaptability throughout iterations.

- Archive management and decision support: An external bounded archive stores all non-dominated solutions found during the search process. At the end of the optimization, a fuzzy logic-based decision support layer is used to select the most balanced solution, considering normalized values of CE and GAC.

C. *Optimization Procedure*

The EMOGWO process involves the following steps:

1. Initialization: Generate an initial population of candidate solutions, each representing DG locations and capacities.
2. Fitness evaluation: For each solution, conduct power flow analysis and compute the two objective functions: total CE E^{total} and GAC C_{GA}.
3. Non-dominated sorting and archive update: Store non dominated solutions in an external archive.
4. Leader selection: Apply environmental density-based scoring to select α, β, and δ wolves.
5. Position update: Use modified GWO position update equations to generate new solutions.
6. Adaptive parameter adjustment: Dynamically adjust convergence parameters based on Pareto front diversity.
7. Termination check: Repeat steps 2 to 6 until the maximum number of iterations is reached or convergence criteria are satisfied.
8. Final decision making: Apply fuzzy logic to identify the best compromise solution from the final Pareto set.

This enhanced optimization methodology ensures not only effective trade-off navigation in a multi-objective space but also explicit alignment with environmental and economic performance targets, which is crucial for sustainable planning in modern power distribution systems.

Performance comparison is based on the following multi-objective evaluation indicators:

- ERR:

$$\text{ERR} = \frac{E^{base} - E^{optimal}}{E^{base}} \times 100\% \quad (11)$$

- GCS: Reduction in environmental accounting cost compared to the no-DG scenario.

The IEEE 33-bus and IEEE 69-bus systems used in this study are publicly available and replicable, as referenced in [10].

IV. RESULTS AND DISCUSSION

This section presents the results and analysis of the proposed multi-objective optimization framework applied to smart DNs with DG. All simulations were performed in MATLAB R2021b on a system equipped with an Intel Core i7 processor and 16 GB RAM. Power flow computations were executed using the Backward/Forward Sweep method, appropriately modified to interface with the optimization routines. The EMOGWO was implemented to optimize the placement and sizing of DGs, with the dual objectives of minimizing CE and GAC.

To evaluate the performance of EMOGWO, four benchmark algorithms were used for comparison under identical simulation settings: PSO, AOA, RSA, and the standard GWO. Each algorithm was executed over 30 independent runs, with a population size of 30 and a maximum of 100 iterations. The 33-bus and 69-bus DNs were used as standard test cases. The number of DG units was fixed at three, and their locations and capacities were simultaneously optimized by each algorithm. The allowable DG capacity at each site ranged from 100 kW to 500 kW. The following subsections present and discuss the optimization results for the two test systems. Performance indicators include DG configuration, reduction in carbon dioxide emissions, and GCS relative to a base case without DG.

All algorithms were configured with a population size of 30, 100 iterations, and 30 independent runs. Voltage limits were maintained within 0.95 to 1.05 p.u. for all buses. For EMOGWO, the environmental density weights were set as $w_1 = 0.6$ and $w_2 = 0.4$. The adaptive convergence parameters included a reset value $a_{reset} = 1.5$ and a diversity threshold $\varepsilon = 0.1$. Table II lists the key input parameters used for the simulation study.

TABLE II. KEY PARAMETERS USED IN THE SIMULATION STUDY

Parameter	Symbol	Value / Description
Emission factor of DG [11]	EF_{conv}	0.74 kg CO_2/kWh
Life cycle emission factor of DG [12]	EF_{DG}	0.03 kg CO_2/kWh
Carbon price [13]	λ	0.10 USD/kg CO_2
O&M cost of DG [14]	C_{op}^{DG}	0.01 USD/kWh
Capital cost of DG (converted to daily cost over 20 years) [14]	C_{inv}^{DG}	0.123 USD/kWp/day (900 USD/kWp ÷ 20 years)

A. *The 33-Bus System*

Figure 1 presents the single line diagram of the 33-bus DN, comprising 37 branches, and clearly depicting the connectivity between the main substation, load buses, feeder lines, and candidate nodes for DG integration. The system topology and electrical parameters are adopted from reputable sources [10] to ensure the credibility and reproducibility of the simulation results.

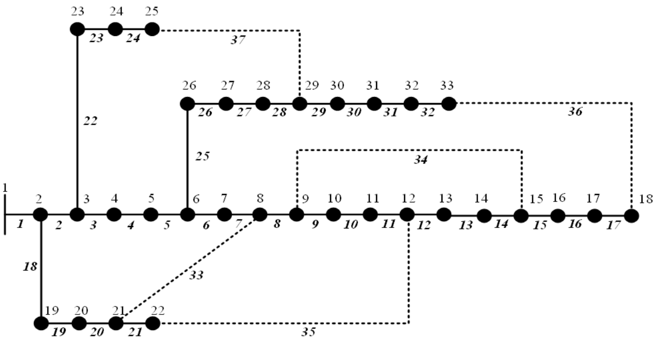

Fig. 1. Single line diagram of the 33-bus system.

Table III and Figure 2 present the simulation results obtained from five optimization algorithms applied to the 33-bus DN. The key indicators evaluated include total power loss (PLoss), CE, GAC, as well as the percentage improvements in ERR and GCS compared to the base case without DG integration. The proposed EMOGWO algorithm consistently outperforms all other methods across all evaluation criteria. It achieves the lowest power loss of 104.91 kW, corresponding to a substantial reduction in system losses compared to PSO (120.85 kW) and RSA (117.43 kW). This improvement is directly associated with its effective siting and sizing of DG units, which are strategically located at buses 7, 18, and 31, a configuration distinct from those selected by most baseline algorithms.

TABLE III. SIMULATION RESULTS ON THE 33-BUS SYSTEM

Method	LDG	PDG (kW)	Ploss (kW)	CE (kg/day)	GAC (USD/day)	ERR (%)	GCS (%)
PSO	6, 14, 30	350, 250, 200	120.85	2,502.30	294.56	35.86	24.52
RSA	6, 18, 32	320, 270, 230	117.43	2,387.10	283.44	38.83	27.37
AOA	7, 15, 31	340, 260, 210	113.26	2,300.70	276.15	41.03	29.26
GWO	6, 14, 30	360, 260, 180	110.18	2,260.20	272.61	42.06	30.15
EMOGWO	7, 18, 31	340, 270, 210	104.91	2,170.40	264.80	44.36	32.16

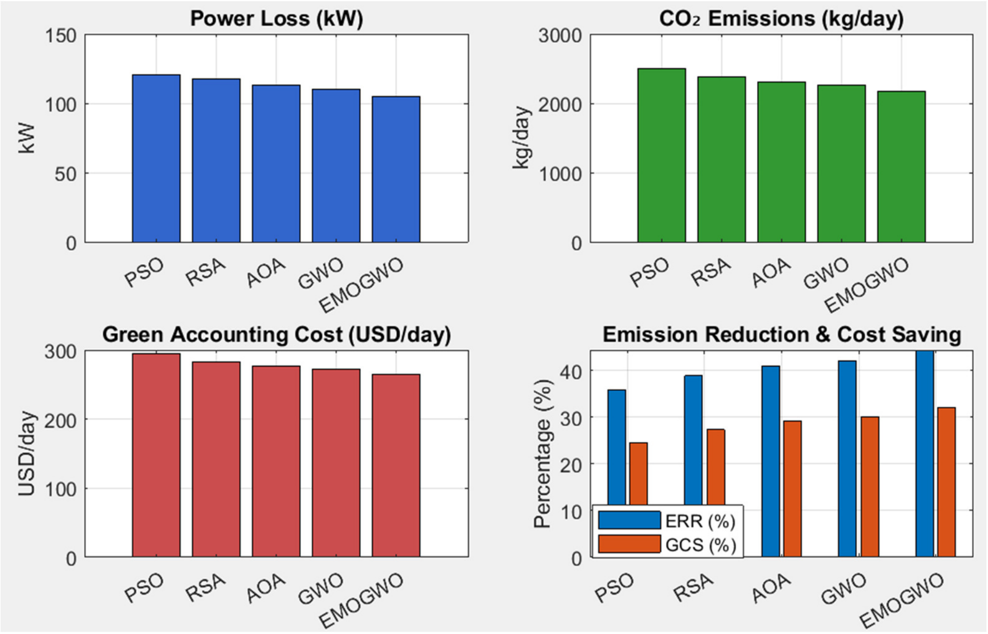

Fig. 2. Comparison of optimization methods on the 33-bus system.

In terms of CE, EMOGWO produces the lowest daily emission level of 2,170.40 kg/day, achieving an ERR of 44.36%, the highest among all methods. For comparison, the second-best performing method (GWO) reaches only 42.06% ERR, whereas PSO lags behind with 35.86%.

EMOGWO also achieves the lowest GAC (264.80 USD/day), corresponding to a 32.16% cost saving, highlighting its balance between technical efficiency and sustainability. Although AOA and RSA perform reasonably well, their savings remain consistently lower. EMOGWO's superior performance stems from its environmentally guided leader selection and adaptive convergence, confirming its suitability for sustainable DG planning in modern DNs.

B. 69-Bus System

Figure 3 shows the single line diagram of the 69-bus DN. It depicts the connections among the main substation, load buses, feeders, and potential sites for renewable integration. The network structure and data are based on trusted sources [10] ensuring consistency in simulation. This configuration provides a robust testbed for evaluating optimization algorithms in reducing power losses and improving voltage profiles in large scale DNs.

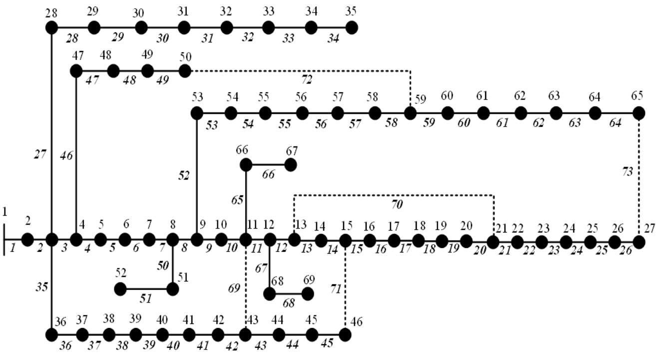

Fig. 3. Single line diagram of the 69-bus system.

Table IV and Figure 4 present the results obtained for the 69-bus, which features a larger and more topologically complex network compared to the 33-bus case. The increased system size introduces greater variability in power flow, loss distribution, and DG allocation challenges, serving as a robust testbed for algorithm evaluation under realistic operational conditions. Across all evaluated metrics, EMOGWO demonstrates superior performance. It achieves the lowest power loss of 114.35 kW, compared to 133.12 kW for PSO and 123.91 kW for AOA. Notably, the loss reduction in this case is more pronounced than in the 33-bus system, highlighting the algorithm's ability to exploit deeper branches and weak voltage zones in larger DNs.

TABLE IV. SIMULATION RESULTS ON THE 69-BUS SYSTEM

Method	LDG	PDG (kW)	Ploss (kW)	CE (kg/day)	GAC (USD/day)	ERR (%)	GCS (%)
PSO	17, 50, 61	450, 320, 280	133.12	2,712.5	317.44	34.74	23.59
RSA	21, 53, 64	440, 330, 290	128.65	2,590.10	305.37	37.65	26.49
AOA	22, 54, 66	460, 310, 300	123.91	2,491.00	298.12	40.03	28.25
GWO	17, 50, 61	460, 330, 270	120.78	2,440.30	292.88	41.26	29.53
EMOGWO	22, 54, 66	450, 320, 300	114.35	2,332.20	283.47	43.86	31.78

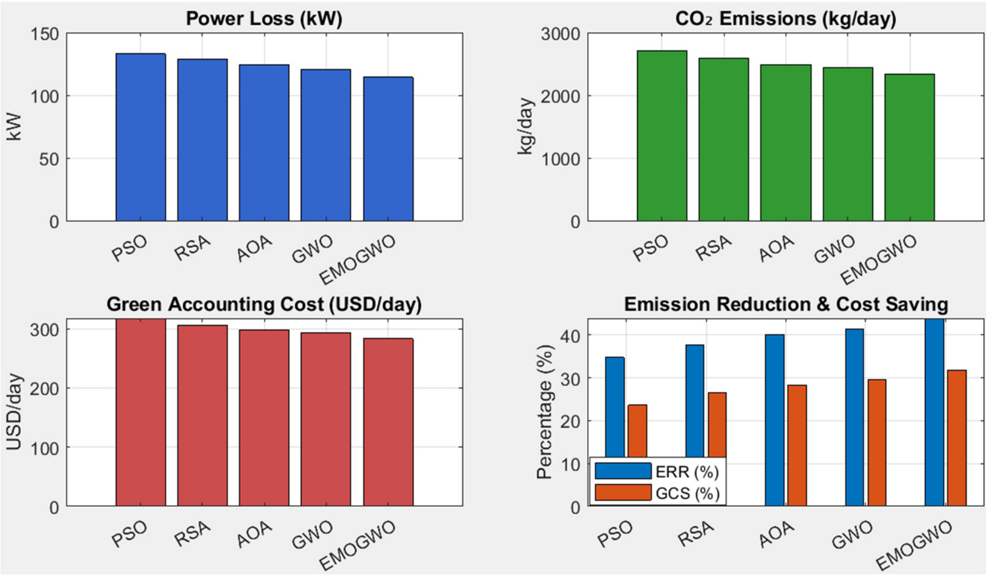

Fig. 4. Comparison of optimization methods on the 69-bus system.

In terms of environmental performance, EMOGWO also yields the lowest daily CE of 2,332.20 kg/day, resulting in the highest ERR of 43.86%. This represents a significant improvement over baseline methods such as PSO (34.74%) and RSA (37.65%), reaffirming the effectiveness of its environmentally guided optimization strategy in larger scale networks.

Regarding GAC, EMOGWO achieves the most economical outcome, reducing daily environmental costs to 283.47 USD/day, which corresponds to a GCS of 31.78% relative to the no-DG scenario. While GWO and AOA show competitive results, their GCS values remain approximately 2–3% lower, suggesting that EMOGWO achieves a better balance between technical and cost-related objectives. Another notable finding is EMOGWO's consistent preference for DG locations at buses 22, 54, and 66, which are deeper points in the network and typically associated with higher losses and voltage drops. In contrast, PSO and GWO often target shallower buses, potentially overlooking optimization opportunities in remote areas.

Overall, the 69-bus results confirm that EMOGWO scales well with network complexity and consistently achieves superior emission and cost outcomes, making it a strong candidate for real world smart grid applications. A brief qualitative sensitivity check shows that increasing the carbon price or adjusting the DG emission factor slightly affects absolute GAC and CE values but does not change the algorithm ranking. EMOGWO consistently maintains top performance, confirming its robustness across different policy scenarios.

V. CONCLUSION

This study proposed a multi-objective optimization framework for Distributed Generation (DG) planning in smart Distribution Networks (DNs), aiming to jointly minimize lifecycle carbon dioxide emissions (CO_2) and Green Accounting Costs (GAC). By integrating environmental impacts directly into the optimization process, the model aligns technical planning with financial and sustainability goals. The enhanced Eco-Aware Multi-Objective Grey Wolf Optimizer (EMOGWO) demonstrated superior performance on the IEEE 33-bus and IEEE 69-bus systems, outperforming Particle Swarm Optimization (PSO), Reptile Search Algorithm (RSA), Arithmetic Optimization Algorithm (AOA), and the standard Grey Wolf Optimizer (GWO) in reducing power loss, emissions, and environmental costs. Results highlight a clear link between CO_2 reduction and financial savings.

From a practical perspective, the framework supports DG investment decisions, enables the integration of carbon pricing into planning, and aligns with Environmental, Social, and Governance (ESG)-driven grid strategies. It provides a useful tool for utilities seeking sustainable and cost-effective solutions. Future work will extend the model to address uncertainties, dynamic pricing, and broader environmental metrics.

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