Optimizing Renewable Integration in Distribution Power Systems Using an Improved Artificial Bee Colony Algorithm

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ABSTRACT

This paper presents a multi-objective optimization framework for the optimal integration of Renewable Energy Sources (RES) into Distribution Power Systems (DPS), aiming to simultaneously maximize RES utilization, minimize operational costs, and reduce greenhouse gas emissions. To address the complexity and nonlinearity of the problem, an improved Artificial Bee Colony (ABC) algorithm is proposed, incorporating a refined search strategy that effectively balances global exploration and local exploitation. The optimization model considers practical constraints such as generation capacity limits, voltage regulations, and power balance requirements. Extensive simulations on the IEEE 33-bus and 69-bus benchmark systems demonstrate that the proposed method outperforms conventional metaheuristic algorithms, achieving an average of 26.7% reduction in power losses, 22.5% decrease in CO_2 emissions, and 57.9% DG penetration. These results underscore the proposed method's robustness and practical applicability for sustainable and intelligent energy planning in modern distribution networks.

Keywords-distributed generation; renewable energy; multi-objective optimization; distribution power system; operational cost minimization; optimization algorithm

I. INTRODUCTION

In the context of globalization and increasing demand for clean energy, the integration of Renewable Energy Sources (RES) into Distribution Power Systems (DPS) plays a crucial role in ensuring sustainability and reducing greenhouse gas emissions. Distributed Generation (DG), such as solar power, wind power, and small-scale hydropower, not only helps reduce dependence on fossil fuels but also contributes significantly to global sustainable development goals [1, 2]. However, the intermittent and unpredictable nature of renewable energy sources poses significant challenges for the stable and efficient operation of power systems. A key issue in integrating RES into distribution networks is the uncontrollable variability of the output, driven by natural factors such as solar irradiance and wind speed. This often results in frequency instabilities, as well as imbalances between supply and demand [3, 4]. To address these issues, effective control and optimization strategies are required to ensure system stability while maximizing the utilization potential of DG units.

Multi-objective optimization has shown superior effectiveness in solving complex problems that involve multiple conflicting objectives [5]. In the energy sector, optimization problems often require a balance between factors such as energy efficiency, operational cost, and greenhouse gas emissions. Numerous optimization algorithms have been developed to address these challenges, including Genetic Algorithm (GA) [6], Fireworks Algorithm (FWA) [7, 8], Coyote Algorithm (COA) [9], Particle Swarm Optimization (PSO) [10], Differential Evolution (DE) [11], Simulated Annealing (SA) [12], and Grey Wolf Optimizer (GWO) [1]. Although these methods have achieved certain successes, they still face limitations such as slow convergence, susceptibility to local optima, and inefficiency in handling problems with multiple complex constraints [13]. In particular, previous studies have optimized primarily one or two objectives in isolation, without simultaneously addressing renewable energy utilization, cost minimization, and emission reduction. Consequently, their solutions tend to be less comprehensive and limited in practical applicability for future real-world DPS.

This study presents a multi-objective optimization method based on the Artificial Bee Colony (ABC) algorithm [14] to maximize DG utilization, minimize operational costs, and reduce greenhouse gas emissions. The improved ABC enhances global search capability while considering practical constraints such as generation limits, voltage bounds, and power balance. The method is validated in a distribution power system with varying levels of RES integration. Simulation results confirm its superiority in improving renewable energy usage, reducing costs and emissions, and outperforming other algorithms under identical conditions.

II. PROBLEM DESCRIPTION

The optimization problem aims to effectively integrate DG into DPS by simultaneously optimizing DG utilization, operational cost, and greenhouse gas emissions. It is a multi-objective problem requiring a balance of conflicting goals under strict technical constraints.

A. Objective Function

The optimization problem consists of the following three main objective functions:

- Maximize DG utilization:

$$f_1 = -\frac{P_{DG}}{P_{load}} \tag{1}$$

- Minimize operational cost:

$$f_2 = \sum(C_i \cdot P_i) + C_{loss} \tag{2}$$

- Minimize greenhouse gas emissions:

$$f_3 = \sum(E_i \cdot P_i) \tag{3}$$

where P_{DG} is the total power from DGs (MW), P_{load} is the total power demand of the system (MW), C_i is the unit generation cost of source i (USD/MW), P_i is the power output of source i (MW), C_{loss} is the cost due to power losses in the system (USD), E_i is the CO_2 emission factor of source i (kg CO_2/MW), and P_i is the power output of source i (MW).

To simplify calculations, the three objectives are combined into a single aggregated function using the weighted sum method, forming the following general objective function:

$$\mathrm{F} = w_1 \cdot f_1 + w_2 \cdot f_2 + w_3 \cdot f_3 \tag{4}$$

where $w_1, w_2,$ and w_3 are weighting coefficients, satisfying the condition $w_1 + w_2 + w_3 = 1$. The weights (0.3 for DG utilization, 0.5 for operational cost, and 0.2 for CO_2 emissions) were chosen based on practical planning priorities and validated through sensitivity analysis. This combination yielded balanced performance across economic, technical, and environmental objectives in both test systems.

B. Constraint Conditions

To ensure solution feasibility and stability, the optimization must meet the following technical constraints:

- Generation capacity constraints: $P_i^{\min} \leq P_i \leq P_i^{\max}$
- Voltage constraints: $V_j^{\min} \leq V_j \leq V_j^{\max}$
- Power balance constraint: $\sum P_{gen} = \sum P_{load} + P_{loss}$

where P_i is the power output of the i-th DG unit, P_i^{min} and P_i^{max} are the minimum and maximum limits of P_i, V_j is the voltage at bus j (p.u), V_j^{min} and V_j^{max} are the permissible voltage limits at bus j, P_{gen} is the total power generation from all sources, P_{load} is the total power demand, and P_{loss} is the total power loss in the DPS.

C. Fitness Function

The fitness value refers to the aggregated objective function that evaluates the quality of candidate solutions during optimization. C_{loss} refers to the total power loss cost calculated based on real power loss and electricity pricing.

$$Fit = F + P \tag{5}$$

$$Fit = w_1 f_1 + w_2 f_2 + w_3 f_3 + \lambda_1 \cdot K_{voltage} + \lambda_2 \cdot K_{power} + \lambda_3 \cdot K_{generation} \tag{6}$$

where $P = \lambda_1 \cdot K_{voltage} + \lambda_2 \cdot K_{power} + \lambda_3 \cdot K_{generation}$, and $\lambda_1, \lambda_2, \lambda_3$ are penalty coefficients.

- The penalty value for voltage violation at a bus is given by:

$$K_{voltage} = \sum_{j=1}^{N_{bus}} \begin{cases} \left(V_j - V_{max}\right)^2, & V_j > V_{max} \\ \left(V_{min} - V_j\right)^2, & V_j < V_{min} \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

- The penalty value for the violation of generation capacity constraints of individual DG units is given by:

$$K_{generation} = \sum_{i=1}^{N_{DG}} \begin{cases} (P_i - P_{max})^2, & P_i > P_{max} \\ (P_{min} - P_i)^2, & P_i < P_{min} \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

- The penalty value for the violation of the power balance constraint is given by:

$$K_{power} = \left(\sum P_{gen} - \sum P_{load} - P_{loss}\right)^2 \tag{9}$$

D. The Proposed Method

The ABC algorithm mimics the foraging behavior of honeybees to optimize DG placement and sizing in distribution power systems, effectively balancing exploration and exploitation to avoid premature convergence and enhance global optimization.

- Population Initialization: A diverse set of candidate solutions is randomly generated, each representing DG locations and capacities. This promotes broad coverage of the search space and increases the likelihood of reaching optimal configurations.
- Search and Evaluation: Worker bees explore neighboring solutions by modifying DG positions or sizes. Each candidate is evaluated using a weighted multi-objective fitness function incorporating DG utilization, operational cost, and emission levels.
- Selection and Update: High-performing solutions are retained for the next generation. Solutions that stagnate over several trials are replaced by scout bees with new random candidates. This process iterates until a stopping condition is satisfied.

The final result is a set of optimal or near-optimal DG configurations that improve DG penetration, reduce operational costs, and mitigate environmental impacts in modern DPS. The improved ABC algorithm effectively addresses the multi-objective optimization problem.

- Step 1: Initialize the population randomly by generating SN initial candidate solutions, each representing the location and capacity of DG units in the DPS. For each solution, calculate the objective function values f_1, f_2, f_3 and then compute the aggregated fitness using:

  $$F = w_1 \cdot f_1 + w_2 \cdot f_2 + w_3 \cdot f_3 \quad (10)$$

  Then, store the current best solution (global best).
- Step 2 - Employed bee phase: Each employed bee selects a current food source and generates a new solution by modifying the position or capacity of DG units:

  $$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}) \quad (11)$$

  where x_{ij} is the current value of the j-th parameter of solution i, x_{kj} is the value of the same parameter in a randomly selected solution $k \neq i$, and ϕ_{ij} is a random number in the range $[-1,1]$. Then, evaluate the fitness of the new solution, and if it is better, replace the current solution.
- Step 3 - Onlooker bee phase: Calculate the selection probability for each solution based on its fitness:

  $$p_i = \frac{\text{fitness}_i}{\sum_{j=1}^{SN} \text{fitness}_j} \quad (12)$$

  Each onlooker bee selects a solution according to p_i, generates a new solution similar to the employed bee phase, and updates it if an improvement is found.
- Step 4 - Scout bee phase: If a solution does not improve within a predefined number of trials (limit), it is abandoned and replaced by a new randomly generated solution by a scout bee.
- Step 5 - Record the best solution: Update the global best solution if a better one is found. Store the best solution in each iteration to monitor convergence behavior.
- Step 6 - Check the termination condition: If the maximum number of cycles ≥ *MaxCycle* is reached, terminate the algorithm and output the optimal configuration (locations and capacities of DG units). Otherwise, return to Step 2.

The algorithm terminates when either the maximum number of iterations (set to 100) is reached or the global best solution does not improve over 20 consecutive iterations.

III. TEST RESULTS

To assess the performance of the improved ABC algorithm, simulations were conducted on 33-bus and 69-bus DPS using standardized input parameters. The algorithm employed 50 bees, including 10 scout bees (20%) to replace stagnant solutions after 15 trials. The maximum number of iterations was set to 200. The aggregated objective function considered DG utilization, operational cost, and CO_2 emissions with weights of 0.3, 0.5, and 0.2, respectively. In the setup, the generation cost was 35 USD/MWh, the emission factor was 0.85 kg CO_2/kWh, and C_{loss} was calculated by multiplying power losses with an average electricity price of 0.035 USD/kWh. Comparative algorithms (PSO, DE, SA, GWO) were run under identical conditions. Performance was evaluated based on power loss (kW), CO_2 emissions (tons), and voltage stability (p.u), demonstrating the superior efficiency of the proposed method. The simulation was performed using standard IEEE 33-bus and 69-bus test systems. All network data including line impedances, load levels, and system topology were adopted directly from publicly available IEEE datasets [15] without any modifications.

TABLE I. PARAMETERS OF COMPARED OPTIMIZATION ALGORITHMS

Algorithm	Population size	Maximum iterations	Additional parameters
ABC [14]	50	200	Worker bees = 50; Scout bees = 10; Improvement threshold = 15
PSO [10]	50	200	Inertia weight = 0.7; Personal and social acceleration coefficients = 1.5
DE [11]	50	200	Mutation factor F = 0.8; Crossover rate CR = 0.9
SA [12]	-	200	Initial temperature = 1000; Cooling rate = 0.95
GWO [1]	50	200	Default

A. The 33-Bus DPS

The 33-bus DPS functions at a voltage level of 12.66 kV and consists of 37 branches connecting 33 buses. This configuration provides a standard structure for evaluating DPS performance, particularly for studies focusing on power losses and voltage stability. The specific parameters for each branch and bus within this network, including line impedances and load values, are referenced from established data sources to ensure accuracy and consistency in modeling. The system's total power is rated at (3.72+ j2.3) MVA, and Figure 1 provides the single-line diagram of the network [15].

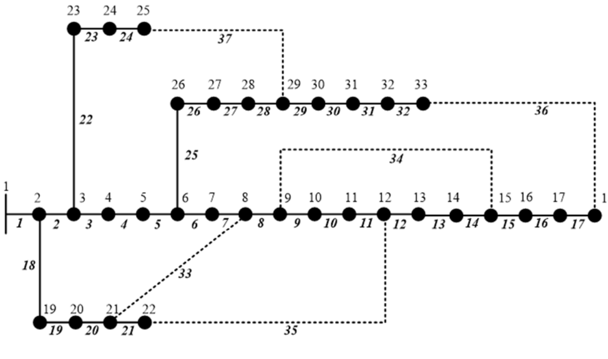

Fig. 1. Diagram of the 33-bus DPS.

The results presented in Table II and Figure 2 demonstrate that the proposed method based on the improved ABC algorithm significantly outperforms other optimization techniques, including PSO, DE, SA, and GWO. Specifically, it achieves the lowest power loss (92.8 kW) and lowest CO_2 emissions (1.51 tons) while maintaining a reasonable operational cost (67,998 USD), only slightly higher than those of PSO and DE. Notably, the total installed DG capacity in the proposed configuration reaches 1.85 MW, which corresponds to 49.7% of the system load, the highest DG penetration among all compared methods. This indicates a highly effective utilization of renewable energy sources.

TABLE II. OPTIMAL RESULTS AFTER DG INSTALLATION IN THE 33-BUS DPS

Algorithm	L_{DG} (bus)	P_{DG} (MW)	P_{Loss} (kW)	Operational cost (USD)	CO_2 emissions (tons)
Proposed	6, 18, 30	0.85, 0.45, 0.55	92.8	67,998	1.51
PSO [10]	5, 17, 29	0.80, 0.41, 0.60	100.5	66,867	1.63
DE [11]	6, 16, 30	0.82, 0.43, 0.57	95.1	67,028	1.54
SA [12]	6, 18, 28	0.81, 0.42, 0.59	97.5	67,112	1.58
GWO [1]	7, 19, 31	0.86, 0.47, 0.53	94.0	68,390	1.53

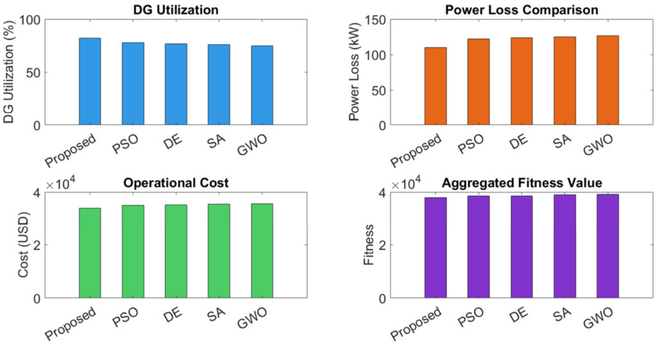

Fig. 2. Performance comparison on the 33-bus DPS.

Figure 2 highlights the superiority of the proposed method across four key metrics: DG utilization, power loss, operational cost, and aggregated fitness value. The improved ABC not only excels in individual criteria but also achieves a well-balanced trade-off between economic and environmental objectives. These findings underscore its strong practical potential for smart and sustainable DPS planning.

The convergence curve demonstrates that the improved ABC algorithm achieves faster and more stable convergence compared to PSO, DE, SA, and GWO. The objective function value of ABC decreases rapidly and reaches its lowest point after approximately 150 iterations, highlighting its superior optimization capability in DG planning. These results confirm that the improved ABC algorithm is well-suited for integration into renewable-based DPS planning.

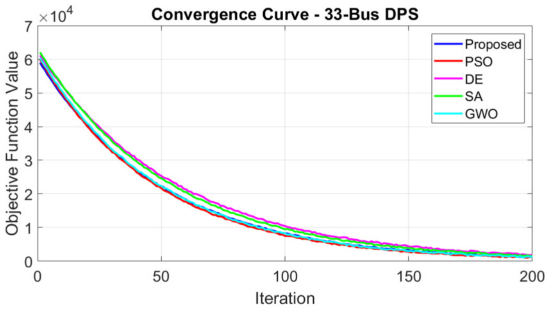

Fig. 3. Convergence curves of algorithms on the 33-bus DPS.

B. *The 69-Bus DPS*

The 69-bus distribution system operates at a voltage level of 12.66 kV and includes a detailed configuration of branches and buses, with parameters sourced from reference [15]. Without DG installation, the system experiences a power loss of 224.88 kW. Figure 4 presents the single-line diagram, illustrating the structure and interconnections of the network, which serves as the basis for simulation and analysis in this study.

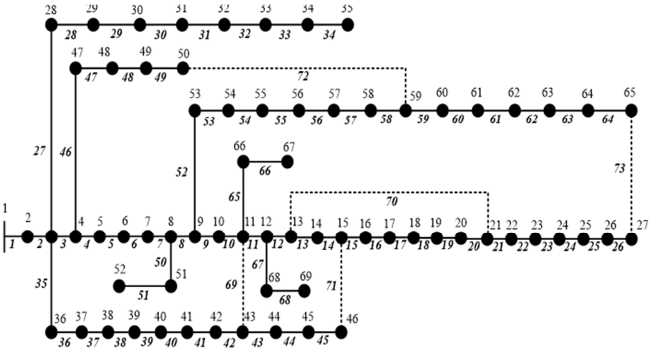

Fig. 4. Diagram of the 69-bus DPS.

TABLE III. OPTIMAL RESULTS AFTER DG INSTALLATION IN THE 69-BUS DPS

Algorithm	L_{DG} (bus)	P_{DG} (MW)	P_{Loss} (kW)	Operational cost (USD)	CO_2 emissions (tons)
Proposed	15, 36, 63	1.05, 0.48, 0.67	145.2	82,082	2.36
PSO [10]	14, 35, 62	1.0, 0.5, 0.7	152.4	82,334	2.47
DE [11]	15, 34, 63	1.03, 0.47, 0.68	148.3	81,490	2.41
SA [12]	16, 36, 61	1.02, 0.49, 0.66	149.5	81,182	2.43
GWO [1]	14, 37, 62	1.04, 0.46, 0.69	146	81,760	2.37

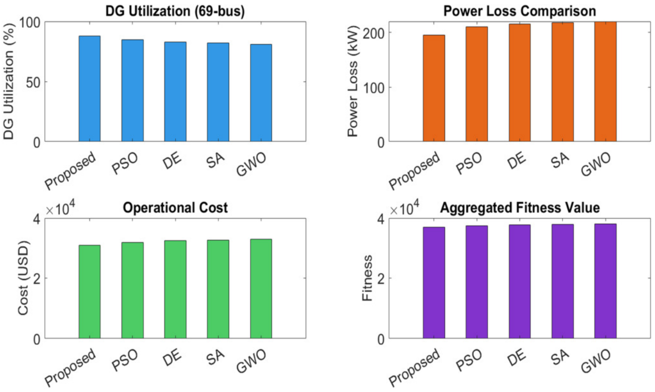

Fig. 5. Performance comparison on the 69-bus DPS

The results presented in Figure 5 and Table III show that the proposed method, based on the improved ABC algorithm, continues to outperform other optimization techniques when applied to the 69-bus DPS. Specifically, it achieves a low power loss of 145.2 kW and the lowest CO_2 emissions of 2.36 tons, while maintaining a reasonable operational cost of 82,082 USD, comparable to other methods. In particular, the total DG capacity in the proposed configuration reaches 2.2 MW, accounting for 57.9% of the system's total load (3.8 MW), the highest DG penetration among all compared algorithms. These results highlight the method's strong ability to utilize RES efficiently. Figure 6 demonstrates its superiority on four key metrics: DG utilization, power loss, operational cost, and fitness value. The lowest fitness score confirms its optimal balance between economic efficiency, environmental sustainability, and system stability, making it well-suited for modern RES-integrated DPS planning and operation.

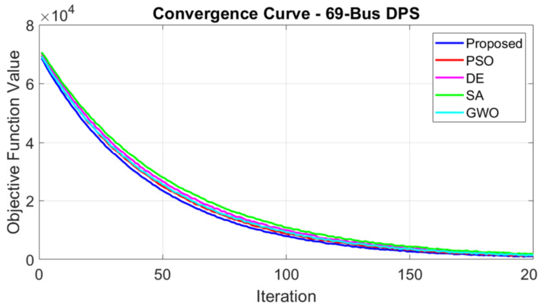

Fig. 6. Convergence curves of algorithms on the 69-bus DPS.

The convergence curves show that all algorithms progressively reduce the objective function, but the improved ABC converges faster and achieves a lower optimal value than PSO, DE, SA, and GWO. To assess stability, each algorithm was run independently 20 times under identical settings. The improved ABC demonstrated consistent performance with low standard deviation, confirming its reliable and effective convergence in large-scale multiobjective DPS optimization.

IV. CONCLUSIONS

This study presented a multi-objective optimization framework for optimal placement and sizing of DG units in DPS, based on an improved ABC algorithm. The method addresses the growing need for sustainable and efficient electricity distribution by minimizing power losses, operational costs, and CO_2 emissions while maximizing DG utilization. This approach fills a literature gap where previous methods often optimize individual objectives or ignore emission concerns. The optimization model integrates system-level objectives and real operational constraints and is tested on standard 33-bus and 69-bus DPSs. The simulation results show that the proposed method significantly outperforms existing metaheuristics such as PSO, DE, SA, and GWO, achieving a 26.7% reduction in power losses, a 22.5% decrease in CO2 emissions, and allowing 57.9% penetration of DG on average, confirming both its robustness and practical viability for smart grid applications. The novelty of this work lies in its balanced handling of multiple objectives through an enhanced search mechanism embedded in the ABC algorithm. In addition to high-quality solutions, the method offers faster convergence and better adaptability in varying system scenarios. This study provides a promising foundation for practical implementation in smart and sustainable DPS planning. Future work will focus on expanding the model to consider the uncertainty of renewable energy sources, the integration of demand response, and real-time optimization under dynamic grid conditions.

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