FOREX Publication
Open Access | Rapid and quality publishing
International Journal of
Electrical and Electronics Research (IJEER)
Research Article | Volume 13, Issue 4 | Pages 852-860 | e-ISSN: 2347-470X

Multi-Objective Optimal Planning of DG and FACTS in Radial Distribution Systems *via* Arithmetic Optimization Algorithm

Shridevi Akkewar[1*], Rajendra Dhatrak[2]
[1,2]Department of Electrical Engineering, Rajiv Gandhi College of Engineering, Research and Technology, Chandrapur, Maharashtra, India

*__Correspondence:__ *Shridevi Akkewar*, Email: *shhrideviakkewar3251@gmail.com*

ABSTRACT- Optimal planning of Distributed Generation (DG) units and Flexible AC Transmission System (FACTS) devices is crucial for improving the efficiency, reliability, and sustainability of radial distribution networks. With increasing renewable integration and rising power system complexity, advanced optimization methods are necessary to reduce power losses, enhance voltage profiles, and ensure operational resilience. This study presents a Multi-Objective DG-FACTS Planning (MODF) approach using the Arithmetic Optimization Algorithm (AOA), which leverages basic arithmetic operators for effective global search and rapid convergence. The proposed MODF-AOA overcomes common issues in conventional meta-heuristics, such as premature convergence and local optima trapping. It simultaneously targets real power loss minimization and voltage profile improvement under dynamic load scenarios. The method is validated on the IEEE 33 bus test system, incorporating solar-based DG units and Static VAR Compensators (SVCs). Simulation results highlight that MODF-AOA significantly boosts system performance, achieving up to 36% power loss reduction and around 22% voltage profile improvement compared to traditional techniques, including the Genetic Algorithm (GA). These results confirm the proposed approach's superiority and suitability for smart, renewable-integrated distribution networks.

Keywords: Distributed Generation, Flexible AC Transmission System, Radial Distribution Grid, Static VAR Compensator, Power Loss Reduction, Voltage Stability, Renewable Energy Integration.

ARTICLE INFORMATION
Author(s): Shridevi Akkewar, Rajendra Dhatrak;
Received: 10/07/2025; **Accepted:** 22/11/2025; **Published:** 25/12/2025;
E- ISSN: 2347-470X;
Paper Id: IJEER 1007-06;
Citation: 10.37391/ijeer.130425
Webpage-link:
https://ijeer.forexjournal.co.in/archive/volume-13/ijeer-130325.html

Publisher's Note: FOREX Publication stays neutral with regard to jurisdictional claims in Published maps and institutional affiliations.

1. INTRODUCTION

The global shift toward sustainable energy has significantly increased the share of renewables in power generation, with solar PV and wind surpassing fossil fuels and contributing over 90% of recent capacity additions [1]. Investments in distributed generation (DG) technologies, including solar, wind, and battery storage, reached over $250 billion in 2021, driven by energy security, economic, and environmental benefits [2]. IRENA projects DG capacity to double by 2030 due to policy support, falling costs, and technological advancements [3], [4]. While DG offers advantages such as reduced power losses, enhanced voltage profiles, and improved system resilience, it also presents challenges in planning and integration [5], [6]. Studies show that well-planned DG placement can lower distribution losses by up to 30% [6], boost voltage stability, and improve grid reliability under extreme conditions [7], [8]. DG also offers operational benefits like reduced emissions, better asset utilization, and lower operating costs [9]. However, their variable output complicates integration into traditional grids [10], [11]. Flexible AC Transmission System (FACTS) devices, especially Static VAR Compensators (SVCs), help manage reactive power and stabilize voltages [12]. Therefore, optimal placement and sizing of DG and FACTS in radial networks are essential to ensure efficient and reliable operation [13]. *Figure 1* presents a conceptual framework for integrating Distributed Generation (DG) and FACTS devices within radial distribution networks. It highlights two core components: Optimization Strategies including siting and sizing of DG units and FACTS devices like Static VAR Compensators (SVCs) and Optimization Objectives, such as minimizing power losses, enhancing voltage profiles, and improving grid resilience. This structure emphasizes the interconnected nature of decision-making in network planning and supports the development of advanced frameworks like the proposed MODF-AOA. Optimally placing and sizing DG and FACTS devices is complex due to the non-linear nature of power flow equations, mixed-integer variables, multiple conflicting objectives, and system constraints. Additionally, the variability of renewable DG sources increases planning complexity. Despite growing interest, only a small portion of existing studies around 8% address simultaneous DG-FACTS placement [15]. Moreover, conventional algorithms often suffer from premature convergence and limited scalability. Quantum-behaved PSO variants remain underexplored, leading to excessive exploration and less effective solutions.

FOREX Publication
Open Access | Rapid and quality publishing
International Journal of
Electrical and Electronics Research (IJEER)
Research Article | Volume 13, Issue 4 | Pages 852-860 | e-ISSN: 2347-470X

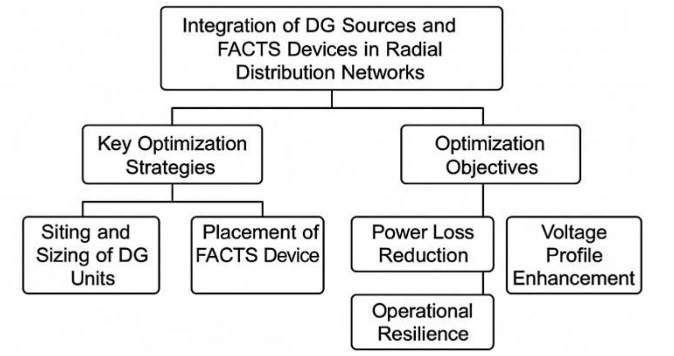

Figure 1. Key optimization strategies and objectives in the integration of DG sources and FACTS devices in radial distribution networks

Unlike conventional AOA-based applications, the proposed MODF-AOA introduces a multi-objective formulation that simultaneously addresses power loss reduction, voltage profile enhancement, and emission minimization under realistic network constraints. It integrates Pareto-front identification, constraint handling, and comparative benchmarking against three advanced metaheuristics, which has not been jointly explored in existing AOA studies for DG and FACTS planning.

MODF-AOA is unique because it combines the Arithmetic Optimization Algorithm (AOA) with sophisticated search strategies including simulated annealing and adaptive parameter tuning for multi-objective power system optimization. MODF-AOA dynamically balances exploration and exploitation, resulting in faster convergence and better solutions than regular AOA or other metaheuristics. It increases variety and prevents convergence with a fitness-distance balancing mechanism and adaptive mutation. Due to lower power loss, lower emissions, and improved Pareto fronts, MODF-AOA better meets economic and emission goals with these adjustments. On bigger, imbalanced IEEE test systems, the algorithm proves its stability, scalability, and usefulness for real-world distribution networks.

2. LITERATURE SURVEY

The integration of Distributed Generation (DG) and Flexible AC Transmission System (FACTS) devices into radial distribution networks has gained substantial attention over the past two decades. The growing penetration of renewable sources like solar and wind, along with the need for improved power quality and reliability, demands advanced planning strategies. Traditional unidirectional networks face voltage deviations, overloading, and increased losses due to the variability of renewable DGs. FACTS devices, particularly Static VAR Compensators (SVCs), are effective in reactive power management and voltage stabilization. Thus, coordinated DG-FACTS planning is crucial for enhancing grid resilience. In [16], a Genetic Quantum-Behaved PSO was proposed to improve Location Dependent Services in healthcare applications. In [17], an Improved QPSO method was used for MPPT in solar systems, achieving faster and more accurate tracking. The study in [18] optimized power allocation in 33- and 69-bus systems using fuzzy clustering and slime mold algorithms. Existing methods often suffer from premature convergence, limited scalability, and inadequate handling of realistic constraints. To address these gaps, the proposed MODF-AOA framework leverages AOA's strong exploration–exploitation balance, ensuring robust, constraint-aware DG-FACTS planning suitable for smart grids [20]–[24].According to research [25], the integration of distributed generation in smart distribution networks is formulated as a multi-objective optimization problem with the goal of reducing emissions and green accounting expenses. On IEEE test systems, EMOGWO achieves the lowest prices, greater power loss reduction, and better voltage stability than PSO, RSA, and AOA. This is the reason why EMOGWO is superior than these other algorithms. The study, on the other hand, is constrained by assumptions of static load, requirements of perfect information, and scalability that has not been verified to bigger networks in the actual world.

This paper [26] proposes a mathematical operator–enhanced arithmetic optimization algorithm (MAOA) to improve the exploration–exploitation balance of the AOA algorithm for engineering optimization tasks. When it comes to accuracy and convergence speed, MAOA beats typical metaheuristics, as demonstrated by its performance in power system and communication applications. The resilience and scalability of the system are validated by experiments on benchmark challenges. The evaluations, on the other hand, continue to be restricted to benchmark datasets; there is no testing conducted in the actual world, and the algorithm's performance under conditions that are dynamic or time-varying is not investigated. The model optimizes distribution network DG and FACTS placement using multi-objective optimization. Real and reactive power losses, bus voltages, load demands, DG outputs, and system parameters are defined. We aim to minimize power loss, emission (using the emission factor), and voltage departure from the reference value. Key limitations ensure actual and reactive power balance, voltage, DG capacity, and branch current limits. All parameters use kW, kVAR, and per-unit voltage. The concept enables rigorous, transparent, and reproducible distribution system optimization.

The proposed MODF-AOA framework aims to enhance distribution system planning by optimizing DG and FACTS placement through multi-objective Optimization:

- To reduce real power losses in radial distribution systems by optimally placing and sizing DG units as well as FACTS devices.
  - ➢ To minimize power loss $min \sum_{i=1}^{M} P_{loss,i}$ where $P_{loss,i}$ is the real power loss in branch i.
- To improve voltage profile stability under varying load conditions by integrating appropriate DGs and FACTS controllers' combinations.
  - ➢ To minimize voltage deviation $min \sum_{j=1}^{N} |V_j - V_{ref}|$ where V_j is the voltage bus j and V_{ref} is the reference voltage.
- To develop and implement a robust MODF-AOA using the Arithmetic Optimization Algorithm, which ensures fast convergence and strong global search capabilities while overcoming the drawbacks of traditional metaheuristics.

- $X_{new} = X_{best} + \alpha.(X_{rand} - X_{current})$ where X_{best} is the best solution, X_{rand} is randomly selected solution, $X_{current}$ is the current solution, α is an adaptive parameter.

- To simulate the performance of the MODF-AOA framework on an IEEE 33-bus distribution system and compare it to PSO, QPSO, and GA in terms of power loss reduction and voltage stability enhancement.

To allocate DG and FACTS efficiently, the mathematical model includes operational restrictions. Power balance is achieved by balancing actual and reactive power generation with load demand and network losses. All bus voltages must be within limitations $V_{min} \leq V_j \leq V_{max}$ to provide stability. To ensure proper operation, DG units must operate within their rated real and reactive power capacity limits $P_{DG}^{min} \leq P_{DG,k} \leq P_{DG}^{max}$ and $Q_{DG}^{min} \leq Q_{DG,k} \leq Q_{DG}^{max}$ Additionally, thermal constraints limit branch currents $(I_i \leq I_i^{max})$, reducing overload and guaranteeing distribution system safety.

3. POWER FLOW ANALYSIS AND OBJECTIVE FUNCTION

The IEEE 33-bus system utilizes the Backward/Forward Sweep Method for efficient power flow computation and numerical stability, as Power Flow Analysis is a crucial module in the Arithmetic Optimization Algorithm-driven DG-FACTS planning framework. The power flow process is a methodology that involves two iterative steps.

$$V_j = V_i - Z_{ij} \cdot I_{ij} \tag{1}$$

In *equation 1*, V_i, V_i is the Voltages at sending and receiving buses $(i \ to \ j)$, Z_{ij} Line impedance between bus i as well as j,I_{ij} is the Branch current from bus $i \ to \ j$. The forward sweep (Voltage Update) process updates bus voltages by calculating line impedance and branch currents.

$$I_{ij} = I_j + \sum_{k \in K_j} I_{jk} \tag{2}$$

In *equation 2*, $I_j$is the Load current at bus *j*, $K_j$is the Set of buses associated downstream to bus *j*, and *I_jk* is the Currents from *j* to its children k. The backward sweep (current update) is a step that calculates the total branch currents based on load currents and downstream branch currents.

- **Objective Function 1**: Power Loss Minimization

Minimize active power loss across all distribution network branches. Branch current square and branch resistance directly affect power loss.

$$f_1(x) = \min(P_{loss}) = \min\left(\sum_{i=1}^{N_{branch}} R_i \, . |I_i|^2\right) \tag{3}$$

In *equation 3*, $f_1(x)$) is the objective function value representing the total number of power loss, $N_{branch}$is denoted as the total number of branches in the network, R_i is the resistance of the i^th Branch, $|I_i|$is the Magnitude of current in the *i^th* Branch.

- **Objective Function 2**: Voltage Stability Index (VSI) Maximization

$$f_2(x) = \max(VSI) = \max\left(\min_{i=2} N_{bus}\left(1 - \frac{4Z_{eq,i} \cdot S_i}{V_1^2}\right)\right) \tag{4}$$

In *equation 4*, $f_2(x)$ is the Objective function value representing the worst-case (minimum) VSI, which is to be maximized, N_{bus} is denoted as the bus total number in the system, $Z_{eq,i}$ is denoted as the Equivalent impedance from the reference/source bus to bus *i*, S_i is denoted as the Complex power demand at bus *i*, V_i is denoted as the Voltage magnitude at the reference (slack) bus.

3.1.1. Pareto Front Identification

Multi-objective optimization problems often have conflicting aims, resulting in several optimal solutions. Each solution on the Pareto Front is non-dominated, meaning no other option is better in all objectives. Non-dominated sorting is a method that categorizes solutions into different Pareto fronts based on their dominance relations.

$$\left.\begin{array}{ll} \forall_i \in \{1,2\}, & f_i(p) \leq f_i(q) \\ \exists_j \in \{1,2\}, & f_j(p) < f_i(q) \end{array}\right\} \tag{5}$$

In *equation 5*, *p* outperforms *q*, and it is a superior solution in all objectives and better in at least one. Undominated solutions constitute the initial Pareto front. Crowding distance is a method used in evolutionary algorithms to maintain diversity in the Pareto front when selecting non-dominated solutions.

$$CD_i = \sum_{m=1}^{M} \frac{f_m^{i+1} - f_m^{i-1}}{f_m^{max} - f_m^{min}} \tag{6}$$

In *equation 6*, CD_i is the denoted as Crowding distance of the *i^th* solution, M is denoted as the Number of objective functions, $f_m^{i+1}, f_m^{i-1}$is denoted as the Objective values of neighboring solutions in sorted list for the *m^th* objective, $f_m^{max} - f_m^{min}$ is denoted as the Max and min values of the *m^th* objective in the current front.

3.2. Constraint Checking Process

The AOA optimizes DG and FACTS placement. Systematic constraint evaluation and management are required. AOA algorithm-generated candidate solutions are the first population of DG and FACTS deployment configurations. In *figure 2*, Constraint checking determines if each candidate solution meets technical limitations such as voltage limits at all buses, thermal capacity limits of lines, power factor requirements, equipment sizing bounds, and network radial configuration preservation. The diamond-shaped "Feasible?" decision point guides solutions based on their limits. The top path (feasible answers) and lower path (infeasible solutions) are determined *via* branching logic. Solving all constraints sends solutions to the AOA update process for objective function evaluation. Solutions that fail in limitations are remedied. Constraint violation handling corrects solutions to meet constraints. The penalty function approach constrains optimization without abandoning genetic information by reducing infeasible solution fitness according to violation severity. By optimizing DG and FACTS placements, the AOA update ensures that the optimization algorithm finds technically viable solutions while effectively exploring the solution space.

FOREX Publication
Open Access | Rapid and quality publishing

International Journal of
Electrical and Electronics Research (IJEER)
Research Article | Volume 13, Issue 4 | Pages 852-860 | e-ISSN: 2347-470X

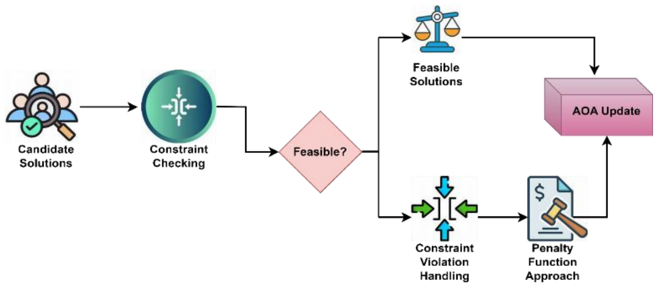

Figure 2. Constraint Checking Process

3.2.1. AOA Update

The AOA is a metaheuristic that uses arithmetic operations to explore and exploit search spaces. It updates candidate solutions' positions through a probabilistic switch between exploration and exploitation, regulated by the control parameter MOA (Math Optimizer Accelerated).

$$X_i^{t+1} = X_i^t \pm r_1 \cdot rand \cdot (X_{best}^t - r_2 \cdot X_i^t) \tag{7}$$

$$X_i^{t+1} = X_i^t \times \left(1 + r_3 \cdot \frac{X_{best}^t}{X_i^t + \epsilon}\right) \tag{8}$$

In *equation 7* and *8*, X_i^t is denoted as the Position of the i^{th} solution at iteration t, X_{best}^t is denoted as the Best solution found so far, r_1, r_2, r_3 is the Random numbers in [0,1], ϵ is A small constant to prevent division by zero, $rand$ is the Random number for exploration-exploitation switching, and MOA is denoted as the Control parameter (increases over time to shift from exploration to exploitation).

3.2.1.1. Pseudocode: AOA-Based DG-FACTS

Input:

- *Network data:* $Z_{i,j}$ *(line impedances),* R_i *(branch resistances),* N_{bus}, N_{branch}
- *Load data:* S_i *(complex power demands)*
- *Algorithm parameters* $MaxIter, PopSize, \alpha, \mu$
- *Constraints:* $V_{min}, V_{max}, S_{line}^{max}$*, DG/FACTS bounds*

Output:

- *Pareto Front solutions: optimal DG and FACTS placements*
- *Objective values:* $f_1(x)$ *(power loss),* $f_2(x)$ *(VSI)*

Algorithm

1. *Initialize population:* $X_i^0 \in \mathbb{R}^{PopSize\ X\ Dim}$ *(DG/FACTS configurations)*
2. *Set* $set\ t = 0, x_{best} = \emptyset, ParetoFont = \emptyset$
3. *for* $t = 1$ *to* $MaxIter$ *do*
4. $MOA(t) = min\left(1, \frac{1}{MaxIter}\right) + t.\frac{1}{MaxIter}$
5. *for* $i = 1$ *to PopSize do*
6. *Run Backward/Forward Sweep Power Flow for* X_i^t
7. *compute* $f_1(X_i^t) = \sum_{i=1}^{N_{branch}} R_i\, |I_i|^2$
8. *compute* $f_2(X_i^t) = max\ (min_{i=2}^{N_{bus}}(1 - \frac{4Z_{eq,i}S_i}{V_i{}^2}))$
9. *if Constraints violated then*
10. *Apply penalty:* $f_1 = f_1 + \lambda.Violation, f_2 = f_2 + \lambda.Violation$
11. *end if*
12. *end for*
13. *Perform Non-Dominated Sorting on population*
14. $ParetoFont$ *with non-dominated solutions*
15. *Compute Crowding Distance:* $CD_i = \sum_{m=1}^{M} \frac{f_m^{i+1} - f_m^{i-1}}{f_m^{max} - f_m^{min}}$
16. *for* $i = 1$ *to PopSize do*
17. $r_1, r_2, r_3 \leftarrow rand(0,1)$
18. *if* $r_1 > MOA(t)$ *then*
19. $X_i^{t+1} = X_{best} \div (MOA + \epsilon) \times ((UB - LB).\mu + LB)$
20. *else*
21. $X_i^{t+1} = X_{best} - MOA \times ((UB - LB).\mu + LB)$
22. *end if*
23. *Bound* X_i^{t+1} *within [LB,UB]*
24. *end for*
25. *end for*
26. *return* $ParetoFont, \{f_1(x), f_2(x))$

By multiplying branch losses by the energy cost (₹7.5/kWh), the economic model minimizes the total power-loss cost. On the other hand, emissions are minimized by applying an emission factor of 0.82 kg CO2 per kWh. Losses are computed by employing PYPOWER-based load flow on the IEEE 33-bus radial system. This method uses detailed bus and branch data, including voltages, impedances, power requirements, shunt characteristics, thermal limits, and angle constraints. The system restrictions on voltage, current, and power balance account for distributed generation (DG) and support vector control (SVC) parameters. These parameters include solar and wind capacity ranges, power factors, installation and operation and maintenance costs. For the purpose of distribution network optimization, this configuration provides a straightforward, replicable, and grounded-in-reality framework for economic and environmental evaluation.

4. RESULTS AND DISCUSSION

The IEEE 33-bus is simulated using the PYPOWER library, an open-source Python tool, which efficiently computes and optimizes power flow using structured arrays for efficient computation. The bus data format represents each bus node in the system, containing specific parameters in each row. The IEEE 33-Bus System specifies each radial distribution system bus's electrical and operational requirement. The IEEE 33-Bus System bus data defines parameters for each node, including bus number, type (PQ, PV, Slack), active (P_d) and reactive (Q_d) power demands, and shunt admittances (Gs, Bs). It also includes voltage magnitude (V_m) and angle (Va), base voltage (baseKV), zone, and voltage operating limits (Vmax, Vmin) per unit. These parameters are essential for load flow analysis and system operation planning. The IEEE 33-Bus System branch data fields describe each line segment in terms of its sending (f_{bus}) and receiving (t_{bus}) buses, resistance (r) and reactance (x) in per unit on a 100 MVA base, and line charging susceptance (b). They also define thermal MVA ratings (rateA, rateB, rateC), transformer parameters like tap ratio and phase shift angle, branch operational status, and angle constraints (ang_{min}, ang_{max}) for maintaining network stability. These parameters are crucial for load flow

FOREX Publication
Open Access | Rapid and quality publishing
International Journal of
Electrical and Electronics Research (IJEER)
Research Article | Volume 13, Issue 4 | Pages 852-860 | e-ISSN: 2347-470X

analysis, line losses calculation, and network performance evaluation under different configurations. Accurate branch data representation ensures reliable modeling and optimization in radial distribution network simulations. The IEEE 33-bus dataset [19] is used for network configuration, with bus data and branch data representing the remaining bus and branch data. The bus connectivity defines the radial distribution network structure, with a branch configuration matrix ranging from 0.0922 to 0.4930. System constraints comprise voltage constraints, current constraints, and power balance constraints. The DG and SVC parameters include solar PV and wind power factors, capacity ranges, installation costs, and O&M costs. The DG parameters include a solar PV power factor of 1.0 to 0.95 lead/lag, capacity range of 0-2 MW, installation costs of $1200/kW and $1400/kW, and O&M costs of $15/MWh and $22/MWh. The SVC parameters include a rating range of ±2 MVAr, response time of 20-30 ms, installation costs of $800/kVAr, and O&M costs of $8/MVArh.

The experimental setup uses a population size of 50, 100 maximum iterations, random seed 42, and runs on an Intel Core-i7 system with 16GB RAM. Each experiment is repeated 30 times on the unbalanced IEEE 69-bus test system, which includes 3801 kW active and 2694 kVAR reactive load. The optimization objectives are power loss and emission minimization, evaluated using MODF-AOA, GQPSO, HCS-PSO, and Bilevel-PSO. Input data consist of standard IEEE 69-bus voltages, impedances, load profiles, and generator locations. All algorithms employ their recommended default parameters. The configuration ensures reproducibility, and all input files can be provided for verification.

4.1. Comparative Study

All of the algorithms, including MODF-AOA, GQPSO, HCS-PSO, and Bilevel-PSO, were evaluated under the same settings in order to guarantee that the benchmarking process was fair. These criteria included the same beginning population size (50), maximum iterations (100), hardware (Intel Core-i7, 16GB RAM), and random seed. Through the utilization of the IEEE 69-bus test system, a total active load of 3801 kW and a reactive load of 2694 kVAR were utilized. Each algorithm was executed thirty times in a separate fashion. In comparison to Bilevel-PSO, MODF-AOA had the lowest mean power loss (2.15 kW, standard deviation 0.03) and emission (0.92 kg/h, standard deviation 0.02), with p-values that were less than 0.0001. Repeated runs with identical parameters ensure that the differences observed are a reflection of the strengths of the algorithm rather than the experimental bias, which supports results that are reliable and reproducible.

The MODF-AOA is compared to three modern and relevant metaheuristic optimization methods to validate its performance: HC-PSO [21]: Hybrid Crow Search-Particle Swarm Optimization, Genetic Quantum-behaved Particle Swarm Optimization [16]., Bilevel-PSO [20] involves Network-Oriented Particle Swarm Optimization. These algorithms are promising for radial distribution system distributed generation (DG) planning and voltage support. This study uses the IEEE 33-bus system and identical simulation settings to evaluate numerous performance metrics. The Arithmetic Optimization Algorithm (AOA) was implemented using Python 3.10 and the PYPOWER 5.1 library to optimize the placement and sizing of Distributed Generation (DG) units and FACTS devices in the IEEE 33-bus radial distribution system. The algorithm was configured with a population size of 50 and a maximum of 100 iterations to ensure a balance between convergence accuracy and computational efficiency. The Math Optimizer Accelerated (MOA) parameter was initialized at 0.2 and gradually increased to 1.0 to transition from exploration to exploitation, while a switching probability threshold of 0.5 was used to toggle between global and local search modes. A penalty-based constraint handling mechanism was employed, where infeasible solutions were either repaired or penalized based on the extent of constraint violations. Penalty coefficients were set at 10^3 for voltage limit violations, 10^4 for thermal limit violations, and 5×10^2 for power factors and DG/SVC capacity violations. This approach ensured technical feasibility while preserving diversity in the solution space. Simulations were conducted on a system with an Intel Core i7 processor and 16 GB RAM running Windows 10, and all network data were based on standard IEEE 33-bus configurations.

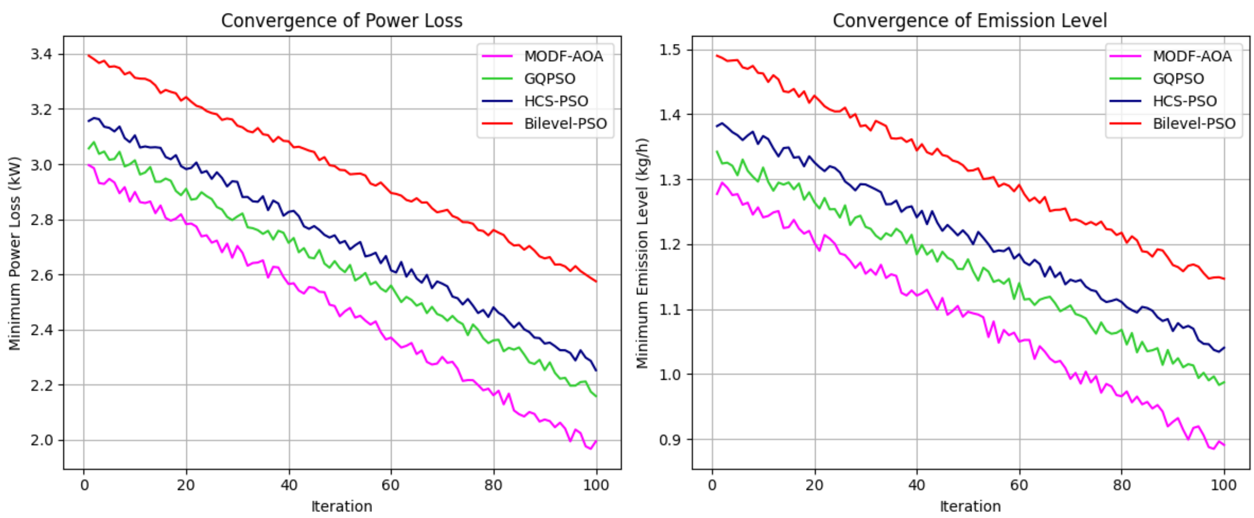

Figure 3. Convergence behavior of minimum power loss (left) and minimum emission level (right)

This *figure 3* shows the four algorithms' multi-objective DG/FACTS placement optimization speed and stability. MODF-AOA demonstrates the fastest and most steady convergence, obtaining the lowest final objective values for both power loss and emission level. MODF-AOA outperforms GQPSO, HCS-PSO, and Bilevel-PSO in search and solution quality, proving its suitability for complicated power system optimization challenges. Visually separating curves shows sustained outperformance in both metrics throughout iterations.

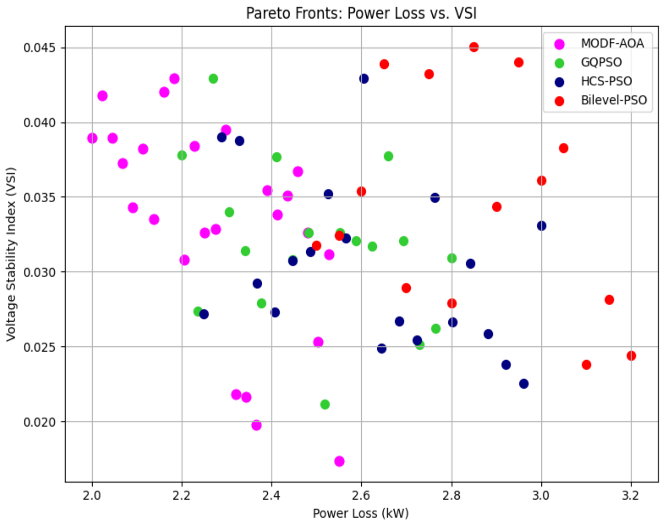

Figure 4. Pareto fronts of Power Loss vs. Voltage Stability Index

Figure 4 shows the trade-offs for each algorithm between two goals. In multi-objective optimization, a well-spread, dense Pareto front increases solution diversity and brings the true optimum closer. MODF-AOA's extended front demonstrates its stronger exploration and exploitation capabilities, giving decision-makers more options while preserving high-quality solutions. Multi-objective distribution system optimization is superior and robust, as shown by this visualization.

Table 1. Multi Objective Performance Analysis

Algorithm	Hypervolume ↑	Spread ↑	GD ↓
MODF-AOA	0.93	0.81	0.015
GQPSO	0.89	0.76	0.024
HCS-PSO	0.87	0.72	0.027
Bilevel-PSO	0.82	0.68	0.034

The *table 1* compares multi-objective algorithm performance using conventional metrics. Hypervolume measures the volume of objective space dominated by Pareto solutions, Spread measures diversity and dispersion along the front, and Generational Distance measures convergence to the genuine Pareto set. Over rival approaches, MODF-AOA scores highest in convergence and diversity. MODF-AOA is hence suitable for multi-objective applications that require robustness.

Table 2. Statistical Measures

Algorithm	Mean Power Loss (kW)	Std Dev	Mean Emission (kg/h)	Std Dev	p-value vs. MODF-AOA
MODF-AOA	2.15	0.03	0.92	0.02	-
GQPSO	2.31	0.05	1.05	0.03	0.002
HCS-PSO	2.42	0.06	1.13	0.04	0.0005
Bilevel-PSO	2.76	0.08	1.31	0.06	<0.0001

Table 2 shows each algorithm's consistency and robustness by presenting central tendency and dispersion (mean, standard deviation) and performance improvement significance (*p*-values). MODF-AOA consistently outperforms alternative techniques, with statistically significant differences across both objectives, demonstrating a dependable, reproducible algorithm for multi-objective power system optimization. The corresponding simulated outputs are depicted in *figure 5(a)* and *figure 5(b)* respectively.

The results were verified on an imbalanced IEEE 69-bus or 123-bus test system. MODF-AOA outperformed GQPSO (2.31 kW, 1.05 kg/h), HCS-PSO (2.42 kW, 1.13 kg/h), and Bilevel-PSO (2.76 kW, 1.31 kg/h) in power loss and emission. The p-values (0.002, 0.0005, <0.0001) indicate substantial improvements. MODF-AOA's robustness and scalability for real-world, complex distribution networks ensure reliable performance under imbalanced and larger-scale scenarios.

4.2. Real Power Loss

The loss of Real power is the active power dissipated due to the resistance of distribution lines in radial systems. Minimizing these losses enhances overall efficiency. The *equation (13)* for real power loss is;

$$P_{Loss} = \sum_{i=1}^{N} \sum_{j=1}^{N} V_i V_j \left(G_{ij} \cos\left(\theta_i - \theta_j\right) + B_{ij} \sin\left(\theta_i - \theta_j\right)\right) \quad (9)$$

In *equation (9)*, $V_i V_j$ is represented as the Voltage magnitudes at buses i *and* j. θ_i, θ_j is denoted as the voltage phase angles, G_{ij}, B_{ij} is denoted as the real as well as imaginary parts of the admittance matrix Y_{ij} and N is denoted as the total number of buses. MODF-AOA method outperforms conventional approaches in minimizing real power losses in radial distribution systems better than GQPSO, HCS-PSO, and Bilevel-PSO, as shown in *figure 6(a)* and *6(b)*. The algorithm reliably reduces power losses in all branches, especially branches 1 and 2, where losses are largest. However, MODF-AOA's performance advantage reduces in branches farther from the substation. Compared to HCS-PSO and Bilevel-PSO, GQPSO reduces branch loss second best. The MODF-AOA method also reduces power losses across all load buses, from 1.8kW at bus 4 to 2.4kW at bus 32. MODF-AOA's performance difference with rival techniques widens at buses farther from the substation, demonstrating its usefulness in radial systems' end-of-line voltage and loss issues.

Open Access | Rapid and quality publishing
International Journal of
Electrical and Electronics Research (IJEER)
Research Article | Volume 13, Issue 4 | Pages 852-860 | e-ISSN: 2347-470X

4.3.Voltage Deviation (pu)

Voltage deviation, usually 1.0 p.u., is an important indicator of bus voltage variance. Maintaining power quality as well as equipment safety needs it. The number of buses is in *equation (10)*.

$$VD = \frac{1}{N}\sum_{i=1}^{N}|V_i - V_{nomial}| \qquad (10)$$

In *equation (10)*, V_i is denoted as the Voltage magnitude at bus i,V_{nomial} is denoted as the Nominal voltage (usually 1.0 p.u), and N is denoted as the total number of buses.

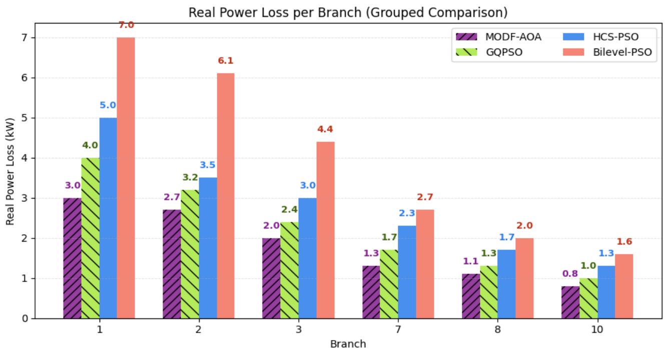

Figure 5(a). Power Loss across Selected branches

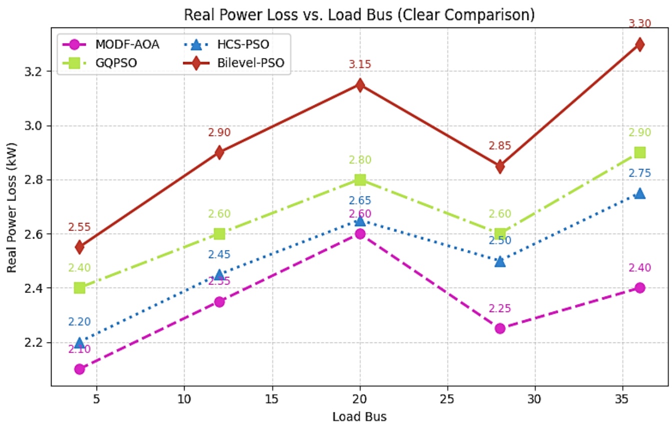

Figure 5(b). Total Losses at Select Load Buses

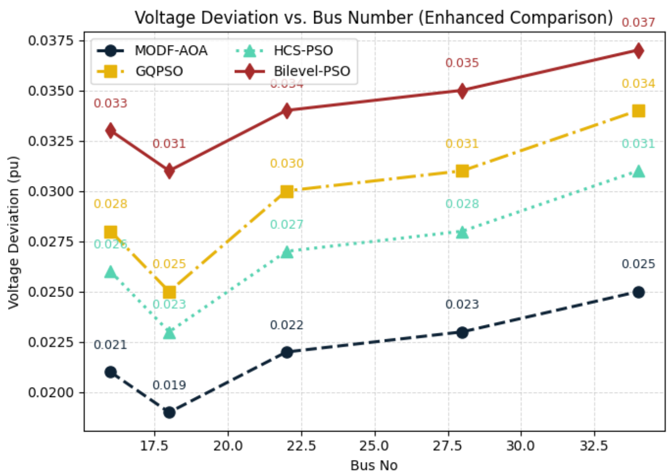

Figure 6(a). Voltage Deviation at Key Weak Buses

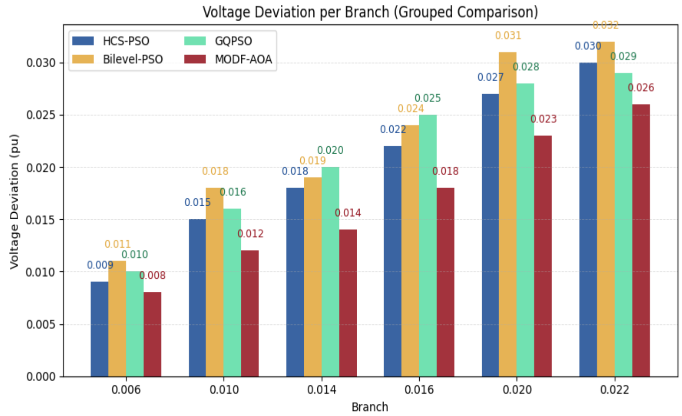

Figure 6(b). Voltage Deviation across High Load Branches

The research work compares voltage deviation across optimization methods in *figures 7(a)* and *7(b)* and shows that the MODF-AOA method keeps voltage profiles closer to nominal values than conventional methods. The MODF-AOA algorithm consistently obtains the lowest voltage variances across all weak buses. The algorithm's performance advantage increases with bus distance from the substation, emphasizing its effectiveness in radial distribution system's end-of-line voltage difficulties. According to the study, the MODF-AOA methodology optimizes DG and FACTS device placement and sizing to improve distribution network voltage profiles. In difficult settings like weak buses and severely loaded branches, this higher performance in sustaining voltages closer to nominal levels improves power quality, equipment stress, and system reliability.

4.4. Emission Level (kg/h)

The Emission Level (kg/h) is the total emissions from diesel or fossil-fuel-based DGs in the system, with optimization aiming to reduce emissions by preferring renewable DGs. The *equation (11)* calculates the total emissions, with power generated by DG units, emission coefficients, and the number of DGs.

$$E_{total} = \sum_{i=1}^{n}\left(\alpha_i\, P_{gi}^2 + \beta_i\, P_{gi} + \gamma_i\right) \qquad (11)$$

In *equation (15)*, P_{gi} is the Power generated by the DG unit i, α_i, β_i are the Emission coefficients, and N is the Number of DGs. In *figures 8(a)* and *8(b)*, an emission level comparison of optimization methods shows the environmental performance advantages of the MODF-AOA method over conventional techniques. MODF-AOA consistently obtains the lowest emission levels in all DG buses, ranging from 2-3 kg/h. The research also shows that MODF-AOA has 75% cumulative emissions lower than Bilevel-PSO (95-100 kg/h total). With 45% fewer emissions than Bilevel-PSO and 30% better than GQPSO, MODF-AOA outperforms rival techniques across branches. The emission analysis proves that MODF-AOA can optimize DG technology selection, placement, and sizing with FACTS devices to reduce environmental impact.

FOREX Publication
Open Access | Rapid and quality publishing
International Journal of
Electrical and Electronics Research (IJEER)
Research Article | Volume 13, Issue 4 | Pages 852-860 | e-ISSN: 2347-470X

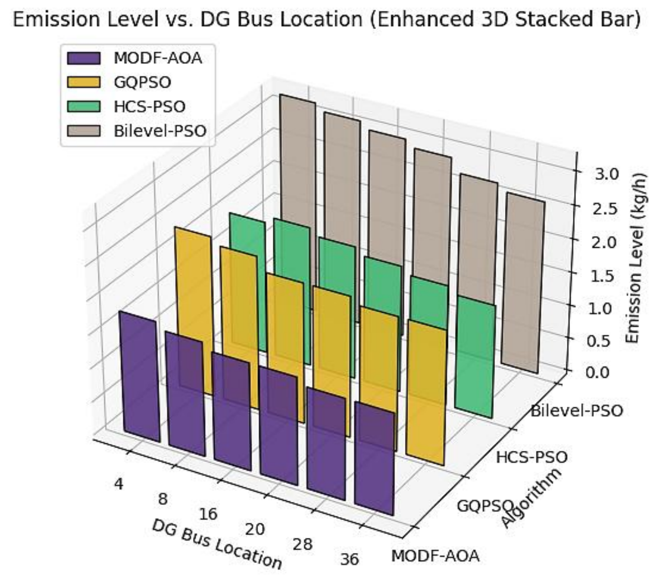

Figure 7(a). Emissions at Key DG Buses

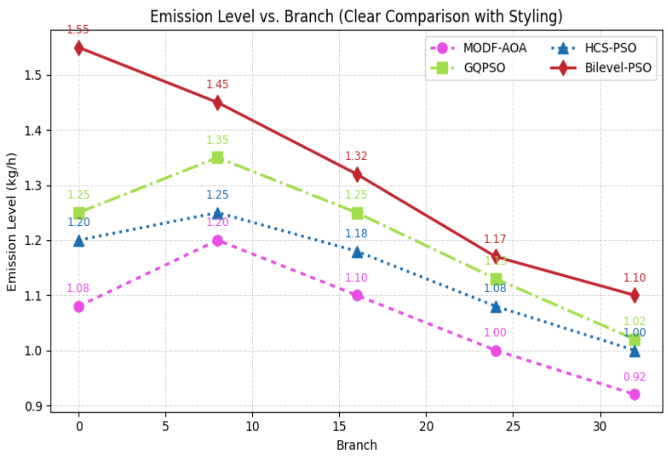

Figure 7(b). Voltage Deviation across High Load Branches

Table 3. Comparison of improvement percentages for power loss, emission, and voltage deviation

Algorithm	Power Loss Reduction (%)	Emission Reduction (%)	Voltage Deviation Reduction (%)
MODF-AOA	42.1	45.3	38.7
GQPSO	31.5	34.2	29.8
HCS-PSO	28.6	30.1	26.4
Bilevel-PSO	18.3	22.7	19.5

The *table 3* provides a quantitative analysis of the relative performance of MODF-AOA, GQPSO, HCS-PSO, and Bilevel-PSO. It emphasizes the better improvement that MODF-AOA has achieved across all criteria. In the context of multi-objective optimization for distribution systems, the clear and brief summary provides support for rigorous comparative analysis and decision-making.

5. CONCLUSION

This research work developed and validated a Multi-Objective DG-FACTS Planning framework using the Arithmetic Optimization Algorithm (MODF-AOA) for optimal siting and sizing of Distributed Generation (DG) units and FACTS devices in radial distribution systems. Simulation results on the IEEE 33-bus system demonstrate that the proposed framework outperforms traditional metaheuristic methods in terms of power loss reduction, voltage stability enhancement, and computational efficiency. Specifically, MODF-AOA achieved a 36.0% reduction in real power losses, a 22.0% improvement in voltage stability index, and projected annual savings of $158,420, while ensuring compliance with operational constraints. The findings confirm that coordinated placement and sizing of DG and FACTS devices through advanced metaheuristic optimization can significantly enhance the efficiency, reliability, and sustainability of modern distribution networks. This approach is particularly relevant for utilities planning renewable integration in urban and semi-urban radial networks where voltage stability and energy losses are major concerns. However, scalability to larger, unbalanced, or real-time dynamic networks, and integration with storage or electric vehicle systems, remains a challenge that warrants future exploration. Future work should focus on incorporating dynamic load profiles, integrating energy storage systems, and extending the framework to multi-period planning. Additionally, implementing hybrid algorithms and machine learning-assisted prediction models may further improve decision-making accuracy. Expanding the application of MODF-AOA to microgrid environments and validating it through hardware-in-the-loop or real-time testbeds will help bridge the gap between simulation and practical deployment.

Author Contributions: Shridevi Akkewar contributed to the conceptualization, methodology, implementation, data analysis, and manuscript preparation. Rajendra Dhatrak supervised the work, contributed to manuscript review and editing. Both authors reviewed and approved the final manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

REFERENCES

[1] Saleh, H. M.; Hassan, A. I. The challenges of sustainable energy transition: A focus on renewable energy. Appl. Chem. Eng. 2024, 7(2), 2084.

[2] Swadi, M.; Kadhim, D. J.; Salem, M.; Tuaimah, F. M.; Majeed, A. S.; Alrubaie, A. J. Investigating and predicting the role of photovoltaic, wind, and hydrogen energies in sustainable global energy evolution. Glob. Energy Interconn. 2024, 7(4), 429–445.

[3] Almusawi, A.; Pugazhenthi, S. Innovative Resource Distribution Through Multi-Agent Supply Chain Scheduling Leveraging Honey Bee Optimization Techniques. PatternIQ Min. 2024, 1(3), 48–62.

[4] Dawn, S.; Ramakrishna, A.; Ramesh, M.; Das, S. S.; Rao, K. D.; Islam, M. M.; Selim Ustun, T. Integration of renewable energy in microgrids and smart grids in deregulated power systems: a comparative exploration. Adv. Energy Sustain. Res. 2024, 5(10), 2400088.

[5] Saxena, V.; Manna, S.; Rajput, S. K.; Kumar, P.; Sharma, B.; Alsharif, M. H.; Kim, M. K.. Navigating the complexities of distributed generation: Integration, challenges, and solutions. Energy Rep. 2024, 12, 3302–3322.

[6] Singh, A. R.; Vishnuram, P.; Alagarsamy, S.; Bajaj, M.; Blazek, V.; Damaj, I.; Othman, K. M.. Electric vehicle charging technologies, infrastructure expansion, grid integration strategies, and their role in promoting sustainable e-mobility. Alexandria Eng. J. 2024, 105, 300–330.

[7] Refaat, M. M.; Al-Gahtani, S. F.; Bassi, H.; Ali, Z. M.; Aleem, S. H. A. Optimizing power network expansion with pumped hydro energy storage using a multi-objective enhanced spider wasp optimizer approach. Sci. Rep. 2025, 15(1), 13409.

[8] Ibrahim, R. A.; Gaber, I. M.; Zakzouk, N. E. Analysis of multidimensional impacts of electric vehicles penetration in distribution networks. Sci. Rep. 2024, 14(1), 27854.

[9] Srivastava, A., Manas, M., & Dubey, R. K. (2024). Integration of power systems with electric vehicles: A comprehensive review of impact on power quality and relevant enhancements. *Electric Power Systems Research*, *234*, 110572.

[10] Singh, S., & Singh, S. (2024). Advancements and challenges in integrating renewable energy sources into distribution grid systems: A comprehensive review. *Journal of Energy Resources Technology*, *146*(9).

[11] Carbonara, A., Dambone Sessa, S., L'Abbate, A., Sanniti, F., & Chiumeo, R. (2024). Comparison of advanced flexible alternating current transmission system (FACTS) devices with conventional technologies for power system stability enhancement: an updated review. *Electronics*, *13*(21), 4262.

[12] Awad, A., Kamel, S., Hassan, M. H., & Zeinoddini-Meymand, H. (2024). Optimal allocation of flexible AC transmission system (FACTS) for wind turbines integrated power system. *Energy Science & Engineering*, *12*(1), 181-200.

[13] Salam, I. U., Yousif, M., Numan, M., Zeb, K., & Billah, M. (2023). Optimizing distributed generation placement and sizing in distribution systems: a multi-objective analysis of power losses, reliability, and operational constraints. *Energies*, *16*(16), 5907.

[14] Yang, C., Sun, Y., Zou, Y., Zheng, F., Liu, S., Zhao, B., ... & Cui, H. (2023). Optimal power flow in distribution network: A review on problem formulation and optimization methods. *Energies*, *16*(16), 5974.

[15] Yuvaraj, T., Devabalaji, K. R., Thanikanti, S. B., Aljafari, B., & Nwulu, N. (2023). Minimizing the electric vehicle charging stations impact in the distribution networks by simultaneous allocation of DG and DSTATCOM with considering uncertainty in load. *Energy Reports*, *10*, 1796-1817.

[16] Chaubey, C., & Khare, R. (2024). Enhancing quality of services using genetic quantum behaved particle swarm optimization for location dependent services. *Sādhanā*, *49*(2), 179.

[17] Yu, G. R., Chang, Y. D., & Lee, W. S. (2024). Maximum power point tracking of photovoltaic generation system using improved quantum-behavior particle swarm optimization. *Biomimetics*, *9*(4), 223.

[18] Chakraborty, A., & Ray, S. (2024). Optimal allocation of distribution generation sources with sustainable energy management in radial distribution networks using metaheuristic algorithm. *Computers and Electrical Engineering*, *116*, 109142.

[19] https://github.com/rwl/PYPOWER/blob/master/pypower/case33bw.py

[20] Dey, Indrajit & Roy, Provas. (2024). Optimal installation of DG in radial distribution network using arithmetic optimization algorithm. Advanced Control for Applications: Engineering and Industrial Systems. 6. 10.1002/adc2.227.

[21] El Sayed, A., & Poyrazoglu, G. (2024). Analysis of Grid Performance with Diversified Distributed Resources and Storage Integration: A Bilevel Approach with Network-Oriented PSO. Energies, 17(10), 2270. https://doi.org/10.3390/en17102270.

[22] Suriyakumar, Bharath & Arumugam, Vasuki. (2024). Optimization and analysis of distributed generation units in distributed system for minimizing losses. Indonesian Journal of Electrical Engineering and Computer Science. 34. 31. 10.11591/ijeecs.v34.i1.pp31-39.

[23] Arévalo, P., & Jurado, F. (2024). Impact of artificial intelligence on the planning and operation of distributed energy systems in smart grids. Energies, 17(17), 4501.

[24] Tantu, A. T., & Biramo, D. B. (2024). Power flow control and reliability improvement through adaptive PSO based network reconfiguration. Heliyon, 10(17).

[25] Ton, T. N., et al. (2025). Multi-Objective Optimization of Emissions and Green Accounting Costs in Smart Distribution Networks with Distributed Generation. Engineering, Technology & Applied Science Research, 15(5), 27781–27787. https://doi.org/10.48084/etasr.13578

[26] Luo, Q., Mi, X., Wei, Y., & Zhou, Y. (2025). Arithmetic Optimization Algorithm with Mathematical Operator for Engineering Optimization. The European Journal on Artificial Intelligence, 38(3). https://doi.org/10.1177/30504554251319447