Algorithmic Approaches for Optimal Placement of Flexible Resources in Distribution Systems

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***Abstract*—This paper investigates the optimal placement and sizing of Distributed Generation (DG) in power distribution networks using various metaheuristic algorithms. It introduces a novel method for optimizing Hosting Capacity, which helps Distribution System Operators (DSOs) improve long-term grid planning and delay the need for grid upgrades. The study establishes a common benchmarking tool to test several algorithms, including Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Grey Wolf Optimizer (GWO), Differential Evolution (DE), Coyote Optmization Algorithm (COA), and Artificial Bee Colony (ABC). The results indicate that PSO is the most effective method for enhancing grid stability and efficiency as it consistently minimizes costs and improves voltage profiles, making it a reliable choice for DG optimization. The study also highlights the potential of hybrid approaches and the need to address dynamic grid conditions. Despite the effectiveness of these algorithms, challenges such as scalability and parameter adjustment remain.**

***Index Terms*—Distributed Generation, Metaheuristic Algorithms, Particle Swarm Optimization, Power Distribution Networks, Grid Optimization**

I. INTRODUCTION

A. Motivation and Incitement

The global energy landscape is undergoing a significant transition driven by the increasing emphasis on sustainability and the need to address climate change. Traditionally, power generation was centralized, with electricity being generated at large plants and transmitted over long distances to consumers. Distribution System Operators (DSOs) planned grid investments based on predictable patterns of demand growth and reinforcement needs. However, the increasing penetration of Distributed Energy Resources (DERs) has introduced significant variability and complexity into the grid. This has made traditional grid planning methodologies inadequate for managing the dynamic nature of modern distribution networks. Additionally, unbundling plays a crucial part by splitting the roles each part now can take in the system. In Europe, due to the unbundling of activities, DSOs have seen their discretion or authority to oversee generation investments limited. This separation of activities is a necessary step that comes with both advantages and disadvantages. This structural separation is aimed at ensuring that generation and distribution functions are conducted independently to create a level playing field in the market. However, this also means that DSOs need interactive solutions that require collaboration between both the DSOs and the DERs.

Our electricity distribution networks play a vital role in our daily lives, ensuring that power generated from various sources reaches us reliably and efficiently. There's a growing global demand for renewable energy, as it's a cleaner and more sustainable alternative to fossil fuels. This surge presents both opportunities and challenges for our existing power grids. Distribution System Operators (DSOs) face significant challenges in integrating Distributed Generation (DG) into the grid. The current infrastructure and validation processes often struggle to keep up with the increasing number of DG connection requests.

The use of renewable energy is becoming critical in this transformation, influencing the way power is produced and distributed. Distributed Generation (DG) has emerged as a key player in this shift, where electricity is generated near the point of consumption rather than at centralized power stations. This method involves renewable energy sources like solar photovoltaic, wind turbines, and bio-energy systems, which can reduce transmission losses and increase the reliability of power supply by diversifying energy sources.

Hosting Capacity (HC) is defined as the maximum amount of generation a power distribution system can accommodate without exceeding operational limits [1]. These limits include voltage stability, thermal capacity of lines, and other critical parameters. HC is a crucial concept, particularly in the integration of renewable energy sources into the grid. When a distribution network reaches its HC, any additional generation can lead to issues such as voltage violations, line overloading, and power quality problems.

The integration of DG into current distribution networks presents both advantages and challenges. On the one hand, DG can decrease energy losses, improve voltage profiles, and enhance the overall efficiency for certain low penetration levels in the power distribution system. However, the intermittent nature of renewable-based DG requires advanced control strategies to maintain grid stability and ensure operations stay within set limits.

Randomly locating these resources on the grid leads to an electrically and economically inefficient scenario. Consequently, innovative optimization algorithms have been developed to optimize the placement, sizing, and operation of DG units, aiming to reduce operational costs and improve power system efficiency.

B. Literature Review

The research in optimizing DG placement and sizing builds on a wide array of methods:

- Classical methods, such as linear and nonlinear programming, provide a solid foundation but often lack the flexibility needed for modern power systems [2]. These methods struggle with the non-convex, multi-objective, and mixed-integer nature of real-world, specially medium and large, power system optimization problems.
- Sensitivity analysis-based approaches focus on finding the optimal location for DG units by using a sensitivity index to identify the most sensitive locations [3]. While sensitivity analysis offers low computational time, the degree of optimality of the solutions is uncertain, and these methods typically do not determine the optimal size of DG units, therefore, they need to be combined with other methods.
- Metaheuristic algorithms are advanced search algorithms designed for optimization problems. They are particularly useful for complex, medium-scale systems where traditional methods fall short. These are usually population-based stochastic approaches that do not impose preconditions on objective functions or constraints [4]. These methods are highly effective in solving DG allocation problems and are among the most commonly used approaches [5].
- Hybrid approaches combine classical methods with modern algorithms to leverage the strengths of both [6]. These approaches aim to improve efficiency and effectiveness by addressing the limitations of individual techniques.

Classical approaches to DG sizing and placement have been explored for many years. Some notable applications can be seen in various studies. For example, [7] uses power flow continuation to identify the most sensitive buses to voltage collapse, thus improving voltage profiles and enhancing stability margins. [8] employs Sequential Quadratic Programming (SQP) to optimize both DG and battery storage capacities simultaneously, emphasizing the critical role of battery storage in managing generation variability. Additionally, research in [9] uses Mixed-Integer Nonlinear Programming (MINLP) to minimize power losses and generation costs, significantly reducing search space and computational time.

However, classical methods face several challenges as covered in some modern papers. Newer approaches based on [4] and [5] typically rely on gradient-based techniques that can become trapped in local optima, failing to find the global solution [4]. Furthermore, classical methods struggle with optimization problems that involve both mixed integer and continuous variables. They are generally designed for continuous variables and require complex modifications to handle discrete variables, making them less suitable for problems involving generator statuses, switch positions, or other binary decisions [5]. Lastly, multi-objective optimization involves finding solutions that balance multiple goals at once, such as cost, reliability, and environmental impact. Traditional optimization methods struggle with these problems, especially when dealing with discontinuous or concave Pareto fronts. Power systems often need to address these competing objectives, which classical methods cannot handle easily without major simplifications or adjustments. [4], [5].

The rise of metaheuristic methods like Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Grey Wolf Optimizer (GWO) have shown significant promise in handling complex, multi-objective optimization problems where traditional approaches fail to work.

It is clear that various metaheuristic methods have been applied to major optimization tasks in the smart grid. However, it is impossible to single out one method or class of methods that performs better across all tasks, as highlighted by the "no free lunch" theorem [10]. This principle implies that no algorithm will perform equally well across all types of problems. As a result, the literature in this field explores many algorithms for the same applications.

For instance, [11] was among the first to implement PSO to minimize power losses in a 33-bus system, demonstrating the algorithm's robustness. Over the years, PSO has remained one of the most tested and developed algorithms. [12] and [13] reviewed the algorithm's suitability for this application in larger test systems and with different objective functions, including not only system power losses but also improved voltage profiles and load management with Battery Storage Systems (BES). Other authors have developed iterations of this algorithm, such as the Crow Search Algorithm Auto-Drive PSO (CSA-PSO) in [14], or compared it with other algorithms to determine which had better suitability, as seen in [15] and [16].

Genetic Algorithms (GA) are particularly effective in exploring large solution spaces and have been widely used for DG optimization, as demonstrated in [15]. They work by mimicking the process of natural selection, making them robust in finding near-optimal solutions for complex problems. In [17], a hybrid approach utilizing both GA for location and power factor, combined with analytical methods for active power optimization, effectively minimized system losses compared to methods using only GA or only analytical approaches. Differential Evolution (DE) is another powerful metaheuristic that optimizes problems by iteratively improving candidate solutions with regard to a given measure of quality. DE has been applied successfully in various studies to minimize power losses and optimize DG placement, as seen in [18].

Other novel approaches failed to remain successful even though they showed promising results, simply because other algorithms performed better. An example of this is [19], where the Cuckoo Search Algorithm was used to minimize total real power losses and improve voltage stability by determining the optimal location and size of PQ-type DG units. However, research on more renowned algorithms was published shortly after, leading to this research being almost immediately discarded and never continued.

Hybrid approaches started to become popular as knowledge in this field grew. With a better understanding of how algorithms work, techniques were developed that combined the best attributes of various methods. One example is combining Loss Sensitivity Factor (LSF) with Simulated Annealing (SA), as seen in [20], which has proven effective in reducing power losses and improving voltage profiles in various test systems. Another example is the hybrid method in [6], which integrates Sequential Quadratic Programming with a Branch and Bound algorithm to solve the Mixed Integer Nonlinear Programming (MINLP) formulation, reducing real power losses and optimizing DG distribution. Examples of these mixed techniques are scattered throughout the literature, but they have been less implemented due to their added complexity compared to simpler techniques using a single algorithm.

Recent advancements include innovative algorithms like the Grey Wolf Optimizer (GWO), utilized in [21] to minimize reactive power losses and improve voltage profiles. In [22], GWO is used to enhance voltage stability and reduce losses across various scenarios in 33-bus and 69-bus networks. And more recently in [23], GWO effectively minimized costs by optimizing generation and load management, demonstrating substantial cost reductions compared to traditional management methods. Some other novel algorithms include The Ant Lion Optimization Algorithm (ALOA), applied in [24], minimizes total power losses and enhances voltage profiles by optimizing the size and location of wind turbines (WT) and photovoltaic (PV) DGs. War Optimization, applied in [25] provided high-quality solutions, outperforming other metaheuristics in terms of power loss reduction and voltage stability improvement. Or the Coyote Optimization Algorithm (COA) in [26] which tries to minimize power losses by optimizing voltage regulator tap changes. These newer algorithms have shown very promising results.

These studies underscore the evolution of methodologies over time and highlight areas where current research excels and where gaps still exist. Through this extensive review, the following gaps in current research have been identified:

- Handling dynamic grid conditions,
- Managing large-scale integration of DG and,
- The lack of common benchmarking standards.

These gaps are critical as they highlight the areas where further research is needed to improve the practical implementation of optimization algorithms in real-world power grids. By addressing these gaps and leveraging the strengths of various optimization algorithms, this research aims to enhance the efficiency, reliability, and sustainability of power system operations.

This paper contributes establishing a baseline for common benchmarking different metaheuristic algorithms for the optimal placement and sizing of DG units in power distribution networks. The goal is to determine the best algorithm to enhance the hosting capacity of distribution networks, thus improving grid stability and efficiency while minimizing the need for costly grid reinforcements. The optimization model selected in this research is intended to serve as a tool for DSOs to establish criteria for making the most of the existing network hosting capacity and accelerating the network connection request process.

Section II details the problem formulation, including the objective function and constraints, and the implementation approach. Section III discusses the test systems used for validation. Section IV presents the outcomes of the implemented algorithms. Section V summarizes key findings, contributions, and suggestions for future research.

This structured approach ensures a comprehensive exploration of the optimal DG placement in distribution networks, from theoretical foundations to practical applications and market considerations.

II. Methodology

A. Problem Formulation

This section outlines the formulation and implementation of the optimization problem focused on Distributed Generation optimal dispatch. The problem at hand is to identify the best points to connect DG in a given distribution network. This will help to optimally utilize the current hosting capacity or minimize the need for network reinforcements.

The main objective is to minimize power losses and ensure voltage stability under high demand conditions without additional technical solutions like reactive power injection, tap changing, or reconfiguration. This objective function is used when the DSO seeks to determine the optimal configuration of the distribution network to maximize HC. The function aims to increase the integration of DG units, enhancing the network's capacity to host renewable energy sources, while maintaining system reliability.

The primary goal is to determine the optimal number, placement, and size of DG units to be dispatched in the grid.

Due to the nature of metaheuristics, typical optimization problem constraints must be applied as a penalization over the objective function. Thus, the objective function is defined as the sum of two parts: one part representing the direct cost $f(x)$, and the other part representing the associated penalties $g(x)$:

$$\min_{x} f(x) + g(x) \tag{1}$$

The direct cost $f(x)$ includes the following terms: I_{Gen} incentivizes DG integration, C_{PL} evaluates power losses, $C_{V_{\triangle}}$ quantifies voltage deviations C_{Bal} represents the cost associated with power imbalances. It is presented as follows:

$$\min_{x} f(x) = I_{Gen} + C_{PL} + C_{V_{\triangle}} + C_{Bal} \tag{2}$$

Additional Power: This term represents the cost associated with the additional power generation required, calculated by multiplying the total additional generation capacity (P_g) by the injection cost[1].

[1] Average European Injection Cost is 0.22 €/MWh [27]

$$I_{Gen} = -C_{Gen} \times \sum_{g} P_g \tag{3}$$

Power Losses: This term represents the cost associated with power losses due to resistance in the distribution lines ($P_{\text{in},j}$, Injected Power in a given line (j) and $P_{\text{out},j}$, Output Power in a given line (j)). It is calculated based on the cost of energy in the wholesale market (C_e).

$$C_{PL} = C_e \times \sum_{j} (P_{\text{in},j} - P_{\text{out},j}) \tag{4}$$

Voltage Stability: This term quantifies the cost associated with voltage deviations from the target value of 1 pu. Significant deviations exceeding 0.05 pu are penalized to maintain a stable voltage profile. Therefore, bus voltage in pu V_m is multiplied by the penalty cost C_v and by the voltage base V_{base}.

$$C_{V_\Delta} = C_v \times (\sum_{m} |V_m - 1|) \times V_{base} \quad \forall Vm \quad / \quad |V_m - 1| > 5\% \tag{5}$$

Balance: This term represents the cost associated with the mismatch between feeder power, encouraging a balance between generation and demand with zero net imports or exports. Consequently, net power through the feeder P_{feeder} is multiplied by the penalty C_{Bal}.

$$C_{Bal} = C_{Bal} \times P_{feeder} \tag{6}$$

To ensure a feasible and practical solution, voltage and thermal limits need to be satisfied. These limits must be enforced through penalties in the objective function $g(x)$. To calculate these penalties, a power flow analysis must be conducted using an external tool. This analysis determines if the proposed solution remains within the specified voltage and thermal ranges. Based on the results, the corresponding penalty is applied, and the value of the objective function or cost is obtained. If these conditions are not met, the objective function of the metaheuristic assigns a very high cost to these results, effectively marking them as infeasible for the algorithm.

The constraints checked by the power flow are described in the following equations [28]:

$$\text{s. t.} \qquad g(x) = 0 \ , \tag{7a}$$
$$h(x) \leq 0 \tag{7b}$$

The equality constraints in (7a) are real and reactive power balance equations. These ensure that the real and reactive power generation equals the total power demanded at each bus (accounting for power losses).

$$g_P(\Theta, V_m, P_g) \quad = P_{\text{bus}}(\Theta, V_m) + P_d - C_g P_g = 0 \tag{8a}$$
$$g_Q(\Theta, V_m, Q_g) \quad = Q_{\text{bus}}(\Theta, V_m) + Q_d - C_g Q_g = 0 \tag{8b}$$

The inequality constraints in (7b) limit the apparent power flow on each transmission line to stay within safe operating limits to prevent equipment damage.

$$h_f(\Theta, V_m) \quad = |F_f(\Theta, V_m)| - F_{\max} \leq 0 \tag{9a}$$
$$h_t(\Theta, V_m) \quad = |F_t(\Theta, V_m)| - F_{\max} \leq 0 \tag{9b}$$

The overload condition constraint ensures no transmission line operates above its nominal rating, preventing wear and tear, higher stress levels, and potential regulatory fines. By ensuring that no line exceeds its nominal rating, this constraint helps maintain the integrity and reliability of the power system. The cost associated with overloads includes maintenance costs, potential fines, and the cost of accelerated asset depreciation. These costs are typically internalized by the DSO and can vary significantly depending on the situation.

Additionally, some variable limits must be set to tackle voltage phase and magnitude limits. These constraints ensure that the voltage magnitude at each bus stays within specified lower and upper bounds for proper operation of power system equipment. For instance, voltage deviation is measured against the nominal voltage level (1 per unit, p.u.). Deviations exceeding 0.05 p.u. significantly reduce system efficiency and are penalized. Maintaining acceptable voltage levels is crucial for system reliability and efficiency. Voltage fluctuations are penalized when the voltage rises or falls outside the set band. These costs may differ, but penalties are usually determined by the cost of equipment damage, decreased efficiency, and potential lost time. In some regions, fines can vary between several hundred to several thousand euros, depending on the nature and extent of the deviation.

$$\theta_i^{\text{ref}} \leq \theta_i \leq \theta_i^{\text{ref}}, \qquad i \in \mathcal{I}_{\text{ref}} \tag{10a}$$
$$v_m^{i,\min} \leq v_m^i \leq v_m^{i,\max}, \qquad i = 1, \ldots, n_b \tag{10b}$$

Furthermore, some additional constraints must be set to limit the search space. Given the metaheuristic approach used to solve this optimization problem, it is essential to define clear boundaries for the search space. Metaheuristic algorithms rely on exploring a limited search space to find optimal or near-optimal solutions efficiently. In this context, constraints are imposed on the maximum number of DGs that can be placed within the network and on their maximum capacity. These boundaries are predetermined based on system requirements and operational considerations, ensuring the feasibility and practicality of the solutions obtained.

$$2 \leq p_i^L \leq N_{buses} \qquad i = 1, \ldots, n_g \tag{11a}$$
$$p_{\min}^C \leq p_i^C \leq p_{\max}^C \qquad i = 1, \ldots, n_g \tag{11b}$$

The decision variables for this optimization problem include:

- Number of DGs: The total number of DG units to be installed.
- DG Bus Locations: Each DG is assigned a specific bus number.
- DG Sizes: The capacity of each DG in MW.

A typical decision variable vector is $[n_g, p_1^L, p_1^C, \ldots, p_{n_g}^L, p_{n_g}^C]$. Where n_g is the number of DGs, p_i^L and p_i^C are the corresponding found best particle location and capacity respectively.

This objective function aims to determine the optimal allocation strategy for DG units within the distribution system. The resulting allocation plan will serve a dual purpose. Firstly, it will inform the DSO's own DG deployment decisions in the countries where there is no market unbundling. Secondly, if market unbundling exists, the plan can be used to guide market participants towards the most suitable DG options for the system.

B. Implementation

The implementation of the optimization problem uses MATLAB, leveraging the MATPOWER toolbox for power flow simulation and analysis. The process involves several steps and applies to all tested metaheurstics:

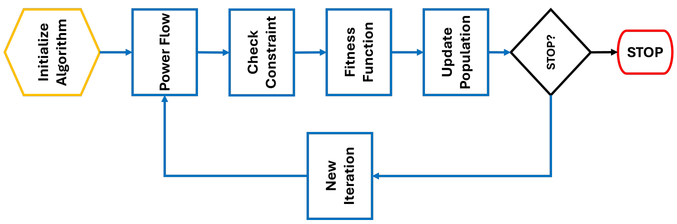

Fig. 1. Block diagram of the optimization process.

1) Initialize the Algorithm: Load the MATPOWER case file to define the power grid structure and set up algorithm parameters. Create an initial population of potential solutions, representing different bus locations and capacities for the DG units.
2) Power Flow Analysis: Perform an initial power flow analysis using the initial population to determine power distribution across the grid.
3) Constraint Checking: Ensure the system operates within its technical constraints, checking voltage and thermal limits. Calculates associated penalties for constraint violations.
4) Fitness Function Evaluation: Evaluate the fitness function for each individual in the population. If any constraints are not met, a penalty is applied to the fitness score, and further calculations are skipped. Otherwise, the cost for each particle is calculated solely based on eq. (2).
5) Population Update: Update the population based on the fitness function, using the corresponding algorithm operations, eg. crossover and mutation in the case of GA.
6) Iteration: Proceed to the next iteration if stopping criteria have not been met, such as a maximum number of iterations or a convergence threshold.
7) Final Solution: Conclude the optimization process once the stopping criteria are satisfied, outputting the best solution found, which represents the optimal bus location and sizing for the DG units under the given load profile and constraints.

This structured approach ensures that the optimization process is thorough and the solutions obtained are practical and effective in real-world power distribution networks.

C. Evaluation

The selection of an appropriate optimization algorithm is crucial for the efficient operation of distribution networks. This paper outlines a systematic grading system designed to evaluate and compare different optimization algorithms based on several key criteria. The grading system aims to ensure that the chosen algorithm aligns with the specific characteristics and requirements of the distribution network. It is based on five weighted criteria (weights in parentheses):

- **Cost** (*30%*): The algorithm's ability to achieve the defined objective function effectively. This measures how well the algorithm minimizes cost in achieving the optimization goals for the distribution network. The lower the cost the better.
$$\text{Cost} = f(x) + g(x) \tag{12}$$
- **Robustness** (*20%*): This checks how well the algorithm handles larger population sizes. It looks at whether increasing the number of particles leads to a lower cost and considers the trade-offs involved.
$$\text{Robustness} = \overline{Cost}_{200} - \overline{Cost}_{500} \tag{13}$$
- **Consistency** (*20%*): This evaluates how repeatable the results are by measuring the variation in cost across different tries under the same conditions. It shows the algorithm's stability despite its random nature. It compares standard deviation σ_{Cost} across all trials (10 trials per algorithm, 3 configurations, and 3 case studies, totaling 90 trials).
$$\text{Consistency} = \frac{1}{90}\sum_{i=1}^{90} \sigma_C \tag{14}$$
- **Scalability** (*15%*): The algorithm's adaptability to increasing network sizes. This looks at how well the algorithm performs when applied to different network configurations and test systems. It assesses if the algorithm consistently achieves low costs across various scenarios. It ranks from best to worst (in term of lower cost) the performance of each algorithm in the different test scenarios and compares the average position $\overline{Pos}$.
- **Time** (*15%*): This measures how quickly the algorithm reaches an optimal solution. It considers the time and resources needed, which is important for practical use. It compares average time $\overline{T}$.

D. Algorithms

Metaheuristic algorithms are broadly classified into three categories: Evolutionary Algorithms, Physical Algorithms, and Behavior Algorithms.

- Evolutionary Algorithms: Inspired by biological evolution and natural selection. Examples include Genetic Algorithms (GA) and Differential Evolution (DE).
- Physical Algorithms: These simulate physical processes. Examples include Simulated Annealing and Gravitational Search Algorithms.
- Behavior Algorithms: Mimic the behavior of social animals and other collective systems. Examples include Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), and Artificial Bee Colony (ABC).

For this paper, the following algorithms have been selected due to their effectiveness and popularity in optimization problems related to power systems:

- Particle Swarm Optimization (PSO): Chosen for its simplicity and ability to efficiently explore large search spaces.
- Genetic Algorithm (GA): Selected for its robustness in finding globally optimal solutions in complex problems.
- Artificial Bee Colony (ABC): Preferred for its ability to balance exploration and exploitation through social behavior mimicking.
- Grey Wolf Optimizer (GWO): Included for its innovative approach based on the social hierarchy and hunting strategies of grey wolves.
- Differential Evolution (DE): Picked for its effectiveness in handling continuous and non-differentiable optimization problems.
- Coyote Optimization Algorithm (COA): Added for its unique approach inspired by coyote social behavior, despite being relatively new.

These algorithms are compared to determine the most effective method for optimal DG placement and sizing in power grids.

Some attention should be paid to these algorithms as the complexity of metaheuristic algorithms like PSO and GWO can make them challenging to implement, requiring significant computational resources. Scalability issues also arise, as some algorithms may not perform consistently with larger networks or higher numbers of DG units. Additionally, the performance of these algorithms is often sensitive to the parameters set for their operation, necessitating careful tuning to achieve optimal results.

III. Case Studies

This section discusses the test systems and algorithms used to validate the proposed validation methodology for DG placement and sizing.

A. Test Systems

The IEEE 33-bus [29], 69-bus [30] and 141-bus [31] distribution systems will be used as case studies. These systems are selected for their similarity to real distribution networks and their complexity, which makes them suitable for testing advanced optimization algorithms. Table I provides a first overview of these test systems. Additionally, Figs. 2, 4, 6 provide the single line diagram of all test systems.

TABLE I
Test Systems

	33-Bus System	**69-Bus System**	**141-Bus System**
Base Voltage	12.66 kV	12.66 kV	12.47 kV
Base Generation	3.92 MW	4.03 MW	12.58 MW
Power Factor	≈0.85	≈0.85	≈0.85
Base Demand	3.72 MW	3.80 MW	11.94 MW
Base Losses	202.68 kW	224.99 kW	632.69 kW
Min Voltage	0.9131 pu	0.9092 pu	0.9279
Characteristics	Radial	Radial	Radial
Advantages	Simple Test Network	Balanced complexity	Large and complex

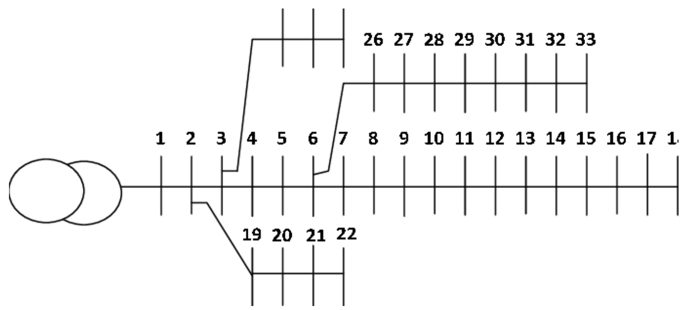

Fig. 2. 33-bus Test Systems Single Line Diagram.

For this problem, a specific load profile representing a high demand scenario without additional technical solutions is selected for al test systems (see Figs. 3, 5, 7). This profile is used to simulate system conditions and identify the best dispatch strategy for DG units to maintain voltage stability.

Initially, algorithms are compared to identify the best-performing one. The selected algorithm is then evaluated under different load profiles across various times and seasons to ensure a comprehensive understanding of its effectiveness under varying conditions.

By applying the proposed optimisation algorithms to these test systems, conclusive results can be drawn and identify which is more effective in improving the operational efficiency and stability of distribution networks with high penetration of DG units. Detailed results and analysis are presented in the following section.

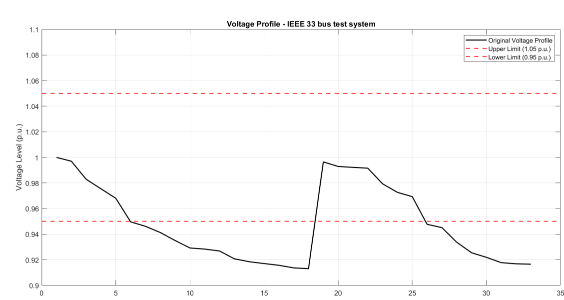

Fig. 3. 33-bus Test System Base Voltage Profile.

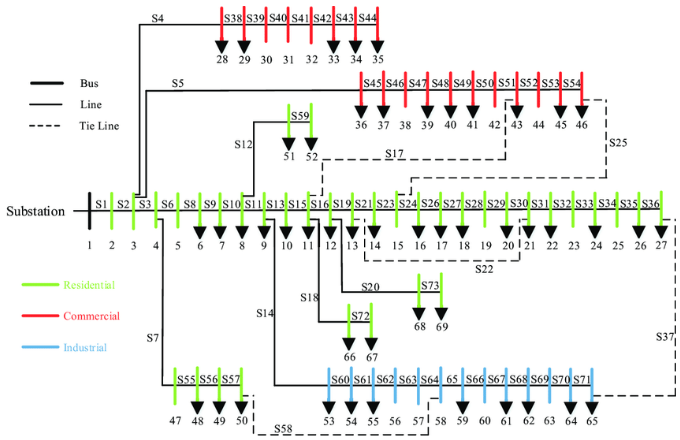

Fig. 4. 69-bus Test Systems Single Line Diagram.

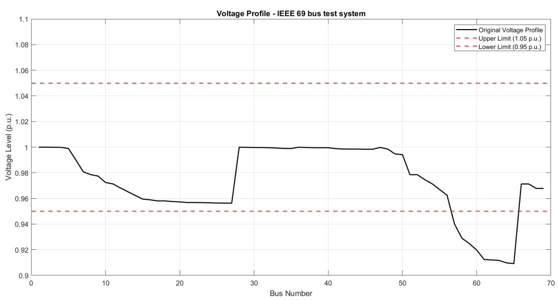

Fig. 5. 69-bus Test System Base Voltage Profile.

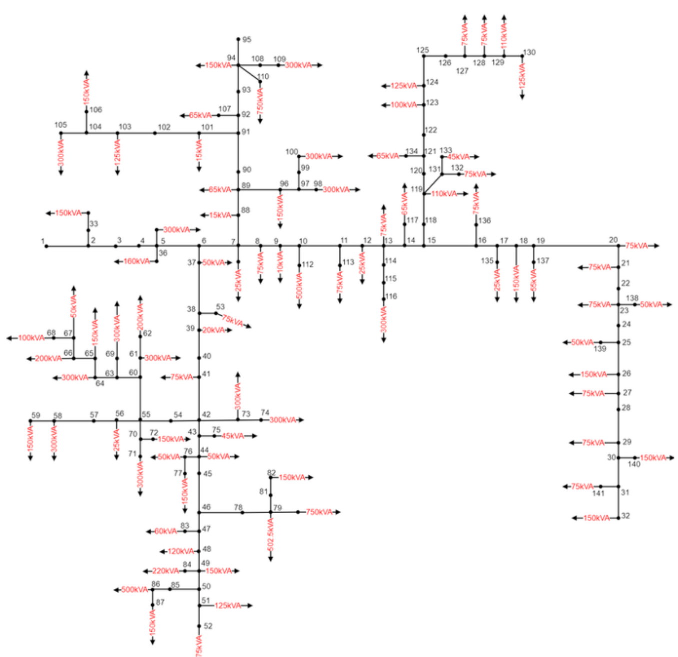

Fig. 6. 141-bus Test Systems Single Line Diagram.

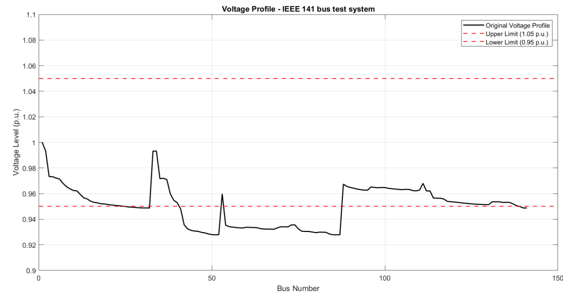

Fig. 7. 141-bus Test System Base Voltage Profile.

IV. Results and Benchmarking of the Algorithms

This section presents a comparative analysis of the different optimization algorithms applied to the two problems described previously. The primary objective is to assess the performance of each algorithm in terms of their ability to find optimal solutions for DG placement and dispatch under specified conditions. The evaluation is based on the results obtained from multiple runs of the algorithms, ensuring robust and reliable performance metrics. Each algorithm was executed several times (10) to account for variability in performance due to the stochastic nature of the metaheuristic methods. This approach provides a comprehensive understanding of the algorithms' consistency and effectiveness. Half the times the algorithm runs with a small population size (200 particles) the other half with a big one (500 particles).

Each test system was evaluated by testing configuration with one, three, and an unrestricted optimal number of DG units. This helped me assess the algorithms' ability to manage multiple DG units and their impact on the power grid's stability and efficiency.

To ensure reliable results given the stochastic nature of these algorithms, the outcomes from 10 executions for each algorithm were averaged. This process was repeated for both population sizes, all algorithms, the three DG configuration, and the three test systems. In total, 540 trials were conducted, generating over 3000 data points to thoroughly assess the efficiency of each algorithm.

The primary performance metric analysed is the cost associated with each algorithm under different configurations. Cost metrics are critical as they directly show the value of the objective function, which represents the efficiency of the algorithm in DG placement and sizing. Fig. 8 shows the mean cost for each algorithm across different test systems. PSO demonstrated the lowest mean costs across different configurations, making it a reliable choice for minimizing expenses. GA shows higher variability compared to other algorithms. COA provided good cost metrics with some variability, indicating potential but not the best performance, expected for such a new algorithm. ABC showed extreme variability in costs, with some configurations resulting in much higher expenses, additionally with more decision variables and a narrower search space, the algorithm would not run. However,

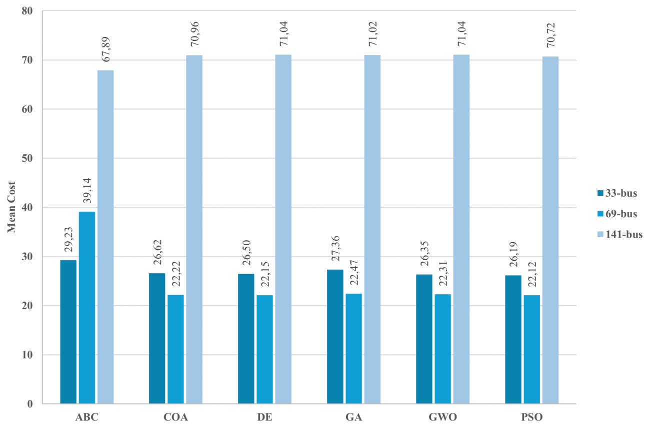

Fig. 8. Mean Cost Graph per Test System

if correctly optimized and set to operate it was showing promising results in terms of computational efficiency. DE had good cost metrics but with notable variability, indicating inconsistency in performance, moreover, it is the algorithm with longer operating times. GWO Balanced cost metrics with moderate consistency, making it a good alternative.

Overall, PSO and GWO emerged as the algorithms with the most favourable cost metrics, with PSO showing superior consistency.

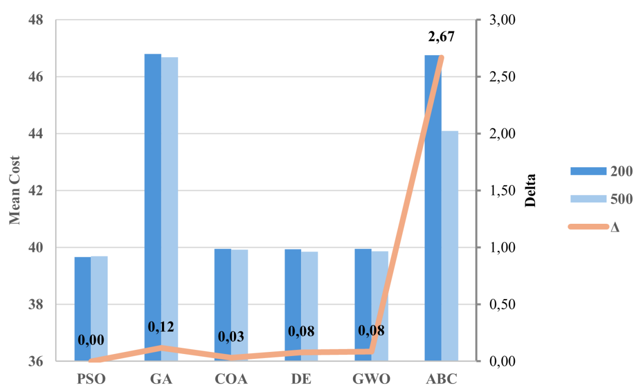

Fig. 9. Robustness Analysis

Robustness is assessed by comparing cost metrics for different population sizes (200 vs 500) in Fig. 9. PSO maintained the lowest costs consistently, demonstrating excellent scalability. GA also scaled well but with higher costs than PSO. COA showed variability with larger populations, indicating potential scalability issues. ABC experienced errors with larger populations, suggesting poor scalability. DE had mixed results, with some improvement in costs but increased variability with larger populations. GWO scaled well, showing moderate increases in cost and variability but the best percentage improvement.

Consistency is measured by the standard deviation of the results across different trials, as shown in Table II. PSO, followed by GWO, showed superior reliability with lower standard deviations.

TABLE II
STANDARD DEVIATION OF RESULTS

	33	69	141	AVG
PSO	0,014	0,023	0,075	0,037
GWO	0,074	0,075	0,108	0,086
COA	0,613	0,094	0,098	0,269
DE	0,650	0,008	0,225	0,295
GA	0,838	0,407	0,309	0,518
ABC	2,933	21,261	3,125	9,107

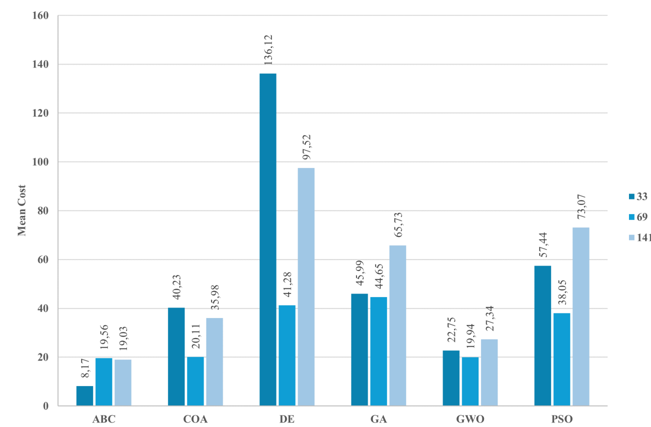

Fig. 10. Mean Time Across All Test Systems

Computational efficiency is evaluated by comparing the number of iterations and execution time against performance metrics like cost and losses. PSO achieved low costs with fewer iterations and reasonable execution time, indicating high computational efficiency. GA required more iterations and time but delivered competitive costs, showing moderate efficiency. COA had moderate efficiency, with some configurations taking longer to converge. ABC showed potential for quick execution but had extremely variable performance. DE showed mixed efficiency, with some scenarios converging quickly and others taking longer. GWO balanced efficiency, achieving reasonable costs with moderate iterations and time. As illustrated in Fig. 10, PSO and GWO maintained reasonable execution times with consistent performance, highlighting their computational efficiency.

The Pareto front in Fig. 11 illustrates the relationship between cost and computation time for different algorithms and population sizes in the 141-bus test system with 3 DGs. There is no significant trade-off between smaller (200 particles) and larger (500 particles) population sizes when the smaller sizes already identify near-optimal solutions. Increasing particle size extends computation time without substantial cost reduction benefits. Therefore, smaller population sizes are preferred for speed-efficient processes, balancing optimal results and manageable computation times.

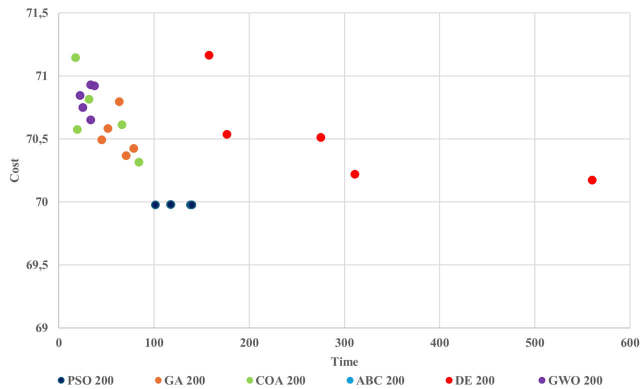

Fig. 11. Pareto Front

Table II provides a detailed comparison of the performance differences between the algorithms.

TABLE III
ALGORITHM SELECTION RESULTS

		PSO	GA	COA	DE	GWO	ABC
Cost	30%	39,67	40,28	39,93	39,89	39,90	45,42
Robustness	20%	0,00	0,12	0,03	0,08	0,08	2,67
Consistency	20%	0,02	0,52	0,27	0,29	0,09	9,11
Scalability	15%	1,33	4,67	3,33	3,33	4,00	4,33
Time	15%	56,18	52,12	32,10	91,64	23,34	15,58

In Table III, the raw scores represent the various performance metrics for all algorithms. Each algorithm has a different raw score for each metric. The goal is to convert the raw performance scores from Table III into a common scale, making it easier to compare different algorithms.

The normalization process is used to scale the raw scores to a common range. This allows for a fair comparison between algorithms across different metrics. The normalization formula used is:

$$N_X = 10 - \frac{10 \times (X - \min(X_1, X_2, \ldots, X_n))}{\max(X_1, X_2, \ldots, X_n) - \min(X_1, X_2, \ldots, X_n)} \quad (15)$$

Where, X is the raw score for a specific algorithm and metric from Table III, and $(X_1, X_2, \ldots, X_n)$ are the raw scores for that metric across all algorithms.

Each algorithm is scored from 1 (poor performance) to 10 (excellent performance) for each criterion. The scores are then multiplied by the weights and summed to obtain a total score.

The comparative analysis highlights the strengths and weaknesses of each algorithm across various metrics:

PSO demonstrated quick convergence and was particularly effective in minimizing the objective function. It showed robustness in finding near-optimal solutions across different test systems. Stands out for its excellent performance across all metrics, achieving high scores in cost efficiency, robustness, consistency, scalability, and computational efficiency.

TABLE IV
ALGORITHM SELECTION RESULTS NORMALIZED

		PSO	GA	COA	DE	GWO	ABC[a]
Cost	30%	10,0	8,9	9,6	9,6	9,6	0,0
Robustness	20%	10,0	9,6	9,9	9,7	9,7	0,0
Consistency	20%	10,0	9,4	9,7	9,7	9,9	0,0
Scalability	15%	10,0	0,0	4,0	4,0	2,0	1,0
Time	15%	4,7	5,2	7,8	0,0	9,0	10,0
	100%	**9,52**	7,27	8,56	7,37	8,45	1,65

[a]The algorithm is difficult to set up, often failing with large samples and not producing analysable results.

The downside is that PSO sometimes converged prematurely to local optima, especially in more complex scenarios with higher numbers of DG units.

GA was effective in exploring large solution spaces and avoiding local optima due to its stochastic nature. It provided a good balance between exploration and exploitation. GA required similar computational time compared to PSO, however it showed more variability of the results, finding worse solutions.

GWO was also effective in handling the objective function with multiple parameters, balancing power losses, and voltage stability. It showed better performance in scenarios with significant variability in load and generation. The convergence rate of GWO was faster compared to PSO, requiring more iterations to reach an optimal solution but lower times. Nevertheless, while PSO was consistently among the best algorithms, GWO did not perform equally good in every tested scenario, lacking scalability potential. Overall, it offers a well-rounded performance with high computational efficiency and strong consistency, making it a reliable alternative to PSO.

DE was highly effective in minimizing power losses and improving voltage profiles. It was particularly robust in finding global optima due to its differential mutation strategy. DE required careful tuning of parameters and had a relatively extremely high computational cost.

COA, despite being the newest and least develop algorithm, demonstrates good computational efficiency and robustness, but needs improvement in consistency and scalability to become more competitive.

Lastly, ABC displays moderate performance in computational efficiency but falls short in other metrics, particularly in cost efficiency, robustness, and consistency. Difficulties to set up might have affected its performance.

PSO emerges as the most reliable and efficient algorithm for DG placement and sizing, with GWO as a potential alternative. COA, despite being a new method, stands in second place with very promising results. Further research could explore hybrid approaches to combine the strengths of different algorithms for enhanced performance in power grid optimization at the cost of an increased complexity in the implementation.

V. RESULTS

The best-performing algorithm, PSO, is tested in a realistic long-term planning scenario using time and solar profiles for a detailed electrical analysis.

To incorporate a time-based analysis, the objective function needs slight adaptation. Previously, it focused on the worst-case high demand scenario. Now, the objective function for Enhanced PSO must minimize costs for each hour and the total cost across all hours. Therefore, eq. (1) is thus modified accordingly:

$$\min_{x} \quad \sum^{t} f(x) + g(x) \tag{16}$$

A. Time and Solar Profiles

To simulate realistic operation, load profiles based on seasonal and daily variations are used. The base load is adapted using load factors derived from historical data, reflecting typical demand patterns throughout the day and across seasons. Different profiles are created for winter, spring, summer, and fall, as shown in Fig. 12. This ensures accurate assessment of network performance under varying conditions.

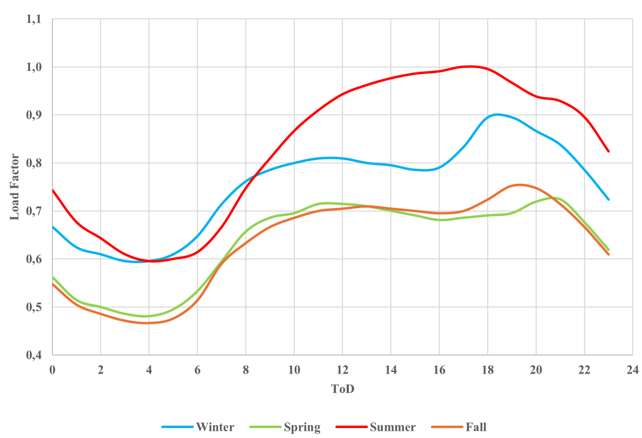

Fig. 12. Applied Load Factors to adapt test system's base load [32]

Average energy consumption is higher in summer and winter due to air conditioning and heating, with peak demand in the mid-afternoon during summer and morning and afternoon peaks in other seasons.

Solar irradiance data, provided by AEMET for Madrid, models potential power generation from PV systems. Monthly values are grouped into seasons. Average global irradiance is calculated for each season, refined for daily variations. Table V summarizes irradiance values and sunlight hours.

TABLE V
SEASONAL IRRADIANCE

Season	kWh/m^2/day	From	To	Hours
Winter	2.46	7	17	10
Spring	5.67	6	19	13
Summer	7.59	5	21	16
Fall	3.82	6	18	12

The irradiance data is used to estimate daily solar power generation, considering system efficiency. Fig. 13 illustrates the implemented solar capacity.

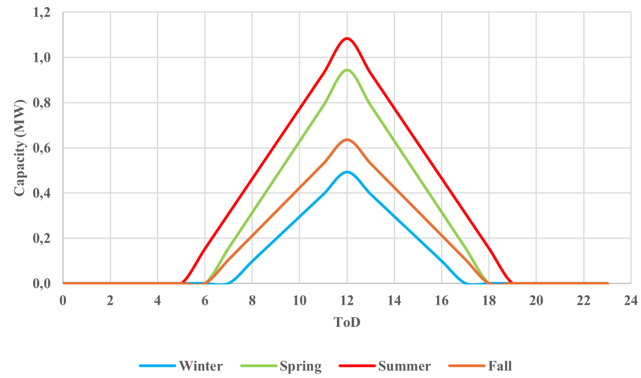

Fig. 13. Implemented Solar Capacity

The electrical analysis of the results involves evaluating the performance of different distribution network configurations under various scenarios. The trials include different test systems with varying numbers of DGs and load profiles, both with and without solar profiles.

B. IEEE 33-bus

The results from the metaheuristic exploration in the first case study involves implementing a single 2.1 MW solar DG unit at bus 15 in the 33-bus test system. The results indicate that during low demand, no solar generation occurs, and all power comes from the substation (see Fig. 14). In high demand scenarios, solar generation helps, but additional power is still needed from the substation. At peak solar generation, there is slightly higher solar output and reduced substation power import. Solar integration significantly reduces midday loads and improves voltage profiles, but potential overvoltages during low demand times are a concern.

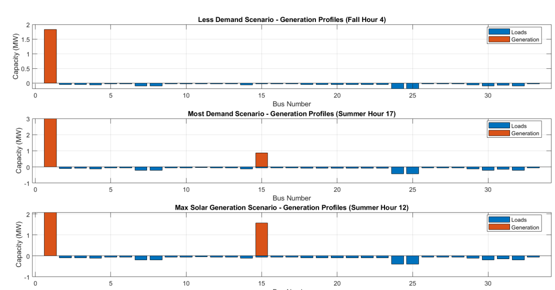

Fig. 14. 33-Bus Test System 1 DG Generation and Demand at each bus

In the second case study, the algorithm implements three DG units: 1.05 MW at bus 13, 0.62 MW at bus 17, and 1.5 MW at bus 32. This setup significantly reduces power imported from the substation, distributes generation more evenly, and improves voltage stability across the network, particularly at tail buses. The total system losses are reduced by 29%, from 202.7 kW to 144.9 kW.

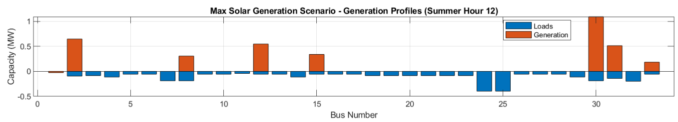

Fig. 15. 33-Bus Test System 7 DGs Generation and Demand at each bus

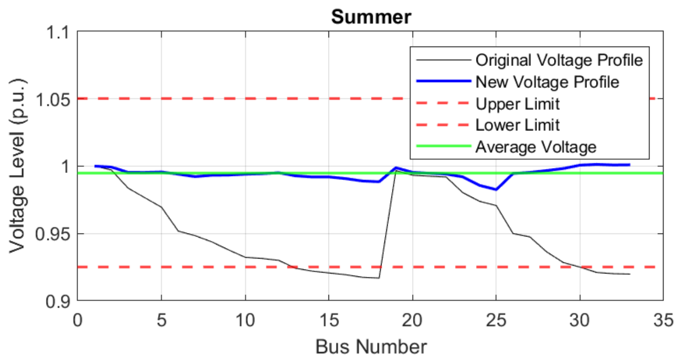

Fig. 16. 33-Bus Test System 7 DG Summer Bus Voltage Profile (12pm, max solar generation)

The final case study aims to maximize PV generation with seven DG units to eliminate active power imports from the substation. This configuration maintains a flat voltage profile and optimally distributes generation, reducing total power losses to 119.64 kW (see Fig. 15). However, beyond this point, additional PV units lead to increased power losses, highlighting a trade-off between voltage stability, system efficiency, and complexity. The optimal balance depends on the DSO's priorities and goals.

C. IEEE 141-bus

The IEEE 141-bus test system evaluates the impact of DG allocation in a real MV distribution grid. In the first case, the algorithm locates a single 2.1 MW PV plant at bus 86 which reduces power losses by 51.5% to 307.16 kW. Although this configuration improved voltage profiles and reduced load during peak solar generation, it highlighted the need for additional backup systems like BESS to handle periods when solar generation does not align with peak demand.

Incorporating only PV showed significant load reductions during daylight hours but also created valleys in the load profile that require other power sources for balance. Demand Response Programs can help by shifting energy usage to off-peak times, such as incentivizing daytime use when solar power is abundant.

The voltage profile with a single DG showed improvement but still had seasonal fluctuations. The algorithm found that introducing five DGs (2.06 MW at bus 44, 2.00 MW at bus 64, 2.06 MW at bus 71, 2.05 MW at bus 76, and 2.06

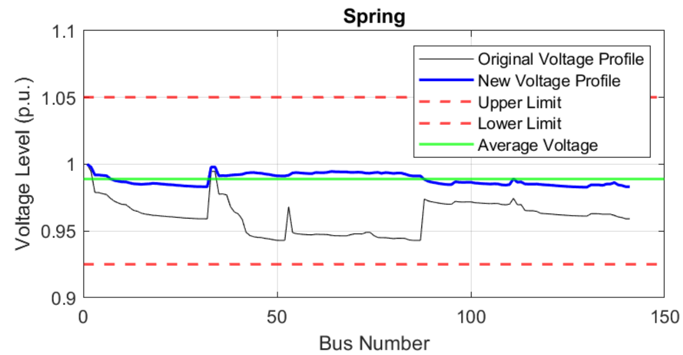

Fig. 17. 145-Bus Test System 5 DG Spring Bus Voltage Profile

MW at bus 71) further stabilized the voltage (see Fig. 17) and reduced system losses to 189.48 kW, a 70.1% reduction. This configuration showed more distributed and stable voltage profiles, indicating the effectiveness of multiple DGs in large systems.

However, integrating more PV without an Energy Management System (EMS) poses a significant threat due to deep valleys in the load profile, requiring substantial backup systems. A distributed approach with multiple DGs is preferable for maintaining voltage stability and system reliability, though it increases system complexity.

VI. Conclusion

The study underscores the importance of selecting appropriate algorithms for specific network conditions to improve overall performance.

The correct comparison of algorithms, such as PSO, GA, and GWO, highlights the strengths and weaknesses of each. This comparison is critical for determining the best-suited algorithm for optimizing DG placement and sizing in distribution networks. Metaheuristic algorithms, particularly PSO, show significant promise in handling complex, multi-objective optimization problems. These algorithms excel in scenarios where traditional methods fall short, especially in managing the variability and complexity introduced by DERs. Although this paper demonstrates that PSO is the most complete algorithm for this particular application, it is followed by GWO as a very complete and powerful algorithm, especially for large test systems. On the other hand, it emphasises the great capacity of COA despite being a very new algorithm and it is hoped that its development will reduce the small failures that it has when it gets lost in the local optimum.

The paper shows the integration of DG using optimized algorithms can lead to reduced power losses, improved voltage profiles, and increased reliability of the power supply. This optimization is crucial for modernizing electrical distribution networks to handle the dynamic nature of renewable energy sources.

The are several limitation in this study. The paper only serves as a benchmark for a specific application. Moreover, test systems used only cover grids with nodes up to a certain size, whereas there are much bigger ones. Additionally, constraints were incorporated as penalties in the objective function, which might not fully capture all real-world complexities. This narrow focus means the results may not be broadly applicable to all types of distribution networks or configurations.

Future research should explore hybrid approaches that combine the strengths of multiple metaheuristic methods to enhance performance. Another important area for future study is modeling problems that also address the flexibility of demand or generation (curtailment), which aligns well with European Union guidelines. Instead of focusing solely on real-time optimization and dynamic grid conditions, integrating advanced techniques to handle demand flexibility and generation curtailment could improve the overall reliability and efficiency of the power distribution network. This direction offers a promising path for future research.

By addressing these limitations and exploring new research directions, future studies can further enhance the application of optimization algorithms in electrical power systems.

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