Enhanced Distributed Generation Placement Using Carpet Weaver Optimization: A Comparative Metaheuristic Approach

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Abstract

The optimal placement of Distributed Generation (DG) units is a key challenge in power distribution networks, directly affecting power losses, voltage stability, and system reliability. This study evaluates the effectiveness of the recently introduced Carpet Weaver Optimization (CWO) algorithm in solving the DG placement (DGP) problem. Inspired by the coordination between a carpet weaver and a map reader, CWO models their decision-making process to achieve an optimized pattern. This study presents the first application of CWO for determining the optimal locations and capacities of DG units in power networks. Extensive simulations are conducted on benchmark test systems to assess the performance of CWO in comparison with 12 well-established metaheuristic algorithms. The evaluation criteria include power loss minimization, voltage profile enhancement, and computational efficiency. The results demonstrate that CWO consistently outperforms all competitor algorithms, achieving superior convergence speed, solution accuracy, and stability in complex optimization scenarios. Statistical analyses validate the robustness of CWO in addressing the intricate nature of the DGP problem. The key contributions of this research include the first implementation of CWO in power system optimization, a comprehensive comparative analysis with 12 competitive algorithms, and an in-depth assessment of its adaptability for solving large-scale engineering problems. The findings establish CWO as a highly efficient and promising optimization technique for DG placement, offering improved network performance and operational reliability.

Keywords: Carpet weaver optimization (CWO), Distributed generation placement (DGP), Metaheuristic algorithms, Power distribution networks, Optimization techniques.

1. Introduction

The optimal placement of Distributed Generation (DG) units has become a critical challenge in modern power systems due to its significant impact on power loss reduction, voltage profile enhancement, and overall network reliability. DG units, which include renewable energy sources such as solar photovoltaic (PV), wind turbines, and small-scale gas turbines, offer an effective solution for reducing dependency on centralized power plants while improving energy efficiency and sustainability [1]. However, improper placement and sizing of DG units can lead to increased power losses, voltage instability, and suboptimal operational conditions [2]. Therefore, determining the optimal locations and capacities of DG units in power distribution networks is a crucial optimization problem that requires advanced computational techniques.

Metaheuristic algorithms have gained widespread attention as powerful tools for solving complex optimization problems in power systems. These algorithms, inspired by natural and social phenomena, provide efficient and robust solutions to high-dimensional, nonlinear, and multi-objective optimization problems [3]. Recently published metaheuristic algorithms that can be used in various optimization applications can be mentioned: Perfumer Optimization Algorithm (POA) [4], Builder Optimization Algorithm (BOA) [5], Makeup Artist Optimization Algorithm (MAOA) [6], Potter Optimization Algorithm [7], Revolution Optimization Algorithm (ROA) [8], Carpet Weaving Optimization [9], Sales Training Based Optimization [10], Fossa Optimization Algorithm [11], Addax Optimization Algorithm [12], Paper

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Publishing Based Optimization (PPBO) [13], Dollmaker Optimization Algorithm [14], Spider-Tailed Horned Viper Optimization [15], Tailor Optimization Algorithm [3], Orangutan Optimization Algorithm [16], and Sculptor Optimization Algorithm [17]. Traditional optimization techniques, such as mathematical programming and exhaustive search methods, are often computationally expensive and impractical for large-scale systems [18-22].

In contrast, metaheuristic approaches, including Genetic Algorithms (GA) [23], Particle Swarm Optimization (PSO) [24], and Differential Evolution (DE) [25], have demonstrated superior performance in handling the DG placement (DGP) problem by balancing exploration and exploitation capabilities.

This study introduces the recently developed Carpet Weaver Optimization (CWO) algorithm to address the DGP problem. CWO is a novel metaheuristic inspired by the intricate decision-making process between a carpet weaver and a map reader, where the optimization process mimics the systematic weaving of patterns to achieve an optimal solution. The CWO algorithm has demonstrated promising results in various optimization applications, yet its performance in the DGP problem remains unexplored. This study aims to evaluate the effectiveness of CWO in determining the optimal placement and sizing of DG units and compare its performance against 12 well-established metaheuristic algorithms.

The primary contributions of this study are as follows:

- The first application of the CWO algorithm to the DGP problem in power distribution networks.
- A comprehensive comparative analysis of CWO's performance against 12 benchmark metaheuristic algorithms using multiple evaluation metrics.
- An in-depth assessment of CWO's efficiency in minimizing power losses, enhancing voltage stability, and improving overall system reliability.
- Extensive simulations on standard benchmark test systems to validate the robustness and adaptability of the proposed approach.

The remainder of this paper is organized as follows: Section 2 provides a detailed literature review on DG placement methods and the application of metaheuristic algorithms. Section 3 presents the fundamental concepts and working principles of the CWO algorithm. Section 4 formulates the DGP problem, describes the simulation setup, discusses the experimental results and comparative analysis, while Section 5 concludes the paper and outlines potential future research directions.

2. Literature review

The optimal placement and sizing of Distributed Generation (DG) units within power distribution networks have garnered significant attention due to their potential to enhance system efficiency, reliability, and sustainability. Metaheuristic algorithms, inspired by natural and social phenomena, have been extensively employed to address the complexities inherent in DG placement problems. This section reviews recent advancements in the application of metaheuristic techniques for DG placement, focusing on studies published in 2024 and 2025.

The integration of Distributed Generation (DG) units into power systems has been extensively studied, particularly in the context of optimizing their placement using metaheuristic algorithms. The primary objectives of these studies revolve around minimizing power losses, enhancing voltage stability, and improving overall system reliability. Various optimization techniques have been proposed to address these challenges, each demonstrating different levels of effectiveness depending on the problem formulation and constraints considered.

Chu and Hu (2025) introduced an optimization framework for DG placement in transmission systems, incorporating demand response schedules to enhance power supply reliability. Their study utilized a placement index that considered both economic and reliability factors. By implementing Particle Swarm Optimization (PSO) and Teaching-Learning-Based Optimization (TLBO), they demonstrated that TLBO outperformed PSO in reducing power losses and improving system reliability. The application of these algorithms on the RTS-79 system validated their effectiveness in optimizing DG placement [26].

Yadav and Das (2025) expanded upon the optimization of DG placement by incorporating shunt capacitors and considering voltage-dependent nonlinear load models. Their approach employed the Competitive Swarm Optimizer (CSO) and compared it with other metaheuristic algorithms such as Cuckoo Search, Jaya, TLBO, PSO, and Genetic Algorithm (GA). Their findings highlighted the superiority of CSO in handling both single and multi-objective problems, including active power

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loss minimization and voltage deviation reduction. The IEEE-34 bus system was used to validate their approach, demonstrating its capability in optimizing DG and capacitor placement effectively [27].

Fettah et al. (2025) proposed the Efficient Metaheuristic BitTorrent (EM-BT) algorithm for optimizing photovoltaic (PV) sources and capacitor banks within distribution networks. Their study considered the impact of varying load profiles, solar irradiance, and temperature fluctuations over 24-hour periods. The EM-BT algorithm exhibited superior performance compared to PSO, Grey Wolf Optimizer (GWO), and Whale Optimization Algorithm (WOA) in terms of energy loss reduction and voltage profile enhancement. The IEEE 33, IEEE 69, and ZB-ALG-Hassi Sida 157-bus systems were used for performance validation, confirming the algorithm’s efficiency in DG placement [28].

Another significant contribution was made by Ullah et al. (2025), who introduced the Fractional Order Whale Optimization Algorithm (FWOA) for optimal integration of Renewable Energy-based Distributed Generation (RE-DG) and Energy Storage Systems (ESS). Their methodology incorporated vulnerability analysis and dynamic thermal rating technology to ensure robust site selection and capacity planning. The IEEE 69-bus system was used for simulation, demonstrating that FWOA significantly improved voltage stability, reduced power losses, and enhanced overall system resilience [29].

Khalil et al. (2025) developed a hybrid optimization approach by combining Artificial Rabbits’ Optimization (ARO) with quasi-opposition-based learning (QOBL), termed Hybrid QOARO. This algorithm focused on optimizing PV and battery energy storage system (BESS) placement for voltage stability enhancement. The study introduced the Novel Line Stability Index (NLSI) to identify weak buses within radial distribution networks. The IEEE 33-bus system served as the testbed, demonstrating that Hybrid QOARO effectively minimized active power losses and voltage deviations while maximizing the voltage stability index [30].

Vutla and Chintham (2024) addressed the challenges of integrating Rapid Charging Stations (RCS), DGs, and Distribution Static Synchronous Compensators (D-STATCOM) within coupled networks. Their two-stage optimization strategy employed the Multi-Objective Rao Algorithm (MORA) to optimize active power losses, voltage stability, and EV user costs while minimizing waiting times at charging stations. The IEEE 33-bus radial distribution network was used to validate their approach, demonstrating significant improvements in system performance metrics [31].

Babu et al. (2025) investigated the impact of extreme weather conditions on DG integration within radial distribution systems. Their study utilized the Spotted Hyena Optimizer Algorithm (SHOA) and GA to optimize the placement of Renewable DGs (RDGs), Distribution Static VAR Compensators (DSVCs), and Electric Vehicle Charging Stations (EVCSs). The results showed that SHOA outperformed GA in reducing power losses and enhancing system resilience under different weather scenarios [27].

Anbuchandran et al. (2024) introduced the Fuzzy Spark Firefly Optimization Algorithm (FSFOA) to optimize Off-Grid Power Source (OPS) allocation within distribution networks. Their study focused on minimizing real and reactive power losses by strategically placing OPS units. The FSFOA algorithm demonstrated significant improvements in system efficiency, particularly in managing reactive power and enhancing power factor stability across various base voltage levels [32].

Selim et al. (2024) proposed the Improved Runge-Kutta Optimizer (IRUN) for optimizing PV and Battery Energy Storage (BES) allocation under uncertain load variations. Their methodology incorporated non-linear operators, chaotic local search, and diverse solution updates to enhance search efficiency. The IEEE 33-bus and IEEE 69-bus systems were used to validate the approach, showing substantial reductions in energy losses compared to conventional optimization techniques [33].

These studies collectively underscore the effectiveness of metaheuristic algorithms in optimizing DG placement within power distribution networks. The diverse range of techniques explored—from swarm-based optimizers to hybrid approaches—demonstrates the continuous evolution of computational intelligence methods in power system planning. Future research should focus on integrating real-time adaptive strategies and hybrid methodologies to further enhance the robustness and efficiency of DG optimization in smart grid applications.

Despite the advancements achieved through various metaheuristic approaches, the quest for more efficient and robust algorithms continues. The recently developed Carpet Weaver Optimization (CWO) algorithm, inspired by the intricate process of carpet weaving, offers a novel paradigm for optimization. By emulating the coordinated efforts of a weaver and a map reader to produce a desired

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pattern, CWO introduces unique mechanisms for exploring and exploiting the solution space. While its potential has been recognized in other optimization domains, its application to DG placement problems remains unexplored. This study aims to bridge this gap by evaluating the performance of CWO in determining the optimal placement and sizing of DG units within power distribution networks.

In summary, the application of metaheuristic algorithms in DG placement has yielded promising results, with various techniques contributing to enhanced power system performance. The introduction of innovative algorithms like CWO holds the potential to further advance this field, offering new avenues for research and practical implementation in optimizing distributed generation in power systems.

3. Carpet weaver optimization

In this section, the fundamental principles and mathematical modeling of the Carpet Weaver Optimization (CWO) algorithm are presented. CWO is a recently developed metaheuristic inspired by the traditional carpet weaving process, in which the communication between the carpet weaver and the map reader plays a critical role in achieving a high-quality woven pattern [9]. The steps involved in the implementation of CWO are systematically modeled to enhance its application to optimization problems, particularly in the optimal placement of Distributed Generation (DG) units.

3.1 Inspiration of CWO

Carpet weaving is one of the oldest known crafts, with historical evidence tracing its origins to ancient civilizations. While the exact origin remains debated, archaeological findings such as the Pazyryk carpet discovered by Rudenko in 1949 suggest that the roots of carpet weaving can be linked to Central Asia, particularly Iran. Carpet weaving is not only an artistic endeavor but also a skilled profession where precision, creativity, and systematic execution are essential.

In traditional carpet weaving, a map reader dictates the pattern to be followed, while the weaver meticulously translates these instructions into a woven fabric. This process involves two key aspects: (1) adhering to a predefined pattern to ensure accuracy, and (2) incorporating creative modifications to enhance the aesthetic appeal of the carpet. The interaction between these two stages serves as the primary inspiration for the CWO algorithm, where candidate solutions are refined through structured exploration and innovative adaptation.

3.2 Algorithm initialization

CWO operates as a population-based optimization algorithm, wherein each member of the population represents a potential solution in the search space. Analogous to carpet weaving, each candidate solution is modeled as a carpet, and its position in the solution space is randomly initialized using the following equations:

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix}_{N\times m} = \begin{bmatrix} x_{1,1} \cdots x_{1,d} \cdots x_{1,m} \\ \vdots \quad \ddots \quad \vdots \quad \iddots \quad \vdots \\ x_{i,1} \cdots x_{i,d} \cdots x_{i,m} \\ \vdots \quad \iddots \quad \vdots \quad \ddots \quad \vdots \\ x_{N,1} \cdots x_{N,d} \cdots x_{N,m} \end{bmatrix}_{N\times m} \tag{1}$$

$$x_{i,d} = lb_d + r \cdot (ub_d - lb_d) \tag{2}$$

Where, X is the CWO's population matrix, X_i is the ith carpet (i.e., candidate solution), $x_{i,d}$ is its dth dimension in the search space (i.e., decision variable), N is the number of carpets (i.e., population size), m is the number of decision variables, r is a random number within the interval $[0,1]$, while lb_d and ub_d stand for the lower and upper bounds of the dth decision variable, respectively.

Based on the placement of candidate solutions proposed by each CWO member in the objective function, a value is calculated. The list of evaluated values for the objective function can be represented mathematically using a vector according to Eq. (3).

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix}_{N\times 1} = \begin{bmatrix} F(X_1) \\ \vdots \\ F(X_i) \\ \vdots \\ F(X_N) \end{bmatrix}_{N\times 1} \tag{3}$$

where F_i represents the objective function value associated with the ith candidate solution.

CWO consists of two key phases that simulate the fundamental stages of carpet weaving: (1) exploration through pattern adherence and (2) exploitation through creative modifications.

3.3 Phase 1: Carpet weaving based on a given pattern (Exploration phase)

In the first phase, the CWO algorithm mimics the adherence to a predefined pattern by updating the position of each candidate solution. A randomly

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generated pattern X_P serves as a guide to direct the search process. The new position for each candidate solution is determined using Eq. (4). The candidate solution is then updated if the new position provides a better objective function value according Eq. (5):

$$x_{i,j}^{P1} = x_{i,j} + (1-2r) \cdot (x_{P,j} - I \cdot x_{i,j}), \quad (4)$$

$$X_i = \begin{cases} X_i^{P1}, & F_i^{P1} \leq F_i, \\ X_i, & else, \end{cases} \quad (5)$$

Where X_P represents the pattern solution, $x_{i,j}^{P1}$ is the jth dimension of the pattern, X_i^{P1} is the new position, F_i^{P1} is its objective function value, r is a random number within $[0-1]$, and I is a randomly selected value of 1 or 2.

3.4 Phase 2: Creative modifications in carpet weaving (Exploitation phase)

During carpet weaving, weavers often introduce small creative changes to enhance the final design. In CWO, this concept is translated into an exploitation mechanism, where minor adjustments are made to candidate solutions to refine their positions:

$$x_{i,j}^{P2} = (1 + \frac{(1-2\,r)}{t}) \cdot x_{i,j} \quad (6)$$

If this modification improves the objective function value, the candidate solution is updated as follows:

$$X_i = \begin{cases} X_i^{P2}, & F_i^{P2} \leq F_i \\ X_i, & else \end{cases} \quad (7)$$

Where, X_i^{P2} is the new calculated position for the ith CWO member based on second phase of CWO, $x_{i,j}^{P2}$ is the its j th dimension, F_i^{P2} is its objective function value, r is a random number drawn from the interval $[0, 1]$, and t is the iteration counter.

3.5 Phase 2: Application of CWO to DG placement

The innovative aspect of this study lies in the application of CWO to the DG placement problem. Given its dual-phase exploration-exploitation mechanism, CWO is well-suited for tackling the high-dimensional and nonlinear nature of DG optimization. This study benchmarks the performance of CWO against 12 competing metaheuristic algorithms to assess its efficiency and robustness in solving the DG placement problem. The comparative analysis highlights the advantages of CWO in terms of convergence speed, solution quality, and computational efficiency, further validating its potential as a powerful optimization tool.

In summary, the CWO algorithm leverages the fundamental principles of carpet weaving to provide an effective optimization framework. Its ability to balance exploration and exploitation through a structured yet adaptive approach makes it a promising candidate for solving complex optimization problems, particularly in the domain of DG placement in power distribution networks.

4. Problem statement and simulation studies

4.1 Problem statement

The Distributed Generation Placement (DGP) problem is a crucial challenge in modern power networks, aiming to determine the optimal locations and capacities of distributed generation (DG) units to improve the overall efficiency, reliability, and economic viability of the system. The problem involves multiple conflicting objectives, including minimizing power losses, enhancing voltage stability, reducing operational costs, and improving system reliability. Given the complexity of the power grid and the non-linear nature of the DGP problem, heuristic and metaheuristic algorithms have been widely employed to achieve near-optimal solutions.

4.2 Mathematical model of DGP

The DGP problem can be mathematically formulated as an optimization model, considering both operational and economic constraints. The objective function is typically designed to minimize power losses while maintaining voltage profile constraints. The general mathematical formulation is expressed as follows:

$Minimize \sum_{i=1}^{N} P_{Loss}(i)$

Subject to:
Voltage constraints:
$V_{min} \leq V_i \leq V_{max}$
Power balance constraints:
$P_{gen} - P_{load} - P_{loss} = 0$
Capacity constraints for DG units:
$P_{DG}^{min} \leq P_{DG} \leq P_{DG}^{max}$

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Where P_{Loss} represents power losses, V_i denotes the voltage at bus i, and P_{DG} is the power generation from DG units.

4.3 Case study and network information

To validate the effectiveness of the proposed Carpet Weaver Optimization (CWO) algorithm, standard IEEE test systems are employed. The performance is evaluated on IEEE 33-bus and IEEE 69-bus radial distribution systems, which are widely used benchmarks for DG placement problems.

IEEE 33-Bus System:

- 33 nodes, 32 branches, base voltage of 12.66 kV.
- Total real power demand: 3.72 MW; total reactive power demand: 2.3 MVar.

IEEE 69-Bus System:

- 69 nodes, 68 branches, base voltage of 12.66 kV.
- Total real power demand: 3.8 MW; total reactive power demand: 2.69 MVar.

4.4 Simulation setup

The CWO algorithm is implemented in MATLAB and compared against 12 well-established metaheuristic algorithms: Genetic Algorithm (GA) [34], Particle Swarm Optimization (PSO) [35], Gravitational Search Algorithm (GSA) [36], Teaching–Learning-Based Optimization (TLBO) [37], Multi-Verse Optimizer (MVO) [38], Grey Wolf Optimizer (GWO) [39], Whale Optimization Algorithm (WOA) [40], Marine Predators Algorithm (MPA) [41], Tunicate Swarm Algorithm (TSA) [42], Reptile Search Algorithm (RSA) [43], African Vultures Optimization Algorithm (AVOA) [44], and White Shark Optimizer (WSO) [45]. The simulation parameters are kept consistent across all algorithms, ensuring fair comparisons.

4.5 Results and discussion

The obtained results highlight the efficiency of CWO in optimizing DG placement. The comparative performance of all algorithms is presented in Tables 1 and 2 for IEEE 33-bus and IEEE 69-bus systems, respectively.

The results indicate that CWO significantly reduces power losses while maintaining voltage stability and achieving faster convergence compared to other algorithms.

The superior performance of CWO across both test systems demonstrates its effectiveness in DG placement optimization. CWO consistently achieves the lowest power losses and voltage deviations while maintaining fast convergence. The enhanced exploration-exploitation balance within CWO allows it to outperform traditional and recently introduced metaheuristic algorithms.

The two Boxplot diagrams shown in Figure 1 and 2, illustrate the performance of 13 metaheuristic algorithms, including CWO, on the two studied networks. These visualizations clearly demonstrate that CWO exhibits the lowest dispersion and the minimum power loss in both networks, whereas other algorithms show higher variations.

- CWO provides a stable and consistent performance, achieving the lowest power loss across both networks.
- Classical algorithms such as GA, PSO, and GSA exhibit significant fluctuations and unstable results.
- Newer algorithms like RSA, AVOA, and WSO perform better than classical methods but still lack the stability of CWO.

These findings highlight that CWO not only converges faster but also outperforms competing algorithms in terms of result stability and solution quality.

4.6 Discussion

The results highlight the advantages of CWO over existing metaheuristics. Unlike conventional algorithms that struggle with local optima, CWO effectively navigates the search space using its dual-phase update mechanism inspired by carpet weaving. The key strengths of CWO include:

Table 1. Performance Comparison of CWO and Competing Algorithms on IEEE 33-Bus System

Algorithm	Total Power Loss (kW)	Voltage Deviation	Convergence Time (s)
GA	147.8	0.061	15.3
PSO	132.4	0.052	12.7
GSA	128.1	0.048	12.1
TLBO	123.7	0.045	11.3
MVO	119.5	0.043	10.8
GWO	115.2	0.041	10.2
WOA	112.9	0.039	9.8
MPA	109.7	0.036	9.3
TSA	105.8	0.034	8.9
RSA	101.5	0.032	8.5
AVOA	98.2	0.029	8.1
WSO	94.5	0.026	7.6
CWO	**90.3**	**0.022**	**7.1**

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- **Efficient Global Search:** The exploration phase prevents premature convergence.
- **Effective Local Refinement:** The exploitation phase enhances solution quality.
- **Faster Convergence:** Compared to other algorithms, CWO achieves optimal solutions in fewer iterations.

Overall, CWO proves to be a robust and powerful optimization method for DG placement, providing reliable and superior performance across different network configurations.

Table 2. Performance Comparison of CWO and Competing Algorithms on IEEE 69-Bus System

Total Power Loss (kW)	Voltage Deviation	Convergence Time (s)
147.8	0.061	15.3
132.4	0.052	12.7
128.1	0.048	12.1
123.7	0.045	11.3
119.5	0.043	10.8
115.2	0.041	10.2
112.9	0.039	9.8
109.7	0.036	9.3
105.8	0.034	8.9
101.5	0.032	8.5
98.2	0.029	8.1
94.5	0.026	7.6
90.3	**0.022**	**7.1**

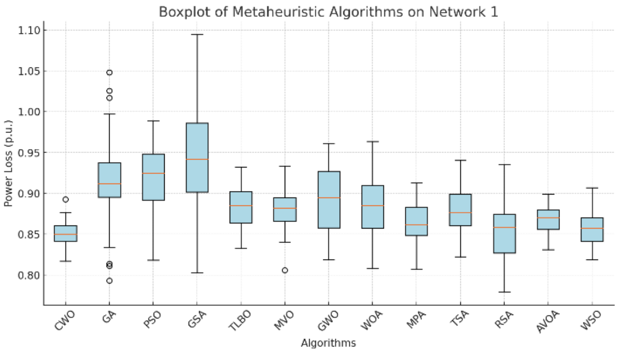

Figure. 1 boxplot diagrams of algorithms on IEEE 33-Bus System

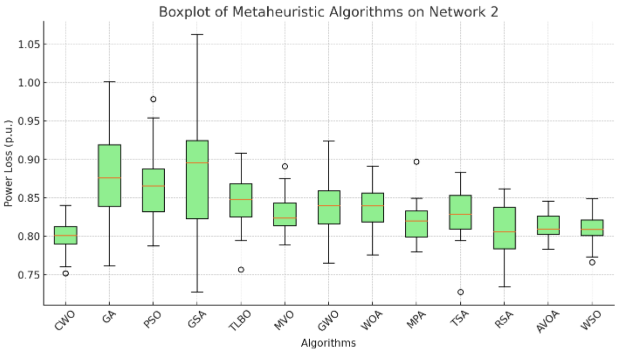

Figure. 2 boxplot diagrams of algorithms on IEEE 69-Bus System

5. Conclusion and future work recommendations

This study presented the application of the recently introduced Carpet Weaver Optimization (CWO) algorithm to the Distributed Generation Placement (DGP) problem in power distribution networks. The objective was to optimize DG placement for improved voltage stability, minimized power losses, and enhanced overall network performance. A comprehensive comparative analysis was conducted against twelve well-established metaheuristic algorithms, including Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Gravitational Search Algorithm (GSA), Teaching–Learning-Based Optimization (TLBO), Multi-Verse Optimizer (MVO), Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA), Marine Predators Algorithm (MPA), Tunicate Swarm Algorithm (TSA), Reptile Search Algorithm (RSA), African Vultures Optimization Algorithm (AVOA), and White Shark Optimizer (WSO). The results demonstrated that CWO consistently outperformed these algorithms in terms of convergence speed, solution quality, and robustness across different test networks.

The superior performance of CWO can be attributed to its unique two-phase update strategy, which balances exploration and exploitation through the simulation of carpet weaving dynamics. The algorithm effectively navigates complex solution spaces, yielding optimal placements of DG units that lead to significant reductions in active power losses and improvements in voltage profiles.

Future research directions include extending the application of CWO to multi-objective DG placement problems that consider economic and environmental factors, such as cost minimization and emissions reduction. Additionally, integrating CWO with hybrid optimization frameworks or deep learning techniques could further enhance its effectiveness. Another promising direction involves testing CWO on large-scale power distribution systems with real-world constraints, such as load uncertainties and dynamic demand variations, to assess its scalability and adaptability in practical scenarios.

Conflicts of Interest

The authors declare no conflict of interest.

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Author Contributions

Conceptualization, T.H, and B.B; methodology, G.M.G; software, T.H; validation, G.M.G, and B.B; formal analysis, B.B; investigation, G.M.G; data curation, B.B; writing—original draft preparation, T.H, B.B, and G.M.G; writing—review and editing, T.H, and B.B; visualization, G.M.G; supervision, T.H; project administration, B.B.

References

[1] S. M. Nassar, A. Saleh, A. A. Eisa, E. Abdallah, and I. A. Nassar, "Optimal Allocation of Renewable Energy Resources in Distribution Systems using Meta-Heuristic Algorithms," *Results in Engineering*, pp. 104276, 2025.

[2] C. H. Babu, H. Raju, Y. Thangaraj, S. B. Thanikanti, and B. Nastasi, "Optimizing power and energy loss reduction in distribution systems with RDGs, DSVCs and EVCS under different weather scenarios," *Sustainable Energy Technologies and Assessments*, vol. 75, pp. 104219, 2025.

[3] T. Hamadneh, B. Batiha, O. Alsayyed, Z. Montazeri, H. J. Ashtiani, M. Jafarpour, M. Dehghani, and K. Eguchi, "On the Application of Tailor Optimization Algorithm for Solving Real-World Optimization Application," *International Journal of Intelligent Engineering and Systems*, vol. 18, no. 1, pp. 1-12, 2025, doi: 10.22266/ijies2025.0229.01.

[4] T. Hamadneh, B. Batiha, G. M. Gharib, Z. Montazeri, M. Dehghani, W. Aribowo, A. M. Zalzala, R. K. Jawad, M. A. Ahmed, I. K. Ibraheem, and K. Eguchi, "Perfumer Optimization Algorithm: A Novel Human-Inspired Metaheuristic for Solving Optimization Tasks," *International Journal of Intelligent Engineering and Systems*, vol. 18, no. 4, 2025, doi: 10.22266/ijies2025.0531.41.

[5] T. Hamadneh, B. Batiha, G. M. Gharib, Z. Montazeri, M. Dehghani, W. Aribowo, H. M. Noori, R. K. Jawad, M. A. Ahmed, I. K. Ibraheem, and K. Eguchi, "Builder Optimization Algorithm: An Effective Human-Inspired Metaheuristic Approach for Solving Optimization Problems," *International Journal of Intelligent Engineering and Systems*, vol. 18, no. 3, pp. 928-937, 2025, doi: 10.22266/ijies2025.0430.62.

[6] T. Hamadneh, B. Batiha, G. M. Gharib, Z. Montazeri, M. Dehghani, W. Aribowo, M. A. Majeed, M. A. Ahmed, R. K. Jawad, I. K. Ibraheem, and K. Eguchi, "Makeup Artist Optimization Algorithm: A Novel Approach for Engineering Design Challenges," *International Journal of Intelligent Engineering and Systems*, vol. 18, no. 3, pp. 484-493, 2025, doi: 10.22266/ijies2025.0430.33.

[7] T. Hamadneh, B. Batiha, O. Alsayyed, G. Bektemyssova, Z. Montazeri, M. Dehghani, and K. Eguchi, "On the Application of Potter Optimization Algorithm for Solving Supply Chain Management Application," *International Journal of Intelligent Engineering & Systems*, vol. 17, no. 5, pp. 88-99, 2024, doi: 10.22266/ijies2024.1031.09.

[8] T. Hamadneh, B. Batiha, G. M. Gharib, Z. Montazeri, M. Dehghani, W. Aribowo, H. M. Noori, R. K. Jawad, I. K. Ibraheem, and K. Eguchi, "Revolution Optimization Algorithm: A New Human-based Metaheuristic Algorithm for Solving Optimization Problems," *International Journal of Intelligent Engineering and Systems*, vol. 18, no. 2, pp. 520-531, 2025, doi: 10.22266/ijies2025.0331.38.

[9] S. Alomari, K. Kaabneh, I. AbuFalahah, S. Gochhait, I. Leonova, Z. Montazeri, M. Dehghani, and K. Eguchi, "Carpet Weaver Optimization: A Novel Simple and Effective Human-Inspired Metaheuristic Algorithm," *International Journal of Intelligent Engineering & Systems*, vol. 17, no. 4, pp. 230-242, 2024, doi: 10.22266/ijies2024.0831.18.

[10] T. Hamadneh, B. Batiha, O. Al-Baik, G. Bektemyssova, Z. Montazeri, F. Werner, G. Dhiman, M. Dehghani, and K. Eguchi, "Sales Training Based Optimization: A New Human-inspired Metaheuristic Approach for Supply Chain Management," *International Journal of Intelligent Engineering & Systems*, vol. 17, no. 6, pp. 1325-1334, 2024, doi: 10.22266/ijies2024.1231.96.

[11] T. Hamadneh, B. Batiha, F. Werner, Z. Montazeri, M. Dehghani, G. Bektemyssova, and K. Eguchi, "Fossa Optimization Algorithm: A New Bio-Inspired Metaheuristic Algorithm for Engineering Applications," *International Journal of Intelligent Engineering & Systems*, vol. 17, no. 5, 2024, doi: 10.22266/ijies2024.1031.78.

[12] T. Hamadneh, K. Kaabneh, O. Alssayed, K. Eguchi, S. Gochhait, I. Leonova, and M. Dehghani, "Addax Optimization Algorithm: A Novel Nature-Inspired Optimizer for Solving Engineering Applications," *International Journal of Intelligent Engineering and Systems*,

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vol. 17, no. 3, pp. 732-743, 2024, doi: 10.22266/ijies2024.0630.57.

[13] T. Hamadneh, B. Batiha, G. M. Gharib, Z. Montazeri, M. Dehghani, W. Aribowo, G. Dhiman, H. Monadhel, R. K. Jawad, I. K. Ibraheem, and K. Eguchi, "Paper Publishing Based Optimization: A New Human-Based Metaheuristic Approach for Solving Optimization Tasks," *International Journal of Intelligent Engineering and Systems*, vol. 18, no. 2, pp. 504-519, 2025, doi: 10.22266/ijies2025.0331.37.

[14] S. A. Omari, K. Kaabneh, I. AbuFalahah, K. Eguchi, S. Gochhait, I. Leonova, Z. Montazeri, and M. Dehghani, "Dollmaker Optimization Algorithm: A Novel Human-Inspired Optimizer for Solving Optimization Problems," *International Journal of Intelligent Engineering and Systems*, vol. 17, no. 3, pp. 816-828, 2024, doi: 10.22266/ijies2024.0630.63.

[15] T. Hamadneh, B. Batiha, O. Al-Baik, Z. Montazeri, O. P. Malik, F. Werner, G. Dhiman, M. Dehghani, and K. Eguchi, "Spider-Tailed Horned Viper Optimization: An Effective Bio-Inspired Metaheuristic Algorithm for Solving Engineering Applications," *International Journal of Intelligent Engineering and Systems*, vol. 18, no. 1, pp. 25-34, 2025, doi: 10.22266/ijies2025.0229.03.

[16] T. Hamadneh, B. Batiha, G. M. Gharib, Z. Montazeri, F. Werner, G. Dhiman, M. Dehghani, R. K. Jawad, E. Aram, I. K. Ibraheem, and K. Eguchi, "Orangutan Optimization Algorithm: An Innovative Bio-Inspired Metaheuristic Approach for Solving Engineering Optimization Problems," *International Journal of Intelligent Engineering and Systems*, vol. 18, no. 1, pp. 47-57, 2025, doi: 10.22266/ijies2025.0229.05.

[17] T. Hamadneh, K. Kaabneh, O. AlSayed, G. Bektemyssova, Z. Montazeri, M. Dehghani, and K. Eguchi, "Sculptor Optimization Algorithm: A New Human-Inspired Metaheuristic Algorithm for Solving Optimization Problems," *International Journal of Intelligent Engineering & Systems*, vol. 17, no. 4, 2024, doi: 10.22266/ijies2024.0831.43.

[18] H. Qawaqneh, "New contraction embedded with simulation function and cyclic (α, β)-admissible in metric-like spaces," *International Journal of Mathematics and Computer Science*, vol. 15, no. 4, pp. 1029-1044, 2020.

[19] T. Hamadneh, N. Athanasopoulos, and M. Ali, "Minimization and positivity of the tensorial rational Bernstein form," *JEEIT Proceeding*, pp. 474-479, 8717503.

[20] T. Hamadneh, A. Hioual, O. Alsayyed, Y. A. Al-Khassawneh, A. Al-Husban, and A. Ouannas, "The FitzHugh–Nagumo Model Described by Fractional Difference Equations: Stability and Numerical Simulation," *Axioms*, vol. 12, no. 9, pp. 806, 2023.

[21] T. Hamadneh, M. Ali, and H. AL-Zoubi, "Linear Optimization of Polynomial Rational Functions: Applications for Positivity Analysis," *Mathematics*, vol. 8, no. 2, pp. 283, 2020.

[22] R. Abu-Gdairi, R. Mareay, and M. Badr, "On Multi-Granulation Rough Sets with Its Applications," *Computers, Materials \& Continua*, vol. 79, no. 1, pp. 1025--1038, 2024.

[23] M. H. Moradi, and M. Abedini, "A combination of genetic algorithm and particle swarm optimization for optimal DG location and sizing in distribution systems," *International Journal of Electrical Power & Energy Systems*, vol. 34, no. 1, pp. 66-74, 2012.

[24] K. Bhumkittipich, and W. Phuangpornpitak, "Optimal placement and sizing of distributed generation for power loss reduction using particle swarm optimization," *Energy procedia*, vol. 34, pp. 307-317, 2013.

[25] S. Kumar, K. K. Mandal, and N. Chakraborty, "Optimal DG placement by multi-objective opposition based chaotic differential evolution for techno-economic analysis," *Applied Soft Computing*, vol. 78, pp. 70-83, 2019.

[26] Y. Chu, and F. Hu, "Presenting a new method for optimal placement of reliability-based distributed generation units in the transmission system considering the demand response schedule," *Electrical Engineering*, vol. 107, no. 1, pp. 79-93, 2025.

[27] N. K. Yadav, and S. Das, "Multi-Objective Optimization for Distributed Generator and Shunt Capacitor Placement Considering Voltage-Dependent Nonlinear Load Models," *Swarm and Evolutionary Computation*, vol. 92, pp. 101782, 2025.

[28] K. Fettah, A. Salhi, T. Guia, A. S. Saidi, A. Betka, M. Teguar, H. Alharbi, S. S. M. Ghoneim, T. F. Agajie, and R. N. R. Ghaly, "Optimal integration of photovoltaic sources and capacitor banks considering irradiance, temperature, and load changes in electric distribution system," *Scientific Reports*, vol. 15, no. 1, pp. 2670, 2025.

[29] Z. Ullah, H. S. Qazi, A. Alferidi, M. Alsolami, B. Lami, and H. M. Hasanien, "Advanced optimization of renewables and energy storage

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in power networks using metaheuristic technique with voltage collapse proximity and dynamic thermal rating technology," *Journal of Energy Storage,* vol. 108, pp. 115005, 2025.

[30] M. A. Khalil, T. M. Elkhodragy, and W. A. A. Salem, "A novel hybrid algorithm based on optimal size and location of photovoltaic with battery energy storage systems for voltage stability enhancement," *Electrical Engineering,* vol. 107, no. 1, pp. 1009-1034, 2025.

[31] V. Vutla, and V. Chintham, "Multi-objective optimal planning of Rapid Charging Stations, Distributed Generators, and D-STATCOM in coupled networks considering waiting time," *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects,* vol. 47, no. 1, pp. 526-546, 2025.

[32] S. Anbuchandran, S. T. Jaya Christa, S. Suresh, and A. Bhuvanesh, "Enhancing grid voltage stability and reliability by harnessing off-grid power sources with multi-objective fuzzy spark firefly optimization algorithm," *Journal of the Chinese Institute of Engineers,* vol. 48, no. 1, pp. 53-65, 2025.

[33] A. Selim, S. Kamel, E. H. Houssein, F. Jurado, and F. A. Hashim, "A modified Runge–Kutta optimization for optimal photovoltaic and battery storage allocation under uncertainty and load variation," *Soft Computing,* vol. 28, no. 17, pp. 10369-10389, 2024.

[34] D. E. Goldberg, and J. H. Holland, "Genetic Algorithms and Machine Learning," *Machine Learning,* vol. 3, no. 2, pp. 95-99, 1988.

[35] J. Kennedy and R. Eberhart, "Particle swarm optimization", In: *Proc. of ICNN'95 - International Conference on Neural Networks*, Perth, WA, Australia, 1995, pp. 1942-1948 vol.4, doi: 10.1109/ICNN.1995.488968.

[36] E. Rashedi, H. Nezamabadi-Pour, and S. Saryazdi, "GSA: a gravitational search algorithm," *Information sciences,* vol. 179, no. 13, pp. 2232-2248, 2009.

[37] R. V. Rao, V. J. Savsani, and D. Vakharia, "Teaching–learning-based optimization: a novel method for constrained mechanical design optimization problems," *Computer-Aided Design,* vol. 43, no. 3, pp. 303-315, 2011.

[38] S. Mirjalili, S. M. Mirjalili, and A. Hatamlou, "Multi-verse optimizer: a nature-inspired algorithm for global optimization," *Neural Computing and Applications,* vol. 27, no. 2, pp. 495-513, 2016.

[39] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey Wolf Optimizer," *Advances in Engineering Software,* vol. 69, pp. 46-61, 2014.

[40] S. Mirjalili, and A. Lewis, "The whale optimization algorithm," *Advances in engineering software,* vol. 95, pp. 51-67, 2016.

[41] A. Faramarzi, M. Heidarinejad, S. Mirjalili, and A. H. Gandomi, "Marine Predators Algorithm: A nature-inspired metaheuristic," *Expert Systems with Applications,* vol. 152, pp. 113377, 2020.

[42] S. Kaur, L. K. Awasthi, A. L. Sangal, and G. Dhiman, "Tunicate Swarm Algorithm: A new bio-inspired based metaheuristic paradigm for global optimization," *Engineering Applications of Artificial Intelligence,* vol. 90, pp. 103541, 2020/04/01/, 2020.

[43] L. Abualigah, M. Abd Elaziz, P. Sumari, Z. W. Geem, and A. H. Gandomi, "Reptile Search Algorithm (RSA): A nature-inspired meta-heuristic optimizer," *Expert Systems with Applications,* vol. 191, pp. 116158, 2022.

[44] B. Abdollahzadeh, F. S. Gharehchopogh, and S. Mirjalili, "African vultures optimization algorithm: A new nature-inspired metaheuristic algorithm for global optimization problems," *Computers & Industrial Engineering,* vol. 158, pp. 107408, 2021.

[45] M. Braik, A. Hammouri, J. Atwan, M. A. Al-Betar, and M. A. Awadallah, "White Shark Optimizer: A novel bio-inspired meta-heuristic algorithm for global optimization problems," *Knowledge-Based Systems*, pp. 108457, 2022.

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