A Multi-Objective ESTO Framework for Efficient PV Siting and Sizing in Radial Distribution Systems

Zaid Alhadrawi*, Ali Q. Almousawi, and Ali H. Majeed
Department of Electrical Engineering, Faculty of Engineering, University of Kufa, Najaf, Iraq
Email: zaidt.alhaddrawi@uokufa.edu.iq (Z.A.), ali.almousawi@uokufa.edu.iq (A.Q.A.), alih.alasady@uokufa.edu.iq (A.H.M.)

Manuscript received August 8, 2025; revised September 20, 2025; accepted September 28, 2025
*Corresponding author

***Abstract*—Photovoltaic (PV) systems have become one of the most prominent renewable energy technologies for reducing losses and improving efficiency in power distribution networks. Achieving these benefits requires proper decisions on where PV units should be installed and how large they should be. This paper presents an Enhanced Search and Tuning Optimization (ESTO) algorithm developed to address this allocation problem. The algorithm introduces an adaptive mechanism that balances wide-ranging exploration with local fine-tuning, which enhances solution precision while preventing premature convergence. The proposed method is applied to the IEEE 33-bus and 69-bus distribution test systems using a backward/forward sweep power flow. Results indicate a significant improvement in bus voltage levels—where the lowest voltage in the 33-bus system increased from 0.931 p.u. to 0.968 p.u.—together with a 64.7% reduction in real power losses. Comparisons with existing approaches such as Particle swarm optimization (PSO), Genetic Algorithm (GA), and Ant Lion Optimizer (ALO) confirm that ESTO provides faster convergence, improved reliability, and higher-quality solutions.**

***Index Terms*—Enhanced Search and Tuning Optimization (ESTO), photovoltaics, power system losses, renewable energy, voltage deviation**

I. Introduction

The rapid growth in electricity demand, coupled with environmental concerns, has accelerated the deployment of Renewable Energy Resources (RES). Among these, Photovoltaic (PV) generation has attracted particular attention due to its scalability and declining costs. However, distribution networks, which are often characterized by high losses and voltage deviations, require careful integration of PV units to maximize their benefits [1, 2]. This makes the determination of optimal PV locations and capacities an essential task for network planners [3–8].

The performance of the electrical power system is influenced by the capacity of PVs and their installation locations. Therefore, many researchers have addressed determining the optimal siting and size to regulate voltage and reduce losses.

Electrical power systems are complex and nonlinear systems that require unique algorithms to handle them. Particle Swarm Optimization (PSO) [9–11], Genetic Algorithm (GA) [12–14], Ant Lion Optimizer (ALO) [15, 16], and Grey Wolf Optimization (GWO) [17, 18] have been used and have proven their ability to obtain satisfactory results. Combined methods, such as GWO-PSO and GA-PSO, have also shown increased convergence speed and solution accuracy [2, 19, 20].

In this context, this work introduces an Enhanced Search and Tuning Optimization (ESTO) framework, specifically for dynamically balancing the discovery and utilization phases. The adaptive procedure is designed to address the issue of premature convergence at local optima and to find an effective solution.

The main contribution is the development of an adaptive ESTO algorithm for the optimal location and size of multiple PV installations under practical operating constraints.

Simulation is executed for the IEEE (33-bus and 69-bus) distribution networks using MATLAB and compared with the most recent optimization methods for the purpose of checking the efficacy of the suggested algorithm in decreasing the losses and boosting the voltage profile. The performance of the ESTO method is compared with the existing methods involving PSO, GA, ALO, and IWOA.

This work is structured in the following manner: Section II presents the system modelling and load flow. The next section describes the ESTO method optimization framework. Section IV is dedicated to the implementation and results. Finally, Section V summarized the conclusion and future work.

II. System Modelling and Load Flow

This section outlines the modelling of Radial Distribution Systems (RDS) and the method used for load flow analysis.

Distribution networks represent the final stage of electric power delivery and are generally arranged in a radial configuration extending from the primary substation to consumers. For analysis purposes, the per-unit system is normally adopted, where all quantities are expressed relative to a chosen base power S_b in MVA and

doi: 10.18178/ijeetc.14.6.373-381

base voltage V_b in kV, so the base impedance Z_b can be calculated using:

$$Z_b = \frac{V_b^2}{S_b} \tag{1}$$

An important characteristic of distribution feeders is their relatively high resistance-to-reactance ratio (R/X) compared with transmission lines. In transmission systems, line reactance is usually dominant, and the R/X ratio is very small. In contrast, distribution conductors are shorter in length, operate at lower voltage levels, and are made of a smaller cross-sectional area. These factors increase the effective resistance of the line, giving rise to higher R/X ratios.

The presence of high R/X ratios leads to several consequences:

- Voltage drops along the feeder are strongly influenced by both active and reactive power flows.
- Real power losses become more pronounced due to the higher resistive component of the lines.
- Conventional transmission-oriented load flow methods, which assume reactance-dominated lines, may not provide accurate results when applied directly.

For this reason, distribution load flow studies often employ methods such as the Backward/Forward Sweep or Modified Gauss–Seidel, which are more suitable for radial topologies with high R/X ratios.

This normalization helps ensure consistent comparisons between variables and simplifies numerical analysis. The backwards/forward sweep (BFS) algorithm is used in this study to implement the load flow analysis. BFS is a fast convergence method and is accurate in results, so it has been adopted.

Backwards Sweep: The current is calculated starting from the far point and ending at the near point using the following relation [21].

$$I_l(i) = \left(\frac{S_l(i)}{V_l(i)}\right)^* \tag{2}$$

where $I_l(i)$ is the current entering bus i, $S_l(i)$ is the complex load power at bus i, and $V_l(i)$ is the voltage at bus i.

Forward Sweep: The current is calculated starting from the near point and ending at the far point using the relation:

$$V(j) = V(i) - I_n(k)Z(k) \tag{3}$$

where $V(i)$ is the voltage of the sending end, $V(j)$ is the voltage of receiving end, $I_n(k)$ is the line current, and is the line impedance. Fig. 1 summarizes the procedures of BFS method.

A. Concept of ESTO

The Enhanced Search and Tuning Optimization (ESTO) method is a nature-inspired metaheuristic developed to solve complex, nonlinear engineering optimization problems such as optimal photovoltaic (PV) siting and sizing. Unlike conventional algorithms that often struggle with premature convergence, ESTO incorporates an adaptive mechanism to balance exploration (global search) and tuning (local refinement). This dynamic balance helps ensure that the search process maintains diversity in the early stages while moving toward higher accuracy in later iterations.

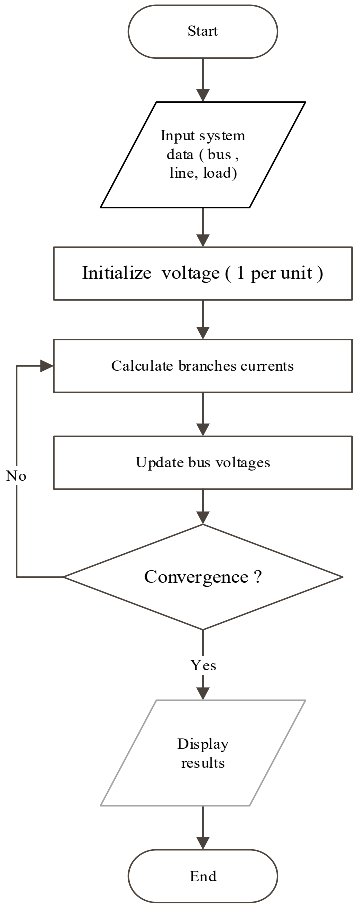

Fig. 1. Procedures of the BFS method.

III. Proposed ESTO-Based Optimization Framework

A. Representation of Solutions

Each candidate solution is described by two vectors:

Location vector: identifies the buses at which PV units can be placed (excluding the slack bus and existing generator buses).

Location = [bus1, bus 2, ···, bus$n$]

Size vector: assigns the output power of each installed PV unit, subject to lower and upper bounds. A vector responsible for allocating the size of the PV, with unit in kW:

$$\text{Size} = [P_1, P_2, \cdots P_n]$$

B. Objective Function

The optimization goal is to minimize a weighted function that combines:

Active power loss reduction is defined as the difference between losses before and after PV integration.

Voltage profile improvement, expressed as the overall deviation of bus voltages from 1 p.u.

The combined objective function is expressed as:

$$f = w_1 \frac{P_A}{P_B} + w_2 V_D \tag{4}$$

where P_A represents the total real power loss before PV installation, P_B is the real power loss after PV systems have been added, $V_D = \sum_{i=1}^{N} |V_i - 1.0|$ indicates the overall voltage deviation across all buses, and w_1 and w_2 are the weighting factors (e.g., w_1=0.7, w_2=0.3) used to balance the importance of each objective.

C. Constraints

The problem is solved under realistic operational limits:

- Voltage levels must stay within defined limits: $V_{\min} \le V_i \le V_{\max}$
- PV capacities must fall within allowable bounds: $P_{\min} \le P_{\text{PV}} \le P_{\max}$
- PV units can only be placed at selected candidate buses—excluding both the slack bus and any generator buses.
- Each scenario includes a fixed number of PV units, whether a single unit or multiple.

D. Implementation Steps of ESTO

There are many steps in the ESTO Algorithm as follows

Initialization: Generate an initial population of solutions with random PV sizes and siting locations.

Evaluation: Assess each solution using the objective function under the stated constraints.

E*xploration phase*: Perform a broad search to locate promising regions of the solution space.

Tuning phase: Apply local refinement near the best-performing solutions to enhance accuracy.

Update procedure: Candidate solutions are adaptively updated based on feedback from previous iterations.

Termination: Repeat exploration and tuning until a maximum number of iterations is reached or convergence is achieved.

A flowchart of these steps is presented in Fig. 2.

E. Comparative Advantage of ESTO

To demonstrate the performance of the proposed framework, extensive comparisons with well-known algorithms—including Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Ant Lion Optimizer (ALO), Whale Optimization Algorithm (WOA), and Improved Whale Optimization Algorithm (IWOA)—were conducted.

The results reveal that ESTO consistently outperforms the other techniques by:

Achieving higher power loss reduction (up to 64.7% in the IEEE 33-bus and 27.3% in the IEEE 69-bus system).

Improving minimum bus voltages from 0.913 p.u. to 0.968 p.u. in the 33-bus case, and from 0.909 p.u. to 0.928 p.u. in the 69-bus case.

Converging faster, stabilizing within ~50 iterations, while GA and PSO often require more iterations.

The results reveal that ESTO consistently outperforms the other techniques by:

Achieving higher power loss reduction (up to 64.7% in the IEEE 33-bus and 27.3% in the IEEE 69-bus system).

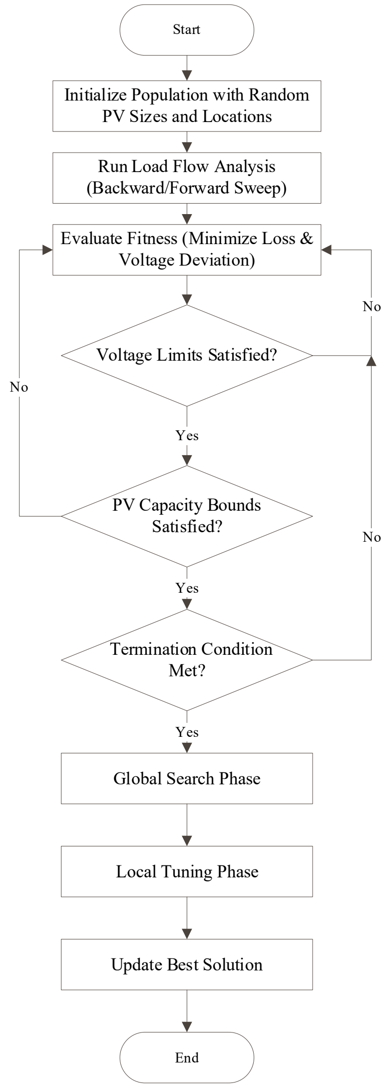

Fig. 2. ESTO flowchart.

Improving minimum bus voltages from 0.913 p.u. to 0.968 p.u. in the 33-bus case, and from 0.909 p.u. to 0.928 p.u. in the 69-bus case.

F. Summary

In summary, the ESTO framework combines adaptive global search and local refinement strategies, making it a reliable and computationally efficient approach for PV integration in distribution systems. Its superior performance compared with classical metaheuristics demonstrates its suitability for both medium- and large-scale networks.

IV. IMPLEMENTATION AND RESULTS

This section deals with the application of the ESTO method, which was tested on two test systems: the first IEEE 33-bus system and the second IEEE 69-bus system. Its performance was evaluated based on the results obtained to reduce real power losses and improve bus voltages, and then the results were compared with other algorithms. Simulation results were carried out using MATLAB R2023a, and all values were normalized using:

$$S_b = 100 \text{ MVA and } V_b = 12.66 \text{ kV}$$

The PV systems were only considered for installation on buses other than the slack bus (Bus 1). The optimization objective was to reduce power losses while simultaneously improving voltage levels, all within the defined per-unit (p.u.) constraints. The following four cases are studied in the two test models:

Case 1: No PV integration
Case 2: Optimal one PV integration
Case 3: Optimal two PV integration
Case 4: Optimal three PV integration

A. IEEE 33-Bus System

The suggested method is examined using the IEEE 33-bus system. The comprehensive overview of this test system, covering the line and load data, was taken from the standard IEEE test system. The network structure is displayed in Fig. 3.

1) Case 1: No PV integration

The power flow is performed based on the BFS method without PV integration. The results show the total real power loss is 202.68 kW, and the lowest bus voltage is 0.913 p.u at bus 18.

2) Case 2: Optimal one PV integration

In this case, the ESTO algorithm was used to find the optimal siting and size of one PV station. The results showed that the best location is bus 6, and PV capacity is 2575.7 kW, where the total power loss becomes 103.9 kW, which means that power loss reduction is 48.7%. The buses' voltage was improved, and the minimum bus voltage was raised to 0.9511 p.u.

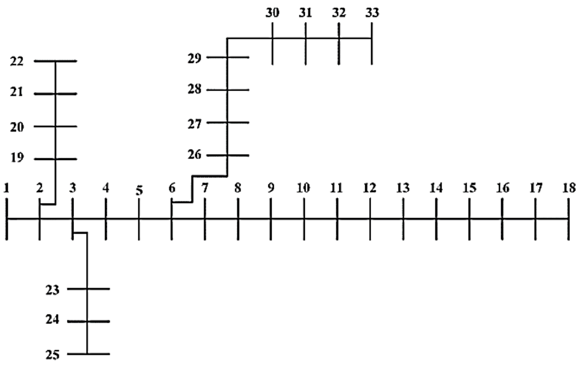

Fig. 3. IEEE 33-bus test system.

The voltage profile in Fig. 4 shows improvement across all buses after placing one PV unit at Bus 6. The minimum voltage increased from 0.913 p.u. to 0.9511 p.u., which indicates better voltage support. The results also show a noticeable reduction in total system losses, confirming that a single, well-sited PV unit can positively impact network performance.

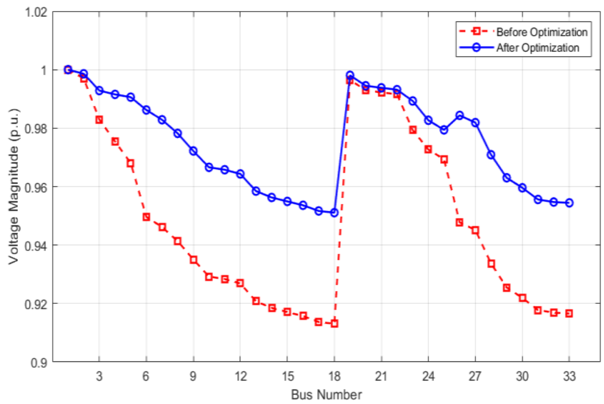

Fig. 4. Bus voltage of the IEEE 33 bus for one PV installation.

Practical Implication: A single, strategically located PV system can significantly reduce network losses and voltage dips, thereby reducing energy purchase from upstream substations and improving compliance with regulatory voltage limits.

3) Case 3: Optimal two PV integration

The optimal location and size of two PV units are summarized:

Optimal bus: 13 and bus 30
Optimal PV sizes: 855.3 kW and 1155.6 kW
Total power loss: 85.9 kW
Minimum voltage: 0.968 p.u.
Power loss reduction: 57.6%

Fig. 5 presents the voltage profile when two PV units are integrated at bus 13 and bus 30. The minimum voltage rises further to 0.968 p.u., and the profile appears more balanced compared to the previous case. The additional PV unit leads to further loss reduction, showing that distributing generation at multiple points enhances both voltage and efficiency.

Practical Implication: Distributed placement of PV units along the feeder enhances voltage stability across distant buses and reduces the risk of equipment maloperation due to undervoltage conditions.

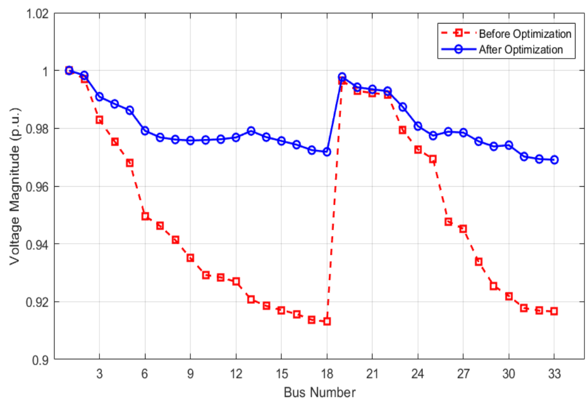

Fig. 5. Buses' voltage of the IEEE 33 bus for two PV installations.

4) Case 4: Optimal three PV integration

In this case, three PV units were selected to install for optimal allocation in the IEEE 33-bus system. The obtained results are:

PV locations: bus 14, bus 24, and bus 30

PV capacities: 743 kW, 1102.7 kW, and 1061.23 kW

Total power loss: 71.47 kW

Minimum voltage: 0.968 p.u.

Power loss reduction: 64.7%

The influence of the PV integration on the buses' voltage in the test system is presented in Fig. 6.

Practical Implication: While the incremental benefit over two PVs is modest, the results show how utilities can prioritize investments—deciding between fewer high-capacity PVs or multiple distributed installations for reliability and resilience.

In Fig. 6, with three PV units installed at bus 14, bus 24, and bus 30, the voltage profile remains consistently high, with a minimum of 0.968 p.u. Although the improvement over the two-PV case is not dramatic, the result indicates that this configuration achieves the lowest power loss among all tested cases.

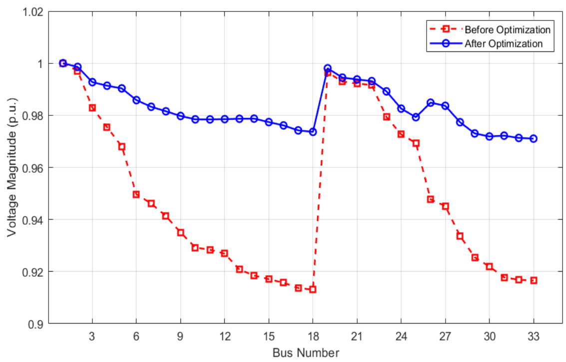

Fig. 6. Bus voltage of the IEEE 33 bus for three PV installations.

Table I summarizes the results for all cases. It indicates that the optimal PV allocation directly translates to reduced energy losses, lower operational costs, and extended asset lifespan in real-world feeders.

TABLE I: OPTIMAL RESULTS OF IEEE 33-BUS SYSTEM

Min Voltage (p.u.)	Power Loss (kW)	Optimal location	Optimal size	No. PV	Case No.
0.913	202.68	-	-	-	1
0.9511	103.9	6	2575.7	1	2
0.968	85.9	13 30	855.3	2	3
0.968	71.47	14 24 30	743 1102.7 1061.23	3	4

B. IEEE 69-Bus System

In this subsection, the results of the IEEE 69-bus test system obtained by the proposed ESTO method. The overall data of this system are obtained from the standard IEEE system. This system configuration is shown in Fig. 7.

1) Case 1: No PV integration

This case performs without PV to implement the load flow. The power losses and lowest bus voltage as follow:

Total real power loss: 224.95 kW

Lowest voltage: 0.909 p.u.

2) Case 2: Optimal one PV integration

The ESTO algorithm was repeated on an IEEE 69- bus to find the optimal siting and size of one PV station. The results showed that the best location is bus 9, and PV size is 3000 kW, so the total power loss becomes 170.78 kW, which means that power loss reduction is 24%. The buses' voltage was improved, and the minimum bus voltage was raised to 0.9282 p.u. as shown in Fig. 8.

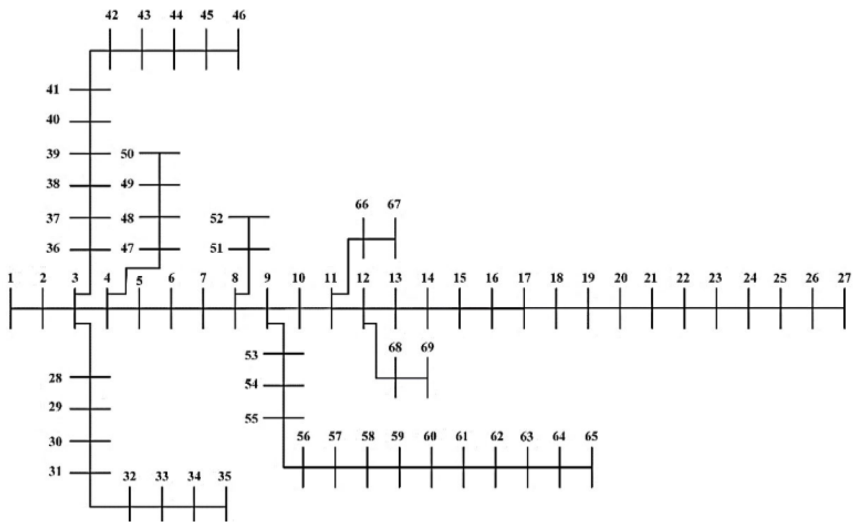

Fig. 7. IEEE 69-bus test system.

Fig. 8 shows the voltage profile for the IEEE 69-bus system with a single PV unit placed at bus 9. The minimum voltage improves from 0.909 p.u. to 0.9282 p.u., reflecting a clear benefit. While the improvement is smaller than in the 33-bus system, it still demonstrates the effectiveness of proper PV allocation in larger networks. That is, even in large networks, a single well-sited PV installation can relieve feeder stress and delay costly upgrades.

3) Case 3: Optimal two PV integration

In this case, two PV units were used, so the optimal siting and size are summarized:

Optimal bus 9 and bus 18

PV sizes: 2530.5 kW and 452.2 kW

Power loss: 163.49 kW
Minimum voltage: 0.9281 p.u.
Power loss reduction: 27.3%

With two PV units at bus 9 and bus 18, Fig. 9 shows a slight improvement in voltage uniformity across the network. The minimum voltage is nearly unchanged at 0.9281 p.u., but the profile is more stable. This suggests that additional PV units contribute to better voltage regulation, especially in later sections of the feeder.

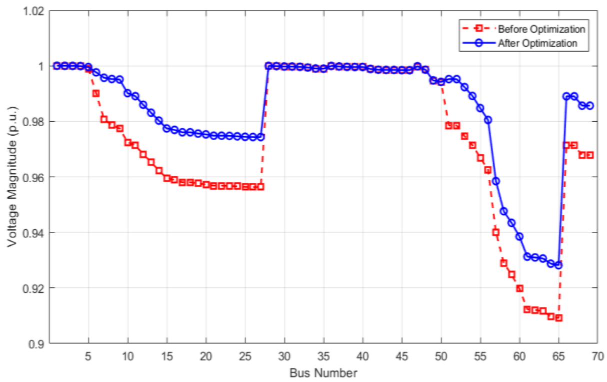

Fig. 8. Bus voltage of the IEEE 69 bus for one PV installation.

Practical Implication: Multiple PV units distribute the generation closer to load centers, improving voltage uniformity and reducing energy losses in downstream feeders.

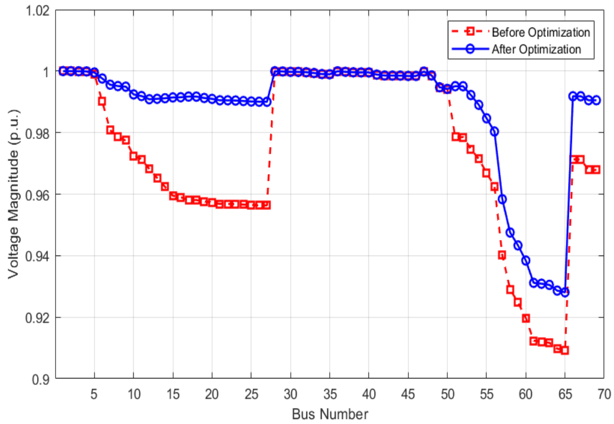

Fig. 9. Bus voltage of the IEEE 69 bus for two PV installations.

4) Case 4: Optimal three PV integration

In this case, three PV units were selected to install for optimization in the IEEE 69-bus system. The obtained results are:

Siting at bus 3, bus 9, and bus 18
PV sizes: 74.31 kW, 2530.68 kW, and 453.32 kW
Power loss: 163.52 kW
Minimum voltage: 0.9280 p.u.
Power loss reduction: 27.3%

The impact of the PV integration on the buss' voltage in this system is shown in Fig. 10. Fig. 10 illustrates the case of three PV units located at bus 3, bus 9, and bus 18. The overall voltage profile remains close to the two-PV case, with the minimum voltage at 0.9280 p.u.. The small change suggests that beyond a certain point, adding more PV capacity has limited impact, though it may still improve voltage balance across the system.

Practical Implication: Beyond two optimally placed PVs, the incremental improvement is marginal, suggesting a saturation point where further PV addition provides diminishing returns. This insight can guide planners in determining the optimal number of PV installations.

Table II provides a summary of these results. It implies that the loss reductions, though smaller than in the 33-bus system, still represent tangible cost savings and environmental benefits for utilities operating large distribution networks.

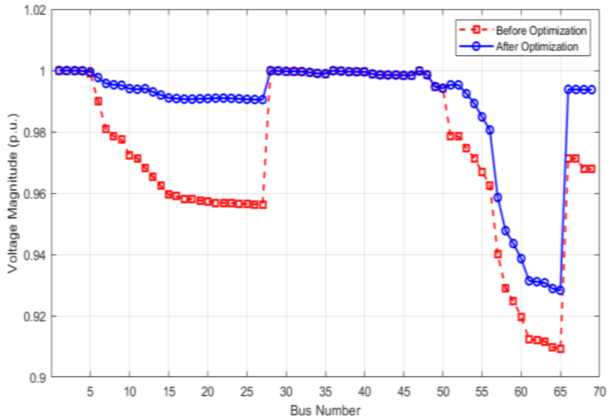

Fig. 10. Bus voltage of the IEEE 69 bus for three PV installations.

TABLE II: OPTIMAL RESULTS OF IEEE 66-BUS SYSTEM

Case No.	No. PV	Optimal size	Optimal location	Power Loss (kW)	Min Voltage (p.u.)
1	-	-	-	224.95	0.909
2	1	3000	9	170.78	0.9282
3	2	2530.5 452.2	9 18	163.49	0.9281
4	3	74.31 2530.68 453.32	3 9 18	163.52	0.9280

C. Comparative Analysis with Other Algorithms

To demonstrate ESTO's advantage, a comparison was carried out using other well-known optimization methods, namely PSO, GA, ALO, and IWOA, on the IEEE 33-bus system. Results from this evaluation are presented in Table III.

Beyond its performance in optimization, ESTO also showed strong computational reliability. Multiple independent simulation runs revealed almost zero variation in the final power loss results, as shown in Fig. 10, indicating excellent consistency. Additionally, ESTO typically reached convergence within about 50 iterations, and each run took an average of just 5.39 seconds—highlighting both its efficiency and practical applicability.

Fig. 11 shows the convergence behavior of the ESTO algorithm. The objective function stabilizes within 50 iterations, and the curve is smooth with minimal fluctuation. This indicates that the algorithm reliably converges to a solution and maintains consistent performance across multiple runs.

TABLE III: COMPREHENSIVE COMPARISON OF OPTIMIZATION METHODS ON IEEE 33-BUS SYSTEM

References	Min Voltage (p.u.)	Loss Reduction (%)	Power Loss (kW)	Locations	PV Sizes (kW)	Method
–	0.913	–	202.68	–	–	Base Case
[22]	-	38.32	125	30	1542	HBA
[12]	0.95084	48.68	104	6	2552.9	GA
[23]	0.9425	45.22	111.02	6	2590.2	WOA
[This Study]	0.9511	48.7	103.9	6	2575.7	ESTO (Proposed)

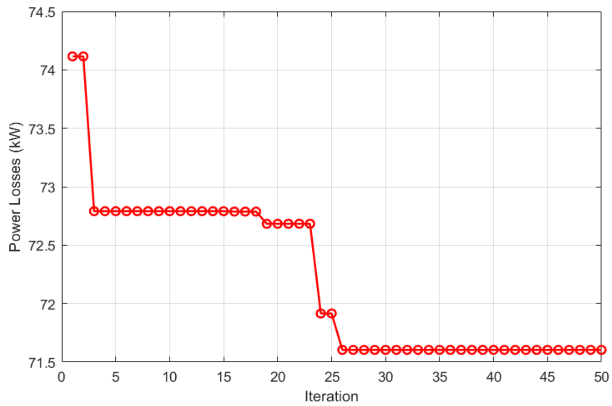

Fig. 11. ESTO convergence.

The obtained results confirm the effectiveness of the proposed ESTO algorithm in achieving the desired goals, as it achieved a significant reduction in power losses and an improvement in the bus voltages. STO is distinguished from other methods by the following:

Higher solution quality
Reduced need for parameter fine-tuning
Better voltage profile improvements
Strong scalability for large-scale distribution networks.

D. Practical Applications

The results obtained from applying the enhanced search and tuning optimization (ESTO) framework to the IEEE 33-bus and 69-bus systems provide several insights that are directly transferable to real-world power distribution networks:

Utility planning and investment: The significant reduction in active power losses (up to 64.7% in the 33-bus system and 27.3% in the 69-bus system) demonstrates the economic value of optimally sited PV units. For utilities, this means lower energy procurement from upstream grids, deferred reinforcement of feeders and transformers, and extended asset lifespans—all of which directly translate into cost savings.

Operational reliability: Improved minimum bus voltages (from 0.913 p.u. to 0.968 p.u. in the 33-bus case) ensure better compliance with regulatory voltage standards. This improvement reduces the risk of undervoltage conditions that may lead to equipment malfunction, frequent complaints from consumers, or service interruptions.

Renewable energy integration: The results illustrate that distributing multiple PV units across the feeder enhances overall voltage stability and efficiency more effectively than a single large unit. This finding supports national and regional goals for scaling renewable integration while maintaining grid reliability.

Environmental benefits: Lower distribution losses imply reduced overall generation requirements, leading to decreased greenhouse gas emissions. This aligns with global sustainability initiatives and provides a measurable environmental benefit alongside the technical improvements.

Scalability and real-time applications: Since the ESTO algorithm converges rapidly (within ~50 iterations) and demonstrates consistent solutions across independent runs, it is well-suited for integration into Distribution Management Systems (DMS) or planning software. Utilities can apply the algorithm not only in long-term expansion planning but also for near real-time operational decision-making.

By bridging theoretical optimization with practical implications, the proposed ESTO framework offers actionable insights for engineers, planners, and decision-makers. It provides a reliable and computationally efficient tool for ensuring that PV integration improves system performance while supporting cost-effectiveness, reliability, and sustainability.

V. CONCLUSION AND FUTURE WORK

In this study, an advanced ESTO algorithm was used to obtain the optimal location and size of photovoltaic (PV) systems in radial distribution networks. ESTO has achieved the appropriate solution to complex engineering problems, where it finds a high balance between early convergence and solution accuracy. The active power losses have been reduced from 202.68 kW to 71.51 kW in the IEEE 33-bus and from 224.95 kW to 163.52 kW in the IEEE 69-bus test systems. In addition to bus voltage enhancements, the minimum bus voltage has also been improved from 0.913 to 0.968 pu. We conclude this paper with following remarks.

1) Key takeaways from the study

- ESTO accurately and consistently identifies optimal PV placements and capacities.
- It outperforms other metaheuristic methods in reducing losses and improving voltage levels.
- The algorithm scales effectively, making it suitable for both mid-sized and large distribution networks.

2) Limitations of the study

The study assumes steady-state operating conditions, without considering time-varying load profiles or fluctuations in solar irradiance. While this simplifies the analysis, it does not capture the full variability of real-world PV output.

Also, PV units are modeled as ideal sources within defined capacity limits, neglecting inverter dynamics and reactive power control strategies, which may influence voltage stability in practice.

3) Future work directions

- Incorporate time-series analysis to reflect real-world fluctuations in load and solar generation.
- Include uncertainty modelling for factors like solar irradiance and energy demand.
- Expand the optimization goals to account for cost, environmental impact, and system reliability.

Integrate energy storage systems and develop strategies for real-time control in dynamic grid environments.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Zaid Alhadrawi and Ali H. Majeed conducted the research and wrote the paper. Ali Q. Almousawi reviewed and validated the work. All authors had approved the final version.

REFERENCES

[1] M. Khasanov, S. Kamel, F. Nazarov, M. Rizayeva, and N. Shodiyeva, "Optimal distributed generation allocation in distribution system for power loss minimization and voltage stability improvement," in *Proc. E3S Web Conf.*, 2023. doi: 051/e3sconf/202340103071

[2] A. B. Alyu, A. O. Salau, B. Khan, and J. N. Eneh, "Hybrid GWO-PSO based optimal placement and sizing of multiple PV-DG units for power loss reduction and voltage profile improvement," *Sci. Rep.*, vol. 13, no. 1, pp. 1–17, Dec. 2023.

[3] W. Bai, W. Zhang, R. Allmendinger, I. Enyekwe, and K. Y. Lee, "A comparative study of optimal PV allocation in a distribution network using evolutionary algorithms," *Energies*, vol. 17, no. 2, 511, 2024.

[4] A. M. Nassef, M. A. Abdelkareem, H. M. Maghrabie, and A. Baroutaji, "Review of metaheuristic optimization algorithms for power systems problems," *Sustainability (Switzerland)*, Multidisciplinary Digital Publishing Institute, vol. 15, no. 12, p. 9434, Jun. 12, 2023.

[5] K. Singh, K. D. Mistry, and H. G. Patel, "Whale optimization-based distributed generation placement in distribution system for loss minimization," in *Proc. 2023 7th International Conference on Computer Applications in Electrical Engineering-Recent Advances*, Oct. 2023. doi: 10.1109/CERA59325.2023.10455513

[6] G. H. Valencia-Rivera, M.T. Benavides-Robles, A. V. Morales *et al.*, "A systematic review of metaheuristic algorithms in electric power systems optimization," *Appl. Soft Comput.*, vol. 150, 111047, Jan. 2024.

[7] Y. Wang and G. Xiong, "Metaheuristic optimization algorithms for multi-area economic dispatch of power systems: Part I—a comprehensive survey," *Artif. Intell. Rev.*, vol. 58, no. 4, pp. 1–48, Apr. 2025.

[8] Z. H. Leghari, M. Kumar, P. H. Shaikh, L. Kumar, and Q. T. Tran, "A critical review of optimization strategies for simultaneous integration of distributed generation and capacitor banks in power distribution networks," *Energies*, vol. 15, no. 21, 8258, Nov. 2022.

[9] A. S. Mohammed, G. V. Murphy, and M. Ndoye, "A PSO based control strategy for combined emission economic dispatch with integrated renewables," in *Proc. 2020 52nd North Am. Power Symp.*, Apr. 2021. doi: 10.1109/NAPS50074.2021.9449740

[10] G. A. Adepoju, B. A. Aderemi, S. A. Salimon, and O. J. Alabi, "Optimal placement and sizing of distributed generation for power loss minimization in distribution network using particle swarm optimization technique," *Eur. J. Eng. Technol. Res.*, vol. 8, no. 1, pp. 19–25, Jan. 2023.

[11] G. Wahby, I. I. M. Manhrawy, B. Bouallegue, A. A. M. El-Gaafary, and A. A. Elbaset, "Enhancing conventional power grids: analyzing the impact of renewable distributed generation integration using PSO in the 118-bus IEEE system," *Int. J. Energy Res.*, vol. 2025, no. 1, 3601747, Jan. 2025.

[12] M. Madhusudhan, N. Kumar, and H. Pradeepa, "Optimal location and capacity of DG systems in distribution network using genetic algorithm," *Int. J. Inf. Technol.*, vol. 13, no. 1, pp. 155–162, Feb. 2021.

[13] M. Hanjalić, E. Melić, M. Šarić, and J. Hivziefendić, "Hosting capacity assessment in electrical power distribution systems using genetic algorithm," *Electr. Power Components Syst.*, vol. 51, no. 19, pp. 2354–2366, Nov. 2023.

[14] N. Bouchikhi, F. Boussadia, R. Bouddou, S. Zaidi, S. Adiche, and A. Belabbes, "A modified genetic algorithm for optimizing the placement and sizing of distributed generators in radial distribution systems including security analysis," *J. Renew. Energies*, pp. 131–149, Oct. 2024.

[15] B. P. Nanda, D. P. Mishra, and S. R. Salkuti, "A modified ant lion optimization algorithm for efficient distributed generation allocation in power distribution networks," *Electr. Power Syst. Res.*, vol. 246, art no. 111705, Sep. 2025.

[16] P. Rajakumar, P. M. Balasubramaniam, M. H. Aldulaimi *et al.*, "An integrated approach using active power loss sensitivity index and modified ant lion optimization algorithm for DG placement in radial power distribution network," *Sci. Rep.*, vol. 15, no. 1, pp. 1–26, Dec. 2025.

[17] M. Abbas, M. A. Alshehri, and A. B. Barnawi, "Potential contribution of the grey wolf optimization algorithm in reducing active power losses in electrical power systems," *Appl. Sci.*, vol. 12, no. 12, 6177, Jun. 2022.

[18] N. Bouchikhi, F. Boussadia, R. Bouddou *et al.*, "Optimal distributed generation placement and sizing using modified grey wolf optimization and ETAP for power system performance enhancement and protection adaptation," *Sci. Rep.*, vol. 15, no. 1, pp. 1–31, Dec. 2025.

[19] I. Khenissi, R. Sellami, M. A. Fakhfakh, and R. Neji, "Power loss minimization using optimal placement and sizing of photovoltaic distributed generation under daily load consumption profile with PSO and GA algorithms," *J. Control. Autom. Electr. Syst.*, vol. 32, no. 5, pp. 1317–1331, Oct. 2021.

[20] M. Ntombela, K. Musasa, and M. C. Leoaneka, "Power loss minimization and voltage profile improvement by system reconfiguration, DG sizing, and placement," *Comput.*, vol. 10, no. 10, 180, Oct. 2022.

[21] S. Kawambwa, R. Mwifunyi, D. Mnyanghwalo, N. Hamisi, E. Kalinga, and N. Mvungi, "An improved backward/forward sweep power flow method based on network tree depth for radial distribution systems," *J. Electr. Syst. Inf. Technol*., vol. 8, no. 1, pp. 1–18, Mar. 2021.

[22] M. H. Khan, A. Ulasyar, A. Khattak *et al.*, "Optimal sizing and allocation of distributed generation in the radial power distribution system using honey badger algorithm," *Energies*, vol. 15, no. 16, 5891, Aug. 2022.

[23] H. P. C, K. Subbaramaiah, and P. Sujatha, "Optimal DG unit placement in distribution networks by multi-objective whale optimization algorithm & its techno-economic analysis," *Electr. Power Syst. Res.*, vol. 214, 108869, 2023.

Zaid Alhadrawi received a bachelor of electrical engineering in 2006 at University of Kufa, Iraq and a master of science in electrical power engineering from the University of Technology, Baghdad in 2012. He also received a Ph.D. degree in electrical power engineering from the University of Tun Hussein Onn Malaysia, in 2022. Currently, he is a lecturer at Department of Electrical Engineering, University of Kufa, Najaf, Iraq.

Ali Qasim Almousawi was born in Nasiriyah, Iraq in 1982. He received the B.Sc. in electrical engineering from the University of Kufa in 2002. He received the M.Sc. and Ph.D. degrees in electrical engineering from the University of Basrah, in 2014 and 2022, respectively. His research interests are control theory, renewable energy, microgrid, power electronics converters, isolated microgrids, hierarchical control, energy management, and distributed generation.

Ali H. Majeed received the B.Sc degree in electronic engineering from the University of Kufa, Najaf in 2006 and the M.Sc degree from the University of Technology, Baghdad in 2012. He received his Ph.D. in electronic engineering from Universiti Tun Hussein Onn Malaysia (UTHM), Malaysia in 2022. Now he is working as an assistant prof at the University of Kufa. His research interests are focused on nanoelectronics circuits and systems as well as artificial intelligence.