International Journal of Applied Power Engineering (IJAPE)
Vol. 15, No. 3, September 2026, pp. 1243~1252
ISSN: 2252-8792, DOI: 10.11591/ijape.v15.i3.pp1243-1252

Multi-objective planning of distributed resources (PV and SVC) with NSGA-II for radial networks: application to the IEEE 33-bus test system

Hassane Ousseyni Ibrahim[1], Abdoul Malik Maman Issaka[2], Moussa Gonda[1,3], Arouna Oloulade[3], François-Xavier Fifatin[3]
[1]Electrical Engineering Department, Polytech Maradi, University Dan Dicko Dankoulodo of Maradi, Maradi, Niger
[2]Faculty of Science and Technology, University Dan Dicko Dankoulodo of Maradi, Maradi, Niger
[3]LETIA, University of Abomey-Calavi, Cotonou, Benin

Article Info

Article history:

Received Oct 11, 2025
Revised Apr 6, 2026
Accepted Jun 9, 2026

Keywords:

Distributed resources
Distribution network
Loss reduction
NSGA-II
Optimal location

ABSTRACT

The quality of electricity supply in distribution networks is critically dependent on minimizing active power losses and ensuring voltage stability. This study proposes a unified multi-objective optimization approach for the simultaneous placement and sizing of a photovoltaic (PV) source and a static var compensator (SVC) in radial networks. The non-dominated sorting genetic algorithm II (NSGA-II) is employed as the robust methodology to generate the Pareto optimal front, effectively exploring the trade-offs between two conflicting objectives: active loss minimization and voltage profile improvement. Unlike sequential or single-unit optimization strategies, this joint optimization framework is the key novelty, leveraging the specific physical interaction between PV active power injection and SVC-based dynamic reactive support to maximize overall network efficiency. Simulations are performed on the standard IEEE 33-bus test system. The results demonstrate that the optimal and coordinated integration of a 0.97 MW PV system at bus 14 and a 1.32 MVAr SVC at bus 30 yields superior electrical performance. Specifically, the system achieves a substantial active power loss reduction of 62.53% and decreases the voltage deviation index from 0.117 p.u. to a minimum of 0.0169 p.u., confirming the effectiveness of the proposed NSGA-II approach for comprehensive distributed resource planning.

Corresponding Author:

Hassane Ousseyni Ibrahim
Electrical Engineering Department, Polytech Maradi, University Dan Dicko Dankoulodo of Maradi
Maradi, Niger
Email: hassane2025@yahoo.fr

1. INTRODUCTION

Effective management of active losses and voltage profiles in radial distribution networks remains a major challenge for electricity operators, particularly in environments with high load variability. These networks are characterized by a tree-like structure and long line lengths. As a result, they are particularly sensitive to voltage imbalances and energy losses, which can compromise supply quality and system stability.

Driven by the global priority of the energy transition and the fight against climate change, the integration of renewable energy sources into distribution networks is accelerating. Photovoltaics (PV), as an efficient and decentralized source of generation, is an increasingly crucial solution for developing countries, particularly in rural areas where it directly addresses rapid energy demand growth and infrastructure constraints [1], [2]. In addition to providing active energy, PV systems can contribute to voltage regulation when properly sized and positioned. Their ability to inject power locally reduces current flows on the lines, thereby decreasing active losses and improving grid stability [3]-[5]. However, the impact of PV on the voltage profile depends heavily on its location and injected power, making its integration non-trivial. Poor location can exacerbate voltage imbalances or cause overvoltage. This is why optimizing PV placement and sizing is essential to ensure a real improvement in grid performance [6], [7]. At the same time, the lack of reactive power control is a major cause of voltage instability in distribution networks [8]. To overcome the challenge of dynamic load variations, system operators increasingly utilize flexible alternating current (AC) transmission systems (FACTS) devices, such as the static var compensator (SVC), which provide automatically adjustable and highly effective reactive power management [9]-[11]. Driven by advancements in power electronics, SVCs are increasingly preferred over traditional fixed capacitors. SVCs offer dynamic and precise reactive power control, enabling them to effectively manage fast load variations, support voltage stability, and ensure high power quality [12]-[14].

However, this integration can only be effective if the placement and sizing of this equipment are optimized using a rigorous approach capable of addressing several conflicting objectives [15]. Traditional single-objective methods are often inadequate as they fail to capture the necessary trade-offs between conflicting goals like energy efficiency and voltage stability. Since distribution networks present a complex combinatorial problem involving numerous nodes, the optimal siting and sizing of equipment (PV and SVC) becomes critical to ensuring technical feasibility and maximum network benefit [16]. Metaheuristics, and in particular multi-objective evolutionary algorithms such as NSGA-II [17], [18], offer a robust and flexible solution to this type of problem. NSGA-II can generate a set of non-dominated solutions, offering the network operator several balanced alternatives.

Unlike previous works such as [12], which focused solely on SVC placement, or [19] which optimized PV allocation without reactive compensation, this paper proposes a joint optimization approach. While [15] discusses PV-inverter regulation, our methodology specifically utilizes the NSGA-II algorithm to simultaneously solve the trade-off between PV active power injection and SVC-based reactive power support. This simultaneous approach allows for capturing the coupling effects between active and reactive power flows, leading to a superior reduction in losses compared to sequential or isolated planning strategies. This study aims to apply NSGA-II to simultaneously optimize the location and sizing of a PV system and an SVC in the standard IEEE 33-bus network. The objectives are to minimize active losses and improve the voltage profile. The proposed methodology is validated by simulation in the MATLAB environment, and the results are analyzed according to purely technical criteria.

2. METHODOLOGY

This section presents the material used and the proposed method of this study. The material used lends credibility to the results obtained using this method.

2.1. Test network

The network used for this study is the standard IEEE 33-bus test model [20], composed of 33 nodes and 32 branches, with a nominal voltage of 12.66 kV and a nominal base power of 100 MVA. This network is widely used as a test bed for distribution network optimization studies. Figure 1 shows its topology.

2.2. Photovoltaic model

The PV is modeled as an active power source. When placed at node i, the power at that node becomes (1).

$$P_{i,new} = P_i + P_{PV} \tag{1}$$

Where $P_{i,new}$ is the new active power at node i, P_i is active power at node i, P_{PV} is the active power injected by the PV. The reactive power of the node remains unchanged because $Q_{PV} = 0$.

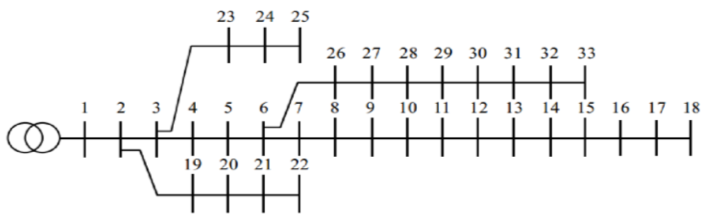

Figure 1. IEEE 33-bus standard network

2.3. SVC model

The SVC is represented as a source of adjustable reactive power. As shown in Figure 2, the shunt reactance is adjusted automatically, depending on the state of the network. It can then inject or absorb current at the node where it is connected. Connected at node k, the current absorbed by the SVC is given by (2).

$$I_{SVC} = jB_{SVC} * V_k \quad (2)$$

Where I_{SVC} is currently absorbed by SVC, B_{SVC} susceptance of SVC, V_k is the voltage amplitude at bus k. Based on this current, the power of the installed SVC is determined by (3).

$$Q_{SVC} = jI_{SVC} * V_k = -B_{SVC} * {V_k}^2 \quad (3)$$

Thus, the power injected into node i is modified in the power flow using Algorithm 1 as (4).

$$Q_{i,new} = Q_i - Q_{SVC} \quad (4)$$

Where $Q_{i,new}$ is the new reactive power at node i, Q_i is reactive power at node i, Q_{SVC} is reactive power injected/absorbed by the SVC.

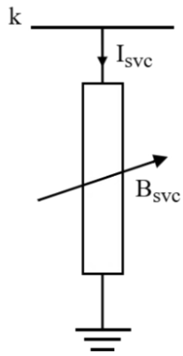

Figure 2. SVC model as variable shunt susceptance

2.4. Power flow

Network analysis is performed using the backward/forward sweep algorithm [21], [22] (Algorithm 1). This algorithm calculates node voltages, line currents, and active and reactive losses for each configuration.

Algorithm 1. BFS algorithm
Step 1:
- Read network data (number of nodes, number of branches, data line, data bus)
- Read voltage and base power.
- Read tolerance (0, 00001)
- Slack bus (1 p.u.)

Step 2:
- Form current and voltage matrices.
- Initialize iterations, k = 1.

Step 3: Perform backward sweep.
- Calculate current injections at different nodes.
- Calculate branch currents.

Step 4: Perform a forward sweep.
- Calculate the voltage drop.
- Calculate the new node voltages, [V (k+1)].

Step 5: Evaluate the termination criterion.
- Calculate the maximum difference between the nodal voltage values of two consecutive iterations.
- Check if the maximum difference is less than the tolerance.
- If yes, go to Step 6.
- If no: proceed to the next iteration, k = k + 1, and return to Step 3.

Step 6: Perform the power balance.

3. OPTIMIZATION PROBLEM FORMULATION
3.1. Decision vector
The decision vector x integrates both topological and sizing parameters. Defined by (5), it comprises four control variables: PV location (bus_{PV}), and active power (P_{PV}), alongside SVC location (bus_{SVC}), and reactive power (Q_{SVC}). This formulation enables the algorithm to determine the optimal joint configuration, as shown in (5).

$$x = [bus_{PV}, P_{PV}, bus_{SVC}, Q_{SVC}] \tag{5}$$

Where bus_{PV} is the PV injection node and bus_{SVC} is the SVC injection node.

3.2. Objective function
The objective functions are technical in nature, minimizing both active losses and voltage deviation:
- $f_1(x)$: total active losses (kW)
- $f_2(x)$: quadratic deviation of voltages from 1 p.u.

3.3. Constraints
Constraints include: The constraint aimed at maintaining voltage within the normative range is formulated by the relationship that defines the acceptable limits for grid voltage. It stipulates that the voltage at each node must remain, as shown in (6).

$$0.95\, p.u \ \leq\ V_i\ \leq 1.05\, p.u \tag{6}$$

The sizing constraints are bounded by the hosting capacity limits of the nodes and the equipment ratings. To ensure proper integration of PV and SVC, the injected power must be expressed as (7) and (8).

$$P_{PV}^{min} \leq P_{PV} \leq P_{PV}^{max} \tag{7}$$

$$Q_{SVC}^{min} \leq Q_{SVC} \leq Q_{SVC}^{max} \tag{8}$$

In this study, the numerical bounds are set to:

$$P_{PV}^{min} = 100\ kW,\ P_{PV}^{max} = 1000\ kW$$

$$Q_{SVC}^{min} = -2000\ kVAr,\ Q_{SVC}^{max} = 2000\ kVAr$$

3.4. Simulation parameters
The population size of 100 was selected to ensure sufficient diversity in the decision space without high computational cost. A maximum of 50 generations was chosen as the stopping criterion, as preliminary tests showed that the Pareto front stabilizes and converges effectively within this range. The crossover probability is set to 0.9 to encourage the combination of good genes, while the mutation probability is set to 1/n (where n is the number of decision variables) to prevent premature convergence. Table 1 shows the configuration of the NSGA-II algorithm for the simulation of Algorithm 2, where N: population size, P: population, G: number of generations, and x: decision vector.

Algorithm 2. NSGA II optimization algorithm for (PV+SVC) location
Step 1: Initialize a population P_0 of N random individuals x_i.
Step 2: Evaluate the objective functions $f_1(x_i)$, $f_2(x_i)$ for each individual.
- f_1: total active losses (via BSF) and f_2: quadratic deviation of voltages.

Step 3: Apply non-dominated sorting to rank individuals in fronts
Step 4: Calculate the crowd distance for each individual in its front
Step 5: Repeat for g = 1 to G:
- Select parents by tournament based on rank + crowd distance
- Apply crossover and mutation to generate a population Qg
- Evaluate f_1 and f_2 for each individual in Qg
- Combine Pg and Qg → Rg
- Apply non-dominated sorting to Rg and select the N best individuals to form Pg+1

Step 6: At the end of G generations:
- Extract the final Pareto front F_1

This is a second pull from step 6, so the pull needs to be added at the beginning.

Table 1. Simulation configuration

Variables	Values
Population size	100
Number of generations	50
Operators	Uniform crossover, Gaussian mutation
Selection	Non-dominated sorting + crowd distance

4. ANALYSIS OF RESULTS AND DISCUSSION

4.1. Separate injection of PV and SVC

Before optimization, the backward/forward sweep algorithm was validated on the base case IEEE 33-bus system. The calculated active losses were 202.68 kW, which matches the standard benchmark values found in the literature [23], with a difference of 0.48%, confirming the accuracy of the power flow method. This section presents the results obtained when the PV system and the SVC are integrated independently into the grid. The objective is to evaluate the individual impact of each technology on active losses and voltage profile.

4.1.1. PV scenario only

In this scenario, a PV source is injected into an optimized bus with variable active power. No reactive compensation devices are used. The NSGA-II algorithm was used to determine the location (node 14) and optimal PV power (973.7 kW) by minimizing active losses and improving voltage. The results show a reduction in losses from 202.68 kW to 128.71 kW, representing an improvement of 36.50 % compared to the baseline network. The voltage profile in Figure 3 (green curve) is improved around the injection point and increases the minimum voltage from 0.9131 p.u. to 0.9319 p.u., but remains insufficient on distant branches, where voltages below 0.95 p.u. persist. The quadratic deviation is reduced to 0.051 p.u., compared to 0.117 p.u. in the base case. These results confirm that active local injection via the PV reduces current flows and losses, but is not sufficient to stabilize the entire grid without reactive compensation.

4.1.2. SVC scenario only

This scenario integrates an SVC into an optimized bus, with variable reactive power shown in Figure 3 (red curve). No PV is used. Optimization using NSGA-II determined the best location (node 30) and compensation level of 1323.9 kVAR of reactive power. Active losses are reduced to 143.6 kW, an improvement of 29.15% compared to the base case. The voltage profile is improved across the entire network with a minimum voltage of 0.9256 p.u. These results show that PV improves the voltage profile and reduces losses much more effectively. The quadratic deviation is reduced to 0.070 p.u., compared to 0.117 p.u. in the base case. Table 2 shows the results from the PV and SVC scenario simulation alone. The SVC acts as a dynamic regulator, capable of absorbing or generating reactive power according to the needs of the grid, thereby improving overall stability.

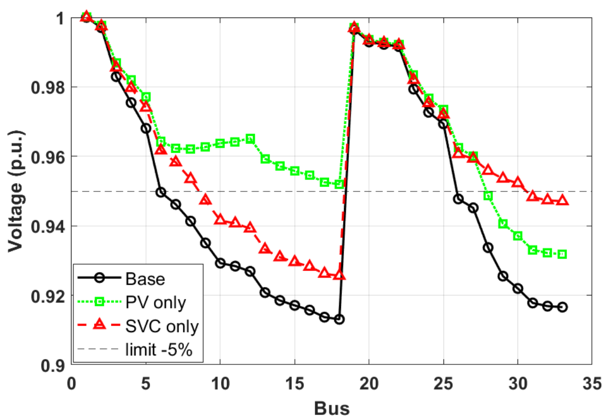

Figure 3. Voltage profile of two scenarios

Table 2. Comparison of separate injection

Scenario	Active losses (kW)	Average voltage deviation (p.u.)	Loss improvement (%)
Base network	202.68	0.117	—
PV only	129.32	0.051	36.50
SVC only	143.60	0.070	29.15

The comparative analysis shows that PV alone offers better performance than SVC alone, both in terms of loss reduction and voltage regulation. However, each technology acts on different levers: PV reduces active flows, while SVC regulates reactive flows. These results suggest that joint injection could combine the advantages of both approaches.

4.2. Joint injection (PV + SVC)

The Pareto front obtained at the end of multi-objective optimization using NSGA-II illustrates the trade-offs between two essential technical criteria: minimizing active losses and regulating the voltage profile. Each point on the front represents a non-dominated solution, i.e., no other solution can simultaneously improve both objectives without degrading one of them. These results are presented in Figure 4. The downward slope of the front confirms the antagonistic nature of the two objectives: solutions that significantly minimize losses tend to exhibit a slight voltage imbalance, while solutions with perfectly regulated voltage show slightly higher losses.

This diversity of solutions offers network operators strategic flexibility, allowing them to choose a configuration tailored to local priorities—whether maximizing energy efficiency or ensuring voltage quality. The optimized point, located at 75.94 kW of losses and 0.0169 p.u. of voltage deviation, represents a particularly interesting technical balance for radial networks with low regulation margins, as the values in Table 3 and Figures 5 and 6 show. The results were obtained when the PV system and the SVC were simultaneously integrated into the grid. Unlike the previous scenarios, this configuration is based on joint optimization of the placement and sizing of both pieces of equipment using the NSGA-II algorithm.

The optimal placement of the PV unit at bus 14 is justified by its topological location; it is situated at the end of a heavily loaded feeder, where voltage drops are most significant. Injecting active power here locally supplies the load and drastically reduces current flow from the substation. Conversely, the SVC is placed at bus 30, located in a different lateral branch. This location allows the SVC to provide reactive support that uplifts the voltage profile in the surrounding area, complementing the PV's action. The PV unit contributes more to loss reduction because the distribution network's R/X ratio is high, making active current reduction more effective for minimizing losses compared to reactive compensation.

Joint optimization achieves the best performance among all simulated scenarios. Active losses are 75.94 kW, or 62.53 % compared to the base network, versus 36.50 % and 29.15% for PV alone and SVC alone, respectively. The voltage profile is stabilized across the entire grid, with a voltage deviation reduced to 0.0169 p.u., and no out-of-limit voltages observed. These results demonstrate the PV synergy between active power generation and SVC-based reactive compensation, which enables more balanced power flow and effective grid regulation.

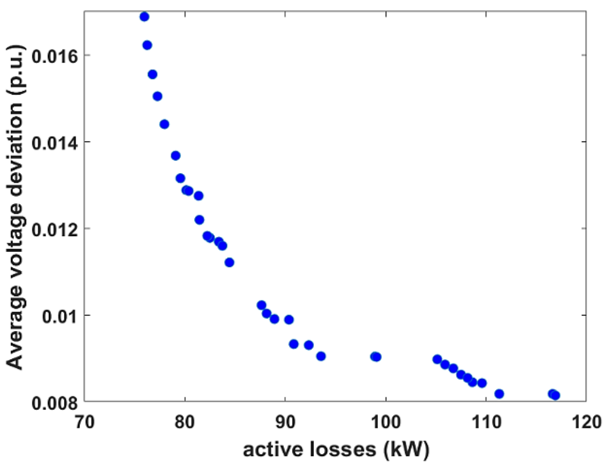

Figure 4. Pareto front

Table 3. Simulation result

Parameters	Results obtained	
Optimal node	14 (PV)	30 (SVC)
Injected power	973.7 kW (PV)	1323.9 kVAR (SVC)
Active losses (kW)	75.94	
Minimum voltage (p.u.)	0.9631	
Average voltage deviation (p.u.)	0.0169	

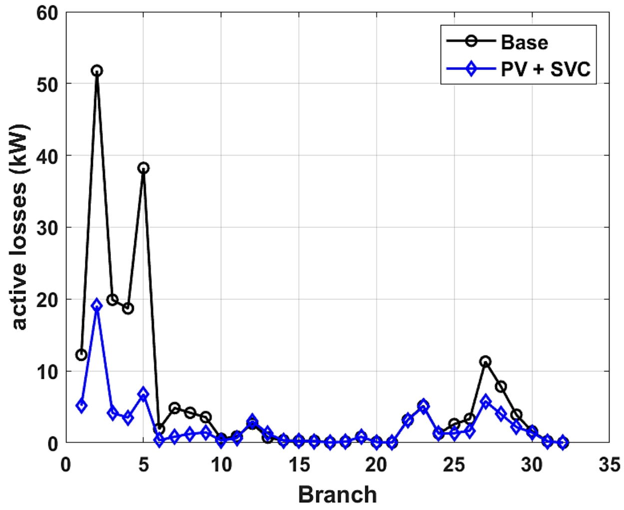

Figure 5. Optimized active power (PV+SVC)

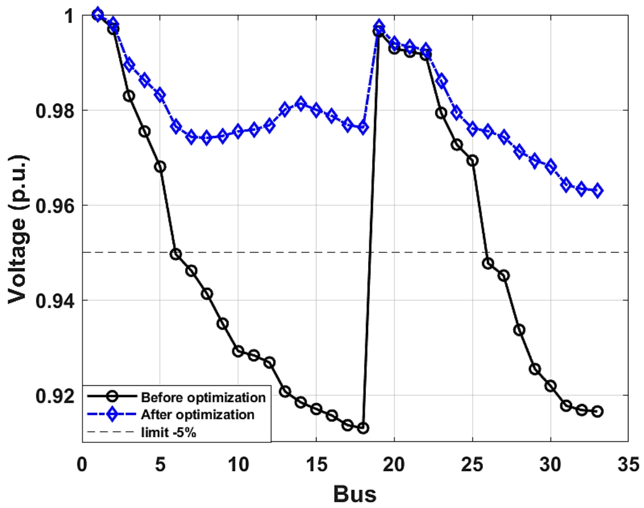

Figure 6. Voltage profile before and after optimization

4.3. Comparative analysis and benchmarking

To confirm the technical merit of the proposed joint optimization (PV+SVC) based on NSGA-II, we conduct a comparative analysis against recent studies that use other algorithms and scheduling strategies on the same 33-node IEEE test network. The data in Table 4 clearly illustrate that the proposed joint optimization of PV and SVC using NSGA-II yields a substantially higher loss reduction (62.53%) compared to single-unit placement strategies using conventional algorithms. This benchmark confirms the robust performance and the superiority of simultaneously coordinating active power injection and reactive power support for maximizing efficiency in radial distribution networks.

Table 4. Comparison of optimized results with literature benchmarks

Reference	Optimization strategy	Algorithm	Active loss reduction (%)
Proposed study	Joint PV + SVC	NSGA-II	62.53
[19]	PV placement	weighted mult-objective electric eel foraging optimization (WMOEEFO)	27.70
[24]	DG placement	Ant colony optimization (ACO)	41
[25]	Single D-STATCOM placement	Ant colony optimization (ACO)	22.42

5. CONCLUSION

This study presented a unified multi-objective optimization approach for the simultaneous placement and sizing of a photovoltaic (PV) source and a static var compensator (SVC) in a radial distribution network. Using the NSGA-II algorithm, known for its ability to generate non-dominated solutions, the analysis successfully explored the trade-offs between two major technical objectives: minimizing active losses and improving the voltage profile.

Simulations performed on the standard IEEE 33-bus network have demonstrated that the joint and optimized integration of PV (0.97 MW at node 14) and SVC (1.32 MVar at node 30) significantly improves the electrical performance of the network. Compared to isolated configurations (PV alone or SVC alone), the joint solution offers a substantial reduction in losses of 62.53% and achieves a voltage deviation reduced to 0.0169 p.u., with all bus voltages maintained above 0.95 p.u. limit. The proposed approach is robust, reproducible, and confirms the value of multi-objective evolutionary methods for comprehensive distributed resource planning in modern electrical systems. Based on the current findings, the following directions are recommended for future research to further advance the study: i) dynamic load modeling: incorporate time-varying load profiles and PV variability into the optimization to assess system performance under realistic operating conditions; and ii) multi-period optimization: extend the framework to a multi-period or yearly optimization horizon, considering seasonal variations in generation and consumption.

ACKNOWLEDGMENTS

The authors gratefully acknowledge the reviewers of this paper for their valuable advice and guidance.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Hassane Ousseyni Ibrahim	✓	✓		✓			✓	✓	✓	✓		✓	✓	✓
Abdoul Malik Maman Issaka		✓	✓		✓	✓		✓	✓	✓	✓			
Moussa Gonda				✓	✓	✓				✓	✓	✓	✓	
Arouna Oloulade					✓					✓	✓			
François-Xavier Fifatin					✓					✓	✓			

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors of this article formally affirm that their contributions are not associated with any material or financial interests.

DATA AVAILABILITY

Derived data supporting the findings of this study are available from the corresponding author, [HOI], on request.

REFERENCES

[1] W. Jie and K. Rabnawaz, "Renewable energy and CO2 emissions in developing and developed nations: a panel estimate approach," *Frontiers in Environmental Science*, vol. 12, Aug. 2024, doi: 10.3389/fenvs.2024.1405001.

[2] K. Kutubuddin and S. Liyakat, "Impact of solar penetrations in conventional power systems and generation of harmonic and power quality issues: a review," *Advance Research in Power Electronics and Devices*, vol. 1, no. 1, pp. 10–16, 2024.

[3] T. Chen, M. M. Othman, and Q. Xiang, "Optimization of storage and photovoltaic configuration in IEEE 33-bus system utilizing jaya algorithm," *International Review of Electrical Engineering (IREE)*, vol. 20, no. 3, p. 215, Jun. 2025, doi: 10.15866/iree.v20i3.26169.

[4] D. Han, W. Deng, Z. Zhao, W. Pei, and H. Xiao, "Coordinated optimization of active distribution network and multi-microgrids considering voltage robustness and economic efficiency: a distributed model predictive control method," *IET Generation, Transmission & Distribution*, vol. 19, no. 1, Jan. 2025, doi: 10.1049/gtd2.70130.

[5] J. Holweger, L. Bloch, C. Ballif, and N. Wyrsch, "Mitigating the impact of distributed PV in a low-voltage grid using electricity tariffs," *Electric Power Systems Research*, vol. 189, p. 106763, Dec. 2020, doi: 10.1016/j.epsr.2020.106763.

[6] S. Nagaballi and V. S. Kale, "Application of metaheuristic algorithms for optimal allocation of DGs in radial distribution system," *International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)*, vol. 5, no. 2, pp. 2394–2320, 2018.

[7] O. A. Zongo and A. Oonsivilai, "Optimal placement of distributed generator for power loss minimization and voltage stability improvement," *Energy Procedia*, vol. 138, pp. 134–139, 2017, doi: 10.1016/j.egypro.2017.10.080.

[8] S. K. Chauhan and V. S. Chauhan, "A comprehensive review on power quality issues and disturbances mitigation through shunt active power filters," *International Journal of Applied Power Engineering (IJAPE)*, vol. 13, no. 4, p. 844, Dec. 2024, doi: 10.11591/ijape.v13.i4.pp844-852.

[9] H. Qi, X. Yan, Y. Kang, Z. Yang, S. Ma, and Y. Mi, "Multi-objective optimization strategy for the distribution network with distributed photovoltaic and energy storage," *Frontiers in Energy Research*, vol. 12, Jul. 2024, doi: 10.3389/fenrg.2024.1418893.

[10] W. Ahmed, A. Selim, S. Kamel, J. Yu, and F. Jurado, "Probabilistic load flow solution considering optimal allocation of SVC in radial distribution system," *International Journal of Interactive Multimedia and Artificial Intelligence*, vol. 5, no. 3, p. 152, 2018, doi: 10.9781/ijimai.2018.11.001.

[11] H. O. Ibrahim, S. L. Rakiatou, and A. M. M. Issaka, "Improvement of voltage profile and reduction of losses in distribution networks via a hybrid PV-DSTATCOM approach," *Smart Grid and Renewable Energy*, vol. 17, no. 02, pp. 13–28, 2026, doi: 10.4236/sgre.2026.172002.

[12] O. Arouna *et al.*, "Technico-economic optimization of distributed generation (DG) and static var compensator (SVC) positioning in a real radial distribution network using the NSGA-II genetic algorithm," *IEEE PES/IAS PowerAfrica Conference: Power Economics and Energy Innovation in Africa, PowerAfrica 2019*, pp. 42–47, 2019, doi: 10.1109/PowerAfrica.2019.8928631.

[13] H. Ibrahim, M. Moustapha, M. Gonda, and A. Issaka, "Multi-objective optimization of the combined sizing and placement of a PV system and an UPQC in an IEEE 69-bus distribution network using a genetic algorithm," *International Journal of Energy and Power Engineering*, vol. 15, no. 1, pp. 37–44, Jan. 2026, doi: 10.11648/j.ijepe.20261501.13.

[14] B. Liu, K. Meng, Z. Y. Dong, P. K. C. Wong, and T. Ting, "Unbalance mitigation via phase-switching device and static var compensator in low-voltage distribution network," *IEEE Transactions on Power Systems*, vol. 35, no. 6, pp. 4856–4869, 2020, doi: 10.1109/TPWRS.2020.2998144.

[15] M. Hussein and A. Ewais, "Combination of SVC with PV-inverter for voltage regulation in distribution networks," *International Journal of Applied Energy Systems*, vol. 4, no. 2, pp. 52–57, Jun. 2022, doi: 10.21608/ijaes.2022.133144.1010.

[16] K. S. Latha, D. P. M. Sharma, and P. M. Manjula, "Heuristic algorithms for power quality analysis in IEEE-33 & IEEE-57 bus systems using fact devices and tracking," *International Journal of Intelligent Systems and Applications in Engineering*, vol. 12, no. 22, pp. 681–700, 2024, doi: 10.36893/ijisae.2024.V12N22.6583.

[17] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE Transactions on Evolutionary Computation*, vol. 6, no. 2, pp. 182–197, Apr. 2002, doi: 10.1109/4235.996017.

[18] S. Verma, M. Pant, and V. Snasel, "A comprehensive review on NSGA-II for multi-objective combinatorial optimization problems," *IEEE Access*, vol. 9, pp. 57757–57791, 2021, doi: 10.1109/ACCESS.2021.3070634.

[19] A. Manjula and G. Yesuratnam, "Optimal allocation of PV units using metaheuristic optimization considering PEVs charging demand," *International Journal of Applied Power Engineering (IJAPE)*, vol. 14, no. 2, pp. 282–290, Jun. 2025, doi: 10.11591/ijape.v14.i2.pp282-290.

[20] M. Duong, T. Pham, T. Nguyen, A. Doan, and H. Tran, "Determination of optimal location and sizing of solar photovoltaic distribution generation units in radial distribution systems," *Energies*, vol. 12, no. 1, p. 174, Jan. 2019, doi: 10.3390/en12010174.

[21] J.-H. Teng, "A direct approach for distribution system load flow solutions," *IEEE Transactions on Power Delivery*, vol. 18, no. 3, pp. 882–887, Jul. 2003, doi: 10.1109/TPWRD.2003.813818.

[22] B. V. Krishna and N. P. Srinivasu, "A direct approach method for distribution system load flow solutions," *International Journal of Engineering and Advanced Technology*, vol. 8, no. 6s3, pp. 749–753, Nov. 2019, doi: 10.35940/ijeat.F1138.0986S319.

[23] J. A. M. Rupa and S. Ganesh, "Power flow analysis for radial distribution system using backward/forward sweep method," *International Journal of Electrical, Computer, Electronics and Communication Engineering*, vol. 8, no. 10, pp. 1628–1632, 2014.

[24] D. P. R. P., V. R. V. C., and G. M. T., "Ant Lion optimization algorithm for optimal sizing of renewable energy resources for loss reduction in distribution systems," *Journal of Electrical Systems and Information Technology*, vol. 5, no. 3, pp. 663–680, Dec. 2018, doi: 10.1016/j.jesit.2017.06.001.

[25] A. Oloulade, A. M. Imano, A. Viannou, and H. Tamadaho, "Optimization of the number, size and placement of D-STATCOM in radial distribution network using Ant Colony Algorithm," *American Journal of Engineering Research and Reviews*, no. November, pp. 1–13, 2018, doi: 10.28933/ajoerr-2018-06-2601.

BIOGRAPHIES OF AUTHORS

Hassane Ousseyni Ibrahim obtained a state engineering diploma in electromechanics from the University of Boumerdes in Algeria, followed by a doctorate in engineering science specializing in electrical engineering from the University of Abomey Calavi in Benin, in 2006 and 2023, respectively. He is currently a lecturer-researcher in the Department of Electrical Engineering and Industrial Computing at the Polytechnic School of University Dan Dicko Dankoulodo of Maradi, Niger. He can be contacted at email: hassane2025@yahoo.fr.

Abdoul Malik Maman Issaka obtained his University Technology Diploma (DUT) in electrical engineering in 2022 at the University Institute of Technology (IUT). With this technical foundation, he continued his studies to specialize, earning a bachelor's degree in automation and industrial computing (Electrical Engineering Department) in 2023. These degrees were obtained at the University Dan Dicko Dankoulodo of Maradi (UDDM). He is currently a student in the Master 2 Sustainable Energy Systems Program at the Faculty of Science and Technology (FST) of UDDM. He can be contacted at email: mamanissaka90@gmail.com.

Moussa Gonda obtained a degree in electronic engineering specializing in communications from the Houari Boumediene University of Science and Technology (USTHB) in Algiers, Algeria, in 2008. In 2016, he obtained a master's degree in applied sciences, specializing in telecommunications networks, from the École de Technologie Supérieure (ETS) in Montreal, Canada. He is currently a Ph.D. student in electrical engineering at the Doctoral School of Engineering Sciences (ED-SDI) at the University of Abomey-Calavi (UAC) in Benin. The focus of his thesis research is the static and dynamic stability of electricity transmission networks in the context of renewable energy integration. He can be contacted at email: moussa.gonda@uddm.edu.ne or ahmad.nai2011@gmail.com.

Arouna Oloulade obtained a degree in electrical engineering from the Abomey-Calavi Polytechnic School in 2011. In 2013, he obtained a postgraduate degree in Engineering Sciences. He has held a doctorate from the University of Abomey-Calavi since 2019. He specializes in electrical network optimization and the reliability of energy transport and distribution systems. As an expert in electrical networks and machines, he is currently consulting on one of SBEE's projects to densify and extend electrical networks. He is the author of several articles. He was director of electricity distribution at the Beninese Electricity Company. He holds certifications in several fields, including corporate finance and project management. His most recent certification is the Project Management Professional (PMP) certification from the Project Management Institute (PMI). He can be contacted at email: olouarou@yahoo.fr.

François-Xavier Fifatin is a full professor at CAMES University. He is affiliated with the Department of Electrical Engineering at the Abomey-Calavi Polytechnic School (EPAC) of the University of Abomey-Calavi (UAC), Republic of Benin. He is currently the director of the Laboratory of Electrical Engineering, Telecommunications and Applied Computer Science (LETIA), as well as the deputy coordinator of the College of Engineering-Energy Infrastructure Environment (CoE-EIE). He can be contacted at email: fifatinf@gmail.com.