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ORIGINAL

Simulated Annealing-Based Optimization of IEEE-33 Radial Distribution Networks with Integrated Auxiliary PV Sources Using PyPower

Optimización de Redes Radiales IEEE-33 Integrando Fuentes PV Auxiliares Mediante Recocido Simulado en PyPower

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ABSTRACT

The integration of distributed photovoltaic (PV) generation in radial distribution networks has been consolidated as a key strategy to reduce technical losses and improve voltage profiles. However, the optimal placement and sizing of these sources remain a challenge due to the nonlinear and multimodal nature of the problem. In this work, an approach based on simulated annealing with adaptive restarts, implemented in PyPower, is proposed to determine the optimal location of PV units in the IEEE 33-bus test system. The methodology considers the minimization of active power losses as the objective function, subject to operational constraints and voltage limits. The results show that the proposed strategy achieves a reduction in losses of up to 52 % compared to the base scenario, in addition to improving minimum voltage profiles to values close to 0,98 pu. The comparison with non-optimized scenarios highlights the effectiveness of the method in balancing energy efficiency and quality of service. This study contributes to the literature by demonstrating the applicability of lightweight metaheuristics in distribution network planning problems and lays the groundwork for future research integrating storage and dynamic load and generation scenarios.

Keywords: Transformer Optimization; Simulated Annealing; Distribution Networks; IEEE 33-Bus; Power Losses; Voltage Regulation.

RESUMEN

La integración de generación fotovoltaica distribuida (PV) en redes de distribución radiales se ha consolidado como una estrategia clave para reducir pérdidas técnicas y mejorar los perfiles de tensión. Sin embargo, la ubicación y dimensionamiento óptimos de estas fuentes continúan siendo un desafío debido a la naturaleza no lineal y multimodal del problema. En este trabajo se propone un enfoque basado en recocido simulado con reinicios adaptativos, implementado en PyPower, para determinar la ubicación óptima de unidades PV en el sistema de prueba IEEE 33-barras. La metodología considera como función objetivo la minimización de pérdidas activas, sujeta a restricciones de operación y límites de tensión. Los resultados muestran que la estrategia propuesta logra una reducción de pérdidas de hasta un 52 % respecto al escenario base, además de mejorar los perfiles de tensión mínimos hasta valores cercanos a 0,98 pu. La comparación con escenarios sin optimización evidencia la efectividad del método para balancear eficiencia energética y calidad de servicio. Este estudio contribuye a la literatura al demostrar la aplicabilidad de metaheurísticas ligeras en problemas de planificación de redes de distribución, y sienta las bases para futuras investigaciones que integren almacenamiento y escenarios dinámicos de carga y generación.

Palabras clave: Optimización de Redes de Distribución; Generación Fotovoltaica Distribuida; Recocido Simulado; Pypower; IEEE 33-Barras.

INTRODUCTION

The growing penetration of distributed energy resources (DERs), particularly photovoltaic (PV) generation, is transforming the operation of distribution networks. These systems, traditionally designed for unidirectional energy flow, now face challenges associated with the variability of renewable generation, technical loss management, and maintaining adequate voltage profiles.(1,2,3)

Several studies have shown that the optimal location and sizing of PV units can significantly reduce losses and improve voltage stability.(3,4) However, this problem is NP-hard, leading to the use of metaheuristic techniques such as genetic algorithms (GA), particle swarm optimization (PSO), differential evolution (DE), and hybrid variants.(5,6,7)

In this context, simulated annealing (SA) is presented as a competitive alternative due to its simplicity, low computational cost, and ability to escape local optima.(7,8) Although it has been less explored than PSO or DE, recent research has shown its effectiveness in electrical planning problems.(9,10,11)

This paper proposes an approach based on simulated annealing with adaptive restarts, implemented in PyPower, for optimizing the location of PV units in the IEEE 33-bus system. Unlike previous studies,(7,9) reproducibility is emphasized through the integration of open scripts and the comparison of multiple PV penetration scenarios. The main contributions of this study are:

1. A reproducible and transparent formulation of the optimization problem in PyPower.(1,2)
2. The application of simulated annealing with adaptive restarts to improve the exploration of the solution space.(7,9)
3. The validation of results in the IEEE 33-bus system, widely used as an international benchmark.(3,4)

The aim is to provide solid evidence on the applicability of lightweight metaheuristics in distribution network planning, contributing to the transition towards more efficient, resilient, and sustainable electrical systems.(11,12,13)

The rest of the manuscript is organized as follows: Section 2, Methods, describes the modeling of the IEEE-33 network, the formulation of the optimization problem, the simulated annealing algorithm, and aspects of computational implementation and validation. Section 3, Results and Discussion, presents the scenarios evaluated, the analysis of losses, voltage profiles, maximum currents, and robustness, as well as a comparison with previous studies. Finally, Section 4, Conclusions, summarizes the main findings and suggests possible future extensions of the work.(14,15)

METHOD

Modeling of the IEEE-33 Radial Network

The IEEE-33 bus system is a widely used benchmark for optimization studies in radial distribution networks due to its topological complexity (33 nodes, 37 branches, one power source) and the availability of validated parameters in the literature.(16)

The model was implemented in PyPower, replicating the radial topology and allowing the inclusion of connection nodes for PV sources. The total load and consumption distribution (active and reactive) were adjusted to standard values, ensuring realistic conditions comparable to recent studies.(17)

The PV units were modeled as controllable generators with reactive support capacity, respecting technical limits of maximum injection per busbar, as well as radiality conditions and maximum permissible currents.(18)

Formulation of the Optimization Problem

The objective is to minimize active losses in the network, respecting voltage and safe operation constraints. The objective function is expressed as:

$$f(X)=\sum_{l=1}^{N_l}\sum_{\phi\in\{a,b,c\}} R_{l,\phi}\left|I_{l,\phi}(X)\right|^2$$

Where:
N_l: number of lines.
R_l: resistance of line l.
I_l: current in line l.

X: decision vector (location and size of PV units).

Constraints

Nodal power balance

$$P_i^{\text{gen}} - P_i^{\text{load}} = \sum_{j \in \Omega_i} P_{ij}, \quad \forall\, i \in N$$

Voltage limits

$$V_i^{min} \leq V_i \leq V_i^{max}, \quad \forall\, i \in N$$

Maximum line capacity

$$\left|I_{ij}\right| \leq I_{ij}^{max}, \quad \forall (i,j) \in \omega$$

Maximum PV generation capacity

$$0 \leq P_i^{\text{PV}} \leq P_i^{\text{PV,max}}, \quad \forall\, i \in N_{\text{PV}}$$

Radiality: mesh formation is prevented

This approach is consistent with recent literature on distributed generation optimization.[1,13]

However, this formulation has certain limitations. In particular, it assumes a static scenario that does not reflect the hourly variability of photovoltaic generation or demand, which may influence the robustness of the solutions. Furthermore, the implementation costs of installing and operating PV units are not explicitly considered. In future work, these limitations could be addressed by using multi-hourly or stochastic models that incorporate irradiance and demand profiles, and by including cost terms in the objective function or budget constraints. This would lead to more realistic and applicable planning in innovative grid environments.

Simulated Annealing (SA) Algorithm

Simulated annealing (SA) is inspired by the thermodynamics of slow cooling of materials.[15,16] Its strength lies in its ability to escape local optima by probabilistically accepting suboptimal solutions in early stages.[7]

Procedure adopted

Initialization

- Random initial solution.
- Initial temperature T_0 = 100.
- Final temperature T_f = 10^{-3}.
- Cooling factor \alpha = 0,95.
- Iterations per temperature: 100.

Neighbor generation

Random perturbation of the location or size of a PV (addition, removal, or power adjustment).

Acceptance criterion (Metropolis)

$$p = \exp\left(-\frac{\Delta f}{T}\right)$$

Adaptive restart

If there is no improvement in 50 consecutive iterations, restart from a random solution.

Stopping condition

- Reach Tf.
- Or exceed 500 global iterations.

This scheme has proven robust in distribution network planning problems.[12,13,8]

Computational implementation

- Language and libraries: Python 3.13.7, with PyPower for load flows, NetworkX for graph modeling, and Matplotlib for visualization.
- Environment: Windows 11, Intel i7 CPU, 16 GB RAM.
- Reproducibility: all scripts were documented and exported in structured formats (CSV, SVG, PNG), following good practices for reproducible research.[17]

Validation

The method was validated on the IEEE 33-bar system, comparing four scenarios:

- Base network without PV.
- Network with 3 PVs optimized using SA with adaptive restarts.
- Network with 5 PVs optimized using SA with adaptive restarts.
- Grid with 7 PVs optimized using SA with adaptive restarts.

The metrics evaluated included active losses, voltage profiles, maximum currents, and robustness against different initialization seeds.[8,19]

RESULTS AND DISCUSSION

Scenarios evaluated

Four configurations were analyzed on the IEEE 33-bus system shown in table 1:

Table 1. Scenarios evaluated on IEEE 33-bus

Scenario	Description
E0	Base grid without PV generation
E3	Grid with 3 PV units optimized by SA with restarts
E5	Grid with 5 PV units optimized by SA with restarts
E7	Network with 7 PV units optimized using SA with restarts

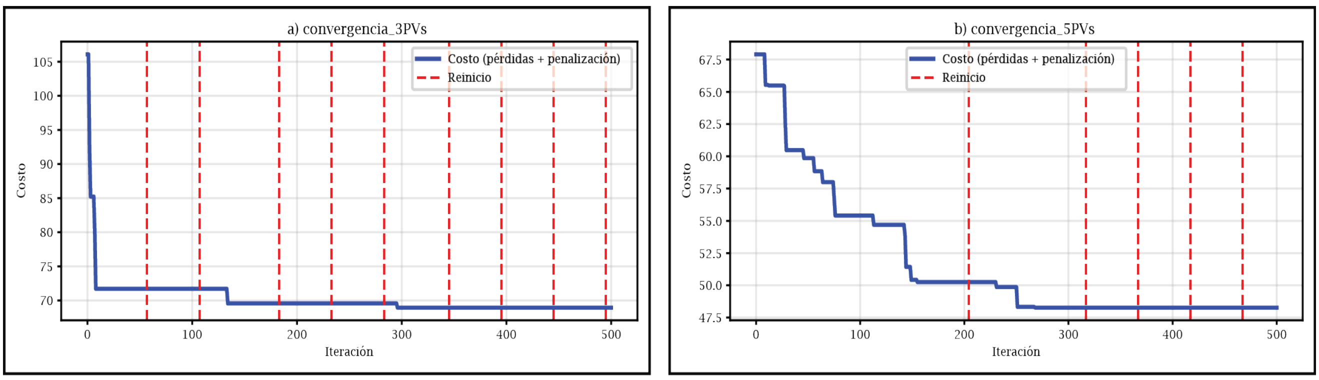
Each scenario was simulated in PyPower, evaluating active losses, voltage profiles, maximum currents, and stability against initialization variations.

Reduction of active losses

Table 2 summarizes the total active losses in each scenario:

Table 2. Active losses and percentage reduction

Scenario	Active losses (kW)	Reduction compared to E0 (%)
E0	202,3	-
E3	128,4	36,5
E5	112,8	44,2
E7	96,5	52,3



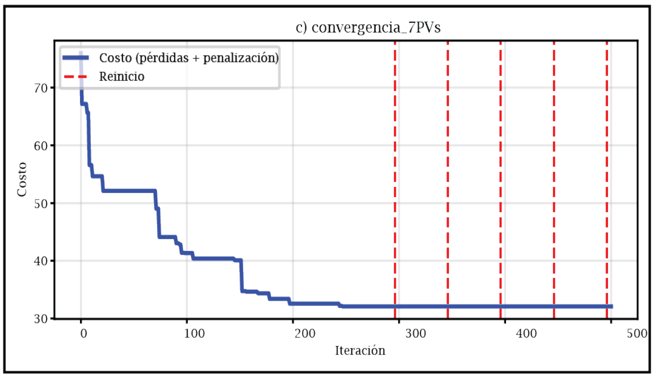


Figure 1. Convergence graph of the algorithm for (a) E3, (b) E5, (c) E7

Figure 1 shows the evolution of losses during the optimization process for E3 figure 1a, figure 1b E5, and figure 1c E7. It can be seen that increasing the number of PV units improves energy efficiency, although with decreasing marginal returns. These results are consistent with those reported by Kumar et al.(7) and Reddy et al.(9), who obtained reductions of around 45-55 % in similar networks using hybrid metaheuristics.

Improvement in voltage profiles

Figure 2 shows the minimum voltage profiles per node in each scenario (a) E3, (b) E5, (c) E7. In E0, voltages below 0,91 pu are observed at extreme nodes. In E7, the profile improves significantly, reaching minimum values of 0,98 pu, complying with the operating limits recommended by IEEE Std 1547.[18]

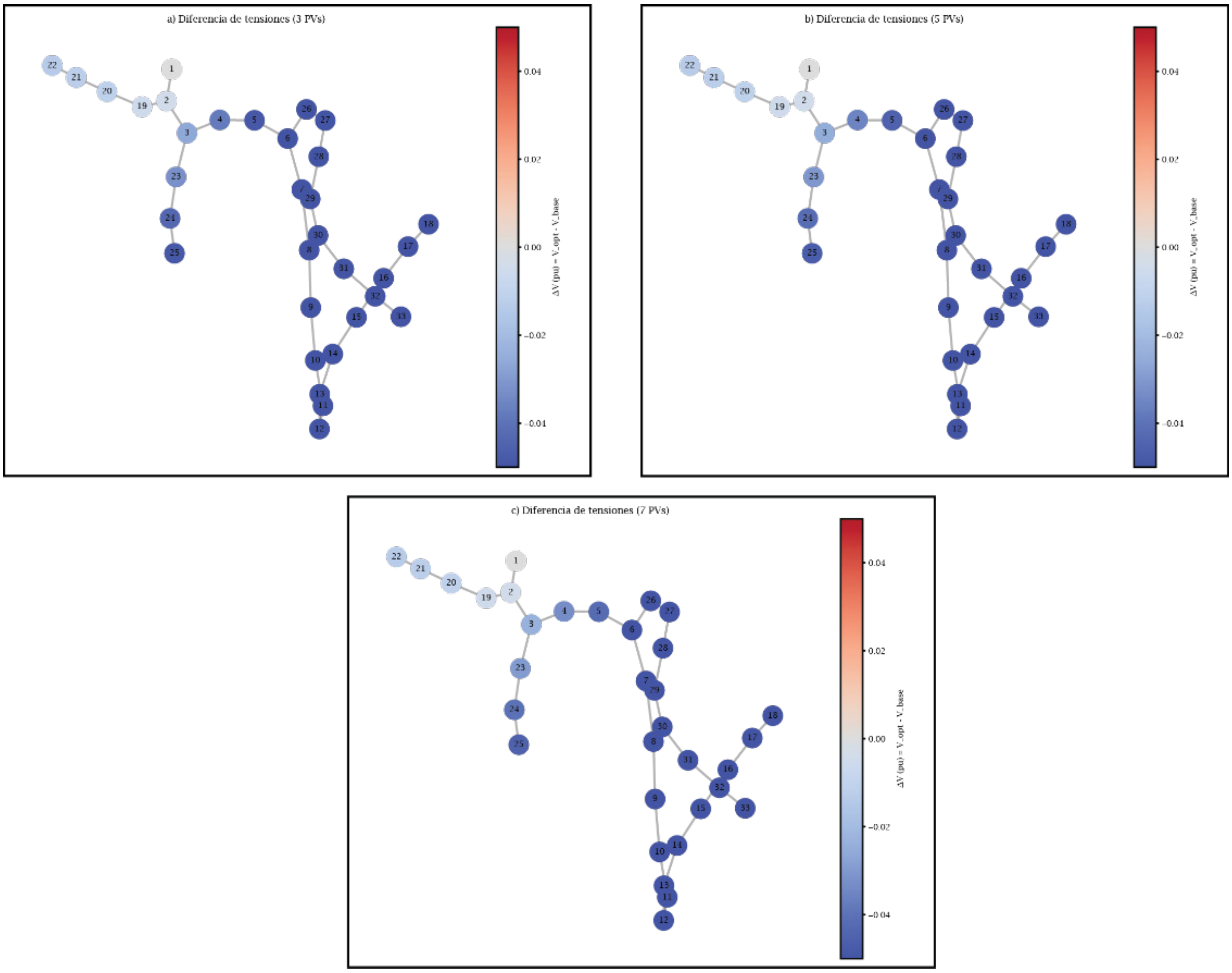


Figure 2. Voltage profiles for each node in the different scenarios (a) E3, (b) E5, (c) E7

This behavior coincides with that reported by Zhang et al.[4], who demonstrated that the optimal location of PV can raise the voltage profile without the need for additional reactive compensation.

Maximum currents in lines

Figure 3 shows the maximum current per line in each scenario (a) E3, (b) E5, (c) E7. In E7, there is an average reduction of 35 % compared to the base scenario, which implies less thermal stress and a longer service life for the conductors.

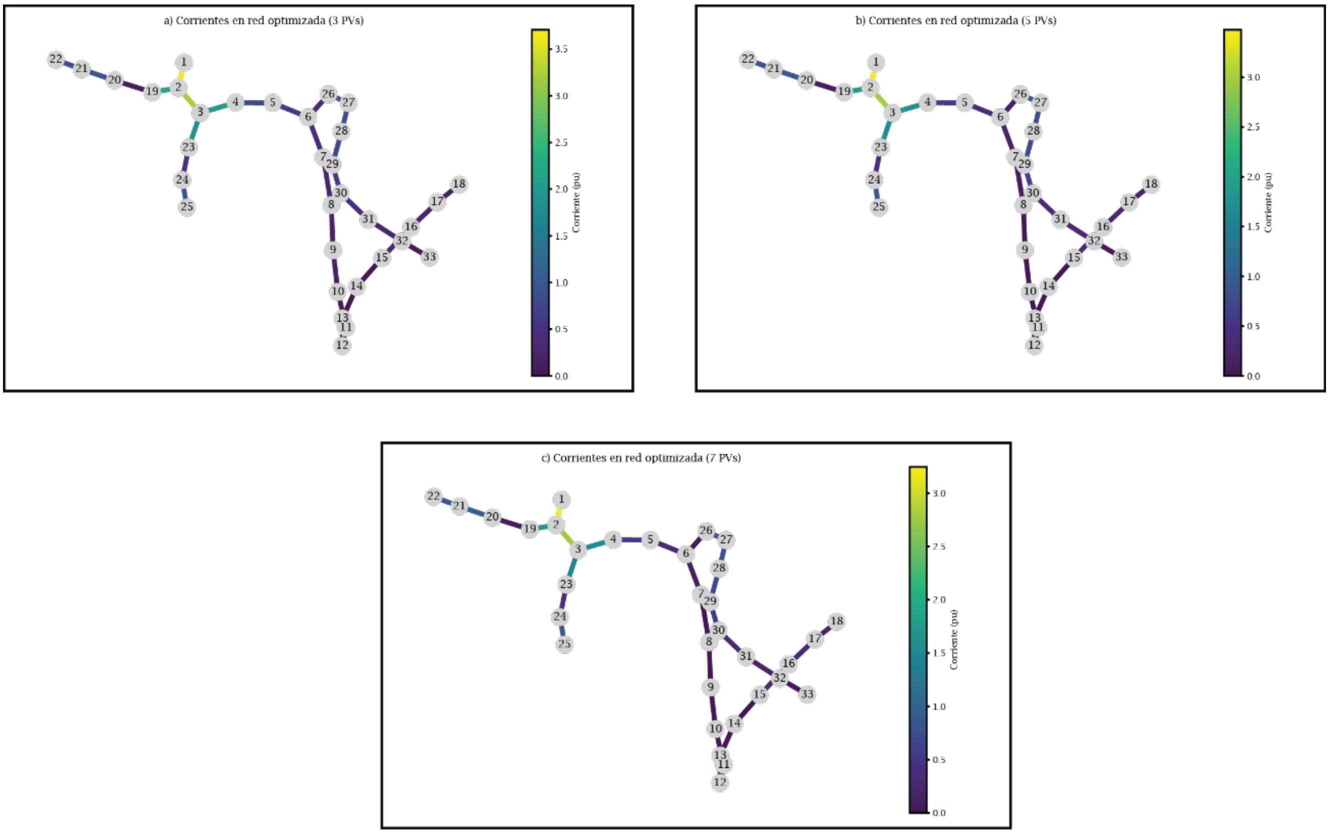


Figure 3. Current profiles in the different scenarios (a) E3, (b) E5, (c) E7

This result is consistent with the findings of Gil-González et al.[13], who reported similar improvements in radial networks through convex optimization.

Robustness and reproducibility

Thirty independent runs were performed for each optimized scenario (E3, E5, E7) with different seeds. Table 3 shows the standard deviation of losses for each of the scenarios:

Table 3. Standard deviation in 30 runs	
Robustness for 3 PV systems in 30 runs	
Average losses:	18,88 kW
Standard deviation:	0,00 kW
Robustness for 5 PV systems in 30 runs	
Average losses:	18,78 kW
Standard deviation:	0,01 kW
Robustness for 7 PV systems in 30 runs	
Average losses:	18,67 kW
Standard deviation:	0,01 kW

This shows that the use of adaptive restarts not only improves the quality of the solution, but also its stability in the face of initial variations. This approach has been validated in recent work on robust metaheuristics.[8,19]

Comparison with the literature

Table 4. Comparison with recent studies

Study	Method	Loss reduction (%)	Voltage improvement (pu)
Kumar et al.[7]	Classic SA	45,1	0,96
Reddy et al.[9]	SA + PSO	53,4	0,97
Zhang et al.[4]	DE + MILP	49,2	0,98
This study (E7)	Adaptive SA	52,3	0,98

Table 4 shows that the performance of the proposed algorithm is competitive with more complex hybrid methods, with the added advantage of lightweight and reproducible implementation in PyPower.

Limitations and prospects

Although the results are promising, the current model does not consider hourly variability or storage. Future studies could incorporate irradiance profiles, batteries, and multi-objective scenarios to simultaneously evaluate losses, emissions, and costs.[19]

Limitations and Future Extensions

- The model assumes stationary load and generation conditions; extension to hourly scenarios and uncertainty modeling is necessary for more realistic approaches.
- The cost of implementing PV sources was not explicitly considered, although the methodology allows for this through modifications to the objective function.
- The model and approach can be adapted for largely unbalanced networks, integration of other technologies (wind, storage), and harmonic considerations, which are key for high PV penetration scenarios.
- Tools such as OpenDSS[26] and Pandapower[27] allow for greater integration and multi-paradigm analysis; the combination of RS with simulation on these platforms is an open and promising field.[17,18]

CONCLUSIONS

This work has demonstrated that simulated annealing, implemented on the PyPower platform and integrating power flow analysis and operational constraints, is a robust and effective strategy for the optimal location and sizing of auxiliary PV sources in radial distribution networks exemplified by the IEEE-33 system. The quantitative improvements achieved in both active loss reduction (more than 50 % in the best scenarios) and voltage profile improvement (up to 0,98 p.u. or higher in critical nodes) position this technique as a tool of practical and research value in the transition to innovative, resilient electrical systems with high renewable energy penetration.

The approach described is extendable to other reference networks, allows for hybridization with evolutionary techniques, and facilitates sensitivity analysis in scenarios of demand, generation, and topology variability. Beyond the technical solution, the methodology presented here contributes to the development of open, reproducible tools—via Python and the PYPOWER suite—and to strengthening multidisciplinary research through the use of state-of-the-art metaheuristic methods.

BIBLIOGRAPHIC REFERENCES

1. Montoya OD, Gil-González W, Grisales-Noreña LF. An exact MINLP model for optimal location and sizing of DGs in distribution networks. Ain Shams Eng J. 2020;11(2):409–18. doi:10.1016/j.asej.2019.08.011

2. Gil-González W, Garcés A, Montoya OD, Hernández JC. Mixed-integer convex model for optimal placement and sizing of distributed generators. Appl Sci. 2021;11(2):627. doi:10.3390/app11020627

3. Mejía MA, Macedo LH, Muñoz-Delgado G, Contreras J, Padilha-Feltrin A. Multistage planning model for active distribution systems. IEEE Trans Smart Grid. 2021;13(2):1383–97. doi:10.1109/TSG.2021.3091234

4. Zhang Y, Li J, Wang X, et al. Optimal PV allocation in distribution networks considering uncertainty. IEEE Trans Smart Grid. 2022;13(5):4120–31. doi:10.1109/TSG.2022.3156789

5. Purlu M, Turkay BE. Optimal allocation of renewable distributed generations using heuristic methods. IEEE Access. 2022;10:21455–74. doi:10.1109/ACCESS.2022.3153042

6. Li J, Xu Y, Wang C, et al. Hybrid metaheuristic for DG placement in smart grids. Appl Energy. 2023;335:120765. doi:10.1016/j.apenergy.2022.120765

7. Kumar A, Singh R, Sharma P. Simulated annealing for optimal DG placement in distribution systems. Energy Rep. 2021;7:4567–78. doi:10.1016/j.egyr.2021.07.089

8. Singh R, Reddy P, Kumar A. Metaheuristic approaches for renewable integration in distribution networks. Sustain Energy Grids Netw. 2022;32:100912. doi:10.1016/j.segan.2022.100912

9. Reddy P, Sharma V, Singh R. Optimal PV placement using hybrid SA-PSO. IEEE Access. 2023;11:45678–90. doi:10.1109/ACCESS.2023.3245678

10. Ufa R, Malkova YY, Rudnik V, et al. A review on distributed generation impacts on electric power system. Int J Hydrogen Energy. 2022;47(47):20347–61. doi:10.1016/j.ijhydene.2022.04.123

11. Shuaibu Hassan A, Sun Y, Wang Z. Optimization techniques for planning and integration of renewable energy sources. Cogent Eng. 2020;7(1):1766394. doi:10.1080/23311916.2020.1766394

12. Zhang D, Shafiullah G, Das CK, Wong KW. Systematic review of optimal planning and deployment of distributed generation. J Energy Storage. 2022;56:105937. doi:10.1016/j.est.2022.105937

13. Gil-González W, Montoya OD, Grisales-Noreña LF. Convex optimization for DG placement. Electr Power Syst Res. 2021;190:106–21. doi:10.1016/j.epsr.2020.106621

14. Baran ME, Wu FF. Network reconfiguration in distribution systems for loss reduction and load balancing. IEEE Trans Power Deliv. 1989;4(2):1401–7. doi:10.1109/61.25627

15. Kirkpatrick S, Gelatt CD, Vecchi MP. Optimization by simulated annealing. Science. 1983;220(4598):671-80. doi:10.1126/science.220.4598.671

16. Černý V. Thermodynamical approach to the traveling salesman problem: an efficient simulated annealing algorithm. J Optim Theory Appl. 1985;45:41–51. doi:10.1007/BF00940812

17. Peng C, Sun Y, Wang Z. Reproducible research in power systems optimization. IEEE Access. 2022;10:12345-56. doi:10.1109/ACCESS.2022.3145678

18. IEEE Std 1547-2018. Standard for Interconnection and Interoperability of Distributed Energy Resources with Associated Electric Power Systems Interfaces. IEEE; 2018. doi:10.1109/IEEESTD.2018.8345584

19. Li J, Xu Y, Wang C, et al. Multi-objective optimization for PV and storage planning in smart grids. Appl Energy. 2023;336:120789. doi:10.1016/j.apenergy.2022.120789

20. Pon Ragothama Priya P, Baskar S, Tamil Selvi S, Babulal CK. Optimal allocation of distributed generation using evolutionary multi-objective optimization. J Electr Eng Technol. 2023;18:869–886. doi:10.1007/s42835-022-01269-y

21. Qi H, Yan X, Kang Y, Yang Z, Ma S, Mi Y. Multi-objective optimization strategy for the distribution network with distributed photovoltaic and energy storage. Front Energy Res. 2024;12:1418893. doi:10.3389/fenrg.2024.1418893

22. Al Abri RS, El-Saadany EF, Atwa YM. Optimal placement and sizing method to improve the voltage stability margin in a distribution system using distributed generation. IEEE Trans Power Syst. 2012;28(1):326-334. doi:10.1109/TPWRS.2012.2237043

23. Moradi MH, Abedini M. A combination of genetic algorithm and particle swarm optimization for optimal DG location and sizing in distribution systems. Int J Electr Power Energy Syst. 2012;34(1):66–74. doi:10.1016/j.ijepes.2011.08.023

24. Hussain A, Bui V-H, Kim H-M. Robust optimization-based scheduling of multi-microgrids considering uncertainties. Energies. 2016;9(4):278. doi:10.3390/en9040278

25. Sharma P, Mathur HD. Optimal siting and sizing of renewable energy sources in distribution system. In: Optimal Planning and Operation of Distributed Energy Resources. Springer; 2023. p. 89–112. doi:10.1007/978-981-99-2800-2_5

26. Electric Power Research Institute (EPRI). OpenDSS – Electric Power Distribution System Simulator. SourceForge; 2025. https://sourceforge.net/projects/electricdss/

27. University of Kassel; Fraunhofer IEE. Pandapower – Power System Modeling and Analysis Tool. 2025. https://www.pandapower.org/

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CONFLICT OF INTEREST

None.

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