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Performance assessment of PSO variants for optimal photovoltaic and DSTATCOM allocation in radial distribution networks

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ABSTRACT

This work presents a comparative evaluation of adaptive particle swarm optimization (PSO) variants for the optimal placement and sizing (OPS) of photovoltaic-based distributed generation (PV-DG) and DSTATCOM units in the standard IEEE 33-bus radial distribution network (RDN). Five adaptive PSO algorithms are investigated, namely adaptive acceleration coefficients PSO (AAC-PSO), autonomous particle groups PSO (APG-PSO), nonlinear dynamic acceleration coefficients PSO (NDAC-PSO), sine-cosine acceleration coefficients PSO (SCAC-PSO), and time-varying acceleration PSO (TVA-PSO). The optimization framework is structured as a single-objective problem focused on maximizing the active power loss index (APLI), which is used as a normalized indicator associated with active power loss reduction. To further assess the technical quality of the obtained solutions, two additional performance indicators are considered, namely the total voltage deviation (TVD) and the voltage stability index (VSI). The simulation outcomes indicate that the TVA-PSO algorithm exhibits superior overall performance compared to other evaluated variants in terms of convergence behavior and solution quality. In particular, it achieves the highest APLI value of 92.52%, corresponding to an active power loss reduction of 91.91%, with active power losses (APL) reduced from 210.99 kW to 17.07 kW. In addition, the obtained solution significantly improves the network voltage profile (VP) and enhances voltage stability. These findings provide evidence that the effectiveness of adaptive PSO strategies for optimizing PV-DG and DSTATCOM integration in RDN.

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1. INTRODUCTION

The integration of renewable energy sources (RES) in modern electrical power systems, specifically photovoltaic distributed generation (PV-DG), into the electrical distribution network has become the cornerstone of efforts being made on a worldwide scale to improve energy efficiency, cut emissions of greenhouse gases, and transition toward sustainable energy systems [1], [2]. PV-DG systems, as a clean and inexhaustible energy source, play a pivotal role in decarbonizing the power sector and mitigating the environmental impact of traditional fossil fuel-based generation [3], [4]. Nonetheless, the natural sporadic characteristics of solar energy and the increasing complexity of modern distribution networks pose significant challenges, including power loss minimization, voltage stability, and efficient energy management

[5]. To address these challenges, the deployment of advanced grid support devices, such as static synchronous compensators (STATCOMs), has arisen as a critical solution. Unlike PV-DG systems, which generate active power, they are meant to offer dynamic reactive power compensation, improve VPs, and enhance grid stability [6]. When optimally integrated, PV-DG and STATCOMs offer synergistic benefits: PV-DG reduces dependency on fossil fuels, while STATCOMs ensure reliable and stable operation of the distribution electrical power network. However, the optimal placement and sizing (OPS) of PV-DG and STATCOMs are crucial to optimizing and maximizing their advantages. Suboptimal integration is capable of causing a rise in energy losses, voltage violations, and reduced system efficiency. As the penetration of RES and the use of grid support devices like STATCOMs continue to grow, the need for robust optimization methods has never been more critical [7], [8].

Adaptive particle swarm optimization (PSO) works better than static algorithms like DE, NSGA-II, and GSO because it reduces losses more (up to 57.89%) and makes voltage more stable [9], [10]. Because it can optimize several objective functions simultaneously, it can simultaneously reduce harmonic distortion, voltage deviation (VD), and power losses (for example, THD was lowered to 3.98%) [9], [11]. The method has been examined and demonstrated efficacy to work on conventional IEEE 33/69-bus test systems and real-world networks like South Kerman DSSK [11], [12]. Adaptive PSO is a strong and scalable solution for distribution systems with a lot of PVs because it can handle the compromise between exploration and exploitation and work around operational limits like 24-hour load profiles [9]. OPS of photovoltaic systems and STATCOMs significantly enhance radial distribution network (RDN) performance through the reduction of power losses, enhancing VPs, and boosting stability. A recent review of the application of the adaptive particle swarm optimization (APSO) approaches, including variants with acceleration coefficients, multi-objective frameworks, and dynamic momentum, demonstrated on this topic found that superior efficacy in solving these complex optimization problems. Shaheen *et al.* [9] proposed a hunter–prey optimization (HPO) algorithm for the optimal allocation of PV-STATCOM units in RDN, aiming to minimize the active energy losses and VDs in 1 day. The suggested approach has been implemented in the IEEE 33- and 69-bus test systems. Where the proposed method was applied to two well-known benchmark test systems, namely the IEEE 33-bus and IEEE 69-bus RDN. The HPO outcomes outperform traditional algorithms like DE (differential evolution), traditional PSO algorithms, artificial rabbits' algorithm (ARA), and golden search optimizer (GSO) in terms of convergence and accuracy while achieving notable gains in power quality and efficiency. In some cases, lowering combined objective metrics by over 85%. However, the marginal benefit decreases after three units are deployed, and the method's performance is constrained when only one device is installed, as it is unable to adequately address voltage constraints. Labed *et al.* in [13] applied an adaptive acceleration coefficients PSO (AAC-PSO) algorithm to determine the OPS of PV-DG and DSTATCOM units in an IEEE 33-bus RDN. The results demonstrated significant minimization of APL and enhancement of VPs, achieving approximately a 27 % reduction in power losses compared to other PSO variants, while their approach, though superior in convergence and solution quality, remains specifically tailored to radial networks and may not generalize well to meshed grids without reconfiguration of constraint handling.

Advanced PSO methods have been very popular in the last several years for tackling multi-objective problems in power distribution networks. Improved versions of multi-objective PSO (MOPSO) that use adaptive grid structures and roulette wheel selection mechanisms have proven to be very good at balancing conflicting goals like reducing network losses, controlling voltage fluctuations, and limiting the capacity of static var generators (SVGs). These methods have shown better results than traditional evolutionary methods, such as the non-dominated sorting genetic algorithm II (NSGA-II), especially when it comes to keeping the variety of the Pareto front in stochastic distributed photovoltaic (PV) settings [14]. To make scalability and convergence even better, a Modified PSO with dynamic momentum (MPSO-DM) was suggested to handle high-dimensional optimization problems in large-scale systems, like the IEEE 79-bus network. This worked better than traditional PSO variants at reducing losses and improving economic performance [15]. Experimental studies on IEEE 33-, 69-, and 79-bus test systems show that adaptive PSO techniques can cut APL from 25 to 76.3% [9], [13], [15], [16], stabilize VPs between 0.95 and 1.05 p.u. with deviations reduced to 42.84% [9], [17], and make the system more economically viable by using D-STATCOMs with payback periods as short as 1.8 years and cost-saving benefits from hybrid PV-STATCOM configurations [17], [18].

Adaptive PSO algorithms prove highly effective for optimizing PV-STATCOM deployment, offering dynamic parameter adjustments that outperform static methods. Key results include substantial loss reductions (25–76.3%), voltage stability within regulatory limits, and cost-efficient solutions with rapid payback periods. While Hunter-prey optimization (HPO) and artificial rabbits' optimization (ARO) show competitive results in specific scenarios, adaptive PSO's flexibility in handling multi-objective constraints particularly in large-scale networks solidifies its utility for modern distribution systems. Some optimization methods are presented in Table 1. Future work could explore hybrid frameworks combining PSO with machine learning for real-time grid adaptability [14], [17].

This study addresses these challenges by employing advanced optimization algorithms to optimize the placement and sizing of PV-DG and STATCOM units in a standard IEEE 33-bus distribution system. The primary objectives are the minimization of APL and the enhancement of voltage stability. By comparing the performance of various optimization techniques, this work seeks to ascertain the most effective approach for achieving optimal system performance. The importance of this study lies in its capacity to improve the efficiency and reliability of electrical distribution systems, paving the way for more sustainable energy management practices. The findings are expected to provide valuable insights for utility operators, policymakers, and researchers, supporting the global transition toward renewable energy integration and the development of smarter, more resilient power grids.

Table 1. Comparative analysis of different optimization methods

Algorithm	Loss reduction	Voltage improvement	Key advantages
Adaptive PSO	76.3%	42.84% reduction in deviations	Dynamic coefficient tuning for exploration-exploitation balance [13], [14]
Hunter-Prey (HPO)	57.89%	44.69% reduction in deviations	Superior consistency in variable load conditions [9]
Artificial Rabbits (ARO)	65.4% (reactive loss)	THD reduced to 3.98%	Excels in harmonic mitigation and global optima [19]
Sine-Cosine (SCA)	35.63%	Efficient computation	Faster convergence than Vortex Search [20]

2. PROBLEM FORMULATION AND CONSTRAINTS

The two main objective functions in this research to optimize are the minimization of APL by increasing the active power losses index (APLI), where higher values translate to higher percentages of loss reduction. The second objective consists of improving voltage profiles and maximizing the voltage stability index to enhance system reliability under various loads and generation conditions.

2.1. Objective functions formulation

First, the minimization of APL by maximizing APLI, which is equivalent to (1) and (2).

$$OF_1 = Max \sum_{i=1}^{N_{Bus}} \sum_{j=2}^{N_{Bus}} APLL(i,j) \tag{1}$$

$$APLI(i,j) = \frac{P_{Loss}^{Befor_PV-DG/DSTATCOM}}{P_{Loss}^{BeforpV-DG/DSTATCOM} + P_{Loss}^{AfterpV-DG/DSTATCOM}} \times 100 \tag{2}$$

Where $P_{Loss}^{Befor_PV-DG/DSTATCOM}$ and $P_{Loss}^{AftepV-DG/DSTATCOM}$ represent the power losses before and after the implementation of the PV-DG and DSTATCOM. The equation below illustrates the active power loss [21]:

$$P_{Loss} = \alpha_{ij}\left(P_iP_j + Q_iQ_j\right) + \beta_{ij}\left(Q_iP_j + P_iQ_j\right) \tag{3}$$

$$\begin{cases} \alpha_{ij} = \frac{R_{ij}}{V_iV_j} cos\left(\delta_i - \delta_j\right) \\ \beta_{ij} = \frac{R_{ij}}{V_iV_j} sin\left(\delta_i + \delta_j\right) \end{cases} \tag{4}$$

Where α_{ij} and β_{ij} are loss coefficients, $R_{i,j}$ denotes the line's resistance, (V_i, V_j) and $(\delta_i,\ \delta_j)$ are the voltages and angles at the buses, respectively. $(P_i,\ P_j)$ denotes active power, while $(Q_i,\ Q_j)$ signifies reactive power. Second, the enhancement of the VP through the reduction of the VD as detailed in (5).

$$OF_2 = Min\ VD = \left|1 - V_j\right| \tag{5}$$

Where V_j denote the voltage magnitude at bus j.

2.2. Constraints of equality

The active and reactive powers of each bus must be equal to the power loads connected to that same bus, as indicated in (6) and (7).

$$P_G + P_{PVDG} = P_{Load} + P_{Loss} \tag{6}$$

$$Q_G + Q_{DST} = Q_{Load} + Q_{Loss} \quad (7)$$

P_G and Q_G represent the active and reactive powers of the generator; P_{PV-DG} is the total active power injected from the PV-DG source and Q_{DST} is the reactive power injected from the DSTATCOM. P_{Load}, Q_{Load} are the total load demand active and reactive powers, respectively. APLs are denoted by P_{Loss} and reactive power losses (RPL) are denoted by Q_{Loss}, respectively.

2.3. Distribution line constraints

The distribution line restrictions are articulated using (8) to (10).

$$V_{min} \leq |V_i| \leq V_{max} \quad (8)$$

$$|1 - V_j| \leq \Delta V_{max} \quad (9)$$

$$|S_{ij}| \leq S_{max} \quad (10)$$

V_{max} and V_{min} signify the maximum and minimum voltage limits, respectively. ΔV_{max} represents the maximum voltage drop. S_{max} and $S_{i,j}$ represent the maximum and apparent power within the distribution line.

2.4. PV-DG constraints

The limits of the PV-DG units are formulated as (11) to (16).

$$P_{PV-DG}^{min} \leq P_{PV-DG} \leq P_{PV-DG}^{max} \quad (11)$$

$$Q_{DST}^{min} \leq Q_{DST} \leq Q_{DST}^{max} \quad (12)$$

$$\sum_{i=1}^{N_{PVDG}} P_{PV-DG} \leq \sum_{i=1}^{N_{Bus}} P_{Load} \quad (13)$$

$$2 \leq PV - DG_{Position} \leq N_{bus} \quad (14)$$

$$N_{PVDG} \leq N_{PV-DG.max} \quad (15)$$

$$n_{PVDG,i}/Location \leq 1 \quad (16)$$

Where, P_{PV-DG}^{min} and P_{PV-DG}^{max} denote the minimum and maximum output power of the PV-DG, respectively. Q_{DST}^{min},Q_{DST}^{max} the minimum and maximum reactive power outputs of the DSTATCOM, respectively. N_{PV-DG} signifies the PV-DG unit's number. $n_{PV-DG,i}$ denotes the location of PV-DG units at bus *i*.

3. OVERVIEW OF VARIOUS ALGORITHMS

In this paper, basic and novel PSO algorithms are applied for the purpose of the OPS of three PV-DG units and three DSTATCOMs in the standard IEEE 33-bus RDN. The basic PSO algorithm is represented by means of (17) and (18).

$$V_i^{k+1} = \omega . V_i^k + c_1 r_1 [P_{best}^k - X_i^k] + c_2 r_2 [G_{best}^k - X_i^k] \quad (17)$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (18)$$

The velocity of the particle is denoted by V_i, the weight of inertia is denoted by ω, and the acceleration coefficients are denoted by c_1, c_2. r_1, r_2 are independent random numbers. The best-known position of the particle is denoted by P_{best}, while the best-known position of the entire swarm is denoted by G_{best}, and X_i is the position of the particle. Table 2 gives a summary of some types of PSO variants and presents their mathematical formulations used to adapt the acceleration coefficients during the optimization process. The table also highlights the corresponding control parameters and constants used in each technique, reflecting distinct adaptive strategies proposed to balance exploration and exploitation in PSO algorithms. Figure 1 displays the variation profiles of the acceleration coefficients c_1 and c_2 of the studied PSO algorithms with respect to the iterative procedure. The latter clearly shows the different adaptation tactics adopted by each variety and highlights how the cognitive and social activities of the particles have evolved to balance exploration and exploitation through optimization.

Table 2. PSO variants and their respective acceleration coefficients

Algorithm	Refs	Formulas for acceleration coefficients	Constants
AAC-PSO	[22]	$c_1 = c_{min} + (c_{max} - c_{min})\, exp\left(-\left(\frac{4\times k}{k_{max}}\right)^2\right)$ and $c_2 = c_{max} - (c_{max} - c_{min})\, exp\left(-\left(\frac{4\times k}{k_{max}}\right)^2\right)$	$c_{min} = 0.5$, $c_{max} = 2.5$
APG-PSO	[23]	$c_1 = 1.95 - \left(\frac{2\times k^{\alpha}}{k_{max}^{a}}\right)$ and $c_2 = 0.05 - \left(\frac{2\times k^{\alpha}}{k_{max}^{a}}\right)$	$\alpha = 1 / 3$
NDAC-PSO	[24]	$c_1 = -(c_f - c_i)\left(\frac{k}{k_{max}}\right)^2 + c_f$ and $c_2 = c_i\left(1 - \frac{k}{k_{max}}\right)^2 + c_f\left(\frac{k}{k_{max}}\right)$	$c_i = 0.5$, $c_f = 2.5$
SCAC-PSO	[25]	$c_1 = \partial . sin\left[\left(1 - \frac{k}{k_{max}}\right) \times \frac{\pi}{2}\right] + \delta$ and $c_2 = \partial . cos\left[\left(1 - \frac{k}{k_{max}}\right) \times \frac{\pi}{2}\right] + \delta$	$\partial = 2$, $\partial = 0.5$
TVA-PSO	[26]	$c_1 = c_{1i} + \left(\frac{c_{1f} - c_{1i}}{k_{max}}\right) k$ and $c_2 = c_{2i} + \left(\frac{c_{2f} - c_{2i}}{k_{max}}\right) . k$	$c_{1i} = 2.5$, $c_{1f} = 0.5$ $c_{2i} = 0.5$, $c_{2f} = 2.5$

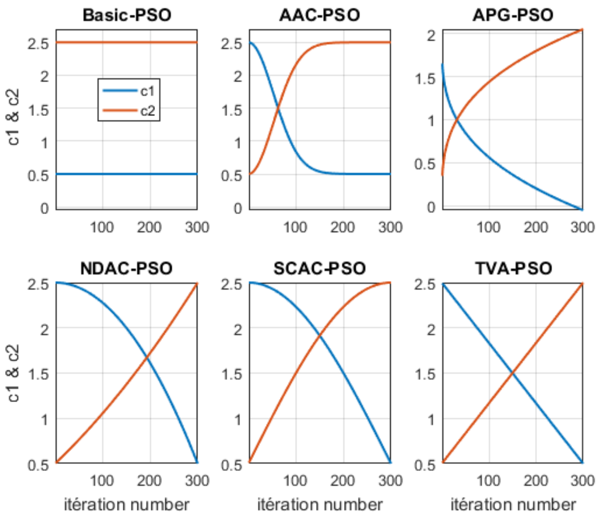

Figure 1. Acceleration coefficient variation curves for PSO algorithms

4. APPLICATION AND ANALYSIS RESULTS

The PSO algorithms used in this paper are programmed in MATLAB and tested on the standard IEEE-33 distribution system illustrated in Figure 2. The system consists of 33 buses and 32 distribution lines with a base voltage of 12.66 kV. It has an active power loss of 210.987 kW and a reactive power loss (RPL) of 143.128 kVar. The programs in MATLAB were executed several times for all PSO variants, and the best result was taken; the comparison between the best results in each group is presented in Figure 3 and in Table 3. These outcomes of the obtained simulation provide convincing evidence that the optimal (maximum) APLI is achieved using the time-varying acceleration PSO (TVA-PSO) algorithm at 92.52%, with 17.06 kW and 13.82 kVar active and reactive losses, respectively. The bus voltage magnitudes were also indicated in Table 3 shows the OPS of the three PV-DG and three DSTATCOM that resulted after the application of each PSO algorithm.

Figure 3 illustrates the convergence curves of multiple PSO variants applied to the OPS of PV and STATCOM units in the IEEE 33-bus RDN. According to the findings, the TVA-PSO algorithm achieved the best performance out of all the examined methods in terms of the highest APLI, where it reaches 92.5% after 225 iterations. Other algorithms, such as APG-PSO and NDAC-PSO, obtained relatively stable APLI values earlier but with lower maximum performance compared to the TVA-PSO algorithm. The BASIC-PSO algorithm takes longer to cover, almost similarly to the TVA-PSO method. However, the BASIC-PSO algorithm gets the lowest APLI (84%) compared to TVA-PSO, which means that it is the worst in terms of both speed and efficiency. These results highlight the superiority of TVA-PSO in terms of convergence efficiency and robustness. According to this finding, the TVA-PSO techniques demonstrate that they outperform the results of other adaptive PSO approaches. Examining the data presented in Table 3, it becomes evident that the concurrent integration of DG and DSTATCOM units effectively decreases total power loss to acceptable levels across all algorithms. The TVA-PSO algorithm yields the best APLI outcome, designating buses 25, 28, and 13 as optimal emplacements for integrating DG units, totaling 2.804 MW. Likewise, the best location for DSTATCOM unit integration is determined to be buses 26, 30, and 14, amounting to a total size of 1.668 MVar. Resulting from this integration, the active power loss was curtailed from 210.9875 kW to 17.0668 kW, showcasing a decrease of 91.9109%. Furthermore, the APLI achieved a heightened value of 92.52%. With the same method, the minimum reactive power loss is obtained, which is 13.8234 kVar. Through the utilization of the TVA-PSO algorithm, the minimum voltage is elevated from 0.9038 to 0.9924 p.u. The best amelioration of the minimal voltage is achieved with the NDAC-PSO algorithm with a value of 0.9938 p.u. These results are also shown in graphing format in Figures 4 and 5, representing a comparison between the different PSO optimization methods for APLI, active losses, reactive losses, minimum, and maximum voltage.

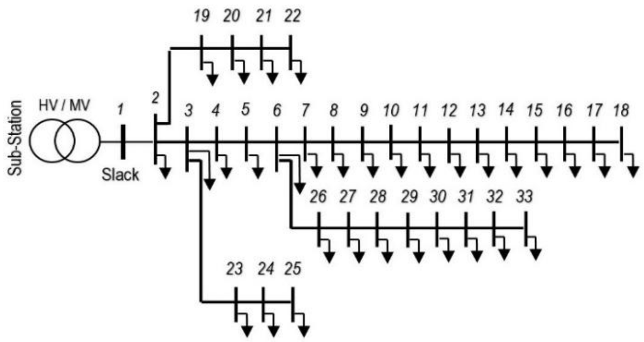

Figure 2. Single-line schematic of the standard IEEE 33-bus system

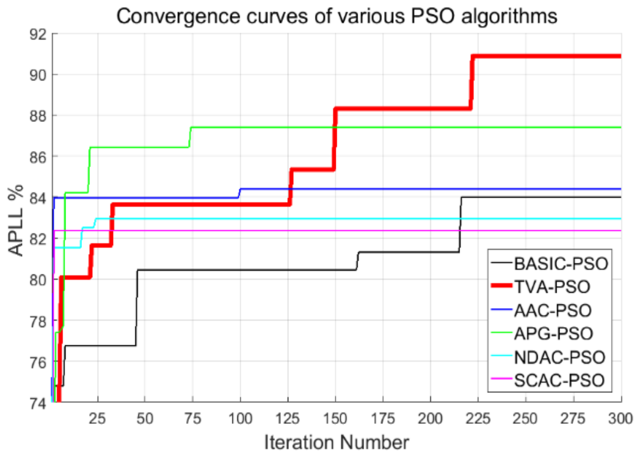

Figure 3. Convergence characteristics of the PSO algorithms and their variants

Table 3. Results of optimization after PV-DG and DSTATCOM installation

Applied algorithm	$P_{PV\text{-}DG}$ (MW), bus number	Q_{DST} (MVar), bus number	$\Sigma\ P_{Loss}$ (kW)	$\Sigma\ Q_{Loss}$ (kVar)	V_{min} (p.u.)	APLI (%)
TVA-PSO	0.787 (25) 1.243 (28) 0.774 (13)	0.308 (26) 1.023 (30) 0.337 (14)	17.0668	13.8234	0.9924	92.52
APG-PSO	0.975 (25) 1.155 (9) 0.658 (30)	0.168 (13) 1.169 (30) 0.010 (23)	23.2666	17.4557	0.9759	90.07
NDAC-PSO	0.880 (16) 0.564 (25) 0.930 (32)	0.579 (10) 0.948 (30) 0.907 (25)	24.5723	19.1017	0.9938	89.57
SCAC-PSO	0.962 (10) 0.889 (31) 1.052 (25)	0.010 (32) 0.010 (24) 1.298 (30)	25.1208	19.3979	0.9742	89.36
BASIC-PSO	0.450 (25) 1.014 (10) 0.714 (30)	0.010 (14) 0.689 (6) 0.786 (30)	25.5511	19.4362	0.9735	89.20
AAC-PSO	0.552 (17) 0.755 (25) 1.018 (28)	0.952 (30) 0.324 (27) 0.778 (5)	27.0564	21.8477	0.9761	88.63

Figures 6 and 7 provide a comparative comparison of voltage profiles and voltage drop distributions throughout all buses in the IEEE 33-bus RDN. Following the proper integration of PV-DG and DSTATCOM units, a notable enhancement in voltage magnitude and uniformity is seen. The minimum bus voltage is elevated from 0.9038 p.u. to 0.9938 p.u., concurrently resulting in a significant reduction in the overall voltage drop across the network, signifying improved voltage stability and enhanced power quality. These improvements confirm the efficacy of the optimization technique in sustaining voltage profiles within permissible thresholds under fluctuating load situations.

Figures 8 and 9 display the distribution of active and RPL across the 33 branches of the IEEE 33-bus RDN. The comparison between pre- and post-integration scenarios reveals significant reductions in both active and reactive losses because of the OPS of PV and STATCOM units. The minimization of loss really contributes to improved energy efficiency and the overall performance of the system. The improvement is more evident in branches that are nearer to the optimal integration points, illustrating the efficacy of the implemented optimization strategy. Figure 10 highlights the effectiveness of integrating an OPS of DG and DSTATCOM units by comparing the total APL, reactive power losses, and minimum voltage levels in the IEEE 33-bus distribution system. These outcomes show a significant enhancement in terms of power-losses curtailment and a clear improvement in minimum voltage; this means enhanced voltage stability and overall distribution system performance. The latter confirms the impact of the OPS of DG and DSTATCOM units when using TVA-PSO.

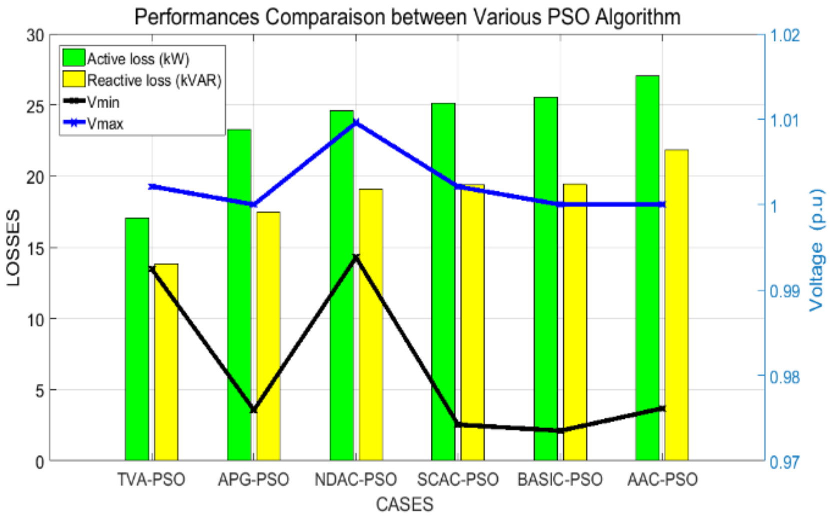

Figure 4. Power losses and minimum/maximum voltages of the PSO algorithm and its variants

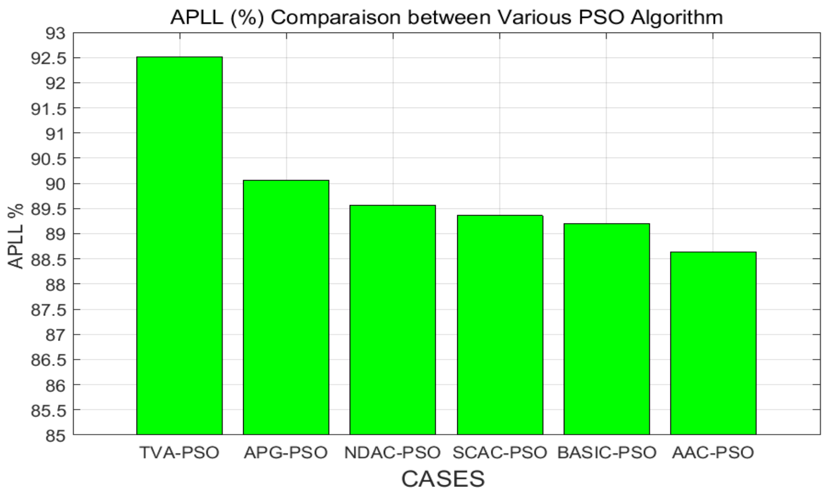

Figure 5. APLI of the PSO algorithm and its variants

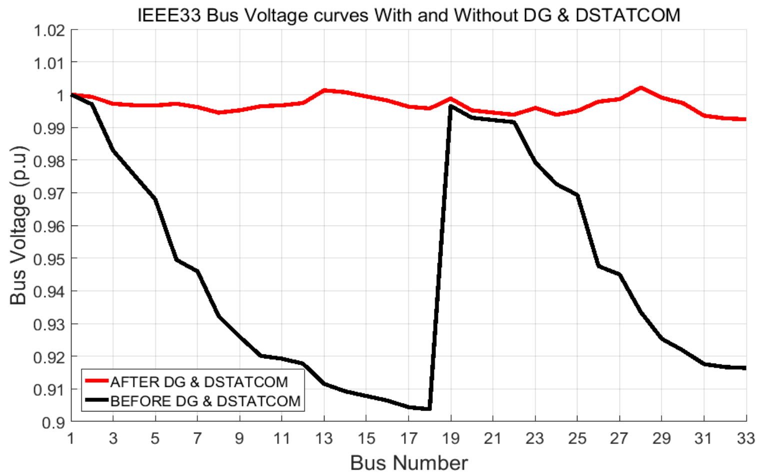

Figure 6. Bus voltage profiles before and following the integration of DSTATCOM and PV-DG

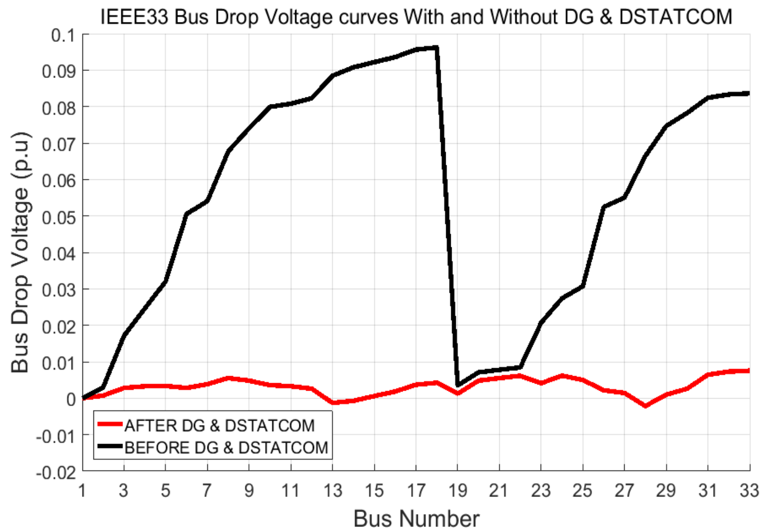

Figure 7. Bus voltage drop profiles before and after the PV-DG and DSTATCOM integration

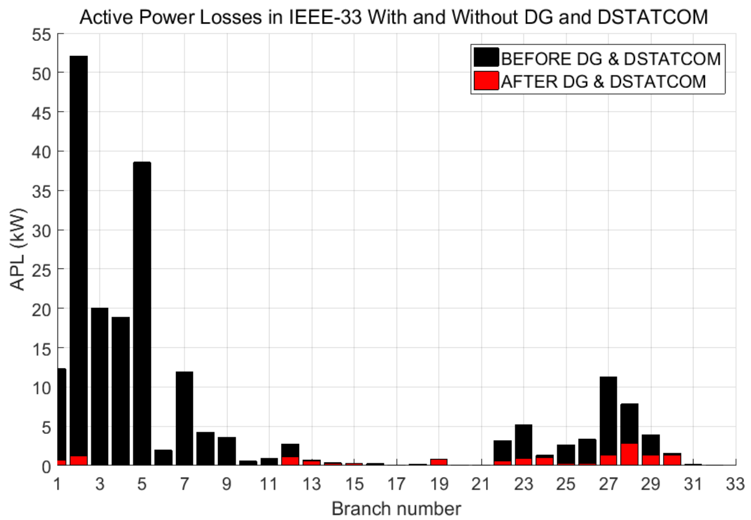

Figure 8. Branch active power loss prior to and during the integration of DSTATCOM and PV-DG

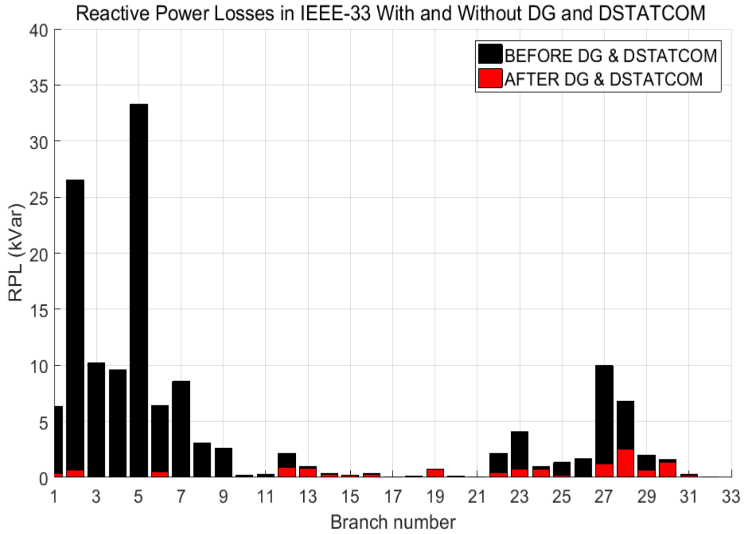

Figure 9. Branch reactive power loss before and after the PV-DG and DSTATCOM integration

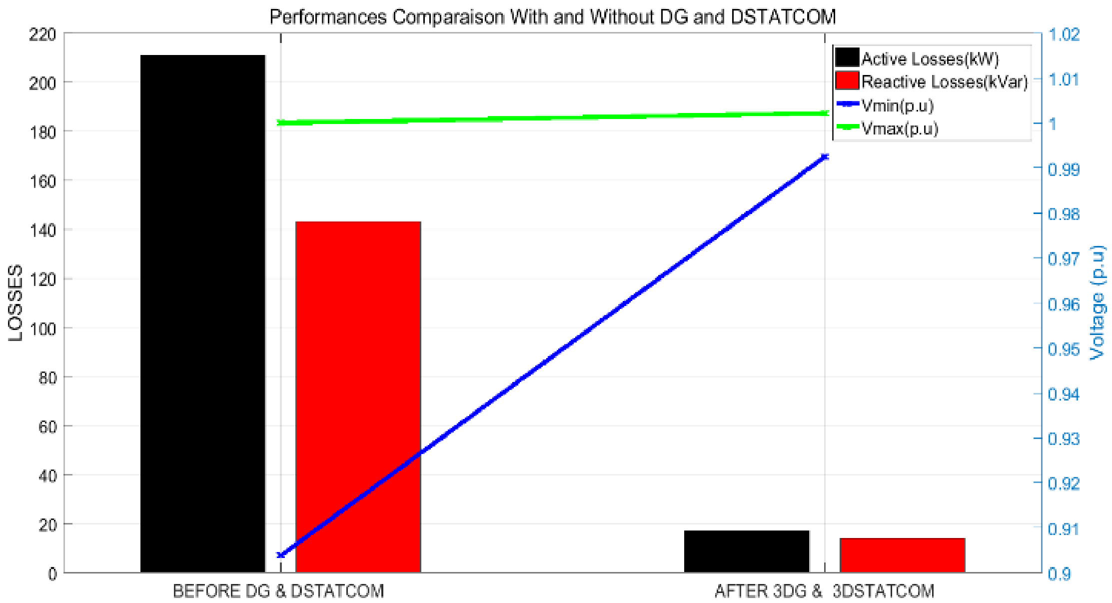

Figure 10. Active and RPL and minimum/maximum voltages before and after PV-DG and DSTATCOM integration

5. CONCLUSION

This study investigated the utilization of diverse PSO algorithms for the purpose of optimizing the simultaneous integration of PV-DG and STATCOM units in a standard IEEE 33-bus electrical RDN. The primary objective was to maximize the APLI, which directly correlates with minimizing APL as well as improving the overall efficiency of the energy management system. Through a comprehensive comparison of different PSO algorithms, the obtained outcomes demonstrated clearly that the TVA-PSO outperformed other variants in terms of efficiency and robustness. Specifically, TVA-PSO achieved a significant reduction in APL, from 210.987 kW to 17.066 kW, and increased the APLI to 92.52%. Additionally, the voltage profile was notably improved, with the minimum voltage rising from 0.9038 p.u. to 0.9924 p.u., ensuring better voltage stability across the network.

The simulation results also highlighted the importance of simultaneous and optimal placement of PV-DG and STATCOM units. When properly integrated, these components synergistically enhance system performance through the mitigation of power losses, improving voltage stability, and increasing the overall reliability of the distribution system. In conclusion, this study validates TVA-PSO as a highly effective and practical method for addressing the complex challenges associated with the OPS of PV-DG and STATCOM units in electrical RDN. The results yield valuable and significant insights for utility operators, policymakers, and researchers, offering a robust framework for improving the efficiency and sustainability of contemporary power grids. Future work could explore the application of these optimization techniques in larger and more complex distribution networks, as well as their integration with other RES and smart grid technologies.

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AUTHOR CONTRIBUTIONS STATEMENT

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

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C : **C**onceptualization
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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 claim no conflict of interest.

INFORMED CONSENT

All study participants gave informed consent.

DATA AVAILABILITY

The corresponding author can provide the data used in this study upon request.

REFERENCES

[1] M. Daneshvar, B. Mohammadi-Ivatloo, and K. Zare, “An innovative transactive energy architecture for community microgrids in modern multi-carrier energy networks: a Chicago case study,” *Scientific Reports*, vol. 13, no. 1, p. 1529, Jan. 2023, doi: 10.1038/s41598-023-28563-7.

[2] S. Adak, “Control strategy evaluation for reactive power management in grid-connected photovoltaic systems under varying solar conditions,” *Scientific Reports*, vol. 15, no. 1, p. 24697, Jul. 2025, doi: 10.1038/s41598-025-08918-y.

[3] D. Singh, N. Elgeberi, M. Aljaidi, R. Kumar, R. E. Al Mamlook, and M. K. Singla, “Optimal location of renewable energy generators in transmission and distribution system of deregulated power sector: a review,” *Energy Engineering*, vol. 122, no. 3, pp. 823–859, 2025, doi: 10.32604/ee.2025.059309.

[4] M. Bajaj and A. K. Singh, "Grid integrated renewable DG systems: A review of power quality challenges and state-of-the-art mitigation techniques," *International Journal of Energy Research*, vol. 44, no. 1, pp. 26–69, Jan. 2020, doi: 10.1002/er.4847.

[5] N. Khosravi, D. Çelik, H. Bevrani, and S. Echalih, "Microgrid stability: A comprehensive review of challenges, trends, and emerging solutions," *International Journal of Electrical Power & Energy Systems*, vol. 170, p. 110829, Sep. 2025, doi: 10.1016/j.ijepes.2025.110829.

[6] B. Boubekeur, "Application of STATCOM to increase transient stability of wind farm," *American Journal of Electrical Power and Energy Systems*, vol. 2, no. 2, p. 50, 2013, doi: 10.11648/j.epes.20130202.14.

[7] A. M. Shaheen, R. A. El-Sehiemy, A. Ginidi, A. M. Elsayed, and S. F. Al-Gahtani, "Optimal allocation of PV-STATCOM devices in distribution systems for energy losses minimization and voltage profile improvement via hunter-prey-based algorithm," *Energies*, vol. 16, no. 6, p. 2790, Mar. 2023, doi: 10.3390/en16062790.

[8] R. O. Bawazir and N. S. Cetin, "Comprehensive overview of optimizing PV-DG allocation in power system and solar energy resource potential assessments," *Energy Reports*, vol. 6, pp. 173–208, Nov. 2020, doi: 10.1016/j.egyr.2019.12.010.

[9] A. M. Shaheen, R. A. El-Sehiemy, A. Ginidi, A. M. Elsayed, and S. F. Al-Gahtani, "Optimal allocation of PV-STATCOM devices in distribution systems for energy losses minimization and voltage profile improvement via hunter-prey-based algorithm," *Energies*, vol. 16, no. 6, p. 2790, Mar. 2023, doi: 10.3390/en16062790.

[10] M. N. M Saud and M. Md Rasid, "Adaptive hybrid differential evolution particle swarm optimization algorithm for optimization distributed generation in distribution networks," *Jurnal Teknologi (Sciences & Engineering)*, vol. 87, no. 2, pp. 203–216, Jan. 2025, doi: 10.11113/jurnalteknologi.v87.19769.

[11] F. Fardinfar and M. J. K. Pour, "Optimal placement of D-STATCOM and PV solar in distribution system using probabilistic load models," in *2023 10th Iranian Conference on Renewable Energy & Distributed Generation (ICREDG)*, Mar. 2023, pp. 1–5. doi: 10.1109/ICREDG58341.2023.10091990.

[12] P. V. K. Babu and K. Swarnasri, "Adaptive PSO technique for optimal placement and sizing of DG in 3-phase unbalanced radial secondary distribution system," in *2019 IEEE International Conference on Intelligent Systems and Green Technology (ICISGT)*, Jun. 2019, pp. 85–854. doi: 10.1109/ICISGT44072.2019.00034.

[13] M. A. Labed, M. Zellagui, M. Benidir, H. Sekhane, and N. Tebbakh, "Optimal hybrid photovoltaic distributed generation and distribution static synchronous compensators planning to minimize active power losses using adaptive acceleration coefficients particle swarm optimization algorithms," *Electrical Engineering & Electromechanics*, no. 6, pp. 84–90, Oct. 2023, doi: 10.20998/2074-272X.2023.6.15.

[14] H. Liu, H. Li, J. Li, and L. Shao, "Distributed photovoltaic reactive power control strategy based on improved multiobjective particle swarm algorithm," *Energy Science & Engineering*, vol. 12, no. 11, pp. 4904–4917, Nov. 2024, doi: 10.1002/ese3.1902.

[15] A. Moreira, Y. Molina, R. Aquino, and Z. Ñaupari, "Allocation and sizing of photovoltaic systems to reduce power losses and economic aspects using a new PSO approach," *IEEE Latin America Transactions*, vol. 20, no. 6, pp. 977–985, Jun. 2022, doi: 10.1109/TLA.2022.9757741.

[16] P. Raghuwanshi and S. K. Jain, "Impact analysis of simultaneous integration of optimal DG and D-STATCOM allocation in distribution system with intermittent nature of load," in *2024 2nd International Conference on Advancements and Key Challenges in Green Energy and Computing (AKGEC)*, Nov. 2024, pp. 1–6. doi: 10.1109/AKGEC62572.2024.10868611.

[17] B. Singh, N. K. Saxena, A. Kumar, W. Gao, and F. Ma, "Optimal allocation of hybrid renewable energy sources using progressive L-index method for voltage stability margin enhancement and impact of storage devices," *International Journal of Emerging Electric Power Systems*, vol. 26, no. 5, pp. 879–903, Oct. 2025, doi: 10.1515/ijeeps-2024-0165.

[18] E. F. Getahun, A. S. Yimer, and W. A. Haile, "Distribution network performance enhancement through optimal sizing and placement of D-STATCOM using particle swarm optimization technique (case study-woldya distribution network)," *Engineering World*, vol. 6, pp. 264–276, Dec. 2024, doi: 10.37394/232025.2024.6.29.

[19] C. R. Rao, R. Balamurugan, and R. K. R. Alla, "Artificial rabbits optimization based optimal allocation of solar photovoltaic systems and passive power filters in radial distribution network for power quality improvement," *International Journal of Intelligent Engineering and Systems*, vol. 16, no. 1, pp. 100–109, Feb. 2023, doi: 10.22266/ijies2023.0228.09.

[20] O. D. Montoya, C. A. Ramírez-Vanegas, and L. F. Grisales-Noreña, "A sine-cosine algorithm approach for optimal PV and D-STATCOM integration in distribution systems," *Statistics, Optimization & Information Computing*, vol. 13, no. 3, pp. 1266–1279, Nov. 2024, doi: 10.19139/soic-2310-5070-2232.

[21] A. Lasmari, M. Zellagui, R. Chenni, S. Semaoui, C. Z. El-Bayeh, and H. A. Hassan, "Optimal energy management system for distribution systems using simultaneous integration of PV-based DG and DSTATCOM units," *Energetika*, vol. 66, no. 1, Aug. 2020, doi: 10.6001/energetika.v66i1.4294.

[22] T. Ziyu and Z. Dingxue, "A modified particle swarm optimization with an adaptive acceleration coefficients," in *2009 Asia-Pacific Conference on Information Processing*, Jul. 2009, pp. 330–332. doi: 10.1109/APCIP.2009.217.

[23] S. Mirjalili, A. Lewis, and A. S. Sadiq, "Autonomous particles groups for particle swarm optimization," *Arabian Journal for Science and Engineering*, vol. 39, no. 6, pp. 4683–4697, Jun. 2014, doi: 10.1007/s13369-014-1156-x.

[24] K. Chen, F. Zhou, Y. Wang, and L. Yin, "An ameliorated particle swarm optimizer for solving numerical optimization problems," *Applied Soft Computing*, vol. 73, pp. 482–496, Dec. 2018, doi: 10.1016/j.asoc.2018.09.007.

[25] K. Chen, F. Zhou, L. Yin, S. Wang, Y. Wang, and F. Wan, "A hybrid particle swarm optimizer with sine cosine acceleration coefficients," *Information Sciences*, vol. 422, pp. 218–241, Jan. 2018, doi: 10.1016/j.ins.2017.09.015.

[26] A. Ratnaweera, S. K. Halgamuge, and H. C. Watson, "Self-organizing hierarchical particle swarm optimizer with time-varying acceleration coefficients," *IEEE Transactions on Evolutionary Computation*, vol. 8, no. 3, pp. 240–255, Jun. 2004, doi: 10.1109/TEVC.2004.826071.

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