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Improvement of Voltage Profile and Reduction of Losses in Distribution Networks via a Hybrid PV-DSTATCOM Approach

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Abstract

This study focused on optimizing distribution networks through the strategic integration of photovoltaic (PV) systems and D-STATCOM compensators. Using the particle swarm optimization (PSO) algorithm, three scenarios were evaluated to minimize active losses and stabilize the voltage profile. The individual results showed that while PV alone effectively reduces losses (47.79%) and D-STATCOM alone improves reactive regulation (24.08%), neither solution offers total performance. The joint optimization of both pieces of equipment proved to be the most effective, achieving a 69.18% reduction in losses and ensuring a voltage profile that strictly complies with wave quality standards across all nodes, including the most remote ones.

Keywords

Minimize Active Losses, Photovoltaic (PV), D-STATCOM, Particle Swarm Optimization (PSO) Algorithm, Distribution Networks

1. Introduction

The growing integration of renewable energy sources (RES) and the sophistication of global energy demand are posing unprecedented challenges to electricity distribution networks. Historically designed for unidirectional power flows, these networks are now facing critical issues such as voltage instability, increased ohmic losses and deterioration in power quality [1]. In this context, the modernization of distribution networks, particularly through the concept of Smart Grids, has become a top priority for network operators [2]. Among the most promising solutions, the integration of decentralized generation, particularly photovoltaics (PV), offers a major opportunity to reduce dependence on fossil fuels while injecting active power close to the load. However, massive and uncoordinated insertion of PV can lead to flow reversals and voltage limit violations [3]. To overcome these drawbacks, the use of fast reactive compensation devices, such as DSTATCOM (Distribution Static Compensator), is essential. DSTATCOM enables dynamic voltage regulation and effective reactive power compensation, thus complementing the energy contribution of PV [4] [5].

The issue of optimal placement and sizing of decentralized power sources (PD) has been the subject of extensive research over the last decade. Initially, researchers focused on single-objective optimization, primarily aimed at reducing active power losses. However, with the emergence of power quality requirements, research has shifted towards more complex multi-objective approaches. For example, the use of fixed and switchable capacitors has been widely documented for voltage support, but their inability to provide continuous regulation has led to the adoption of the more flexible and responsive DSTATCOM [6].

In terms of algorithms, the literature shows a transition from deterministic methods to metaheuristics inspired by nature. Studies based on the ant colony optimization (ACO) algorithm or teaching-learning-based optimization (TLBO) have demonstrated clear effectiveness on the IEEE bus network [7]-[9]. Nevertheless, the challenge remains the simultaneous management of decision variables for PV (active power) and DSTATCOM (reactive power). Recent work has attempted to combine these two technologies, but often at the cost of high computational complexity or premature convergence to local optima. The PSO algorithm [10], thanks to its mechanism for sharing information between particles, offers an optimal compromise between exploring the search space and exploiting the best solutions found. This study differs from existing work in its rigorous multi-objective formulation, which treats the PV-DSTATCOM synergy not as two isolated problems, but as an integrated power flow management system [11]. The major challenge then lies in optimization: where to place these devices and how much capacity to allocate to them? Sub-optimal placement can not only reduce technical benefits but also unnecessarily increase investment costs. This problem is inherently complex, non-linear and multi-objective, requiring robust optimization tools. Although many metaheuristic techniques have been explored, the Particle Swarm Optimization (PSO) algorithm stands out for its simplicity of implementation, speed of convergence and proven ability to escape local optima in electrical planning problems [12]-[14].

This paper proposes a multi-objective optimization approach for the simultaneous determination of the optimal size and location of PV and DSTATCOM units in the IEEE 33-bus radial network. The main objective is to minimize total active power losses while maximizing voltage profile improvement. Through rigorous comparative analysis, this study demonstrates the effectiveness of coordination between PV and DSTATCOM via the PSO algorithm, thus offering a reliable solution for more efficient and resilient operation of modern distribution networks.

2. Methodology and Problem Formulation

2.1. Photovoltaic Model

Since the photovoltaic system acts as an active energy source, its connection to node i transforms the energy flow at this injection point as follows:

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

where $P_{i,new}$ is the new active power at node *i*, P_i is active power at node *i*, P_{PV} is active power injected by the PV.

The reactive power at the node remains constant, given that $Q_{PV} = 0$.

2.2. DSTATCOM Model

2.2.1. The Configuring a D-STATCOM

The D-STATCOM is defined as a synchronous static compensator incorporating a DC/AC converter, a storage capacitor, a magnetic circuit and a coupling transformer (see Figure 1). Its main function is to regulate the characteristics of a network node by injecting or absorbing reactive power. Based on a Voltage Source Converter (VSC), this equipment acts as a static generator capable of modulating the amplitude, phase and frequency of its output voltage. Its parallel configuration allows it to control capacitive or inductive currents independently of the grid voltage. By generating a voltage drop in quadrature with the line current, it modifies the apparent impedance of the line. It is a versatile tool that is essential for stabilizing the voltage plane, correcting the power factor and mitigating disturbances such as voltage dips, harmonics or load imbalances [15].

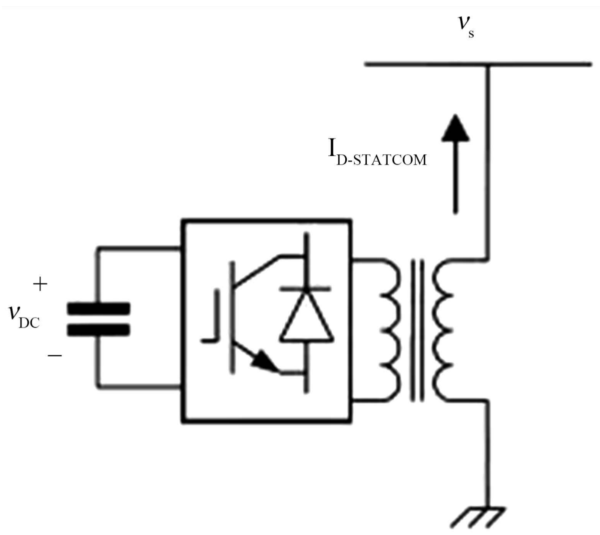

Figure 1. General diagram of a D-STATCOM.

Following the installation of the D-STATCOM at node *j* (see Figure 2), the voltage undergoes a change, going from V_j to V_{jnew}.

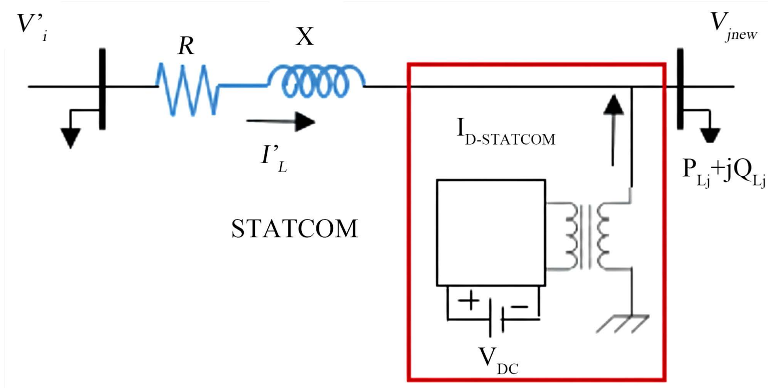

Figure 2. Basic distribution network with a DSTATCOM.

2.2.2. Mathematical Model of a DSTATCOM

The D-STATCOM is modelled as an AC current injector within the distribution network when studying power flow. Neglecting internal losses according to [15], its behavior in a two-node system is represented by the vector diagram in **Figure 3** [15].

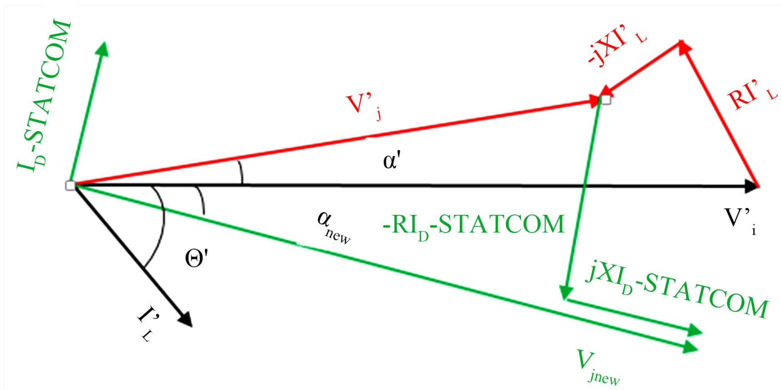

Figure 3. Phase diagram of voltages and currents.

The phase shift of the current $I_{\text{D-STATCOM}}$ relative to the voltage and the expression of the voltage V_{jnew} represented in the form [15] [16]:

$$\arg\left(I_{\text{D-STATCOM}}\right) = \alpha_{new} + \frac{\pi}{2} \tag{2}$$

$$V_{jnew}\mathrm{e}^{j(\alpha_{new})} = V_i'\mathrm{e}^{j\theta} - \left(R + jX\right)I_L'\mathrm{e}^{j\theta} - \left(R + jX\right)I_{\text{D-STATCOM}}\mathrm{e}^{j(\alpha_{new})} \tag{3}$$

With $I_{\text{D-STATCOM}}\mathrm{e}^{(\alpha_{new})}$ and $V_{jnew}\mathrm{e}^{j(\alpha_{new})}$ being respectively the current injected by the DSTATCOM and the voltage of node *j* after compensation.

By separating the real and imaginary parts of Equation (3), we obtain Equations (4) and (5):

$$\begin{aligned} V_{jnew}\cos\left(\alpha_{new}\right) = {} & R_e\left\{V_i'\mathrm{e}^{j\theta} - \left(R + jX\right)I_L'\mathrm{e}^{j\theta}\right\} - RI_{\text{D-STATCOM}}\cos\left(\alpha_{new} + \frac{\pi}{2}\right) \\ & + XI_{\text{D-STATCOM}}\sin\left(\alpha_{new} + \frac{\pi}{2}\right) \end{aligned} \tag{4}$$

$$V_{jnew}\sin(\alpha_{new}) = I_m\left\{V_i' e^{j\theta} - (R + jX) I_L' e^{j\theta}\right\} - RI_{\text{D-STATCOM}}\sin\left(\alpha_{new} + \frac{\pi}{2}\right) - XI_{\text{D-STATCOM}}\cos\left(\alpha_{new} + \frac{\pi}{2}\right) \tag{5}$$

The data:

$$d = V_{jnew} \tag{6}$$

$$a = R_e\left\{V_i' e^{j\theta} - (R + jX) I_L' e^{j\theta}\right\} \tag{7}$$

$$b = I_m\left\{V_i' e^{j\theta} - (R + jX) I_L' e^{j\theta}\right\} \tag{8}$$

$$c_1 = -R(9) \tag{9}$$

$$c_2 = -X \tag{10}$$

The unknowns:

$$x_1 = I_{\text{D-STATCOM}} \tag{11}$$

$$x_2 = \alpha_{new} \tag{12}$$

Thus, Equations (4) and (5) become Equations (13) and (14), respectively:

$$d\cos x_2 = a - c_1 x_1 \sin x_2 - c_2 x_1 \cos x_2 \tag{13}$$

$$d\sin x_2 = b + c_1 x_1 \cos x_2 - c_2 x_1 \sin x_2 \tag{14}$$

We can derive x_1 respectively from Equations (15) and (16):

$$x_1 = \frac{d\cos x_2 - a}{-c_1\sin x_2 - c_2\cos x_2} \tag{15}$$

$$x_1 = \frac{d\sin x_2 - b}{c_1\cos x_2 - c_2\sin x_2} \tag{16}$$

By equating these two Equations (15) and (16) and then making a change of variable $x = \sin x_2$, after an arrangement, the following can be observed:

$$\left(ac_2 - bc_1\right)^2 + \left(ac_1 + bc_2\right)^2 x^2 + 2dc_1\left(ac_2 - bc_1\right)x + d^2c_1^2 - \left(ac_1 + bc_2\right)^2 = 0 \tag{17}$$

We then obtain:

$$\Delta = B^2 - 4AC \tag{18}$$

$$A = \left(ac_2 - bc_1\right)^2 + \left(ac_1 + bc_2\right)^2 \tag{19}$$

$$B = 2dc_1\left(ac_2 - bc_1\right) \tag{20}$$

$$C = d^2c_1^2 - \left(ac_1 + bc_2\right)^2 \tag{21}$$

We also obtain:

$$x = \frac{-B \pm \sqrt{\Delta}}{2A} \tag{22}$$

where: $x = \sin x_2$.

x represents the initial conditions before installation of the D-STATCOM. The solution adopted [16] is as follows:

$$x = \frac{-B + \sqrt{\Delta}}{2A} \tag{23}$$

Subsequently:

$$x_2 = \arcsin(x) \tag{24}$$

And we would like to remind you that $x_2 = \alpha_{new}$. So, $x_1 = I_{\text{D-STATCOM}}$ is defined using Equations (15) or (16).

After determining x_2 and x_1 in this order, from Equations (24) and (16) respectively, we recall the following:

$$\alpha_{new} = x_2 \tag{25}$$

$$I_{\text{D-STATACOM}} = x_1 \tag{26}$$

Then we define:

$$\underline{V}_{jnew} = V_{jnew} \angle \alpha_{new} \tag{27}$$

$$\underline{I}_{\text{D-STATACOM}} = I_{\text{D-STATACOM}} < \alpha_{new} \frac{\pi}{2} \tag{28}$$

Finally, the reactive power injected by the D-STATCOM can be written as follows:

$$jQ_{\text{D-STATACOM}} = \underline{V}_{jnew} \times \underline{I}^{*}_{\text{D-STATACOM}} \tag{29}$$

where: $\underline{I}^{*}_{\text{D-STATACOM}}$ is the complex conjugate of the D-STATCOM current.

The D-STATCOM is modelled such that the voltage amplitude at the node where it is installed is equal to 1pu. The phase of this same node is calculated using Equation (24), the current injected by the D-STATCOM is calculated using Equation (28) and the reactive power injected is determined using Equation (29).

2.3. Problem Formulation

The main objective of this study is to determine the optimal location and size of PV and DSTATCOM units in order to minimize power losses and improve the voltage profile. The problem is formulated as a weighted multi-objective fitness function.

2.3.1. Minimization Active Losses

Total losses in a radial distribution network, such as the IEEE 33-bus system, can be calculated using the "Exact Loss" method:

$$f_1(x) = P_{loss} = \sum_{i=1}^{nb} R_i \frac{P_i^2 + Q_i^2}{V_i^2} \tag{30}$$

2.3.2. Improvement of the Voltage Profile

To ensure that the voltage at each node remains close to the nominal value (1.0 p.u.), the voltage deviation index is used:

$$f_2(x) = DT = \sum_{i=1}^{N} \left(\frac{V_i - V_i^{spec}}{V_i^{max} - V_i^{min}} \right)^2 \tag{31}$$

where:

R_i branch resistance; P_i active power of the branch; Q_i is the reactive power of the branch; nb number of branches in the network; V_i denotes the voltage of node i and V_i^{spec} its specific voltage; V_i^{max} the maximum voltage representing the nominal voltage +0.5% of the rated voltage; V_i^{min} the minimum voltage representing the nominal voltage −0.5% of the rated voltage; N the total number of nodes.

2.3.3. Weighted Overall Objective Function

To simultaneously optimize loss reduction and voltage profile improvement, a weighted overall objective function is formulated as follows:

$$F = w_1 \cdot \frac{P_{loss}}{P_{loss,Base}} + w_2 \cdot \frac{DT}{DT_{Base}} \tag{32}$$

where: P_{loss} represents the total active losses calculated by Equation (30), DT represents the voltage deviation index calculated by Equation (31), $P_{loss,Base}$ and DT_{Base} are the initial values of the network without any compensation (base case), w_1 and w_2 are the weighting coefficients assigned to each objective.

In this study, the weight values were set at $w_1 = 0.5$ and $w_2 = 0.5$. This choice reflects equal priority given to energy efficiency (reduction of losses) and wave quality (voltage stability).

2.4. Particle Swarm Optimization Algorithm

Particle swarm optimization (PSO), initially developed by Kennedy and Eberhart, is a metaheuristic inspired by the social behavior of birds or schools of fish. In this study, PSO is selected for its robustness and ability to navigate the non-linear and multidimensional search spaces specific to distribution networks [17].

2.4.1. Particle Coding and Search Space

For the optimization of the IEEE 33 bus network, each particle in the swarm represents a candidate solution encoded as a vector. The decision variables include discrete parameters (node numbers) and continuous parameters (equipment capacities):

$$X_i = \left[Bus_{PV}, P_{PV}, Bus_{STAT}, Q_{STAT} \right] \tag{33}$$

where Bus_{PV} and Bus_{STAT} are the indices of the connection nodes, while P_{PV} and Q_{STAT} represent the respective sizes of the installations.

2.4.2. Update Mechanism

The evolution of the swarm is based on the exchange of information between particles. At each iteration t, the velocity V_{je} and position X_{je} of each particle are adjusted according to the following equations:

$$V_{je}^{t+1} = w \cdot V_{je}^{t} + c_1 \cdot r_1 \cdot \left(Pbest_{je}^{t} - X_{je}^{t} \right) + c_2 \cdot r_2 \cdot \left(Gbest_{je}^{t} - X_{je}^{t} \right) \tag{34}$$

$$X_{je}^{t+1} = X_{je}^{t} + V_{je}^{t+1} \tag{35}$$

In these expressions, $w = 0.7$ is the inertia factor that controls exploration. The acceleration constants $c_1 = 1.5$ (cognitive component) and $c_2 = 1.5$ (social component) guide the particle towards its best individual performance ($Pbest$) and towards the best solution found by the entire swarm ($Gbest$). The parameters r_1 and r_2 are random values uniformly distributed in [0, 1].

The PSO parameters are selected according to standards in the literature to ensure an optimal balance between global exploration and convergence toward the global optimum.

2.4.3. Resolution Procedure

The integration of PSO into the planning process follows the iterative steps described below:

1) Initialization: Random generation of N particles respecting the capacity limits and topological constraints of the IEEE 33-bus network.

2) Power Flow Calculation: For each particle, a load flow algorithm (Backward/Forward Sweep) is executed to determine the electrical state of the network.

3) Evaluation: Calculation of the multi-objective fitness function (losses and voltage) and update of Pbest and Gbest.

4) Convergence: The process stops when the maximum number of iterations is reached or when the solution remains stable over several generations.

2.4.4. Constraints

To ensure operational stability, the voltage constraint is defined by a set of permissible limits for the network. This relationship stipulates that the voltage at each node must be maintained within the following range:

$$0.95\ \text{p.u} \le V_i \le 1.05\ \text{p.u} \tag{36}$$

The size of these devices is limited by both the nodal capacity and the nominal characteristics of the equipment. In order to ensure the seamless integration of PV and DSTATCOM units, the power injected at each location must be limited by:

$$100\ \text{kW} \le P_{PV} \le 5000\ \text{kW} \tag{37}$$

$$-5000\ \text{kVAr} \le Q_{SVC} \le 5000\ \text{kVAr} \tag{38}$$

3. Results

3.1. IEEE 33-Bus Standard Network

Widely used as a test bed for optimization studies in distribution networks. The standard IEEE 33-bus test model presented in Figure 4 [5], consisting of 33 nodes and 32 branches, with a base voltage of 12.66 kV and a base power of 100 MVA. Network analysis is performed using the Backward/Forward Sweep (BFS) algorithm.

The study of the power flow in the network (33 nodes) enabled us to obtain the results of different voltages in (p.u.) for each node, as shown by the red curve in the figure, as well as the active and reactive losses. The maximum and minimum voltages are equal to 1 p.u. and 0.9131 p.u. respectively, while the active and reactive losses are 202.68 kW and 143.60 kVAr respectively.

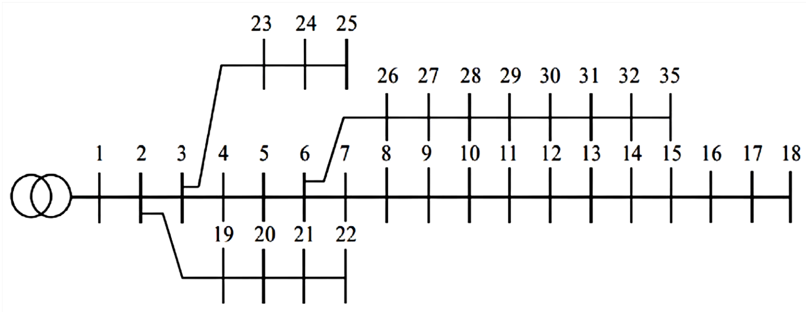

Figure 4. Single-line diagram of the IEEE network (33 nodes).

3.2. PV Scenario Only

This configuration evaluates the injection of a variable active power photovoltaic (PV) source on an optimized busbar, in the absence of reactive compensation. The application of the PSO algorithm identified node 26 as the ideal location for a power of 2410 kW, with the objectives of reducing joule losses and rectifying voltages. The simulations reveal a significant reduction in losses, which fall from 202.68 kW to 105.83 kW (a gain of 47.79%). Although the minimum voltage rises from 0.9131 p.u. to 0.9487 p.u., it remains below the critical threshold of 0.95 p.u. as can be seen in Figure 5. on the peripheral branches. These observations show that while active power injection effectively reduces current flows, it remains insufficient to stabilize the entire network without the support of a reactive compensation device.

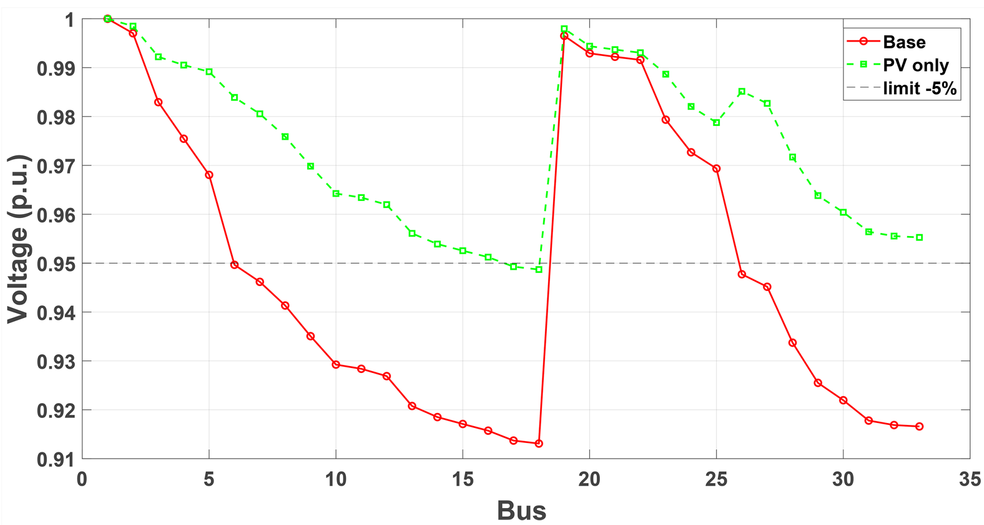

Figure 5. Voltage profile for the PV-only scenario.

3.3. DSTATCOM Scenario Only

This scenario explores the integration of a variable reactive power D-STATCOM at an optimized node, disregarding any photovoltaic sources. The PSO algorithm identified node 26 as the optimal location for a compensation capacity of 1680 kVAR. The results indicate a decrease in active losses to 153.87 kW, a gain of 24.08% compared to the initial state. Although the voltage profile (**Figure 6**) is generally higher, with a minimum value of 0.9294 p.u., the comparison with the previous scenario is clear: the injection of active power by PV offers a more significant reduction in losses and a better improvement in voltage.

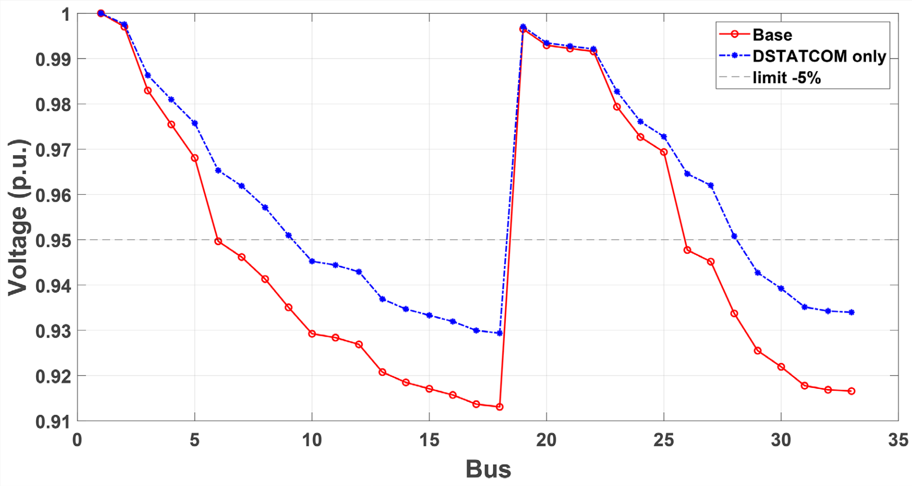

Figure 6. Voltage profile for the DSTATCOM-only scenario.

3.4. Joint Scenario

This scenario presented in **Figure 7** examines network performance during the simultaneous integration of a photovoltaic (PV) system and a D-STATCOM compensator. Unlike previous studies, this configuration is based on a joint optimization approach. The PSO algorithm is used here to simultaneously determine the strategic location and optimal sizing of these two pieces of equipment, with the aim of maximizing their synergy within the network.

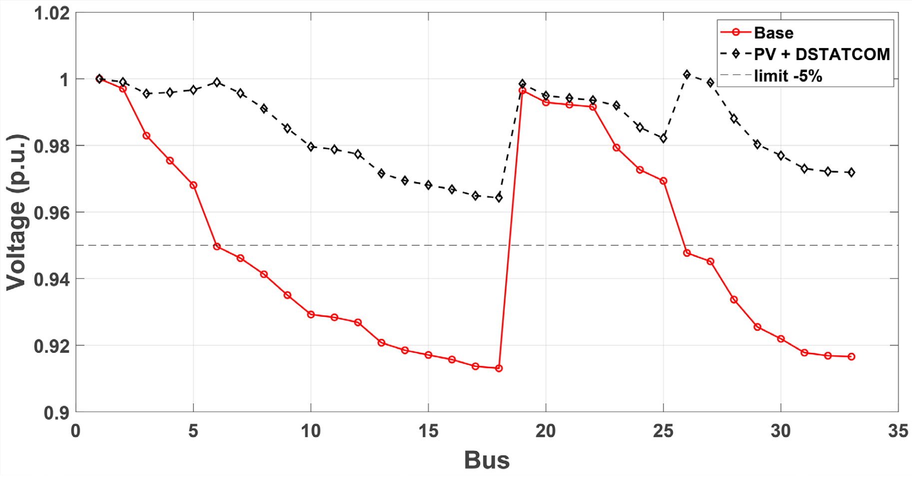

Figure 7. Voltage profile of the PV-DSTATCOM scenario in conjunction.

The most successful in the study, with a reduction in active losses of up to 69.18% (or 62.47 kW) and the minimum voltage is 0.9643 p.u., a result well above that of isolated PV-only (47.79%) or D-STATCOM-only (24.08%) configurations as shown in Table 1. This superiority can be explained by a technical synergy whereby the injection of active power by the PV reduces the apparent load while the D-STATCOM corrects the power factor, thus optimally minimizing the total current flowing through the conductors. By stabilizing the voltage profile across the entire network without violating any regulatory limits, this scenario demonstrates that only combined management of active and reactive flows can compensate for end-of-line voltage drops that PV alone cannot resolve. Finally, these results prove that the PSO algorithm can effectively coordinate these two technologies to transform a constrained distribution network into a balanced, high-performance system that complies with wave quality requirements.

Node 26 is optimal because it is located on a critical branch prone to significant voltage drops. Its systematic selection confirms its role as a strategic point for compensation. However, the co-location of the two pieces of equipment requires rigorous management of physical space and synchronization of controls to avoid mutual interactions.

Table 1. Simulation results.

Optimization Scenario	Active Losses (kW)	Loss Reduction (%)	Minimum Voltage (p.u.)	Network Status
Base Case	202.68	-	0.9131	Criticism
D-STATCOM only	153.87	24.08 %	0.9294	Improved (but insufficient)
PV only	105.83	47.79 %	0.9487	Good (unstable at the ends)
PV + DSTATCOM	62.47	69.18 %	0.9643	Optimal & Compliant

3.5. Discussion and Limitations

The superiority of the PSO-optimized hybrid approach lies in the synergy of power flows; active power injection by the PV reduces the apparent load, while the D-STATCOM provides dynamic reactive power regulation, thus enabling higher photovoltaic penetration without violating voltage limits. This optimal coordination minimizes the total current flowing through the conductors, which explains the drastic reduction in losses of 69.18%.

Nevertheless, the scope of this study is limited by certain constraints:

- The use of a static load model does not reflect the actual temporal variability of demand and solar radiation.
- The study focuses on technical benefits without including the capital expenditure (CAPEX) and operating expenditure (OPEX) costs of D-STATCOM units.

Although conclusive on the IEEE 33-bus network, these results must be validated on larger and more complex networks to confirm their industrial applicability.

4. Comparative Summary of Scenarios

Simulations carried out on the standard IEEE 33-bus network have demonstrated that the joint and optimized integration of PV and DSTATCOM significantly improves the electrical performance of the network. Compared to isolated configurations (PV alone or DSTATCOM alone), the joint solution offers a reduction in losses of more than 60% and more consistent voltage profile regulation across all nodes.

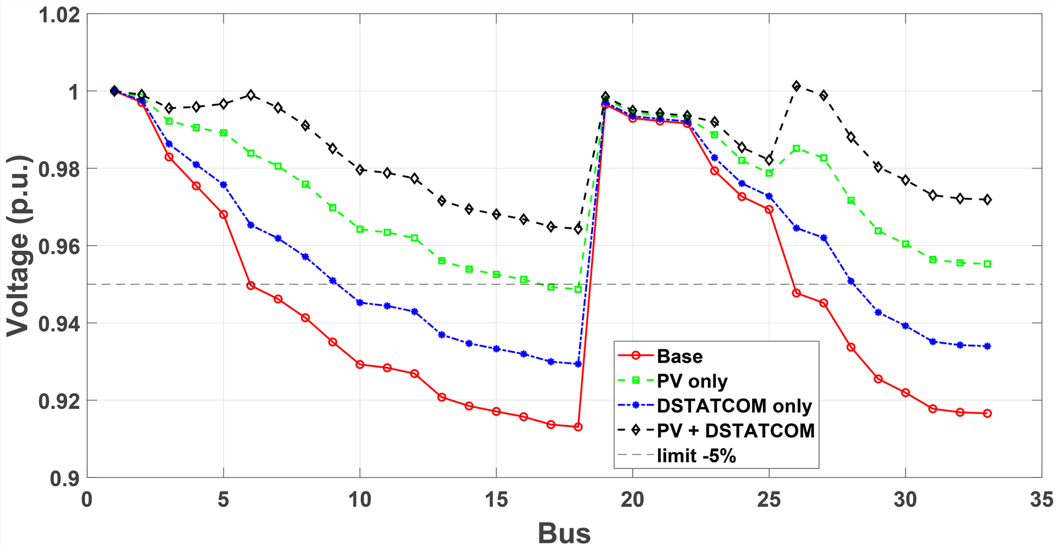

Figure 8. Voltage profile for all scenarios.

In **Figure 8**, A comparative analysis of the three configurations reveals a clear hierarchy in terms of energy efficiency and grid stability. The D-STATCOM-only scenario, although useful for local regulation, has the most limited impact, with a reduction in losses of only 24.08%. Conversely, the integration of PV alone proves to be significantly more effective in reducing active losses (47.79%), although it fails to stabilize voltages at the most distant nodes. The superiority of joint optimization is clear: by combining the benefits of active injection and reactive compensation, it achieves a loss reduction rate of 69.18%. This qualitative leap confirms that the synergy between the two devices does not simply add up their advantages, but multiplies them, thus offering the only scenario capable of guaranteeing total compliance with the voltage profile (no node below 0.95 p.u.).

Analysis of energy loss reduction (**Figure 9**) reveals a gradual and significant improvement depending on the optimization strategy adopted. In the base network, losses amount to 202.68 kW, indicating significant thermal constraints on the distribution lines. The installation of D-STATCOM alone only allows for a moderate reduction of 24.08%, as its action is limited to reducing reactive current. The photovoltaic system is more effective, acting directly on the active power demand and reducing losses by 47.79%. However, it is the hybrid approach that truly optimizes the efficiency of the grid: by reducing losses to only 62.47 kW (a decrease of 69.18%), it demonstrates that the coordination of PV and D-STATCOM minimizes the total current flowing in the branches much more significantly than any isolated solution. This massive reduction in joule losses not only translates into improved energy efficiency, but also increases the network's transit capacity.

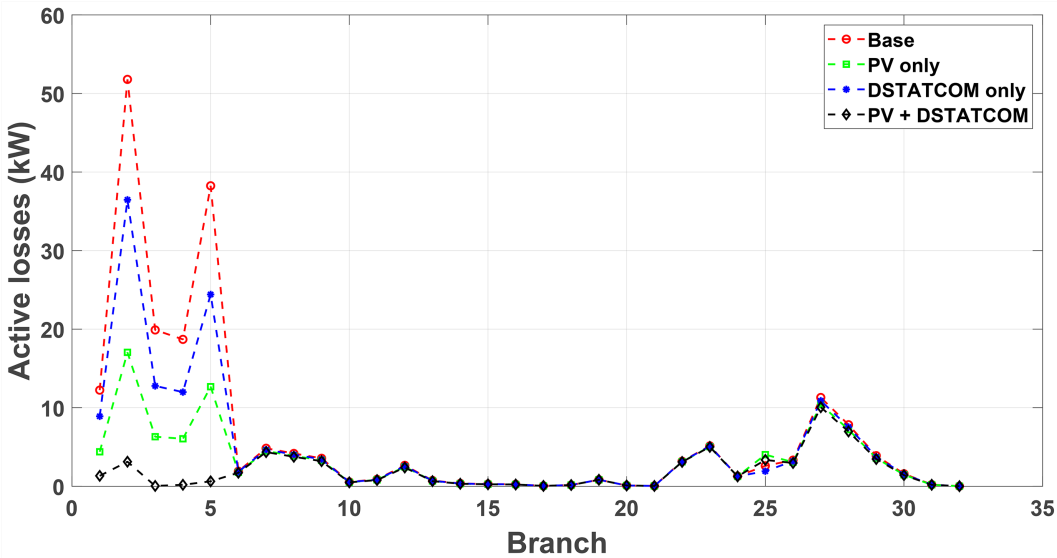

Figure 9. Active losses in all scenarios.

5. Comparison with Another Research

The comparative performance analysis (Table 2) highlights the remarkable effectiveness of the joint optimization strategy proposed in this study. While the work in [17], based on the WMOEEFO algorithm for PV placement alone, achieves a 27.70% reduction in losses, and the use of a single D-STATCOM via the ACO algorithm in [5] peaks at 22.42%, our hybrid approach based on the PSO algorithm achieves a significantly higher reduction rate of 69.18%. This significant difference can be explained by the fact that conventional methods focus on a single type of compensation, thus limiting the overall impact on the grid. In contrast, the simultaneous optimization of the positioning and sizing of PV and D-STATCOM allows active and reactive power imbalances to be addressed jointly. It is important to note that the performance gap observed between this study and the references cited stems from two factors. On the one hand, the technical superiority is intrinsically linked to the hybrid hardware configuration (PV + D-STATCOM) adopted here. Unlike approaches involving the simple placement of PV or D-STATCOM alone, the combined action makes it possible to simultaneously handle active and reactive power flows. On the other hand, the PSO algorithm has demonstrated its ability to effectively manage the increased complexity of this multidimensional search space, ensuring optimal convergence for the four decision variables (location and size of the two units). Thus, the 69.18% reduction in losses is the result of the synergy between a robust technological choice and a high-performance optimization method.

Table 2. Comparison of optimized results with bibliographic references.

Reference	Optimization Strategy	Algorithm	Active Loss Reduction (%)
Proposed Study	Joint PV + DSTATCOM	PSO	69.18
[18]	PV Placement	weighted Mult objective electric eel foraging optimization (WMOEEFO)	27.70
[5]	Single D-STATCOM Placement	Ant Colony Optimization (ACO)	22,42

6. Conclusion

The work presented demonstrates that the synergy between active power injection (PV) and reactive compensation (D-STATCOM) is key to modern and efficient distribution network management. Comparison with existing literature confirms the superiority of the proposed hybrid approach: the loss reduction rate achieved (69.18%) far exceeds methods based on a single piece of equipment, such as those using WMOEEFO (27.70%) or ACO (22.42%) algorithms. The PSO algorithm has proven to be a robust tool for coordinating the placement and sizing of these technologies. Finally, this hybrid strategy not only improves energy efficiency, but also offers a viable solution for increasing the capacity to accommodate renewable energies while maintaining the stability and reliability of the electrical system.

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Conflicts of Interest

The authors declare no conflicts of interest.

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