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Optimal hybrid photovoltaic distributed generation and distribution static synchronous compensators planning to minimize active power losses using adaptive acceleration coefficients particle swarm optimization algorithms

The paper ***aims*** *to identify the optimum size and location of photovoltaic distributed generation systems and distribution static synchronous compensators (DSTATCOMs) systems to minimize active power losses in the distribution network and enhance the voltage profile. The* ***methodology*** *employed in this article begins by thoroughly discussing various acceleration algorithms used in Particle Swarm Optimization (PSO) and their variations with each iteration. Subsequently, a range of PSO algorithms, each incorporating different variations of acceleration coefficients was verified to solve the problem of active power losses and voltage improvement. Simulation* ***results*** *attained on Standard IEEE-33 bus radial distribution network prove the efficiency of acceleration coefficients of PSO; it was evaluated and compared with other methods in the literature for improving the voltage profile and reducing active power.* ***Originality.*** *Consists in determining the most effective method among the various acceleration coefficients of PSO in terms of minimizing active power losses and enhancing the voltage profile, within the power system. Furthermore, demonstrates the superiority of the selected method over others for achieving significant improvements in power system efficiency****. Practical value*** *of this study lies on its ability to provide practical solutions for the optimal placement and sizing of distributed generation and DSTATCOMs. The proposed optimization method offers tangible benefits for power system operation and control. These findings have practical implications for power system planners, operators, and policymakers, enabling them to make informed decisions on the effective integration of distributed generation and DSTATCOM technologies.* References 30, table 3, figures 7.
Key words: **photovoltaic distributed generation, distribution static synchronous compensators, power losses, voltage profile, acceleration coefficients particle swarm optimization algorithms.**

Метою *статті є визначення оптимального розміру та розташування фотоелектричних систем розподіленої генерації та систем розподільних статичних синхронних компенсаторів (DSTATCOM) для мінімізації втрат активної потужності у розподільній мережі та покращення профілю напруги.* ***Методологія****, що використовується в цій статті, починається з детального обговорення різних алгоритмів прискорення, що використовуються в оптимізації рою частинок (PSO), та їх варіацій на кожній ітерації. Згодом було перевірено низку алгоритмів PSO, кожен з яких включає різні варіанти коефіцієнтів прискорення, для вирішення проблеми втрат активної потужності та покращення напруги.* ***Результати*** *моделювання, одержані на радіальній розподільній мережі шини стандарту IEEE-33, підтверджують ефективність коефіцієнтів прискорення PSO; він був оцінений та порівняний з іншими описаними в літературі методами покращення профілю напруги та зниження активної потужності.* ***Оригінальність****. Полягає у визначенні найбільш ефективного методу серед різних коефіцієнтів прискорення PSO з погляду мінімізації втрат активної потужності та покращення профілю напруги в енергосистемі. Крім того, демонструє перевагу обраного методу над іншими для досягнення значного підвищення ефективності енергосистеми.* ***Практична цінність*** *цього дослідження полягає у його здатності надати практичні рішення для оптимального розміщення та визначення розмірів розподіленої генерації та DSTATCOM. Запропонований метод оптимізації дає відчутні переваги для експлуатації та керування енергосистемою. Ці результати мають практичне значення для фахівців із планування енергосистем, операторів та розробників політики керування, дозволяючи їм приймати обґрунтовані рішення щодо ефективної інтеграції технологій розподіленої генерації та технологій DSTATCOM.* Бібл. 30, табл. 3, рис. 7.
Ключові слова: **фотоелектрична розподілена генерація, розподільні статичні синхронні компенсатори, втрати потужності, профіль напруги, коефіцієнти прискорення, алгоритми оптимізації рою частинок.**

1. Introduction. With the increasing demand for electricity and the share of distributed generation, including based on renewable energy sources, there is a need to solve a number of problems [1], power losses have become a significant concern for power system operators. In recent years, the deployment of distributed energy resources such as photovoltaic distributed generation (PVDG) systems and distribution static synchronous compensators (DSTATCOMs) has gained attention as a means to minimize power losses. PVDG systems generate electricity from solar energy and supply it to the distribution network, while DSTATCOMs provide reactive power compensation to increase the power quality of the network.

The incorporation of sustainable energy sources into the electrical grid has become increasingly important in latest years, due to the rising demand for clean energy and the need to reduce greenhouse gas emissions. Previously generation and transmission power systems were responsible for the power quality transmitted to customers [2], but currently, there is a significant focus on distribution networks, as they are prone to electrical breakdowns and considered a vulnerable point in the power grid. Among the Renewable Energy Sources (RES), PVDG systems have gained popularity due to their ease of installation and maintenance, low operating costs, and environmental benefits. However, the fitful nature of solar energy and the variability of the generated power can cause issues such as voltage fluctuations, power quality problems, and power losses in the distribution network.

In order to overcome these issues, DSTATCOMs can offer reactive power compensation and improve the quality of network. The effective integration of PVDG and DSTATCOM systems can enhance the dependability and stability of the power system while effectively harnessing RES. Therefore, the planning and optimization of PVDG and DSTATCOM systems have become crucial for the successful integrating of RES into the network.

It has been proven in the literature beyond any doubt that metaheuristic optimization algorithms perform well by optimally handling several versatile real-world optimization tasks [3].

Particle Swarm Optimization (PSO) is a powerful metaheuristic method for optimization derived from the demeanor of bird flocking or fish schooling. This approach involves a group of particles working to find the most optimal solution in a given problem space by iteratively adjusting their positions and velocities guided by their individual experience and the finest experiences of their neighbors. PSO has been widely applied in assorted domains, including engineering, finance, and science, due to its simplicity, flexibility, and ability to successfully tackle intricate optimization problems.

Different algorithms have been employed to investigate the suitable capacity and placement of Distributed Generation (DG) and DSTATCOM units are mentioned as follows: the Bacterial Foraging Optimization Algorithm (BFOA) [4], Multi-Verse Optimization Algorithm (MVOA) [5], Differential Evolution Optimization Algorithm (DEOA) [6], Slime Mould Algorithm [7], Multi-Objective Grasshopper Optimization Algorithm [8], Teaching Learning Based Optimization-Particle Swarm Optimization [9], Genetic Salp Swarm Algorithm [10], Northern Goshawk Optimization algorithm [11], Dwarf Mongoose Optimization Algorithm [12], Elitist Harris Hawks Optimization Algorithm [13], African Vultures Optimization Algorithm [14], Flower Pollination Algorithm [15], Butterfly-based PSO algorithm [16], hybrid Firefly PSO algorithms [17], Bald Eagle Search Algorithm [18], Modified Shuffled Frog Leaping Algorithm [19].

The goal of the paper is to identify the optimum placement and size of photovoltaic distributed generation and distribution static synchronous compensators on a radial distribution network according to the best-obtained result from the different particle swarm optimization applied algorithms and compare it to the other algorithms existing in the literature. The study was conducted using a standard IEEE-33 bus as the testing system by lessening active power dissipation and voltage profile enhancement.

2. Problem formulation.

2.1. Objective function. The primary aim of this paper has been to minimize the total active power losses, where the objective function is focused on achieving the least possible value of active power losses:

$$Ob = \min \sum_{i,j}^{N_b} P_{loss} , \quad (1)$$

where N_b is the number of busses; P_{loss} is the active power losses.

The following equation represents the branch power loss (P_{loss}) is:

$$P_{loss\, i,j} = \left(\frac{P_{i,j}^2 + Q_{i,j}^2}{V_i^2} \right) P_{i,j} , \quad (2)$$

where $R_{i,j}$, $P_{i,j}$, $Q_{i,j}$ are the resistance, active and reactive powers respectively from bus i to bus j; V_i is the voltage in the bus.

2.2. Constraints.

2.2.1. Distribution line constraints. The power conversation constraints [20-24]:

$$P_G + P_{DG} = P_D + P_{loss}; \quad (3)$$

$$Q_G + Q_{DSTATCOM} = Q_D + Q_{loss}, \quad (4)$$

where (P_{DG}, $Q_{DSTATCOM}$), (P_G, Q_G), (P_D, Q_D) are the active and reactive powers of PVDG and DSTATCOM, the generator and load respectively.

Bus voltage limits are:

$$V_{\min} \le |V_i| \le V_{\max} , \quad (5)$$

where $V_{\min}$, $V_{\max}$ are the predetermined minimum and maximum voltage values for the bus; V_i is the voltage magnitude at i^{th} bus in p.u.

Voltage drop limit is:

$$|1 - V_i| \le \Delta V_{\max} , \quad (6)$$

where $\Delta V_{\max}$ is the maximum permitted voltage drop at each branch.

Line capacity limit is:

$$|S_{ij}| \le |S_{\max}| , \quad (7)$$

where S_{ij}, $S_{\max}$ are the apparent and maximum apparent power in the line distribution between i and j bus.

2.2.2. DG constraints. The limitations of the DG unit are expressed through inequality constraints:

$$P_{DG}^{\min} \le P_{DG} \le P_{DG}^{\max} ; \quad (8)$$

$$\sum_{i=1}^{N_{DG}} P_{DG}(i) \le \sum_{j=1}^{N_{bus}} P_{DG}(i); \quad (9)$$

$$2 \le DG_{position} \le N_{bus} ; \quad (10)$$

$$N_{DG} \le N_{DG\max} ; \quad (11)$$

$$(n_{DG,i} / Location) \le 1 ; \quad (12)$$

where $P_{DG}^{\min}$ and $P_{DG}^{\max}$ are the allowable range for power generation by the PVDG, encompassing both upper and lower limits; N_{DG} and $N_{DG\max}$ are the number and maximum number of PVDG, that are limited for one unit and location.

2.2.3. DSTATCOM constraints. The DSTATCOM unit's limits can be represented by inequality constraints formulated as follows:

$$Q_{DSTATCOM}^{\min} \le Q_{DSTATCOM} \le Q_{DSTATCOM}^{\max} ; \quad (13)$$

$$\sum_{i=1}^{N_{DST}} Q_{DSTATCOM}(i) \le \sum_{j=1}^{N_{bus}} Q_D(i); \quad (14)$$

$$2 \le DSTATCOM_{position} \le N_{bus} ; \quad (15)$$

$$N_{DSTATCOM} \le N_{DSTATCOM\max} ; \quad (16)$$

$$(n_{DSTATCOM,i} / Location) \le 1 , \quad (17)$$

where $Q_{DSTATCOM}^{\min}$ and $Q_{DSTATCOM}^{\max}$ are the allowable range for power generation by the DSTATCOM, encompassing both upper and lower limits; $N_{DSTATCOM}$ and $N_{DSTATCOM\max}$ are the number and maximum number of DSTATCOM, that are limited for one unit for one location.

3. Adaptive acceleration coefficients PSO algorithms. PSO algorithm was first introduced in 1995, which can be seen as a global search technique. In this algorithm, each particle, denoted by i, has a velocity vector (V_i) and a position vector (X_i) [20]. It can be modeled by the following equations:

$$V_i^{k+1} = \omega V_i^k + c_1 r_1 \left[P_{best}^k - X_i^k \right] + c_2 r_2 \left[G_{best}^k - X_i^k \right]; \quad (18)$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} , \quad (19)$$

where ω, r are the inertia weight and random values between 0 and 1 respectively; C_1, C_2 are the acceleration coefficients; G_{best} is the global best position; k is the iterations number.

This paper proposes novel PSO strategies that utilize time-varying acceleration coefficients (C_1 and C_2) to improve the global search performance. The primary concept behind employing PSO with time-varying acceleration coefficients is to increase the global search during the initial phase of the optimization process.

This is accomplished by altering C_1 and C_2 over time in such a way that the cognitive component decreases while the social component increases [25].

In this work, it should be noted that the names assigned to the various PSO methods are not mere abbreviations. Instead, they represent unique and distinct algorithms, each with its own set of characteristics and features. These names serve as identifiers for specific approaches in the field of PSO. The following equations show the acceleration formulas and their corresponding constants.

The Adaptive Accelerated Coefficients for the PSO algorithm (AAC PSO) and constants [26] are:

$$c_1 = c_{\min} + (c_{\max} - c_{\min})e^{-\left(\frac{4k}{k_{\max}}\right)^2} ; \qquad (20)$$

$$c_2 = c_{\max} - (c_{\max} - c_{\min})e^{-\left(\frac{4k}{k_{\max}}\right)^2} , \qquad (21)$$

with

$$c_{\min} = c_{\max} = 0.5 , \qquad (22)$$

where $c_{\min}$, $c_{\max}$ are the constants of the AAC PSO method; k, $k_{\max}$ represent the iteration number and the maximum number of iterations, respectively.

The Autonomous Particles Groups for PSO (APG PSO) acceleration coefficient formula and constants [27] are:

$$c_1 = 1.95 - \left(\frac{2k^a}{k_{\max}^a}\right); \qquad (23)$$

$$c_2 = 0.05 - \left(\frac{2k^a}{k_{\max}^a}\right), \qquad (24)$$

with

$$a = 1/3, \qquad (25)$$

where a is the constant of APG PSO method.

The Nonlinear Dynamic Acceleration Coefficients for PSO (NDAC PSO) acceleration coefficient formula and constants [28] are:

$$c_1 = -\left(c_f - c_i\right)\cdot\left(\frac{k}{k_{\max}}\right)^2 + c_f ; \qquad (26)$$

$$c_2 = c_i \cdot \left(1 - \frac{k}{k_{\max}}\right)^2 + c_f \cdot \left(\frac{k}{k_{\max}}\right), \qquad (27)$$

where the constants of this method c_i, c_f are:

$$c_i = 0.5, \qquad (28)$$

$$c_f = 2.5, \qquad (29)$$

The acceleration coefficient formula and constants for Sine Cosine Acceleration Coefficients for PSO (SCAC PSO) [29]:

$$c_1 = \partial \cdot \sin\left[\left(1 - \frac{k}{k_{\max}}\right)\cdot\frac{\pi}{2}\right] + \delta ; \qquad (30)$$

$$c_2 = \partial \cdot \cos\left[\left(1 - \frac{k}{k_{\max}}\right)\cdot\frac{\pi}{2}\right] + \delta , \qquad (31)$$

with the constants ∂, δ:

$$\partial = 2, \qquad (32)$$

$$\delta = 0.5. \qquad (33)$$

Finally, Time Varying Acceleration for PSO (TVA PSO) acceleration coefficient formula and constants [30] are:

$$c_1 = c_{1i} + \left(\frac{c_{1f} - c_{1i}}{k_{\max}}\right)\cdot k ; \qquad (34)$$

$$c_2 = c_{2i} + \left(\frac{c_{2f} - c_{2i}}{k_{\max}}\right)\cdot k , \qquad (35)$$

with

$$c_{1i} = c_{1f} = c_{2i} = c_{2f} = 0.5, \qquad (36)$$

where k is the iterations number; c_{1i}, c_{2i}, c_{1f}, c_{2f} are the constants of the method.

Figure 1 displays diverse updating strategies for the C_1 and C_2 acceleration coefficients across the various PSO algorithms.

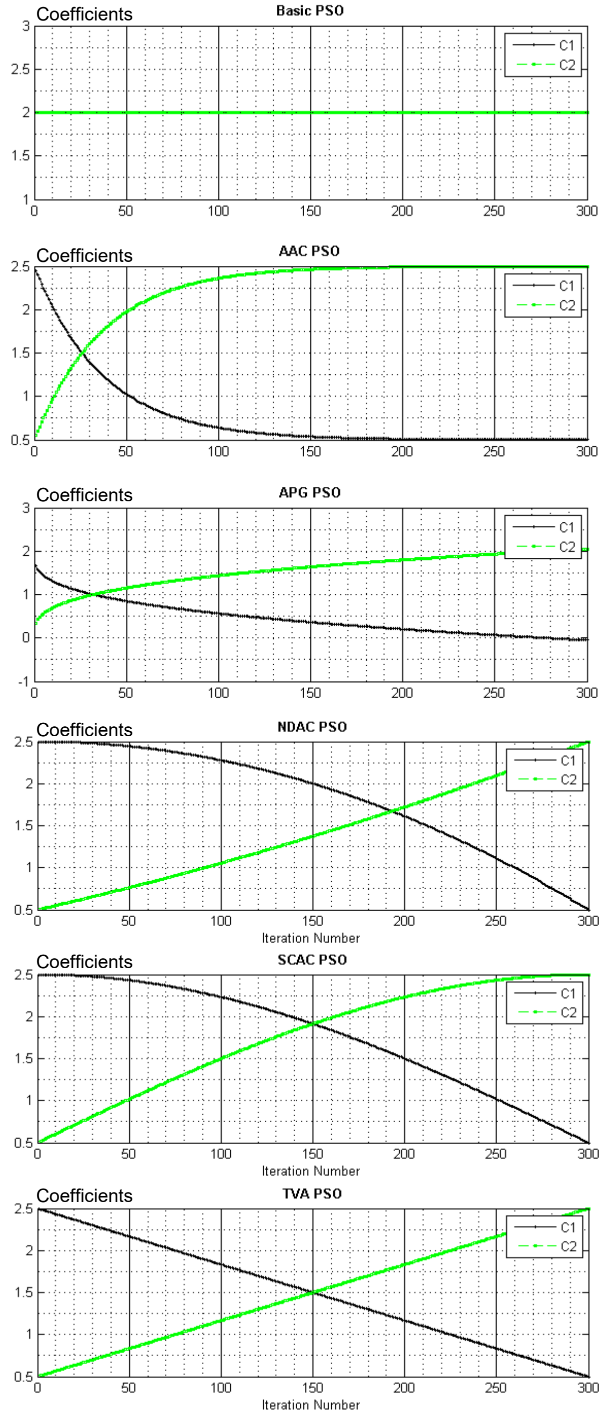

Fig. 1. Time-varying acceleration coefficients

In Fig. 1 the acceleration coefficients exhibit a varying trend with iterations, typically ranging from 0 to 2.5. The values of C_1 generally decrease over the iterations, whereas the values of C_2 tend to increase. These changes are dependent on the update function of C_1 and C_2, which can be linear, polynomial, or exponential. When C_1 is bigger than C_2, the particles conduct local search, whereas when C_2 is bigger than C_1, the particles conduct global search. The succeeding section will discuss the outcomes of these algorithms in achieving the efficient allocation of DG and DSTATCOM.

4. Test system, results and comparison. This section describes the test systems used for evaluation, results and comparison of various PSO algorithms applied to the IEEE 33 bus system for optimal planning of PVDG and DSTATCOM size and location.

The work's objective has been to enhance the voltage profile and reduce the active power losses of the system through the identification of the optimal locations and sizes of PVDG and DSTATCOM units. The presented Fig. 2 depicts the IEEE 33 bus radial distribution system, which serves as a widely adopted benchmark system for power system analysis that allows for fair comparison of different optimization algorithms. A range of PSO algorithms with different variations of the acceleration coefficients was applied and performance comparison of speed convergence, solution quality, and computational efficiency. The results are presented in terms of the total active power loss reduction, voltage profile improvement, and optimal locations and sizes of PVDG and DSTATCOM.

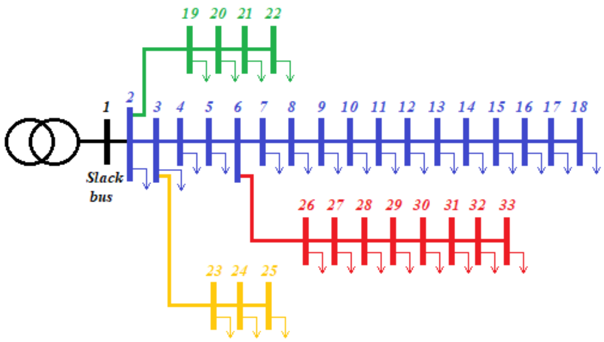

Fig. 2. IEEE 33 bus model

Finally, strengths and weaknesses of each PSO algorithm were analyzed and discussed as well as the comparison of the best method obtained from the different PSO coefficients with other algorithms existing in the literature. The comparison is performed in terms of the total active power loss reduction, voltage profile improvement, and computational efficiency. The results demonstrate the superiority of the suggested PSO algorithm and providing valuable insights into the optimal placement of PVDG and DSTATCOM units for power systems.

The results were obtained after 20 runs with 300 iterations each, using different PSO coefficients. It should be reminded that in the initial case, the active power losses were 210.987 kW and the initial $V_{\min}$ and $V_{\max}$ were 0.9038 p.u. and 1.000 p.u, respectively.

The results presented in Table 1, 2 suggest that the AAC PSO method outperforms the other PSO methods in terms of both active power losses reduction, with a reduction of 72.23 %, and voltage profile improvement, with a value of 0.95 for minimal voltage and 1.02 for maximal voltage.

Table 1

Test results in term of power losses

Method	P_{Loss}, kW	ΔP_{Loss}, %	PVDG		D-STATCOM	
			Bus location	P, kW	Bus location	Q, kVar
Basic PSO	59.00	72.03	6	2666.4	30	1358.7
AAC PSO	58.58	72.23	6	2437.2	30	1281.3
APG PSO	58.69	72.18	6	2502.3	30	1168.4
NDAC PSO	58.80	72.12	6	2370.1	30	1240.0
SCAC PSO	59.12	71.97	6	2390.2	30	1141.5
TVA PSO	59.45	71.82	6	2773.9	30	1173.4

Table 2

Test results in term of voltage profile improvement

Method	$V_{\min}$, p.u.	$V_{\max}$, p.u.	PVDG		D-STATCOM	
			Bus location	P, kW	Bus location	Q, kVar
Basic PSO	0.98	1.03	6	2666.4	30	1358.7
AAC PSO	0.95	1.02	6	2437.2	30	1281.3
APG PSO	0.95	1.02	6	2502.3	30	1168.4
NDAC PSO	0.95	1.00	6	2370.1	30	1240.0
SCAC PSO	0.95	1.01	6	2390.2	30	1141.5
TVA PSO	0.95	1.00	6	2773.9	30	1173.4

These results are attributed to the integration of a 2.43 kW DG unit at bus 6 and a 1.28 kW DSTATCOM at bus 30. The APG PSO and NDAC PSO methods also demonstrated good results regarding the reduction of active power losses.

It should be noted that, even with the same allocation of DG units and DSTATCOM, the AAC PSO method produced the best results. Therefore, it may be the most suitable choice for the simultaneous installation of PVDG and DSTATCOM in the IEEE 33-bus radial distribution system. However, further analysis is needed to confirm the robustness of the method under different conditions and constraints.

In order to gain a deeper insight into the behavior of the different PSO methods, the curves of active power losses versus the number of executions for each method were plotted.

Figure 3 shows clearly the obtained results, after 20 trials for each method, it is clear that the range of variation for the basic PSO, NDAC PSO, and TVA PSO is approximately between 59 kW and 64 kW, while the range of variation for AAC PSO and APG PSO is between 59 kW and 69 kW.

These results highlight the importance of selecting the appropriate PSO parameters and coefficients, as some methods converge faster and reach lower losses than others.

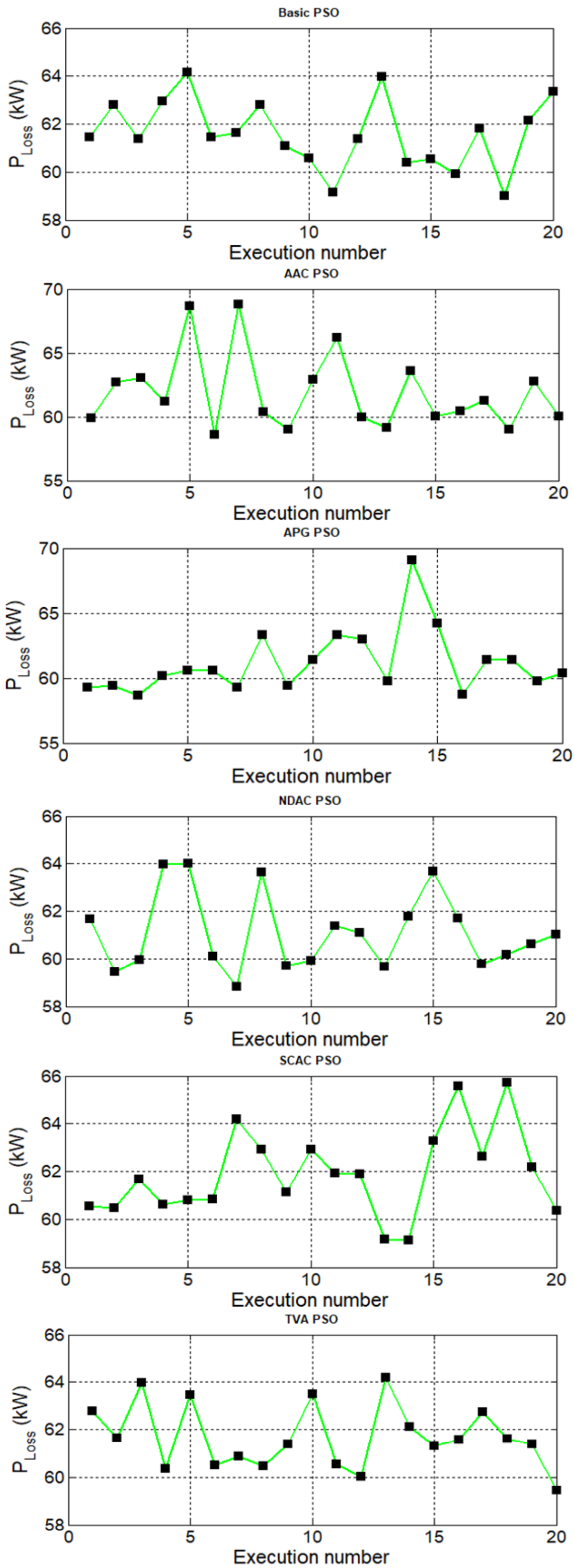

Fig. 3. Curves of active power losses versus the number executions

Figure 4 depicts the convergence curves of various algorithms applied to the simultaneous installation of DG and DSTATCOM, after 20 executions.

The results for the 33-bus system reveal that all algorithms converge at a total power loss reduction of 85 kW. Notably, the AAC PSO method shows superior convergence compared to the other PSO algorithms. It reaches a lower objective function value in less iteration, demonstrating its superior performance in optimizing the implementation of PVDG and DSTATCOM.

The AAC PSO method also achieves faster convergence and enhances the voltage profile, resulting in minimized active power losses.

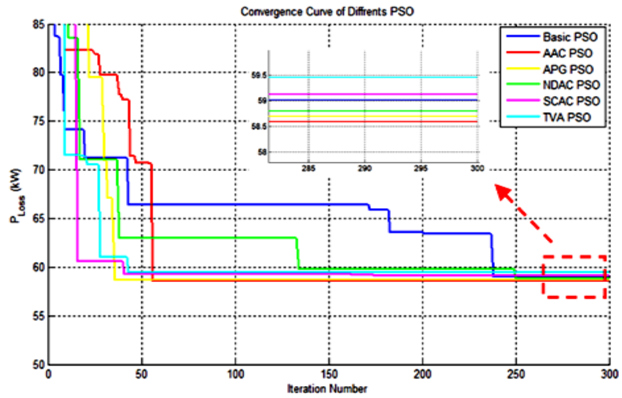

Fig. 4. Convergence curve of different PSO method

As seen in Fig. 5, the integrating of DG and DSTATCOM in simultaneous operation results in a significant improvement of the voltage profile compared to the base case. The implementation of DG and DSTATCOM together leads to a greater enhancement of the voltage profile, with the minimum voltage improving from 0.9038 to 0.9894 p.u.

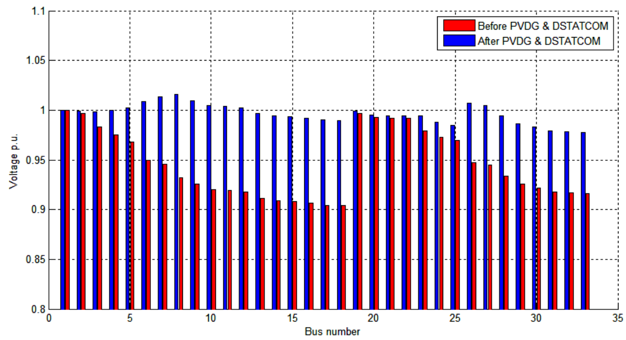

Fig. 5. Improved voltage profile with PVDG and DSTATCOM

The results from Table 3 manifest the efficiency and superiority of the AAC PSO algorithm over other algorithms in the literature for the simultaneous installation of DG and DSTATCOM for an IEEE 33 bus system, achieving the minimum active power losses and improving the optimum deployment of PVDG and DSTATCOM units.

Table 3

Comparison between our best method and others existing in the literature

Method	P_{Loss}, kW	ΔP_{Loss}, %	PVDG		D-STATCOM	
			Bus location	P, kW	Bus location	Q, kVar
AAC PSO	58.58	72.23	6	2437.2	30	1281.3
BFOA [3]	70.87	65	10	1239.8	30	1094.6
MVOA [4]	59.94	71.59	6	2848.8	30	1334.4
DEOA [5]	80.48	61.85	7	2327.5	26	1446.4

Figure 6 clearly shows that the proposed method resulted in a lower value of active power losses, with a value of 58.58 kW, which is superior to MVOA's value of 59.94 kW.

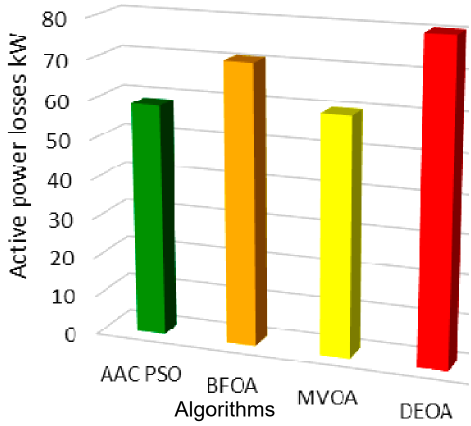

Fig. 6. Comparison between proposed method and others existing in the literature in term of active power losses

Figure 7 provides a visual representation of the percentage reduction in active power losses between the proposed method and the other method. The proposed method resulted in the highest reduction of active power, with a 27 % reduction compared to the other method.

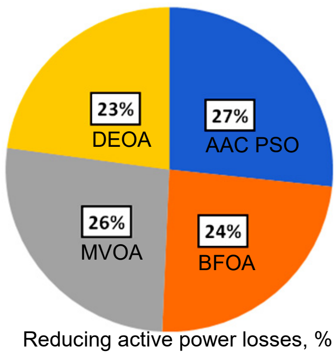

Fig. 7. Minimization rate of the active power losses for each method

Conclusions. The study aim has been to optimize the simultaneous implementation of photovoltaic distributed generation and distribution static synchronous compensator units in a standard IEEE 33-bus radial distribution system with the objective of reducing active power losses and enhancing the voltage profile.

Assorted particle swarm optimization methods with variable acceleration coefficients were applied, and the findings were evaluated against each other existing algorithms in the literature. The tables exhibited that the adaptive accelerated coefficients for particle swarm optimization method provided the best results in terms of active power loss reduction and voltage profile improvement, and the optimum size and location of the photovoltaic distributed generation and distribution static synchronous compensator. The figures demonstrated that the adaptive accelerated coefficients for particle swarm optimization method had the best convergence among the different particle swarm optimization algorithms and the losses curve according to the number of executions for each method.

Overall, the study demonstrated that the optimization of photovoltaic distributed generation and distribution static synchronous compensator installation using the adaptive accelerated coefficients for particle swarm optimization algorithm could significantly reduce active power losses and enhancement of voltage profile in the distribution system.

Conflict of interest. The authors of the article declare that there is no conflict of interest.

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