Sustainable Energy and Artificial Intelligence 1(2) (2025) 77-90 DOI: 10.61186/seai.2409-1010

Hamedan University of Technology
Iranian Association of Electrical and Electronics Engineers

Sustainable Energy and Artificial Intelligence

Online ISSN: 3060-8015

Journal Homepage: www.enai.hut.ac.ir

Accurate Allocation of PV-DSTATCOM and Supercapacitors in Distribution Networks Using an Adaptive Learning Strategy to Enhance Operation Indices

Mahyar Abasi[1,3*], Arash Zeinalzadeh[2], Mohammad Amin Bahramian[1,3], Javad Ebrahimi[3]

[1] *Department of Electrical Engineering, Faculty of Engineering, Arak University, Arak 38156-8-8349, Iran*
[2] *North Khorasan Electric distribution company (NKEDC)*
[3] *Research Institute of Renewable Energy, Arak University, Arak 38156-8-8349, Iran.*
** Corresponding Author: m-abasi@araku.ac.ir*

Article Info

Article type:
Original Article

Article history:
Received 2024-09-28;
Revised 2024-11-03;
Accepted 2024-11-09.

How to cite this article:
Abasi, M., Zeinalzadeh, A., Bahramian, M. A. and Ebrahimi, J. (2025). Accurate Allocation of PV-DSTATCOM and Supercapacitors in Distribution Networks Using an Adaptive Learning Strategy to Enhance Operation Indices. *Sustainable Energy and Artificial Intelligence*, *1*(2), 77-90.
DOI: 10.61186/seai.2409-1010

Abstract

A significant portion of electrical energy in power grids is wasted in distribution systems. Distribution systems typically have radially shaped feeders. Today, increased demand resulted in the expansion of distribution systems and their dimensions, which in turn causes greater voltage drop, increased losses, and consequently reduced stability, decreased node voltage, and load imbalance. Nowadays, using modern methods and employing power electronics devices such as flexible alternating current transmission system (FACTS) devices can enhance the quality of electrical power. Additionally, considering the global warming, most power generation companies are inclined towards renewable energies such as photovoltaic panels. One of the suitable FACTS devices used in the PV distribution system is PV-DSTATCOM. These devices are based on reactive power control and use a photovoltaic (PV) system to supply their required energy. Therefore, they should be installed in a way that coordinates with capacitor banks installed in the distribution network and improves power quality parameters, including reduced network losses, improved network performance, deferred investment, increased reliability, and enhanced power quality. In this paper, the problem of locating and sizing of PV-DSTATCOM and shunt supercapacitors is solved based on a simultaneous multi-objective manner, with the objectives focused on power and energy losses, voltage profile, and voltage stability. To solve this multi-objective problem, the Fuzzy-ALPSO algorithm is adopted and implemented on standard IEEE 33- and 69-bus systems.

***Keywords*:** Parallel Supercapacitors; PV-DSTATCOM; Power Loss; Voltage Stability; FUZZY-ALPSO Algorithm.

1. Introduction
1-1. Statement of the Problem

Improving the stability and quality of electrical power in distribution networks using compensating equipment such as DSTATCOM, parallel capacitors, and other power electronic devices has become amongst the challenging issues for most utilities. Such equipment plays an important role in voltage management, degrade power losses, and boost the reliability of distribution networks. Also, population growth has intensified the ever-increasing need for energy in the world, where fossil fuel cannot provide sufficient energy and respond to consumers' energy demand. They also harm the earth's ecosystem by creating environmental pollutants. Therefore, today, the use of wind, solar and geothermal alternative sources has flourished in many countries of the first world and is expanding day by day. Also, in distribution systems, due to having radial feeders, high R/X ratio, and considerable voltage drop, large losses occur. With increasing demand and load, these losses increase and lead to reduced stability, voltage drop in nodes, and load imbalance. In this regard, the use of FACTS such as DSTATCOM has increased to deal with these challenges [1].

Compensating devices such as DSTATCOM are very effective as one of the suitable FACTS devices used in distribution systems due to several properties like small power dissipation, low harmonic generation, high adjustability, and inexpensiveness. This equipment helps adjust and balance the voltage by injecting a compensating current that is adjusted according to bus voltages and the amount of reactive power required when the network faces sudden load changes or fault conditions [2]. These devices can be effective in improving the dynamic stability of networks and reducing voltage fluctuations. In addition, DSTATCOM has more advantages than its counterparts due to its benefits, including the absence of operating issues like resonance or temporal coordination. The particle group optimization algorithm for implementing and allocating DSTATCOM was used considering the presence of distributed generation sources, where loss reduction remained as the main objective function [3].

1-2. Literature Review

The use of combining DSTATCOM with energy storage systems (ESS) is proposed as an effective method for voltage management and improving the stability of distribution networks. By using voltage duration curves (VDCs) for voltage management, this combination performs better than traditional methods in conditions of sudden load and generation changes [4]. In addition, the use of combination of DSTATCOM and series compensators such as static var compensator (SVC) to improve the dynamic stability of distribution networks is also considered. These compounds can effectively reduce voltage fluctuations and improve system stability in different conditions [5].

Also, hybrid compensator configurations that are a combination of series and parallel compensators can simultaneously improve voltage stability and reduce network harmonics. These configurations show significant performance improvements, especially in unbalanced conditions and when asymmetrical loads are present [6]. Studies have shown that the development and improvement of control methods for compensating equipment such as DSTATCOM in order to improve their efficiency in distribution networks with variable loads has also been an important topic in recent research. These control methods, which are designed based on combining these equipment's with other compensators and optimizing the control parameters, can effectively stabilize the network voltage and reduce its fluctuations [7]. On the other hand, several researches have investigated the effect of using hybrid compensators. Hybrid compensator configurations that combine series and parallel compensators simultaneously provide improved voltage stability and reduced grid harmonics. These configurations show significant performance improvements, especially in unbalanced conditions and when asymmetrical loads are present [6]. Also, new control methods, which are designed based on the combination of compensating equipment with other equipment and optimization of control parameters, have shown that they can effectively stabilize the grid voltage and reduce its fluctuations, while optimizing energy consumption at the same time [7].

Optimizing the site and size of compensating equipment in distribution systems with the help of optimization algorithms such as particle swarm optimization (PSO) and genetic algorithm (GA) has also attracted a lot of attention. Research results have shown that the use of these algorithms can significantly diminish power loss as well as enhancing the stability of distribution networks [8]. Optimizing the parameters of fuzzy logic controllers (FLC) using these algorithms also effectively improves the performance of power systems in unbalanced conditions and load fluctuations [9]. Also, these methods have been used in combination as a multi-objective approach to optimization that can achieve better results than using each of these algorithms alone [10].

Optimal placement of DSTATCOM is amongst the cases to be discussed in this category of research. To deal with this problem, using various approaches such as fuzzy algorithms, ant colony, and immune algorithms are proposed. In particular, these methods help to improve losses, voltage profile, and voltage level [2,11,12]. Reference [13] has presented the optimal placement of DSTATCOM to degrade power loss and harmonic distortion, while improving the voltage level by using the Firefly algorithm. In reference [14], Both genetic and ant colony hybrid algorithms have been used for optimal location, and its modeling has been done on IEEE 30-bus standard network. Reorganization of distribution networks and placement of DSTATCOM were investigated both simultaneously and separately in order to reduce losses [15].

Studies have shown that the use of hybrid methods and advanced optimization can significantly improve the stability and power quality of distribution networks. Various combinations of compensating equipment and utilizing optimization approaches like PSO and GA provide versatile approaches to voltage management and power loss reduction that can significantly improve the efficiency of distribution networks [16]. These approaches not only improve the system performance in different operating conditions, but also can help reduce costs and increase the reliability of distribution networks [17].

Finally, the findings show that the use of DSTATCOM can dramatically impact voltage stability of distribution networks. This equipment is capable of reducing voltage fluctuations and improving system stability in the face of load changes and fault conditions, which indicates the importance of using DSTATCOM in improving network stability and reducing the need for other compensation measures in distribution systems [18,19].

1-3. Innovation and Research Contributions

Many researches have investigated and optimized the location of parallel capacitors and DSTATCOM in distribution networks. However, the current research seeks to provide a comprehensive and multi-objective approach that simultaneously locates and determines the optimal capacity of both devices, that is, parallel capacitors and DSTATCOM. This approach is designed in such a way that optimal coordination between injection and absorption of reactive power by DSTATCOM and the task of constant injection of reactive power of capacitor banks is provided to achieve the best quality of electric power. In this research, the main goals include reducing costs related to power and energy loss, modifying the network voltage profile, and boosting voltage stability in different operating conditions. To address this complex and multi-objective problem, the optimization algorithm (FUZZY-ALPSO) has been used as one of the efficient and powerful methods in the field of optimization. The results of simulations and implementations performed on the standard IEEE 33- and 69-bus distribution networks show the efficiency and effectiveness of this method in enhancing the technical performance of distribution networks. This research, focusing on practical applications and real results, can be used as a suitable solution to boost the stability and power quality in modern distribution networks. The most important innovations of this article are as follows:

- Using a new optimization algorithm
- Combining meta-heuristic algorithm with fuzzy logic
- Implementation of the multi-objective method on different sample networks

2. Methodology

In this article, the problem of optimal allocation and sizing of a PV-DSTATCOM and suitable supercapacitor banks are considered, which has equal and unequal constraints and is presented as follows.

2-1. Objective Functions

Regarding the allocation and sizing of PV-DSTATCOMs, this paper aims to enhance technical operation of the network, which is formulated as an improvement of power losses, voltage regulation and enhanced stability. Thus, the presented objective function is introduced as a multi-objective function. In addition, the problem includes equality, protection and performance constraints introduced as Equation (1).

$$\min \ F = [f_1, f_2, f_3] \tag{1}$$

Functions f_1, f_2, f_3 are obtained from Equations (2) to (6) respectively:

$$f_1 = P_{loss} \tag{2}$$

P_{loss} represents the real power loss. Function f_2 is related to the voltage deviation index as follows:

$$f_2 = \sum_{i=1}^{N_n} (V_i - V_{rated})^2 \tag{3}$$

Function f_3 concerns the voltage stability index in distribution networks, and it was presented to evaluate all nodes of the distribution network in [20], and the equations for evaluating this index, which are formulated by the information obtained from power flow, were provided in [21]. Fig. 1 shows a typical two-bus system.

$$SI(n_2) = |V_1|^4 - 4[P_2R_1 + Q_2X_1]|V_1| - 4[P_2R_1 + Q_2X_1]^2 \tag{4}$$

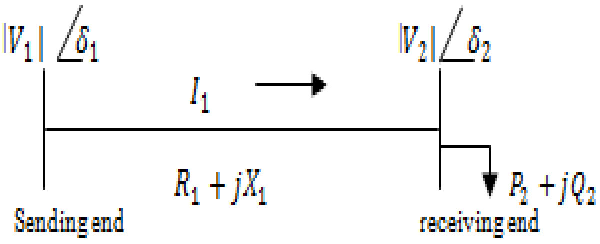

Fig. 1. A branch of the distribution system

And in Equation (4), n_1: sending node, n_2: receiving node, I_1: branch current, V_1: voltage of node 1, V_2: voltage of node 2, P_2: the sum of real power of load fed into node 2, Q_2: the total reactive power of load fed into node 2, R_1: resistance of branch 1, X_1: reactance of branch 1.

$$f'_3 = \min\left(SI(n_i)\right), i = 2,3, \dots, N_n \quad (5)$$

and finally, we define function f_3 as Equation (6).

$$f_3 = \frac{1}{f'_3} \quad (6)$$

2-2. Total Objective Function

The total objective function is obtained from Equation (7) using the penalty factor method:

$$Obj\ \text{Func} = w_1.f_1 + w_2.f_2 + w_3.f_3 \quad (7)$$

In this Equation, w_1, w_2 and w_3 are 0.5, 0.25 and 0.25, respectively.

2-3. Limitations of PV-DSTATCOM

The Installation of PV-DSTATCOM has limitations that are expressed as Equations (8) to (10).

$$0.9pu \le V_n \le 1.1pu \quad (8)$$

$$0 \le Q_{D-statcom} \le 5000KVAR \quad (9)$$

$$0 \le I_{max} \le 400\ A \quad (10)$$

Q_D and I_{max} are the injected reactive power of PV-DSTATCOM and the current of network sections, respectively.

2-4. Constraints on the Number and Size of Supercapacitors

Parallel supercapacitors are available discretely in the industry. Parallel supercapacitors, according to Equation (11), are obtained as an integer multiple of the smallest available supercapacitor capacity.

$$Q_{Ci} = L.Q_0 \quad (11)$$

Q_0: The smallest available supercapacitor capacity

Moreover, due to economic problems and the limitation on space, according to Equation (12), the size of a single supercapacitor located on a bus must meet a certain limit as follows:

$$\sum_{i=1}^{nc} Q_{Ci} \le Q_t \quad (12)$$

Q_t: reactive power limit

In this article, the smallest supercapacitor size is 150kVar and the allowed number of supercapacitors for a single bus is 15.

3. Power Flow and PV-DSTATCOM Model

Distribution system power flow are expected to be fast and provide high performance due to widespread application in the optimization process. In this article, the backward/forward swap method has been adopted. If we consider the two-basin system in Fig. 2, then we have Equation (13):

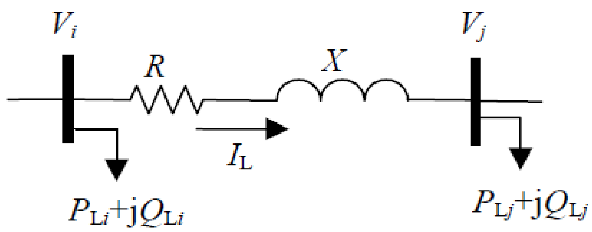

Fig. 2. A sample two-bus system

$$V_j \angle \alpha = V_i \angle \delta - Z I_L \angle \theta \quad (13)$$

In this Equation, V_i, α, V_j, δ, Z, I and θ are respectively the voltage amplitude and angle of bus j, voltage amplitude and angle of bus i, line impedance, and amplitude and angle of the line current.

After installing PV-DSTATCOM on branch j, the equations and phasor diagram will be as Equation (14).

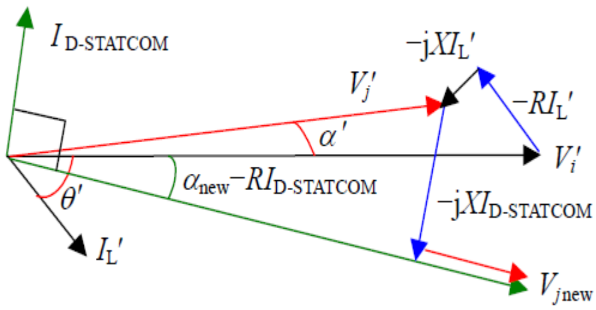

Fig. 3. Phasor diagram after installing PV-DSTATCOM

$$V_{jnew} \angle \alpha_{New} = V_i{}' \angle \delta' - (R + jX) I_L{}' \angle \theta' - (R + jX) I_{Dstatcom} \angle \left(\alpha_{New} + \frac{\pi}{2}\right) \quad (14)$$

As a result, the injected reactive power is obtained from Equation (15).

$$jQ_{Dstatcom} = V_{jnew} I_{Dstatcom}{}^{*} \quad (15)$$

where Equations (16) and (17) are expressed as:

$$V_{jnew} = V_{jnew} \angle \alpha_{New} \quad (16)$$

$$\measuredangle I_{\text{PV-DSTATCOM}} = \frac{\pi}{2} + \alpha_{New}, \ \alpha_{New} < 0 \quad (17)$$

Equation (15) shows the injected reactive power of bus j, voltage after compensation and injected current by PV-DSTATCOM. In the above equations, α_{new} is the corrected angle of the compensated bus. This parameter is obtained and the elements obtained from the power flow in each iteration.

4. Fuzzy-ALPSO Algorithm

4-1. Fuzzy Method Steps Allocation of Supercapacitors and the PV-DSTATCOM

1. First, by means of sensitivity analysis using Equations (18) to (20), the sensitivity of the changes in active losses of the network to the changes in reactive power is calculated for all buses (Fig. 4) and this index is considered as the first input of the fuzzy system.

$$\frac{\partial P_{lineloss}[m2]}{\partial Q[m2]} = \frac{(2 * Q(m2) * R(jj))}{(V(m2))^2} \quad (18)$$

$$P_{lineloss}[m2] = \frac{R(jj) * (P^2(m2) + Q^2(m2))}{|V^2(m2)|} \quad (19)$$

$$Q_{lineloss}[m2] = \frac{X(jj) * (P^2(m2) + Q^2(m2))}{|V^2(m2)|} \quad (20)$$

where, $P_{lineloss}$ and $Q_{lineloss}$ are active and reactive power losses of the transmission line, respectively, and $\frac{\partial P_{lineloss}[m2]}{\partial Q[m2]}$ is the coefficient of active power loss sensitivity to the reactive power.

2. Power flow on the studied network is done, the voltage value of the buses is obtained, which is considered as another indicator for the fuzzy system input.
3. The input (voltages of the buses) as well as the sensitivity analysis of the buses are normalized between [0,1].
4. Five membership functions are considered for each input: triangular sensitivity factor membership functions for loss sensitivity factor and triangular and trapezoidal voltage factor membership functions for voltage factor.
5. Five triangular membership functions are determined to obtain the fitness index (suitable location) of the supercapacitor and PV-DSTATCOM as the output of the fuzzy system according to Figs. 5-7.
6. Determining fuzzy rules for decision making

The fuzzy rules governing the fuzzy inference system (FIS), which is of Mamdani type, are in if-then form, which after applying the inputs to FIS, the output gives the proper location of the supercapacitor and PV-DSTATCOM. The larger the output, the better the location of the supercapacitor and PV-DSTATCOM. Membership functions for inputs and outputs are introduced according to Table 1.

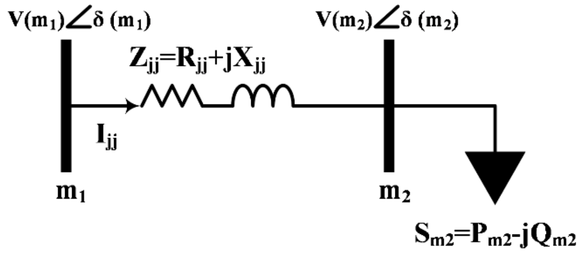

Fig. 4. Single-line schematic of the system

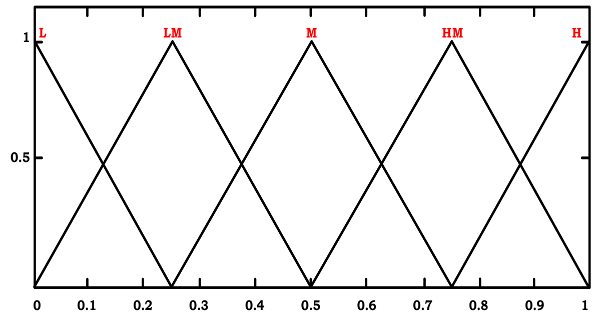

Fig. 5. Input membership functions of loss sensitivity factor

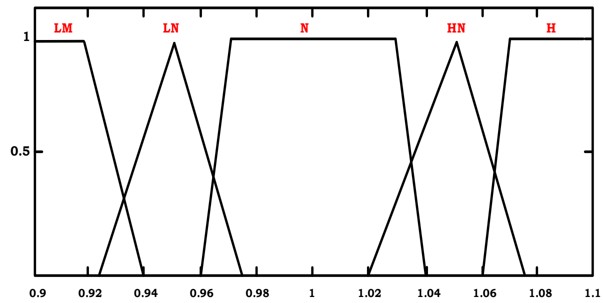

Fig. 6. Input membership functions of bus voltage value

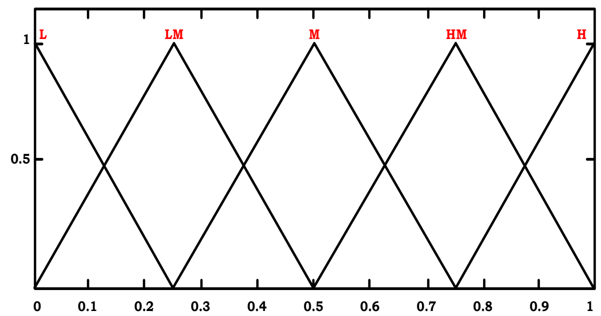

Fig. 7. Membership functions of supercapacitor fitness index output and PV-DSTATCOM

Also, the table of fuzzy rules is in the form of Table 2, which is determined and written according to the conditions of the problem.

Table 1. Membership functions

Voltage membership functions	Loss and output membership functions	Fuzzy value
L	L	very little
LN	LM	less
N	M	good
HN	HM	a lot
H	H	too much

Table 2. Fuzzy rules for DG allocation problem.

AND		Voltage				
		L	LN	N	HN	H
	L	LM	LM	L	L	L
L	LM	M	LM	LM	L	L
S	M	HM	M	LM	L	L
F	HM	HM	HM	M	LM	L
	H	H	HM	M	LM	LM

4-2. Steps of the ALPSO Algorithm for Optimal Sizing of Supercapacitors and the PV-DSTATCOM

To avoid getting trapped in the local optimum, this algorithm rereads and improves the search process in three steps so that it can reach the best solution. In ALPSO, the TSDM has been used. In this method, the algorithm adjusts the search path to adaptively avoid getting trapped in local optima and reduce the search space. In addition, a candidate particle generation strategy based on self-learning is used to produce the candidate particle as a learning target from the group. This step improves the search process in the response space. Then, to guarantee the algorithm's precise functionality, a potential prediction strategy has been implemented to forecast the potential capabilities of potential particles to lead the group so that the best particle is selected and followed by other particles as the best particle of the group [22].

4-2-1. TSDM

Usually, in the PSO algorithm, the particle group may become ensnared in a local optimum while exploring the problem space. In a certain dimension, the evolutionary state is illustrated by Fig. 8a, indicating that particles predominantly explore one dimension, while the red curve represents the variation of the fitness value inside this dimension.

In Fig. 8a, P_g is a local optimum. Each particle, such as X_1 and X_2, search along the P_g direction. After several iterations, the group reaches the local optimum. Assume that $f(P_i)^t$ is the fitness value of the best position of particle i in iteration t. The current position of the particle i, that is X_i is equal to P_i, where updates of P_i and $f(P_i)^t$ are given in each iteration. The situation where the best position of the particles is not modified in one iteration is justified according to Equation (21).

$$\sum_{i=1}^{n} f(P_i)^t - f(P_i)^{t-1} = 0 \tag{21}$$

where n shows the population size and t denotes the number of iterations. Obviously, if Equation (21) holds, it means that the algorithm is trapped in a local optimum. According to Fig. 8b, P_g represents the best particle of the group and is close to the global optimum. X_1^t and X_2^t particles in iteration t, it may be along the P_g direction to search but if the best position of these particles is not improved in iteration $t+1$, then Equation (21) is also valid.

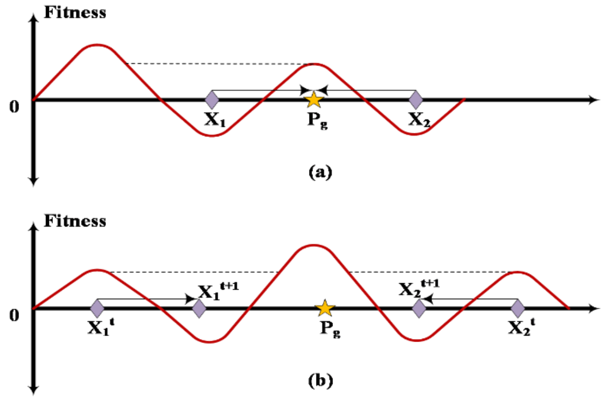

Fig. 8. State of particles in the search space

Consequently, in every iteration the TSDM is used in order to prevent the particles from being caught in the local optimum. In this method, the search path of the particle group can be adjusted when Equation (21) is established. For this purpose, a counter like T is considered, whose initial value is zero, and increases by one unit every time Equation (21) is established. The larger T for a group, the greater the probability that the group of particles is stuck in the local optimum, and this probability is calculated exponentially from Equation (22) [22].

$$Prob_{adjust} = \frac{exp(T) - 1}{exp(10) - 1} \tag{22}$$

here, $Prob_{adjust}$ is updated after each iteration. If $Prob_{adjust}$ is greater than a random number between 0 and 1, the learning algorithm from P_g stops the current one and sets its search path to a new particle. The pseudocode of TSDM is as follows.

Initialize T = 0
if $\sum_{i=1}^{n} f(P_i)^t - f(P_i)^{t-1} = 0$ **then**
T = T + 1
end
Generate a random number *rand* () between [0,1]
if $Prob_{adjust} > rand$ () **then**
Stop the swarm from learning the current P_g
end

If all particles remain unimproved in subsequent iterations, the value of T will continuously increase, indicating a higher likelihood of the group being trapped in a local optimum. Consequently, the group modifies its search trajectory by assimilating information from a new particle, referred to as a candidate, with its production details outlined in the "Self-learning candidate generation strategy (SCGS)" section, as follows.

4-2-2. Self-Learning Based Candidate Generation Strategy (SCGS)

To create a candidate that saves the algorithm from the local optimum, a candidate generation strategy based on self-learning is proposed. This strategy learns by using the best particles in all iterations to guide itself towards the global optimum. Obviously, the current fitness value of P_g is still the best and P_g still preserves the preferred solution in most dimensions of D; therefore, the solution of P_g is worth learning during candidate generation. Furthermore, as the fitness value of a particle depends on the particle structure in all of the dimensions, a particle with a slightly worse fitness value may have a good solution structure in some specific dimensions. This has the condition expressed as Equation (23).

$$f(Particle_i) = f(x_i^1, x_i^2, \ldots, x_i^D) \tag{23}$$

The pseudo-code mechanism (SCGS) is as follows.

for each dimension d from 1 to D **do**
Generate a random number rand () between [0, 1]
if $Prob_{Candidate} > rand\ ()$ **then**
Candidate^d = P_g^d
else
randomly select two P_k and P_m from the swarm
if f(P_i(k)) < f(P_i(m)) **then**
Candidate^d = P_k^d + Gaussian (p^d)
else
Candidate^d = P_m^d + Gaussian (p^d)
end
end
end

In the above pseudocode, Gaussian (σ^d) is determined according to Equations (24) and (25). Also, $Prob_{Candidate}$ is expressed based on Equation (26).

$$Average^d = \frac{1}{n}\sum_{i=1}^{n} P_i^d \tag{24}$$

$$Gaussian\ (\sigma^d) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i^d - Average^d)^2} \tag{25}$$

$$Prob_{Candidate} = \frac{exp(\,iter) - 1}{exp(\,10) - 1} \tag{26}$$

The global optimum and the candidate's search path may be identified following an iterative process. This approach guarantees that the algorithm can utilize the optimal solution structure of all particles and, at the same time, mitigates the impact on the convergence rate.

4-2-3. Competitive Learning Based Prediction Strategy (CLPS)

As discussed in the previous section, the candidate generation process is almost random, so updating P_g without considering a validation criterion is unreasonable to work. Therefore, to increase the efficiency of the algorithm and use P_g and the current candidate, a competitive learning strategy is proposed to forecast the candidate particle's potential steering capability in the ALPSO.

The speed of these two particles is updated as follows.

When particles learn from the current P_g, the velocity is updated by Equation (27):

$$v_i^d = \omega v_i^d + c_1 R_1^d\left(P_i^d - x_i^d\right) + c_2 R_2^d\left(P_g^d - x_i^d\right) \tag{27}$$

And, if the particles learn from the candidate P_g, the velocity is updated by Equation (28):

$$v_i^d = \omega v_i^d + c_1 R_1^d\left(P_i^d - x_i^d\right) + c_2 R_2^d\left(Candadate^d - x_i^d\right) \tag{28}$$

After one iteration, a competitive relationship appears between current and candidate P_gs, and the algorithms selects the better particle as the new P_g for the next sequential iterations. To measure the particle conduction capability of P_g and candidate P_g, Equation (29) is described as follows,

$$Competitiveness_L = \sum_{i=i}^{n} f(x_i)^{t+1} - f(x_i)^t \tag{29}$$

where L represents the swarm learning particle. If $Competitiveness_{Pg}$ is greater than $Competitiveness_{Candidate}$, this means that the optimality improves when the particles learn from the current P_g, and vice versa. The pseudocode of this strategy is given below.

for iteration from t to t + 1 do
for each particle i and i from 1 to n **do**
$$Competitiveness_{Candidate} = \sum_{i=i}^{n} f(x_i)^{t+1} - f(x_i)^t$$
end
end

for iteration from t to t + 1 **do**
  for each particle i and i from 1 to n **do**

$$Competitiveness_{P_g} = \sum_{i=i}^{n} f(x_i)^{t+1} - f(x_i)^t$$

  end
end
if $Competitiveness_{Candidate} > Competitiveness_{P_g}$ **then**
  Update P_g: P_g = Candidate
  T = 0
else
  P_g doesn't change
  T = T-1
end

The ALPSO algorithm framework can be succinctly summarized as follows:
[22].

Initialize positions and velocities of the particles in the search space
Initialize T = 0, $Prob_{adjust} = 0$
Evaluate the fitness values of particles
Update P_i^t and P_g^t
while (termination criteria in not met) **do**
  Update X_i^t and V_i^t for all particles
  Asses the fitness values
  Update P_i^t and P_g^t
  if $Prob_{adjust}$ > rand () **then**
    Terminate the swarm learning from the current P_g
    Produce a candidate particle based on the SCGS
    Select a better particle as the new P_g from the current and candidate P_g using the CLPS
    Update T and $Prob_{adjust}$ using the TSDM
  end
end

In the following, the solution process and method are described in Fig. 9.

5. Simulations

In this section, the results of implementing the suggested approach for optimal allocation and sizing of PV-DSTATCOM and parallel supercapacitors standard in IEEE 33- and 69-bus distribution systems [16,23] are presented and analyzed. To measure the performance of the method, Fuzzy-ALPSO was adopted to achieve the best location and capacity of this equipment in the investigated distribution networks. Simulations results demonstrate the positive effect of optimal installation of this equipment on technical performance of the network, including minimizing power losses, enhancing the voltage profile, and augmenting voltage stability. Information about this system was obtained from [23].

5-1. Results Related to the 33-base System

First, the suggested approach was implemented on the IEEE 33-bus distribution system. In Table 3, the results obtained from the optimal installation of PV-DSTATCOM and parallel supercapacitors in this system are presented. Optimizing the location and capacity of the PV-DSTATCOM and supercapacitors has led to a considerable enhancement in node voltage and reduced network losses. The optimal location for PV-DSTATCOM installation is determined at bus 30 and for supercapacitor banks at buses 7 and 14. The optimal size has been calculated as 792kVar for PV-DSTATCOM and 750 and 450kVar for supercapacitors, respectively.

Table 4 compares the results before and after installing the optimal equipment. According to this table, the lowest network voltage in bus 18 has increased from 0.9038 to 0.9392, which indicates a meaningful boost in the network voltage profile. Furthermore, the maximum network voltage has also changed significantly and has reached from 0.9970 to 0.9978. In addition, the real power losses of the network decreased from 210.99kW to 111kW, which is equivalent to a 47% reduction in losses. Reactive power loss has also decreased from 143.12kW to 84kW.

Fig. 10 illustrates the voltage profile of the 33-bus network before and after installing the optimal equipment. Fig. 11 illustrates the location of the equipment. As can be seen, the installation of PV-DSTATCOM and super-parallel capacitors has significantly reduced the voltage fluctuations and kept the grid voltage level within an acceptable range. Also, the voltage stability index in critical bus 18 has improved from 0.6671 to 0.7780, which indicates an increase in network stability.

Table 3. PV-DSTATCOM installation results on the 33-bus system

	Capacitor bank	PV-DSTATCOM	PV
Location (Bus)	7 and 14	30	30
Size	750 and 450kVar	792kVar	1000kW

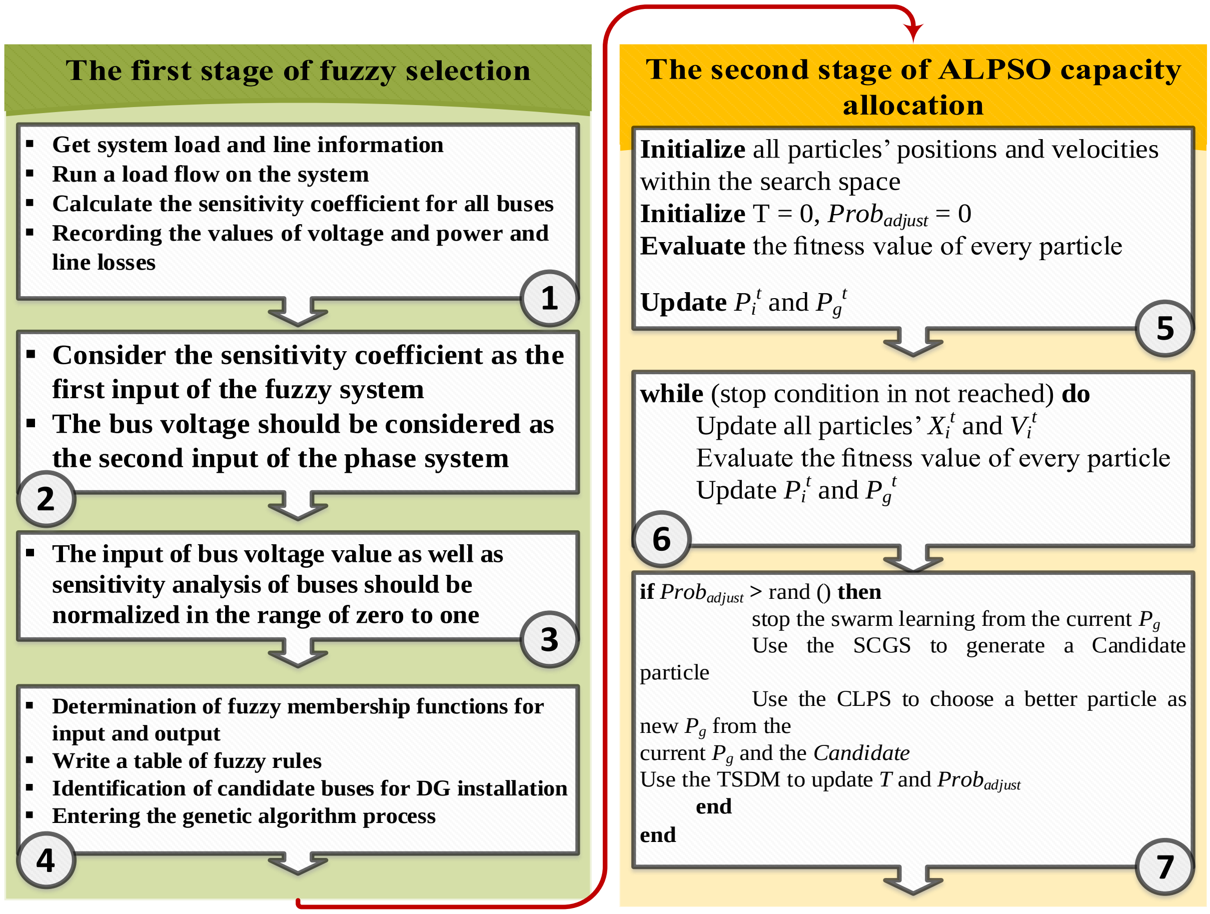

Fig. 9. Flowchart of the fuzzy-ALPSO algorithm

Table 4. Comparison of system results before and after installation of PV-DSTATCOM and supercapacitor in the 33-bus system

33-Bus system	Before installing PV-DSTATCOM and supercapacitor	After installing PV-DSTATCOM and supercapacitor
The lowest voltage (p.u.)	Bus 18-0.9038	Bus 18-0.9392
The highest voltage (p.u.)	Bus 2-0.9970	Bus 3-0.9978
power loss (kW)	210.99kW	111kW
power loss (kVar)	143.12kVar	84kVar
Minimum stability index (p.u.)	0.6671 related to Bus 18	0.7780 related to Bus 18

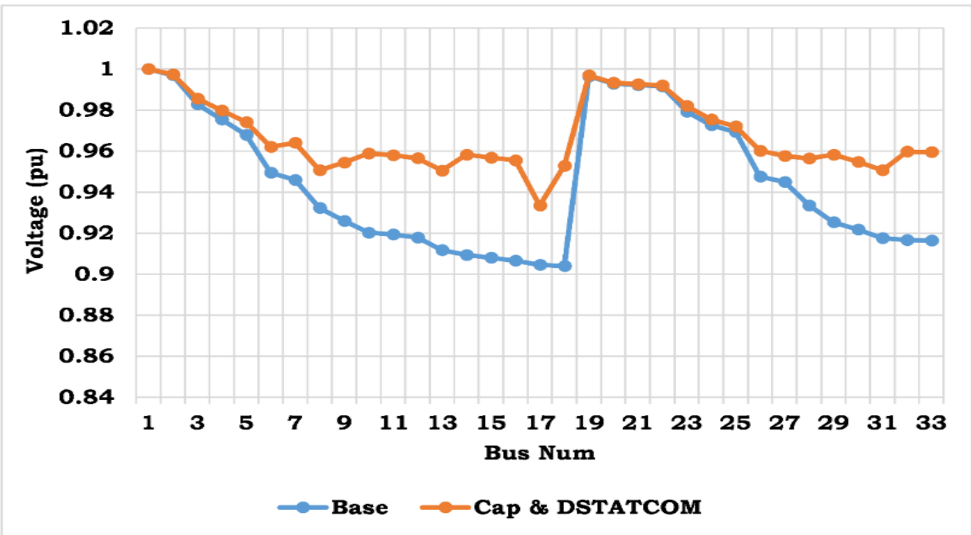

Fig. 10. Comparing the voltage profile of the 33-bus network

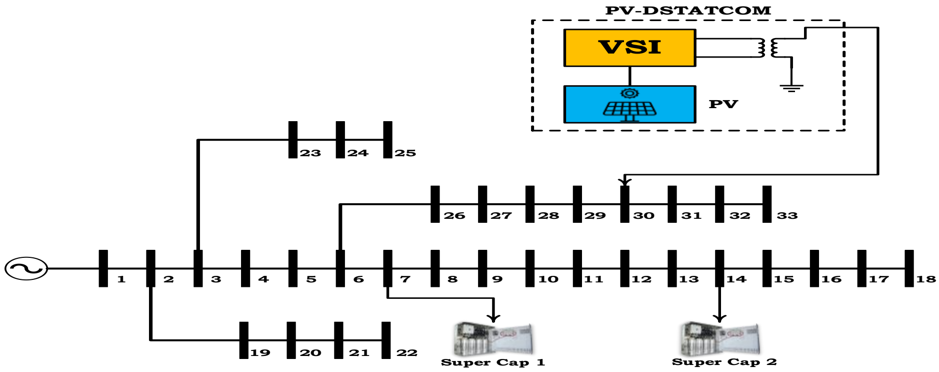

Fig. 11. Schematic of the 33-bus network after optimal installation of PV-DSTATCOM and supercapacitor

5-2. Results Related to the 69-base System

In the following, the suggested method was also implemented on the IEEE 69-bus system. As pet the results provided in Table 5, the optimal place of PV-DSTATCOM is bus 61 and for parallel supercapacitors is buses 18 and 50. The optimal capacity of the PV-DSTATCOM and supercapacitors is 1550kVar and 450kVar, respectively, for each supercapacitor bank.

Table 6 compares the results of the 69-bus system before and after installing the equipment. The lowest network voltage in bus 65 has increased from 0.9092 to 0.9392, which indicates a significant boost of the voltage profile in this critical bus. The maximum voltage has also decreased from 1 to 0.9978, which indicates a better voltage balance across the network. The real power loss of the network has decreased from 224.9kW to 149.4kW, which is equivalent to a 33% reduction in losses. The loss of reactive power has also decreased from 102.1kW to 67.6kW.

Fig. 12 compares the voltage profile of the 69-bus network before and after installing the optimal equipment and Fig. 13 shows the location of the equipment. As can be seen, the installation of PV-DSTATCOM and parallel supercapacitors has effectively reduced voltage fluctuations and improved voltage stability in this system. The voltage stability index in critical bus 65 has also increased from 0.6833 to 0.7658.

In Table 7, the advantages and disadvantages of optimization methods are presented along with explanations and key references.

Table 5. PV-DSTATCOM installation results on the 69-bus system

	Capacitor bank	PV-DSTATCOM	PV
Location (Bus)	18 and 50	61	61
Size	450 and 450kVar	1550kVar	2000kW

Table 6. Comparing the results of the system before and after installing PV-DSTATCOM and supercapacitor in the 69-bus system

33-Bus system	Before installation of PV-DSTATCOM and supercapacitor	After installation of PV-DSTATCOM and supercapacitor
The lowest voltage (p.u.)	Bus 65-0.9092	Bus 65-0.9392
The highest voltage (p.u.)	Bus 2-1	Bus 3-0.9978
Power loss (kW)	224.9kW	149.4kW
power loss (kVar)	102.1kVar	67.6kVar
The minimum stability index (p.u.)	0.6833 related to Bus 65	0.7658 related to Bus 65

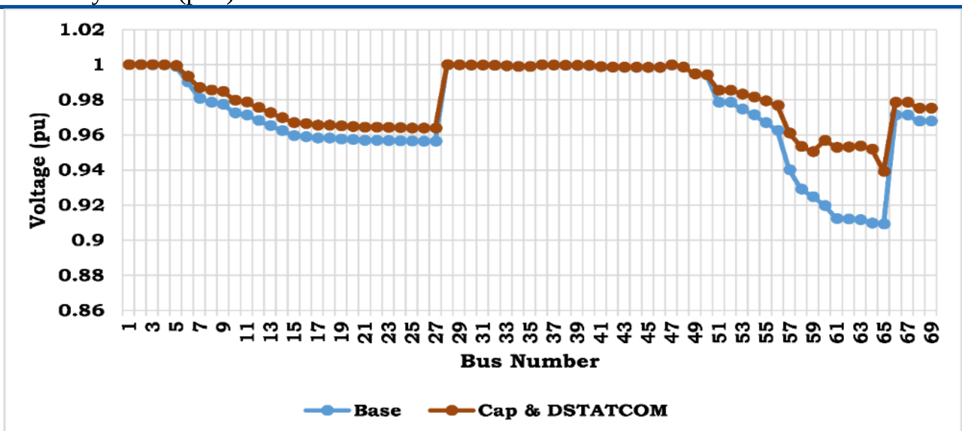

Fig. 12. Comparing the voltage profile of the 69-bus network

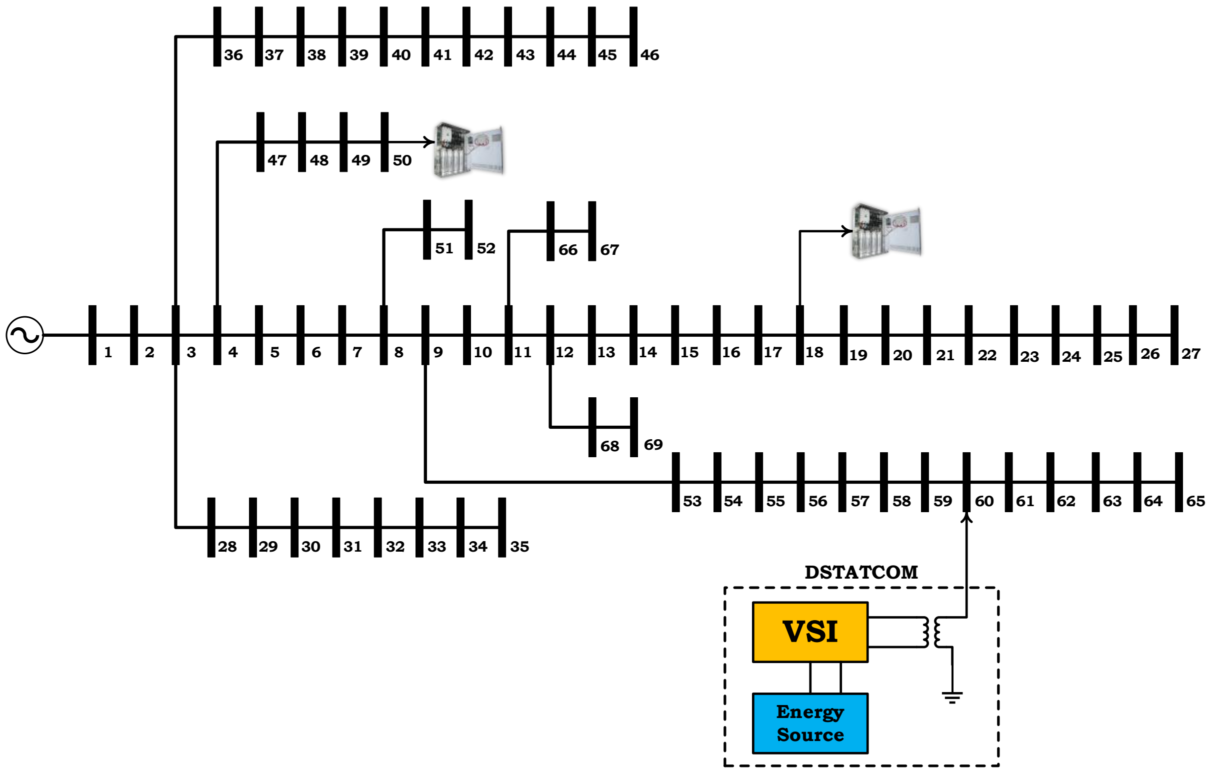

Fig. 13. Schematic of the 69-bus network after optimal installation of PV-DSTATCOM and supercapacitor

Table 7. Comparison of different optimization methods to improve the performance of compensating systems and reduce power losses

Method	Description	Benefits	Disadvantages	Key references
Firefly Algorithm	Used for optimal placement of DSTATCOM	Effective for improving power quality	It may require high computational effort	[24]
Particle Swarm Optimization (PSO)	Algorithm to optimize placement of capacitors and DSTATCOM	High speed and flexibility in solving multi-objective problems	may converge to local optima	[25]
Combined algorithm of genetics and colony of ants	Combination of genetic algorithm and ant colony optimization for optimal placement	Combining the strengths of both algorithms for better results	Complex implementation	[26]
Analytical method	Direct calculation method for placement	Simplicity in implementation	It may lack flexibility and adaptability	[27]
Particle swarm optimization with concurrent optimization	Using Fuzzy-ALPSO to locate and determine the optimal size of PV-DSTATCOM and supercapacitors simultaneously	Reducing power loss, improving voltage profile and increasing voltage stability	It may require more computing time for larger systems	The proposed method of this article: simultaneous optimization of PV-DSTATCOM placement and supercapacitors using Fuzzy-ALPSO algorithm

6. Conclusion

The results indicate that the proper installation of PV-DSTATCOM in distribution networks reduces line losses, enhances voltage profiles, and increases the voltage stability of bus lines. Given the controllability of PV-DSTATCOM and its ability to improve power quality parameters, the issue of locating and sizing capacitor banks and PV-DSTATCOM is of high importance. The current study adopted a multi-objective particle algorithm to solve the problem on standard 33- and

69-bus distribution systems. As per the results and analysis of all considered objectives, it demonstrates the high efficiency and power of this algorithm for solving multi-objective optimization problems. The algorithm and method's rapid speed, exceptional performance, and adaptability suggest their suitability for optimal installation of PV-DSTATCOM and other FACTS devices in real distribution networks. The summary of the paper's results is presented below:

Power Loss Reduction: With the optimal installation of PV-DSTATCOM and supercapacitors in IEEE 33- and 69-bus distribution systems, power losses have significantly decreased.

- In the 33-bus system, active power losses reduced from 210.99kW to 111kW, and reactive power losses from 143.12kVar to 84kVar.
- In the 69-bus system, active power losses reduced from 224.9kW to 149.4kW, and reactive power losses from 102.1kVar to 67.6kVar.

Voltage Profile Improvement: The installation of PV-DSTATCOM and supercapacitors has improved the voltage profile in all buses of the systems under study.

- The minimum per-unit voltage in the 33-bus system increased from 0.9038 to 0.9392.
- The minimum per-unit voltage in the 69-bus system increased from 0.9092 to 0.9392.

Voltage Stability Enhancement: The voltage stability index in both 33- and 69-bus systems has improved after the optimal installation of PV-DSTATCOM and supercapacitors.

- In the 33-bus system, the minimum stability index increased from 0.6671 to 0.7780.
- In the 69-bus system, the minimum stability index increased from 0.6833 to 0.7658.

Efficiency of the Fuzzy-ALPSO Algorithm: The use of the Fuzzy-ALPSO algorithm for simultaneous optimal allocation and sizing of the PV-DSTATCOM and supercapacitors has shown that this method has effectively improved the optimal performance and stability of distribution systems. in the future, to continue the work, you can briefly work on the following items:

- Problem solving in the presence of solar power plant uncertainty
- Considering the presence of other resources such as fuel cell and simultaneous planning

References

[1] Tolabi, H. B., Ali, M. H., & Rizwan, M. (2014). Simultaneous reconfiguration, optimal placement of DSTATCOM, and photovoltaic array in a distribution system based on fuzzy-ACO approach. *IEEE Transactions on sustainable Energy*, *6*(1), 210-218.

[2] Taher, S. A., & Afsari, S. A. (2014). Optimal location and sizing of DSTATCOM in distribution systems by immune algorithm. *International Journal of Electrical Power & Energy Systems*, *60*, 34-44.

[3] Devi, S., & Geethanjali, M. (2014). Optimal location and sizing determination of Distributed Generation and DSTATCOM using Particle Swarm Optimization algorithm. *International Journal of Electrical Power & Energy Systems*, *62*, 562-570.

[4] Pezeshki, H., Arefi, A., Ledwich, G., & Wolfs, P. (2017). Probabilistic voltage management using OLTC and dSTATCOM in distribution networks. *IEEE transactions on power delivery*, *33*(2), 570-580.

[5] Chakraborty, S., Mukhopadhyay, S., & Biswas, S. K. (2021). Coordination of D-STATCOM & SVC for dynamic VAR compensation and voltage stabilization of an AC grid interconnected to a DC microgrid. *IEEE Transactions on Industry Applications*, *58*(1), 634-644.

[6] Chakraborty, S., Mukhopadhyay, S., & Biswas, S. K. (2022). A hybrid compensator for unbalanced AC distribution system with renewable power. *IEEE Transactions on Industry Applications*, *59*(1), 544-553.

[7] Behera, M. K., & Saikia, L. C. (2023). A Seamless Control of Grid-connected PV System for Alleviating PV Penetration in Rural Grid Using Supercapacitor Accompanying with DSTATCOM and Improved CTF Control. *IEEE Transactions on Industry Applications*.

[8] Zhang, T., Xu, X., Li, Z., Abu-Siada, A., & Guo, Y. (2020). Optimum location and parameter setting of STATCOM based on improved differential evolution harmony search algorithm. *IEEE access*, *8*, 87810-87819.

[9] Hannan, M. A., Sebastian, G., Al-Shetwi, A. Q., Ker, P. J., Rahman, S. A., Mansor, M., ... & Uddin, M. (2023). Particle swarm optimization algorithm based fuzzy controller for solid-state transfer switch toward fast power transfer and power quality mitigation. *IEEE Transactions on Industry Applications*, *59*(5), 5570-5579.

[10] Moghbel, M., Masoum, M. A., Fereidouni, A., & Deilami, S. (2017). Optimal sizing, siting and operation of custom power devices with STATCOM and APLC functions for real-time reactive power and network voltage quality control of smart grid. *IEEE Transactions on Smart Grid*, *9*(6), 5564-5575.

[11] Hussain, S. S., & Subbaramiah, M. (2013, April). An analytical approach for optimal location of DSTATCOM in radial distribution system. In *2013 international conference on energy efficient technologies for sustainability* (pp. 1365-1369). IEEE.

[12] Jain, A., Gupta, A. R., & Kumar, A. (2014,

December). An efficient method for D-STATCOM placement in radial distribution system. In *2014 IEEE 6th India International Conference on Power Electronics (IICPE)* (pp. 1-6). IEEE.

[13] Farhoodnea, M., Mohamed, A., Shareef, H., & Zayandehroodi, H. (2013, June). Optimum D-STATCOM placement using firefly algorithm for power quality enhancement. In *2013 IEEE 7th international power engineering and optimization conference (PEOCO)* (pp. 98-102). IEEE.

[14] Azli, N. A. (2013). Optimal placement of D-STATCOM using hybrid genetic and ant colony algorithm to losses reduction. *International Journal of Applied*, *2*(2), 53-60.

[15] Jazebi, S., Hosseinian, S. H., & Vahidi, B. (2011). DSTATCOM allocation in distribution networks considering reconfiguration using differential evolution algorithm. *Energy conversion and Management*, *52*(7), 2777-2783.

[16] Ebrahimi, J., Abedini, M., Rezaei, M. M., & Nasri, M. (2020). Optimum design of a multi-form energy in the presence of electric vehicle charging station and renewable resources considering uncertainty. *Sustainable Energy, Grids and Networks*, *23*, 100375.

[17] Ebrahimi, J., & Abasi, M. (2024). Design of a Power Management Strategy in Smart Distribution Networks with Wind Turbines and EV Charging Stations to Reduce Loss, Improve Voltage Profile, and Increase Hosting Capacity of the Network. *Journal of Green Energy Research and Innovation*.

[18] Ismail, B., Wahab, N. I. A., Othman, M. L., Radzi, M. A. M., Vijyakumar, K. N., & Naain, M. N. M. (2020). A comprehensive review on optimal location and sizing of reactive power compensation using hybrid-based approaches for power loss reduction, voltage stability improvement, voltage profile enhancement and loadability enhancement. *IEEE access*, *8*, 222733-222765.

[19] Zeinalzadeh, A., Estebsari, A., & Bahmanyar, A. (2019, June). Simultaneous optimal placement and sizing of DSTATCOM and parallel capacitors in distribution networks using multi-objective PSO. In *2019 IEEE Milan PowerTech* (pp. 1-6). IEEE.

[20] Ranjan, R., & Das, D. (2003). Voltage stability analysis of radial distribution networks. *Electric Power Components and Systems*, *31*(5), 501-511.

[21] Vovos, P. N., & Bialek, J. W. (2005). Direct incorporation of fault level constraints in optimal power flow as a tool for network capacity analysis. *IEEE Transactions on Power Systems*, *20*(4), 2125-2134.

[22] Wang, F., Zhang, H., Li, K., Lin, Z., Yang, J., & Shen, X. L. (2018). A hybrid particle swarm optimization algorithm using adaptive learning strategy. *Information Sciences*, *436*, 162-177.

[23] Baran, M., & Wu, F. F. (1989). Optimal sizing of capacitors placed on a radial distribution system. *IEEE Transactions on power Delivery*, *4*(1), 735-743.

[24] Chaithra, C., & Padmaja, K. (2015). Optimum placement of DSTATCOM using firefly algorithm for enhancing power quality. *IJARCCE: International Journal of Advanced Research in Computer and Communication Engineering*, *4*(6), 20-24.

[25] Prabu, J., & Muthuveerapan, S. (2016). Optimum placement and sizing determination of distributed generation and DSTATCOM using penguins search. *International Journal of Innovative Research in Science, Engineering and Technology*, *3297*, 6675-6680.

[26] Castiblanco-Pérez, C. M., Toro-Rodríguez, D. E., Montoya, O. D., & Giral-Ramírez, D. A. (2021). Optimal Placement and sizing of D-STATCOM in radial and meshed distribution networks using a discrete-continuous version of the genetic algorithm. *Electronics*, *10*(12), 1452.

[27] Mumtahina, U., Alahakoon, S., & Wolfs, P. (2023). A Literature Review on the Optimal Placement of Static Synchronous Compensator (STATCOM) in Distribution Networks. *Energies*, *16*(17), 6122.

Biography

Mahyar Abasi was born in Iran in 1989. He graduated with a Ph.D. in Electrical Power Engineering from the Shahid Chamran University of Ahvaz, Ahvaz, Iran, in 2021. His research background is more than 60 published journal and conference papers, more than 10 authored books, 11 industrials research projects, and a patent in power systems. In 2021, he was introduced as the top researcher of Khuzestan province, Iran, and in the years 2021 to 2023, he successfully received four titles from the membership schemes of the National Elite Foundation in Iran. He is currently an Assistant Professor at the Electrical Engineering Department of Arak University, Arak, Iran. His specialized interests are fault protection, detection, classification, and location in HVAC and HVDC transmission lines, control of reactive power and FACTS devices, evaluation and improvement of power quality, and power system studies.

Arash Zeinalzadeh was born in Iran, in 1986. He received his M.Sc. degrees in Electrical Engineering (Power system) from Science and Research Branch, Islamic Azad University, Iran. Also, he taught for 3 years at Borujerd Islamic Azad University. he has published 10 research paper and many conference paper. His current research interest includes power system reliability, smart Grid, demand side management and microgrids.

Mohammad Amin Bahramian received a B.Sc. degree in electrical engineering from Arak University, Arak, Iran, in 2020. He is now an M.Sc. graduate in electrical engineering from Arak University, having completed his degree in 2022. He also is currently employed at "Camellia Electronics Industry Innovators," a knowledge enterprise company, where he contributes to the field of power electronics, specializing in DC-DC converters and LED drivers. His research interests include Power Converters, Renewable Energy Systems, Smart Grid Technologies and Digital Control Systems.

Javad Ebrahimi was born in Iran in 1988. He received his Ph.D. degree in Electrical Engineering (Power system) from Khomeinishahr Branch, Islamic Azad University, Khomeinishahr /Isfahan, Iran, in 2020. He currently works as a technical teacher in the Technical and Vocational Academy of Isfahan province. Also, he has taught for ten years at Borujerd Islamic Azad University and Ayatollah Borujerd University. He has published ten research papers, eight conference papers, and one industrial research project. His research interests include power quality, smart grids, demand-side management, and microgrids.