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Integration of Photovoltaic and DSTATCOM In the Distribution Network Using Rat Swarm Optimization Technique

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Abstract. *Power loss minimization and improved voltage profile have been major challenges faced by the electrical distribution network (DN) mainly because of the long length of the feeders and the high resistance to reactance (R/X) ratio of the DN. A lot of techniques have been investigated to solve these problems. One of the most prominent is the optimal integration of distributed generation (DG) such as photovoltaic (PV) as well as the integration of Distribution Static Synchronous Compensator (DSTATCOM) into the network. The main challenge with this solution has been the determination of the optimal sizes and sites of the DG and/or DSTATCOM. This paper seeks to optimize the simultaneous allocation of multiple DSTATCOMs and PVs in the DN for power loss reduction and voltage profile improvement using the rat swarm optimization (RSO) technique, which is a simple, yet robust optimization technique. The optimization problem is formulated to minimize power loss, voltage deviation index, and maximize the voltage stability index. The IEEE 33 node DN is used as a test network and the simulation results show the effectiveness of the RSO technique in finding the best sizes and locations of the PVs and the DSTATCOMs. The power losses of the network are reduced from 210.996 kW, and 143.129 kVAr when there is no DSTATCOM nor PVs in the network to 26.155 kW, and 19.128 kVAr when DSTATCOM and PVs are simultaneously allocated into the network. A remarkable improvement in the voltage profile of the network is also observed with the minimum node voltage being 0.98 p.u. compared to 0.9038 p.u. when there are no DSTATCOMs or PVs. The RSO results were compared with other techniques from the literature, and it proved its superiority.*

Keywords: *DSTATCOM, Rat swarm optimization, Photovoltaic, Distributed generation, Optimization.*

1. Introduction

As a result of the long lengths of distribution networks (DNs) having high resistance to reactance (R/X) ratios, power loss minimization, voltage profile improvement, and network reliability improvement have been major challenges faced by DNs [1]. Distributed generation (DG) installed close to load centers where power is consumed has been a potential solution. Meanwhile, as the need to cut down the emission of greenhouse gases into the atmosphere keeps growing, renewable energy DGs especially photovoltaic (PV) that directly convert sunlight into electricity have gained a very strong interest.

The penetration of PVs is fast increasing in the modern DN as green electricity for discerning consumers keeps improving as manufacturing efficiencies are upgraded. In addition, PVs present potential benefits to the DN such as peak shaving, voltage support, and reduction in losses [2]. Also, power is produced where it is consumed, leading to a reduction in the net feeder load and electricity bills paid by the prosumers [3].

The DN was designed to be balanced and should be able to provide high-quality power to the consumers, but due to the long feeders and the reactive power needs of some loads, considerable power is lost along the lines [4]. To compensate for this, a Distribution Static Synchronous Compensator (DSTATCOM) could be used [5]. The DSTATCOM, which is a shunt connected with loads stabilizes the DN voltage by regulating the reactive power flow in the DN, that is, it absorbs reactive power when in excess in the network and injects reactive power into the network when in deficit [6]. STATCOMs were initially designed for high voltage alternating current transmission network applications but have since then been of great interest in DN applications, with the name being adjusted to DSTATCOM [7]. The installation of DSTATCOM into the DN has proven to be beneficial to the network in terms of increased grid reliability, and reduction in power losses [8]. Notwithstanding, these benefits could only be obtained if strategically allocated [9].

A combination of DSTATCOM and DGs like PVs in the DN will be very profitable to the network as they will be able to minimize power losses, improve the network voltage profile, and improve the network's stability [10]. Nevertheless, integrating both systems into the DN needs to be done optimally to avoid the collapse of the network [11]. Their sizes and locations need to be carefully determined, and because of this, a lot of research has been done to determine the optimal sizes and locations of DSTATCOM and DG in the DN. The authors in [12] used the Cuckoo Search Optimization (CSO) technique to determine the optimal size and location for DG and STATCOM integration into the DN to minimize power losses, and the results obtained showed good performances when compared with other techniques. In [13], the authors proposed the Chu–Beasley Genetic Algorithm for the optimal integration of DSTATCOM into the DN. Meanwhile, in [14], the focus was on using the Bald Eagle Search technique for the allocation of DG and shunt reactive compensators (SRC), and the simulation showed noticeable results. In [15], the authors planned the allocation of numerous DGs and DSTATCOM in the power grid making use of the Student Psychology-Based Optimization technique, and the results obtained were compared with well-known techniques like PSO. In [16], long-term planning of DGs and DTATCOM into the DN was carried out using the light search algorithm. Testing was done on the IEEE 33 and 69 node networks. The authors in [17] used PSO to optimize the integration of DGs and DSTATCOMs in the DN for power loss reduction and voltage profile improvement.

This research focuses on the optimal sizing and siting of PVs and DSTATCOMs in the DN using the rat swarm optimization (RSO) technique. The RSO technique is chosen because of its simplicity and robustness. The optimization problem has been formulated as a multi-objective problem minimizing active power loss, and voltage deviation index while maximizing the voltage stability index. The technique has been tested on the IEEE 33 DN and the results have been compared with past works.

The contribution of this work to the body of knowledge is the adaptation/utilization of the Rat Swarm Optimization (RSO) technique for the optimal allocation of PVs and DSTATCOM into the DN to minimize power loss and improve the voltage profile of the network made up of purely commercial loads. Despite the RSO being a simple yet robust optimization technique, it had not yet been used for such applications. The results obtained are then compared with published results under the same conditions for validation.

The rest of this paper is organized as follows; the section after this is the methodology. The methodology is followed by the presentation and discussion of the results obtained, and then a conclusion.

2. Methodology

2.1. Study Network

The IEEE test DNs are well-known DNs that were first introduced by W. H. Kerstinq in 1991 to provide a common set of data to be utilized by program developers and users to validate the effectiveness of their solutions [18]. Since then, other benchmarked networks have been developed. The test network used in this research is the IEEE 33 node whose single line diagrams are shown in Fig. 1. The IEEE 33 node network is a balanced network at a voltage of 12.66kV with a total load power of 3715 kW and 2300 kVAr as shown in Table 1 [19]. This network as its name implies has 33 nodes or buses of which one is a generator bus, with the rest load buses. Connected to the load buses are balanced loads that consume both active and reactive powers. It is chosen for this study because it is a balanced network that is not too large nor too small. In addition to that, many past works have made use of this network, and therefore using it makes results comparison and validation more realistic.

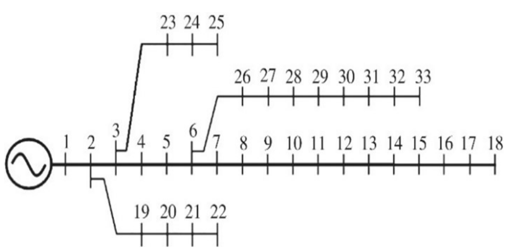


Fig. 1: IEEE 33 node test DN.

Tab. 1: IEEE 33 node DN power demand

Active Power (kW)	Reactive Power (kVAr)	Apparent Power (kVA)
3715	2300	4369.35

In this study, the network is studied as being purely commercial network (a network with commercial customers), made up of small offices, and retail shops. The normalized daily load curve for the study area used in this research is obtained from [20] as shown in Fig. 2.

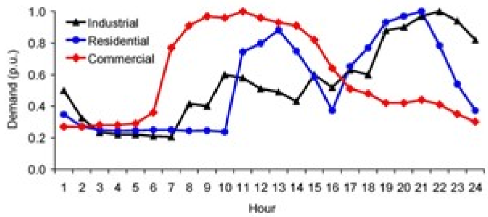


Fig. 2: Normalized daily load profile: industrial, residential, and commercial loads (the commercial is considered).

2.2. Modelling of the PVs and DSTATCOMs

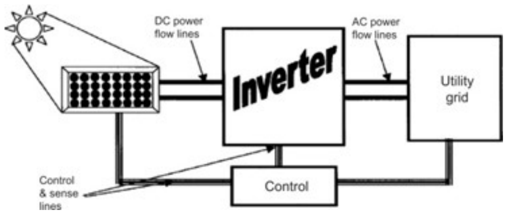
PV modules or panels that produce direct current (DC) power are connected to the grid (alternating current (AC) power) through inverters as shown in Fig. 3a. The inverters used could be of two types: voltage source inverters (VSIn) or current source inverters (CSIn). VSIn makes use of DC capacitor links, and this gives them the ability to inject reactive power into the grid making them effective for applications in low and medium voltage networks [21]. In so doing, they work at a power factor different from unity. Equations 1 and 2 show the power expressions of a PV array with VSIn [22]. On the other hand, CSIn works at a unity power factor [23], because of the absence of a DC capacitor link, and therefore, they can only inject active power into the network at a unity power factor (equation (1) only applies in this case).

$$P_{PV} = \left[\frac{V_i^2}{R_i}P_{PV,loss} - (P_i^2 + Q_i^2) - (Q_{PV}^2 - 2P_iP_{PV} - 2Q_iQ_{PV})\left(\frac{G}{L}\right)\right]^{\frac{1}{2}} \tag{1}$$

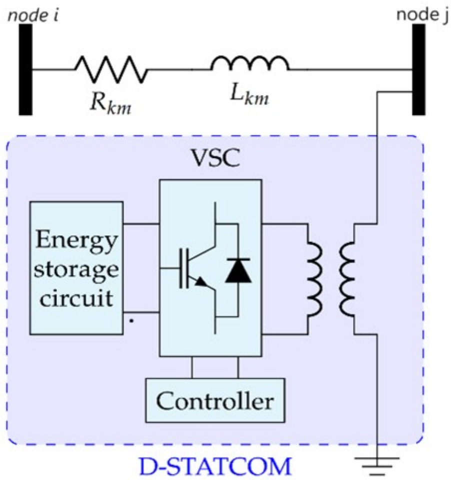
$$Q_{PV} = \left[\frac{V_i^2}{R_i}P_{PV,loss} - (P_i^2 + Q_i^2) - (P_{PV}^2 - 2P_iP_{PV} - 2Q_iQ_{PV})\left(\frac{G}{L}\right)\right]^{\frac{1}{2}} \tag{2}$$

where P_{PV} is the real power produced by the PV, Q_{PV} is the reactive power produced by the PV, V_i is the voltage at the node i, R_i is the resistance of the line between node i, and $i+1$, $P_{(PV,loss)}$ is the PV active power loss, G is the distance between the source and the PV location in km, and L is the feeder's length from the node i in km.

The PV systems considered here are without any storage system and are made up of CSIn and hence inject only active power into the networks. They are subjected to the following environmen-

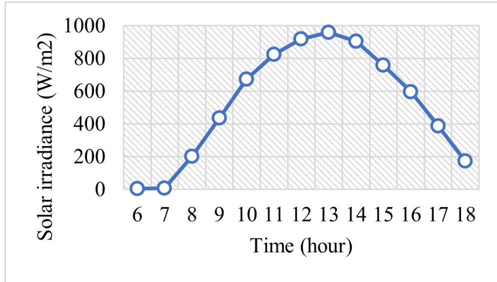


(a) Grid Connected PV system [24]

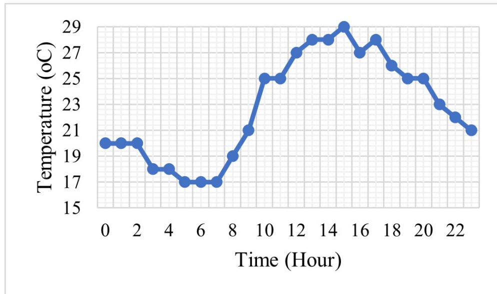


(b) DSTATCOM connected to the grid [25]

Fig. 3: PV and DSTATCOM connected to the grid.



(a) Daily solar irradiance



(b) Daily temperature variation

Fig. 4: Daily solar irradiance and temperature.

tal conditions (Fig. 4) from [26] which are for the hot season (month of March) in Kenya.

On the other hand, DSTATCOMs are always shunt-connected to the grid so that they can regulate reactive power in the grid according to needs. As shown in Fig. 3b, a DSTATCOM consists of a voltage source converter (VSC), energy storage, a coupling transformer, and a controller. In addition to providing reactive power to the grid, a DSTATCOM could also provide active power through its direct current energy storage, so long as the output voltage of the converter is set to be higher than that of the network to which it is coupled at the point of common coupling [27]. As obtained from [22], equations 3 and 4 give expressions of the active and reactive power of a DSTATCOM

$$P_{DSTATCOM} = \frac{V_i V_j}{X_L} sin\delta \tag{3}$$

$$Q_{DSTATCOM} = \frac{V_i^2}{X_L} - \frac{V_i V_j}{X_L} cos\delta \tag{4}$$

Where V_i is the voltage at the node i, V_j is the voltage of the DSTATCOM, X_L is the reactance of the line, and δ is the phase angle between V_i and V_j.

In this study, the DSTATCOM injects only reactive power into the networks, and therefore, only equation 4 applies.

2.3. Optimal allocation of the PVs and DSTATCOMs

The optimal allocation of PVs and DSTATCOMs into the DN is done during peak load demand. Since the loads are commercial loads, this corresponds roughly to between 10 am to 2 pm. This time slot coincides with peak solar insolation, and therefore the PVs are producing at their peak as well.

1) Formulation of the optimization problem

The optimization problem is formulated as a minimization problem as adapted from [28].

a. Power loss minimization

$$f_i(j) = min\sum_{a=1}^{N_{br}} R_a * I_a^2 \tag{5}$$

where f_i (j) is the total active power loss, N_{br} is the number of branches in the DN, I_a is the branch current, and R_a is the branch resistance.

b. Average voltage deviation index (AVDI) minimization

$$f_{ii}(j) = \frac{1}{N_n}\sum_{k=1}^{N_n} |1 - V_k|^2 \tag{6}$$

c. Voltage stability index (VSI) maximization at a receiving end node, k, the VSI is calculated as

$$\begin{aligned} f_{iii}(k) = |V_k|^4 - 4\Big(P_k x_{jk} + Q_k r_{jk}\Big)^2 \\ - 4(P_k r_{jk} + Q_k x_{jk})|V_k|^2 \end{aligned} \tag{7}$$

where V_k is the node voltage at node k, P_k is the active power demand at node k, Q_k is the reactive power demand at node k, r_{jk} is the resistance of branch $j-k$, and x_{jk} is the impedance of branch $j-k$.

The VSI is given as a maximization problem hence it is converted to a minimization problem to be combined with the power loss and AVDI equations to form the multi-objective function of the optimization problem as shown in equation 8.

$$F(k) = \min\{e_1 f_i(k) + e_2 f_{ii}(k) - e_3 f_{iii}(k)\} \tag{8}$$

where e_1, e_2, and e_3 are weights assigned to each objective function. All the objective functions have been given an equal weight of 1. That is;

$$e_1 = e_2 = e_3 = 1$$

2) Constraints

a. Equality constraints: Power balance constraints

$$P_G + \sum_{k=1}^{N_{PV}} P_{PV} = \sum_{k=1}^{N_n} P_l + \sum_{i=1}^{N_{br}} P_{loss} \tag{9}$$

where P_G is the active power from the grid, P_{PV} is the PV active power produced, P_l is the active power demand of the loads, N_n is the number of nodes, N_{PV} is the number of PVs, P_{loss} is the network active power loss, and N_{br} is the number of branches in the network.

$$Q_G + \sum_{k=1}^{N_D} Q_D = \sum_{k=1}^{N_n} Q_l + \sum_{i=1}^{N_{br}} Q_{loss} \tag{10}$$

where Q_G is the reactive power from the grid, $Q_D$is the reactive power generated by the DSTATCOM, N_D is the number of DSTATCOM, Q_l is the reactive power demand of the loads, and Q_{loss} is the network reactive power loss.

b. Inequality Constraints
- Voltage constraints: Node voltages should be within limits.

$$\begin{aligned} V_k^{min} \le V_k \le V_k^{max} \\ V_k^{min} = 0.95p.u. \\ V_k^{max} = 1.05p.u. \end{aligned} \tag{11}$$

- PV power constraints

$$\begin{aligned} P_{PV}^{min} \le P_{PV} \le P_{PV}^{max} \\ P_{PV}^{min} = 100kW \\ P_{PV}^{max} = 2000kW \end{aligned} \tag{12}$$

The maximum PV rating is chosen not to exceed 50% of the total active power demand of the network.

- DSTATCOM power constraints

$$\begin{aligned} Q_D^{min} \le Q_D \le Q_D^{max} \\ Q_D^{min} = 100kVar \\ Q_D^{max} = 2000kVar \end{aligned} \tag{13}$$

The maximum DSTATCOM rating is chosen not to exceed 50% of the total reactive power demand of the network.

3) Rat swarm optimization

RSO is the technique of choice in this work for the optimal allocation of PVs and DSTATCOM in the DN because of its simplicity, high accuracy, high convergence speed, and robustness [29]. RSO is a novel optimization technique inspired by rats' behavior of chasing and fighting their prey. Rats are social animals that hunt and fight in packs, and this trait of aggression is what gives the RSO algorithm its core motivation [30]. Each rat in RSO stands for a distinct solution. The RSO begins by randomizing the initialization of the solution set (rats), then evaluates them using an objective function, where the best rat $\vec{R_r}$ is considered the optimal solution. As a result, the following processes are repeatedly carried out a certain number of times (t), beginning by first updating the position of every rat based on the two modeled behaviors: chasing and fighting prey. A second step is the updating of the parameters, and any solution outside the search space is adjusted. Lastly, the recalculation of the fitness of every rat in the swarm is done, and the best rat's position is updated if it is better that $\vec{R_r}$. The best solution $\vec{R_r}$ is returned after that is completed. The RSO is summarised in the flowchart in Fig. 5.

A. Mathematical model of the RSO i. Chasing the prey In the RSO, chasing the prey is usually a general task wherein the rat who knows the location of the prey is seen as the best search argent, while the rest of the swarm align themselves according to the position of the best rat as shown in the equation below [31]

$$\vec{R}_r = A.\vec{R}_i(j) + C.\left(\vec{R}_l(j) - \vec{R}_i(j)\right) \tag{14}$$

Where $\vec{R}_r$ is the optimal solution, $\vec{R}_i$ (j) is the optimal solution which is the position of the i^{th} rat, $\vec{R}_l$ (j) is the solution of the l^{th} and j is the number of iterations. Parameters A and C are calculated as shown in equation 1, where j^{max} is the maximum iteration.

$$\begin{aligned} A &= B - j\left(\frac{B}{j^{max}}\right) \\ B &= rand(1,5) \\ C &= 2 * rand(0,2) \end{aligned} \tag{15}$$

ii. Fighting the prey
The equation describing how the rats fight the prey is shown below.

$$\vec{R}_i(j+1) = \left|\vec{R}_i(j) - \vec{R}\right| \tag{16}$$

where $\vec{R}_i(j+1)$ is the next position of the i^{th} rat. A and C are used to balance between exploration and exploitation. Making A too small for example 1 and making C moderate will result in a stressed exploitation, while a large value will lead to a stressed exploration. To achieve a balance, equation 13 which is the sum of intra-cluster distances is used.

$$\sum c_k \in C \sum x \in C_k d^2(x, \mu_k) \tag{17}$$

where μ_k is the middle of the cluster k, and d^2 $(\dots)$ is the square of the Euclidean distance.

A summary of the RSO is shown in Fig. 5 below.

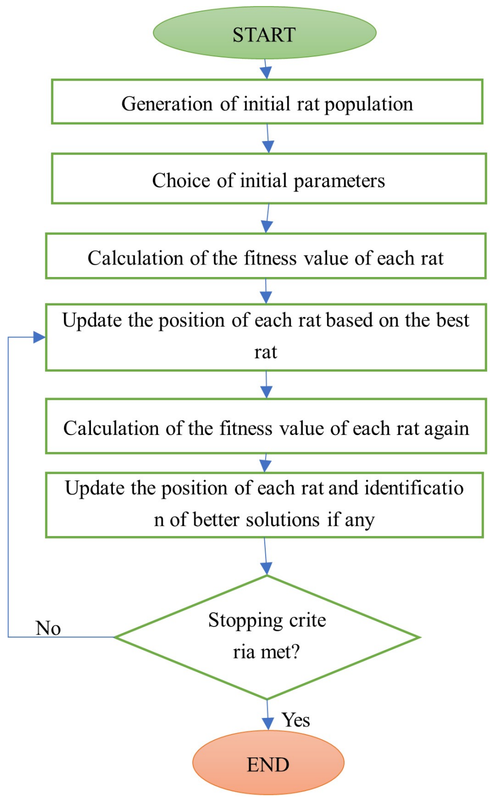


Fig. 5: Flowchart of the RSO.

2.4. Optimal integration of PVs and DSTATCOMs

The steps through which the optimal sizing and allocation of PVs and DSTATCOMs into the test DN using the RSO technique as adapted from [31] are done are shown below. The steps apply for the optimal integration of PVs and then DSTATCOM. MATLAB R2018a is used for the simulation.

Step 1: Enter the network data.
Step 2: Perform the base case load flow analysis using the Newton-Raphson iterative method.
Step 3: Record the following results: active and reactive power losses, network voltage profile, AVDI, and VSI.
At a time, t = 0, perform Steps 4 and 5.
Step 4: Initialize the RSO parameters.

- The search space dimension, d
- Number of rats, r
- Number of iterations, j
- Maximum number of iterations, j^{max}

Step 5: Initialize the population.

- The position of the i^{th} rat, $\vec{R}_i(j)$
- The best rat's position, $\vec{R}_r$
- Initialize the parameters, A, B, and C
- Result assessment is performed, and the best solution is assigned to $\vec{R}_i(j)$.

while $(j < j^{max})$
for every rat,
Step 6:

- Update the current rat's position using equation (16).
- Update A, B, and C using equation (15).
- Verify if there is any rat that goes beyond the set search space and if so, adjust its position.
- Calculate the fitness value of each rat.
- Update $\vec{R}_i(j)$ if a better solution than the previous optimal solution is found.
- $j = j + 1$

End while
Return $\vec{R}_i(j)$
End the procedure.
Step 7: Output load flow results (power losses, node voltage, AVDI, AVSI) and the optimal size and locations for the PVs or DSTATCOM.

The RSO parameters used in the simulation are shown in Table 2. The parameters are an adjustment of the empirical values used in [31]

Tab. 2: RSO Initial parameters

Parameter	Symbol	value
Search space dimension	d	30
Number of rats	r	30
Random parameters	B	5
	C	1
Maximum number of iterations	j^{max}	1000

3. Results and discussion

The results obtained using the RSO technique for the optimal allocation of PVs and DSTATCOMs in the IEEE 33 node DN are shown in this section.

3.1. Simulation scenarios

Simulation is done using MATLAB R2018a. It is arbitrarily chosen to optimally size and site 3 PV units and 3 DSTATCOM units in the test network. The following scenarios are simulated.

Base Case: Load flow analysis of the network without PV and DSTATCOM

Case 1: Load flow analysis of the network with optimally sized and placed DSTATCOMs only

Case 2: Load flow analysis of the network with optimally sized and placed PVs only

Case 3: Load flow analysis of the network with PV and DSTATCOM simultaneously sized and sited

3.2. Optimal sizes and sites of DSTATCOMs and PVs

The obtained optimal sizes and sites when only DSTATCOMs, only PVs, and both DSTATCOMs and PVs are simultaneously integrated into the network are shown in Tables 3, 4, and 5 respectively. Looking at the three tables, it is observed that the simultaneous integration of DSTATCOMs and PVs into the DN using RSO yields the lowest objective function values (0.2647). This is followed by the integration of PVs only (0.3812) and in the last position the integration of DSTATCOM only (0.5446). The objective function being a minimization one therefore implies that the best solution is achieved when both DSTATCOMs and PVs are integrated into the DN for power loss reduction and voltage profile improvement as compared to integrating them separately.

Tab. 3: Optimal integration DSTATCOM only

Size (kVAr)	Location (node)	Objective Function value
634.48	31	
480.85	30	0.5446
880.71	15	

Tab. 4: Optimal integration of PVs only

Size (kVAr)	Location (node)	Objective Function value
665.05	31	
915.2	12	0.3812
883.42	6	

Tab. 5: Optimal integration of PVs and DSTATCOM

DSTATCOMs		PVs		
Size (kVAr)	Location (node)	Size (kW)	Location (node)	Objective Function value
482.68	12	1015.09	12	
503.95	30	893.41	30	0.2647
851.67	25	436.91	25	

3.3. Voltage profile

The network voltage profile without PVs and DSTATCOMs, with DSTATCOMs only, with PVs only, and with PVs and DSTATCOMs is shown in Fig. 6. It is seen that the introduction of PVs only yields a better voltage profile with the minimum node voltage being 0.969 p.u. (node 18) than the introduction of DSTATCOMs whose lowest network voltage is 0.957 p.u. (node 18). This can be justified using active and reactive power generation equations shown below (equations 18, and 19). From equation 18, the load voltage V_L can be expressed to give equation 20. From equation 16, it is observed that an increase in the active power generated will lead to a greater increase in the load voltage compared to the load voltage expressed in terms of reactive power (equation 21). The optimal simultaneous integration of PVs and DSTATCOMs into the DN by the RSO yields the best network voltage profile with the lowest node voltage being 0.982 (node 33) because of the combined effect of the PVs and DSTATCOMs.

$$\begin{aligned} P_G &= \frac{V_G V_L}{X} sin\delta \\ Q_G &= \frac{V_G^2}{X} - \frac{V_G V_L}{X} cos\delta \end{aligned} \tag{18}$$

Where P_G is the active power generated, Q_G is the reactive power generated, V_G is the generator voltage, V_L is the load voltage, X is the line reactance, and δ is the power angle.

$$\begin{aligned} &\Rightarrow \quad V_L = \frac{P_G X}{V_G sin\delta} \\ &\Rightarrow \quad V_L = \frac{\left(V_G^2 - \frac{Q_G X}{cos\delta}\right)}{V_G} \end{aligned} \tag{19}$$

3.4. Power losses

The allocation of the PVs and DSTATCOMs into the DN leads to a drop in the total active and reactive power losses of the network as shown in Fig. 7. This is because they are sized and placed at load centers where power is consumed and hence lead to a reduction in the amount of current flowing in the DN feeders

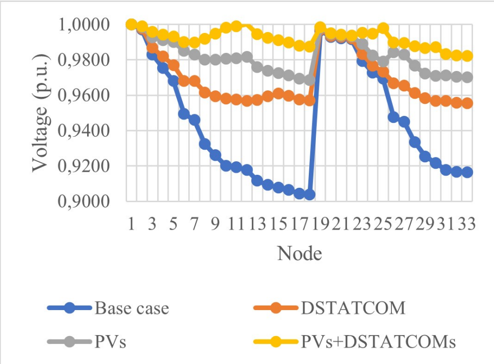
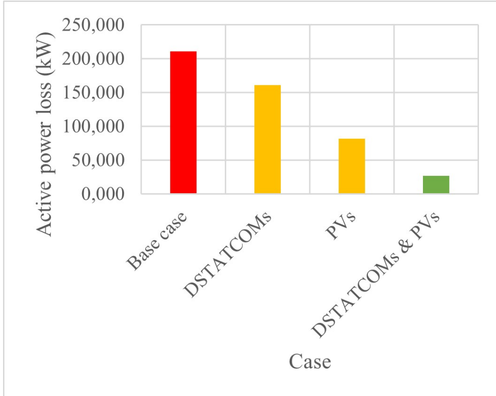
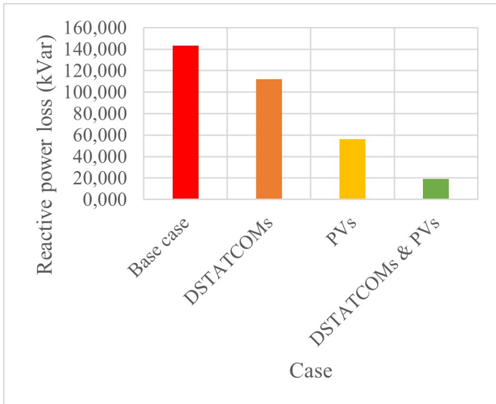


Fig. 6: Network voltage profile without DSTATCOM nor PVs, with DSTATCOMs only, with PVs only, and with both DSTATCOMs and PVs.



(a) Active power loss



(b) Reactive power loss

Fig. 7: Total power loss in the network in all simulation cases.

from the slack bus. Since power loss is a function of current, a reduction in current, therefore, leads to a reduction in both active and reactive power losses, the reason why a power loss of 210.996 kW, 143.129 kVAr experienced when there are no PVs nor DSTTACOMs is dropped to 26.155 kW, 19.128 kVAr when PVs and DSTATCOMs are simultaneously sized and placed in the network. Again, it is noted that the allocation of PVs yields lesser active and reactive power loss (81.171 kW, 56.048 kVAr) than the DSTATCOMs (160.629 kW, 112.075 kVAr). This could be because the DSTATCOMs is a reactive power compensator, that is, it injects reactive power into the network when it senses a deficiency in reactive power while it absorbs reactive power when it senses an excess. In other words, it ensures that just enough reactive power is present in the network. Whereas, in the case of the PVs all through its operation, it injects active power into the network therefore the amount of active power drawn from the slack bus by the loads is immensely definitely reduced leading to better total power loss reduction.

3.5. Voltage deviation index (VDI)

The voltage deviation index is useful to visualize how much a node voltage differs from the expected nominal voltage which is usually 1 p.u. The smaller the VDI of a node in the network, the closer the node voltage is to the reference value. An average of the voltage deviation indices of the network gives the average voltage deviation index (AVDI) which gives an idea of how good the voltage profile of the network is. The smaller the value, the better the voltage profile of the network. The simultaneous sizing and allocation of PVs and DSTATCOM in the DN led to a drop in the AVDI from 0.00406 (base case) to 0.00008 as seen in Fig. 8. It is observed here again that the PVs result in a better AVDI of 0.00042 compared to the DSTATCOMs which is of 0.00112. The reason is because of the greater impact of the PVs on the network voltage profile as explained earlier than the DSTATCOMs.

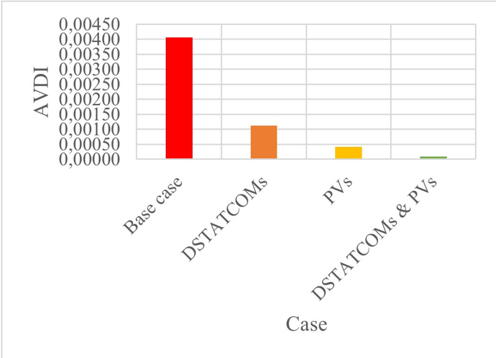


Fig. 8: AVDI in all simulation cases.

3.6. Voltage stability index (VSI)

The VSI is very useful in predicting how unstable a network is. It can estimate proximity to collapse as well as identify critical nodes or line segments, making it very useful in online voltage stability analysis [32]. When there are no DSTATCOMs nor PVs in the network, the minimum VSI of the network is as low as 0.6671 (node18) as shown in Fig. 9. This is improved to 0.8335 (node 33) when the DSTATCOMs are integrated, and better to 0.8804 (node 18) when the PVs are integrated. The best minimum VSI is of course seen when both DSTATCOMs and PVs are simultaneously integrated into the network with the resulting lowest node VSI being 0.93019 (node 33). Therefore, the presence of the DSTATCOMs and PVs in the network results in the network being less susceptible to collapse.

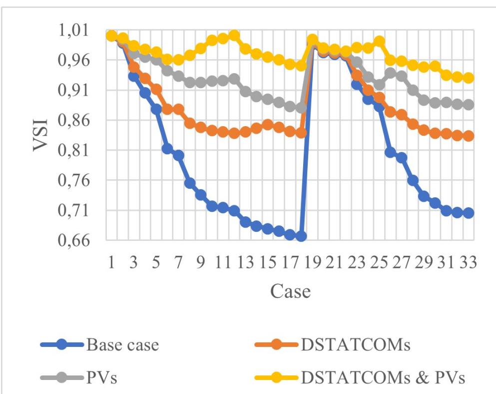


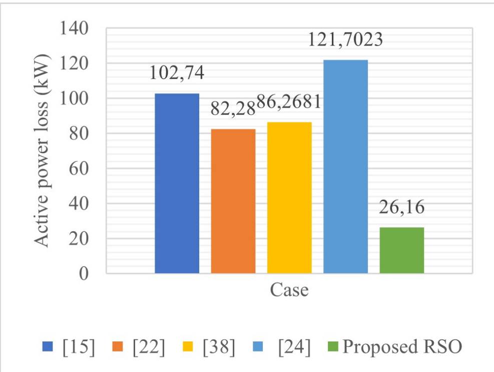
Fig. 9: VSI in all simulation cases.

3.7. Comparison with other techniques

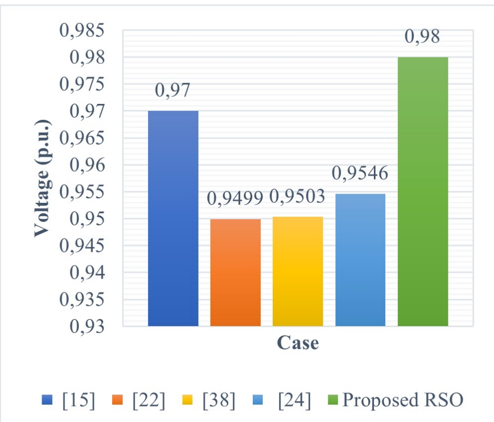
To validate the efficiency of the RSO in the simultaneous sizing and siting of DSTATCOMs and PV/DG in the distribution, the results obtained from this research are compared with those obtained using other optimization techniques in the literature under the same c as shown in Table 6, with Fig. 10 showing a graphical comparison of the active power loss and minimum node voltage. All work was carried out under the same conditions with the IEEE 33-node test DN used. In some cases, 3 DG/PV and DSTATCOM units are sized and allocated, while others deal with the integration of a single DG/PV and DSTATCOM. In the comparison presented in Table 6, the total DG/PV and DSTATCOM capacities are highlighted, and their impact on the DN is examined. It is seen that the minimum node voltage when the proposed RSO is used is 0.98p.u., which is higher than that when the other techniques are used. In addition to that, the resulting total active power loss of the network is lowest when the proposed RSO is used to optimally size and site the DSTATCOMs and PVs in the network. Furthermore, the minimum VSI of the network is highest (0.9302) when the proposed RSO is used compared to that obtained in other research works that examined the VSI. This, therefore, shows the superiority of the RSO over other techniques used in the literature for the optimal sizing and allocation of DSTATCOM and PV/DG units in the DN for power loss reduction and network voltage profile improvement.

Tab. 6: Comparison of the proposed RSO technique with other works

Used Optimization techniques	Ploss (kW)	Min Voltage (p.u.)	Min VSI	Sizes	
				DG/PV (kW)	DSTATCOM (kVAr)
Fractional Lévy Flight Bat Algorithm (FLFBA) [33]	102.74	0.97	-	2000	2000
Enhanced Artificial Bee Colony (EABC) algorithm-based optimization method [34]	82.28	0.9499	0.81	1098.778	1232.5
Loss Sensitivity Factor (LSF) [35]	86.2681	0.9503	-	1000	1500
Analytical approach-based technique [36]	121.7023	0.9546	-	203.4	1250
Proposed RSO	26.16	0.98	0.9302	2345.41	1838.3



(a) Total active power loss



(b) Minimum node voltage

Fig. 10: Comparison of the proposed RSO with other techniques.

4. Conclusions

This study focused on the simultaneous optimal sizing and siting of DSTATCOMs and PVs in the DN for power loss reduction and network voltage profile improvement. Also, simulation cases of only DSTATCOMs as well as only PVs being integrated into the DN were performed. The IEEE 33 node DN was used as the test network with the network made up of commercial loads. The allocation of DSTATCOMs and PVs in the distribution network is an important task as there is a need to obtain the best network parameters without violating certain conditions. Therefore, the choice of the optimization technique for such a task is crucial. Because of its simplicity and robustness compared to other techniques, the rat swarm optimization (RSO) technique was therefore used. It was observed that the simultaneous sizing and siting of DSTATCOMs and PVs yields good load flow parameters as the power loss of the network dropped tremendously from 210.996kW, 143.129kVAr in the base case to 26.155kW, 19.128kVAr. Also, an improvement in the voltage profile of the network was noticed with the minimum node voltage being 0.98p.u. compared to 0.9p.u. in the base case. The effectiveness of the RSO was validated against other techniques and it was shown that the performance of RSO was superior to the other techniques.

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