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Energy Saving Analysis on Distribution Network with Incorporation of D-STATCOM Using Firefly Algorithm and Power Loss Index

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ABSTRACT

This present work investigated the effects of reactive power compensation with the use of a Distribution Static Synchronous Compensator (D-STATCOM) on a practical distribution network. In the approach proposed, the network steady-state parameters were obtained with a backward forward sweep power flow technique, the possible sites for D-STATCOM were predetermined with power loss index while the firefly algorithm was employed for determining the optimal sizes and sites respectively. Three different levels of D-STATCOM penetrations were investigated and their effects on voltage profile enhancement, active power loss reduction, cost of energy savings, payback times, and cost of procurement were assessed. The best optimal sites and sizes obtained after several simulations for case I, case II, and case III are (6, 1000kVar); (12, 349.69kVar; 22, 867.29kVar) and (5, 1200kVar; 14, 424.34kVar; 21, 350kVar) respectively. Also, the percentage improvements at the bus with minimum voltage magnitude for cases I to III are 0.6, 0.78, and 0.79% while the accompanied active power loss reductions are 59.03, 70.57 and 91.78 %. From the economic perspective, the cost of procurement ($), annual energy savings ($), and the payback time (years) for the three cases examined are (5,303.5, 1,461.00, 3.63); (6,454.25, 1,746.66, 3.69); (10,471, 2, 271.58, 4.61) respectively. Also, results validation showed that the approach proposed outsmarts particle swarm optimization and network feeder reconfiguration. The outcome of this work findings application in performance enhancement of real-life distribution networks.

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1. INTRODUCTION

The power industries ensure the flow of power from generating stations via a transmission network to the distribution network (DN) and the latter is saddled with the primary responsibility of serving the received energy to the immediate end-users [1], [2]. The end-users could be maximum-demand users and residential users operating either a single or three-phase supply system [1], [3]. Generally, the end-users' energy demand from the DN is never uniform and this non-uniformity is a big threat to the health of the network. It is the primary cause of the high resistance to reactance ratio on the DN [1], [3] and of all forms of DN configurations, radial configuration enjoyed wide utilization in many countries around the world [2], [3]. The radial nature offers several merits such as enhanced coordination of the system protection scheme, encouraged lengthy extension of feeder route length, diminished fault current level in the event of a short circuit, and lower investment cost since the feeder arms are mostly fed from a single source. Similarly, trouble-shooting is made an easy task if there is a need to trace the feeder route length either for routine maintenance or for fault identification and rectifications [2], [4].

Unfortunately, many of these aforementioned merits are predisposing factors contributing to the inherent problems of the RDN, and to a mammoth extent, it has prevented it from faithfully performing its envisioned functions [1], [4]. For instance, a lengthy feeder route encourages energy theft by unpatriotic customers or a deliberate attempt by unauthorized users who want to be connected to the grid [5]. Similarly, the nature of customers' connected loads which are more inductive (electric motors, electric fans, air-conditioners, electric blenders, and freezers among others) and non-linear loads are responsible for an acute shortage of reactive power flow along the radial length of the distribution network [4], [6], [7]. Furthermore, recent times have witnessed a surge in demand for electrical energy to cope with the dynamic nature of activities of domestic, industrial, or commercial users [8]. Regrettably, this surge in demand is still being accommodated by existing distribution feeders which are neither upgraded in capacity nor have new substations constructed [9]. In addition, reference [6] reported a projection that energy demand from the DN is envisioned to rise by 37% by 2040, this was further buttressed that about 0.6% annual growth in electrical energy demand from the DN is envisioned from 2013 to 2040 and this was premised on the fact that more of middle-class people are struggling to improve on their home comfort [7].

Suffice it to know that research findings have also shown that about 13% of the entire power that is being generated is reportedly wasted as ohmic loss (I^2R) through network lines [1], [4] while, a good number of end-users at the farthest ends of RDN substations in many Sub-Sahara African countries suffer extremely from the drop in voltage magnitude [3], [5], [7]. The voltage drop issue is of great concern to the end-users as their connected appliances are highly susceptible to short life spans, untimely damage, and burns in severe cases [5], [7]. With these scenarios, the need to harness cost-effective techniques to strengthen the existing RDN given its present overloaded conditions becomes non-negotiable [10], [11]. The traditional approaches usually employed to enhance the performance of RDN include the construction of new distribution network infrastructures, which is quite too expansive [12], reordering of network switches (sectional and tie switch), which is incapable of injecting reactive power for RDN inadequacies [7], [12]. Also, load reduction and load shedding are another strategies that are predominantly suitable for strengthening energy availability at the RDN in the event of acute energy supply from the interconnected generation stations [12], [14]. Furthermore, the optimal selection of conductor sizes is also another approach to reducing the network loss caused by conductor peculiarities such as cable resistance and resistivity. However, the efficacy of this approach is subject to an appropriate choice of conductors for different parts of the network. This approach is capital-intensive and encourages the utilization of multiple conductors within a single distribution network [2], [15], [17].

Having seen the shortcomings of the above techniques, recent times have witnessed the incorporation of shunt capacitors to enhance the performance of radial networks as seen in several pieces of literature in public domains [2], [5]. Shunt capacitors are an inexpensive means of injecting reactive power into the system locally. It can improve the system power factor, enhance power handling capacity, amplify network voltage profile, and encourage good voltage regulation in addition to an appreciable reduction in investment cost [18], [20]. However, the application of shunt capacitors is prone to Ferro-resonance issues and cannot supply reactive power continuously since they are available in discrete sizes [3], [5], [18], [21], [24]. Therefore, for a continuous supply of reactive power, D-STATCOM a member of custom power devices was developed credence to advancement in power electronics [15]. They are usually coupled to the RDN through a coupling transformer to inject reactive power into the system [15], [26], [29].

The placement and sizing of D-STACOM can done with analytical or artificial intelligence-based optimization algorithms. However, analytical approaches like variational technique [30], and optimal power flow analysis [31] among others have their inherent shortcomings such as the inability to select the most beneficial sites for inclusion of D-STATCOM, and it is more of guesswork as it is majorly based on the rule of thumb [27], [29]. Also, different sizes of D-STATCOMs have to be tried to get the best size which makes this approach grossly time-consuming and computationally complex [29], [31]. Also, artificial intelligence (AI)-based optimization algorithms such as improved bacterial foraging search, gravitational search algorithm, novel lightning search algorithm, cuckoo search algorithm, improved cat swarm optimization algorithm, harmonic search optimization algorithm, differential evolution algorithm, and ant colony optimization among others are suitable for any constrained multi-objectives optimization problems [31], [34]. Although each of these techniques has its pros and cons. One of the major strengths of these optimization algorithms lies in the generation of a sizable search space which can easily facilitate effective exploration and exploitation [32], [33]. This explains the rationale for adopting techniques that can effectively handle the preselection of suitable sizes and sites in a large set of variables prior to adopting the AI-based techniques for optimal exploration and exploitation [5], [29].

Such preselection techniques include the index vector method (IVM), loss sensitivity factor (LSF), power loss index (PLI), and voltage stability index (VSI) [35], [37]. among others. These preselection techniques help in reducing the computational time and facilitate quicker convergence of the algorithm. On the strength of AI and analytical techniques for preselection, this work presents multiple integration of D-STATCOM on Nigerian RDS using PLI and firefly algorithm (FA) to minimize real power loss, enhance the network voltage, evaluate the cost of inclusion of the DSTATCOM and the corresponding payback time on the investment. The justification for the choice of the approach proposed for instance, PLI can be easily computed following load flow results, it is faster, saves time, requires less computer memory, is less mathematically complex, and demonstrates greater prediction accuracy in identifying the most vulnerable buses [5], [6]. Also, the FA used as the optimization algorithm is a few-parameter swarm-based algorithm with efficient exploration and exploitation search techniques, the search space is usually divided into sub-groups for better exploration and it achieves global optimal results with fewer iterations [2], [3], [38]. This present work has contributed to knowledge in the following ways;

i) The status of a typical Nigerian radial feeder (Pama 11kV, 24 bus) in a densely populated area in Southern Kaduna, Northern Nigeria was assessed by estimating its system voltage profiles and entire power losses (kW).
ii) The system voltage profile was enhanced while the real power loss in the network was appreciably minimized with the approach proposed as compared to PSO and Network feeder reconfiguration.
iii) The cost of energy saved was found to be significant while the payback time on the investment cost of DSTATCOM was minimal.

2. METHODS

2.1. Power Flow Studies

One of the major power system analyses that can be regarded as the forerunner for many analyses in power system analyses is power or load flow studies. It is a means of digging to know the steady-state condition of the network, and with load flow studies; the network essential parameters like voltage angle, voltage magnitude, and network losses -real and reactive power- can be determined. Distribution network (DN) being so entirely different in characteristics from transmission network has rendered most of the proven transmission power flow techniques such as Newton-Raphson technique, Gauss-Seidel technique, Fast-decoupled technique(FDT), and Decouple technique to be inefficient. They have reportedly failed to converge when applied to DN which is known to be heavily characterized by unbalanced loads and sometimes it is usually overloaded [34], [35], [39]. Also, the high resistance-to-reactance ratio of DN significantly affects the formation of the Jacobian matrix which is a must in NR and FDT [40]. Also, if the characteristics of DN are to be captured in NR and FDT, the procedure becomes computationally complex without assurance of getting a feasible solution [41]. Therefore, any suitable techniques for DN power flow studies should be able to capture without mincing words the inherent characteristics of this ill-conditioned network, and have been found to be majorly built around the concept of Kirchhoff's laws [2], [3].

One of such method is the backward-forward sweep load flow technique (BFS); the BFS technique is known to be simple since it is based on network theory. It is highly robust as it makes provision for capturing the high resistance to reactance ratio of DN and also guarantees quick convergence since it has eliminated the formulation of the Jacobian matrix which is one of the core issues in transmission load flow techniques [2], [3], [43], [44]. Also, unlike transmission load flow techniques, BFS requires less memory and its accuracy does not depend on the initial guess [44]. In addition, among other strengths of BFS is its ability to handle relatively large networks even with different forms of loads and generators [2], [5]. The convergence criterion for the BFS technique has always been the voltage mismatch based on the tolerance pre-set. The BFS employs fundamental circuit principles to compute line current, nodal voltage, and complex power on the sweep principle [5], [45]. It is staged in two steps; step one is the backward sweep which computes the branch current given the nodal voltages, while the forward stroke is the second phase and is employed to compute nodal voltages given the branch current and the cycle continued in that order. The forward stroke usually starts from

the source node and terminates at the last node and vis-a-vis for the backward sweep [3], [46]. The procedural steps for the implementation of BFS are as follows;
Step I: Start
Step II: Initialize the network parameters such as load data (real (P) and reactive power (Q) and line data (Resistance (R) and reactance (X))
Step III: Set a flat voltage of 1.0 p.u for all the buses within the network
Step IV: Compute the network power flow – real and reactive power- using backward sweep using these sets of equations (1) to (3);
Complex power injected;

$$S_i^* = P_i - jQ_i \tag{1}$$

The magnitude of load current flowing as;

$$I_i = \frac{P_i - jQ_i}{V_i^*} \tag{2}$$

The branch current flowing between bus i^{th} and j^{th}

$$I_{i,j} = I_j + \sum_{i=1}^{N} I_i \tag{3}$$

Step IV: Compute the system nodal voltage using forward sweep with equation (4);

$$V_j = V_i - I_{ij}Z_{ij} \tag{4}$$

Step V: Check if the tolerance set is achieved, if yes go to step VI else, go to step II
Step VI: Compute the network index; the line loss -real and reactive-, and the voltage magnitude and angle of each bus; $V_i^* =$ Conjugate of nodal voltage at bus i^{th}
Step VII: Print the results
Step VII: Stop
Where; i =1,… N; P_i *and* Q_i represent the real and reactive power demanded i^{th} bus; V_i and V_j are the sending and receiving end bus voltage; I_{ij} and Z_{ij} stand for the branch current and impedance between the buses i and j, $V_i^* =$ Conjugate of nodal voltage at bus i^{th}

2.2. Behavioral Description of D-STATCOM

The advancement in power electronics has extended the scope of FACTs devices to include their employability on DN and one of such device is the distribution static synchronous compensation (D-STATCOM). It is a member of a dedicated custom power device (CPD) suitable for compensating reactive power inadequacy on active DN. The inclusion of D-STATCOM on DN can potentially reduce the real power loss and significantly improve the RDN voltage profile. It is noteworthy to bring to mind that the D-STATCOM is designed to operate in three distinctive modes capacitive, inductive, and no load mode. The mode the D-STATCOM assumes is largely dependent on the voltage condition of the network, for instance, when the system voltage profile is extremely poor, it operates in capacitive mode to inject adequate reactive power sufficient enough to boost the network voltage. Also, when the system voltage is far above the approved window, it operates in inductive mode to consume reactive power from the system and lastly, it assumes dormant mode (no-load state) without consuming or injecting reactive power when the system voltage is within the approved window [30], [47]. The basic equations for D-STATCOM are comprehensively detailed in the work presented by authors in [31]. The bus at which the D-STATCOM will be integrated will have reactive power expanded as given by (5). The appreciable loss reduction expected will be a function of the difference between the power loss before and after the inclusion of D-STATCOM as given with (6), [18];

$$Q_i^{new} = Q_i - Q_{DSTATi} \tag{5}$$

$$\Delta P_{T,Loss}^{D-STAT} = \frac{P_{T,Loss}^{D-STAT}}{P_{T,Loss}} \tag{6}$$

2.3. Procurement Cost of D-STATCOM

The cost of reactive power injected via D-STATCOM installed added to the utility operational cost of supplying real power to the end-user. This cost can be greatly minimized by ensuring that the system loss is reduced appreciably. The installation cost by kVar supplied by the D-STACOM can be computed by multiplying the present worth factor of D-STATCOM with the cost per kVar of the D-STATCOM using (7) and (8), [4];

$$The\ present\ worth\ factor\ (PWF) = \frac{[1+B]^n \times B}{[1+B]^n - 1} Q_i^{new} = Q_i - Q_{DSTATi} \tag{7}$$

$$Cost_{D-STAT} = CP(kVar) \times PWF \tag{8}$$

where; $Cost_{D-STAT}$ is cost of purchasing D-STATCOM ($); $CP(kVar)$ is cost per kVar of D-STATCOM; B is rate of return on the asset (10%); n is active year of the D-STATCOM (usually 30 years).

2.4. Annual Cost of Energy Saving

To compute the annual cost of energy saving, it is assumed in this current work that the loads on the system are static loads, and also effect of fluctuating energy prices billing rate was also not considered. The reason for adopting these assumptions was based on the fact that the network data sets used for load flow analysis are static datasets for the line and bus data. It is expected that with the appropriate inclusion of the right sizes of D-STATCOM at the optimal locations within the network, a considerable saving in the cost of energy should be achieved, this is computed using (9).

$$COEL_{Annual} = [(TRPL) \times (ER) \times (T)]_{BSE} - [(TRPL) \times (ER) \times (T)]_{ASE}] \tag{9}$$

where; $COEL_{Annual}$ is annual cost of energy loss in ($); BSE is before system enhancement; ASE is after reinforcement, ER is energy billing rate($\$/kWh = 0.06\$/kWh$), T is time in hours usually 8760hrs.

2.5. Payback Time

It is profitable that the period of payback on the investment on procurement of D-STATCOM should be minimal, the payback time is computed using (10).

$$Payback\ Time = \frac{Investment\ Cost\ on\ D-STATCOM}{Net\ Annual\ Return(Net\ saving\ for\ DSTATCOm} \tag{10}$$

2.6. Objective Function

The objective function of interest in this present study seeks to minimize the real power loss, voltage deviation, and system operational cost. If the line real power loss between bus k and $k+1$ is given by (11) and the corresponding network aggregate real power loss is modeled with (12), [48] thus;

$$P_{Loss}(k, \quad k+1) = R_{k,} \times \frac{P_k^2 + Q_k^2}{|V_k|^2} \tag{11}$$

$$P_{Total\ Loss} = \sum_{k=1}^{n} P_{Loss}(k, \ k+1) \tag{12}$$

where; P_{Loss} is line real power loss (kW), $R_{k,}$ is line resistance in ohms, $P_k and\ Q_k$ is real and reactive power at bus k^{th}

Similarly, the flat voltage magnitude at each bus is expected to be 1.0 p.u, any deviation from this flat voltage is captured as voltage deviation, hence, the voltage deviation at each bus can be modeled using (13);

$$VD = \sum_{k=1}^{n} |1 - V_k| \tag{13}$$

where; VD is Total voltage deviation; k= 1,2,3,…, n; V_k is voltage of k^{th} bus in per unit.

With the weighted approach, equations (8), (12), and (13) can be combined to form a single equation which will now be regarded as the objective function for this work and is as given;

$$F_{min.} = W_1 \times P_{Total\ loss} + W_2 \times \sum_{k=1}^{n} (1 - V_k)^2 + W_3 \times Cost_{D-STAT} \tag{14}$$

where; W_1, W_2 and W_3 represents weighted coefficient assigned to (8), (12), (13)

It should be noted that the weighting coefficient (W_1, W_2 and W_3) assigned to all entities in the formulated objective function is subject to (15). Also, during the simulation, $W_1 = 0.6$, $W_2 = 0.2$ and $W_3 = 0.2$ [2], [3]. The choice of the weight was based on the significance attached to each of the objective functions and in this case, real power loss was given higher significance compared to the other two objectives and this is in line with reference [2], [3].

$$\sum_{i=1}^{3} w_i = 1;\ w_i \epsilon |0, 1| \qquad i = 1, 2\ and\ 3 \tag{15}$$

Since the goal is to get the global optimal results, the fitness function was introduced to compare the potential solutions during the optimization exercise. The fitness of the potential solution was evaluated in line with the objective function formulated for the optimization and is as given with (15) thus;

$$Fitness\ Function = \frac{1}{1 + (W_1 \times P_{Total\ loss} + W_2 \times \sum_{k=1}^{n} (1 - V_k)^2 + W_3 \times Cost_{D-STAT}\ )^2} \tag{16}$$

2.7. System Constraints

The amount of reactive power in kVar from the D-STATCOM and the window defined for the voltage magnitude at each bus form the system inequality constraints. The window defined by these constraints is as follows;

i) The flat bus voltage magnitude was confined by $\pm 5\%$ tolerance and as given;

$$V_i^{min} \leq V_i \leq V_i^{max} \tag{17}$$

where; V_i^{min} is 0.95 $p.u$ and V_i^{max} is 1.05 $p.u$

ii) Limit on the compensation from the D-STATCOM is obtained using equation (18) thus;

$$Q_{D-STAT\ i}^{min} \leq Q_{D-STAT\ i} \leq Q_{D-STAT\ i}^{max} \tag{18}$$

where; $Q_{D-STAT\ i}^{min}$ is 0 $kVar$ and $Q_{D-STAT\ i}^{max}$ is 1900 $kVar$

The conventional power flow equations are regarded as the equality constraints on the system and as defined thus;

$$P_i = |V_i| \sum_{j=1}^{n} |y_{ij}|\, |V_j| cos(\delta_i - \delta_j - \theta_{ij}) \tag{19}$$

$$Q_i = |V_i| \sum_{j=1}^{n} |y_{ij}|\, |V_j| Sin(\delta_i - \delta_j - \theta_{ij}) \tag{20}$$

where; P_i and Q_i connotes the real and reactive power flowing out of bus i, $|y_{ij}|$ and θ_{ij} is size and angle of admittance, δ_i and δ_j is voltage angle at buses i and j.

2.8. Optimal Siting and Sizing

This section discusses the procedural approach to achieving the optimal sizes of D-STATCOM and the most suitable locations for this compensating device. The first stage starts with the preselection of the most vulnerable buses for inclusion of D-STATCOM using the power loss index which is based on efficient/suitable load flow technique. The justification for the choice of PLI has been extensively discussed in the introduction section of this work. After pre-selection, the next stage employed the Firefly algorithm to explore and exploit the search space to find the optimal sizes and sites.

2.8.1. Power Loss Index

It is essential to check the level of security of the system to avoid the phenomenon of voltage collapse, and of the several indices available for checking the level of system security is the power loss index (PLI). The PLI is an analytical technique capable of fishing out nodes that are highly susceptible to voltage collapse, this it does by indicating where the highest real power loss exists within the network [35], the approach is quite simple mathematically and easy to implement compared to other approaches available to fishing out sensitive nodes within the network. The PLI is computed using (21);

$$\text{PLI} = \frac{X(k) - Py}{Px - Py} \tag{21}$$

where; $X_{(k)}$ is Power loss at bus k; Px is maximum reduction in power loss; Py = minimum reduction in power loss

The use of PLI is subjected to the researcher's ingenuity to select the most suitable size of D-STATCOM to be injected into all buses except the source node for a re-run of load flow analysis before power loss index calculation can be done, otherwise, the approach will be messy. The nodes that carried peak values for the PLI have more likelihood to be preselected for the inclusion of D-STATCOM. In principle, the results obtained for PLI are usually arranged in descending order to give good visibility of the buses to be selected. Some authors argued that the first topmost five buses should be selected [18]. However, there is no specific number to be selected, notwithstanding the number of buses in the network under consideration should be a key factor in determining the number of nodes to be preselected, more nodes give the algorithm more search space for exploration and exploitation.

2.8.2. Firefly Optimization Algorithm

The myth behind the FA optimization algorithm can be traced to a researcher in reference [49], who closely studies the behavioral attitudes of insects called fireflies and mimics these behaviors to bring to birth the firefly optimization algorithm. The FA is a member of the meta-heuristics algorithm which is entirely based on the swarm intelligence principle. It can address both simple and complex discrete or continuous optimization problems in Engineering and Natural Sciences [50], [51]. The fundamental laws employed in FA are summarized thus;

- Fireflies are unisex so one firefly will be attracted to other fireflies regardless of their sex.
- The attractiveness is proportional to the brightness, and they both decrease as their distance increases. Thus, for any two flashing fireflies, the less bright one will move towards the brighter one. If there is no brighter one than a particular firefly, it will move randomly.
- The brightness of a firefly is determined by the landscape of the objective function [49]

The key components of FA are the light intensity variation and attractiveness, the landscape determines the attractiveness of each firefly since they are assumed to be unisex and the objective function of any optimization problem is codded as the brightness of each fly. The light intensity at a known distance (r) with respect to the light source is captured with inverse-square law, expressed with (22), [49];

$$I \,\alpha\, \frac{1}{r^2} \tag{22}$$

If the light absorption coefficient for a given medium is fixed, then the relationship between the light absorption coefficient (γ), the light intensity (I), and the distance (r) is expressed with (23), [49];

$$I = I_0 e^{-\gamma r} \tag{23}$$

Similarly, since each is unisex as described with the first rule, the attraction only exists when there is a difference in brightness of each fly and this is modeled with (24), [49], [50].

$$\beta(r_{i,j}) = \beta_{(0)} e^{-\gamma r_{n,m}^2} \tag{24}$$

where; β is firefly attractiveness, $\beta_{(0)}$ is firefly attractiveness at a distance $(r = 0)$, γ is fixed light absorption coefficient, $r_{n,m}$ is cartesian distance

The two-dimensional geometrical distance between two flies (n) and (m) in space at a distance x_n and x_m is given by (25), [49];

$$r_{n,m} = \sqrt{(x_n - x_m)^2 + (y_n - y_m)^2} \tag{25}$$

The difference between the best fitness function shortened as $(G_{best}FF)$ (that is the best fitness function say of m^{th} firefly) and fitness function abbreviated as (FF) of the n^{th} firefly [49] thus;

$$r_{n,m} = G_{best}FF - FF_{rnm} \tag{26}$$

where; $G_{best}FF$ is best fitness function; FF_{rnm} is fitness function between firefly n and m.

If the firefly (n) situated at a distance x_n gets attracted to the firefly (m) situated at distance x_m since Firefly(m) is brighter than that of a firefly(n), the movement between is given by (27) [2], [49];

$$x_n = x_n + \beta_{(0)} e^{-\gamma r_{n,m}^2}(x_m - x_n) + \alpha\left(rand - \frac{1}{2}\right) \tag{27}$$

where; $rand$ is random number $[0, 1]$

The global solution obtained with the use of this algorithm largely depends on how the randomization is manipulated to achieve good and quick convergence of the algorithm.

2.8.3. The Proposed Flow Chart for the Optimization

The flow chart representing the essential stages involved in achieving the set-out objectives is shown in the flow chart of Fig. 1. The details of the processes involved in each box are further broken down into two distinctive stages. Stage one represents the analytical approach while stage two shows the optimization processes involved in selecting the suitable locations and optimal sizes of D-STATCOM required to achieve substantive savings in network energy.

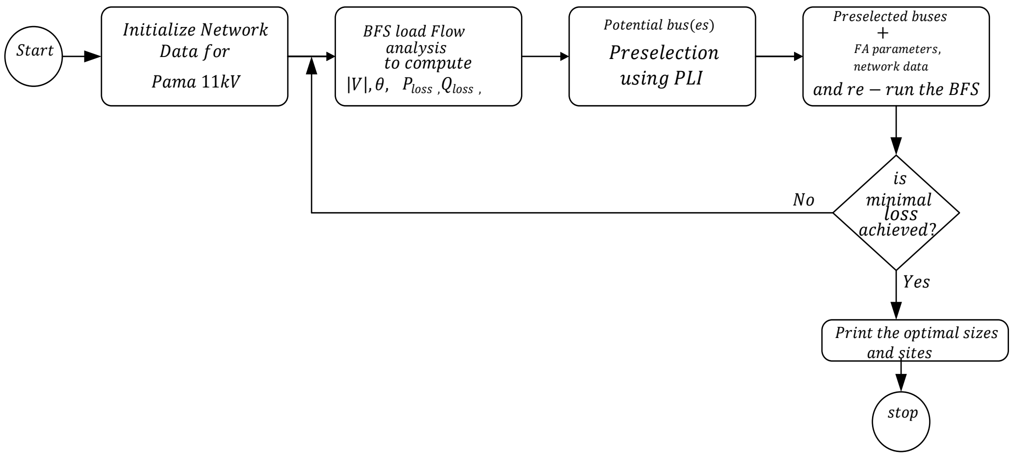

Fig. 1. Flow chart for the approach proposed

Stage I: Analytical Stage
Step 1: Initialize the DN data (line and bus)
Step 2: run the initial load flow (LF) analysis with BFS to obtain the DN steady-state indices such as voltage magnitude, angle, and system losses (Ploss and Qloss) using (1) to (4), (19) and (20)
Step 3: extend the BFS technique to accommodate D-STATCOM mathematical modeling and inject the same amount of kVAr to all buses except the source node
Step 4: re-run LF using extended BFS to obtain DN indices (Ploss and Qloss, Voltage magnitude and angle)
Step 5: evaluate the PLI based on results in steps II and III using (21)
Step 6: re-arrange the results in step V in descending order and pick the topmost seven buses as the potential buses
Stage II: Optimization with FA
Step 7: create the search space of the vector matrix $(size_{D-STAT}, location_{D-STAT})\}$ based on (18)
Step 8: initialize optimization parameters $(\beta_0, \alpha_{min}, \alpha_{max}, \gamma, iter_{max}, No_{fireflies})$, and other required parameter essential parameters $(W_1, W_2, W_3; Q_{D-STAT}^{min}, Q_{D-STAT}^{max}; ; V_i^{min}, V_i^{max})$ in addition to DN data (line and bus)

Step 9: perform a re-run LF using BSF to select possible optimal sizes and sites for DSTAT alongside DN indices (Ploss, Qloss, and Voltage magnitude and angles) based on (1) to (3) ; (19) to (20), and (23) to (27)
Step 10: evaluate the fitness of each potential solution using (16),
Step 11: evaluate the attractiveness by computing geometrical distance among the initially selected optimal sizes using (22) to (25).
Step 12: create a population based on the results of steps 9 to 11 using (27)
Step 13: establish the new DN indices (TLP, TLQ, voltage magnitude) with a re-run LF and obtain new optimal locations and sizes for DSTAT
Step 14: with the result of step V, check if (17) and (18) are satisfied and maximum iteration is reached go to step 16, else, return to step 7
Step 15: display optimal sizes and locations for D-STATCOM
Step 16: with the result obtained in step 14; determine the economic metrics described with (8), (9), and (10)
Step 17: print the results in steps 15 and 16
Step 18: stop the program

2.8.4. Description of Test Case System: Pama 11-kV Feeder, 24 bus RDN in Northern Nigeria

Pama 11kV RD feeder has twenty-four (24) buses, twenty-three (23) branches, with twenty-three (23) and three (3) sectionalizing and tie switches respectively. This feeder takes its supply from Ungwan Boro Injection substation which is a single 33/11kV transformer fed directly from a 132/33kV Kaduna Town 1 Transmission Station situated in the southern area of Kaduna State, Nigeria. Its single-line diagram is shown in Fig. 2. while its precise location on the map is shown in the extract portion of Google Maps depicted with Fig. 3. The base MVA of the Pama feeder is 100, and the total real (P) and reactive power (Q) load is 3838 kW and 2880kVAr respectively.

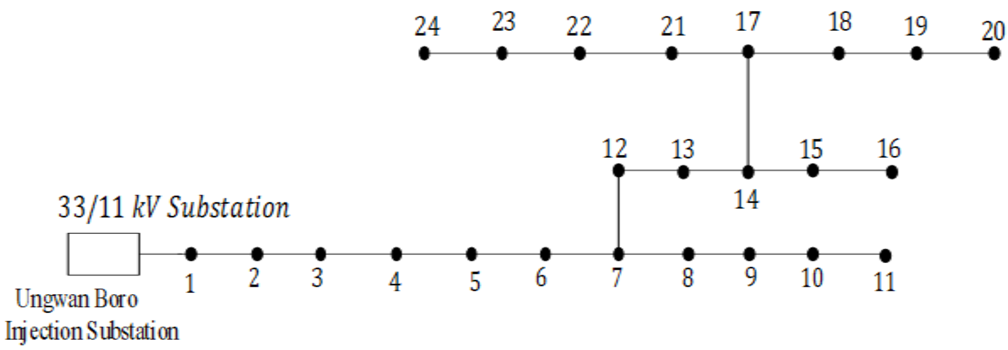

Fig. 2. One-line diagram of Pama 11kV, 24-bus RDN

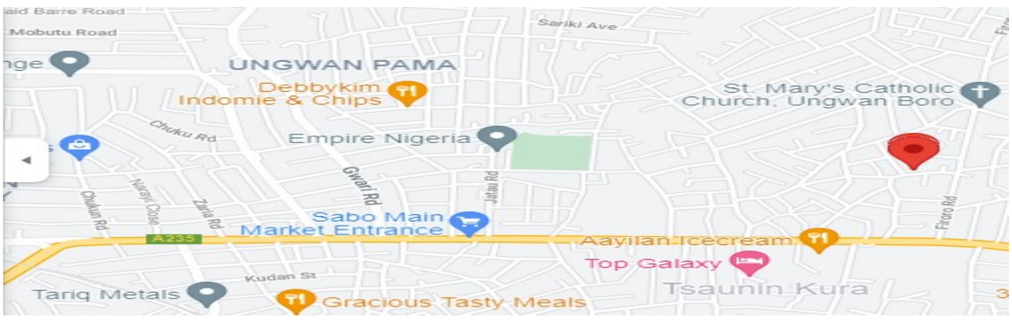

Fig. 3. Pama location on the google map

3. RESULTS AND DISCUSSION

3.1. Discussion of Numerical Results

The effectiveness of the approach proposed which is PLI and FA was investigated at 100 MVA load conditions on a typical Nigerian radial distribution system serving a residential location that is highly densely populated in Southern Kaduna, Northern Nigeria [52]. The result obtained was compared with that of PSO and network feeder reconfiguration technique. The analyses were set to critically evaluate the techno-economic impact of the inclusion of single and multiple D-STATCOM based on the following configurations;

Case I: One optimal location and one optimal size
Case II: two optimal locations and two optimal sizes
Case III: three optimal locations and three optimal sizes

All analyses were executed with MATLAB software to perform the load flow, selection of optimal sizes, sites, and the economic implication of the inclusion of D-STATCOM.

3.2. Base Case Load Flow on Pama 11kV Feeder

The network data: the line and bus data was adapted from reference [53] and following the load flow analysis without incorporation of D-STATCOM, the total active power loss was obtained to be 4.70886kW, the corresponding losses in each branch of the network was as shown in Fig. 4. A significant amount of power loss was observed in branch seven which is about 1.52422kW. Also, other branches with appreciable losses include two (1.22858 kW), three (0.66048kW), and five (0.50242kW) while the rest branches of the network have their value below 0.22849 kW. Similarly, as expected of a typical distribution line, the system voltage profile for buses far from the substation experienced significant voltage deviation from 1.0 p.u and affected buses span from bus seventeen (17) to bus twenty-four (24). The voltage profile for the base case is as shown in Fig. 5.

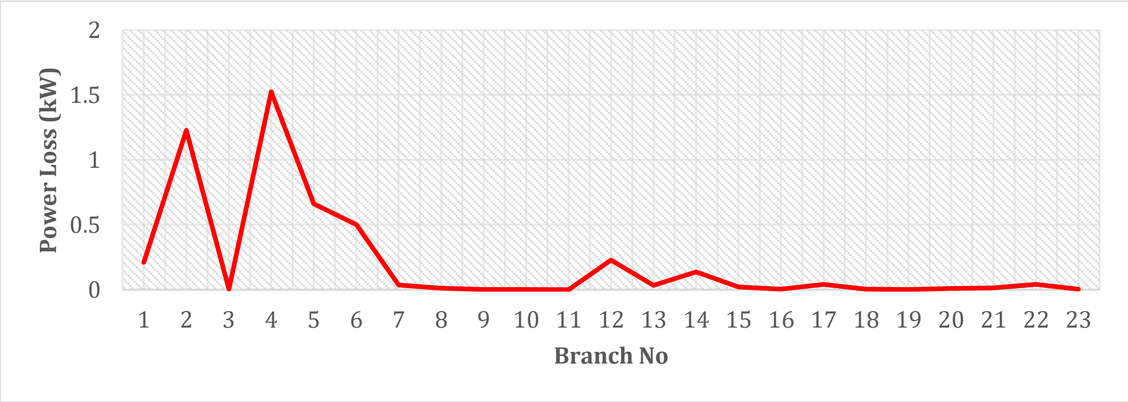

Fig. 4. Base case branch real power loss

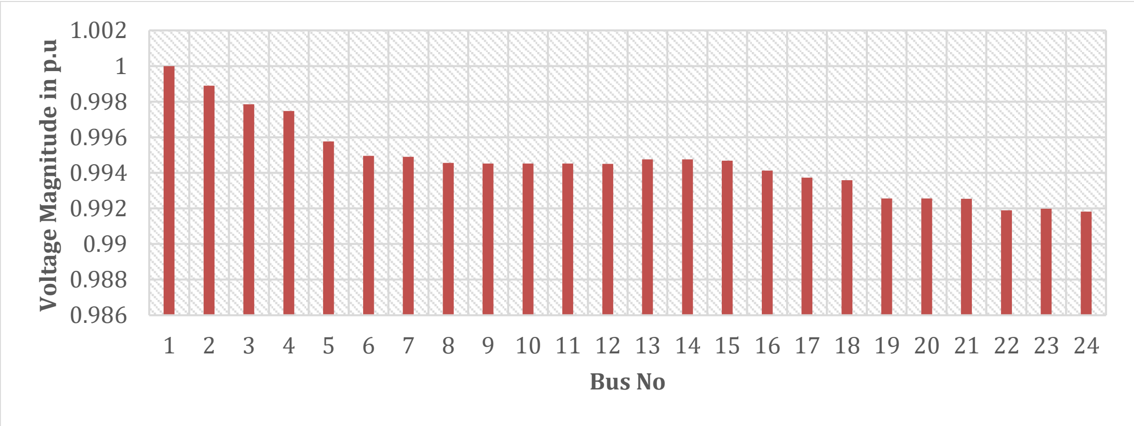

Fig. 5. Base-case voltage profile

To be able to compute the power loss index, several values of kVAr from the D-STATCOM were injected at all the node,50 kVar was attached to all these buses in the network except the source node, the PLI obtained for the network as shown in Fig. 5. The results presented in Fig. 6 showed that potential buses for inclusion of D-STATCOM are 6, 7, 2, 3, 4, 5, 12, 13, 14, 15, 21 and 22.

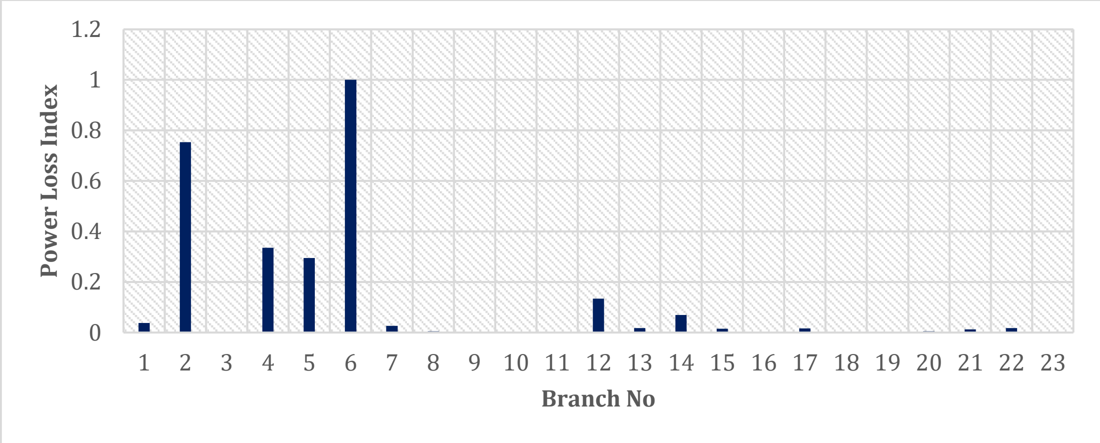

Fig. 6. Power loss index for Pama 11kV feeder

3.2.1. Case I: One D-STATCOM

Of these preselected buses, the exact bus and the right amount of D-STATCOM to be injected were determined in the optimization process with FA. To obtain the optimal values of the core parameters of FA that yield the global convergence, the randomness was varied from 0.001 to 1.0 in the step of 0.0005, the absorption coefficient was also varied in the step of 0.0005 from 0.001 to 1.0, the attractiveness was also toggled with in step of 0.0001 from 0.001 to 1.0, the population size was also toggled in the step of 5 from 5 to 50. At the end of several trials of varying the core parameter value, the optimal parameter setting for the FA is shown in Table 1 and the corresponding convergence curve is shown in Fig. 7. With these parameter settings, the algorithm was observed to converge in about six iterations as against the maximum iteration of twenty projected.

Table 1. FA parameter settings

S/N	Core FA Control parameters	Simulation values that yield global convergence
1.0	Randomness (α)	0.01
2.0	Absorption Coefficient (γ)	0.0272
3.0	Attractiveness (β)	0.05
4.0	Population Size (N)	25.00
5.0	Maximum No of Iterations	20.00
6.0	Attractiveness (β_0) at r=0 (null distance)	1.00

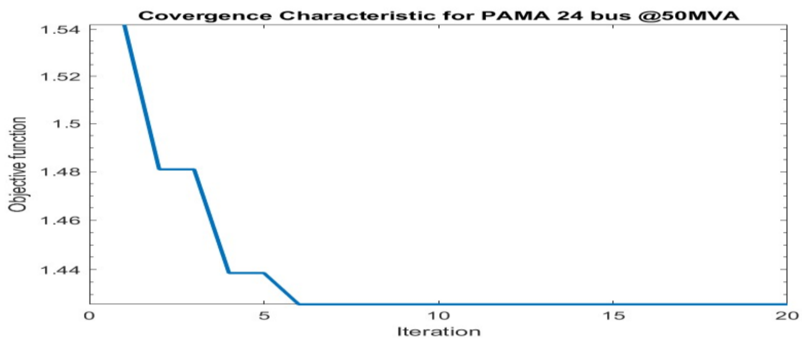

Fig. 7. Convergence curve for 1-D-STATCOM

The optimal site selected was bus six and the optimal value of kVar injected was 1000kVar, with this, the network active power loss reduced from 4.70886 to 1.929177 kW which is about 59.03% reduction, similarly, the bus with the least voltage magnitude also improved from 0.9918138 to 0.9980758 p.u which is equivalent to 0.6% improvement. The comparison of the branch real power and system voltage profile prior to and after the inclusion of D-STATCOM was shown in Fig. 8 and Fig. 9 respectively.

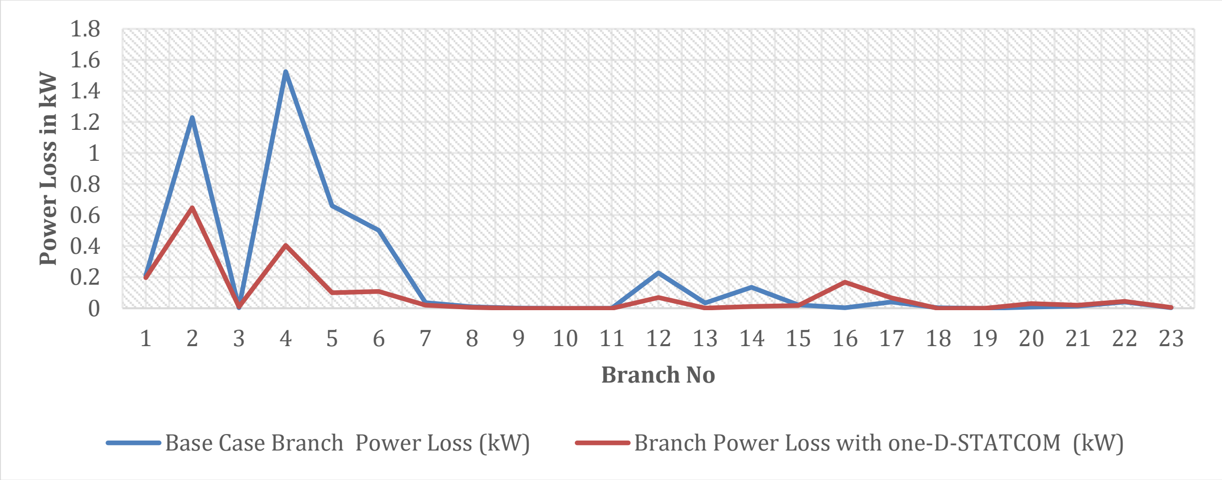

Fig. 8. Comparison of power loss profile in the network branches

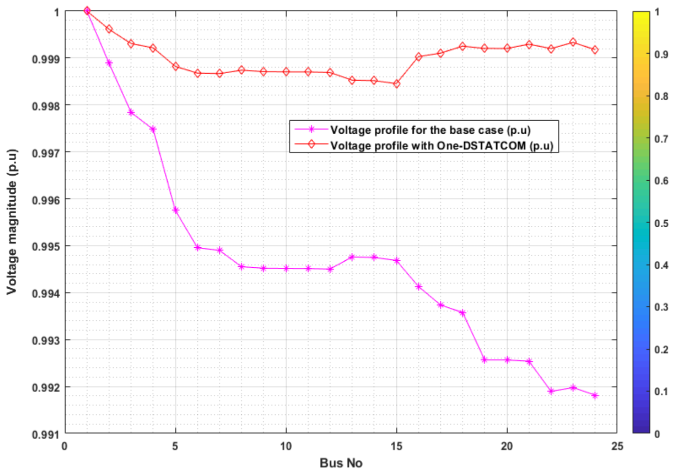

Fig. 9. Voltage profile comparison

3.2.2. Case II: Optimal Location of Two D-STATCOM

The parameter value for FA presented in Table 1 and the pre-selected bus as reported in sub-section 4.2 were used at this stage to determine two optimal sizes and two optimal locations for inclusion of D-STATCOM. The convergence characteristic curve obtained with this scenario was as shown in Fig. 10, the convergence occurred at about thirteen iterations with a sharp slope initial and gradually ended with a step-like shape curve.

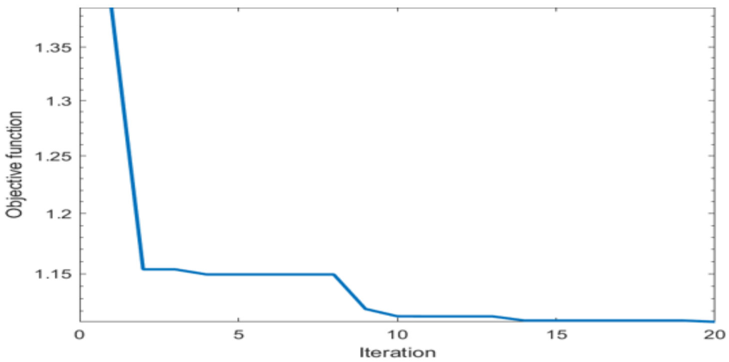

Fig. 10. Convergence curve for two D-STATCOM

The selected optimal locations from the preselected sites are bus twelve (12) and twenty-two (22), the optimal sizes injected are 349.69kVar and 867.29kVar. The base case power loss reduced from 4.70886 to 1.38568 kW which is about 70.57% reduction, the corresponding reduction in active power loss in all the network branches as compared to the base-case scenario is as shown in Fig. 11. Also, the minimum bus voltage rose from 0.99181 to 0.999616 p.u which is equivalent to a 0.78% improvement, the comparison of the system voltage profile to the base case scenario was as shown in Fig. 12.

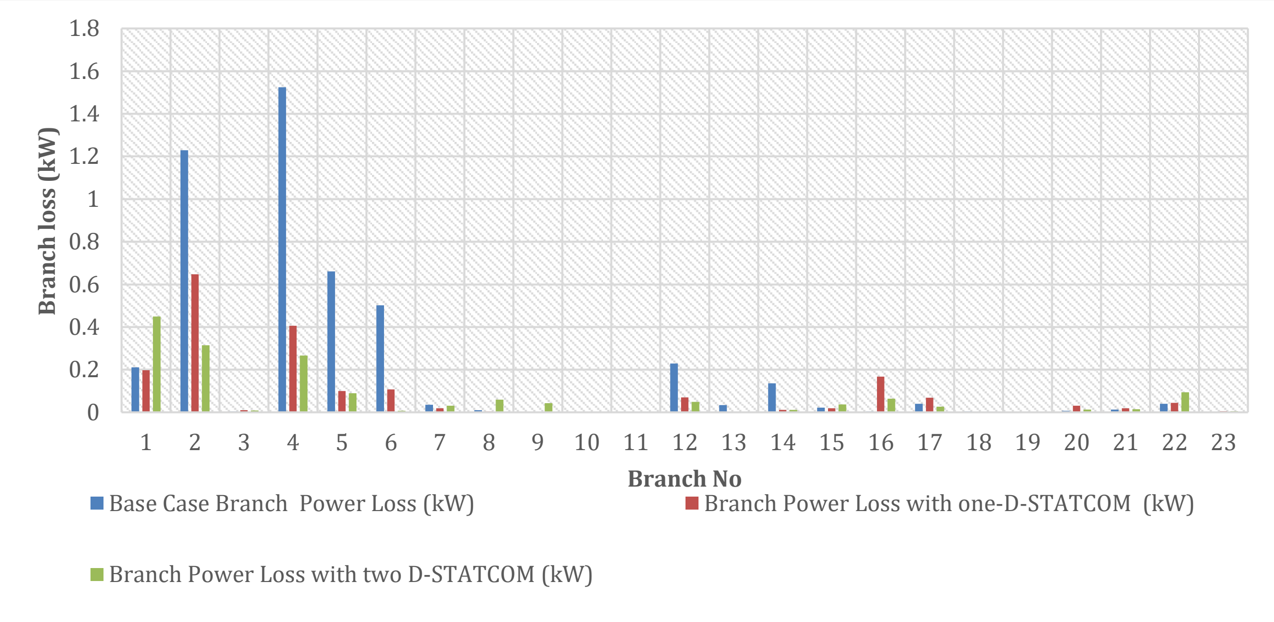

Fig. 11. Comparison of the profile of branch active power loss

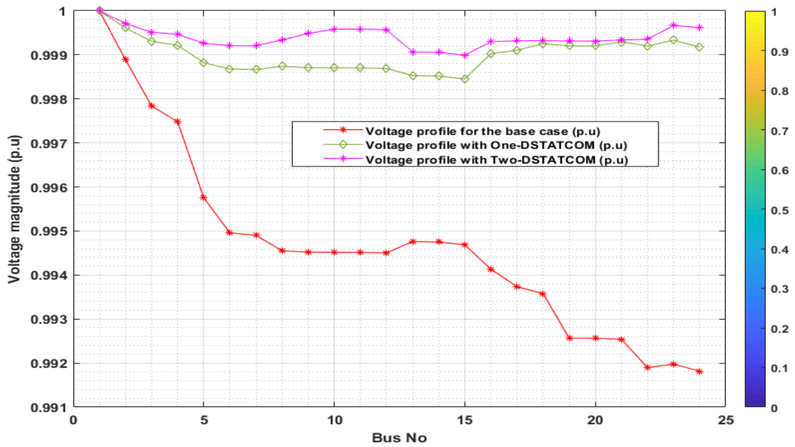

Fig. 12. Comparison of voltage profile for the base case, case I, and case II

3.3.3. Case III: Optimal Location of Three D-STATCOM

With the parameter values reported for FA as depicted in Table 1 alongside the pre-selected buses as reported in sub-section 4.2 were utilized in the optimization process at this stage to determine three optimal sizes and two optimal locations for inclusion of D-STATCOM. The convergence characteristic curve obtained with this scenario is shown in Fig. 13, the convergence occurred at about twelve iterations with a rapidly decelerating step-like curve. The optimal sites selected are buses five, fourteen, and twenty-one and the corresponding optimal sizes are 1200kVar, 424.34 kVar, and 350kVar respectively.

With the optimal sites and sizes selected, the base-case power loss reduced colossally from 4.70886kW to 0.386981kW which translated to about 91.78 % reduction, the corresponding effect of three D-STATCOM injection on the entire branch loss reduction is as presented in Fig 14. Fig. 13 shows the comparison branch loss profile for base case, one-DSTATCOM, two-DSTATCOM, and three-DSTATCOM.

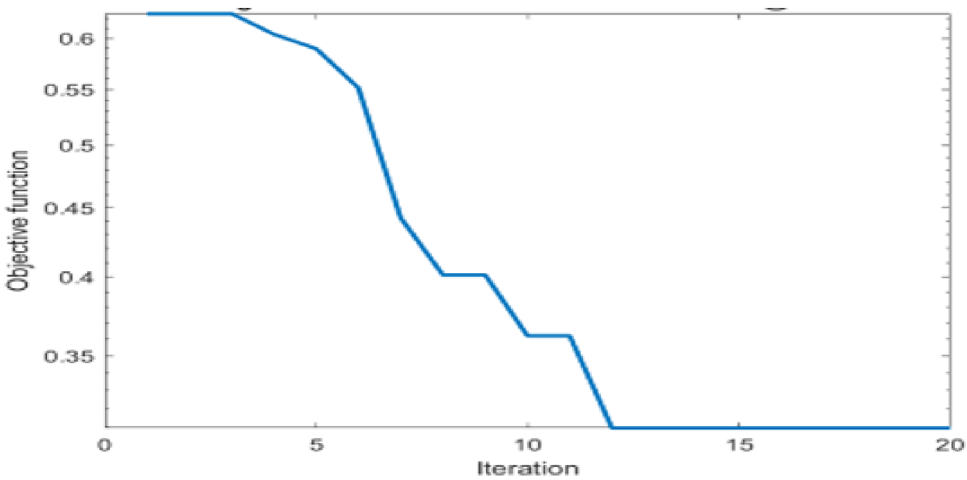

Fig. 13. Convergence curve for optimal 3-DSTATCOM location

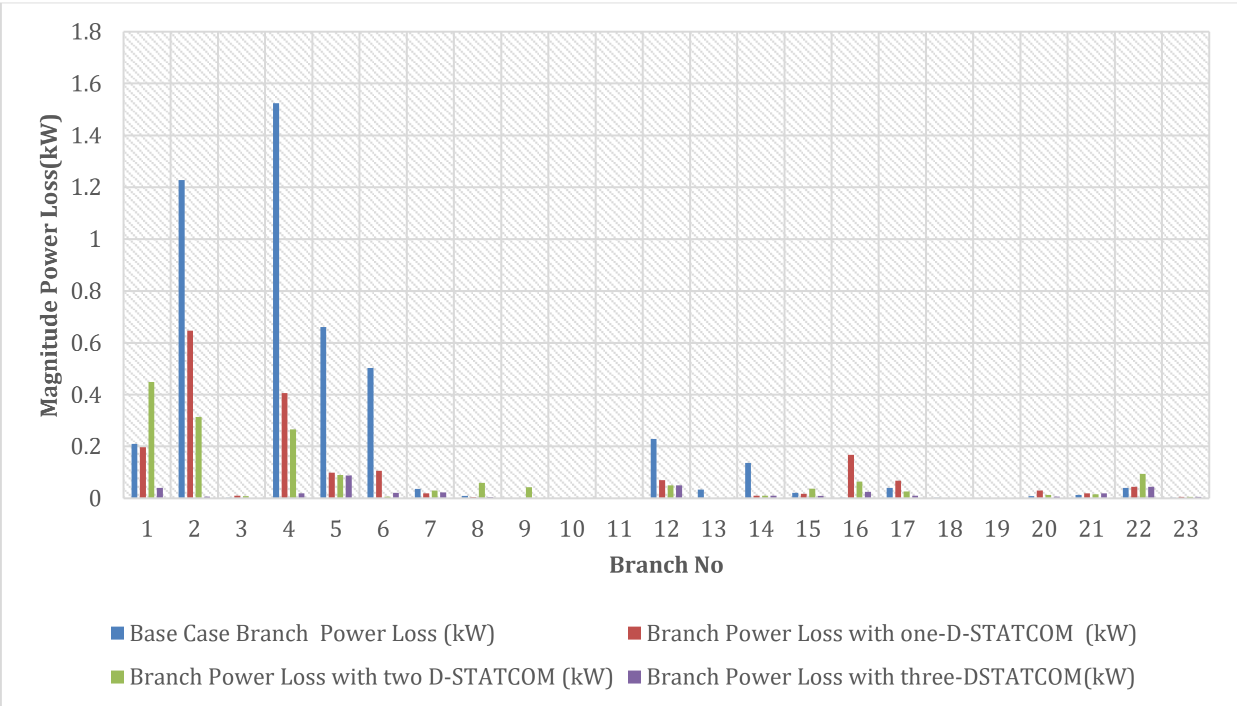

Fig. 14. Comparison of branch power loss profile

Similarly, the bus with minimum voltage magnitude also experienced an outstanding improvement as it rose from 0.9918138 to 0.9997619 p.u which amounted to a 0.79% improvement. Furthermore, a good number of the buses within the network have their voltage magnitude raised above 1.0 p.u as seen in Figure 15. Presented in Table 2, Table 4 are the results obtained for the cost of D-STATCOM installed into the network, the monetary value of energy loss, the annual cost of energy savings due to inclusion of the D-STATCOM, and payback time for the investment on D-STATCOM. The energy billing rate was estimated at 1kWh for 0.06 dollars [4], a time duration of 8760 hours annually was used, the active year of D-STATCOM was taken to be 30 years, and the rate of return on the asset was taken to be 10% [34], and cost of D-STATCOM was taken to be 50$/ kVar, the maintenance and operating cost of D-STATCOM was taken as 0.05 and 0.02 $/kWh respectively [37].

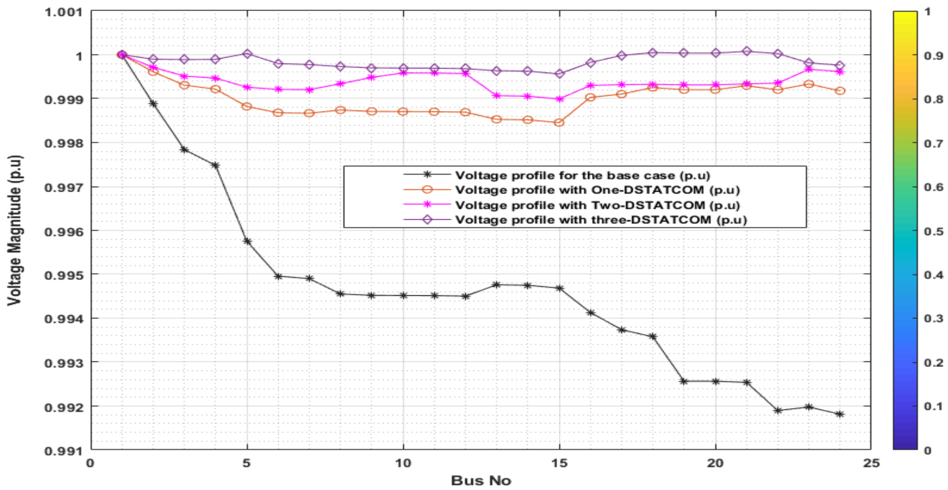

Fig. 15. Voltage profile comparison

Table 2. Summary of Technical and Economic Implications for Case I

S/N	Performance Metrics	Before the inclusion of D-STATCOM	After the inclusion of D-STATCOM
1	V_{min} in (p.u)	0.9918138	0.9980758
2	% improvement in V_{min}		0.6%
3	Site and size of D-STATCOM (kVar)	-	[6, 1000]
4	Total Injected (kVar)	-	1000
5	Cost of D-STATCOM (US($))		5,303.5
6	Total Power Loss (kW)	4.70886	1.929177
7	% Reduction in total power loss	-	59.03%
8	Annual Cost of Energy loss (US($))	2,474.97	1013.98
9	Annual Energy Savings (US($))		1,461.00
10	Payback time (year)		3.63

Table 3. Summary of Technical and Economic Implications for Case II

S/N	Performance Metrics	Before the inclusion of D-STATCOM	After the inclusion of D-STATCOM
1	V_{min} in (p.u)	0.9918138	0.999616
2	% improvement in V_{min}		0.78%
3	Sites and sizes of D-STATCOM (kVar)	-	[12, 349.69; 22, 867.29]
4	Total Injected (kVar)	-	1,216.98
5	Cost of D-STATCOM (US($))		6,454.25
6	Total Power Loss (kW)	4.70886	1.38568
7	% Reduction in total power loss	-	70.57%
8	Annual Cost of Energy loss (US($))	2,474.97	728.313
9	Annual Energy Savings (US($))		1,746.66
10	Payback time (years)		3.69

3.3. Results Validation

Authors in reference [53] have worked on the same network using network feeder reconfiguration and particle swarm optimization to minimize the active power loss and improve the voltage profile. The results obtained from the proposed approach in this work were thus compared with the results presented by authors in reference [54] and as summarized in Table 2-Table 4.

Table 4. Summary of Technical and **Economic** Implications for Case III

S/N	Performance Metrics	Before the inclusion of D-STATCOM	After the inclusion of D-STATCOM
1	V_{min} in (p.u)	0.9918138	0.9997619
2	% improvement in V_{min}		0.79%
3	Sites and sizes of D-STATCOM (kVar)	-	[5, 1200; 14, 424.34; 21, 350]
4	Total Injected (kVar)	-	1,974.34
5	Cost of D-STATCOM (US($))		10,471
6	Total Power Loss (kW)	4.70886	0.386981
7	% Reduction in total power loss		91.78 %
8	Annual Cost of Energy loss (US($))	2,474.97	203.39
9	Annual Energy Savings (US($))		2, 271.58
10	Payback time (years)		4.61

Table 5. Result Validation

Authors/ Evaluation Indices	Base Case	Reference [53] PSO and NFR	**Proposed Approach PLI and FA**		
			Case I	**Case II**	**Case III**
Minimum voltage magnitude (p.u)	0.99181	0.99632	**0.9980758**	**0.999616**	**0.9997619**
% Improvement in voltage magnitude	-	0.45	**0.63**	**0.78**	**0.80**
Total Power loss (kW)	4.7088	2.0176	**1.929177**	**1.38568**	**0.386981**
%Loss Reduction		57.15	**59.03**	**70.57**	**91.78**

3.4. Sensitivity Analysis

Presented Fig. 16 is the effect of change in the rate of energy billing on the annual cost of energy savings for the three levels of penetration of the D-STATCOM on the network considered. It was observed that the annual energy saving shows a linear relationship with a change in the rate of energy billing. As the rate of energy billing rises, the annual energy saving increases proportionately. The inference that can be drawn from this sensitivity analysis is that a rise in the rate of energy will result in an appreciable rise in the annual cost of energy savings. This implies that the utility stands to make money gains while much financial burden will be borne by the end-users even for the same kW of energy consumed.

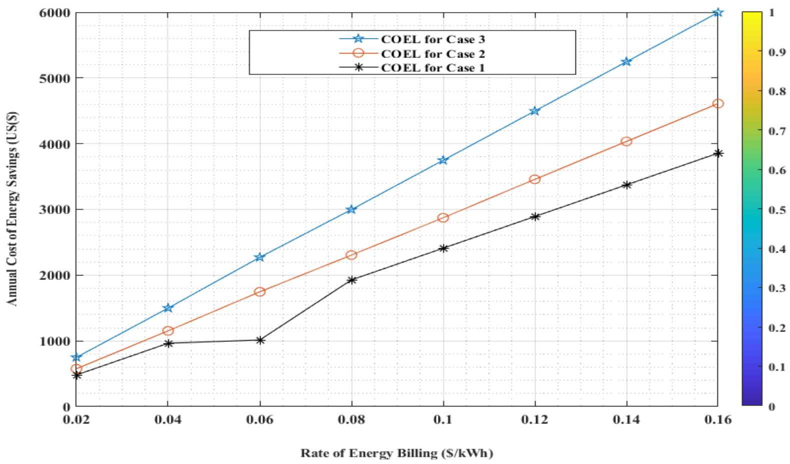

Fig. 16. Rate of change in energy billing on the annual cost of energy savings

4. CONCLUSIONS

Energy-saving effect of reactive power compensation through the use of D-STATCOM on a practical Nigerian radial distribution network was investigated in this present study. The metrics of evaluation used for performance evaluation of the approach proposed in this work include enhancement of bus voltage magnitude, reduction of real power loss, cost of installing the D-STATCOM, annual cost of energy-saving, and payback time on the investment on D-STATCOM. Also, both the optimal sizes and sites for the integration of D-STATCOM were achieved with the help firefly algorithm while the preselection of the suitable sites was done with the power loss index technique. In addition, the forward-backward sweep power flow technique was employed to compute the network parameters with and without integration of D-STATCOM. The simulation results obtained were as presented above and were compared with PSO and NFR that used the same network for achieving voltage magnitude enhancement and reduction in active power loss. The results obtained with the approach proposed were found to be comparatively better than that of PSO and NFR. Furthermore, the annual energy saving and payback period on the investment on D-STATCOM for all the cases examined is pretty good relative to the expected active life of D-STATCOM. Also, sensitivity analysis showing the effect of change in energy billing rate with annual cost of energy saving was investigated which revealed a linear relationship. This present work considered static load datasets while further studies can investigate exploring other optimization techniques, considering different load conditions, and the impact of renewable energy integration. Also, regulatory frameworks, environmental impact, and long-term financial sustainability are crucial for making sound policies on the operation of distribution in the face of the integration of D-STATCOM can also be investigated.

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