International Journal on Electrical Engineering and Informatics - Volume 17, Number 4, December 2025

Performance Enhancement of EDS with Integration of DGs, D-STATCOM and NR for Varying Load Profiles using advanced Metaheuristic -based Pufferfish Optimization Algorithm

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Abstract: This research introduces a novel integrated approach to enhance the performance and efficiency of radial distribution systems (RDS) by simultaneously optimizing the placement and sizing of Distributed Generation (DG) units and Distribution static compensator (D-STATCOM) devices, considering varying load profiles. Utilizing the backward and forward sweep (BFS) load flow method for accurate power flow analysis, combined with the latest Metaheuristic -based Pufferfish Optimization Algorithm (POA) for the optimal allocation, the proposed methodology aims to minimize total system power losses and improve voltage stability. The approach incorporates load variation scenarios normal, light, and peak loads and evaluates the system's voltage. Additionally, Network Reconfiguration (NR) through tie-line switching is integrated to further reduce losses and enhance system reliability. The effectiveness of the methodology is validated on IEEE 33-bus and 69-bus systems, demonstrating significant reductions in power losses (up to 69%) and improvements in voltage profiles across different loading conditions. The results affirm that the combined deployment of DGs, D-STATCOM, and network reconfiguration, guided by metaheuristic optimization, can substantially improve distribution system performance, ensuring enhanced stability, reduced losses, and better voltage regulation under varying load demands.

Keywords: Distributed Generation, D-STATCOM. Backward Forward Sweep Methodology, Radial Distribution Systems, Pufferfish Optimization Algorithm

1. Introduction

The phenomenon of global warming is causing a transition from the use of fossil fuels to the adoption of green energy sources for the purpose of generating power. The growing global focus on sustainable energy and the pressing necessity to reduce environmental effects have expedited the integration of renewable energy technology in power systems. Distributed generation (DG), which includes small-scale energy sources like solar panels, wind turbines, and microturbines, has become an essential element in contemporary electrical distribution networks, especially in microgrids and active distribution systems. Distributed Generation (DG) has multiple benefits, such as diminished transmission losses, increased voltage stability, augmented system reliability, and ecological advantages through lower emissions. Microgrids are essential components of the smart grid, and DGs play a vital role in their functioning [1]. DG utilizes compact technology to produce power near end-users, resulting in cost reduction, enhanced dependability, emission reduction, and increased energy alternatives [2]. This research aims to enhance the efficiency of D-STATCOM and DG units and improve the network layout of radial distribution systems (RDS) through optimization of bus capacity. The study highlights the need to appropriately size and position DG units in the context of deregulated electricity sectors to optimize the reliability and efficiency of the distribution system [3]. The increasing demand for electricity is causing power losses, which is why DG units are being added to DNs. DG enhances the voltage profile (vp), energy security, reliability, and power quality, while simultaneously decreasing power losses. Deregulation leads to voltage fluctuations, sags, and instability problems, which in turn cause higher power losses [4]. Real power loss in distribution systems accounts for approximately 13% of the generated power. To address this issue, DGs and D-STATCOM were installed in the

Received: May 26th, 2025. Accepted: December 30th, 2025
DOI: 10.15676/ijeei.2025.17.4.10

system. When it comes to radial DNs, the dimensions and positioning of DGs and D-STATCOMs are crucial in enhancing voltage stability and decreasing power losses [5]. When sensitive loads are linked, active DNs become even more important in ensuring the main grid's stability, reliability, power quality, and protective coordination [6]. Microgrids and active DNs make extensive use of distributed energy resources (DERs) to alleviate transmission congestion, carbon footprints, the need to reinforce networks, and the expenses associated with delivering electricity. DGs are placed close to electrical loads, enhancing power reliability and quality. However, there are economic, technical, and regulatory issues to consider, such as frequency stabilization, voltage stabilization, and system loss minimization [7]. The optimal size and placement of DG sources help minimize overall losses and ensure economical operation. Microgrids, fueled by renewable energy resources, are becoming essential parts of active DNs. DG makes the transmission and distribution systems more efficient and less dependent on each other. Improved power quality, power factor, and voltage management are all benefits of FACTS devices. One dependable and efficient device is the D-STATCOM. Size and placement are best determined using loss sensitivity indices and stability indicators [8]. The DS is an important part of the power grid and is often used when there are many loads. To effectively meet the demand for electricity, it is important to address distribution losses and cut them down as much as possible.

To mitigate these issues, the strategic positioning and dimensioning of distributed generators, in conjunction with auxiliary devices such as D-STATCOM, are crucial for enhancing system performance. The appropriate distribution of these resources can markedly boost voltage profiles, diminish power losses, and improve voltage stability, thus guaranteeing a dependable and efficient power supply [9]. The deregulated electricity market underscores the necessity of optimization to enhance economic advantages while ensuring system stability and power quality. The intricacy of the optimal allocation problem, defined by various conflicting objectives and numerous restrictions, requires the application of sophisticated optimization methods. Metaheuristic algorithms, including PSO, GWO, and bio-inspired methods, have been widely utilized to efficiently traverse the intricate search space. Recently, innovative algorithms such as the POA have exhibited significant potential in addressing large-scale, nonlinear optimization challenges with enhanced convergence and solution precision [10].

In this context, the present work proposes a comprehensive approach that integrates the backward and forward sweep (BFS) method for load flow analysis with advanced metaheuristic optimization techniques to determine the optimal locations and sizes of DGs and D-STATCOM in RDS under varying load conditions. The methodology aims to enhance voltage stability, minimize power losses, and improve voltage profiles across different load scenarios. The effectiveness of the proposed approach is validated through extensive simulations on standard IEEE radial distribution system models, including the 33-bus and 69-bus networks, and further evaluated on practical distribution networks. This study contributes to the ongoing efforts in power system optimization by introducing a hybrid solution framework that leverages the BFS load flow method, the novel POA, and other bio-inspired techniques.

A. Distributed generation

DG differs from conventional generation in that it creates power on a smaller scale and then trades it with the grid. Embedded, scattered, or decentralized generation are all terms that describe small power sources that are linked to a distribution network (DN); they are all forms of DG. The four categories of DGs are classified according to the amount of reactive and actual power they deliver [11].

Type 1: This DG delivers solely active electricity from photovoltaics, micro turbines, and fuel cells, integrated into the grid via converters/inverters.

Type 2: Reactive-only DG. Examples of synchronous compensators include gas turbines and capacitor banks, which run at zero power factors.

Type 3 DG: Power generation with reactive power consumption. Induction generators, which are widely utilized in wind farms, fall within this type. Nonetheless, when it comes to reactive power consumption or production, doubly fed induction generator (DFIG) systems mimic synchronous generators.

Type 4: DG with reactive and active power. DG units utilizing synchronous machinery (e.g., cogeneration, gas turbines) fall under this category.

B. D-STATCOM

It is a device that has the capacity to either inject or absorb active or reactive power at a specific location within an electrical system, thereby enhancing the voltage profile. Readers are advised to consult the reference [12] to gain a comprehensive comprehension of the D-STATCOM model.

C. Network Reconfiguration

NR in a distribution system refers to the process of changing the operational topology of the network by switching certain circuit elements (like switches, circuit breakers, or sectionalizes) on or off. The main goal is to alter how loads are supplied, optimize system performance, reduce losses, improve reliability, or accommodate changes in load demands or outages. In essence, it involves selectively opening and closing switches within the distribution network to create a different configuration of feeders and load paths—while typically maintaining a radial (tree-like) structure. This process helps utilities manage their systems more efficiently without physically modifying the infrastructure. [13]

D. Literature

Particle Swarm Optimization (PSO) is proposed for the allocation and sizing of Distributed Generators (DGs) in the IEEE 33-Bus radial distribution system [14]. The Bacterial Foraging Optimization Algorithm (BFOA) calculates the sizes of distributed generation (DG) and capacitors. BFOA enhances the installation of capacitors and distributed generation (DG) by recommending their simultaneous implementation in power distribution systems. Utilized IEEE 33-bus system this robust and efficient allocation technique for NR DG and D-STATCOM incorporates techno-economic objectives as discussed in. The gravitational search algorithm (GSA) minimizes power loss, optimizing allocation in the IEEE 33 bus system by simultaneously distributing NR, D-STATCOM, and DG, hence reducing network losses and improving RDS voltage. A virtual STATCOM configuration utilizing a controlled manner functions as a singular STATCOM with numerous distributed generators interconnected within the system [15]. This study proposes a teaching-learning-based hybrid optimization approach for the optimal placement of distributed generation (DG) and static synchronous compensators (STATCOM). Multi-objective function employed in the IEEE-33 and real-time 52-bus systems. A cuckoo search-based technique is used to show how to assign D-STATCOM. Even though the optimal network reconfiguration (ONR) method has many benefits, it is challenging to decide what to do. The goal of is to suggest a way to assign ONR and DG at the same time so that loss is reduced, the feeder load is balanced, and the voltage profile is improved. A grasshopper optimization algorithm is used to improve the RDS voltage profile under different loading situations. This best method is suggested in [16]. In [17], a copula theory is suggested as a way to describe how errors in dynamic NR are not correlated in a straight line. Develops an improved heap-based optimizer to address the NR with DG allocation combinatorial optimization issue. To minimize power loss in RDS, it is recommended to address the simultaneous NR and DG allocation problem. Use of the chaotic search group technique, a method for planning multi-period NR for RDSs with automatic transitions, is put forward [17]. There is an idea in for a parallel slime mold method that could solve the NR problem by distributing DG. As a multi-objective RDS problem, the study in [18] addresses the ONR problem by satisfying several network conditions, including the minimization of voltage deviation, power losses, and load imbalance. The ONR has been mentioned as a way to make the RDS voltage less volatile [19]. The suggested method proposes new ways to look at the problem of regulating voltage in a world where green energy sources are being used by many people. Several well-known methods that have been developed in the literature don't solve the problem at the same time because they don't take into account the NR and the best way to assign DGs and D-STATCOMs. The voltage profile (vp) in a distribution system refers to the variation of voltage levels at different points along the network, from the substation to the end-user loads. Maintaining a proper voltage profile is essential to ensure power quality, system reliability, and efficient operation. Typically, voltage tends to drop as it moves away from the substation due to line losses; thus, voltage regulation devices and control strategies are used to keep voltages within acceptable limits throughout the distribution network. [20]. In a radial distribution system, active power loss occurs due to resistance in conductors when real power flows from the source to loads, resulting in heat dissipation. Reactive power losses involve the transfer of reactive energy primarily caused by inductive loads, leading to additional current flow that increases losses in the system. Both types of losses affect efficiency: active power losses directly waste energy as heat, while reactive power losses increase overall current, thereby indirectly increasing active losses. Managing these losses improves system efficiency and voltage stability. [21]

E. Paper Contribution

This paper proposes the PAO to optimize DG allocation and size, reducing network power losses and improving voltage profiles with minimal iterations. The findings were assessed for power loss reduction and voltage profile improvement. The study developed a PAO technique to optimize DG allocation and size on both IEEE 33-bus and 69-bus systems. The study examined the effects of three DGs with D-STATCOM and reconfiguration.

The summary of PAO's contribution includes:

1. In this manuscript, both BFS and PAO are implemented to solve problems related to the optimal allocation and sizing of DGs.
2. Evaluation of the effect of multiple DGs and D-STATCOM with reconfiguration at various locations while considering different loading conditions of two distribution systems.
3. A multi-objective optimization strategy that balances power loss reduction and voltage profile improvement under dynamic loading conditions.
4. A coordinated placement strategy for DGs and D-STATCOMs combined with NR, which enhances both operational efficiency and flexibility.
5. Comparative performance analysis that demonstrates the advantages of the integrated method over existing single-technique approaches.

E. Paper Organization: Remaining arrangement of paper in the following order: Segment 2: presented problem formulation; Segment 3: an overview of the suggested PAO method is presented. Segment 4: Result and discussion of two systems 5. The conclusion of the paper is given.

2. Problem formulation

Fast Decoupled load flow, Newton-Raphson, and Gauss-Seidel are not applicable to DN because of their low reactance to resistance ratios (X/R). Methods for the distribution of power use radial line forward and reserve sweeps to ascertain line flows and voltage magnitudes. The accuracy and strong convergence of backward/forward sweep-based distribution load flow were the deciding factors in this paper's selection. NR, modified NR, and fast decoupling approaches are unsuitable for distribution systems. They are reliable only for transmission systems with a high X/R ratio, but their ill-conditioned meshed topology prevents convergence in DN. Thus, distribution system analysis requires an efficient load flow approach [22]

a. Load current computation: The complex power S at bus i can be represented as in equation (1) for any node or bus in the distribution system. The corresponding load or node current injected during the kth iteration of bus i is depicted in equation (2).

$S_i = P_i + JQ_i$ for i =1,…..Nbus (1)

$I_i^k = (\frac{PI_i+QI_i}{V_i^{k-1}})^*$ where i = 2,3,…..Nbus (2)

b. Bus power computation: Here in Figure 1, the sending end is denoted as i and the receiving end as i+1. A power flow's active and reactive components are [23].

$$P_{i+1} = P_i - P_{D(i+1)} - \left(\frac{P_i^2+Q_i^2}{V_i^2}\right) R_i \quad (3)$$

$$Q_{i+1} = Q_i - Q_{D(i+1)} - \left(\frac{P_i^2+Q_i^2}{V_i^2}\right) X_i \quad (4)$$

c. Bus voltage computation: (i+1)th bus voltage is calculated using

$$V_{i+1}^2 = V_i^2 - 2(P_iR_i + Q_iX_i) + (R_i^2 + X_i^2)\left(\frac{P_i^2+Q_i^2}{V_i^2}\right) \quad (5)$$

d. Branch Losses computation: In Radial distribution network with branches B={1,2,...,Nb}

The current through branch i:

$$I_{i(i+1)} = \frac{S_i}{V_{s,i}} = \frac{P_i+jQ_i}{V_{s,i}}; \Rightarrow \quad |I_i|^2 = \frac{S_i}{V_{s,i}} = \frac{P_i^2+Q_i^2}{|V_{s,i}|^2} \quad (6)$$

Si is the complex power flow through branch i

a. Power loss computation: In Section 1, the active and reactive power loss is determined by applying the formula where i is the starting bus and i+1 is next bus and k is the branch between starting and next bus. R and X is resistance and reactance of k_{th} branch.

$$P_{i,i+1}^{loss} = \left(\frac{P_k^2+Q_k^2}{V_i^2}\right) R_k \quad (7)$$

$$Q_{i,i+1}^{loss} = \left(\frac{P_k^2+Q_k^2}{V_i^2}\right) X_k \quad (8)$$

By summing the losses in all parts, the total active power and reactive power losses may be determined, and the result is given by. Whare N is no of buses.

$$P_{TL} = \sum_{i=i}^{N_{bus}} P_{i,i+1}^{loss}\ ; \quad Q_{TL} = \sum_{i=i}^{N_{bus}} Q_{i,i+1}^{loss} \quad (9)$$

A. Objective function

Min F = $w_1 \cdot f_1 + w_2 \cdot f_2$ (10)

Where:

F = Total objective function to minimize

f_1 = Active power loss in the distribution system (in kW)

f_2 = Voltage deviation from nominal value (typically 1.0 p.u.)

w_1,w_2 = Weighting factors such that $w_1+w_2=1$ assigned based on the relative importance of each objective

Minimize Total Active Power Loss

$$f_1 = \sum_{i=1}^{n} R_i.\frac{(P_i^2+Q_i^2)}{V_i^2} \quad (11)$$

Where:

Ri = resistance of branch i

Pi,Qi = active and reactive power flow in branch i

Vi = voltage at the sending bus of branch i

n = total number of branches

Minimize Voltage Deviation

$$f_2 = \sum_{j=1}^{m} \left| V_j - 1.0 \right| \tag{12}$$

Where:
Vj = voltage magnitude at bus j
m = total number of buses

B. Constraints and Control Variables

1. DG generation limits: The real and reactive power introduced by the DG unit must lie within the prescribed range, as expressed in equation.

$$P_{DG,i}^{min} \leq P_{DG,i} \leq P_{DG,i}^{max},\ Q_{DG,i}^{min} \leq Q_{DG,i} \leq Q_{DG,i}^{max} \tag{13}$$

Where i=1……N_{DG} $P_{DG,i}^{min}, P_{DG,i}^{max}, Q_{DG,i}^{min}$ *and* $Q_{DG,i}^{mimaxn}$ are the active and reactive power limits of each generator or DG unit

2. D-STATCOM power limits: Active and reactive power delivered by the D-STATCOM unit must be within this prescribed range as expressed in equation.

$$P_{D-STATCOMG,i+1}^{min} \leq P_{D-STATCOMG,i+1} \leq P_{DD-STATCOMG,i+1}^{max} \tag{14}$$
$$Q_{D-STATCOMG,i+1}^{min} \leq Q_{D-STATCOMG,i+1} \leq Q_{DD-STATCOMG,i+1}^{max} \tag{15}$$

Where $P_{D-STATCOMG,i+1}^{min}, P_{DD-STATCOMG,i+1}^{max}, Q_{D-STATCOMG,i+1}^{min}$ *and* $Q_{DD-STATCOMG,i+1}^{max}$ are active and reactive power limits of D- SATATCOM at i+1 bus.

1. Bus voltages constraints: Restriction of bus voltage given by using this equation
   $V_i^{min} \leq V_i \leq V_i^{max}$ i = 1, 2,….. N Bus (typically 0.95–1.05 pu) (16)
   Where V_i^{min} *and* V_i^{max} are bus voltage at i_{th} bus

2. Constraints of line current: Restriction of line current given by equation
   $I_i \leq I_i^{max}$ i = 1, 2,…..N_{Line} (17)

3. DG size limits: The maximum size of the DG unit should not exceed the maximum burden on the network, as this could result in the DG unit consuming power from the network instead of supplying it, which could result in the distribution network becoming unstable [24].
   $$DG_{size}^{min} \leq DG_{size} \leq DG_{size}^{max} \tag{18}$$
   Where DG_{size}^{min}, DG_{size}^{max} are 100 KW and 3000 KW respectively.

4. Power Balance Constraints of DGs: The power output from a DG system can be quantified using a specified mathematical equation.
   $$\sum_{i=1}^{N_{Bus}} P_{DG,i} \leq \sum_{i=1}^{N_{Bus}} \left(P_{D,i} + P_{loss,i}\right) \tag{19}$$
   $$P_{DG}^{min} \leq P_{DG} \leq P_{DG}^{max} \tag{20}$$
   The load demand + total power losses should be equivalent to the power supplied by the substation in addition to the DG output power.

5. D-STATCOM power balance constraints: This relation can be used to express the quantity of power output from D-STATCOM units.
   $$\sum_{i=1}^{N_{Bus}} Q_{DG,i} \leq \sum_{i=1}^{N_{Bus}} \left(Q_{D,i} + Q_{loss,i}\right) \tag{21}$$
   $$P_{D-STATCOM}^{min} \leq P_{D-STATCOM} \leq P_{D-STATCOM}^{max} \tag{22}$$

The power supplied by substation in addition to D-STATCOM output power should be equivalent to the load demand plus total power losses.

3. Methodology

Initially, the power loss is determined using the Load Flow procedure. The Grey Wolf Optimization PAO algorithm is employed to gradually adjust the size of the DG after it has been placed. Compute the losses for DGs of varying capacities. The DG size that leads to the lowest loss is considered the most optimal DG size at the moment. The procedure is repeated until no additional minimum losses from the DG placement are attained.

A. Forward –Backward Sweep Methodology

The single-source network load flow is obtained by iteratively solving two equations. The initial set of equations is employed to ascertain the reverse power transfer from the root node to the final branch. The other equations determine the voltage magnitude and angle for each node, working their way up from the root node to the last node. In fig.1 layout of 6 bus system is considered only for understanding BFS methodology [25].

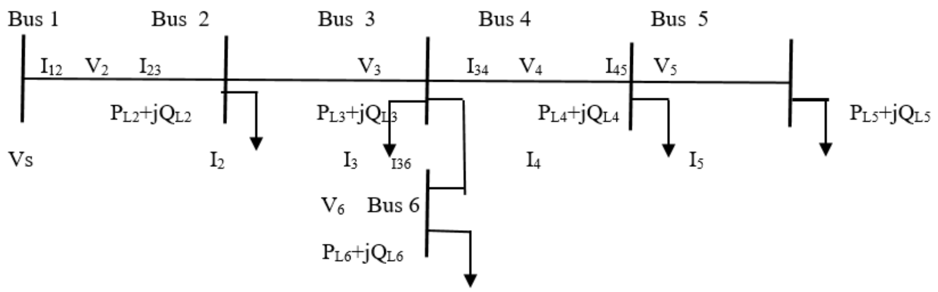

Figure 1. Redial distribution bus system

Methodology of forward and backward sweep load flow of given bus system is as followed. Assume bus voltage $V_2 = V_3 = V_s\angle 0^0$ for simplicity of understanding Current of i_{th} bus is simply given by equaion

$I_i^* = \left(\frac{P_{Li}+jQ_{Li}}{vi}\right)^*$ For j: 2,3………..N=6 (23)

Calculate the current of each bus $I_n = \left(\frac{S_n}{V_n}\right)^*$ (24)

Calculate each line current starting from the end of feeder (Backward sweep)

$I_{n-1}^{line} = I_n + \sum_{k=n} I_k^{line}$ (25)

Calculate the voltage of each bus starting from the first bus (Forward sweep)

$V_{n+1} = V_n - Z_n^{line} \times I_n^{line}$ (26)

B. Application of BFS to calculate branch current and bus voltage

Step 1: initialization of V_0 voltage

$V_i^{(0)} = V_s\angle 0^0$ for i= 2, 3,….N (27)

Step 2: Count Iteration initialization k=1

Step 3: $I_i^k = \left(\frac{P_{Li}+jQ_{Li}}{V_i^{k-1}}\right)^*$ for i=2,3,……N load current computation. (28)

Step 4: Apply backward sweep

$I_{mn}^{(k)} = I_n^{(k)} + \sum of\ all\ the\ current\ of\ branchs\ emanated\ from\ bus\ n$ (29)

Step 5: forward sweep

$V_n^{(k)} = V_m^{(k)} - Z_{mn} I_{mn}^{(k)}$ for all i = 2,3,………..N where e is error (30)

Step 6: $e_i^k = V_i^k - V_i^{k-1}$ for all i= 2, 3,………..N (31)

Step 7: $e_{max}^k = max(e_2^k, e_3^k, e_4^k \ldots\ldots e_N^k)$ (32)

Step 8: If this condition satisfies then print result

$$e_{max}^{k} \ll \in (tolarance) \tag{33}$$

If not, set the iteration count to k+1 and go to step 3.

4. Optimization Method

Initially, the power loss is determined using the Load Flow procedure. The PAO algorithm is employed to gradually adjust the size of the DG after it has been placed. Compute the losses for DGs of varying capacities. The DG size that leads to the lowest loss is considered the most optimal DG size at the moment. The procedure is repeated until no additional minimum losses from the DG placement are attained.

A. Pufferfish Optimization Algorithm

Pufferfish are small to medium marine fish with large spines and a beak-like mouth. They lack certain fins and bones, and defend themselves by inflating into a spiky ball, deterring predators. The proposed POA technique models both predator attacks and the pufferfish's defense mechanism [26].

The POA strategy uses population search in an iterative optimization process, with each member representing a potential solution as a decision variable vector. These members form a matrix (Equation 34), and their initial positions are set at the start (Equation 35).

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_n \end{bmatrix}_{N\times m} = \begin{bmatrix} x_{1,1} & \cdots & x_{1,d} & \cdots & x_{1,m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i,1} & \cdots & x_{i,d} & \cdots & x_{i,m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{N,1} & \cdots & x_{N,d} & \cdots & x_{N,m} \end{bmatrix}_{N\times m} \tag{34}$$

$$x_{i,d} = lb_d + r(ub_d - lb_d) \tag{35}$$

Evaluate each POA member \(X_i \) as a candidate solution using Equation (36), resulting in a vector of objective function values.

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_n \end{bmatrix}_{N\times 1} = \begin{bmatrix} F(X_1) \\ \vdots \\ F(X_i) \\ \vdots \\ F(X_N) \end{bmatrix}_{N\times 1} \tag{36}$$

F represents the objective function vector, with Fi being contingent upon the ith element of the POA. POA assesses candidate solutions according to objective criteria, refining the optimal and suboptimal alternatives with each repetition. The model simulates interactions between pufferfish and their predators: predators focus on weaker pufferfish, necessitating positional adjustments. During the exploration phase, predator assaults emulate a worldwide search, advancing POA members toward superior solutions. Pufferfish subjected to predation are characterized by elevated objective values as determined by Equation (37).

$$CPi = \{X_k : F_k < F_i \text{ and } k \neq i\}, \text{ where } i = 1, 2, \ldots, N \text{ and } k \in \{1, 2, \ldots, N\} \tag{37}$$

CPi lists possible pufferfish locations for predator i. Xk is a population member with a higher objective value, Fk. POA randomly selects a pufferfish (Equation 5) to guide predator movement, and a better position (Equation 38) replaces the previous one.

$$x_{i,j}^{p1} = x_{i,j} + r_{i,j}.(SP_{i,j} - I_{i,j}.x_{i,j}), \tag{38}$$

$$X_i = \begin{cases} X_i^{p1}, & F_i^{p1} \le F_i \\ X_i, & else, \end{cases}$$

In the Pufferfish Optimization Algorithm:
Phase 1: Randomly generate new placements for predators based on selected pufferfish (SPi) and their dimensions, utilizing random integers ri, j and Ii, j.
Phase 2 (Exploitation): When threatened, a pufferfish inflates its spines by filling with water, thereby mimicking a localized search. It retreats from predators, and positions are revised according to Equation (38). If the new location enhances the goal function (as verified by Equation (39)), the position is approved; if not, it remains unaltered.

$$x_{i,j}^{p2} = x_{i,j} + (1 - 2r_{i,j}).\frac{ub_j - ib_j}{t} \quad (39)$$

$$X_i = \begin{cases} X_i^{p2}, & F_i^{p2} \le F_{i;} \\ X_i, else, & \end{cases}$$

Here, X_i^{p2}i is the new position calculated for the ith predator based on the second phase of the proposed POA, X_i^{p2}
i,j is its jth dimension, FP2
i is its objective function value, ri,j
are random numbers from the interval [0, 1], and t is the iteration counter.

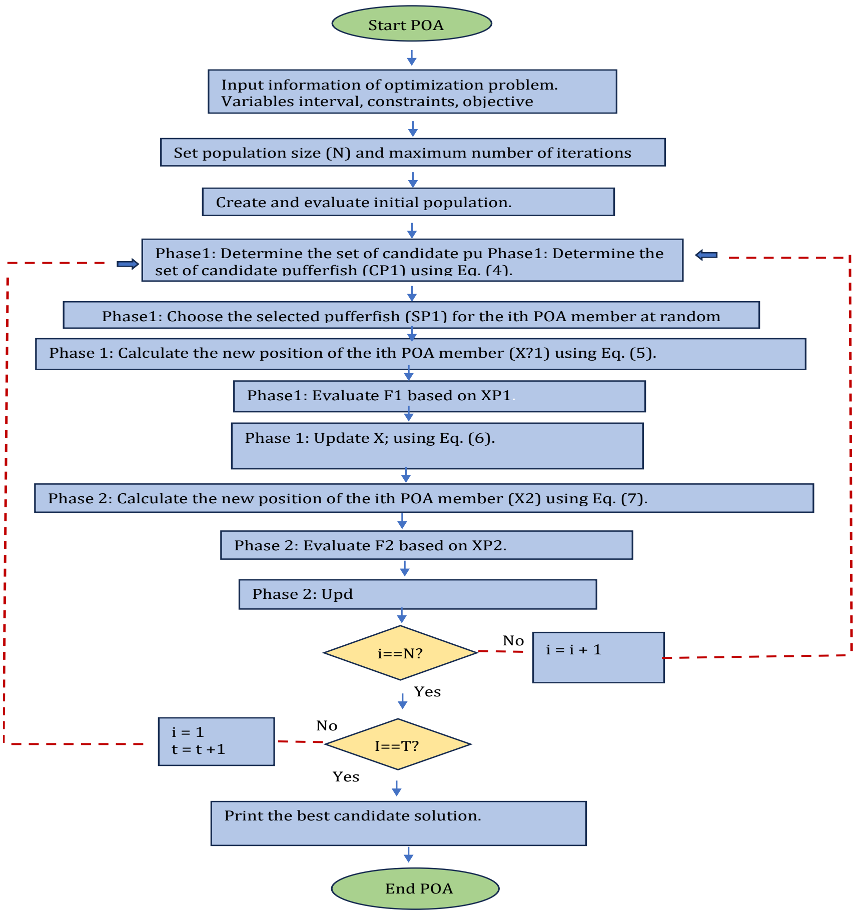

Figure 2. Flow chart of POA

5. Results and Discussion

POA was applied to two distribution networks, IEEE 33-bus system and IEEE 69-bus system. The objective function of the optimization was to minimize the active and reactive power losses by optimally allocating and sizing multiple DG units with D-STATCOM and reconfiguration.

Simulations were carried out utilizing MATLAB R2023a platform and Direct load flow technique (Backward and Forward Sweep) was employed to ascertain the stable condition of the system. Variable load profile is considered here. Load factor (LF) considered from normal load (LF=1), light load (LF=0.75) and peak load (LF=1.5)

The following three different test cases are considered for both systems to find optimum values

Case1: Base Case
Case2: DG units penetration
Case3: Combined DGs and D-STATCOM penetration
Case4: Simultaneous DGs, D-STATCOM and NR

A. IEEE 33-bus system

The optimization problem of RDS is executed utilizing the IEEE 33 bus system. [27]. The system has a power rating of base 100 MVA and operates at a voltage of 12.62 kV. Furthermore, the system has a capacity of 420 kilovolt-amperes (kVA) and a power factor (pf) of 0.85 per unit. The RDS has a reactive power need of 2.3 MVAr and an active power requirement of 3.7 MW. Real and reactive power losses are 202.47 kW and 135.03 KVAr respectively at base case.

Table 1. Summary of results for the four cases with different loading considered for 33-bus network.

Load Variation Conditions	Evaluated Parameters	Optimal DG	DG + D-STATCOM		DG, D-STATCOM and NR (Tie line opened at bus)		
Base Case Load Factor (LF = 1)	Optimal Sizing & Siting	782.30 kW (13) 1096.50 kW (23) 1100.60 kW (29)	865.30 kW (13) 1100.0 1kW (23) 1075.40 kW (29)	1125.8 kVAr (30)	860.30 kW (12) 1110.0 1kW (20) 1060.40 kW (32)	1250.8 kVAr (28)	9, 14, 28, 33
	Total Power Loss (kW, kVAR)	78.16, 62.30	68.96, 55.60		61.5, 50.60		
	% Loss Reduction	61.37, 53.86	65.944, 58.24		69.62, 62.52		
	Min Bus Voltage (p.u)	0.9690p.u.(28)	0.9769 p.u.(32)		0.9859 p.u.(32)		
Load Factor (LF = 0.70 - Light Load)	Optimal Sizing & Siting	775.30 kW (12) 1010.50 kW (25) 1096.60 kW (27)	850.30 kW (10) 1094.01 kW (21) 1068.40 kW (25)	1110.8 kVAr (27)	800.30 kW (12) 1050.0 1kW (15) 1160.40 kW (33)	1150.8 kVAr (28)	9, 12, 25, 30
	Total Power Loss (kW, kVAR)	71.3, 60.30	58.4, 51.60		52.3, 45.30		
	% Loss Reduction	64.74, 55.34	71.15, 61.78		74.16, 66.45		
	Min Bus Voltage (p.u)	0.9790p.u.(27)	0.98591 p.u.(30)		0.995 (32)		
Load Factor (LF = 1.5 - Peak Load)	Optimal Sizing & Siting	792.30 kW (15) 1100.50 kW (22) 1130.60 kW (26)	870.30 kW (12) 1130.01 kW (22) 1090.40 kW (28)	1180.8kVAr (28)	960.30 kW (11) 1210.0 1kW (18) 1160.40 kW (32)	1350.8 kVAr (28)	6, 16, 26, 33
	Total Power Loss (kW, kVAR)	82.2, 75.50	71.6, 66.50		68.2, 55.60		

Load Variation Conditions	Evaluated Parameters	Optimal DG	DG + D-STATCOM	DG, D-STATCOM and NR (Tie line opened at bus)
	% Loss Reduction	59.40, 44.08	64.63, 50.75	66.31, 58.82
	Min Bus Voltage (p.u)	0.9590p.u.(28)	0.9669 p.u.(30)	0.9759 p.u.(28)

The table 1 presents a comparative analysis of the IEEE 33-bus distribution system under three different load conditions—Base Load (LF = 1), Light Load (LF = 0.70), and Peak Load (LF = 1.5)—by evaluating the performance of three configurations: (1) integration of only DG, (2) integration of DG with D-STATCOM, and (3) a comprehensive solution combining DG, D-STATCOM, and NR through tie-line switching. For each load scenario, the table shows optimal DG sizing and siting (in kW and bus numbers), D-STATCOM sizing (in kVAr), and the tie lines opened for NR.

At Base Load (LF = 1), using only DG reduces total power loss from its base value to 78.16 kW and 62.30 kVAr, with a minimum bus voltage of 0.9690 p.u. at bus 28. Adding D-STATCOM further improves the voltage profile (0.9769 p.u. at bus 32) and reduces losses to 68.96 kW and 55.60 kVAr. When DG, D-STATCOM, and NR are combined, the system shows the best performance, with power loss dropping to 61.5 kW and 50.60 kVAr—a total loss reduction of 69.62% and 62.52%, respectively—and the minimum voltage rising to 0.9859 p.u. at bus 32.

Under Light Load (LF = 0.70), similar trends are observed. With just DG, the power losses drop to 71.3 kW and 60.30 kVAr, and the minimum voltage is 0.9790 p.u. With DG and D-STATCOM, losses decrease further (58.4 kW, 51.60 kVAr), and the minimum voltage improves to 0.98591 p.u. The integration of all three methods yields the most efficient outcome—losses drop to 52.3 kW and 45.30 kVAr (a reduction of 74.16% and 66.45%), and the minimum voltage reaches a high of 0.995 p.u., indicating excellent voltage support.

At Peak Load (LF = 1.5), the benefits of these strategies are even more significant due to higher demand stress. DG alone reduces losses to 82.2 kW and 75.50 kVAr (with a low voltage of 0.9590 p.u.), but with DG and D-STATCOM, performance improves—losses drop to 71.6 kW and 66.50 kVAr, and voltage improves to 0.9669 p.u. The full combination (DG + D-STATCOM + NR) again offers the best performance with losses reduced to 68.2 kW and 55.60 kVAr and a minimum bus voltage of 0.9759 p.u. The percentage loss reductions for this configuration are 66.31% and 58.82%, respectively.

In summary, across all loading conditions, the results demonstrate that while DG improves system efficiency and voltage profile, its effectiveness is significantly enhanced by adding D-STATCOM. The greatest improvement is consistently achieved when DG, D-STATCOM, and NR are all applied together, providing optimal loss reduction and voltage stability for the 33-bus system.

Fig. 3 presents the impact of different power loss reduction strategies under varying loading conditions, represented by Load Factors (LF) of 1, 0.75, and 1.5. It looks at active and reactive power losses in three situations: when only an Optimal DG is used, when DG is used with D-STATCOM, and when DG, D-STATCOM, and NR are all used together (through tie-line switching).

As the load factor increases from 0.75 to 1.5, both active and reactive power losses also increase across all cases due to higher system loading. Among the strategies, the combination of DG, D-STATCOM, and NR consistently yields the lowest power losses in all loading conditions. For instance, at LF = 1, active and reactive losses are reduced to 61.5 kW and 50.6 kVAr, respectively, compared to 78.16 kW and 62.3 kVAr using only DG. Similarly, under light load (LF = 0.75), the combined method brings active loss down to 52 kW, and under heavy load (LF = 1.5), to 68.2 kW—both significantly better than other cases. This demonstrates that integrating DG, D-STATCOM, and NR provides a more effective solution for minimizing power losses under all loading conditions.

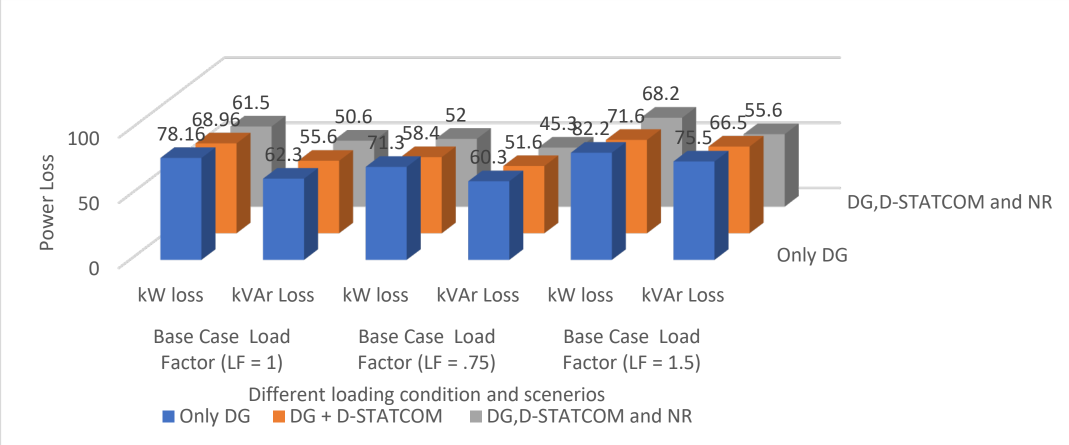

Figure 3. Active and reactive power loss at different conditions

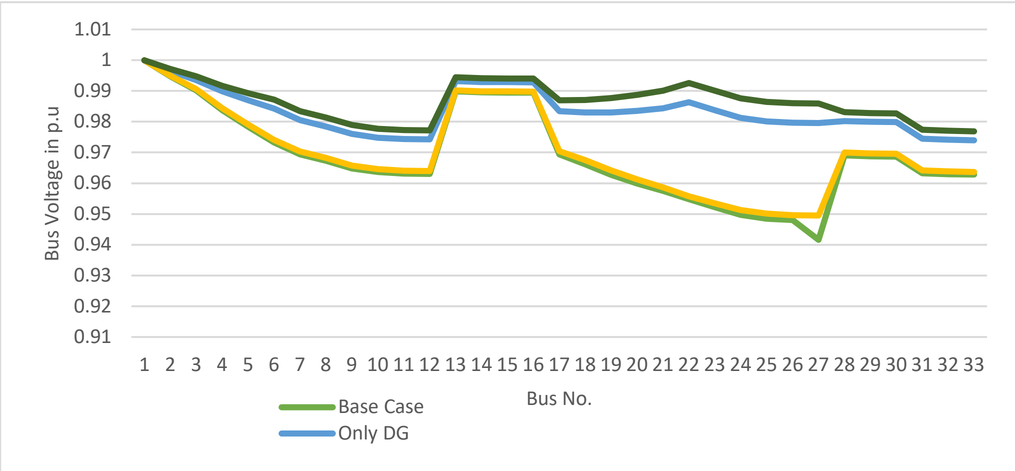

Figure 4. Voltage profile at different cases

The graph shows in fig. 4 for 33 bus voltage profiles under different scenarios. The lowest voltages occur with only DG and D-STATCOM. The best voltage improvement across all buses is achieved when DG, D-STATCOM, and NR are combined. This pattern is approximately the same for all loading conditions, so here only the normal loading condition is shown.

B. IEEE 69-bus system

This test system's line and bus data is taken from the IEEE 69 bus system. A base apparent power of 100 MVA and a base voltage of 2.66 kV are characteristics of this testing equipment. This RDS has an active power load of 3.80 MW and a reactive power load of 2.69 MVAr [28]. Real and reactive power losses are 224.98 kW and 102.15 KVAr respectively at the base case.

Table 2. Summary of results for the four cases with different loading considered for 69-bus network.

Loading Condition	Evaluated Parameters	Optimal DG	DG + D-STATCOM		DG,D-STATCOM and NR (Tie line opened at bus)		
Base Case Load Factor (LF = 1)	Optimal Sizing & Siting	483 kW (10) 351 kW (16) 1486 kW (29)	512.0 kW (11) 371.4 kW (19) 1569.3 kW (61)	1282.6 kVAr (61)	550.0 kW (13) 380.4 kW (21) 1269.3 kW (60)	1282.6 kVAr (52)	9, 14, 28, 37, 45
	Total Power Loss (kW, kVAR)	82.611, 65.30	73.27, 61.50		64.6, 54.60		
	% Loss Reduction (Active & Reactive)	63.48, 36.07	67.46, 39.79		68.31, 46.54		
	Min Bus Voltage (p.u)	0.9637 (65)	0.9774 (65)		0.9880 (62)		
Load Factor (LF = 0.70 - Light Load)	Optimal Sizing & Siting	450 kW (12) 340 kW (20) 1386 kW (35)	480.0 kW (11) 350.4 kW (22) 1469.3 kW (68)	1182.6kVAr (56)	450.0kW (13) 340.4kW (20) 1100.3kW (56)	1200.6 kVAr (58)	9, 5, 27, 33,46
	Total Power Loss (kW, kVAR)	72.45, 61.80	68.27, 56.40		61.56, 50.40		
	% Loss Reduction (Active & Reactive)	67.79, 39.50	69.65, 44.78		72.63, 50.06		
	Min Bus Voltage (p.u)	0.9737 (65)	0.9874 (65)		0.9980 (62)		
Load Factor (LF = 1.5 - Peak Load)	Optimal Sizing & Siting	583 kW (11) 452 kW (25) 1586 kW (40)	550.0 kW (11) 365.4 kW (25) 1580.3 kW (60)	1382.6kVAr (58)	660.0 kW (13) 450.4 kW (25) 1450.3 kW (650)	1360.6 kVAr (55)	9, 12, 26, 35, 55
	Total Power Loss (kW, kVAR)	91.65, 72.60	78.27, 68.48		69.63, 59.48		
	% Loss Reduction (Active & Reactive)	59.26, 28.92	65.21, 32.96		69.05, 41.72		
	Min Bus Voltage (p.u)	0.9537 (60)	0.9674 (58)		0.9780 (52)		

The IEEE 69-bus system was analyzed, as shown in table 2, under varying load conditions to evaluate the impact of different combinations of DG, D-STATCOM (Distribution Static Compensator), and NR on power losses and voltage profiles. At the base load condition (Load Factor = 1), the best DG units were sized and placed at buses 10, 16, and 29. These units had capacities of 483 kW, 351 kW, and 1486 kW, respectively. When combined with D-STATCOM, the DG sizes slightly changed, and reactive power support was provided by D-STATCOM at specific buses, leading to improved system performance. The addition of NR, achieved by opening tie lines at selected buses (9, 14, 28, 37, and 45), further optimized the system. This coordinated approach resulted in a significant reduction in total power losses from 82.61 kW active and 65.30 kVAR reactive losses in the base case to just 64.6 kW and 54.6 kVAR losses, respectively. Correspondingly, the percentage loss reductions reached up to 68.31% for active power and 46.54% for reactive power. Moreover, the minimum bus voltage increased from 0.9637 p.u. to 0.9880 p.u., indicating enhanced voltage stability.

a. Under light load conditions (Load Factor = 0.70), the optimal DG capacities were smaller and sited at buses 12, 20, and 35, with ratings around 450 kW, 340 kW, and 1386 kW, respectively. The combination of DG with D-STATCOM and NR continued to deliver improved loss reductions, reaching 72.63% for active and 50.06% for reactive losses. The minimum bus voltage was remarkably close to nominal at 0.9980 p.u., demonstrating excellent voltage support during low demand periods.
b. In peak load conditions (Load Factor = 1.5), the system required higher DG capacities, placed at buses 11, 25, and 40, with sizes of 583 kW, 452 kW, and 1586 kW, respectively. Despite the increased demand, the coordinated use of DG, D-STATCOM, and NR still yielded meaningful improvements, reducing losses by approximately 69.05% for active power and 41.72% for reactive power compared to the base scenario without these measures. The minimum bus voltage improved from 0.9537 p.u. to 0.9780 p.u., helping to maintain voltage levels within acceptable limits even under heavy load.

Overall, the study demonstrates that combining DG units, reactive power compensation through D-STATCOM, and strategic NR can substantially reduce power losses and improve voltage profiles across different loading scenarios in the IEEE 69-bus system. This integrated approach not only enhances system efficiency but also ensures better voltage stability, contributing to more reliable and resilient power distribution.

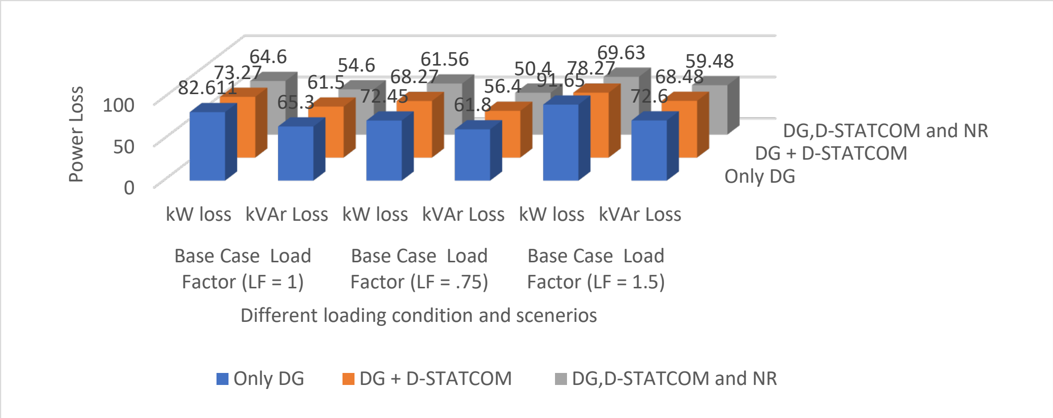

Figure 5. Active and reactive power loss at different conditions

The bar chart shown in fig. 5 compares the performance of different configurations—Optimal DG, DG + D-STATCOM, and DG + D-STATCOM with NR—in reducing both active and reactive power losses under three different load factor conditions: LF = 1 (base case), LF = 0.75, and LF = 1.5. Across all load conditions, the combination of DG, D-STATCOM, and NR consistently results in the lowest power losses. For example, under the base case (LF = 1), active power loss decreases from 82.61 kW (Optimal DG) to 64.6 kW with all three methods. Similarly, reactive power loss reduces from 65.3 kVAR (Optimal DG) to 54.6 kVAR. The trend continues for LF = 0.75 and LF = 1.5, indicating that integrating DG with D-STATCOM and NR significantly enhances loss reduction performance. Moreover, the highest losses are observed at

LF = 1.5, as expected due to increased load, whereas the lowest occur at LF = 0.75, aligning with reduced load levels. This demonstrates the effectiveness of combined strategies in optimizing power system efficiency across varying load conditions.

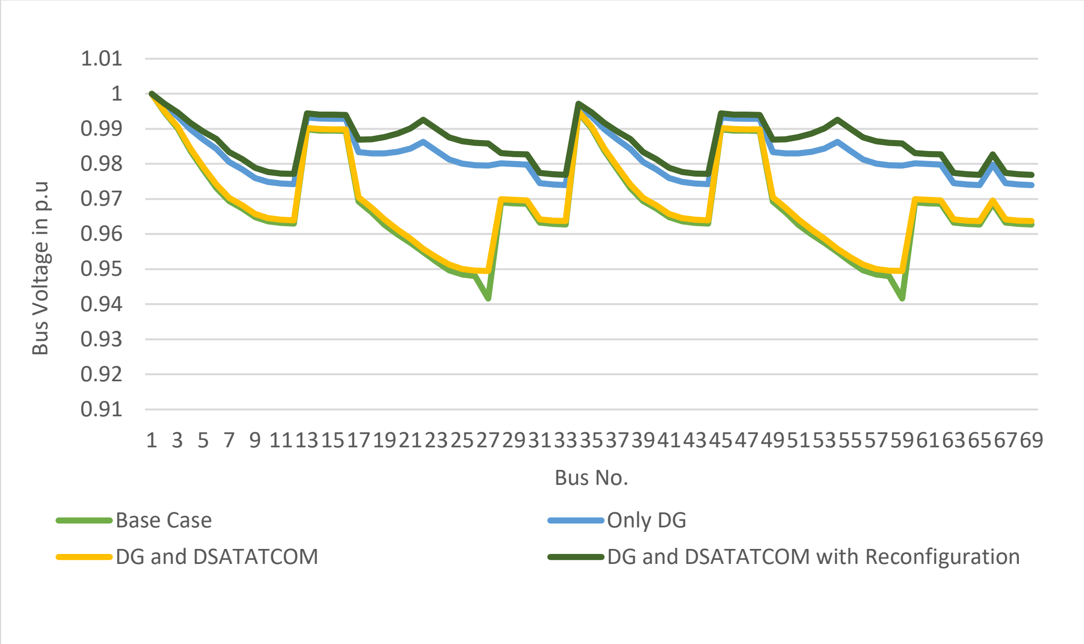

Figure 6. Voltage profile at different cases

The graph in fig. 6 shows voltage profiles of a 69 bus system under different scenarios. The lowest voltages occur with only DG and D-STATCOM. The best voltage improvement across all buses is achieved when DG, D-STATCOM, and NR are combined. This pattern is approximately the same for all loading conditions, so here only the normal loading condition is shown.

C. Compare with previous work

Table 3 represents and illustrates the results for comparative analysis of the PAO technique against existing techniques in terms of PL and loss reduction [29].The proposed PAO method demonstrates clear superiority over existing state-of-the-art techniques in minimizing Total Active Power Loss (TAPL). While earlier methods like IWO, BSOA, and BFOA focus only on DG placement and achieve around 57–61% loss reduction, and multi-DG approaches like GA, CTLBO, and MOHHO remain below 60%, hybrid methods incorporating D-STATCOM such as MOWOA and TLBO show better performance (up to 64.2%). The KHA algorithm, which combines DGs, D-STATCOM, and NR, slightly improves to 64.26%. In contrast, the proposed PAO method, integrating all three components—DGs, D-STATCOM, and NR—in a single optimization framework, achieves the highest reduction of 69.62%, with the lowest TAPL of 61.5 kW. This is the highest loss reduction achieved among all tested algorithms and scenarios, demonstrating the novelty and superiority of the proposed PAO-based hybrid approach in enhancing power system efficiency and resilience.

Table 3. Comparative evaluation of the presented PAO approach with recent optimization approach listed in literature review

Method	**Scenario**	**Total TAPL (KW)**	**% TAPL**
Base case	—	210.99	—
IWO (Invasive Weed Optimization)	DG Only	85.86	59.30613
BSOA	DG Only	89.05	57.79421

Method	Scenario	Total TAPL (KW)	% TAPL
(Black Sine Optimization Algorithm)			
BFOA (Bacterial Foraging Optimization Algorithm)	DG Only	89.9	57.39135
HAOP (Hybrid Adaptive Optimization Process)	DG Only	81.05	61.62
GA (Genetic Algorithm)	Multi DGs	95.8	54.595
CTLBO (Chaotic Teaching-Learning-Based Optimization)	Multi DGs	85.9595	59.25897
MOHHO (Multi-Objective Hyper-Heuristic Optimization)	Multi DGs	92.95	55.94578
MOIHHO (Multi-Objective Improved Hyper-Heuristic Optimization)	DG with D-STATCOM	92.25	56.27755
MOPSO (Multi-Objective Particle Swarm Optimization)	DG with D-STATCOM	83.99	60.19243
MOWOA (Multi-Objective Whale Optimization Algorithm)	DG with D-STATCOM	79.72	62.21622
TLBO (Teaching-Learning-Based Optimization)	DG with D-STATCOM	75.54	64.19736
KHA (Krill Herd Algorithm)	DGs, D-STATCOM & NR	75.412	64.25802
PAO (Proposed)	DGs, D-STATCOM &NR	61.5	69.62

D. Positioning of POA relative to existing bio-inspired algorithms

Here is a brief but thorough comparison of bio-inspired optimization approaches that are frequently employed in electrical distribution systems (EDS). These methods are mostly utilized for placing DGs, allocating D-STATCOMs, minimizing losses, improving voltage profiles, and reconfiguring networks [30].

Table 4. Comparative Analysis of Major Bio-Inspired Algorithms

Algorithm	Inspiration	Key Strengths	Limitations	Typical Applications in EDS
Genetic Algorithm (GA)	Natural evolution	Robust global search, flexible encoding	Slow convergence, parameter tuning	DG placement, feeder reconfiguration
Particle Swarm Optimization (PSO)	Bird flocking	Fast convergence, simple structure	Premature convergence	DG & D-STATCOM sizing
Ant Colony Optimization (ACO)	Ant foraging	Good for discrete problems	High computational burden	Network reconfiguration
Artificial Bee Colony (ABC)	Bee foraging	Balanced exploration	Weak exploitation	DG placement
Differential Evolution (DE)	Evolutionary mutation	Strong global search	Sensitive to control parameters	Loss minimization
Firefly Algorithm (FA)	Firefly attraction	Efficient multimodal search	Local optima trapping	Voltage stability
Bat Algorithm (BA)	Echolocation	Adaptive search	Parameter sensitivity	DG allocation

Algorithm	Inspiration	Key Strengths	Limitations	Typical Applications in EDS
Grey Wolf Optimizer (GWO)	Social hierarchy	Strong exploitation	Poor diversity	DG placement
Whale Optimization Algorithm (WOA)	Bubble-net hunting	Simple implementation	Slow convergence	Multi-objective optimization
Harris Hawks Optimization (HHO)	Cooperative hunting	Good exploration–exploitation balance	Unstable in early iterations	DG-DSTATCOM coordination
Pelican Optimization Algorithm (POA)	Cooperative fishing	Strong adaptive exploration & exploitation	New algorithm, limited studies	DG & D-STATCOM placement

Table 5. Evaluation of Performance

Criterion	GA	PSO	GWO	HHO	POA
Global search ability	High	Medium	Medium	High	Very High
Convergence speed	Slow	Fast	Fast	Medium	Fast
Avoidance of local minima	High	Low	Medium	High	High
Parameter sensitivity	High	Medium	Low	Medium	Low
Suitability for DG–DSTATCOM	Good	Very Good	Good	Very Good	Excellent

Bio-inspired optimization strategies have demonstrated significant efficacy in addressing distributed generation placement, reactive power compensation, loss minimization, and voltage regulation issues within electrical distribution networks. Although conventional algorithms are dependable, contemporary techniques like POA and HHO exhibit enhanced adaptability, accelerated convergence, and greater solution quality, rendering them valuable instruments for advanced distribution networks.

6. Challenges

This research does not account for the optimal allocation of D-STATCOM and DGs on a balanced IEEE 33 bus RDS in conjunction with NR. However, its imbalanced nature restricts its practical application on an RDS. The authors of this study did not incorporate the uncertainty modeling of renewable-based DG units like wind and solar power and their specific type. The optimal allocation problem of RDS can also be addressed by evaluating the system's dependability indices. The precise geographical location of the network is a potential constraint of this work when designing and allocating Distributed Generators (DGs) in practical Renewable Distributed Systems (RDSs). The voltage profile can be enhanced, and power loss can be reduced by incorporating electric vehicles and electric vehicle aggregators into the RDS.

7. Conclusion and future work

This research presents a comprehensive and integrated methodology to enhance the performance, efficiency, and reliability of RDS by synergistically optimizing the placement and sizing of DG units, D-STATCOM devices, and NR strategies. Leveraging the backward and forward sweep (BFS) load flow method in conjunction with Grey Wolf Optimization (PAO), the proposed approach effectively minimizes active and reactive power losses while improving voltage stability across varying load profiles, including normal, light, and peak conditions.

Validation on IEEE 33-bus and 69-bus systems demonstrates substantial reductions in system losses—up to 69%—and significant enhancements in voltage profiles, confirming the efficacy of the combined deployment of DGs, D-STATCOM, and reconfiguration. The results demonstrate the potential of metaheuristic-based multi-objective optimization frameworks to facilitate smarter, more resilient, and energy-efficient distribution networks capable of adapting to dynamic load demands. Future research can expand this framework by incorporating the stochastic nature of renewable energy sources, such as wind and solar, modeling uncertainties to improve robustness. Multi-objective and multi-period optimization approaches can be developed to balance technical, economic, and environmental considerations over time. Additionally, integrating electric vehicle charging/discharging, energy storage systems, and reliability analysis can further enhance system flexibility and demand-side management.

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