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Network Reconfiguration based Simultaneous allocation of DGs and EVCSs for Enhancing the Voltage Stability of RDS using POA approach

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Abstract

Objectives: The objective of this study is to improve voltage stability and decrease network losses in Radial Distribution Systems (RDS) through the application of an innovative optimization algorithm. This research incorporates the concept of effective Network Reconfiguration (NR) alongside the optimal placement of Distributed Generators (DGs) and the recently introduced Electric Vehicle Charging Stations (EVCSs). The primary goals of this work are to minimize the active power loss index (PLI), voltage deviation index (VDI), voltage stability index (VSI), and investment cost index (ICI). The problem is framed as a multi-objective nonlinear optimization function (MOF). **Methods:** A powerful and recently developed optimization algorithm of Pelican Optimization Algorithm (POA) is implemented to solve the MOF and achieve the best compromised solutions. The implementation of the POA approach is carried out using MATLAB 14.0 software. This algorithm is parameter-free, consisting solely of common control parameters, such as a population size of 40 and a total of 500 iterations **Findings:** A case study utilizing the IEEE-33 node test system is presented, detailing the numerical results of compromised solutions for PLI, VDI, VSI, and ICI. The results obtained are compared with those from other existing methodologies to demonstrate the effectiveness of the proposed approach. Notably, the PLI of the proposed test system shows an improvement of 48.82% when contrasted with the base case method **Novelty:** The suggested Plan of Action effectively enhances the performance of the Renewable Distributed Systems through the optimal distribution and sizing of Electric Vehicle Charging Stations and Distributed Generators.

Keywords: Distributed generators; Electric Vehicles; Charging Stations; Network reconfiguration; Pelican Optimization Algorithm; Voltage stability

1 Introduction

Electric Vehicles (EVs) are increasingly favoured for their minimal maintenance requirements, enhanced performance, and zero carbon emissions. To facilitate broader adoption, it is essential to effectively integrate Electric Vehicle Charging Stations (EVCS) with Distribution Systems (DS) to enable the charging of EVsThe EVCS have several impacts on Radial Distribution Systems (RDS) such as increased power consumption, increased the thermal limits of distribution transformer and distribution feeders, network congestion, overloads, high power loss, poor voltage stability and reliability of RDS[1]. Generally, compensating devices of capacitor banks, Distribution Generators (DGs), FACTS devices are interconnected with RDS to enhance the voltage stability and reduce the active power loss of the system[2], [3].

Researchers have devised a range of mathematical[4]-[5] and meta-heuristic strategies[6]-[7] aimed at optimizing the placement and sizing of Distributed Generation (DG) units and capacitors. These strategies also focus on implementing reconfiguration topologies to limit power losses and enhance voltage levels within the electric vehicle charging station (EVCS) integrated radial distribution system (RDS). A practical urban area in China, served by a 31-bus distribution network, was utilized for the integration of the EVCS and DG units. The study employed mathematical methods using commercially available solvers[4], which yielded significant numerical results. Additionally, Teaching Learning Based Optimization[8] was introduced to evaluate the performance of the RDS in relation to the EVCS. The influence of the EVCS on the RDS was examined through five distinct test cases.

The implementation of reconfiguration and Vehicle-to-Grid technologies has been carried out in RDS. A MIP method[5] has been introduced to optimally coordinate the charging and discharging of autonomous electric vehicles in conjunction with dynamic distribution network reconfiguration (DDNR), all while adhering to the original travel plans of the autonomous electric vehicles. Fuzzy logic[6] has been applied to enhance the voltage profile of EVCS integrated RDS. the compensating devices of DGs and shunt capacitors with NR. The issue is regarded as a multi-objective problem, and the charging of Li-Ion batteries has been employed for load flow analysis to develop models for electric vehicle battery charging loads. The fuzzy membership functions[9] have been implemented for battery swapping stations considering dynamic NR to improve the performance of power grid. The strategy improves the positioning and capacity of battery swapping stations, in conjunction with NR, to bolster grid reliability and efficiency.

A two-tier Energy Management Scheme (EMS)[10] for AC-DC hybrid smart distribution systems has been introduced. This scheme is structured as a multi-objective optimization problem aimed at reducing operational costs and energy losses through the application of the (NR method The Demand Side Management tool[11] has been implemented to minimize the total cost of micro grid by process of generation scheduling and feeder NR. The EVs and DGs were modeled along with the uncertainty of micro grid components. The uncontrolled and controlled pattern was used for charging of EVs. A case study has been proposed to integrate the EVCS and RDS in Allahabad, India. Balanced Mayfly algorithm[12] was proposed to allocate the EVCS at the proper location and determines the various Index. A two-stage electric vehicle charging process and network reconfiguration have been implemented to reduce power losses in Low-Voltage and Medium-Voltage distribution systems. The UPSO technique[13] has been utilized to decrease network losses under varying load demands

A cooperative co-evolutionary Genetic Algorithm[14] was utilized for the planning of Fast Charging Stations (FCS) and NR of the distribution network. The locations of the FCSs and the network switches were encoded independently, allowing them to evolve collaboratively as two distinct species. Honey badger algorithm[15] was applied to allocate the removable DGs in a EVCS loaded 33-node RDS considering the NR. Here, analyzed the network loss and greenhouse gas (GHG) emissions with various EV load penetration

A hybrid optimization algorithm combining African vulture optimization and pattern search[16] has been developed to minimize the power loss index, VSI, voltage deviation index, and investment cost index. This issue has been formulated as a multi-objective function that incorporates a penalty factor. The solution achieved involves the allocation of EVCS alongside (NR, taking into account the presence of DG) and DSTATCOM. The Bald Eagle Search Algorithm[17] has been applied to same problem with same compensating devices was considered. A hybrid GA–SFLA approach[18] has been applied to solve multi-objective problem considered NR with DG and EVs. The performance of the algorithm GA–SFLA tested standard IEEE test system and obtained the lower loss, lower operating costs and greater reliability.

Crow search algorithm[19] has been implemented to solve multi-objective-problem considering NR with Renewable DGs and EVCS. The NR problem has been solved by bearing in mind 17 bus unbalanced and balanced RDS. Modified chicken swarm optimization[20] has been developed to optimally place the solar-powered EVCS in RDS. Results were compared with Jaya and TLBO technique. Dynamic NR has been executed to determine the power loss rate, active power loss, load balancing index, and the maximum deviation in node voltage. Subsequently, a hybrid approach combining levy-light and chaos disturbed beetle antennae search[7] was proposed to enhance the operational efficiency and power quality of the RDS.

This research presents a robust and straightforward methodology for identifying the optimal placement and sizing of combined Distributed Generators (DGs) and Electric Vehicle Charging Stations (EVCS) alongside network reconfiguration in Radial Distribution Systems (RDS). The study addresses a multi-objective optimization problem, adhering to established constraints for DGs and EVCS. The primary aim is to enhance the voltage profile and VSI, while simultaneously minimizing active power loss and various performance indices, including the Power Loss Index (PLI), Voltage Deviation Index (VDI), and Investment Cost Index (ICI). To tackle this challenge, the research employs the recently developed and effective POA. The POA is tested on a 33-node benchmark system to demonstrate its efficacy. The simulation outcomes are then compared with existing methodologies in the literature to confirm the proposed approach's effectiveness.

2 Methodology

2.1 Problem Formulation

2.1.1. Multi-Objective Function

In this study, Multi-objective optimization function (MOF) is developed by integrating the active power loss index (PLI), voltage deviation index (VDI), voltage stability index (VSI), and investment cost index (ICI) into a single equation through the application of a weighting factor, as presented in **Equation (1)**.

$$\text{MOF} = \min\{\rho_1 * PLI + \rho_2 * VDI + \rho_3 * [main(VSI(y))]^{-}1 + \rho_4 \times ICI\} \tag{1}$$

The influence of Electric Vehicle Charging Stations (EVCS) under various operational scenarios on PLI is represented by the following equations.

$$\text{PLI} = \frac{P_{loss}^{CSWC}}{P_{loss}^{0}} \tag{2}$$

$$P_{loss} = \sum_{y=1}^{\beta} P_u(y-1, y) \tag{3}$$

$$P_u(y-1, y) = \frac{(P_y^2 + Q_y^2)}{V_y^2} Ry \tag{4}$$

The mathematical representation of the reduction in power loss resulting from DG installations, in conjunction with the NR on of the network over an EVCS-loaded RDS, can be articulated as follows.

$$\text{RRPL} = 1 - \frac{P_{loss}^{CSWC}}{P_{loss}^{CS}} \tag{5}$$

The second term of the MOF is employed to reduce the average voltage deviation within the system, with a lower value indicating an enhancement in the voltage profile of the buses, as expressed in **Equation (6)**

$$\text{VDI} = \frac{\sum_{y=1}^{\eta} \left(1 - V_y^{CSWC}\right)}{\sum_{y=1}^{\eta} 1 - V_y^{0}} \tag{6}$$

The third term of the MOF serves to improve the voltage stability of the system. The value of VSI at bus y can be calculated using **Equation (7)**.

$$\text{VSI(y)} = \{V_{y-1}^2 - 2\left(P_y R_y + Q_y X_y\right)\}^2 - \left(P_y^2 + Q_y^2\right)\left(R_y^2 + X_y^2\right) \tag{7}$$

The investment cost index (ICI) represent as follows

$$\text{ICI} = \frac{C_{DG} + C_{DST}}{C_{DGmax} + C_{DSTmax}} \tag{8}$$

2.1.2. Equality and Inequality Constraints

- Power Balance Constraint

$$P_{ss}+\sum_{i=1}^{N_{DG}} P_i^{DG}=P_{ld}+\sum_{i=1}^{N_{EV}} P_i^{CS}+P_{loss} \tag{9}$$

$$Q_{ss}+\sum_{i=1}^{N_{DS}} Q_i^{DS}=Q_{ld}+Q_{loss} \tag{10}$$

- Line Current Limit Constraint

$$I_{(y-1,y)}<I_{(y-1,y)}^{\max} \tag{11}$$

- Voltage Limitation constraint

$$0.95<V_y<1.05 \tag{12}$$

- VSI Limitation constraint

$$\text{VSI(y)} \geq 0 \text{ for } y=2,3,\ldots,\eta \tag{13}$$

- DGs Operating Limits

$$P_{y,\min}^{DG}<P_y^{DG}<P_{y,\max}^{DG} \tag{14}$$

$$\sum_{i=1}^{N_{DG}} P_i^{DG}<P_{ld} \tag{15}$$

- DSTATCOM Operating Limits

$$Q_{y,\min}^{DS}<Q_y^{DS}<Q_{y,\max}^{DS} \tag{16}$$

$$\sum_{i=1}^{N_{DS}} Q_i^{DS}<Q_{ld} \tag{17}$$

- Rituality Checking Constraint

$$\text{Det(B)}=1 \text{ or } -1 \tag{18}$$

2.2 Proposed Pelican Optimization Algorithm (POA) for multi-objective Voltage Stability Problem

The POA is a population-based nature inspired optimization method developed by Pavel Trojovský and Mohammad Dehghani in the year of 2022[21]-[22]. POA is based on natural life cycle of pelican birds searching the food sources and hunting behaviour in the water surface. The two searching operators of POA like progress towards food and surfing on the water outside are efficiently searching the optimal solution for constrained problems The mathematical modelling of initialization function, creating the population, current positions, updating of search agents, and representation of searching agents are clearly described in the following sections.

Initialization of Populations:

The lower and upper boundaries of POA randomly generate the initial population by the following equation with help of random number.

$$x_{i,j} = l_j + rand.\left(u_j - l_j\right), i = 1,2,3,\ldots..,N, j = 1,2,3,\ldots.,m, \tag{19}$$

The randomly generated populations are reprinted in the matrix form. The size of the matrix $N \times m$ is represented in the below equation:

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix}_{N \times m} = \begin{bmatrix} X_{1,1} & \cdots & X_{1,j} & \cdots & X_{1,m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ X_{i,1} & \cdots & X_{i,j} & \cdots & X_{i,m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ X_{N,1} & \cdots & X_{N,j} & \cdots & X_{N,m} \end{bmatrix}_{N \times m} \tag{20}$$

The above initial populations are used to determine the objective functions of the projected work and are represented in the vector form as shown in **equation (21)**:

$$\mathrm{F} = \begin{bmatrix} \mathrm{F_1} \\ \vdots \\ \mathrm{F_i} \\ \vdots \\ \mathrm{F_N} \end{bmatrix}_{\mathrm{N} \times 1} = \begin{bmatrix} \mathrm{F(X_1)} \\ \vdots \\ \mathrm{F(X_i)} \\ \vdots \\ \mathrm{F(X_N)} \end{bmatrix}_{\mathrm{N} \times 1} \tag{21}$$

The POA methodology is illustrated through two distinct phases that mimic the hunting behaviour of pelicans.

Phase 1: Moving towards Prey

The movement of pelican towards the prey is mathematically represented by the following equations:

$$X_{i,j}^{P_1} = \begin{cases} X_{i,j}, + rand.\left(P_j - I.X_{i,j}\right). & F_p < F_i; \\ X_{i,j}, + rand.\left(X_{i,j} - P_j\right), & else, \end{cases} \tag{22}$$

The position of the POA is updated using the below equation:

$$X_i = \begin{cases} X_i^{P_1}, & F_i^{P_1} < F_i; \\ X_i, & else, \end{cases} \tag{23}$$

Phase 2: Winging on the Water Surface

This behaviour of pelicans during hunting in the water surface is mathematically defined as follows:

$$X_{i,j}^{P_2} = X_{i,j} + R.\left(1 - \frac{t}{T}\right).(2.rand - 1).X_{i,j}, \tag{24}$$

The position of the phase 2 is updated using the following equation:

$$X_i = \begin{cases} X_i^{P_2}, & F_i^{P_2} < F_i; \\ X_i, & else, \end{cases} \tag{25}$$

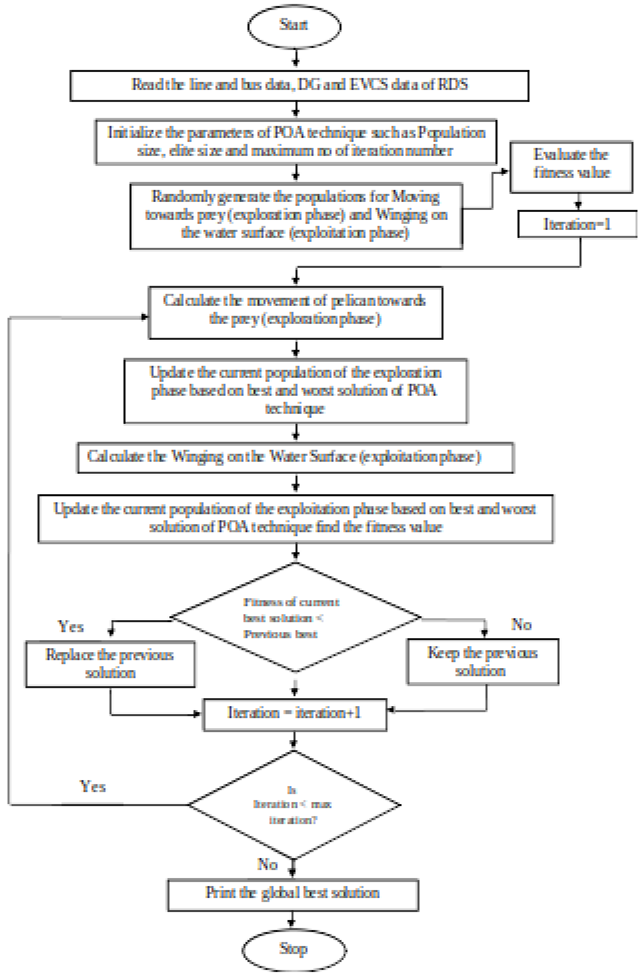

Fig 1. Flowchart illustrating the proposed algorithm for Reconfiguration with DG allocation for EVCS loaded RDS

2.3 Implementation of proposed POA for EVCS loaded RDS

The subsequent procedures are implemented to address the multi-objective voltage stability issue associated with Electric Vehicle Charging Stations (EVCS) in a reconfigured Radial Distribution System (RDS). The proposed POA identifies the most suitable open switches, optimal locations, and ideal values for EVCSs and Distributed Generators (DGs) to improve the voltage profile and minimize network losses within the proposed test system. A flow diagram illustrating the reconfiguration process along with DG allocation for EVCS-loaded RDS utilizing the POA is presented in Figure 1.

1. Read the line data, bus data, load data, and characteristics of electric vehicles (EVs) and charging stations (CSs) within the proposed 33-node test systems.
2. Execute the distribution power flow analysis for the base case scenario and compute the power loss, Voltage Deviation Index (VDI), Voltage Stability Index (VSI), and voltage levels at each bus utilizing the precise loss formula applicable to the base case.
3. Ascertain the quantity of tie-line switches, distributed generation (DG) units, and electric vehicle charging stations (EVCSs), as well as the number of charging points (CPs) and their respective ratings to be incorporated in the radial distribution system (RDS).
4. Set the parameters for the POA, including population size, dimensionality, maximum number of iterations, and the lower and upper bounds of the control parameters
5. Set iteration=1.

6. Compute the fitness value of each population (i.e. open switches for reconfiguration, optimal location and value of DGs and EVCSs, power loss in a network) in exploration and exploitation phase of POA.
7. Evaluate the multi-objective functions (PLI, VDI, VSI and ICI for each exploration and exploitation phase of POA.
8. Update the position of exploration and exploitation phase of POA and then memory the most excellent fitness values in an array.
9. Compute the present position of two phases (exploration and exploitation phase.) of POA and save the best fitness value.
10. Verify that all constraints have been met: if they have, proceed to the subsequent step; if not, return to step 6.
11. Determine whether the number of iteration processes has reached the maximum allowable iterations: if it has, advance to the next step; if not, revert to step 5.
12. Project the global best results of multi objective problem such as enhanced voltage profile, minimized power loss, PLI, VDI, improved VSI, ICI and STOP the program.

2.4 Impact of utility company on EV transition and energy demand in the power grid

When utility companies plan for power system stability with the integration of Distributed Generation (DG) and Vehicle-to-Grid (V2G) technologies, they need to consider several factors to ensure the grid remains stable, efficient, and reliable. Here's an outline of key considerations and strategies that need to be addressed in planning for the integration of DG and V2G [23], [24].

- Grid Stability and Frequency Regulation.
- Energy Storage Integration.
- Demand Response (DR) and V2G for Grid Balancing.
- Voltage Control and Power Quality.
- Market Design and Incentives for DG and V2G.
- Predictive Analytics and Forecasting
- Cyber security and Data Management:

The large-scale transition to EVs will undoubtedly put increased demand on the power grid, creating challenges for voltage stability. However, through a combination of smart grid technologies, advanced voltage control strategies, energy storage, and predictive analytics, utilities can mitigate these challenges [25]. Proper integration of V2G, distributed energy resources, and smart charging infrastructure can not only help eliminate voltage stability issues but also unlock new opportunities for grid flexibility and efficiency. The key to success will be developing a holistic and proactive approach that involves grid modernization, incentives for off-peak charging, and the adoption of advanced control systems to ensure the grid remains stable and reliable as the EV transition accelerates.

3 Results and Discussion

The 33-node test system comprises a primary feeder along with three interconnected laterals within the network. The maximum capacities for real and reactive power loads are 3715 kW and 2300 kVAr, respectively [26]-[27]. The proposed POA method is employed to determine the optimal solution for the standard IEEE 33-node test system. This problem is framed as a multi-objective optimization challenge, incorporating both equality and inequality operating constraints. The POA is capable of addressing multiple objectives, including the Active Power Loss Index (PLI), Voltage Deviation Index (VDI), Voltage Stability Index (VSI), and Investment Cost Index (ICI). The line and bus data for the test system are derived from reference [13].

The simulations are conducted on the MATLAB 14.0 platform, utilizing a computer equipped with an Intel Core i5 4210U processor, capable of reaching speeds up to 2.5 GHz, and featuring 8 GB of RAM. This research focuses on network reconfiguration involving three Electric Vehicle Charging Stations (EVCSs) and their associated Distributed Generation (DG) units to address the proposed optimization problem. The specifications for the EVCSs are sourced from reference [11], which details the power rating of the EVs, the number of charging points (CPs), and the charging station rating in kilowatts (KW).

Initially, the distribution load flow methodology is applied and finds the base case values of the voltage violations, VSI, and power loss of given RDS. Enhance the voltage stability and minimize the transmission losses by optimally allocating the tie-line switches and capacitors in proper locations in RDS.

Following the reconfiguration process, the optimal allocation and sizing of Electric Vehicle Charging Stations (EVCS) alongside Distributed Generation (DG) are processed concurrently. The proposed POA Operators identify the most suitable locations and dimensions for both DG and EVCS while also restructuring the existing test system by opening specific switches.

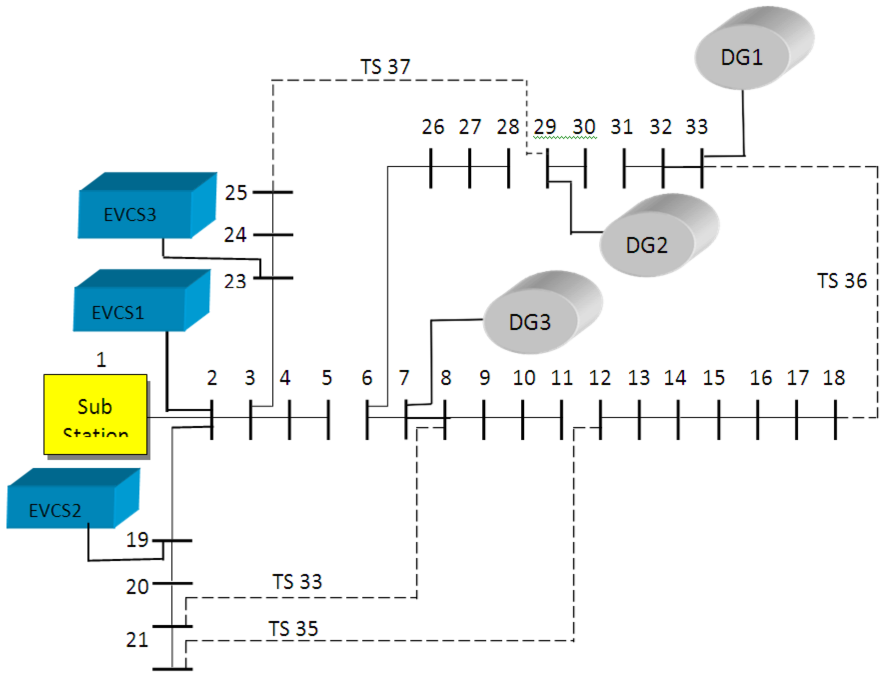

Fig 2. Structure of IEEE-33 node system after reconfiguration and Integrated with DG and EVCS

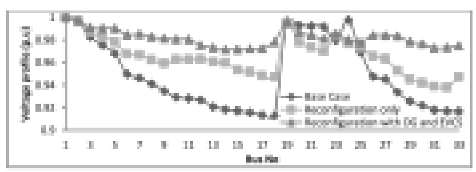

Fig 3. Comparison of voltage profile with different cases

Table 1. Simulation results of 33-node test system

Parameters	Base Case	Reconfiguration with EVCS and DG units placement
Open switches	-	28, 5, 11, 30, 34
Tie-line switches	-	33,35,36,37
Optimal location of DG	-	33, 29,7
Sizing of DG (MW)	-	0.9612, 1.1, 1.0524
Optimal location of EVCS	-	2, 19, 23
Sizing of EVCS (KW)	-	975, 975, 975
Minimum Voltage (p.u)	0.9131	0.9785
Voltage stability index	0.6951	0.89754
Power loss (KW)	**210.870**	**67.191**
PLI	-	0.38086
ICI	-	0.000108
VDI	-	0.02932
Objective function	-	0.27159
CPU time	-	30.50

In this context, the total load demand is 6,640 kW, and the optimization process aims to determine the best placement of Charging Stations (CS) and DG with the least number of Control Points (CP).

The control parameters for the POA approach include a population size of 40, a random number range from 0 to 1, a total of 8 variables, and a maximum of 500 iterations. These parameters were derived through a trial and error method. The switches that have been opened include 28, 5, 11, 30, and 34, with the corresponding tie line switches being TS33, TS35, TS36, and TS37. The optimal placement of DG is 33, 29, 7 and the size of the DG is 965.2 KW, 1102 KW, and 1050.4 KW respectively. The best placement of EVCS is 2, 19, 23 and the size of all EVCS is 975 KW respectively. The structure of IEEE-33 node system after reconfiguration integrating with DG and EVCS is shown in Figure 2.

The three EVCS and three DG units are installed in the proper location with optimal size in the RDS and run the distribution load flow using POA technique..Now the voltage profile and VSI are enhanced, PLI, VDI and ICI are effectively minimized. The voltage profile is evaluated under the different test cases such as base cas, only reconfiguration, reconfiguration with EVCS and DG units. It is numerically and graphically compared and reported in Table 1 and Figure 3. The proposed POA effectively improves the voltage profile by considering optimal network reconfiguration with EVCS and DG units. The improved minimum voltage and VSI is 0.9785 (p.u) and 0.89754 (p.u) respectively.

Table 2. Comparison Simulation results of proposed with existing methods for 33-node test system

Parameters	POA (Proposed)	GA [13]	GWO [13]	MPA [13]
APL (KW)	67.191	72.247	71.059	70.506
MVSI	0.89754	0.8478	0.8965	0.8892
PLI	0.38086	0.3432	0.3368	0.3344
VDI	0.02932	0.32.4	0.3186	0.3208
ICI	0.8012	0.8318	0.8331	0.8383
Vimi @ bus	0.9785 @ bus 18	0.9626 @ bus 18	0.9731 @ bus 17	0.9711 @ bus 17
Swiches opened	28, 5, 11, 30, 34	7, 12, 9, 17, 28	7,14,9,16,28	7,14,9,16,28
Sit and size of DGs (KW)	33(965.2), 29(1102), 7(1050.4)	21(1261.4), 15(483.8), 25(1606.2)	21(1658.6), 32(813.2), 25(884.6)	21(1724.2), 32(730.8), 25(922.4)
DG capacity (KW)	3117.6	3351.4	3356.4	3377.4
APL reduction	73.28 %	71.28 %	71.75 %	71.95
CPU time (s)	30.50	44.522	30.782	37.511

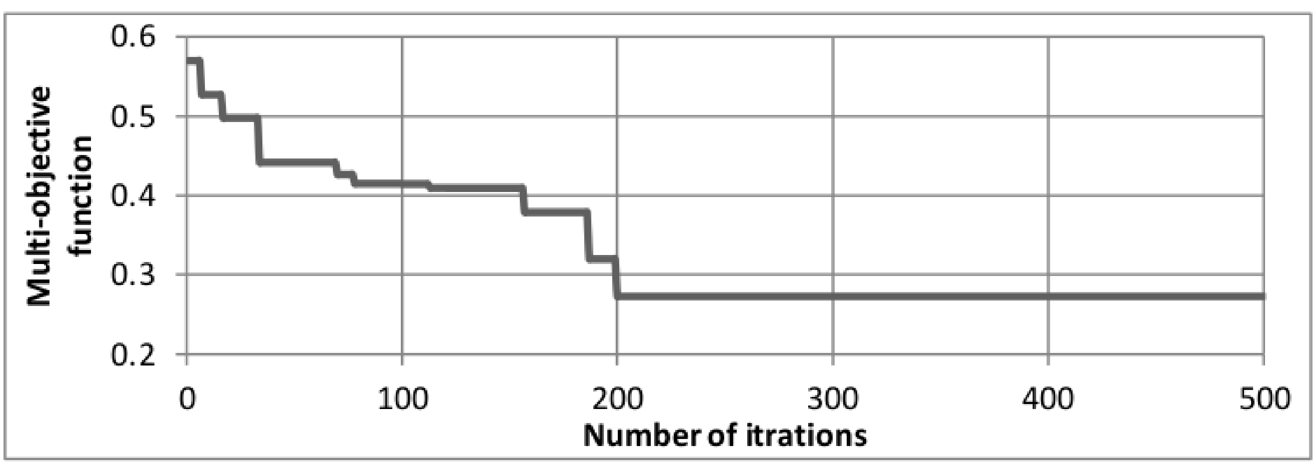

Fig 4. Convergence curve of 33-node distribution system

The outcomes of the simulation for both the base case and the reconfiguration involving Distributed Generation (DG) and Electric Vehicle Charging Stations (EVCS) are presented in Table 2. The power loss for the proposed test system is recorded at 67.191 KW, with a computational time of 30.50 seconds. The optimized values for the four multi-objective criteria are as follows: PLI = 0.38086, VDI = 0.02932, VSI = 0.89754, and ICI = 0.000108. The convergence characteristics of the proposed reconfiguration involving distributed generation (DG) are illustrated in Figure 4. The simulation outcomes of the proposed POA are juxtaposed with those of other established methods, including Genetic Algorithm (GA), Grey Wolf Optimization (GWO), and Multi-Population Algorithm (MPA), as detailed in Table 2. By integrating the reconfiguration process with the optimal allocation of DG and EVCS, a significant reduction in power loss is achieved when compared to other available methodologies.

The proposed simulation results are validated with previous results based on the existing approaches such as GA, GWO and MPA algorithm. The proposed POA technique is the parameter less algorithm and has two searching operators like moving towards prey (exploration phase) and Winging on the water surface (exploitation phase). By using these operators, the POA achieved the optimal solutions with less computational time then the existing approaches of GA, GWO and MPA The results indicate that the proposed POA method effectively minimizes power loss while achieving superior voltage stability indices and voltage profiles in comparison to existing methods documented in the literature.

4 Conclusion

This study addresses the multi-objective voltage stability optimization challenge in Electric Vehicle Charging Stations (EVCS) within Redial Distribution Networks (RDN) by employing a commanding and innovative optimization algorithm known as POA. The compensating devices of DGs and network reconfiguration (NR) topology has been implemented in this work. The proposed work considered the four different objectives such as PLI, VDI, VSI and ICI and is combined with penalty factor. The suggested POA technique concurrently reconfigures the RDN while identifying the optimal placement and sizing of Distributed Generators (DGs) and Electric Vehicle Charging Stations (EVCS) to improve the voltage profile and minimize active power loss. The performance of the POA method is evaluated using the standard IEEE-33 node test system on the MATLAB 21.0 platform. Network reconfiguration with EVCS and DGs placement provides better solutions. Simulation outcomes are compared with other intelligent optimization techniques of GA, GWO, and MPA. From the comparison the projected POA achieved the improve voltage profile and VSI, minimized VDI and active power loss with minimum computational time. It is evident that the proposed POA is an effective and successful optimization tool for solution various power system optimization problems. The novelty of the proposed work is that POA provides a unique, effective, and adaptable strategy for enhancing voltage stability in RDS, surpassing traditional optimization techniques regarding convergence speed, robustness, and computational efficiency.

5 Appendix-A: Notations

Parameters	Notations
PLI	Active power loss index
VDI	Voltage deviation index
VSI	Voltage stability index
ICI	Investment cost index
ρ_1, ρ_2 and ρ_3	Waiting factor of Multi-objective function
NR	Network reconfiguration
CSWC	Circuit Switch with Control
RRPL	Resistive Reactive Power Loss
x_{jk}	Reactance of bus J and K
Q_k	Reactive power at k^{th} bus
P_i^{DG}	Real Power generation of i^{th} DG unit
P_{loss}	Real Power Loss
P_{ld}	Real Power Demand
Q_i^{DS}	Reactive Power generation of k^{th} DG unit
Q_{loss}	Reactive Power Loss
Q_{ld}	Reactive Power Demand
$P_{y,\min}^{DG}$	Minimum Real Power generation of y^{th} DG unit
$P_{y,\max}^{DG}$	Maximum Real Power generation of y^{th} DG unit

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