Enhancing of Distribution System performance in the Presence of DGs and EVCSs using Evolutionary Optimization Techniques

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Abstract:

Electric vehicles (EVs) are rapidly penetrating the transportation sector, leading to a sharp increase in electric vehicle charging stations (EVCSs), which significantly affect power distribution networks. Improper placement of EVCSs can cause transformers and feeder overloading, higher energy losses, degraded voltage profiles, and reduced voltage stability. This paper proposes a multi-objective optimization framework for the optimal allocation and sizing of Distributed Generators (DGs) in the presence of EVCSs using the Whale Optimization Algorithm (WOA) and Puma Optimization Algorithm (POA). The objective functions are minimizing real power losses and enhancing the Voltage Stability Index (VSI). The proposed methods are validated on the IEEE 33-bus distribution system. Simulation results show that, compared to the base case with 201.99 kW active losses, minimum voltage 0.913 pu, optimally placed EVCSs with Type-I DGs reduce power losses by 66.8% (POA) and 64.7% (WOA), while improving the minimum voltage to 0.9679 pu and 0.9690 pu, respectively. For Type-II DGs, power losses are reduced by 24.15% (POA) and 25.08% (WOA) with minimum voltages of 0.9371 pu and 0.9264 pu, respectively. The findings confirm that PQ-mode DGs provide the most effective enhancement in reducing losses, improving voltage profiles, and strengthening system stability. The results highlight the superior performance of the proposed optimization techniques in mitigating the adverse impacts of EVCSs on distribution systems.

Keywords: *Optimal Placement, Charging Station, Distribution Generation, Loss Reduction, Whale Optimization Algorithm (WOA), (PO) Puma Optimizer*

I. INTRODUCTION

The steady improvement of transportation in recent years has bolstered the expansion of the electric vehicle (EV) industry. Several factors, including the potential to lower CO2 emissions from gasoline burning in fuel-powered vehicles, economic feasibility, environmental concerns, renewable resources, and growing oil costs, have made electric vehicles (EVs) a compelling option for new urban transportation systems. The power delivery system's operator faces new difficulties because of the EVs' explosive rise. In cities where EV adoption is high, many charging stations are necessary to recharge batteries. The choice of EVCS location is crucial to the whole life cycle, as it has a direct impact on service quality and EVCS operational efficiency **[1].** The widespread installation of EVs for charging in the distribution network will impact on the aging infrastructure, power losses, and aid voltage. To reduce the negative effects of EVs, the right EVCS location must be chosen. Distribution System Operators (DSOs) should give serious thought to EV charging stations to improve operational flexibility and prevent network overload.

To increase EV penetration and decrease the impact of EVCSs on distribution system operational components including current, voltage, and losses, distributed generation (DG) units are added **[2].** To satisfy the necessary demand from consumers, distributed generation is becoming essential. DG uses modular technologies to greatly reduce the load on the distribution system that is integrated into it.

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During the last ten to fifteen years, there have been significant advancements in this small-scale power generator. Determining the appropriate capacity and placement of DG sources in distribution networks is crucial for maximizing their potential **[3].** One of the finest methods for lowering losses brought on by the widespread use of EVs is the deployment of DG. EVCS and DG units work together to lessen the impact of EV charging. To avoid larger losses and voltage increases, increased losses, issues with reverse power flow, and the necessity of properly allocating and sizing the DGs in conjunction with EVCS to offer protection. Setting up DG and EVCS in the network optimally is crucial for maximizing efficiency and reaping the benefits of EVCS deployment. Utilizing the potential of future electric vehicles is seen as one way to encourage the integration of renewable energy sources into energy networks **[4].** DGs are placed at fast charging stations to maintain energy supply and demand between the network system and the fast-charging stations to recover electrical energy needs of EVs from the grid. This helps to improve the issues mentioned **[5-6].**

Therefore, the final goal is to use an optimization technique that reduces overall losses while maintaining the stability and dependability of the power system to guarantee the best possible placement and size of both renewable and non-renewable DGs with EVCS.

The primary contributions of this research can be outlined as follows:
• An optimal siting approach for Electric Vehicle Charging Stations (EVCSs) is proposed, aiming to enhance the voltage profile and reduce power losses within the distribution network.
• A coordinated optimization framework is developed for the simultaneous placement and sizing of Distributed Generators (DGs) and EVCSs, where EVCSs are modeled as load entities, subject to system operational constraints, to achieve minimal total power losses.

The following is the arrangement of the remaining sections: The classification of distributed generation and charging stations are covered in Section II, the formulation of the problem is covered in Section III, the proposed method is shown in Section IV. The results are discussed in Section V, and the conclusion is covered in Section VI.

II. DISTRIBUTED GENERATION (DG) AND ELECTRIC VEHICLE CHARGING STATIONS CLASSIFICATION TECHNOLOGIES

Distributed generation (DG) units can be classified based on their capability to generate or absorb real and reactive power **[7].**

- Type 1: Units that produce only real power, such as photovoltaic (PV) systems.
- Type 2: Units that supply solely reactive power, for instance, capacitor banks.
- Type 3: Units capable of generating real power while either supplying or absorbing reactive power, such as synchronous generators.

Along with the EV models (Chevrolet Volt, Chang an w, Tesla Model X, and BMW i3) shown in **Table1**, the CS design also considers AC/DC level 2 type charging ports (CPs). As specified in the **SAE J1772** standard, **Level 2** charging points (CPs) operate using an AC supply and support a maximum power output of **7 kW**. These chargers are compatible with both **battery electric vehicles (BEVs)** and **plug-in hybrid electric vehicles (PHEVs)**, making them suitable for residential, commercial, and public charging applications. **[8]**

TABLE 1 EVCS Features for simulation

EV Type	EV power rating(kw)	NO. of CPS	CS rating(kw)
Chevrolet volt	2.2	35	77
Chang An Yidong	3.75	30	112.5
Tesla Model X	13	25	325
BMW I3	44	20	880
SAE J1772 Standard	7	40	280
Total power rating of CS(KW)		150	1674.5

III. PROBLEM FORMULATION:

I. Backward-Forward Sweep Load Flow:

This study proposes a backward/forward sweep (BFS) method for performing power flow analysis in radial distribution systems (RDSs). Owing to the high R/X ratio and radial structure of such systems, conventional load-flow methods like Newton–Raphson and fast decoupled techniques are ineffective. To overcome these challenges, the BFS approach is adopted, as it is one of the most suitable and efficient techniques for load-flow analysis in radial networks. Using this method, the voltage magnitude at each bus and the power losses in each branch are accurately determined. The proposed algorithm is implemented in MATLAB and validated on the IEEE 33-bus radial distribution system, yielding effective and reliable results. The BFS algorithm operates in two primary stages: backward sweep and forward sweep. In the backward sweep, Kirchhoff's Current Law (KCL) and Kirchhoff's Voltage Law (KVL) are applied starting from the node farthest from the substation to calculate branch currents and node voltages. In the forward sweep, the bus voltages are updated sequentially from the source node toward the end nodes. The algorithm employs a node-branch-oriented data structure that includes active and reactive power demands, sending and receiving node identifiers, and the positive-sequence impedance of each branch. The main steps of the proposed procedure are summarized as follows:

• Step 1: Initialize the system by assuming rated voltage at all terminal nodes.
• Step 2: Starting from the terminal nodes, compute the node current using *Equation (1)*. Apply KCL with *Equation (2)* to determine the current flowing from node *i* to node *i+1*, proceeding iteratively toward the source node.

$$I = \frac{Si^*}{Vi} \tag{1}$$

Si^*: is the complex conjugate of the power at bus i, (in the form $Si^* = P\,i - j\,Q\,i$

Pi is the active power

Q i is the reactive power at bus i).

Vi: the voltage at bus iii (as assumed or computed).

$$I(i, i+1) = Ii - Ii + 1 \tag{2}$$

Ii, i+1: is the current passing from bus i to node i+1, Ii: is the current at bus I, Ii+1: is the current at bus i+1

- Calculate the voltage at each node using the Ohm's Law equation for the branch impedance:

$$V_i = V_{i+1} - I_{(i,i+1)} * (Ri + jXi) \tag{3}$$

(R_i+jX_i): is the impedance of the branch between nodes i and i+1

Vi: is the voltage at bus i

Vi+1:is the voltage at bus i+1

The iterative procedure proceeds until every node in the distribution network is updated and convergence criteria are satisfied.

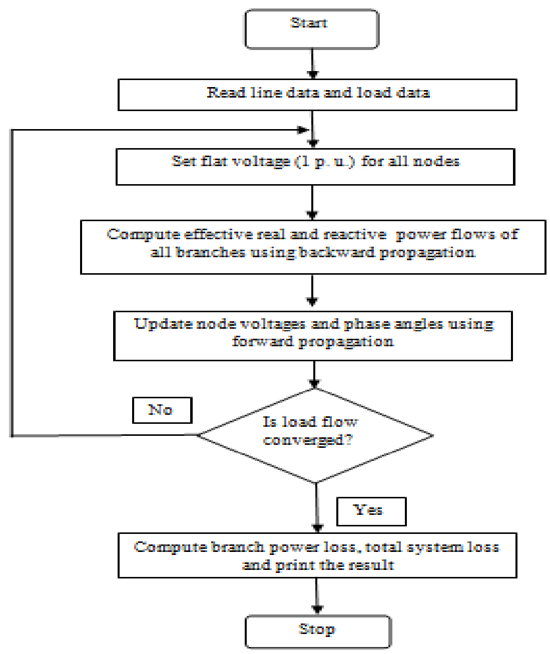

Figure (1) Flow Chart of Backward-Forward Sweep Load Flow

II. *Power Losses Reduction (f1)*

Appropriate allocation and sizing of EVCSs and DGs are necessary to reduce the negative influence of growing EV demand on the overall performance of the distribution network. The huge R/X ratio of the Radial Distribution System (RDS) makes it impossible to obtain correct findings with simple load flow tools like Newton-Raphson or fast decoupled methods. In **[9]**, An efficient load-flow method based on the forward–backward sweep technique is proposed for solving the power flow in radial distribution systems (RDSs). The primary objectives of this study are to minimize power losses and enhance the voltage profile of the system. The objective function representing the total power loss of the system is expressed as:

$$f1 = min \sum_{i=1}^{b} Ri * i^2 \quad (4)$$

where Ri is the resistance of the i^{th} branch, i is the current passing throw the branch, i is the branch number and b is the total number for the branches.

III. *Improvement of the VSI (f2)*

The objective of *f2* is to enhance the Voltage Stability Index (VSI) by utilizing the following equation (5)

$$f2 = \min \frac{1}{VSI(m2)} \quad (5)$$

$$VSI = \left[|V_K^4| - 4\left(P_K X_{jK} + Q_K r_{jk}\right)^2 - 4\left(P_K X_{jK} + Q_K r_{jk}\right)|V_K^2|\right] \quad (6)$$

where $r_{jk}$is the resistance of the branch "jk," x_{jk} is the reactance of the branch "jk," Vk is the voltage at the$k^{\ th}$ bus, Pk is the sum of active power demands at the $k^{\ th}$ bus, and Qk is the total reactive power demand at the kth bus.

To reduce power losses, and maximize the voltage stability index, the ultimate fitness function is created. In terms of math

$$f(k) = w1\ f1 + w2\frac{1}{f2} \tag{7}$$

Where w_1=w_2=0.5 which impacts on reduction in real power losses and voltage stability index respectively

IV. Constraints:

- . ***Equality Conditions:***

Restrictions associated with maintaining power balance

$$\sum_{k=1}^{nG} PG_K - PL = Pd \tag{8}$$

$$\sum_{k=1}^{nG} QG_K - QL = Qd \tag{9}$$

where nG is the total number of buses, PL and QL are the active and reactive loss power related with the $k^{\ th}$ bus, Pd and Qd are the active and reactive power demands related with the $k^{\ th}$ vehicle, and PGk and QGk are the active and reactive powers injected by DG at k^{th} the bus.

- ***Inequality Conditions:***

The operating limits of the distribution system must not exceed the maximum power output of the distributed generators (DGs), and voltage deviations should be maintained within ±5%.

$$PG_k^{min} \le PG_k \le PG_k^{max} \qquad QG_k^{min} \le QG_k \le QG_k^{max} \tag{10}$$

$$Vmin \le V_k \le Vmax \qquad k = 1,2,3 \ldots .\,n \tag{11}$$

$$\left| I_{line} \right| \le \left| I_{line}^{max} \right| \tag{12}$$

Equation (12) used to ensure that the current through any distribution feeder does not exceed its rated ampacity, preventing thermal overloading.

IV. ***<u>OPTIMZATION ALGORITHMS FOR EVCS AND DG</u>***

A. WOA algorithm

Mirjalili and Lewis developed the WOA, a nature-inspired meta-heuristic optimization method in this field, by imitating humpback whale hunting **[10]**.

Three steps make up the mathematical model of the humpback whales' bubble-net feeding strategy.

A. Surrounding the target

B. Using the bubble-net technique for hunting (exploitation phase)

i. Shrink mechanism

ii. Positional spiral update

C. Search globalization (exploration phase)

i. Surrounding the target:

When humpback whales detect prey, they often encircle it. Drawing inspiration from this behavior, the Whale Optimization Algorithm (WOA) assumes that the optimal solution lies near the current best search agent within the search space. Under this assumption, the algorithm considers the current best agent as either the prey itself or a position close to the global optimum. Once the best search agent is identified, the remaining agents update their positions accordingly to move toward it, as described by the following equations.

$$\vec{D} = \left|\vec{C}.\overrightarrow{X^{*}}(t) - \overrightarrow{X(t)}\right| \tag{13}$$

$$\vec{X}(t+1) = \overrightarrow{X^{*}}(t) - \vec{A}.\vec{D} \tag{14}$$

The current iteration is denoted by *t*, while A and C represent coefficient vectors. The position vector of the best solution obtained so far is indicated by X*, and $\vec{x}$ denotes the position vector of a given search agent. The operator (·) signifies element-wise multiplication, whereas |·| represents the absolute value. It is important to note that X* is updated in each iteration whenever a better solution is identified. The vectors $\vec{A}$ and $\vec{C}$ are considered as follows:

$$\vec{A} = 2\vec{a}.\vec{r} - \vec{a} \tag{15}$$

$$\vec{C} = 2.\vec{r} \tag{16}$$

Where $\vec{a}$ decreases linearly from 2 to 0 to model the shrinking encircling mechanism of the spiral movement, while $\vec{\mathbf{r}}$ is a random vector uniformly distributed in the range [0, 1].

ii. Using the bubble-net technique for hunting (exploitation phase)

This behavior is modeled by linearly decreasing the value of $\vec{a}$ in Equation (15) from 2 to 0. Consequently, the value of $\vec{A}$ also decreases randomly within the interval [−a, a]. At this stage, the attacking mechanism is initiated, and the distance between the whale's position (X, Y) and the prey's position (X*, Y*) is determined. Subsequently, a spiral updating equation is formulated to link the whale's and prey's positions, thereby simulating the whales' helix-shaped motion, as expressed in Equation (17).

$$\vec{X}(t+1) = \vec{D}.e^{bl}.\cos(2\pi l) + \overrightarrow{X^{*}}(t) \tag{17}$$

$$\vec{D} = \left|\overrightarrow{X^{*}}(t) - \vec{X}(t)\right| \tag{18}$$

Equation (18) represents the distance between the i^{th} whale and the prey (i.e., the best solution found so far). Here, l is a random number uniformly distributed within the range [−1, 1], and b is a constant that defines the shape of the logarithmic spiral. It is noteworthy that humpback whales swim in a spiral trajectory while simultaneously encircling their prey in a shrinking path. To model these concurrent behaviors, it is assumed that there is a 50% probability of selecting either the spiral motion or the shrinking encircling motion to update the whales' positions during the optimization process, as expressed below:

$$\vec{X}(t+1) = \begin{cases} \overrightarrow{X_{rand}} - \vec{A}.\vec{D} \ \ if & p < 0.5 \\ \vec{D}.e^{bt} \ \ .\cos(2\Pi l) + \vec{X} * (t) \ \ if & p \geqslant 0.5 \end{cases} \tag{19}$$

iii. C. Search globalization (exploration phase)

In the exploration phase, unlike the exploitation phase, the position of a search agent is updated with reference to a randomly selected search agent rather than the current best agent. This mechanism, characterized by |A| > 1, enables the Whale Optimization Algorithm (WOA) to perform an effective global search across the solution space. The corresponding mathematical model is expressed as follows:

$$\vec{D} = \left|\vec{C}.\overrightarrow{X_{rand}} - \vec{X}\right| \tag{20}$$

$$\vec{X}(t+1) = \overrightarrow{X_{rand}} - \vec{A}.\vec{D} \tag{21}$$

Where $\vec{x}$_rand represents a randomly selected position vector (randomly chosen whale) from the current population. This global exploration mechanism provides a balance between local exploitation and global exploration within the search process. The optimal solution to the problem corresponds to the best candidate solution, as illustrated in **Figure (2)**.

B. WOA approach for location and sizing of DG and EVCS:

1. Input: Power system data, including bus and line parameters, load demand, fixed sizes of Electric Vehicle Charging Stations (EVCSs) (i.e., known charging capacities), and the minimum and maximum capacity limits of Distributed Generators (DGs).
2. Execute the Backward-Forward Sweep Load Flow load flow for the base case.
3. Set parameters of N and T and algorithm constants (a, A, b, C, L)
4. Randomly initialize the positions for EVCS locations (bus assignments), DG locations (bus assignments), and DG sizes within the specified limits. Evaluate the objective function, which aims to minimize power losses and calculate the Voltage Stability Index (VSI).
5. Ensure that all initial solutions satisfy voltage constraints and DG capacity limits.
6. for t= 1 to T. Update the parameter **a**, which decreases linearly from 2 to 0.
7. For each whale (i = 1 to N):
8. Phase 1 – Exploitation (Bubble-Net Technique): Compute coefficient vectors **A** and **C**, and generate a random number p between [0, 1].
9. If P<0.5 & $|A| < 1$ update the whale's position using (13), (14)
10. If $|A|$>=1 select a random whale X_{rand} and update its position using Equations (20) and (21)
11. Otherwise, if ($p \geq 0.5$): perform the spiral movement using Equations (17) and (18).
12. Phase 2: If (|A| > 1): update the whale's position using a randomly selected whale to promote global exploration.
13. Constraint Handling: Ensure that the updated positions and DG sizes satisfy all specified operational and voltage constraints.
14. Update Best Solution: Replace X* with the current solution if it yields better objective function performance.
15. Store Best Candidate Solution: Record the best solution found in the current iteration
16. After completing all iterations (*t = 1 to T)*
17. Output the optimal DG placement and sizing configuration obtained using the Whale Optimization Algorithm (WOA).

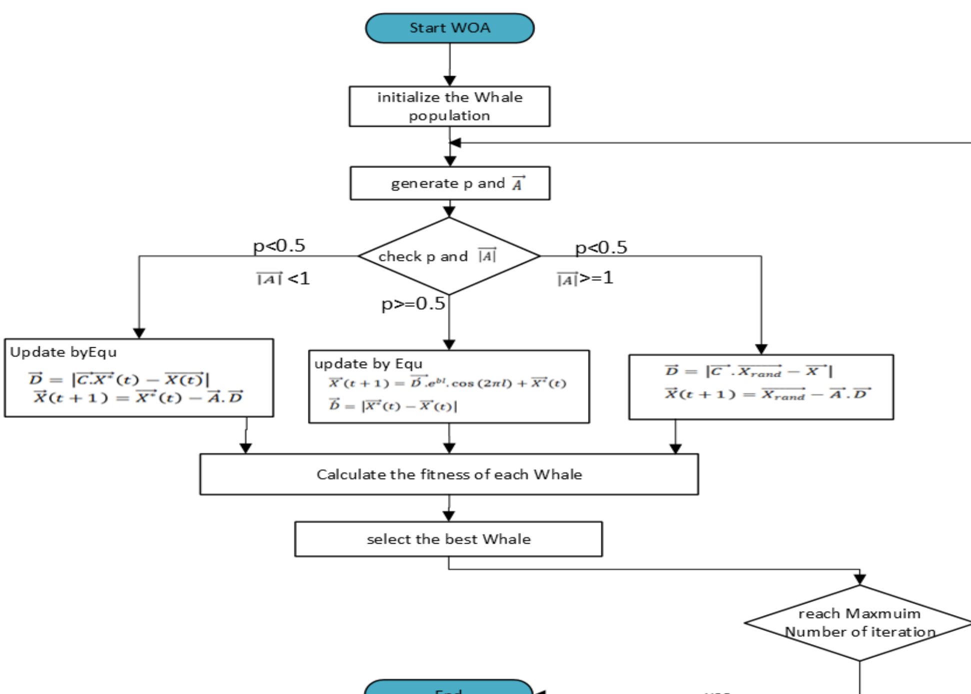

Figure (2): Flow Chart of Whale Optimization Algorithm (WOA)

C. Puma optimizer

The Puma Algorithm is inspired by the hunting behavior of pumas, large predatory cat's native to South America, commonly known as mountain lions or cougars **[11].**

i. Puma's stage of change

In this phase, two scenarios are considered: one where the puma is in its early stages of development and lacks hunting experience, and another where it has gained sufficient experience. In the first scenario, the inexperienced puma primarily engages in exploratory behavior to identify potential hunting zones within its territory. Consequently, it simultaneously performs searching and investigative actions in promising areas. During this phase, the Puma Optimization Algorithm (POA) alternates between exploration and exploitation until it approaches the initial optimal point.

After the third iteration, the algorithm transitions to selecting either the exploration or exploitation phase. The positions corresponding to these two behaviors are computed using specific equations, as experienced pumas are capable of adaptively choosing between exploration and exploitation based on environmental conditions (22) as well as (23)

$$Score_{Explore} = \left(C_1 \cdot f1_{Explor}\right) + \left(C_2 \cdot f2_{Explor}\right) \tag{22}$$

$$Score_{Exploit} = \left(C_1 \cdot f1_{Exploit}\right) + \left(C_2 \cdot f2_{Exploit}\right) \tag{23}$$

After computing the exploration and exploitation scores using the algorithm, the puma transitions to the exploration phase if $S_{explore} > S_{exploit}$; otherwise, it proceeds to the exploitation phase.

ii. Phase of exploration

This behavior reflects the pumas' tendency to search over long distances within their territory in pursuit of food. Such locations are identified either by returning to previously successful hunting grounds or by exploring new areas that may contain potential prey. During the exploration phase, the population is initially sorted in ascending order, after which each puma refines its search strategy according to Equations (24)–(25).

$$If\ rand_1 > 0.5, \quad Z_{i,G} = R_{Dim} * (Ub - Lb) + Lb \tag{24}$$

$$Otherwise \quad Z_{i,G} = X_{a,G} + G \cdot (X_{a,G} - X_{b,G}) + G \cdot \left(\left(\left(X_{a,G} - X_{b,G}\right) - \left(X_{c,G} - X_{d,G}\right)\right) + \left(\left(X_{c,G} - X_{d,G}\right) - \left(X_{e,G} - X_{f,G}\right)\right)\right), G = 2 \cdot rand_2 - 1 \tag{25}$$

where R_{Dim} , $rand_{1,2,3..}$ are random numbers between 0 and 1, and Ub and Lb are the problem's lower and upper bounds. In contrast, X are solutions chosen at random from the whole population. An alternative solution is then implemented for the present solution improvement after one of the two equations is selected in accordance with Eq. (24).

$$X_{new} = \begin{cases} M_{i,G}, & \text{if } j = j_{rand} \quad or \quad rand_3 \le U \\ X_{a,G}, & otherwise \end{cases} \tag{26}$$

$$NC = 1 - U \tag{27}$$

$$p = \frac{NC}{Npop} \tag{28}$$

$$if\ \ CostX_{new} < CostX_i , \quad U = U + p \tag{29}$$

$$X_{a,G} = X_{new},\ if\ X_{i,new} < X_{a,G} \tag{30}$$

where Pop is the aggregate number of Pumas, (U) is a parameter with a predetermined value maintained throughout the optimization procedure $M_{i,G}$ is the created solution, and j_{rand} is an integer randomly generated based on the problem's dimensions. The improvement in dimensions of the solution complies with the requirement in Eq. (29). Using Eq. (30), the current answer is substituted for the revised ones. Therefore, if the new solution is more affordable than the present one, it takes the place of the old one.

iii. Phase of exploitation

In this phase, two distinct operators — the ambush and fast-running strategies — are employed to enhance the optimization outcome. These operators are inspired by the hunting behavior of pumas, which either lie in wait to ambush their prey from concealment or, under certain conditions, pursue their targets through rapid chases. This tendency is seen in Eq. (31).

$$X_{new} = \begin{cases} if\ rand_4 \geq 0.5, \quad X_{new} = \dfrac{\left(\dfrac{mean(Sol_{total})}{Npop}\right) \cdot X_1^r - (-1)^{\beta} \times X_i}{1 + (\alpha \cdot rand_5)} \\ otherwise, \quad if\ rand_6 \geq k, X_{new} = Puma_{male} + (2 \cdot rand_7) \cdot exp(randn_1) \cdot X_2^r - X_i \\ otherwise, \quad X_{new} = (2 \times rand_8) \times \dfrac{(F_1 \cdot R \cdot X(i) + F2 \cdot (1 - R) \cdot Puma_{male})}{(2 \cdot rand_9 - 1 + randn_2)} - Puma_{male} \end{cases} \quad (31)$$

$$round(1 + (Npop - 1) \cdot rand_{10}) \quad (32)$$

The first procedure is applied if rand > 0.5, as per the preceding equation. If not, the ambush tactic is used. The average function is represented by *mean*, while the sum of all solutions is denoted as Sol_{total}. The parameter β is a randomly generated value within the range [0, 1], and X_1^r refers to a randomly selected solution from the entire population. In each iteration, X_i denotes the current solution, and *(k)* represents predefined parameters that have been fine-tuned prior to the optimization process. The optimal candidates, $Puma_{male}$ and $rand_n$, are randomly generated values following a normal distribution. The optimal solution is shown in **Figure (3).**

D. *POA approach for optimal sitting and sizing of DG and EVCS:*

1.Inputs: Power system data, including bus and line parameters, as well as EVCS and DG characteristics.

2. Perform the Backward–Forward Sweep Load Flow analysis for the base case.

3. Create a random population of solutions X_i (i = 1, 2, …, N) and evaluate the objective function (minimizing power losses and computing the Voltage Stability Index (VSI)).

4. for iteration= 1:50
   - Apply exploration phase (Algorithm 1)
   - Apply exploitation phase (Algorithm 2)
   - End loop

5.Apply Unexperienced Phase Algorithm

6.For iteration = 50 (Max iteration)
   - Apply experienced Phase
   - if Score Explore > Score Exploit then apply the Exploration Phase (algorithm 1)
   - if Exploration New Best Xi Cost < Puma male Cost update $Puma_{male} = X_i$.
   - End loop

7.Output: The optimal DG sizing and allocation along with the best EVCS placement obtained by the Puma Optimization Algorithm (POA).

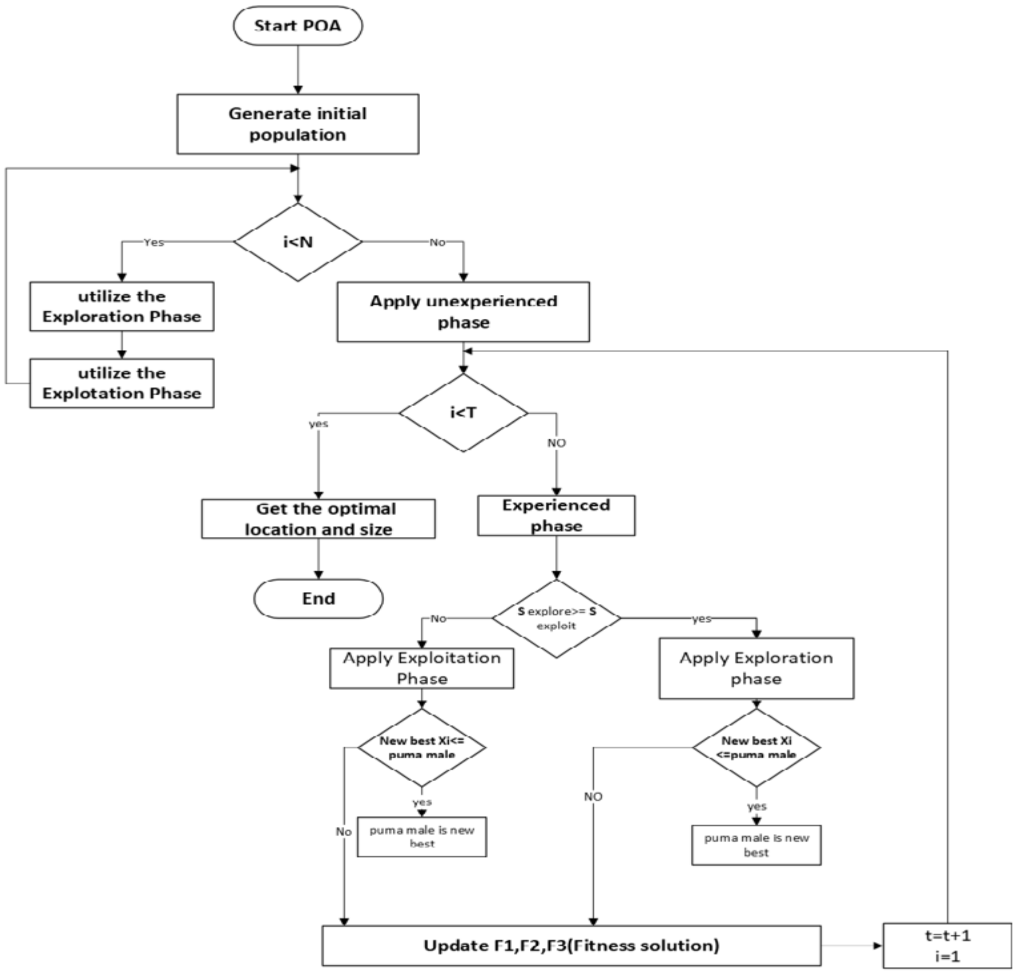

Figure (3) Flow Chart of Puma Optimization Algorithm (POA)

V. SIMULATION RESULTS AND DISCUSSION:

IEEE test system with 33 nodes, the suggested Puma Optimizer (PO)and Whale optimization (WOA) algorithms are estimated, and MATLAB is utilized to evaluate the performance, reliability, and efficiency of the proposed Puma Optimization (PO) algorithm. From the reference **[12]**, the test system's line and load data are modified. The single line diagram for test system is depicted in **Figure (4).**

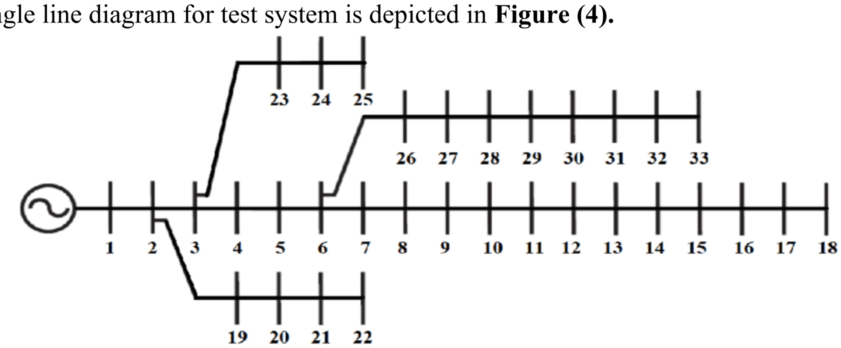

Figure (4) Single-line diagram of the IEEE 33-bus test system.

The machine with an Intel Core i7-11800H processor running up to 5 GHz and 16 GB of RAM memory is used to run the simulations using the MATLAB 15.0 platform. To obtaining the multi-objective optimization problems, this study examines EVCSs and DGs. The EVCS data is derived from reference **[13].** The rating of CS (kW), the number of CPs, and the EV power rating are all included, the following test scenarios are taken into consideration.

- Case 1: Radial Distribution System (RDS) operating without EVCS or DG integration.
- Case 2: Integration of three Electric Vehicle Charging Stations (EVCSs) with a total capacity of 3 × 1674.5 kW, without optimal placement.
- Case 3: Integration of three EVCSs, each rated at 1674.5 kW, optimally located using the proposed algorithms.

A. Results for IEEE 33 bus

i. RDS without EVCS and DG integration

The proposed algorithms are implemented on IEEE 33-bus radial distribution network with a base apparent power of 100 MVA, a substation voltage of 12.66 kV, and a total load demand of 3.715 MW and 2.300 MVAr. The model is developed and simulated in the MATLAB environment to perform load flow analysis and calculate power losses. The system exhibits a total active power loss of 201.9922 kW and a reactive power loss of 134.7406 kVAR. The minimum bus voltage, recorded at Bus 18, is 0.913374 p.u., which exceeds the permissible deviation limit of ±5%. **[21].** The optimizer's standard control settings, such as population size = 50 and maximum iteration = 50

First, the distribution load flow analysis technique is used to evaluate the base case voltage, minimum VSI, minimum voltage, and power loss for the suggested networks. The generated simulation results are displayed in Table 2. The results indicate that the suggested algorithms are superior than previously published methods such as TELBO, HHO, PSO, FBA, CSA, and ALO As depicted in **Table (2)**

ii. *Optimal locations with Type-I DGs using three electric vehicle charging stations*

results than HHO and TELBO, and PO's simulation results are compared with WOA to show the efficiency of the suggested approach (PO) with Type-I DG in **Table (3).** The total power losses are reduced by 66.8%, and 64.747% for Type-I (3 DGs) sited, respectively, and the voltage profile is enhanced. The minimum voltage is 0.967975and 0.9690 for POA and WOA, respectively. Convergence curve for 3EVCS and 3DG in **Figure (5).**

iii. *Optimal locations with Type-II DGs using three electric vehicle charging stations*

The stations (3*1674.5 kw) were integrated with Type-II DGs in **Table (4).** The reduction in the total power losses is 24.151% and 25.075% for Type II (three DGs) and the minimum voltage with POA and WOA is 0.9371 and 0.926374, respectively. It was observed that this type performs less effectively in minimizing losses and enhancing voltage compared to other types. The convergence curve for the 3EVCS with 3DG configuration is depicted in **Figure (6).** Puma's algorithm demonstrates superior performance compared to the other proposed algorithms.

The Voltage Profiles and the Total Power Losses of 33 bus test system with 3 DGs of various Types and 3EVCS with rated power 1674.5 KW are depicted in **Figure (7)** and **Figure (8).**

Figure (9) shows the Comparison of VSI as a minimum voltage magnitude between selected literature and the proposed method. For Type-I POA/WOA and Type-II POA/WOA shows significantly higher minimum voltages, indicating better stability performance.

TABLE 2. System Performance of 33 BUS System with EVCS (3*1674.5 KW) and Random location of DG

CASE	ALGORITHM	EV_LOCATIONS	F1, PLOSS(KW)	F2, VSI min(Pu)	Vmin (Pu)
1	Base Case		201.99	0.697817	0.913374
2	Random location		1684.17381	0.307450	0.744292
3	TELBO [14]	2,19,25	390.6266	0.6381	0.8941
	HHO [15]	2,19,25	390.6266	0.6381	0.8941
	PSO [16]	2,19,25	390.6266	0.6381	0.8941
	FBA [17]	2,19,25	390.6266	0.6381	0.8941
	CSA [18]	2,19,25	390.6266	0.6381	0.8941
	ALO [19]	2,19,25	390.6266	0.6381	0.8941
	WOA(Proposed)	2,19,3	296.4820	0.670928	0.904435
	PO(Proposed)	2,19,3	296.4820	0.670928	0.904435

TABLE 3. System Performance of 33 BUS Test System with 3 EVCS each one has 1674.5 KW and 3DG Integration at Optimal Location for Type I

Algorithm	EV and DG locations	DG Size (KW)	Total DG_Size (KW)	Ploss (KW)	Reduction in Ploss%	VSI_{min} (Pu)	Vmin (Pu)
HHO [15]	2,19,25 13,24,30	880.91,1500 and 1227.81	3608.72	137.4507	64.81	0.8606	0.9633
TLBO [14]	2,19,25 13,24,30	881.1, 1500 and1229.58	3610.68	137.4506	64.81	0.8606	0.9633
WOA	2,3,19 24,31,11	1652.9612,804.8236 and 1258.9042	3716.689	104.51722	64.747	0.88181	0.9690
POA	2,3,19 30,10.3	1064,1070,2100	4234	98.3815	66.8	0.8800	0.967975

TABLE 4. System Performance of 33 BUS System with 3 EVCS each one has 1674.5 KW and 3DG Integration at Optimal Location for Type II

Algorithm	EV and DG locations	DG Size (KW)	Total DG_Size (KW)	Ploss (KW)	Reduction in Ploss%	VSI_{min} (Pu)	Vmin (Pu)
HHO [15]	2,19,25 13,24,30	389.72,638.12 and 1040.4	2068.24	311.0932	20.36	0.7258	0.923
TELBO [14]	2,19,25 13,24,30	389.82,638.11 and 1041.18	2069.11	311.0911	20.36	0.7258	0.923
WOA	2,3,19 30,7,25	1000,607.393and 415.88674	2023.279	224.8783	24.151	0.738308	0.926374
POA	2,3,19 20,14,24	1000,431,522.4	1953.4	222.1378	25.075	0.77322	0.9371

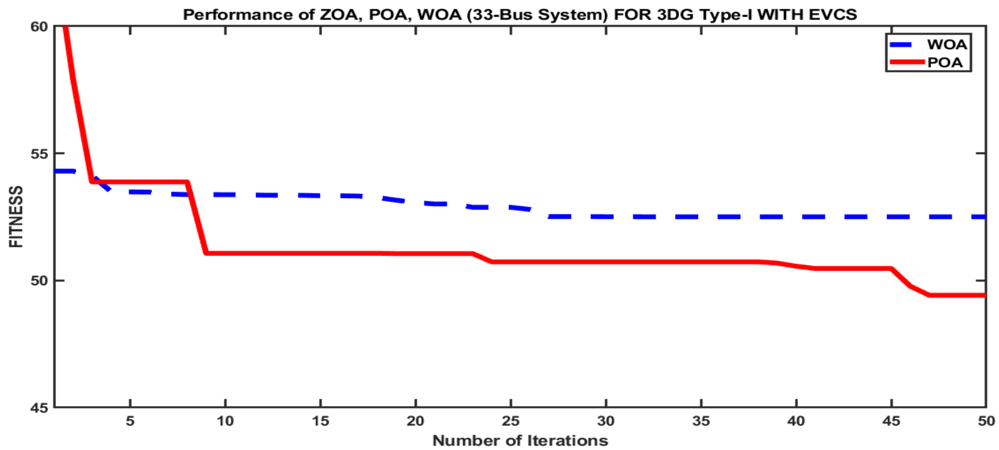

Figure (5) the convergence performance of EVCS with 3DGType-I

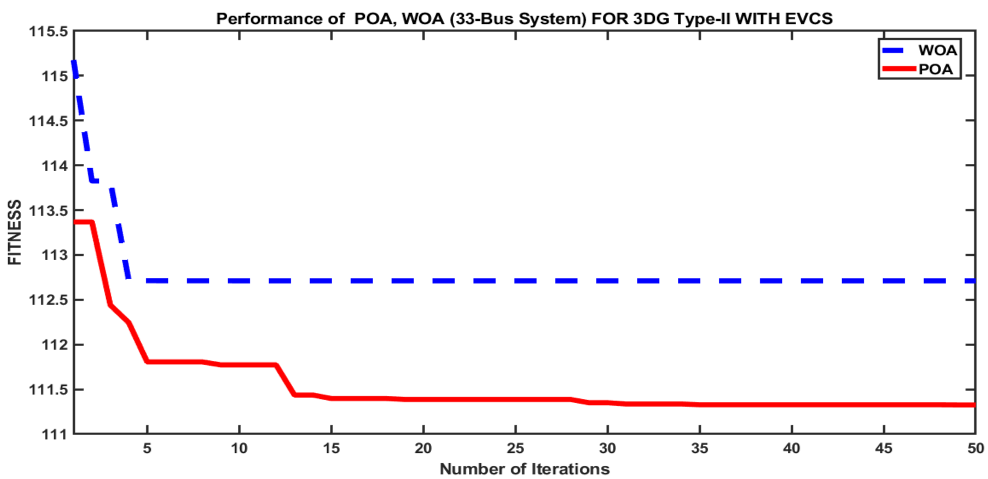

Figure (6) the convergence performance of EVCS with 3DGType-II

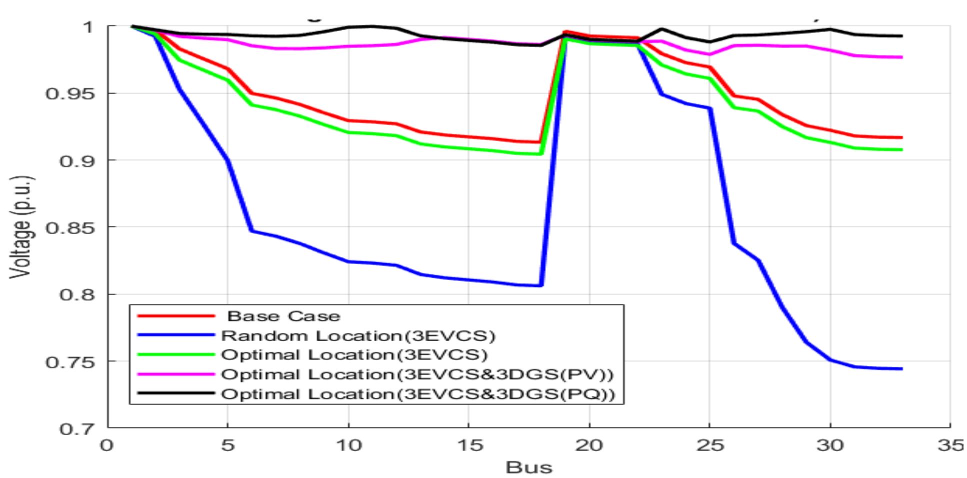

Figure (7) Voltage Profile at 33-bus to 3 DGS with different Types and 3 EVCS (1674.5KW)

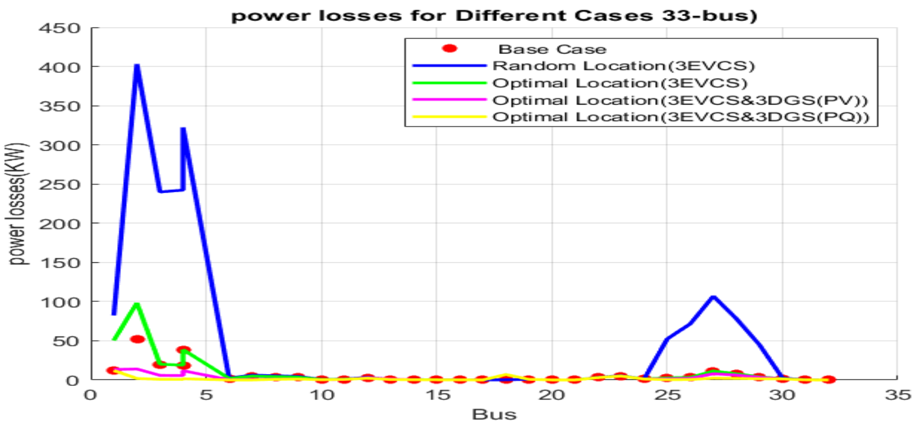

Figure (8) Power Losses at 33-bus to 3DGS with different Types and 3 EVCS (1674.5 KW)

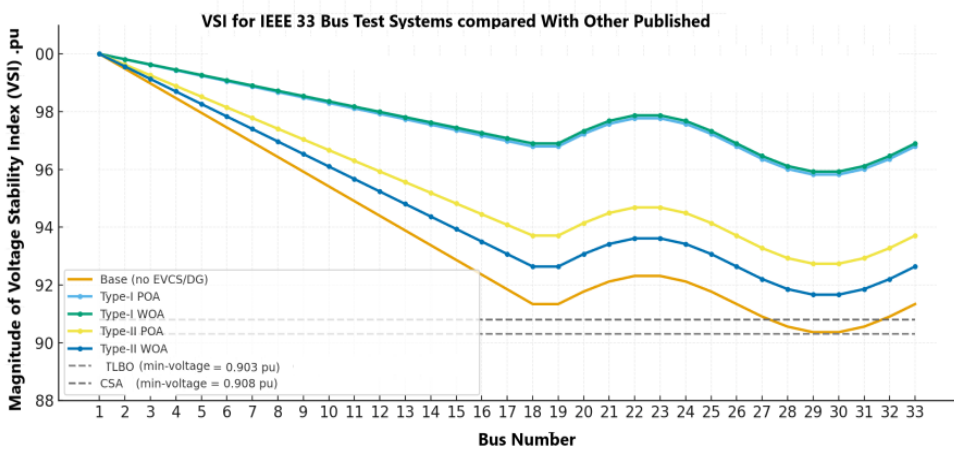

Figure (9) Magnitude of Voltage Stability Index VSI with integration of DG/EV

VI. CONCLUSION

The large-scale integration of electric vehicle charging stations (EVCSs) negatively impacts the electrical distribution system by increasing power losses, reducing voltage stability, and degrading voltage profiles. This work proposed the optimal allocation and sizing of Distributed Generators (DGs) with EVCSs using Whale Optimization Algorithm (WOA) and Puma Optimization Algorithm (POA). The IEEE 33 bus test system was used for validation. Simulation results confirmed that the proposed methods significantly improve system performance compared with the base case. Without EVCSs and DGs, the system recorded 201.99 kW active losses and a minimum voltage of 0.913 pu. With optimally placed EVCSs and Type-I DGs, power losses decreased by 66.8% (POA) and 64.7% (WOA), while the minimum voltage improved to 0.9679 pu and 0.9690 pu, respectively. For Type-II DGs, power losses were reduced by 24.15% (POA) and 25.08% (WOA), with corresponding minimum voltages of 0.9371 pu and 0.9264 pu. Overall, the findings show that PQ-mode DGs deliver the highest efficiency in reducing losses, enhancing the voltage profile, and strengthening the Voltage Stability Index (VSI). The comparative analysis demonstrates the superiority of POA and WOA over previously published optimization methods, making them robust tools for future distribution system planning with high EV penetration.

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