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Evaluating the Computational Efficiency and Convergence Characteristics of Crow Search Algorithm for Strategic Placement and Sizing of Distributed Generator Units in Radial Distribution Networks to Enhance Network Reliability

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Abstract: *This paper evaluates the computational efficiency and convergence characteristics of the Crow Search Algorithm (CSA) for the strategic placement and sizing of Distributed Generator (DG) units in Radial Distribution Networks (RDNs). The objectives are to minimize total power losses and improve the voltage profile. The CSA's performance was tested on the IEEE 33-bus distribution system. Results indicate that CSA typically converges with fewer iterations, averaging 7 iterations, and requires less computational time, approximately 3.343 seconds, due to its efficient search mechanism and minimal parameter adjustment requirements. Introducing up to 3 DGs using CSA resulted in a 40.99% reduction in system losses and a 53.13% improvement in the overall voltage profile compared to the base case without DGs. These findings highlight the effectiveness of CSA in solving optimal DG allocation problems, demonstrating its computational efficiency and robust convergence characteristics.*

Keywords: *Distributed Generation, Crow Search Algorithm, Voltage profile, Power losses, MATLAB.*

1. INTRODUCTION

Persistently poor voltage profiles are a common issue in many areas of Nigeria, particularly affecting consumers situated at considerable distances or connected to distribution networks at moderately distant locations from their service transformers. Voltage distribution in Nigeria typically operates at 230V for single-phase and 415V for three-phase systems. However, voltages in numerous Nigerian locations often plummet to as low as 180V, regularly exposing many power consumers' appliances to operational failures and damages (Nwohu *et al.,* 2018).

The strategic incorporation of Distributed Generators (DG) into distribution systems provides numerous advantages for both power consumers and DG equipment owners. This integration not only stabilizes voltage at the consumer level but also generates income for DG operators. The inefficiencies prevalent in many Nigerian distribution networks, marked by substantial line losses, voltage drops, and continuous fluctuations, highlight the urgent need to reduce these losses and improve overall efficiency, particularly in terms of voltage quality and reliability. This is the foundation of the current research.

Various researchers are exploring optimal sizing and placement of DG units using different algorithms. For example, Mahmoud *et al.* (2014) developed an efficient method for identifying the optimal location and size of DG units in distribution power systems. By combining well-established techniques, they achieved results that closely matched simulation outcomes. Additionally, Moein *et al.* (2018) used a population-based metaheuristic approach called the clonal algorithm for DG placement in radial distribution systems. Their study showed a significant reduction in power losses, demonstrating the potential for considerable improvements with DG integration.

Furthermore, Mark *et al.* (2017) modeled an 11 kV Piggery distribution feeder of the Abuja Electricity Distribution Company in ETAP and used Ant Colony Optimization (ACO) in MATLAB to determine the optimal DG location, achieving a 10.7% improvement in voltage profile and a 66% reduction in power losses, though only a single DG was considered without sizing. Conversely, Jagan *et al.* (2017) hybridized Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) to reduce real power losses, operating costs, and enhance voltage stability in radial distribution systems. Their hybrid algorithm, validated on IEEE-33 and 69 bus systems, demonstrated superior effectiveness compared to using GA and PSO independently for optimal DG placement and sizing.

Lastly, Eshan *et al.* (2020) proposed a Multi-leader Particle Swarm Optimization (MLPSO) method to determine the optimal locations and sizes of DGs for minimizing active power losses. They identified DG locations using a voltage stability index (VSI) and determined DG sizes using the MLPSO algorithm, with power flow simulations conducted via the backward-forward sweep method. Applied to the IEEE-33 bus system and a Malaysian bus system, the MLPSO method showed improved loss reduction and reduced computational time compared to standard PSO.

In this paper, we evaluate the computational efficiency and convergence characteristics of the Crow Search Algorithm (CSA) for the strategic placement and sizing of DG units in radial distribution networks. The effectiveness of CSA in optimizing DG integration is assessed on the IEEE 33-bus radial distribution system, focusing on its ability to minimize power losses and improve voltage profiles with efficient convergence and computational performance.

2. METHODOLOGY

The methodology adopted for this research comprises the following steps:

1. Deployment of the Crow Search Algorithm (CSA) on IEEE 33-Bus System:
    a. Formulation of the optimization function with objectives focused on power loss reduction and voltage improvement.
    b. Definition of optimization constraints.
    c. Implementation of CSA to optimize the formulated objective functions.
    d. Application of CSA specifically on the IEEE 33-bus system within the MATLAB platform to identify optimal DG placements.

e. Comparison of results from CSA with the base case scenario, evaluating improvements in power loss reduction and voltage profile enhancement.

2. Evaluation of Computational Efficiency and Convergence Characteristics:
   a. Assessment of CSA's computational efficiency, including execution time of simulations.
   b. Analysis of CSA's convergence characteristics to determine its effectiveness in optimizing DG locations and sizes on the IEEE 33-bus system.

3.0 PROBLEM FORMULATION

The problem formulation encompasses the objective functions and constraints of the Smell Agent Optimization Algorithm to solve the optimization problem.

3.1 Objective Functions Formulation

The objective functions in this work aim to minimize power losses across the distribution line length.

To minimize a function comprising several parameters, the general function is expressed as a summation of those parameters.

$$f = f_1 + f_2 + \cdots + f_N = \sum_{i=1}^{N} f_i \quad (1)$$

3.1.1 The parameter of the DG size

It is vital that the optimal DG size be deployed on the network buses and is given by equation (2)

where; $$f_1 = \sum_{i=1}^{N} P_{DG_i} \quad (2)$$

Where, P_{DG_i} is the DG capacity of the ith bus, N is the set of possible locations.

3.1.2 Parameter of the total power loss of the network

The power loss of the network is calculated in equation (3)

$$f_2 = f(P_{loss}) = P_{loss} \quad (3)$$

Here, P_{loss} is the total power loss of the network. Real and reactive power loss analysis will be evaluated for the system with and without DG. The loss in the system can be calculated using equation (4) (Witchit *et at.*,2006) also called the exact loss formula.

$$f_2 = \sum_{i=1}^{N} \sum_{j=1}^{N} \left[\alpha_{ij} \left(P_i P_j + Q_i Q_j \right) + \beta_{ij} \left(Q_i P_j + P_i Q_j \right) \right] \quad (4)$$

Where, $$\alpha_{ij} = \frac{R_{ij} \cos(\delta_i - \delta_j)}{V_i V_j} \quad (5)$$

$$\beta_{ij} = \frac{R_{ij} \sin(\delta_i - \delta_j)}{V_i V_j} \quad (6)$$

P_i and Q_i are net real and reactive power injection in bus i, respectively.

$R_{ij}$is the resistance between buses i and j

$V_i$andδ_i are the voltage and angle at bus i respectively.

According to the preceding equations, the final objective function to be minimized is acquired as follows : $f = f_1 + f_2$ (7)

Substituting the values of f_1 and f_2 into equation (7) yields:

$$f = \sum_{i=1}^{N} P_{DG_i} + \sum_{i=1}^{N} \sum_{j=1}^{N} \left[\alpha_{ij} \left(P_i P_j + Q_i Q_j \right) + \beta_{ij} (Q_i P_j + P_i Q_j) \right] \quad (8)$$

3.2 Constraints

Constraints are issue of great importance in optimization procedures. An optimal answer is the answer that satisfies all of the constraints of the optimization problem. The following constraints will be considered while locating and sizing DGs.

3.2.1 Power Injection constraints

This is given by:

$$\sum_{i=1}^{N} P_{DG_i} \leq \sum_{i=1}^{N} P_{D_i} + P_L \quad (9)$$

Where, $P_L$is the real power loss in the system

$P_{DG_i}$is the real power generation of DG at bus i.

$P_{D_i}$is the power demand at bus i.

3.2.2 Voltage constraints

The variation range of all of the distribution buses should be within a specified limit. The voltage constraint is given below:

$$|V_i|^{min} \leq V_i \leq |V_i|^{max} \quad (10)$$

Here,

$$|V_i|^{min} = 0.95(\text{pu}) \quad (11)$$

$$|V_i|^{max} = 1.05(\text{pu}) \quad (12)$$

Voltages lower or higher than (±6%) exposes many power consumers’ appliances to operation failure and damages.

3.2.3Total Power Balanced Constraint

$$\sum_{i=1}^{N} P_{DG} + P_{substation} = P_{load} + P_{losses} \quad (13)$$

Where, P_{DG} is the Power supply by DG

$P_{substation}$is the Power supply from substation

P_{load} is the Power delivered to the network connected loads

P_{losses} is the Power losses on the network

N is the Number of distributed generators connected

4. Crow Search Algorithm (CSA)

Crow search algorithm is a recent metaheuristic algorithm developed in 2016 by (Askarzadeh, 2016), inspired on the intelligence behavior conducted by crows of hiding their excess food in a place and get it back when needed. CSA has been applied for different problems with different constraints. As an algorithm based on population, the size of the flock is confirmed by NC individuals (crows) which are of n−dimensional where n denotes the problem dimensions. Each crow (individual) is assumed to have the capability of remembering the best visited location to hide food. The position of each crow represents a potential solution of the problem. At iteration$i$, the position of crow i is represented as:

$$x^{i,iter} = [x_1^{i,iter}, x_2^{i,iter}, \ldots., x_d^{i,iter}] \qquad (14)$$

Where $i, iter$ is the iteration number; and i is the crow number. It is assumed that each crow saves the position of its cache in its memory. At iteration no. $i, iter$, the position of the cache of crow i is called $m^{i,iter}$. This considers the best position of crow i that is found so far. Indeed, the position of the best experience of each crow has been saved in its memory. In the environment, crows move to find better food sources (caches) (Menna *et al.,* 2018).

The position is then modified according to Pursuit and Evasion behaviors.

Pursuit: a crow j follows crow i with the purpose to discover its hidden place. The crow i does not notice the presence of the other crow, as consequence the purpose of crow j is achieved.

Evasion: the crow i knows about the presence of crow j and in order to protect its food, crow i intentionally takes a random trajectory. This behavior is simulated in CSA through the implementation of a random movement.

The expression for cases 1 and 2 (pursuit and evasion) is as follows:

$$x^{i,iter+} = \begin{cases} x^{i,iter} + r_i \times fl^{i,iter} \times \left(m^{j,iter} - x^{i,iter}\right), r_j \geq AP^{j,iter} \\ a\ randomtrajectory, \qquad otherwise \end{cases} \qquad (15)$$

Wherer_i and $r_j$are random numbers uniformly distributed between 0 and 1; fl is the flight length of crow i at iteration i *ter*; and $AP^{j,iter}$is the awareness probability of crow j at iteration, $iter.$

The type of behavior considered by each crow i is determined by an awareness probability (AP).Once crow i updates its position, it will update its memory by:

$$m^{i,iter+1} = \begin{Bmatrix} x^{i,iter+} \ , & f(x^{i,iter+1})\ is\ better\ than\ f(m^{i,iter}) \\ m^{i,iter}, & otherwise \end{Bmatrix} \quad (16)$$

The flight length (*fl*) parameter indicates the magnitude of movement from crow position towards the best position of crow j.

CSA has two specific parameters, which distinguish CSA from any other search technique; flight length (f *l*) and awareness probability (A P). f *l* calculates the step size of the movement of crow i towards the cache of crow j . If the value f *l* is set between 0 and 1, the new position of crow i will be between $x^{i,iter}$ and $m^{j,iter}$ (local search), while if its value is set more than 1, the crow can reach beyond the cache (global search). A P mainly controls intensification and diversification. By reducing the value of A P, the search will be on a local region and intensification will increase. On the other hand by increasing its value, crows will search on a global scale (Mohamed *et al*., 2019).

A brief flowchart of the standard CSA is illustrated in Figure 1

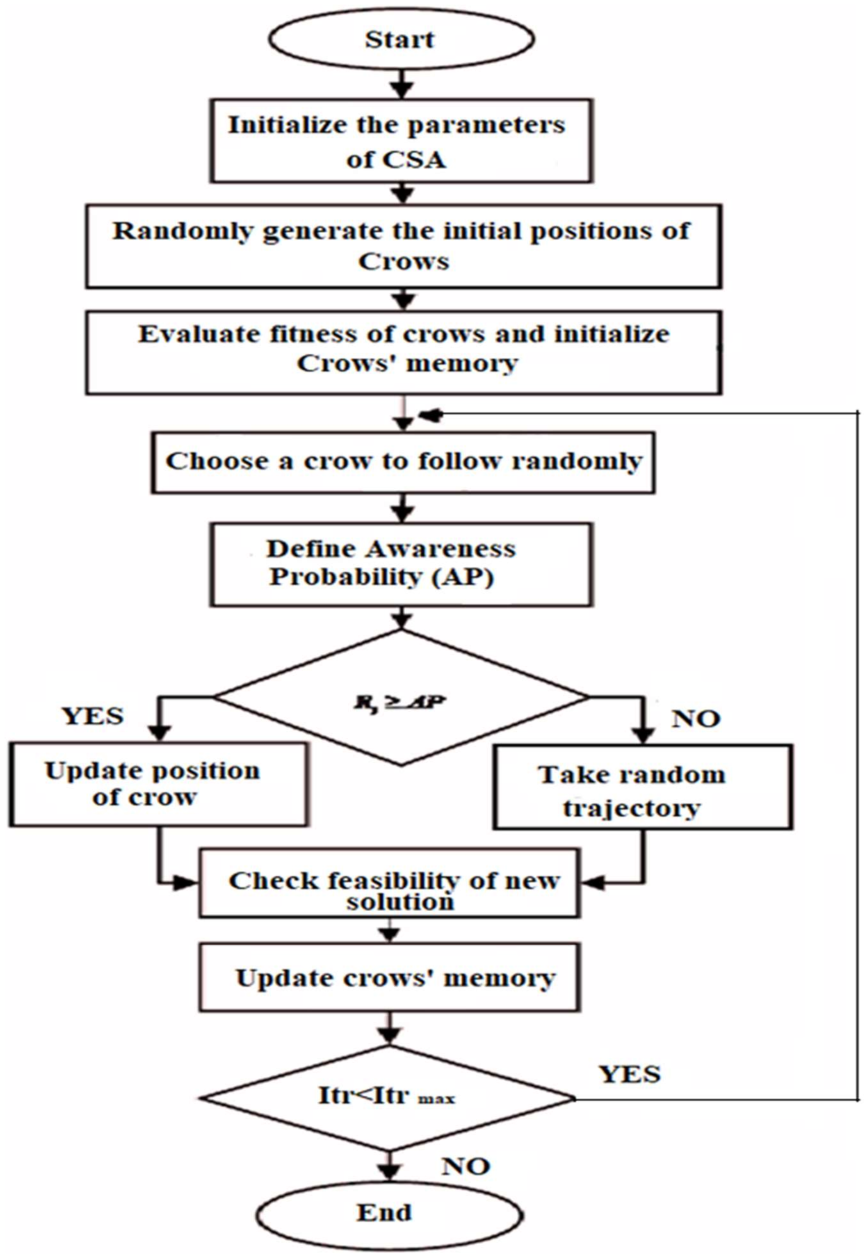

Figure 1: Flowchart of the standard CSA (Mohamed *et al.,* 2019)

5.0 SIMULATION RESULTS AND DISCUSSION

5.1 Results from the IEEE-33 Bus Test System

The bus and line data for the standard IEEE 33-bus system were used to model the system in MATLAB 2016a, and the base case voltage for each bus was noted. The Crow Search Algorithm (CSA) was employed to determine the optimal locations and sizes of Distributed Generators (DGs) for the IEEE 33-bus network. In both scenarios, the bus voltages, total real power losses, and voltage profiles before and after DG placement were recorded for comparative analysis.

5.1.1 Base Case Total System Loss and Average Voltage Profile

Initially, load flow analysis was conducted on the 33-bus system to ascertain the voltage at each bus and the total real power loss across the system. This analysis provided the baseline voltage and active power loss figures for the IEEE-33 bus system prior to incorporating DGs. The total real power loss in the base case was measured at 202.7 kW, with an average voltage of approximately 0.9488 across the buses.

5.1.2 Effect of DG Allocation on System Losses Using CSA

Using the Crow Search Algorithm, optimal placement of DGs was performed on the IEEE-33 bus system. Table 1 presents the optimal sizes and locations of the DGs. Following the optimal placement, the total real power loss decreased significantly to 119.6 kW, and the enhanced voltage levels at each bus are depicted in Figure 2-3. Additionally, the average simulation time is detailed in Table 1.

Table 1: Effect of DG placement on network losses reduction for IEEE-33 bus

Number of DGs	Location (Bus number)	DG size (kW)	Loss without DG(kW)	Loss With DG(kW)	% Loss Reduction	Time of Simulation(s)
2	11	2.24	202.7	126.6	37.54	2.765
	14	1.47				
3	11	0.74		119.6	40.99	3.343
	17	1.69				
	23	0.96				

The table illustrates the impact of distributed generators (DGs) on reducing network losses within a distribution system. Installing two DGs results in a notable reduction in system losses, decreasing from 202.7 kW without DG to 126.6 kW, representing a 37.54 percent reduction in losses. The simulation time for this setup is efficient at 2.765 seconds, demonstrating effective computational management.

Expanding to three DGs deployed at different bus locations (Buses 11, 17, and 23) with disparatecapacities, the combined effect is a reduction in system losses from 202.7 kW to 119.6 kW with DGs operational, achieving a 40.99 percent reduction in losses. Despite the added complexity from multiple DGs, the simulation time remains efficient at 3.343 seconds, indicating robust computational handling of network dynamics.

These findings underscore the benefits of DG integration in distribution networks. Strategic placement of DGs enables engineers to significantly mitigate energy losses, enhance voltage stability, and improve overall network efficiency. The efficient simulation times further highlight the practical feasibility of DG integration in real-world applications, promising operational cost savings and environmental benefits.

In conclusion, the simulation times presented in the table, 2.765 seconds for two DGs and 3.343 seconds for three DGs demonstrate efficient computational handling despite the complexity introduced by multiple distributed generators.

The figures 3 and 4 illustrate the real power loss plot subsequent to the successful power flow analysis of the IEEE-33 network, demonstrating the influence of varying numbers of installed DGs. These figures emphasize the convergence characteristics of the Crow Search Algorithm (CSA), highlighting its ability to reach an optimal solution. Specifically, CSA achieved convergence after 3 iterations for 2 DGs and after 7 iterations for 3 DGs, underscoring its effective convergence capabilities. This capability underscores CSA's efficacy in reducing system losses and optimizing DG placement within distribution networks.

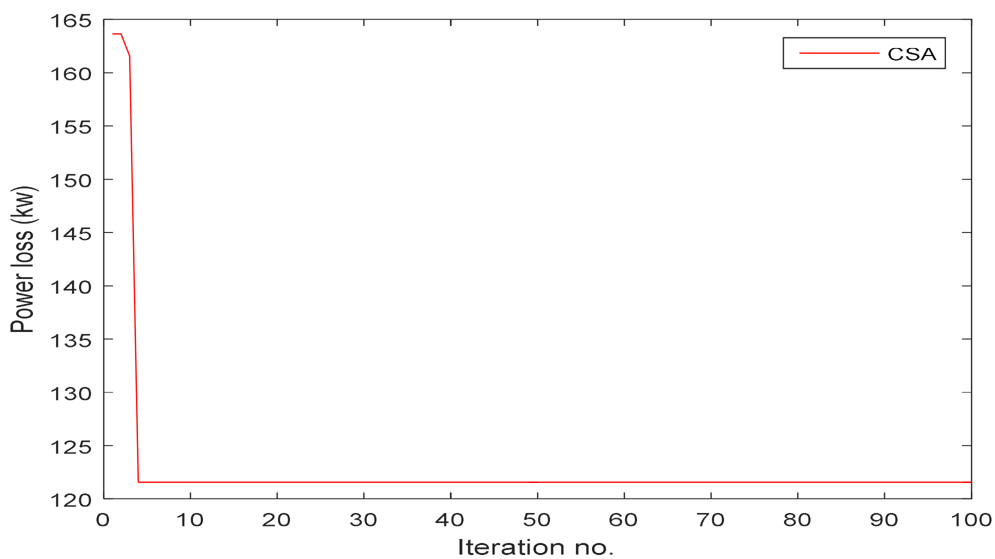

Figure 2: Real power loss of IEEE-33 bus after introducing 2 DGs using CSA

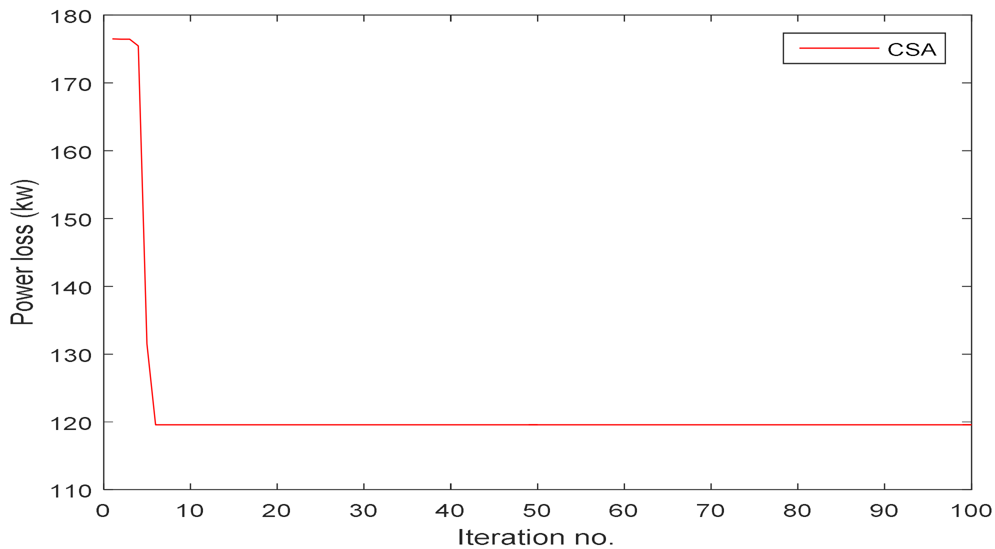

Figure 3: Real power loss of IEEE-33 bus after introducing 3 DGs using CSA

5.1.3 Voltage profile after DG allocation using CSA

The base case and improved voltage magnitudes obtained from the simulation results were plotted against their respective bus numbers to visualize the enhancement in voltage profile following DG allocation using the CSA method. The average base case voltage was 0.9488. After integrating 2 DGs, the average voltage profile improved to 0.9734, and integrating 3 DGs further improved it to 0.9760.

Figure 4 depicts the voltage profiles obtained after integrating 2 and 3 DGs, with a red line representing the base case voltage of 0.9488. The black line in Figure 4 represents the improved voltage profile after integrating 2 DGs using the CSA algorithm. In Figure 5, identical black line represents the improved voltage profile after integrating 3 DGs using the CSA algorithm.

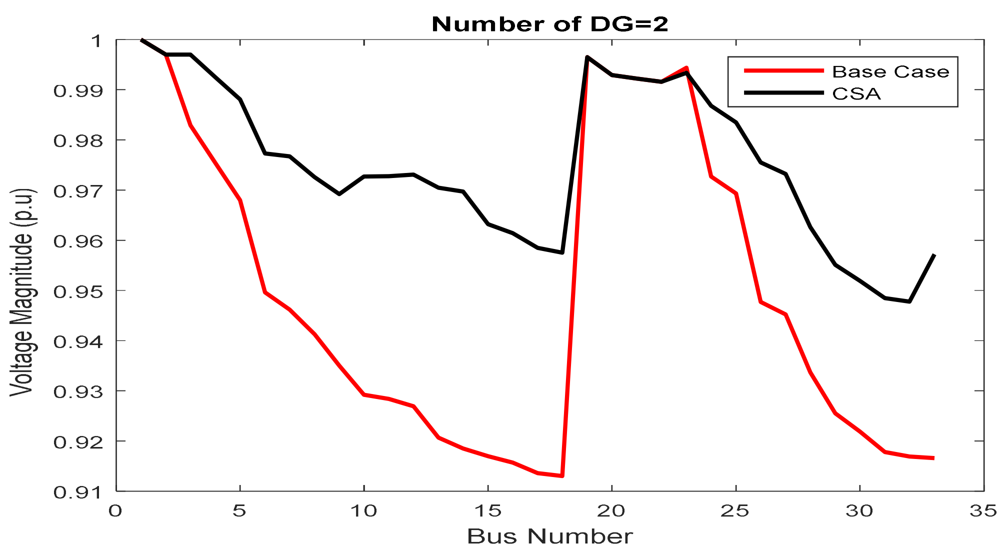

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Figure 4:Voltage Profile for IEEE 33-Bus Network after 2 DG installation Using CSA

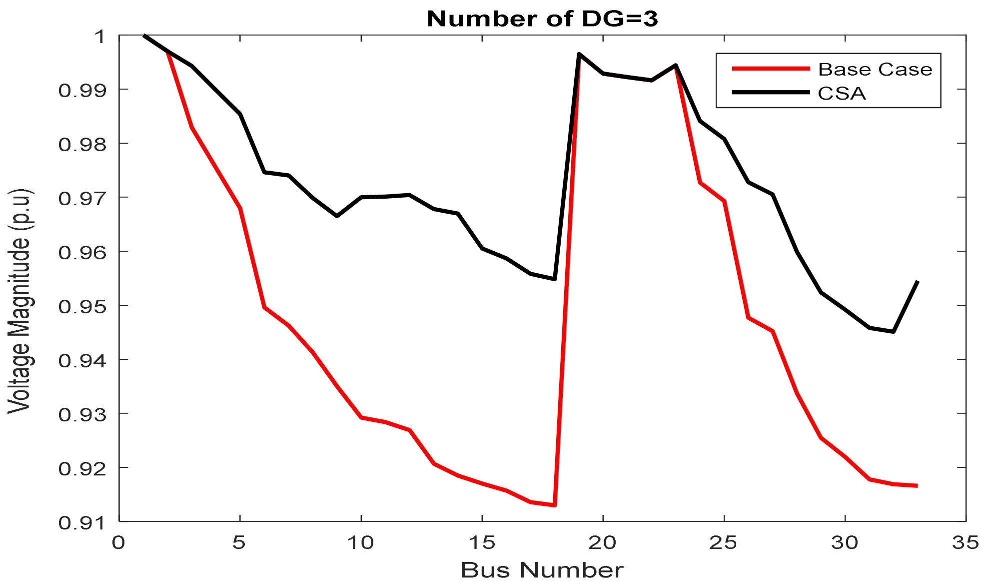

Figure 5: Voltage Profile for IEEE 33-Bus Network after 3 DG installation Using CSA

6.0 CONCLUSION

In conclusion, this study evaluates the computational efficiency and convergence characteristics of the Crow Search Algorithm (CSA) for optimizing the placement and sizing of Distributed Generator (DG) units in Radial Distribution Networks (RDNs). Through simulations on the IEEE 33-bus distribution system, CSA demonstrated robust performance, achieving convergence within an average of 7 iterations. The computational time for CSA was approximately 3.343 seconds, highlighting its efficient search mechanism and minimal parameter adjustment requirements. By strategically introducing up to 3 DGs using CSA, the study achieved significant improvements in network performance, including a 40.99% reduction in system losses and a notable 53.13% enhancement in the voltage profile compared to scenarios without DGs.

These findings accentuate CSA's effectiveness in solving optimal DG allocation problems within distribution networks, showcasing its computational efficiency and reliable convergence characteristics. This research contributes to advancing methodologies for enhancing power distribution network operations, emphasizing the strategic deployment of DGs to minimize losses, improve voltage stability, and meet operational demands effectively.

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