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Enhancing Power Delivery through Optimal Deployment of Distributed Generators on Nigerian Radial Distribution Networks: A Hybrid Crow Search Algorithm and Smell Agent Optimization Approach

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Abstract: *This study presents a novel hybridized approach that combines the Crow Search Algorithm (CSA) and Smell Agent Optimization (SAO) algorithm to determine the optimal location and size for integrating Distributed Generation (DG) into power networks. The proposed method is applied to the 11kV GRA feeder of the Abuja Electricity Distribution Company (AEDC), demonstrating remarkable outcomes. The results reveal a significant 49.47% reduction in power losses and an impressive 67.95% respectively overall enhancement in voltage profiles after the installation of three DGs. These findings highlight the performance of the hybrid approach for power delivery improvement on a Nigerian network.*

Keywords: *Crow Search Algorithm; Smell Agent Optimization; Voltage profile; Power losses; Distributed Generation*

1. INTRODUCTION

The depletion of our energy sources is rapidly accelerating due to increasing pressure and the continually growing population. As a result, there is an urgent need to explore innovative and improved methods for energy generation. It is imperative to discover environmentally friendly and self-sustaining approaches that can effectively meet the escalating demand for energy resulting from human activities.

Finding the ideal location and size for Distributed Generators (DGs) in a distribution network can be quite challenging. Typically, the methods employed for locating and sizing DGs in such networks consist of analytical and heuristic approaches.

When it comes to the challenge of achieving optimal allocation of DGs, the analytical method may seem simple to understand and implement, but it is computationally intensive and time-consuming. On the other hand, while meta-heuristic methods are known for their robustness, they often struggle to produce optimal solutions. Meta-heuristic methods have gained recognition as effective and potent tools for addressing intricate engineering optimization problems.

Meta-heuristic methods operate on a distinct principle compared to traditional optimization methods. Instead of relying on derivative or gradient information, these methods only require the function value of the problem. Initially, these methods generate function values by employing random operators across various solution spaces, a process known as exploration or diversification. Subsequently, the algorithm thoroughly explores these solution spaces in search of the optimal solution through exploitation or intensification. Striking a balance between exploration and exploitation poses a significant challenge to avoid getting trapped in local optima. To address this issue, the most common approach involves dynamic parameter selection or the fusion of advantageous characteristics from two or more algorithms (Salawudeen *et al*., 2021)

The principle of these methods differs from traditional optimization methods, as they only rely on function values rather than derivative or gradient information of the problem. These function values are initially generated using random operators across different solution spaces, a process known as exploration or diversification. Subsequently, the algorithm thoroughly searches these solution spaces for the optimal solution through exploitation or intensification. Striking a balance between exploration and exploitation is a major challenge that must be carefully considered to avoid getting trapped in local optima. The most common approach to address this problem is through dynamic parameter selection or by hybridizing the positive features of two or more algorithms (Salawudeen *et al*., 2021)

Numerous researchers have made significant contributions in the pursuit of finding the best sizing and placement of DG units through the utilization of different algorithms. In one study, Moein (2014) employed a clonal algorithm to determine the optimal placement of DGs in radial distribution systems. Another study by Karar *et al.* (2014) introduced a combined analytical and complete AC optimal power flow approach to calculate the optimal location and size of DGs, considering the complete AC system. These researchers have made valuable contributions to the development of efficient methods for determining the optimal sizing and placement of DGs in distribution power systems. In addition, Raghab *et al*. (2016) introduced the Cat Swarm Optimization (CSO) algorithm and Parallel Cat Swarm Optimization (PCSO) algorithm for allocating distributed generation (DG) units in distribution networks. Their objective was to minimize total generation costs, power losses, and emissions while improving voltage stability. Similarly, Savya *et al.* (2016) utilized the artificial bee colony (ABC) algorithm to determine the optimal sizing and placement of DG units. The proposed algorithm was tested on the IEEE 33 bus system to assess its reliability in reducing total system real power loss and enhancing voltage profiles. These studies contribute to the advancement of methodologies for optimizing DG allocation in distribution systems, considering multiple objectives and system performance.

Furthermore, Jagan *et al.* (2017) developed a hybrid approach combining Genetic Algorithm and Particle Swarm Optimization for the optimal deployment of Distribution Generation units. They aimed to find the best allocation and sizing strategy considering multiple objectives. In a separate study, Abdulhamid (2018) proposed a PSO-based technique for the allocation and sizing of DGs in a radial distributed system. The objective was to minimize voltage deviation and total power loss. Simulation results showed a significant reduction in total power loss (89.83%) when three DGs were allocated with sizes ranging from 0.2233MW to 0.0227MW. The proposed technique was evaluated using the standard IEEE-33 radial test system. However, a comparison with other meta-heuristic techniques was not provided in the study.

Anand *et al.* (2021) introduced the Crow search algorithm (CSA) for the optimal allocation of multiple DGs with different types in distribution networks. Their objective was to minimize active power loss. The proposed method was evaluated using the IEEE-33 and 69 bus test systems, and the results were compared with the improved analytical (IA) and particle swarm optimization (PSO) methods. The findings demonstrated that the proposed CSA method outperformed the existing PSO and IA methods.

The strength of the Crow Search Algorithm (CSA) lies in its ability to efficiently avoid getting trapped in local optima when dealing with complex search spaces in multimodal optimization problems. However, the exploitation phase of CSA is not highly effective. To enhance the results, it is recommended to hybridize CSA with an algorithm that excels in exploitation.

In this paper, the deployment and sizing of distributed generation units will be optimized using a hybrid approach that combines the Crow Search Algorithm and the Smell Agent Optimization Algorithm.

2. MATERIALS AND METHODS

2.1 Stages of research

This research study was conducted in four distinct stages. The initial stage involved gathering relevant line data, bus data, and the single-line diagram of the 11kV GRA Feeder of Abuja Electricity Distribution Company in Minna. Power flow analysis was performed to determine the system's voltage profile and power losses, with these values serving as the baseline.The second stage focused on the development of a MATLAB program for the Hybrid Crow Search Algorithm and Smell Agent Optimization. This program aimed to identify the optimal sizes and locations of multiple DGs within the network. The results obtained from this optimization process provided valuable information on the most suitable DG sizes and placent locations.

In the third stage, the identified DGs were placed at the designated buses, and an additional load flow analysis was conducted to evaluate the impact of the DGs on distribution line losses and voltage profiles at various buses.

The final stage involved a comparative analysis of the results obtained from load flow analyses using different numbers of DGs.

2.2 Optimal placement of DG

To optimally determine locations of multiple DGs, hybrid Crow Search Algorithm and Smell Agent Optimization was adopted. The hybridized algorithm was used in realizing the optimal locations and sizes of the DGs.

2.3 Hybrid Crow Search Algorithm and Smell Agent Optimization

The step-by-step procedures for the development and evaluation of the hybrid CSA-SAO algorithm are outlined as follows:

i. Development of the Hybrid Crow Search Algorithm and Smell Agent Optimization:

a. The standard Crow Search Algorithm was implemented.

b. The best and worst positions of the crows were determined based on the evaluation of their fitness.

c. The hybrid CSA-SAO was modeled by incorporating the trailing mode behavior from SAO, ensuring that all crows follow the position of the best crow discovered thus far.

ii. Determination of the effectiveness of the Hybrid approach for optimal location and sizing of distributed generators:

a. The optimization function was formulated, considering the objective of minimizing power loss and improving voltage.

b. Constraints for the optimization were formulated, taking into account network control variables, voltage limits, generation limits, and other relevant factors.

c. The formulated objective function was optimized using the developed hybrid algorithm from step (i) above.

2.4 Problem Formulation

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

2.4.1 Objective Functions Formulation

The objective functions in this work are to minimize power losses and improve voltage profiles across the distribution line length.

The test system used to verify the effectiveness of the technique is described below;

To minimize a function consisting of some parameters, the general function is written as a summation of those parameters

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

2.4.1.1 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;

$$f_1 = \sum_{i=1}^{N} P_{DG_i} \tag{2}$$

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

2.4.1.2 Parameter of the total power loss of the network.

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

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

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. al.,* 2007) also called the exact loss formula.

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

Where,

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

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

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 and δ_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

$$f = f_1 + f_2 \tag{7}$$

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

$$f = \sum_{i=1}^{N} P_{DG_i} + \sum_{i=1}^{N}\sum_{j=1}^{N}\left[\alpha_{ij}\left(P_iP_j + Q_iQ_j\right) + \beta_{ij}(Q_iP_j + P_iQ_j)\right] \tag{8}$$

2.4.2 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 siting and sizing DGs.

2.4.2.1 Power Injection constraints

This is given by

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

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.

2.4.2.2 Voltage constraints

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

$$|V_i|^{min} \leq V_i \leq |V_i|^{max} \tag{10}$$

Here,

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

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

Voltages lower or higher than (±6%) exposes many power consumers' appliances to operation failure and damages (Mark *et al.*, 2017)

2.4.2.3 Summation of the DG sizes.

The sum of all the active power produced from all the DG units in the network should be less or equal to 20% of substation power

$$\sum_{i=1}^{N} P_{DG_i} \leq 20\% P_{substation} \tag{13}$$

Here, N is the number of DG units.

P_{DG_i} is the DG active power

2.4.2.4 Total Power Balanced Constraint;

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

(14)

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

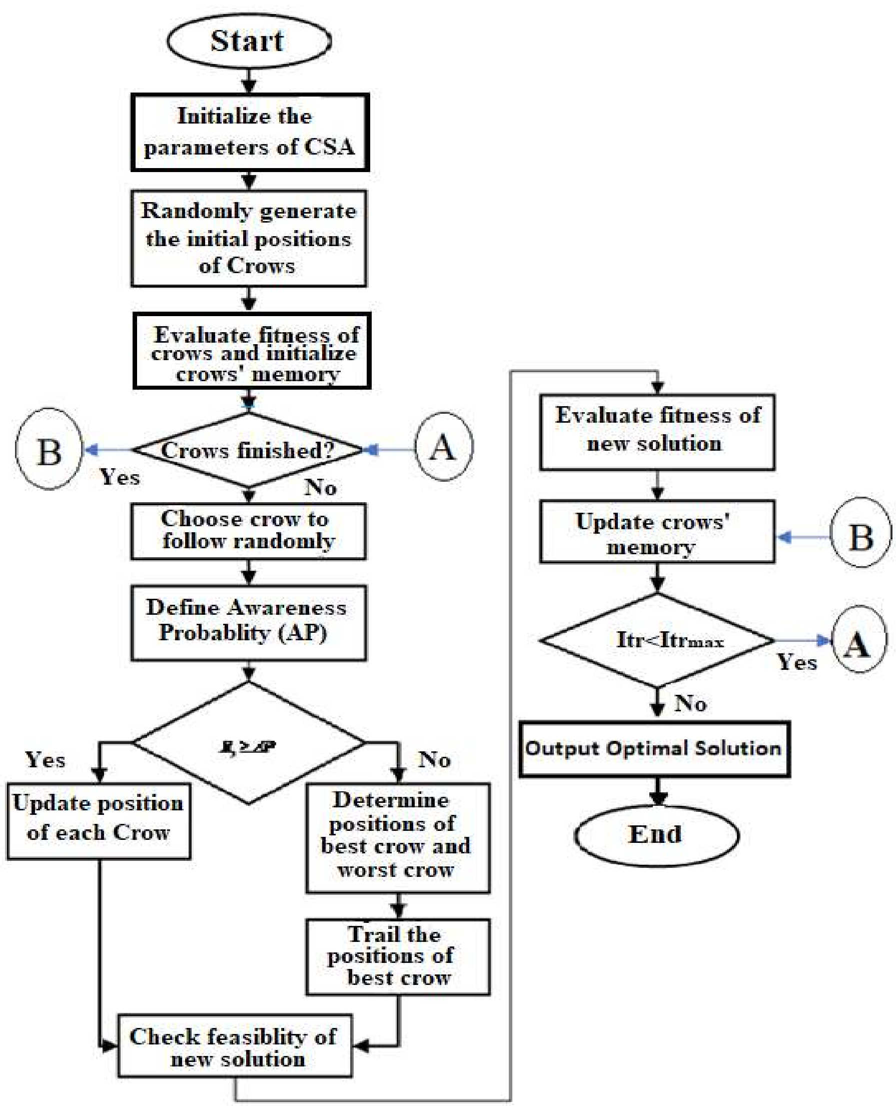

Figure 1: Flowchart of HCSA-SAO

3. SIMULATION RESULTS AND DISCUSSION

3.1 Effect of DG placement using the proposed hybrid algorithm (HCSA-SAO)

The hybrid method was used for optimal allocation of DG for the selected GRA feeder. Optimal DG placement was done on the. The total real power loss after optimum DG placement is presented in table 1. The average time of simulation was also noted and presented.

Table 1: Effect of DG placement on network losses reduction for GRA feeder using HCSA-SAO

Number of DGs	Location (Bus number)	DG size (MW)	Total Installed Capacity (MW)	Loss without DG (kW)	Loss With DG (kW)	% Loss Reduction	Simulation Time (s)
2	3	0.17	0.36	182.3	93.25	48.84	7.22
	6	0.19					
	6	0.19					
3	12	0.24	0.72		92.11	49.47	8.25
	18	0.29					

The table presents results related to the integration of Distributed Generators (DGs) into the distribution network, specifically focusing on different scenarios with varying numbers of DGs, their locations (bus numbers), DG sizes, total installed capacity, power loss without DGs, power loss with DGs, percentage loss reduction, and simulation time.

The results indicate that both the location and size of DGs play a significant role in determining the extent of power loss reduction. Different combinations of DG locations and sizes yield varying levels of loss reduction.

The simulation time is provided in the table, and it's noticeable that the addition of more DGs and their optimization increases the computational load, as reflected in the slightly longer simulation times for scenarios with more DGs

Figures 2 and 3 display real power loss plots after successfully conducting power flow analysis on the GRA distribution network. These plots represent the best fitness function against the number of iterations specifically for the Hybrid Algorithm. The variations in the number of optimally installed Distributed Generators (DGs) are depicted in these Figures.

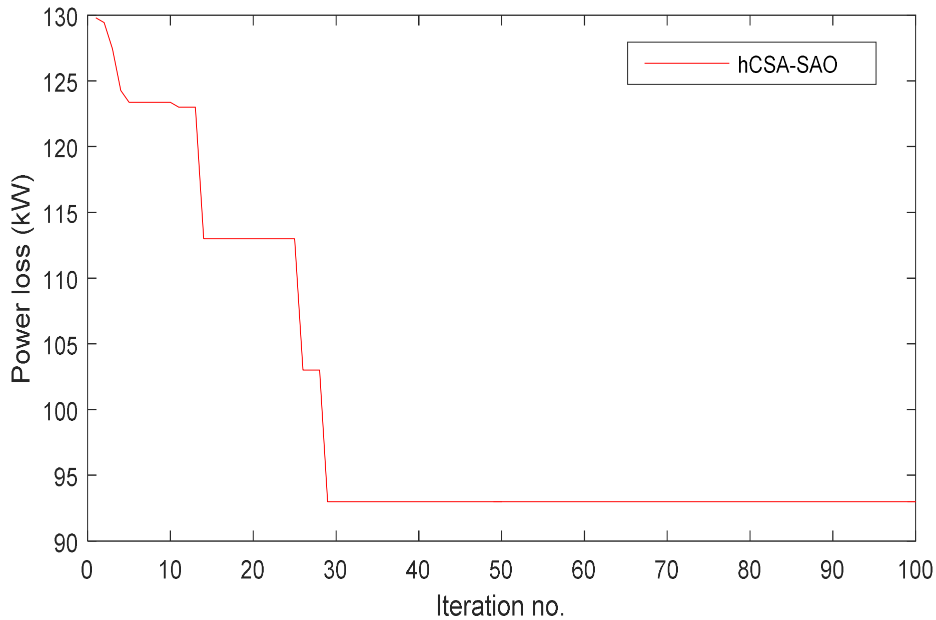

Figure 2: Real power loss of GRA distribution network after introducing 2 DGs optimally using HCSA-SAO

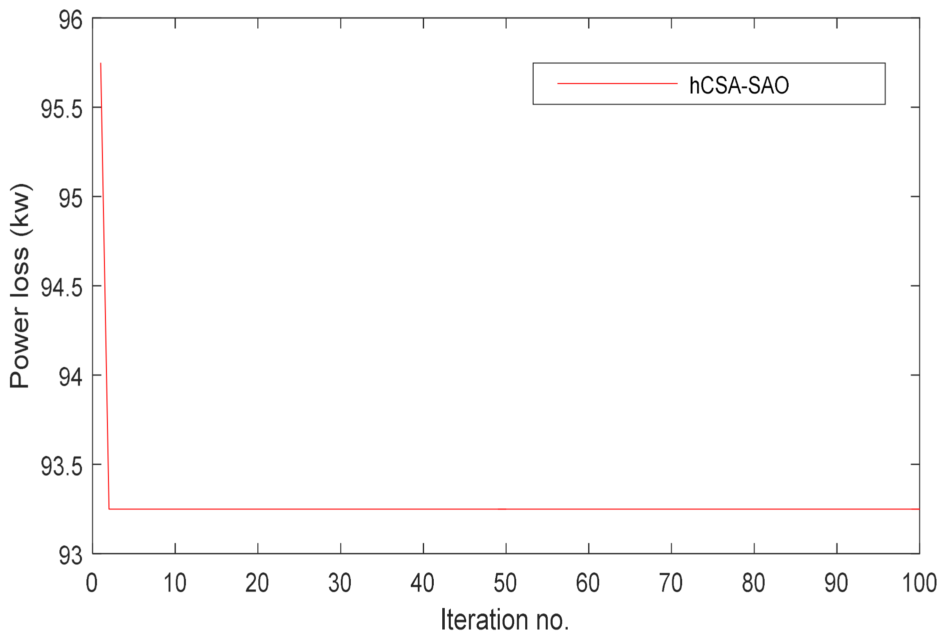

Figure 3: Real power loss of GRA distribution network after introducing 3 DGs optimally using HCSA-SAO

3.2 Voltage profile after DG allocation using the proposed hybrid algorithm (HCSA-SAO)

The base case and improved voltage magnitudes were plotted against their respective bus numbers in order to see the improvement in voltage profile after DG location and sizing was done using the proposed hybrid algorithm.

The average base case voltage is **0.8512**. The overall voltage profile improvement after introduction of 2 and 3 numbers of DG is **50.16%** and **67.95%** respectively.

The voltage profiles obtained after integrating 2 and 3 DGs are shown in Figures 4, and 5

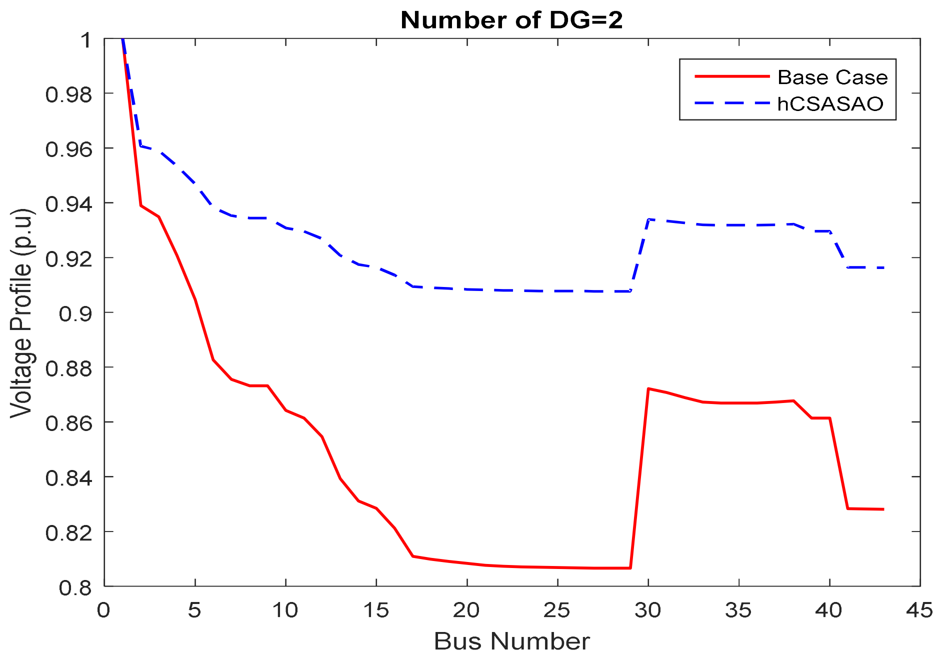

Figure 4: Voltage Profile for GRA Distribution Network after 2 DGs installation Using HCSA-SAO

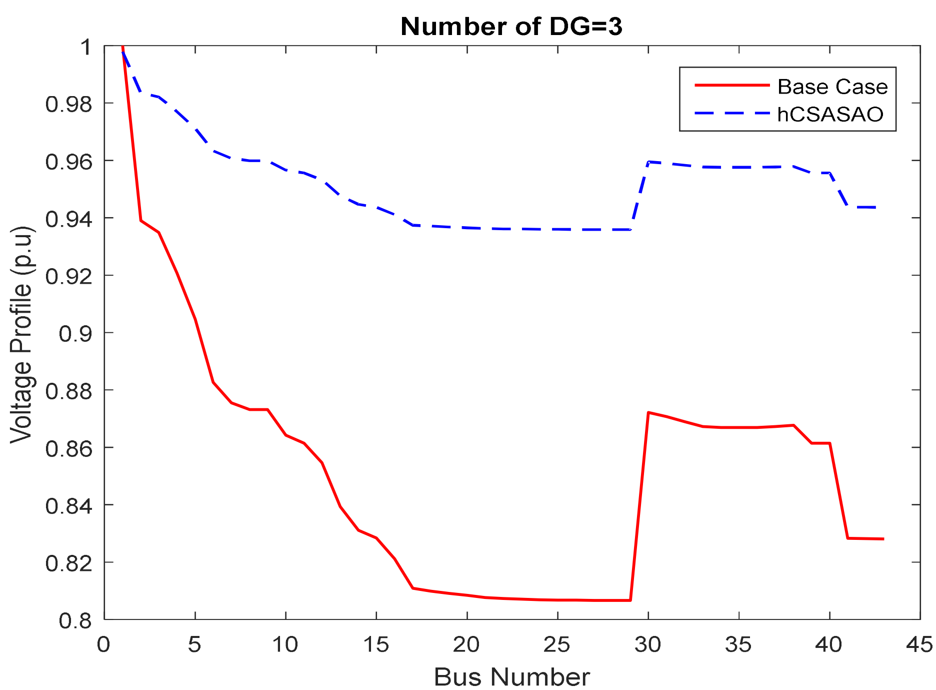

Figure 5: Voltage Profile for GRA Distribution Network after 3 DGs installation Using HCSA-SAO

The lower solid line, representing the base case, serves as a reference point, indicating the initial voltage profile without any Distributed Generators (DGs) in the network. It represents the existing conditions of the distribution network.

The dashed line, which represents the Hybrid Algorithm, depicts how the voltage profile improves as the number of DGs increases. This line showcases the impact of the Hybrid Algorithm on enhancing voltage profile within the distribution network.

In general, it can be observed that the MATLAB-modeled network clearly illustrates that almost all buses (42 buses) experienced acceptable voltage drops of more than 5% during Load Flow Analysis when examining the GRA Feeder without DG installation In contrast, after integrating a maximum of 3 DGs into the same feeder, it was observed that 20 buses out of the total number of buses exhibited voltage drops exceeding 5% during Load Flow Analysis. Consequently, the simulation with DGs showcased substantial enhancement in the network's voltage profile. These findings underscore the algorithm's effectiveness in enhancing voltage profiles and diminishing power losses.

4 CONCLUSIONS

The research successfully conducted a power flow analysis to determine the current voltage profile and power losses within the 11 kV GRA feeder of the Abuja Electricity Distribution Company (AEDC). The resulting insights provide valuable perspectives on the present condition of the distribution network, indicating that all buses, except one, experienced acceptable voltage drops of more than 5%. The average voltage profile is 0.8512 pu, with active power losses of 182.3 kW. These findings facilitate an evaluation and open the possibility of enhancing voltage levels and implementing power loss mitigation strategies to improve operational efficiency.

Finally, the study conducted an examination of the influence of optimally positioned Distributed Generators (DGs) within the 11 kV GRA feeder. Employing the developed hybrid algorithm, the analysis centered on evaluating enhancements in voltage profiles and decreased power losses. This investigation not only gauged the algorithm's effectiveness but also illuminated the advantages of strategically located DGs in terms of enhancing voltage profiles and mitigating power losses within the distribution network. The results demonstrated a 49.47% reduction in losses and a 67.95% improvement in the overall voltage profile after introducing 3 DGs within the GRA feeder.

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