

# Optimizing the Location and Capacity of DGs and SOPs in Distribution Networks using an Improved Artificial Bee Colony Algorithm

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## ABSTRACT

This study proposes an improved method of the Artificial Bee Colony (ABC) algorithm for the distribution network in scenarios where distributed generation sources and Soft Open Points (SOPs) are connected to optimize power control. Improvement is achieved by integrating the ABC algorithm with the Grenade Explosion Method and Cauchy to accelerate the ABC algorithm's speed. The objective function is considered to reduce power losses over a day. The proposed method was tested on the IEEE-33 bus test system under various scenarios: Case 1 with 3 DGs installed, Case 2 with 3 DGs and 1 SOP simultaneously installed in the distribution network, and Case 3 having the same configuration as Case 2 but operating for 24 hours. In addition to reducing power losses, the voltage at the nodes in the distribution grid was also improved, maintained above 0.95 pu and close to 1 pu. Case 3 showed that integrating a Wind Turbine (WT), two Photovoltaic (PV) generators, and one SOP during operation resulted in the lowest energy losses, smaller than a system with only one WT and two PVs, and significantly lower than the baseline system without any DGs and SOPs. Therefore, employing SOPs in a distribution network with integrated DGs can offer significant benefits in reducing energy losses.

*Keywords-artificial bee colony; Cauchy algorithm; grenade explosion method; reconfiguration distribution network; soft open point; optimization power loss reduction*

## I. INTRODUCTION

The Distribution Network (DN) is tasked with supplying electricity to electrical loads and plays a crucial role in a country's power system. Total power losses in DNs often represent a high percentage, typically between 12-13% of total generated power [1]. Therefore, eliminating power losses on the DN is always a research focus. Nowadays, the diverse development of renewable energy sources and unpredictable loads, such as electric vehicles, make the DN more complex. In addition to utilizing open and close switches, the DN operation involves engaging power control devices, known as soft open points. Certain solutions considered to reduce power losses, involve decreasing current and line resistance [2] by installing capacitors [3], Distributed Generation (DG) [4], Wind Turbines (WTs) [5], Photovoltaic generators (PV) [6], distributed biomass generation [7], restructuring the grid [8], installing Soft Open Points (SOPs) [9], and more. This study proposes improvements to the Artificial Bee Colony (ABC) algorithm

for optimal placement of DGs and SOPs to achieve economic benefits and meet the technical conditions for the DN.

The development of DGs can provide active and reactive power to mitigate the need for power supply from conventional grid sources, while SOPs can alter power flow on the lines [10]. Thus, the combined use of DGs and SOPs can lessen the current flows on the lines, a solution aimed at achieving the objective of minimizing losses on the distribution grid. In [11], DG penetration levels of 0 to 200% were evaluated, with the best results from installing SOPs displaying a 58.4% reduction in losses, a 68.3% load balancing improvement, and a 62.1% voltage profile enhancement. In [12], SOPs, various DG penetration levels, and flexible AC transmission systems were combined, and the results disclosed that penetration levels of 48% and 79% were optimal for systems at 50% and 200% load, respectively. In [13], the penetration level of DGs and active and reactive power flows of SOPs were optimized throughout the day, achieving a 10% reduction in energy losses. In [14], the focus was on minimizing power losses and load balancing

indices for the IEEE 33-node DN system. The findings demonstrated that deploying SOPs was more effective than restructuring the grid alone. However, combining both SOPs and network restructuring was even more efficient. In [15], the location and capacity of 3 DGs and 5 SOPs in the IEEE 33-node network were optimized deploying PSO to reduce power losses and improve voltage profiles. The results revealed that using 3 DGs and 5 SOPs reduced power losses by 79.5% compared to the systems without DGs and SOPs. In [16], SOPs were put into service along with restructuring the IEEE 33- and 69-node grids. The network was tested in five scenarios, with the number of SOPs increasing from 1 to 5. Power losses decreased significantly as the number of SOPs increased, reducing losses from 30.94% to 58.65% for the 33-node and from 56.16% to 75.05% for the 69-node grid. However, the investment and maintenance costs of each SOP are very high, thus the use of 2, 3, 4, or 5 SOPs, as in [15, 16], is not feasible for DN systems.

Previous studies have made significant contributions to minimizing losses, evaluating the penetration levels of renewable energy, and improving voltage profiles in standard IEEE distribution grids. However, the extensive use of SOPs in these DNs has not been practical, and the effectiveness of the algorithms applied has been suboptimal. This study aims to address the specific limitations. The metaheuristic ABC algorithm [17] was combined with the Cauchy and Grenade Exploration Method (GEM) to optimize the location and capacity of DGs and SOPs within the DN. The proposed method was tested on a 33-node IEEE network, simulated over 24 hours, employing actual wind speed and solar radiation data from [16, 17] to calculate the power output of WTs and PVs during the DN operation.

## II. MODEL AND CONSTRAINT CONDITIONS

SOP is a power electronic device that has recently been utilized in radial distribution networks in place of tie switches (Figure 1) or sectionalizing switches (Figure 2). This state-of-the-art power electronic device can efficiently deliver enhanced system performance in terms of load flow balancing, voltage profile improvement, and system loss reduction [10]. Figures 1 and 2 portray the basic layout of two terminal VSCs positioned in sectionalizing and tie switches. As a DC bus connects the two converters, their output reactive powers are independent [13]. The proposed SOP structure can be simulated using the following equations.

$$P_n^{SOP} + P_m^{SOP} + P_n^{SOPloss} + P_m^{SOPloss} = 0 \quad (1)$$

where  $P_n^{SOP}$  and  $P_m^{SOP}$  are the injected active powers of SOP at the  $n^{th}$  and  $m^{th}$  nodes, respectively, and  $P_n^{SOPloss}$  and  $P_m^{SOPloss}$  denote the internal power losses of SOP converters at the  $n^{th}$  and  $m^{th}$  nodes, accordingly, which can be calculated by multiplying the loss coefficient and the injected apparent power of SOP at the  $n^{th}$  and  $m^{th}$  nodes, correspondingly. Given that SOP has sufficient operational efficiency, internal power losses from a small-scale power transfer can be ignored [13]. This study considered lossless SOPs. In the case of lossless SOP installation, the summation of the injected SOP powers to the  $m^{th}$  and  $n^{th}$  nodes is equal to zero [14]. The active power boundaries for a SOP are described by:

$$P_n^{SOP} + P_m^{SOP} = 0 \quad (2)$$

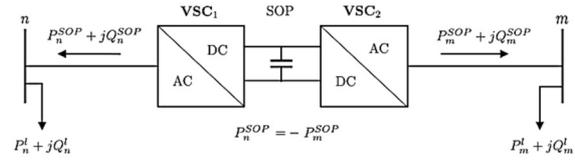


Fig. 1. SOP model placed at the sectionalizing switch.

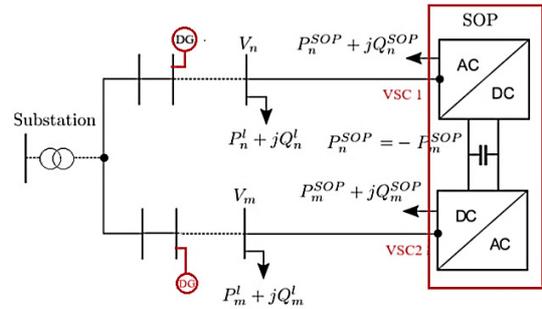


Fig. 2. SOP connecting line 1 and line 2 in the distribution grid.

The total reactive powers that SOP injects into the DS should not be more than the total reactive powers of the system loads, which may be described by:

$$\sum_{k=1}^{N_{SOP}} (Q_n^{SOP}(k) + Q_m^{SOP}(k)) \leq \sum_{u=1}^{N_{load}} Q_u^1, \quad \forall u \in N_{load}, \forall k \in N_{SOP} \quad (3)$$

where  $Q_u^l$  represents the load reactive power at the  $u^{th}$  node,  $N_{load}$  and  $N_{SOP}$  denote the total number of loads and SOPs, respectively, and  $Q_n^{SOP}$  and  $Q_m^{SOP}$  are the injected reactive powers of SOP at the  $n^{th}$  and  $m^{th}$  nodes, respectively. The SOP capacity limits can be expressed by:

$$\sqrt{(P_n^{SOP})^2 + (Q_n^{SOP})^2} \leq (S_{rated}^{SOP}) \quad (4)$$

$$\sqrt{(P_m^{SOP})^2 + (Q_m^{SOP})^2} \leq (S_{rated}^{SOP}) \quad (5)$$

where  $S_{rated}^{SOP}$  is the rated size of SOP.

### A. Objective Function (OF)

Minimizing energy loss during one day of operation is the main goal, determined by the formula:

$$OF = \sum_{h=1}^{24} \sum_{dl=1}^{N_{dl}} (3 \cdot I_{dl,h}^2 \cdot R_{dl}) \quad (kWh) \quad (6)$$

where  $OF$  is the total energy loss in a day.

### B. Constraints Function

#### 1) Line Current Limit

The operating current must be less than or equal to the maximum current limit:

$$I_{dl,h} \leq I_{dl}^{max} \quad (7)$$

#### 2) Voltage Limits

In a distribution grid, the voltage at each node is greater than or equal to the minimum voltage limit, and less than or equal to the maximum voltage limit:

$$V^{min} \leq V_{i,h} \leq V^{max}; i = 1, \dots, N_n \quad (8)$$

### 3) Power Balance Constraints

This study examines the installation of WTs, PVs, and SOPs on the distribution grid. SOPs can provide reactive power, whereas WT and PV can supply active power. Therefore, the balance between active power and reactive power is described as:

$$\sum_{f=1}^{N_{SOP}} P_{SOPf,h} + \sum_{m=1}^{N_{PV}} P_{PVM,h} + \sum_{k=1}^{N_{WT}} P_{WTK,h} + P_{cps,h} = \sum_{dl=1}^{N_{dl}} 3 \cdot R_{dl} \cdot I_{dl,h}^2 + \sum_{j=1}^{N_n} P_{Lj,h} \quad (9)$$

$$\sum_{f=1}^{N_{SOP}} Q_{SOPf,h} + Q_{cps,h} = \sum_{dl=1}^{N_{dl}} 3 \cdot X_{dl} \cdot I_{dl,h}^2 + \sum_{j=1}^{N_n} Q_{Lj,h} \quad (10)$$

### 4) PV and WT Power Generation Limits

Each hour, the power output from these electrical devices is constrained by their maximum and minimum capacities:

$$P_{PVM}^{min} \leq P_{PVM,h} \leq P_{PVM}^{max} \quad (11)$$

$$P_{WTK}^{min} \leq P_{WTK,h} \leq P_{WTK}^{max} \quad (12)$$

where  $P_{PVM}^{min}$  and  $P_{PVM}^{max}$  represent the minimum and maximum power generation limits of the  $m^{\text{th}}$  PV unit.  $P_{WTK}^{min}$  and  $P_{WTK}^{max}$  denote the minimum and maximum power generation limits of the  $k^{\text{th}}$  WT.

### 5) PV and WT Location Limits

This study considers only active power generation for PVs and WTs, and these devices cannot be installed at the same location. Essentially, these units can be installed in the distribution network at positions ranging from node 2 to node  $N_n$ . Therefore, the inequalities below serve as location constraints:

$$2 \leq L_{PVM}, L_{WTK} \leq N_n \quad (13)$$

$$L_{PVM} \neq L_{WTK} \quad (14)$$

where  $L_{PVM}$  and  $L_{WTK}$  are the locations of the  $m^{\text{th}}$  PV and  $k^{\text{th}}$  WT.

## II. METHODOLOGY

The quality of the initial population affects the global convergence speed and the quality of the algorithm. An initial population with satisfactory diversity is very helpful in ameliorating the optimization performance of the algorithm. However, before the iteration of the basic ABC algorithm, the initial population is randomly generated, which cannot guarantee its diversity and affects its search efficiency to some extent. This study proposes an Improved ABC (IABC) algorithm, which is an enhanced version of the basic ABC, incorporating GEM and Cauchy operators to upgrade performance.

### A. Introduction to Artificial Bee Colony (ABC) Algorithm

The ABC algorithm [18] is inspired by intelligent honeybee colony foraging patterns and is applied to solve numerical optimization problems. This algorithm consists of three bee

roles: employed bees, onlookers, and scouts. In the ABC framework, the colony is divided into two halves, with the first half comprising the employed bees and the second half consisting of onlooker bees. Employed bees become scouts when the food source they are exploiting is exhausted. Within the ABC algorithm, the location of a food source represents a potential solution to the optimization problem, and the amount of nectar from the food source correlates with the quality or fitness of that solution. The number of employed bees is equal to the number of active food sources, which also equates to the number of solutions explored within the population at any given time.

#### ALGORITHM 1: MAIN STEPS OF ABC

- 1: Preset the values of control parameters:  $D$ ,  $SN$ ,  $limit$ ,  $MCN$ .
- 2: Initialize the population of food sources using (15)
- 3: Evaluate the population using (16)
- 4:  $cycle = 1$
- 5: Repeat
- 6: Produce new food sources for the employed bees and evaluate them, then apply the greedy selection process {employed bees' phase}:  
for  $i = 1$  to  $SN$   
Produce a new food source  $V_i$  from  $X_i$  (based on  $X_k, i = k /$ ) using (17)  
Calculate the fitness of the food source  $V_i$  using (15)  
Apply the greedy selection between the new food source and the old one.  
end for
- 7: Calculate the probability values for food sources using (18)
- 8: Produce new food sources for the onlooker bees from the food source  $X_i$ , selected depending on  $p(X_i)$  and evaluate them, then apply the greedy selection process {onlooker bees' phase}:  
for  $i = 1$  to  $SN$   
if  $random < p(X_i)$   
Produce a new food source  $V_i$  from  $X_i$  (based on  $X_k, i = k /$ ) using (15)  
Calculate the fitness of the food source  $V_i$  using (16)  
Apply the greedy selection between the new food source and the old one.  
end if.  
end for
- 9: Determine the abandoned food source for the scout bee, if exists, and replace it with a new randomly produced one using (15) {scout bees' phase}
- 10: Memorize the best food source achieved so far.
- 11:  $cycle = cycle + 1$
- 12: until  $cycle$

### 1) Initialization Phase

The algorithm begins by setting the parameters, including the Maximum Number of Cycles (MCN) and the maximum number of searches for abandoned food sources. With  $D$  representing dimensions, a food source  $x$  is generated at random within the solution space, denoted as  $x = \{x_1, x_2, \dots, x_{SN}\}$ . Each food source  $x_i$  corresponds to a potential solution of the optimization problem and is represented as  $x_i = \{x_{i1}, x_{i2}, \dots,$

$x_{iD}$  for  $i$  ranging from 1 to  $SN$ . The initialization process includes assigning values to  $x_i$ .

$$x_{id} = x_{id,min} + \text{rand}(0,1)(x_{id,max} - x_{id,min})$$

with  $d = 1, 2, \dots, D$  (15)

where,  $x_{id,max}$  and  $x_{id,min}$  are the upper and lower limits of the search space, respectively, and  $\text{rand}(0, 1)$  is a random number on  $(0, 1)$ . Determine the food source's concentration and fitness level by:

$$f_{it}(x_i) = \begin{cases} 1 + f(x_i) & f(x_i) \geq 0 \\ \frac{1}{1+|f(x_i)|} & f(x_i) \leq 0 \end{cases} \quad (16)$$

where  $f(x_i)$  and  $f_{it}(x_i)$  are the objective function and food concentration of the first food source, respectively.

2) *Employed Bee Phase*

Lead the bees to search for the corresponding food sources in the neighborhood. The formula for producing new food sources is  $v_i = \{v_{i1}, v_{i2}, \dots, v_{iD}\}$ , where:

$$v_{id} = \begin{cases} x_{id} + r_{id}(x_{id} - x_{qd}) & \text{if } d = d_{rand} \\ x_{id} & \text{if } d \neq d_{rand} \end{cases} \quad (17)$$

where  $q$  is a random number between  $[1, SN]$ , and  $q \neq i$  means that one food source, not equal to  $i$ , is randomly selected from  $SN$  food sources.  $d_{rand}$  is a random number between  $[1, D]$ . A random number  $r_{id} \in [-1, 1]$  controls the scope of the search.

3) *Onlooker Bee Phase*

$$P(x_i) = \frac{f_{it}(x_i)}{\sum_{i=1}^{SN} f_{it}(x_i)} \quad (18)$$

Similarly, the follower bee performs a neighborhood search around the chosen food source using (18) and employs the greed principle for selection. If the food concentration at the new source discovered by the follower bee exceeds that of the old source initially identified by the lead bee, the old source is replaced and a role exchange is completed. If not, the original selection remains unchanged.

4) *Scout Bee Phase*

After the greedy selection process, if the concentration of the food source has not been updated for a consecutive limit period, it indicates that the food source has fallen into local optimization and should be abandoned. At this point, the bee employed becomes a scout and generates a new food source according to (16). Once a new food source is found, the scout bee transforms back into an employed bee.

B. *Improved ABC Combining GEM and Cauchy OBL to Reconfigure the Distribution using SOPs and DGs*

The proposed IABC algorithm follows the general procedure of the ABC algorithm. The main difference between IABC and ABC lies in the exploitation and exploration strategies executed by the onlooker and scout bees, respectively. This means that the main steps of IABC remain similar to those of ABC, except for Steps 8 and 9. Figure 3 illustrates the IABC framework. The IABC algorithm incorporates a new exploitation strategy for onlooker bees.

Traditionally, an onlooker bee in the ABC algorithm selects a food source  $X_i$  and exploits a neighboring source  $V_i$ . This neighboring source  $V_i$  is derived by altering a single parameter of  $X_i$ , specifically  $X_{ij} \neq V_{ij}$ , using (17). The modification involves comparing  $x_{ij}$  with a position randomly selected from its neighboring solution  $x_{kj}$ , emphasizing the difference between these positions along a randomly chosen dimension  $j$ . However, choosing a random dimension may not always be effective, potentially leading to slower convergence or getting stuck in local optima.

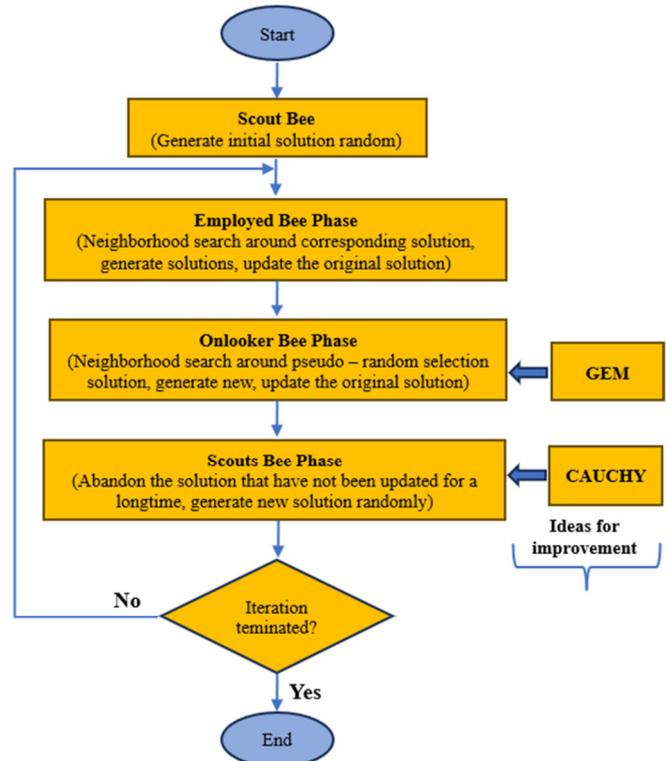


Fig. 3. Diagram of the IABC algorithm.

1) *Optimize Food Sources for Onlooker Bees*

To address these issues, GEM is introduced to the onlooker bees' phase to aid in selecting the optimal search dimension. GEM [21] draws inspiration from the impact of grenade shrapnel, where the damage caused helps to identify valuable targets in an area. It deploys the damage concept, where the next grenade is thrown at the location of the greatest damage, optimizing the search process. In GEM's application within IABC, the overall damage is equated to the fitness of a solution. This method allows the onlooker bees to choose their new candidate food source based on the greatest damage (highest fitness) observed, thereby orienting the search towards globally optimal positions more efficiently. Each cycle of IABC throws  $D$  pieces of shrapnel across all dimensions to explore around the current position of the old food source. Each onlooker bee then evaluates the fitness of each candidate food source where the shrapnel lands and decides on the new candidate food source that corresponds to the highest fitness. Thus, employing GEM, IABC aims to reduce randomness in

dimension selection and enhance the effectiveness of the search for optimal solutions.

$$V_{iOSD} = x_{iOSD} + \phi_{iOSD}(x_{iOSD} - x_{kOSD})$$

$$\text{fit}(V_{iOSD}) = \max \{\text{fit}(V_{it}) \mid t = 1, 2, \dots, D\} \quad (19)$$

where  $k$  from the set  $\{1, 2, \dots, SN\}$  is chosen randomly and differs from  $i$ , and  $k \neq i$ .  $iOSD$  from the set  $\{1, 2, \dots, D\}$  denotes the optimal search dimension,  $\phi_{iOSD}$  is a random number selected from the interval  $[-1, 1]$ ,  $V_{it}$  is the newly proposed food source, created by altering the value of the previous food source  $X_i$  in dimension  $t$ , specifically  $V_{it} \neq x_{it}$ , while the other dimensions of  $V_{it}$  remain unchanged as in  $X_{it}$ .  $V_{iOSD}$  is defined similarly to  $V_{it}$  and also indicates that  $V_i$  achieves maximum fitness in the  $iOSD$  rather than in other dimensions. Similarly, after an onlooker bee identifies a new candidate food source near its current food source engaging (19) and (16), a greedy selection process is applied to choose between the new and the existing food source. From this description, Algorithm 2 presents Step 8 of IABC.

ALGORITHM 2: STEP 8 OF THE IABC ALGORITHM – OPTIMIZE FOOD SOURCES FOR ONLOOKER BEES

Generate new food sources for every onlooker bee across all dimensions based on probability, identify the optimal search dimension ( $iOSD$ ), and select the best new candidate food source using (19) and (16). Then, implement the greedy selection method in the onlooker bees' phase.

```

for  $i = 1$  to  $SN$ 
  if  $\text{random} < p(X_i)$ 
    for  $t = 1$  to  $D$ 
      Produce a new food source  $V_{it}$  from  $X_i$ 
      (based on  $X_k$ ,  $k \neq i$ ) using (17)
      Calculate the fitness of a food source  $V_{it}$  using
      (16)
      if  $t = 1$ 
         $V_{iOSD} = V_{it}$ 
         $\text{fit}(V_{iOSD}) = \text{fit}(V_{it})$ 
         $iOSD = 1$ 
      else
        if  $\text{fit}(V_{it}) > \text{fit}(V_{iOSD})$ 
           $V_{iOSD} = V_{it}$ 
           $\text{fit}(V_{iOSD}) = \text{fit}(V_{it})$ 
           $iOSD = t$ 
        end if
      end if
    end for
    Apply the greedy selection between the new food
    source and the old one
  end if
end for

```

## 2) Optimize Food Sources for Onlooker Bees

Although searches often risk settling in local optima, the Cauchy operator facilitates exploration within the global region, preventing premature convergence to local optima [20]. For instance, in [21], Evolutionary Programming (EP) was enhanced by integrating the Cauchy operator, which substantially improves performance over traditional EP with Gaussian mutation. In [22], Bayesian methods were followed to augment the PSO capacity to exploit historical particle positions, employing the Cauchy operator to explore superior

solutions. In [23], Chaos and the Cauchy operator were combined with an advanced biogeography-based optimization algorithm to identify optimal solutions for core backbone networks. The efficacy of the Cauchy operator in global search is validated by its propensity for longer jumps. While the Gaussian distribution is heavily concentrated around the mean within the interval  $[-3, 3]$ , it almost vanishes outside this range. In contrast, the Cauchy distribution, although similar in shape to the Gaussian, maintains a higher likelihood in its tails, enhancing the probability of producing values far from the mean. Therefore, the Cauchy operator is incorporated into the ABC scout bee phase to generate broader solutions, helping the algorithm escape local optima and augment global search capabilities. In IABC, when a food source  $X_i$  is abandoned, a scout bee creates a new food source using:

$$x_{ij} = x_{ij} \cdot \text{Cauchy}(0,1) \quad (20)$$

where  $\text{Cauchy}(0, 1)$  refers to the standard Cauchy distribution, representing a random value drawn from a Cauchy distribution with a center at zero and a scale parameter of one. Specifically,  $\text{Cauchy}(0, 1)$  is characterized as:

$$\text{Cauchy}(0,1) = \frac{1}{\pi(1+x_{ij}^2)} \quad (21)$$

Algorithm 3 presents Step 9 of the IABC.

ALGORITHM 3: STEP 9 OF THE IABC ALGORITHM

Determine the abandoned food source for the scout bee, if exists, and replace it with a newly produced one based on the Cauchy operator using (20) and (21) {scout bees phase}

## III. RESULTS AND DISCUSSION

The proposed IABC method was simulated and evaluated on the IEEE 33-node test grid under three specific cases:

- Case 1 optimizes the location and capacity of 3 DGs.
- Case 2 involves the simultaneous optimization of the location and capacity of 3 DGs and 1 SOP.
- Case 3 uses the optimal solution of Case 2 to operate one WT, PV1, PV2, and SOP for 24 hours. Simulations were performed in Matlab R2019a on a workstation with an Intel Core i7 3770, 16GB RAM, and a GeForce GT 1030.

Figure 4 exhibits the IEEE 33-node distribution grid configuration. The system data are provided in [29]. SOPs can be installed at one of the five possible locations: L1 (8-21), L2 (9-15), L3 (12-22), L4 (18-33), and L5 (25-29) [15]. The system's nominal voltage is 12.66 kV. The active power and the reactive load is 3.715 MW and 2.3 MVar, respectively. The initial active power losses of the base system without SOPs and DGs amount to 210.999 kW [15, 29]. Minimum and maximum voltage limits are set at 0.95 pu and 1.05 pu. The SOP has minimum and maximum apparent power limits of 0 and 3 MVA. Meanwhile, the limits for DG are set between 0 and 2 MW. The results from the IABC method are compared with those from the Taguchi Method (TM) [30], Multi-Objective Taguchi Approach (MOTA) [30], Bat Algorithm (BA) [31], and Harmony Search Algorithm (HSA) [32].

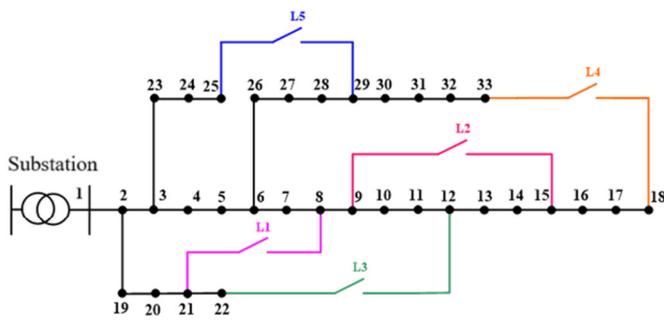


Fig. 4. The optimal DG and SOP for the IEEE 33-node.

A. Case 1: Optimize the Location and Capacity of 3 DGs

Table I presents a comparison of the location and capacity of 3 DGs and power losses among various algorithms. The IABC method results in the lowest power loss at 72.78 kW, followed by PSO [15] at 72.85 kW, BA [31] at 75.05 kW, MOTA [30] at 96.32 kW, TM [30] and HSA [32] at 96.76 kW with the highest power loss at 102.3 kW. IABC places the 3 DGs at nodes 24, 13, and 30 with respective capacities of 1091.33 kW, 801.7 kW, and 1053.64 kW. The locations for the 3 DGs set by IABC coincide with those from the PSO method [15], yet the total capacity of the 3 DGs under IABC (2946.67 kW) is 93.33 kW less than that calculated by PSO [15]. These results indicate that IABC is more efficient than the algorithms in [15, 30-32] in deploying 3 DGs within the distribution network.

TABLE I. RESULTS AND COMPARISON ON IEEE 33-NODE AND 3 DGs

Method	$P_{DG}$ (kW)	Location DG	$P_{loss}$ (kW)
PSO [15]	3040.00	13; 30; 24	72.85
TM [28]	2879.50	15; 33; 26	102.31
MOTA [28]	3280.00	7; 30; 14	96.32
BA [9]	2721.00	15; 30; 25	75.05
HSA [30]	1725.60	18; 33; 17	96.76
IABC (proposed)	2946.67 DG1: 1091.33 DG2: 801.71 DG3: 1053.64	24 13 30	72.78

B. Case 2: Optimize 3 DGs and 1 SOP

Figure 5 manifests the power losses on the calibrated IEEE 33-node distribution grid for different scenarios. In the base case, without the installation of 3 DGs and SOP, the system experiences the highest power loss at 210.999 kW. In Case 1 (3DG) in Figure 6, optimizing the placement of 3 DGs in the distribution grid reduces the power losses to 72.883 kW. Power losses further decrease with the simultaneous IABC optimization of 3 DGs and 1 SOP at locations L3 (3DG\_SOP\_L3), L1 (3DG\_SOP\_L1), L2 (3DG\_SOP\_L2), L4 (3DG\_SOP\_L4), and L5 (3DG\_SOP\_L5), resulting in power losses of 44.691 kW, 39.512 kW, 38.281 kW, 21.235 kW, and 17.419 kW, respectively. Thus, L5 exhibits the least power loss at 17.419 kW, proving to be the optimal location for placing an SOP in conjunction with 3 DGs.

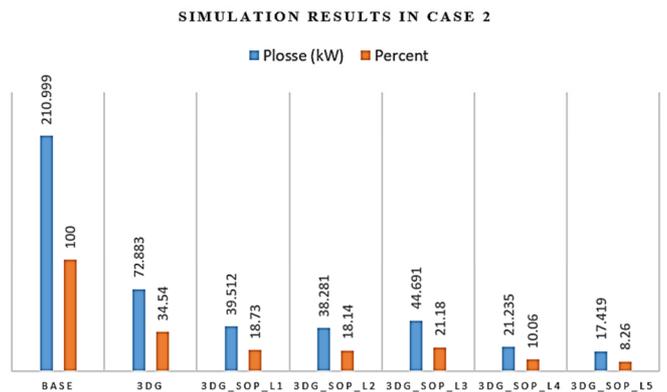


Fig. 5. The optimal DG and SOP for the IEEE 33-node.

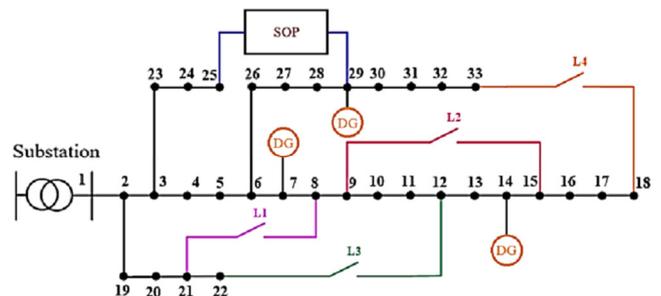


Fig. 6. The optimal 3 DG and 1 SOP for the IEEE 33-node.

Table II details the installation positions and optimized capacities of 3 DGs combined with an SOP at location L5, compared with the PSO method [15]. Optimizing an SOP at L5 (connecting nodes 25 and 29) together with 3 DGs achieves a 91.74% reduction in power losses compared to the base system, and a 12.24% reduction compared to PSO [15].

TABLE II. RESULTS ON IEEE 33-NODE WITH 3 DG AND 1 SOP

Method	Location-Capacity of DG (kW)	Optimal capacity of SOPs (MVA)	Power loss (kW)	Power loss reduction (%)
PSO [15]	8 - Not reported 24 - Not reported 32 - Not reported	Not reported	43.167	79.50
Proposed IABC 3DG - L5- SOP	7 - 762.08 14 - 632.79 29 - 1617.12	$S_{VSC,25} = 0.9$ $S_{VSC,29} = 1.46$	17.41	91.74

Figure 7 presents the voltage configuration for different cases. In the base case (Base), without the installation of 3 DGs and SOP, many nodes violate voltage standards, with voltages less than 0.95 pu from nodes 6 to 18 and 26 to 33. In contrast to the base case, the 3DG case (installing 3 DGs) and the 3 DG and 1 SOP case (installing 3 DGs and 1 SOP at L5) improved the voltage at all nodes, with all node voltages above 0.95 pu, particularly in the 3DG - 1 SOP case where the voltage is close to 1.0 pu at all nodes. The results indicate a substantial contribution when integrating DGs and an SOP in the 33-node distribution network.

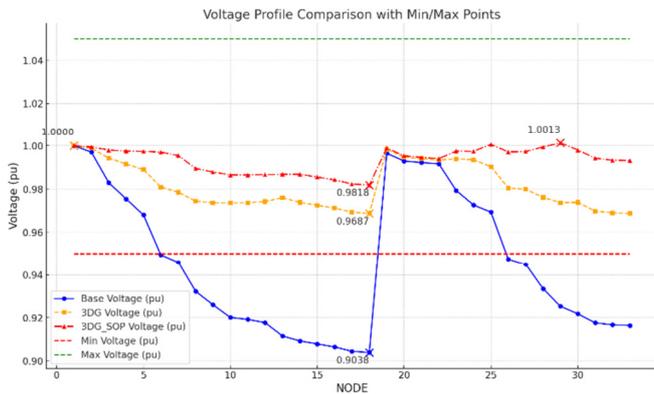


Fig. 7. Voltage graphs at nodes of 33-node IEEE.

C. Case 3: Optimal Operation of SOPs in a Day with Changes in Load and DG

Case 3 utilizes the optimal solution achieved in Case 2 to simulate the operation of the IEEE 33-node distribution network over one day in Figure 8. The SOP is connected at L5 (connects node 25 and node 29), 2 DGs at nodes 7 and 14 are PV1 and PV2 respectively, while the DG at node 29 is a WT. The rated power for WT, PV1, and PV2 was selected as 2 MW, 900 kW, and 700 kW, respectively.

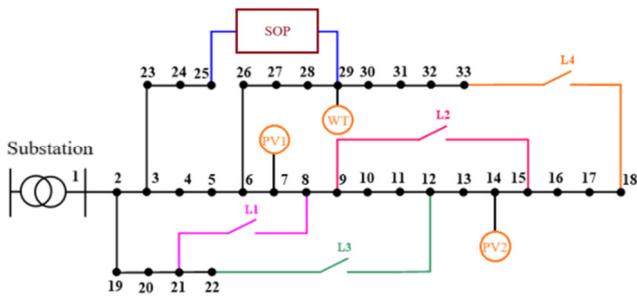


Fig. 8. The optimal 3 DG (2 PV – 1 WT) and 1 SOP for the IEEE 33-node network.

Figure 9 presents the load variation, WT, PV1, and PV2 over 24 hours. Figure 10 depicts the optimal operational power of the SOP at node 25 (SOP\_25), and SOP at node 29 (SOP\_29) over a day. Figure 11 shows the energy losses of the three different systems. The base system without WT, PV1, PV2, and SOPs has the least energy loss at 61.7443 kWh at 4 and 5 AM, the highest energy loss at 210.999 kWh at noon, 2 PM, and 3 PM, with a total energy loss over 24 hours amounting to 3557.2479 kWh. System 1, including WT, PV1, and PV2, has a minimum energy loss of 34.5273 kWh at 7 AM, and a maximum energy loss of 111.1021 kWh at 2 PM, with the total energy loss for one day being 1847.8695 kWh. System 2, which incorporates WT, PV1, PV2, and SOPs, experiences the smallest energy loss of 11.7905 kWh at 7 AM, and the highest energy loss of 72.3473 kWh at 10 PM, totaling 694.076 kWh over 24 hours. Consequently, with the optimal operation of SOPs over one day, system 2 displays a reduction of 2863.1719 kWh (80.49%) compared to the base system, and a decrease of 1153.7935 kWh (62.44%) compared to system 1.

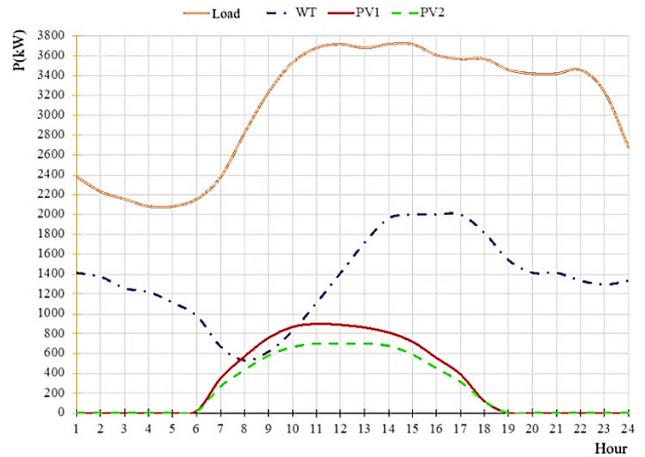


Fig. 9. Graph of load, WT, PV1, and PV2 over 24 hours.

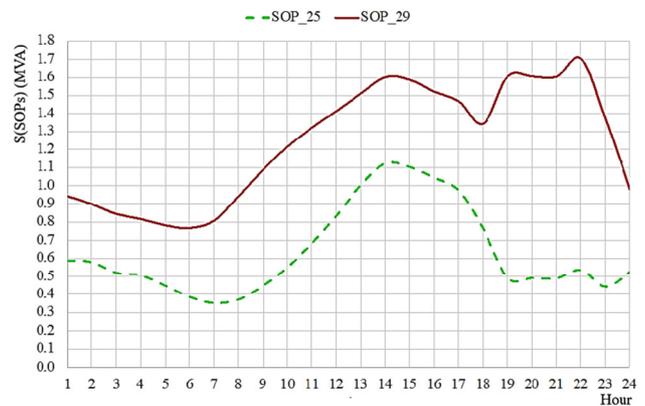


Fig. 10. Graph of optimal operating capacity of SOPs over 24 hours.

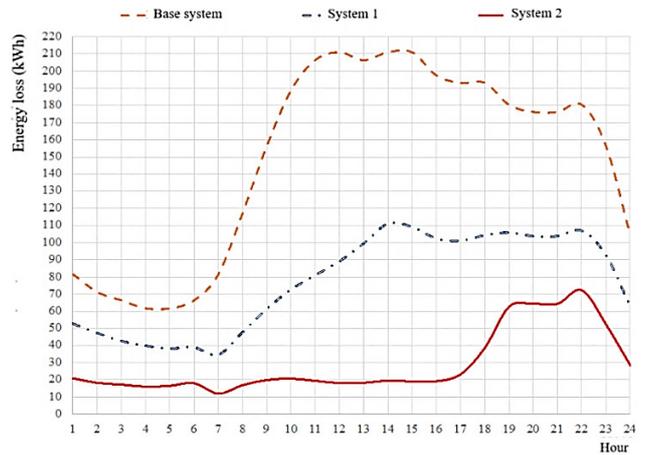


Fig. 11. Capacity loss of 3 systems over 24 hours.

IV. CONCLUSION AND RECOMMENDATIONS

The simulation results demonstrate that the combination of GEM and Cauchy to improve Steps 8 and 9 in the original ABC algorithm has effectively improved power control. This study aimed to determine the optimal locations and capacities of DGs and SOPs to minimize hourly power losses and daily energy losses. Additionally, simulations were carried out in

three different cases. Case 1 was deployed to optimize the location and capacity of 3 DGs. Case 2 involves the simultaneous optimization of the location and capacity of 3 DGs and one SOP. Case 3 employs the optimal solution from Case 2 to operate WT, PV1, PV2, and one SOP over 24 hours to provide reliable results, accelerating the computation speed compared to the traditional ABC algorithm. The results were also compared with other algorithms for evaluation. However, since this study did not consider the operational costs of DGs and SOPs in the objective function, future studies should focus on this issue.

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