Multi-Objective Ant Lion Optimization for Performance Improvement of Modern Distribution Network

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ABSTRACT Multi-objective ant lion optimization (MALO) is a technique developed by imitating the behavior of the ant king foraging. This method has many advantages: straightforward, scalable, flexible, good balance, and fast response. The MALO technique consists of five stages: ants perform optimization by random walking by updating their position, building traps, inserting ants into traps, capturing prey, and rebuilding traps. MALO has attracted the attention of many researchers and has been used successfully to find optimal solutions for power system problems. Computer-assisted operations characterize modern distribution networks to solve complex problems. The complexity of the distribution network problem is due to the integration of distributed energy resources (DER). DER is a renewable energy power plant with up to 10 MW, gaining popularity in recent times. In its application, the integration of DER into the distribution network can cause new problems, namely, load imbalances or excessive voltage increases on the buses where the DER is injected. Therefore, sound planning is needed to place DER. This research proposes a multi-objective optimization technique based on MALO to determine the optimal DER location and capacity. The MALO is a relatively new optimization method that has the potential to improve distribution network performance. Test cases have been carried out for the IEEE 33-bus distribution network. Four scenarios have been carried out, namely integrating DER type-I, type-II, type-III, and type-IV. In each design, the placement of 1 DER, 2 DERs, and 3 DERs is modelled to optimize the location and capacity. The results of multi-objective optimization show that the MALO technique can improve the distribution network performance, characterized by a significant reduction in power losses, an increase in the bus voltage profile, and a balanced load on each feeder.

INDEX TERMS MALO, Multi-objective, Optimization, Distribution Network, Distributed Energy Resources, Network Performance.

I. INTRODUCTION Artificial intelligence (AI)-based techniques have been widely applied in various fields. AI-based techniques, in particular using a metaheuristic approach, have become very popular in the last decade. One of the essential advantages of AI-based techniques with a metaheuristic approach is that they are simple but capable of solving complex problems. Some of these techniques are developed based on intelligent computing and are used for optimization purposes. One technique worth considering for solving complex optimizations is multi-objective ant lion optimization (MALO). MALO is a technique developed by imitating the behavior of the ant king foraging.

One field that utilizes this artificial intelligence technology is electric power systems, especially electricity distribution networks. The modern power distribution network is characterized by computer-based technology and the integration of renewable energy power plants in various places. The application of computer-based technology allows for more effective and efficient network monitoring and management. The integration of renewable energy power plants is expected to improve network performance [1]. Renewable energy power plants integrated into the...
distribution network are called distributed energy resources (DER) [2]. DER injected into modern distribution networks has become popular since the last decade. The advantage of integrating DER into the distribution network is that it can increase electrical power supply, reduce network losses, increase voltage stability, increase network reliability, and reduce environmental pollution, which continues to be a hot issue today [3]-[5].

The integration of distributed energy resources (DER) into the distribution system is becoming increasingly prevalent as demand load increases, pollution emissions decrease, and the electrical power market becomes deregulated [6], [7]. Numerous DER unit technologies are used and are classified into dispatchable and non-dispatchable units based on the amount of fuel energy consumed. Diesel generators, micro-turbines, and fuel cells are all examples of the former [8]-[10]. At the same time, the latter category encompasses renewable energy sources that utilize DER units, such as solar photovoltaic systems, wind turbine generators, biomass, and micro-hydro generators [11], [12].

The effectiveness of DER performance is more closely related to the location, type, and size of the DER units used, with the optimal selection maximizing the benefits of the DER units used and avoiding their disadvantages for the system, such as increased system losses, increased operating cost, and voltage instability [13], [14]. Integrating DER units into the system has a variety of effects under steady-state and transient situations. In the steady-state, there are several issues such as reverse power flow, high power losses, voltage fluctuation, reactive power management, protection scheme miscoordination, poor power quality, regulation, and reliability of the over-load tap changer [15]-[17]. On the other hand, temporary consequences emerge from DER unit islanding and the phenomenon of production uncertainty caused by wind speed variation and shading effects in zones with PV [18]. The intensity of these effects varies according to the location of DER units, their penetration level, and the DER’s technology [19], [20].

Additionally, due to the nature of renewable DER units, concurrent changes in the generation of DER units for supplying the demand load may result in under or overvoltage [21], [22]. The effects of such phenomena may vary according to the location of DER units and weather conditions [23], [24]. Additionally, the system performs better at a certain penetration level of DER units, but, above this level, the system degrades due to substation and feeder loads, voltage variation, and increasing power losses [25]. Additionally, as the number of DER units increases, the operation of the automatic voltage regulator within the OLTC of the transformer becomes more sophisticated and capable due to the occurrence of reverse power flow and associated high voltage and current, which can be controlled using various methods summarized [26].

As a result, the problem of determining the optimal location and size of DER units has garnered considerable attention recently to achieve a variety of objectives, including minimizing actual power losses, improving voltage profile, improving power system quality, and increasing the distribution system's efficiency and reliability. As a result, numerous techniques to resolving this issue have been offered in the literature. The techniques that have been developed consist of conventional techniques and artificial intelligence-based techniques [27]-[29].

Several studies on the optimization of the location and capacity of DER or the like have been carried out by researchers worldwide using other methods. Elattar and Elsayed [30] proposed a modified moth fire optimization algorithm (MMFO) to find the optimal location and capacity of DER in a distribution system. In their research, DER derived from renewable energy power plants considers fuel cell, micro-turbine, solar photovoltaic, wind power, hydropower, and biomass power plants. Their study aims to minimize active power losses, bus voltage deviation, DER unit cost, and CO₂, SO₂, and NOₓ emissions. All these objective functions play an essential role in minimizing the operating costs of the distribution system. In their work, multi-objective functions are converted into coefficients of a single objective function but have different limitations. The MMFO technique in their study has been applied to the IEEE 69-bus model distribution network. They also compared the MMFO method with other methods.

Haishen et al. [31] proposed a SNOP-based method to determine the allowable DER capacity in a distribution network. The first step is to model the allowable DER capacity in the distribution network. Thus, the step is to apply a multi-population genetic algorithm for optimization. In their study, the 33-bus model IEEE distribution network was used as a test case. The study results show that the SOP method allows more DERs integrated into the distribution network with a specified optimal capacity.

Nagaballi et al. [32] proposed using an artificial intelligence-based optimization method, namely a combination of fuzzy logic and particle swarm optimization, to determine the best location and size of the DER. The study departs from the problem of power losses and voltage regulation in the electric power distribution system. DER integration can help solve the problem of high losses in the distribution network. However, efforts are still needed to determine the best location and the most appropriate generator size in the distribution network. Both of these factors are useful for obtaining optimal distribution network operations. The test distribution system used in their work is the IEEE 33-bus standard distribution network. The simulation results have been described by showing the advantages of the applied method.

Selim et al. [33] proposed the chaotic sine cosine algorithm (CSCA) method for the optimal allocation of DER in a radial distribution network. This CSCA method is a development of the sine cosine algorithm (CSA) method, which has limitations in terms of a relatively low level of
convergence and can be trapped in local minima in optimization. This limitation is due to random search in finding solutions in the exploration and exploitation phase. The addition of chaotic to the CSA method is based on an iterative chaotic map. Furthermore, this map is used to update the SCA random parameters, which can be used for single or multi-objective. In order to test the reliability of the CSCA method, the 33-bus and 69-bus IEEE distribution network models are used as validation tests. The test results have been described and show the effectiveness in reducing distribution network losses with DER allocation in the appropriate place.

This paper proposes applying the Ant lion technique for optimizing the location and capacity of DER in an electric power distribution network. Today's modern distribution network has been widely integrated with DER, which comes from renewable energy sources. It is essential to locate the most optimal DER location and capacity to create a distribution network that has high performance. The optimal criteria in this paper are the minor power losses, the best voltage profile, and the balance of each feeder is maintained. Ant lion optimization technique is a technique that can solve this problem, with a truly global minimum convergence result [34].

The novelty and contribution of this paper are that a relatively new multi-objective ant lion optimization (MALO) technique can be applied to optimize the location and capacity of DER properly. Optimization results using MALO can produce global optimal in solving optimization problems because of the following advantages:

- The MALO technique is a population-based method so that it is more guaranteed to achieve the global minima and avoid the local minima in optimizing the location and capacity of the DER.
- In conducting exploration in the search space, ease of convergence can be guaranteed due to the random selection of ants and ant paths and the adaptively shrinking boundary of the ant lion trap.
- The parameters used in the MALO technique are very few and gradient-free, making it easier to achieve convergence and lighter computations.

II. MALO TECHNIQUE FOR MULTI-OBJECTIVE PROBLEM OF DISTRIBUTION NETWORK

A. ANT LION TECHNIQUE

Ant lion (AL) technique is a family of artificial intelligence-based techniques. This technique was first proposed by Mirjalili [34]. The MALO technique is inspired by a natural phenomenon: ant lion animals in hunting prey to find food. The mechanism used by ant lions in hunting prey includes building traps to trap ants that pass through a path, catching ants that have been trapped, then rebuilding traps for other ant traps, and so on. Ant lions go through 2 life phases: the larval phase, which lasts for 3 to 5 weeks, and the adult phase, which lasts up to 3 years. The life process of ant lions is similar to that of butterflies, where to reach adulthood, they must go through metamorphosis in the form of a cocoon. Hunting activity to find food is in the larval stage. Furthermore, in the adult phase in the cocoon, to carry out the reproductive process.

The method for trapping prey by ant lions is to dig holes in sandy soil using their large, sturdy jaws. The hole in the sandy soil that is dug produces a cone-shaped crater. After successfully making a cone-shaped crater, an ant lion hides by sinking itself precisely in the middle at the tip of the cone, as shown in Figure 1. The position of the ant lion is a hidden body because it is covered in sand, while its strong jaw is facing upwards to prepare ready to welcome the small ant prey that fell. The shape of such a crater is possible for tiny ants to be trapped and fall to the bottom of the cavity so that the ant lion quickly catches them. This mechanism is repeated until sufficient food is obtained for the adult phase in the cocoon.

![Figure 1. Mechanism of trapping prey by an ant lion.](image)

The ants that fall prey to the ant lion move randomly in search of food, so to model the interaction of ants with their predators, it is assumed that the ants move in a search space. In this case, the ants move stochastically in search of food to explain the random walk model as ant movement, according to the following equation.

$$V(s) = \{0, \ cs(2w(s_1) - 1), \ cs(2w(s_2) - 1), \ldots, \ cs(2w(s_n) - 1)\}$$

(1)

The notations in equation (1) can be explained as follows. The $cs$ is the cumulative counter operator of an addition operation. The $n$ is the maximum possible iteration of this process. The $s$ is a random ant step; the ant step is analogous to iteration in the ant lion method. The $w(s)$ is a stochastic function in this case. The stochastic function $w(s)$ can be defined as follows.

$$w(s) = \begin{cases} 1 & \text{if } gen \geq 0.5 \\ 0 & \text{if } gen < 0.5 \end{cases}$$

(2)

where $s$ is a random ant step which is analogous to the iteration process and $gen$ is a random number that is generated at a set interval of $[0, 1]$.

Every step taken by the ants to perform optimization is updating the position of the ants. Each ant food search space for the optimization step has a variable range so that to update the role of the ant cannot directly use equation...
For this reason, it is necessary to normalize to maintain random paths in the search space using the following min-max normalization equation.

$$W_i^s = \frac{(W_i - a_i) \times (d_i^s - c_i^s)}{(b_i - a_i)} + c_i^s$$  (3)

The notations in equation (1) can be explained as follows. The $a_i$ is the minimal step of the random ant for the $i$-th variable. The $b_i$ is the top step of the random ant for the $i$-th variable. The $c_i^s$ is the minimum value of the $i$-th variable in the $s$-th iteration. The $d_i^s$ is the maximum value of the $i$-th variable in the $s$-th iteration.

Next is the formation of an optimization matrix based on the position of the ants as follows.

$$T_{OAL} = \begin{bmatrix} T_{OAL_{1,1}} & T_{OAL_{1,2}} & \cdots & T_{OAL_{1,d}} \\ T_{OAL_{2,1}} & T_{OAL_{2,2}} & \cdots & T_{OAL_{2,d}} \\
\vdots & \vdots & \ddots & \vdots \\ T_{OAL_{n,1}} & T_{OAL_{n,2}} & \cdots & T_{OAL_{n,d}} \end{bmatrix}$$  (4)

Based on equation (4), $T_{OAL}$ is a matrix that states the position of each stored ant. $T_{ij}$ is the value of the $j$-th variable of the $i$-th ant, where $n$ is the total ant and $d$ is the real variable. Let's look at other AI-based optimization methods. It can be seen that the ants in the ant lion method are similar to individuals in the genetic algorithm or particles in the partial swarm optimization method. In the ant lion method, the ant's position indicates the parameters used to represent the variables in a particular solution.

The matrix $T_{OAL}$ has been designed to accommodate the positions of all ants that can be saved during optimization. Furthermore, the objective functions will be used in the optimization by evaluating each ant stored in the following matrix.

$$T_{Oant} = \begin{bmatrix} f(T_{Oant_{1,1}}) & f(T_{Oant_{1,2}}) & \cdots & f(T_{Oant_{1,d}}) \\ f(T_{Oant_{2,1}}) & f(T_{Oant_{2,2}}) & \cdots & f(T_{Oant_{2,d}}) \\
\vdots & \vdots & \ddots & \vdots \\ f(T_{Oant_{n,1}}) & f(T_{Oant_{n,2}}) & \cdots & f(T_{Oant_{n,d}}) \end{bmatrix}$$  (5)

Based on equation (5), it can be seen that $T_{Oant}$ is a matrix used to store the fitness of each ant. The matrix $T_{Oant}$ consists of the $i$-th ants in the $j$-th dimension to be expressed by the components of the matrix $T_{ij}$. The notation $n$ indicates the total number of ants, and $f$ represents the cost function.

In this ant lion technique, it is also assumed that ants can hide somewhere using the search space. Furthermore, a matrix is used to store the position and fitness value of the ants as follows.

$$T_{AL} = \begin{bmatrix} TL_{1,1} & TL_{1,2} & \cdots & TL_{1,d} \\ TL_{2,1} & TL_{2,2} & \cdots & TL_{2,d} \\
\vdots & \vdots & \ddots & \vdots \\ TL_{n,1} & TL_{n,2} & \cdots & TL_{n,d} \end{bmatrix}$$  (6)

Based on equation (6), it can be defined that $T_{AL}$ is the matrix used to store the position of each ant lion. The matrix $T_{AL}$, which consists of the $i$-th ant lion with the $j$-th dimension value, states the components of the $TL_{ij}$ matrix.

The $n$ is the total number of ant lions, and $d$ is the total number of variables or dimensions considered in a case.

$$T_{DAL} = \begin{bmatrix} f([TL_{1,1} \ TL_{1,2} \ \cdots \ TL_{1,d}]) \\ f([TL_{2,1} \ TL_{2,2} \ \cdots \ TL_{2,d}]) \\
\vdots & \vdots & \ddots & \vdots \\ f([TL_{n,1} \ TL_{n,2} \ \cdots \ TL_{n,d}]) \end{bmatrix}$$  (7)

Based on equation (7), it can be defined that $T_{DAL}$ is the matrix used to store the fitness of each ant lion. The matrix $T_{DAL}$, which consists of the $i$-th ant lion with the $j$-th dimension value, states the components of the $TL_{ij}$ matrix. The notation $n$ indicates the total number of ant lions, and $f$ represents the cost function.

In further describing the working process of the ant lion technique, the hunting ability of the ant lion can be modelled with a roulette wheel, as illustrated in Figure 2. The ants are assumed to be trapped in only one ant lion in the roulette wheel space, which is selected based on its fitness using a roulette wheel operator. The mathematical model of this process is shown in the following two equations.

$$c_i^s = AL_i^s + c^s$$  (8)

$$d_i^s = AL_i^s + d^s$$  (9)

The notations in equation (8) and (9) can be explained as follows. The $c^s$ indicates the smallest value for all variables at the $s$-th iteration. The $c_i^s$ is the smallest value of the $j$-th ant. The $d^s$ is the vector containing the maximum values for all variables during the $s$-th iteration. The $d_i^s$ indicates the highest value of the $j$-th ant. The $AL_i^s$ indicates the position of the $j$-th ant lion at the $s$-th iteration.

A further mechanism of this ant lion technique is the response of the ant when it realizes that it has fallen into the ant lion's trap. By the time the ant has entered the cone-shaped sand device until it sinks to the bottom, the ant usually only realizes that there is an ant lion ready to prey that is hiding at the bottom of the center of the sandpit. The ants try to escape with the assumption that they are in good health by sprinkling sand around the hole so that the radius of the hole that becomes the ant's path is reduced adaptively. This mechanism can be modelled in two mathematical equations as follows.

$$c^s = \frac{c^s}{R}$$  (10)

$$d^s = \frac{d^s}{R}$$  (11)

The notations in equation (10) and (11) can be explained as follows. $R$ indicates a ratio factor. The $c^s$ indicates the smallest value for all variables at the $s$-th iteration, and $d^s$ is the vector containing the maximum values for all variables during the $s$-th iteration.
The last mechanism of the ant lion technique is elitism. Elitism shows the most powerful ant lion in the computational process; the best ant lion is stored in each iteration to be considered elite. The following equation shows the mathematical model of elitism.

\[
\text{Ant}_i^s = \frac{R_{\text{AL}}^s + R_{\text{Elite}}^s}{2}
\]

The notations in equation (12) can be explained as follows. \(\text{Ant}_i^s\) represents the position of the \(i\)-th ant in the \(s\)-th iteration. \(R_{\text{AL}}^s\) represents a random walk around the ant lion selected by the roulette wheel in the \(s\)-th iteration while \(R_{\text{Elite}}^s\) represents a random walk around the elite in the \(s\)-th iteration.

### B. Problem Formulation of DER Location and Capacity on Distribution Network

Today, the electricity distribution network has received much additional power supply from power plants with a capacity of up to 10 MW. These power plants are usually renewable energy generators such as solar, wind, hydro, fuel cells, and biomass. The locations of these power plants are scattered in various locations, so they are often called distributed energy resources (DER). In this study, the types of DER considered for integrated modeling in the distribution network are DER from solar, wind, hydro, biomass, and fuel cells. The advantage of implementing DER is to take advantage of the local potential available in the development of energy sources. The cost invested is also not too significant to be built and managed by small to medium-sized companies or community groups. The advantages of the distribution network with the integration of DER are the increased supply of electrical power, a better quality of network voltage, and reduced losses. However, proper DER location and capacity planning are needed for an electric power distribution network.

The optimization test case in this study is optimizing the location and capacity of distributed energy resources (DER) in the electricity distribution network. As mentioned in the Introduction section, the current trend is a distribution network integrated with DER. The problem with DER integration is determining the most suitable location and capacity for the available distribution network. After the location and capacity of the DER have been determined optimally, the next step is to reconfigure the distribution network to get the best performance. The distribution network is said to have good performance if it has low power losses, a suitable voltage profile, and a load of each feeder is maintained in balance. These three parameters are essential factors that are objective functions in optimizing distribution networks with DER integration. Therefore, the first objective function for minimizing active power losses, the priority target in optimization, can be defined as follows.

\[
F_1 = \min (\Delta P_{\text{loss}})
\]  

The second objective function is the function to minimize the voltage deviation index \(V_d\) as stated in the following equation.

\[
F_2 = \min (V_d)
\]

The third objective function is the function to maximize the voltage stability index \(V_S\) as stated in the following equation.

\[
F_3 = \max (\min V_S)
\]

The formulation of the multi-objective function problem using the MALO method can be expressed in the following equation.

\[
\min, \max F(x) = [f_1(x), f_2(x), f_3(x)]
\]

\[
g(x) = 0
\]

\[
h(x) \leq 0
\]

The notations in equation (16) can be explained as follows. \(F\) is a multi-objective function that includes three single objective functions, namely the function of minimizing power losses \(f_1\), minimizing voltage deviation \(f_2\), and maximizing voltage stability index \(f_3\). The variable \(x\) is the destination input vector. The variable \(h\) is the set of equal constants, and \(g\) is the set of unequal constants. If an objective function is required to be maximized, it is equivalent to minimizing its inverse.

The notations in equation (13) can be explained as follows. \(F\) is the notation function of the minimization function. \(\Delta P_{\text{loss}}\) is the reduced active power losses of the distribution network to be obtained. The reduced active power losses \(\Delta P_{\text{loss}}\) are calculated based on the total active power losses after network reconfiguration \(P_{\text{loss}}^{\text{after}}\) to active power losses before network reconfiguration \(P_{\text{loss}}^{\text{before}}\).

\[
\Delta P_{\text{loss}} = \frac{P_{\text{loss}}^{\text{after}}}{P_{\text{loss}}^{\text{before}}}
\]

The distribution network active power loss can be calculated using the following equation.
The following voltage deviation index equation is needed to obtain the voltage profile on each bus $i$-th.

$$ V_d = \sum_{i=1}^{N} \left( V_{base} - V_i \right)^2, i = 1, 2, 3, \ldots, N $$

The voltage stability index is used as an indicator to determine the performance of the distribution network. Many distribution networks experience low bus voltage, mainly due to long lines and being far from the feeder. The voltage stability index is expressed by the magnitude of the voltage on each distribution network bus. The expected voltage stability index is a voltage that is close to the nominal value. The following equation can express the voltage index [33].

$$ VS_i = V_i^4 - 4(P_iR_i + Q_iX_i)V_i^2 - 4(P_iX_i - Q_iR_i) $$

In this study, the formulation of multi-objective functions is expressed by the inclusion of weights. The formulation of multi-objective functions is expressed in the sigma form of the multiplication of weights and single-objective functions as stated in the following equation.

$$ \min_{i, \max} \sum_i w_i f_i(x), i = 1, 2, 3. $$

The next challenge is to determine an accurate weight for each objective function. Determining this weight becomes difficult, especially if there is insufficient information about the problem. In this study, a fuzzy rule approach is used to determine the weights that are carried out simultaneously to optimize an objective function and its constraints.

Multi-objective optimization (MOO) can be appropriately solved using the fuzzy technique through membership function adjustment. This technique helps get the best compromise solution [35]. The multi-objective function is transformed into a single-objective model to express the fuzzy membership function in a fuzzy environment. The objective and constraint functions must be defined in the membership function first. Furthermore, the fuzzy membership functions $\mu_i$ defined for each objective function in the multi-objective optimization solution are formulated.

$$ \mu_i = \frac{f_i - f_{i, max}}{f_{i, max} - f_{i, min}}, i = 1, 2, 3. $$

The value of $\mu_i$ is the result of comparing the difference between $f_{i, max}$ and $f_i$ and the difference between $f_{i, max}$ and $f_{i, min}$. Each objective function must be solved to calculate the minimum value of the overall objective function. The mathematical equation to express the solution of a multi-objective function is as follows.

$$ \mu_x = \min \left[ \mu_{1,x}, \mu_{2,x}, \mu_{3,x} \right] $$

The variables in equation (24) can be explained as follows. $\mu_i$ is a weighted multi-objective function. $\mu_{1,i}$ is the weighted objective function of active power losses, $\mu_{2,i}$ is the weighted objective function of voltage deviation, and $\mu_{3,i}$ is the weighted objective function of the voltage stability index.

The constraints used in this optimization problem consist of bus voltage constraints, branch currents, DER active power, DER reactive power, load balance on each feeder, DER location, and DER capacity. In the following, the constraint equations needed for optimization in this study are presented.

- **Bus voltages limits**
  $$ V_{min} \leq V_i \leq V_{max}, \quad i = 1, 2, 3, \ldots, N $$

- **Branch currents limits**
  $$ I_{min} \leq I_i \leq I_{max}, \quad i = 1, 2, 3, \ldots, N $$

- **DER active power limits**
  $$ P_{der}^{min} \leq P_{der} \leq P_{der}^{max}, \quad i = 1, 2, 3, \ldots, N $$

- **DER reactive power limits**
  $$ Q_{der}^{min} \leq Q_{der} \leq Q_{der}^{max}, \quad i = 1, 2, 3, \ldots, N $$

- **Load balance on each feeder limits**
  $$ P_{balance} = \sum_{i=1}^{N_b} P_{D}(i) + \sum_{j=1}^{N_l} P_{loss}(j) - \sum_{k=1}^{N_{der}} P_{DER}(k) $$

  $$ Q_{balance} = \sum_{i=1}^{N_b} Q_{D}(i) + \sum_{j=1}^{N_l} Q_{loss}(j) - \sum_{k=1}^{N_{der}} Q_{DER}(k) $$

In this study, the power balance of the electrical load on each feeder has been considered. This constraint on power balance is one of the essential contributions in this study to improve distribution network performance. As stated in equations (31) and (32), the calculated electrical load power is active and reactive power.
Figure 3. Flowchart of MALO technique for DER location and capacity optimization on distribution network.
• DER location limits

\[ 2 \leq \text{DER}_{\text{position},i} \leq N, \quad i = 1, 2, 3, \ldots, N \]  \quad (31)

In this study, the DER location is shown between bus 2 to the last bus of the distribution network. DER is not possible to be placed between bus 1 and bus 2 because usually there is a feeder where the power transformer is placed.

• DER capacity limits

\[ 0.1 \sum_{k=2}^{N} P_{\text{load}(k)} \leq \sum_{k=1}^{N} \text{ DER}(k) \leq 0.3 \sum_{k=2}^{N} P_{\text{load}(k)}, \quad k = 1, 2, 3, \ldots, N \]  \quad (32)

The minimum and maximum power capacity of the DER is subject to limitations following the actual limits of reasonableness. In this study, the minimum limit is 10%, and the maximum limit is 30% of the total active power of the distribution network load.

A flowchart of the MALO technique for DER location and capacity optimization on distribution networks can be seen in Figure 3. The MALO technique begins by inputting network resource data, namely the capacity and voltage of power transformers, transmission line parameters consisting of network resistance and inductance between buses, load capacity on each bus, grouping buses based on feeders, and an initial capacity of DER. Furthermore, the configuration of the ant lion parameters is carried out. The MALO technique requires generating the initial positions of the ant and ant lion. Along with that, the process in the distribution network is run the load flow program to obtain losses, voltage profiles, and load balance for each feeder. The process of running the first program load flow is used as a reference as the first iteration. Maximum iterations must be determined to see how far the convergence of the MALO technique is when it is applied. Using the roulette wheel, choose an ant lion. The next step is to slide the ants in the direction of the ant lion, followed by creating and normalizing a random walk of ants and updating the position of the ants. After all, these procedures are carried out, the fitness of all ants and collect data on power losses, voltage profiles, and feeder balances can be calculated. The last step is to update the elite ant lion and check whether the criteria are as expected. If the criteria have been met, the optimization procedure has been completed.

III. RESULTS AND DISCUSSION

In this study, a system test was conducted on the IEEE 33-bus distribution network to prove the superiority of the optimization technique used. The original IEEE 33-bus distribution network is shown in Figure 4. The system voltage in this distribution network is 12.66 kV which is used as the base voltage in the analysis. The number of buses that represent the load group is 33 buses with 32 sections divided into three feeders. The number of conductors connecting one bus to the next bus is 37 pieces, wherein in this conductor, there is a switch used to open or close the connection. There are two types of switches that are applied, namely sectionalizing switches and tie switches. Sectionalizing switches are switches that are typically connected, while tie switches are switches that are typically open. This connected and open position is indispensable when network reconfiguration is required. In the original condition, the 33-bus network has 32 Sectionalizing switches and five tie switches, namely switch 33, 34, 35, 36, and 37, as illustrated in Figure 4. The total active power of the 33-bus network load is 3715 kW, while the reactive power of the load is 2300 kVAr. The complete line and load data for the IEEE 33-bus distribution network can be found in reference [36]. MALO technique is used to determine the optimal DER location and capacity. The AL parameters consist of a population of 100, a DER capacity limit of at least 10% and a maximum of 30% of the total network load, DER locations that can be located on bus 2 to bus 33, and a maximum number of iterations of 100.

Figure 4. The original IEEE 33-bus distribution network [21].

There are four scenarios applied in this study, namely:

• Scenario #1: type-I DER integration, a type of power plant capable of injecting pure active power such as photovoltaic solar power plants.

• Scenario #2: type-II DER integration, a power plant capable of injecting pure reactive power such as a power plant that uses a synchronous compensator.
- Scenario #3: type-III DER integration is a power plant capable of injecting active power and absorbing reactive power, such as a power plant that uses an asynchronous generator.
- Scenario #4: type-IV DER integration, which is a type of power plant capable of injecting both active and reactive power simultaneously, for example, a power plant that uses a synchronous generator.

In each of the above scenarios, installation tests of 1 DER, 2 DER, and 3 DER were carried out to find the optimal location and capacity on the IEEE 33-bus distribution network.

A. SCENARIO #1: TYPE-I DER INTEGRATION

In this section, the first scenario is to test the location and capacity of DER optimization using the multi-objective MALO technique, with the type of DER injected into the IEEE 33-bus distribution network is type-I DER. This type-I DER is a power plant capable of injecting pure active power. The type of renewable energy power plant includes photovoltaic solar power plants. The AL parameter used consists of a population of 100, and the maximum number of iterations is 100. The maximum power capacity of the DER is 30% of the total load power, where the full load power is 3715 kW, while the minimum ability is 10% of the entire load.

Optimization of the DER location and capacity on the IEEE 33-bus distribution network through the steps shown in Figure 3. The optimization test begins by assuming 1 DER of type-I injected into the distribution network. This optimization process is shown in Figure 5(a), where the optimal DER location and capacity are obtained in the 11th iteration. The optimal DER location is on bus 17, with a total of 1027.28 kW. Under this condition, the IEEE 33-bus distribution network produces a power loss of 162.86 kW. The optimization test is continued by assuming 2 DER of type-I injected into the distribution network. This optimization process is shown in Figure 5(b), where the optimal DER location and capacity are obtained in the 26th iteration. The optimal DER location is on bus 13 with a total of 885.16 kW and bus 31 with a capacity of 919.91 kW. Under this condition, the IEEE 33-bus distribution network produces power losses of 125.42 kW. The final optimization test of scenario #1 is injection 3 DERs on the IEEE 33-bus distribution network. The optimization process for these 3 DERs is shown in Figure 5(c), where the optimal DER location and capacity are obtained in the 67th iteration. The optimal DER locations are on bus 7 with a power of 992.17 kW, bus 16 with a total of 983.25 kW, and bus 31 with a capacity of 1110.34 kW. The integration of these 3 DERs in the IEEE 33-bus distribution network results in an optimal power loss of 94.25 kW. The optimization results from scenario #1 are summarized in Table I.

Figure 5. The process of optimizing the location and capacity of DER, which results in power losses in the IEEE 33-bus distribution network in scenario #1: (a) 1 DER injected, (b) 2 DERs injected, and (c) 3 DERs injected.

Figure 6. Pareto front of the IEEE 33-bus distribution network in scenario #1.
Figure 6 shows the Pareto front of the IEEE 33-bus distribution network in scenario #1. The figure shows that the MALO method is very effective in producing a Pareto optimal solution. This Pareto front also proves that all multi-objective aspects of minimizing power losses, minimizing voltage deviation, and maximizing voltage stability index have been achieved. The optimal solution is obtained by considering the multi-objective function with weighting. The proposed method can find a widely distributed set of non-dominant points based on the Pareto front.

The MALO technique optimization process shows that the more DER injected into the distribution network, the more iterations are needed to achieve optimal results. One important thing to note in this optimization is that the load balance on each feeder is maintained. Optimizing the IEEE 33-bus distribution network with DER integration can improve the voltage quality on almost all buses, shown in Figure 7. In general, it is found that the integration of 3 DERs gives a better voltage profile than the integration of 2 DERs and 1 DER. This voltage profile can be seen graphically in Figure 7 and numerically in Table I. The integration of 1 DER of type-I results in the average voltage magnitude on each bus being 0.968 p.u. The lowest voltage on bus 33 is 0.932 p.u. on a 12.66 kV system voltage base. The importance of this voltage increases significantly compared to the network's original condition, which has an average voltage of 0.950 p.u per bus. The lowest voltage in this original condition is 0.911 p.u. on bus 18. Integration of 2 DERs in the distribution network further improves the quality of the network voltage. The average voltage magnitude is 0.977 p.u. The lowest voltage is 0.966 p.u. on bus 18. Bus 18 is a bus that is relatively far from the power transformer voltage source and the DER location, thus causing the lowest voltage value compared to other buses. The best performance of the IEEE 33-bus distribution network is the integration of 3 DERs of type-I, which results in the average voltage magnitude on each bus being 0.981 p.u. The lowest voltage is 0.972 p.u. on bus 11. This lowest voltage is much better than the lowest voltage in the original condition of the network.

![Figure 7. Voltage profile of Scenario #1: Type-I DER Integration in IEEE 33-bus distribution network.](image)

![Figure 8. Power loss scattered of Scenario #1: Type-I DER Integration in IEEE 33-bus distribution network.](image)

Table I resumes the results of Scenario #1: Type-I DER Integration in IEEE 33-bus distribution network.

| DER Integration | DER Location (Bus) | DER Capacity (kW) | Power Factor | Power Loss (kW) | Minimum Bus Voltage (p.u.) | Average Bus Voltage (p.u.) |
|-----------------|--------------------|-------------------|--------------|-----------------|----------------------------|---------------------------|
| Without DER     | NA                 | NA                | NA           | 202.71          | 0.911                      | 0.950                     |
| 1 DER           | 17                 | 1027.28           | 1            | 162.86          | 0.932                      | 0.968                     |
| 2 DERs          | 13                 | 885.16            | 1            | 125.42          | 0.966                      | 0.977                     |
|                 | 31                 | 919.91            | 1            |                 |                            |                           |
| 3 DERs          | 7                  | 992.17            | 1            | 94.25           | 0.972                      | 0.981                     |
|                 | 16                 | 983.25            | 1            |                 |                            |                           |
|                 | 31                 | 1110.34           | 1            |                 |                            |                           |

Figure 8 shows power loss scattered of Scenario #1: Type-I DER Integration in IEEE 33-bus distribution network. Power loss in each branch of the distribution network is very dependent on the length of the conductor. The longer a branch connects a bus to another bus, the higher the losses in that branch. This phenomenon can be
seen in Figure 8 that the enormous power losses occur in branch 18. Branch 18 is the conductor connecting bus 2 and bus 19. This branch is the most extended in the IEEE 33-bus distribution network. In all conditions, namely the original condition, the integration of 1 DER, 2 DERs, and 3 DERs, the highest power losses occurred compared to other branches. The power loss in the original network condition at branch 18 is 44 kW. This loss decreased slightly to 34 kW with the integration of 1 DER on bus 17. The integration of 2 DERs on buses 13 and 31 reduced losses in branches 18 to 32 kW. The lowest losses in this network are achieved at the integration of 3 DERs on buses 7, 16, and 31, respectively.

Power loss at branch 18 is decreasing at 29 kW. This phenomenon shows that although there is an addition of distribution network power plants that can increase the voltage on many buses, the power loss in each branch is still dominantly affected by branch length.

B. SCENARIO #2: TYPE-II DER INTEGRATION

In this section, the second scenario is to test the location and capacity of DER optimization using the multi-objective MALO technique, with the type of DER injected into the IEEE 33-bus distribution network is type-II DER. This type-II DER is a power plant capable of injecting pure reactive power. The type of renewable energy power plant includes a synchronous compensator, for example, a static var compensator (SVR) [37], [38]. The AL parameter used consists of a population of 100, and the maximum number of iterations is 100. The maximum power capacity of the DER is 30% of the total load power, where the full load power is 3715 kW, while the minimum ability is 10% of the entire load.

The steps used in optimizing the location and capacity of DER on the IEEE 33 bus distribution network still refer to Figure 3. The optimization test begins by assuming 1 DER of type-II injected into the distribution network. This optimization process is shown in Figure 9(a), where the optimal DER location and capacity are obtained in the 11th iteration. The optimal DER location is on bus 15, with a total of 873.19 kW. Under this condition, the IEEE 33-bus distribution network produces a power loss of 180.71 kW. The optimization test is continued by assuming 2 DER of type-II injected into the distribution network. This optimization process is shown in Figure 9(b), where the optimal DER location and capacity are obtained in the 30th iteration. The optimal DER location is on bus 15 with a total of 752.39 kW and bus 32 with a capacity of 781.92 kW. Under this condition, the IEEE 33-bus distribution network produces power losses of 136.17 kW. The final optimization test of scenario #2 is injection 3 DER of type-II on the IEEE 33-bus distribution network. The optimization process for these 3 DERs is shown in Figure 9(c), where the optimal DER location and capacity are obtained in the 69th iteration. The optimal DER locations are on bus 15 with a power of 843.34 kW, bus 26 with a total of 855.43 kW, and bus 33 with a capacity of 910.20 kW. The integration of these 3 DERs in the IEEE 33-bus distribution network results in an optimal power loss of 106.16 kW. The optimization results from scenario #2 are summarized in Table II.

![Figure 9](image_url)

Figure 9. The process of optimizing the location and capacity of DER, which results in power losses in the IEEE 33-bus distribution network in scenario #2: (a) 1 DER injected, (b) 2 DERs injected, and (c) 3 DERs injected.

The Pareto front of the IEEE 33-bus distribution network in scenario #2 is shown in Figure 10. The MALO method is very effective in producing the Pareto optimal solution, as shown in the figure. This Pareto front also proves that all multi-objective aspects of minimizing power losses, minimizing voltage deviation, and maximizing voltage stability index have been achieved. The optimal solution is obtained by considering the multi-objective function with
weighting. The proposed method can find a widely distributed set of non-dominant points based on the Pareto front.

The MALO technique optimization process shows that the more DER injected into the distribution network, the more iterations are needed to achieve optimal results. One important thing to note in this optimization is that the load balance on each feeder is maintained. Optimizing the IEEE 33-bus distribution network with DER integration can improve the voltage quality on almost all buses, shown in Figure 11. In general, it is found that the integration of 3 DERs gives a better voltage profile than the integration of 2 DERs and 1 DER. This voltage profile can be seen graphically in Figure 11 and numerically in Table II. The integration of 1 DER of type-II results in the average voltage magnitude on each bus being 0.967 p.u. The lowest voltage on bus 33 is 0.929 p.u. on a 12.66 kV system voltage base. The importance of this voltage increases significantly compared to the network's original condition, which has an average voltage of 0.950 p.u per bus. The lowest voltage in this original condition is 0.911 p.u. on bus 18.

Integration of 2 DERs in the distribution network further improves the quality of the network voltage. The average voltage magnitude is 0.976 p.u. The lowest voltage is 0.966 p.u. on bus 18. Bus 18 is a bus that is relatively far from the power transformer voltage source and the DER location, thus causing the lowest voltage value compared to other buses. The best performance of the IEEE 33-bus distribution network is the integration of 3 DERs of type-II, which results in the average voltage magnitude on each bus being 0.981 p.u. The lowest voltage is 0.972 p.u. on bus 11. This lowest voltage is much better than the lowest voltage in the original condition of the network.

The distribution of power losses in the IEEE 33-bus distribution network for scenario #2: Type-II DER integration is shown in Figure 12. Power loss in each branch of the distribution network is very dependent on the length of the branch. The longer a branch connects a bus to another bus, the higher the losses in that branch. This phenomenon can be seen in Figure 12 that the enormous power losses occur in branch 18. Branch 18 is the conductor connecting bus 2 and bus 19. This branch is the most extended in the IEEE 33-bus distribution network. In all conditions, namely the original condition, the integration of 1 DER, 2 DERs, and 3 DERs, the highest power losses occurred compared to other branches. The power loss in the original network condition at branch 18 is 44 kW. This loss decreased slightly to 40 kW with the integration of 1 DER on bus 15. The integration of 2 DERs on buses 15 and 32 reduced losses in branches 18 to 35 kW. The lowest losses in this network are achieved at the integration of 3 DERs on buses 15, 26, and 33, respectively. Power losses at branch 18 are decreasing at 31 kW. This phenomenon shows that although there is an addition of distribution network power plants that can increase the voltage on many buses, the power losses in each branch are still dominantly affected by branch length.

![Figure 10. Pareto front of the IEEE 33-bus distribution network in scenario #2.](image)

### Table II

| DER Integration (DER Location (Bus)) | DER Capacity (kW) | Power Factor | Power Loss (kW) | Minimum Bus Voltage (p.u.) | Average Bus Voltage (p.u.) |
|-------------------------------------|------------------|-------------|----------------|--------------------------|--------------------------|
| Without DER | NA | NA | 202.71 | 0.911 (bus 18) | 0.950 |
| 1 DER | 15 | 873.19 | 0.9 | 180.71 | 0.929 (bus 33) | 0.967 |
| 2 DERs | 15 | 752.39 | 0.9 | 136.17 | 0.966 (bus 18) | 0.976 |
| 3 DERs | 15 | 843.34 | 0.9 | 106.16 | 0.972 (bus 11) | 0.981 |

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Figure 11. Voltage profile of Scenario #2: Type-II DER Integration in IEEE 33-bus distribution network.

The distribution of power losses in the IEEE 33-bus distribution network for scenario #2: Type-II DER integration is shown in Figure 12. Power loss in each branch of the distribution network is very dependent on the length of the branch. The longer a branch connects a bus to another bus, the higher the losses in that branch. This phenomenon can be seen in Figure 12 that the enormous power losses occur in branch 18. Branch 18 is the conductor connecting bus 2 and bus 19. This branch is the most extended in the IEEE 33-bus distribution network. In all conditions, namely the original condition, the integration of 1 DER, 2 DERs, and 3 DERs, the highest power losses occurred compared to other branches.

Figure 12. Power loss scattered of Scenario #1: Type-I DER Integration in IEEE 33-bus distribution network.

The power loss in the original network condition at branch 18 is 44 kW. This loss decreased slightly to 40 kW with the integration of 1 DER on bus 15. The integration of 2 DERs on buses 15 and 32 reduced losses in branches 18 to 35 kW. The lowest losses in this network are achieved at the integration of 3 DERs on buses 15, 26, and 33, respectively. Power losses at branch 18 are decreasing at 31 kW. This phenomenon shows that although there is an addition of distribution network power plants that can increase the voltage on many buses, the power losses in each branch are still dominantly affected by branch length.

C. SCENARIO #3: TYPE-III DER INTEGRATION

In this section, the third scenario is to test the location and capacity of DER optimization using the multi-objective MALO technique, with the type of DER injected into the IEEE 33-bus distribution network is type-III DER. This type-III DER is a power plant capable of injecting active power and absorbing reactive power. The type of renewable energy power plant includes an asynchronous generator, for example, a wind power plant that uses an induction generator [39], [40]. The AL parameter used consists of a population of 100, and the maximum number of iterations is 100. The maximum power capacity of the DER is 30% of the total load power, where the full load power is 3715 kW, while the minimum ability is 10% of the entire load.

Figure 13. The process of optimizing the location and capacity of DER, which results in power losses in the IEEE 33-bus distribution network in scenario #3: (a) 1 DER injected, (b) 2 DERs injected, and (c) 3 DERs injected.
The steps used in optimizing the location and capacity of DER on the IEEE 33 bus distribution network still refer to Figure 3. The optimization test begins by assuming 1 DER of type-III injected into the distribution network. This optimization process is shown in Figure 13(a), where the optimal DER location and capacity are obtained in the 12th iteration. The optimal DER location is on bus 17, with a total of 1107.92 kW. Under this condition, the IEEE 33-bus distribution network produces a power loss of 155.44 kW.

The optimization test is continued by assuming 2 DER of type-III injected into the distribution network. This optimization process is shown in Figure 13(b), where the optimal DER location and capacity are obtained in the 25th iteration. The optimal DER location is on bus 13 with a total of 962.88 kW and bus 31 with a capacity of 973.05 kW. Under this condition, the IEEE 33-bus distribution network produces power losses of 119.65 kW. The final optimization test of scenario #3 is injection 3 DER of type-III on the IEEE 33-bus distribution network. The optimization process for these 3 DERs is shown in Figure 13(c), where the optimal DER location and capacity are obtained in the 66th iteration. The optimal DER locations are on bus 7 with a power of 1065.24 kW, bus 16 with a total of 994.91 kW, and bus 31 with a capacity of 1119.05 kW. The integration of these 3 DERs in the IEEE 33-bus distribution network results in optimal power losses of 92.15 kW. The optimization results from scenario #3 are summarized in Table III.

Figure 14 shows the Pareto front of the IEEE 33-bus distribution network in scenario #3. The figure shows that the MALO method is very effective in producing a Pareto optimal solution. This Pareto front also proves that all multi-objective aspects of minimizing power losses, minimizing voltage deviation, and maximizing voltage stability index have been achieved. The optimal solution is obtained by considering the multi-objective function with weighting. The proposed method can find a widely distributed set of non-dominant points based on the Pareto front.

The MALO technique optimization process shows that the more DER injected into the distribution network, the more iterations are needed to achieve optimal results. One important thing to note in this optimization is that the load balance on each feeder is maintained. Optimizing the IEEE 33-bus distribution network with DER integration can improve the voltage quality on almost all buses, shown in Figure 15. In general, it is found that the integration of 3 DERs gives a better voltage profile than the integration of 2 DERs and 1 DER. This voltage profile can be seen graphically in Figure 15 and numerically in Table III. The integration of 1 DER of type-III results in the average voltage magnitude on each bus being 0.969 p.u. The lowest voltage on bus 33 is 0.932 p.u. on a 12.66 kV system voltage base. The importance of this voltage increases significantly compared to the network's original condition, which has an average voltage of 0.950 p.u. per bus. The lowest voltage in this original condition is 0.911 p.u. on bus 18. Integration of 2 DERs in the distribution network further improves the quality of the network voltage. The average voltage magnitude is 0.978 p.u. The lowest voltage is 0.967 p.u. on bus 18. Bus 18 is a bus that is relatively far from the power transformer voltage source and the DER location, thus causing the lowest voltage value compared to other buses. The best performance of the IEEE 33-bus distribution network is the integration of 3 DERs of type-III, which results in the average voltage magnitude on each bus being 0.982 p.u. The lowest voltage is 0.973 p.u. on bus 11. This lowest voltage is much better than the lowest voltage in the original condition of the network.
power losses occur in branch 18. Branch 18 is the conductor connecting bus 2 and bus 19. This branch is the most extended in the IEEE 33-bus distribution network. In all conditions, namely the original condition, the integration of 1 DER, 2 DERs, and 3 DERs, the highest power losses occurred compared to other branches. The power loss in the original network condition at branch 18 is 44 kW. This loss decreased slightly to 32 kW with the integration of 1 DER on bus 17. The integration of 2 DERs on buses 13 and 31 reduced losses in branches 18 to 30 kW. The lowest losses in this network are achieved at the integration of 3 DERs on buses 7, 16, and 31, respectively. Power loss at branch 18 is decreasing at 28 kW. This phenomenon shows that although there is an addition of distribution network power plants that can increase the voltage on many buses, the power losses in each branch are still dominantly affected by branch length.

**TABLE III**

| DER Integration | DER Location (Bus) | DER Capacity (kW) | Power Factor | Power Loss (kW) | Minimum Bus Voltage (p.u.) | Average Bus Voltage (p.u.) |
|-----------------|--------------------|-------------------|--------------|----------------|---------------------------|---------------------------|
| Without DER     | NA                 | NA                | NA           | 202.71         | 0.911 (bus 18)            | 0.950                     |
| 1 DER           | 17                 | 1107.92           | 0.9 (lead)   | 155.44         | 0.932 (bus 33)            | 0.969                     |
| 2 DERs          | 13                 | 962.88            | 0.9 (lead)   | 119.65         | 0.967 (bus 18)            | 0.978                     |
|                 | 31                 | 973.05            | 0.9 (lead)   |                |                           |                           |
| 3 DERs          | 7                  | 1065.24           | 0.9 (lead)   | 92.15          | 0.973 (bus 11)            | 0.982                     |
|                 | 16                 | 994.91            | 0.9 (lead)   |                |                           |                           |
|                 | 31                 | 1119.05           | 0.9 (lead)   |                |                           |                           |

![Figure 16. Power loss scattered of Scenario #3: Type-III DER Integration in IEEE 33-bus distribution network.](image)

Optimization of the DER location and capacity on the IEEE 33-bus distribution network through the steps shown in Figure 3. The optimization test begins by assuming 1 DER of type-IV injected into the distribution network. This optimization process is shown in Figure 17(a), where the optimal DER location and capacity are obtained in the 12th iteration. The optimal DER location is on bus 17, with a total of 1111.33 kW. Under this condition, the IEEE 33-bus distribution network produces a power loss of 164.55 kW.

The optimization test is continued by assuming 2 DER of type-IV injected into the distribution network. This optimization process is shown in Figure 17(b), where the optimal DER location and capacity are obtained in the 27th iteration. The optimal DER location is on bus 13 with a total of 912.64 kW and bus 31 with a capacity of 945.09 kW. Under this condition, the IEEE 33-bus distribution network produces power losses of 129.89 kW. The final optimization test of scenario #4 is injection of 3 DER of type-IV on the IEEE 33-bus distribution network. The optimization process for these 3 DERs is shown in Figure 17(c), where the optimal DER location and capacity are obtained in the 65th iteration. The optimal DER locations are on bus 7 with a power of 1006.23 kW, bus 16 with a total of 992.28 kW, and bus 31 with a capacity of 1110.99 kW. The integration of these 3 DERs in the IEEE 33-bus distribution network results in optimal power losses of 98.73 kW. The optimization results from scenario #4 are summarized in Table IV.

**D. SCENARIO #4: TYPE-IV DER INTEGRATION**

In this section, the fourth scenario is to test the location and capacity of DER optimization using the multi-objective MALO technique, with the type of DER injected into the IEEE 33-bus distribution network is type-IV DER. This type-IV DER is a power plant capable of injecting both active and reactive power simultaneously. The type of renewable energy power plant includes a wind power plant that uses a synchronous generator. The AL parameter used consists of a population of 100, and the maximum number of iterations is 100. The maximum power capacity of the DER is 30% of the total load power, where the full load power is 3715 kW, while the minimum ability is 10% of the entire load.

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Figure 17. The process of optimizing the location and capacity of DER, which results in power losses in the IEEE 33-bus distribution network in scenario #4: (a) 1 DER injected, (b) 2 DERs injected, and (c) 3 DERs injected.

The Pareto front of the IEEE 33-bus distribution network in scenario #4 is shown in Figure 18. The MALO technique is very effective in producing the Pareto optimal solution, as shown in the figure. This Pareto front also proves that all multi-objective aspects of minimizing power losses, minimizing voltage deviation, and maximizing voltage stability index have been achieved. The optimal solution is obtained by considering the multi-objective function with weighting. The proposed method can find a widely distributed set of non-dominant points based on the Pareto front.

![Graph](image1)

**Figure 18.** Pareto front of the IEEE 33-bus distribution network in scenario #4.

![Graph](image2)

**Figure 19.** Voltage profile of Scenario #4: Type-IV DER Integration in IEEE 33-bus distribution network.

The MALO technique optimization process shows that the more DER injected into the distribution network, the more iterations are needed to achieve optimal results. One important thing to note in this optimization is that the load balance on each feeder is maintained. Optimizing the IEEE 33-bus distribution network with DER integration can improve the voltage quality on almost all buses, shown in Figure 19. In general, it is found that the integration of 3 DERs gives a better voltage profile than the integration of 2 DERs and 1 DER. This voltage profile can be seen graphically in Figure 19 and numerically in Table IV.
The integration of 1 DER of type-IV results in the average voltage magnitude on each bus being 0.967 p.u. The lowest voltage on bus 33 is 0.932 p.u. on a 12.66 kV system voltage base. The importance of this voltage increases significantly compared to the network's original condition, which has an average voltage of 0.950 p.u per bus. The lowest voltage in this original condition is 0.911 p.u. on bus 18. Integration of 2 DERs in the distribution network further improves the quality of the network voltage. The average voltage magnitude is 0.977 p.u. The lowest voltage is 0.966 p.u. on bus 18. Bus 18 is a bus that is relatively far from the power transformer voltage source and the DER location, thus causing the lowest voltage value compared to other buses. The best performance of the IEEE 33-bus distribution network is the integration of 3 DERs of type-IV, which results in the average voltage magnitude on each bus being 0.981 p.u. The lowest voltage is 0.972 p.u. on bus 11. This lowest voltage is much better than the lowest voltage in the original condition of the network.

The longer a branch connects a bus to another bus, the higher the losses in that branch. This phenomenon can be seen in Figure 20 that the enormous power losses occur in branch 18. Branch 18 is the conductor connecting bus 2 and bus 19. This branch is the most extended in the IEEE 33-bus distribution network. In all conditions, namely the original condition, the integration of 1 DER, 2 DERs, and 3 DERs, the highest power losses occurred compared to other branches. The power loss in the original network condition at branch 18 is 44 kW. This loss decreased slightly to 35 kW with the integration of 1 DER on bus 17. The integration of 2 DERs on buses 13 and 31 reduced losses in branches 18 to 33 kW. The lowest losses in this network are achieved at the integration of 3 DERs on buses 7, 16, and 31, respectively. Power loss at branch 18 is decreasing at 29 kW. This phenomenon shows that although there is an addition of distribution network power plants that can increase the voltage on many buses, the power losses in each branch are still dominantly affected by branch length.

### E. PERFORMANCE OF MALO

The MALO technique has successfully optimized the DER location placement and capacity for system testing on the IEEE 33-bus distribution network. The performance of the proposed MALO technique can be analyzed by comparing it with other methods. In this study, comparisons were made with the methods of teaching-learning-based optimization (TLBO) [33], [41], genetic algorithm (GA) [33], [42], particle swarm optimization (PSO) [33], [42], Taguchi method (TM) [33], [43], and multi-objective Taguchi approach (MOTA) [33], [43]. The comparison of the optimization results of the MALO technique with these methods is shown in Table V. The table shows that optimizing DER location and capacity using the MALO technique results in more minor power losses than other methods. Power losses of 92.15 kW were achieved by integrating DER on buses 7, 16, and 31 with capacities of 1065.24 kW, 994.91 kW and 1119.05 kW, respectively. Optimization using the MOTA method produces power losses of 96.30 kW, the TM method produces 102.30 kW, the PSO method produces 105.30 kW, the GA method

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| DER Integration | DER Location (Bus) | DER Capacity (kW) | Power Factor | Power Loss (kW) | Minimum Bus Voltage (p.u.) | Average Bus Voltage (p.u.) |
|----------------|--------------------|-------------------|--------------|----------------|--------------------------|--------------------------|
| Without DER    | NA                 | NA                | NA           | 202.71         | 0.911                    | 0.950                    |
| 1 DER          | 17                 | 1111.33           | 0.9 (lag)    | 164.55         | 0.932                    | 0.967                    |
| 2 DERs         | 13                 | 912.64            | 0.9 (lag)    | 129.89         | 0.966                    | 0.977                    |
|                | 31                 | 945.09            | 0.9 (lag)    | 98.73          | 0.972                    | 0.981                    |
| 3 DERs         | 7                  | 1006.23           | 0.9 (lag)    | 98.73          | 0.972                    | 0.981                    |
|                | 16                 | 992.28            | 0.9 (lag)    | 98.73          | 0.972                    | 0.981                    |
|                | 31                 | 1110.99           | 0.9 (lag)    | 98.73          | 0.972                    | 0.981                    |

| Minimum Bus Voltage (p.u.) | Average Bus Voltage (p.u.) |
|---------------------------|---------------------------|
| (bus 18)                  | 0.950                     |
| (bus 33)                  | 0.967                     |
| (bus 18)                  | 0.977                     |
| (bus 11)                  | 0.981                     |

---

**Figure 20.** Power loss scattered of Scenario #4: Type-IV DER Integration in IEEE 33-bus distribution network.

Figure 20 shows power loss scattered of Scenario #4: Type-IV DER Integration in IEEE 33-bus distribution network. Power loss in each branch of the distribution network is very dependent on the length of the conductor.
produces 106.30 kW, and the TLBO method produces 127.70. The original condition of the IEEE 33-bus distribution network has a power loss of 202.71 kW. The comparison of the optimization results of these various methods can be seen graphically in Figure 21.

In order to test the superiority of the proposed MALO technique, a comparison of the convergence characteristics with other methods has been carried out. The comparison methods used are particle swarm optimization (PSO), artificial immune system (AIS), and fuzzy multi-objective methods. The first characteristic test was the optimization of the IEEE 33-bus distribution network with the integration of 1 DER type-III. The selection of type-III DER is because the type of DER provides the best distribution network performance in this study.

The comparison test of the convergence characteristics of the MALO technique with other methods for the integration case of 1 DER is shown in Figure 22. It can be seen that the MALO technique is so superior in carrying out the task of optimizing the location and capacity of DER to produce minor power losses. Optimization is achieved in the 12th iteration, where the value converges on power losses of 155.44 kW.

Meanwhile, the PSO method produces a convergence value at power losses of 158.32 kW, achieved in the 13th iteration. The AIS and fuzzy multi-objective methods are achieved in the 17th, and 19th iterations, respectively. The AIS method produces losses of 160.16 kW, and the fuzzy multi-objective method produces power losses of 163.98 kW. This comparative test of distribution network optimization with 1 DER integration shows the superiority of the MALO technique in the speed of convergence and the resulting power losses.

This study also carried out a statistical analysis of the performance of the proposed method and compared it with

![Figure 21. Comparison of the optimization results of various methods for IEEE 33-bus distribution network.](image-url)

![Figure 22. The convergence characteristics of the MALO technique were compared with other methods for the 1 DER integration case.](image-url)

![Figure 23. SP-metric of the MALO technique were compared with other methods for the 1 DER integration case.](image-url)
other methods. Figure 23 shows the SP-metric of the MALO technique compared with other methods for the 1 DER integration case. The SP-metric (or box and whisker plot), as shown in Figure 23, can show statistically significant optimization variables. The lower and upper bounds of the box indicate the first quartile (25%) and the third quartile (75%), respectively. In comparison, the middlebox is the median or second quartile containing 50% of the solution set. As shown in Figure 23, in a test of 30 runs, the characteristics of the MALO, PSO, AIS, and fuzzy multi-objective methods for normalized power losses optimization values have been shown. The median for the MALO method in the 1 DER integration test case is 0.7188. PSO, AIS, and fuzzy multi-objective methods yielded medians of 0.7286, 0.7735, and 0.8416, respectively. In this statistical test of the 1 DG location and capacity optimization process for 30 runs, the MALO method has a lower median than the PSO, AIS, and fuzzy multi-objective methods.

The second characteristic test is optimizing the IEEE 33-bus distribution network with the integration of 2 type-III DERs. Type-III DER is a type of DER capable of injecting active power while absorbing the reactive power of the distribution network. Type-III DER is the type of DER that provides the best distribution network performance in this study because it has ideal generating characteristics. The comparison test of the convergence characteristics of the MALO technique with other methods for the 2 DERs integration case is shown in Figure 24. It can be seen that the MALO technique is superior in carrying out the task of optimizing the location and capacity of DER to produce minor power losses. Optimization is achieved in the 25th iteration, where the value converges on power losses of 119.65 kW. For comparison, the PSO method produces a convergence value at power losses of 121.17 kW, also achieved in the 25th iteration. The AIS and fuzzy multi-objective methods are achieved in the 28th and 31st iterations, respectively. The AIS method produces 122.34 kW losses, and the multi-objective fuzzy method produces 124.76 kW power losses. This comparative test of distribution network optimization with 2 DERs integration shows the advantages of the MALO technique in the speed of convergence and the resulting power losses.

The performance of optimization methods for the 2 DER integration test cases is statistically shown in Figure 25. As shown in Figure 25 that in the 60 runs test, the characteristics of the MALO, PSO, AIS, and fuzzy multi-objective methods for normalized power loss optimization values have been shown. The median for the MALO method in the 2 DER integration test cases is 0.5752. PSO, AIS, and fuzzy multi-objective methods each produce medians of 0.5824, 0.5889, and 0.6101, respectively. In this case, the proposed MALO method produces a lower median than the PSO, AIS, and fuzzy multi-objective methods. These results indicate that the network optimization for the 2 DER integration test case statistically shows the superior performance of the MALO method compared to the other three methods.
The third characteristic test is optimizing the IEEE 33-bus distribution network with the integration of 3 DER type-III. Type-III DER is the type of DER that provides the best distribution network performance in this study because it has ideal generating characteristics capable of injecting active power while absorbing the reactive power of the distribution network. The comparison test of the convergence characteristics of the MALO technique with other methods for the case of 3 DER integration is shown in Figure 26. It can be seen that the MALO technique is superior in carrying out the task of optimizing the location and capacity of DER to produce minor power losses. Optimization is achieved in the 66th iteration, where the convergent value of power losses is 92.15 kW. For comparison, the PSO method produces a convergence value at power losses of 103.98 kW, achieved in the 56th iteration. The convergence of the AIS and fuzzy multi-objective methods is achieved in the 70th and 68th iterations. The AIS method produces losses of 105.12 kW, and the fuzzy multi-objective method produces power losses of 105.45 kW. This comparative test of distribution network optimization with 3 DER integration shows the superiority of the MALO technique in the speed of convergence and the resulting power losses.

In this 3 DER integration test case, the performance of statistical optimization methods is shown in Figure 27. As shown in Figure 27, in the 100 runs test, the characteristics of the MALO, PSO, AIS, and fuzzy multi-objective methods for normalized power losses optimization values have been shown. The median for the MALO method in the 3 DER integration test cases is 0.4751. This median is the lowest value when compared to the median of the other three methods. PSO, AIS, and fuzzy multi-objective methods yielded medians of 0.5189, 0.5897, and 0.5801, respectively. In this case, the proposed MALO method produces a lower median than the PSO, AIS, and fuzzy multi-objective methods. These findings also reveal that the MALO approach outperforms the other three methods statistically when it comes to network optimization for the 3 DER integration test scenario.

IV. CONCLUSION

In this study, the location and capacity optimization of DER in the power distribution network has been tested using the multi-objective ant lion optimization (MALO) technique. The MALO technique has been applied to the IEEE 33-bus distribution network test system. Four scenarios have been carried out, namely, DER integration type-I, type II, type-III, and type-IV. The test results have shown the effectiveness of the applied MALO technique. Optimization with type-III DER integration provides the best distribution network performance. In this scenario, the integration of 1 DER produces a network power loss of 155.44 kW, where the power loss in the original network condition is 202.71 kW. The integration of 2 DERs can reduce losses up to 119.65 kW, and finally, losses of 92.15 kW are achieved by integrating 3 DERs. DER type-III is a renewable energy power plant that injects active power while absorbing reactive power from the distribution network. Power plants that use asynchronous generators such as wind power plants are included in this type. The ability to supply active power while absorbing reactive power significantly improves distribution network performance. Another indicator of successful optimization is the network voltage profile. The best voltage profile of the IEEE 33-bus distribution network has been achieved with the type-III DER integration. The performance of the MALO technique has been compared with other methods, and the results show that the proposed MALO technique produces superior multi-objective optimization. The next challenge of this research is to determine the accurate weights on the objective functions, especially when there is not enough information about the problem. The strategy applied in this research is to apply fuzzy optimization. Future research can apply other strategies to determine accurate weights on multi-objective functions.

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