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HYBRID LOSS SENSITIVITY FACTOR AND MUTATED ANT LION OPTIMIZER FOR OPTIMAL DISTRIBUTED GENERATION PLACEMENT WITH MULTIPLE LOADINGS

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ABSTRACT

In power system planning and operation, the main objective is to deliver consistent electrical power at low power losses and stable voltage magnitude. One of the ways in which this objective can be accomplished is by incorporating Distributed Generation (DG) into distribution network. DG uses small-scale technologies to generate electricity close to consumers. Improper planning of DG invites several unwanted consequences which can lead to unstable system and inefficient use of electrical energy. Thus, placement of DG units at the right location with adequate size is of necessary. This paper proposes a new method for DG placement using hybrid Loss Sensitivity Factor (LSF) and Mutated Ant Lion Optimizer (MALO). The incorporation between LSF technique and optimization algorithm for optimal DG placement, in addition to the development of a new hybrid MALO algorithm are the contributions of this study. The objectives of this study are; (1) to improve voltage stability in distribution network using optimal DG placement and; (2) to develop a new hybrid optimization algorithm for optimal solution and fast computation. The proposed technique was tested under various loading conditions to see its robustness. Several experiments and comparative studies have demonstrated that the proposed hybrid LSF-MALO technique has successfully minimized real power losses while ensuring a stable voltage stability condition in the system. In terms of the optimization performance, the proposed LSF-MALO managed to offer a reasonable computation with optimal solution concurrently.

Keywords: *Distributed Generation, Loss Sensitivity Factor, Mutated Ant Lion Optimizer, MALO, Loss Minimization, Voltage Stability*

1. INTRODUCTION

One of the primary goals of power system planning is to ensure consistent power delivery while minimizing power losses. To achieve the goal, placement of Distributed Generation (DG) units is one of the methods used in distribution system. Electrical power has traditionally been supplied to consumers by a centralized power generation system which comprises of a few large generation systems and a complex electricity transmission network for final use. Implementation of DG in distribution network can enhance voltage profile, reducing real power loss, increasing dependability and power quality, and avoiding long distance transmission of electricity [1], [2]. Integrating DG into the distribution network can provide substantial benefits in terms of technical, economic, and environmental aspects. For instance, network dependability and stability can be

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improved, transmission and distribution operating costs can be reduced, and greenhouse gas emissions can be avoided as well [3], [4]. Most DG systems are powered by renewable energy sources such as photovoltaic panels and wind turbines. Diesel generators, micro-turbines, solar DG (PV), wind power, hydroelectricity, and fuel cells are among the most utilized DG technologies [5].

Despite delivering several benefits to the network, severe integration and poorly managed integration can have negative repercussions to the network. This involves substantial power losses, voltage instability, and deterioration of power quality and protection in power distribution networks [6]. To avoid such occurrences, effective DG integration planning must be addressed. This can be accomplished by appropriately positioning the DG units at the optimal location with optimal size. Many techniques have been proposed by researchers in order to properly integrate the DG units in the distribution network. These techniques are classified into three types: conventional, metaheuristic optimization and hybrid techniques. Analytical techniques, exhaustive analysis, optimal power flow (OPF), and probabilistic techniques are a few examples of conventional techniques.

The advantages of analytical techniques include quick computation, straightforward implementation, and avoidance of convergence issues. However, their applicability might be constrained when dealing with complex issues, which could lead to errors and a lack of robustness [6]. Exhaustive analysis also saves time on computation for a single DG implementation. However, when considering the placement of multiple DG units with varying load generation, it can be computationally impractical [6].

OPF typically displays a notable balance between precision and computational effectiveness. However, its application is limited because closed formulations for technical parameters are required, which limits its adaptability and range [7]. Like other approaches, probabilistic techniques have shown to be effective in DG placement. These methods, however, frequently require a sizable amount of data, as well as substantial data processing power. [7]

Metaheuristic approaches have become the most commonly used technique to solve the optimal location of DG in distribution networks due to their efficacy and simplicity. This is due to the fact that the techniques do not require any settings on pre-condition of the concerned optimization problem, making them a popular technique to be implemented. One example of a metaheuristic technique is the Genetic Algorithm (GA), which incorporates selection, crossover, mutation, and inheritance into its process [6]. The method has been utilized in the research conducted in [8] with the goal of reducing the line losses, voltage deviation, and associated costs. The technique shows to be effective with multi-objective problems.

Apart from that, the research published in [9] has made use of PSO technique that imitates the behaviors of flocks of birds in order to find the optimal location and size for DG and static compensator devices. This was done in order to reduce losses and improve voltage profile. PSO was also used in [10] for DG optimal location with the goal of minimizing Total Harmonic Distortion (THD), losses, cost, and improving the voltage profile. When compared to GA, the technique requires fewer iterations and takes less computation time. Nevertheless, there is a possibility of getting stuck in local optima when working on complex problems.

Tabu Search (TS) is another metaheuristic technique that has been documented in the literature. Based on the theory of adaptive memory and sensitive exploration, the technique allows the solution space to be searched economically and efficiently until no progress is made [3]. Similar to GA and PSO, the solution generated by the technique may become stuck in local optima despite its ability to work in complex problems. Later, the Ant Colony Optimization (ACO) is another method that most researchers have implemented, as conducted in [11]. The method provides a quick solution, but the time it takes for the solution to converge can be unpredictable, and the distribution is likely to shift with each iteration.

Afterwards, the Cuckoo Search Algorithm (CSA) has been implemented in [12]. The research formulated the CSA for DG and DSTATCOM placement which have worked effectively for simultaneous placement. However, the research focused only on the balanced network which has limited the capability of the algorithm. Another metaheuristics algorithm is the Firefly Algorithm (FA) [13]. The study shown that the FA have effectively provide a better solution for DG placement when compared to GA. However, the

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research only focusses on base condition without any variation of loads for DG integration; thus, limiting the overall capability of the algorithm.

The next method is Stimulated Annealing (SA) [14]. This method is simple to use and computationally effective, but it is prone to becoming trapped in local optima [6]. Harmony Search (HS) has been proposed in [15]. This method has the ability to get past local optima, but it might lead to long and complex iterations without improving the solution [16]. The last example of metaheuristic algorithm is the Bat Algorithm (BA) which has been proposed in [17]. This study does not provide a comparative analysis to determine whether or not its solutions are better than those proposed by other studies because it focuses solely on multi-objective problems with various loading conditions.

There are many more metaheuristic techniques that have been applied by researchers in order to solve the optimal DG placement problem. Even though the algorithms might be different, there is one similarity between them: the need to have a fast computation speed during optimization while maintaining optimal solutions concurrently.

To address these shortcomings, hybrid techniques for optimal DG placement and sizing have gained popularity. By combining several different techniques, the solution can be improved, simplified, and the search space can be reduced. Research in [18] applied the LSF as well as another hybrid technique called Particle Swarm Optimization and Gravitational Search Algorithm (PSOGSA). This combination successfully reduces the search space, and PSOGSA was used to determine the optimal size of DG units to be installed. Furthermore, it improves power loss minimization, voltage stability, and cost reduction.

On the other hand, research in [19] aims to minimize real power losses and improve voltage profile by combining sensitivity analysis with Evolutionary Programming (EP). Sensitivity analysis identifies the most sensitive buses to be installed with DG units. This combination requires fewer generations to converge and is also computationally efficient. Apart from hybridizing conventional technique and metaheuristic technique, there are studies that combine different metaheuristic techniques. Rank Evolutionary Particle Swarm Optimization (REPSO) is a hybrid technique proposed in [20] that combines two metaheuristic techniques, namely EP and PSO. The proposed technique provides a simpler process that requires fewer iterations and has a shorter computational time.

To achieve various goals such as minimizing power losses, improving voltage stability as well as lowering operational costs, hybrid techniques are the current best technique for DG placement problem. The significant benefit of utilizing hybrid approaches is the capability of condensing the search space while simultaneously enhancing the efficiency of computational process. The different strategies, when combined, provide superior performance to those of their individual components.

Even though a lot of research and methods have been put forth for distributed generation (DG) placement, the majority of placements still rely on trial and error rather than a methodical approach. In addition, most of the previous studies did not take account of the algorithm performance under various loading conditions, which should be verified to see the robustness of the algorithm. This must also include comparative studies not only between different algorithms, but also between different parameters setting such as population size and essential parameter of that algorithm. The questions such as to what extend the algorithm can perform and under what situation the algorithm starts to collapse should be justifiably answered in this study.

Therefore, in order to solve the optimal DG placement and sizing problem, this paper proposes a new approach that combines the LSF technique with a new hybrid metaheuristic algorithm known as the Mutated Ant Lion Optimizer (MALO). The primary goal of this research is to improve voltage stability in distribution network under various loading conditions with sufficient power losses reduction. The proposed method incorporates the LSF technique in order to identify the best locations for DG placement. By eliminating the need for a trial-and-error approach and reducing the size of the search space, this strategy facilitates the process of DG placement in power system. In addition, the development of hybrid MALO algorithm offers a tremendous solution for a sizing engine in DG placement problem. The proposed algorithm can have small computation time in delivering the optimal solution at post-optimization. This paper is organized as follows: methodology section will explain some related theories on the selected techniques, the proposed problem formulation and

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the development of overall algorithm, followed by analysis and results after conducting several experiments on the concerned case studies, which is finally summarized in the conclusion section.

2. METHODOLOGY

This study presents a new method for the optimal DG placement by integrating the loss sensitivity factor (LSF) with the proposed hybrid algorithm, known as Mutated Ant Lion Optimizer (MALO). Locating the sensitive buses in the power system will be conducted via LSF technique, which then will be used for suitable buses identification in placing the DG units at the right locations. Subsequently, the developed MALO algorithm will be implemented for optimally sizing the DG units in accordance with the specified constraints and objective function.

2.1 Loss sensitivity factor (LSF)

The loss sensitivity factor (LSF) approach is based on the proposition of linearizing the original nonlinear equation around the initial operating point, which alleviates in the reduction of solution space [21]. The sensitivity factor of real power loss in relation to DG real power injection is given by (1):

$$\gamma_i = \frac{\partial P_L}{\partial P_i} = 2\sum_{i=1}^{N}\left(\alpha_{ij}P_j - \beta_{ij}Q_j\right) \quad (1)$$

Sensitivity factors are calculated for each bus in the distribution system, starting with the values acquired from the base case power flow. To build a priority list, the buses are ordered in descending order by the values of their sensitivity factors. The bus at the top of the priority list will be the first to be selected for DG integration. Incorporating LSF with MALO, hence known as LSF-MALO, will help to minimize the total computation time for the overall optimization process. This is because, only the buses in the priority list will be selected for DG integration as they are the most sensitive buses in the overall network.

2.2 Development Of Mutated Ant Lion Optimizer (MALO)

This research proposes a hybrid optimization algorithm namely the Mutated Ant Lion Optimizer (MALO) for optimal sizing of DG in distribution network. The proposed technique is based on the hybridization of two algorithms: Ant Lion Optimizer (ALO) and Evolutionary Programming (EP).

2.2.1 Ant Lion Optimizer (ALO)

Ant Lion Optimizer (ALO) is one of the nature-inspired algorithms that was developed by Seyedali Mirjalili in 2015 that emulates the practice of antlions hunting ants in nature [22]. The development of ALO begins with the initialization of the population of ants and antlions using a random walk. This is done because ants and antlions move in a random manner in their natural environments. The expression is as follows:

$$X(t) - [0, cumsum(2r(t_1) - 1, cumsum(2r(t_2) - 1, \ldots, cumsum(2r(t_n) - 1] \quad (2)$$

where *cumsum* computes the cumulative sum, *n* is the maximum number of iterations, *t* represents the random walk step, and *r(t)* is a stochastic function defined in the following equation:

$$(t) = \begin{cases} 1 & if\ rand > 0.5 \\ 0 & if\ rand \leq 0.5 \end{cases} \quad (3)$$

where *t* represents a random walk step and *rand* is a random number generated with a uniform distribution in the range [0, 1]. At each step of optimization, ants will update their position with random walk using the normalized equation as follow:

$$X_i^t = \frac{(X_i^t - a_i) \times (d_i - c_i^t)}{(d_i^t - a_i)} + c_i \quad (4)$$

where a_i is the minimum random walk of *i-th* variable, d_i is the maximum of random walk in *i-th* variable, c_i^t is the minimum of *i-th* variable at *t-th* iteration, and d_i^t indicates the maximum of *i-th* variable at *t-th* iteration. Equation 4 should be applied at each iteration to ensure the existence of a random walk in the search space.

The antlions' trap had an effect on the ants' random walks, which can be represented by the following equations:

$$c_i^t = Antlion_j^t + c^t \quad (5)$$

$$d_i^t = Antlion_j^t + d^t \quad (6)$$

where c^t is the minimum of all variables at *t-th* iteration, d^t is the vector including the maximum of all variables at *t-th* iteration, c_i^t is the minimum of all variables for i-*th* ant, d_i^t is the maximum of all variables for *i-th* ant and $Antlion_j^t$ indicates the position of the selected *j-th* antlion at *t-th* iteration.

To replicate the constructing trap, a roulette-wheel is used to choose the antlions depending on their fitness, giving the fitter antlions a better chance of catching ants. The following equations were used to model the sliding ants toward the bottom of the trap:

$$c^t = \frac{c^t}{I} \tag{7}$$

$$d^t = \frac{d^t}{I} \tag{8}$$

where I is a ratio, c^t is the minimum of all variables at *t-th* iteration, and d^t is the vector including the maximum of all variables at *t-th* iteration. The antlions will rebuild their trap after catching their prey to increase their chances of catching the next prey, as shown by the following equation:

$$Antlion_j^t = Ant_i^t \;\; if\; f(Ant_i^t) > f\left(Antlion_j^t\right) \tag{9}$$

where t is the current iteration, $Antlion_j^t$ is the position of selected *j-th* antlion at *t-th* iteration and Ant_i^t is the position of *i-th* ant at *t-th* iteration.

The final part of this algorithm is elitism which allows them to maintain the best solution obtained at any stage of optimization process. The following equation represents this step:

$$Ant_i^t = \frac{R_A^t + R_E^t}{2} \tag{10}$$

where R_A^t is the random walks around the antlion selected by roulette wheel at *t-th* iteration, R_E^t is the random walk around the elite at *t-th* iteration and Ant_i^t is the position of *i-th* ant at *t-th* iteration.

2.2.2 Mutated Ant Lion Optimizer (MALO)

The purpose of hybridizing the original ALO with the EP's mutation is to provide wide variety of solutions by taking into consideration certain features or characteristics of the current solutions. This mutation is used to generate a mutated antlion, through which the random walk is to be performed. The existence of the mutated antlion will decrease the dependency of other solutions on the elite antlion, thus, allowing the algorithm to explore for other regions in the search space. In the original ALO, random walk was determined around the elite antlion and roulette antlion. However, in the proposed algorithm an additional random walk is also determined based on the mutated antlion. For each solution in the population, the parent antlion is chosen, and mutation process based on Gaussian distribution is performed to generate an offspring (i.e. mutated antlion). The offspring (x_i') for each parent (x_i) is done by adding a random number sampled from the normal distribution, with zero mean and standard deviation, to each vector of parent. The mathematical equation to generate offspring based on mutation process is given in equation (11) [23]:

$$x_i' = x_i + N(0, \sigma_i^2), for\; i = 1,2, \ldots\ldots n \tag{11}$$

where $N(0, \sigma_i^2)$ represent Gaussian random number with zero mean and standard deviation σ_i.
Random walk is then determined around these three antlions; elite antlion, roulette- wheel antlion and mutated antlion which can be determined by equation (12):

$$Ant_i^t = \frac{R_A^t + R_E^t + R_M^t}{3} \tag{12}$$

where R_A^t is the random walks around the antlion selected by roulette wheel at *t-th* iteration, R_E^t is the random walk around the elite antlion at *t-th* iteration, R_M^t is the random walk around the mutated antlion at *t-th* iteration, and Ant_i^t is the position of *i-th* ant at *t-th* iteration. The overall flowchart for the proposed hybrid LSF-MALO technique is presented in Figure 1.

2.3 Proposed Problem Formulation

In this section, the use of LSF technique, the implementation of the proposed MALO and the mathematical modelling of the problem will be explained.

2.3.1 Power losses in distribution system

The main purpose of DG optimal placement is to minimize the power losses. In the proposed algorithm, the real power losses will be evaluated through load flow simulation. For *N*-bus distribution system, the power loss can be expressed as in equation (13) [2]:

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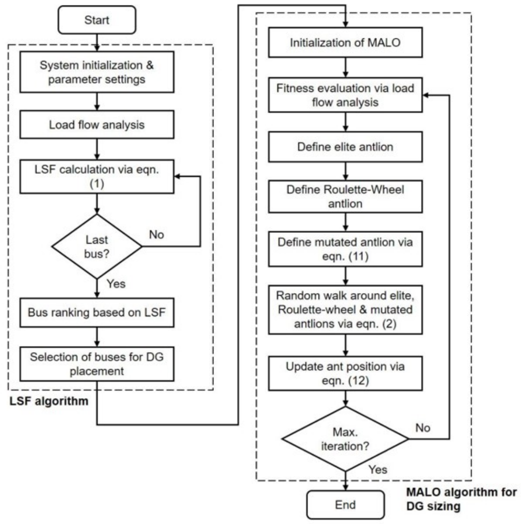

Figure 1: Flowchart for the proposed LSF-MALO algorithm

$$P_{Loss} = \sum_{i=1}^{N}\sum_{j=1}^{N}[\alpha_{ij}(P_iP_j + Q_iQ_j) + \beta_{ij}(Q_iP_j - P_iQ_j)] \quad (13)$$

where,

$$\alpha_{ij} = \frac{r_{ij}}{V_iV_j}\cos(\delta_i - \delta_j) \quad (14)$$

$$\beta_{ij} = \frac{r_{ij}}{V_iV_j}\sin(\delta_i - \delta_j) \quad (15)$$

$$Z_{ij} = r_{ij} + jx_{ij} \quad (16)$$

where Z_{ij} is the impendence of the line between bus i and bus j; r_{ij} is the line resistance between bus i and bus j; x_{ij} is the line reactance between bus i and bus j; V_i is the voltage magnitude at bus i; V_j is the voltage magnitude at bus j; δ_i is the voltage angle at bus i; δ_j is the voltage angle at bus j; P_i and Q_i is the active and reactive power injections at bus i and P_j and Q_j is the active and reactive power injections at bus j.

The calculation of real power losses in load flow simulation is subjected to the following equality and non-equality constrains as follows:

$$P_{Gi} - P_{Di} = \sum_{j=1}^{N} V_iV_j\,[G_{ij}\cos(\delta_i - \delta_j) + B_{ij}\sin(\delta_i - \delta_j)]\,;\ \forall i = 1,2,3,\ldots N \quad (17)$$

$$Q_{Gi} - Q_{Di} = \sum_{j=1}^{N} V_iV_j\,[G_{ij}\sin(\delta_i - \delta_j) - B_{ij}\cos(\delta_i - \delta_j)]\,;\ \forall i = 1,2,3,\ldots N \quad (18)$$

$$P_{Gi}^{min} \le P_{Gi} \le P_{Gi}^{max} \quad (19)$$

$$Q_{Gi}^{min} \le Q_{Gi} \le Q_{Gi}^{max} \quad (20)$$

$$V_i^{min} \le V_i \le V_i^{max} \quad (21)$$

where, G_{ij} is the conductance of the line between bus i and bus j and B_{ij} is the susceptance of the line between bus i and bus j. $P_{Gi}$and Q_{Gi} are power generations of generators at bus i. P_{Di} and Q_{Di} are the loads at bus i and V_i is the bus voltage magnitude.

2.3.2 Implementation of MALO algorithm

Specifying the key components of optimization, such as the control variables, equality, and non-equality constraints as well as the objective function is necessary prior to implementing any optimization algorithm. For the case of DG placement using the proposed LSF-MALO, the followings are the mathematical modelling of the problem.

Control variables – the variables to be optimized by the proposed MALO are the size of DG units in Megawatts (MW), which is represented by the following individual solution vector:

$$S_i = [P_{DG1}, P_{DG2}, \ldots, P_{DGk}, \ldots, P_{DGn}] \quad (22)$$

where, S_i and P_{DG} are the *i-th* solution and the real power injection of DG into the network respectively.

DG constraints – the following are the constraints to be considered in the optimization problem.

The inclusion of the constraints will limit the search space, thus, contributing to small computation time during optimization. In addition, the consideration of the constraints as in (17) to (21) will help preventing violation on load flow constraints and promising an accurate calculation of real power losses.

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$$DG\ rating: P_{DGmin} < P_{DGk} < P_{DGmax} \quad (23)$$

$$DG\ Scale: 0.05\ MW < P_{DG} < 5\ MW \quad (24)$$

$$Bus\ voltage: 0.95\ p.u < V_{min} < 1.05\ p.u \quad (25)$$

$$DG\ power\ factor: 0 < \mathrm{PF}_{DG} < 1 \quad (26)$$

Objective function – this research focuses on single objective optimization problem to minimize the power losses via optimal placement of DG in distribution system. Hence, the problem can be summarized as follows:
Objective function:

$$\text{minimize: } P_{Loss} = \sum_{i=1}^{N}\sum_{j=1}^{N}[\alpha_{ij}(P_iP_j + Q_iQ_j) + \beta_{ij}(Q_iP_j - P_iQ_j)] \quad (27)$$

Subject to constraints (17) – (21) and (23) – (26).

3. RESULTS AND DISCUSSION

The proposed LSF-MALO has been tested on IEEE 33-bus radial distribution system using MATLAB software. The goal of this study is to assess the efficacy of the proposed technique in solving the optimal DG placement problem. The simulation was conducted to determine the best size and position of the DG units in order to reduce real power losses while maintaining the distribution network's standard voltage magnitude of 0.95 to 1.05 per-unit (p.u.).

Two (2) cases were run under various reactive loading situations to assess the performance of the proposed LSF-MALO technique in terms of voltage profile and power loss improvement. The 2 situations are as follows:

Case 1: 50% reactive loading increment
Case 2: 100% reactive loading increment

Comparative studies involve two states of the power system, namely before and after the placement of DG. In every case study, the performance of the proposed LSF-MALO will be compared with LSF and EP techniques to see the effectiveness of the different algorithms. The number of DG units installed in each case is two and PV-type DG unit was used in the simulation.

3.1 Case 1: DG placement under 50% reactive loading increment

Table 1 presents the results for case 1 with 50% reactive loading increment. In the table, P_{loss} and V_{min} represent the real power losses and minimum bus voltage magnitude in the distribution network respectively.

Table 1: Case 1 (50% load increment) - real power losses and minimum voltage magnitude with multiple DG placement

Case	Method	DG Location	DG Size (MW)	P_{loss} (MW)	$\%\Delta P_{loss}$	V_{min} (p.u)	$\%\Delta V_{min}$	Time (s)
50% Reactive Load Increment	No DG	-		0.2101	-	0.909	-	-
	LSF	Bus 6 Bus 5	2.6690 3.0020	0.1718	18.22	0.974	7.24	8.02
	R-EP	Bus 32 Bus 5	2.2229 0.7376	0.1060	49.53	0.942	3.70	20.15
	LSF-MALO	Bus 25 Bus 6	0.2875 5.0000	0.1818	13.46	0.982	8.03	20.16

Based on Table 1, the minimum voltage magnitude in the distribution network, V_{min}, before DG integration drops below the standard operating range of 0.95 p.u. to 1.05 p.u.. The value was recorded to be 0.909 p.u. In addition, the real power losses were also recorded to be the highest at this condition. With proper DG placement by LSF-MALO and LSF, the voltage magnitude has been improved to the standard operating range, and the losses have been substantially reduced as well.

Although the EP technique results in the highest reduction of power losses, which is 49.53 percent, the minimum voltage magnitude of 0.942 p.u. is below the minimum standard value of 0.95 p.u.. Comparing the proposed LSF-MALO to the other two techniques, it has demonstrated superior

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improvement on the distribution system performance, with minimum voltage magnitude and power losses of 0.982 p.u. and 0.1818 MW, and these are equivalent to 8.03 percent and 13.46 percent of improvement respectively.

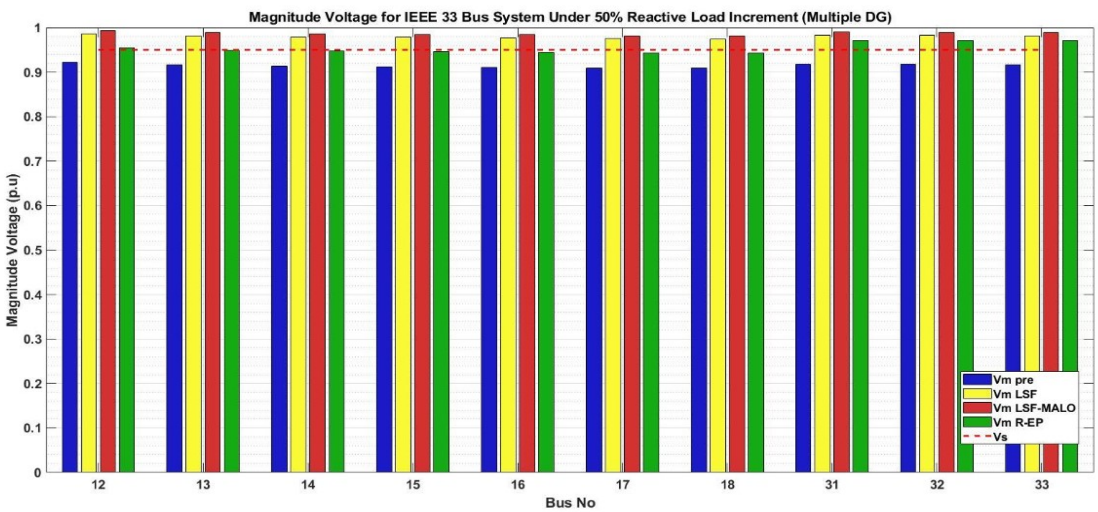

Figure 2: Voltage profile for ten buses with the lowest voltage magnitude (50% loading)

Figure 2 presents the voltage profile for ten buses with the lowest voltage magnitude in the distribution network. Based on the figure, the EP technique results in under-voltage from bus 14 to bus 18 as their voltage magnitudes below the minimum limit of 0.95 p.u.. On the other hand, the proposed LSF-MALO shows a consistent trend of voltage magnitude at all buses, where the voltage deviates between 0.98 p.u. and 1.02 p.u.. Hence for this case, the proposed technique is still able to produce satisfying results with reduced power losses and stable voltage magnitude on overall.

3.2 Case 2: DG placement under 100% reactive loading increment

For the purpose of observing the ability of DG to mitigate the voltage profile and power losses in distribution network, an additional analysis up to 100% reactive loading increment, the worst case scenario, was conducted. Table 2 shows the results after the experiment.

Table 2: Case 2 (100% load increment) - real power losses and minimum voltage magnitude with multiple DG placement

Case	Method	DG Location	DG Size (MW)	P_{loss} (MW)	$\%\Delta P_{loss}$	$V_{\min}$ (p.u)	$\%\Delta V_{\min}$	Time (s)
100% Reactive Load Increment	No DG	-		0.2489	-	0.898	-	-
	LSF	Bus 6 Bus 5	2.5025 2.8355	0.2029	18.48	0.965	7.42	8.77
	R-EP	Bus 32 Bus 5	1.1413 2.5189	0.1454	41.57	0.939	4.56	20.19
	LSF-MALO	Bus 25 Bus 6	0.2902 5.0000	0.2129	14.44	0.972	8.22	20.02

According to Table 2, the voltage magnitude V_{min} before DG integration drops to 0.898 p.u as the reactive loading reaches 100%, which is well outside its normal operating range. In addition, the real power losses under this situation were recorded at their highest level of 0.2489 MW. The minimum voltage magnitude, on the other hand, has been restored to its standard value after proper DG placement via LSF and LSF-MALO as shown in Table 2. Even at the maximum reactive loading condition, the proposed LSF-MALO has resulted in voltage magnitude of 0.972 p.u., which is the highest as compared to other techniques.

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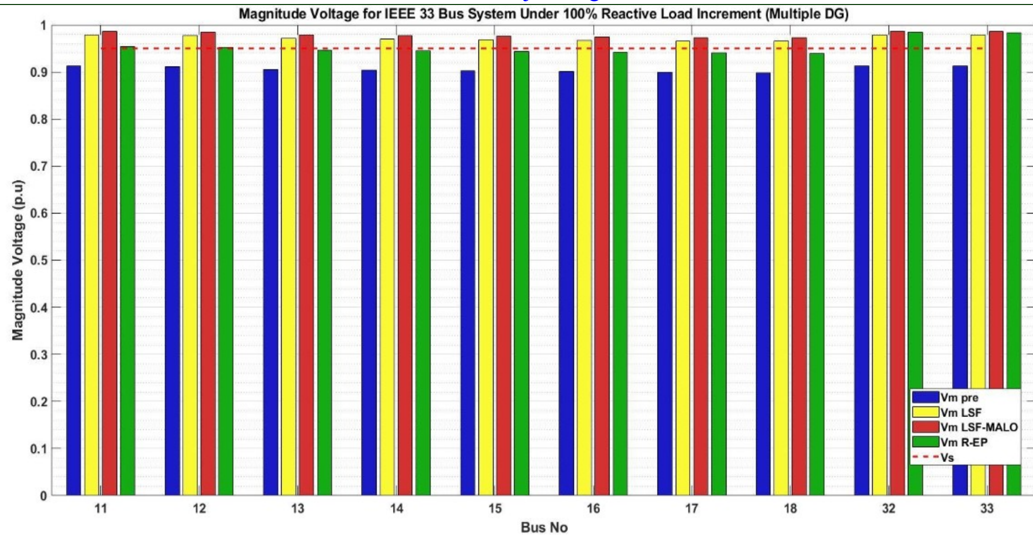

Figure 3: Voltage profile for ten buses with the lowest voltage magnitude (100% loading)

The same improvement on real power losses is observed as well, where it has been further minimized after DG integration to the system. The real power losses have been recorded to be 0.2129 MW, equivalent to 14.44 percent of reduction, using LSF-MALO technique. This is the lowest reduction percentage as compared to EP technique, which results in 41.57 percent of losses reduction. Again, the EP technique is unable to ensure a safe level of operating voltage as its magnitude of 0.939 p.u. is below the minimum level.

The proposed LSF-MALO ensures the voltage magnitude to be within 0.97 p.u. and 1.02 p.u. at all buses in the system, as can be seen in Figure 3. This thorough analysis has demonstrated the robustness of the proposed technique as well as the significance of having a proper DG placement in the distribution network.

3.3 Voltage stability improvement under several reactive loadings

As depicted in Figure 4, the summary of minimum voltage magnitude under several reactive loadings, from base case up to 100% loading, is presented. From the figure, it is clear that with DG integration to the system, either through LSF, EP or LSF-MALO, the voltage magnitude's stability has been consistently improved at all reactive loadings. Thus, the role of DG as a device to improve distribution network performance is justified. In addition, with regard to the optimality of solution between the three methods, the proposed LSF-MALO resulted in the highest minimum voltage magnitude for most of the reactive loadings. These findings justify the reason for hybridizing the original ALO with the EP's mutation, that is, to enhance the exploration of the search space towards global optimum solution.

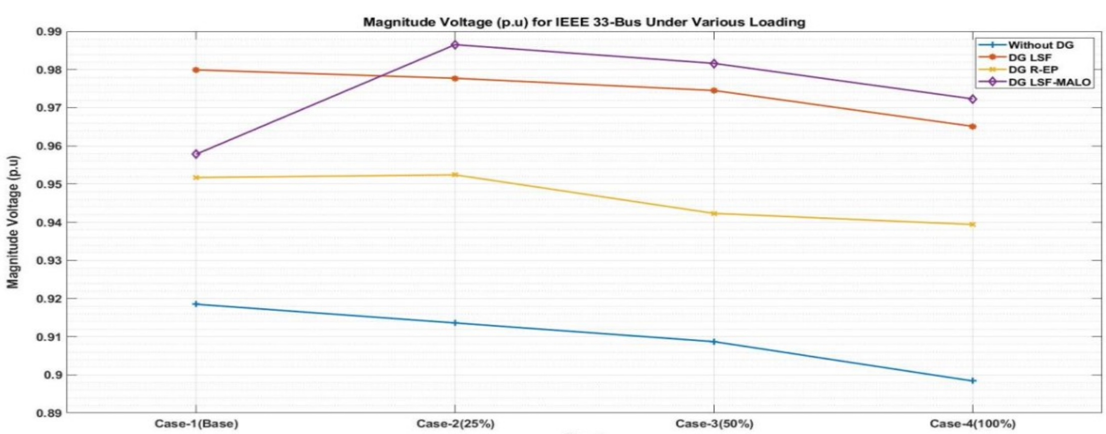

Figure 4: Minimum voltage magnitude under several reactive loadings (base case to 100% loading)

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3.4 Comparative study between MALO and EP

In order to further evaluate the capability of the proposed hybrid MALO algorithm in searching for optimal solution, this study has extended the simulation by varying the mutation scale for both MALO and EP. The number of iterations in the simulation is set to 100, the size of the population is 10, and the mutation scale, abbreviated as beta, was varied between 0.5 and 0.85. The results are tabulated in Table 3.

Table 3: Minimum voltage magnitude with different mutation scales (beta) under several reactive loadings

		beta = 0.5				*beta* = 0.85			
Reactive loadings	V_{min} without DG (p.u.)	V_{min} by EP (p.u.)	Time (s)	V_{min} by MALO (p.u.)	Time (s)	V_{min} by EP (p.u.)	Time (s)	V_{min} by MALO (p.u.)	Time (s)
Base case	0.918	0.952	19.22	0.958	18.84	0.951	21.96	0.954	22.39
25% increment	0.914	0.952	19.97	0.987	19.02	0.947	21.85	0.987	21.71
50% increment	0.909	0.942	20.15	0.982	20.16	0.943	21.86	0.982	21.70
75% increment	0.904	0.945	20.12	0.977	20.16	0.936	21.80	0.978	21.83
100% increment	0.898	0.939	20.19	0.972	20.02	0.930	21.85	0.973	21.70

Based on Table 3, it is clear that the proposed MALO is able to produce a higher value of $V_{\min}$ within the tolerable amount of time when the mutation scale is set to 0.5. For EP, when the mutation scale is set to 0.85, the computation time is satisfying but the voltage magnitude is below the standard limit for most of the reactive loading situations. In addition, the value of $V_{\min}$ as found by EP is lower than that of MALO for both mutation scales. This result demonstrates that the proposed MALO is capable of finding the optimal solution significantly faster than any other techniques as discussed in this paper, with a better solution simultaneously.

Figure 5 shows a summary of the minimum voltage magnitude under several loading conditions with 0.85 mutation scale. The figure demonstrates that the proposed MALO algorithm successfully restores the voltage magnitude to its standard operating value (0.95 p.u. to 1.05 p.u.) at all loading situations, which is not fulfilled by the EP.

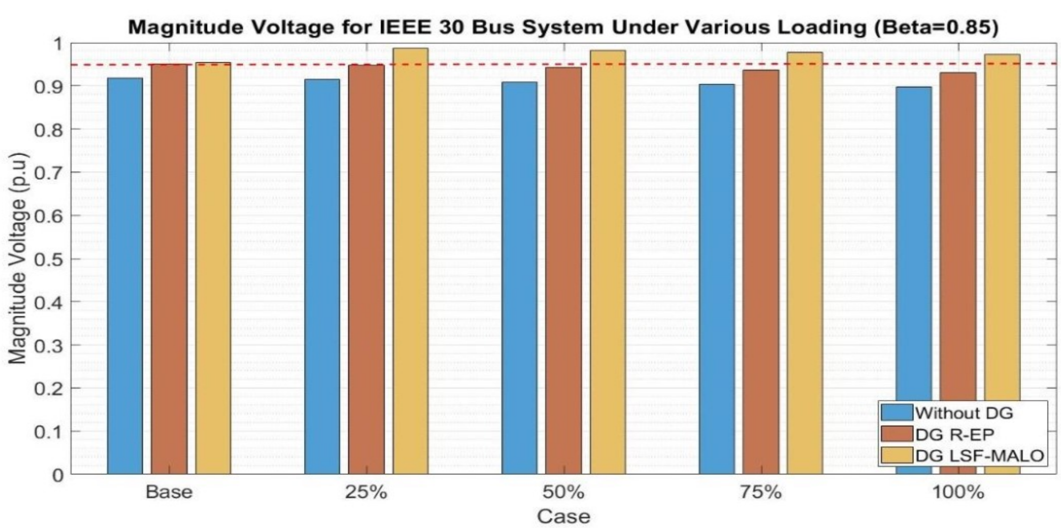

Figure 5: Minimum voltage magnitude under several loadings (beta = 0.85)

4. CONCLUSION

In conclusion, this paper has proposed a hybrid method for optimal DG placement in distribution network using LSF-MALO. The incorporation between LSF technique and MALO algorithm is one of the contributions from this study. After implementation in IEEE 33-bus radial distribution system, the proposed LSF-MALO has consistently improved the voltage magnitude and power losses at all loading conditions, i.e. from base case to the maximum loading. The voltage magnitude was successfully maintained above 0.95 per-unit at all buses under multiple loading conditions, with the corresponding percentage of losses reduction between 13 to 14 percent. This study has also revealed that by incorporating the LSF, the proposed MALO algorithm can perform faster optimization with optimal solution concurrently. At all loading conditions, the optimization completed less than 25 seconds, which is considerably fast. This is because the only control variables to be considered in the algorithm are the sizes of the DG units, since the suitable locations for DG placement has firstly been determined by the LSF. Hence, there will be a great reduction in the size of the search space, which has led to faster computation time of MALO. In addition, incorporating EP into the original ALO to become MALO has improved the algorithm for solution variety. The use of mutation operator by MALO has overcome the possibility of pre-mature convergence by allowing the algorithm to explore the entire search space during optimization. With the mutation scale set to 0.5 and 0.85, the proposed MALO was able to produce good solutions that have voltage magnitude above 0.95 per-unit for all loading conditions, which is much better than EP.

On overall, the results obtained from this study will be beneficial for power system operators who deal with planning and simulation. Furthermore, the proposed technique and algorithm will be useful for solving other optimization problems in the future. This can be done by minor alteration on the proposed algorithm with appropriate modification that suits the concerned problem.

AUTHOR CONTRIBUTIONS

The contributions produced by authors through this article are summarized as follows:

1. The idea of hybridizing both conventional technique and metaheuristic algorithm - this article has proposed the LSF-MALO, a hybrid approach for optimal DG placement in distribution system. The proposed technique has improved the algorithm performance by separating two sequential tasks for DG placement; (1) identifying the locations for DG units using LSF and; (2) sizing the DG units using MALO algorithm.
2. Development of a hybrid metaheuristic algorithm from two existing algorithms – in addition to the first contribution, this article has developed the MALO algorithm, a hybrid metaheuristic algorithm hybridized from EP and ALO. The developed algorithm combines the features from both algorithms; (1) ensuring a fast optimization from ALO's characteristic and (2) providing wide variety of solutions to prevent pre-mature convergence from EP's mutation.
3. A thorough analysis on DG placement in power system – this article has performed detailed and in-depth analysis on optimal DG placement problem. The robustness of the proposed algorithm has been verified in three different analyses, including the pros and cons of the technique. The findings have been justified with appropriate discussion, which can benefit any utility providers or communities that deal with power system planning and computational intelligence.

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