



A Comparative Study on DG Placement Using Marine Predator and Osprey Algorithms to Enhance Loss Reduction Index in the Distribution System

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Abstract: The Marine Predator Algorithm (MPA) and Osprey Optimization Algorithm (OOA) are nature-inspired metaheuristic techniques used for optimizing the location and sizing of distributed generation (DG) in power distribution systems. MPA simulates marine predators' foraging strategies through Lévy and Brownian movements, while OOA models the hunting and survival tactics of ospreys, known for their remarkable fishing skills. Effective placement and sizing of DG units are crucial for minimizing network losses and ensuring cost efficiency. Improper configurations can lead to overcompensation or undercompensation in the network, increasing operational costs. Different DG technologies, such as photovoltaic (PV), wind, microturbines, and generators, vary significantly in cost and performance, highlighting the importance of selecting the right models and designs. This study compares MPA and OOA in optimizing the placement of multiple DGs with two types of power injection which are active and reactive power. Simulations on the IEEE 69-bus reliability test system, conducted using MATLAB, demonstrated MPA's superiority, achieving a 69% reduction in active power losses compared to OOA's 61%, highlighting its potential for more efficient DG placement in power distribution systems. The proposed approach incorporates a DG model encompassing multiple technologies to ensure economic feasibility and improve overall system performance.

Keywords: Distributed Generation, Nature Inspired Algorithm, Marine Predator Algorithm, Osprey Optimization Algorithm, MATLAB, Power Distribution, IEEE 69-Bus, Loss Reduction Index.

1 Introduction

DISTRIBUTED Generation (DG) refers to small-scale electricity production typically integrated into the power distribution system. The concept of DG encompasses deploying modular technologies distributed across a service area of utility, integrated with the sub-

transmission or transmission system which is known as grid. DG demonstrates a capacity to function as an alternative to traditional forms of electricity generation for use in industrial, commercial, and residential settings. DG emerges as a prominent technological aspect in the power industry domain where the installation of DG in the existing power grid has exhibited a rising trend in distribution networks globally. These installations are designed to address the increasing electricity demand in specific regions, making certain operations self-sustaining in terms of power supply and achieving energy efficiencies [7],[8],[9]. DG expansion is evidently on the rise due to its major impacts on power system operation and energy availability, attributed to the increasing interest in utilizing renewable energy sources and constructing co-generation facilities. In this scenario, DG plays a major role in power

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generation, influenced by factors like electricity market deregulation, environmental considerations, and the advantages for consumers and utilities due to their proximity to end-users [1].

Current research indicates that DG deployment can improve voltage profiles, reduce system losses [2], enhance reliability and power quality [3], energy cost savings, and positive effect on the environment [4], [5]. However, the increasing utilization of DG in distribution systems has created new technical challenges and uncertainties for grid operation. These challenges include voltage fluctuations, reduced protection, and higher fault levels [11]. Additionally, the high penetration of DG can cause voltage rise, which may be difficult for distribution network operators to manage effectively [12]. With the rise of DG and microgrids, strategic implementation of DGs within distribution networks is needed to enhance network performance. In several past studies, traditional mathematical approaches such as stochastic and analytics have been applied to resolve the optimal installation regarding DG problem. These conventional methods have been replaced with advanced optimization techniques as they are often limited in their ability to handle the complexity of modern optimization problems, particularly those involving non-linear, high-dimensional, or non-convex objective functions.

Nature-inspired algorithms (NIA), particularly those that are population and swarm-based, such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA) and Ant Colony Optimization (ACO), are well-suited for DG optimization to facilitate coordinate control and enhancement among several agents or subsystems [4]. Both MPA and OOA have been selected due to their recent development as advanced metaheuristic techniques, which demonstrate exceptional performance as high-efficiency optimizers. They are particularly effective at maintaining a delicate balance between exploration and exploitation, thereby enhancing the search process and reducing the probability of becoming trapped in local minima. Their innovative algorithms and adaptability to various complex optimization problems make them valuable tools in achieving optimal solutions in challenging scenarios [14], [15].

In this paper, a comparative study between the Marine Predator Algorithm (MPA) and the Osprey Optimization Algorithm (OOA) have been conducted to assess their effectiveness in reducing total system losses and improving the minimum operating voltage (V_{\min}) after the installation of DGs in the IEEE 69-bus Reliability Test System (RTS) by using MATLAB simulation software. Both optimization techniques successfully identified the optimal placement and sizing of DGs under various operational and technical constraints, leading to significant improvements in the power loss

reduction index (LRI). While both algorithms deliver promising results, a thorough evaluation will be conducted to assess their performance in key areas, including the consistency of predictions, simulation time, and solution convergence speed. Additionally, the robustness of each technique in handling different load scenarios and their adaptability to varying system conditions will be analyzed. The findings from this comprehensive comparison will guide the recommendation of the superior technique, which will be proposed as the preferred optimizer for enhancing the efficiency and reliability of power systems.

2 Literature Review

2.1 Distributed Generation

Distributed Generation (DG) is defined as the production of electricity from a variety of small-scale energy sources situated in close proximity to the point of use [6]. These sources encompass renewable energy systems like solar photovoltaic (PV) panels, wind turbines, and small-scale hydroelectric generators, along with traditional fossil fuel-based generators [7]. DG involves the decentralized generation of electricity, scattering numerous smaller power sources across a microgrid to provide electricity to nearby consumers [8]. The distribution of electricity is made more resilient, dependable, and efficient with this structure. DG has a number of benefits and drawbacks that affect the energy system and society as a whole. By being close to the point of consumption, DG technologies minimize energy losses during long-distance transmission [9]. Diverse energy sources of DG, specifically renewable energy, allow the system to generate power with low greenhouse gas emissions, helping to combat climate change and lower carbon footprints. In addition, it provides the users with a degree of energy independence, reducing their dependency on external energy sources [10]. Consequently, it gives DG the ability to lower grid peak demand, which could result in cost savings.

DG systems can be categorized into four main types, each with distinct roles in the power grid based on their power output and the nature of the power they inject. DG Type 1 is designed to inject only real power into the system, with solar PV panels and fuel cells being common examples of this type. Although Type 1 DGs contribute to the reduction of active power losses, they do not influence the reactive power or voltage profile of the system. Type 2, in contrast, is solely dedicated to supplying reactive power, which is crucial for maintaining and raising the voltage profile of the distribution network. This type is particularly beneficial in scenarios where voltage stability is a primary concern, but it does not address active power losses. DG Type 3 is more versatile, as it has the capability to inject both active and reactive power into the distribution network.

This dual functionality allows Type 3 DGs to simultaneously reduce power losses and improve voltage stability, making them an attractive option for integrated power system optimization [8]. Type 4 DG systems focus on storage and flexible generation technologies that can supply both active and reactive power as needed, offering dynamic support for grid balancing. However, this study focuses exclusively on DG Types 1 and 2.

The installation of DG into the conventional power grid presents new technological difficulties and challenges, particularly concerning the quality of active power transmitted and faults occurrence. The rise of DG installation will modify the characteristics of the network power system, impacting fault detection, protection mechanisms and overall grid stability [12]. DG units are spread out and typically linked at lower voltage levels, which can add complexity to fault identification and isolation. Furthermore, the unpredictable and fluctuating nature of renewable DG sources may affect fault currents and voltage profiles, requiring more advanced protection strategies to ensure dependability and security [13]. Understanding the interaction between faults and DG is crucial for developing resilient and adaptive power systems that can support an increasing installation of distributed energy sources. The reliability test system in power system operations, as per IEEE standards, holds immense

significance in ensuring the robustness and dependability of power systems. It assists in determining how well the system can recover from unanticipated events, such as failures or load variations [1].

The chosen system for this experiment is IEEE 69-bus radial distribution system as shown in Fig. 1. This RTS consists of 69 buses or nodes, and 81 branches that act as lines or transmission elements. Each of these branches has its own parameters such as resistance, reactance, and line loadings. In this study, DG will be installed at various locations between bus number 2 and bus number 69. Bus number 1 is designated as the slack bus or feeder bus, serving as the reference point for voltage and phase angle in the electrical power generation or transmission network. The slack bus also compensates for power losses within the system, ensuring that the total power generated equals the total power consumed plus losses. The remaining buses, from 2 to 69, are being thoroughly evaluated for their suitability to accommodate DG units of varying sizes, selected from a specified range under consideration. This evaluation involves analyzing each bus's voltage profile, load demand, and the impact of potential DG integration on the system's overall efficiency and reliability. The goal is to identify optimal bus locations where the installation of DGs will maximize benefits such as power loss reduction, voltage stability improvement, and enhanced reliability of the distribution network [8].

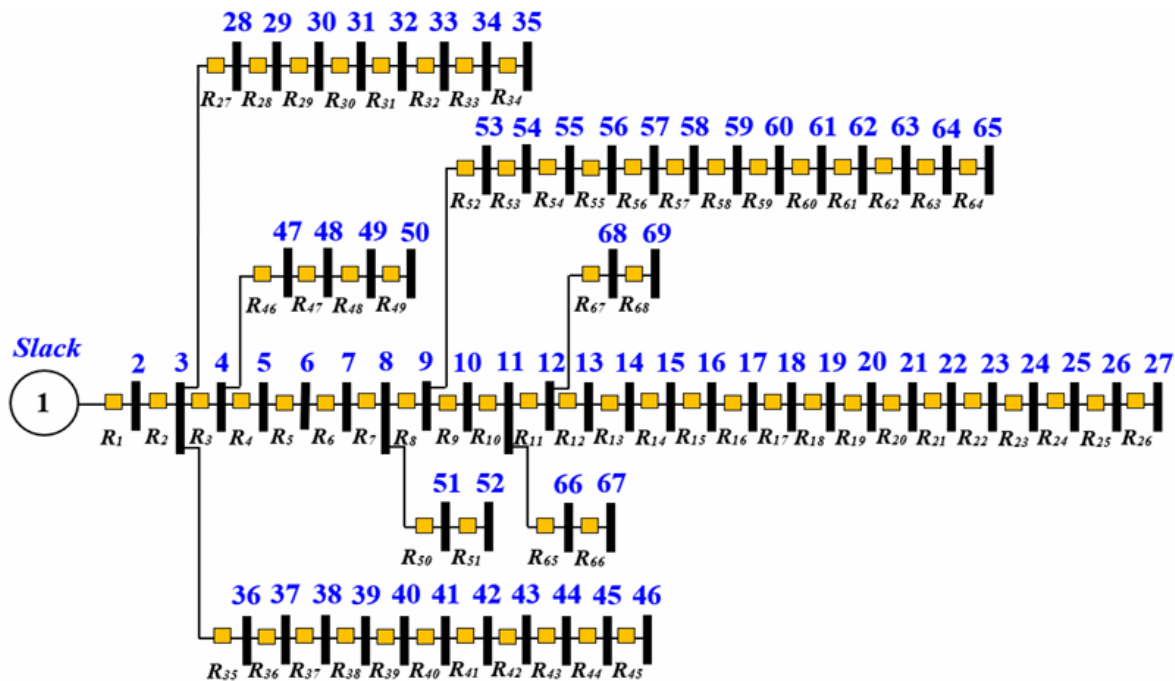


Fig 1. Test system IEEE 69-bus radial distribution system

Nature-inspired algorithms have gained considerable traction in the field of power systems and distribution due to their robust performance and ability to handle complex optimization problems. Mimicking natural processes and behaviours, these algorithms offer significant advantages over traditional methods [19]. They are particularly adept at navigating the complexity and non-linearity of power systems, managing numerous variables and constraints with ease. This adaptability is essential for addressing the specific challenges and requirements of different power systems. Furthermore, nature-inspired algorithms are ideal for real-time optimization, as their iterative and heuristic nature enables continuous improvement under changing conditions and constraints [20].

2.2 Marine Predator Algorithm

MPA is a population-based technique, like most metaheuristics, where the initial solution is uniformly distributed as the first trial over the search space:

$$X_0 = L_B + rand(U_B + L_B) \quad (1)$$

where *rand* is a consistent random vector within the range of 0 until 1, and L_B and U_B are lower bound and upper bound for the variables. Top predators in the natural world are said to be more adept at foraging, according to the survival of the fittest idea. The first part of the coding has been developed by nominating the top predator using the best fit solution to create a matrix as in Eq. (2) which is known as Elite.

$$Elite = \begin{bmatrix} X_{1,1}^I & X_{1,2}^I & \dots & X_{1,d}^I \\ X_{2,1}^I & X_{2,2}^I & \dots & X_{2,d}^I \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ X_{n,1}^I & X_{n,1}^I & \dots & X_{n,d}^I \end{bmatrix} \quad n \times d \quad (2)$$

where \vec{X}^I stands for the vector of top predator, which is repeated n numbers of times to establish Elite matrix. The amount of search agent is represented by n while the number of dimensions is d. Search agents include both prey and predators. This matrix's arrays are responsible for looking for and locating the target using the data of the prey's position. Another matrix named Prey with the same dimension as Eq. (2) has been constructed to serve as the reference for the predators to adjust their positions accordingly. The whole optimization process is directly related to both matrices. The MPA optimization procedure is divided into three primary phases of optimization, which simultaneously simulate the complete life cycle of a predator and its prey, including the consideration of various velocity ratios, as illustrated in Fig. 2.

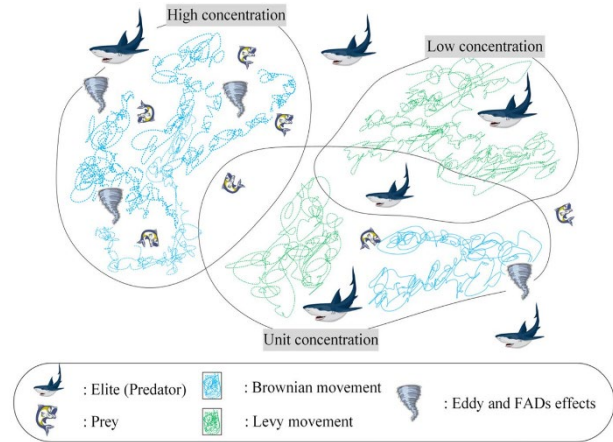


Fig 2. The three primary phases of MPA optimization process

The coding process continues with marine memory-saving. During the first phase, the prey advances at a higher rate than the predator in a high-velocity ratio or high-concentration scenario. The second phase is characteristic of a unit velocity ratio or unit concentration scenario, in which the predator and prey are moving at comparable rates. The predator moves quicker than the prey in a low-velocity ratio or low-concentration scenario, during which the third phase occurs. Each phase is assigned to a specific iteration period by predetermined regulations that control the movement of predators and prey while emulating their natural behaviors.

In addition to behavioral changes across different phases, environmental factors such as eddy formation and the influence of Fish Attracting Devices (FADs) also contribute to behavioral shifts in marine predators. To enhance the efficiency of exploration and exploitation in optimization, these factors have been incorporated into the algorithm's coding, reflecting their role in shaping predator behavior and improving performance in the targeted optimization field.

2.3 Osprey Optimization Algorithm

The Osprey Optimization Algorithm (OOA) is a recently developed bio-inspired metaheuristic algorithm designed to solve various optimization problems in engineering and other fields. OOA is developed based on the behavior of birds namely osprey. Osprey is also called river hawks, sea hawks and fish hawks [14]. Ospreys employ a natural hunting strategy that involves capturing fish from rivers or seas and then relocating their catch to a suitable location where they can consume it comfortably and safely. This efficient and adaptable behavior reflects a natural intelligence that has inspired the development of the OOA. By mimicking this strategy, OOA applies the principles of natural selection and survival to solve complex real-world optimization problems. The algorithm's ability to efficiently identify

and secure optimal solutions, much like an osprey's ability to catch and handle prey, makes it a powerful tool for addressing a wide range of practical challenges in various fields [15].

The algorithm is structured around two main phases which are Phase 1, exploration and Phase 2, exploitation. The proposed fitness function considered in this paper is optimized by mathematically modelling the intelligent strategy of ospreys capturing fish. The initialization of the population is the first step in the implementation of OOA where the position of the osprey is randomly initialized in the search space using Eq. 1. Then, the fitness of osprey is evaluated using the objective function. Osprey then identifies the location for hunting of fish where Phase 1 begins. Once the optimal location has been determined and updated, Phase 2 will begin where the osprey will be carrying the prey to a suitable safe location to consume it. Both Phase 1 and Phase 2 will be repeated until maximum iteration is achieved.

3 Proposed Methodology

DG has emerged as a prominent approach within the electric power system domain in recent times. However, the allocation of DG presents numerous challenges that require careful consideration. The placement of DG units within distribution systems must be approached strategically to harness optimal output from the DG setup. Inadequate sizing and positioning of DG units can cause overcompensation or under compensation issues [16], highlighting the critical need to determine optimal placement and sizing parameters for effective integration into distribution networks. The commercial scope of DG

systems exhibits a broad variety in terms of size, depending upon the specific technology employed. Inappropriate selection of DG models for various categories such as photovoltaic (PV) systems, microturbines, and wind generators may escalate the cost per unit of energy [17]. In addition, there is a need to develop effective optimization techniques that can perform and optimize the DG sizing and allocation by minimizing loss and cost and improving the voltage profile [18].

The objectives of this paper have been approached with several key steps, and it has been designed as shown in Fig. 3. Knowledge acquisition and background study of previous problems regarding the implementation of DG such as the advantages and disadvantages of DG technologies have been approached first, in order to suggest suitable optimization techniques to be used. MPA and OOA have been chosen due to their unique characteristics as a high-performance optimizer that can effectively balance exploration and exploitation while avoiding local minima. Both recently developed algorithms will be implemented to predict proper placement and sizing of DG when installed into the distribution network. The results from the simulations will be verified against research's objective functions such as active power loss (Ploss), reactive power loss (Qloss), minimum voltage (Vmin) and the speed of convergence as well as time taken to finish the simulations. The IEEE 69-bus system will act as primary test system to check and verify the results.

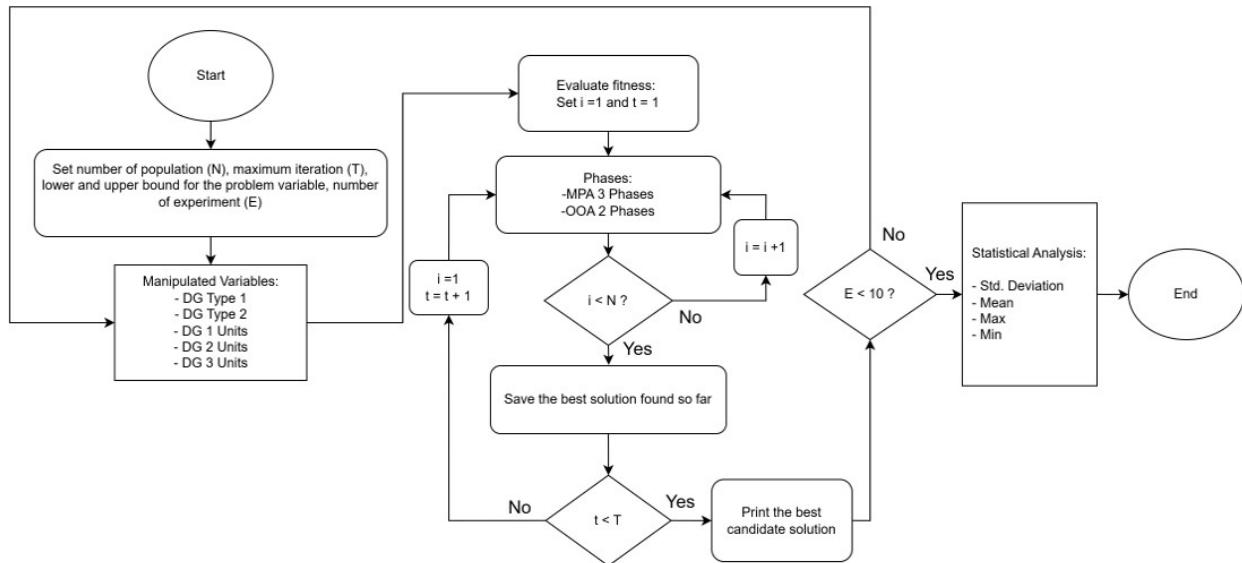


Fig 3. General flowchart of the research approach design

Fig. 3 presents the flowchart of how the objective of this research has been approached. Several parameters such as number of population or search agent has been set to 30, maximum iteration has been set to 100 iterations and base power has been set to 100 MVA, before performing the simulation. To investigate the performance of the proposed techniques, the test system has been assessed with different units of DG installation with different types of DG. The lower and upper bound of DG placement is influenced by how many DG units need to be installed. For example, when installing 3 units of DGs, three different ranges of buses have been set which are bus number 2 to 22, 23 to 45 and 46 to 69. This step has been taken as the algorithm may provide some repetitive prediction of the best location for DG placement. This experiment was repeated 20 times to evaluate the behavior of each optimization technique under varying constraints through statistical analysis.

3.1 Problem Formulation

Power loss needs to be minimized to achieve the maximum advantages of introducing DG in a distribution system by determining the best placement and size of the DG. The formula for loss reduction index follows the Eq. (3):

$$LRI = \frac{PL_{WDG} - PL_{DG}}{PL_{WDG}} \times 100\% \quad (3)$$

where, PL_{WDG} is the power loss without DG installation and is the power loss with the installation of DG in the network.

DGs available for commercial purposes are characterized by discrete sizes, therefore, the DGs that

require attention consist of multiples of the smallest capacitance size that is currently available. This is a result of coordination between the sizes of DG to be placed and the practical methods that are accessible [8]. The constraint follows the formula as shown in Eq. (4):

$$P_{inject-DGi} \leq LP_0, L = 1, 2 \dots n \quad (4)$$

where P_0 stands for the minimum DG size available. For this study, three different units of DGs have been installed in the distribution system. The size of DG has been set between 0.1MW to 5.0MW.

4 Results and Discussion

This section examines the performance of the Marine Predator Algorithm (MPA), and Osprey Optimization Algorithm (OOA) simulated in MATLAB for the optimal placement and sizing of DGs in the IEEE 69-bus radial distribution system. The study focuses on two types of DGs: Type 1, which injects only active power (P) in Megawatts (MW), and Type 2, which injects only reactive power (Q) in Megavolt-Amperes Reactive (MVAR). Although Type 3 DG, capable of injecting both active and reactive power, exists, this analysis considers only Types 1 and 2. For each type of DG, three different units of DG have been installed to analyze the reliability of the algorithm. Before starting the simulations, the parameters for both optimization techniques and the limits of the controlled variables were carefully set. The experiment has been repeated 20 times, and the mean and standard deviation of the results were recorded, as shown in Table 1.

Table 1. MATLAB simulation results of MPA and OOA

Algorithm	DG Units	Type of DG	Best Pos.	Best Sizing	Avg. Ploss (MWatt)	Ploss Std. Deviation	Avg. QLoss (MVAR)	Vmin (P.U.)	Real Power LRI(%)	Avg. Elapsed Time(s)	Avg. Iteration Converge	
N/A	N/A	N/A	0	N/A	0.227	N/A	0.105	0.909	0	N/A	N/A	
Marine Predator Algorithm (MPA)	1	1(MW)	61	1.873	0.083	0	0.042	0.968	63.44	21.04	15	
			17	0.532	0.072	0	0.037	0.979	68.28	21.95	48	
			61	1.781								
	2	1(MW)	11	0.563	0.07	0	0.036	0.979	69.16	20.34	69	
			23	0.343								
			61	1.782								
	3	2 (MVAR)	61	1.33	0.152	0	0.073	0.93	33.04	21.76	15	
			17	0.361	0.146	0	0.071	0.932	35.68	22.27	48	
			61	1.275								
	3	2 (MVAR)	11	0.419	0.145	0	0.071	0.932	36.12	22.79	68	
			23	0.225								
			61	0.419								
Osprey Optimized Algorithm (OOA)	1	1(MW)	61	1.873	0.083	0	0.042	0.941	63.44	21.86	18	
			19	0.62	0.078	0.003	0.056	0.977	65.64	22.74	46	
			61	1.886								
	2	1(MW)	12	0.717	0.08	0.004	0.058	0.973	64.76	22.63	42	
			36	2.318								
			61	1.847								
	3	2 (MVAR)	61	1.33	0.152	0	0.074	0.931	33.04	21.07	20	
			12	0.779	0.151	0.002	0.073	0.932	33.48	21.68	31	
			61	1.171								
	3	2 (MVAR)	11	0.713	0.151	0.002	0.073	0.932	33.48	22.59	33	
			36	1.208								
			61	1.286								

The results show a significant decrease in total power loss within the distribution system. In Fig. 4, the blue dot

represents the initial active power loss before the installation of DG. After injecting DG into the

distribution network, the loss reduction index (LRI) improved by 33% to 69% depending on the DG type and placement. When a single DG unit is installed, both MPA and OOA achieve the same loss reduction index (LRI) for each type of DG injection. However, when two or three DG units are integrated into the distribution network, MPA exhibits superiority by delivering greater loss reduction, as illustrated in Fig. 4. This enhancement with MPA is due to its more optimized placement and sizing strategies, which allow for better distribution of power, reduced line losses, and improved overall efficiency of the network. Additionally, the MPA's ability to better handle multiple DG units highlights its robustness in complex scenarios, making it a more effective approach for minimizing losses in larger-scale implementations.

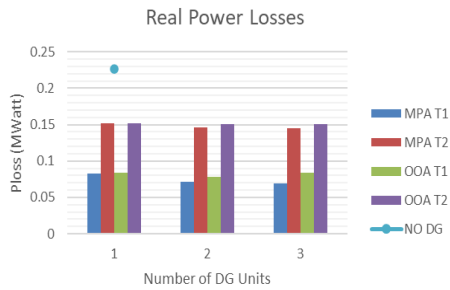


Fig 4. Bar chart of active power loss

MPA has also proven to provide more stable output compared to OOA. Throughout the simulations, MPA consistently predicted DG placement and sizing with greater accuracy across 20 repeated experiments. As a result, the output deviation for MPA is zero, while OOA exhibits variability, as shown in Table 1. When injecting MegaVAR (Type 2) into the system, both MPA and OOA result in the same minimum operating voltage

(Vmin), which is higher compared to when DG is not installed as shown in Fig 5. But, when injecting Megawatts (Type 1), MPA provides a better Vmin compared to OOA. A higher Vmin enhances the stability of the power distribution system, ensuring that voltage levels remain adequate to support the connected loads and maintain power quality.

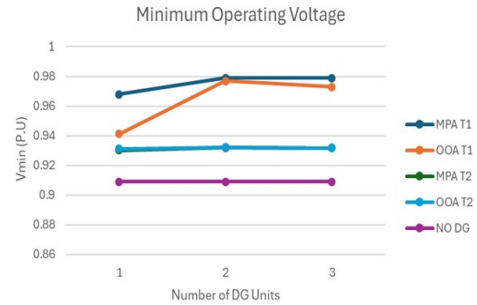


Fig 5. Graph of Vmin with and without DG installation

In terms of the time required to complete a single simulation, MPA and OOA exhibit similar performance, indicating that both methods are equally efficient in terms of computational speed. However, the number of iterations needed for convergence reveals a different outcome. As shown in Fig. 6, MPA demonstrates superior results, achieving consistent convergence speed across all 20 experiments, thus avoiding premature converging of iteration. Additionally, MPA shows greater stability, with minimal variation in convergence speed and fewer outliers, highlighting its robustness and reliability compared to OOA, which exhibits more variability and inconsistency. The results of a fitness function in an optimization process show that the standard deviation is zero, it indicates that all the individuals or solutions in the population have the same fitness value.

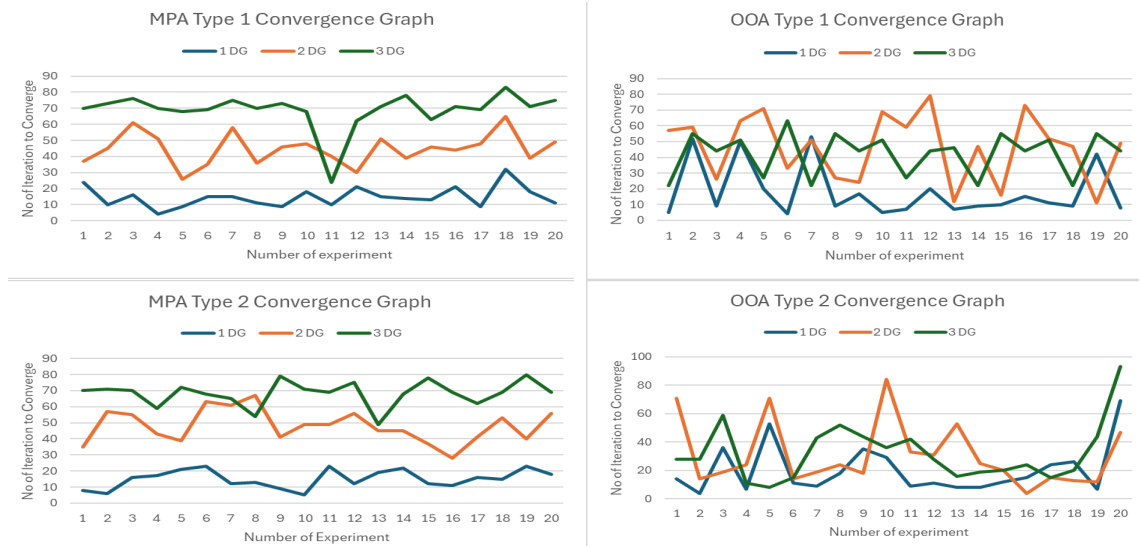


Fig 6. The convergence characteristics of MPA and OOA

The optimization algorithm may have converged to a single solution. All individuals have the same fitness, indicating that the algorithm has reached a point where further iterations are not improving the solution, and the population has become homogeneous.

5 Conclusions

This paper proposed current nature-inspired optimization techniques, which are Marine Predator Algorithm (MPA) and Osprey Optimization Algorithm (OOA) to solve optimization problem. Both techniques have been simulated in MATLAB in order to evaluate the performance of each algorithm on finding the best methods to find the optimal location and sizing of DG within IEEE-69 distribution network. The experimental data from the simulations suggests that MPA is a better choice compared to OOA. MPA achieved superior power loss reduction when optimizing multiple DG units. For two DG units, MPA reduced the active power loss to 0.072 MW, compared to 0.078 MW with OOA. With three DG units, MPA further lowered the loss to 0.070 MW, while OOA resulted in a higher loss of 0.084 MW.

Additionally, when injecting Type 2 DG into the network, MPA again demonstrated its superiority, achieving lower losses of 0.146 MW and 0.145 MW for two and three units, respectively, compared to OOA, which recorded 0.151 MW for both configurations. MPA also provides a better solution for increasing the minimum operating voltage (V_{min}), showing a significant difference with a V_{min} of 0.968 p.u. for MPA compared to 0.941 p.u. for OOA when a single DG unit is installed in the system. Lastly, MPA has proven to be the preferred optimization technique for consistency and stability in output prediction. It offers more reliable predictions for DG placement and sizing, significantly reducing result deviations. Additionally, MPA avoids premature convergence and maintains a consistent number of iterations to reach convergence, ensuring more robust and accurate outcomes. Both simulations prove that bus-61 is an ideal bus to inject DG into the power distribution system. It is advisable to address additional optimization challenges across various fields to further assess the capabilities of MPA. Given that MPA operates on velocity principles, the creation of binary and multi-objective adaptations of MPA could offer significant value.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

The author's contributions to this research include conceptualizing the study by investigating the use of nature-inspired metaheuristic algorithms, specifically the Marine Predator Algorithm (MPA) and the Osprey

Optimization Algorithm (OOA), for optimizing Distributed Generation (DG) placement and sizing in power distribution systems. The author applied and compared the performance of these algorithms, demonstrates the proposed system's capability to improve the Loss Reduction Index, achieving a 69% reduction in active power losses with MPA compared to 61% with OOA. To validate these findings, the author conducted simulations on the IEEE 69-bus system using MATLAB, ensuring the practical relevance and reliability of the proposed methods. Additionally, a comprehensive DG model was developed, integrating multiple DG types to balance economic feasibility with system performance. By emphasizing the importance of optimal DG placement and sizing, the research provides significant practical insights for improving network efficiency, reducing operational costs, and enhancing power distribution systems' overall performance.

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Informed Consent Statement

Not applicable

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Stability, Distributed Generation Optimization, Artificial Intelligence Applications, Optimization Algorithms Derivations and Machine Learning Applications

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