Optimal Allocation of DERs Considering Existing Distribution Infrastructure Using Mountain Gazelle Optimizer: Practical Case Study

Chintan D Patel[1] and Tarun Kumar Tailor[1,*]

[1]Department of Electrical Engineering, Institute of Technology, Nirma University, Ahmedabad, India

*Corresponding Email: tarun.tailor@nirmauni.ac.in

Received January 2, 2025, Revised June 23, 2025, Accepted September 10, 2025, Published December 30, 2025

Abstract. *The inclusion of distributed energy resources (DERs) in the power distribution network (DN) encountered rapid growth across the countries due to technological and environmental advantages. Moreover, this inclusion not only enhances diversity in resources but can improve the quality of service to users as well. However, the unplanned integration of DERs and their deployment in non-optimal locations can adversely affect the performance of DN. Hence, optimal positioning and sizing of DERs is very important aspects. Further, few studies have focused on DER and shunt capacitors (SCs) allocation in combination with the presence or absence of OLTC infrastructure. Therefore, in this paper, the recently developed Mountain Gazelle Optimizer (MGO) algorithm suitable for solving complex problem and addressing global optimization issues, is applied for optimal positioning of the DERs along with existent distribution infrastructure. In this work, considered objective is decreasing the cost of annual energy loss (CAEL). In order to showcase the usefulness of MGO algorithm in solving DER allocation problem this has been implemented on IEEE 33 bus and Indian 108 bus radial DN (real-life practical DN). The comparative analysis between MGO and other applied methods in the literature on same problem has also been presented. The obtained results indicate that simultaneous consideration of DERs, SCs and existing OLTC not only offers improved utilization of existing DN infrastructure but also minimizes the overall cost. The considerable improvement in results pertaining to CAEL for different scenarios, for an example around 10.6 % better compared to best reported results (IEEE-33 bus system, scenario-5), confirm the suitability of MGO algorithm.*

Keywords: distributed energy resources, on-load tap changing transformer, MGO algorithm, distribution Network

1. Introduction

Technological advancements drive a rapidly evolving business environment, where maintaining a competitive edge requires the ability to respond swiftly and efficiently to consumer demands. In particular, the online retail or e-commerce market in Thailand is expected to grow by 19% in 2023, reflecting consumer trends that favor online shopping [1]. This trend has compelled entrepreneurs across various industries, including the mattress and bedding sector, to continuously expand online marketing platforms to remain competitive.

In recent years, there is significant rise in electricity demand. The escalation of world's population, economic and technological development are some of the critical factors responsible for this electricity demand hike. To manage the demand, countries across the globe are utilizing conventional (coal, diesel, gas)-power generation systems. However, conventional energy resources are limited and also harmful to environment [1]. Therefore, integration of renewable based generation has turned up as a probable alternate option to conventional power generation [2]. The global renewable-based generation capacity is rising considerably after each passing year. In the year 2014, global renewable generation capacity was 1829 GW which rises nearly 86.34 % and reached to 3382 GW in 2022 [3]. Furthermore, the addition of renewable-based distributed generation (DG) in power DN is also rising worldwide due to environmental advantages, diversification of energy resources, lower transmission and distribution costs, reduced losses, probably improvement in quality of service [4]. In 2017, worldwide addition of Total DERs Power Capacity were 132.4 GW, which is likely to rise to 528.4 GW in 2026 [5]. However, addition of DERs in unplanned manner and at non-optimal locations may result in higher losses and thereby higher costs. Therefore, in order to exploit maximum benefit of DERs, optimal positioning and sizing of DERs is very important aspects [6]. The optimal DER integration problem, in single or multi-objective frameworks, has attracted many researchers.

For the above-mentioned allocation problem, researchers have considered objectives such as real power loss [7,8], voltage profile improvement [9,10], energy loss [11], voltage stability [12], power quality [13], and reliability [14]. Out of these, minimizing power loss is widely adopted objective function. It is known that electricity demand varies with time as a consequence the associated power loss also varies and further price of electricity is also time-dependent. Therefore, in [15,16], the considered objective function is CAEL instead of annual energy loss (AEL) which is considered by various researchers. Multi-objective framework has also been adopted to enhance the performance of DNs in the literature [17-19].

In [17], authors modified the salp swarm optimizer (SSO) based approach to make it suitable for multi-objective problems and applied this approach for improving the DN performance. In [18], authors presented adaptive fuzzy-based technique to solve single and multi-objective problems. They applied the same to integrate DER, DSTATCOM and BESS optimally. In [19], authors proposed multi-objective framework that considers different technical and non-technical objectives. They evaluated different cases on standard test system at different load models. In [20], two-stage ANN based approach has been employed to optimally integrate DERs in DN. They presented that in the first stage, suitable location is determined, whereas in the second stage, optimal size is found.

An analytical approach has been proposed in [21] to enhance DN performance by minimizing losses and improving voltage profile. In [22], authors applied dynamic programming for allocating DG in DNs to enhance reliability and decrease the loss of the system. In [23], authors suggested that allotment of DGs and SCs in parallel is a useful way to strengthen the performance of DNs as SCs offer comparatively cheaper voltage support in comparison to DGs. Further, OLTC and voltage regulators are also available in DN to support voltage controlling and their deliberation can minimize penetration of DG that in-turn can minimize CAEL. In [15], a new multi-agent based sine-cosine algorithm (MA-SCA) is applied to optimally integrate DERs with consideration of existent DN infrastructure. In [24] A new oppositional-based optimization named OARO is introduced for achieving optimal allocation and sizing of nonlinear DG in DNs. A novel bi-level multi-objective framework for the planning of solar photovoltaic-battery storage-based DERs within smart DN is delineated in [25]. In [26], an advanced algorithm is elaborated upon for the incorporation of DER and solid-state transformers (SSTs) within forthcoming distribution networks. The objective is to enhance the economic operations of DERs in conjunction with the SST to augment system efficiency and voltage profiles. In [27], the Non-dominated Sorting Genetic Algorithm (NSGA-II) was utilized to ascertain the optimal sites for the installation of electric vehicle (EV) charging stations, taking into account target functions such as total energy loss, voltage unbalance factor (VUF), and central load distance. In [28], a metaheuristic algorithm designated as the student psychology-based optimization (SPBO) algorithm, has been employed for the strategic placement of various categories of DGs and distribution static compensators (DSTATCOMs) within DN. Also, different indices have been integrated to tackle diverse technical, economic, and environmental aspects.

Additionally, it is important to mention that metaheuristic techniques have been widely employed for complex problem of optimal DERs integration. Some of the adopted techniques are water cycle algorithm (WCA) [29], teaching learning based optimization (TLBO) [23], hiking optimization algorithm (HOA) [30], dynamic node priority list genetic algorithm (DNPL-GA) [31], corrected moth search optimization (CMSO) [16], ant lion optimization algorithm (ALOA) [32], honey badger optimization [33].

However, sometimes algorithms suffer from premature convergence to local optima, sensitivity to parameter settings, and limited adaptability to mixed-variable or real-world constraints. Therefore, there is quest for developing and applying new optimization algorithms to solve or improve these issues. Further, from the literature review, it is observed that, few studies have focused on DER and SCs allocation in combination with the presence or absence of OLTC infrastructure.

The main contributions of the proposed work are as follows:

- A recently developed MGO algorithm is being utilized, for integration of the DERs and SCs optimally into power DNs with inclusion and exclusion of existent OLTC, in this presented work.
- More realistic objective of minimizing CAEL is considered under multiple loading conditions in place of minimizing active power loss.
- Demonstrated the practical value of the proposed MGO-based optimization approach by validating it on both a benchmark test system (IEEE 33-bus) and a realistic Indian 108-bus network, highlighting its scalability and real-world applicability.
- The comparative analysis between MGO and other applied methods in the literature on same problem has also been presented and results pertaining to CAEL confirms the suitability of MGO algorithm.

The organization of this paper is as per the following: Section 2 describes the mathematical modelling of objective function and formulation of considered problem. The discussion on the applied MGO algorithm has been carried out in section 3. The discussion about used test systems, different considered cases, obtained results and its analysis has been provided in section 4 and conclusion in the last section.

2. Mathematical Formulation

This section describes the mathematical formulation of considered optimization problem, which is optimal positioning of DERs in DN. The modelling of objective function and related constraints have been presented. The mathematical formulations proposed in many articles have not considered presence of existing OLTC in their formulation. Nonetheless, consideration of existing OLTC not only offers improved utilization of existing DN infrastructure but also minimizes the overall cost [16,31]. Therefore, in this work, the presence of existing OLTC while optimizing DERs has been included.

The discussion on objective function and their associated constraints have been presented in following subsections.

A. Cost Minimization

It is well-known that energy losses vary with variation in load demand and further electricity prices are also load dependent thereby time-varying as well. Hence, minimization of CAEL is the main objective in this work. Several cases with distinct scenarios have been presented for accommodating different loading patterns and corresponding price effects. The objective function of minimizing CAEL can be expressed as:

$$min\, F_1 = \sum_{l=1}^{Nl} T_l * P_l \sum_{k=1}^{Nb} |I_{kl}|^2 * R_k \tag{1}$$

$$I_{kl} = \frac{V_{el} - V_{fl}}{Z_k} \tag{2}$$

B. Constraints

The considered constraints are as per the following

$$P_{kl} = \sum_{j=1}^{N} V_{jl} Y_{kj} \cos\left(\theta_{kj} + \delta_{jl} - \delta_{kl}\right) \forall k, l \tag{3}$$

$$Q_{kl} = -V_{kl}\sum_{j=1}^{N} V_{jl}Y_{kj}\cos\left(\theta_{kj} + \delta_{jl} - \delta_{kl}\right) \qquad \forall k, l \tag{4}$$

where $P_{kl} = P_{kl}^{der} - P_{kl}^{d}$ and $Q_{kl} = Q_{kl}^{SC} - Q_{kl}^{d}$

$$V_{min} \le V_{jl} \le V_{max} \tag{5}$$

$$0 \le L_k^{der} \le L_{max}^{der} \tag{6}$$

$$\sum_{k=1}^{n_{der}} L_k^{der} \le \alpha \sum_{k=1}^{N} L_k^{d} \tag{7}$$

Here, constraints in Eq. (3)-(4) ensure power balancing of nodal real and reactive power respectively. P_{kl}, Q_{kl}, and δ_{kl} signify the real power supplied, reactive power supplied, and voltage angle at the kth bus in the course of the lth loading scenario. Furthermore, Y_{kj} and θ_{kj} are picked up from bus impedance matrix. P_{kl}^{d}, Q_{kl}^{d} , are representing the demand of real and reactive power at kth bus during the lth loading level.

P_{kl}^{der} and Q_{kl}^{SC} implies the real power offered by DER and reactive power offered by SC at kth bus at the lth loading level. Eq. (5) puts a limit on voltages magnitude and Eq. (6) puts a limit on maximum penetration at individual nodes, wherein Eq. (7) restricts the overall penetration of DERs. L_k^{der} and L_k^{d} are the recommended DERs sizing and normal loading condition at bus-k. L_{max}^{der} represents the maximum permissible penetration of DER on individual node and at the peak loading level the multiplying factor is considered as α.

In the above-discussed formulation, variables like DG sizes are continuous variables, whereas discrete variables like OLTC tap settings, location and size of SCs, and location of DERs. Further the primary objective of this study is to demonstrate how current VR schemes affect DER planning. As a result, OLTC will only engage in VR if the DER sites and sizes recommended during the optimization process are unable to sustain the necessary voltage levels. Consequently, the secondary voltage regulation will be provided by the OLTC.

3. MGO Algorithm

MGO algorithm [34] is recently included meta-heuristic algorithm which is created on the way of living and social conduct of mountain gazelles. This algorithm executes optimization considering number of important factors of gazelle's life and discussion on these factors have been presented in sub-sections. In the course of optimization operation in MGO method, every single gazelle (Xi) can turn out to be a member to herds of maternity herds, bachelor male herds or solitary, territorial male. Any of these mentioned herds can give birth to a new gazelle.

The overall best obtained solution in MGO is adult male gazelle in the herd territory. Furthermore, other available solutions represent the gazelles which have been considered in maternity herds. The strong gazelles having superior solutions are conserved while sick/old gazelles with weaker cost are eliminated from the total population. In this technique, exploitation and exploration are carried out parallelly by applying four mechanisms. It means that a solution can move in the direction of the best solution and at the same time can also perform the exploration, as accordance with mechanisms of MGO algorithm. The mathematical formulation of MGO algorithm for performing optimization is explained in the following section.

A. Territorial Solitary Males (TSM)

Once male gazelles attain maturity and becomes stronger, they form individual territory and exhibit territorial behavior. Also, the territories are separated by considerable distances. The male gazelles fight for the territorial command or ownership of the female. Gazelles which are young, they put efforts for the possession of territory or female whereas the adult gazelles strive hard for the protection of territory. Eq. (8) is employed for modelling the territory of the adult male.

$$TSM = M_g - |(r_1 \times CV_{YMH} - r_2 \times X(t) \times F)| \times CV_r \tag{8}$$

where M_g signifies the position vector of optimal global solution. The variables r_1 and r_2 are the randomly generated integers which can have values either 1 or 2. Eq. (9) is used to calculate the coefficient vector of the young male herd (CV_{YMH}) and to compute 'F' Eq. (10) is used. Eq. (11) is used to calculate 'CV_r' which represents coefficient vector and updated in every single iteration for improving the searching ability.

$$CV_{YMH} = X_{ra} \times \lfloor rv_1 \rfloor + M_{pr} \times \lceil rv_2 \rceil, \quad \left\{\left\lceil \frac{N}{3} \right\rceil \dots . N\right\} \tag{9}$$

In Eq. (9), X_{ra} denotes a random solution (young male) in the interval of *ra*. Rv_1 and rv_2 are randomly generated values in the range of 0 and 1. M_{pr} is the average count of search agents selected at random ⌈N/3⌉ and N indicates overall count of herd gazelles.

$$F = N_1(\mathrm{D}) \times \exp\left(2 - Iter \times \left(\frac{2}{Itermax}\right)\right) \tag{10}$$

In Eq. (10), N_1 is a random number derived from a standard distribution. *Iter* and *Itermax* are the ongoing iterations' number and the total iterations' number, respectively. The coefficient vector 'CV_r' is selected initially randomly and then in each iteration updated using Eq. (11) to improve the search capability.

$$CV_r = \begin{cases} (a+1) + rv_3\,, \\ a \times N_2(D)\,, \\ rv_4(D)\,, \\ N_3(D) \times N_4(D)^2 \times \cos\big((rv_4 \times 2) \times N_3(D)\big), \end{cases} \tag{11}$$

Here, rv_3, and rv_4 are randomly selected number in interval [0, 1]. Also, the numbers N_2, N_3, and N_4 are fixed at random as per the normal range and the problem dimensions. Eq. (12), is used to express 'a'.

$$a = -1 + \text{Iter} \times \left(\frac{-1}{\text{Itermax}}\right) \tag{12}$$

B. Maternity Herds (MH)

Similar to life cycle of all animals, maternity herds play very important role in of mountain gazelle's life cycle because these ensure continuity and produces strong male gazelles and they can also play a part in producing new gazelles and young males endeavoring for acquiring female gazelles in accordance with Eq. (13).

$$MH = (CV_{YMH} + CV_r) + \left|(r_3 \times M_g - r_4 \times X_{rand})\right| \times CV_r \tag{13}$$

In Eq. (13), CV_{YMH} signifies the young males' impact factor vector which is computed by Eq. (8). M_g indicates best global solution (adult male) in the ongoing iteration. X_{rand} indicates the vector position of a arbitrarily picked gazelle from the whole population.

C. Bachelor Male Herds (BMH)

When the male gazelles attain adulthood, they not only make an attempt to build own territory and but also aspire to attract females and compete for their control. In this phase of life, violent behavior rises within the male groups and this behavior is formulated mathematically in Eq. (14).

$$BMH = (X(t) - D) + \left|(r_5 \times M_a - r_6 \times CV_{YMH})\right| \times CV_r \tag{14}$$

In Eq. (14), X(t) signifies the position vector of the gazelle in the ongoing iteration. As discussed earlier, r_5 and r_6 are randomly picked to be 1 or 2, M_g represents the best obtained solution. CV_{YMH} and CV_r are determined using Eq. (9) and Eq. (11) respectively. D is computed using Eq. (15) wherein, rv_6 is random value between 0 and 1.

$$D = \left(|X(t)| + |M_g|\right) \times (2 \times rv_6 - 1) \tag{15}$$

D. Migration to Search for Food (MSF)

Generally, MGs travel great distances in quest of food source and explore wider horizon in search for food, taking advantage of their natural ability, faster speed of running, sprinting, and jumping. This behavior of gazelles is formulated mathematically using Eq. (16).

$$MSF = (ub - lb) \times r_7 + lb \tag{16}$$

In Eq. (16), *ub* and *lb* represents the upper and lower bounds of the problem respectively and r_7 is randomly generated integer in-between 0 and 1.

All above mentioned mechanisms have been adapted to all gazelles in order to create next era of gazelle which is included into total population and new era is also taken into consideration to classify gazelles. After each of the era, the ranking of gazelles is performed based on quality of the solutions in increasing order. The best gazelles (superior solutions indicating adult gazelles who dominates the territory) are kept while the weak gazelles (inferior solutions) are excluded from the population.

E. Computational complexity analysis

To assess the applicability of the algorithm, it is important to understand the computational complexity, which indicates execution time. In literature, it generally uses Big-O (O) notation, and it depends on the number of dimensions (D), maximum iteration (T_max), and number of gazelles (N). For MGO, the computational complexity is mathematically expressed as follows:

$$O(MGO) = O(problem\ defination) + O(population\ initialization) + O(fitness\ evaluation) + O(solution\ update) \tag{17}$$

$$O(MGO) = O(1) + O(N \times D) + O(4 \times T_{max} \times N) + O(4 \times T_{max} \times N \times D) \tag{18}$$

4. Results and Discussion

This section presents discussion on results attained by applying the MGA algorithm on considered optimization problem. Further, several loading patterns have been assessed while achieving the minimized cost of AEL. The details about load levels and other related parameters have been taken from [16]. The IEEE 33 bus radial DN as well as practical Indian 108 bus DN have been used to validate the usefulness of adopted algorithm in order to achieve the minimized CAEL. Moreover, in order to compare the obtained results, similar scenarios as considered in literature [16] have been realized which are as per the following:

Scenario Number	DERs	SCs	Existent OLTC
1	-	-	-
2	√	-	-
3	√	-	√
4	√	√	-
5	√	√	√

IEEE 33 bus radial test system:- This test system has operating voltage of 12.66 kV and the value of reactive and active power are 2.300 MVAr and 3.715 MW respectively. The information with regard to node and branch data is acquired from [35]. For the purpose of fair comparison, the number of DERs which can be deployed in the distribution system is considered same as in [16,31].

In Table 1, the results obtained for all considered scenarios through MGO algorithm have been shown. These tabulated results provide information, for all the cases, about DERs (location, size and penetration) and other important data like OLTC tap positions, minimum voltage, power loss, AEL and CAEL. The DER penetration has been calculated by taking the ratio of summation of maximum power by all DERs to the apparent demand of the system during peak load.

In scenario-1, as revealed in Table 1, AEL and CAEL values are at higher side and voltage profile at various load levels is also poor. The reason is DERs support not included and energy requirements are satisfied by the substation only. On the other hand, due to consideration of DERs penetration in scenarion-2, significant decrement in CAEL values have been achieved.

In scenario-3, in order to effectively utilize the existing infrastructure, optimal positioning of DERs is obtained by considering existent OLTC. The examination of results reveals that OLTC tapings gets altered depending upon loading level in order to control the voltage. For the reason that voltage support is also contributed by OLTC, therefore as compared to scenario-2, almost 7.9 % decrement in CAEL values have been achieved.

In scenario-4, simultaneous optimization of DERs and SCs have been carried out. For this, the capacitor size of 100 kVAr is considered. Since, reactive power support is provided by SCs, significant decrement in AEL and CAEL have been achieved compared to previously discussed two scenarios. Furthermore, with simultaneous allocation of SCs with DERs, the decrement in penetration of DERs in to the system is observed.

In scenario-5, the consideration of the existent OLTC is added compared to previous scenario. From the obtained results, it can be seen that with consideration of the existent OLTCs, more decrement in AEL and associated CAEL can be attained, even with comparatively less penetration of DERs. Further, it can be observed that in comparison to scenario-3, lesser tap settings are required because the reactive power support is being obtained by means of SCs.

Table 2 demonstrate that applied MGO algorithm provides better results as compared to other adopted approaches in the literature for all the case. Further, the comparison of results obtained using adopted approaches for different scenarios is also illustrated in Figure 1 wherein the most inferior result is selected as 100 percentage, other results show percentage change in CAEL in comparison to this.

Figure 2 presents a comparative analysis of the AEL values obtained using various optimization techniques. The results clearly demonstrate that the MGO outperforms the other methods in terms of minimizing AEL. Figure 3 illustrates the voltage profiles under different scenarios (scenario 1 to 5) across peak load conditions. It is evident that Scenario 1, which involves no optimization or corrective action, results in a suboptimal voltage profile. In contrast, Scenario 5, which incorporates existing OLTC, DERs, and SCs, achieves a significantly improved voltage profile—highlighting the effectiveness of coordinated optimization strategies.

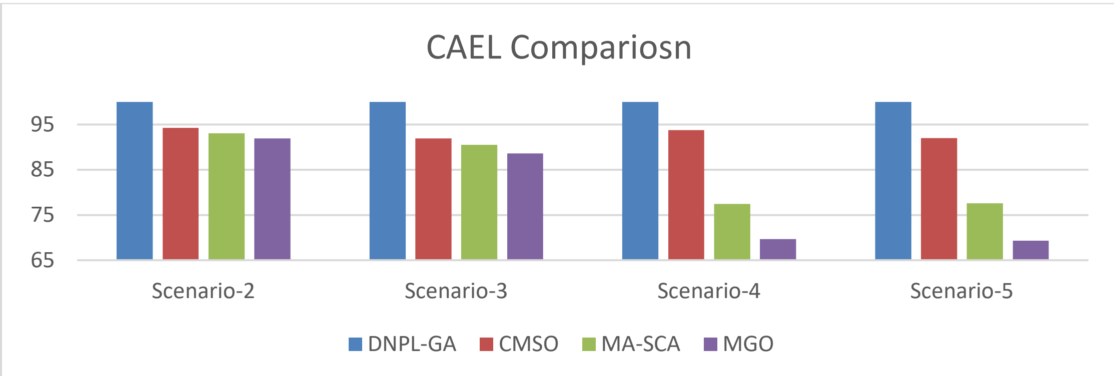

Figure 1. Comparison of CAEL obtained for the different scenarios (IEEE 33-bus system)

Table 1 Simulation results obtained by MGO algorithm for IEEE 33 bus radial test system

Scenarios	Optimal sites of [DERs] and {SCs}	Optimized capacities [DERs in kW] {SCs in kVAr}	OLTC tap position	DER Penetration %	Minimum Voltage in pu	Active power losses in kW	AEL (MWh)	CAEL (USD)
Scenario -1	-	-	-	-	0.96 L 0.91 N 0.85 P	47.07L 202.68N 575.39P	2023.32	185507
Scenario -2	[24, 14, 30]	[543, 373, 527] L [1099, 753,1071] N [1787, 1219, 1747] P	-	67.99	0.98 L 0.97 N 0.95 P	17.3L 71.45N 190.18P	695.81	63203
Scenario -3	[14, 24, 30]	[374, 543, 528] L [595, 1063, 1024] N [1216, 1780, 1739] P	1 L 3 N 4 P	67.73	1 L 1 N 1 P	16.88 L 67.59 N 170.81 P	645.55	58204
Scenario -4	[14, 24, 30] {30, 26, 14}	[372, 539, 523] L {300, 100, 100} L [746, 1080, 1049] N {700, 600, 200} N [1198, 1731, 1687] P {1600, 400, 400} P	-	66.03	0.99 L 0.99 N 0.99 P	5.23 L 14.54 N 36.04 P	141.01	12570
Scenario -5	[24, 14, 30] {24, 12, 30}	[541, 373, 522] L {600, 200, 300} L [1080, 748, 1047] N {600, 400, 700} N [1731, 1206, 1680] P {700, 800, 1200} P	0 L 1 N 1 P	66.05	0.99 L 1 N 1 P	5.09 L 14.14 N 33.98 P	135.52	12031

Table 2 Results comparison for IEEE 33 bus radial test system

	Scenario-2		Scenario-3		Scenario-4		Scenario-5	
Optimization Methods	**AEL (MWh)**	**CAEL (USD)**	**AEL (MWh)**	**CAEL (USD)**	**AEL (MWh)**	**CAEL (USD)**	**AEL (MWh)**	**CAEL (USD)**
DNPL-GA [31]	742.05	68753	711.41	65659	178.15	18033	172.73	17350
CMSO [16]	712.20	64820	666.72	60372	177.40	16906	165.60	15960
MA-SCA [15]	702.17	63965	656.15	59412	144.21	13961	140.56	13462
MGO	**695.81**	**63203**	**645.55**	**58204**	**141.01**	**12570**	**135.52**	**12031**

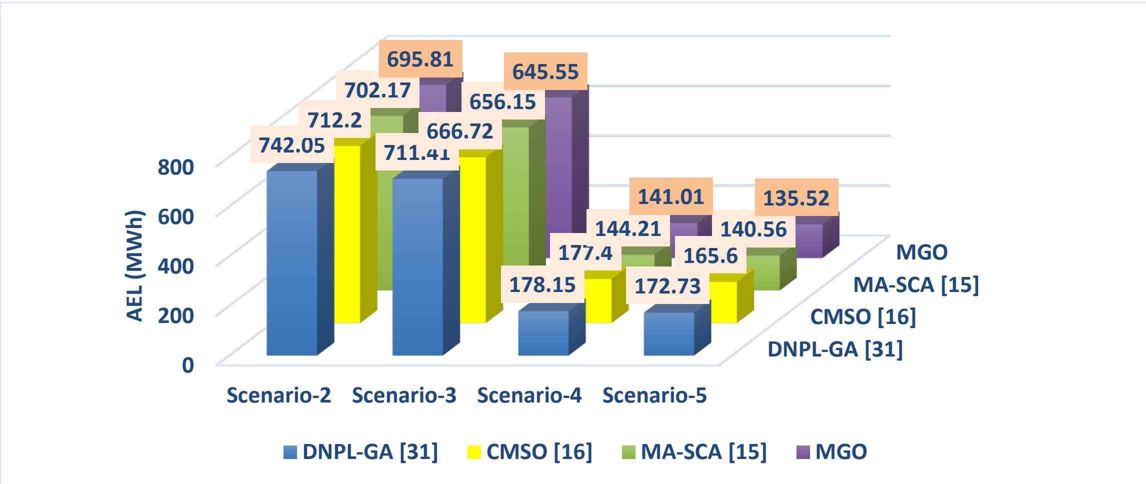

Figure 2. Comparison of AEL obtained for the different scenarios (IEEE 33-bus system)

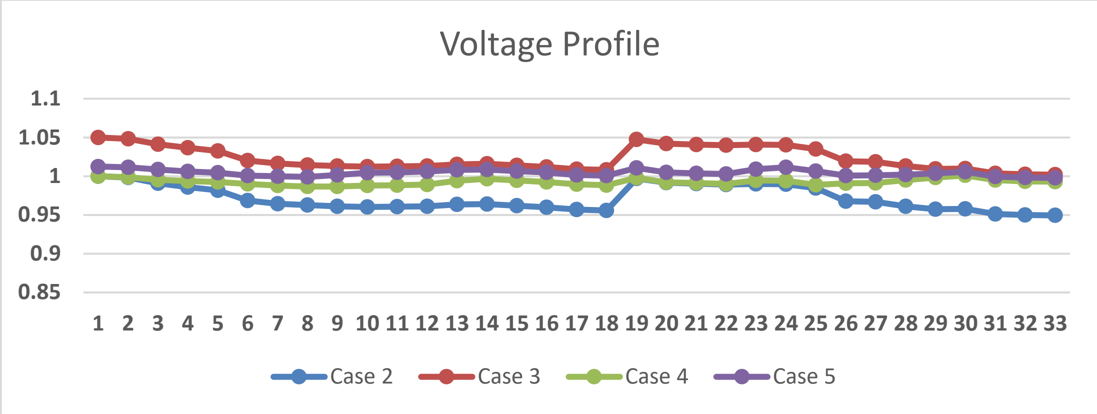

Figure 3. Voltage profile during peak loading for the different scenarios (IEEE 33-bus system)

Indian 108 bus radial system:- To demonstrate the performance of the MGO algorithm in solving real world optimization problem, it is executed on a larger practical DN. This system consists of 29.099 MVAr and 12.132 MW reactive and real power demand respectively and operates at the 11 kV voltage. The information with regard to node and branch data is acquired from [26]. Once again for the fair comparison with results reported in [16,26], the same number of DERs which can be installed in the DN is considered. The results attained, for all considered scenarios, with the application of MGO algorithm are presented in Table 3. Additionally, the values for the key parameters like OLTC tap settings, power loss and minimum voltage in each load level etc. are presented in the same table. It can be observed from results presented in Table 3, similar to IEEE 33-bus system, here also AEL and CAEL values are at higher side due to accomplishment of entire energy requirements from substation only in scenario-1.

The voltage profile during various load levels is also poor. In scenario-2, due to consideration of DERs penetration, significant decrement in AEL as well as in CAEL has been observed in comparison to previous scenario.

In scenario-3, for better utilization of existing distribution infrastructure, the optimal deployment of DERs is decided in conjunction with OLTC tap settings. The examination of results reveals that OLTC tap position gets altered depending upon loading to control the voltage.

For the reason that voltage support is also contributed by OLTC, therefore as compared to scenario-2, almost 5.82 % decrement in CAEL values have been achieved. In scenario-4, along with deployment of DERs, the simultaneous allocation of SCs with the rating in step of 100 kVAr is explored. Due to additional support of SCs in terms of reactive power, the combination of DERs and SCs are able to achieve a significant decrement in terms of AEL and CAEL compared to all previously discussed scenarios. Additionally, the decrement in power loss in each load level is achieved and compared to scenario-1 and scenario-2 the better voltage profile is also observed.

In scenario-5, already existent OLTC has been taken into account while simultaneously deciding the optimal location and size of SCs and DERs. From the obtained results, it can be seen that with consideration of the existent OLTCs, more decrement in AEL and associated CAEL can be attained, even with comparatively less penetration of DERs. This confirms that scenario-5 (consideration of DERs, SCs and existing OLTC) offers better solution in comparison to all other considered cases and consequently greater utilization of existing infrastructure. The observation of Table 4 reveals that the applied MGO algorithm provides better results as compared to other adopted approaches in the literature for all the case. Further, the comparison of results obtained using adopted approaches for the different scenarios is also illustrated in Figure 4.

As depicted in Figure 5, the MGO method outperforms the other approaches in minimizing the AEL. Figure 6 illustrates the voltage profiles across different scenarios under peak load conditions. The results highlight the effectiveness of coordinated optimization strategies in maintaining voltage and enhancing overall system performance.

It is important to note that the real-world implementation of optimized DER and SC placements may necessitate infrastructure upgrades and could encounter grid integration challenges. Nevertheless, the significant improvements observed in the results validate the effectiveness of the applied technique in addressing the DER integration problem. Furthermore, the analysis demonstrates that leveraging existing infrastructure (OLTC) alongside the optimal placement of SCs during DER allocation not only enhances technical performance but also leads to more economically efficient solutions.

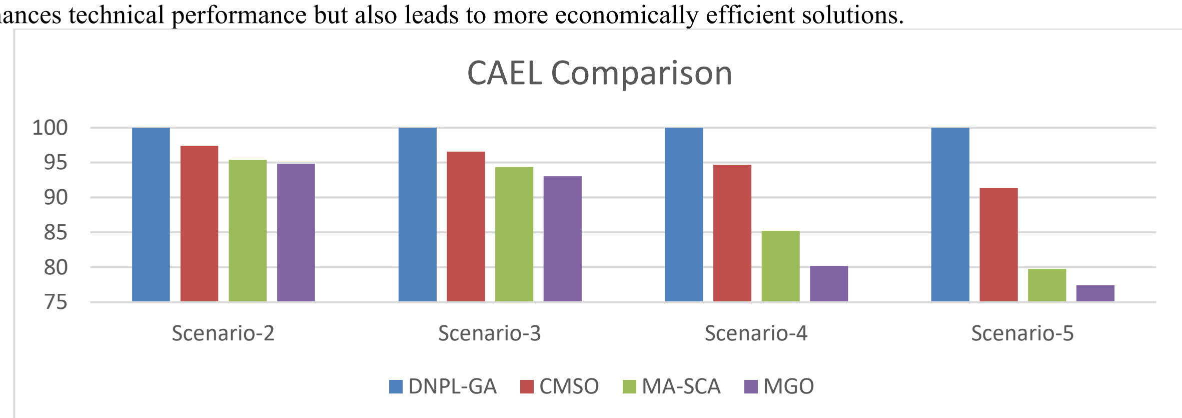

Figure 4. Comparison of CAEL obtained for the different scenarios (Indian 108 bus system)

Table 3 Simulation results obtained by MGO algorithm for Indian 108 bus radial system

Scenarios	**Optimal sites of [DERs] and {SCs}**	**Optimized capacities [DERs in kW] {SCs in kVAr}**	**OLTC tap position**	**DER Penet-ation %**	**Minimum Voltage (in pu)**	**Active power losses (in kW)**	**AEL (MWh)**	**CAEL (USD)**
Scenario -1	-	-	-	-	0.95L 0.89N 0.82P	151.53L 645.02N 1802.8P	6400	585454
Scenario -2	[21, 31, 85, 67, 108, 63, 60]	[1339, 443, 379, 496, 561, 1207, 776] **L** [2707, 891, 765, 1004, 1147, 2429, 1571] **N** [3000, 1802, 1236, 1631, 1889, 3000, 2561] **P**	-	62.32	0.99 L 0.97 N 0.95 P	62.05 L 253.68 N 683.62 P	2484	225954
Scenario -3	[63, 108, 67, 85, 45, 60, 29]	[1207, 561, 496, 379, 767, 776, 653] **L** [2426, 754, 1002, 764, 1548, 1570, 1315] **N** [3000, 1838, 1625, 1233, 2508, 2551, 2124] **P**	1 L 4 N 4 P	61.33	1 L 1 N 1 P	62.32 L 245.70 N 627.14 P	2358	212795
Scenario -4	[108, 85, 23, 32, 60, 63, 67] {21, 108, 77, 85, 28, 63, 60}	[556, 379, 1258, 362, 767, 1200, 494] **L** [1123, 761, 2524, 726, 1537, 2400, 997] **N** [1819, 1223, 3000, 1467, 2462, 3000, 1614] **P** {800, 400, 200, 400, 600, 1100, 600} **L** {1000, 800, 100, 700, 1300, 1600, 1000} **N** {2900, 1200, 100, 1000, 1200, 2800, 1700} **P**	-	60.09	0.99 L 0.98 N 0.97 P	16.43 L 69.84 N 189.69 P	684.74	62401
Scenario -5	[108, 85, 23, 32, 60, 63, 67] {21, 108, 77, 85, 28, 63, 60}	[1228, 767, 1200, 364, 550, 461, 838] **L** [2458, 1537, 2400, 731, 1103, 926, 1703] **N** [3000, 2462, 3000, 1173, 2118, 1476, 2764] **P** {400, 200, 900, 500, 300, 900, 600} **L** {900, 400, 1300, 1200, 400, 1700, 900} **N** {1000, 900, 2000, 1800, 1200, 2600, 1100} **P**	1 L 2 N 3 P	65.91	1 L 1 N 1 P	17.67 L 68.70 N 173.18 P	656.46	59134

Table 4 Results comparison for Indian 108 bus radial system

	Scenario-2		Scenario-3		Scenario-4		Scenario-5	
Optimization Methods	**AEL (MWh)**	**CAEL (USD)**	**AEL (MWh)**	**CAEL (USD)**	**AEL (MWh)**	**CAEL (USD)**	**AEL (MWh)**	**CAEL (USD)**
DNPL-GA [31]	2585.54	238313	2489.59	228701	788.96	77819	780.19	76367
MA-SCA [15]	2534.79	232177	2425.65	220909	752.33	73680	717.38	69771
HBO [33]	2510.73	227287	2399.58	215863	765.38	66324	679.82	60928
MGO	**2484**	**225954**	**2358**	**212795**	**684.74**	**62401**	**656.46**	**59134**

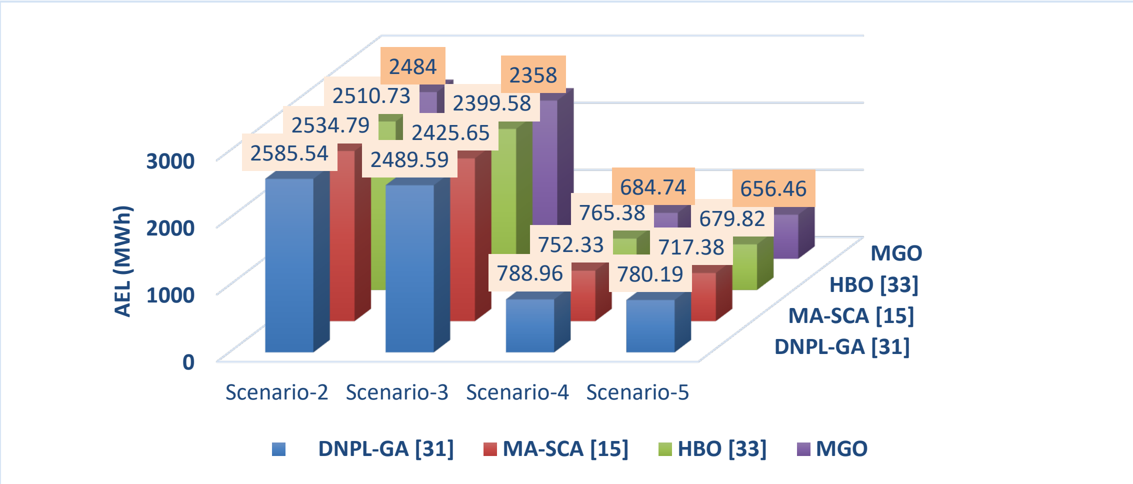

Figure 5. Comparison of AEL obtained for the different scenarios (Indian 108 bus system)

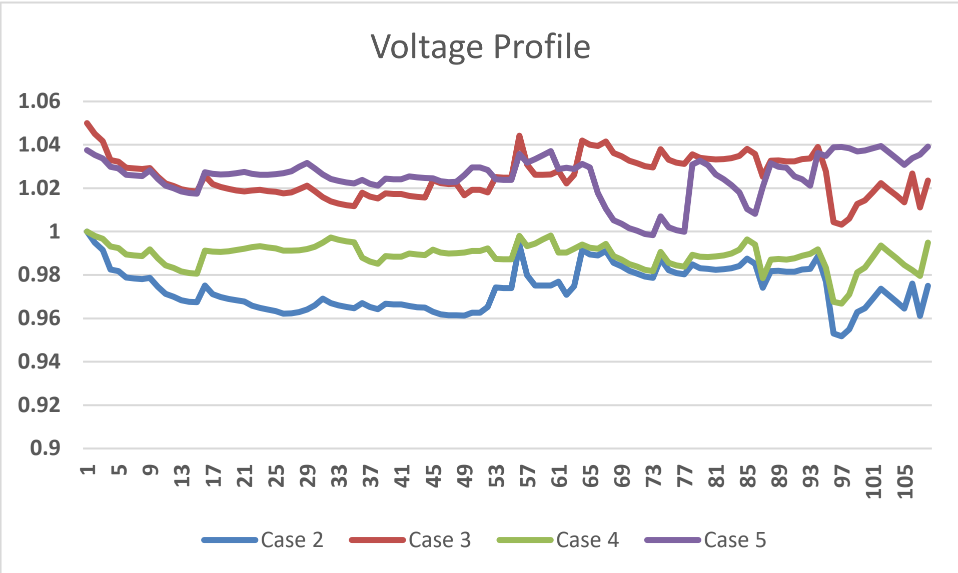

Figure 6. Voltage profile during peak loading for the different scenarios (Indian 108-bus system)

5. Conclusion

This paper attempts to solve the complex engineering problem of optimal integration of both DERs and SCs placement with and without OLTC coordination, which is addressed in limited prior research. The use of the Mountain Gazelle Optimizer (MGO) for this application is also a novel contribution. The objective of the presented work is reduction of CAEL under multiple loading conditions with different electricity price. The different cases have been simulated and implemented on standard IEEE-33 bus and real life practical Indian 108 bus radial DN. The obtained results indicate that simultaneous consideration of DERs, SCs and existing OLTC not only offers improved utilization of existing DN infrastructure but also minimizes the overall cost. Comparison of obtained results with well-established optimization algorithms has been presented which clearly indicates the solutions provided by MGO algorithm offer more economic advantages and also results in better technical performance. The results of the present investigation may be limited by the magnitude and intricacy of the examined networks, as well as the dependence on static load models. In future work, consideration of uncertainties associated with renewables and coordinated planning can be investigated. Furthermore, the proposed method could be adapted for larger, urban distribution networks, and extended to include dynamic load models, demand response strategies, and real-time optimization in smart grids.

References

[1] S. Islam and N. K. Roy, "Renewables integration into power systems through intelligent techniques: Implementation procedures, key features, and performance evaluation," *Energy Reports*, vol. 9, pp. 6063–6087, Dec. 2023, doi: 10.1016/j.egyr.2023.05.063.

[2] C. Cadena-Zarate, J. Caballero-Peña, and G. Osma-Pinto, "Simulation-based probabilistic-harmonic load flow for the study of DERs integration in a low-voltage distribution network," *AIMS electronics and electrical engineering*, vol. 8, no. 1, pp. 53–70, Jan. 2024, doi: 10.3934/electreng.2024003.

[3] International Renewable Energy Agency. Renewable Energy Statistics, Available online: https://www.irena.org/Publications/2023/Jul/Renewable-energy-statistics-2023.

[4] P. S. Georgilakis and N. Hatziargyriou, "Optimal Distributed Generation Placement in Power Distribution Networks: Models, Methods, and Future Research," *IEEE Transactions on Power Systems*, vol. 28, no. 3, pp. 3420–3428, Jan. 2013, doi: 10.1109/TPWRS.2012.2237043.

[5] Navigant research, white paper on distributed energy resourcemanagement systems. Available online : https://plma.memberclicks.net/assets/resources/Navigant%20Research%20%20AutoGrid%20DERMS%20White%20Paper.pdf

[6] K. Seepromting, "Feed-in Tariff Premium for Optimal Solar PV Allocation Case of Phitsanulok 1st Substation:", *Engineering Access*, vol. 4, no. 2, pp. 50–55, Dec. 2018. doi: 10.14456/mijet.2018.9

[7] M. Esmaili, "Placement of minimum distributed generation units observing power losses and voltage stability with network constraints," *Iet Generation Transmission & Distribution*, vol. 7, no. 8, pp. 813–821, Jul. 2013, doi: 10.1049/IET-GTD.2013.0140.

[8] N. K. Meena, A. Swarnkar, N. Gupta and K. R. Niazi, "A Taguchi-based approach for optimal placement of distributed generations for power loss minimization in distribution system," *2015 IEEE Power & Energy Society General Meeting*, Denver, CO, USA, 2015, pp. 1-5, doi: 10.1109/PESGM.2015.7286180.

[9] S. Sultana and P. Roy, "Multi-objective quasi-oppositional teaching learning based optimization for optimal location of distributed generator in radial distribution systems," *International Journal of Electrical Power & Energy Systems*, vol. 63, no. 63, pp. 534–545, Dec. 2014, doi: 10.1016/J.IJEPES.2014.06.031.

[10] D. R. Prabha and T. Jayabarathi, "Optimal placement and sizing of multiple distributed generating units in distribution networks by invasive weed optimization algorithm," *Ain Shams Engineering Journal*, vol. 7, no. 2, pp. 683–694, Jun. 2016, doi: 10.1016/J.ASEJ.2015.05.014.

[11] J. Y. Park, J. -M. Sohn and J. -K. Park, "Optimal Capacitor Allocation in a Distribution System Considering Operation Costs," in *IEEE Transactions on Power Systems*, vol. 24, no. 1, pp. 462-468, Feb. 2009, doi: 10.1109/TPWRS.2008.2009489.

[12] M. H. Moradi and M. Abedini, "A combination of genetic algorithm and particle swarm optimization for optimal DG location and sizing in distribution systems," *International Journal of Electrical Power & Energy Systems*, vol. 34, no. 1, pp. 66–74, Jan. 2012, doi: 10.1016/J.IJEPES.2011.08.023.

[13] H. Hamedi and M. Gandomkar, "A straightforward approach to minimizing unsupplied energy and power loss through DG placement and evaluating power quality in relation to load variations over time," *International Journal of Electrical Power & Energy Systems*, vol. 35, no. 1, pp. 93–96, Nov. 2011, doi: 10.1016/J.IJEPES.2011.10.001.

[14] A. S. Awad, T. H. M. EL-Fouly, and M. M. A. Salama, "Optimal Distributed Generation Allocation and Load Shedding for Improving Distribution System Reliability," *Electric Power Components and Systems*, vol. 42, no. 6, pp. 576–584, Mar. 2014, doi: 10.1080/15325008.2014.880962.

[15] C. Patel and T. Tailor, "Multi-agent based sine-cosine algorithm for optimal integration of DERs with consideration of existing OLTC in distribution networks," *Applied Soft Computing*, vol. 117, p. 108387, Jan. 2022, doi: 10.1016/j.asoc.2021.108387.

[16] P. Singh, S. K. Bishnoi and N. K. Meena, "Moth Search Optimization for Optimal DERs Integration in Conjunction to OLTC Tap Operations in Distribution Systems," in *IEEE Systems Journal*, vol. 14, no. 1, pp. 880-888, March 2020, doi: 10.1109/JSYST.2019.2911534.

[17] A. M. Shaheen and R. A. El-Sehiemy, "A Multiobjective Salp Optimization Algorithm for Techno-Economic-Based Performance Enhancement of Distribution Networks," in *IEEE Systems Journal*, vol. 15, no. 1, pp. 1458-1466, March 2021, doi: 10.1109/JSYST.2020.2964743.

[18] A. Sunil and C. Venkaiah, "Multi-objective Adaptive Fuzzy Campus Placement based Optimization Algorithm for optimal integration of DERs and DSTATCOMs," *Journal of energy storage*, Jan. 2024, doi: 10.1016/j.est.2023.109682.

[19] M. Z. Iftikhar, K. Imran, M. I. Akbar, and S. Ghafoor, "Optimal distributed generators allocation with various load models under load growth using a meta-heuristic technique," *Renewable Energy Focus*, Feb. 2024, doi: 10.1016/j.ref.2024.100550.

[20] K. Sandhya and K. Chatterjee, "Two-stage ANN based intelligent technique for optimal positioning and sizing of DERs in distribution system," *Engineering Applications of Artificial Intelligence*, vol. 121, p. 105932, May 2023, doi: 10.1016/j.engappai.2023.105932.

[21] H. Khan and M. A. Choudhry, "Implementation of Distributed Generation (IDG) algorithm for performance enhancement of distribution feeder under extreme load growth," *International Journal of Electrical Power & Energy Systems*, vol. 32, no. 9, pp. 985–997, Nov. 2010, doi: 10.1016/J.IJEPES.2010.02.006.

[22] N. Khalesi, N. Rezaei, and M.-R. Haghifam, "DG allocation with application of dynamic programming for loss reduction and

reliability improvement," *International Journal of Electrical Power & Energy Systems*, vol. 33, no. 2, pp. 288–295, Feb. 2011, doi: 10.1016/J.IJEPES.2010.08.024.

[23] N. Kanwar, N. Gupta, K. R. Niazi, and A. Swarnkar, "Simultaneous allocation of distributed resources using improved teaching learning based optimization," *Energy Conversion and Management*, vol. 103, pp. 387–400, Oct. 2015, doi: 10.1016/J.ENCONMAN.2015.06.057.

[24] A. Ghorai, B. Mandal, P. K. Roy, and C. Paul, "Oppositional based artificial rabbits optimization applied for optimal allocation of nonlinear DG in distribution networks considering total harmonic distortion limit," Electric Power Systems Research, vol. 231, p. 110334, 2024. https://doi.org/10.1016/j.epsr.2024.110334

[25] S. K. Wankhede, P. Paliwal and M. K. Kirar, "Bi-Level Multi-Objective Planning Model of Solar PV-Battery Storage-Based DERs in Smart Grid Distribution System," in *IEEE Access*, vol. 10, pp. 14897-14913, 2022, doi: 10.1109/ACCESS.2022.3148253.

[26] F. Meng, B. Chowdhury, and M. S. Hossan, "Optimal integration of DER and SST in active distribution networks," International Journal of Electrical Power & Energy Systems, vol. 104, pp. 626-634, 2019. https://doi.org/10.1016/j.ijepes.2018.07.035

[27] N. Chitgreeyan, "Multi-Period Optimization of Energy Demand Control for Electric Vehicles in Unbalanced Electrical Power Systems Considering the Center Load Distance of Charging Station Areas," Engineering Access, vol. 10, no. 2, pp. 90–102, Jun. 2024. doi:10.14456/mijet.2024.12

[28] S. K. Dash, S. Mishra, A. Y. Abdelaziz, J. Hong, and Z. W. Geem, "Optimal planning of multitype DGs and D-STATCOMs in power distribution network using an efficient parameter-free metaheuristic algorithm," Energies, vol. 15, no. 9, p. 3433, 2022. [Online]. Available: https://doi.org/10.3390/en15093433.

[29] A. A. A. El-Ela, R. A. El-Sehiemy and A. S. Abbas, "Optimal Placement and Sizing of Distributed Generation and Capacitor Banks in Distribution Systems Using Water Cycle Algorithm," in *IEEE Systems Journal*, vol. 12, no. 4, pp. 3629-3636, Dec. 2018, doi: 10.1109/JSYST.2018.2796847.

[30] C. D. Patel, T. K. Tailor, S. S. Shah, G. Sharma, and P. N. Bokoro, "Techno-Economic Enhancement of Distribution Network by Optimal DG Allocation Along with Network Reconfiguration Considering Different Load Models and Levels," Energies, vol. 18, no. 12, p. 3005, 2025. https://doi.org/10.3390/en18123005

[31] N. K. Meena, A. Swarnkar, N. Gupta, and K. R. Niazi, "Optimal integration of DERs in coordination with existing VRs in distribution networks," *Iet Generation Transmission & Distribution*, vol. 12, no. 11, pp. 2520–2529, Jun. 2018, doi: 10.1049/IET-GTD.2017.1403.

[32] E. S. Ali, E. S. Ali, S. M. Abd Elazim, and A. Y. Abdelaziz, "Ant Lion Optimization Algorithm for optimal location and sizing of renewable distributed generations," *Renewable Energy*, vol. 101, pp. 1311–1324, Feb. 2017, doi: 10.1016/J.RENENE.2016.09.023.

[33] A. A. Iyer and C. D. Patel, "Optimal Placement of Distributed Energy Resources and Shunt Capacitors with Consideration of Existing On-line tap changer using Honey Badger Optimization," *2023 Third International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT)*, Bhilai, India, 2023, pp. 1-6, doi: 10.1109/ICAECT57570.2023.10117805.

[34] B. Abdollahzadeh, F. Soleimanian Gharehchopogh, N. Khodadadi, and S. Mirjalili, "Mountain Gazelle Optimizer: A new Nature-inspired Metaheuristic Algorithm for Global Optimization Problems," *Advances in engineering software*, vol. 174, p. 103282, Dec. 2022, doi: 10.1016/j.advengsoft.2022.103282.

[35] M. E. Baran and F. F. Wu, "Network reconfiguration in distribution systems for loss reduction and load balancing," in *IEEE Transactions on Power Delivery*, vol. 4, no. 2, pp. 1401-1407, April 1989, doi: 10.1109/61.25627.