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Assessment and Optimization of Distributed Generationand Capacitor Allocation in Distribution Systems Using Artificial Intelligence Approaches

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WHAT IS ALREADY KNOWN ON THIS TOPIC?

- *Minimizing energy losses and voltage drops in electrical distribution systems has long been a subject of research aimed at improving efficiency and reducing costs. In the literature, the integration of distributed generation (DG) systems and capacitors has been commonly used as an approach to reduce these losses and voltage drops.*
- *In the optimization of energy systems, the use of metaheuristic algorithms, particularly for minimizing active power losses, is a widely adopted approach.*

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ABSTRACT

In recent years, considerable efforts have been allocated to enhance the performance of electric distribution systems. Among the most effective approaches to enhancing the performance of electric distribution systems is the installation of distributed generation (DG) and compensation capacitors, which play a critical role in reducing power losses and voltage deviations. The main objective of this study is to reduce active power losses and total voltage deviation in the system by determining the optimal locations and sizes of DG and capacitors to be installed in the distribution network. To achieve this goal, seven different scenarios were analyzed to evaluate the impact of the number of buses where DG and capacitors are installed on system performance, while keeping the total injected power constant. To solve the optimization problem, various optimization algorithms such as Artificial Bee Colony, Dragonfly, Particle Swarm Optimization (PSO), and Stochastic Fractal Search algorithms were used. These methods were tested on the standard IEEE 85-bus distribution system. The results show that allocating the total capacity of DG and capacitors to three different buses yields better results compared to locating them on a single bus or two buses. Following the placement of DG and capacitors using the aforementioned algorithms, a reduction of up to 74.1% in active power loss and up to 81.95% in voltage deviation was achieved. Although all algorithms produced similar results, the PSO algorithm generally exhibited better convergence behavior under the tested scenarios.

Index Terms— Capacitors, distributed generation (DG), distribution system, metaheuristic algorithms,

Nomenclature and Abbreviation

ABC	Artificial Bee Colony	**PSO**	Particle Swarm Optimization
AEO	Artificial Ecosystem Optimizer	**p.u.**	Per-unit
A_i	The average velocity of neighbors around the i[th] individual	O_{Cj}	Reactive power injection at bus j.
AQIEA	Adaptive Quantum Inspired Evolutionary Algorithm	Q_{Cj}^{min}	Minimum values of reactive power supplied by the j[th] C.
BA	Bat Algorithm	Q_{Cj}^{max}	Maximum values of reactive power supplied by the j[th] C.
BPSO	Binary Particle Swarm Optimization	Q_L	Total reactive power loss in the system
CABC	Chaotic Artificial Bee Colony	**r**	Step size of the Gaussian Walk Function
CBA	Chaotic Bat Algorithm	$rand_{1,2}()_{ij}$	Random numbers uniformly distributed in the range [0,1]
C_i	The difference between the average position of neighbors and the position of the i[th] individual	R_L	The resistance of the line

WHAT THIS STUDY ADDS ON THIS TOPIC?

- *This study presents a multi-objective optimization method that simultaneously minimizes total active power loss and total voltage deviation, providing a more comprehensive performance improvement compared to single-objective methods commonly found in the literature.*
- *The impact of the number of buses where DG and capacitors are installed is systematically analyzed across seven different scenarios with constant total injected power, highlighting the benefits of multi-bus allocation.*
- *Four advanced metaheuristic algorithms—Particle Swarm Optimization, Artificial Bee Colony, Stochastic Fractal Search, and Dragonfly—are employed and compared to solve the optimization problem, showcasing the robustness of the proposed methodology.*
- *Results demonstrate that distributing the total capacity of DG and capacitors over three different buses significantly outperforms placement on one or two buses with respect to reducing power losses and voltage deviations.*

Nomenclature and Abbreviation

CSA	Cuckoo Search Algorithm	***s, a, c***	Respectively separation, alignment, and cohesion coefficients
CSO	Crow Search Algorithm	**SCA**	Sine Cosine Algorithm
CWOA	Chaotic Whale Optimization Algorithm	**SDO**	Supply Demand Optimizer
c_1	Personal coefficient	**SFS**	Stochastic Fractal Search
c_2	Social coefficient	S_i	The amount by which the i[th] individual moves away from others
DE	Differential Evaluation	***SOS***	Symbiotic Organism Search
DF	Dragonfly	**SSA**	Salp Swarm Algorithm
DG	Distributed generation	**SWA**	Sperm Whale Algorithm
E_i	The repulsion force of the i[th] individual moving away from the enemy	u_x	Position of the propagating fractal
ENS	Energy not supplied	$u_{xbest,}$	Fractal position associated with the best fitness value obtained up to the current iteration
F	Objective function of this sudy	***V***	Nominal voltage magnitude for every bus in the system
f, e, w	Respectively the food factor, enemy factor, inertia coefficient	V_D	Total voltage deviation of the system
F_i	The attraction force of the i[th] individual towards the food source	***Vi***	Voltage magnitude at bus i
GA	Genetic Algorithm	v_{ij}	New position
$gbest_{ij}^{k}$	The global best position for particle *i* in dimension *j* at iteration *k*.	v_{ij}^{k}	Velocity of particle *i* in dimension *j* at the k^{th} iteration.
GWO	Grey Wolf Optimization	v_{ij}^{k+1}	Velocity of particle *i* in dimension *j* after update at iteration *k+1*.
HBA	Honey Badger Algorithm	V_{min}	Minimum voltage value in the system
ICA	Imperialist Competitive Algorithm	V^{min}	Minimum acceptable voltage at each bus
I_L	Line current	V^{max}	Maxsimum acceptable voltage at each bus
IPSO	Improved Particle Swarm Optimization	***w***	Inertia weight
JFS	Jellyfish Search Optimizer	**WOA**	Whale Optimization Algorithm
JO	Jaya Optimization	x_{best}	Position of the best point in the group
k_p, k_{VD}	Weighting factors	x_{ij}^{k}	Current Position of the i[th] particle in the j[th] dimension at the k[th] iteration.
MFO	Moth Flame Optimization	x_{ij}^{k+1}	The new position of particle *i* along the *j*[th] dimension at iteration *k+1*.
MPSO	Mixed Particle Swarm Optimization	x_i	Position of the i[th] point
n	Number of line	x_{inew}^{d}	Updated position of the x_i point in the diffusion process
N	Number of neighboring dragonflies considered	x_{kj}	Position of a randomly selected different solution
Nb	Total number of buses	x^{+}	Food source position
$pbest_{ij}^{k}$	The personal best position of particle *i* in dimension *j* at iteration *k*.	x^{-}	Position of the enemy
P_{DGj}	Active power injection at bus j.	X_t	Position of the dragonfly at iteration t
P_{DGj}^{min}	The minimum active power output provided by the j[th] DG	ΔX_{t+1}	Change in position of the dragonfly at iteration t+1
P_{DGj}^{max}	Maksimum values of active power supplied by the j[th] DG.	**£′, £**	Random numbers in the range [0, 1]
P_L	The total amount of active power loss in the system	p_{ij}	Random number, usually in the range [−1,1]

I. INTRODUCTION

Electric power systems are generally composed of three main sections: generation, transmission, and distribution. Among these, the distribution section accounts for the highest power loss rate as a result of the low voltage level and high current. Specifically, losses in the low voltage distribution level lines represent approximately 5%–13% of the total electricity generation [1]. Thus, efforts to reduce losses in distribution networks have become crucial. It is not possible to eliminate all the losses in electrical systems. However, these losses can be minimized through effective loss reduction techniques, such as network reconfiguration, installation of distributed generation (DG), and capacitors into the system [2-4].

Capacitors regulate the voltage at the point of connection in the distribution system and provide reactive power flow. This reduces power losses in the lines and improves the voltage profile. Properly placed capacitors in the distribution network enhance the overall performance of the system through regulation of voltage levels to acceptable ranges [5, 6]. Incorrect placement of capacitors results in increased system losses and voltage drops. Therefore, appropriate planning and design are required for capacitor placement. Recent research has focused on capacitor placement in distribution networks. Various optimization techniques have been proposed to find the optimal location and capacity of capacitors in the distribution network [7-9].

On the other hand, DGs have emerged as an alternative source to meet both the increasing electricity demand and the aforementioned losses. The DGs are power sources linked directly to the distribution network or positioned on the consumer side of the meter [10]. This system offers several advantages over centralized energy production, including lower transmission and distribution costs, fuel diversity, reduced carbon emissions, improved supply continuity and security, decreased power losses, and improved voltage profiles [11, 12]. However, to take advantage of these benefits, proper DG placement and sizing should be conducted during the planning stage of the distribution system. Otherwise, as with capacitors, non-optimal DG placement and sizing may lead to increased power losses and cause the voltage profile of the network to exceed the permissible limits [13].

The literature includes various studies where metaheuristic algorithms are applied to problems such as DG and capacitors placement in distribution systems. In [14], Particle Swarm Optimization (PSO) and Genetic Algorithm methods were proposed for the optimal placement of DG sources and shunt capacitors to reduce power losses and improve the voltage profile. Simulations were conducted on IEEE 70 and 86-bus test systems, and the performance of the algorithms was compared. In [15], the optimal placement and sizing of DG units to improve voltage stability were carried out using the Multi-objective performance index and the CABC algorithm. Also, different load models were considered. In [16], the optimal placement of capacitor banks to reduce energy losses in medium voltage distribution networks was addressed, and five metaheuristic algorithms were compared. Simulation studies conducted on the IEEE 33-bus test system and a real 215-bus distribution network demonstrated that the newly developed Sperm Whale Algorithm yielded the most favorable results. In [17], the Cuckoo Search Algorithm was used to optimally size and place DGs and capacitors to minimize power losses and enhance voltage stability. The simultaneous placement method provided higher loss reduction and better voltage stability compared to separate placement. In [18], the Honey Badger Algorithm and the combined loss sensitivity factor were used for the optimal placement of DG and capacitors to minimize active power loss. Tests conducted on the IEEE 69-bus system showed that the Honey Badger Algorithm produced successful results in different DG types and capacitor scenarios and significantly reduced system losses. In [19], DG and capacitors are placed in 34-bus test systems and Stochastic Fractal Search (SFS) is present better result for a small system. However, the performance of the algorithms was not evaluated for larger systems. In [20], sensitivity analysis based on a voltage stability index and a GA were employed to determine the optimal placement and sizing of dispatchable DG and shunt capacitors. The objective focused on reducing network losses and optimizing the voltage profile. The proposed method was tested on a 33-bus distribution test system, and the results demonstrated superior performance compared to existing approaches. In [21], a hybrid Moth Flame Optimization (MFO)-Sine Cosine Algorithm (SCA) method—developed by combining the MFO and SCA—was employed in conjunction with the Combined Power Loss Sensitivity approach to determine the optimal placement of DG and capacitors. The method was tested on IEEE 33 and 69-bus distribution systems, and the results indicated that it outperformed existing techniques in minimizing total active power losses. In [22], the optimal placement and sizing of DG and capacitors in a radial distribution network were determined using the Chaotic Whale Optimization Algorithm and the Loss Sensitivity Factor. The proposed method was tested on the IEEE 69-bus system, and the results demonstrated superior performance compared to other techniques in terms of voltage profile improvement, increased system capacity, and total power loss reduction. In [23], the focus was placed on enhancing voltage stability and reducing power losses through the optimal placement of DG units. The study examined the economic, environmental, and technical benefits of non-traditional DG technologies such as solar photovoltaic (PV) and wind turbines. The effectiveness of hybrid meta-heuristic algorithms in DG allocation was emphasized. It was concluded that proper placement of DG significantly improves the voltage profile and minimizes system losses. In [24], a Mixed PSO (MPSO) approach—combining BPSO and conventional PSO algorithms—was developed to minimize active power losses and improve the voltage profile in distribution networks. The method was tested on IEEE 33 and 69-bus systems and demonstrated superior performance in both switch configuration and DG placement and sizing compared to other optimization techniques. In [25], the Imperialist Competitive Algorithm was employed to determine the optimal placement and capacity of PV DG and capacitor banks. The method was validated on both the IEEE 33-bus system and a real 130-bus distribution network from Jaipur City. The results showed that DG integration was effective in reducing power losses and enhancing the voltage profile. In [26], a hybrid approach combining the GA and Improved PSO was proposed to decrease active power loss and enhance the voltage profile. The method was implemented on the IEEE 30-bus test system, where it exhibited faster convergence and achieved nearly 40% reduction in power losses compared to other optimization algorithms. In [27], Artificial Bee Colony (ABC) algorithm was utilized to determine the optimal placement and sizing of DG sources and capacitor banks. Simulations conducted on the standard 37-bus system demonstrated the effectiveness of the algorithm in reducing power losses and enhancing system

TABLE I. SUMMARY OF LITERATURE IN THE PROPOSED RESEARCH AREA

References	Solution Method(s)	Objective Function(s)	Test Bus System(s)	Year	Examined DG/Combinations
2	ABC DE GA PSO	Minimization of active power losses	69–Bus system	2019	Multiple DGs
3	AGPSO	Minimization of real power losses	69–Bus system	2017	Simultaneous multiple DGs and multiple capacitors
13	PSO	Minimization of power losses	12–Bus system 30–Bus system 33–Bus system 69–Bus system	2013	Simultaneous one DG unit and one capacitor
18	HBA	Minimization of system power losses	69–Bus system	2022	DG units and capacitors were placed separately
21	MFO-SCA	Minimization of total active power losses	33–Bus system 69–Bus system	2021	Single and multiple DGs and capacitors
22	CWOA	Minimization of total power losses Improvement of voltage profile	69–Bus system	2020	Multiple DGs or capacitors, and single DG or capacitor
24	MPSO	Minimization of active power losses	33–Bus system 69–Bus system	2020	Multiple DG units
26	HGAIPSO	Minimization of active power losses	30–Bus system	2022	Multiple DGs unit
27	ABC	Minimization of line losses and ENS index	37–Bus system	2021	Two DGs and two capacitors
29	AQiEA	Minimization of power losses	33–Bus system 69–Bus system	2024	Multiple DG units
30	AQiEA	Maximization of economic gains Minimization of power losses	33–Bus system	2025	Only DG and only capacitor, and combinations multiple DGs and capacitors
32	SSA	Minimization of total active power losses	33–Bus system 69–Bus system	2018	Only DG and only capacitor, and combinations multiple DGs and capacitors
35	DF	Minimization of real power losses	15–Bus system 33–Bus system 69–Bus system	2018	One DG

reliability. In addition, Adaptive Quantum inspired Evolutionary Algorithm, Symbiotic Organism Search, Jaya Optimization, Salp Swarm, Evolutionary, Dragonfly (DF), and Grey Wolf Optimization algorithms have also been employed in the literature as alternative methods for the efficient placement and sizing of capacitors and DGs [28-35].

Table I presents a general evaluation of the studies in the literature related to the proposed research area. As can be seen from the table, the majority of existing studies employ only a single optimization algorithm and are typically conducted on small-scale standard test systems such as 30, 33, 37, and 69-bus networks. Moreover, most of the studies focus on single-objective optimization problems, which leads to the assessment of system performance based on a single evaluation criterion. Besides all this, in most studies in the literature, DG units and capacitors have been analyzed as being integrated either separately or together into the system. The primary novel contributions and objectives of this study are outlined as follows.

- This study presents a multi-objective optimization method that simultaneously minimizes total active power loss and total voltage deviation, providing a more comprehensive performance improvement compared to single-objective methods commonly found in the literature.
- The impact of the number of buses where DG and capacitors are installed is systematically analyzed across seven different scenarios with constant total injected power, highlighting the benefits of multi-bus allocation.
- The majority of studies in the literature are conducted on small-scale standard test systems such as 30, 33, 37, and 69-bus networks. In this study, however, a larger and less commonly used 85-bus distribution system is employed, enabling the analyses to be carried out under conditions that more closely reflect real-world systems.
- Four advanced metaheuristic algorithms—PSO, ABC, SFS (Stochastic Fractal Search) , and DF—are employed and compared to solve the optimization problem, showcasing the robustness of the proposed methodology.

II. PROBLEM FORMULATION

In this study, the issue of optimally placing multiple DG units and capacitors has been formulated using a multi-objective function, taking system constraints into account.

A. Objective Function

In this study, multiple objectives are considered, such as minimizing the total real power loss in the test system and improving the voltage profile by reducing the total voltage deviation. In this context, the total real power loss P_L, which constitutes the first part of the objective function, is calculated using the expression given in (1).

$$f_1=P_L=f_1=P_L=\sum_{L=1}^{n}(I_L^2R_L) \tag{1}$$

In (1), n represents the number of lines, R_L denotes the resistance of the line, and I_L represents the line current. The second component of the objective function, the total voltage deviation of the system V_D, is calculated using (2). Where *Vi* represents the voltage magnitude at bus i, *Nb* indicates the total number of buses, and *V* refers to the nominal voltage magnitude at each bus. In this study, the value of *V* is taken as 1 p.u. (per-unit).

$$f_2=V_D=f_2=V_D=\sum_{i=1}^{Nb}\left(V-Vi\right)^2 \tag{2}$$

Based on the calculated values of P_L and V_D above, the objective function *F* of this study is expressed by (3).

$$F=\min\left(k_p f_1+k_{VD} f_2\right) \tag{3}$$

In (3), k_p and k_{VD} are weighting factors. A weighting factor establishes a balance between objectives with different units and prevents one objective from dominating the other [36]. In this study, $k_p=0.1$ and $k_{VD}=100$ were selected to balance the scale difference between the total active power loss ($P_L=314.5378$) and the voltage deviation ($V_D=0.7875$ p.u.). While Pareto-front based methods can provide more comprehensive solution sets, the primary goal of this study is to obtain a fast and balanced solution for specific scenarios. Therefore, considering computational efficiency and ease of implementation, the weighted sum method was adopted. Furthermore, since significant and acceptable improvements were observed in both objectives with the selected weights, a comprehensive sensitivity analysis was not considered necessary.

B. System Constraints

In the optimization process conducted in this study, various operational and technical constraints were considered to ensure the safe, efficient, and stable operation of the distribution system. These constraints are detailed below. The bus voltage constraint is an important criterion to ensure the stable and safe operation of the distribution system. In this study, the voltage values at each bus are set with lower and upper limits of 0.9 and 1.0 p.u., respectively. Voltages outside these limits can lead to equipment failures and power quality issues.

$$V^{min}\le V_i\le V^{max} \tag{4}$$

In this study, minimum and maximum power generation limits have been defined for each DG and capacitor. These limits are established based on system requirements and ensure that the system operates within its technical boundaries. In (5) and (6), the respective limit values for each DG and capacitor connected to the system [36]. In this study, total installed power limit values are taken as 0-1000 kW/kVAR [30].

$$P_{DGj}^{min}\le P_{DGj}\le P_{DGj}^{max} \tag{5}$$

$$Q_{Cj}^{min}\le Q_{Cj}\le Q_{Cj}^{max} \tag{6}$$

In (5) and (6), P_{DGj} and O_{Cj} represent the real and reactive powers provided to bus j, respectively.

III. ALGORITHMS

A. Artificial Bee Colony Algorithm

Artificial Bee Colony algorithm was first developed by Karaboğa in 2005 and is a swarm intelligence-based algorithm. This algorithm is based on the behavior of bee colonies [37]. The ABC algorithm consists of three main groups of bees: employed bees, onlooker bees, and scout bees. Scout bees search for new food sources randomly, while employed bees visit the found food sources, process them, and return to the hive. If a food source cannot be improved over a certain number of iterations, meaning the limit parameter is exceeded, the corresponding employed bee becomes a scout bee and starts searching for a new food source. In this study, the limit parameter is defined as *L=round(0.6*nVar*nPop)*, where *nVar* is the problem dimension and *nPop* is the population size. Onlooker bees observe the dance of the returning employed bees and decide which food source to visit based on the information provided by the employed bees. The selection of the food sources by onlooker bees is performed within a probability distribution based on the quality value of the sources. The ABC algorithm uses the relationship given in (7) to find new food sources.

$$v_{ij}=x_{ij}+\rho_{ij}\left(x_{ij}-x_{kj}\right) \tag{7}$$

B. Particle Swarm Optimization Algorithm

The PSO algorithm was developed by Kennedy and Eberhart in 1995, inspired by the observed movements of animals in groups while searching for food and fulfilling their basic needs [38]. In PSO, each individual particle searching for a solution is referred to as a particle, and the population of particles is called a swarm. In this algorithm, a fitness function is used to determine how close a particle is to the solution. Particles begin moving with a randomly assigned initial position and velocity. The locations and speeds of the particles are modified in each iteration by comparing them with the particle's best value, known as pbest, and the swarm's best value, known as gbest, in order to find the best solution. The algorithm terminates when the maximum iteration count is reached. The velocities and positions of the particles are updated using (8) and (9) [38].

$$v_{ij}^{k+1}=w*v_{ij}^{k}+c_1*rand_1()_{ij}*\left(pbest_{ij}^{k}-x_{ij}^{k}\right)$$
$$+c_2*rand_2()_{ij}*(gbest_{ij}^{k}-x_{ij}^{k}) \tag{8}$$

$$x_{ij}^{k+1}=x_{ij}^{k}+v_{ij}^{k+1} \tag{9}$$

The learning coefficients c_1 and c_2 in (8) represent the self experience and social experience parameters of a particle, respectively. The coefficient c_1 allows a particle to move according to its own

experience, while c_2 enables a particle to move based on the experiences of other particles in the population. In (9), w represents the inertia weight, and its value generally ranges between 0 and 2. As a result, it is crucial to select the value of w in accordance with the specific problem being addressed. In this study, the values of c_1, c_2, and w have been set to 1.2, 1.2, and 1.0, respectively.

C. Stochastic Fractal Search Algorithm

The SFS algorithm is a metaheuristic algorithm developed by Salimi in 2015 [39]. This algorithm was inspired by the propagation of fractals in nature. The SFS algorithm is based on two fundamental processes: diffusion and update. The first process, diffusion, provides the algorithm with regional search capabilities. In the diffusion process, two statistical methods, Gaussian Walk and Levy Flight, are employed to create new particles. However, the Gaussian Walk method is more successful in finding the global optimum. In this study, the probability of applying the Gaussian Walk method was set to 1, meaning that the Gaussian Walk is always applied during the diffusion process. Additionally, the maximum diffusion count was set to 2. This parameter represents the number of new candidate points generated around each point in each iteration. During the diffusion procedure, two functions are proposed for the propagation of fractals, which are given in (10) and (11) [39].

$$x^{d}_{inew,1} = Gaussian\left(u_{xbest,}\mathrm{r}\right) + \left(£.x_{best} - £'.x_i\right) \tag{10}$$

$$x^{d}_{inew,2} = Gaussian\left(u_x, r\right) \tag{11}$$

In (10), £ and £′ are random numbers in the range [0, 1]. x^{d}_{inew} represents the updated position of the x_i point in the diffusion process, x_{best}, denotes the position of the best point in the group, and x_i represents the position of the ith point. u_{xbest}, refers to the position of the fractal that provides the best fitness value found up to the iteration. The u_x in (11) shows the position of the propagating fractal. r is the standard deviation value that represents the step size of the Gaussian Walk Function. The value of the standard deviation r is calculated using (12) [39].

$$\mathrm{r} = \left|\frac{\log(g)}{g}.\left(x_i - x_{best}\right)\right| \tag{12}$$

D. Dragonfly Algorithm

Dragonfly is an optimization algorithm inspired by nature [40]. The solution search process is carried out by mimicking the swarm behavior of dragonflies. The primary goal of each swarm is survival, so all individuals must exhibit behaviors that involve moving toward food sources and avoiding external threats. Based on these behaviors, five key factors that determine the position of individuals in the algorithm are defined: separation, alignment, cohesion, attraction, and distraction.

The separation process ensures that each DF in the swarm moves within its neighborhood without colliding with other dragonflies in the search space. The alignment process ensures that each DF in the swarm moves in synchronization with the other dragonflies in its neighborhood. The cohesion operator describes the tendency of a DF to steer toward the average position of its neighboring dragonflies. The attraction process expresses the tendency toward the global best solution, while the distraction process represents moving away from the worst solution. The calculations for Separation (S_i), Alignment (A_i), Cohesion (C_i), Attraction (F_i), and Distraction (E_i) are given in (13), (14), (15), (16), and (17), respectively.

$$S_i = -\sum_{j=1}^{N} X - X_j \tag{13}$$

$$A_i = \frac{\sum_{j=1}^{N} V_j}{N} \tag{14}$$

$$C_i = \frac{\sum_{j=1}^{N} X_j}{N} - X \tag{15}$$

$$F_i = X^{+} - X \tag{16}$$

$$E_i = X^{-} - X \tag{17}$$

After the completion of the five operations mentioned above, if there is a neighbor within the neighborhood radius, the position of each DF is updated sequentially using (18) and (19).

$$\Delta X_{t+1} = \left(sS_i + aA_i + cC_i + fF_i + eE_i\right) + w\Delta X_t \tag{18}$$

$$X_{t+1} = X_t + \Delta X_t \tag{19}$$

In (18), the values of s, c, and a represent the separation, cohesion, and alignment coefficients, respectively, while the values of f, w, e, and t represent the food factor, inertia coefficient, enemy factor, and the number of iterations, respectively. These coefficients and factors enable the algorithm to simulate exploratory and exploitative behaviors during the optimization process. The coefficients related to separation, alignment, cohesion, and enemy factors are defined to start from values that can reach up to 0.2 and gradually decrease to zero as the number of iterations increases. On the other hand, the food factor is randomly determined within the range of [0, 2] at each iteration, providing directional diversity to the agents' movement behavior. Additionally, the inertia weight is designed to decrease from 0.9 to 0.4 as the iterations progress.

IV. SIMULATION RESULTS

In recent years, the installation rates of DG and capacitors into electrical distribution systems have been rapidly increasing. However, determining which bus to place DG and capacitors on, as well as the capacities of these placed resources, has become an important issue. Based on this idea, this study focuses on the optimal placement of DG and capacitors, which will affect the overall performance of the system, using various metaheuristic algorithms, and the obtained results are presented comparatively. For the simulation studies conducted in the MATLAB environment, an 85-bus radial distribution test system was used [41]. The single-line diagram of the IEEE 85-bus radial distribution test system is shown in Fig. 1. Forward-Backward Sweep algorithm was used for the load flow analysis in the power distribution system [42].

The data for the 85-bus test system is provided in [41]. In the base case of the 85-bus test system, the total active power loss is P_L = 314.5378 kW, the reactive power loss is Q_L = 197.6246 kVAR, the voltage deviation value V_D = 0.7875 p.u. and the minimum voltage value is V_{min} = 0.8743 p.u. at bus 54. The decision variables for the problem are the bus to which DG and capacitors will be connected, and their respective capacities. It is assumed that the DGs provide

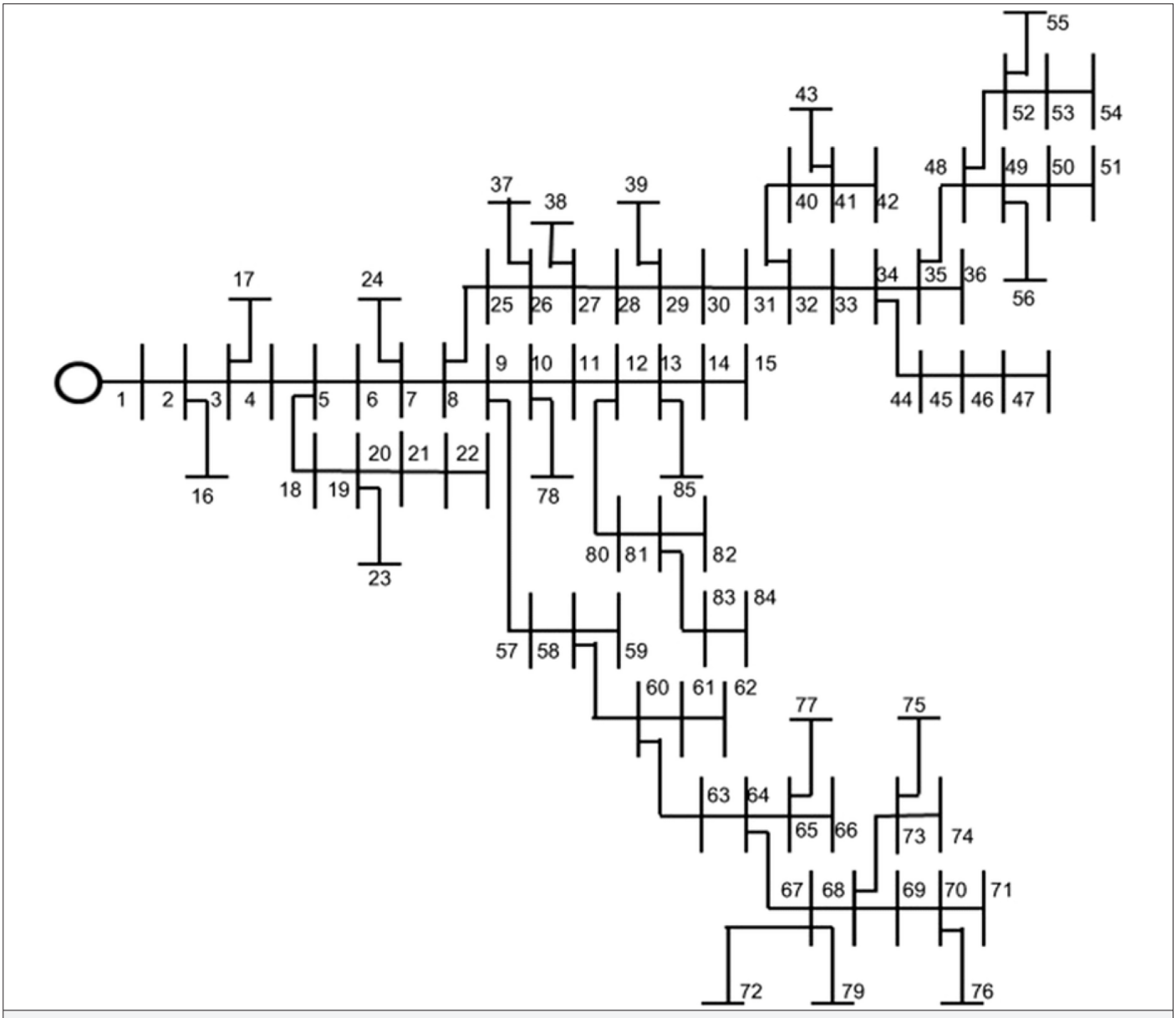


Fig. 1. Single-line diagram of the IEEE 85-bus radial distribution test system.

only active power to the system, while the capacitors provide only reactive power. Additionally, to ensure a proper comparison of the algorithms' performances, the maximum number of iterations for each algorithm was set to 50, and the population size was set to 20. For the simulation studies conducted in the MATLAB environment, seven different scenarios, excluding the Base Case, were considered. Each scenario is based on different combinations of DG and capacitors integrated into the distribution system. The scenarios are explained below. To ensure that the total capacity constraints of the units are not exceeded during the optimization process, the capacities of all units except the last one in each group were predefined within certain limits. The capacity of the last unit was dynamically calculated by subtracting the sum of the other units' capacities from the total maximum capacity. These constraints were directly integrated into the power flow calculations.

Base Case: No DG unit or capacitor has been added to the test system.

Case 1: A capacitor with maximum size of 1000 kVAR is integrated into the system. In this case, only reactive power compensation is provided.

Case 2: One DG unit with a maximum size of 0–1000 kW is integrated into the system. This scenario includes a DG unit that provides only active power generation.

Case 3: One DG with a maximum size of 0–1000 kW and one capacitor with maximum size of 0–1000 kVAR are integrated into the system.

Case 4: A DG with a maximum size of 1000 kW and three capacitors with a maximum total size of 1000 kVAR are integrated into the system.

Case 5: Three DGs with a maximum total size of 1000 kW and one capacitor with a maximum size of 1000 kVAR are integrated into the system.

TABLE II. LOCATIONS AND SIZES OF INSTALLED DGS AND CAPACITORS WITHIN 85-BUS SYSTEM

		Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7
ABC	DG size, kW (bus number)	–	1000 (48)	1000 (48)	1000 (35)	184 (71) 259 (73) 557 (52)	273 (73) 727 (48)	271 (71) 264 (45) 465 (49)
ABC	Capacitor size, kVAR (bus number)	1000 (52)	–	1000 (68)	172 (45) 273 (53) 555 (69)	1000 (34)	431 (69) 569 (35)	210 (50) 300 (55) 490 (68)
PSO	DG size, kW (bus number)	–	1000 (48)	1000 (48)	1000 (48)	291 (70) 138 (74) 571 (52)	307 (70) 693 (48)	198 (46) 255 (70) 547 (52)
PSO	Capacitor size, kVAR (bus number)	1000 (52)	–	1000 (68)	213 (53) 223 (45) 564 (69)	1000 (34)	377 (73) 623 (35)	211 (36) 293 (50) 496 (68)
SFS	DG size, kW (bus number)	–	1000 (48)	1000 (48)	1000 (35)	150 (73) 289 (71) 561 (52)	298 (70) 702 (48)	184 (44) 263 (70) 553 (48)
SFS	Capacitor size, kVAR (bus number)	1000 (52)	–	1000 (68)	182 (46) 268 (53) 550 (69)	1000 (34)	461 (68) 539 (52)	258 (46) 295 (52) 447 (68)
DF	DG size, kW (bus number)	–	1000 (48)	1000 (48)	1000 (48)	130 (75) 208 (70) 662 (48)	307 (70) 693 (48)	232 (70) 300 (53) 468 (48)
DF	Capacitor size, kVAR (bus number	1000 (52)	–	1000 (68)	182 (34) 220 (54) 598 (69)	1000 (34)	377 (73) 623 (35)	215 (46) 241 (35) 544 (68)

ABC, Artificial Bee Colony; DF, Dragonfly; DG, Distributed Generation; PSO, Particle Swarm Optimization; SFS, Stochastic Fractal Search

Case 6: Two DGs with a maximum total size of 1000 kW and two capacitors with maximum total size of 1000 kVAR are integrated into the system.

TABLE III. VALUES OF OBJECTIVE FUNCTION

	Objective Function (0.1*f1 +100*f2)			
Scenarios	**ABC**	**PSO**	**SFS**	**DF**
Base Case	110.2017	110.2017	110.2017	110.2017
Case 1	**66.6038**	**66.6038**	**66.6038**	**66.6038**
Case 2	**48.1765**	**48.1765**	**48.1765**	**48.1765**
Case 3	**26.0813**	**26.0813**	26.1075	**26.0813**
Case 4	**24.7488**	24.7813	24.8759	24.8513
Case 5	24.3948	**24.3724**	24.5860	24.4619
Case 6	23.6812	**23.6313**	23.6785	**23.6313**
Case 7	23.4513	**23.4283**	23.5687	23.5539

Best results in each category is shown with bold characters.
ABC, Artificial Bee Colony; DF, Dragonfly; PSO, Particle Swarm Optimization; SFS, Stochastic Fractal Search.

Case 7: Three DGs with maximum total size of 1000 kW and three capacitors with maximum total size of 1000 kVAR are integrated into the system.

The results obtained by the ABC, PSO, SFS, and DF algorithms for the scenarios presented in Table II. As can be seen, for Case 1, Case 2, and Case 3, the capacities of the DG and capacitors connected to the system were found to be 1000 kW/kVAR. This value found for Case 1, Case 2, and Case 3 represents the maximum capacity allowed by the user for connecting to the system. Additionally, in Case 1, the bus number for capacitor connection was identified as 52 by all four algorithms, while in Case 2, the bus number for DG placement was determined to be 48. As shown in Table II, these values were found to be identical across all algorithms. In Case 3, where both a DG and a capacitor were simultaneously integrated into the 85-bus test system, the DG and capacitor were placed at buses 48 and 68, respectively. In Case 4, the DG capacity was uniformly determined to be 1000 kW by all algorithms. However, the DG placement was identified as bus 35 by the ABC and SFS algorithms, whereas bus 48 was selected by the PSO and DF algorithms. In Case 5, the capacitor's size and connection bus were consistently determined as 1000 kVAR and bus 34, respectively, across all algorithms. Besides, different solutions were provided by the algorithms for the placement and sizing of multiple capacitors in Case 4, and for multiple DGs in Case 5.

In Case 6, bus 48 was consistently identified as the placement location for the high capacity DG by all algorithms. Regarding capacitor

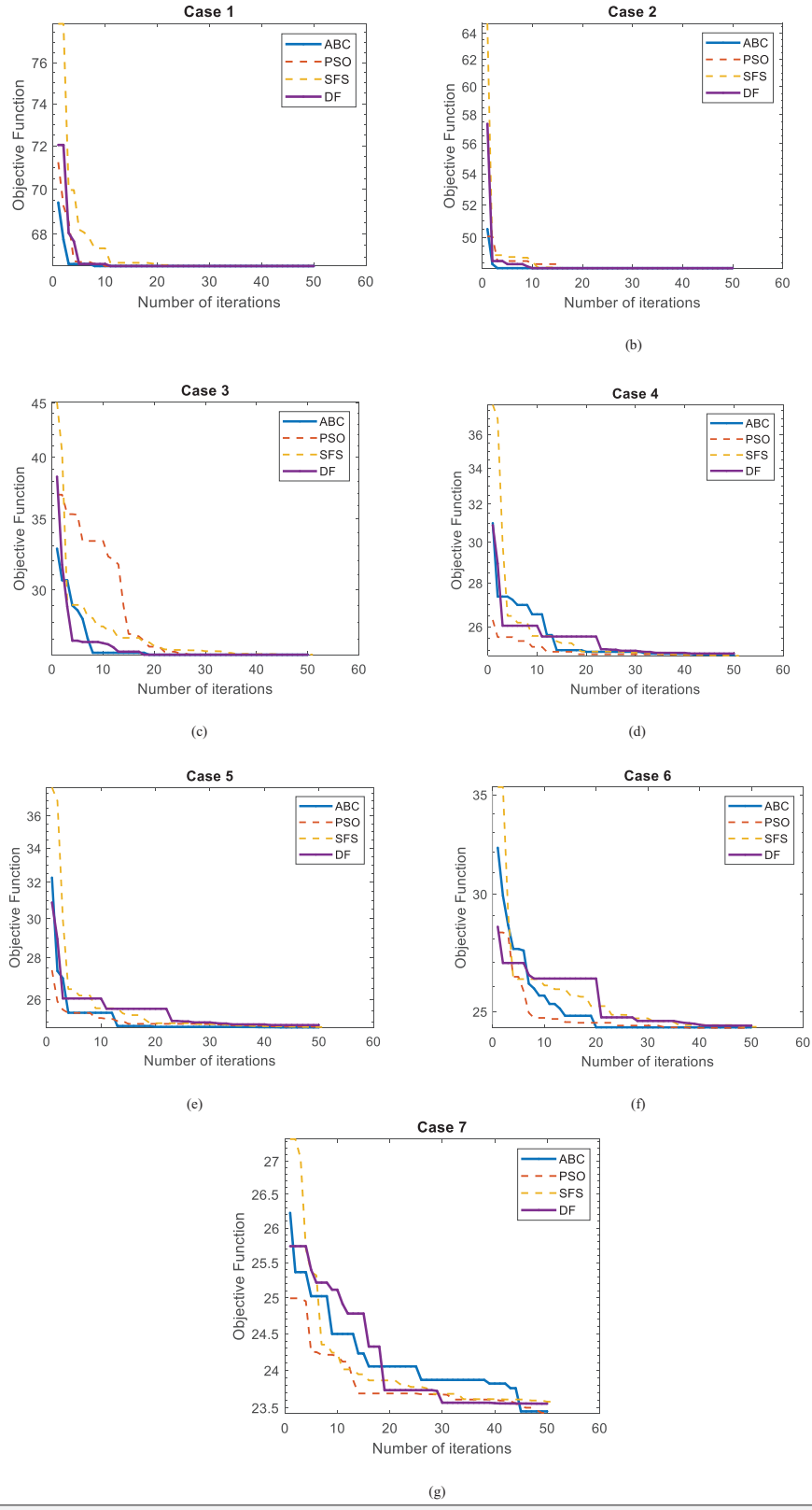


Fig. 2. Convergence curves of the algorithms a) Case 1, b) Case 2, c) Case 3, d) Case 4, e) Case 5, f) Case 6 and g) Case 7.

placement, the PSO and DF algorithms yielded identical results. In both algorithms, a 377 kVAR capacitor was determined to be connected to bus 73, while a 623 kVAR capacitor was to be connected to bus 35. Additionally, in the Case 7 scenario, where three DG units and three capacitors are connected to the test system simultaneously, the algorithms placed DGs of varying capacities at different buses. For the capacitor placement, the high-capacity capacitor group was installed to bus 68 by all algorithms with varying power ratings.

Table III presents a comparative result of the objective function obtained from simulation studies conducted for all scenarios using the ABC, PSO, SFS, and DF algorithms. The objective function is defined as (0.1*$f1$ + 100*$f2$), where $f1$ and $f2$ represent the total real power loss (P_L) and voltage deviation (V_D) of the 85-bus system, respectively. A comparison between Case 1 and Case 2 indicates that all algorithms exhibit a similar improvement relative to the base case, reducing the objective function value to 66.6038 and 48.1765, respectively. From Case 3 onward, minor performance differences among the algorithms become noticeable. In Case 3, all algorithms except for SFS achieve the most optimal value of 26.0813, while SFS yields the worst result with a value of 26.1075. In Case 4, slight improvements in the objective function are observed compared to the previous scenario, with the ABC algorithm attaining the best result with a value of 24.7488.

Although the ABC and PSO algorithms yielded very close results in Case 5, the PSO algorithm attained the most optimal outcome with a value of 24.3724. In Case 6, all algorithms produced results that were quite close to each other; however, the PSO and DF algorithms stood out by achieving the best objective function value of 23.6313. On the other hand, the most optimal objective function value across all algorithms was obtained in Case 7, which involved the simultaneous placement of three DGs and three capacitors each with a total capacity ranging between 0 kW/kVAr and 1000 kW/kVAr within the test system. The objective function values in this case were 23.4283, 23.4513, 23.5539, and 23.5687 for the PSO, ABC, DF, and SFS algorithms, respectively. As seen, the PSO algorithm achieved the best optimization result in Case 7 with a value of 23.4283, while the SFS algorithm produced the least favorable outcome with 23.5687. As observed from Table III, although the PSO algorithm achieved the best result in Case 7, the outcomes obtained by all algorithms are very close.

Fig. 2 illustrates the convergence curves of the algorithms for Case 1, Case 2, Case 3, Case 4, Case 5, Case 6, and Case 7. According to the convergence curves of Case 1, all algorithms rapidly decreased the objective function value within the first few iterations. ABC, PSO, and DF reached a stable value around the 5th iteration, while SFS progressed more slowly and reached a similar optimum value to the others by the 20th iteration. Thus, although all algorithms reached the same final solution, ABC, PSO, and DF performed better in terms of convergence speed. In Case 2, all algorithms showed rapid improvement within the first 5 iterations and reduced the objective function value to around 48. The ABC and DF reached a stable solution quickly, while PSO and SFS showed slight fluctuations initially but approached the optimum early in the iterations. In Case 3, DF exhibited the fastest convergence, stabilizing around the 5th iteration. ABC also showed a rapid decrease with similar performance. However, PSO and especially SFS progressed more slowly and only approached the optimum around the 35th iteration. Overall, DF and ABC stood out with their high performance and fast convergence in the early iterations.

In Case 4, ABC, DF, and SFS started with higher objective function values compared to PSO. PSO quickly approached the minimum in the initial iterations, while the other algorithms reached the minimum value around the 30th iteration. In Case 5, all algorithms demonstrated rapid improvement in the objective function value. The PSO and ABC stood out with a fast decrease in the early iterations, while DF progressed more cautiously and reached a similar level to the others after approximately the 25th iteration. Therefore, PSO had an advantage in initial convergence speed. In Case 6, all algorithms rapidly decreased the objective function value. The PSO showed a sharp improvement within the first few iterations, reaching low values quickly. The ABC was somewhat slower but reached a similar level to PSO after the 15th iteration. The DF and SFS followed a more cautious decline and reached the same point as the others around the 20th iteration. Ultimately, all algorithms converged to similar optimal values, but PSO stood out in terms of early convergence speed.

TABLE IV. ACTIVE POWER LOSS AND VOLTAGE DEVIATION VALUES OF THE 85-BUS SYSTEM

	ABC		PSO		SFS		DF	
Scenarios	**Ploss (kW)**	**V_D (p.u.)**	**Ploss (kW)**	**V_D (p.u.)**	**Ploss (kW)**	**V_D (p.u.)**	**Ploss (kW)**	**V_D (p.u.)**
Base case	314.5378	0.7875	314.5378	0.7875	314.5378	0.7875	314.5378	0.7875
Case 1	212.4892	0.4535	212.4892	0.4535	212.4892	0.4535	212.4892	0.4535
Case 2	202.2766	0.2795	202.2766	0.2795	202.2766	0.2795	202.2766	0.2795
Case 3	118.7191	0.1421	118.7191	0.1421	118.7466	0.1423	118.7191	0.1421
Case 4	95.5265	0.1520	98.3921	0.1494	98.5766	0.1502	99.4427	0.1491
Case 5	92.9664	0.1510	93.1409	0.1506	94.9944	0.1509	92.6094	0.1520
Case 6	83.0636	0.1537	82.5346	0.1538	82.3915	0.1544	82.5333	0.1538
Case 7	81.4883	0.1530	82.8190	0.1515	84.2645	0.1514	84.3007	0.1512

ABC, Artificial Bee Colony; DF, Dragonfly; PSO, Particle Swarm Optimization; SFS, Stochastic Fractal Search.

In Case 7, the PSO algorithm converged to its best value of 23.4283 at the 49th iteration, while the ABC algorithm reached its optimal value of 23.4513 at the 45th iteration. The DF algorithm achieved its best value of 23.5539 at the 48th iteration, and the SFS algorithm converged to its value of 23.5687 also at the 49th iteration. Among the algorithms, the ABC algorithm demonstrated the fastest convergence behavior by reaching its optimum value before the 50th iteration. In contrast, the PSO and SFS algorithms showed the slowest convergence patterns, both reaching their best values at the 49th iteration. In terms of computational time, the DF algorithm completed the 50 iteration run in the shortest time, 7.6818 seconds, whereas the SFS algorithm took the longest, completing in 34.0485 seconds.

Active power loss and voltage deviation values obtained from the outcomes of the cases are presented in Table IV. In the IEEE 85-bus test system, the base case active power loss was determined to be 314.5378 kW. As shown in Table IV, all algorithms achieved identical power loss values in Case 1 and Case 2. In Case 3, all algorithms except for SFS achieve the most optimal value of 118.7191, while SFS yields the worst result with a value of 118.7466. However, in Cases 4 through 7—where the number of decision variables increases—the power loss values obtained by the algorithms exhibit noticeable differences. The ABC algorithm achieved the most optimal power loss in Case 7, whereas the other algorithms yielded their best results in Case 6.

Considering the initial voltage deviation of 0.7875 p.u., the voltage deviation values obtained by the algorithms were found to be very close to each other. In fact, for Cases 1, 2, and 3, identical voltage deviation values were produced by the PSO, ABC, and DF algorithms. For Case 3, however, the highest voltage deviation was observed in the SFS algorithm, with a value of 0.1423. In Cases 5, 6, and 7—where the number of variables increased—more noticeable differences were observed among the voltage deviation results of the algorithms. In particular, for Case 5, the PSO algorithm achieved a more optimal voltage deviation compared to the others, whereas the values obtained by the ABC and SFS algorithms were quite close to each other. On the other hand, the DF algorithm yielded a slightly worse result with a deviation of 0.1520. In Case 6, the ABC algorithm stood out with the lowest voltage deviation of 0.1537, while in Case 7, the DF algorithm provided the best result with a deviation of 0.1512.

V. CONCLUSION

In electrical distribution systems, it is essential to optimally place DG and capacitors to minimize losses and reduce voltage deviations. In this study, the optimal locations and capacities of DG and capacitors in different scenarios are determined using metaheuristic optimization algorithms such as PSO, ABC, SFS, and DF. Seven different scenarios were considered in this study. Among these, Case 1 and Case 2 provide only reactive or active power to the system, respectively. This allows for an opportunity to examine the independent effects of each power type on the system. In Case 3, both active and reactive power are simultaneously integrated into the system. In Case 4, Case 5, Case 6, and Case 7, multiple DG and capacitors are installed while keeping the total injected power constant. The results show that allocating the total capacity of DGs and capacitors to three different buses as in Case 7 presents better results compared to locating them on a single bus or two buses. The voltage deviation and active power loss, initially at 0.7875 p.u. and 314.5378 kW, respectively, are reduced to 0.1421 p.u. and 81.4883 kW using various metaheuristic algorithms. In this study, the total active and reactive power capacities of DG and capacitors installed in the distribution system were kept constant, and performance evaluation was conducted based on seven different scenarios. Future studies can focus on developing models that incorporate dynamic load and generation variations, comparing different optimization techniques, and accelerating algorithms for real-time applications. Moreover, including distribution system reconfiguration processes in the optimization framework can further enhance system performance.

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