UDC 621.3 https://doi.org/10.20998/2074-272X.2025.6.11

S.S. Sabry, O.Sh. Al-Yozbaky

Enhanced siting and sizing of distributed generation in radial distribution networks under load demand uncertainty using a hybrid metaheuristic framework

Introduction**. Constant changes in electrical system loads lead to increased power losses and voltage drops, requiring effective strategies to improve grid performance amid changing power demands.* ***Problem. *Many studies assume constant loads when determining optimal locations for distributed generation (DG) units, when in reality, loads change throughout the day. These changes affect network performance and require efficient solutions that adapt to changes in loads demand to maintain system efficiency and stability.* ***Goal.*** *This research aims to optimize the locations and sizes of DG units to reduce power losses and optimize voltage profile, taking into account changes in loads hourly over a 24-hour period.* ***Methodology.*** *The study analyzes 24 hourly scenarios using 2 optimization techniques: the conventional particle swarm optimization (PSO) algorithm and the hybrid-dynamic PSO algorithm. A multi-objective function is adopted to reduce power losses and improve voltage profile at the same time.* ***Results.*** *The modified IEEE 33 bus system was used to verify the effectiveness of the proposed method. The hybrid-dynamic PSO algorithm has shown superior performance in reducing active and reactive losses compared to the traditional algorithm. It also contributed to a significant improvement in the voltage profile, demonstrating its high efficiency in dealing with changes in loads demand during time.* ***Scientific novelty*** *of this work lies in the integration of hourly load changes into the process of allocating DG units and using a hybrid-dynamic PSO algorithm that combines the benefits of PSO traditional and adaptation mechanisms, leading to realistic and more efficient improvement.* ***Practical value.*** *This methodology enhances the performance of the smart grid by reducing power losses and voltage deviation under daily load, ultimately reducing operational costs and improving grid reliability.* References 28, tables 4, figures 10.

Key words. **distributed generation, renewable energy, optimization algorithms, voltage stability, power losses minimization, uncertain loads demand.**

***Вступ**. Постійні зміни навантаження електросистеми призводять до збільшення втрат потужності та падіння напруги, що вимагає розробки ефективних стратегій для підвищення продуктивності мережі в умовах змінного попиту на електроенергію.* ***Проблема**. У багатьох дослідженнях щодо оптимального розташування установок розподіленої генерації (DG) передбачається наявність статичних навантажень, хоча насправді навантаження змінюються впродовж дня. Ці зміни впливають на продуктивність мережі та потребують динамічних рішень, що адаптуються до змін навантаження у часі для підтримки ефективності та стабільності системи.* ***Мета**. Дане дослідження спрямоване на оптимізацію розташування та розмірів DG установок для зниження втрат потужності та оптимізації профілю напруги з урахуванням щогодинних змін навантаження протягом 24 годин.* ***Методологія**. У дослідженні аналізуються 24-годинні сценарії з використанням двох методів оптимізації: традиційного алгоритму оптимізації роєм часток (PSO) та гібридно-динамічного алгоритму PSO. Для зниження втрат потужності та одночасного покращення профілю напруги використовується багатоцільова функція.* ***Результати**. Для перевірки ефективності запропонованого методу використовувалася система шин IEEE 33. Гібридно-динамічний алгоритм PSO продемонстрував високу ефективність зниження активних і реактивних втрат порівняно з традиційним алгоритмом. Це також сприяло значному покращенню профілю напруги, продемонструвавши його високу ефективність за умов зміни навантаження у часі.* ***Наукова новизна** роботи полягає в інтеграції погодинних змін навантаження у процес розподілу DG установок та використання гібридно-динамічного алгоритму PSO, що поєднує переваги традиційних механізмів PSO та механізмів адаптації, що призводить до реалістичного та ефективнішого покращення.* ***Практична цінність**. Дана методологія підвищує продуктивність інтелектуальної мережі за рахунок зниження втрат електроенергії та відхилення напруги при добовому навантаженні, що знижує експлуатаційні витрати та підвищує надійність мережі.* Бібл. 28, табл. 4, рис. 10.

Ключові слова. **розподілена генерація, відновлювальна енергетика, алгоритми оптимізації, стабільність напруги, мінімізація втрат потужності, невизначені навантаження.**

Introduction. Electrical energy is one of the pillars of modern civilization and one of the basic requirements in the life of modern man. Transmission and distribution networks are one of the most prominent components of the electrical system. One of the main challenges facing the performance of distribution networks is the change in load demand, which leads to differences in active and reactive losses, as well as voltage drops and decreases in network stability [1, 2]. Optimal planning of distributed generation (DG) is one of the most important methods for reducing electrical losses [3] and improving voltage limits in distribution network [4]. However, the installation and operation of these generators require significant investment and operational costs , which calls for the use of standard optimization algorithms in order to ensure that the integration of DG with distribution networks is optimal [5].

DG is called by various terms such as local generation, integrated generation, scattered generation, or decentralized generation, and it generally refers to electrical energy sources (whether renewable or non-renewable) that are connected to the distribution network or directly to the consumption site [6, 7]. The concept of DG includes a variety of technologies, as shown in Fig. 1 [8], that produce energy at sites close to consumers. These systems can serve individual buildings [9] or be used in Microgrids [10]. They can also be operated with on-grid mode [11].

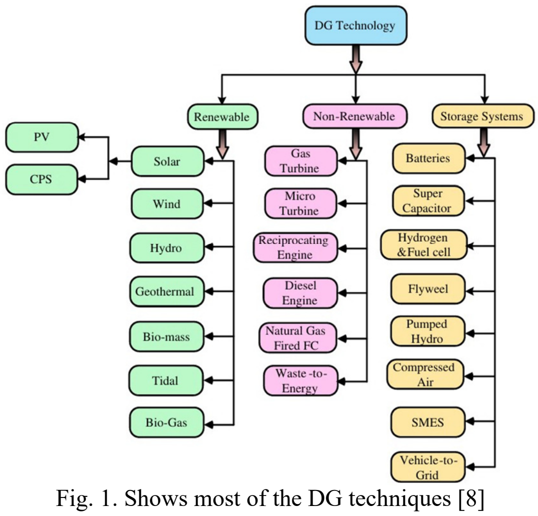

Fig. 1. Shows most of the DG techniques [8]

Methods for searching for the optimal solution to the problem of locating and scaling DG vary depending on the nature of the system studied, the complexity of the objectives and the constraints imposed, and these methods are generally divided into 3 main categories: analytical, numerical, and metaheuristic algorithms. Analytical methods [12] rely on explicit mathematical equations and are often used in simplified systems with few buses and limited targets, but become impractical with the complexity of the network. Numerical methods [13], such as the Newton-Raphson method or linear programming, provide high accuracy but require accurate mathematical models and may suffer from falling into local solutions, and do not fit easily to multi-objectives or nonlinear variables. In contrast, intelligent optimization algorithms [14–20] have been more common in recent years, due to their ability to deal with complex models, multiple targets, and the nature of nonlinear or inaccurately defined constraints. Some studies have also tended to combine more than one algorithm for improved performance, or to use hybrid algorithms that combine artificial intelligence with traditional optimization. The literature shows that the choice of an optimization algorithm depends on several factors such as the number of DG units, load type, network model, and objective function, however, the general trend is leaning towards intelligent multi-objective optimization algorithms due to their flexibility and effectiveness in arriving at practical and workable solutions.

A review of the literature referred to above shows that most researchers have addressed the allocation of DG units based on fixed loads. Some evaluated the allocation of these units under time-varying loads, but the locations and sizes of DG units were often calculated at the average load only. Moreover, some researchers looked at multiple load models, but each allocation was made separately for each given load, rather than a standardized allocation that took into account loads over the time period (24 h) in our current study. Some studies have also shown allocation of DG units under loads and probabilistic generation. However, the majority of these studies relied on constant generation based on (average generation**)** from renewable energy sources, without taking into account the temporal change in production.

In order to simulate the full picture of the actual operating reality of the system, it is necessary to make an allocation of DG units for each time period separately, according to load variables. Hence, the optimal allocation is chosen from among all time assignments based on the desired objectives, such as maximizing system efficiency, reducing losses or optimizing voltage profile.

The main contributions of this research are the application of a modified hybrid metaheuristic optimization algorithm to determine the optimal allocation of DG units across 24 different scenarios, and the problem model was built based on multiple scenarios, so that each scenario represents specific load and generation conditions during a specific hour of the day. The methodology was implemented within a 24-hour time horizon, taking into account the regenerative generation pattern of solar generating units with the use of storage batteries to make the generation constant from the system. The hybrid-dynamic metaheuristic algorithm was also employed in the context of allocating the locations and sizes of DG, and their performance was evaluated in this context. Optimal allocation of DG units was achieved throughout the day, with the aim of reducing the multi-objective function (MOF). The study included the analysis and discussion of active power losses, reactive power losses, as well as voltage profiles at different buses. Total power losses were also calculated and discussed over the full day. Finally, the results of the study were compared with the results of another optimization algorithm, such as particle swarm optimization (PSO), in terms of optimal allocation of single and multiple DG units.

The **goal** of the paper is to optimize the locations and sizes of DG units to reduce power losses and optimize voltage profile, taking into account changes in loads hourly over a 24-hour period.

The formulation of the problem involves the use of backward forward sweep power flow analysis and the results associated with optimal location and size allocation of DG using an optimization algorithm approach, taking into account a set of constraints. Allocation means optimized for DG to introduce these generators into the system at an optimal point in terms of location and size. Figure 2 shows the diagram of the system. The first stage involves entering system data such as a 24-hour variable load. In the second phase, the optimal allocation of DG units is determined according to changes in load demand based on the minimum value of the objective function.

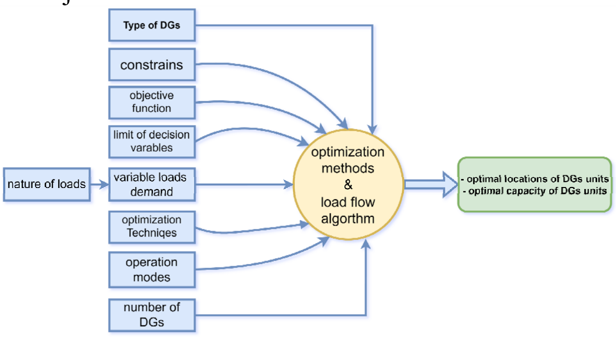

Fig. 2. Factors influencing the optimal location and sizing of DG

Load flow analysis. Power flow analysis technology is used for planning, operation, optimization, and monitoring of electrical power systems, as it contributes significantly to ensuring system stability, reliability and economic efficiency.

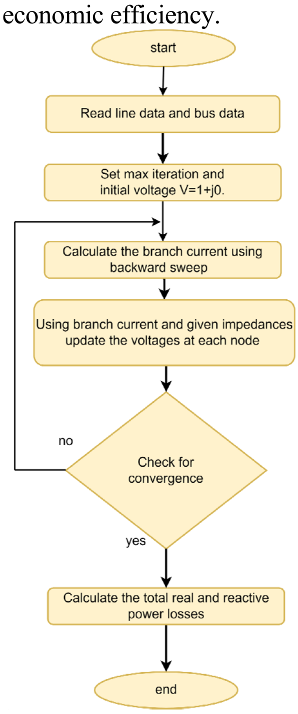

Fig. 3. Flow chart of backward forward sweep algorithm

However, traditional methods used in power flow analysis, such as the Newton-Raphson method and the Gauss-Seidel method, may not be suitable for distribution networks and may not guarantee access to the solution (no convergence) for the following reasons [21]:

1. Radioactive nature or weak entanglement in the network structure.
2. High resistance-to-reactance ratio.
3. Imbalance of the system.
4. The presence of DG sources.

The backward forward sweep algorithm [22] (Fig. 3) is an effective method used in power flow analysis for radial distribution networks, as it is characterized by its ability to provide accurate results with speed of convergence and reduce the number of iterations required to reach the solution. For these reasons, this algorithm is the preferred choice in the analysis of distribution systems.

Steps of implementation of backward forward sweep algorithm.

1) Initializing. Set the current at each node to zero:

$$i_k = 0, \tag{1}$$

where i_k is the complex current at node k.

Set the voltage of all nodes to 1 p.u.:

$$v_k = 1, \tag{2}$$

where v_k is the complex voltage at node k.

2) Calculating the nodal current by using the complex power equation:

$$i_k = s_k^* / v_k^* , \tag{3}$$

where s_k is the complex power at node k [p.u.]; v_k is the voltage at node k [p.u.]; i_k is the calculated current at node k [p.u.]; symbol «$*$» denotes complex conjugate.

3) Backward sweep – branch current calculation. Calculate branch current flowing from node k to node k–1:

$$i_{k,k-1} = i_k + \sum i_{m,k} , \tag{4}$$

where $i_{k,\,k-1}$ is the current in the branch from node k to k–1; $\Sigma i_{m,k}$ is the sum of branch currents from all downstream nodes connected to node k.

4) Perform forward sweep to update the node voltage according to the voltage drop equation across the lines:

$$v_{k+1} = v_k - z_{k,k+1} \cdot i_{k,k+1} , \tag{5}$$

where v_k is the voltage at node k; v_{k+1} is the voltage at the downstream node k+1; $z_{k,k+1}$ is the complex impedance of the line between nodes k and k+1; $I_{k,k+1}$ is the current in the branch between nodes k and k+1.

5) Check the stopping criterion, where the iterative process continues until reaching the acceptable variance between the calculated values in successive iterations:

$$\max\left|v_k^{n+1} - v_k^n\right| \le \varepsilon , \tag{6}$$

where ε is the specified tolerance for convergence (typically 10^{-4}.)

Objective function. The main objective of the goal function is to reduce the multi-objective index to the lowest possible value.

MOF index is a combination of 3 main indicators – the Active Power loss Index (API), the Reactive Power loss Index (RPI) and the Voltage Deviation index (VD) [23]. Optimal allocation of DG units is achieved by minimizing the MOF value. This process is based on (7), where the coefficients $w_1 - w_3$ refer to the weights of API, RPI and VD:

$$MOF = w_1 \cdot API + w_2 \cdot RPI + w_3 \cdot VD ; \tag{7}$$

$$\sum_{i=1}^{3} w_i = 1 ; \tag{8}$$

where w_1 is the weight of *API* objective (w_1=0.5); w_2 is the weight of *RPI* objective (w_2=0.25); w_3 is the weight of *VD* objective (w_3=0.25).

The relative weights of the 3 objectives (reducing real losses, reducing reactive losses and reducing voltage deviation) were determined using the analytic hierarchy process developed by T.L. Saaty, which is one of the most common multi-standard decision-making methods [24] is common and accurate. This method is based on the principle of conducting even comparisons between goals using a numerical preferential scale that reflects the degree of relative importance between each pair, so that the judgments are translated into a comparison matrix used to extract the final weights through mathematical treatment based on normalization and analysis of eigenvalues. In this context, a logical assessment was adopted that the first goal (*API*) is twice as important as the other 2 goals (*RPI* and *VD*), while *RPI* and *VD* were considered equally important. According to this assessment, the comparison matrix is built to reflect these relationships (*PLI* > *RPI* = *VD*), with a preference ratio of (2:1). Based on these provisions, the final weights were derived to be approximately 0.5 for API and 0.25 for each of the *RPI* and *VD*. This distribution reflects the level of technical impact expected for each objective on grid performance and is consistent with the logic of improving the operational efficiency of electrical distribution systems, where priority is given to reducing real losses as directly related to economic losses in energy.

Active power loss index (*API*) is related to the objective of reducing active power losses [25, 26], and is calculated as the ratio between Actual Power Loss in the presence of DG (*APLDG*) to Actual Power Loss (*APL*) in the absence of DG:

$$API = APLDG \,/\, APL. \tag{9}$$

Reactive power loss index (RPI) is the ratio of the Reactive Power Loss [27] when DG is present (*RPLDG*) to the Reactive Power Loss (*RPL*) without DG:

$$RPI = RPLDG \,/\, RPL. \tag{10}$$

Voltage deviation index (*VD*) is the 3rd target considered in this question [28], and is mainly used to monitor the power system. In real time, efforts across buses deviate from their stability limits, and can be adjusted within safe limits through optimal allocation of DG in the system, contributing to voltage profile optimization. The VD indicator in (11) should be minimal, because higher values indicate a greater deviation from the initial value:

$$VD = \max_{b=1}^{n}\left(\left(v_{ini} - v_b\right)/v_{ini}\right), \tag{11}$$

where n is the total number of buses in the system; v_{ini} =1.05p.u.

Constrains. The process of minimizing the objective function is constrained by equality constraints and inequality constraints.

Equality constraints express the balance of real and reactive power of DG within the electrical system:

$$\sum P_{Gi} - \sum P_{Di} - P_{loss} = 0 ; \tag{12}$$

$$\sum Q_{Gi} - \sum Q_{Di} - Q_{loss} = 0 , \tag{13}$$

where P_{Gi} is the active power generated by traditional resources; P_{Di} is the active power generated by DG units; P_{loss} is the active power losses in network; Q_{Gi} is the reactive power injected by traditional resources; Q_{Di} is the reactive power injected by DG units; Q_{loss} is the reactive power losses in network.

Inequality constraints include setting the minimum and upper limits of DG capacity to ensure that permissible operational levels are not exceeded, in addition to restricting the locations of connecting generation units to specific locations to the network to achieve the best technical and economic performance:

$$P_{DG}^{\min} \le P_{DG} \le P_{DG}^{\max} ; \quad (14)$$

$$Q_{DG}^{\min} \le Q_{DG} \le Q_{DG}^{\max} ; \quad (15)$$

$$2 \le DG_{position} \le n_{bus} , \quad (16)$$

where P_{DG} is the active power output of the DG unit; $P_{DG}^{\min}, P_{DG}^{\max}$ are the minimum and maximum limits of the DG's active power; Q_{DG} is the reactive power of the DG unit; $Q_{DG}^{\min}, Q_{DG}^{\max}$ are the minimum and maximum allowable reactive power; $DG_{position}$ is the bus number where the DG is installed; n_{bus} is the total number of buses in the network.

Optimization algorithms. PSO is one of the popular algorithms used to solve multidimensional optimization problems. These algorithms mimic the behavior of flocks of birds and fish in search of food sources, where the positions of particles are updated based on their individual and collective experiences to arrive at optimal solutions. The presented models aim to compare the traditional algorithm with a dynamic hybrid version, which includes additional steps to improve the quality and speed of arriving at the optimal solution by introducing local search mechanisms and handling recessions. PSO algorithm and the improved or modified hybrid algorithm, called the hybrid-dynamic PSO algorithm, were used, where their parameters are dynamically adjusted as the algorithm progresses, in addition to introducing the concept of mutation to the results in case of stagnation to avoid the algorithm falling into the trap of local solutions. The choice of this particular algorithm among the rest of the optimization algorithms for the following reasons:

1. The ability to process dynamic and non-convex equation.
2. The ability to process large and complex data sets.
3. The ability to explore initial search spaces effectively.
4. The speed of convergence towards optimal solutions compared to other methods specially when deals with multi-objectives that have overlap and conflict with each other.

In PSO, the starting particles are distributed randomly across the available search space, and out of all these particles, the best solution is identified. The locations of the particles are updated in the next step based on the previous locations and velocity values, the entire swarm takes actions to improve the value of the objective function and achieve the optimization in the next steps.

The best fitness (min, max) is determined to direct the rest of the particles towards this best solution. The velocity of the particle is updated according to the gap between his current position and the optimal position relative to all other particles (g_{best}), in the same manner, the position of the particle is constantly being updated by adding its current location to its movement.

The position and velocity of the particle are determined according to the following equation:

$$v_i^{k+1} = w v_i^k + c_1 r_1 \left(p_{besti} - s_i^k\right) + c_2 r_2 \left(g_{best} - s_i^k\right); \quad (17)$$

$$s_i^{k+1} = s_i^k + v_i^{k+1} ; \quad (18)$$

where v_i^k is the velocity of particle i at iteration k; s_i^k is the position of particle i at iteration k; p_{besti} is the best position found by particle i (personal best); g_{best} is the best position found by the entire swarm (global best); w is the inertia weight – controls exploration vs. exploitation; c_1, c_2 are the acceleration coefficients (cognitive and social components); r_1, r_2 are the random numbers uniformly distributed in [0, 1].

The PSO algorithm depends on 3 basic steps that are performed during each iteration:

1. Evaluating each solution using the objective function to calculate the fitness value.
2. Updating the best position of the particle (p_{best}) and the best global position (g_{best}).
3. Updating the particle's velocity v_i and its position s_i.

These steps continue until stopping criteria are met, such as reaching a certain number of iterations or achieving a certain accuracy threshold. Despite its efficiency, traditional PSO suffers from some drawbacks when dealing with optimization problems, the most prominent of which is that it may stop at local maximum values (stuck in a local maximum), which reduces its ability to explore the entire search space. The parameters w, c_1, c_2 affect the performance of the algorithm, as tuning inappropriate values can lead to early convergence towards a non-optimal solution or divergence which prevents the algorithm from reaching an optimal solution.

A number of attempts have been made to improve the PSO algorithm in order to find the most suitable control parameters. Numerous methods exist for the search of optimal parameters other than those with fixed values. The variable coefficient PSO or dynamic PSO with control parameters that decrease linearly is given in (19–21). The control parameters of PSO are:

$$w_k = w_{\max} - \frac{k}{k_{\max}} \cdot (w_{\max} - w_{\min}) ; \quad (19)$$

$$c_{1k} = c_{1\max} - \frac{k}{k_{\max}} \cdot (c_{1\max} - c_{1\min}) ; \quad (20)$$

$$c_{2k} = c_{2\max} - \frac{k}{k_{\max}} \cdot (c_{2\max} - c_{2\min}) , \quad (21)$$

where w_k is the inertia weight at iteration k; $w_{\min}$ is the final (minimum) inertia weight; $w_{\max}$ is the initial (maximum) inertia weight; k is the current iteration number; $k_{\max}$ is the total number of iterations; c_{1k} is the cognitive component at iteration k; c_{2k} is the social component at iteration k; $c_{1\max}$ is the initial (maximum) cognitive value; $c_{1\min}$ is the final (minimum) cognitive value; $c_{2\min}$ is the initial (minimum) social value; $c_{2\max}$ is the final (maximum) social value.

Local search and mutation were used on the initial results of the PSO algorithm for the following reasons.

1) *Exploitation.* PSO algorithm is good at exploration but may not be accurate in finding the local optimal solution. Local search comes to fine-tuning on the found solution.

2) *Accelerate-convergence.* Instead of waiting for PSO to reach the optimal solution across many generations, local search can quickly improve good solutions in each or after a certain number of generations.

3) *Increase precision.* Helps to exceed some PSO limits such as oscillating around g_{best} without further optimization, by optimizing locally around g_{best} or p_{best}.

4) *Diversity.* Mutation causes a random change in the location of some particles, preventing premature grouping of particles around imperfect solutions.

5) *Escape from local optima.* If particles stop improving, the mutation gives a random push to each other to exit that area and explore new areas.

6) *Improved exploration.* Especially in the later stages of PSO when particles begin to focus on a small area around the g_{best}.

The method used to determine the best location and value for DG using the hybrid-dynamic PSO algorithm is as follows.

Step 1 (Initialization).

1. Number of iteration k.
2. Number of particles n.
3. Number of parameters per particle m.
4. Limitation of space solution.
5. Set the initial value of control set of PSO as shown in Table 1.
6. Set the initial value of each particle randomly with in the limit of space solution.

Step 2. Modify the load bus by the initial set of particles.

Step 3. Run load flow and calculate *APL*, *RPL*, *VD*.

Step 4. Searching for p_{best} and g_{best}.

Step 5. Update the velocity, position and variable control set to generate new set of solution.

Step 6. Evaluate the new solution.

Step 7. Searching for p_{best} and g_{best}.

Step 8. Apply local search.

Step 9. Check if g_{best} is stagnant? If yes – apply mutation, if don't – check no. of iteration if less or equal to no. of max. iteration.

Step 10. Update the number of iterations.

Step 11. If number of iterations less than or equal number of max iterations then go to step 5.

Table 1

PSO coefficients used in the simulation

Parameter	Value
Number of particles n	50
Number of iterations $k_{\max}$	50–150
Number of parameters per particles m	2
Cognitive component c_1	0.5–2.5
Social component c_2	0.5–2.5
Inertia weight w	0.4–0.9

The traditional PSO algorithm (Fig. 4,*a*) begins by initializing the basic parameters, including the inertia weight w, acceleration coefficients c_1, c_2, swarm size, number of iterations and number of variables. A set of solutions is then randomly generated within the search space. The validity of the solutions is then checked. If the condition is met, the network loads are adjusted, and the load flow is run to evaluate the validity of the solutions. This is followed by a search for the best local and global solutions (p_{best} and g_{best}) based on the calculated validity values. The positions and velocities of the particles are then updated to generate a new set of solutions. This cycle continues with the network loads being updated, solutions being evaluated, and the best solutions being updated, with the number of iterations gradually increasing until the maximum number of iterations is reached, at which point the algorithm terminates.

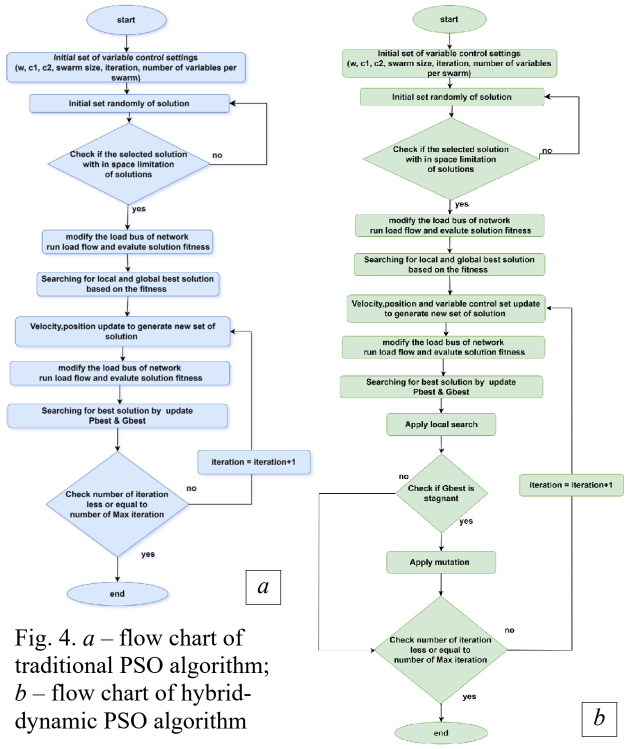

Fig. 4. *a* – flow chart of traditional PSO algorithm; *b* – flow chart of hybrid-dynamic PSO algorithm

The hybrid-dynamic PSO algorithm (Fig. 4,*b*) follows similar steps to the traditional algorithm, starting with initializing the basic settings and generating a random set of solutions. After verifying that the solutions adhere to the permissible space limits, the network loads are adjusted, and the load flow is run to assess the validity. The best local and global solutions are searched according to the validity criteria. After updating the speed and location variables, an additional optimization step is applied, which involve applying a local search to improve the quality of the discovered solutions. If the global solution g_{best} stagnates and does not improve across iterations, a mutation is applied to break this stagnation and stimulate the search for better solutions. The system continues iterating, updating solutions and increasing the number of iterations until a specified maximum number is reached, at which point the algorithm terminates. This hybrid-dynamic approach contributes to accelerating convergence to the optimal solution and increasing the efficiency of the search process.

Test system. Modified IEEE 33 bus distribution system was adopted to test the proposed method. Figure 5 shows the single line diagram of the distribution system, at base load, the total active power is 3715 kW, the reactive power is 2300 kVAr.

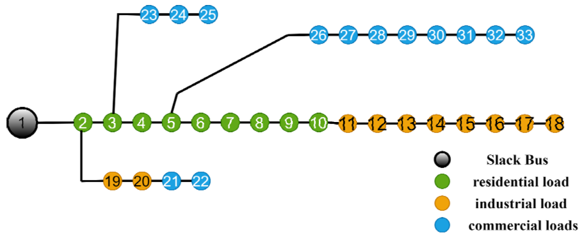

Fig. 5. Modified IEEE 33 bus test system

Limitations. The study's limitations refer to the specific aspects of its design or methodology that had an impact on or influenced the interpretation of the study's conclusions. Below are limitations of this work:

1) *Load flow method*. By backward forward sweep because this method is suitable for distribution networks of radial nature.

2) *Operation mode*. On grid operation mode.

3) *Network type*. Modified IEEE 33 bus test system radial distribution network.

4) *Type of DG*. Renewable energies that they have the ability to inject active power only.

5) *Number of DG*. Single and multiple distribution generation units.

6) *Load type*. Variable load and load model is constant power.

7) *System condition*. Balanced 3 phase system.

8) *Optimization method*. Metaheuristic method and the algorithm is hybrid dynamic PSO.

9) *Objective function*:

- minimize active power losses;
- minimize voltage deviation at each bus;
- maximize voltage stability.

10) *Decision variable*. Optimal location and value of DG with unity power factor.

Result and discussion. To validate the proposed approach and its effectiveness in the analysis and optimization methods presented, the study was applied to the modified IEEE 33 bus test system under different scenarios, including:

- *Base case*. System operation without integration of any DG.
- *1st case*. Integration of one DG unit at the optimal location within the network.
- *2nd case*. Integration of 2 DG units at their optimal locations.
- *3rd case*. Integration of 3 DG units at their optimal locations.

IEEE 33 bus model with variable load demand was chosen as the base case for loss evaluation and power flow analysis without DG, and the analysis was done using backward/forward sweep. The total losses in active and reactive power among the studied cases are shown in Fig. 6, and Fig. 7 shows load demands during 24 hours.

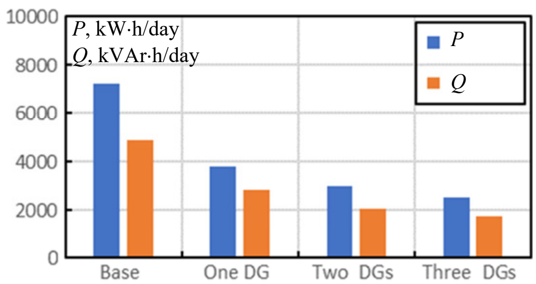

Fig. 6. Active and reactive power losses during 24 h in the 3 cases in addition to the basic case

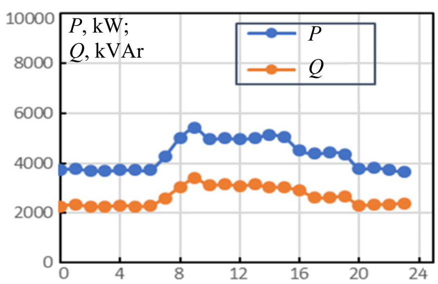

Fig. 7. Active and reactive load demand during 24 h

Initially with base case, energy losses for active and reactive power were measured at 7196.054 kW·h/day and 4887.774 kVAr·h/day, the minimum voltage value recorded for bus number 18 was 0.8459 p.u. In the 1st scenario, where a single DG unit was embedded, the optimal size of the unit was calculated to be 3079.71 kW at bus number 6, which caused total active and reactive energy losses to drop to 3799.023 kW·h/day and 2794.019 kVAr·h/day. In the next case, the system was embedded with 2 DG units, where 2 units of 1056.946 kW and 1322.302 kW were placed at buses number 13 and 30, respectively. This led to active energy losses of 2980 kW·h/day and reactive power losses of 2050 kVAr·h/day.

In case 3, where 3 DG units were considered, 957.925 kW, 1262.393 kW and 1231.201 kW units were put in buses 14, 24 and 30, respectively, which brought the total active losses down to 2506.591 kW·h/day and the reactive losses down to 1750 kVAr·h/day. Figure 6 shows how the inclusion of several DG units into distribution systems provides greater improvements on the reduction of active and reactive losses than single generation unit systems.

The changes within the average bus voltage for employing the optimal size and location of the DG in various scenarios with basic case is illustrated in Fig. 8. The application of the optimal distribution generator enhances the performance of all the bus voltages in terms of stability in comparison with the base case.

Table 2 presents the statistical results of 100 running of proposed method for MOF along 24 h with 3 DG along with the corresponding minimum, maximum, mean and standard deviation values. Additionally, the success rate (SR) is reported, which indicates the percentage of runs that achieved a solution within 2 % of minimum objective function value among all running.

The high effectiveness of the algorithm attributed to its inherent optimization capabilities and the adequacy of the selected number of particles and iterations in the PSO algorithm for consistently reaching the optimal solution.

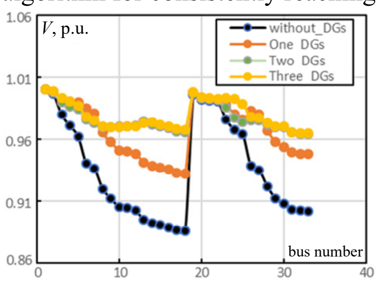

Fig. 8. Average voltage's buses during 24h in the 3 cases in addition to the basic case

Table 2
The results of statistical analysis

Statistical indices	Result
Minimum	0.291
Maximum	0.310
Mean	0.291
Standard deviation	0.003
Success rate (SR)	0.96

The PSO algorithm was chosen and preferred over the rest of the algorithms based on previous studies that outweighed it over the rest of the algorithms for many reasons, including the ease of understanding its work and the simplicity of the way it is based on it, in addition to that it can be suitable for large and complex networks and speed of convergence to the optimal solution.

Despite the many advantages of this algorithm, it can fall into the trap of local solutions. In this research, this study proposed to use a simple algebraic method to overcome this problem, which is the method of adjusting the algorithm parameters in a dynamic way so that it makes the algorithm strong in terms of exploration, exploitation and choosing the best global solution.

To ensure the effectiveness of the proposed method, a comparison was made between it and the regular PSO algorithm with fixed parameters in a statistical way.

To increase competition between the 2 methods, a few particles were used repeats to combine 3 DG units to observe the difference between the 2 methods and which of them can get closer to the optimal solution in light of the small number of particles and iterations (Table 3).

Table 3

Statistical result comparison of PSO and hybrid-dynamic PSO

Statistical indices	PSO result	Hybrid-dynamic PSO result
Minimum	0.351	0.291
Maximum	0.372	0.310
Mean	0.362	0.291
Standard deviation	0.012	0.003
Success rate (SR)	0.18	0.96

Figures 9, 10 show the convergence of the proposed hybrid-dynamic PSO algorithm, which is characterized by its ability to explore a good region of the search space in the early iterations, and quickly reach the optimal solution. Figures 9, 10 show a comparison between the performance of 2 algorithms for optimization of location and the optimal size of DG units in electrical distribution networks, based on the value of a MOF.

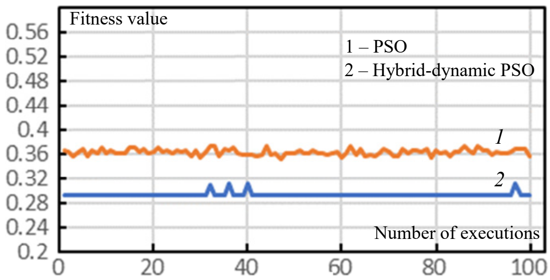

Fig. 9. The fluctuation of solutions across different executions

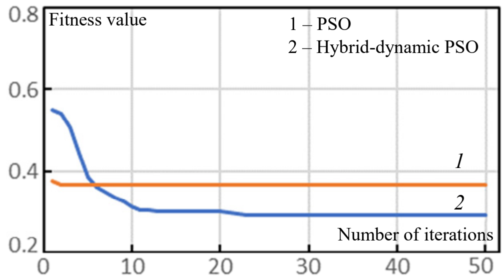

Fig. 10. The convergence of the solution to the optimal value along to iterations

By tracking objective function changes across a number of executions, the traditional PSO algorithm shows a continuous fluctuation in value, with results centered at relatively high levels (≈0.36), indicating poor stability and the likelihood of falling into local solutions without being able to improve them effectively. In contrast, the hybrid-dynamic PSO algorithm shows more stable performance, maintaining a relatively low value of the objective function (≈0.29) with a very limited number of sudden changes, indicating has a better ability to explore and converge towards the optimal solution. This superior performance demonstrates that the use of a hybrid-dynamic PSO algorithm contributes to improved search efficiency, reduced losses, and more reliable results in distribution network optimization applications.

In Table 4 the proposed methodology is compared with other methodologies, that using PSO algorithm to find the optimal location and size for DG. Note that when using more than 1 DG in different locations, it leads to an improvement in the results, as the 2nd case required injecting less power than the 1st case, and this led to improvements over the 1st case in terms of reducing total losses and improving voltage deviation and stability.

Table 4

Summary of the results obtained by following the proposed methodology

Number of DG	No DG	One DG	2 DG	3 DG
Best location of DG	–	Bus 6	Bus 13 Bus 30	Bus 14 Bus 24 Bus 30
Best capacity of DG, kW	–	3079.710@ Bus 6	1056.946@ Bus 13 1322.302@ Bus 30	957.925@ Bus 14 1262.393@ Bus 24 1231.201@ Bus 30
Total capacity of DG, kW	–	3079.710	2379.248	3451.519
Active energy loss, kW·h/day	7196.054	3799.023	2980	2506.591
Active energy loss reduction, %	–	0.472	0.586	0.652
Reactive energy loss, kVAr·h/day	2792.894	2794.019	2050	1750
Reactive energy loss reduction, %	–	0.4.28	0.582	0.642
Min voltage profile	0.8459	0.8959	0.9318	0.9337
Min voltage profile at bus no.	18	18	18	18
Min voltage profile at hour	9	9	9	9
Max voltage profile	0.9970	0.9989	0.9985	0.9991
Max voltage profile at bus no.	2	2	2	2
Max voltage profile at hour	23	23	23	23

*Note: the symbol «@» refers to the bus number that DG unit with right capacity should be connected to it

The results show that the integration of DG units in the distribution network contributes significantly to improving the performance of the system in terms of reducing electrical losses and improving voltage profiles. When only 1 DG unit was added, the active losses (P_{loss}) during 24 h decreased from 7196.054 kW·h/day to 3799.023 kW·h/day, achieving a reduction of 47.2 %. With the addition of 2 DG units, the P_{loss} during 24 h reduction rate improved to 58.6 %, while it reached 65.2 % when 3 DG units were used. As for reactive losses (Q_{loss}) during 24 h also a clear improvement is recorded, decreasing by 42.8 % with 1 DG unit, rising to 58.2 % and 64.2 % with 2 and 3 DG units respectively. On the other hand, the addition of DG units led to a clear improvement in the minimum voltage profile, with the lowest voltage rising from 0.8459 without DG units to 0.8959 with 1 unit, and reaching 0.9318 and 0.9337 with 2 and 3 units respectively, indicating enhanced voltage stability. Note that the lowest voltage value was fixed at bus 18 and 9AM, while the highest voltage value was achieved at bus 2 and 11PM across all scenarios. In addition, it is clear that increasing the number of DG units not only reduces overall losses, but also contributes to a more balanced load distribution across the network. With the use of a 1 DG unit, the entire power was concentrated in one location 3079.71 kW at bus 6, resulting in a significant improvement in performance, but the improvement was limited compared to multi-unit of DG. When 2 DG units were added, power injection capacities were distributed between bus 13 and bus 30, allowing for more effective reduction in losses, as losses were further reduced even though the total power injection capacity was less than the single capacity per unit. By integrating 3 DG units distributed over buses 14, 24 and 30 achieve a more uniform distribution of generation power capacities, which is clearly reflected in the improvement of loss and voltage profile. This highlights the importance of the spatial distribution of DG units and the optimal capacity of each unit, as the multi-point injected reduces long electrical paths that cause greater losses, and enhances voltage stability across the grid. Therefore, the use of more than one DG unit with optimal locations and sizes provides a more improvement that exceeds the improvement of a single unit with a large capacity concentrated, which effectively contributes to raising the efficiency of the network.

Future works. Dynamic planning requires consideration of a long time period to determine the optimal locations for DG. Other future work below:

1. *Island operation*. It is recommended to develop models for intentional island operation with the integration of energy storage systems.
2. *Improving optimization algorithms*. Improving the tuning of parameters of metaheuristic optimization algorithms such as PSO and GA to achieve greater efficiency.
3. *Achieving accuracy and computational efficiency*. In order to improve the accuracy of convergence and computational efficiency, hybrid techniques should be further studied by combining analytical methods, optimization algorithms, and computational methods.

Conclusions. This paper presents an effective method to optimize the allocation of DG units based on the variable daily load profile. The performance of this methodology was tested using the IEEE 33 Bus test system, where a set of scenarios covering different periods during the day were analyzed to study the effect of variable load on the selection of the best location and capacity for DG.

The locations and sizes of DG units were determined based on the lowest values resulting from a MOF, which helped improve the overall performance of the network. The results showed the effectiveness of the proposed approach in reducing overall system losses along hourly loads demand, as well as improving voltage levels at buses.

In this context, the hybrid-dynamic PSO algorithm was used to determine the optimal distribution of generating units. The results showed that this algorithm significantly reduced both active and reactive power losses compared to the traditional PSO algorithm. The hybrid algorithm also showed a higher ability to improve the lowest voltages in the grid.

In addition, the analyses showed that a significant reduction in total active power losses across all scenarios studied when using the hybrid method, compared to the decrease achieved when using the traditional algorithm. The same applied to reactive power losses, where the hybrid method showed significantly better results.

These results highlight the importance of the proposed approach based on the hybrid-dynamic PSO algorithm, especially in its ability to reduce losses and enhance voltage stability, making it a promising candidate for application in modern smart electricity grids that require flexibility and high dynamic response.

Acknowledgement. The authors would like to thank University of Mosul, College of Engineering, Electrical Department, for the support given during this work.

Conflict of interest. The authors declare that they have no conflicts of interest.

REFERENCES

1. Shaheen A.M., Elsayed A.M., Ginidi A.R., Elattar E.E., El-Sehiemy R.A. Effective Automation of Distribution Systems With Joint Integration of DGs/ SVCs Considering Reconfiguration Capability by Jellyfish Search Algorithm. *IEEE Access*, 2021, no. 9, pp. 92053-92069. doi: https://doi.org/10.1109/ACCESS.2021.3092337.

2. Shaheen A., Elsayed A., Ginidi A., El-Sehiemy R., Elattar E. Improved Heap-Based Optimizer for DG Allocation in Reconfigured Radial Feeder Distribution Systems. *IEEE Systems Journal*, 2022, vol. 16, no. 4, pp. 6371-6380. doi: https://doi.org/10.1109/JSYST.2021.3136778.

3. Srinivas D. Optimal Planning of Type-1DGs in EV Incorporated Radial Distribution Network. *International Journal on Recent and Innovation Trends in Computing and Communication*, 2024, vol. 11, no. 11, pp. 1152-1161. doi: https://doi.org/10.17762/ijritcc.v11i11.10675.

4. Othman R.A., Yehya Al-Yozbaky O.S.A.-D. Influence of reactive power compensation from PV systems on electrical grid. *International Journal of Power Electronics and Drive Systems (IJPEDS)*, 2023, vol. 14, no. 2, pp. 1172-1183. doi: https://doi.org/10.11591/ijpeds.v14.i2.pp1172-1183.

5. Shi Q., Li F., Kuruganti T., Olama M.M., Dong J., Wang X., Winstead C. Resilience-Oriented DG Siting and Sizing Considering Stochastic Scenario Reduction. *IEEE Transactions on Power Systems*, 2021, vol. 36, no. 4, pp. 3715-3727. doi: https://doi.org/10.1109/TPWRS.2020.3043874.

6. Yuvaraj T., Ravi K., Devabalaji K.R. Optimal Allocation of DG and DSTATCOM in Radial Distribution System Using Cuckoo Search Optimization Algorithm. *Modelling and Simulation in Engineering*, 2017, vol. 2017, art. no. 2857926. doi: https://doi.org/10.1155/2017/2857926.

7. Suresh M.C.V., Belwin E.J. Optimal DG placement for benefit maximization in distribution networks by using Dragonfly algorithm. *Renewables: Wind, Water, and Solar*, 2018, vol. 5, no. 1, art. no. 4. doi: https://doi.org/10.1186/s40807-018-0050-7.

8. Alajmi B.N., AlHajri M.F., Ahmed N.A., Abdelsalam I., Marei M.I. Multi-objective Optimization of Optimal Placement and Sizing of Distributed Generators in Distribution Networks. *IEEJ Transactions on Electrical and Electronic Engineering*, 2023, vol. 18, no. 6, pp. 817-833. doi: https://doi.org/10.1002/tee.23784.

9. Al-Kaoaz H.N.A., Al-Yozbaky O.S.A.Y. Influence of natural clouds on the performance of solar cell systems in Iraq. *Bulletin of Electrical Engineering and Informatics*, 2023, vol. 12, no. 4, pp. 1867-1880. doi: https://doi.org/10.11591/eei.v12i4.4703.

10. Li X., Jones G. Optimal Sizing, Location, and Assignment of Photovoltaic Distributed Generators with an Energy Storage System for Islanded Microgrids. *Energies*, 2022, vol. 15, no. 18, art. no. 6630. doi: https://doi.org/10.3390/en15186630.
11. Ntombela M., Musasa K., Leoaneka M.C. Power loss minimization and voltage profile improvement by distributed generation(DG) sizing and placement. *2022 IEEE PES/IAS PowerAfrica*, 2022, pp. 1-5. doi: https://doi.org/10.1109/PowerAfrica53997.2022.9905254.
12. Gopiya Naik S.N., Khatod D.K., Sharma M.P. Analytical approach for optimal siting and sizing of distributed generation in radial distribution networks. *IET Generation, Transmission & Distribution*, 2015, vol. 9, no. 3, pp. 209-220. doi: https://doi.org/10.1049/iet-gtd.2014.0603.
13. Rider M.J., López-Lezama J.M., Contreras J., Padilha-Feltrin A. Bilevel approach for optimal location and contract pricing of distributed generation in radial distribution systems using mixed-integer linear programming. *IET Generation, Transmission & Distribution*, 2013, vol. 7, no. 7, pp. 724-734. doi: https://doi.org/10.1049/iet-gtd.2012.0369.
14. Rocha L., Castro R., de Jesus J.M.F. An improved particle swarm optimization algorithm for optimal placement and sizing of STATCOM. *International Transactions on Electrical Energy Systems*, 2016, vol. 26, no. 4, pp. 825-840. doi: https://doi.org/10.1002/etep.2110.
15. Bhullar S., Ghosh S. Optimal Integration of Multi Distributed Generation Sources in Radial Distribution Networks Using a Hybrid Algorithm. *Energies*, 2018, vol. 11, no. 3, art. no. 628. doi: https://doi.org/10.3390/en11030628.
16. Gumus T.E. Thevenin equivalent based stability index for identifying optimal location of DGs by using HFPSO algorithm. *Measurement*, 2025, vol. 249, art. no. 116970. doi: https://doi.org/10.1016/j.measurement.2025.116970.
17. Saud M.N.M., Rasid M.M. Adaptive hybrid differential evolution particle swarm optimization algorithm for optimization distributed generation in distribution networks. *Jurnal Teknologi*, 2025, vol. 87, no. 2, pp. 203-216. doi: https://doi.org/10.11113/jurnalteknologi.v87.19769.
18. Cikan M., Cikan N.N., Kekezoglu B. Determination of optimal island regions with simultaneous DG allocation and reconfiguration in power distribution networks. *IET Renewable Power Generation*, 2025, vol. 19, no. 1, art. no. e12942. doi: https://doi.org/10.1049/rpg2.12942.
19. Hidayat R., Lomi A., Budi Sulistiawati I. Implementasi Metode Artificial Bee Colony Untuk Penempatan Distributed Generator Pada Penyulang Rayon Tanjung. *Jurnal JEETech*, 2024, vol. 5, no. 2, pp. 113-125. (Id). doi: https://doi.org/10.32492/jeetech.v5i2.5202.
20. Hadjidj N., Benbrahim M., Ounnas D., Mouss L.H. Global maximum power point tracking method for photovoltaic systems using Takagi-Sugeno fuzzy models and ANFIS approach. *Electrical Engineering & Electromechanics*, 2025, no. 2, pp. 31-38. doi: https://doi.org/10.20998/2074-272X.2025.2.05.
21. Meena N.K., Swarnkar A., Gupta N., Niazi K.R. Multi-objective Taguchi approach for optimal DG integration in distribution systems. *IET Generation, Transmission & Distribution*, 2017, vol. 11, no. 9, pp. 2418-2428. doi: https://doi.org/10.1049/iet-gtd.2016.2126.
22. Jena S., Mishra A., Rastogi V. Network Topology Based Back/Forward Sweeping for Load Flow of Radial Distribution Systems. *International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering*, 2014, vol. 3, no. 11, pp. 12914-12920. doi: https://doi.org/10.15662/ijareeie.2014.0311018.
23. Nageswari D., Kalaiarasi N., Geethamahalakshmi G. Optimal Placement and Sizing of Distributed Generation Using Metaheuristic Algorithm. *Computer Systems Science and Engineering*, 2022, vol. 41, no. 2, pp. 493-509. doi: https://doi.org/10.32604/csse.2022.020539.
24. Bajaj M., Singh A.K., Alowaidi M., Sharma N.K., Sharma S.K., Mishra S. Power Quality Assessment of Distorted Distribution Networks Incorporating Renewable Distributed Generation Systems Based on the Analytic Hierarchy Process. *IEEE Access*, 2020, vol. 8, pp. 145713-145737. doi: https://doi.org/10.1109/ACCESS.2020.3014288.
25. Han Z., Li J., Wang Q., Lu H., Xu S., Zheng W., Zhang Z. Deep learning-aided joint DG-substation siting and sizing in distribution network stochastic expansion planning. *Frontiers in Energy Research*, 2023, vol. 10, art. no. 1089921. doi: https://doi.org/10.3389/fenrg.2022.1089921.
26. Labed M.A., Zellagui M., Benidir M., Sekhane H., Tebbakh N. Optimal hybrid photovoltaic distributed generation and distribution static synchronous compensators planning to minimize active power losses using adaptive acceleration coefficients particle swarm optimization algorithms. *Electrical Engineering & Electromechanics*, 2023, no. 6, pp. 84-90. doi: https://doi.org/10.20998/2074-272X.2023.6.15.
27. Abbas A., Qaisar S.M., Waqar A., Ullah N., Al Ahmadi A.A. Min-Max Regret-Based Approach for Sizing and Placement of DGs in Distribution System under a 24 h Load Horizon. *Energies*, 2022, vol. 15, no. 10, art. no. 3701. doi: https://doi.org/10.3390/en15103701.
28. Akbar M.I., Kazmi S.A.A., Alrumayh O., Khan Z.A., Altamimi A., Malik M.M. A Novel Hybrid Optimization-Based Algorithm for the Single and Multi-Objective Achievement With Optimal DG Allocations in Distribution Networks. *IEEE Access*, 2022, vol. 10, pp. 25669-25687. doi: https://doi.org/10.1109/ACCESS.2022.3155484.

Received 04.05.2025
Accepted 12.07.2025
Published 02.11.2025

S.S. Sabry [1], *MSc, Student,*
O.Sh. Al-Yozbaky [1], *PhD, Associate Professor,*
[1] Department of Electrical Engineering,
College of Engineering, University of Mosul, Iraq,
e-mail: sayf.23enp22@student.uomosul.edu.iq;
o.yehya@uomosul.edu.iq (Corresponding Author)

How to cite this article:
Sabry S.S., Al-Yozbaky O.Sh. Enhanced siting and sizing of distributed generation in radial distribution networks under load demand uncertainty using a hybrid metaheuristic framework. *Electrical Engineering & Electromechanics*, 2025, no. 6, pp. 84-92. doi: https://doi.org/10.20998/2074-272X.2025.6.11