Received: 3 April 2023 | Revised: 18 July 2023 | Accepted: 27 July 2023

IET Renewable Power Generation

DOI: 10.1049/rpg2.12815

The Institution of Engineering and Technology WILEY

REVIEW

A comprehensive review of recent advances in optimal allocation methods for distributed renewable generation

Said Mirza Tercan[1] | Alpaslan Demirci[1] | Yesim Esra Unutmaz[2] | Onur Elma[3] | Recep Yumurtaci[1]

[1]Department of Electrical Engineering, Yildiz Technical University, Istanbul, Turkey

[2]Electric Department, Eti Bakir AS, Samsun, Turkey

[3]Department of Electrical and Electronics Engineering, Canakkale Onsekiz Mart University, Canakkale, Turkey

Correspondence
Dr. Said Mirza Tercan, Department of Electrical Engineering, Yildiz Technical University, Istanbul, Turkey.
Email: stercan@yildiz.edu.tr

Abstract

Distributed generation (DG) has a key role in enlarging the implementation of renewable energy resources (RES). However, the intermittent and uncontrollable nature of RES can lead to several severe power quality-related issues. Therefore, many efforts have been made to overcome these issues by optimizing DG sizes and locations. Hence, optimal DG allocation (ODGA) is significant for DG performance and provides advantages to the power system, such as improved power quality, voltage stability, reliability, and profitability. This study reviews recent ODGA studies eliminating the main DG integration problems. Often used ODGA methods have been categorized, and the main differences have been discussed, giving the details of features of optimization methods such as convergence performance and computational burden. A deep analysis for categorizing the objectives of ODGA has been done. In addition, optimization methods applied in ODGA studies have been presented by comparing the superiorities of algorithms and validated test network models. The objectives and significant findings of the ODGA applications are summarized with the advantages and disadvantages. It can be concluded that ODGA has a critical role in RES integration on the DG side and in reducing carbon emissions. This paper leads and provides a perspective for researchers working on recent ODGA methods.

1 | INTRODUCTION

The rapid increase in energy demands by the development of technology makes achieving sustainable energy and environmental targets difficult. The problems of conventional large and central power plants, such as distance to consumption areas, low efficiency, the sensitivity of unit energy cost against raw material price, and high CO_2 emission, increase the tendency towards alternative energy sources. Unlike traditional centralized generation, distributed generation (DG) means that consumers' power demands are met by their generation or nearby small generation units [1]. DG covers various local power generation units, which can be both renewable and conventional, as seen in Figure 1. DGs' optimum selection, sizing, and placement can benefit the economic, technical, and environmental power systems [2]. These benefits have led to a rapid trend towards alternative energy sources such as wind, solar, biomass [3], hydrogen, and wave [4]. Energy storage systems (ESSs) can also improve DGs supporting power quality, such as capacity firming and load following. Therefore, optimal DG allocation (ODGA) studies cover various energy sources and communication technologies to elevate the overall power quality and flexibility and reduce emissions, as seen in Figure 2. It is predicted that the prevalence of DG will increase even more with the instantly developing smart grid concept in recent years [5–7]. Thus, it is evident that this topic remains an interesting area of research. This paper contributes a new comparison perspective for DG studies and compares each proposed method in the reference studies. Also, the related ODGA studies' main points have allowed readers and researchers to quickly and broadly perceive optimum DG implementations such as integration, allocation, and grid effects. Besides, multi objectives, including DG's environmental, technical, and economic benefits, have enhanced the solutions of ODGA in terms of emissions, power losses, and total energy generation costs simultaneously. Modified or hybrid metaheuristic methods have been presented to

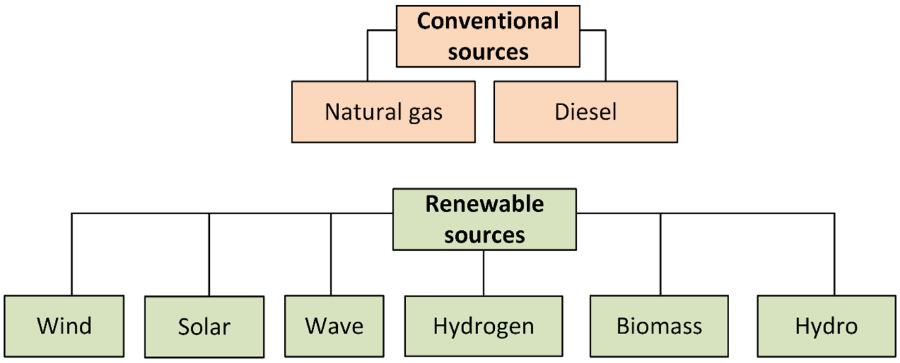

FIGURE 1 Distributed generation sources

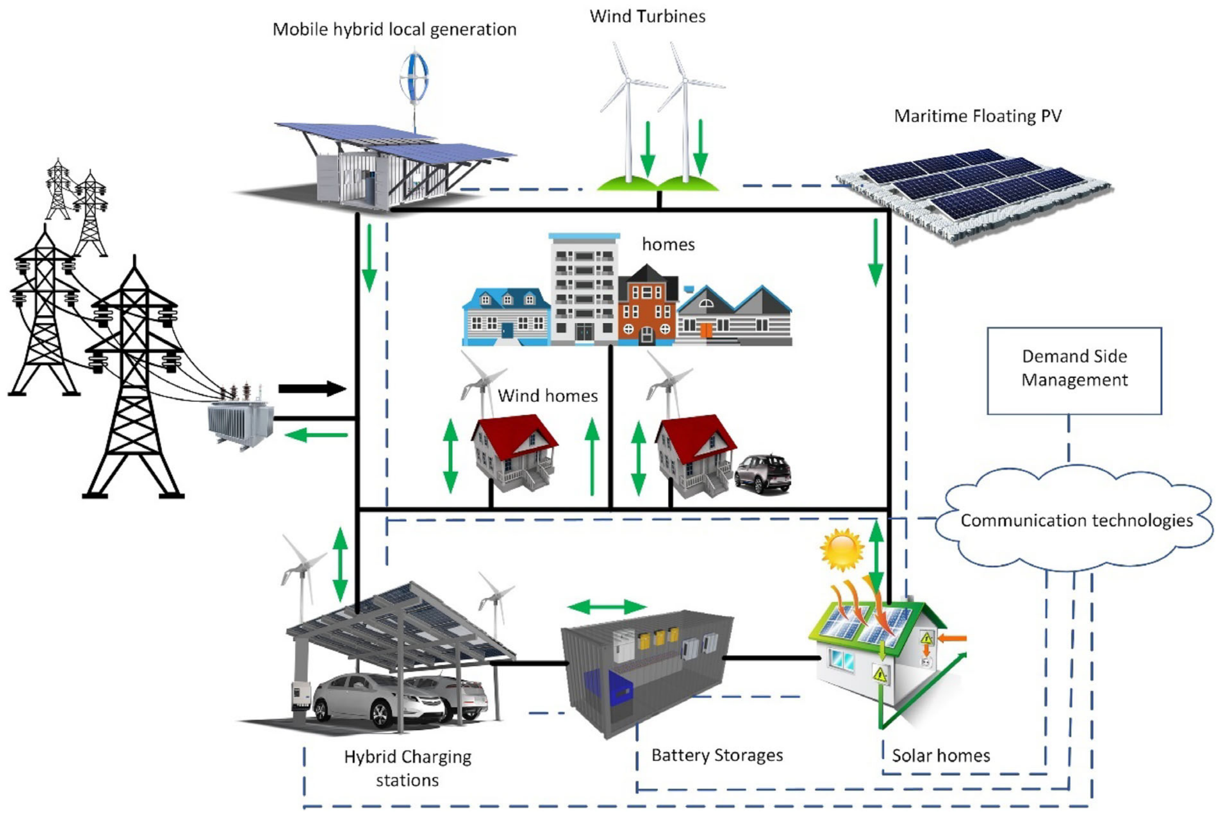

FIGURE 2 DG integration overview

eliminate the main challenges like weak convergence performance, falling into local maxima, and computational burden. This paper also collects several real DN networks and widely used test feeders' data.

1.1 | The purpose of DG integration and allocation

Due to renewable energy's intermittent and uncontrollable nature, installation points and the size of RES power plants must be carefully determined to integrate into DN in ODGA studies. ODGA incorporates DG and RES to increase power system (PS) dependability, sustainability, and efficiency [8]. ODGA may improve voltage stability [9], reliability [10], and DN loading ability [11] and reduce power losses and harmonic distortion [12]. Besides, ODGA can reduce unit energy cost and peak loading [13] and defer the distribution expansion [14] and infrastructure upgrade investment [15]. However, improper allocation of DG may cause protection equipment to malfunction and reverse the benefits due to the increase of short circuit current [16, 17].

Also, DG may effectively increase the stability and energy quality and provide the opportunity for generation by many

TABLE 1 Different DG capacities

DG size	Customer profile	Capacity
Micro	Residential, commercial	1–5000 W
Small	Residential, commercial, industrial	5–5000 kW
Medium		5–50 MW
Large		50–300 MW

environmentally friendly energy sources [11]. DG sizes vary from a few kW to hundreds of MW. Also, DG can respond to the power demands of various consumer types, such as residential, commercial, and industrial, allowing bidirectional power flow between the grid and DG. Therefore, several ODGA studies have determined the optimum DG location, size, and unit quantity, considering the power loss, voltage profile, and short circuit level for residential, commercial, and industrial load models (LMs) given in Table 1 [18, 19].

Examples of the main application scenarios of ODGA can be given through the main topics in the fields that are popular studies today. One is a microgrid, a compact electrical network that may run apart from or in combination with the primary power grid. Microgrids may optimize the distribution of DG resources like solar panels, wind turbines, and energy storage devices by applying ODGA approaches. ODGA enables microgrids to boost resilience, decrease reliance on the primary grid, and increase the incorporation of RES. RES integration is another use of ODGA. ODGA is necessary for effective integration as the power system's proportion of RES rises. The ODGA can choose the best sites for DGs by considering generation capacity, variability of RES, and grid infrastructure. ODGA makes it possible to use renewable energy more effectively and reduces the demand for long-distance transmission, leading to a more robust and sustainable power grid. Additionally, by allowing the integration of dispersed generation resources into urban settings, ODGA can aid in the growth of smart cities. The ODGA can optimize the location and scale of DGs, such as rooftop solar panels, within metropolitan regions by examining energy consumption trends, load profiles, and geographical data, encouraging local energy production, lowering transmission losses, and improving overall city energy efficiency. Moreover, ODGA may be used to find the best location for DG resources for rural electrification initiatives in regions with restricted access to the main power grid. The ODGA can assist in determining the most effective and economical design of DGs by examining energy demand, resource availability (solar potential), and infrastructural restrictions for supplying rural areas with dependable and sustainable electricity. ODGA techniques can be employed in emergency power planning scenarios. For example, in the aftermath of a natural disaster or a grid failure, ODGA can assist in identifying critical facilities or areas that require an immediate power supply. By strategically allocating DG resources, emergency response teams can restore electricity timely and efficiently, ensuring essential services are operational. Overall, ODGA offers different options and solutions to maximize the distribution of DG resources in various situations, from smart cities and the integration of renewable energy to microgrids and rural electrification. Decision-makers may improve system performance, boost resilience, and encourage the adoption of sustainable energy solutions by utilizing ODGA methodologies.

1.2 | Basic optimal power flow calculation for ODGA

Things to consider for DG integration are purpose, location, rating, power delivery area, technology, environmental impact, mode of operation, ownership, and penetration rate [20]. Many studies are carried out to make this correct and feasible integration decision specified as to be made with the calculations before integration of DG to DN. DG integration studies determine the most suitable location and size in coordination with the distribution system operator (DSO), considering access to energy sources and climatic conditions [21]. ODGA examinations use multi-purpose functions that may include different goals and constraints [22]. ODGA is calculated by considering the load and power factor variations and the voltage, especially radial DN (RDN) [23]. The optimally sized DG increases the power quality while reducing the energy cost of the prosumer. The effects of different load types are investigated with multi-purpose ODGA approaches [24, 25].

Microgrid planning by optimization techniques can enhance the overall performance of PS [26], such as reliability [27] and optimal power flow (OPF) [28]. The suggested optimization algorithm indicated that the reliability was increased by 23.92% after system typology adjustment [29]. ODGA may be considered an OPF problem with non-linear operation variables and constraints. The OPF may determine the economic operation conditions of PS considering generation costs, system models, and load profiles without hampering system safety [30]. It also determines distributed renewable generation (DRG) allocation by optimizing the energy losses. It may also minimize the total active power loss through reactive power control [31].

Moreover, the economic applicability between energy losses and generation capacity can also be determined. For instance, a new OPF method for determining DG size was suggested by including voltage constraints in the load flow solution to determine the effect of voltage level and network connectivity capacity [32]. Solutions are presented to minimize power and energy losses using OPF and embedded smart grid-based approaches [33]. Extra advantages may be obtained by including the technologies such as power factor, voltage control, and online loss follow-up and management in OPF equations of DG control schemes which are expected to be a part of the smart grid [7]. Three-phase AC power flow equations are given in Equations 1–6, including an energy storage system (ESS).

$$P_{G_{i,t}} - P_{D_{i,t}} - P^{ch}_{ESS_{b,t}} = \sum_{j=1}^{N} V_{i,t}.V_{j,t}.Y_{ij} . \cos\left(\theta_{ij} + \delta_{j,t} - \delta_{i,t}\right) \forall i, j, t, b \quad (1)$$

$$P_{G_{i,t}} - P_{D_{i,t}} + P^{dis}_{ESS_{b,t}} = \sum_{j=1}^{N} V_{i,t}.V_{j,t}.Y_{ij} .\cos\left(\theta_{ij} + \delta_{j,t} - \delta_{i,t}\right) \ \ \forall i, j, t, b \tag{2}$$

$$Q_{G_{i,t}} - Q_{D_{i,t}} = -\sum_{j=1}^{N} V_{i,t}.V_{j,t}.Y_{ij}.\sin\left(\theta_{ij} + \delta_{j,t} - \delta_{i,t}\right) \ \forall i, j, t \tag{3}$$

$$I_{ij,t} = \left|Y_{ij}\right| .\left[V_{i,t}^2 + V_{j,t}^2 - 2.V_{i,t}.V_{j,t}.\cos(\delta_{j,t} - \delta_{i,t})\right]^{1/2} \ \forall i, j, t \tag{4}$$

$$P_{loss} = \sum_{j=1}^{N} I_{ij}^2.r_{ij} \tag{5}$$

$$V_{min} \leq V_{i,t} \leq V_{max}, \ \forall \ i, t \tag{6}$$

Equation (1) determines active power flow while ESS is charging where $P_{G_{i,t}}$ and $P_{D_{i,t}}$ are generated and demand active power at bus i, at time t, respectively. Equation (2) also determines active power flow while ESS is discharging. Equation (3) defines the reactive power balance where $Q_{G_{i,t}}$ and $Q_{D_{i,t}}$ are generated and desired reactive power generated at bus i, at time t. Equation (4) defines the line current from bus i to bus j through lines where $V_{i,t}$ and $\delta_{i,t}$ are magnitude and angle of the voltage of bus i at time t. Y_{ij} and θ_{ij} are magnitude and angle of the admittance of bus between i and j. Equation (5) calculates the total active power losses in all lines. Equation (6) is the voltage constraint widely used in DN stability. Slack bus voltage and angle are equal to $V_{i,t} = 1, \ \delta_{i,t} = 0°$. If there is no battery, $P^{ch}_{ESS_{b,t}}$ and $P^{dis}_{ESS_{b,t}}$ are equal to "0" where b denotes the set of ESS units.

1.3 | Main challenges associated with integrating RES into DG

The installation of DG on conventional networks has many effects on system parameters. For example, contrary to conventional power plants, some changes occur in energy generation in terms of continuity, stability, and voltage profiles by integrating DGs into the system [34]. In addition, power quality problems can occur due to changes in network topology as the number of DGs increases. The main challenges were examined: reverse power flow, harmonic formation, changing short circuit currents, flicker, and losses [35]. The effects of DG on active-reactive power flow and voltage regulation in DN are given in Figure 3.

DG can decrease loadings on distribution and transmission systems depending on location and interruptions due to overloading, equipment aging, and power losses. However, the unidirectional power flow in conventional energy systems has been turned into a bidirectional power flow after integrating DRGs. Bidirectional power flow can cause varying power generation, high short circuit current, and undesired voltage increase [36]. The increased DG number and size on the network increases the reverse power flow that negatively affects the coordination of protection relays adjusted and designed according to unidirectional power flow. For instance, relays' fault current and tripping time settings affected by bidirectional power flow may cause incorrect protection or longer interruptions [37]. Providing proper and sufficient protection requires optimizing the settings of relays according to variable fault current levels to prevent unwanted interruptions and operate the relays without delay [38]. Short circuits are the leading problem causing the most significant effect on electrical networks. A short circuit on the transmission network may cause the disconnection of numerous DG units resulting in damaging incidents such as voltage sag [39]. Hence, properly performing the short circuit analyses for every integrated DG is required to examine the negative effects of failure. Before DG integration, the protection equipment should be selected by checking the short circuit resistance capacity and power transmission distances of lines and busbars through short circuit analyses [40]. Besides, islanding as the result of short circuits should be managed by controlling the safety of life and the system against the hazards in cases of controlled islanding [41, 42]. DG causes flickers and harmonics during power generation and distribution using renewable energy sources. The harmonics disrupt the quality of energy due to the use of high-powered nonlinear converters during energy dispatch. In addition, DG engagements or disengagements change the equivalent impedance of DN and may form new harmonics due to the resonance frequency change [43]. Compensation reduces reactive power flow from DN to the loads generating required reactive power for loads at its location. Therefore, it increases economic and technical benefits by increasing lines' current carrying capacity and minimizing power losses. However, integrating DGs requires re-planning or dynamically controlling the current compensation system for the changing reactive power demand [44, 45]. DN voltages both at the points of generation and connection of DG decrease or increase due to improper selections of DG size and site, tie lines cross-section, and the number of parallel units. However, DG integration with a high penetration rate was performed without disrupting the voltage stability [46]. It was suggested to increase the voltage stability by integrating PV into the network along with ESS. In addition, it was intended to improve the load factor by reserve energy offers in cases of supply and demand-side management [47, 48]. Voltage stability should be examined in detail while integrating DG, micro source, ESS, and inverter controls into the current microgrid structure [49]. It is possible to eliminate DG-oriented voltage instabilities by planning the total electrical load demand within DN [50] and improving the resiliency against natural events [51].

ODGA considers various factors such as load demand, available renewable resources, network constraints, and economic considerations to identify the best locations and capacities for RES integration. In this way, ODGA can ensure efficient utilization of RES and minimize the impact on the existing grid infrastructure. The intermittent nature of renewable energy sources like solar and wind leads to fluctuations and

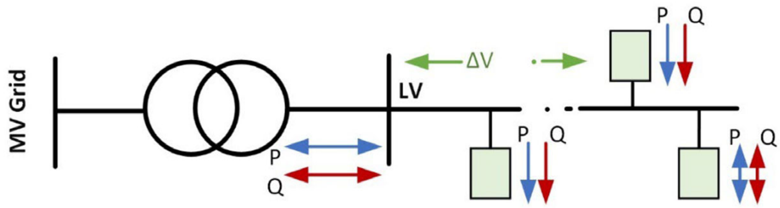

FIGURE 3 The impacts of bidirectional power flow of DG on DN

uncertainties [52]. ODGA balances the generation and demand to mitigate grid instability issues for smooth integration and maintaining power quality and reliability. ODGA identifies RES's optimal locations and capacities to maintain voltage levels within acceptable limits and manage power flows effectively. Additionally, ODGA offers opportunities for energy cost savings, such as reducing transmission and distribution losses and avoiding peak demand charges. Therefore, ODGA helps minimize the required upgrade costs for infrastructure and transmission capacity enhancements. Thus, ODGA promotes the economic viability of integrating RES into DG systems. Furthermore, it enables decision-makers to evaluate the optimal scale-up of DG by optimizing resource allocation, ensuring grid stability, managing voltage regulation and power flows, promoting cost-effectiveness, and facilitating scalability and future planning.

2 | OPTIMIZATION METHODS FOR DG INTEGRATION

Several key factors influence the optimal size and location of DG units in a power system. These factors are considered during the ODGA process to determine the most effective configuration. The load profile and electricity demand patterns are crucial in determining the optimal size and location of DG units. ODGA typically places DG units near buses with high distribution system losses to reduce losses, improve voltage profiles and increase overall system efficiency. According to the area width to accommodate the DG, the availability of RES, such as solar, wind, or hydropower, affects ODGA regarding optimal size and location. Also, line and transformer loadings and network topology are considered in determining the optimal size and location of DG units. ODGA should consider voltage limits, thermal limits, and power flow constraints to maintain system stability during both normal and abnormal operating conditions. Besides, cost-benefit analysis is often performed in ODGA to achieve the best economic feasibility, considering investment, operation, and maintenance costs. Since ODGA generally aims to minimize environmental impacts and promote sustainability, environmental impacts are evaluated in terms of emissions reduction and carbon footprint.

Several reviews have reported many methods to solve ODGA problems, categorizing analytical techniques, metaheuristic algorithms (MAs), and hybrid optimization methods, as seen in Figure 4. The main purposes of optimization algorithms in power systems are the minimization of generation costs [53], power losses [54], and greenhouse gas emissions

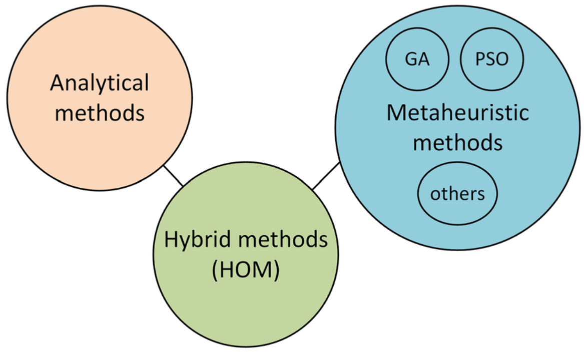

FIGURE 4 The map of ODGA methods

[55]. ODGA for DN is a nonlinear optimization problem. The solution to these problems with traditional methods converges slowly due to many iterations. Easily applicable analytic methods are often unable to find the optimum solution because they are based on simplified assumptions. According to analytic methods, heuristic and metaheuristic approaches provide more suitable and simple solutions, especially in complex problems [56]. Numerical methods are transformed into a simplified optimization problem using objective functions and heuristic algorithms' constraints. Evolutionary algorithms try to properly solve large, complex, and multi-purpose problems [35]. However, heuristic algorithms in solving optimization problems cannot guarantee the global optimum solution due to many iterations and algorithm parameters [57, 58].

The optimization practices on power systems were examined in the following sections under different headings as analytic techniques and heuristic optimization algorithms. Optimal allocation essentially consists of objective functions and constraints. These objectives are formed considering technical and economic criteria such as loss or cost minimization and voltage improvement. An example of an objective function used in ODGA is given in Equation (7). ODGA minimizes or maximizes single or multiple objective function $f(x)$ subject to M numbers of inequality and N numbers of equality constraints in Equations (8) and (9). Constraints include active and reactive power balance, DG generation capacity, bus voltage and line thermal limits, and environmental limitations.

$$f\ (x) = \begin{cases} total\ \ power\ loss \\ voltage\ stability \\ total\ \ cost \\ \ldots \end{cases} \tag{7}$$

$$g(x) \leq \begin{cases} g_1(x) \\ g_2(x) \\ \ldots \\ g_m(x) \end{cases}, \forall x \in M \tag{8}$$

$$h\ (x) = \begin{cases} h_1(x) \\ h_2(x) \\ \ldots \\ h_n(x) \end{cases}, \forall x \in N \tag{9}$$

2.1 | Analytical techniques for optimal distributed generation allocations

An examined problem in analytic approaches is modelled generally by a numerical equation. The accuracy of the optimization method depends on the developed model. The analytical solutions may be obtained using other models, theoretical calculations, and mathematical analyses [59]. These methods provide the solution's convergence and ease of calculation time and application. The suitability of DRG planning is analyzed by comparing the analytic techniques regarding optimization criteria [60]. The capacity and location of possible DGs connected to DN are examined to find the most suitable voltage increase or power loss solution. Thus, the most suitable DG capacity is obtained by technical constraints. Comprehensive studies evaluate the improved analytic techniques regarding optimal DRG planning [61]. An analytic analysis uses linear and nonlinear programming methods per the problem's type. Linear programming (LP) is an optimization method seeking a solution using the linearized power flow form [62]. In this analysis, nonlinear functions or incidents are modelled like linear functions. For instance, the operation strategy for DG that intends minimum energy consumption during the year was solved using GAMS (general algebraic modelling system) as being optimized with MILP (mixed-integer linear programming). The optimized strategy provided 11.8% energy saving [58]. In addition, some optimization problems may be challenging to solve using MILP as the computational load increases due to increased complexity and variables in the system [63]. If objective functions and constraints are not linear, and the variables in the mathematical model required to be solved are continuous and discrete, mostly used programming is called MINP (mixed-integer nonlinear programming) (e.g. power balance and cost). It was determined that the most suitable methods for solving the placement and sizing problem in DRG integration are LP and MINP [55]. In another study, it was specified that the most frequently used and most efficient techniques and algorithms for the ODGA problem are NLP (nonlinear programming), SQP (sequential quadratic programming), and OO (ordinal optimization) [21].

2.2 | Metaheuristic algorithms in ODGA

Meta means beyond or higher level; heuristic means discovering through testing or empirical observation. The metaheuristic method is an iterative process directing the information to a heuristic search converging to an optimal solution by combining different concepts. Complex and dissociated technical and non-technical problems are modelled and involved in the PS optimization process [62]. Heuristic methods find the most suitable solution by the least number of calculations. Metaheuristic methods can combine more than one heuristic method. For instance, bio-inspired metaheuristic classifications frequently use evolutionary and swarm algorithms [29]. Contrary to mathematical programming, the accuracy of the suggested global optimum by MAs should be checked because the results are approximate and probabilistic [63, 64].

The superiority of a particular optimization algorithm depends on various factors, including problem characteristics, algorithm design, parameter tuning, and computational resources. Most MAs may have strengths and weaknesses based on specific problem requirements. The most suitable algorithm should be selected based on carefully comparing the characteristics of the algorithm and the problem.

GA and PSO have been mentioned earlier since they are the mostly used meta-heuristic methods. The stochastic nature of GA introduces randomness that encourages search space exploration. Some MAs may give a single solution, which can limit their exploration capability. Since GA and PSO can balance exploration and exploitation, effectively exploring and converging for global optima while avoiding premature convergence to local optima. GA and PSO can be applied to various problems, including engineering, finance, and artificial intelligence. A few parameters and easier configuration allow PSO simple and easy implementation. MAs may be more sensitive to noisy environments and require additional modifications or adaptations. Parallelization of GA and PSO allows faster convergence and reduced computational time. Unlike gradient-based optimization methods that require the computation of derivatives, GA does not rely on derivatives, which makes GA suitable for problems where derivatives are difficult to compute or unavailable. Genetic operators, such as crossover and mutation, help GA explore multiple good solutions in a wide range. The iterative evolution process allows GA to handle dynamic optimization problems more effectively than other MAs. Metaheuristic Algorithms have been categorized in Table 2.

2.2.1 | Genetic algorithm (GA)

John Holland presented GA in 1960, then extended by his student David E. Goldberg in 1989 [65]. GA is an algorithm technique formed considering the evolution mechanism

TABLE 2 Metaheuristic algorithms

Bio-inspired	Physics-based	Swarm-based	Evolution-based
Firefly algorithm (FA)	Gravitational search algorithm (GSA)	Particle Swarm Optimization (PSO)	Genetic algorithm (GA)
Cuckoo search algorithm (CSA)	Simulated annealing (SA)	Artificial bee colony optimization (ABCO)	Differential evolution (DE)
Bat algorithm (BA)	Charged system search (CSS)	Spotted hyena optimizer (SHO)	Biogeography-based optimization (BBO)
Bacteria foraging algorithm (BFA)	Tabu search (TS)	Artificial bee colony optimization (ABCO)	Evolutionary strategy (ES)
Sunflower optimization algorithm (SOA)	Teaching-learning based ABCO (TLABCO)	Coyote optimization algorithm (COA)	
Antlion optimization algorithm (AOA)		Grey wolf optimization (GWO)	
Shuffled frog-leaping algorithm (SFLA)		Whale optimization algorithm (WOA)	
Grasshopper optimization algorithm (GOA)		Elephant herding optimization (EHO)	
Chimp optimization algorithm (ChOA)		Harris hawk optimization (HHO)	
		Cat swarm optimization (CSO)	
		Salp swarm algorithm (SSA)	

in nature. GA seeks optimal solutions to a complex problem by natural selection methods starting with more than one individual. GA works with a group of individuals in which each individual reflects a different solution [57]. A random candidate solution set, namely population, is formed considering the number of variables in the fitness function. It is directed to a better solution by applying genetic operators such as mutation and crossing. The purpose is to find the best solution by eliminating the poor solutions. The suitability of new solutions generated and genetically improved using the objective function is evaluated. The optimization process is terminated when the appropriate solution or the maximum number of iterations is reached. New populations are generated if a suitable solution is found [17]. Powerful search algorithm features make GA the most preferable among traditional algorithms [66]. Therefore, it is seen that the methods proposed in many ODGA studies that sought a solution using GA yield more appropriate results than the others [65]. For instance, ODGA was performed using GA to minimize power losses and improve the voltage profile in RDN [67]. The effect of load patterns on ODGA was investigated by GA using 16 and 37-bus RDN models [25]. DG location and contract pricing were examined using a GA-based approach using IEEE–34 and IEEE–85 DN test systems [68]. In addition, optimum TMS and PCS values were investigated to solve the relay coordination problem considering the increase in the number of DGs with GA [17] and FA (Firefly Algorithm) [69]. ODGA studies performed as per different objective functions are available in Table 3.

2.2.2 | Particle swarm optimization (PSO)

PSO is a population-based optimization algorithm developed by Kennedy and Eberhart in 1995 as inspired by fish training and social behaviours of wisps to optimize multi-dimensional problems [70, 71]. It is a field search algorithm in which randomly generated individuals called particles change their positions [72]. In PSO, while moving in a multi-dimensional search area, the particles proceed toward the best location per their own experiences and the neighbouring particles' experiences [2]. Each particle moves in a D-dimensional search universe with a random speed. While calculating the updated location of the particles according to the new velocity value, the operation continues until reaching the minimum error [16]. The PSO is easy to implement, as the velocities and positions of the particles are updated in equations, and there are only a few parameters to set. [72, 73]. Particles are moved in the search area along with restrictions by assigning velocity to each particle. Each particle is assessed in conformity with the local solution obtained from the objective function [74]. PSO is widely used as a hybrid with heuristic methods such as artificial neural networks (ANN), GA, and evolutionary programming (EP). Because the local and global optimum calculated at each iteration gives a potential to find the optimum solution to PSO [75]. Solutions in EP begin searching for the most optimum with random populations. PSO generally requires fewer parameters than GA [71]. For example, it does not require evolutionary parameters such as mutation or crossing. Global optimum solutions may be obtained rapidly using particles (potential solutions) [31]. The solution time of PSO is shorter than GA, and it can be implemented easily for related problems [49]. It is evident that evolutionary PSO (EPSO) offers a faster and superior solution for RDN compared to traditional PSO. Moreover, the versatility and simple applicability of using the PSO algorithm to calculate DG units OPF with Newton–Raphson (NR) seems to converge well in the performed studies [76]. The objective function, which minimizes the total cost of the power produced by the DG units with the DN active management, provides the optimal energy distribution among the DGs [31]. The single and multiple ODGA objective functions and algorithms were compared to decrease the total system losses, operating costs, and voltage fluctuations of RDN. It was observed that while PSO

TABLE 3 Categories of the recent ODGA studies

#	Category	HOM	Objectives	Findings	Ref.
1	ODGA	Single PSO	Minimizing the active power loss	Losses were decreased, and optimal sizing was realized	[74]
2	ODGA	Single WOA	Balancing the voltage profile and minimizing the power loss	Power losses were decreased, and the voltage profile was improved	[22]
3	ODGA	Hybrid PSO, ANN	Finding the optimum cost of loss and power generation	The suggested method is helpful in DG sizing and load dispatch to minimize the loss in the planned and real-time operation of DN	[71]
4	ODGA	Single CSO, PCSO	Decreasing the total production cost, power losses, and emissions, and improving the voltage stability	Optimum size and location were found through superior performance of the CSO algorithm compared to parallel CSO	[54]
5	ODGA	Single GWO, PSO	Restructuring the system by DG	Active and reactive power loss was decreased, and the voltage profile was improved	[110]
6	ODGA	Single EHO	considering the short circuit level	Overloading, unbalancing voltage, active and reactive Power losses, and energy production costs were decreased.	[56]
7	ODGA	Hybrid GWO, DE	Minimizing the power loss	Power loss decreased with better performance than other metaheuristic methods, and the voltage profile was improved.	[64]
8	ODGA	Single EHO	Minimizing the active power losses by safety constraints and improving the voltage stability	Active power loss was decreased, and voltage stability was increased	[65]
9	ODGA	Single PSO	Reducing the loss and improving the voltage profile	Better results and performance of PSO were indicated	[113]
10	Multi ODGA	Single PSO	Improving the voltage and minimizing power loss	Losses were decreased, and the voltage profile was improved	[114]
11	Multi ODGA	Single PSO	Increasing the voltage stability and minimizing the power losses	The voltage stability was improved, and losses were decreased effectively.	[115]
12	Multi ODGA	Single GA	Improving power loss reduction, voltage profile, and short circuit level	The efficiency of the method was verified considering the required objectives, including the decrease of power losses and improvement of the voltage profile	[19]
13	Multi ODGA	Single AOA	Increasing the voltage stability and renewable energy share, minimizing the active power loss and installation cost	The suggested method was found to be more compatible with the current engineering practices that may improve the operation status of DN and the stability of the system.	[45]
14	Multi ODGA	Single FA, GA	Finding the optimum TMS and PCS values as per variable fault currents and line impedances	The new TMS (Time Multiplier Setting) and PCS (Pickup Current Setting) values were found for all the configurations.	[17]
15	Multi ODGA	Hybrid SFLA, DE	Decreasing the energy losses, emissions, and energy cost	The superior performance and applicability of the suggested method were indicated	[108]
16	Single and multi ODGA	Single PSO	Improving voltage profile and stability and reducing active and reactive losses.	It was indicated that PSO was similar or more successful than the analytic method for a single ODGA and more successful for multiple ODGA.	[116]
17	Multi ODGA	Hybrid TLBO, ABC	Minimizing the active power loss and cost	The suggested hybrid algorithm obtained superior convergence and calculation efficiency.	[4]
18	ODGA with LMs	Single PSO	Improving the voltage stability, decreasing the losses, and increasing the loading ability	Voltage profile was improved, power loss was decreased, and voltage stability and load ability were increased	[24]
19	ODGA with LMs	Single GA	Indicating the effect of LMs on ODGA	Effects of LMs on ODGA performance indices were determined.	[25]
20	ODGA with capacitors	single CSA	Minimizing the power loss in an unbalanced RDN	The voltage profile and power loss reduction were significantly improved.	[117]
21	Multi-period OPF	Single NLP	Minimizing the energy losses by the power factor settings required for peak loading conditions	Significant benefits were obtained in multi-period OPF. Moreover, OPF was formed to perform the power factor control of DGs to decrease the losses more.	[33]

(Continues)

TABLE 3 (Continued)

#	Category	HOM	Objectives	Findings	Ref.
22	ODGA with energy tariff	Single GA	The location of DG systems in DN and their pricing	DN payments were minimized, and the location of DGs and contract price were determined with the highest profit	[68]
23	OPF with DGs	Single NR	Analyzing the OPF of DGs	OPF decreased the losses and system costs with DG	[76]
24	Single and Multi ODGA	Single MSA, PSO	Decreasing the total power losses and operating costs and improving the voltage profile	Power losses, operating costs, and voltage fluctuations were decreased	[70]
25	ODGA with DSTAT-COM	Single PSO	Improving the voltage profile and decreasing the total power loss	The voltage profile was improved, and power loss was decreased	[72]
26	ODGA with biomass	Single PSO	Determining the most suitable supply area and location for a biomass energy production plant	The biomass potential of the area, transportation costs, access to DN, and plant location was determined using the performance of the suggested binary PSO algorithm.	[118]
27	Single and multi ODGA	Single HHO	Minimizing the total active power loss, reducing the voltage deviation, and increasing the voltage stability	Minimizing the total power loss and voltage fluctuation with superior performance	[97]
28	ODGA with ESS	Single PSO	Enabling ESS integration with high penetration PV and decreasing the energy losses	ESS decreased energy loss and improved the voltage profile	[119]
29	ODGA with hybrid generation	Single GWO	Minimizing the total active losses along with PV and WT	The superiority of the suggested algorithm in the calculation of ODGA was indicated through comparison with other optimization techniques	[88]
30	ODGA with TEP	Single BBO	Optimizing the presence of DGs for TEP (transmission expansion planning) on long transmission lines	It was observed that BBO had more quality solutions, good convergence, and robustness. It was indicated that DG was providing more economic TEP.	[120]
31	Multi ODGA	Single PSO	Power loss reduction and voltage profile improvement	Adding constriction factors to PSO has obtained superior power loss reduction and voltage profile improvement. Gravity ESS is considered.	[121]
32	Multi ODGA	Single EO	Minimize the cost of energy not supplied, the investment and operational costs, and the power losses	A directly proportional relationship between power losses-emissions and system load and an inversely proportional relation between the minimum voltage and the total demand changes have been determined.	[122]

effectively decreased the voltage fluctuation, the moth swarm algorithm (MSA) effectively decreased the losses and operating costs [70].

The cost optimization of the steel industry with highly variable loads has been made by mathematical modelling with PSO. Therefore, the self-consumption rate has been increased by performing the DG-integrated ESS discharge control [77]. In addition, the optimization of biomass fuel DG systems with PSO was investigated. The power plant's optimum location and supply area was determined for the widely used gas engine, gas turbine, and fuel cell-microturbine hybrid power system [78]. ODGA study for Solar, wind, and solar-wind RES have been achieved to better hybrid sizing [79]. Additionally, PSO has been improved for multi-objective ODGA, considering the correlation, economic and safety, and environmental benefits [80]. Other related ODGA studies performed by PSO can be found in Table 4.

2.2.3 | Other metaheuristic algorithms

In many ODGA studies, it is observed that GA and PSO are being used as MAs. However, different MAsemerged in recent years due to their successful performances. The leading ones are given in brief as follows. Tabu Search (TS) is a metaheuristic approach by Fred Glover that solves optimization problems by randomly searching the whole solution area. The search uses adaptive memory effectively and economically until the optimum solution is found. Simulated Annealing (SA) is inspired by the similarity between metal transformation to its crystal construct of minimum energy through cooling and freezing (annealing process) and the search for minimum in a system. It was initially presented in 1983 by Kirkpatrick et al. as an optimization technique. SA is a probability-based algorithm that intends to reach the best solution in a minimum time. It is generally used in combinatorial optimization problems that are costly

TABLE 4 Summary of optimization methods for ODGA

Applied method	Test systems	Components	Features	Compared methods	Ref.
NBA	23-bus	PW/ESS	Easily applicable and good convergence performance	GA	[46]
CBA	34 and 118 bus	DG/C	Chaotic maps improve BA escaping from local minima and enhancing global convergence	BA, GA, PSO, ACO, etc.	[128]
OPF with NLP	61-bus	WT	Widely and mainly used to solve the economic dispatch problem, adaptable to different objectives and constraints	N/A	[33]
PSO and BFA	American 69-bus	PV/WT/MGT	Combining a strong ability in local search and quick converges of PSO and strong global search ability of BFA	BFA, PSO-BFA, GPSO-BFA	[35]
Binary PSO	Generic power system	BG/FC/MGT	Initialize with random exploration and then changes variables binarily to get result in a few iterations	N/A	[118]
MINLP	IEEE-16, -33	DG/SVC	Contrary to the metaheuristics, obtaining a more confident optimum solution independent of random initials	GA, PSO, PPSO, PSO-CFA, SBA	[107]
Hybrid MINLP and MA	IEEE-24	PV/ESS	Improving the accuracy of the results and reducing computational burden by hybridization	Binary PSO and Binary GA	[125]
PSO	IEEE-30 and 38-bus	PV	Finding a global or near global optimum solution in a very short time	GA	[24]
EO	IEEE-30, -69	PV/EES	Fast convergence, high explorative and exploitative search mechanisms	GA, GWO, DE, PSO	[122]
TLBO and ABC	IEEE-33	PV/WT	Superior characteristics such as steady convergence, computational efficiency, real power loss and maximum cost saving	EVPSO, PSOPC, BSOA, GA, Hybrid, EAM	[4]
GA	IEEE-33	WT/ESS	Superior performance compared to other metaheuristic techniques in terms of the solution error and the execution time	N/A	[124]
CPSO	IEEE-33	PV/WT/ESS	Quality and effectiveness obtained in quick convergence with CPSO	GA	[121]
μGA	IEEE-33	FC/EL/ESS	Adequate for complex and nonlinear data problem	N/A	[129]
Improved NSGA-II	IEEE-33	PV/WT/ESS	Improving the deficiencies of NSGA in terms of globality, uniformity and diversity	NSGA-II, MOPSO	[130]
SSA	IEEE-33 and -69	PV/WT	Better performance in minimization of power loss nd voltage deviation	GA, RGA, HSA, FWA, UVDA	[105]
EO	IEEE-33, 141-bus	BG	The generation rate term is proven to stimulate ability in exploration, exploitation, and local minima avoidance.	GWO, DE, RAO	[131]
Improved WHO	IEEE-33, 69, and 119	DG	Lofty performance in the exploration-exploitation balance and convergence speed	WHO, GWO, TSA, SGOA	[123]
Hybrid MOPSO and MATPOWER	IEEE-33, 69, and Tunisian network	PV/WT	Robust results in power loss reduction and voltage improvement, providing ODGA	PSO	[126]
GA	Iranian power system	PV	Obtaining the fastest and global answers capable of adapting weighting factors	N/A	[19]
NLP	404-bus Canada RDN	PV, BG	Performing OPF considering several operational constraints	PSO, GA, TS, GSO, AGSO	[30]

to solve with mathematical models. Fuel costs of generators are minimized under optimum operating conditions. As a result, it has been seen that SA gives more successful and reliable results in economically distributing the load compared to traditional methods [81].

Ant colony optimization (ACO) is an optimization method inspired by the social behaviour of insects (ants) while foraging. Like other metaheuristic methods, ants start randomly searching for food in all directions. They return to their colonies by secreting pheromones after finding the food. Ants follow pheromone trails directly to find food [82]. Sunflower optimization algorithm (SOA) is one of the newest metaheuristic methods inspired by the movements of sunflowers for capturing sunlight. It is recommended for OPF and ODGA problems in power systems because of its speed of convergence, simple computation, and convenient design [83]. The coyote optimization algorithm (COA) is one of the recent metaheuristic methods that offer a different algorithm compared to other methods in the literature, considering the social organization and adaptation to the environment of coyotes. Each coyote is a possible solution for the optimization problem [84, 85].

Grey wolf optimization (GWO) was inspired by the social leadership and hunting technique of grey wolves by Mirjalili and Lewis in 2014 [86]. In the social hierarchy of wolves, the correct solution is alpha (α) wolf, the second-best and the third-best solutions are beta (β) and delta (δ) wolves, respectively, and the rest are called omega (ω) wolves. The hunt, or optimization, is driven by α, β, and δ wolves and continues to search for the global optimum [87]. GWO-based optimizations are used for multi-purpose ODGA, such as minimizing reactive power loss and improving the voltage profile. Total active losses in RDN are reduced for two different DG, PV, and WT (Wind Turbine), using GWO in ODGA. The lowest decrease in PV-type single DG was 47.38%, and the highest was 96.74% in WT-type double DG [88]. Numerical results showed that GWO has a better performance compared to gravitational search algorithm (GSA) and bat algorithm (BA) over the voltage profile and characteristic convergence curves [89].

The whale optimization algorithm (WOA) is a metaheuristic optimization technique suggested by Mirjalili and Lewis in 2016. It is a smart search method simulating the hunting behaviour of whales [90]. It is effective for multi-purpose ODGA, such as minimizing power loss and cost [91] and improving the voltage profile [92]. WOA has been applied to technic and economic analyses of multi ODGA on RDN of IEEE-33 and IEEE-69 [93]. The results suggested by WOA for installing DG on 30 bus RDN were better than FA, and its superiority was emphasized in minimizing total losses [94]. Elephant herding optimization (EHO) is a metaheuristic algorithm based on the herd behaviour of elephant groups. The elephants of different clans live under the management of matriarchy. It is an algorithm developed by modelling the male elephant's feed and shelter pursuit process by leaving its family group when it becomes a grown-up [95]. It has been observed that the proposed EHO-based approach for ODGA has been tested on different DN and gives the best results [56].

Harris hawk optimization (HHO) is another innovative metaheuristic algorithm that arose in 2020 based on hawks' hunting behaviour. It can be applied to many different optimization problems. It can rapidly and efficiently reach the solution compared to many MAs [96]. The single and multi-purpose HHO approaches proposed for ODGA have been applied on the RDN, demonstrating voltage and power stability improvements and loss reduction [97]. Cat swarm optimization (CSO) and parallel CSO algorithms have also been proposed for single and multi-purpose ODGA. It was stated that CSO and parallel CSO suggested in IEEE-33 and IEEE-69 bus test systems were efficient for ODGA [54]. Shunt capacitors and electric vehicle charging stations were evaluated within the scope of ODGA using the two-stage multi-purpose grasshopper optimization algorithm (GOA). It has been observed that the two-stage multi-objective optimization is more advantageous than the single-objective function [98]. Although it has been stated so far, some of the preferred MAs for ODGA are as follows: artificial bee colony optimization (ABCO) [99], teaching-learning based ABCO (TLABCO) [4], cuckoo search algorithm (CSA) [100], antlion optimization algorithm (AOA) [45, 101], shuffled frog-leaping algorithm (SFLA) [102], GSA [103], and salp swarm algorithm (SSA) [104, 105]. chimp optimization algorithm (ChOA) has been used for ODGA in 119-bus RDN regarding cost objectives [106].

2.3 | Hybrid optimization methods (HOM)

Numerous studies show the efficiency of MAs. However, they have several disadvantages: global optimum is not always guaranteed, the solution depends on random initials, and they can provide different solutions for different runs [107]. Many hybrid optimization methods (HOM) can combine analytic techniques and metaheuristic algorithms within the scope of the ODGA problem [108]. HOM aims to increase efficiency by completing insufficiencies in one method with another optimization method [109]. HOM is frequently used in solving many ODGA problems and gives successful results. Some examples of HOM are as follows: TS-PSO, ACO-ABCO, PSO-ABCO, and GA-JFPSO (Jumping Frogs PSO). For example, the accuracy in the GA-JFPSO study is higher than GA and standard DPSO (discrete PSO) for the same number of evaluations. The suggested hybrid GA-JFPSO converges better than standard DPSO in low-quality solutions [73]. ODGA was applied on different DG units using an interactive method based on the hybrid modified shuffled frog leaping algorithm (MSFLA) and differential evolution (DE). The simulation results on 69 bus DN showed that the suggested method was better and more applicable to the techno-economic and sustainable environment [108]. Hybrid GWO is one of the best among the global optimum solutions in the literature [64]. Two MAs, GWO and PSO, were performed for ODGA to reduce active and reactive power loss and improve the voltage profile on the IEEE-33 test system [110]. Hybrid SSA-PSO has been performed for multi-ODGA considering time-varying loads in DN [111]. The hybridization of the Jaya algorithm (JA) and Luus–Jaakola algorithm (LJA) has been applied to three different objectives of minimization of active power loss and voltage deviation and maximization of voltage stability and resulting in better convergence characteristics [112]. Several HOM studies are given in Table 3, indicating specifically which algorithms are combined. Besides, several ODGA studies have been empowered by more than one algorithm separately.

3 | COMPREHENSIVE COMPARISON OF ODGA STUDIES AND METHODS

Objectives of ODGA studies are voltage profile improvement, reduction of line losses, reliability robustness, peak demand reduction, emission reduction, total production cost decrease, operation costs, and line upgrade deferral, as seen in Figure 5.

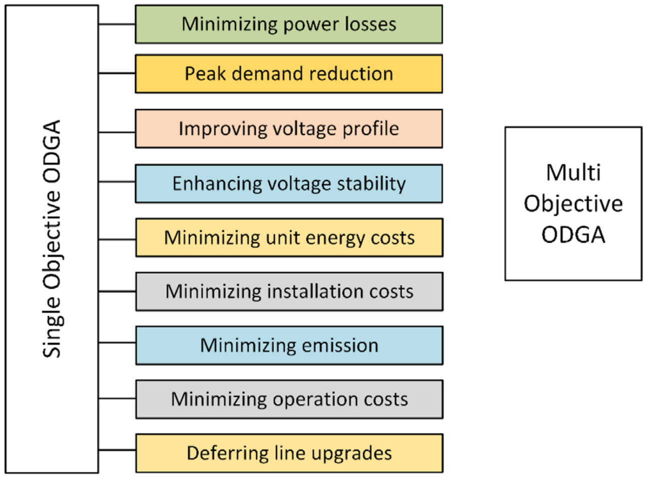

FIGURE 5 Objectives of ODGA studies

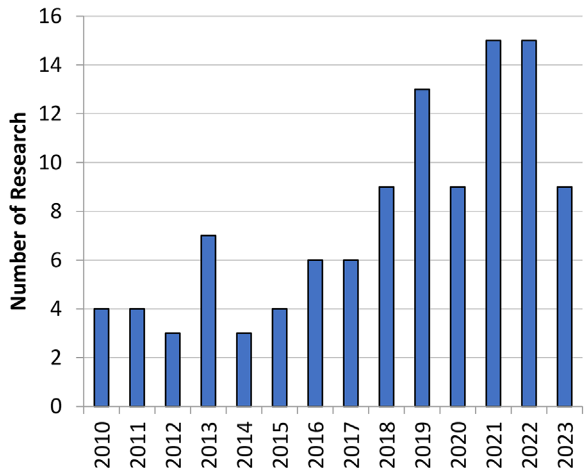

FIGURE 6 Summary of the reviewed literature

3.1 | Categorizing objectives of ODGA studies

Since optimum location detection with ODGA will reduce distribution losses in the system, it will positively reduce direct power losses. Power flow analyses based on ODGA, and optimum voltage parameters calculations will also effectively reduce losses. Since a stable integration will be achieved with the right optimization, reductions in current-induced losses are expected. Besides, implementing the optimal allocation strategy in the DG system investment and maintenance costs can be more affordable. The goals of limiting power losses and costs can be verified by monitoring the system's performance, including power flows, voltage levels, and losses.

ODGA can increase voltage stability and decrease voltage fluctuations, maximizing renewable energy use. ODGA strategically places DRGs, such as solar panels or wind turbines, to control voltage levels, minimize voltage dips, and provide reactive power assistance when necessary. It considers how DRGs and voltage control devices can work together to provide effective voltage control. System resilience is increased by the ability of DRGs to operate dynamically, enabling them to actively engage in voltage control during load changes or grid disruptions. In general, ODGA maximizes the distribution of DRGs to increase voltage stability, reduce fluctuations, and build a more dependable and effective DG system.

In other words, the power injection from DG units can influence system frequency, especially in islanded operations or under conditions where the DG units contribute a significant portion of the overall power supply. ODGA can help maintain frequency stability by balancing generation and load demand, reducing frequency deviations to ensur system stability. Placing DG units at strategic locations can help improve voltage regulation by reducing the voltage drop and minimizing voltage deviations within acceptable limits. In summary, ODGA studies should consider the dynamic voltage and frequency characteristics to ensure voltage regulation, frequency stability, and overall power quality.

To optimize these benefits, it is essential to determine the optimal sizes and locations of DG units in DN. Prior ODGA studies aim to maximize one objective to encourage proper DG allocation. Thus, optimizing ODGA according to a single objective may lead to improper results in other parameters like economic and environmental. Therefore, objective functions have been required to consider environmental and economic objectives besides technical benefits. Recent ODGA problems have been optimizing more than one objective simultaneously. Power system protection devices have been properly set according to the solutions of multi ODGA; meanwhile, total emissions could be reduced simultaneously. Thank to multi-ODGA approaches, proposed methods prevent overloading and voltage unbalance, reduce active and reactive power losses, decreasing energy production costs. Summary of reviewed ODGA studies regarding considered objectives and the findings are analyzed. The details of the categorized ODGA studies as single, multi, and other approaches to ODGA are given in Table 3. The distribution of the related ODGA studies reviewed in this study is depicted depending on the publication year in Figure 6.

3.2 | Effectiveness of optimization methods

The following drawbacks of existing ODGA methods limit their effectiveness and efficiency: complexity and computational burden, lack of scalability, sensitivity to model assumptions, limited consideration of network constraints, rigidity, inflexibility, lack of integration with renewable energy sources, and incomplete cost consideration. The elimination of these drawbacks necessitates the development of more sophisticated and thorough optimization approaches that consider the dynamics and complexity of modern power systems, incorporate a variety of restrictions, and offer flexible, scalable, and adaptive solutions.

Due to the large number of variables and the nonlinearity of ODGA problems, meta-heuristic techniques have been widely used. However, these MAs have faced challenges such as that weak convergence performance, obtaining local minima or maxima instead of global solutions, and computational burden. Determining the controlling parameters generally improves the optimal solution in a meta-heuristic. For example, superior performance in the exploration-exploitation balance and convergence speed has been obtained by modifying a WHO algorithm [123]. Moreover, the improvement in GA has been aimed at reducing the solution error and obtaining the execution time [124]. However, modifications generally provide a near-optimal solution due to many variables and difficulty changing the algorithm parameters. On the other hand, many researchers have considered combining two or more optimization methods to obtain a better solution. Combining stronger local and global PSO and BFA search abilities has given better solutions [35]. Additionally, HOM can increase computational efficiency and provide better convergence performance in solving ODGA problems [4]. A summary of optimization methods for ODGA is given with features in Table 4. Proposed algorithms solving ODGA problem are generally tested on DN models such as IEEE 14-bus [114], 16-bus [74], [107], 24-bus [125], 30-bus [24], 33-bus [121], 69-bus [105]. These widely used DN test models are preferred because of their radiality nature and easy adaptability. On the other hand, several studies have also been used to validate their proposed ODGA methods using real distribution networks like American [35], Tunisian [126], and Iranian [19]. In addition, DG integrations with ESS have been examined in ODGA studies to eliminate the effects of the intermittency and uncertainty of renewable generation [105] on voltage [115] and power stability [127].

On the other hand, large-scale power systems require computationally efficient algorithms that can handle various complex constraints, such as transmission capacity limits, voltage limits, and environmental regulations. MAs explore an optimum solution through a random search process for different DG combinations in an ample solution space incorporating constraints as penalty functions. They can perform multi-objective optimization, aiming to find a set of Pareto-optimal solutions representing the trade-off between different objectives, such as cost minimization, emission reduction, and system reliability enhancement. Additionally, they can be parallelized and distributed across multiple computational resources to accelerate optimization by reducing the computational load associated with large-scale systems. Therefore, MAs provide powerful tools to explore the solution space, handle complex constraints, perform multi-objective optimization, utilize parallel processing, and adapt to dynamic conditions for efficient and effective ODGA in large-scale power systems.

Besides the ODGA simulation on standard IEEE power systems, some real-world implementations of ODGA methods are as follows. The proposed ODGA method empowered with PSO has been implemented successfully to the real distribution system of Korea Electric Power Corporation in Korea regarding power losses and voltage profile improvement. The convergence performance of analytic hybrid PSO has improved by 32%, 42.59%, 50.91%, and 55.56% for the IEEE 10-bus, IEEE 33-bus, IEEE 69-bus, and KEPCO distribution systems, respectively. The standard PSO takes 18 iterations, while the analytic hybrid PSO algorithm takes 8 iterations to converge [132]. The proposed method is applied to the actual power system of Zanjan Province in Iran. The implementation of ODGA using GA has successfully reduced the power losses, improved the voltage profile, and prevented the excessive increase in the short-circuit level. Also, after implementation, none of substation transformers does not exceed the acceptable loading limit [19]. The ODGA for DRG in Brookhaven National Laboratory campus in USA demonstrates the capability of optimization analyses to increase the effectiveness of renewable energy integration and economic benefits and to help implement net-zero buildings, campuses, and communities [133]. Through the ODGA using a hybrid gradient PSO-BFA algorithm for the American PG&E 69-node system, the system operation cost, risk, and the load loss of the important nodes can be effectively reduced and implemented in a reliable and cost-effective power grid [35]. The ODGA implemented to the Western Danish energy-system using the EnergyPLAN computer model has effectively integrated a high renewable energy penetration, with around 55% of wind penetration [134]. Besides the successful implementations of ODGA methods in the real world, their success often involves a combination of supportive government policies, regulations, financial incentives, and stakeholder collaboration toward a sustainable and resilient grid.

3.3 | Deployment of emerging technologies into ODGA

Several emerging technologies show promise in improving the efficiency and reliability of DRG. The combination of these technologies with ODGA can be further enhanced their deployment. ESS can address the intermittent nature of RES by storing excess energy during high generation and discharging during high demand or low generation. ODGA can be used to determine the optimal sizing and placement of ESS units, considering load patterns and renewable generation profiles, to maximize their effectiveness in balancing supply and demand and improving grid stability. Also, power converters and inverters can be optimized in ODGA to integrate DRG into the grid efficiently. Furthermore, ODGA enables easier planning and management of demand response programs that allow consumers to adjust their electricity usage based on grid conditions and RES availability for efficient utilization and enhancing the supply and demand balance in real-time. Peer-to-peer energy trading platforms leverage blockchain technology to enable direct transactions between prosumers. ODGA can help identify optimal configurations and control strategies for microgrids and peer-to-peer energy trading systems, considering generation capacity, load profiles, and network constraints. Artificial intelligence can improve forecasting accuracy for RES generation, load demand, and grid conditions. Therefore, integrating ODGA with these emerging technologies can facilitate data-driven decision-making, system optimization, and effective deployment of DRG.

4 | CONCLUSION AND FUTURE TRENDS

DG is a key of the power system for green energy and decarbonization aims. Many benefits can be achieved with ODGA, such as better power quality, stable voltage profile, high reliability, and reduced losses and emissions. However, improper allocation of DGs can adversely affect power quality and reliability. Therefore, ODGA has considered various goals that increase DN performance, such as minimizing power losses and costs, improving the voltage profile, and maximizing DG penetration. In this paper, analytic techniques and MAs, and hybrid methods for ODGA were evaluated critically. Most optimization methods used in related studies have been categorized depending on their test system and compared features of optimization methods such as convergence performance and computational burden. Also, the methods for the ODGA were criticized from different perspectives, such as distributed generation integration, allocation, effects on the grid, superiorities of algorithms, and validated test network models. This review shows that ODGAs made with metaheuristic methods require less computation. Contrary, analytic methods are based on theoretical calculations and mathematical analyses. One of the most preferred optimization methods is GA, which directs the best solution by eliminating possible solutions through selection. Another preferred method is PSO which can find the optimum solution iteratively, requiring fewer parameters that can be easily implemented. According to the deep literature research, we can say that GA and PSO have widely preferred MAs for ODGA studies. Besides, hybrid optimization methods with more robust solution performance are obtained by completing the deficiencies of the other methods. It is seen that the proposed hybrid ODGA methods obtain effective results. This review can help the researchers and readers to get a wide perspective on ODGA applications and the main differences in the optimization methods used in DG systems. In future studies, investigations about ODGA may shift to the prosumer level considering peer-to-peer energy trading for improving prosumer community benefits as well as the connected power grid relief. Furthermore, emerging technologies like blockchain may enhance the peer-to-peer energy market among prosumers.

NOMENCLATURE

ABCO	Artificial bee colony optimization
ACO	Ant colony optimization
ANN	Artificial neural networks
AOA	Antlion optimization algorithm
BA	Bat algorithm
BFA	Bacteria foraging algorithm
BG	Biomass generation
BSOA	Backtracking search optimization algorithm
CBA	Chaotic bat algorithm
COA	Coyote optimization algorithm
CPSO	Constriction coefficient PSO
CSA	Cuckoo search algorithm
CSO	Cat swarm optimization
DE	Differential evolution
DG	Distributed generation
DN	Distribution network
DPSO	Discrete PSO
DRG	Distributed renewable generation
DSO	Distribution system operator
EAM	Efficient analytical method
EHO	Elephant herding optimization
EO	Equilibrium optimizer
EP	Evolutionary programming
EPSO	Evolutionary particle swarm optimization
ESS	Energy storage system
EVPSO	Escape velocity with PSO
FA	Firefly algorithm
FC	Fuel cell
FWA	Fire work algorithm
GA	Genetic algorithm
GAMS	General algebraic modelling system
GOA	Grasshopper optimization algorithm
GPSO	Gradient PSO
GSA	Gravitational search algorithm
GWO	Grey wolf optimization
HAS	Harmony search algorithm
HHO	Harris hawk optimization
HOM	Hybrid optimization methods
JFPSO	Jumping frogs PSO
LP	Linear programming
LSF	Loss sensitivity factor
MA	Metaheuristic algorithm
MGT	Micro gas turbine
MILP	Mixed-integer linear programming
MINP	Mixed-integer nonlinear programming
MOPSO	Multi objective PSO
MSA	Moth swarm algorithm
MSFLA	Modified shuffled frog leaping algorithm
NBA	New best algorithm
NLP	Nonlinear programming
NR	Newton–Raphson
NSGA-II	Non-dominated sorting genetic algorithm-II
ODGA	Optimal DG allocation
OO	Ordinal optimization
OPF	Optimal power flow
PS	Power system
PSO	Particle swarm optimization
PSOPC	PSO with passive congregation
PV	Photovoltaic
RDN	Radial distribution network
RGA	Refined genetic algorithm
SA	Simulated annealing
SBA	Shuffled BA
SFLA	Shuffled frog-leaping algorithm
SGOA	Sea-gull optimization algorithm
SOA	Sunflower optimization algorithm
SQP	Sequential quadratic programming
SSA	Salp swarm algorithm
TLABCO	Teaching-learning based ABCO
TS	Tabu search

TSA	Tunicate swarm algorithm
UPSO	Unified PSO
UVDA	Uniform voltage distribution algorithm
WHO	Wild horse optimization
WOA	Whale optimization algorithm
WT	Wind turbine

AUTHOR CONTRIBUTIONS

Said Mirza Tercan: Investigation, Writing-Reviewing and Editing, Methodology. **Alpaslan Demirci**: Conceptualization, Methodology, Writing-Reviewing and Editing, Supervision. **Yesim Esra Unutmaz**: Investigation, Resources, Writing-Original draft. **Onur Elma**: Investigation, Formal analysis, Visualization, Writing-Reviewing and Editing. **Recep Yumurtaci**: Supervision, Project administration.

CONFLICT OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

ORCID

Said Mirza Tercan https://orcid.org/0000-0003-1663-713X
Alpaslan Demirci https://orcid.org/0000-0002-1038-7224
Onur Elma https://orcid.org/0000-0002-4812-2117

REFERENCES

1. Harish, V.S.K.V., Anwer, N., Kumar, A.: Applications, planning and socio-techno-economic analysis of distributed energy systems for rural electrification in India and other countries: a review. Sustainable Energy Technol. Assess. 52, 102032 (2022)
2. Pesaran, M.H.A., Huy, P.D., Ramachandaramurthy, V.K.: A review of the optimal allocation of distributed generation: objectives, constraints, methods, and algorithms. Renewable Sustainable Energy Rev. 75, 293–312 (2017)
3. Demirci, A., Akar, O., Ozturk, Z.: Technical-environmental-economic evaluation of biomass-based hybrid power system with energy storage for rural electrification. Renewable Energy 195, 1202–1217 (2022)
4. Khasanov, M., Kamel, S., Xie, K., Zhou, P., Li, B.: Allocation of distributed generation in radial distribution networks using an efficient hybrid optimization algorithm. In: 2019 IEEE Innovative Smart Grid Technologies - Asia (ISGT Asia), pp. 1300–1305. IEEE, Piscataway, NJ (2019)
5. Bertolini, M., Buso, M., Greco, L.: Competition in smart distribution grids. Energy Policy 145, 111729 (2020)
6. Hoang, A.T., Van Viet Pham, Nguyen, X.P.: Integrating renewable sources into energy system for smart city as a sagacious strategy towards clean and sustainable process. J. Cleaner Prod. 305, 127161 (2021)
7. Kim, H., Choi, H., Kang, H., An, J., Yeom, S., Hong, T.: A systematic review of the smart energy conservation system: from smart homes to sustainable smart cities. Renewable Sustainable Energy Rev. 140, 110755 (2021)
8. Singh, B., Mishra, D.K.: A survey on enhancement of power system performances by optimally placed DG in distribution networks. Energy Rep. 4, 129–158 (2018)
9. Diaaeldin, I.M., Abdel Aleem, S.H.E., El-Rafei, A., Abdelaziz, A.Y., Calasan, M.: Optimal network reconfiguration and distributed generation allocation using Harris hawks optimization. In: 2020 24th International Conference on Information Technology (IT), pp. 1–6. IEEE, Piscataway, NJ (2020)
10. Ali, M.H., Mehanna, M., Othman, E.: Optimal planning of RDGs in electrical distribution networks using hybrid SAPSO algorithm. Int. J. Electr. Comput. Eng. 10(6), 6153 (2020)
11. Prakash, P., Khatod, D.K.: Optimal sizing and siting techniques for distributed generation in distribution systems: a review. Renewable Sustainable Energy Rev. 57, 111–130 (2016)
12. Sambaiah, K.S., Jayabarathi, T.: Loss minimization techniques for optimal operation and planning of distribution systems: a review of different methodologies. Int. Trans. Electr. Energy Syst. 30(2), e12230 (2020)
13. Liu, J., Xu, Z., Wu, J., Liu, K., Guan, X.: Optimal planning of distributed hydrogen-based multi-energy systems. Appl. Energy 281, 116107 (2021)
14. Ashoornezhad, A., Falaghi, H., Hajizadeh, A., Ramezani, M.: A bi-level multistage distribution network expansion planning framework with the cooperation of residential private investors (a case study in Iran). IET Renewable Power Gener. 17, 1881–1898 (2023)
15. Tercan, S.M., Elma, O., Gokalp, E., Cali, U.: An expansion planning method for extending distributed energy system lifespan with energy storage systems. Energy Explor. Exploit. 40(2), 599–618 (2022)
16. Chakraborty, N., Chandra, S., Banerji, A., Biswas, S.K.: Optimal placement of DG using swarm intelligence approach in distributed network: status & challenges. In: 2016 21st Century Energy Needs - Materials, Systems and Applications (ICTFCEN), pp. 1–5. IEEE, Piscataway, NJ (2016)
17. Orazgaliyev, D., Tleubayev, A., Zholdaskhan, B., Nunna, H.S.V.K., Dadlani, A., Doolla, S.: Adaptive coordination mechanism of overcurrent relays using evolutionary optimization algorithms for distribution systems with DGs. In: 2019 International Conference on Smart Energy Systems and Technologies (SEST), pp. 1–6. IEEE, Piscataway, NJ (2019)
18. Yadav, A., Srivastava, L.: Optimal placement of distributed generation: an overview and key issues. In: 2014 International Conference on Power Signals Control and Computations (EPSCICON), pp. 1–6. IEEE, Piscataway, NJ (2014)
19. HOSSEINI, S.A.: Optimal sizing and siting distributed generation resources using a multi objective algorithm. Turkish J. Electr. Eng. Comput. Sci. 21, 825–850 (2013)
20. Gupta, A.R., Kumar, A.: Deployment of distributed generation with D-FACTS in distribution system: a comprehensive analytical review. IETE J. Res. 68(2), 1195–1212 (2022)
21. Georgilakis, P.S., Hatziargyriou, N.D.: Optimal distributed generation placement in power distribution networks : models, methods, and future research. IEEE Trans. Power Syst. 28(3), 3420–3428 (2013)
22. Zenhom, Z.M., Boghdady, T.A.: Optimal allocation of distributed generation in a part of the Egyptian electrical network using whale optimization algorithm. In: 2019 21st International Middle East Power Systems Conference (MEPCON), pp. 365–370. IEEE, Piscataway, NJ (2019)
23. Shayani, R.A., de Oliveira, M.A.G.: Photovoltaic generation penetration limits in radial distribution systems. IEEE Trans. Power Syst. 26(3), 1625–1631 (2011)
24. El-Zonkol, A.M.: Optimal placement of multi DG units including different load models using PSO. Smart Grid Renew. Energy 01(03), 160–171 (2010)
25. Singh, D., Singh, D., Verma, K.S.: Multiobjective optimization for DG planning with load models. IEEE Trans. Power Syst. 24(1), 427–436 (2009)
26. Arfeen, Z.A., Sheikh, U.U., Azam, M.K., et al.: A comprehensive review of modern trends in optimization techniques applied to hybrid microgrid systems. Concurr. Comput. Pract. Exp. 33(10), e6165 (2021)
27. Wang, Z., Perera, A.T.,: Robust optimization of power grid with distributed generation and improved reliability. Energy Proc. 159, 400–405 (2019)
28. Papadimitrakis, M., Giamarelos, N., Stogiannos, M., Zois, E.N., Livanos, N.A.-I., Alexandridis, A.: Metaheuristic search in smart grid: a review

with emphasis on planning, scheduling and power flow optimization applications. Renewable Sustainable Energy Rev. 145, 111072 (2021)
29. Gamarra, C., Guerrero, J.M.: Computational optimization techniques applied to microgrids planning: a review. Renewable Sustainable Energy Rev. 48, 413–424 (2015)
30. Shawon, S.M.R.H., Liang, X., Janbakhsh, M.: Optimal placement of distributed generation units for microgrid planning in distribution networks. IEEE Trans. Ind. Appl. 59, 1–11 (2023)
31. Rugthaicharoencheep, N., Lantharthong, T., Auchariyamet, S.: Optimal operation for active management of distribution system with distributed generation. In: 2011 International Conference on Clean Electrical Power (ICCEP), pp. 715–719. IEEE, Piscataway, NJ (2011)
32. Dent, C.J., Ochoa, L.F., Harrison, G.P.: Network distributed generation capacity analysis using OPF with voltage step constraints. IEEE Trans. Power Syst. 25(1), 296–304 (2010)
33. Ochoa, L.F., Harrison, G.P.: Minimizing energy losses: optimal accommodation and smart operation of renewable distributed generation. IEEE Trans. Power Syst. 26(1), 198–205 (2011)
34. Singh, B., Sharma, J.: A review on distributed generation planning. Renewable Sustainable Energy Rev. 76, 529–544 (2017)
35. Xiong, X., Wu, W., Li, N., Yang, L., Zhang, J., Wei, Z.: Risk-based multi-objective optimization of distributed generation based on GPSO-BFA algorithm. IEEE Access 7, 30563–30572 (2019)
36. Fekadu Teshome, D., Xu, W., Bagheri, P., Nassif, A., Member, S., Zhou, Y.: A reactive power control scheme for DER-caused voltage rise mitigation in secondary systems; a reactive power control scheme for DER-caused voltage rise mitigation in secondary systems. IEEE Trans. Sustain. Energy 10(4), 1684–1695 (2019)
37. Takele, H.: Distributed generation adverse impact on the distribution networks protection and its mitigation. Heliyon 8(6), e09624 (2022)
38. Turan, M.T., Gökalp, E.: Relay coordination analysis and protection solutions for smart grid distribution systems. Turkish J. Electr. Eng. Comput. Sci. 24(2), 474–482 (2016)
39. Bakhshi-Jafarabadi, R., Sadeh, J., Serrano-Fontova, A., Rakhshani, E.: Review on islanding detection methods for grid-connected photovoltaic systems, existing limitations and future insights. IET Renew. Power Gener. 16, 3406–3421 (2022)
40. Souza Junior, F.C., Sanca, H.S.: Adaptive overcurrent protection applied to power systems with distributed generation and active network management. J. Control. Autom. Electr. Syst. 32(5), 1429–1437 (2021)
41. Mohapatra, S.S., Maharana, M.K., Pati, S.B.: Comprehensive review to analyze the islanding in distributed generation system. In: 2021 1st International Conference on Power Electronics and Energy (ICPEE), pp. 1–7. IEEE, Piscataway, NJ (2021)
42. Gupta, N., Dogra, R., Garg, R., Kumar, P.: Review of islanding detection schemes for utility interactive solar photovoltaic systems. Int. J. Green Energy 19(3), 242–253 (2022)
43. Harasis, S., Albatran, S., Almaita, E., et al.: Enhanced dynamic performance of grid feeding distributed generation under variable grid inductance. Int. J. Electr. Comput. Eng. 12(2), 1113 (2022)
44. Arulraj, R., Kumarappan, N.: Optimal economic-driven planning of multiple DG and capacitor in distribution network considering different compensation coefficients in feeder's failure rate evaluation. Eng. Sci. Technol. Int. J. 22(1), 67–77 (2019)
45. LIU, H., XU, L., ZHANG, C., SUN, X., CHEN, J.: Optimal allocation of distributed generation based on multi-objective ant lion algorithm. in 2019 IEEE Innovative Smart Grid Technologies - Asia (ISGT Asia), pp. 1455–1460. IEEE, Piscataway, NJ (2019)
46. Tercan, S.M., Demirci, A., Gokalp, E., Cali, U.: Maximizing self-consumption rates and power quality towards two-stage evaluation for solar energy and shared energy storage empowered microgrids. J. Energy Storage 51, 104561 (2022)
47. Toledo, O.M., Oliveira Filho, D., Diniz, A.S.A.C.: Distributed photovoltaic generation and energy storage systems: a review. Renewable Sustainable Energy Rev. 14(1), 506–511 (2010)
48. Uemichi, A., Yagi, M., Oikawa, R., Yamasaki, Y., Kaneko, S.: Multi-objective optimization to determine installation capacity of distributed power generation equipment considering energy-resilience against disasters. Energy Proc. 158, 6538–6543 (2019)
49. Ansari, M.M., Guo, C., Shaikh, M.S., Ali Jatoi, M., Yang, C., Zhang, J.: A review of technical methods for distributed systems with distributed generation (DG). In: *2019 2nd International Conference on Computing, Mathematics and Engineering Technologies—iCoMET 2019*, pp. 1–7. IEEE, Piscataway, NJ (2019)
50. Yan, Y., Kang, M., Zhang, J., Xu, Z., Liu, Y.: Layered real-time optimization and coordinated control of active distribution network considering distributed generation. In: 2019 IEEE Innovative Smart Grid Technologies - Asia (ISGT Asia), pp. 4074–4079. IEEE, Piscataway, NJ (2019)
51. Zare-Bahramabadi, M., Farzin, H., Ehsan, M.: A mixed integer linear programming model for risk-based remote-controlled switches, distributed generation, and tie line placement in distribution systems with complex topologies to improve the resilience. IET Renewable Power Gener. 17, 2149–2159 (2023)
52. Chen, Y., Zhang, Z., Chen, H., Zheng, H.: Robust UC model based on multi-band uncertainty set considering the temporal correlation of wind/load prediction errors. IET Gener. Transm. Distrib. 14(2), 180–190 (2020)
53. Dulău, L.I.: Optimization of a power system with distributed generation source. In: 2015 9th International Symposium on Advanced Topics in Electrical Engineering (ATEE), pp. 903–906. IEEE, Piscataway, NJ (2015)
54. El-Ela, A.A.A., El-Sehiemy, R.A., Kinawy, A., Ali, E.S.: Optimal placement and sizing of distributed generation units using different cat swarm optimization algorithms. In: 2016 Eighteenth International Middle East Power Systems Conference (MEPCON), pp. 975–981. IEEE, Piscataway, NJ (2016)
55. Abdmouleh, Z., Gastli, A., Ben-Brahim, L., Haouari, M., Al-Emadi, N.A.: Review of optimization techniques applied for the integration of distributed generation from renewable energy sources. Renewable Energy 113, 266–280 (2017)
56. Vijay, R., Abhilash, M.: Elephant herding optimization for optimum allocation of electrical distributed generation on distributed power networks. Asian J. Electr. Sci. 7(2), 70–76 (2018)
57. Tan, W.-S., Hassan, M.Y., Majid, M.S., Abdul Rahman, H.: Optimal distributed renewable generation planning: a review of different approaches. Renewable Sustainable Energy Rev. 18, 626–645 (2013)
58. Tian, Z., Fu, F., Niu, J., Sun, R., Huang, J.: Optimization and extraction of an operation strategy for the distributed energy system of a research station in Antarctica. J. Cleaner Prod. 246, 119073 (2020)
59. Ehsan, A., Yang, Q.: Optimal integration and planning of renewable distributed generation in the power distribution networks: a review of analytical techniques. Appl. Energy 210, 44–59 (2018)
60. Mittal, M.: Analytical approaches for optimal placement and sizing of distributed generation in power system. IOSR J. Electr. Electron. Eng. 1(1), 20–30 (2012)
61. Theo, W.L., Lim, J.S., Ho, W.S., Hashim, H., Lee, C.T.: Review of distributed generation (DG) system planning and optimisation techniques: comparison of numerical and mathematical modelling methods. Renewable Sustainable Energy Rev. 67, 531–573 (2017)
62. Keane, A., Ochoa, L.F., Member, S., et al.: State-of-the-art techniques and challenges ahead for distributed generation planning and optimization. IEEE Trans. Power Syst. 28(2), 1493–1502 (2013)
63. Ooka, R., Ikeda, S.: A review on optimization techniques for active thermal energy storage control. Energy Build. 106, 225–233 (2015)
64. Sanjay, R., Jayabarathi, T., Raghunathan, T., Ramesh, V., Mithulananthan, N.: Optimal allocation of distributed generation using hybrid grey wolf optimizer. IEEE Access 5, 14807–14818 (2017)
65. Sukhwal, P.B.: Optimization of distributed generation using elephant herding optimization (EHO) techniques and improvement in multi-objective function. Int. J. Res. Appl. Sci. Eng. Technol. 7(10), 400–407 (2019)
66. Moradi, M.H., Abedini, M.: Optimal multi-distributed generation location and capacity by Genetic Algorithms. In: 2010 4th International Power

Engineering and Optimization Conference (PEOCO). IEEE, pp. 440–444 (2010)
67. Biswas, S., Goswami, S.K.: Genetic algorithm based optimal placement of distributed generation reducing loss and improving voltage sag performance. in Proc. of Int. Conf. on Advances in Electrical & Electronics. pp. 21–23 (2011)
68. López-Lezama, J.M., Contreras, J., Padilha-Feltrin, A.: Location and contract pricing of distributed generation using a genetic algorithm. Int. J. Electr. Power Energy Syst. 36(1), 117–126 (2012)
69. Kumar, V., Kumar, D.: A systematic review on firefly algorithm: past, present, and future. Arch. Comput. Methods Eng. 28(4), 3269–3291 (2021)
70. Saleh, A.A., Mohamed, A.A.A., Hemeida, A.M.: Impact of optimum allocation of distributed generations on distribution networks based on multi-objective different optimization techniques. In: Proceedings of 2019 International Conference on Innovative Trends in Computer Engineering, ITCE 2019, pp. 401–407. IEEE, Piscataway, NJ (2019)
71. Golestani, S., Tadayon, M.: Distributed generation dispatch optimization by artificial neural network trained by particle swarm optimization algorithm. In: *2011 8th International Conference on the European Energy Market (EEM)*, pp. 543–548. IEEE, Piscataway, NJ (2011)
72. Devi, S., Geethanjali, M.: Optimal location and sizing determination of distributed generation and DSTATCOM using particle swarm optimization algorithm. Int. J. Electr. Power Energy Syst. 62, 562–570 (2014)
73. Gomez-Gonzalez, M., López, A., Jurado, F.: Optimization of distributed generation systems using a new discrete PSO and OPF. Electr. Power Syst. Res. 84(1), 174–180 (2012)
74. Kumar, T., Thakur, T.: Comparative Analysis of Particle Swarm Optimization Variants on Distributed Generation Allocation For Network Loss Minimization. In: *2014 First International Conference on Networks & Soft Computing (ICNSC2014)*, pp. 167–171. IEEE, Piscataway, NJ (2014)
75. Jamian, J.J., Mustafa, M.W., Mokhlis, H., Baharudin, M.A.: Implimentation of evolutionary particle swarm optimization in distributed generation sizing. Int. J. Electr. Comput. Eng. 2(1), 137–146 (2012)
76. Zhijian, L., Jun, Y., Qi, S.: Optimal power flow research on distributed network considering distributed generation. In: 2016 China International Conference on Electricity Distribution (CICED), pp. 1–6. IEEE, Piscataway, NJ (2016)
77. Alzahlan, M.W., El-Faouri, F.S., Batarseh, M.G., Mohammad, A., Zarter, M.E.: Particle swarm optimization of a microgrid's cost function involving distributed generation and highly fluctuating ;oad. In: 2019 IEEE Jordan International Joint Conference on Electrical Engineering and Information Technology (JEEIT), pp. 319–324. IEEE, Piscataway, NJ (2019)
78. Eid, A., Kamel, S., Korashy, A., Khurshaid, T.: An enhanced artificial ecosystem-based optimization for optimal allocation of multiple distributed generations. IEEE Access 8, 178493–178513 (2020)
79. Rekha, R., Channappa Byalihal, S.: Optimal allocation of solar and wind distributed generation using particle swarm optimization technique. Int. J. Electr. Comput. Eng. 13(1), 229 (2023)
80. Gao, F., Yuan, C., Li, Z., Zhuang, S.: Multi-objective optimal allocation of distributed generation considering the spatiotemporal correlation of wind-photovoltaic-load. Electr. Power Syst. Res. 214, 108914 (2023)
81. Çetin, G., Keçebaş, A.: Optimization of thermodynamic performance with simulated annealing algorithm: a geothermal power plant. Renewable Energy 172, 968–982 (2021)
82. Ogunsina, A.A., Petinrin, M.O., Petinrin, O.O., Offornedo, E.N., Petinrin, J.O., Asaolu, G.O.: Optimal distributed generation location and sizing for loss minimization and voltage profile optimization using ant colony algorithm. SN Appl. Sci. 3(2), 248 (2021)
83. Shaheen, M.A.M., Hasanien, H.M., Mekhamer, S.F., Talaat, H.E.A.: Optimal power flow of power systems including distributed generation units using sunflower optimization algorithm. IEEE Access 7, 109289–109300 (2019)
84. Chang, G.W., Cong Chinh, N.: Coyote optimization algorithm-based approach for strategic planning of photovoltaic distributed generation. IEEE Access 8, 36180–36190 (2020)
85. Pierezan, J., Dos Santos Coelho, L.: Coyote optimization algorithm: a new metaheuristic for global optimization problems. In: *2018 IEEE Congress on Evolutionary Computation (CEC)*, pp. 1–8. IEEE, Piscataway, NJ (2018)
86. Mirjalili, S., Mirjalili, S.M., Lewis, A.: Grey wolf Optimizer. Adv. Eng. Software 69, 46–61 (2014)
87. Mirjalili, S., Saremi, S., Mohammad, S.: Multi-objective grey wolf optimizer : a novel algorithm for multi-criterion optimization. Expert Syst. Appl. 47, 106–119 (2016)
88. Mohsen, M., Youssef, A.-R., Ebeed, M., Kamel, S.: Optimal planning of renewable distributed generation in distribution systems using grey wolf optimizer GWO. In 2017 Nineteenth International Middle East Power Systems Conference (MEPCON), pp. 915–921. IEEE, Piscataway, NJ (2017)
89. Sultana, U., Khairuddin, A.B., Mokhtar, A.S., Zareen, N., Sultana, B.: Grey wolf optimizer based placement and sizing of multiple distributed generation in the distribution system. Energy 111, 525–536 (2016)
90. Ang, S., Leeton, U.: Optimal placement and size of distributed generation in radial distribution system using whale optimization algorithm. Suranaree J. Sci. Technol. 26(1), 1–12 (2019)
91. Prakash, D.B., Lakshminarayana, C.: Multiple DG placements in radial distribution system for multi objectives using whale optimization algorithm. Alexandria Eng. J. 57(4), 2797–2806 (2018)
92. Kamel, S., Selim, A., Jurado, F., Yu, J., Xie, K., Yu, C.: Multi-objective whale optimization algorithm for optimal integration of multiple DGs into distribution systems. In: 2019 IEEE Innovative Smart Grid Technologies - Asia (ISGT Asia), pp. 1312–1317. IEEE, Piscataway, NJ (2019)
93. C, H.P., Subbaramaiah, K., Sujatha, P.: Optimal DG unit placement in distribution networks by multi-objective whale optimization algorithm & its techno-economic analysis. Electr. Power Syst. Res. 214, 108869 (2023)
94. Morshidi, M.N., Musirin, I., Rahim, S.R.A., Adzman, M.R., Hussain, M.H.: Whale optimization algorithm based technique for distributed generation installation in distribution system. Bull. Electr. Eng. Inf. 7(3), 442–449 (2018)
95. Wang, G.G., Deb, S., Coelho, L.D.S.: Elephant Herding Optimization. In: *2015 3rd International Symposium on Computational and Business Intelligence (ISCBI)*, pp. 1–5. IEEE, Piscataway, NJ (2016)
96. Asghar, A., Mirjalili, S., Faris, H., Aljarah, I.: Harris hawks optimization : algorithm and applications. Futur. Gener. Comput. Syst. 97, 849–872 (2019)
97. Selim, A., Kamel, S., Alghamdi, A.S., Jurado, F.: Optimal placement of DGs in distribution system using an improved Harris hawks optimizer based on single- and multi-objective approaches. IEEE Access 8, 52815–52829 (2020)
98. Gampa, S.R., Jasthi, K., Goli, P., Das, D., Bansal, R.C.: Grasshopper optimization algorithm based two stage fuzzy multiobjective approach for optimum sizing and placement of distributed generations, shunt capacitors and electric vehicle charging stations. J. Energy Storage 27, 101117 (2020)
99. Kamarposhti, M.A., Colak, I., Eguchi, K.: Optimal energy management of distributed generation in micro-grids using artificial bee colony algorithm. Math. Biosci. Eng. 18(6), 7402–7418 (2021)
100. Aranizadeh, A., Niazazari, I., Mirmozaffari, M.: A novel optimal distributed generation planning in distribution network using cuckoo optimization algorithm. Eur. J. Electr. Eng. Comput. Sci. 3(3), 1–5 (2019)
101. Li, Y., Feng, B., Li, G., Qi, J., Zhao, D., Mu, Y.: Optimal distributed generation planning in active distribution networks considering integration of energy storage. Appl. Energy 210, 1073–1081 (2018)
102. Li, R., Jiang, Z., Li, A., Yu, S., Ji, C.: An improved shuffled frog leaping algorithm and its application in the optimization of cascade reservoir operation. Hydrol. Sci. J. 63(15–16), 2020–2034 (2018)
103. Geleta, D.K., Manshahia, M.S.: Gravitational search algorithm-based optimization of hybrid wind and solar renewable energy system. Comput. Intell. 38, 1–27 (2020)
104. Abdel-mawgoud, H., Kamel, S., Yu, J., Jurado, F.: Hybrid Salp Swarm Algorithm for integrating renewable distributed energy resources in distribution systems considering annual load growth. J. King Saud Univ. - Comput. Inf. Sci. 34(1), 1381–1393 (2022)

105. Sambaiah, K.S., Jayabarathi, T.: Optimal reconfiguration and renewable distributed generation allocation in electric distribution systems. Int. J. Ambient Energy 42(9), 1018–1031 (2021)
106. Borousan, F., Hamidan, M.A.: Distributed power generation planning for distribution network using chimp optimization algorithm in order to reliability improvement. Electr. Power Syst. Res. 217, 109109 (2023)
107. Ahmed, E.M., Rakočević, S., Ćalasan, M., et al.: BONMIN solver-based coordination of distributed FACTS compensators and distributed generation units in modern distribution networks. Ain Shams Eng. J. 13(4), 101664 (2022)
108. Doagou-Mojarrad, H., Gharehpetian, G.B., Rastegar, H., Olamaei, J.: Optimal placement and sizing of DG (distributed generation) units in distribution networks by novel hybrid evolutionary algorithm. Energy 54, 129–138 (2013)
109. Twaha, S., Ramli, M.A.M.: A review of optimization approaches for hybrid distributed energy generation systems: off-grid and grid-connected systems. Sustainable Cities Soc. 41, 320–331 (2018)
110. Abu Haggar, M.F., Beshr, E., Eteiba, M.B.: Minimizing power loss in distribution system by optimal sizing and sitting of distributed generators with network reconfiguration using grey wolf and particle swarm optimizers. In: 2018 IEEE International Conference on Environment and Electrical Engineering and 2018 IEEE Industrial and Commercial Power Systems Europe (EEEIC /I&CPS Europe), pp. 1–6. IEEE, Piscataway, NJ (2018)
111. Ahmed, A., Nadeem, M.F., Kiani, A.T., Ullah, N., Khan, M.A., Mosavi, A.: An improved hybrid approach for the simultaneous allocation of distributed generators and time varying loads in distribution systems. Energy Rep. 9, 1549–1560 (2023)
112. Meena, V.P., Yadav, U.K., Mathur, A., Singh, V.P., Guerrero, J.M., Khan, B.: Location and size selection using hybrid Jaya-Luus-Jaakola algorithm for decentralized generations in distribution system considering demand-side management. IET Renewable Power Gener. 17, 1535–1544 (2023)
113. Sarfaraz, Bansal, A., Singh, S.: Optimal allocation and sizing of distributed generation for power loss reduction. In: International Conference & Workshop on Electronics & Telecommunication Engineering (ICWET 2016), pp. 15–20. IEEE, Piscataway, NJ (2016)
114. Mahajan, S., Vadhera, S.: Optimal sizing and deploying of distributed generation unit using a modified multiobjective particle swarm optimization. in 2016 IEEE 6th International Conference on Power Systems (ICPS), pp. 1–6. IEEE, Piscataway, NJ (2016)
115. Aman, M.M., Jasmon, G.B., Bakar, A.H.A., Mokhlis, H.: A new approach for optimum DG placement and sizing based on voltage stability maximization and minimization of power losses. Energy Convers. Manag. 70, 202–210 (2013)
116. Tanneru, M., Krishna, V., Sumanth, M.Y., Tech, M.: Particle swarm optimization based method for optimal siting and sizing of multiple distributed generators. In: 16th Natıonal Power Systems Conference, pp. 669–674. IEEE, Piscataway, NJ (2010)
117. Samal, P., Mohanty, S., Ganguly, S.: Planning of distributed generation and capacitor in an unbalanced radial distribution system using cuckoo search algorithm. In: 19th International Conference on Electrical Machines and Systems, ICEMS 2016, pp. 1–5. IEEE, Piscataway, NJ (2017)
118. L´opez, P.R., Gonzalez, M.G., Reyes, N.R., et al.: Optimization of biomass fuelled systems for distributed power generation using particle swarm optimization. Electr. Power Syst. Res. 78(8), 1448–1455 (2008)
119. Raptis, D.A., Periandros, P.S., Gkaidatzis, P.A., Bouhouras, A.S., Labridis, D.P.: Optimal siting of BESS in distribution networks under high PV penetration. In: 2018 53rd International Universities Power Engineering Conference (UPEC), pp. 1–6. IEEE, Piscataway, NJ (2018)
120. Hosny, N.S., Youssef, H.K.M.: Biogeography-based optimization for transmission network planning problem considering distributed generation impacts. J. Mod. Math. Front. 2(2), 65–73 (2013)
121. Rathore, A., Patidar, N.P.: Optimal sizing and allocation of renewable based distribution generation with gravity energy storage considering stochastic nature using particle swarm optimization in radial distribution network. J. Energy Storage 35, 102282 (2021)
122. El-Ela, A.A.A., El-Seheimy, R.A., Shaheen, A.M., Wahbi, W.A., Mouwafi, M.T.: PV and battery energy storage integration in distribution networks using equilibrium algorithm. J. Energy Storage 42, 103041 (2021)
123. Ali, M.H., Kamel, S., Hassan, M.H., Tostado-Véliz, M., Zawbaa, H.M.: An improved wild horse optimization algorithm for reliability based optimal DG planning of radial distribution networks. Energy Rep. 8, 582–604 (2022)
124. Awad, A.S.A.A., EL-Fouly, T.H.M.M., Salama, M.M.A.: Optimal ESS allocation for load management application. IEEE Trans. Power Syst. 30(1), 327–336 (2015)
125. Javadi, M.S., Gough, M., Mansouri, S.A., et al.: A two-stage joint operation and planning model for sizing and siting of electrical energy storage devices considering demand response programs. Int. J. Electr. Power Energy Syst. 138, 107912 (2022)
126. SELLAMI, R., SHER, F., NEJI, R.: An improved MOPSO algorithm for optimal sizing & placement of distributed generation: a case study of the Tunisian offshore distribution network (ASHTART). Energy Rep. 8, 6960–6975 (2022)
127. Zhang, Z., Chen, Y., Ma, J., Liu, X., Wang, W.: Two-stage robust security constrained unit commitment considering the spatiotemporal correlation of uncertainty prediction error. IEEE Access 7, 22891–22901 (2019)
128. Mouwafi, M.T., El-Sehiemy, R.A., El-Ela, A.A.A.: A two-stage method for optimal placement of distributed generation units and capacitors in distribution systems. Appl. Energy 307, 118188 (2022)
129. Bragatto, T., Carere, F., Cresta, M., et al.: Location and sizing of hydrogen based systems in distribution network for renewable energy integration. Electr. Power Syst. Res. 205, 107741 (2022)
130. Gu, T., Wang, P., Liang, F., et al.: Placement and capacity selection of battery energy storage system in the distributed generation integrated distribution network based on improved NSGA-II optimization. J. Energy Storage 52, 104716 (2022)
131. Abo El-Ela, A.A., Allam, S.M., Shaheen, A.M., Nagem, N.A.: Optimal allocation of biomass distributed generation in distribution systems using equilibrium algorithm. Int. Trans. Electr. Energy Syst. 31(2), e12727 (2021)
132. Muhammad Arif, S., Hussain, A., Tjing Lie, T., Muhammad Ahsan, S., Abbas Khan, H.: Analytical hybrid particle swarm optimization algorithm for optimal siting and sizing of distributed generation in smart grid. J. Mod. Power Syst. Clean Energy 8(6), 1221–1230 (2020)
133. Jung, J., Villaran, M.: Optimal planning and design of hybrid renewable energy systems for microgrids. Renewable Sustainable Energy Rev. 75, 180–191 (2017)
134. Salgi, G., Lund, H.: System behaviour of compressed-air energy-storage in Denmark with a high penetration of renewable energy sources. Appl. Energy 85(4), 182–189 (2008)

How to cite this article: Tercan, S.M., Demirci, A., Unutmaz, Y.E., Elma, O., Yumurtaci, R.: A comprehensive review of recent advances in optimal allocation methods for distributed renewable generation. IET Renew. Power Gener. 17, 3133–3150 (2023). https://doi.org/10.1049/rpg2.12815