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A Review of Metaheuristic Techniques for Optimal Integration of Electrical Units in Distribution Networks

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ABSTRACT The optimal integration of electrical units, such as distributed generation units, power electronic devices, and electric vehicles, is a significant development of smart grids. This development has effectively transformed the traditional grid system, promising numerous advantages for economic values and autonomous energy source control. In smart grids development, metaheuristic algorithms are one of the optimization algorithms that have been applied extensively to mitigate the accompanying problems such as voltage instability, power loss, and high installation cost. This paper presents a comprehensive review of metaheuristic techniques for the optimal integration of electrical units in distribution networks, considering different phases of the optimization process. These include the approaches for handling of crucial objective functions and the optimal integration methods for different electrical units. This review shows a need for more research on developing efficient metaheuristic algorithms and the effective handling of multiple objective functions.

INDEX TERMS Decision making, distributed generation, distribution networks, electric vehicles, metaheuristic optimization algorithms, multi-objective optimization, optimal location and sizing, smart grids.

I. INTRODUCTION

Metaheuristic optimization techniques have become quite popular for solving engineering problems due to peculiar reasons such as simplicity and flexibility. One significant benefit of metaheuristic algorithms is their capability to solve highly computational tasks at a substantial efficiency. These algorithms use stochastic operators to search for optimal solutions based on diversification and intensification [1], where the former is a sporadic search of a whole solution search, and the latter is the search of a particular region of the search space [2]. Metaheuristic algorithms are independent of any problem, and their high-level nature permits them to roam in and out of several local optima. They are mostly nature-inspired and are based majorly on two concepts: evolution theory and swarm-based intelligence [3], [4]. Evolutionary algorithms begin with the initialization of a random population, where the best individuals move to the next generation (clearly imitating the theory of evolution). Swarm-based intelligent algorithms mimic the social behavior of animals and how they interact with each other to achieve a common goal. This concept is fundamental for reaching a global optimum, hence finding optimal solutions. Metaheuristic algorithms are very dynamic such that they extensively search for a solution within a single objective or multi-objective space [5], [6]. Hence, they have been applied heavily to solve the optimal integration of electrical units in distribution networks.

Electrical units have been integrated into distribution networks for better power delivery and power compensation. These units are categorized as energy sources and Power Electronic (PE) devices, where the energy sources are Distributed Generation (DG) units, Energy Storage System (ESS) units, and Electric Vehicles (EV), and the PE devices are capacitor banks, Synchronous Static Compensator (STATCOM), and voltage regulators. Distribution Networks (DG) units are the most prevalent for optimal

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integration because of their dual purpose of compensating power and stabilizing the grid. Renewable Energy Sources (RES)-based DG units are even more prevalent due to their environmental benefits. Generally, electrical unit integration benefits include voltage stability improvement, power loss minimization, operating cost reduction, and emission reduction. These benefits can only be achieved if the electrical units are integrated appropriately.

The inappropriate integration of electrical units causes extreme power loss and voltage instability. For instance, a continuous real power penetration from a DG unit can cause extreme reverse power, leading to a voltage breakdown in a power distribution network. For RES-based DG units, the intermittent power supply can affect a distribution network performance and reliability. Therefore, optimization algorithms have been developed to solve these issues faced with the optimal integration of electrical units.

Optimal integration of electrical units has revealed many advantages in distribution networks, which has led to numerous reviews on different algorithms, applications, and objectives. The authors of [7] and [8] reviewed different technologies and benefits of ESS and the methods for optimal location, sizing, and control. They emphasized on further studies on the performance and control of ESS units. Sirjani and Jordehi [9] reviewed different techniques used in the optimal placement and sizing of the Distribution Synchronous Static Compensator (D-STATCOM). They carried out a qualitative analysis of the storage type, objective functions, constraints, and solutions; concluding that there is a need to place D-STATCOM in different conditions, and improve the speed and accuracy of solving the optimal placement and sizing of D-STATCOM. Sheibani *et al.* [10] reviewed ESS installation and expansion in distribution and transmission networks.

Some authors have focused majorly on optimization techniques in distribution networks as in [11], where a comprehensive review conducted for analytical methods for solving optimal integration and planning in distribution networks. The study encompasses different types of techniques and compares them according to DG unit types, decision variables, and objective functions. It was suggested that more work should be carried out on the combined integration of DG units and EVs in distribution networks. The authors of [12] and [13] focused on different techniques used for solving the optimal location and sizing of DG units, considering the objective functions, indices, and constraints, while Theo *et al.* [14] focused on the comparison of numerical and mathematical methods and their application in optimal DG planning. In [15], multi-agent system applications to power system problems were reviewed. Some of the applications reviewed are DG units management system, electric vehicle management system, electricity market, energy management & control, power generation expansion, and fault detection & protection.

Askarzadeh [16] reviewed the application of a metaheuristic algorithm, a harmony search in power systems. The study focused on economic dispatch/unit commitment, optimal power flow, control, optimal placement of FACTS devices, expansion and planning, prediction, parameter identification, reconfiguration, and optimal reactive power dispatch. In [17], six metaheuristic algorithms were selected in the categories of swarm intelligence, evolutionary, and teacher/learner. The algorithms were reviewed and analyzed using benchmarked functions. In addition, a microgrid consisting of DG units such as solar photovoltaics, wind turbines, microturbines, diesel generator, and fuel cell, was modeled to find the minimum operating cost. Results from the analysis show that the Teaching Learning-Based Optimization (TLBO) performs better than the Particle Swarm Optimization (PSO), Differential Evolution (DE), Whale Optimization Algorithm (WOA), Genetic Algorithm, and the Firefly algorithm.

Metaheuristic algorithms are used extensively because of their ability to produce near-optimal results in a computationally efficient manner. They have also been used for solving multiobjective optimization problems in the optimal integration of electrical units in distribution networks. However, these metaheuristic algorithms have not been compared in literature. This paper discusses the different categories of metaheuristic techniques, and their applications to the single and multiobjective problems in the optimal integration of electrical units in distribution networks. The paper discusses the opportunities and future research directions that may be needed to improve results from the optimal integration of electrical units in distribution networks.

The rest of this paper is as follows: Section II discusses the electrical units in a smart grid. Section III explains the phases in the optimal integration of electrical unit problem. Section IV discusses the application of metaheuristic algorithms to optimal integration of electrical units in distribution networks. Section V discusses metaheuristic algorithms based on multiobjective optimization in the optimal integration of electrical units in distribution networks. Section VI presents the summary of findings from the review. Finally, conclusions are drawn in Section VII.

II. ELECTRICAL UNIT INTEGRATION IN SMART GRIDS

The National Institute for Standards and Technology (NIST) coined out concepts from a standard smart grid as ''architecture, architecture process, energy services interface, functional requirement, harmonization, interchangeability, and inter-operability'' [18]. All of these concepts are related to the optimal integration problem in microgrids, distribution and transmission networks. They come in play depending on the (i) number of integrated units (ii) type of units (iii) mode of operations. For example, RES-based DG units can be integrated to serve the smart grid at their peak hours only, or they can be merged with Energy Storage Systems (ESS) to store energy for high demand hours, which promotes the demand side management in a smart grid. The ESS unit can be used for smoothening power output through frequency variation [19] and [20]. A representation of the integration of BESS, solar Photovoltaic (PV) plant, wind turbine plant,

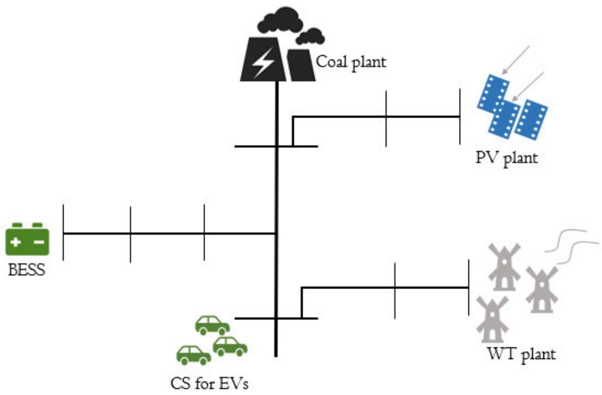

FIGURE 1. Configuration of a distribution network with the integration of different electrical units (adapted from [21]).

and EVs in a distribution network is shown in Figure 1 [21], [22]. Some major integrated units are discussed below.

A. ENERGY SOURCES

Energy sources are central to the development of smart grids. These energy sources can be RES-DG units and may be configured as a single or multiple DG units. Either type of energy source configuration should have an appropriate size and location of the energy source itself [23]. Some examples of energy sources used in literature are Battery Energy Storage Systems (BESS), wind turbines, PV modules, and diesel generators. BESS units are used mostly to compensate for the intermittent nature of the RES. While BESS units have been enhanced with improvement in chemical composition and structure [8], [24], there is also a need to optimally place them at strategic locations to achieve optimum power delivery.

Researches such as in [25]–[28] proposed algorithms to find optimal size and location of BESS in distribution networks. The authors of [29]–[33] have also developed meta-heuristic algorithms to optimally size and place BESS-based DG units in distribution networks. Independent energy sources such as PVs and wind turbines have also been optimally placed and sized for optimum energy transfer [34]. Most of the energy sources have also been integrated into microgrids to reduce cost of energy, net present cost, etc. [35], [36].

B. POWER ELECTRONIC UNITS

The inception of the smart grid comes with the power delivery problem, which is mostly power stability. PE units have been used to compensate for distorted power, thereby enhancing power quality. Over time, these units have been sized and placed at strategic locations. Examples are capacitors (or capacitor banks), D-STATCOM, and Dynamic Voltage Restorer (DVR). Capacitors are generally the most economical; hence they attract more studies. Chunks of research such as in [37]–[43] worked on the optimal sizing and allocation of capacitors in a distributed network through the use of meta-heuristic algorithms. Other power electronic devices such as STATCOM, which consists of coupling transformers, energy storage devices, and inverters [44], have also been optimally placed and sized.

C. ELECTRIC VEHICLES

Electric vehicles are emerging technology that can be an energy source or a PE device. They are eco-friendly vehicles that are fully or partially powered by electric propulsion. These vehicles are categorized into three, which are Plug-in Hybrid Electric Vehicles (PHEV), Fuel Cell Electric Vehicles (FCEV), and Battery Electric Vehicles (BEV). The PHEV combines the Internal Combustion Engine (ICE) with an on-board battery system to enhance fuel economy. FCEVs are powered by hydrogen fuel cells, which is the newest and developing technology. BEVs are only run on battery technology and are considered the most efficient way to reduce carbon emissions. This distinction has made the BEV draw more attention than other EV categories [45], both in the global market and research. Naturally, the use of EVs in any form (as a load or support) will always cause a deterrent to the grid; hence there is a need to control its implementation.

Firstly, charging an EV is an extra load to the grid network, causing voltage fluctuations and sudden peak loads if charging is uncoordinated. An uncoordinated charging refers to an arbitrary charging of EVs [46]. Ahmadi *et al.* [45] had highlighted the impacts of EVs on distribution networks. One method to control EVs is the optimal EV scheduling, which is assigning time slots for EV charging. To encourage the participation of EV owners, charging costs are minimized along with other objectives. Adetunji *et al.* [47] proposed an EV charging model that reduces the charging cost alongside the minimization of power loss and load variance.

Secondly, EVs can discharge power to support the grid. Optimal EV scheduling can also control this phenomenon. Another method to control EV implementation in a grid network is the Energy Management System (EMS), which, most times, incorporates DG units. EMS is the maximum strategic utilization of energy sources in a smart grid while considering its technical, economic, and environmental impacts. In this context, EVs are implemented to charge from or discharge to the grid network and is done using the Vehicle-to-Grid (V2G) technology.

V2G is the management and control of EVs to the distribution network, which involves an aggregator and a distribution system operator (DSO). Some common objectives of the V2G technology are to minimize charging cost, maximize profit, improve power quality, and reduce carbon emissions. V2G technology is categorized based on power flow direction, namely unidirectional and bidirectional. Unidirectional V2G uses a one-way power flow to control the charging rates of EVs. It primarily provides ancillary services to the grid. These ancillary services must involve energy trading policies that should encourage the participation of EV owners [48]. Bidirectional V2G uses a two-way power flow between the grid and EV. There are extra benefits, such as frequency regulation, voltage regulation, reactive power support, and peak load shaving.

Furthermore, EV charging stations are also an important factor in the mix because their allocation to the bus locations may deter the technical characteristics of the network. Some studies have formulated and solved the charging station allocation problem as in [49]–[52].

III. PHASES IN THE OPTIMAL INTEGRATION OF ELECTRICAL UNITS

This section discusses the phases and factors involving optimal integration in a distribution network. The following are discussed: power flow models, objective functions and constraints, and non-arbitrary datasets.

A. POWER FLOW MODELS

Power flow is an essential factor in distribution systems. Power flow methods range from optimal power flow (OPF), continuous power flow (CPF), probabilistic power flow (PPF) and so on. These methods have been used to analyze the components on a power bus line, hence determining the calculation of power losses and voltage stability on such lines. However, power loss equations will be based on the type of generator source. For example, the output power of diesel generators will defer from the power from PVs or WT. Also, a single- or three-phase type will change the model of its power flow. The schematic for the single-phase power supply is shown in Figure 2 [53].

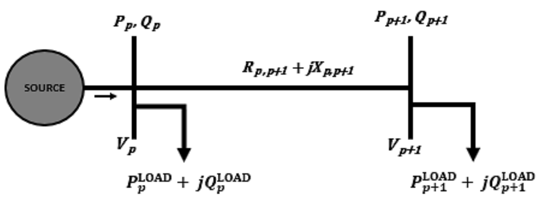

FIGURE 2. Schematic of a single line illustration of a distribution network.

Figure 2 is represented with the equations below.

$$P_{p+1} = P_p - P_{p+1}^{\text{LOAD}} - R_{p,p+1}\frac{(P_{p,p+1}^2 - Q_{p,p+1}^2)}{|V_P|^2}, \quad (1)$$

$$Q_{p+1} = Q_p - Q_{p+1}^{\text{LOAD}} - X_{p,p+1}\frac{(P_{p,p+1}^2 - Q_{p,p+1}^2)}{|V_P|^2}, \quad (2)$$

$$|V_{p+1}|^2 = |V_p|^2 - 2(R_{p,p+1}^2 P_{p,p+1}^2 + X_{p,p+1}^2 Q_{p,p+1}^2) + (R_{p,p+1}^2 + X_{p,p+1}^2)\frac{(P_{p,p+1}^2 + Q_{p,p+1}^2)}{|V_P|^2}, \quad (3)$$

where p is the sending bus and $p+1$ is the receiving bus. P, Q, and V are respectively the real power, reactive power, and voltage at bus p or $p+1$, while R and X are the resistance and reactance at branch $p, p+1$.

The total power loss of the system is represented in (4)

$$P_{total}^{\text{loss}} = \sum_{p=1}^{n-1} P_{p,p+1}^{\text{loss}}. \quad (4)$$

The derived equations from Eq. (1) can be supplemented by the addition of energy devices such as capacitors and STATCOM. Capacitors are used for supporting power flow through reactive power enhancement. On the other hand, STATCOM devices consist of Voltage Source Converters (VSCs) coupled with transformers and energy devices. It dynamically injects and/or absorbs reactive power for improving voltage stability and profile [9].

With the addition of other energy sources. Eq. (5) - (7) may be updated as follows:

$$P_{p+1} = P_p - P_{p+1}^{\text{LOAD}} - R_{p,p+1}\frac{(P_{p,p+1}^2 - Q_{p,p+1}^2)}{|V_P|^2} + P^{\text{RES}} + P^{\text{BATT}}, \quad (5)$$

$$Q_{p+1} = Q_p - Q_{p+1}^{\text{LOAD}} - X_{p,p+1}\frac{(P_{p,p+1}^2 - Q_{p,p+1}^2)}{|V_P|^2} + \alpha_q Q_{p+1}^C. \quad (6)$$

The reactive power can be updated as shown in (7)

$$Q_{p+2} = Q_{p+1} + Q_{p+2}^{\text{STATCOM}}, \quad (7)$$

where P^{RES} can be integrated as solar modules or wind turbines, αQ^C is the reactive power compensation by the capacitor with an α factor and Q_{p+2}^{STATCOM} is the reactive power compensation by the STATCOM at bus $p+2$.

B. COMMON OBJECTIVES FUNCTIONS

Objective functions are mainly mathematical equations that are formulated to simulate the characteristics of a system. The most common objective function in the optimal integration problem is real power loss minimization, followed by others, such as voltage stability improvement, voltage profile improvement, cost minimization, and profit maximization. Figure 3 illustrates the different types of objectives.

1) POWER LOSS MINIMIZATION

Power loss is almost inevitable in power systems, yet its mitigation cannot be overemphasized. The objective is the most common objective of optimal integration, and it is used mostly as a base objective to solve metrics such as voltage profile. Basically, power loss can be formulated by Kirchhoffs' laws, where the summation of injected power on each bus can represent the total distribution network loss. A miscalculation of power loss can cause either shortage of power supply or oversupply, which is economically inefficient. The power loss minimization is defined as

$$min \sum_{n=1}^{N} I_{n,t}^2 R_n. \quad (8)$$

Here, $I_{n,t}$ is the current on the n^{th} at time t and R_n is the resistance of the n^{th} line.

2) VOLTAGE STABILITY IMPROVEMENT

Voltage stability is a crucial factor in loading distribution networks. A sudden increase or fluctuations in the network

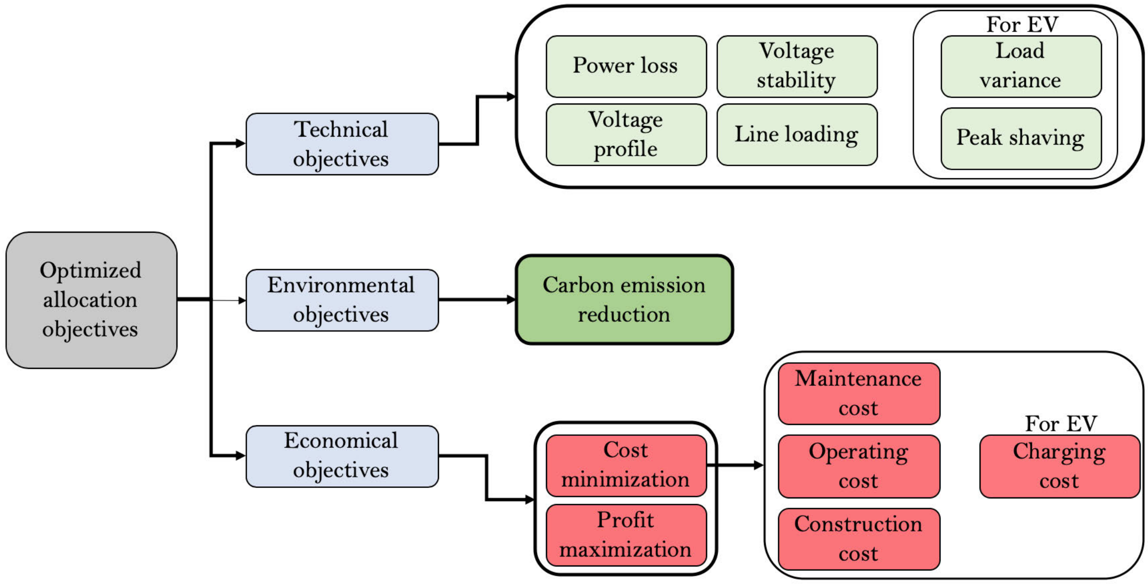

FIGURE 3. Common objectives of optimal integration in distribution networks.

can cause a voltage collapse. The inability to compensate for reactive power loss will also cause voltage instability [44], especially with small-scale network microgrids. Voltage Stability Index (VSI) is used as an indicator for network stability and loadability and can be used alone to solve the planning of distribution systems. In place of this, several methods have been developed with deviating strategies [44]. Some of the proposed methods are Line Stability Index (Lmn), Line Stability Index (Lp), Novel Line Stability Index (NLSI), Line Voltage Stability Index (LVSI), Fast Voltage Stability Index (FVSI), Voltage Collapse Proximity Index (VCPI) etc. Over time, VSI has been combined with meta-heuristic algorithms for distribution network planning. A standard equation for solving VSI is given in (9):

$$\begin{aligned} \mathrm{VSI}_{(p+1)} = V_p^4 - 4[P_{(p+1)}X_p - Q_{(p+1)}R_p]^2 \\ - 4[P_{(p+1)}R_p + Q_{(p+1)}X_p]^2 V_p^2 \end{aligned} \tag{9}$$

3) LOAD VARIANCE MINIMIZATION

This objective is related to the integration of EVs. Given the fact that EVs act as a load, there is a need to minimize the fluctuations on the grid through a proper scheduling. An optimal cancellation of this objective can reduce power loss. A typical load variance objective is formulated as

$$min\ \frac{1}{T}\sum_{t=1}^{T}\left[(P_t^{\text{conv}} + \sum_{n=1}^{N} P_{t,n}^{\text{EV}} - \beta)\right]^2, \tag{10}$$

where

$$\beta = \frac{1}{T}\sum_{t=1}^{T}\left(P_t^{\text{conv}} + \sum_{n=1}^{N} P_{t,n}^{\text{EV}}\right). \tag{11}$$

Here, P_t^{conv} is the conventional load without the EV load at time t; $P_{t,n}^{EV}$ is the charging power of the n^{th} EV at time t. It is crucial to note that N is the maximum number of charging stations which is assumed to be occupied by EVs at a predetermined time slot, t.

Theoretically, this objective should also cater for peak shaving and load leveling to improve the grid efficiency. A well-controlled load variance will improve network stability (synonymous with VSI).

4) PEAK LOAD SHAVING

Peak shaving is a key objective in the V2G implementation, where electricity demand is met by utilizing available resources, rather than increasing the grid capacity. In a PV and EV-present distribution network, the peak load can be reduced through

$$min\ max\ \left\{P_t^{\text{conv}} + \sum_{n=1}^{N} P_{n,t}^{\text{EV}} - P_t^{\text{PV}}\right\}, \tag{12}$$

where P_t^{conv} is the conventional load at time t, which is the base load without the EV load; P_t^{PV} is the PV output power at time interval, t and $P_{n,t}^{\text{EV}}$ is the rated power of charging the n^{th} EV.

5) COST MINIMIZATION

The economic aspect of optimal integration has to be considered for sustainability and acceptability. Without this consideration, most of the projects might not be signed off for commencement. Therefore, there is a need to minimize the cost of carrying out the optimal integration of DG units project. Most studies sum the total cost as the summation of installed DG units construction cost, and operation and maintenance cost [54], [55]. A typical example of optimal integration of DG units is shown here

$$DG_{IC} = \sum_{i=1}^{N_{\rm DG}} P_i^{\rm DG} \times INV_{\rm cost}, \quad (13)$$

where DG_{IC} is the installation cost of DG units, $P_i^{\rm DG}$ represents the capacity of the i^{th} DG unit, and $INV_{\rm cost}$ investment costs of the DG units. The operation and maintenance cost is defined as

$$DG_{OM} = \sum_{i=1}^{N_{\rm DG}} \sum_{j=1}^{N_N} P_i^{\rm DG} \times OM^{\rm cost} \times R \times CF_i \times T, \quad (14)$$

where $OM^{\rm cost}$ is the operation and maintenance cost, R is the approximate value of interest and inflation rate, CF_i is its capacity factor, and T is the duration of the planning period (counted in days). The cost of purchasing excess power from substation can be expressed as

$$COST_{\rm sub} = \sum_{t=1}^{24} P_t^{\rm sub} \times P_{\rm cost} \times R \times T, \quad (15)$$

where $P_t^{\rm sub}$ is the summation of the active load connected to the distribution network, the power generated from DG units, and the accumulated power loss. $P_{\rm cost}$ is the cost of active power from the substation.

For EVs, there is a need to reduce the cost of charging at specific periods. This act is beneficial to the grid and also to EV drivers. A load-shifting scheme is applied where cheaper tariffs will be available as an incentive at off-peak hours. The standard form of charging cost minimization is defined as

$$min \sum_{n=1}^{N} \sum_{t=1}^{T} P_{n,t}^{\rm EV} \cdot C_t \cdot \triangle t, \quad (16)$$

where N is the total number of plugged-in EVs; $\triangle t$ is the time horizon; C_t is the current TOU price at time t; $P_{n,t}$ is the n^{th} EV charging power at time t.

6) OPERATING PROFIT MAXIMIZATION

Investing in the improvement of power systems should also be profitable for investors. Taking an EV scheduling as an example, an aggregator should serve an appealing charging cost while considering profits. In the same vein, an investor in the construction of a DG integration project should have a projected profit [54].

C. CONSTRAINTS

For a more practical scenario, constraints are modeled into an optimization problem in order to limit specific parameters. Constraints are mostly applied to technical objectives, where power, voltage, and current flow within and into the grid are confined. Some essential constraints are highlighted

- *Bus voltage limits* are applied to maintain the stability of the grid. While injecting power from DG units or EVs, a permissible voltage is allowed on each bus, which has a maximum variation of 5%, some cases will allow a variation of 10%.
- *Bus capacity limits* are applied to regulate the maximum allowable load to a bus. This constraint is well applicable to EV charging, where some number of EVs are only allowed to be charged from a bus. This inequality constraint must be equal or lesser than the sum of conventional (residential or commercial) load and the total number of EVs connected to the same bus
- *DG penetration limit* refers to the maximum allowable power from installed DG units like PV and WT. EV penetration is also controlled except when gradual steps are allowed [46], or maximum penetration is used, as in [47].
- *Power flow balance* ensures that the total real and reactive power of the grid network is equal to the sum of real and reactive power flowing from DG units, substation, and real and reactive power loss in the network.

D. NON-ARBITRARY DATA-SET

Optimal sizing and placement of energy sources and power electronic devices are based on parameters such as real & reactive power of buses and resistance & reactance of branches that connect the buses. These parameters influence the major objective functions such as power loss, voltage profile, and voltage stability. The IEEE dataset is a standard for solving sizing and placement problems and has been prioritized strongly for choosing research papers for this review. Real data from location grids were also considered from literature.

Other required data such as load, PV power output, and electricity prices can be influenced by weather, human behavior, etc. These factors can cause uncertainties in data; therefore, several models have been developed to handle such cases. While recent studies in literature have considered the uncertainties, this study only focuses on the optimization process that applies metaheuristic algorithms in a single objective or multiobjective framework.

IV. METAHEURISTIC ALGORITHMS FOR THE OPTIMAL INTEGRATION OF ELECTRICAL UNITS

The concept of most meta-heuristic algorithms is based on a characterized agent or set of agents that operate without human interaction, to achieve an objective or a set of objectives [56]. Particle Swarm Optimization (PSO) [57] and Ant Colony Optimization (ACO) [58] are good examples of the use of agents. Other examples, such as the Genetic Algorithm (GA) [59] uses a slightly different approach. Figure 4 shows the categories of algorithms and their examples.

The advent of benchmark functions has seen the development of other algorithms such as Bat Algorithm (BA) [60], Cuckoo Search (CS) [61], Harmony Search Algorithm (HSA) [62], Flower Pollination Algorithm (FPA) [63], and Firefly Algorithm (FA) [64]. Other new meta-heuristic algorithms have also been developed such as Ant Lion Optimizer (ALO) [65], Whale Optimization Algorithm (WOA) [66], Grey Wolf Optimizer (GWO) [67].

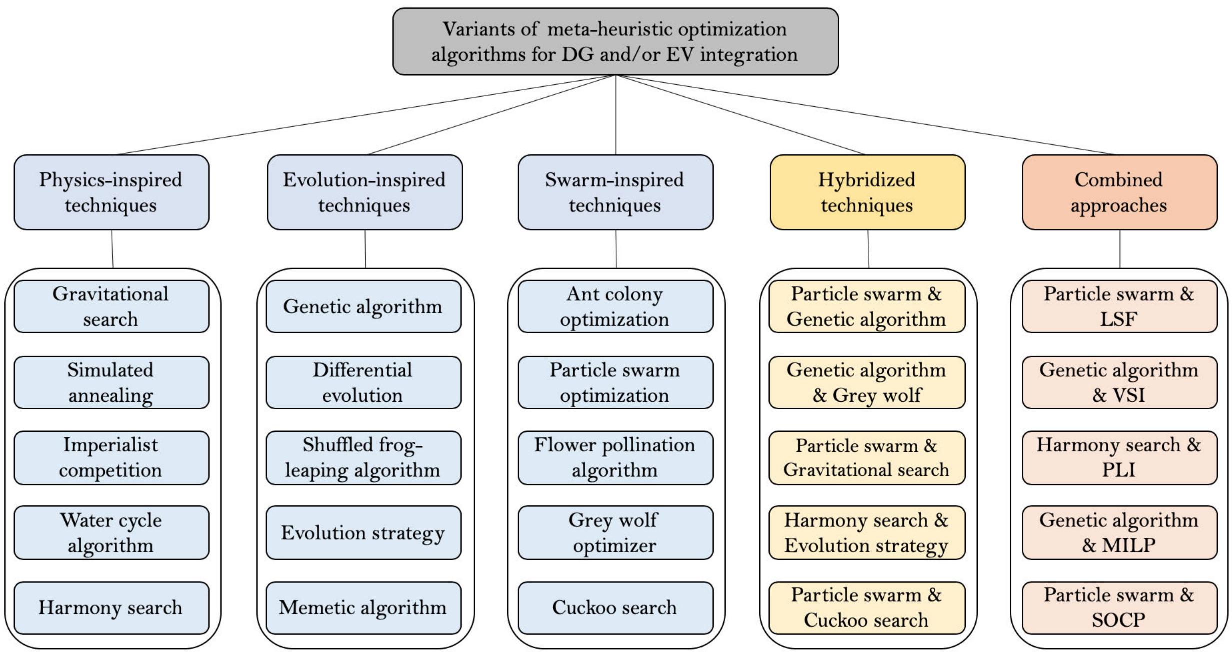

FIGURE 4. Metaheuristic optimization algorithms for smart grids network.

Figure 5 shows a general framework of metaheuristic algorithms to solve the optimal integration problem. The categories of metaheuristic algorithms are discussed in the following subsections.

A. EVOLUTIONARY-BASED ALGORITHMS

These kinds of algorithms use Darwinian evolution and the natural selection theory for obtaining optimal solutions. Examples in this category are GA, Differential Evolution (DE), and Evolution Strategy (ES). Like the evolution process, a generation will consist of parents and children who inherit their parents' features. Evolutionary algorithms use three major operators: selection, crossover, and mutation. The selection operator takes two parents while the crossover operator handles the mating process to generate children. Lastly, the mutation operator is used mostly for developing stronger children. Many types of research have applied evolutionary algorithms to optimal integration of electrical units as in [68]–[72].

In [68], GA was utilized to acquire the optimal data for load flow analysis. The algorithm enhances reactive power flow for the optimal placement of capacitor banks in strategic locations along bus lines. It uses a combinatorial approach to switch between different load scenarios, and was tested on the Saudi Electricity Company (SEC). In the same vein, Liu *et al.* [73] considered the optimal placing of BESS in a Virtual Power Plant (VPP) for optimal planning of a distribution network. The GA was used to reduce the power loss and the power fluctuation induced by PV plants while considering uncertainties of power output and load growth.

The authors of [69] used a modified GA to enhance power loss minimization objective, for optimal capacitor placement in an unbalanced distribution system. The GA was utilized mainly for optimum compensation values of the reactive power on the bus, and was tested on the IEEE 4- and 123-bus, and 85-bus feeder. Similarly, Babacan *et al.* [70] optimally sized and placed BESS units in a PV-integrated grid distribution system using a GA-based bi-level optimization framework. The aim was to reduce voltage fluctuations caused by PV outputs through real power injection and BESS units through power absorptions from the distribution network. Voltage fluctuations could also be termed as voltage instability since its effect can also break down a distribution network. A possible extension of this study could be the comparison of the proposed algorithm with other metaheuristic algorithms in terms of objective values, convergence time, and computational time.

The DE is another evolutionary algorithm developed by Storn and Price [74] to achieve better performance such as fast convergence. The operation of the DE produces target and difference vectors which further generate trial vectors through the EA classical operators such as crossover and mutation. This operation allows the DE to handle both discrete and continuous variables [75]. Huy *et al.* [76] applied the DE to find optimal locations, sizes, and power factors of DG units while minimizing the energy losses in a meshed power network. Kumar and Chakraborty [77] applied a chaotic operator to avoid premature convergence while solving the optimal DG unit integration problem in distribution networks. Injeti [78] applied a similar algorithm, the Differential Search Algorithm (DSA) to optimize total

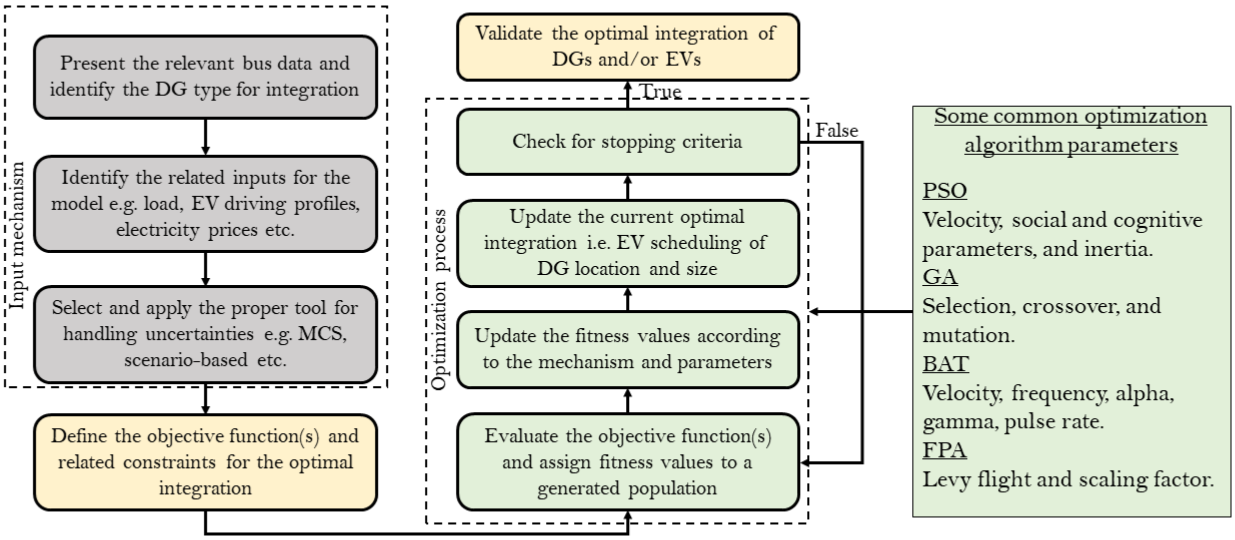

FIGURE 5. Generic flowchart of a meta-heuristic algorithm application to the optimal integration problem.

power loss, voltage deviation, and total operating cost in distribution network planning. It is reported that the improved DSA produces better final objective values than the GA.

Modified Shuffled Frog Leaping Algorithm (MSFLA) was suggested to optimally allocate and size DG and D-STATCOM units in a distribution network [79]. The objective was to minimize distribution line losses, increase voltage stability, and improve power quality. The algorithm was tested on the IEEE 33-bus system and was compared to the GA algorithm. It was reported that the MSFLA generates a lesser DG and STATCOM capacity than the GA. The MSFLA also improves the voltage profile better than the GA. The authors of [80] also applied the MSFLA to an energy management system in a dynamic distribution network. They integrated DG and BESS units considering the optimal switches and objectives, such as voltage stability, operational cost, and reliability index.

Recently, Singh *et al.* [81] developed a GA-based optimization that was implemented for the integration of DG, STATCOM, PHEV, and FACTS units to reduce total real power loss in the distribution network. The DG units and loads were modelled into four types to savour the real-world characteristics. The GA evaluates the fitness values of each chromosome, which represents each bus power state. The algorithm was evaluated on the IEEE 37-bus distribution network, concluding that the integration of DG, STATCOM, and PHEV units will deliver enhanced real and reactive power support and increased system power factor. The new model can be evaluated on other test bus systems. That way, other algorithms can be implemented to improve the model.

Constraint is an important feature of the optimal integration problem; hence its handling is a major concern. Most studies switch to the mathematical approach to properly handle constraints, but the GA can also solve this effectively. Vuletic and Todorovski [71] developed a Penalty-Free Genetic Algorithm (PFGA) that handles constraints and eliminates the process of selecting a penalty parameter in a capacitor placement and sizing problem. Instead of assigning a function or a parameter value to penalize constraints violations, two chromosomes are adopted to handle constraints violations with conditions: if both chromosomes do not violate constraints, then one of the chromosomes will be selected according to their fitness value; if one of the chromosomes violates the constraints, the other chromosome is selected to continue the algorithm; and if both chromosomes violate the constraints, then the chromosome with the lower constraints violation value is selected. The PGFA uses a single-point crossover and a non-uniform probability wheel to select the next gene for a new chromosome. During each iteration, the best fitness value is kept as an elite for the next iteration. This process reduces the complexity that may be caused by applying the random parameters in the mutation operator. The PFGA was used to minimize power and energy losses and was tested on 18-, 68-, and 141-bus systems.

Celli *et al.* [82] varied both crossover and mutation operators for properly installing BESS units in a distribution network. They used a blend crossover operator that uniformly picks a value within the two parents' genes. This method yields a good compromise between the exploration and exploitation areas of the genes. Their mutation operator uses a non-uniform approach based on a polynomial probability distribution function and a mutation clock scheme. The mutation clock's addition enhances the computational time because unlike in [71], where the number of extraction is based on the number of genes, it allows for only one extraction of genes per chromosome. In [83], a Normal Distribution Crossover (NDC) was used to produce new chromosomes to optimize power loss and voltage deviation. It was reported that the NDC-based GA converges faster than the PSO and PSO-GA algorithms.

Xiao *et al.* [72] modified the implementation of the GA for the optimal integration of BESS in a distribution network. An OPF method handles the BESS scheduling and minimizes network losses while the GA optimizes the Net Present Value (NPV). Their implementation involves deleting a generation if the BESS capacity at the initialization stage cannot satisfy the constraints. This effort saves time and reduces the number of generations to solve the optimal integration problem. The algorithm was tested on the IEEE 33-bus system and was tested with a previous GA implementation. The results show that the number of generations of a GA can be optimized while reducing computational time.

B. SWARM-BASED ALGORITHMS

This category of algorithms is based on simulating the interaction among a swarm (or flock) of animals (called search agents or particles) to achieve a common goal. The simulation is enhanced with parameters, which have the most influence on the algorithms' performance. Therefore, studies on the optimal integration of electrical units have optimally tuned and reduced the number of parameters to improve voltage stability and minimize power loss, thereby enhancing the overall grid performance. Some studies have also modified the algorithms' mechanism to achieve better computational efficiency. Lee *et al.* [84] proposed different PSO topologies for the optimal placement of capacitors, considering load patterns in distribution systems. Instead of using a uniform probability distribution, Gaussian and Cauchy probabilistic distributions were implemented for generating random numbers to update the velocity equation. The distribution functions were applied alternatively to the social and cognitive components such that fifteen PSO mechanism types were generated. All the PSO types were compared to the GA and Tabu search algorithm. It is evident that a modification of the PSO social component improves the algorithms' performance than other permutations.

Although swarm-based algorithms generally converge faster than evolutionary algorithms, they however are prone to a premature convergence. To avoid this setback, Deveci and Guller [85] proposed a competitive-based PSO to produce the optimal levelized cost of energy and electricity generation cost while integrating renewable energy sources in distribution networks. The particle position, instead of being updated from their personal and global best, updates through a competitive mechanism applied to a randomly selected pairs of particles [86].

In [87], the PSO algorithm was applied to find optimal DG unit locations and sizes, while considering harmonic power flow computations for different harmonics according to non-linear loads in a 31-bus distribution network. The authors evaluated the power loss, cost of DG units, emissions, and fuel, with the major constraint of maintaining an acceptable harmonic distortion level. Mosbah *et al.* [88] proposed a modified PSO to optimally allocate and size shunt capacitors in a radial distribution system. The algorithm was implemented by reducing the high current that causes a voltage drop, which minimizes the real power loss and reduces capacitor costs. It was reported that the proposed PSO implementation produces a cheaper capacitor cost than the PSO implementation from [89]. In the same vein, Karimi *et al.* [90] also used the PSO for solving objective functions to optimally place and size capacitor banks in a 10-, 33-, and 69-bus distribution network. The objective was to minimize real and reactive power loss and maximize net savings from distribution companies. Another consideration was to ensure that voltage violations were minimal by adding a function used to penalize line voltage drops.

Das *et al.* [29] presented a method to optimally place distributed BESS units in a distribution network using Artificial Bee Colony (ABC), with improvements being made through addressing power loss alongside voltage deviation and line loading. It was reported that the algorithm improves the real power loss minimization than the PSO.

Mostafa *et al.* [91] optimally integrated BESS units in a microgrid to inject and absorb real power according to change in electricity prices. The Symbiotic Organism Search (SOS) algorithm was implemented alongside the VSI method to minimize power loss, improve voltage profiles, and boost microgrids' voltage stability. The study can be further extended by evaluating the algorithm on a test bus system and comparing with other algorithms. In [43], PSO was suggested to optimally size and allocate capacitors in a distribution network, to reduce real power losses and economic costs. The algorithm was evaluated on 34-bus and 85-bus system, and results from a comparison with the WOA show that the PSO had higher voltage profile improvement.

Some authors mainly focused on the strengths of two algorithms, as in [92], where two swarm-based metaheuristic algorithms, Bat Algorithm (BA) and Cuckoo Search (CS) were compared while solving the optimal capacitor sizing and location problem. The objective was to minimize the real power loss and maximize network savings on a 34- and 85 bus system. It was concluded that the CS is better than the BA in solution quality, but slower to converge than the BA.

One major drawback of swarm algorithms is the subjective tuning of parameters. The inappropriate setting of parameters can lead to a premature convergence [93], which can produce local optima results. A simple hack is to find efficient ways to minimize or, if possible, eliminate parameter tuning. This concept has been studied in [94], where a Chaos Symbiotic Organisms Search (CSOS) algorithm with fewer parameters, was developed to place and size DG units in distribution networks. A chaotic variable was introduced to replace the parameters, making it less prone to local optima. The algorithm was tested on 33-, 69-, and 118-bus RDS, and it outperforms the original SOS in terms of convergence. Authors of [95] developed a hybrid Grey Wolf Optimizer that requires no parameter tuning except for population size. The algorithm was applied to solve the optimal DG allocation problem in a distribution network to minimize real and reactive power loss. The sizes of DG units and their power factor on each bus, and bus voltages were kept within realistic boundaries.

In light of implementing a substantial number of parameters, metaheuristic algorithms like WOA, ALO, and JAYA were developed. George *et al.* [96] used the ALO-based optimization technique to optimally place fixed shunt capacitors in a distribution system, considering the minimization of total power loss and total annual cost. Boktor *et al.* [33] also utilized the ALO for the optimal placing of shunt capacitors in a distribution network while optimizing the objective functions such as power loss and voltage profile. The ALO was evaluated on the IEEE 33- and 69-bus networks. The JAYA algorithm was used by [97] for optimal flow in a renewable energy-present distribution network. The JAYA algorithm is parameterless and quite simple to implement in the optimal integration problem [98].

The authors of [41] implemented WOA for optimal sizing and placement of capacitors in an RDN. Their objective was to reduce power loss, improve voltage profile, and minimize cost. The WOA was compared to other meta-heuristic algorithms, such as PSO and BFOA, and was tested on the IEEE 34- and 85-bus system. Wong *et al.* [99] investigated the impacts of optimal integration of BESS and PV-DG units in various scenarios. The WOA was applied to a 25-bus meshed network to minimize total real power loss and was compared to PSO and FA. The WOA and PSO performed distinctively better than FA, with the WOA surpassing the PSO by a small margin.

Other algorithms have also been applied to the optimal integration problem, such as in [100], which used the Discrete Lightning Search Algorithm (DLSA) for optimal placement of capacitors in wind farms. The proposed objectives were based on energy loss minimization and management cost reduction. The DLSA was compared with the GA and Discrete Harmony Search Algorithm (DHSA). From [101], the Moth Fly Algorithm (MFA) was used to optimally size and place capacitor banks in distribution networks. Power flow was solved for loss minimization using an iterative algorithm, while an arbitrarily simulated real and reactive load profile with a 15-minute interval was used for the load conditioning.

The Flower Pollination Algorithm (FPA), which uses a Levy flight based on a heavy-tailed probability distribution to attain global optimal solution was implemented by [38] to reduce the total cost of installed capacitors while solving the optimal capacitor sizes in a distribution network. The Moth Search Algorithm (MSA), similarly uses the Levy flight approach and was proposed by [102] for regulating bus voltage while placing and sizing DG units in a distribution network.

C. PHYSICS-INSPIRED ALGORITHMS

These algorithms emulate the workings of physical phenomena, which can be observations from chemistry, human interaction, or any natural occurrence. This category can be classified as an extension of swarm-based algorithms, especially in terms of their mechanisms. A significant distinction between them is that, instead of a swarm of search agents, the physics-based algorithms can use one search agent to interact within a solution search space or vice-versa. Ali *et al.* [40] proposed the Improved Harmony Algorithm (IHA) for optimally sizing capacitors in a distribution network, where the Power Loss Index (PLI) determines possible buses for the optimal installation of capacitors. The algorithm was tested on a 69-bus distribution system and was compared to other algorithms such as the PSO, ABC, DE, and HSA.

Ali *et al.* [103] studied the impacts of the stochastic nature of EV and the uncertain power output from PV-DG units in a distribution network. The optimal integration was formulated as a two-layer problem, using Gravitational Search Algorithm (GSA) to maximize the benefits of PV integration and to minimize annual energy losses. The EV battery was modeled to update the state of charge at every horizon and every charge/discharge state. The first layer produces optimal locations and sizes of PV-DG units considering the charging/discharging power of EVs, while the second layer produces optimal charging/discharging power profiles.

The HSA is another efficient metaheuristic based on the aesthetic combination of sounds. A well-detailed approach can be found in [62] and Askarzadeh [16] extensively discussed its implementation in power systems improvement. Liu *et al.* [104] implemented an improved HSA for the optimal integration of units in a distribution network to minimize the total operating cost. The HSA was hybridized with FA in [105], which is discussed in the next subsection.

D. HYBRID ALGORITHMS

Hybrid algorithms are a combination of two or more metaheuristic algorithms. The algorithms can either be combined as a single algorithm to solve the whole optimization problem, or not combined to solve different subproblems. Some applied examples are seen in works of literature. Lotfi *et al.* [106] proposed a hybrid algorithm to optimally allocate capacitors for the reconfiguration of distribution feeders fed with ESS, DG, and solar PV. An improved PSO and MSFLA were used alongside the VSI technique to achieve power loss minimization and voltage deviation reduction. The VSI uses a penalty factor to manipulate unstable decision parameters, hence avoiding buses with VSI values greater than zero. A competition function determines the best fitness values, where the population is split into two for each algorithm to solve the same problem. Afterward, the IPSO-MSFLA continues to select the best fitness value until the maximum iteration is met. It was reported that the algorithm produces a better voltage stability and operational cost than previous variants of the algorithm.

From [30], a hybrid algorithm, PSO-GA, was proposed to optimally allocate energy storage systems in a wind farm grid, considering uncertainties. Their objective was to improve voltage deviation and to reduce operating costs and carbon emissions. The proposed algorithm was tested on the IEEE 30-bus system, and was reported that the PSO-GA performs better than the GSA on all the objectives except for voltage deviation.

TABLE 1. Hybridized metahueristic optimization algorithms for smart grid networks.

Ref.	Algorithm	Application	Objective	Strength	Drawbacks
[30]	GA & PSO	ESS allocation	Carbon emission reduction Voltage deviation improvement Operating cost reduction	High accuracy of results	High computational time
[106]	PSO & MSFLA	Capacitor allocation	Voltage stability improvement	High accuracy of results	Uncertain convergence
[32]	GA & IWD	DG units location and sizing	Power loss minimization	Very good computational time,	Uncertain convergence
[107]	CSO & TBLO	CS allocation	Power loss minimization Voltage stability improvement	Fast convergence	High computational time Good results subject to prameter tuning
[108]	DE & HSA	STATCOM allocation	Cost reduction Voltage stability improvement Power loss minimization	Fast convergence	High computational time
[109]	GA & DE & SPEA-II	DG units location and sizing Capacitor allocation EV scheduling	Voltage stability improvement, Emission reduction, Cost reduction	High accuracy of results	High computational time Uncertain convergence Multiple parameters
[105]	HSA & FA	DG units location and sizing	Profit maximization Cost reduction	High accuracy of results	High computational time

Moradi *et al.* [32] utilize GA and Intelligent Water Drops (IWD) to optimize and allocate DG units in a distribution network. VSI was used to reduce active power losses through the identification of candidate buses. The IWD computes the fitness values while the GA operators produces a new generation of chromosomes. The hybrid algorithm was tested on a 33-bus and 69-bus system and shows an excellent computational time, which even increases linearly with the number of DG units.

Deb *et al.* [107] developed a hybrid algorithm (comprising chicken swarm optimization and TBLO) in a multi-objective space to improve grid stability while allocating charging stations in the IEEE 33-bus network. The grid stability consists of voltage stability index, reliability index, and power loss index. The CSO and TLBO are directly merged to speed up convergence and to reduce the likelihood of a premature convergence. The INV parameter in the CSO-TLBO, just like in the CSO, is user-defined and must be tuned properly to avoid local optima solutions. It was reported that the CSO-TLBO converges faster than the Multi-Objective Evolutionary Algorithm with Decomposition (MOEA/D) and the NSGA-II but with a higher computational time.

The authors of [105] hybridized the HSA and FA (CHSFA) to maximize profits of distribution network companies by reducing operational costs and increasing income in a distribution network. A robust framework was implemented to handle uncertainties from load demand, which, rather than probabilistic, uses a deterministic approach based on a confidence interval or historical data estimate. The CHSFA uses the HSA mechanism to search towards the best objective values in the harmony memory and uses the FA mechanism for a random search. This process is repeated twice to achieve an optimal solution. The CHSFA was validated on a 38-bus distribution network and was reported to converge faster than the HSA. Although the computational time comparison was not reported, it is assumed that the CHSFA, due to its complex mechanism, will have a higher computational time than the HSA.

Zhang *et al.* [108] developed a hybrid of DE and Harmony Search (DEHS) algorithm to find the optimum location of multiple STATCOM units in the IEEE 30-bus meshed network. The study uses the DE mutation operator to extensively search for an optimal solution in the harmony memory without changing the search mechanism of the HSA. The opposition learning principle was implemented to hasten the search process, thereby speeding up the convergence time. The DEHS algorithm improves the stability index of the network than the HSA. It also converges faster than the HSA.

Zeynali *et al.* [109] hybridized a family of the evolutionary algorithm: GA, DE, and Strength Pareto Evolutionary Algorithm (SPEA-II) to simultaneously integrate RES-based DG units (solar and wind), capacitor banks, and EV in a distribution network. The algorithm uses a varietized crossover function to select from three mutation strategies randomly. The objectives are voltage stability improvement, gas emission reduction, and installation cost reduction.

The summary of reviewed hybrid metaheuristic algorithms with their applications, objective functions, strengths and drawbacks, is shown in Table 1.

E. COMBINED TECHNIQUES

Unlike the hybrid algorithm category, this category is a combination of two different optimization techniques. Examples are analytical/metaheuristic and mathematical/metaheuristic techniques. These techniques can be used to (i) reduce the complexity of the optimal integration of electrical units problem and (ii) manipulate high-level problems for simplex computation. They are also a starting point to optimize a newly modified model. Generally, algorithms are combined with other techniques for optimization in power systems to achieve better efficacy. Tang *et al.* [110] studied the optimal location and size of ESS and PV-DG units in a 33-bus distribution network. This was done by using an analytical sensitivity analysis and a flame propagation model to determine DG units' location. The study exploits the partition method to help minimize power loss and improve power supply reliability.

In [111], Power Loss Reduction Factor and an improved Multi-Objective Golden Ratio Optimization was used to optimally allocate and size capacitors and STATCOM in distribution networks respectively. The algorithm was tested on a 13-bus and the IEEE 69- and 118-bus distribution networks to minimize power loss, reactive power investment, and improve voltage profile. The authors of [112] proposed a hybrid ABC-PSO approach with load flow calculation based on fuzzy load flow to minimize power loss and to improve voltage profile while finding the optimal capacitor sizes. The Loss Sensitivity Factor (LSF) technique was used to detect buses sensitive to power loss, and then a fuzzy inference system was used to select the optimal location of the capacitors. A hybridized ABC-PSO algorithm was used to size the capacitors and the algorithm was tested on a 34-node RDN. Also, Muthukumar *et al.* [113] developed a hybrid algorithm, HSA-ABC, to optimize capacitor size and placement in an RDN, considering different load models. PLI, VSI, and LSF were implemented to calculate total network power loss, to detect low-quality voltage in nodes, and to identify high active power loss in nodes for capacitor placement respectively.

In [42], an LSF technique to select the possible candidate buses for capacitors in a 69-bus distribution network. An MFA-based algorithm was developed to optimally size the capacitors to reduce energy losses considering the variation of load. From [114], ALO was implemented alongside LSF to allocate and size optimally renewable DGs in a microgrid respectively. The proposed algorithm was evaluated on a 69-bus RDS and compared to other algorithms to show the improvement of total power loss reduction and net savings enhancement. Kishore *et al.* [115] added the VSI to the LSF technique to optimally place capacitors in distribution networks. An improved bacterial foraging optimization algorithm (IBFOA) with symmetric fuzzy methods were implemented alongside the techniques to minimize power loss and improve voltage stability and was tested on a 33-, 69-, and 141-node networks.

The authors of [37] worked on the optimal location and size of capacitors in a distribution network. Here, the LSF technique was implemented to select candidate buses for the capacitor placement, which led to the GSA's implementation to optimally size the capacitors on the selected buses. From [116], LSF was also used to assign candidate buses with the lowest capacitor placement values. The FPA-based algorithm was used to optimally determine the capacitor sizes, with the main objective of minimizing real power loss. The algorithm was evaluated on a 10-, 33-, and 69-bus system.

Lim *et al.* [117] proposed a GA optimization method to minimize peak-to-average ratio energy demand and the price of electricity in a multi-level optimization framework. The framework uses convex programming in a stepwise manner to incorporate energy demand scheduling, ESS units, and PV-based DG units for households. Das *et al.* [118] combined a chaotic process with an artificial bee colony algorithm for the optimal placement of distributed BESS in a PV- and WT-present IEEE 33-bus distribution network. The goal was to minimize power loss, voltage deviation, and maximize line loading.

V. MULTIOBJECTIVE OPTIMIZATION METHODS IN THE OPTIMAL INTEGRATION OF ELECTRICAL UNITS

The efficient use of optimization algorithms is dependent on the mode of handling objective functions. Multiobjective functions stand the risk of not being optimized correctly due to the distinctive interference among them. Therefore, it is imperative to select a suitable multiobjective framework in an optimization model, particularly in the optimal integration of electrical units in distribution networks.

There are two major approaches for solving multiple objectives, namely *apriori* and *aposteriori*. The *apriori* approach is applied to sort multiple objective functions before processing. A simple method is the sequential programming, where different objectives are dependent on each other. That is, the first objective must be solved to calculate the second objective, or two objectives can form an equation to determine the main objective. This is done in [119], where a modified Imperialistic Competitive Algorithm (ICA) was proposed to optimally place and size DG units in the planning of distribution networks. The algorithm minimizes real power loss and improves the voltage stability in different load variations. A summation method was used to compute the objectives into a single objective. The algorithm was tested on a 34-bus and 69-bus test system and was compared with the CS algorithm, which shows improvement in the voltage profile and real power loss. The objective function, which is the division of real power loss equation and total voltage stability index, subjectively represents the technical impacts in a distribution network.

The weighted sum aggregate (WSA) is another typical method, where objective functions are assigned different weights according to their importance, where the sum of the weights is always approximate to one. This method is quite simple since all objectives are weighted and summed for a final objective value. El-Ela *et al.* [120] proposed a newly developed algorithm, Water Cycle Algorithm (WCA), and applied the WSA to handle multiple objectives while integrating DG units and capacitor banks in a distribution network. The weights were applied in different scenarios such that it alternatively reflects grid performance, economic benefits, and environmental benefits. Mukhopadhyay and Das [121] focused on technical objectives while using the PSO to optimally allocate PV-DG and BESS units in a reconfigurable distribution network. The objectives, which are, power loss minimization, voltage deviation minimization, and line loading maximization, were normalized before applying an equal weighting to them.

Applying weights to multiple objectives will require experience; otherwise, one can use weights from previous studies. However, the values of weights are subjective and bias to the researchers. In lieu of this, some studies have tried to subdue the subjectivity of weight values by applying an additional technique to generate weights with respect to the objective functions. In [122], a fuzzy multi-objective approach was applied to a two stage-based Grasshopper Optimization Algorithm to optimally place and size DG units, capacitors, and EV-CS. The first stage is to allocate and size DG units and capacitors to reduce real power loss and improve power factor and voltage profile. The second stage is to identify optimal locations for EV-CS. To reduce the subjectivity, the study applied weights with a fuzzified voltage limit to all objectives. The proposed approach converges faster than the regular GOA, PSO, and GA techniques. Adetunji *et al.* [47] also proposed a concept of fuzziness to assign different weights to objective functions on an iterative scale. The WOA was used to carry out several runs while changing the weighting factors of the multiobjective framework. The weights were assigned to represent different decision-maker preferences and find a solution through a competition model. Note that the varying of weights does not produce a Pareto optimal solution set.

Shaheen *et al.* [123], instead of directly assigning weights to the objective functions, used the Analytical Hierarchical Process (AHP) for calculating the weights to reduce bias while applying the Enhanced Grey Wolf Algorithm (EGWA) to optimally integrate DG units, capacitors banks, and voltage regulators. The relationship between objective functions is graded according to a certain level of importance, which forms a pairwise matrix. Gangwar *et al.* [124] also used the AHP to assign weights to objective functions while solving the optimal DG units location problem in a reconfigurable distribution network.

While studies have used different techniques to minimize the bias for assigning weights to objective functions, other studies have implemented the *aposteriori* approach to completely avoid the bias.

The *aposteriori* approaches involve the processing of multiple objective functions before sorting the values. All objective functions are optimized collectively, and the non-conflicting solutions are selected as the best outputs [4]. A non-dominating solution means that two or more sets of objective function values are not better than one another. The set of non-dominating solutions, also called the Pareto optimal set, is solved by a decision-making technique to find the best solution.

Instead of performing different runs of possible alternatives, as in the case of ϵ-constraint, weight combination, or other mathematical techniques, metaheuristic algorithms simultaneously handle many potential options that produce a set of Pareto optimal fronts. NSGA-II technique is the commonly used evolutionary algorithm due to its robustness and efficiency. The technique uses a domination-based approach to assign fitness through non-domination ranking and crowding distance [125]. Some applications [25], [31], [82], [126]–[129] of NSGA-II to the optimal integration problems are discussed below.

Dehghanian *et al.* [31] proposed a special multi-objective, non-dominated sorting genetic algorithm (NSGA-II) for the optimal siting of DG units in a power system, with objective functions to minimize network power losses, reduce costs, and increase system reliability. The NSGA-II produces a Pareto optimal set of solutions that are not better than each other in terms of their objective values. The NSGA-II was also suggested in [25] for solving the optimal integration of DG and BESS units in a distribution network. The objective function was to reduce the energy losses and the total investment cost of DG and BESS units. A Utopian method was used to select the compromise solution from the Pareto set. The method entails the running of the optimization algorithm for each normalized objective to derive the Utopian point, the calculation of the Euclidean distance between the Utopian point and each solution in the Pareto set, and the selection of the solution with the shortest distance as the compromise solution. This method, although not frequently used, eliminates the subjectivity in assigning importance to objectives. The study used voltage regulation and temperature to increase the lifespan of the BESS units. The algorithm was tested on an IEEE 906 bus European test feeder.

In [126], NSGA-II was used for power loss minimization and voltage profile improvement. Electricity prices and probabilistic load (with peak) were modeled based on time series for optimally sizing and placing capacitors in a distribution network, and the fuzzy decision model was used to select the compromise solution. The algorithm was tested on the IEEE 33-bus distribution test network. Zhang *et al.* [108] also applied the fuzzy decision model to select a compromise solution from non-dominating solutions in the optimal location of STATCOM in the IEEE 30-bus meshed network. The focus is on the technical and economic benefits, which are investment and operation cost reduction, voltage stability improvement, and real power loss minimization.

Battapothula *et al.* [127] simultaneously allocated DG units and CS in a distribution network while minimizing power losses, energy consumption, charging station development cost, voltage deviation of the system. The NSGA-II was used for generating Pareto optimal solutions, while the min-max technique was used to determine the compromise solution. The min-max method is adopted from goal programming where distances between large deviations are minimized to obtain a final solution. Jannat *et al.* [128] also developed a method based on the min-max technique to determine a compromise solution from Pareto fronts. They used the NSGA-II for the optimal capacitor placement in distribution networks and an RE-based power flow was implemented to consider uncertainties from wind, solar, and load. The algorithm was evaluated on the Serbia grid network to improve the voltage profile and minimize power from the installed capacitors. Generally, the min-max falls among the categories of varied weights and ϵ-constraints where a weakly set of Pareto solutions are produced. Only recently studies have improved the min-max to produce better Pareto optimal solutions [130], [131].

Recently, Nagaballi and Kale [132] used a minimax-based game theory approach to choose the compromise solution among non-dominating solutions from the Improved Raven Roosting Optimization (IRRO) algorithm application in the optimal allocation of DG units in distribution networks. The minimax algorithm uses a competitive two-player mode, where each player tries to reach the optimal minimum or optimal maximum for the final utility value. This approach proves to be computationally efficient than other methods such as the TOPSIS and fuzzy decision-making technique.

Mahesh *et al.* [133] implemented the PSO in a non-dominated sorting multi-objective as an advanced Pareto front. A mutation factor is applied to modify the position vector after the particle position is updated. This approach is to avoid a fast convergence that mostly produces a false Pareto front. The algorithm was applied alongside the VSI and PLI techniques and minimize total power loss and improve voltage profiles while sizing and placing DGs optimally in a distribution network. The study uses cases of single and multiple objectives, with three DG types being integrated categorically. Solutions from the multi-objective space were computed from a fuzzy-decision model. Deb *et al.* [107] developed a hybrid algorithm (comprising chicken swarm optimization and TBLO) in a multi-objective space to improve grid stability while allocating charging stations in the IEEE 33-bus network. The grid stability consists of voltage stability index, reliability index, and power loss index. The fuzzy decision-making technique was also used to determine the compromise solution from the Pareto optimal solution.

Zhang *et al.* [134] used Chance Constrained Programming (CCP) to solve the probabilistic power flow in the optimal planning of distribution systems. The objective was to reduce economic cost through the correlation of uncertainties using NSGA-II for the Pareto optimal fronts, and a 61-bus test system was used for evaluation. However, no comparison was made with other algorithms to test for performance. It is to note that the proposed multi-objective technique integrates uncertainties from different DG units during the optimization, but cannot handle BESS DG units. A decision-maker is to choose from the Pareto front; hence a decision technique was not implemented. The same decision was made in [129], where the compromise solution is left for the decision-maker to choose. In the study, Fault Current Limiters (FCL) were installed in series with DG units to reduce the adverse effects on the grid while finding an optimal location. The NSGA-II was implemented to reduce power losses and FCL sizes.

Li *et al.* [135] used a two-stage optimization framework to optimally place and size BESS and DG units in an active distribution network. The framework consists of an LSF technique and a multi-objective ALO (MOALO), which solves the location and capacity of the DG and BESS units, respectively. The MOALO was initially used to find a Pareto-optimal solution, followed by obtaining the order of significance of each Pareto solution. The final results address the objective that minimizes the power losses and maximizes the voltage stability and investment benefits while considering the uncertain outputs of energy sources (DG and BESS). The framework was tested on the PG & E 69-bus and was compared to the NSGA-II, Multi-Objective PSO (MOPSO), and Multi-Objective Harmony Algorithm (MOHA). Results showed that their two-stage optimization method is better than the algorithms mentioned above in terms of line losses, voltage stability, and investment costs.

Sharma *et al.* [136] suggested the NSGA-II to optimally allocate BESS for demand response in the presence of WT-based DG units and capacitors. The bi-objective framework consists of power loss minimization and grid demand cost minimization. The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) approach was used to select a compromise solution based on the relative closeness index. The TOPSIS approach uses the Euclidean geometry such that it minimizes the Euclidean distance between each alternative and its best solution set (positive ideal solution), and simultaneously maximizes each alternative from its worst solution set (negative ideal solution). The study compared the performance of the developed multiobjective optimization framework to the MOPSO. The framework was evaluated on an Indian power distribution network, showing a significant reduction in power loss and grid energy consumption cost.

Meena *et al.* [137] also used TOPSIS to select a compromise solution from a multiobjective Elephant Herding Optimization (ELO) algorithm. The approach used for selecting Pareto optimal solutions is unclear; however, a spacing metric was used to quantify the quality of Pareto solutions for comparison with other variants of the ELO. The spacing metric was used to measure statistical values to compare with other variations of the ELO. The framework was applied to optimize power loss minimization, voltage deviation, and voltage stability. Selim *et al.* [138] proposed an improved Harris Hawks Optimizer (IHHO) in a multi-objective space to optimally place DG units in distribution networks. The objective was to minimize total real power loss, voltage deviations, and improve the voltage stability index, based on different operating power factors. The Grey Relational Projection (GRP) technique was used to identify the best compromise solution from non-dominating solutions. Although computationally efficient, the GRP method can only be used to select compromise solutions among closely related objectives; hence, only the technical objectives were considered.

Huiling *et al.* [83] formed a stochastic fuzzy chance-constrained model for coordinated charging and discharging of EVs and the integration of RES-based DG units in a multi-objective space. A modified NSGA-II algorithm was developed for minimizing power loss and voltage deviation. Instead of using the crowding distance, the study proposed a congestion comparison operator for calculating the distance among three close solutions of each objective function, to avoid overconcentration and improve the uniform distribution of the Pareto front. In [139], a decomposition approach was used to produce final utility value from a Pareto set in the optimal integration problem in distribution networks. The approach decomposes the main problem into numerous subproblems in order to assign a set of evenly-spread weights to each subproblem. This approach enables the emulation of a uniformly distributed set of solutions in a multiobjective space. However, the adopted objectives, real power loss and reactive power loss, are not clearly conflicting, which may not reveal the full strength of the proposed approach. Conflicting objectives should be adopted to solve the nonconvex Pareto front problem from weight assignments [140], [141].

While the primary application of a multiobjective framework is to simultaneously optimize multiple objectives, there should be a consideration of the types of objectives to optimize in an optimal integration problem. In modern distribution networks, it is more practical to consider the simultaneous optimization of grid performance (technical), economic, and environmental benefits for network planning. Fewer research works [30], [109], [142] have implemented such studies.

Zeynali *et al.* [109] developed a multi-objective optimization framework to simultaneously integrate RES-based DG units, capacitor banks, and EV in a distribution network. A family of the evolutionary algorithm was hybridized as a GA-DE-SPEA-II algorithm, which has its strength from a varietized crossover function and synthesized mating strategy to produce good Pareto optimal solutions. The study considered one objective from all collective objectives, which are voltage stability, carbon emissions, and installation cost. The Fuzzy decision-making technique handled the selection of compromise solutions from the Pareto front. An extended version of the NSGA-II (E_NSGA-II) with a fuzzy decision model was developed by [142] to determine the best solution from a non-dominating set. The aim is to optimally integrate solar PV, BESS, and D-STATCOM to a smart microgrid, using a probabilistic power flow model. A VPI technique was used to compute voltage profile improvement after the integration of the three units. The algorithm was tested on a 69-bus test system to evaluate objectives, such as voltage profile, environmental benefit, reliability, and benefit-cost ratio. Thereafter, a non-parametric test was performed to compare the proposed algorithm's performance to other multi-objective algorithms such as MOGA, MOPSO, and NSGA-II.

In [30], a hybrid MOPSO and NSGA-II and a multi-objective GSA were proposed to optimally allocate energy storage systems in a wind farm-infused IEEE 30-bus meshed network. Their objective was to improve voltage deviation and to reduce operating costs and carbon emissions while using TOPSIS to select compromise solutions from the generated Pareto set. The authors formulated a single-, two-, and three-objective study to compare the best objective values for each formulation. The single objective produced the best voltage deviation and emission cost value while the three-objective produced the best installation cost value. Further work can be done to compare the quality of Pareto solutions distribution.

The multi-objective handling techniques used in the optimal integration of electrical units in distribution networks are summarized in Table 2.

VI. COMPARISONS AND DISCUSSIONS

This study identified many significant issues by reviewing metaheuristic techniques for the optimal integration of distributed generation and power electronic units in distribution networks. This section discusses the observations and suggestions regarding the implementation of metaheuristic algorithm applications to single objective and multi-objective frameworks in the optimal integration of electrical units in distribution networks.

A. DISCUSSIONS ON METAHEURISTIC TECHNIQUES FOR THE OPTIMAL INTEGRATION OF ELECTRICAL UNITS IN DISTRIBUTION NETWORKS

As explained previously in Section IV, metaheuristic algorithms are the common choice for solving optimal integration problems in smart grids due to their flexibility. However, in this context, flexibility might not necessarily mean simplicity. The successful implementation of metaheuristic algorithms requires a good knowledge of both the algorithm's inner workings and the optimal integration problem. Studies may directly apply algorithms to the optimal integration problem, given their availability as a toolbox or library in optimization software applications. While this direct approach may be simplistic, the researcher or engineer would implement the algorithm as a black box and may omit some important details. Hence, studies may not attain optimal or practical results. The GA is a typical example.

The GA is the most commonly used evolutionary algorithm, which may be due to its availability as a toolbox or library in optimization software applications, or its efficiency to produce good results from the optimal integration problem. It is observed that other algorithms in the evolutionary algorithms category, such as the DE, have fewer studies when compared to the GA. The DE has been reported to perform better in other studies than the GA, as shown in [143]. Moreover, the DE primary operators are synonymous to the recently modified GA operators, which means that current GA research can be used to improve the DE. Therefore, future research works can explore the DE algorithm to achieve better results from the optimal integration problem.

As seen in the study, swarm and physics-inspired algorithms have also been widely applied to the optimal integration of electrical units in distribution networks. They have been modified by tuning their parameters, which shows the high impact of parameter values on the optimization result. A high number of parameters may increase the subjectivity of the algorithm's performance; hence, future studies may focus on finding a substantial amount of the algorithm's parameters. Dimensionality reduction techniques, such as factor analysis

TABLE 2. Summary of reviewed multi-objective metaheuristic algorithms.

Ref.	Algorithm	Objectives	MOO approach	Summary of findings
[128]	NSGA-II	Voltage profile improvement, Capacity reduction	Pareto optimal solutions	A new approach on min-max method was used to select the best solution. Technical and economic benefits are considered. Works best with two objectives.
[122]	GOA	Real power loss minimization, Power factor improvement, Voltage profile improvement	WSA	The weights are fuzzified to reduce bias. Preference is done prior to handling the objectives. Technical benefits were the main focus.
[83]	NSGA-II	Real power loss minimization, Voltage deviation	Pareto optimal solutions	Fuzzy-based approach is used to select the best solution. It requires the input of weights for the final decision.
[127]	NSGA-II	Power loss minimization, CS development cost reduction, Voltage deviation reduction	Pareto optimal solutions	A min-max method was used to select the best solution. Different forms of cost were considered.
[138]	IHHO	Real power loss minimization, Voltage deviation reduction, Voltage profile improvement	Pareto optimal solutions	Grey relational projection was used to select the best solution. Computation is very fast. The GRP can only handle closely related objectives. Economic or environmental cost were not considered.
[136]	NSGA-II	Power loss minimization, Grid demand cost reduction	Pareto optimal solutions	TOPSIS was used to select the best solution. No strict requirement for assigning weights. Involves more computational time.
[135]	MOALO	Power loss minimization, Voltage profile improvement	Pareto optimal solutions	Grey relational projection was used to select the best solution. Method for selecting non-dominating solutions is not clearly stated. Objectives considered can technically be solved as a single objective.
[133]	MOPSO	Power loss minimization, Voltage stability improvement	Pareto optimal solutions	Fuzzy-based approach is used to select the best solution. Economic or environmental benefits are not considered.
[142]	NSGA-II	Voltage profile improvement, Energy not supplied improvement, Carbon emission reduction	Pareto optimal solutions	Fuzzy-based approach is used to select the best solution. Considers the technical, economic and environmental benefits. It requires the input of weights for the final decision.
[123]	EGWA	Savings Maximization, Investment cost reduction, Voltage profile improvement Power loss minimization	WSA	AHP was used to choose the weights to reduce bias. Technical and economic benefits are considered. Preference is done prior to handling the objectives.
[47]	WOA	Power loss minimization, Load variance, Charging cost minimization	WSA	Weights were assigned according to the number of iterations. Consideration of two decision makers. Technical and economic benefits were considered.
[134]	NSGA-II	Annual cost reduction, Investment risk reduction	Pareto optimal solutions	Selection of best solution is left for the user. Economic benefits was the main focus.
[82]	NSGA-II	ESS cost reduction, Investment cost reduction, Voltage regulation improvement, Voltage dip reduction	WSA	Preference is done prior to handling the objectives. Equal weighing is assigned to objectives. Economic and Technical benefits are considered.
[126]	NSGA-II	Power loss minimization, Voltage profile improvement	Pareto optimal solutions	Fuzzy-based approach is used to select the best solution. It requires the input of weights for the final decision. Objectives considered can technically be solved as a single objective.
[25]	NSGA-II	Energy loss minimization, Investment cost reduction	Pareto optimal solutions	Utopian point method is used to select the best solution. Selection of a solution is free of bias.
[31]	NSGA-II	Power loss minimization, Investment cost reduction	Pareto optimal solutions	Fuzzy-based approach is used to select the best solution. Economic or environmental benefits are not considered.
[120]	WCA	Real power loss minimization, Installation cost reduction, Installation cost reduction, Voltage profile improvement	WSA	Preference is done prior to handling the objectives. Technical, economic, and environmental benefits are considered in different case studies.
[129]	NSGA-II	Power loss minimization, Cost reduction	Pareto optimal solutions	Selection of best solution is left for the user.
[121]	MOPSO	Power loss minimization, voltage deviation minimization, line loading maximization	WSA	AHP is used to choose the weights to reduce bias. Economic or environmental benefits are not considered. Preference is done prior to handling the objectives.

TABLE 2. ***(Continued.)*** **Summary of reviewed multi-objective metaheuristic algorithms.**

[124]	MOPSO	Power loss minimization, Voltage profile improvement, Network reliability improvement	WSA	AHP is used to choose the weights to reduce bias. Technical benefits was the main focus. Preference is done prior to handling the objectives.
[107]	CSO-TLBO	Power loss minimization, Voltage stability improvement, Reliability improvement	Pareto optimal solutions	Fuzzy-based approach is used to select the best solution. Technical benefits was the main focus.
[30]	NSGA-II-MOPSO & MOGSA	Voltage deviation improvement, Installation cost reduction, Emission cost reduction	Pareto optimal solutions	TOPSIS is used to select the best solution. Technical, economic, and environmental benefits are considered.
[137]	MOELO	Power loss minimization, Voltage deviation improvement, Voltage stability improvement	Pareto optimal solutions	TOPSIS is used to select the optimal solutions and the best solution. Not clear about the distribution of the Pareto solutions. Economic and environmental benefits are not considered.
[109]	GA-DE-SPEA-II	Voltage stability improvement, Carbon emission reduction, Cost reduction	Pareto optimal solutions	Nearest neighbour approach to select Pareto solutions. No specific technique to select the best solution. Technical, economic, and environmental benefits are considered.
[108]	DEHS	Power loss minimization, Voltage stability improvement, operational cost reduction	Pareto optimal solutions	Fuzzy-based approach is used to select the best solution. Technical and environmental benefits are considered.
[132]	IRRO	Real power loss minimization, Reactive power loss minimization, Voltage stability improvement, Voltage profile improvement, Line loading improvement	Pareto optimal solutions	Game theory approach based on a minimax algorithm was used to select compromise solution. Environmental benefit is not considered. Computationally efficient.
[139]	MOEA/D	Real power loss minimization, Reactive power loss minimization	Pareto optimal solutions	Uniform weights are applied to generate Pareto solutions. Economic or environmental benefits are not considered. Adopted objectives are closely related which may not prove strength of the decomposition approach.

and principal component analysis, can be used to find an optimal amount of parameters for any algorithm. Although this process may be exhaustive, it will aid studies on the optimal integration of electrical units to further improve grid performance and boost economic benefits.

It is also observed that hybrid algorithms are trending since they can be easily implemented to produce good results from the optimal integral problem. However, some studies directly merge two or more mechanisms to improve grid performance and boost economic benefits. This effort poses a risk of increasing the algorithm runtime; hence, they become computationally inefficient. This is evident in works of [30], [105]. One way to overcome this setback is to find and eliminate duplicate steps or attributes of the algorithms. Future studies on the optimal integration of electrical units can focus on implementing each algorithm's unique features rather than directly implementing the whole features of each algorithm.

Another observation is that most of the combined techniques, especially the analytical/metaheuristic, reduce the computational complexity of the optimal integration problem. However, these techniques may not guarantee optimal solutions because they are based on an approximate derivation of mathematical equations [7], [11]. Moreover, results from approximate derivations can only give a snapshot of the distribution network characteristics, e.g., power loss or voltage stability values, at one run. It will be interesting to see more research on better supporting techniques for metaheuristic algorithms. That way, there will be increased computational efficiency with a lesser risk of losing optimality in the optimal integration problem's final results.

B. DISCUSSIONS ON MULTIOBJECTIVE OPTIMIZATION FOR THE OPTIMAL INTEGRATION OF ELECTRICAL UNITS IN DISTRIBUTION NETWORKS

As discussed in Section V, metaheuristic algorithms deal with multiobjective problems in two major ways, either by computing preference aggregation before or after problem manipulation. The *apriori* approach is quite easy to implement and is computationally efficient. However, based on intuition for a better practical scenario, most *aposteriori* methods are preferred to the *apriori* ones. Studies on the optimal integration of electrical units have implemented both approaches according to different philosophies. A comparison of different multi-objective optimization techniques is shown in Table 3.

Previous studies have handled multiple objectives in a non-categorized manner, where, irrespective of the multi-objective handling method used, every objective function is pushed to a multiobjective framework for a final decision value. This approach may not represent a practical scenario where all collective objectives, such as technical (or grid performance), economic, and environmental objectives are

TABLE 3. Comparison of decision-making techniques.

Techniques	Strengths	Drawbacks
WSA	-Easy to compute -Suitable for professional decision makers	-Results may be flawed by bias
Fuzzy decision method	-Rich in Literature -Easy to implement	-Some level of subjectivity with the input of weights
Min-max method	-Easy to implement -Low computational complexity	-May be unrealistic for real-world problems
Utopian method	-Eliminates subjectivity -Easy to implement	-Few studies in literature -Mostly suitable for two objective functions
GRP	-Easy to implement -Low computational complexity	-Only suitable for closely similar objectives
TOPSIS	-Can handle several objectives in form of alternatives -Weights assignment can be skipped -Can involve many decision makers	-High computational complexity -Some level of subjectivity if weights are assigned

thought differently from each other. For example, studies in [108] adopted two objective functions for grid performance and one for economic benefits but assigned equal weighting for all objectives in the decision making phase. An equal assignment of weights or direct summation already shows a high preference for grid performance than economic benefits. Some studies have avoided this drawback by either focusing on only one of the collective objectives or selecting one objective to represent each collective objective. For instance, Sharma *et al.* [136] adopted power loss minimization and grid demand cost reduction to represent grid performance and economic benefits, respectively. Another example is from [121], where all adopted objectives represent only the grid performance.

These examples beg the questions:

1) Can one objective, such as power loss minimization, satisfactorily represent grid performance?
2) Can we always optimize only a collective objective, such as grid performance, without including economic or environmental benefits?

To find a balance among all collective objectives, it is suggested that future studies should develop a multi-stage multi-objective framework to find a balance among all collective objectives, where all similar objectives can be optimized categorically.

The trend of optimal integration of electrical units in a distribution network grid is shifting towards a full-blown smart grid, where clean energy will be prevalent. Hence, more studies will need to be carried out on the optimal integration of ESSs, wind turbines, solar PVs, and EVs. Another observation is the trend in the integration of EV units in recent studies, where EVs are used to support the grid in terms of voltage regulation or power compensation. The EV aggregator (EVA) has been added to new optimal integration models to communicate EV data for charging or discharging schedule. They are practically in the business space, while the DSO is concerned about the health of the distribution network. Hence, the EVA can also become a decision-maker along with the DSO. It is only practical since the EVA is an integral part of the model. Future studies can explore the possibilities of including the DSO and EVA as major decision makers in the optimal integration of EVs and other electrical units model.

VII. CONCLUSION

This paper reviewed the application of metaheuristic algorithms for solving the optimal integration problem and its dynamic implementation to solve objective functions. Metaheuristic algorithms were extensively discussed and categorized as evolutionary, swarm intelligence, physics, hybrid, and combined. Each of these categories was thoroughly discussed with examples from the literature regarding the type of application, decision variables, objective functions, and results. All of the techniques should determine the optimal location and sizes of electrical units while considering specific objective functions.

Given that optimal integration problem is based practically on improving more than one objective, researchers are faced with an additional decision making, which is to choose a convenient but correct method to handle multiple objective functions. It is noteworthy that the handling of multiple objective functions is directly related to the authenticity of the results. Additionally, the simultaneous integration and handling of uncertainties in distribution networks can significantly add to the complexity of the model, depending on the grid scenario. Therefore, it is important to develop a model that can efficiently handle such complexity.

Suggested future works regarding the optimal integration problem in distribution networks may be required in

- development of new metaheuristic algorithms that require minimal input from the user, e.g., an optimal number of parameters,
- development of hybrid algorithms that converge quickly and have a lesser computational time,
- development of better supporting techniques for selecting candidate buses for optimal location of electrical units in a distribution network,
- combination of EV charging stations and other electrical units for optimal integration in distribution networks,
- development of a multi-objective optimization framework that further helps multiple decision-makers regarding the optimal integration problem.

ABBREVIATIONS

BESS	Battery Energy Source System
CS	Charging Station

D-STATCOM	Distributed Synchronous Static Compensator
DG	Distributed Generation
EV	Electric Vehicles
PV	Photovoltaic
RES	Renewable Energy Sources
V2G	Vehicle to Grid
WT	Wind Turbine
MCS	Monte Carlo Simulation
GRP	Grey Relational Projection
WSA	Weighted Sum Approach
AHP	Analytical Hierarchical Process
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
ABC	Artificial Bee Colony
ACO	Ant Colony Optimization
ALO	Ant Lion Optimizer
CS	Cuckoo Search
DE	Differential Evolution
DLSA	Discrete Lightning Search Algorithm
FA	Firefly Algorithm
FPA	Flower Pollination Algorithm
GA	Genetic Algorithm
GWO	Grey Wolf Optimizer
HHO	Harris Hawks Optimization
HSA	Harmony Search Algorithm
ICA	Imperialistic Competitive Algorithm
MOALO	Multi-Objective Ant Lion Optimizer
MOPSO	Multi-Objective Particle Swarm Optimization
NSGA-II	Non-dominating Sorting Genetic Algorithm
PSO	Particle Swarm Optimization
TLBO	Teaching Learning Based Optimization
WCA	Water Cycle Algorithm
WOA	Whale Optimization Algorithm
LSF	Loss Sensitivity Factor
PLI	Power Loss Index
MILP	Mixed Integer Linear Programming
MINLP	Mixed Integer Non-Linear Programming
NLP	Non-Linear Programming
SOCP	Second Order Cone Programming
VSI	Voltage Stability Index

REFERENCES

[1] X.-S. Yang, *Nature-Inspired Metaheuristic Algorithms*. Frome, U.K.: Luniver Press, 2010.

[2] J.-S. Chun, H.-K. Jung, and S.-Y. Hahn, "A study on comparison of optimization performances between immune algorithm and other heuristic algorithms," *IEEE Trans. Magn.*, vol. 34, no. 5, pp. 2972–2975, Sep. 1998.

[3] G. Venter, *Review of Optimization Techniques*. Atlanta, GA, USA: American Cancer Society, 2010. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1002/9780470686652.eae495

[4] N. M. Pindoriya, S. N. Singh, and K. Y. Lee, "A comprehensive survey on multi-objective evolutionary optimization in power system applications," in *Proc. IEEE PES Gen. Meeting*, Jul. 2010, pp. 1–8. [Online]. Available: http://ieeexplore.ieee.org/document/5589511/

[5] X.-S. Yang, "Review of meta-heuristics and generalised evolutionary walk algorithm," *Int. J. Bio-Inspired Comput.*, vol. 3, no. 2, pp. 77–84, 2011.

[6] S. Daud, A. F. A. Kadir, C. K. Gan, A. Mohamed, and T. Khatib, "A comparison of heuristic optimization techniques for optimal placement and sizing of photovoltaic based distributed generation in a distribution system," *Sol. Energy*, vol. 140, pp. 219–226, Dec. 2016, doi: 10.1016/j.solener.2016.11.013.

[7] L. A. Wong, V. K. Ramachandaramurthy, P. Taylor, J. B. Ekanayake, S. L. Walker, and S. Padmanaban, "Review on the optimal placement, sizing and control of an energy storage system in the distribution network," *J. Energy Storage*, vol. 21, pp. 489–504, Feb. 2019, doi: 10.1016/j.est.2018.12.015.

[8] C. K. Das, O. Bass, G. Kothapalli, T. S. Mahmoud, and D. Habibi, "Overview of energy storage systems in distribution networks: Placement, sizing, operation, and power quality," *Renew. Sustain. Energy Rev.*, vol. 91, pp. 1205–1230, 2018, doi: 10.1016/j.rser.2018.03.068.

[9] R. Sirjani and A. Rezaee Jordehi, "Optimal placement and sizing of distribution static compensator (D-STATCOM) in electric distribution networks: A review," *Renew. Sustain. Energy Rev.*, vol. 77, pp. 688–694, Sep. 2017, doi: 10.1016/j.rser.2017.04.035.

[10] M. R. Sheibani, G. R. Yousefi, M. A. Latify, and S. Hacopian Dolatabadi, "Energy storage system expansion planning in power systems: A review," *IET Renew. Power Gener.*, vol. 12, no. 11, pp. 1203–1221, Aug. 2018.

[11] A. Ehsan and Q. Yang, "Optimal integration and planning of renewable distributed generation in the power distribution networks: A review of analytical techniques," *Appl. Energy*, vol. 210, pp. 44–59, Jan. 2018, doi: 10.1016/j.apenergy.2017.10.106.

[12] Y. Latreche, H. R. E. H. Bouchekara, F. Kerrour, K. Naidu, H. Mokhlis, and M. S. Javaid, "Comprehensive review on the optimal integration of distributed generation in distribution systems," *J. Renew. Sustain. Energy*, vol. 10, no. 5, Sep. 2018, Art. no. 055303.

[13] P. Prakash and D. K. Khatod, "Optimal sizing and siting techniques for distributed generation in distribution systems: A review," *Renew. Sustain. Energy Rev.*, vol. 57, pp. 111–130, May 2016, doi: 10.1016/j.rser.2015.12.099.

[14] W. L. Theo, J. S. Lim, W. S. Ho, H. Hashim, and C. T. Lee, "Review of distributed generation (DG) system planning and optimisation techniques: Comparison of numerical and mathematical modelling methods," *Renew. Sustain. Energy Rev.*, vol. 67, pp. 531–573, Jan. 2017.

[15] A. Sujil, J. Verma, and R. Kumar, "Multi agent system: Concepts, platforms and applications in power systems," *Artif. Intell. Rev.*, vol. 49, no. 2, pp. 153–182, Feb. 2018.

[16] A. Askarzadeh, "Solving electrical power system problems by harmony search: A review," *Artif. Intell. Rev.*, vol. 47, no. 2, pp. 217–251, Feb. 2017.

[17] B. Khan and P. Singh, "Selecting a meta-heuristic technique for smart micro-grid optimization problem: A comprehensive analysis," *IEEE Access*, vol. 5, pp. 13951–13977, 2017.

[18] *NIST Special Publication 1108R2 NIST Framework and Roadmap for Smart Grid Interoperability Standards*, NIST, Nist Special Publication, 2012, pp. 1–90.

[19] J. Li, R. Xiong, Q. Yang, F. Liang, M. Zhang, and W. Yuan, "Design/test of a hybrid energy storage system for primary frequency control using a dynamic droop method in an isolated microgrid power system," *Appl. Energy*, vol. 201, pp. 257–269, Sep. 2017, doi: 10.1016/j.apenergy.2016.10.066.

[20] P. S. Indu and M. V. Jayan, "Frequency regulation of an isolated hybrid power system with superconducting magnetic energy storage," in *Proc. Int. Conf. Power, Instrum., Control Comput. (PICC)*, vol. 1, Dec. 2015, pp. 5–10.

[21] I. Patrao, E. Figueres, G. Garcerá, and R. González-Medina, "Microgrid architectures for low voltage distributed generation," *Renew. Sustain. Energy Rev.*, vol. 43, pp. 415–424, Mar. 2015, doi: 10.1016/j.rser.2014.11.054.

[22] O. Palizban and K. Kauhaniemi, "Energy storage systems in modern grids—Matrix of technologies and applications," *J. Energy Storage*, vol. 6, pp. 248–259, May 2016, doi: 10.1016/j.est.2016.02.001.

[23] B. Pinnangudi, M. Kuykendal, and S. Bhadra, "Smart grid energy storage," in *The Power Grid*. Amsterdam, The Netherlands: Elsevier, 2017, pp. 93–135.

[24] C. K. Das, O. Bass, G. Kothapalli, T. S. Mahmoud, and D. Habibi, "Overview of energy storage systems in distribution networks: Placement, sizing, operation, and power quality," *Renew. Sustain. Energy Rev.*, vol. 91, pp. 1205–1230, Aug. 2018, doi: 10.1016/j.rser.2018.03.068.

[25] K. Khalid Mehmood, S. U. Khan, S. Lee, Z. M. Haider, M. K. Rafique, and C. Kim, "Optimal sizing and allocation of battery energy storage systems with wind and solar power DGs in a distribution network for voltage regulation considering the lifespan of batteries," *IET Renew. Power Gener.*, vol. 11, no. 10, pp. 1305–1315, Aug. 2017.

[26] M. Ramírez, R. Castellanos, G. Calderón, and O. Malik, "Placement and sizing of battery energy storage for primary frequency control in an isolated section of the Mexican power system," *Electric Power Syst. Res.*, vol. 160, pp. 142–150, Jul. 2018, doi: 10.1016/j.epsr.2018.02.013.

[27] C. D. Rodríguez-Gallegos, D. Yang, O. Gandhi, M. Bieri, T. Reindl, and S. K. Panda, "A multi-objective and robust optimization approach for sizing and placement of PV and batteries in off-grid systems fully operated by diesel generators: An Indonesian case study," *Energy*, vol. 160, pp. 410–429, Oct. 2018.

[28] W. Dong, Y. Li, and J. Xiang, "Optimal sizing of a stand-alone hybrid power system based on Battery/Hydrogen with an improved ant colony optimization," *Energies*, vol. 9, no. 10, p. 785, Sep. 2016, doi: 10.3390/en9100785.

[29] C. K. Das, O. Bass, G. Kothapalli, T. S. Mahmoud, and D. Habibi, "Optimal placement of distributed energy storage systems in distribution networks using artificial bee colony algorithm," *Appl. Energy*, vol. 232, pp. 212–228, Dec. 2018, doi: 10.1016/j.apenergy.2018.07.100.

[30] V. Jani and H. Abdi, "Optimal allocation of energy storage systems considering wind power uncertainty," *J. Energy Storage*, vol. 20, pp. 244–253, Dec. 2018, doi: 10.1016/j.est.2018.09.017.

[31] P. Dehghanian, S. H. Hosseini, M. Moeini-Aghtaie, and A. Arabali, "Optimal siting of DG units in power systems from a probabilistic multi-objective optimization perspective," *Int. J. Electr. Power Energy Syst.*, vol. 51, pp. 14–26, Oct. 2013, doi: 10.1016/j.ijepes.2013.02.014.

[32] M. H. Moradi and M. Abedini, "A novel method for optimal DG units capacity and location in microgrids," *Int. J. Electr. Power Energy Syst.*, vol. 75, pp. 236–244, Feb. 2016, doi: 10.1016/j.ijepes.2015.09.013.

[33] C. G. Boktor, A.-R. Youssef, A. H. Ali, and S. Kamel, "Optimal distribution power flow including shunt capacitor allocation based on voltage deviation and power loss minimization," in *Proc. 19th Int. Middle East Power Syst. Conf. (MEPCON)*, Dec. 2017, pp. 909–914.

[34] M. Dixit, P. Kundu, and H. R. Jariwala, "Optimal placement of PV array in distribution system for power loss minimization considering feeder reconfiguration," in *Proc. IEEE 16th Int. Conf. Environ. Electr. Eng. (EEEIC)*, Jun. 2016, pp. 1–6.

[35] K. E. Adetunji, O. A. Akinlabi, and M. K. Joseph, "Developing a microgrid for tafelkop using HOMER," in *Proc. Int. Conf. Adv. Big Data, Comput. Data Commun. Syst. (icABCD)*, Aug. 2018, pp. 1–6.

[36] V. Motjoadi, K. E. Adetunji, and P. Meera K. Joseph, "Planning of a sustainable microgrid system using HOMER software," in *Proc. Conf. Inf. Commun. Technol. Soc. (ICTAS)*, Mar. 2020, pp. 1–5.

[37] Y. M. Shuaib, M. S. Kalavathi, and C. C. A. Rajan, "Optimal capacitor placement in radial distribution system using gravitational search algorithm," *Int. J. Electr. Power Energy Syst.*, vol. 64, pp. 384–397, Jan. 2015, doi: 10.1016/j.ijepes.2014.07.041.

[38] A. Y. Abdelaziz, E. S. Ali, and S. M. Abd Elazim, "Optimal sizing and locations of capacitors in radial distribution systems via flower pollination optimization algorithm and power loss index," *Eng. Sci. Technol., Int. J.*, vol. 19, no. 1, pp. 610–618, Mar. 2016, doi: 10.1016/j.jestch.2015.09.002.

[39] M. Montazeri and A. Askarzadeh, "Capacitor placement in radial distribution networks based on identification of high potential busses," *Int. Trans. Elect. Energy Syst.*, vol. 29, no. 3, pp. 1–15, 2019.

[40] E. S. Ali, S. M. Abd Elazim, and A. Y. Abdelaziz, "Improved harmony algorithm for optimal locations and sizing of capacitors in radial distribution systems," *Int. J. Electr. Power Energy Syst.*, vol. 79, pp. 275–284, Jul. 2016, doi: 10.1016/j.ijepes.2016.01.015.

[41] D. B. Prakash and C. Lakshminarayana, "Optimal siting of capacitors in radial distribution network using whale optimization algorithm," *Alexandria Eng. J.*, vol. 56, no. 4, pp. 499–509, Dec. 2017, doi: 10.1016/j.aej.2016.10.002.

[42] N. Upper, A. M. Hemeida, and A. A. Ibrahim, "Moth-flame algorithm and loss sensitivity factor for optimal allocation of shunt capacitor banks in radial distribution systems," in *Proc. 19th Int. Middle East Power Syst. Conf. (MEPCON)*, Dec. 2017, pp. 851–856.

[43] G. E. Mendoza, V. M. Vacas, and N. R. Ferreira, "Optimal capacitor allocation and sizing in distribution networks using particle swarm optimization algorithm," in *Proc. Workshop Commun. Netw. Power Syst. (WCNPS)*, Nov. 2018, pp. 1–5.

[44] J. Modarresi, E. Gholipour, and A. Khodabakhshian, "A comprehensive review of the voltage stability indices," *Renew. Sustain. Energy Rev.*, vol. 63, pp. 1–12, Sep. 2016, doi: 10.1016/j.rser.2016.05.010.

[45] A. Ahmadi, A. Tavakoli, P. Jamborsalamati, N. Rezaei, M. R. Miveh, F. H. Gandoman, A. Heidari, and A. E. Nezhad, "Power quality improvement in smart grids using electric vehicles: A review," *IET Electr. Syst. Transp.*, vol. 9, no. 2, pp. 53–64, Jun. 2019.

[46] K. Ginigeme and Z. Wang, "Distributed optimal vehicle-to-grid approaches with consideration of battery degradation cost under real-time pricing," *IEEE Access*, vol. 8, pp. 5225–5235, 2020.

[47] K. Adetunji, I. Hofsajer, and L. Cheng, "A coordinated charging model for electric vehicles in a smart grid using whale optimization algorithm," in *Proc. IEEE 23rd Int. Conf. Inf. Fusion (FUSION)*, Jul. 2020, pp. 1–7, doi: 10.23919/FUSION45008.2020.9190284.

[48] Y. Zheng, Y. Song, A. Huang, and D. J. Hill, "Hierarchical optimal allocation of battery energy storage systems for multiple services in distribution systems," *IEEE Trans. Sustain. Energy*, vol. 11, no. 3, pp. 1911–1921, Jul. 2020.

[49] M. Z. Zeb, K. Imran, A. Khattak, A. K. Janjua, A. Pal, M. Nadeem, J. Zhang, and S. Khan, "Optimal placement of electric vehicle charging stations in the active distribution network," *IEEE Access*, vol. 8, pp. 68124–68134, 2020.

[50] H. Parastvand, V. Moghaddam, O. Bass, M. A. S. Masoum, A. Chapman, and S. Lachowicz, "A graph automorphic approach for placement and sizing of charging stations in EV network considering traffic," *IEEE Trans. Smart Grid*, vol. 11, no. 5, pp. 4190–4200, Sep. 2020.

[51] B. Zeng, H. Dong, F. Xu, and M. Zeng, "Bilevel programming approach for optimal planning design of EV charging station," *IEEE Trans. Ind. Appl.*, vol. 56, no. 3, pp. 2314–2323, Jun. 2020.

[52] Y. Zhang, Q. Zhang, A. Farnoosh, S. Chen, and Y. Li, "GIS-based multi-objective particle swarm optimization of charging stations for electric vehicles," *Energy*, vol. 169, pp. 844–853, Feb. 2019.

[53] A. Mohamed Imran, M. Kowsalya, and D. P. Kothari, "A novel integration technique for optimal network reconfiguration and distributed generation placement in power distribution networks," *Int. J. Electr. Power Energy Syst.*, vol. 63, pp. 461–472, Dec. 2014, doi: 10.1016/j.ijepes.2014.06.011.

[54] E. Grover-Silva, R. Girard, and G. Kariniotakis, "Optimal sizing and placement of distribution grid connected battery systems through an SOCP optimal power flow algorithm," *Appl. Energy*, vol. 219, pp. 385–393, Jun. 2018, doi: 10.1016/j.apenergy.2017.09.008.

[55] C. Ju, P. Wang, L. Goel, and Y. Xu, "A two-layer energy management system for microgrids with hybrid energy storage considering degradation costs," *IEEE Trans. Smart Grid*, vol. 9, no. 6, pp. 6047–6057, Nov. 2018.

[56] M. Pipattanasomporn, H. Feroze, and S. Rahman, "Multi-agent systems in a distributed smart grid: Design and implementation," in *Proc. IEEE/PES Power Syst. Conf. Expo.*, Mar. 2009, pp. 1–8.

[57] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *Proc. IEEE ICNN*, vol. 4, Nov./Dec. 1995, pp. 1942–1948.

[58] M. Dorigo and C. Blum, "Ant colony optimization theory: A survey," *Theor. Comput. Sci.*, vol. 344, nos. 2–3, pp. 243–278, Nov. 2005.

[59] L. Davis, *Handbook of Genetic Algorithms*. New York, NY, USA: CumInCAD, 1991.

[60] X. S. Yang, "A new metaheuristic bat-inspired algorithm," in *Studies in Computational Intelligence*, vol. 284. Cham, Switzerland: Springer, 2010, pp. 65–74.

[61] X.-S. Yang and S. Deb, "Engineering optimisation by cuckoo search," *Int. J. Math. Model. Numer. Optim.*, vol. 1, no. 4, pp. 330–343, 2010.

[62] Z. W. Geem, J. H. Kim, and G. V. Loganathan, "A new heuristic optimization algorithm: Harmony search," *Simulation*, vol. 76, no. 2, pp. 60–68, Feb. 2001. [Online]. Available: http://sim.sagepub.com/cgi/doi/10.1177/003754970107600201

[63] E. Nabil, "A modified flower pollination algorithm for global optimization," *Expert Syst. Appl.*, vol. 57, pp. 192–203, Sep. 2016.

[64] X-S. Yang, "Firefly algorithm, stochastic test functions and design optimisation," *Int. J. Bio-Inspired Comput.*, vol. 2, no. 2, pp. 78–84, 2010.

[65] S. Mirjalili, "The ant lion optimizer," *Adv. Eng. Softw.*, vol. 83, pp. 80–98, May 2015.

[66] S. Mirjalili and A. Lewis, "The whale optimization algorithm," *Adv. Eng. Softw.*, vol. 95, pp. 51–67, May 2016. [Online]. Available: http://www.alimirjalili.com/WOA.html

[67] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey wolf optimizer," *Adv. Eng. Softw.*, vol. 69, pp. 46–61, Mar. 2014.

[68] M. H. Shwehdi, S. R. Mohamed, and D. Devaraj, "Optimal capacitor placement on west–east inter-tie in Saudi Arabia using genetic algorithm," *Comput. Electr. Eng.*, vol. 68, pp. 156–169, May 2018, doi: 10.1016/j.compeleceng.2018.04.002.

[69] L. R. de Araujo, D. R. R. Penido, S. Carneiro, and J. L. R. Pereira, "Optimal unbalanced capacitor placement in distribution systems for voltage control and energy losses minimization," *Electr. Power Syst. Res.*, vol. 154, pp. 110–121, Jan. 2018, doi: 10.1016/j.epsr.2017.08.012.

[70] O. Babacan, W. Torre, and J. Kleissl, "Siting and sizing of distributed energy storage to mitigate voltage impact by solar PV in distribution systems," *Sol. Energy*, vol. 146, pp. 199–208, Apr. 2017, doi: 10.1016/j.solener.2017.02.047.

[71] J. Vuletić and M. Todorovski, "Optimal capacitor placement in distorted distribution networks with different load models using penalty free genetic algorithm," *Int. J. Electr. Power Energy Syst.*, vol. 78, pp. 174–182, Jun. 2016.

[72] J. Xiao, L. Bai, Z. Zhang, and H. Liang, "Determination of the optimal installation site and capacity of battery energy storage system in distribution network integrated with distributed generation," *IET Gener., Transmiss. Distrib.*, vol. 10, no. 3, pp. 601–607, Feb. 2016.

[73] Y. Liu, J. Yang, Y. Tang, J. Xu, Y. Sun, Y. Chen, X. Peng, and S. Liao, "Bi-level fuzzy stochastic expectation modelling and optimization for energy storage systems planning in virtual power plants," *J. Renew. Sustain. Energy*, vol. 11, no. 1, Jan. 2019, Art. no. 014101.

[74] R. Storn and K. Price, "Differential evolution—A simple and efficient heuristic for global optimization over continuous spaces," *J. Global Optim.*, vol. 11, no. 4, pp. 341–359, 1997.

[75] S. Das and P. N. Suganthan, "Differential evolution: A survey of the state-of-the-art," *IEEE Trans. Evol. Comput.*, vol. 15, no. 1, pp. 4–31, Feb. 2011.

[76] P. D. Huy, V. K. Ramachandaramurthy, J. Y. Yong, K. M. Tan, and J. B. Ekanayake, "Optimal placement, sizing and power factor of distributed generation: A comprehensive study spanning from the planning stage to the operation stage," *Energy*, vol. 195, Mar. 2020, Art. no. 117011, doi: 10.1016/j.energy.2020.117011.

[77] S. Kumar, K. K. Mandal, and N. Chakraborty, "Optimal DG placement by multi-objective opposition based chaotic differential evolution for techno-economic analysis," *Appl. Soft Comput.*, vol. 78, pp. 70–83, May 2019, doi: 10.1016/j.asoc.2019.02.013.

[78] S. K. Injeti, "A Pareto optimal approach for allocation of distributed generators in radial distribution systems using improved differential search algorithm," *J. Electr. Syst. Inf. Technol.*, vol. 5, no. 3, pp. 908–927, Dec. 2018, doi: 10.1016/j.jesit.2016.12.006.

[79] M. Moazzami, G. B. Gharehpetian, H. Shahinzadeh, and S. H. Hosseinian, "Optimal locating and sizing of DG and D-STATCOM using modified shuffled frog leaping algorithm," in *Proc. 2nd Conf. Swarm Intell. Evol. Comput. (CSIEC)*, Mar. 2017, pp. 54–59.

[80] A. Azizivahed, A. Arefi, S. Ghavidel, M. Shafie-khah, L. Li, J. Zhang, and J. P. S. Catalao, "Energy management strategy in dynamic distribution network reconfiguration considering renewable energy resources and storage," *IEEE Trans. Sustain. Energy*, vol. 11, no. 2, pp. 662–673, Apr. 2020.

[81] B. Singh and S. Singh, "GA-based optimization for integration of DGs, STATCOM and PHEVs in distribution systems," *Energy Rep.*, vol. 5, pp. 84–103, Nov. 2019, doi: 10.1016/j.egyr.2018.09.005.

[82] G. Celli, F. Pilo, G. Pisano, and G. G. Soma, "Distribution energy storage investment prioritization with a real coded multi-objective genetic algorithm," *Electr. Power Syst. Res.*, vol. 163, pp. 154–163, Oct. 2018, doi: 10.1016/j.epsr.2018.06.008.

[83] T. Huiling, W. Jiekang, W. Fan, C. Lingmin, L. Zhijun, and Y. Haoran, "An optimization framework for collaborative control of power loss and voltage in distribution systems with DGs and EVs using stochastic fuzzy chance constrained programming," *IEEE Access*, vol. 8, pp. 49013–49027, 2020.

[84] C.-S. Lee, H. V. H. Ayala, and L. D. S. Coelho, "Capacitor placement of distribution systems using particle swarm optimization approaches," *Int. J. Electr. Power Energy Syst.*, vol. 64, pp. 839–851, Jan. 2015, doi: 10.1016/j.ijepes.2014.07.069.

[85] K. Deveci and Ö. Güler, "A CMOPSO based multi-objective optimization of renewable energy planning: Case of turkey," *Renew. Energy*, vol. 155, pp. 578–590, Aug. 2020.

[86] X. Zhang, X. Zheng, R. Cheng, J. Qiu, and Y. Jin, "A competitive mechanism based multi-objective particle swarm optimizer with fast convergence," *Inf. Sci.*, vol. 427, pp. 63–76, Feb. 2018.

[87] H. HassanzadehFard and A. Jalilian, "Optimal sizing and location of renewable energy based DG units in distribution systems considering load growth," *Int. J. Electr. Power Energy Syst.*, vol. 101, pp. 356–370, Oct. 2018, doi: 10.1016/j.ijepes.2018.03.038.

[88] M. Mosbah, R. D. Mohammedi, S. Arif, and A. Hellal, "Optimal of shunt capacitor placement and size in Algerian distribution network using particle swarm optimization," in *Proc. 8th Int. Conf. Modeling, Identificat. Control (ICMIC)*, University of MEDEA, Algeria, Nov. 2016, pp. 192–197.

[89] A. Elsheikh, Y. Helmy, Y. Abouelseoud, and A. Elsherif, "Optimal capacitor placement and sizing in radial electric power systems," *Alexandria Eng. J.*, vol. 53, no. 4, pp. 809–816, Dec. 2014, doi: 10.1016/j.aej.2014.09.012.

[90] H. Karimi and R. Dashti, "Comprehensive framework for capacitor placement in distribution networks from the perspective of distribution system management in a restructured environment," *Int. J. Electr. Power Energy Syst.*, vol. 82, pp. 11–18, Nov. 2016, doi: 10.1016/j.ijepes.2016.02.025.

[91] M. H. Mostafa, S. G. Ali, S. H. E. A. Aleem, and A. Y. Abdelaziz, "Optimal allocation of energy storage system for improving performance of microgrid using symbiotic organisms search," in *Proc. 20th Int. Middle East Power Syst. Conf. (MEPCON)*, Dec. 2018, pp. 474–479.

[92] S. K. Injeti, V. K. Thunuguntla, and M. Shareef, "Optimal allocation of capacitor banks in radial distribution systems for minimization of real power loss and maximization of network savings using bio-inspired optimization algorithms," *Int. J. Electr. Power Energy Syst.*, vol. 69, pp. 441–455, Jul. 2015, doi: 10.1016/j.ijepes.2015.01.040.

[93] A. Rezaee Jordehi and J. Jasni, "Parameter selection in particle swarm optimisation: A survey," *J. Experim. Theor. Artif. Intell.*, vol. 25, no. 4, pp. 527–542, Dec. 2013.

[94] S. Saha and V. Mukherjee, "Optimal placement and sizing of DGs in RDS using chaos embedded SOS algorithm," *IET Gener., Transmiss. Distrib.*, vol. 10, no. 14, pp. 3671–3680, Nov. 2016.

[95] R. Sanjay, T. Jayabarathi, T. Raghunathan, V. Ramesh, and N. Mithulananthan, "Optimal allocation of distributed generation using hybrid grey wolf optimizer," *IEEE Access*, vol. 5, pp. 14807–14818, 2017.

[96] T. George, A.-R. Youssef, M. Ebeed, and S. Kamel, "Ant lion optimization technique for optimal capacitor placement based on total cost and power loss minimization," in *Proc. Int. Conf. Innov. Trends Comput. Eng. (ITCE)*, Feb. 2018, pp. 350–356.

[97] E. E. Elattar and S. K. ElSayed, "Modified JAYA algorithm for optimal power flow incorporating renewable energy sources considering the cost, emission, power loss and voltage profile improvement," *Energy*, vol. 178, pp. 598–609, Jul. 2019.

[98] M. Kumawat, N. Gupta, N. Jain, and R. C. Bansal, "Optimally allocation of distributed generators in three-phase unbalanced distribution network," *Energy Procedia*, vol. 142, pp. 749–754, Dec. 2017.

[99] L. A. Wong, V. K. Ramachandaramurthy, S. L. Walker, P. Taylor, and M. J. Sanjari, "Optimal placement and sizing of battery energy storage system for losses reduction using whale optimization algorithm," *J. Energy Storage*, vol. 26, Dec. 2019, Art. no. 100892, doi: 10.1016/j.est.2019.100892.

[100] R. Sirjani, "Optimal capacitor placement in wind farms by considering harmonics using discrete lightning search algorithm," *Sustainability*, vol. 9, no. 9, p. 1669, Sep. 2017.

[101] O. Ceylan and S. Paudyal, "Optimal capacitor placement and sizing considering load profile variations using moth-flame optimization algorithm," in *Proc. Int. Conf. Mod. Power Syst. (MPS)*, Jun. 2017, pp. 1–6.

[102] P. Singh, S. K. Bishnoi, and N. K. Meena, "Moth search optimization for optimal DERs integration in conjunction to OLTC tap operations in distribution systems," *IEEE Syst. J.*, vol. 14, no. 1, pp. 880–888, Mar. 2020.

[103] A. Ali, D. Raisz, K. Mahmoud, and M. Lehtonen, "Optimal placement and sizing of uncertain PVs considering stochastic nature of PEVs," *IEEE Trans. Sustain. Energy*, vol. 11, no. 3, pp. 1647–1656, Jul. 2020.

[104] C. Liu, S. S. Abdulkareem, A. Rezvani, S. Samad, N. Aljojo, L. K. Foong, and K. Nishihara, "Stochastic scheduling of a renewable-based microgrid in the presence of electric vehicles using modified harmony search algorithm with control policies," *Sustain. Cities Soc.*, vol. 59, Aug. 2020, Art. no. 102183, doi: 10.1016/j.scs.2020.102183.

[105] B. Jeddi, V. Vahidinasab, P. Ramezanpour, J. Aghaei, M. Shafie-khah, and J. P. S. Catalão, "Robust optimization framework for dynamic distributed energy resources planning in distribution networks," *Int. J. Electr. Power Energy Syst.*, vol. 110, pp. 419–433, Sep. 2019, doi: 10.1016/j.ijepes.2019.03.026.

[106] H. Lotfi, R. Ghazi, and M. B. Naghibi-Sistani, "Multi-objective dynamic distribution feeder reconfiguration along with capacitor allocation using a new hybrid evolutionary algorithm," *Energy Syst.*, vol. 11, pp. 779–809, 2019.

[107] S. Deb, K. Tammi, X.-Z. Gao, K. Kalita, and P. Mahanta, "A hybrid multi-objective chicken swarm optimization and teaching learning based algorithm for charging station placement problem," *IEEE Access*, vol. 8, pp. 92573–92590, 2020. [Online]. Available: https://ieeexplore.ieee.org/document/9091834/

[108] T. Zhang, X. Xu, Z. Li, A. Abu-Siada, and Y. Guo, "Optimum location and parameter setting of STATCOM based on improved differential evolution harmony search algorithm," *IEEE Access*, vol. 8, pp. 87810–87819, 2020. [Online]. Available: https://ieeexplore.ieee.org/document/9088950/

[109] S. Zeynali, N. Rostami, and M. R. Feyzi, "Multi-objective optimal short-term planning of renewable distributed generations and capacitor banks in power system considering different uncertainties including plug-in electric vehicles," *Int. J. Electr. Power Energy Syst.*, vol. 119, Jul. 2020, Art. no. 105885, doi: 10.1016/j.ijepes.2020.105885.

[110] X. Tang, K. Deng, Q. Wu, and Y. Feng, "Optimal location and capacity of the distributed energy storage system in a distribution network," *IEEE Access*, vol. 8, pp. 15576–15585, 2020.

[111] A. Noori, Y. Zhang, N. Nouri, and M. Hajivand, "Hybrid allocation of capacitor and distributed static compensator in radial distribution networks using multi-objective improved golden ratio optimization based on fuzzy decision making," *IEEE Access*, vol. 8, pp. 162180–162195, 2020.

[112] S. Sharma and S. Ghosh, "FIS and hybrid ABC-PSO based optimal capacitor placement and sizing for radial distribution networks," *J. Ambient Intell. Humanized Comput.*, vol. 11, no. 2, pp. 901–916, Feb. 2020.

[113] K. Muthukumar and S. Jayalalitha, "Multiobjective hybrid evolutionary approach for optimal planning of shunt capacitors in radial distribution systems with load models," *Ain Shams Eng. J.*, vol. 9, no. 4, pp. 1975–1988, Dec. 2018, doi: 10.1016/j.asej.2017.02.002.

[114] E. S. Ali, S. M. Abd Elazim, and A. Y. Abdelaziz, "Optimal allocation and sizing of renewable distributed generation using ant lion optimization algorithm," *Electr. Eng.*, vol. 100, no. 1, pp. 99–109, Mar. 2018.

[115] C. Kishore, S. Ghosh, and V. Karar, "Symmetric fuzzy logic and IBFOA solutions for optimal position and rating of capacitors allocated to radial distribution networks," *Energies*, vol. 11, no. 4, p. 766, Mar. 2018.

[116] A. Y. Abdelaziz, E. S. Ali, and S. M. Abd Elazim, "Flower pollination algorithm and loss sensitivity factors for optimal sizing and placement of capacitors in radial distribution systems," *Int. J. Electr. Power Energy Syst.*, vol. 78, pp. 207–214, Jun. 2016, doi: 10.1016/j.ijepes.2015.11.059.

[117] K. Z. Lim, K. H. Lim, X. B. Wee, Y. Li, and X. Wang, "Optimal allocation of energy storage and solar photovoltaic systems with residential demand scheduling," *Appl. Energy*, vol. 269, Jul. 2020, Art. no. 115116, doi: 10.1016/j.apenergy.2020.115116.

[118] C. K. Das, O. Bass, T. S. Mahmoud, G. Kothapalli, M. A. S. Masoum, and N. Mousavi, "An optimal allocation and sizing strategy of distributed energy storage systems to improve performance of distribution networks," *J. Energy Storage*, vol. 26, Dec. 2019, Art. no. 100847, doi: 10.1016/j.est.2019.100847.

[119] B. Poornazaryan, P. Karimyan, G. B. Gharehpetian, and M. Abedi, "Optimal allocation and sizing of DG units considering voltage stability, losses and load variations," *Int. J. Electr. Power Energy Syst.*, vol. 79, pp. 42–52, Jul. 2016, doi: 10.1016/j.ijepes.2015.12.034.

[120] A. A. A. El-Ela, R. A. El-Sehiemy, and A. S. Abbas, "Optimal placement and sizing of distributed generation and capacitor banks in distribution systems using water cycle algorithm," *IEEE Syst. J.*, vol. 12, no. 4, pp. 3629–3636, Dec. 2018.

[121] B. Mukhopadhyay and D. Das, "Multi-objective dynamic and static reconfiguration with optimized allocation of PV-DG and battery energy storage system," *Renew. Sustain. Energy Rev.*, vol. 124, May 2020, Art. no. 109777, doi: 10.1016/j.rser.2020.109777.

[122] S. R. Gampa, K. Jasthi, P. Goli, D. Das, and R. C. Bansal, "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*, vol. 27, pp. 101–117, Feb. 2020, doi: 10.1016/j.est.2019.101117.

[123] A. M. Shaheen and R. A. El-Sehiemy, "Optimal co-ordinated allocation of distributed generation units/ capacitor banks/ voltage regulators by EGWA," *IEEE Syst. J.*, early access, May 6, 2020. [Online]. Available: https://ieeexplore.ieee.org/document/9086471/, doi: 10.1109/JSYST.2020.2986647.

[124] P. Gangwar, S. N. Singh, and S. Chakrabarti, "Multi-objective planning model for multi-phase distribution system under uncertainty considering reconfiguration," *IET Renew. Power Gener.*, vol. 13, no. 12, pp. 2070–2083, Sep. 2019.

[125] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE Trans. Evol. Comput.*, vol. 6, no. 2, pp. 182–197, Apr. 2002.

[126] M. Farsadi, T. S. Dizaji, and H. Hosseinnejad, "Capacitor allocation in order to maximize the loss reduction benefit and improve the voltage profile based on NSGA-II," in *Proc. 9th Int. Conf. Electr. Electron. Eng. (ELECO)*, Chamber of Electrical Engineers of Turkey, Nov. 2015, pp. 515–520.

[127] G. Battapothula, C. Yammani, and S. Maheswarapu, "Multi-objective simultaneous optimal planning of electrical vehicle fast charging stations and DGs in distribution system," *J. Mod. Power Syst. Clean Energy*, vol. 7, no. 4, pp. 923–934, Jul. 2019, doi: 10.1007/s40565-018-0493-2.

[128] M. B. Jannat and A. S. Savić, "Optimal capacitor placement in distribution networks regarding uncertainty in active power load and distributed generation units production," *IET Gener., Transmiss. Distrib.*, vol. 10, no. 12, pp. 3060–3067, Sep. 2016.

[129] M. E. Hamidi and R. M. Chabanloo, "Optimal allocation of distributed generation with optimal sizing of fault current limiter to reduce the impact on distribution networks using NSGA-II," *IEEE Syst. J.*, vol. 13, no. 2, pp. 1714–1724, Jun. 2019.

[130] C. Buchheim and J. Kurtz, "Min-max-min robustness: A new approach to combinatorial optimization under uncertainty based on multiple solutions," *Electron. Notes Discrete Math.*, vol. 52, pp. 45–52, Jun. 2016, doi: 10.1016/j.endm.2016.03.007.

[131] H. Salmei and M. A. Yaghoobi, "Improving the min–max method for multiobjective programming," *Operations Res. Lett.*, vol. 48, no. 4, pp. 480–486, Jul. 2020, doi: 10.1016/j.orl.2020.05.013.

[132] S. Nagaballi and V. S. Kale, "Pareto optimality and game theory approach for optimal deployment of DG in radial distribution system to improve techno-economic benefits," *Appl. Soft Comput.*, vol. 92, Jul. 2020, Art. no. 106234, doi: 10.1016/j.asoc.2020.106234.

[133] K. Mahesh, P. Nallagownden, and I. Elamvazuthi, "Advanced Pareto front non-dominated sorting multi-objective particle swarm optimization for optimal placement and sizing of distributed generation," *Energies*, vol. 9, no. 12, p. 982, Nov. 2016.

[134] H. Zhang, S. J. Moura, Z. Hu, and Y. Song, "PEV fast-charging station siting and sizing on coupled transportation and power networks," *IEEE Trans. Smart Grid*, vol. 9, no. 4, pp. 2595–2605, Jul. 2018.

[135] Y. Li, B. Feng, G. Li, J. Qi, D. Zhao, and Y. Mu, "Optimal distributed generation planning in active distribution networks considering integration of energy storage," *Appl. Energy*, vol. 210, pp. 1073–1081, Jan. 2018, doi: 10.1016/j.apenergy.2017.08.008.

[136] S. Sharma, K. R. Niazi, K. Verma, and T. Rawat, "Coordination of different DGs, BESS and demand response for multi-objective optimization of distribution network with special reference to Indian power sector," *Int. J. Electr. Power Energy Syst.*, vol. 121, Oct. 2020, Art. no. 106074, doi: 10.1016/j.ijepes.2020.106074.

[137] N. K. Meena, S. Parashar, A. Swarnkar, N. Gupta, and K. R. Niazi, "Improved elephant herding optimization for multiobjective DER accommodation in distribution systems," *IEEE Trans. Ind. Informat.*, vol. 14, no. 3, pp. 1029–1039, Mar. 2018.

[138] A. Selim, S. Kamel, A. S. Alghamdi, and F. Jurado, "Optimal placement of DGs in distribution system using an improved Harris Hawks optimizer based on single- and multi-objective approaches," *IEEE Access*, vol. 8, pp. 52815–52829, 2020.

[139] P. P. Biswas, R. Mallipeddi, P. N. Suganthan, and G. A. J. Amaratunga, "A multiobjective approach for optimal placement and sizing of distributed generators and capacitors in distribution network," *Appl. Soft Comput.*, vol. 60, pp. 268–280, Nov. 2017, doi: 10.1016/j.asoc.2017.07.004.

[140] K. Deb, "Multi-objective optimization," in *Search Methodologies*. Cham, Switzerland: Springer, 2014, pp. 403–449.
[141] J. Branke, J. Branke, K. Deb, K. Miettinen, and R. Słowiński, *Multiobjective Optimization: Interactive and Evolutionary Approaches*, vol. 5252. Cham, Switzerland: Springer, 2008.
[142] S. Roy Ghatak, S. Sannigrahi, and P. Acharjee, "Multi-objective approach for strategic incorporation of solar energy source, battery storage system, and DSTATCOM in a smart grid environment," *IEEE Syst. J.*, vol. 13, no. 3, pp. 3038–3049, Sep. 2019.
[143] T. Tušar and B. Filipič, "Differential evolution versus genetic algorithms in multiobjective optimization," in *Evolutionary Multi- Criterion Optimization*, vol. 4403. Berlin, Germany: Springer, 2007, pp. 257–271. [Online]. Available: http://link.springer.com/10.1007/978-3-540-70928-2_22

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