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Category-Based Multiobjective Approach for Optimal Integration of Distributed Generation and Energy Storage Systems in Distribution Networks

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ABSTRACT Distributed generation (DG) units are power generating plants that are very important to the architecture of present power system networks. The primary benefits of the addition of these units are to increase the power supply and improve the power quality of a power grid while considering the investment cost and carbon emission cost. Most studies have simultaneously optimized these objectives in a direct way where the objectives are directly infused into the multiobjective framework to produce final values. However, this method may have an unintentional bias towards a particular objective; hence this paper implements a multi-stage framework to handle multiple objectives in a categorical manner to simultaneously integrate DG units and Battery Energy Storage System (BESS) in a distribution network. A new hybrid metaheuristic technique is developed and combined with the Technique Order for Preference by Similarity to Ideal Solution (TOPSIS) approach and the crowding distance technique to produce Pareto optimal solutions from the multiple collective objectives, namely technical, economic, and environmental. Compared to the conventional direct way approach in multiobjective handling, the proposed categorical approach reduces bias towards a set of objective(s) and efficiently handles more objectives. Results also show that the Whale Optimization Algorithm and Genetic Algorithm (WOAGA) produces the smallest power loss of 101.6 kW compared to Whale Optimization Algorithm (WOA) and Genetic Algorithm (GA), which produces 105.1 kW and 105.8 kW respectively. The algorithm, although does not have a faster convergence than the WOA, has a better computational time than the WOA and GA. The multiobjective WOAGA also performs better than the Non-dominating Sorted Genetic Algorithm (NSGA-II) and the multiobjective WOA in terms of the quality of Pareto optimal solutions.

INDEX TERMS Battery energy storage system (BESS), hybrid metaheuristic algorithm, distribution networks, multiobjective optimization, renewable energy, whale optimization algorithm, genetic algorithm, pareto optimal solutions.

I. INTRODUCTION

The integration of Distribution Generation (DG) units is an essential feature in the modern-day electric utility grid. Certain parameters can be considered, such as quantity and size of DG units, the best location, bus configuration, and even the most suitable DG unit technology to be used [1]. A common and central problem is the placing and sizing of DG units [1]. Inappropriate installation of DG units can have adverse effects on power flow and voltage stability, which

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can cause an upsurge in line losses [2], [3], thereby inferring an increase in economic costs [4]. Besides, the installation of DG units is a non-linear problem, which means that the increase in the number of DG units does not directly improve grid performance. Therefore, it is essential to find the optimal location and size of DG units in power networks to solve certain objectives. To reduce carbon emissions, most studies have integrated the renewable energy-based DG units in distribution networks. However, renewable energy (RE) sources, such as Photo-voltaic (PV) panels intermittent power supply is a setback for constant power flow. To obviate this drawback Battery Energy Storage Systems (BESS) are integrated into the grid to store energy from the renewable energy DG units at their peak times. The integration of BESS units also comes with additional complexity and extra cost; therefore, there is a need to (i) apply an efficient optimization algorithm and (ii) mitigate its cost effect. Several methodologies have been proposed for solving the optimal integration, such as the analytical approaches (mathematical methods) and metaheuristic techniques. The combined combinatorial and nonconvex nature of the placing and sizing problem has influenced the frequent use of metaheuristic algorithms which is mainly because of its better computational time and efficiency rate [5], [6].

While some techniques have been developed to reduce the problem's complexity, they do not guarantee suboptimal solutions. They are mostly used to grade the current technical status of each bus in a distribution network. By that, the technique would suggest the bus location for DG units. Some examples are power loss index (PLI), voltage stability index (VSI), and most recently, loss sensitivity factor (LSF). These techniques have also been researched and improved over time [7].

Numerous optimization techniques have been applied to solve the optimal integration problem in distribution networks and have been in a multiobjective space. Although some recent studies have focused on one objective (mostly power loss minimization), some of those studies emphasize more on new models and then validate it by formulating and optimizing an objective function. Otherwise, a multiobjective framework will be formulated. Related studies are discussed in Section II.

To the best of the authors' knowledge, researchers have not studied the categorization of objectives in a multiobjective optimization framework. This is corroborated by [8] where it is reported that previous studies have only handled multiple objective functions in a non-categorized manner where all adopted objective functions are pushed to a multiobjective framework for a final decision value. For instance, when power loss, voltage stability, and installation cost are optimized simultaneously, the final utility value will automatically have a bias towards the technical objective because they possess similar parameters. As explained in [9], uncontrollable bias will occur when there are closely similar parameters in some objectives. Unless the decision-maker prefers this bias, the optimal integration problem's final objective values will be termed flawed.

Another instance is where a study focuses on only one collective objective, where power loss, voltage stability, and line loading can be the adopted functions in a multiobjective framework. While this type of study focuses on the project's technical aspects, it lacks an equilibrium approach to handle all collective objectives. Hence, the practicality of the study is questionable. The two instances previously mentioned may not represent a practical scenario where all collective objectives are thought differently from each other. In a real-world scenario, modern distribution networks' planning should compulsorily consider the technical, economic, and environmental aspects.

Another vital point is explained in [10], [11] where it is discussed that the higher number of objectives in a multiobjective optimization framework increases the number of nondominated solutions, which adversely affects the computational burden of the optimization model. To avoid the aforementioned setbacks, this paper proposes a multi-stage multiobjective framework, which uses a categorical approach that can intelligently accommodate and optimize all collective objectives. A categorical approach can separately handle a group of objectives, followed by the final objective handling (the conventional method).

The main contributions of this paper can be stated as follows.

- The investigation for the optimal integration of PV-DG and BESS units is carried out by focusing on power loss minimization, voltage stability improvement, voltage deviation reduction, installation cost reduction, operational cost reduction, and emission cost reduction. Research works [12]–[14] have studied one or more of these objectives in different variations but not all of the objectives.
- A novel approach for optimal distribution network planning is introduced, where PV-DG and BESS units are integrated simultaneously by injecting real power from the PV modules and the BESS units. The proposed approach enables a seamless interactive mechanism between DG allocation and BESS allocation, unlike in [12], [13] where PV is either fixed or initially integrated based on physical observation before the integrating the BESS units, the approach assigns bus locations to PV-DG units at every second round of iterations.
- In contrast to developing a hybrid metaheuristic algorithm that requires the whole mechanism of each algorithm to solve the optimal integration problem (as in [15]), this paper splits the problem into subproblems and assigns each algorithm according to their strengths. As a result, the proposed algorithm becomes more computationally efficient.
- A new approach based on a multistage multiobjective framework is proposed to optimize all objectives in a categorized manner. Earlier studies have either applied weights to multiple objectives or produce Pareto optimal

solutions from the objectives without considering each objective's categories.

- A Technique Order for Preference by Similarity to Ideal Solution (TOPSIS) approach is combined with the crowding distance technique to produce Pareto optimal solutions from the multiple objectives.

The rest of the paper is organized as follows. Section II discusses the related works. Section III discusses the problem formulation of the study which explains the handling of uncertainties and all adopted objectives. The section further explains the power flow constraints and BESS constraints. The optimization strategy is discussed in Section IV. Here the new multi-stage multiobjective framework is discussed, and the multiobjective approach is introduced. The proposed algorithm and its implementation to the optimal integration of PV-DG units in distribution networks are also discussed. Section V presents the results from the analysis. In doing so, the IEEE 33-bus test network is used as the testbed for evaluation. Finally, the conclusion is entailed in Section VI.

II. RELATED WORKS

According to literature, optimization in distribution network planning can be categorized into deterministic and stochastic algorithms. The algorithms can be subdivided into single objective and multiobjective frameworks. Some significant contributions have been made in applying stochastic algorithms, such as metaheuristic algorithms, to distribution network planning. Xiao *et al.* [16] used the GA to optimally allocate and size BESS units in a renewable energy-present distribution network. The algorithm was implemented such that every violated constraint in the solution is discarded during each generation, making the algorithm computationally efficient. Xiao *et al.* [17] used a bi-level optimization approach to allocate DG and BESS units to plan distribution networks optimally. The first level minimizes the overall costs using a summation method while the second level ensures optimal coordinated operation of the integrated units. It is to note that handling multiple objectives is as important as the optimization technique applied. Das *et al.* [13] used the summation method to simultaneously optimize voltage deviation, flickers, power losses, and line loading while using the fitness-scaled chaotic Artificial Bee Colony (ABC) to optimally allocate and size BESS units in a distribution network. Although simple and less complex, the summation approach is arguably not a proper approach to simultaneously handle multiple objectives. Wong *et al.* [12] applied the WOA to minimize the real power loss. The study experimented with two methods of siting and sizing BESS DG units in a conventional and PV-integrated distribution network: the (i) two-step method and (ii) simultaneous siting and sizing method. The performance of both methods was validated by comparing the WOA to the firefly algorithm and the Particle Swarm Optimization (PSO).

Previous studies have developed hybrid metaheuristic algorithms to solve the optimal integration problem in distribution networks. Moradi and Abedini [18] proposed a hybrid algorithm of Intelligent Water Drops (IWD) and GA for optimally allocating and sizing DG units in a microgrid for solving objectives such as power loss minimization, voltage stability improvement, and total voltage variation improvement. The proposed algorithm was applied in a stepwise manner where the GA finds the optimal location while the IWD finds the optimal sizes. The authors handled the multiple objectives by assigning weights before the optimization process, which is not a very practical solution in a multiobjective space. They, however, varied the weights to observe the effect on simulation results. In [19], the PSO and ABC were hybridized to optimally size capacitor banks while minimizing power loss and energy loss in a 34-node and 69-bus distribution network. A summation method was used to handle the objectives which may not produce accurate results for real-world scenarios. Jeddi *et al.* [15] hybridized a Harmony Search Algorithm (HSA) and the Firefly Algorithm (FA) in a chaotic model (dubbed CHSFA) to maximize profits of distribution network companies by reducing operational costs and increasing income in a distribution network. The proposed algorithm uses the HSA mechanism to search towards the best objective values in the harmony memory and uses the FA mechanism for a random search, was validated on a 38-bus distribution network and reported to converge faster than the HSA. Since the process is repeated twice to achieve an optimal solution, it is assumed that the CHSFA, due to its complex mechanism, will have a higher computational time than the HSA.

The handling of multiple objectives is a crucial feature in the optimal integration problem in distribution networks, and proper handling is synonymous to the practicality of results. A direct weight assignment approach (WSA) is the simplest form of handling multiple objectives and has been used in the optimal integration problem, as in [20]. The authors created different multiobjective aggregation scenarios for siting and sizing capacitors and DG units. The WSA technique always comes with bias since the preference level is carried out before the optimization process. Shaheen and El-Sehiemy [21] considered four objective functions, and unlike a direct WSA method like in [3], the Analytical Hierarchical Process (AHP) was used to determine the weights for each objective function. They proposed an enhanced grey wolf optimizer to optimally allocate DG units, capacitor banks, and voltage regulators. The AHP was also used in [22] and [23] to select the weights required for each objective in a multiobjective integration of DG and BESS units in distribution networks. The AHP technique only douses the effect of weight input bias in the optimization process. The *aposteriori* method proves to overcome the bias problem since preference evaluation is done after the optimization process.

Selim *et al.* [24] proposed an improved Harris Hawks Optimization (IHHO) algorithm to allocate and size DG units in a multiobjective framework. The multiobjective framework was based on the Pareto optimal front, where the power loss minimization, voltage deviation reduction, and voltage stability improvement were considered as the objectives. The final solution was determined using the Grey Relational Projection (GRP) method and was tested on the IEEE 33- and 69-bus distribution networks. Although computationally efficient, the GRP method can only select compromise solutions among closely related objectives; hence, only the technical objectives are considered. Zeynalli *et al.* [25] hybridized the GA, DE, and Strength Pareto Evolutionary Algorithm (SPEA-II) to generate Pareto optimal solutions from the integration of RES-based DG units (solar and wind), capacitor banks, and EV in a distribution network. The study considered voltage stability, carbon emissions, and installation cost as objectives, and the fuzzy decision-making technique was used to handle the selection of compromise solutions from the Pareto optimal solutions. The fuzzy-based technique applies a three-scale fuzziness to each alternative solution and compares each solution to the best individual solution to select the compromise solution.

Recent studies have used the Technique for Order Preference by Similarity to Ideal Solution approach to finding the best solution from a set of alternatives in the field of multiobjective DG unit integration. The TOPSIS approach efficiently chooses a compromise solution based on the relative closeness index. The approach minimizes the Euclidean distance between each alternative solution and its best solution set (positive ideal solution) and simultaneously maximizes each alternative solution from its worst solution set (negative ideal solution). Meena *et al.* [26] used the TOPSIS approach to (i) produce non-dominating solution from the proposed multiobjective Elephant Herding Optimization (ELO) algorithm and (ii) select a compromise solution. The proposed algorithm was applied to optimize power loss minimization, voltage deviation, and voltage stability and the spacing metric was used to measure statistical values to compare with other variations of the ELO. From [27], a multiobjective hybrid algorithm PSO and GA was proposed to optimally allocate energy storage systems in a wind farm-infused IEEE 30-bus meshed network, considering the uncertainties. Their objective was to improve voltage deviation and 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 formulation produced the best voltage deviation and emission cost value, while the three-objective produced the best installation cost value. However, further work can be done to compare the quality of Pareto solutions distribution. The TOPSIS was also used in [14] to select the compromise solution from a Pareto optimal set. The authors implemented the Non-dominating Sorted Genetic Algorithm (NSGA-II) to allocate and place BESS units in a distribution network while minimizing power loss and grid demand cost.

Despite the multiobjective techniques seen in literature, a categorical approach of handling multiple objectives simultaneously in a distribution network planning problem has not been studied. Furthermore, most studies used a one-way approach to allocate DG and BESS units in a distribution network, although this approach reduces the computational complexity, it may not produce practical results. This paper implements a novel iterative approach to allocate DG and BESS units in distribution, and a hybrid metaheuristic algorithm is developed to handle the additional computational complexities.

III. PROBLEM FORMULATION

This section discusses the modelling that aims to find the optimal locations and sizes of multiple PV-DG and BESS units while observing the objective functions. The uncertainty handling approach, adopted objective functions, and constraints are explained in the following subsections.

A. MODELLING UNCERTAINTY

This paper takes PV power output and electricity pricing as uncertain input, given that there can be exact values throughout a season. The PV power output solely depends on solar irradiance, with temperature, and the PV module characteristics. The solar irradiance is modelled as a beta distribution function [28], [29], which is shown as

$$f_b(s) = \begin{cases} \dfrac{\Gamma(p+q)}{\Gamma(p)\Gamma(q)} s^{(p-1)}(1-s)^{(q-1)}, & \underset{p,q\geqslant 0}{0 \leqslant s \leqslant 1} \\ 0, & \text{else} \end{cases} \tag{1}$$

where $f_b(s)$ is the beta distribution function of solar irradiance, s. The input parameters are p and q are calculated using the mean, μ and variance, σ of the solar irradiance data, and are defined as

$$q = (1-\mu)\left(\frac{\mu(1+\mu)}{\sigma^2} - 1\right) \tag{2}$$

$$p = \frac{\mu \times \beta}{1-\mu}, \tag{3}$$

where

$$\rho_s^y = \int_{s_y}^{s_{y+1}} f_b(s)\, \mathrm{d}\, s \tag{4}$$

is the probability of occurrence from the boundaries of solar irradiance at states s_y and s_{y+1}. The PV output power is evaluated as [30]

$$P_t^{pv} = N \times FF \times V_t \times I_t, \tag{5}$$

given that

$$FF = \frac{V_{mpp} \times I_{mpp}}{V_{oc} \times I_{sc}}, \tag{6}$$

$$V_t = V_{oc} - K_v \times T_t^c, \tag{7}$$

$$I_t = s_t\left[I_{sc} - K_I \times \left(T_t^c - 25\right)\right], \tag{8}$$

and

$$T_t^c = T_a + s_t\left(\frac{T_{nom} - 20}{0.8}\right). \tag{9}$$

The PV power output, P_t^{pv} at time t, is a factor of the fill factor, FF, the output voltage V_t and the output current I_t. The FF is defined in (6) where V_{mpp} and I_{mpp} represent the voltage and current at maximum power point, respectively, V_{oc} represents the open circuit voltage and I_{sc} is the short circuit current. Equations (7) and (8) define V_t and I_t, respectively and K_v is the voltage temperature coefficient, K_I is the current temperature coefficient, and T_t^c is the cell temperature in *celcius* which is defined in (9); s_t is the solar irradiance at time t, T_a is the ambient temperature, T_{nom} is the nominal operating temperature. The electricity prices are modelled as a log-normal distribution function to characterize the tariff at each hour. It is expressed as

$$f_b(P) = \frac{1}{P\sigma\sqrt{2\pi}} exp\left(-\frac{(\ln P - \mu)^2}{2\sigma^2}\right), \tag{10}$$

where the μ and σ represent the mean and standard deviation values, and P is the distribution function parameter. The Probability Density Functions (PDFs) are sliced into multiple intervals such that each interval produces a probability of occurrence and a mean value.

The backward technique is used to eliminate duplicate scenarios to reduce the number of scenarios generated. This technique also helps to reduce the computational burden of the whole algorithm [31].

B. OBJECTIVE FUNCTIONS

The considered collective objectives of the study are expressed by the following objectives

1) POWER LOSS INDEX

This objective is based on the power loss of the distribution network, before and after DG unit allocation. Power loss minimization has a significant impact on distribution networks, as improves the voltage profile. It is defined as [26]

$$P_t^{\text{LOSS}} = \sum_{i=1}^{N}\sum_{j=1}^{N} \alpha_{ij}\left(P_i^tP_j^t + Q_i^tQ_j^t\right) + \beta_{ij}\left(Q_i^tP_j^t - P_i^tQ_j^t\right) \tag{11}$$

where

$$\alpha_{ij} = \frac{r_{ij}}{V_iV_j} cos\left(\delta_i - \delta_j\right) \tag{12}$$

and

$$\beta_{ij} = \frac{r_{ij}}{V_iV_j} sin\left(\delta_i - \delta_j\right). \tag{13}$$

Here, i and j are the sending and the receiving bus indices respectively, while $Z_{ij} = r_{ij} + jx_{ij}$ represents the branch impedance from bus i to bus j, P and Q are the real and reactive power at each bus.

2) VOLTAGE DEVIATION

Voltage regulation and monitoring are a primary, yet important task of the distribution network operator, which is also a concern for the consumer given that appliances and meters. It is therefore essential to measure the voltage deviation while injecting the DG and BESS units. It is defined as [32]

$$VD = \sum_{i=2}^{N} |V_i^t - V_{ref}|, \tag{14}$$

where the reference voltage, V_{ref} is set at one and V_i represents the voltage at each bus after the addition of DG or BESS units.

3) VOLTAGE STABILITY INDEX

Voltage collapse is a phenomenon that is a consequence of random load increase in distribution networks. While integrating DG units, the VSI is applied to monitor the degree of voltage collapse of the system. The VSI needs to be maximized and is defined by [30]

$$\begin{aligned} vsi_{i+1,t+1} &= \left(|V_{i,t}|^2 - 2P_{i,t}R_{i,t} - 2Q_{i,t}X_{i,t}\right)^2 \\ &\quad - 4\cdot\left(P_{i,t}^2 + Q_{i,t}^2\right)\cdot\left(R_{i,t}^2 + {X_{i,t}}^2\right), \end{aligned} \tag{15}$$

$$VSI_{i,t} = \frac{1}{\min(vsi_{i+1,t+1})}, \tag{16}$$

$$VSI = \frac{1}{24}\sum_{i=2}^{N}\sum_{t=1}^{24} VSI_{i,t}. \tag{17}$$

4) INSTALLATION COST

The cost generated while sizing the DGs is very important. Therefore, there is a need to minimize it simultaneously with the sizing objective [33]–[35] which is

$$C_{\text{inst}} = \sum_{i=1}^{N}(n_i^{\text{PV}} \times c^{\text{PV}} + n_i^{\text{BESS}} \times c^{\text{BESS}}), \tag{18}$$

where n_{PV} and n_{BESS} are the unit number of solar PV and BESS units respectively, and c_{PV} and c_{PV} are the unit cost of solar PV and BESS units respectively.

5) OPERATIONAL COST

The operational cost includes the cost of maintaining DG and BESS units and the cost of power from the grid. It is formulated as [30], [36]

$$C_{\text{op}} = \sum_{y=1}^{Y}\sum_{t=1}^{24}\sum_{s=1}^{N_s} \rho_s(C_{t,s}^{\text{ss}} \times P_{t,s}^{\text{ss}} + PV_{t,s}^{OM}) \times \left(\frac{1+inf}{1+int}\right)^{y-1}, \tag{19}$$

where $C_{t,s}^{\text{ss}}$ represents the cost of power from the substation, $P_{t,s}^{\text{ss}}$ indicates the power from the substation, $PV_{t,s}^{OM}$ is the operation and maintenance cost of the PV-DG units, and ρ_s is the probability of scenario s. The *inf* and *int* respectively represents the inflation and interest rates over a 10-year period.

6) EMISSION COST

The emission cost objective is formulated as the real power from the substation [25], and can be defined as

$$\sum_{y=1}^{Y}\sum_{t=1}^{24} P_{t,s}^{\text{ss}} \times E_f, \tag{20}$$

where E_f is the emission in kg/kWh and $P_{t,s}^{\text{ss}}$ is the real power from the substation.

C. CONSTRAINTS

$$P_i^t = \sum_{j=1, j\neq i}^{N} Y_{ij} V_i^t V_j^t \cos(\theta_{ij} + \delta_j - \delta_i) \tag{21}$$

and

$$Q_i^t = \sum_{j=1, j\neq i}^{N} Y_{ij} V_i^t V_j^t \sin(\theta_{ij} + \delta_j - \delta_i). \tag{22}$$

Although there was no injection of reactive power, it is necessary to monitor boundaries during the injection of real power. The operating voltage at every bus must satisfy the range at all buses. The admittance on branch is represented as Y_{ij}. The bus voltage limit is formulated as

$$V_i^{min} \leq V_i \leq V_i^{max} \quad i = 1, 2, \ldots, N, \tag{23}$$

where V_i is the current voltage at bus i. Then V_i^{min} and V_i^{max} are 0.98 and 1.01 respectively.

The power flow balance is also considered. The total real power generation (from all DG and BESS units) must be equal to the total real load, total real power loss, and the BESS charging and discharging power [37]. Therefore, a balance of the power flow is calculated as

$$\sum_{i=1}^{N} P_i^{\text{DG}} + \sum_{j=1}^{J} P_j^{\text{Dis}} = \sum_{i=1}^{N} P_i^{\text{LOSS}} + \sum_{i=1}^{N} P_i^{\text{LOAD}} + \sum_{j=1}^{J} P_j^{\text{Ch}}, \tag{24}$$

where the P_j^{Dis} and P_j^{Ch} represent the BESS discharging and charging power to and from the grid from bus j.

D. BESS OPERATION CONSTRAINTS

Given that BESS's performance in any application depends on the BESS technology, this paper selected the Lead-acid battery technology. Lead-acid batteries are reliable, economically viable, and can be left on a float charge for more extended periods; hence their overcharging tolerance. These characteristics are well suited for the ESS integration in distribution networks.

For a practical scenario, the BESS model is subject to certain constraints such as SOC limit prevents excessive charging or discharging from the battery, and defined as [38]

$$SoC^{min} < \frac{E_t^B}{E_t^{BA}} < SoC^{max}, \tag{25}$$

where the SoC^{min} and SoC^{max} are 0.2 and 0.9 respectively. The charging and discharging power are specified as [39], [40]

$$E_{t+1}^B = \begin{cases} E_t^B - P_t^B \triangle t \eta_{Bc} & P_t^B \leqslant 0 \\ E_t^B - \dfrac{P_t^B \triangle t}{\eta_{Bd}} & P_t^B > 0, \end{cases} \tag{26}$$

where E_t^B is the energy of the BESS unit at time t, P_t^B is the charging power of the BESS unit at time t, $\triangle t$ is the time interval, η_{Bd} and η_{Bc} are the discharging and charging efficiency of the BESS unit respectively, the battery power is limited by

$$E^{\min} \leqslant E_{i,t}^B \leqslant E^{\max}, \tag{27}$$

where $E_{i,t}$ is the energy of the i^{th} BESS unit at time t.

IV. OPTIMIZATION STRATEGY

A. MULTISTAGE MULTIOBJECTIVE FRAMEWORK IN AN OPTIMAL INTEGRATION PROBLEM IN DISTRIBUTION NETWORKS

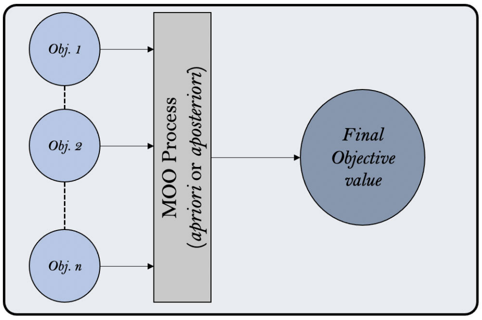
In the optimal integration problem, objective functions are categorized into three collective objectives: grid performance (or technical benefits), economic benefits, and environmental benefits. Each of these collective objectives can consist of many objective functions except for the environmental benefits, which only deals with the greenhouse gas emission cost. The proposed framework categorically handles the adopted objectives according to their respective collective objectives. Fig. 1 shows the conventional and proposed method for handling multiple objectives.

As seen in the Fig. 1a, the conventional approach, irrespective of the approach, the objectives are fed into the MOO framework without considering the collective objectives. Fig. 1b illustrates the initial handling of categorized objectives, followed by the final handling of the collective objectives. The first stage of optimization adopts the apriori approach, which implements the Weighted Sum Aggregate method (WSA) to all concerned objectives to get subfinal values. The subfinal values represent the value for each collective objective, which are handled using a TOPSIS approach.

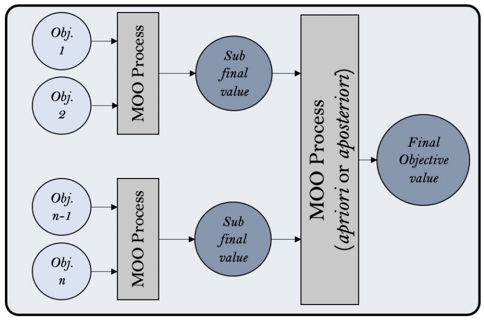
B. MULTIOBJECTIVE FRAMEWORK USING THE TOPSIS APPROACH

This process is merged with the multistage multiobjective framework to produce non-dominating solutions. The TOPSIS method is used to solve the multiobjective optimal integration problem in distribution networks. This method applies the Euclidean geometry between positive ideal solutions (P^{+ve}) and the negative ideal solutions (P^{-ve}). The shortest distance from $P^{+ve}$and longest from P^{-ve} helps identify the best compromise solution from the Pareto optimal set. The following steps explain the process of the TOPSIS method.

Step 1 all objectives are transformed into a nondimensional entity and stored in a normalized decision matrix. The



(a) Conventional approach to handle multiple objectives



(b) Proposed categorical approach to handle multiple objectives

FIGURE 1. **Approaches for handling multiple objectives in an optimal integration problem in distribution networks.**

normalization is defined as

$$D_{ij} = \frac{F_{ij}}{\sqrt{\sum_{i\in M, j\in N} F_{ij}^2}}, \tag{28}$$

where M represents the number of alternatives and F_{ij} is the i^{th} alternative value of the j^{th} objective.

Step 2 as an option, weights are assigned to determine the importance level of all objectives. The element in the decision matrix are determined as

$$WD_{ij} = W_j D, \tag{29}$$

where the sum of weight W_j of the j^{th} objective is equals to one.

Step 3: The values of P^{+ve} and P^{-ve} which represents the best and worst solutions of the objective functions. They are expressed as

$$P^{+ve} = B_1^+, B_2^+, \ldots, B_M^+ \tag{30}$$

$$P^{-ve} = B_1^-, B_2^-, \ldots, B_M^- \tag{31}$$

where

$$B_j^+ = \begin{cases} max(B_{ij}), & \textit{if objectives are benefits} \\ min(B_{ij}), & \textit{if objectives are cost-wise} \end{cases}$$

$$B_j^- = \begin{cases} max(B_{ij}), & \textit{if objectives are cost-wise} \\ min(B_{ij}), & \textit{if objectives are benefits} \end{cases}$$

Step 4 Find the Euclidean distance from the ideal solutions of P^{+ve} and P^{-ve} to their alternative solutions, P_i. It is represented as

$$d_i^+ = \sqrt{\sum_{J=1}^{N} (B_{ij}^2 - B_j^{+2})} \tag{32}$$

$$d_i^- = \sqrt{\sum_{J=1}^{N} (B_{ij}^2 - B_j^{-2})} \tag{33}$$

Step 5 Calculate the relative closeness index, ζ based on the Euclidean distance from step 4, and expressed as

$$\zeta = \frac{d_i^-}{d_i^+ + d_i^-} \tag{34}$$

Step 6 Select the best solution based on the highest value of ζ.

C. PROPOSED ALGORITHM

1) OVERVIEW OF THE WHALE OPTIMIZATION ALGORITHM

The WOA was developed by Mirjalili [41] and has been applied successfully to many optimization problems, including the optimal sizing problem. The algorithm involves the feeding nature of whales (specifically humpback whales). According to whales' intelligent behavioural nature, they use a specific technique to target small fish that are close to the sea surface. This technique is called the bubble net feeding, where whales swim round a school of fish (prey) to form a 9-shaped bubble trail. In this algorithm, an initial solution is termed as the objective prey and assumed as the current best solution. During iterations, other whales update their positions towards the best whale position. The WOA is mathematically modelled in three sections. (i) encircling prey (ii) bubble net hunting method and (iii) search the prey.

a: ENCIRCLING PREY

This form of hunting is based on a circular positioning around a prey. The position of the whale moves towards the prey in a step-wise manner. It can be modelled as

$$\overrightarrow{X}_{t+1} = \overrightarrow{X}_t^* - A \cdot \overrightarrow{D}, \tag{35}$$

where $A = 2a \cdot r - a$ and a is linearly reduced from 2 to 0, and $r \in [0, 1]$ where r can take up random in 0 and 1 interval. $\overrightarrow{D} = |C \cdot \overrightarrow{X}_t^* - \overrightarrow{X}_t|$, is the distance between the current whale position and the best whale position where $C = 2 \cdot r$ is a random parameter that is updated at every round of iteration. The current iteration is denoted by subscript t and $t+1$ for the next iteration. $\overrightarrow{X}$ represents the position vector and $\overrightarrow{X}^*$ represents the current best solution.

b: BUBBLE NET HUNTING METHOD

This method is the exploitative phase of the algorithm. This behaviour is attained by decreasing the value of a, as explained in Section IV-C1.a. This behaviour is modelled

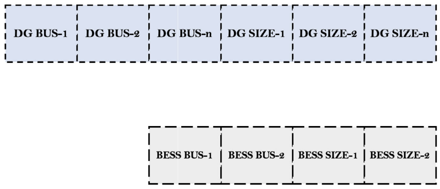


FIGURE 2. Structure of a whale chromosome for each population.

as shown in Equation (35). The spiral equation is created as follows:

$$\overrightarrow{X}_{t+1} = \overrightarrow{D}' \cdot e^{bl} \cdot cos(2\pi l) + \overrightarrow{X}^{*}. \tag{36}$$

The component $cos(2\pi l)$ simulates the spiral shape of the whale's path, l takes a value between [-1,1], and b is a constant (usually 1) that gives the spiral shape regular definition. Since the whales can be shrink towards a prey or move spirally, there is a need to model this behaviour. A probability of 50% is chosen for both feeding mechanisms. The model is as follows:

$$\overrightarrow{X}_{t+1} = \begin{cases} \overrightarrow{X}^{*}_{t} - A \cdot \overrightarrow{D}, & p < 0.5 \\ \overrightarrow{D} \cdot e^{bl} \cdot \cos(2\pi l) + \overrightarrow{X}^{*}_{t} & p \geqslant 0.5 \end{cases} \tag{37}$$

where p is a random number between [0, 1].

c: SEARCH FOR PREY

The WOA uses this technique to overcome a possible local optimum mainly. This is called the exploration phase, where whales search randomly according to check other possible solutions. If the best solution is not global, the search agent can still find other better solutions in the global space. The use of this approach is dependent on the value of A. If the value of A is lesser than 1, Equation (35) is triggered, else Equation (38) is triggered, as shown below.

$$\overrightarrow{X}_{t+1} = \overrightarrow{X}_{rand} - A \cdot \overrightarrow{D}, \tag{38}$$

where $\overrightarrow{D} = \left| C \cdot \overrightarrow{X}_{rand} - \overrightarrow{X}_{t} \right|$, $\overrightarrow{X}_{rand}$ represents the random whales' position in current iteration, $\overrightarrow{D}$ is the distance between current whale position, $\overrightarrow{X}_{t}$ and the randomly selected whales' position while C is a random parameter generated anew in every round of iteration.

2) PROPOSED HYBRID WOA-GA APPROACH

The WOA-GA is a hybrid method to find improved solutions from the optimal integration of DG and BESS units. The optimal integration of units in distribution networks is a combinatorial problem due to the discrete nature of finding optimal locations, and a non-convex problem due to the non-linear nature of power constraints while finding optimal DG unit sizes. The WOA-GA exploits the GA's binary encoding attribute and the fast convergence attribute of the WOA, which is excellent for solving the complex and large iterative computations. Fig. 2 shows how the problem is structured in the WOA-GA algorithm.

Firstly, the WOA mechanism finds the optimal sizes for DG units for pre-selected bus locations. The WOA possesses a fast convergence capability, which is an excellent attribute for solving the complex and large iterative computations.

The second stage uses the GA to find the optimal locations of the DG and BESS units, through an integer-based technique. The GA deploys the crossover and mutation operators to generate a child for each parent in a population. A condition is set for each offspring to replace their parent if they have a better fitness value. Otherwise, the parent is rolled over to the next generation. The tournament selection process is used to select the parents in the current generation while a heuristic crossover operator is adopted as applied in [42], is used to produce new whales solution. Lastly, a vectorized mutation operator, as in [43], is used to improve the health of each whale. For the crossover rate (as in [44]), we consider a pair of parent $x^1 = \{x_1^1, x_2^1, \ldots, x_n^1\}$ and $x^2 = \{x_1^2, x_2^2, \ldots, x_n^2\}$ to produce an offspring $u^1 = \{u_1, u_2, \ldots, u_n\}$, therefore

$$u_i = \sigma(x_i^2 - x_i^1) + x_i^2, \tag{39}$$

where σ is a uniformly distributed value in the range [0,1] and parent x^2 would have a better fitness value than parent x^1. This kind of crossover operator utilizes parents' fitness value to produce offsprings; hence, the crossover probability is relatively proportional to the fitness value. The mutation operator is adopted from the differential evolution algorithm and expressed as

$$\overrightarrow{V}_i^G = \overrightarrow{X}_{r_1^i}^j + F \times (\overrightarrow{X}_{r_2^i}^G - \overrightarrow{x}_{r_3^i}^G), \tag{40}$$

where $\overrightarrow{V}_i^G$ is the donor vector created from the target vector $\overrightarrow{X}_i^G$ and F is the scaling parameter for controlling the difference vectors. The notations r_1^i, r_2^i, and r_3^i are random integers in the range $[1, N_{var}]$, where N_{var} is the number of decision variables.

3) IMPLEMENTATION OF THE MULTIOBJECTIVE WOA-GA

This section discusses the implementation of the proposed multi-stage multiobjective WOA-GA framework in the optimal integration of DG and BESS units in a distribution network. The variables and parameters of the WOA-GA are presented in Table 2. To solve the integration problem using the proposed framework, a pod of whales is modelled as a set of solutions. Each whale has a chromosome representing their fitness in terms of DG and BESS units locations and their sizes. Fig. 2 illustrates the structure of each whales' chromosomes. The first part of the whales' chromosome represents the DG or BESS location and the second part represents the DG or BESS sizes, which are used as the decision variables. The whales' population is illustrated as

$$\overrightarrow{X}_{\text{pop}} = \begin{pmatrix} L_1^1 & \cdots & L_N^1 & S_1^1 & \cdots & S_N^1 \\ L_1^2 & \cdots & L_N^2 & S_1^2 & \cdots & S_N^2 \\ \vdots & \cdots & \vdots & \vdots & \cdots & \vdots \\ L_1^M & \cdots & L_N^M & S_1^M & \cdots & S_N^M \end{pmatrix}, \tag{41}$$

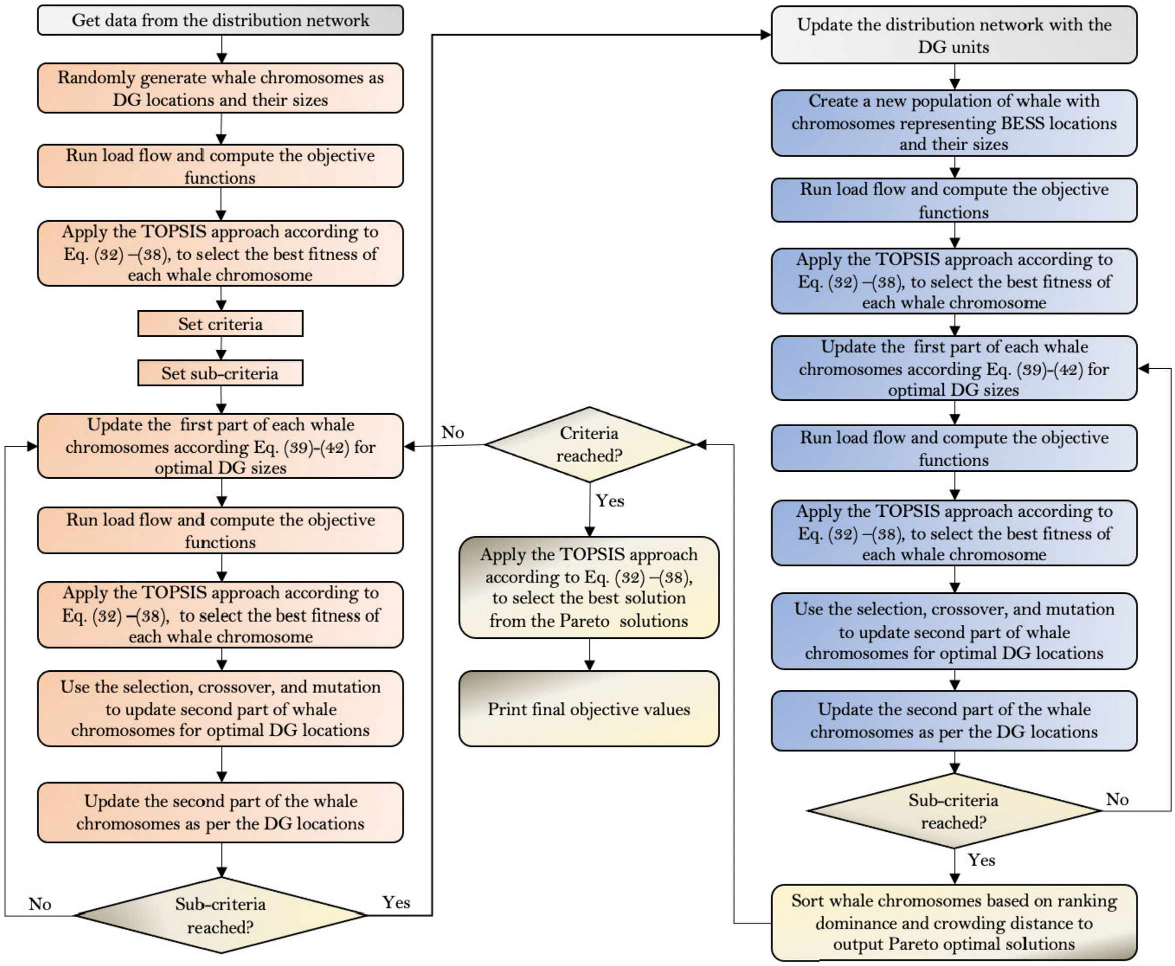


FIGURE 3. Flowchart of the proposed MOWOAGA implementation to the optimal DG and BESS unit integration.

where L_N^M is the total N number of DG or BESS unit location for M number of whales, and S_N^M represents the sizes of the proposed DG or BESS units.

The following steps are involved in the implementation of the hybrid WOA-GA.

1) Read the distribution network data; Power at each bus, Load at each bus, Resistance on each branch, Reactance on each branch.
2) Generate an initial population of whales with chromosomes representing DG locations and sizes.
3) Update the distribution network by injecting the DG sizes (corresponding to their rated power) in the suggested bus locations
4) Run the backward/forward load flow algorithm to determine the new voltage magnitude and real power at each bus.
5) Calculate the objective functions using the new parameters obtained from step 4.
6) Update the chromosomes of all whales in the population (i.e. the DG sizes) according to step 3 - 4.
7) Select the whale with the best chromosome for the second phase.
8) Use the GA to update the DG location.
    - Choose the best two whales as parents
    - Perform the crossover operation to generate offspring from the parent
    - Perform the mutation operation to obtain offsprings with better chromosomes
    - Stop when sub-criteria is reached
9) Generate another population of whales with chromosomes representing BESS locations and sizes.
10) Inject the BESS units into the updated distribution network (with the DG units).
11) Run the load flow algorithm to determine the new voltage magnitude and real power generated at each bus.
12) Update the distribution network according to step 4 - 8.
13) Stop if criteria are reached.
14) Print out final objective values.

These steps are illustrated as a flowchart in Fig. 4.

V. NUMERICAL RESULTS

The proposed algorithm is evaluated on the IEEE 33-bus distribution test network (See Fig. 4), with a total real

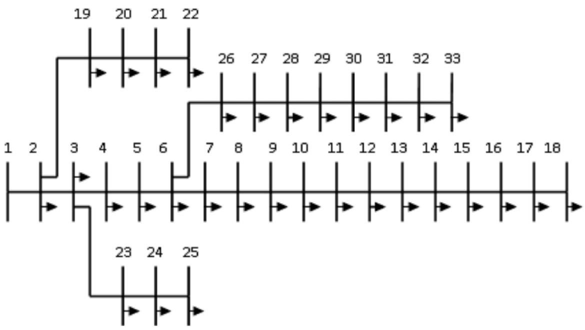


FIGURE 4. A single line diagram of the IEEE 33-bus test distribution network [45].

TABLE 1. Parameters of the system model.

Parameters	Value
Solar PV installation cost	15,000
Solar PV O&M cost	148.55
BESS SoC_{min}, SoC_{max}	0.2, 0.9
Duration of project (yr)	10
Voltage deviation tolerance	0.05
Interest rate	3.5
Inflation rate	3.1
Carbon emissions (Kg/Kwh)	0.55428

TABLE 2. Parameters of the WOAGA.

Parameters	Value/Type
Population size	100
Generations	200
F	0.75
Selection type	Tournament
Crossover type	Heuristic
Mutation type	Vectorized

and reactive power of 3.72 MW and 2.3 MVaR respectively. The voltage and apparent power are 12.66 KV and 100 MVA respectively. All buses are feasible for installing PV-DG or BESS units except the first bus reserved for the substation. The real power from PV-DG units is based on the PV module characteristics, temperature, and solar irradiance, which is considered as an uncertainty; hence modelled as a beta PDF.

The model parameters is listed in Table 1 and the proposed WOAGA, compared to its primary variants; WOA and GA, using the relative parameters is shown in Table 2. This paper proposes a new sub-framework for handling multiple objectives across different collective objectives in an optimal integration problem. As discussed in Section IV-A, there is a need to always consider objectives in the sense of the technical aspect, economic aspect, and due to the rise in reducing carbon emission, environmental aspects. The Pareto front for the collective objectives in a feasible region is shown in Fig. 5. Theoretically, all Pareto optimal solutions, even in a constrained space, should follow a uniform distribution in a multiobjective projection. The combination of TOPSIS and crowding distance substantially projects this characteristic.

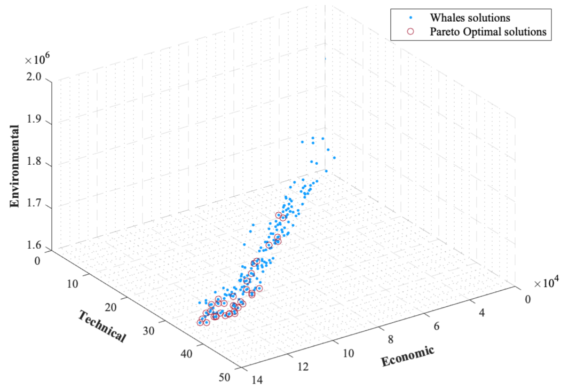


FIGURE 5. Pareto optimal solutions and final whale solutions.

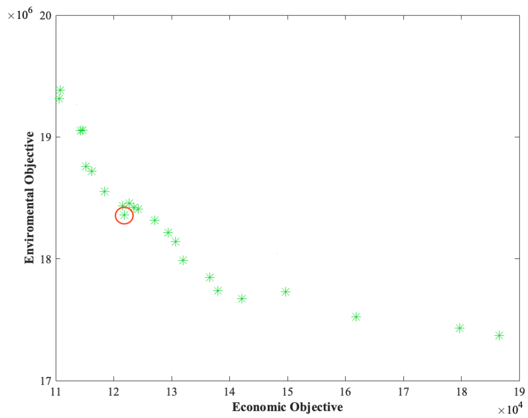


FIGURE 6. Pareto optimal front the economic and environmental objective.

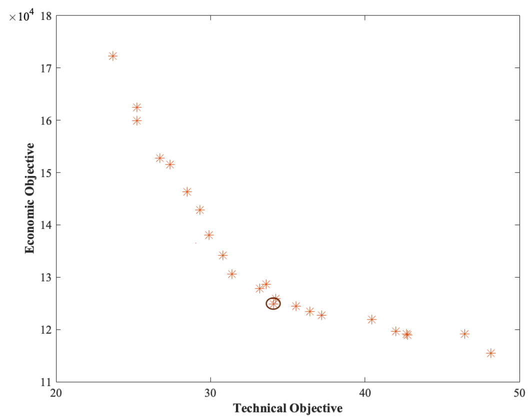


FIGURE 7. Pareto optimal front the economic and technical objective.

The TOPSIS approach was also used to select the best trade-off solution among the Pareto optimal solutions. It is to note that the final compromise solution is neutral to any collective objective; hence no weights have been applied in step 3 of the TOPSIS approach (See Section IV-B). However, weights can be applied at the request of the decision-maker to show other alternative results.

Further Pareto projections can be seen in Figs. 6 and 7, where the economic/environmental and technical/economic

TABLE 3. Final objective values for optimal location and sizing of PV-DG and BESS units.

Approach	PL	VS	VD	IC	OC	EC
Direct	101.2	0.9610	0.0022	61976.97	75749.63	1876211
Categorized	101.6	0.9610	0.0023	58294.39	71248.71	1823457

TABLE 4. Comparison of algorithms performance on collective objectives.

Algorithm	Collective Objectives		
	Technical	Economic	Environmental
	PL, VS, VD	IC, OC	EC
WOAGA	33.853	12954.31	1823457
WOA	35.005	13217.78	1873441
GA	35.239	13291.24	1865168

objectives are projected on a two-dimensional plane respectively. It is seen that to focus more on the technical objectives will be a trade-off for the economic objective. In the same vein, improving the environmental objective, that is reducing carbon emissions, will require more cost; hence a proportional increase in the economic objective.

Table 3 shows the comparison of the final objective values from the conventional direct method and the proposed categorical method. Both approaches are compared based on the MOWOAGA technique, which produces a final fitness value by selecting the best compromise from Pareto optimal solutions. It can be seen that the direct approach produces lesser power loss and voltage deviation values than the categorical approach. The better technical objective values may be influenced by the higher number of (related) technical objectives. Although not on the same scale, the objective values are factored by related parameters, such as voltage, power, and current. On the other hand, the categorical approach produces a more reduced installation, operational cost, and emission cost. A practical scenario like the DG planning problem should consider closely related and conflicting objective functions in producing Pareto optimal solutions; else, a higher number of closely related objectives than other objectives may cause a bias even without applying a preference method. The obtained results are shown in Table 4 where each collective objective values are displayed. The WOAGA is the spotlight as it optimizes all collective objective objectives better than the WOA and GA. According to the table, the WOAGA yields the technical, economic, and environmental objectives as 33.853, 12954.31, and 1823457, respectively.

Table 5 shows the optimal DG and BESS unit locations, their sizes, and the effect on power loss (PL), voltage deviation (VD), and voltage stability (VS). It is seen that the WOAGA produces an optimal location at bus 11, 19, 26, and 32, with their power capacity as 914.2 kW, 865.1 kW, 959.7 kW, and 990.8 kW respectively, and BESS location 6, 26 with their sizes as 791.2 kW and 831.4 kW respectively, which produces favourable technical objective values than the WOA and GA. The GA binary operation's effect can also be seen through the suggested BESS location from the WOAGA and the GA. Compared to the study in [12] where the total power loss is lower without PV-DG integration than

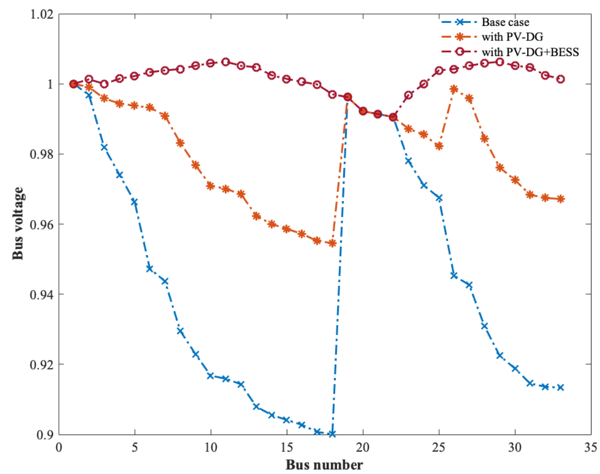


FIGURE 8. A 24-hour mean voltage profile for different cases.

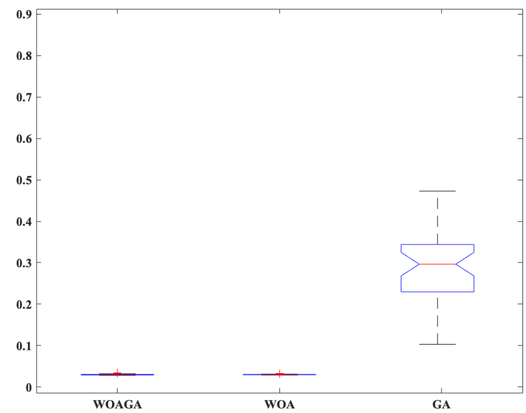


FIGURE 9. Performance of the each algorithm in obtaining the minimum voltage deviation of the distribution network.

with PV-DG units, the total power loss is further reduced when the PV and BESS are integrated simultaneously into the distribution network.

Fig. 8 shows the comparison of mean voltage profile of a full day for three cases; the base case, when DG unit is integrated, and when DG and BESS units are integrated. It can be seen that the integration of DG and BESS units improves the distribution networks' voltage profile.

Different statistical methods are used to understand the proposed algorithm's performance for solving the optimal integration of DG and BESS units in a distribution network. Fig. 9 shows the box plot for the voltage deviation outputs when each algorithm are run 50 times. It is seen that the performance of the WOAGA and WOA are very consistent in producing the optimal values while the GA has a lower consistency with a larger interquartile range.

The convergence characteristics of each algorithm are displayed in Fig. 10. It is observed that the WOAGA, although not faster than the WOA to converge, converges faster than the GA and eventually produces the best value at the 78^{th} iteration. This outcome is attributed to the shared attribute from the WOA and the GA.

TABLE 5. Comparison results for optimal location and sizing of PV-DG and BESS units.

Algorithm	DG location	Sizes (KW)	BESS location	Sizes (KW)	PL	VS	VD
WOAGA	11	914.2	6	791.2	101.6	0.9610	0.0023
	19	865.1	26	831.4			
	26	959.7					
	32	990.8					
WOA	11	896.3	12	679.9	105.1	0.9511	0.0112
	20	711.1	31	834.1			
	25	1064.6					
	30	839.6					
GA	6	951.4	6	804.2	105.8	0.9524	0.0216
	13	560.6	26	812.1			
	25	1087.6					
	31	779.7					

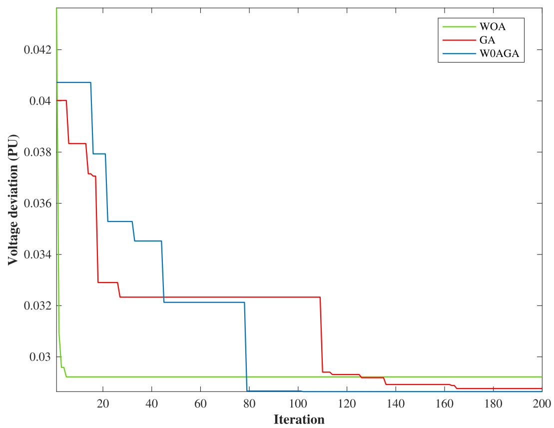


FIGURE 10. Convergence characteristics of each algorithm.

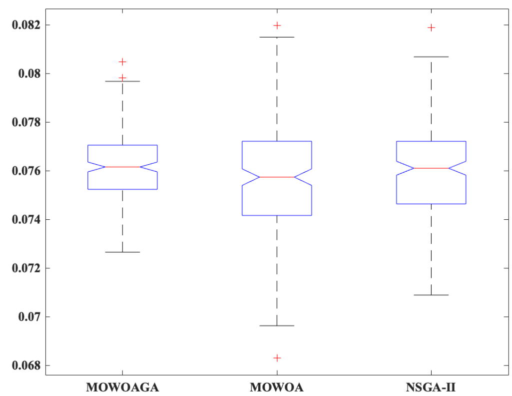


FIGURE 11. Convergence characteristics of the each algorithm.

TABLE 6. Statistics for the grid performance of the distribution network.

	Technical Objective				
Algorithm	**Mean**	**Best**	**Worst**	**Std.**	**C.T.**
WOAGA	34.446	33.853	36.004	0.976	204
WOA	35.257	35.005	36.242	1.22	254
GA	35.342	35.239	36.211	1.03	241
	rank-sum test				
p-value	0.01				

Each algorithm was run 50 times, and a Kruskal Wallis rank-sum test was used to confirm a statistically significant result and a box plot to visualize the performance from each algorithm. Table 6 shows the mean and standard deviation with their p-values. It is also noticed that, unlike some hybrid algorithms where complexity is traded-off with performance, the WOAGA uses the unique features of the WOA and GA to produce better trade-off solutions; hence the better computational time from Table 6.

Furthermore, the performance of the multiobjective methods is analyzed to observe the uniform spread of Pareto solutions. In context, the single objective analysis is similar to the multiobjective space since they both involve the understudy of the change in the distribution of solutions in relation to different techniques. The multiobjective analysis tends to reveal the quality of non-dominated solutions, which is determined mostly by their spatial nature. Since this paper proposed a new multiobjective framework that involves a double production of Pareto optimal solution selection, it is necessary to measure the quality of the solutions; hence, the spacing metric (SP-metric) is adopted for this purpose. SP-metric is the progressive distance between each solution and its closest neighbour. The computed SP-metric for each algorithm is displayed as a box plot in Fig. 11. It can be seen that the MOWOAGA is the centerline of the boxes are almost in line with each other, which shows that the median is similar; hence, the techniques follow the same distribution pattern. The box plot validates the proposed approach as it is observed that the MOWOAGA box has the shortest height, which means a better SP metric than other algorithms. In other words, the MOWOAGA produces non-dominating solutions that are uniformly distributed and close to each other. The TOPSIS approach is responsible for this even and compact distribution due to its consideration of best and worst solutions for final decision value, making it easier for the crowding distance to sort the Pareto optimal solutions at the final stage.

VI. CONCLUSION

This paper developed a novel approach to seamlessly coordinate the interaction between the allocation of the PV-DG and BESS units in a distribution network and developed the

MOWOAGA, a new multiobjective metaheuristic algorithm, to decompose the discrete and nonconvex optimal DG and BESS unit integration problem. In addition to the algorithm, a new multi-stage framework is proposed for handling multiple objectives in a collective manner. The MOWOAGA is validated by applying it to the simultaneous integration of PV-DG and BESS units in the IEEE 33-bus test network, which compares favourably with other variants of the algorithm, such as WOA and GA. The proposed algorithm utilizes the GA's powerful binary operation to manoeuvre the optimization problem's discrete nature and inherits this approach and uses the WOAs' mechanism to produce a faster convergence. The effect is seen in the convergence curve where it converges better than the GA and produces a better fitness value than the WOA. The quality of the non-dominating solutions produced by the MOWOAGA is measured using the SP metric, which shows superiority than the WOA and GA.

The different variation of weights assignment to all objectives in a multi-stage multiobjective optimization framework could be studied in future works. Future work could also implement Pareto optimal solutions in the first and second stage of the multi-stage framework. It will be interesting to see the interactions between the two stages.

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